Forecaster perceptions and climatological analysis of the influence of convective mode on tornado climatology and warning success

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## Abstract

Tornadogenesis occurs in a variety of storm types, or convective modes, each having a unique climatology and challenges in their detection and warning. Some warnings result in false alarms, meaning no tornado occurred within the warning polygon. We used a mixed-methods approach to assess how convective mode—discrete supercell, cell in cluster, cell in line, or quasi-linear convective system (QLCS)—affects the tornado climatology and National Weather Service (NWS) procedures within three County Warning Areas (CWAs): Memphis (MEG), Nashville (OHX), and Morristown (MRX). We used three data sets: tornadoes (2003–2014) categorized by convective mode, false alarms (2012–2016) categorized by convective mode, and 11 interviews of NWS forecasters. The CWAs had no significant difference in mode frequency when removing replication from multiple-tornado events. However, when outbreaks were included, discrete supercell and QLCS signals were identified in MEG and OHX, respectively. Convective mode, season, and time of day were strongly associated. Tornadic discrete supercells followed a traditional severe weather pattern of spring and daytime occurrences, and caused fewer false alarms. More QLCS tornadoes happened at night and in winter. Cells in lines and clusters accounted for larger proportions of events in the false alarm data set than the tornado data set. Forecasters noted challenges in detecting tornadoes in convective modes other than discrete supercells, including short-lived QLCS tornadoes. Key forecaster concerns other than convective mode included storm speed, outbreaks, and lack of ground-truthing at night. Forecasters differed in their motivation to either warn on every tornado or avoid false alarms. *Key words: tornado, climatology, supercell, QLCS, false alarm*

## Introduction

Tornadogenesis occurs in a variety of storm types, or what many researchers refer to as convective modes. Convective modes differ in appearance, structure, and other characteristics, and result from different conditions in their ambient environment (e.g. amount of instability or wind shear). A quasi-linear convective system (QLCS) is a convective mode wherein weak tornadoes rapidly form and decay, stemming from embedded rotation that often appears in only one or two radar scans (Trapp et al. 2005). Meanwhile, rotation within a discrete supercell convective mode is easily spotted on radar. This gives forecasters time to make assessments and issue warnings before the supercell's impending tornado—which may be wide, intense, and long-lasting—becomes an immediate threat to life and property (Brotzge et al. 2013). Because of these differences, each mode comes with a distinctive set of challenges to accurately and precisely detect and warn for a tornado (Brotzge et al. 2013). They also have dramatically different societal effects. Supercells are responsible for 90 percent of tornado fatalities from 1998–2007 (Schoen and Ashley 2010) and caused more financial loss from 2003–2004 than tornadoes from other convective modes (Brotzge et al. 2013).

We used a mixed-methods approach by pairing a climatology of tornadic and false-alarm convective modes with interviews with National Weather Service (NWS) forecasters. We quantitatively and qualitatively assessed the effect convective mode has on tornado detection and warning in three NWS County Warning Areas (CWAs): MEG in Memphis, OHX in Nashville, and MRX in Morristown. Pairing these results allowed us to address the climatological and operational aspects of potentially tornadic convective modes across the state. We had two hypotheses: 1. The three CWAs would have different climatologies of tornadic convective modes, and 2. Warning challenges would increase for non-super cellular events, as demonstrated by false alarm analysis and forecaster interviews.

## Background

### Tornado warnings

A tornado warning is issued by a NWS Weather Forecast Office (WFO) when a tornado has been visually spotted or radar-indicated (NOAA n.d.), with the goal of urging the public to take protective action. Each WFO is responsible for a set of counties, referred to as their CWA. Initially, tornado warnings were county-based, meaning if a tornado was expected to affect any part of the county, the entire county was warned. In October 2007, the NWS moved to a storm-based method, where warnings were drawn as polygons outlining areas with the greatest threat (NOAA 2007). This change reduced the size of warning polygons, time spent under warnings, false-alarm ratios (FARs; discussed in detail in the next section) and a warning's economic impact (Sutter and Erickson 2009).

The decision to issue a warning is complex, as is the public's decision on whether to take protective action (see Figure 1 of Brotzge and Donner (2013)). Weather radar and storm-spotter verification are the primary data used to identify potential tornadogenesis (Brotzge and Donner 2013). Other data, including population vulnerability, tornado climatology, event anticipation, Storm Prediction Center (SPC) guidance, and history (Brotzge and Donner 2013), are also included in warning decisions. Some of these data are subjective or personal in nature and can vary among forecasters. Additionally, forecasters differ in experience and knowledge, which may lead to differences in decision-making (Andra, Quoetone, and Bunting 2002). The ultimate decision to warn is therefore inherently multifaceted, drawing heavily on the cumulative experience of the forecaster. Further complicating the matter, even with the best skill there are still fatalities. During the 2011 outbreak, for example, all tornado fatalities occurred from tornadoes that were within tornado warning polygons (NOAA 2011).

Warning success is often calculated using three parameters: FAR, probability of detection (POD), and lead time. Forecasters balance these three parameters, with the ultimate goal to detect all tornadoes, have no false alarms, give the longest possible lead-time, and draw the most effective warning polygon (Brotzge and Donner 2013). “False alarm” is the term for when a tornado warning is issued but no tornado occurs within the warning polygon. The FAR is the number of false alarms divided by the number of warnings, thus a percentage of warnings that did not verify. The national FAR was between 68 and 80 percent each year from 1998–2018 (NOAA 2019). Issues may arise when using FAR data without sufficient context. For example, see the discussion on “close calls” by Barnes et al. (2007), which details why the “hit or miss” nature of a false alarm does not accurately depict what occurs in the environment or how it affects the public. While their statistics may be misleading at times, false alarms are important to analyze because they may affect public response to future severe weather events, as numerous false alarms may contribute to alarm fatigue or a “cry wolf” effect. Simmons and Sutter (2009) found that tornadoes occurring in areas with higher FARs killed more people, and that in past periods when forecasts notably improved, thus resulting in lower FARs, fatalities and injuries significantly decreased. Interestingly, FAR affects behavioral response even though public perceptions of FAR are often incorrect (Trainor et al. 2015).

Some WFOs or individual forecasters may consciously consider FARs in their decision-making. This may ultimately happen at the expense of the POD, which quantifies the proportion of confirmed tornadoes that are successfully warned for in advance (Brooks 2004). The national

POD was between 57 and 80 percent each year from 1998–2018 (NOAA 2019). Simmons and Sutter (2009) reported that further reduction of FAR would not reduce fatalities given that it would also likely reduce POD. FAR is often highest during times with low POD because limitations in knowledge, technology, and storm spotter availability can impede a forecaster's ability to detect and warn for tornadoes in particular environments (Brotzge, Erickson, and Brooks 2011).

**Convective mode studies: Climatology and effects on warnings**

By analyzing convective modes, researchers provide information about the types of storms that are more hazardous or challenging to forecast. A major challenge to analyzing convective modes is the restraint related to the time it takes to classify storm types. This results in brief study periods, often confined to one or a few years. A longer database of convective mode classifications (2003–2011), which was tediously created by the SPC (see Smith et al. (2012)), has been used in the past and also for this work. For a previous study (Brotzge et al. 2013) and for our own work, it does not entirely overlap the span of the other data sets being used, and thus is not always used to its full potential. Additionally, eight years is still relatively short for a climatology. A second challenge is that convective mode classification relies on archived radar data, thus it is necessary for a storm to be in a place and time with reliable radar coverage. This limits the data temporally and spatially, as well as its precision. Finally, when researchers take on convective-mode classification, it is subjective in nature as there are many different ways to categorize storms. To minimize subjectivity issues, people often work in teams and attempt to adhere to quantifiable thresholds and descriptive characteristics (Gallus, Snook, and Johnson 2008; Schoen and Ashley 2010).

Smith et al. (2012) found that, between 2003 and 2011, more tornadoes were caused by discrete and cluster right-moving cells across the United States than QLCS and disorganized convective modes. The proportion of tornadoes spawned by a QLCS, as opposed to a cell, varies greatly by location. Trapp et al. (2005) found that 18 percent of the 3828 tornadoes they studied from 1998–2000 occurred in a QLCS, but in some locations up to half of the tornado days were associated with QLCSs. Smith et al. (2012) showed that QLCS tornadoes are most common in the Southeast and Midwest. Other differences between these modes include tornado intensity and seasonality. Supercells usually cause most of the significant (EF2+) tornadoes and dominate the springtime climatology, while QLCS tornadoes are weaker and the most prominent tornado-producer in January (Smith et al. 2012).

Previous literature has shown that convective mode affects the ability of NWS forecasters to accurately forecast, detect, or warn for tornadoes. QLCSs are challenging because of their size and lack of prominent rotation. Tornadoes have the potential to initiate rapidly at any point along their ≥100-km length (Trapp et al. 2005) making detection and warning dissemination very difficult. Brotzge and Erickson (2010) showed that tornadoes from linear and other convective modes that were hard to classify (e.g. transitional modes, those evolving into a line) were least likely to be warned on before tornadogenesis. These results were supported by Brotzge et al. (2013), which showed POD dropped from 87.9 percent for discrete supercell to 48.6 percent for QLCS tornadoes. The worst POD (44.2 percent) was for tornadoes from disorganized convection. This work also documented the effect of convective mode on lead time, showing average lead time decreased from 17.8 minutes for discrete supercell to 12.3 minutes for QLCS tornadoes. The worst lead time (11.7 minutes) was associated with disorganized convection

(Brotzge et al. 2013). We are unaware of any research specifically assessing the relationship between convective mode and false alarms.

FAR and POD statistics show that convective mode explains only part of the variability in forecast, detection, and warning challenges. FAR is largest (Brotzge, Erickson, and Brooks 2011) and POD lowest (Brotzge and Erickson 2010) during non-peak storm periods, e.g., at night and during the winter, and on less-active, non-outbreak days. Distance from radar, population, and county size were also significant predictors of FAR, but these results were prior to the onset of storm-based warnings and during a time of county-based warnings (Brotzge, Erickson, and Brooks 2011). FARs (Brotzge, Erickson, and Brooks 2011) and tornadoes occurring without warning (Brotzge and Erickson 2010) are greater in the Southeast than the Great Plains. This may relate to the higher number of out-of-season and nocturnal tornadoes in the Southeast region, as well as non-meteorological factors such as visibility.

## Data and Methods

### Study Area

We analyzed the convective mode climatology and effects in the three CWAs of the WFOs located in Tennessee (Figure 1). The offices are located in Tennessee, but they adhere to county, not state, boundaries, so they also warn for some counties outside of the state. Additionally, some out-of-state offices warn for a few Tennessee counties. MEG warns for western Tennessee, northern Mississippi, northeast Arkansas, and a small part of southeast Missouri. OHX warns for most of middle Tennessee. MRX warns for eastern Tennessee, southwest Virginia, and a small part of southwest North Carolina. These CWAs experience relatively different tornado climatologies, with the most notable difference being the lessened tornado frequency in MRX (Brown, Ellis, and Bleakney 2016) and increased fatalities in MEG (Ashley, Krmenec, and Schwantes 2008; Brown, Ellis, and Bleakney 2016). All of OHX and portions of MEG and MRX are located within the highest frequency of QLCS tornadoes outlined by Smith et al. (2012).

**Tornado Data**

For tornadic convective modes, we relied heavily on the database presented in Smith et al. (2012). This database contains a list of tornadoes from 2003 to 2014, each having an assigned convective mode. Bryan T. Smith of the SPC kindly provided the data for the state of Tennessee for this study, hereafter referred to as the Smith database. The Smith database does not include all tornadoes during this period because of a filtering approach used during its creation. Specifically, the database contains tornado data segmented by county and filtered hourly for the highest-magnitude report on a Rapid Update Cycle (RUC) model (Benjamin et al. 2004), 40-km horizontally spaced analysis grid (Smith et al. 2012). To create a complete data set of observed tornadoes over the time period, we compared the tornadoes listed in the Smith database to those of the SPC (located online at http://www.spc.noaa.gov/gis/svrgis/). The SPC data set currently provides details for each confirmed tornado in the United States from 1950–2017, including date, time, magnitude, track location and length, and fatalities (Schaefer and Edwards 1999). We gathered information on all tornadoes recorded by the SPC in the CWAs that were not in the Smith database, including the tornadoes that occurred outside of the Tennessee border. This resulted in 570 total tornadoes from 2003–2014. We manually assigned the convective mode of the additional tornadoes using the methods described below.

Issues with the SPC tornado database are well documented. Most notable is the apparent increase in frequency through the record because of advancements in technology and reporting practices (Verbout et al. 2006), population sprawl (Elsner et al. 2013), and storm spotters (Doswell, Moller, and Brooks 1999), which have allowed more tornadoes to be observed and recorded in recent times. These biases do not have a large influence on our results because we are using a recent time period and not analyzing long-term trends. One important bias could be differences in observation likelihood based on convective mode. Not all tornadoes are observed, especially in our study area (Ellis et al. 2018), and weaker tornadoes are more likely missed (Verbout et al. 2006). Thus, QLCS tornadoes may be especially undercounted because they are typically weaker and less likely to cause loss of life or property (Brotzge et al. 2013). Trapp et al. (2005) suggested as many as 12 percent of QLCS tornadoes still go unreported, compared to only 1 percent from supercells.

We categorized the tornado data by season and time of day. Tornadoes touching down between sunset and sunrise were labeled nocturnal. We used daily sunrise and sunset times for the cities of Knoxville, Nashville, and Memphis from the United States Naval Observatory (available online at http://aa.usno.navy.mil/data/docs/RS_OneYear.php). Seasons were divided as follows: winter (D-J-F), spring (M-A-M), summer (J-J-A), and fall (S-O-N).

**False Alarm Data**

False alarms from 2012–2016 was gathered using the Iowa Environmental Mesonet (available online at https://mesonet.agron.iastate.edu/cow/). We searched within the three CWAs for storms that were tornado-warned but did not produce any known tornadoes, uncovering 450 false alarms. We categorized the false alarms by time of day and season following the methods used for the tornado data.

The false-alarm period is shorter than the tornadic convective mode period because all of the storms had to be manually classified, which is a time-intensive exercise. A limitation in using this period for false alarms is that it only briefly overlaps with the tornadic convective mode database. We instead wanted to increase the likelihood that this period overlapped with the employment of all those interviewed. False alarms often indicate a challenging forecasting or warning environment, which was the focus of the interviews.

**Convective Mode Classification**

The Smith database distinguishes between six different convective modes: discrete supercell, cell in cluster, cell in line, cluster, QLCS, and bow echo (Smith et al. 2012). We slightly modified these classifications. Specifically, few storms in the Smith database were classified as bow echoes, which are subsets of QLCSs (Weisman and Trapp 2003) composed of quasi-linear convection that "bows" into a comma-like shape due to low-level unidirectional winds. We combined these entries with the QLCS category. Only one tornado during the period of study falls into the convective mode category of "cluster," thus we grouped this into "cell in cluster." This results in four separate convective mode classifications: discrete supercell, cell in cluster, cell in line, and QLCS (Figure 2).

To assign convective modes to the false alarms and additional tornadoes, we used archived NEXRAD Level II radar, obtained from Amazon Web Services. We viewed the radar images in the Gibson Ridge radar viewer (GR2Analyst, available online at http://www.grlevelx.com), referencing scans from the radar site closest to each storm. We used information from adjacent radar sites if the nearest was not available or if more information was needed. We determined convective mode at the starting location of the tornado using the radar scan occurring immediately prior to the time of tornado initiation. We referenced preceding and subsequent radar scans in instances of ambiguity. By observing how the storm changed as it traveled, we obtained additional information about storm characteristics and the depth and strength of rotation to more accurately determine convective mode at the time of tornado initiation. We also used the Smith database as a reference guide to ensure consistent storm classification. We adjusted the time, and occasionally the date, of some of these tornadoes based on radar evidence, as did Smith et al. (2012). Some storms were more challenging to identify because of radar location or challenging storm structure. Each convective mode categorization was reviewed by at least three people, increasing our confidence in the results.

We referenced multiple radar elevation scans and products to arrive at a correct convective mode classification. Most important were the base reflectivity product depicting rainfall intensity, and storm-relative velocity product revealing areas of embedded rotation, referred to as velocity couplets. Lowest-elevation radar tilts were given priority (typically 0.5° above the horizon) while subsequent higher scans were consulted as necessary, especially when distinguishing a cell in line from a QLCS. A clearly defined tornado vortex signature appearing through multiple radar tilts was indicative of a mesocyclone and a cellular convective mode. The mesocyclone was always immediately surrounded by convection with reflectivity above 35 dBZ. We labeled the storm a discrete supercell if the convection was not connected to any other high-reflectivity convection with echoes $\geq$35 dBZ. In other words, the echo had to decrease to below 35 dBZ before reaching another storm. If a mesocyclone was connected to other areas of rotation by reflectivity $\geq$35 dBZ, we labeled the storm as cell in line or cluster. Cell-in-lines were when areas of rotation and reflectivity were oriented linearly; otherwise, the mode was cell-in-cluster. We classified weaker rotation, and a line of convection with reflectivity ≥35 dBZ for a distance of ≥100 km, as a QLCS. Rotation was much weaker and shallower in a QLCS than a cell, and sometimes it was not visible on the radar.

## Interview Data

We interviewed NWS employees (n=11) in early 2017 concerning the effect convective mode has on the tornado forecast, detection, and warning process in Tennessee. We interviewed three employees at OHX, and four each at MEG and MRX. Open-ended questions related to tornado forecasting, tornado detection, warning procedures, and convective mode were posed, and forecaster responses were recorded and transcribed. We interviewed employees with various roles (e.g., Warning Coordinating Meteorologist, Meteorologist in Charge, etc.). We refer to all those interviewed as "forecasters." All were in-person interviews except for one Skype interview. This research was approved by the University of Tennessee Institutional Review Board (UTK IRB-16-03462-XP). The interviewees signed a consent form allowing the interviews to be recoded and transcribed, and the results to be shared anonymously. Each interviews lasted approximately one hour.

## Convective Mode Analyses

The relationships between tornadic convective modes (four categories), CWA (three categories), season (four categories), and time of day (two categories) were assessed using chi-square tests. Cramer's Phi was used post-hoc to test the strength of the associations. We modeled the dependence of convective mode on CWA, season, and time of day using multinomial logistic regression.

Tornado outbreaks may affect the independence of the samples and bias the results. For example, one QLCS may cause 15 tornadoes one night in December. Therefore, we created a new data set of unique tornadic events by counting only one of each convective mode per time of day (nocturnal and daytime) per day at each CWA. This resulted in a sample size of 253 events, approximately 44 percent of the original data. We analyzed relationships between unique tornadic events and CWA, season, and time of day as we did for all tornadoes, including chi-square tests, Cramer's Phi, and multinomial logistic regression.

Lastly, we analyzed false-alarm convective modes via chi-square tests and Cramer's Phi. Because there were some seasons when a CWA did not have a false alarm for a particular mode, we did not do a multivariate analysis.

### Interview Analyses

We coded the interview data using descriptive and interpretive coding (Tracy 2012; Creswell 2013). We used thematic analysis to identify themes from the codes. Each set of interviews was coded separately by two people, then results were compared and discrepancies were reconciled.

## Results

### Tornadic convective modes

A tornado's convective mode was significantly associated with CWA, time of day, and season (Table 1, Appendix A). Nocturnally, more QLCS tornadoes were observed than expected, and fewer discrete supercell tornadoes were observed than expected. There were minimal differences in observed and expected counts for tornadoes from cells in lines and clusters based on time of day. Seasonal variability can be seen in Figure 3. The largest seasonal differences between observed and expected values were that more QLCS tornadoes occurred in the winter and fewer in the spring. Cell-in-line tornadoes were more common in the fall than expected, and cell-in-clusters more common in the summer. QLCS variability was notable among CWAs, too. In OHX, more tornadoes from linear events, both QLCS and cell in line, occurred than expected at the expense of tornadoes from clusters and discrete cells. Meanwhile, MEG observed more tornadoes from discrete cells than expected at the expense of linear events. In MRX, notably more tornadoes from cells in clusters occurred than expected and fewer from cells in lines. CWA had a slightly greater association with convective mode than season or time of day.

There were also significant associations between the time of day, season, and CWA of a tornado (Table 1, Appendix B). Season and time of day had the largest association among these variables, with a larger proportion of tornadoes happening at night in the winter than during the other seasons. Time of day did not vary significantly between CWA, but season did. The biggest differences in observed and expected values occurred with MRX having more tornadoes in the warm seasons and fewer in the cool seasons than expected. OHX was the opposite, observing more tornadoes than expected in the winter and fewer in the spring and summer. MEG demonstrated less of a seasonal signal in tornado occurrences.

We calculated odds ratios by exponentiating the coefficients of the multinomial logistic regression model (Table 2) and found that a tornado occurring at night is 2.69 times more likely to be from a QLCS than a discrete supercell. Nocturnal tornadoes were significantly more likely to be from any mode other than a discrete supercell. Other large differences in odds were the likelihood for tornadoes from linear events in OHX as compared to MEG, and the likelihood of a cell-in-cluster or QLCS tornado in the summer compared to one from a discrete supercell. Most model coefficients were significant, and fall was the only category across the independent variables to not have differences in odds between convective modes.

**Convective mode of unique tornado events**

Next we assessed unique tornado events, i.e., only one of each convective mode was counted per time of day (nocturnal and daytime) per CWA per day. This removed the convective-mode bias from multiple-tornado events. Table 3 shows how the proportions of each convective mode changed as a result. There was still a significant association between convective mode variability and time of day, with more QLCS and fewer discrete supercells than expected nocturnally (Table 4), matching the results from all tornadic convective modes. CWA no longer had a significant association with convective mode and season. We could not assess the relationship between mode and season using chi-square tests because not all expected values were greater than five (Appendix C). The raw data show that QLCSs were the most common wintertime producers of tornadic events, while cell-in-cluster and discrete supercells were the biggest springtime producers. The relationship between time of day and season remained the strongest of all (Table 4, Appendix D).

These relationships were also modeled using multinomial logistic regression (Table 5). There were only two instances of significant differences in odds between the convective modes: a nocturnal tornado was 3.74 times more likely to be from a QLCS versus a discrete supercell, and a cell-in-line tornado was 2.66 times more likely in OHX than one from a discrete supercell.

**False-alarm convective modes**

False-alarm convective modes varied significantly based on season, CWA, and time of day (Table 6). The main differences in observed and expected values for the time-of-day variable were that, nocturnally, more (fewer) QLCS (discrete-supercell and cell-in-cluster) false alarms occurred than expected. Seasonally, there were more false alarms in the winter and spring (Figure 3B). However, it is likely that the FAR was low in the spring because there were also more tornadoes. There are noticeably few false alarms from discrete supercells in the winter, and in every season there are more false alarms from cells in clusters than any other mode. Cell-in-cluster false alarms were the most prominent in all CWAs, and MRX had fewest linear-event false alarms. There were no QLCS false alarms during the study period in the spring or in MRX, causing large residuals in these categories (Appendix E), and leading us to forgo a multivariate analysis.

CWAs varied significantly in the daily and seasonal timing of their false alarms (Table 6, Appendix F). The main difference in observed and expected values was that, in MRX, fewer false alarms occurred nocturnally than expected, while slightly more occurred nocturnally than expected in MEG and OHX. Seasonally, the largest differences were, in MRX, more false alarms occurred in the spring than expected, and fewer in the winter. In MEG, fewer false alarms occurred in the spring than expected and more in the fall, and in OHX more occurred in the winter than expected.

**NWS forecaster interviews**

We identified three themes: (a) forecast, detection, and warning challenges, (b) individual perceptions and decision-making variability, and (c) effects on office management and procedure. Within the discussion of each theme, we demonstrate how convective mode affects each, as well as other inherent storm or forecaster characteristics that emerged as relevant.

*Forecast, detection, and warning challenges*

Most participants noted the ease of and their confidence in forecasting, detecting, and warning for discrete supercells as compared to QLCS events. Reasons given included: being able to use the velocity radar product for supercells, which is not as helpful for linear events; areas of rotation in isolated cells "stand out like a bullseye" whereas for a linear event it is a "needle in a haystack"; QLCS tornadoes form quickly and are short-lived; spotters may not report storm characteristics like wall clouds for QLCS events; and a QLCS usually moves more quickly through the area. Forecasters also expressed that the science behind supercells is more straight-forward. One forecaster mentioned, "…we don't know why some QLCS tornadoes touch down and why some don't." Three forecasters mentioned a benefit to a line—that there is a distinct beginning and end, and thus, can be "nice and contained" and easier to time. Overall, however, the word "easy" was used many more times when discussing tornadic supercells, while "complex" and "tough" were commonly used to describe tornadic QLCS events. Forecasters noted that success metrics likely fare worse for QLCS events, meaning a higher FAR, lower POD, and shorter lead time.

QLCS events were also noted for their need of larger warning polygons. These larger polygons may improve POD but can increase the public's perception of FAR. Many forecasters, especially those at MRX, mentioned their concern for straight-line winds from QLCS events rather than tornadoes. A common strategy mentioned when warning for a QLCS was using a severe thunderstorm warning with a tornado-possible tag in place of a tornado warning. If necessary, forecasters can then issue smaller tornado warnings contained within or overlapping the severe-thunderstorm polygon. However, the forecaster must then keep track of multiple warnings simultaneously.

Cellular events that are non-supercellular, for example, cells in clusters, were mentioned by some forecasters and were the focus of one. They referred to these events as “messy” and making the radar operator’s job “impossible,” stating they “don’t know where to look.” They also mentioned the need for ground-truthing to determine which cell is strongest. MRX forecasters mentioned how storms usually break apart before reaching their CWA, leaving them with messy, transitional “leftovers” compared to the more frequent supercells in western Tennessee. These leftovers are more challenging for spotters to interpret but are fortunately much weaker.

All forecasters expressed concern about other storm characteristics that they perceive as more impactful than convective mode. These characteristics included storm speed, daily and seasonal timing, and outbreak events. Storm speed was mentioned because fast storms rush forecasters and, unfortunately, require bigger polygons, which may increase FARs or public confusion. Additionally, if a storm is moving at 60 mph, a specific speed mentioned by at least three forecasters, even the outflow will be damaging. One forecaster mentioned that it changes their internal rules for warning because they need to work quickly to get the warning out. They “don’t want to mess with these kinds of storms.” Nocturnal events were a concern for many because the public and storm spotters are sleeping, and forecasters recognize the large number of fatalities from nighttime tornadoes in their region. One forecaster suggested that nighttime is almost an equalizer, because there is no information coming in from storm spotters and the public, thus no convective mode is particularly easy. Another, meanwhile, noted that it made the more challenging storms, like cells in clusters, even more difficult:

> *The smaller cellular stuff is probably more of a problem, because you really want that truth. You really want to know what's going on. Which one is worse? Which one do I concentrate on?*

Time of year was mentioned for its influence on storm speed and the availability of different environmental parameters, for example, CAPE and shear, thus affecting convective mode. Outbreaks were noted for their effect on success metrics, as high-end events were perceived to cause lower FARs and higher POD. As one forecaster explains:

> *The bigger events, it's like the Plains. It's like shooting fish in the barrel there. You can't overlook it and you can definitely maybe not get as much lead time on the initial tornado that might develop from a storm, but if you know the storm is going to persist, and you can definitely get a lot of lead time downstream.*

*Individual perceptions and decision-making variability*

There was a noticeable difference in the stated occupational objectives of the forecasters, which related to differences in their decisions on whether to warn. While some forecasters mentioned that they entered this career because they love science and the weather, others mentioned a calling to save lives. One stated:

> *I'm glad that I'm able to serve our public through my career down here. I'm pretty religious and I think there's a pretty good reason why I got selected to come down here. I think I can make a valiant effort on saving lives.*

Those who mentioned a purpose of saving lives were more likely to affirm the importance of POD, especially over considering FARs. Forecasters were split nearly in half on whether concern for the public at night affects their warning procedure during nocturnal events. One forecaster mentioned they are more willing to have a false alarm because they want to look out for the sleeping public. Another forecaster said, when asked about nocturnal events, "…those scare the hell out of me."

Many forecasters mentioned that potential degree of impact plays a role in their warning decision, e.g., whether the storm is headed to a highly populated area. Meanwhile, one forecaster mentioned they "divorce" themselves from the people and are conservative about warnings, detailing how they use specific thresholds to determine whether to warn or not. Another forecaster said thresholds are dangerous because they do not account for the potential impacts. One forecaster mentioned being more cautious (i.e., more likely to warn) with the more dangerous cells, but being more conservative with a potentially tornadic line that would likely cause weaker tornadoes. Another forecaster mentioned how they are thankful that their supervisor understands that they will miss some of the weaker tornadoes.

Differences in decision-making may stem from variability in office philosophy and from forecaster experience level. One forecaster said of office differences:

> *Now, I think between offices there's different philosophies. Some offices want to cover everything as far as I can tell. We all talk about each other in different ways, but some offices want to cover everything, some offices are more conservative. My philosophy has always been we are here for the severe weather, not the almost-severe weather.*

Several forecasters noted that inexperienced forecasters are likely to warn more, with one stating, "…the younger you are or the newer you are, the faster you are to pull triggers, because everything looks good." Another said, "…somehow experience plays in, I think, how you use that experience to give you better foresight to what's severe and what's not."

*Effects on office management and procedure*

Convective mode influences how radar is used in the WFO. Specifically, many forecasters noted that some modes favor sectorizing, a technique mentioned by all three WFOs wherein the radar is divided into sections, each manned by a different radar expert. Sectorizing is necessary when there are many warnings spread across a large space. Complex convection, e.g., a line with leading convection or a discrete mode transitioning to linear, requires sectorizing and more people. A simple, contained line was said to require fewer people, while a more complicated line or one stretching over a long distance benefits from sectorizing. A MEG forecaster mentioned that they think sectorizing is more important for their CWA because of the high likelihood of outbreaks and the size of their CWA, adding, "…we never rely on somebody working the whole CWA. That's dangerous."

Communication techniques and challenges depend on convective mode. One forecaster described how a large, sweeping QLCS, which will likely affect the whole CWA, would be highlighted in warning communications to the public. However, if tornadic supercells were also expected then warnings would focus on the increased threat associated with these storms. The danger of straight-line winds in a QLCS is also important to forecasters to communicate. This is especially true in MRX where these winds are more likely and sometimes more damaging than QLCS tornadoes, and where forecasters perceive that the public does not take them seriously.

Many forecasters mentioned that social media helps them provide updated information during complex convection, and they hope to continue to improve their social media presence.

Partnerships with the media and emergency managers are also important during complex, nocturnal, or out-of-season events. Integrated Warning Team meetings and Media Days are some ways that forecasters mentioned networking with these groups and building trusting relationships.

Convective mode itself does not have a great effect on staffing, but forecasters reported outbreak days and nocturnal events as providing challenges. With outbreak days, one forecaster said, "…you need all hands on deck." Many forecasters mentioned how draining and anxiety-inducing outbreaks and nocturnal events can be. One forecaster mentioned:

> *If I've worked radar, and I've been intensely looking at the radar, after several hours, I start to wear down. And I might start making bad decisions. We try to limit people being on radar to about four hours or less, and we'll switch off to somebody else if we can. If it's right in the middle of a bunch of stuff going on, of course we can't, but because we know people just get worn out.*

A surprise nocturnal event can also make it challenging to get in touch with staff to bring them in, as well as summer and holidays because people may be traveling.

## Discussion

### Convective mode considerations

We accepted our first hypothesis, that the three CWAs would have different climatologies of tornadic convective modes. OHX experienced a large number of tornadoes from linear modes, while MEG favored cellular convection. MRX was most frequented by cell-in-cluster tornadoes. The MRX forecasters mentioned several times that they get unorganized leftovers, which is apparent in the climatology being dominated by cell-in-cluster tornadoes.

However, mode patterns were no longer significant when assessing unique tornado events, suggesting that outbreaks skewed the results. Cells-in-clusters were the most common mode for unique tornado events in all three CWAs. Perhaps the most notable finding here is that QLCS outbreaks in OHX and discrete supercell outbreaks in MEG are unique to their areas, but as a whole Tennessee is similar in having most tornadoes spawn from cells in clusters. The order of the frequency of tornadic modes did not differ in MRX (cell in cluster > discrete supercell > QLCS > cell in line) when comparing all tornadoes and unique tornado events, but did change in both MEG and OHX. This shows that outbreaks are not a factor in MRX. A data set going farther back in time could help determine whether the MEG and OHX outbreaks were unique features of the study period or if they were part of a larger pattern seen in the tornado climatology. The increased odds of a QLCS tornado at night was the only finding that was strengthened by assessing unique tornado events, signaling its importance in the local tornado climatology.

The climatology of discrete-supercell tornadoes, outbreaks, and false alarms complemented comments from forecasters. Tornadic discrete supercells followed a more traditional severe-weather pattern of spring and daytime occurrences. They make up a larger proportion of events in the tornado data set than they do the false alarm data set, as expected based on forecaster discussion of their ease of warning. Discrete supercells also had the largest proportional decrease when moving from individual tornadoes to unique tornado events, meaning they occurred in groups more often than the other modes. This contributes to the "fish in a barrel" effect that one forecaster mentioned. Our findings support prior research suggesting discrete cellular modes and multiple-tornado days contribute positively to warning success (Brotzge and Erickson 2010; Brotzge, Erickson, and Brooks 2011; Brotzge et al. 2013).

Our second hypothesis was that warning challenges would increase for non-supercellular events, as demonstrated by false alarm analysis and forecaster interviews. We accept our hypothesis, but note that forecasters have ways of mitigating potential false alarms from QLCS events. QLCSs were specifically described as a challenging storm mode for tornado detection and warning. Forecasters agreed that POD and lead time are worse in QLCS events, matching the finding of previous literature (Brotzge et al. 2013). Additionally, the tornadic QLCS climatology is skewed more toward winter and nocturnal occurrences than other modes, both of which may increase the challenge in tornado detection, warning, and communication. However, QLCSs had the least total false alarms. While our data sets are not directly compatible because they are of different study periods, QLCSs caused a larger proportion of tornadoes than they did false alarms. More information about QLCS challenges could be gleaned from classifying convective modes of unwarned tornadoes.

Our findings suggest that QLCSs do not have a tornado warning false-alarm problem. This could be in part because of the practice forecasters mentioned of using the severe thunderstorm warning with a tornado-possible tag, recognizing any potential tornado is likely short-lived and weak, and focusing on the straight-line winds. This reduces the FAR in a way that still alerts people of the potential tornado. Previous work describes how it is challenging to improve FAR or POD without worsening the other (Brooks 2004). However, it seems that, for QLCS events, the tornado-possible tag on a severe thunderstorm is a way of communicating a potential weak, short-lived tornado within the severe thunderstorm without increasing FAR. It is important to assess how this type of communication affects public response before calling it a success, but this could be why success metrics for linear modes did not appear as poor in our study as they do in previous studies on POD and lead time. A severe thunderstorm warning is usually issued for a QLCS because of straight-line wind threats, and a major concern of our forecasters was that residents may not take seriously the threats from non-tornadic winds in a QLCS. This concern is warranted, because while organized cellular convection makes up the majority of tornado-related fatalities, unorganized and linear convection are responsible for the bulk of damaging non-tornadic convective winds (Schoen and Ashley 2010).

Many forecaster interviews focused on the differences between QLCSs and discrete supercells, but the false-alarm results and the few discussions about non-discrete cellular convection suggested cells in clusters and lines provide a larger challenge. Cells in clusters and lines made up a larger proportion of false alarms than they did tornadoes, supporting the forecasters' descriptions of their challenges. Unlike discrete supercells, cells in clusters made up a larger proportion of multiple-tornado events than isolated tornadoes, adding to their challenge. Combined, they accounted for about 37 percent of multiple-tornado events in the winter, but 61 percent of false alarms in that season. This seemingly differs from the findings of Brotzge et al. (2013), which said that QLCS metrics fare much worse than cells in clusters and lines. This is likely because of a difference in the categorization of the convective modes— Brotzge et al. (2013) included a "disorganized convection" category, which had the worst success metrics, but our disorganized convection was forced into one of four categories, likely being cell in line or cluster. Also, Brotzge et al. (2013) studied POD and lead time, not false alarms. Future research should assess all three metrics under a single classification scheme so direct comparisons can be made. Ideally that scheme should reflect the convection's organization, as done by Schoen and Ashley (2010), and cellular events could be classified as unorganized, quasi-organized, or organized.

**Other event features: Time of day, season, and outbreaks**

There were significant associations between the convective mode and the time of day and season a tornado occurred, but an even stronger association between the seasonal and diurnal timing tornadoes. According to the forecaster interviews, both season and time of day affect their procedures, mainly through their communication with the public and staffing issues. The biggest effect diurnal timing had on tornado detection and warning was the lack of ground-truthing during nocturnal events, which greatly hinders the forecaster's ability to warn on complex convection. This was the most relevant difference in convective mode timing for forecasters because it affects their ability to do their job accurately. Discrete supercells, the easiest mode to warn for according to forecasters, only accounted for 18 percent of the unique nocturnal tornado events across the CWAs (29 percent during the day), supporting the idea that other types of convection are a more frequent nocturnal warning challenge for forecasters. These findings agree with previous literature showing higher FAR and lower POD are associated with tornadoes at night and outside of the severe weather season (Brotzge and Erickson 2010; Brotzge, Erickson, and Brooks 2011). As Brotzge and Erickson (2010) said, "those tornadoes most likely to strike when the public is least likely to be aware are also those tornadoes with the greatest chance of not being warned." While we did not study POD, we did show through the convective mode climatology and forecaster interviews that the more challenging-to-warn events are occurring during these periods. Additionally, our previous work has shown that residents in these CWAs do not have a clear understanding of their wintertime tornado risk (Ellis, Mason, and Gassert 2019). This, coupled with a more challenging forecast, could cause more confusion for the public and local leaders.

As mentioned by the forecasters, the challenge of a nocturnal event begins at the forecast, but continues through communication of the threat. When Mason et al. (2018) surveyed residents from the three CWAs used for our study, they found that fewer than half of the participants thought there was a high or very high chance they would receive a tornado warning at night if one was issued, compared to 80 percent during the day. However, Walters, Mason, and Ellis (2019) found that if participants did get a warning at night, they may be more likely to make a safe sheltering decision than they would during the day, after first checking other sources of information.

**Forecaster strategies and concerns**

Many of the strategies discussed by the forecasters are in agreement with those in Andra, Quoteone, and Bunting (2002), specifically, the use of sectorizing during a challenging event, selecting radar products appropriate for the expected convective mode, and using ground truth to calibrate their forecasts. Andra, Quoetone, and Bunting (2002) focused on automation of tornado detection and how it cannot be used as a replacement for expertise, and should only be used to enhance forecaster capabilities. Forecasters agreed with this sentiment in the interviews by demonstrating how they often account for people and potential impacts when warning, which cannot be easily automated. For example, a forecaster discussed how a large outdoor event taking place in a potential risk area may affect how they warn. Similarly, Brooks (2004) discussed how unbiased forecasts are not the goal because in some situations the cost of a missed event would outweigh the cost of a false alarm.

Our work supports previous work highlighting the importance of ground truth for accurate tornado detection and warning. Brotzge and Erickson (2010) showed that success metrics decrease when (at night) and where (outside of the Great Plains) it is a challenge to view tornadoes. The forecasters whom we interviewed echoed this sentiment, detailing a clear disadvantage in detection and warning at night, and the challenge being amplified by the type of complex convection that is common at that time. Andra, Quoetone, and Bunting (2002) list ground truth only second to radar data as the most important data set for forecaster warning decision-making. In our study area, where trees and hills dominate the landscape and nocturnal tornadoes are half of the tornado climatology (Ashley, Krmenec, and Schwantes 2008; Brown, Ellis, and Bleakney 2016), forecasters are at a particular disadvantage. Thus, this work adds to those documenting nocturnal tornado challenges, specifically detailing forecaster concerns and additional detection, warning, and communication challenges during nocturnal events.

A concern brought up by many forecasters was storm speed. Faster storms rush forecaster decision-making, cause them to use larger polygons, and create more damaging straight-line winds. These factors increase the challenge of effective warning and communication. There is little literature on the speed of tornadic storms, and we encourage future research in this area in both the climatology of storm speed, its relation to convective mode, and its effects on warning success metrics. In creating a climatology of storm-based warnings, Harrison and Karstens (2016) found that the fastest warned storms were those in the Great Lakes and Ohio Valley regions, and that storms were fastest in winter. However, these results were not specific to tornado-warned events and the authors can only speculate about relationships between speed and convective mode, specifically that QLCS frequency affected average storm speeds (Harrison and Karstens 2016).

**Limitations**

The time-intensive and challenging process of classifying convective modes limited this study in two ways. First, the study period is relatively short, although this is not uncommon in convective mode studies. Second, the study period for the false alarms does not directly coincide with the tornado data. More direct comparisons could be made with a larger data set that matches in space and time. This may be made possible in the future by automation of convective mode classifications, which Ashley, Haberlie, and Strohm (In review) have recently achieved for QLCS events. Until a larger data set is possible, we are left uncertain if our patterns, for example the QLCS outbreaks in OHX, are part of the larger climatology or are only an artifact of limited data. Additionally, it is challenging to compare results across studies because of a lacking universal convective classification scheme (Schoen and Ashley 2010).

Another issue with the data set is that tornado climatologies rely on the observation of a tornado, which is not equal across space. While some locations now have little to no urban bias in their tornado reports (Elsner et al. 2013), this is not true for the Southeast and this study area (Ellis et al. 2018). If these undetected tornadoes are skewed toward more complex convection or weaker tornadoes, then our data may be biased toward certain storm modes.

A strength of our study was an assessment of false alarms and convective modes, which is not yet in the literature. However, weaknesses include only studying one success metric used by the NWS (FAR) and not studying POD and lead time, which are two other important metrics. Assessing all three would more clearly discern the challenges associated with convective mode. While we discussed connections between our work and that of those who researched POD and lead time, it would be more meaningful to have those statistics directly match the spatiotemporal dimensions of our study.

Forecaster interviews revealed differences in their personal purpose of working for the NWS, which was inherently related to their considerations when warning on potential tornadic events. While these forecasters demonstrate differences in purpose and warning plans, it would be valuable to determine if those differences ultimately lead to different warning decisions. For example, does the religious forecaster who wants to "catch them all" warn significantly more often than the forecaster who strictly uses thresholds?

## Conclusion

We used a mixed-methods approach to assess how the convective mode of a storm affects the climatology of tornadoes and NWS procedures within three CWAs that warn for Tennessee and surrounding areas. For the climatological analyses, we used archived radar data and a data set by Smith et al. (2012) to assign convective modes to tornadoes (2003–2014) and false alarms (2012–2016). We assessed associations among these data sets and CWA, time of day, and season. To gain information on how convective mode affects forecasting procedures, we interviewed 11 NWS forecasters across the three offices. The most unique aspects of our work were the direct discussions with the forecasters, which can be related back to the tornado and false alarm climatologies, and the assessment of the relationship between convective mode and false alarms. We hypothesized that the convective mode climatology would differ between the three CWAs, and that forecast challenges would increase for non-supercellular events. We accepted both hypotheses, but note two special considerations: 1. After outbreaks are removed, we observed no statistical difference among tornadic convective mode and CWA, and 2. Forecasters have mitigated some false-alarm issues for tornadoes from QLCS events by often using a severe thunderstorm warning with a tornado-possible tag. Other storm characteristics have affected forecasters more than its convective mode, for example the timing and speed of the storm. Forecasters have different, often personal, reasons to warn or not during a challenging event.

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## Figure Captions

Figure 1. Tornadoes (A; 2003–2014) and false alarms (B; 2012–2016) that occurred in three CWAs, categorized by convective mode.

Figure 2. Archived base reflectivity radar image of one tornadic event for each convective mode type: A. Discrete supercell, B. Cell in cluster, C. Cell in line, and D. QLCS.

Figure 3. Tornadoes (A) and false alarms (B) categorized by convective mode for each CWA.

## Appendix A

Information pertaining to chi-square tests assessing the relationship between tornadic convective mode and season, CWA, and time of day. Included are the observed count (Obs), expected count (Exp), and standardized residual (R).

| | Discrete Supercell | | | Cell in cluster | | | Cell in line | | | QLCS | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R |
| Spr | 117 | 109 | 0.74 | 133 | 126 | 0.59 | 65 | 62 | 0.35 | 47 | 64 | -2.14 |
| Sum | 6 | 11 | -1.40 | 22 | 12 | 2.80 | 1 | 6 | -2.05 | 6 | 6 | -0.08 |
| Fall | 18 | 23 | -1.03 | 26 | 27 | -0.10 | 24 | 13 | 3.03 | 8 | 13 | -1.49 |
| Win | 31 | 29 | 0.32 | 18 | 34 | -2.73 | 8 | 17 | -2.13 | 40 | 17 | 5.50 |
| MEG | 92 | 73 | 2.26 | 91 | 84 | 0.75 | 32 | 41 | -1.47 | 26 | 43 | -2.56 |
| OHX | 34 | 56 | -2.99 | 47 | 65 | -2.26 | 53 | 32 | 3.68 | 53 | 33 | 3.45 |
| MRX | 46 | 43 | 0.48 | 61 | 50 | 1.62 | 13 | 24 | -2.31 | 22 | 25 | -0.63 |
| Day | 112 | 95 | 1.78 | 112 | 110 | 0.23 | 51 | 54 | -0.41 | 39 | 56 | -2.23 |
| Night | 60 | 77 | -1.96 | 87 | 89 | -0.25 | 47 | 44 | 0.45 | 62 | 45 | 2.47 |

## Appendix B

Information pertaining to chi-square tests assessing the relationship between CWA, season, and time of day for the tornadoes in this study. Included are the observed count (Obs), expected count (Exp), and standardized residual (R).

| | MEG | | | OHX | | | MRX | | | Day | | | Night | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R |
| Spr | 142 | 153 | -0.89 | 107 | 119 | -1.08 | 113 | 90 | 2.40 | 215 | 199 | 1.10 | 147 | 163 | -1.22 |
| Sum | 19 | 15 | 1.09 | 3 | 11 | -2.50 | 13 | 9 | 1.45 | 31 | 19 | 2.67 | 4 | 16 | -2.96 |
| Fall | 34 | 32 | 0.33 | 32 | 25 | 1.42 | 10 | 19 | -2.05 | 43 | 42 | 0.18 | 33 | 34 | -0.19 |
| Win | 46 | 41 | 0.78 | 45 | 32 | 2.34 | 6 | 24 | -3.70 | 25 | 53 | -3.89 | 72 | 44 | 4.31 |
| Day | 136 | 132 | 0.28 | 99 | 103 | -0.40 | 79 | 78 | 0.09 | | | | | | |
| Night | 105 | 108 | -0.31 | 88 | 84 | 0.44 | 63 | 64 | -0.10 | | | | | | |

# Appendix C

Information pertaining to chi-square tests assessing the relationship between CWA, season, and time of day for the unique tornado events in this study. Included are the observed count (Obs), expected count (Exp), and standardized residual (R). R are not included when expected values are less than five for one category.

| | Discrete Supercell | | | Cell in cluster | | | Cell in line | | | QLCS | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R |
| Spr | 40 | 37 | - | 54 | 57 | - | 28 | 24 | - | 25 | 28 | - |
| Sum | 5 | 6 | - | 16 | 10 | - | 1 | 4 | - | 3 | 5 | - |
| Fall | 10 | 11 | - | 20 | 17 | - | 7 | 7 | - | 6 | 11 | - |
| Win | 9 | 10 | - | 8 | 15 | - | 6 | 6 | - | 15 | 10 | - |
| MEG | 32 | 28 | 0.74 | 44 | 43 | 0.15 | 15 | 18 | -0.8 | 20 | 21 | -0.32 |
| OHX | 15 | 20 | -1.21 | 30 | 31 | -0.25 | 19 | 13 | 1.51 | 17 | 16 | 0.33 |
| MRX | 17 | 15 | 0.4 | 24 | 24 | 0.08 | 8 | 10 | -0.67 | 12 | 12 | 0.05 |
| Day | 46 | 39 | 1.084 | 62 | 60 | 0.25 | 27 | 26 | 0.25 | 20 | 30 | -1.8 |
| Night | 18 | 25 | -1.36 | 36 | 38 | -0.32 | 15 | 16 | -0.32 | 29 | 19 | 2.3 |

## Appendix D

Information pertaining to chi-square tests assessing the relationship between CWA, season, and time of day for the tornado events in this study. Included are the observed count (Obs), expected count (Exp), and standardized residual (R).

| | MEG | | | OHX | | | MRX | | | Day | | | Night | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R |
| Spr | 57 | 64 | -0.93 | 50 | 47 | 0.43 | 40 | 35 | 0.77 | 94 | 90 | 0.42 | 53 | 57 | -0.52 |
| Sum | 13 | 11 | 0.61 | 3 | 8 | -1.77 | 9 | 6 | 1.21 | 22 | 15 | 1.71 | 3 | 10 | -2.15 |
| Fall | 19 | 19 | 0.03 | 16 | 14 | 0.60 | 8 | 10 | -0.74 | 22 | 26 | -0.85 | 21 | 17 | 1.06 |
| Win | 22 | 17 | 1.30 | 12 | 12 | -0.05 | 4 | 9 | -1.71 | 17 | 23 | -1.30 | 21 | 15 | 1.64 |
| Day | 68 | 68 | 0 | 52 | 50 | 0.34 | 35 | 37 | -0.39 | | | | | | |
| Night | 43 | 43 | 0 | 29 | 31 | -0.42 | 26 | 24 | 0.49 | | | | | | |

## Appendix E

Information pertaining to chi-square tests assessing the relationship between false-alarm convective mode and season, CWA, and time of day. Included are the observed count (Obs), expected count (Exp), and standardized residual (R).

| | Discrete Supercell | | | Cell in cluster | | | Cell in line | | | QLCS | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R |
| Spr | 48 | 34 | 2.39 | 93 | 75 | 2.03 | 22 | 33 | -1.86 | 0 | 21 | -4.58 |
| Sum | 18 | 13 | 1.33 | 31 | 29 | 0.35 | 13 | 13 | 0.11 | 1 | 8 | -2.50 |
| Fall | 20 | 18 | 0.59 | 39 | 39 | 0.03 | 14 | 17 | -0.68 | 11 | 11 | 0.05 |
| Win | 8 | 29 | -3.93 | 45 | 65 | -2.45 | 41 | 28 | 2.46 | 46 | 18 | 6.58 |
| MEG | 31 | 43 | -1.83 | 90 | 95 | -0.53 | 56 | 41 | 2.31 | 29 | 27 | 0.48 |
| OHX | 27 | 32 | -0.84 | 69 | 70 | -0.15 | 27 | 30 | -0.62 | 29 | 20 | 2.13 |
| MRX | 36 | 19 | 3.83 | 49 | 43 | 0.99 | 7 | 18 | -2.66 | 0 | 12 | -3.44 |
| Day | 56 | 43 | 2.05 | 108 | 94 | 1.41 | 35 | 41 | -0.9 | 5 | 26 | -4.12 |
| Night | 38 | 51 | -1.87 | 100 | 114 | -1.29 | 55 | 49 | 0.82 | 53 | 32 | 3.78 |

## Appendix F

Information pertaining to chi-square tests assessing the relationship between CWA, season, and time of day for the false alarms in this study. Included are the observed count (Obs), expected count (Exp), and standardized residual (R).

| | MEG | | | OHX | | | MRX | | | Day | | | Night | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R | Obs | Exp | R |
| Spr | 56 | 75 | -2.16 | 56 | 55 | 0.13 | 51 | 33 | 3.06 | 87 | 74 | 1.52 | 76 | 89 | -1.39 |
| Sum | 27 | 29 | -0.34 | 14 | 21 | -1.58 | 22 | 13 | 2.54 | 52 | 29 | 4.39 | 11 | 34 | -3.99 |
| Fall | 52 | 38 | 2.18 | 22 | 28 | -1.20 | 10 | 17 | -1.73 | 29 | 38 | -1.47 | 55 | 46 | 1.34 |
| Win | 71 | 64 | 0.86 | 60 | 47 | 1.85 | 9 | 29 | -3.67 | 36 | 63 | -3.45 | 104 | 76 | 3.14 |
| Day | 89 | 94 | -0.45 | 63 | 69 | -0.71 | 52 | 42 | 1.59 | | | | | | |
| Night | 117 | 113 | 0.41 | 89 | 83 | 0.65 | 40 | 50 | -1.45 | | | | | | |

Figure 1.

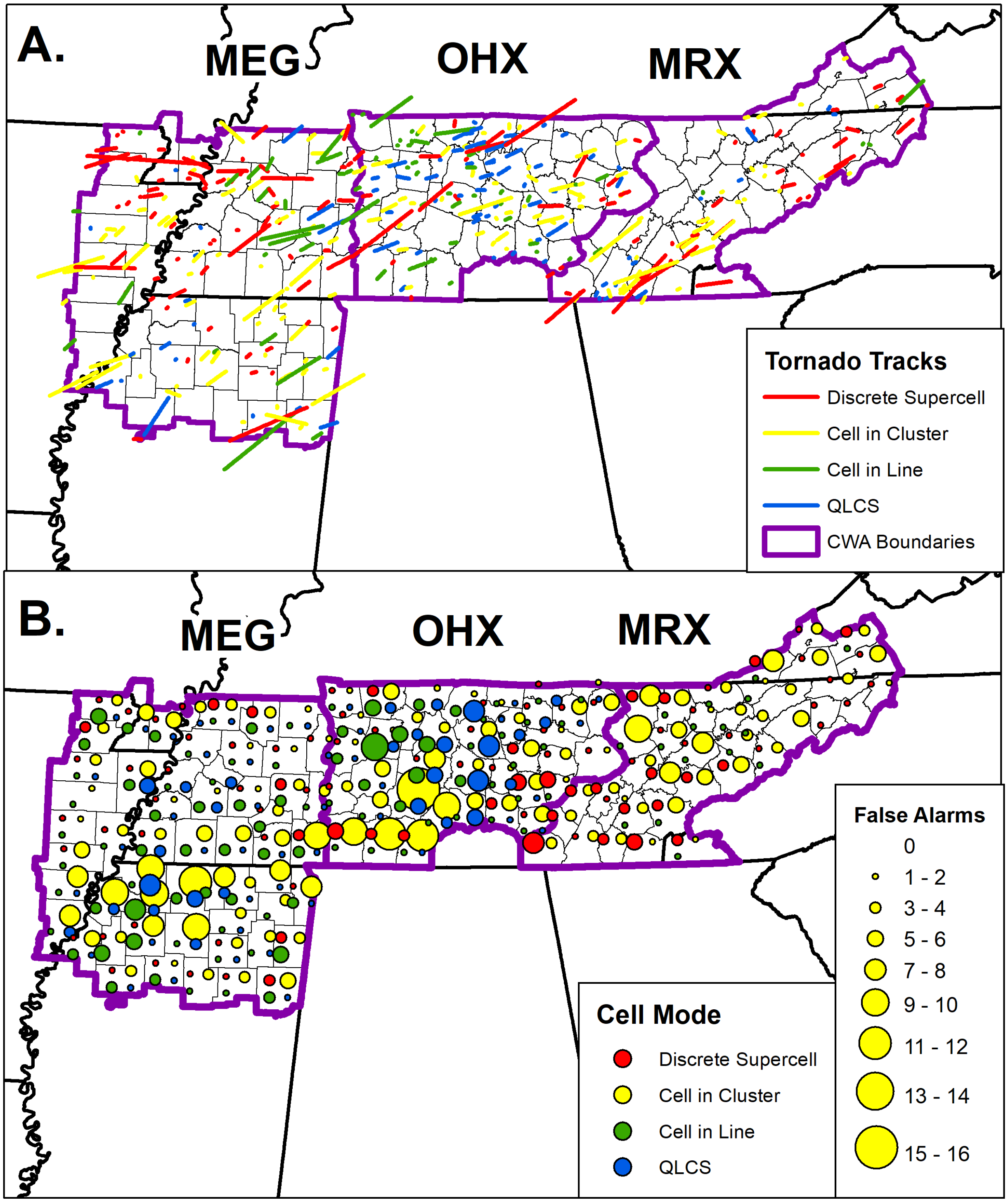

A.
MEG
OHX
MRX
Tornado Tracks
Discrete Supercell
Cell in Cluster
Cell in Line
QLCS
CWA Boundaries
B.
MEG
OHX
MRX
False Alarms
0
1 - 2
3 - 4
5 - 6
7 - 8
9 - 10
11 - 12
13 - 14
15 - 16
Cell Mode
Discrete Supercell
Cell in Cluster
Cell in Line
QLCS

Figure 2.

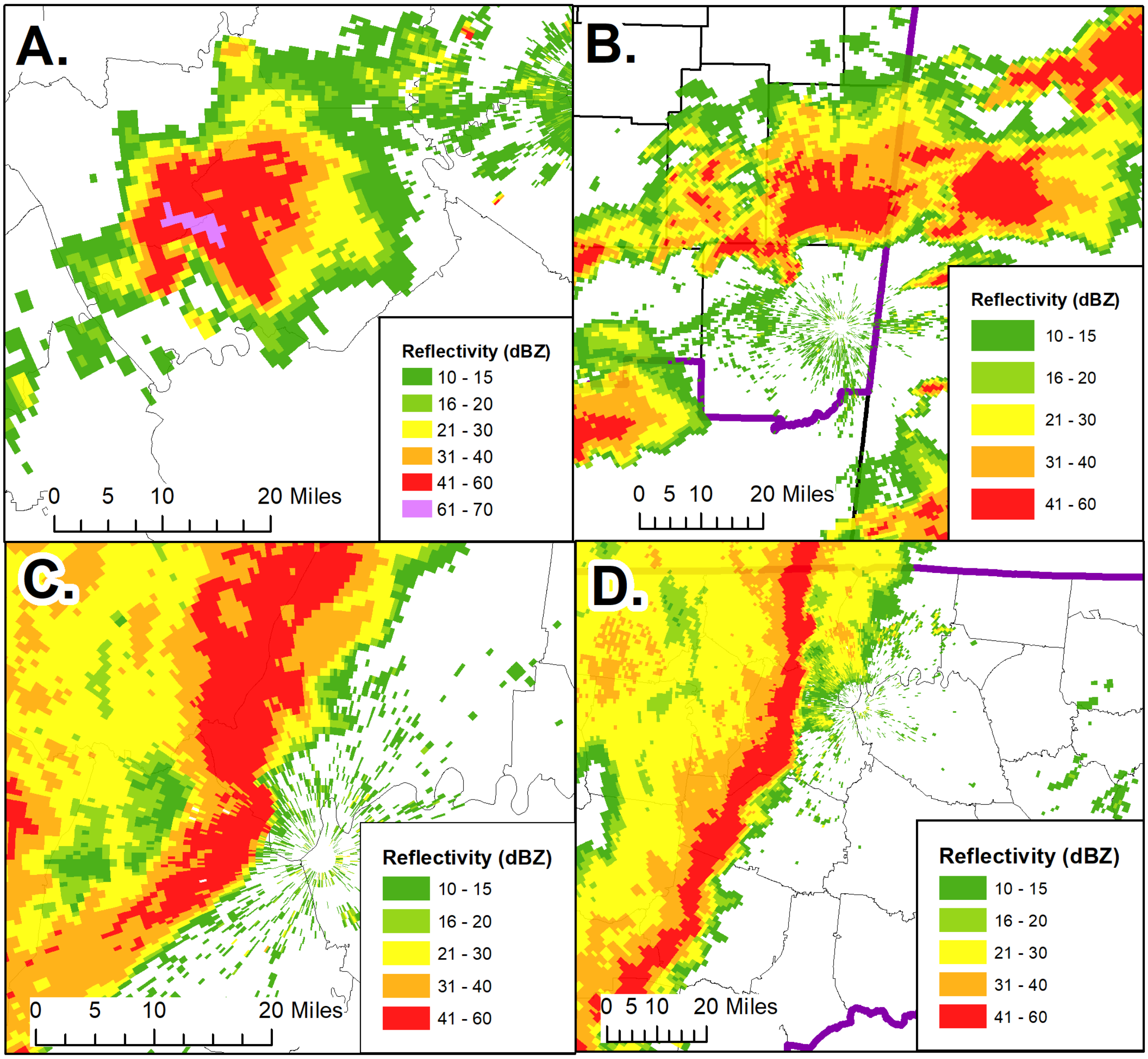
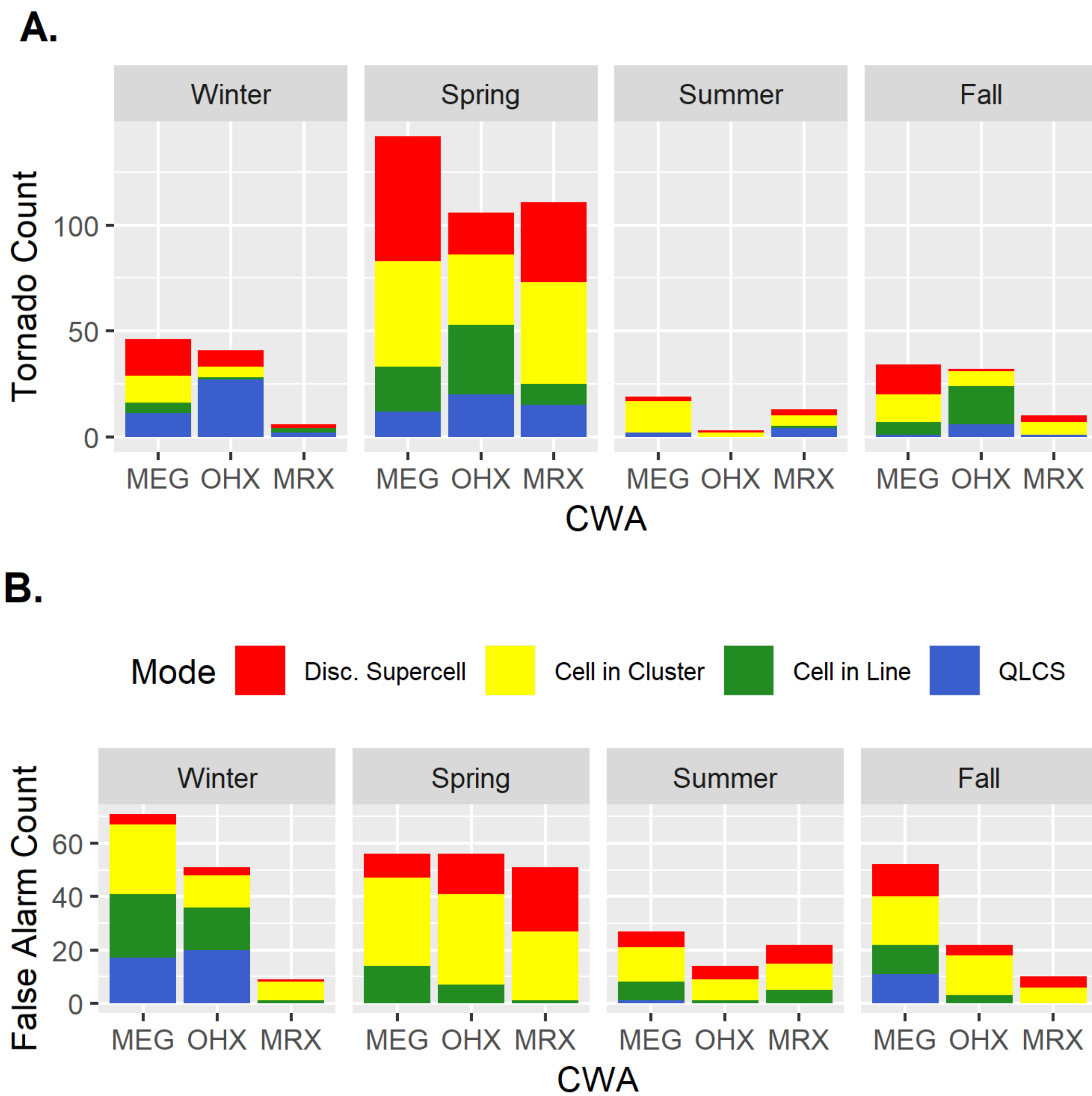

A.
Reflectivity (dBZ)
10 - 15
16 - 20
21 - 30
31 - 40
41 - 60
61 - 70
0 5 10 20 Miles
B.
Reflectivity (dBZ)
10 - 15
16 - 20
21 - 30
31 - 40
41 - 60
0 5 10 20 Miles
C.
Reflectivity (dBZ)
10 - 15
16 - 20
21 - 30
31 - 40
41 - 60
0 5 10 20 Miles
D.
Reflectivity (dBZ)
10 - 15
16 - 20
21 - 30
31 - 40
41 - 60
0 5 10 20 Miles

Figure 3.


A.
Winter
Spring
Summer
Fall
Tornado Count
100
50
0
MEG OHX MRX
CWA
B.
Mode
Disc. Supercell
Cell in Cluster
Cell in Line
QLCS
False Alarm Count
60
40
20
0
CWA