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Nashville-basin tornadoes: using storm types to elucidate the local climatology and forecasting challenges

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1. Introduction and background

Tornadoes and multiple-tornado days are no rare occurrence in Tennessee; they have been and continue to be a significant threat to life and property. In 2011, a storm system quickly spawned 20 tornadoes in our study area, the Nashville National Weather Service (NWS) county warning area (CWA). Notably, in March 2020, a strong EF-3 tornado tore through Nashville at 65 mph, and another EF-4 killed 18 people in Baxter and Cookeville, Tennessee. Though death per population index values have decreased from 1.5 to 0.2 over time with improved technology and forecasting methods (Agee and Taylor 2019), tornadoes continue to threaten at-risk and vulnerable Middle Tennessee residents. As a result, researchers aim to improve forecasting successes and better prepare civilians for dangerous weather events.

1.1 Convective mode

Tornadoes spawn from different types of storms, which can be categorized by their convective mode. With the advent of radar imaging, categorizing storms by convective mode is a modern strategy for understanding the climatology of severe weather in an area (Geerts 1998; Gallus et al. 2008; Smith et al. 2012; Davis and Parker 2014; Ashley 2019; Ellis et al. 2019). Not only can scientists study tornado path length and intensity, but they can also use a vast network of WSR-88D doppler radars to study the morphology and movement of tornado-producing storm systems.

Convective mode determination is a subjective matter. Gallus et al. (2008) defined nine different convective modes that considered linearity, organization, reflectivity (dBZ), and stratiform cloud formation. Alternatively, Smith et al. (2012) created three main categories with several sub-classifications and used a 35-dbZ threshold when determining linearity, discreteness, or clustering. In other studies, storms have been further categorized by how long they keep shape and how long those shapes are (Geerts et al. 1998; Ashley et al. 2019). For this study, the dataset was derived from convective mode classifications created by Ellis et al. (2019), who was influenced by Smith et al. (2012). Classifications were divided into four simple categories, cell in line, cell in cluster, discrete supercell, and QLCS.

Most climatological research using convective mode agrees that the Southeast has a unique tornado portfolio. Contrary to the strong, organized storms in the central plains, the Southeast's generally high-shear, low-cape environment favors linear, nighttime, and cool-season tornadoes (Anderson-Frey et al. 2019). A high-shear environment with low instability produces notoriously difficult to forecast QLCS and linear storms. This is because tornadoes associated with these storm types are generally weak EF-0s and EF-1s that are difficult to identify on radar. Moreover, Ashley (2019) found that 35% of all tornadoes in Tennessee were from QLCSs, which makes this region unique to the rest of the United States.

Research has found that Middle Tennessee faces many QLCS multiple-tornado days. These storms tend to produce many weak EF-0 tornadoes and occur during cool seasons and nighttime hours (Ellis et al. 2019). Though linear storms are uniquely common in the Tennessee Valley, discrete supercells and cells in clusters are still considered the most dangerous (Brotzge et al. 2013). Ellis et al. (2019) found that cells in clusters spawned the most tornadoes in Tennessee between 2003 and 2014. Nashville, in general, has a slightly higher risk for tornado frequency than its surrounding Tennessee CWAs, Memphis and Morristown, which makes it a particularly interesting study area (Ellis et al. 2016).

1.2 Success metrics

Tornado warnings are issued by an NWS Weather Forecasting Office (WFO) when a tornado is spotted or indicated on radar (NWS 2020). To study warning success and its drivers—including convective mode—researchers often use three success metrics: average lead time, false alarm ratio (FAR), and probability of detection (POD). While the mathematics behind success metrics might be over-simplified, they remain a useful tool for understanding general weaknesses and strengths in forecasting (Brooks 2004). Success metrics are calculated according to the glossary of forecast verification metrics issued by the National Oceanic Administration of America (NOAA 2020). Each metric is calculated with variables described in a 2x2 contingency table (Table 1), which defines hits, misses, false alarms, and correct negatives.

Table 1. The 2x2 contingency table used by NOAA to define hits, misses, false alarms, and correct negatives for use in success metrics.

		Tornado Observed	
		Yes	No
Tornado Warned	Yes	Hits	False Alarms
	No	Misses	Correct Negatives

1.3 Objectives

This study expands previous research by assessing convective mode's influence on average lead time, POD, and FAR in the Middle Tennessee CWA. In this study, we categorized the convective mode of tornado-warned and tornado-producing storms from 2012 to 2018 that crossed into the CWA of the Nashville WFO. This CWA-focused research may have reduced bias that is usually seen in datasets containing several CWAs, because each office has different forecasting methods and experience (Doswell and Burgess 1998). In addition to convective mode, success metrics may be affected by time of day and whether the day had multiple tornadoes (Ellis et al. 2019). Thus, convective mode, nocturnality, and multiple-tornado days were considered independent variables in three models that predict lead times, false alarms, and warnings. This study is an expansion of Ellis et al. (2019), who only studied false alarms and noted that more information could be gleaned if all three metrics were studied at once. Furthermore, the purpose of this study was to investigate whether convective mode, nocturnality, and multiple-tornado days can be used to predict false alarms (aka FAR), warnings (aka POD), and lead time.

2. Data and methods

2.1 Tornado and false alarm data

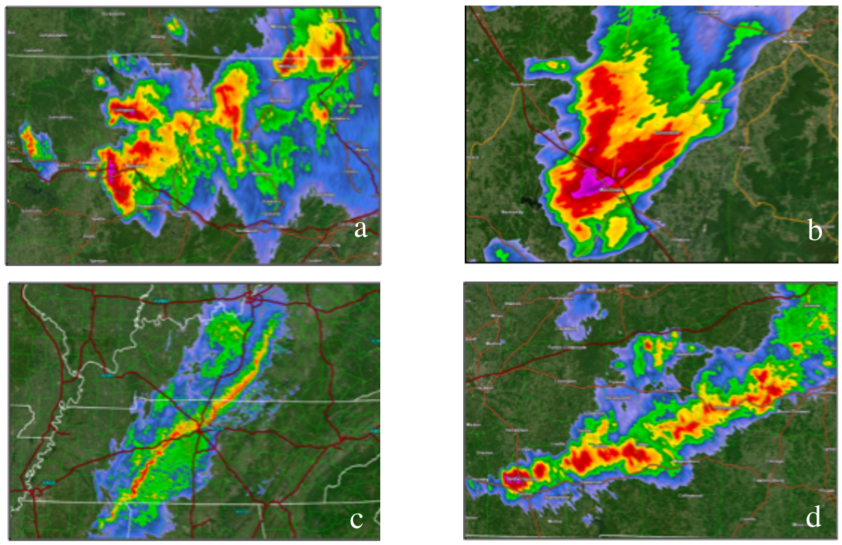
Three datasets were generated for this study. First, the tornado dataset was an extension of one from Ellis et al. (2019). The Ellis et al. (2019) dataset contained tornado information for the three NWS offices located in Tennessee from 2003 to 2014. For each tornado, attributes included the estimated touchdown time and date in UTC, the magnitude on an EF-scale, the number of injuries and fatalities, coordinates for the tornado path, the tornado length and width, the lead time (if any), and convective mode of the storm. To extend the dataset to our study period (2012–2018), we downloaded shapefiles from the storm prediction center (SPC) that contained tornadoes between 2015 and 2018 and appended it to the Ellis dataset. We then created binary (yes/no) columns if the tornado was part of a multiple-tornado day and whether or not it was warned for. This resulted in 89 tornadoes for use in this study.

Next, we created the false alarm dataset. This dataset also began with the Ellis et al. (2019) dataset, which contained false alarm information from 2012 to 2016, including warning issuance/expiration time and date in UTC, the counties included, and the respective convective modes. To extend this dataset to 2018, we downloaded shapefile data from the Iowa State Mesonet API that contained all of the aforementioned attributes attached to warning polygons. Similar to the tornado dataset, we created binary (yes/no) columns if the false alarm was part of a multiple-tornado day. There was a total of 213 false alarms used for this study.

2.2 Warning data

To complete the tornado and false alarm datasets, we manually assigned convective modes to the new samples. Then, we generated a warning dataset with all false alarms and warned tornadoes by appending mode, nocturnality, multi-tornado day, and warned columns (warned = yes) from the tornado dataset to the false alarm dataset. This was used for the false alarm model and contained 270 total warnings.

Figure 1. The four convective modes assigned in this study as cell in cluster (a), discrete supercell (b), quasi-linear convective system (c), and cell in line (d).



The three complete datasets ranged from 2012 to 2018. After all convective modes were assigned and the datasets completed, we generated four dummy variables to represent cell in line, cell in cluster, QLCS, and discrete supercell, which is necessary to perform multiple logistic regressions for binary data. QLCS storms were connected at or above a 35-dbZ threshold for at least 100 km. Shorter, and generally stronger, linearly connected cells were categorized as cell in line. Cell-in-cluster storms were disorganized clusters of convection connected by at least 35-dbZ, and discrete supercells were standalone cells greater than 35-dbZ that were not connected to other areas of convection. All decisions were made favoring the lowest radar tilt and images directly preceding the tornado touchdown or warning, without regard to stratiform cloud formation and duration. In cases where radar data could not be found, such tornadoes and false alarms were not included in the final datasets.

2.3 Analysis methods

First, we calculated three success metrics, lead time, FAR, and POD. Lead time is the amount of time between an issued warning and the arrival of a tornado. Research shows the average lead time has increased from 3 minutes in 1978 to 14 minutes as of 2011 (Stensrud et al. 2013). Respondents from a survey in 2009 tend to prefer a 35-minute lead time, though preferred lead times may vary situationally (Hoekstra et al. 2011). Understandably, a relatively short lead time may not be long enough for people to enact emergency procedures in the wake of a tornado. However, research has found that a lead time greater than 15 minutes does not necessarily reduce death rates (Brotzge et al. 2013), thus the ideal lead time for civilian safety is unknown.

Next, a false alarm is when a forecaster issues a tornado warning, but no tornado enters the warning polygon. False alarm data are used to calculate FAR using this formula:

$$(1)\quad FAR = \frac{false\ alarms}{false\ alarms + hits}$$

A higher FAR has a negative implication in that forecasters are issuing relatively more false positives in proportion to positive hits. Some research suggests that this may or may not result in the cry-wolf effect (Simmons and Sutter 2009; Schultz et al. 2010; Trainor 2015; Lim et al. 2019). This means that if forecasters issue too many false alarms, citizens may not respond to tornado-producing warnings as they should. However, research does not agree that the cry-wolf effect is significant. For example, Simmons and Sutter (2009) suggest that high FAR kills more people, while a Lim et al. (2019) survey suggests that people in the Southeast tend to take warnings seriously regardless of false alarms. Anderson-Frey et al. (2019) found that FAR is worse (78.6%) in the Southeast than the rest of the United States (75.6%), which may be an artifact of the higher frequency of nocturnal tornadoes. However, Anderson-Frey et al. (2016) also found that QLCS-type storms have a lower FAR, and there are an increased proportion of QLCSs in the Tennessee Valley than the rest of the United States (Smith et al. 2012).

Lastly, POD is essentially the likelihood that a forecaster will successfully warn for a tornado. The formula for POD is:

$$(2)\quad POD = \frac{hits}{hits + misses}$$

A high POD is ideal because it means the public had warning prior to the tornado. Anderson-Frey et al. (2019) found that POD is better in the Southeast (71.5%) than the rest of the contiguous United States (65.6%). However, POD tends to be lower for linear storms like cell in line and QLCS (Brotzge at al. 2013).

Finally, multiple logistic regression was used to test if convective mode, nocturnality, and multiple-tornado days can predict whether or not a tornado was warned for, which is the basis of POD. The tornado dataset was used for this model. Multiple logistic regression was used again to answer whether or not those same variables have a measurable effect on false alarms. Multiple logistic regressions were selected because our independent variables are categorical rather than numerical, so the usual multiple linear regression would not work. The combined warned tornado and false alarm dataset was used here. Lastly, three separate Kruskal-Wallis tests were used to assess whether each of the three categorical variables affect lead time, which was based off the warned tornado dataset. Kruskal-Wallis tests were chosen because our data fails the common assumption of normality in parametric one-way ANOVA tests, and it will assess if our continuous lead time variable is significantly different from our three categorical variables.

3. Results and discussion

3.1 Descriptive statistics

The sample sizes for some modes were small (Table 2). The tornado dataset is weak in sample size for all modes except QLCS, which became a large issue for models using the tornado dataset (the likelihood of detection and lead time models). In contrast, the false alarm and warning datasets are larger than the tornado dataset, which means that the false alarm model was more likely to produce trustworthy results.

Table 2. Samples used in analysis of tornadoes (hits and misses), false alarms, and all warnings (the sum of hits and false alarms).

Mode	Hits (n = 57)	Misses (n = 32)	Tornadoes (n = 89)	False Alarms (n = 213)	Warnings (n = 270)
Cell in Cluster	13	9	22	76	89
Cell in Line	6	3	9	34	40
Discrete Supercell	11	7	18	43	54
QLCS	27	13	40	60	87

The FAR for QLCS (Table 3) is particularly low (69%) compared to other convective modes (80–85%), which compares with Ellis et al. (2019). They found that forecasters often include a "tornado-possible" tag on severe thunderstorm warnings, which decreases FAR while still warning citizens of a potential weak tornado (Ellis et al. 2019).

Regarding POD, discrete supercell and cell-in-cluster tornadoes had the lowest at 61% and 59%, respectively. Cell-in-line and QLCS tornadoes had the highest POD at 67% and 68%. These POD results directly contrast those found in Brotzge et al. (2013), which found that QLCSs had lower POD than all other convective modes and discrete supercells had the highest. A possible explanation for these results is that QLCS tornadoes in this dataset usually occurred on multiple-tornado days (68% of QLCS tornadoes), which has shown to bias the data and generate a higher POD (Brotzge and Erickson 2009; Anderson-Frey et al. 2018).

For lead time, cell in line had the best result (16 minutes) and discrete supercell had the worst (7 minutes). In contrast, Brotzge et al. (2013) found that discrete supercells had the highest lead time in the contiguous United States. However, the lead times in this study were most likely affected by the small sample sizes of tornado-producing cells in clusters (n = 22) and cells in lines (n = 9).

Table 3. FAR, POD, and average lead times for each convective mode.

Mode	FAR	Lead Time (min)	POD
Cell in Cluster	0.85	11.18	0.59
Cell in Line	0.85	15.67	0.67
Discrete Supercell	0.80	7.33	0.61
QLCS	0.69	9.85	0.68

Out of all tornadoes, 40% of them were nocturnal. Specifically, 68% of QLCS tornadoes were nocturnal, while no discrete supercell tornadoes were. The higher percent of nocturnal tornadoes is likely a remnant of the high number of QLCS tornadoes that were part of a multi-tornado day. In fact, 82% of all tornadoes occurred on a day with at least one other tornado in this study, in addition to the fact that 45% of the tornadoes that occurred during this time period were from QLCSs. This aligns with findings from Anderson-Frey et al. (2018) that a higher number of nocturnal tornadoes occur in outbreaks (26%), while nocturnal single-events occur less often. This makes the Nashville basin unique to the rest of the contiguous United States and further supports the data shown by Anderson-Frey et al. (2018) that outbreaks are more common in the South (42%) than surrounding vernacular regions.

3.2 Likelihood of detection

A multiple logistic regression model was created to predict whether or not a tornado was warned for in advance (detected) with the predictors: convective mode, nocturnality, and whether or not a tornado was part of a multiple-tornado day (Table 4). The regression showed that, compared to isolated tornadoes, tornadoes on multiple-tornado days were 7 times more likely to be detected. Nocturnal tornadoes were 74 times more likely than daytime tornadoes to be detected. Lastly, QLCS tornadoes were 85% less likely than discrete supercells to be detected. An analysis of deviance table between a null model and the logistic regression shows a significant chi-squared result ($p < 0.05$). While the chi-squared results show that there is a significant difference between the models with and without explanatory variables, the results also suggest collinearity between nocturnal, multiple-tornado day QLCS warnings.

For this reason, it is understandable that this likelihood of detection model is not supported by other research and may not accurately capture the climatology of this study area. The nocturnal QLCS outbreaks biased the small sample area and short time frame. Because QLCSs made up the majority of the dataset, there was not enough data to use lines and clusters as trustworthy predictors in the warning model. The remaining predictors (multiple-tornado days and nocturnality) were then influenced by QLCSs and thus were likely colinear enough to skew the results of the model.

Table 4. The results of the warning multiple logistic regression, showing each coefficient for three convective modes. P-values less than 0.05 are considered significant.

	Coefficient	Std. Error	Odds Ratio	p-value
Intercept	-1.26	0.77	0.28	0.10
Cell in line	-0.40	0.98	0.67	0.70
Cell in Cluster	-0.01	0.72	0.99	0.99
QLCS	-1.87	0.82	0.15	0.02
Multiple-tornado day	1.96	0.76	7.09	< 0.01
Nocturnal	4.30	1.03	73.67	< 0.01

3.3 Likelihood of a false alarm

A second multiple logistic regression model was created for predicting whether or not a false alarm occurred using the same predictors as the likelihood of detection model (Table 5). The regression revealed that, compared to the baseline discrete supercell, QLCSs are 90% less likely to produce a false alarm. All other convective modes did not show a significant, non-random relationship to the dependent variable. All warnings issued on multiple-tornado days were 94% less likely to produce a false alarm. Compared to daytime tornadoes, nocturnal tornadoes were four times more likely to produce a false alarm. An analysis of deviance table between a null model and the false alarm model showed that there was a significant difference between the models with and without explanatory variables with a chi-squared p-value of < 0.05.

Ellis et al. (2019) found that false alarms increase at night and that forecasters felt QLCSs were more difficult to predict than discrete supercells, so they would prefer to issue more tornado warnings during QLCS events and thus produce more false alarms. While the Kruskal-Wallis tests did agree that nocturnal tornadoes were more likely to produce a false alarm, there was no indication that

QLCSs had more false alarms. In fact, QLCSs were less likely than discrete supercells to produce a false alarm in this model. This directly contrasts the research from Ellis et al. (2019) and Anderson-Frey et al. (2016), who found that FAR was higher for QLCSs. The contrasting results from this model were likely attributed to the high number of QLCSs and multiple-tornado days in the dataset.

Table 5. The results of the false alarm multiple logistic regression, showing each coefficient for the three convective modes, binary multi-tornado day, and binomial nocturnality.

	Coefficient	Std. Error	Odds Ratio	p-value
Intercept	3.46	0.58	31.72	< 0.01
Cell in Line	-0.66	0.67	0.52	0.32
Cell in Cluster	-0.07	0.51	0.93	0.88
QLCS	-2.29	0.63	0.10	< 0.01
Multi-Tornado Day	-2.84	0.48	0.06	< 0.01
Nocturnal	1.39	0.48	4.01	< 0.01

3.4 Lead time

Lastly, three Kruskal-Wallis tests were used to model lead time using convective mode, nocturnality, and whether or not a tornado was part of a multi-tornado day as predictors (Table 6). All four convective modes appear to have high variability and right or left-skewed distributions for lead time, especially during the day (Figure 3). The Kruskal-Wallis tests did not reveal any significant relationship between convective mode or multiple-tornado days with regards to lead time. A pairwise comparison between each variable and lead time also did not reveal any significant relationships. However, nocturnal tornadoes had a significant difference in median lead times and are higher than daytime tornadoes, which is visually apparent in Figure 3 and is shown by a high h-statistic and low p-value in Table 6.

It is unlikely that nocturnal tornadoes are easier to warn for than daytime ones, especially because spotters cannot see tornadoes on the ground and because previous research indicates otherwise (Brotzge et al. 2013, Ellis et al. 2019). In fact, Brotzge et al. (2013) suggests that, for the contiguous United States, discrete supercells have the longest lead time. For this study, QLCSs had the longest average lead time. This could be a result of the many QLCS multiple-tornado days unique to this area, in addition to the large sample size of QLCSs compared to the three other convective modes. The bulk of the QLCS data were nocturnal, and the sample sizes were particularly small for each mode. Additionally, there were several outliers for each convective mode, which may skew the results. However, if the outliers are removed, cells in clusters (where n = 6), would be even fewer.

Figure 3. Boxplots of lead times that are categorized by convective mode and faceted by nocturnality.

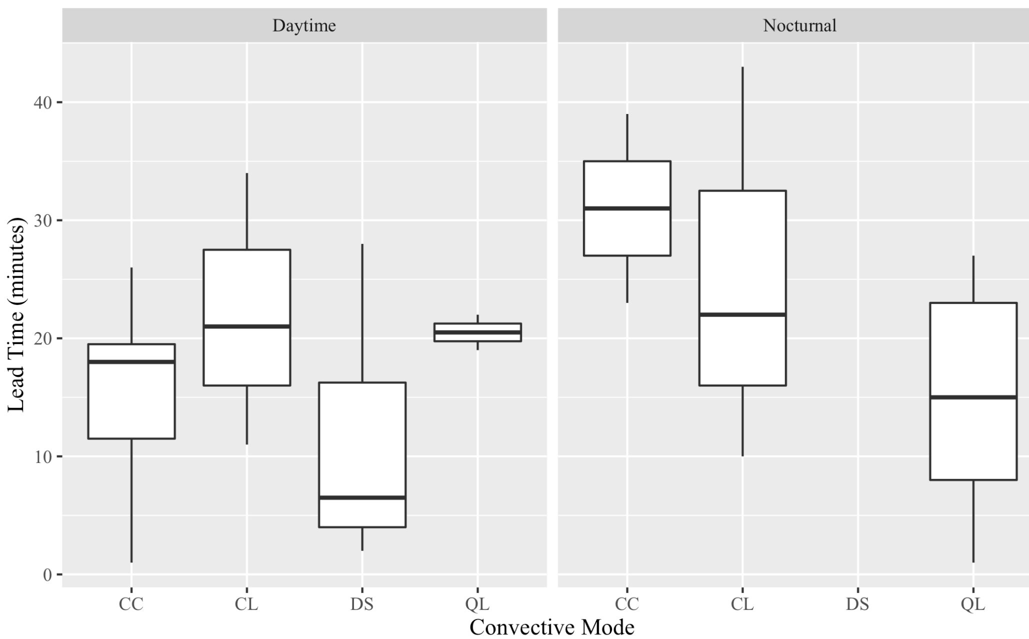


Table 6. The results of the three Kruskal-Wallis tests for lead time.

	h-statistic	p-value
Convective mode	1.32	0.72
Multiple-day tornado	2.38	0.12
Nocturnal	13.09	< 0.01

5. Conclusion

This study has extended the knowledge garnered from Ellis et al. (2019) and created a more complete dataset (by including false alarms) than its counterparts (Smith et al. 2012, Brown et al. 2016, Davis and Parker 2014). The study suggests that the Nashville basin tornado climatology and forecasting metrics are unique to Tennessee. The majority of storms were QLCSs (contrary to the Ellis et al. 2016 findings), which had better success metrics than its counterparts. Multiple-tornado days played a large part in this dataset because the study area is small, and the sample contains mostly multiple-tornado days.

In the future, the dataset should be expanded upon to include more years and other CWAs in the Southeast. This may improve the results gathered from this study and may also create a more trustworthy climatology of the region. It may also be of interest to consider how modern climate change could affect the local climatology. Additionally, research should focus on automating convective mode classification to reduce the inherent bias and subjectivity of the researcher (Ashley 2019). This will improve models and also reduce the amount of time required to identify modes. Lastly, the development of success metrics that include a spectrum of warning types rather than hits and misses would be an interesting way to understand the challenges concurrent with different convective modes.

6. References

Agee, E. and L. Taylor, 2019: Historical Analysis of U.S. Tornado Fatalities (1808–2017): Population, Science, and Technology. *Wea. Clim. and Soc.*, **11**, 355–368, https://10.1175/WCAS-D-18-0078.1

Anderson-Frey, A.K., Y.P. Richardson, A.R. Dean, R.L. Thompson, and B.T. Smith, 2019: Characteristics of Tornado Events and Warnings in the Southeastern United States. *Wea. Forecasting*, **34**, 1017–1034, https://10.1175/WAF-D-18-0211.1

–, 2018: Near-Storm Environments of Outbreak and Isolated Tornadoes. *Wea. Forecasting*, **33**, 1397–1412, https://10.1175/WAF-D-18-0057.1

–, 2016: Investigation of Near-Storm Environments for Tornado Events and Warnings. *Wea. Forecasting*, **31**, 1771–1790, https://10.1175/WAF-D-16-0046.1

Ashley, W.S., 2019: A Climatology of Quasi-Linear Convective Systems and Their Hazards in the United States. *Wea. Forecasting*, **34**, 1605–1631, https://10.1175/WAF-D-19-0014.1

Brooks, H.E., 2004: Tornado-Warning Performance in the Past and Future. *Bull. Amer. Meteor. Soc.*, **85**, 837–844, https://10.1175/BAMS-85-6-837

Brotzge, J.A., S.E. Nelson, R.L. Thompson, and B.T. Smith, 2013: Tornado Probability of Detection and Lead Time as a Function of Convective Mode and Environmental Parameters. *Wea. Forecasting*, **28**, 1261–1276, https://10.1175/WAF-D-12-00119.1

–, and S. Erickson, 2009: NWS Tornado Warnings with Zero or Negative Lead Times. *Wea. Forecasting*, **24**, 140–154, https://doi.org/10.1175/2008WAF2007076.1

Brown, V.M., K.N. Ellis, and S.A. Bleakney, 2016: Tennessee Tornado Climate: A Comparison of Three Cities. *Southeastern Geographer*, **56**, 118–133, https://10.1353/sgo.2016.0008

Davis, J.M., and M.D. Parker, 2014: Radar Climatology of Tornadic and Nontornadic Vortices in High-Shear Low-CAPE Environment in the Mid-Atlantic and Southeastern United States. *Wea. Forecasting*, **29**, 828–853, https://10.1175/WAF-D-13-00127.1

Doswell, C.A., III, and D.W. Burgess, 1988: On Some Issues of United States Tornado Climatology. *Mon. Wea. Rev.*, **116**, 495–501, https://10.1175/1520-0493(1988)116<0495:OSIOUS>2.0.CO;2

Ellis, K.N., D. Burrow, K.N. Gassert, L. Reyes-Mason, and M.S. Porter, 2019: Forecaster Perceptions and Climatological Analysis of the Influence of Convective Mode on Tornado Climatology and Warning Success. *Annals of the American Association of Geographers*, **109**, 1–20, https://10.1080/24694452.2019.1670042

Gallus, W.A., N.A. Snook, and E.V. Johnson, 2008: Spring and Summer Severe Weather Reports over the Midwest as a Function of Convective Mode: A Preliminary Study. *Wea. Forecasting*, **23**, 101–113, https://10.1175/2007WAF2006120.1

Geerts, B., 1998: Mesoscale Convective Systems in the Southeast United States during 1994–95: A Survey. *Wea. Forecasting*, **13**, 860–869, https://10.1175/1520-0434(1998)013<0860:MCSITS>2.0.CO;2

Hoekstra, S., K. Klockow, R. Riley, J. Brotzge, H. Brooks, and S. Erickson, 2011: A Preliminary Look at the Social Perspective of Warn-on-Forecast: Preferred Tornado Warning Lead Time and the General Public's Perceptions of Weather Risks. *Wea. Clim. Soc.*, **3**, 128–140, https://10.1175/2011WCAS1076.1

Lim, J.R., B.F. Liu, and M. Egnoto, 2019: Cry Wolf Effect? Evaluating the Impact of False Alarms on Public Responses to Tornado Alerts in the Southeastern United States. *Wea. Clim. Soc.*, **11**, 549–563, https://10.1175/WCAS-D-18-0080.1

NWS, 2020: Severe Weather Definitions. Accessed 29 April 2020, https://www.weather.gov/bgm/severedefinitions

–, 2011: EF5 Tornado Track: Franklin (AL) to Franklin (TN). Accessed 30 April 2020, https://www.weather.gov/hun/4272011_franklin-al_lawrence_limestone_madison_franklin-tn_counties

Rose, M.A., 2004: A Tornado Climatology of Middle Tennessee (1830–2003). NOAA, Accessed 3 April 2020, https://www.weather.gov/ohx/tornadoclimatology

Schultz D.M., E.C. Gruntfest, M.H. Hayden, C.C. Benight, S. Drobot, and L.R. Barnes, 2010: Decision Making by Austin, Texas, Residents in Hypothetical Tornado Scenarios. *Wea. Clim. Soc.*, **2**, 249–254, https://10.1175/2010WCAS1067.1

Simmons, K.M., and D. Sutter, 2009: False Alarms, Tornado Warnings, and Tornado Casualties. Wea. Clim. Soc., **1**, 38–53, https://10.1175/2009WCAS1005.1

Smith, B.T., R.L. Thompson, J.S. Grams, C. Broyles, and H.E. Brooks, 2012: Convective Modes for Significant Severe Thunderstorms in the Contiguous United States. Part I: Storm Classification and Climatology. *Wea. Forecasting*, **27**, 1114–1135, https://10.1175/WAF-D-11-00115.1

Stensrud, D.J., et al., 2013: Progress and Challenges with Warn-on-Forecast. *Atmos. Res.*, **123**, 2–16, https://doi.org/10.1016/j.atmosres.2012.04.004

Trainor, J.E., D. Nagele, B. Phillips, and B. Scott, 2015: Tornadoes, Social Science, and the False Alarm Effect. Wea. Clim. Soc., **7**, 333–352, https://10.1175/WCAS-D-14-00052.1