Tornado Probability of Detection and Lead Time as a Function of Convective Mode and Environmental Parameters

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ABSTRACT

The ability to provide advanced warning on tornadoes can be impacted by variations in storm mode. This research evaluates 2 yr of National Weather Service (NWS) tornado warnings, verification reports, and radar-derived convective modes to appraise the ability of the NWS to warn across a variety of convective modes and environmental conditions. Several specific hypotheses are considered: (i) supercell morphologies are the easiest convective modes to warn for tornadoes and yield the greatest lead times, while tornadoes from more linear, nonsupercell convective modes, such as quasi-linear convective systems, are more difficult to warn for; (ii) parameters such as tornado distance from radar, population density, and tornado intensity (F scale) introduce significant and complex variability into warning statistics as a function of storm mode; and (iii) tornadoes from stronger storms, as measured by their mesocyclone strength (when present), convective available potential energy (CAPE), vertical wind shear, and significant tornado parameter (STP) are easier to warn for than tornadoes from weaker systems. Results confirmed these hypotheses. Supercell morphologies caused 97% of tornado fatalities, 96% of injuries, and 92% of damage during the study period. Tornado warnings for supercells had a statistically higher probability of detection (POD) and lead time than tornado warnings for nonsupercells; among supercell storms, tornadoes from supercells in lines were slightly more difficult to warn for than tornadoes from discrete or clusters of supercells. F-scale intensity and distance from radar had some impact on POD, with less impact on lead times. Higher mesocyclone strength (when applicable), CAPE, wind shear, and STP values were associated with greater tornado POD and lead times.

1. Introduction

Nationwide, National Weather Service (NWS) tornado probability of detection (POD), false alarm ratio (FAR), and lead time statistics have remained fairly steady since 2003; about 75% of all tornadoes are warned for in advance, with lead times of 13 min (NOAA 2012). Most importantly, a vast majority of the most deadly tornadic storms now have very large lead times. However, a careful review of the mean statistics shows a wide disparity across regions, seasons, times of day, and population densities (Brotzge and Erickson 2009, 2010). Further improvement in warning statistics will require more specific attention to these variables.

Studies have long recognized a relationship between the evolution and morphology of a convective system and the resultant severe weather and subsequent damage produced by it (Gallus et al. 2008; Duda and Gallus 2010; Thompson et al. 2012). Furthermore, as observing technologies have advanced, additional means for classifying storms have been attained. For example, the advent of satellites has allowed for the identification of mesoscale convective complexes (MCCs; Maddox 1980)

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from space, and the deployment of the Weather Surveillance Radar-1988 Doppler (WSR-88D) network permitted supercell structures to be more clearly defined (e.g., Polger et al. 1994). Additional observing capabilities such as dual polarization may allow for even greater differentiation among storm modes.

Because of this strong relationship between storm mode and severe weather, storm-type classification has enhanced warning operations (Andra et al. 2002). New data-mining techniques continue to be developed that provide for the routine, real-time, automated identification of storm type and convective mode (Beatty et al. 2009; Gagne et al. 2009; Lakshmanan and Smith 2009; Lack and Fox 2012). The next step in moving this research to operations is to better quantify how current warning process statistics are impacted by variations in convective mode and environmental parameters. In other words, what does the warning forecaster do with this new storm mode information, and how does it change his/her understanding of the storm and subsequent warning procedures?

This research evaluates 2 yr of NWS tornado warnings, verification reports, and radar-derived convective modes across the continental United States (CONUS) to evaluate the ability of the NWS to warn on tornadoes across a variety of convective modes and environmental conditions. Several specific hypotheses are considered: (i) tornadoes from supercells, including discrete cells, cell clusters, and cells in lines, are the easiest convective modes to warn for and yield the greatest lead times, while tornadoes from more linear nonsupercell convective modes, such as quasi-linear convective systems (QLCS), are more difficult to warn for; (ii) parameters such as tornado distance from radar, population density, and tornado intensity (F scale) introduce significant and complex variability into tornado warning statistics as a function of storm mode; and (iii) tornadoes associated with stronger convective systems, as measured by their mesocyclone strength (when present), convective available potential energy (CAPE), vertical wind shear, and significant tornado parameter (STP), are easier to warn for than weaker systems.

2. Data and methodology

Two independent datasets were combined to carry out this study. First, a database of all tornado events and NWS warnings issued between 2000 and 2004 was obtained from the Performance Branch of the NWS. This database contains information regarding tornado warning issuance and expiration dates and times, the NWS Weather Forecast Office (WFO) that issued the warning, the county or parish warned, and the corresponding tornado reports (including F scale, damage, and casualties). Estimates of county population density were provided by the Population Division of the U.S. Census Bureau and were obtained from the 1 July 2000 population estimates (U.S. Census Bureau 2008). A total of 18 763 tornado warnings and 7019 tornadoes were recorded during the 5-yr period. All data were county based, meaning that if one tornado crossed three counties, it was counted as three separate tornado events and warnings. NWS tornado warning lead times and false alarms have been analyzed using these data (Brotzge and Erickson 2009, 2010; Brotzge et al. 2011).

A second database of tornado and significant severe events between 2003 and 2011 was compiled by the Storm Prediction Center (SPC). The largest magnitude report per hour was extracted from a Rapid Update Cycle (RUC) model (Benjamin et al. 2004) analysis grid of 40-km horizontal grid spacing. In this case, individual long-track tornadoes may have been segmented if their paths crossed multiple grid boxes and/or hours. This database yielded 10 753 tornadoes during the 9-yr period. Next, the closest radar site to each event (within 230 km) was selected, and the associated archived level II (or level III when appropriate) WSR-88D data from the National Oceanic and Atmospheric Administration/National Climatic Data Center (NOAA/NCDC; http://www.ncdc.noaa.gov/nexradinv/) were downloaded for each severe event. Each severe thunderstorm event was then manually classified into one of three broad storm morphology categories based upon its reflectivity and velocity signatures: (i) supercell, (ii) nonsupercell QLCS, and (iii) ‘‘disorganized’’, nonsupercell storms. Supercells were subcategorized as either discrete cells, cells in clusters, or cells in lines. All but five supercells were right-moving (RM) supercells; data from the five left-moving supercells were evaluated separately in this study due to the unusual morphology and rarity of these events. Due to the relatively small sample size, bow echoes were included within the ‘‘nonsupercell QLCS’’ category. Additional specifics on storm classification are described in Smith et al. (2012). This dataset has been used in a series of studies investigating the relationship between storm morphology and storm environmental parameters and prediction (Smith et al. 2012; Thompson et al. 2012; Edwards et al. 2012).

These two datasets overlapped for only two years (2003 and 2004) and so work for this manuscript was limited to those two years. These two datasets were cross-referenced, and only those tornado events that were included in both datasets were used. The cross-referencing procedure yielded a total of 2502 tornadoes, with 9177 county-based tornado warnings issued by the NWS during the 2 yr.

For mesocyclone identification, the volumetric storm-relative velocity data at the volume scan time immediately preceding the start of each tornado were used. To be identified as a mesocyclone required a peak rotational velocity $\geq 10\,\mathrm{m\,s^{-1}}$ and time continuity of identifiable rotation for at least 10–15 min (typically three consecutive volume scans or more). Additionally, mesocyclones required other reflectivity structures consistent with supercells (e.g., hook echoes). QLCS mesovortices were not specifically identified or tracked; if a storm did not meet the supercell criteria, there was no circulation strength information recorded.

The environmental data in this study are the same as those used in Thompson et al. (2012), which were based on the SPC hourly mesoanalyses documented by Bothwell et al. (2002). Specifically, the county warnings were matched to the closest mesoanalysis grid point (40-km horizontal grid with hourly temporal resolution), and all of the parameters were derived from the National Centers Advanced Weather Interactive Processing System Skew T Hodograph Analysis and Research Program (NSHARP) sounding software. Mixed layer CAPE (MLCAPE) was calculated for the lowest 100-mb mean parcel using the virtual temperature correction (Doswell and Rasmussen 1994). The bulk wind differences (BWDs) were calculated over three different layer depths: 0–1, 0–3, and 0–6 km AGL.

For warning operations, multivariate, composite parameters have been useful for discriminating between tornadic and nontornadic storms. One such composite parameter, the STP (Thompson et al. 2003), utilizes MLCAPE, LCL heights based on the lowest 100-hPa mean parcel, 0–1-km storm relative helicity, and 0–6-km BWD, and was found by Thompson et al. (2003) to be a reliable discriminator between significantly tornadic and nontornadic supercells.

To evaluate the proposed hypotheses, tornado POD and warning lead times were calculated for each storm as a function of storm-type morphology, F scale, tornado distance from nearest radar (as measured from the latitude–longitude at the beginning of the damage path), county population density, associated mesocyclone strength (if applicable), and related environmental parameters, including the MLCAPE, vertical wind shear, and STP. POD rates were expressed as a percentage. Tornado warning lead times were calculated with and without negative and zero lead times for comparison.

Some problems with tornado reporting may limit the accuracy of this study. In general, weak (F0) tornadoes often are underreported (Verbout et al. 2006). How well tornado verification is done likely varies as a function of several variables including population density, storm spotter activity, and local weather forecast office procedures. Poor storm verification can overinflate the FAR and overestimate the POD (Smith 1999), and so warning statistics may need to be evaluated with some caution.

Parametric statistical testing was used throughout this manuscript to evaluate differences between categories and percentages of uncertainty (Wilks 1995). Estimates of uncertainty were calculated as a function of sample size with a 95% confidence interval. A two-tailed Student's t test was used to determine the significance between categories.

3. Results

a. Warning statistics as a function of convective mode, tornado intensity, radar range, and population density

The first hypothesis tested was that supercell-based tornadoes are the most likely to have greater lead times, while QLCS tornadoes are more difficult to warn for and often have shorter lead times. As a first step in understanding the impacts from convection as a function of its inherent morphology, all 2003 and 2004 tornado data from the hourly, gridded SPC database were sorted by storm type (Table 1). Tornado fatalities, injuries, and damage were summed for each storm-type bin. A distinct difference is noted between supercells (discrete, cluster, and in line) and QLCS and disorganized storm structures. Over 97% of fatalities (84 out of 86) and 96% of all injuries occurred from supercell tornadoes. The vast majority of the damage was also from supercell morphologies (92.9%). The operational and social implications of these statistics are discussed in the conclusions section. However, results from this 2-yr (2003–2004) sample are encouraging in that, if the proposed hypothesis is correct that tornadoes from supercell morphologies are easier to warn for, then we may conclude that current warning operations are providing positive lead-time tornado warnings on the most dangerous storm types.

A review of Table 1 reveals surprising variability among the supercell convective mode subcategories (e.g., discrete cell, cell in cluster, cell in line). Most intriguing, supercells in lines had much higher fatality and injury rates per tornado than did any other group; the damage per tornado was similar to that of discrete supercells. Supercells in lines, while only 12.7% of all classified supercells, had 25% of all supercell-related tornado fatalities. The reasons for this may be multifaceted; for example, tornadoes from supercells in lines are most frequent across the Deep South, where they tend to occur from the fall through spring months and peak during the spring, making them more dangerous

TABLE 1. Total number of grid-hour tornado events and related fatalities, injuries, and damage as reported across the CONUS during 2003–04, categorized as a function of storm type.

Category	Total No.	Deaths	Injuries	Cost of damage (U.S. dollars)	Deaths per 100 tornadoes	Injuries per 100 tornadoes
Supercells, discrete	766	37	490	638.7	4.8	64.0
Supercells in cluster	925	26	392	350.5	2.8	42.4
Supercells in line	245	21	383	210.7	8.6	156.3
QLCS*	278	1	44	84.4	0.4	15.8
Disorganized	455	1	6	6.9	0.2	1.3

* Note: QLCS includes bow echoes for this and subsequent tables.

than more typical, springtime discrete supercells in the plains states (Smith et al. 2012). Supercells in lines also are associated with less overall storm MLCAPE but greater vertical wind shear than discrete supercells (as discussed in section 3c). Finally and as shown in the next section, tornado warnings are more difficult for supercells in lines, with lower PODs and shorter lead times than all other supercell types. In this limited sample, there was no clear correlation between whether or not a tornado was warned for and those tornadoes with fatalities. However, extraneous factors such as time of day and storm visibility may contribute to lower warning statistics and lower sheltering rates. Brotzge and Erickson (2010) found that the tornadoes most likely to strike when the public is least aware are also those tornadoes with the greatest chance of not being warned for.

Next, the cross-referenced database was sorted by storm type and whether or not each tornado was warned for (Table 2, Fig. 1a). Here again, a distinct difference is noted between supercell and nonsupercell morphologies. The PODs for supercells averaged between 80% and 88% with a median lead time of 13–15 min. The POD for nonsupercell storms varied between 44% and 49% with an average of 45.8%, and with a median lead time between 9 and 10 min. Note that less than half of all nonsupercell tornadoes were warned for. The average tornado lead time for supercells (16.8 min) was statistically higher than those from nonsupercells (11.9 min), such as QLCS and disorganized storms, by an average of 4.8 min.

Five left-moving supercells were identified during the 2-yr study period. Of the tornadoes from these five storms, four were rated F0 and one was rated F1. None of the tornadoes produced any fatalities or injuries, and only the F1 tornado produced damage (estimated at $75,000). Two of the supercells were identified as discrete, with the remaining three supercells identified as supercells in clusters. One discrete left-moving supercell had no NWS tornado warning, while the second discrete storm had a late (−2 min) warning. Of the three supercells in clusters, two tornadoes had positive lead-time warnings of +17 and +21 min, while the third tornado had no warning.

The QLCS category included classic QLCS storms (223 events), bow echoes (31 events), and nonsupercell cells in line (24 events). Overall, this category represented an excellent cross section of QLCS tornado events across the CONUS throughout the year. About 45.3% of events occurred during spring (March–May), and 24.8% occurred during summer (June–August). Only about 7.6% of QLCS tornadoes occurred during the winter months (December–February). No bow-echo or cells-in-line tornadoes were recorded during the winter season. About 36.3% of QLCS tornadoes occurred across the upper Midwest (Iowa, Missouri, Wisconsin, Michigan, Minnesota, Illinois, Indiana, Ohio, Kentucky, Pennsylvania), and about a quarter (26.6%) occurred in the South (South Carolina, Florida, Tennessee, Georgia, Alabama, Mississippi, and Louisiana). Another 19.4% occurred across the southern plains (Texas, Oklahoma, and Arkansas).

One reason for the difference in lead times between supercell and nonsupercell storms is that nonsupercell storm tornado warnings contained a higher fraction of zero and negative warnings. Negative lead times (when the warning was issued after tornadogenesis) with nonsupercell morphologies occurred at over 3 times the rate of supercells (17.8% vs 5.2%, respectively). The percentage of warnings with zero lead times was closer

TABLE 2. POD (%) and median and mean lead time (min) as a function of storm type. The 95% confidence interval is calculated for the POD as a function of sample size.

Category	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
Supercells, discrete	636	88	87.9 ± 2.4	15	17.8
Supercells in cluster	725	132	84.6 ± 2.4	14	16.4
Supercells in line	186	45	80.5 ± 5.1	13	15.0
QLCS	122	129	48.6 ± 6.2	10	12.3
Disorganized	192	242	44.2 ± 4.7	9	11.7

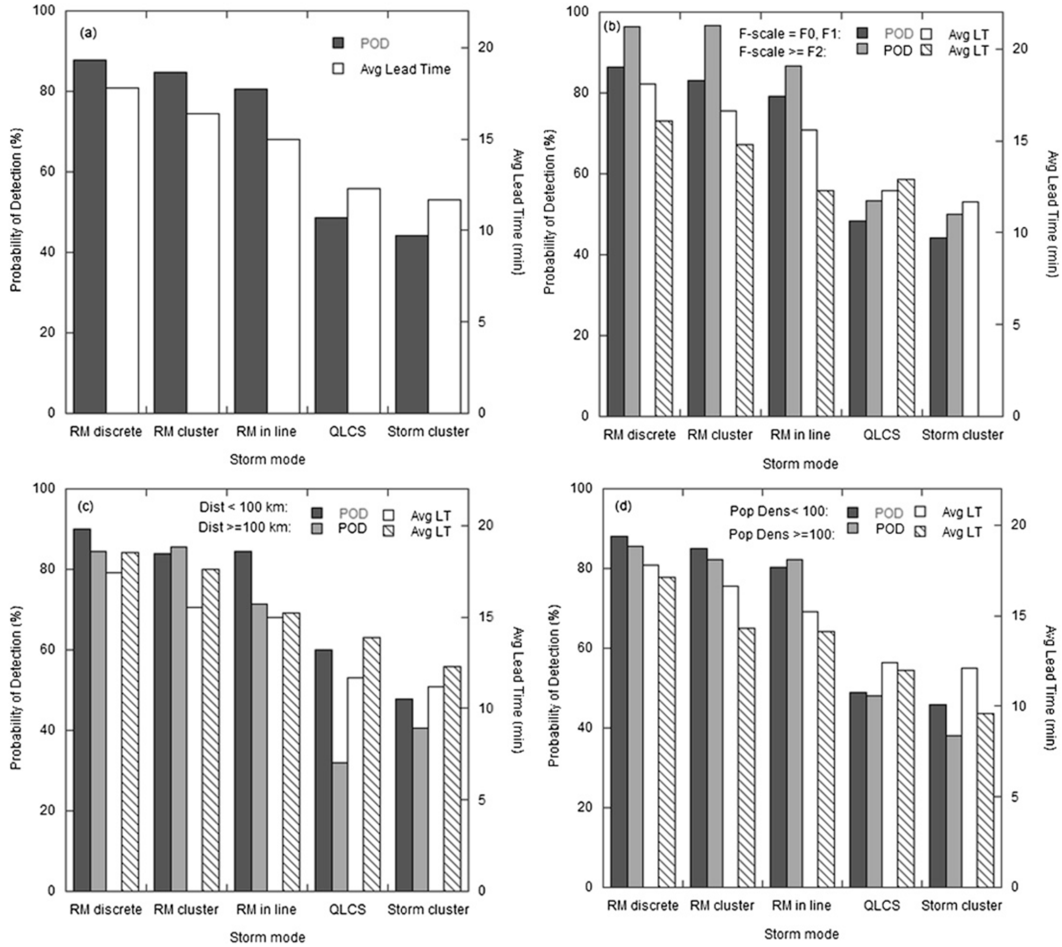

FIG. 1. POD (%) and mean lead time (min) estimated as a function of (a) storm mode. The POD and mean lead time estimated as a function of storm mode and (b) F scale, (c) distance from radar (km), and (d) county population density (persons per square kilometer).

across the two categories, with 4.2% of supercell warnings compared with 5.4% of nonsupercell storms. When zero and negative lead times are removed from the lead-time calculations, the average supercell and nonsupercell tornado warning lead times improved to 18.7 and 16.8 min, respectively.

From this comparison, it is shown that tornado warning POD and lead time varied significantly as a function of

TABLE 3. As in Table 2, but sorted by F scale.

Variable	Category	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
F scale: F0, F1		1624	616	72.5 ± 1.9	14	16.1
	Supercells, discrete	528	84	86.3 ± 2.7	16	18.1
	Supercells, cluster	638	129	83.2 ± 2.7	14	16.6
	Supercells in line	153	40	79.3 ± 5.7	13	15.6
	QLCS	114	122	48.3 ± 6.4	10	12.3
	Disorganized	191	241	44.2 ± 4.7	9	11.7
F scale ≥ F2		237	20	92.2 ± 3.3	13	14.9
	Supercells, discrete	108	4	96.4 ± 3.5	15	16.1
	Supercells, cluster	87	3	96.7 ± 3.7	12	14.8
	Supercells in line	33	5	86.8 ± 10.7	10	12.3
	QLCS	8	7	53.3 ± 25.3	3	12.9
	Disorganized	1	1	50.0 ± 50.0	0	0.0

TABLE 4. As in Table 2, but sorted by distance from nearest radar.

Variable	Category	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
Range < 100 km		1156	324	78.1 ± 2.1	13	15.4
	Supercells, discrete	404	45	90.0 ± 2.8	15	17.4
	Supercells, cluster	422	81	83.9 ± 3.2	13	15.5
	Supercells in line	136	25	84.5 ± 5.6	13	15.0
	QLCS	89	59	60.1 ± 7.9	8	11.7
	Disorganized	105	114	47.9 ± 12.2	10	11.2
Range ≥ 100 km		705	312	69.3 ± 2.8	14	16.9
	Supercells, discrete	232	43	84.4 ± 4.3	15.5	18.5
	Supercells, cluster	303	51	85.6 ± 3.7	14	17.6
	Supercells in line	50	20	71.4 ± 10.6	12.5	15.2
	QLCS	33	70	32.0 ± 9.0	12	13.9
	Disorganized	87	128	40.5 ± 6.6	8	12.3

storm type. Differences in storm type caused average tornado PODs to vary by as much as 40% and lead times to vary by as much as 6 min.

The second hypothesis stated that radar distance, population density, and tornado intensity impact tornado warning statistics as a function of storm mode. The relationship between tornado warning statistics and these additional factors was examined as sorted by storm type. The data first were separated according to their F scale, with weak tornadoes (F0, F1) compared against significant tornadoes, those rated F2 or greater (Table 3, Fig. 1b). Results indicated that the more intense tornadoes tended to have a statistically higher POD (92.2%) than weaker tornadoes (72.5%) at the 95% confidence level. This result is expected as weaker tornadoes often are short lived and transient. The POD was significantly higher for ≥ F2 tornadoes for discrete and cluster supercells; sample sizes were too small to draw conclusions from other storm-type categories. While warning lead times appeared to be shorter for the stronger tornadoes than for the weaker ones, these differences were not statistically significant. The numbers of negative and zero lead times were equally apportioned across weak and significant tornado categories.

Next, the data were sorted by the distance of the tornado from the nearest WSR-88D site and storm type (Table 4, Fig. 1c). Data collected within 100 km of a radar site had a statistically significant higher POD (78.1%) than data from those storms located farther than 100 km away (69.3%). Most category sample sizes were too small to yield significance; only QLCS showed a significant (and large) drop with radar distance. Overall, more linearly oriented storm morphologies (supercells in lines and QLCS) had a much steeper drop in POD with distance than did other morphologies; we speculate that vortices associated with linear-based storms were shallower and had smaller circulations than supercell-based storms, and so were more difficult to analyze far from radar. The POD of QLCS storms nearly doubled as the radar range decreased.

Tornado lead times were significantly greater (using a Student's t test at a 95% confidence interval) by 1.5 min for storms at distances > 100 km when compared to data collected within 100 km of radar. However, when zero and negative lead times were removed from the data, these differences were no longer significant. There were 4% more zero and negative lead times for warnings within 100 km of radar than in data collected beyond

TABLE 5. As in Table 2, but sorted by county population density (persons per square kilometer).

Variable	Category	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
Population density < 100		1644	523	75.9 ± 1.8	14	16.2
	Supercells, discrete	583	79	88.1 ± 2.5	15	17.8
	Supercells, cluster	651	116	84.9 ± 2.5	14	16.6
	Supercells in line	154	38	80.2 ± 5.6	13	15.2
	QLCS	98	103	48.8 ± 6.9	9.5	12.4
	Disorganized	158	187	45.8 ± 5.3	9.5	12.1
Population density ≥ 100		217	113	65.8 ± 5.1	12	14.0
	Supercells, discrete	53	9	85.5 ± 8.8	16	17.1
	Supercells, cluster	74	16	82.2 ± 7.9	11	14.3
	Supercells in line	32	7	82.1 ± 12.0	12.5	14.1
	QLCS	24	26	48.0 ± 13.9	11	12.0
	Disorganized	34	55	38.2 ± 26.4	4	9.6

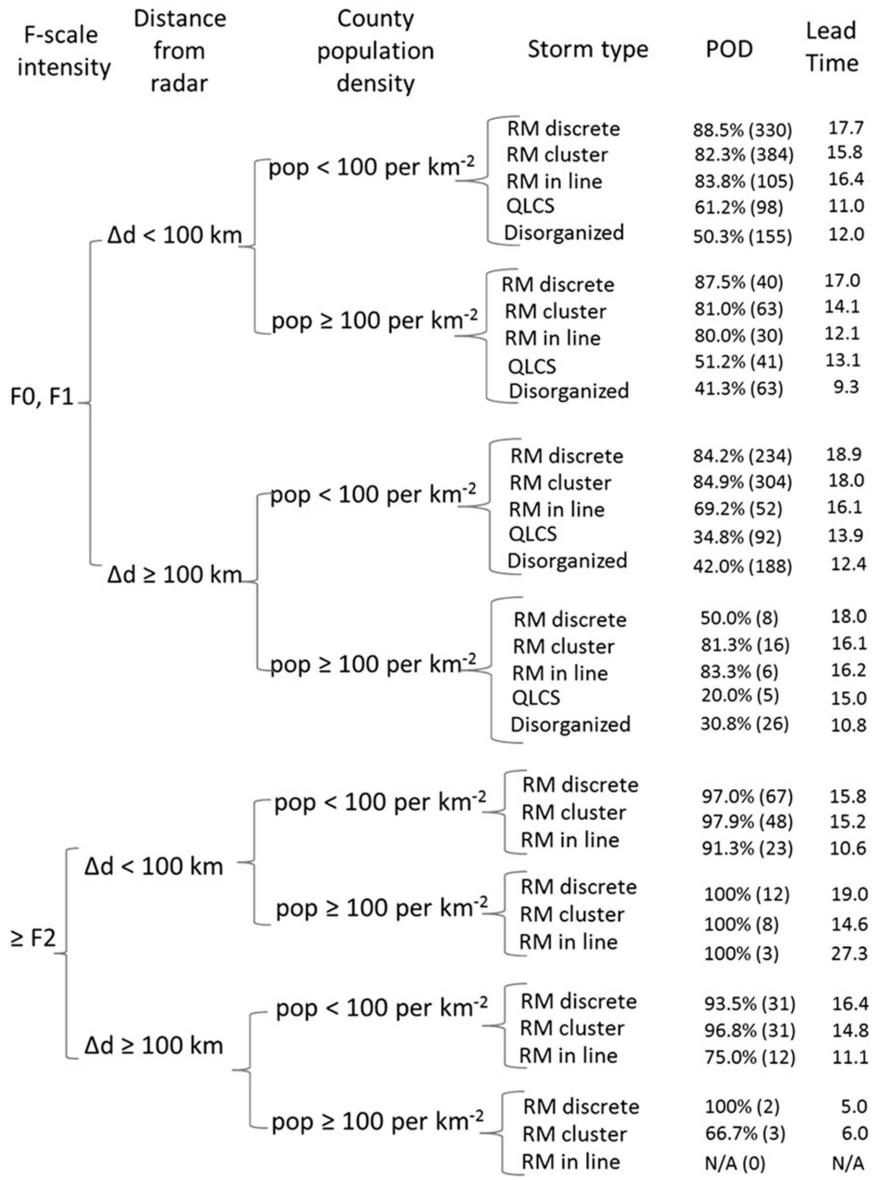

FIG. 2. POD (%) and average lead time (min) calculated as a function of F scale, distance from radar, county population density, and storm type. Category sample sizes are listed in parentheses. Right-moving supercells are abbreviated RM.

100 km from radar, leading to overall lower mean lead times in the short-range data. Average lead times for all storm categories increased with radar distance, but these were not statistically significant, likely due to sample size.

Finally, POD and lead time were compared as a function of county population density and storm type (Table 5, Fig. 1d). Storms in more rural regions (population density < 100 persons per square kilometer) had a significantly higher POD (75.9%) than storms in more urban areas (population density ≥ 100 persons per square kilometer; 65.8%). Of the individual storm types, only supercells in lines had a higher POD in more densely populated counties. Similarly, average lead times were statistically higher in less populated regions than those in higher population density areas (16.2 vs 14.0 min). However, the more urban areas had a 3% greater proportion of zero and negative lead time warnings, and once these were removed from the dataset, the difference in the average lead time between rural and urban areas was insignificant.

In summary, tornado warning performance was impacted significantly by factors including storm type, tornado intensity, radar distance, and county population

TABLE 6. POD (%) and mean lead time (min) as a function of mesocyclone strength.

Category	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
None	311	369	45.7 ± 3.7	9	11.9
Weak	544	162	77.1 ± 3.1	14	16.4
Moderate	415	55	88.3 ± 2.9	13	15.5
Strong	591	50	92.2 ± 2.1	16	18.0

density. Overall, PODs were significantly higher for ≥ F2 tornadoes, storms within 100 km of radar, and for storms in counties with rural (<100 persons per square kilometer) population densities. These impacts varied as a function of storm type. Average lead times were significantly higher for storms far from radar and in rural areas. However, these differences were insignificant once negative and zero lead-time warnings were removed. In other words, one may surmise that more real-time spotter reports from more densely populated regions (often within 100 km of radar) led to greater numbers of negative and zero lead-time warnings, warnings that were likely missed in more rural areas (Brotzge and Erickson 2010).

To better understand the specific, collective impacts of storm type, F scale, radar range, and population density, the POD and average lead times were calculated for each of 40 categories (5 storm type, 2 F scale, 2 radar distance, and 2 county population categories) (Fig. 2). Of particular significance is the high (>90%) POD for F2 or greater tornadoes within 100 km of radar, compared with the much lower PODs for weak (F0, F1) tornadoes located ≥100 km from radar. Similar trends in warning lead time are less coherent.

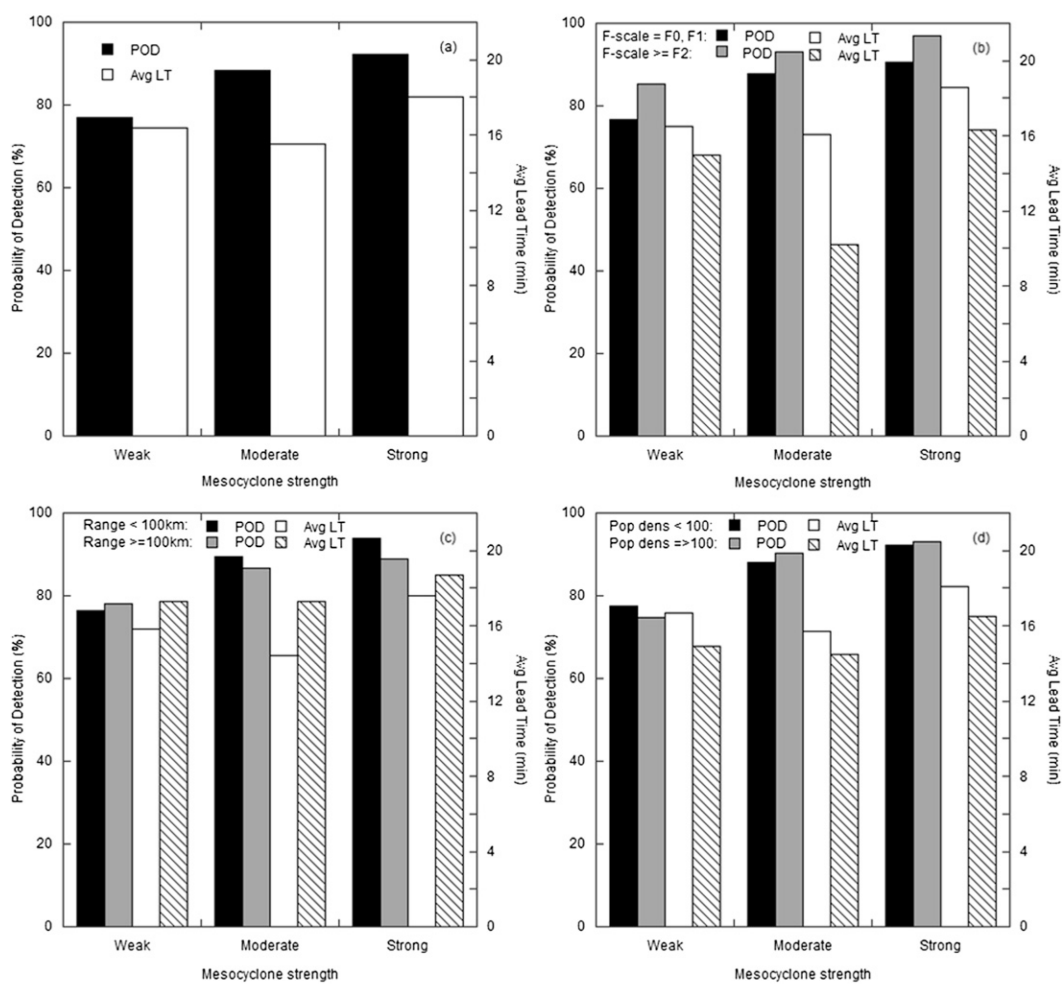

FIG. 3. POD (%) and mean lead time (min) estimated as a function of (a) mesocyclone strength. The POD and mean lead time estimated as a function of mesocyclone strength and (b) F scale, (c) distance from radar (km), and (d) county population density (persons km^{-2}).

TABLE 7. POD (%) and median and mean lead time (min) as a function of mesocyclone strength and storm type.

Category	Variable	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
None reported						
	QLCS	122	129	48.6 ± 6.2	10	12.3
	Disorganized	189	240	44.1 ± 4.7	9	11.7
Weak						
	Supercells, discrete	220	52	80.9 ± 4.7	15	16.6
	Supercells, cluster	270	85	76.1 ± 4.4	13	15.9
	Supercells in line	53	23	69.7 ± 10.3	17	18.0
Moderate						
	Supercells, discrete	170	22	88.5 ± 4.5	14	16.8
	Supercells, cluster	191	22	89.7 ± 4.1	13	15.4
	Supercells in line	53	11	82.8 ± 9.3	10	11.9
Strong						
	Supercells, discrete	246	14	94.6 ± 2.8	18	19.5
	Supercells, cluster	264	25	91.3 ± 3.3	15.5	17.4
	Supercells in line	80	11	87.9 ± 6.7	11.5	15.2

b. *Warning statistics as a function of mesocyclone strength*

Our third hypothesis is that tornado detection and warning are much easier for storms having strong mesocyclones than for storms having a weak (or no) mesocyclone. To begin to test this hypothesis, the mesocyclone for each tornadic supercell was rated manually, as derived from radar velocities in the volume sample preceding tornado events (in many cases, tornadogenesis), as weak, moderate, or strong, based on the mesocyclone nomograms produced by the Warning Decision Training Branch of the NWS (Andra 1997). The warning statistics were calculated then for the subset of tornadoes within each category (Table 6, Fig. 3a). While no parent circulations were identified with nonsupercell categories (i.e., QLCS and disorganized storms), tornado warning statistics for nonsupercell categories were included for comparison (labeled as ''None'' in Table 6).

As hypothesized, the tornadoes with the strongest mesocyclones had the highest PODs and median and average lead times. Tornadoes associated with strong to moderate mesocyclones had significantly higher PODs (92.2% and 88.3%, respectively) than tornadoes with weak or no mesocyclones (77.1% and 45.7%, respectively). Those tornadoes associated with strong mesocyclones also had a significantly greater average lead time (18.0 min) when compared with those from moderate mesocyclones (15.5 min). However, there were no significant differences in the warning statistics between the weak and moderate mesocyclone strength categories. Tornadoes not associated with a distinct mesocyclone had much lower PODs and warning lead times.

Tornado warning statistics, calculated as a function of mesocyclone strength and storm type, are shown in Table 7. For tornadic nonsupercell storms, POD rates and warning lead times were quite low when compared to supercell statistics. POD rates improved significantly when mesocyclones were observed, with POD rates jumping 30%–40%. POD rates improved for all supercell categories as a function of the mesocyclone strength; the stronger the mesocyclone, the higher the POD. Lead times also improved as a general function of the mesocyclone strength. Overall, whether or not a mesocyclone

TABLE 8. As in Table 6, but sorted by F scale.

Variable	Category	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
F scale (F0, F1)						
	None	306	362	45.8 ± 3.8	9	11.9
	Weak	521	158	76.7 ± 3.2	14	16.5
	Moderate	374	52	87.8 ± 3.1	13.5	16.1
	Strong	427	45	90.5 ± 2.7	16	18.6
F scale ≥ 2						
	None	9	8	52.9 ± 23.7	1	11.4
	Weak	23	4	85.2 ± 13.4	16	15.0
	Moderate	41	3	93.2 ± 7.5	7	10.2
	Strong	164	5	97.0 ± 2.6	14	16.3

TABLE 9. Average values of MLCAPE ($J\,kg^{-1}$), BWD (0–1, 0–3, and 0–6 km; $m\,s^{-1}$), and STP estimated as a function of storm type.

Category	MLCAPE	BWD1	BWD3	BWD6	STP
Supercells, discrete	1612	11.6	17.6	24.3	2.85
Supercells, cluster	1588	12.2	17.3	23.9	2.71
Supercells in line	1193	15.0	19.8	26.4	3.21
QLCS	1190	13.6	17.2	23.4	2.00
Disorganized	966	7.7	10.9	15.0	0.59

was detected had a dramatic impact on POD statistics and some impact on warning lead time.

As in section 3a, the data were sorted by mesocyclone strength and F scale, distance from the nearest radar, and county population density (Figs. 3b–d). Once sorted by F scale, the stronger tornadoes had an overall higher POD than weaker ones, as expected, but with lower average lead times as noted previously (Table 8, Fig. 3b). Of note, however, was that those significant tornadoes with strong mesocyclones had an overall 97.0% POD with only 5 tornadoes not warned for from a total 169 tornado events. Contrarily, the POD for weak tornadoes with weak mesocyclones was 76.7%, much lower than the significant tornadoes and strong mesocyclone events, but still relatively high compared to nonsupercell storm morphologies.

Categorized by distance from radar, those tornadoes within 100 km of radar with moderate to strong mesocyclones have slightly higher PODs than those events > 100 km from radar, while weak mesocyclone events have a nearly equal to slightly lower PODs (Fig. 3c). When sorted by population density, very little difference between the categories was noted, with slightly greater mean lead times for less densely populated counties (Fig. 3d).

c. *Warning statistics as a function of environmental parameters*

Variations in storm morphology develop in association with near-storm environmental parameters. Because warning performance varies as a function of morphology, warning performance can be expected to vary in a similar way to the environmental variables associated with the tornadic events. To test this idea, warning performance was calculated as a function of MLCAPE, vertical wind shear, and the derived significant tornado parameter, based on the Thompson et al. (2012) dataset.

1) MLCAPE AND VERTICAL WIND SHEAR

First, MLCAPE and vertical wind shear estimates were calculated for each storm type (Table 9, Figs. 4a and 5a). For this work, the BWD was calculated as a proxy for the vertical wind shear. MLCAPE was highest for discrete and cluster supercells, while low-level (0–1 km) BWD was highest for more linear storm morphologies. The "disorganized" storm category had the lowest MLCAPEs and BWDs at all levels.

Tornado warning performance was examined directly as a function of environmental MLCAPE (Table 10, Fig. 4b). POD was found to vary strongly with MLCAPE; for very low ($\leq 250\,J\,kg^{-1}$) MLCAPE events, the POD was just over 50%, but the POD jumped to over 86% for tornadoes associated with MLCAPE $\geq 2000\,J\,kg^{-1}$. Warning lead times generally increased with increased

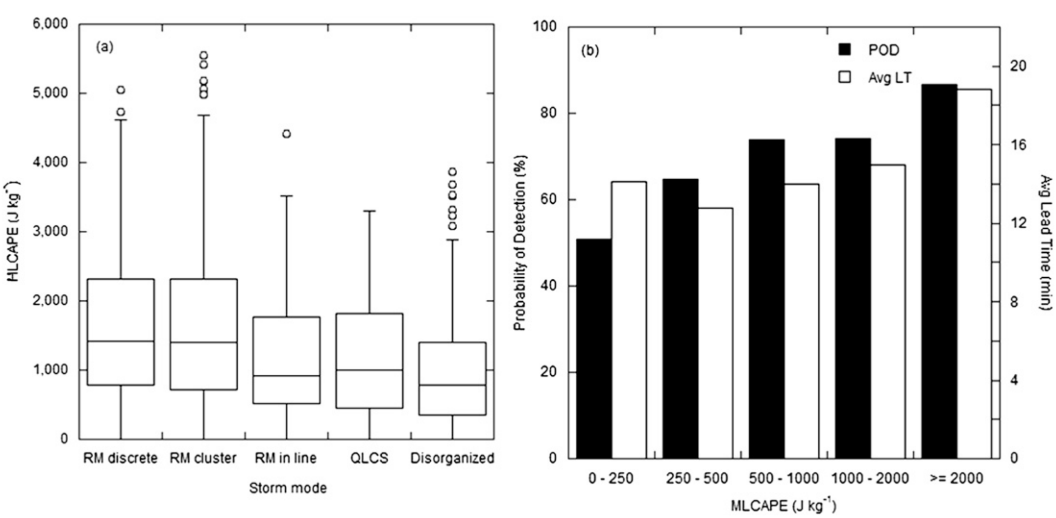

FIG. 4. (a) Box plots showing the distribution of MLCAPE as a function of storm mode. (b) POD (%) and mean lead time (min) estimated as a function of MLCAPE ($J\,kg^{-1}$).

TABLE 10. POD (%) and median and mean lead time (min) as a function of mean layer MLCAPE ($J\,kg^{-1}$).

Category	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
0–250	128	124	50.8 ± 6.1	11.5	14.4
250–500	166	90	64.8 ± 5.8	11	13.1
500–1000	410	142	74.3 ± 3.6	13	14.1
1000–2000	535	186	74.2 ± 3.2	13	15.1
≥2000	605	92	86.8 ± 2.5	17	18.9

MLCAPE, with lead times significantly greater for MLCAPE $\geq 2000\,J\,kg^{-1}$.

Next, tornado warning performance was evaluated as a function of storm type and MLCAPE (Table 11). Results were mixed. For discrete and cluster supercells, PODs and lead times generally increased with MLCAPE. For supercells in lines, PODs generally increased with MLCAPE $> 250\,J\,kg^{-1}$, but appeared to have little impact on lead times. For QLCS, PODs remained relatively low (~36%–56%) regardless of MLCAPE value, but mean lead times for the largest MLCAPE storms were significantly higher. Sample sizes for supercells in lines, QLCS, and disorganized cases were too small to infer statistical significance among subgroups. Overall, MLCAPE was a poor discriminator of tornado POD and lead time for most storm types.

In a similar manner, the values of BWD also were estimated as a function of storm type (Fig. 5a). More linearly oriented storm morphologies (supercells in lines, QLCS) had the highest low-level (0–1 km) BWDs, while disorganized storms had the lowest values. Warning performance also was evaluated as a function of BWD. POD and warning lead times were estimated as a function of 0–1, 0–3, and 0–6 km BWD (Table 12, Figs. 5b–d). In general, POD and lead time increased with BWD. For 0–1-km BWD, POD and lead time peaked at 15–20 $m\,s^{-1}$ and remained steady at higher speeds. For 0–3- and 0–6-km BWDs, PODs peaked at 25 and 30 $m\,s^{-1}$,

TABLE 11. As in Table 10, but sorted by storm type.

Variable	Category MLCAPE ($J\,kg^{-1}$)	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
Supercells, discrete						
	0–250	32	14	69.6 ± 13.3	20	20.1
	250–500	45	11	80.4 ± 10.4	11	14.0
	500–1000	139	16	89.7 ± 4.8	14	15.5
	1000–2000	169	30	84.9 ± 5.0	15	16.6
	≥2000	245	17	93.5 ± 3.0	17	20.2
Supercells, cluster						
	0–250	37	22	62.7 ± 12.3	10	13.5
	250–500	50	21	70.4 ± 10.6	11	14.6
	500–1000	147	28	84.0 ± 5.4	13	14.2
	1000–2000	220	33	87.0 ± 4.1	12	14.9
	≥2000	266	26	91.1 ± 3.3	17	19.2
Supercells in line						
	0–250	22	3	88.0 ± 12.7	10	11.9
	250–500	22	8	73.3 ± 15.8	13	15.2
	500–1000	53	15	77.9 ± 9.9	13	13.5
	1000–2000	50	14	78.1 ± 10.1	14.5	17.9
	≥2000	36	5	87.8 ± 10.0	10	14.1
QLCS						
	0–250	14	24	36.8 ± 15.3	10	11.8
	250–500	14	18	43.8 ± 17.2	9.5	11.4
	500–1000	33	26	55.9 ± 12.7	7	11.2
	1000–2000	38	34	52.8 ± 11.5	8.5	10.5
	≥2000	23	27	46.0 ± 13.8	13	17.7
Disorganized						
	0–250	23	61	27.4 ± 9.5	6	12.0
	250–500	35	32	52.2 ± 12.0	7	9.0
	500–1000	38	57	40.0 ± 9.9	10	12.2
	1000–2000	58	75	43.6 ± 8.4	8.5	12.3
	≥2000	35	17	67.3 ± 12.8	13	12.5

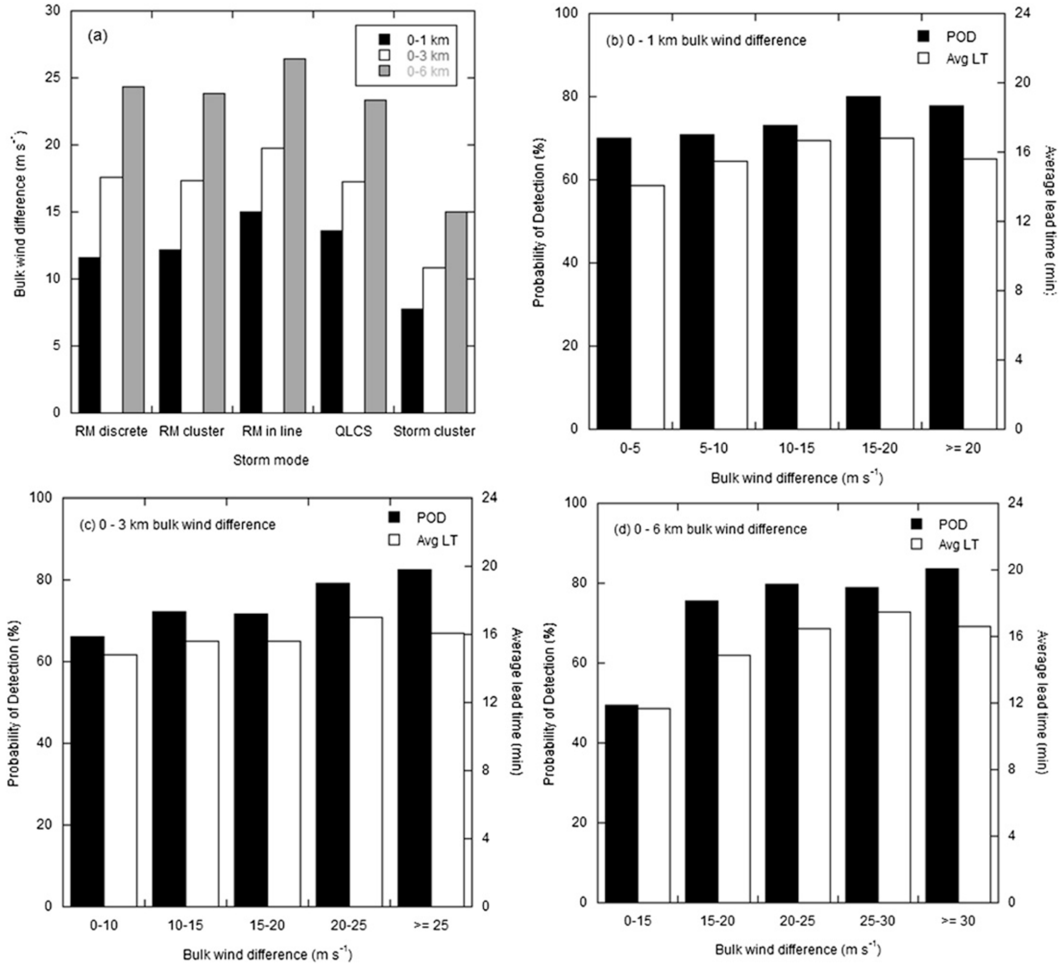

FIG. 5. (a) Mean bulk wind difference (m s^{-1}) is plotted as a function of storm type. The POD (%) and mean lead time (min) estimated as a function of (b) 0–1-, (c) 0–3-, and (d) 0–6-km BWD (m s^{-1}).

respectively. Warning lead times dropped slightly at higher BWDs.

In addition, the POD and mean lead time values were much more sensitive to the 0–6-km BWD than the 0–1-km BWD. For the 0–1-km BWD parameter, PODs ranged between 69.9% and 79.9% with lead times between 14.1 and 16.8 min. For the 0–6-km BWD, PODs ranged between 49.4% and 83.6% with mean lead times between 11.7 and 17.5 min.

Tornado POD and lead time also were examined as a function of 0–6-km BWD and storm mode (Table 13). In general, sample sizes were too small to draw statistically significant conclusions. However, for discrete and cluster supercells, PODs were much lower at low BWDs ($<$15 m s^{-1}). Lead times were several minutes lower. PODs rose for supercells in lines with BWD $\geq$ 30 m s^{-1}. Low shear values were associated most frequently with disorganized storms that had the lowest tornado POD and lead time.

2) SIGNIFICANT TORNADO PARAMETER

In general, tornado warning statistics improved asymptotically with increasing STP (Table 14, Fig. 6). The POD increased rapidly until the STP $\geq$ 4, at which POD $\geq$ 90%. This composite reflects previous results that stronger tornadoes, often associated with stronger buoyancy and vertical wind shear, are much easier to identify and warn for. Similarly, mean warning lead times improved asymptotically with increasing STP. Mean lead times are over 6 min greater for large STP values ($\geq$4) when compared with the lowest STP storms ($<$0.5).

4. Discussion and summary

Three hypotheses relating convective mode and environmental parameters to NWS tornado warning statistics were confirmed. First, tornadoes from supercell storms were much easier to warn for in terms of POD and lead time than tornadoes from either QLCS or more

TABLE 12. POD (%) and median and mean lead time (min) as a function of BWD ($m\,s^{-1}$).

Variable	Category	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
0–1-km BWD						
	0–5	285	123	69.9 ± 4.4	11	14.1
	5–10	346	143	70.8 ± 4.0	13	15.5
	10–15	454	168	73.0 ± 3.5	15	16.7
	15–20	417	105	79.9 ± 3.4	15	16.8
	≥20	343	98	77.8 ± 3.9	13	15.6
0–3-km BWD						
	0–10	272	140	66.0 ± 4.6	12	14.8
	10–15	358	138	72.2 ± 3.9	13	15.6
	15–20	449	177	71.7 ± 3.5	13	15.6
	20–25	402	105	79.3 ± 3.5	14	17.0
	≥25	364	77	82.5 ± 3.5	14	16.1
0–6-km BWD						
	0–15	203	208	49.4 ± 4.8	9	11.7
	15–20	365	118	75.6 ± 3.8	13	14.9
	20–25	509	129	79.8 ± 3.1	14	16.5
	25–30	389	104	78.9 ± 3.6	15	17.5
	≥30	382	75	83.6 ± 3.4	14	16.6

disorganized, nonsupercell storms. Second, storm parameters including F-scale intensity and radar distance had a quantitatively significant impact on tornado POD and lead time, but varied as a function of storm morphology. Third, the stronger, more intense storms, as determined by mesocyclone strength, MLCAPE, and vertical wind shear, had much higher tornado PODs and lead times than did weaker storms. Specific results from this work are listed:

- An overwhelming majority of tornado fatalities (97%), injuries (96%), and damage (92%) occurred from supercells. Supercells in lines had nearly double the fatality rate and over 2.5 times the injury rate per tornado of other supercell storm morphologies.
- The average tornado POD for supercells was 85.4%, compared to 45.8% for nonsupercells. The mean tornado lead time for supercells was 16.8 min, compared to 11.9 min for nonsupercells.
- Tornadoes rated ≥ F2 had a POD of 92.2% compared to a POD of 72.5% for weaker (F0, F1) tornadoes. PODs improved for all storm types with increasing F scale. However, mean lead times were statistically unchanged.
- Tornadoes within 100 km of radar had a POD of 78.1% compared to a POD of 69.3% for tornadoes observed ≥ 100 km from radar. Most storm modes showed improved PODs with the closer radar range. More linear-oriented storm morphologies showed the steepest declines in POD with distance, likely due to shallower systems and smaller circulations. Mean lead times increased slightly with increasing radar distance due to fewer zero and negative lead times events.
- Tornadoes in more rural regions had a POD of 75.9% compared to 65.8% in more urban regions (population density ≥ 100 persons km^{-2}). Most storm types had only a slightly higher POD in rural areas. Mean lead times were slightly lower in more densely populated regions due to more negative and zero lead time events.
- Tornadoes with strong mesocyclones had a POD of 92.2% and lead time of 18.0 min compared with a POD of 45.7% and lead time of 11.9 min for tornadoes with no mesocyclone present. POD increased with mesocyclone intensity for each storm type; however, lead time improvement varied with storm type, with some general improvement in lead time with mesocyclone strength.
- The storm mesocyclone strength and tornado F-scale intensity had an additive impact on tornado POD rates, with less impact on lead time. Tornadoes with an F scale ≥ 2 and a strong mesocyclone had a POD ≥ 97% and mean lead time over 16 min whereas weak (F0, F1) tornadoes with no mesocyclones had a POD < 50% and mean lead time < 12 min.
- In general, tornado POD and lead time varied strongly with MLCAPE. For MLCAPE between 0 and 250 $J\,kg^{-1}$, POD was 50.8% with a mean lead time of 14.4 min. For MLCAPE ≥ 2000 $J\,kg^{-1}$, POD was 86.8% with a mean lead time of 18.9 min. However, results were less clear when subcategorized by storm type. POD and lead time generally increased with MLCAPE for discrete and cluster supercells, but results were less clear for other storm morphologies, partially due to the small sample sizes.

TABLE 13. POD (%) and median and mean lead time (min) as a function of 0–6-km BWD ($m\,s^{-1}$) and storm type.

Variable	Category	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
Supercells, discrete						
	0–15	34	11	75.6 ± 12.5	12.5	14.4
	15–20	115	25	82.1 ± 6.4	15	16.0
	20–25	202	21	90.6 ± 3.8	15	18.0
	25–30	149	17	89.8 ± 4.6	18	19.4
	≥30	134	14	90.5 ± 4.7	15	17.9
Supercells, cluster						
	0–15	52	20	72.2 ± 10.4	10.5	12.1
	15–20	151	25	85.8 ± 5.2	13	15.7
	20–25	213	38	84.9 ± 4.4	14	16.4
	25–30	155	27	85.2 ± 5.2	15	17.3
	≥30	145	19	88.4 ± 4.9	14	17.1
Supercells in line						
	0–15	11	5	68.8 ± 22.7	13	16.8
	15–20	29	8	78.4 ± 13.3	18	19.0
	20–25	40	13	75.5 ± 11.6	9	10.7
	25–30	32	10	76.2 ± 12.9	14	16.4
	≥30	73	9	89.0 ± 6.8	14	15.1
QLCS						
	0–15	12	23	34.3 ± 15.7	17	14.5
	15–20	25	26	49.0 ± 13.7	6	10.4
	20–25	25	28	47.2 ± 13.4	10	14.2
	25–30	37	28	56.9 ± 12.0	11	13.1
	≥30	23	24	48.9 ± 14.3	9	9.9
Disorganized						
	0–15	94	149	38.7 ± 6.1	5	9.7
	15–20	47	34	58.0 ± 10.8	12	10.7
	20–25	27	29	48.2 ± 13.1	15	16.6
	25–30	16	22	42.1 ± 15.7	16	15.8
	≥30	8	8	50.0 ± 24.5	6.5	17.9

- Vertical wind shear (bulk wind difference) had moderate impact on tornado POD and lead times. POD and lead time generally improved with increased BWD; for example, tornadoes from discrete supercells with a 0–6-km BWD $< 25\,m\,s^{-1}$ had a POD of 75.6% and mean lead time of 14.4 min compared with a POD of 90.5% and lead time of 17.9 min for 0–6-km BWD $\geq 40\,m\,s^{-1}$. This highlights weak shear environments as being more difficult when issuing successful tornado warnings.
- STP was a reliable indicator of tornado POD and lead time. For STP values < 0.5, POD was 58.6% with a mean lead time of 12.5 min. For STP values ≥ 8, POD was 94.9% with an average lead time of 18.6 min.

This manuscript has demonstrated a significant relationship between warning statistics and storm mode, and confirms what operational forecasters have known anecdotally for some time. Results point to lower tornado detection rates and shorter lead times associated with nonsupercell storms, weaker tornadic systems, and storms far from radar and in higher populated areas. Real-time access to storm-mode classification and improved low-level analyses may contribute to greater anticipation of expected tornado impacts. Additional low-level radar coverage, such as could be provided by gap-filling radars (e.g., McLaughlin et al. 2009), could likely improve detection of many of these weaker, nonsupercell tornadoes.

Yet as data from this 2-yr study have also shown, those tornadoes with the lowest PODs and lead times are those events least likely to cause damage or injury. Supercells remain the most dangerous storm mode and yet are the most successfully warned for with the longest lead times.

TABLE 14. POD (%) and median and mean lead time (min) as a function of STP.

Category	No. warned	No. not warned	POD (%)	Median lead time	Avg lead time
0–0.5	360	254	58.6 ± 3.9	10	12.5
0.5–1	221	89	71.3 ± 5.0	12	15.6
1–2	352	83	80.9 ± 3.7	15	16.9
2–4	378	79	82.7 ± 3.5	14	16.6
4–6	175	18	90.7 ± 4.1	16	18.2
6–8	108	11	90.8 ± 5.2	15	18.0
≥8	150	8	94.9 ± 3.4	16	18.6

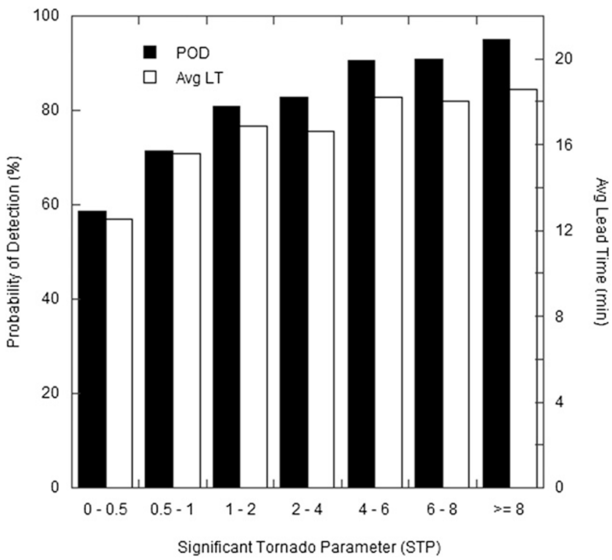

FIG. 6. POD (%) and mean lead time (min) estimated as a function of the STP.

Nonsupercell storms cause few fatalities, injuries, or damage and yet have relatively poor PODs and warning lead times. This is good news, as large violent tornadoes typically are warned tens of minutes in advance, whereas weak, less-threatening tornadoes are the events most likely to be missed. However, these statistics highlight a growing disconnect between gains in warning statistical measures and improved public safety. Simmons and Sutter (2008) found warning lead times > 15 min had no additional impact on reducing fatality rates.

Large reductions in storm casualties will likely not come from increased tornado POD or warning lead time, as the largest gains in POD or lead time will likely be in the warning of small, weak tornadoes that are responsible for relatively few casualties. Public discourse must be careful to note this limitation and recognize that further improvements in POD or lead time cannot promise a safer public. Furthermore, any efforts to increase PODs and lead times for the normally less-impactful, nonsupercell tornadoes should consider unintended consequences on supercell tornado warning credibility (i.e., likely increases in FAR for overall tornado warnings).

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