

UNIVERSITY OF OKLAHOMA
GRADUATE COLLEGE

AN ASSESSMENT OF MESOVORTICES IN QUASI-LINEAR CONVECTIVE
SYSTEMS FROM 2013-2023 USING GRIDRAD-SEVERE

A THESIS
SUBMITTED TO THE GRADUATE FACULTY
in partial fulfillment of the requirements for the
Degree of
MASTER OF SCIENCE

by HANNA J MCDANIEL

Norman, Oklahoma

2026

AN ASSESSMENT OF MESOVORTICES IN QUASI-LINEAR CONVECTIVE
SYSTEMS FROM 2013-2023 USING GRIDRAD-SEVERE

A THESIS APPROVED FOR THE
SCHOOL OF METEOROLOGY

BY THE COMMITTEE CONSISTING OF

Dr. Aaron Hill (Chair)

Dr. Cameron Homeyer

Dr. Michael Coniglio

©Copyright by HANNA J MCDANIEL 2026

All Rights Reserved.

Acknowledgments

I would like to first thank Dr. Aaron Hill for his contributions to my research, his many words of advice and encouragement throughout my academic journey, and for teaching me how to be my most diva-self. I never thought back in 2022, when I worked with both him and Dr. Russ Schumacher at Colorado State University, that I would follow Aaron all the way to OU, but there is no one else I would have rather continued my education and research journey with.

I would also like to thank my committee members, Dr. Michael Coniglio and Dr. Cameron Homeyer, for their guidance and advice throughout this entire thesis process. I would also like to thank all of the professors, scientists, and staff at OU and within the NWC who have helped me further my education and get the most out of my past two years here in this building.

To all of the lifelong friends and connections that I have made, thank you for being the best support system I could ever ask for as I moved halfway across the country knowing no one. And of course, thank you to all of my friends and family who supported me throughout this journey and sent many virtual cheers and hugs along the way.

Boomer for life!!

Table of Contents

Acknowledgments	iv
List of Tables	vi
List of Figures	vii
Abstract	xi
1 Introduction	1
1.1 QLCS tornadoes	1
1.2 Mechanisms behind mesovortexgenesis	2
1.3 Mesovortex warning framework	3
1.4 Project Overview	6
2 Data and Methods	8
2.1 GridRad	8
2.2 QLCS identification and classification	10
2.3 Dataset creation	11
2.3.1 Parameter tuning and testing	13
3 Results	19
3.1 General dataset characteristics	19
3.1.1 Spatial patterns	19
3.1.2 Temporal patterns	21
3.1.3 Storm mode and tornado intensity	26
3.2 Comparison of radar characteristics using probability-matched means	29
3.2.1 Single-polarization variables	31
3.2.2 Dual-polarization variables	39
4 Discussion and Conclusions	55
Reference List	61

List of Tables

1.1	Comparison of previous large-scale QLCS studies and the present study. Studies marked with an asterisk indicate the number of cases is based on QLCS MVs rather than QLCSs as a whole. Studies marked with a double asterisk indicate investigations of MCSs rather than exclusively QLCSs.	7
2.1	List of parameters for the storm classification scheme used in this study as compared to the default values from Potvin et al. (2022).	13

List of Figures

2.1	An example of how the storm identification and storm mode classification technique works on a single radar volume. (a) shows the composite reflectivity for the particular volume in dBZ. (b) has the same composite reflectivity with the contours separating the 40 dBZ values outlined. Within this contoured area, two distinct QLCS regions are identified. (c) contains the same information as (b), but additionally outlines all embedded cells within the two preliminary objects. (d) contains the same information as (c), but with the embedded cells colored by whether they are QLCS_MESO (orange) or QLCS_ORD (purple).	12
2.2	An example of how storm tracks are matched with identified and classified storm objects. (a) shows all classified storm objects with storm type labeled and track points overlaid (x, black). (b) shows the same as (a), but for the next timestep five minutes later. (c) shows the storm objects and track numbers for the same timestep as (a), but labels the storm numbers rather than storm type. (d) shows the same as (c), but for the timestep associated with (b).	14
2.3	A depiction of the classification scheme output for three timesteps during a severe weather outbreak on March 24-25, 2023. Figures (a), (c), and (e) show the composite reflectivity (dBZ) at 2200Z, 0120Z, and 0600Z, respectively. Contours separating the 40 dBZ values are outlined. Figures (b), (d), and (f) visualize the storm mode classification for identified storm objects. The box in (d) highlights the storm that produced the EF-4 tornado that went through Rolling Fork, MS.	16

2.4	A comparison of the classification schemes from GR-S and this study for a severe weather event on April 14-15, 2011. Figures (a), (d), and (g) show the composite reflectivity values for 2100Z, 0000Z, and 0600Z respectively. Figures (b), (e), and (h) represent the classification of storms as either single-cell (green), multicell (pink), or MCS (purple) for the same timesteps. Figures (c), (f), and (i) represent the classification of storms made by this study's seven-mode classification scheme.	18
3.1	Spatial distribution of QLCS tornadoes across the CONUS. (a) shows the point locations of all tornadoes, color-coded by their associated maximum tornado intensity on the EF-scale. (b) shows the count of tornadoes for every state, with darker colors correlating to a higher count. .	20
3.2	Two KDE maps for QLCS tornadoes across the CONUS. (a) shows the KDE map for the data points within this dataset. Darker blue corresponds to a higher density. (b) KDE map of QLCS tornadoes from 2012-2023 from Lyons et al. (2025). Areas with lighter shading correspond to a higher density. Their Figure A2.e.	21
3.3	Same as 3.2a, but split across the four seasons.	22
3.4	Same as 3.2a, but for all QLCSs.	23
3.5	Empirical cumulative distribution functions (ECDFs) for all QLCSs and QLCS tornadoes. (a) shows the average ECDF for all QLCSs throughout the calendar year. Individual years are also plotted (light blue, dashed) and noteworthy years are labeled. (b) is the same as (a), but applies to only QLCS tornadoes.	24
3.6	Bar charts displaying the seasonality of QLCS tornadoes (blue) and all QLCSs (red). Seasonality is expressed as percentages of the total amount of data points that are accounted for in that season.	24
3.7	Bar charts displaying the seasonality of QLCS tornadoes (purple) and all QLCSs (green). Seasonality is expressed as percentages of the total amount of data points that are accounted for in that season.	25
3.8	Same as 3.7, but for an hourly scale.	26

3.9	Geographical distribution of tornado locations stratified by storm mode. (a) is the same as (3.1a), but color-coded by storm mode. (b) only displays the points associated with QLCS objects, (c) QLCS_ORD objects, and (d) QLCS_MESO objects.	28
3.10	Hourly distribution of QLCS tornadoes color-coded by storm mode. . .	29
3.11	Bar chart of maximum tornado intensity for all QLCS tornadoes. . . .	30
3.12	Seasonality of QLCS tornadoes clustered by maximum tornado intensity.	30
3.13	PMMs of azimuthal shear for tornadic MVs at constant altitudes of 0.5, 1.0, 3.0, 5.0, and 7.0 km above mean sea level (AMSL). The tornadic storms are represented at tornadogenesis and in five minute increments of lead time going up to 20 minutes.	33
3.14	Same as 3.13, but for radial divergence.	34
3.15	Same as 3.13, but for reflectivity.	35
3.16	PMMs of azimuthal shear for tornadic and null MVs at constant altitudes of 0.5, 1.0, 3.0, 5.0 km, and 7.0 above mean sea level (AMSL). The tornadic storms are represented at the time of tornadogenesis and null storms are represented at the time during their entire lifetime where max LL azimuthal shear is the highest.	43
3.17	PMM vertical cross sections perpendicular to storm motion for azimuthal shear. The cross sections intersect the center of the MVs as was done in previous plots. Tornadic MVs are represented in three time steps: time of tornadogenesis, 10 minute lead time, and 20 minute lead time. Null MVs are also represented in three comparable time steps: time of maximum LL azimuthal shear, 10 minute lead time, and 20 minute lead time. Height is given in terms of kilometers AMSL.	44
3.18	Same as 3.16, but for radial divergence.	45
3.19	Same as 3.17, but for radial divergence.	46
3.20	Same as 3.16, but for horizontal reflectivity.	47
3.21	Same as 3.17, but for horizontal reflectivity.	48
3.22	Same as 3.13, but for differential reflectivity.	49

3.23	Same as 3.13, but for specific differential phase.	50
3.24	Same as 3.16, but for differential reflectivity.	51
3.25	Same as 3.17, but for differential reflectivity.	52
3.26	Same as 3.16, but for specific differential phase.	53
3.27	Same as 3.17, but for specific differential phase.	54

Abstract

Tornadoes produced by quasi-linear convective systems (QLCSs) often develop abruptly and are generally transient in nature, presenting forecasting challenges for operational meteorologists and posing a significant risk to the public. When nowcasting QLCS tornadogenesis, radar observations provide one of the primary sources of information for warning decision-making. Prior studies and operational techniques, such as the Three Ingredients Method (Schaumann and Przybylinski, 2012), have identified radar patterns that have predictive value and can support warning decision-making for QLCS mesovortex (MV) production and tornadogenesis. However, research supporting many of these signals is limited by small sample sizes, inconsistent storm mode classifications, manual radar interrogation practices, and a lack of dual-polarization variables. The exclusion of polarimetric signatures is particularly notable given recent findings that suggest signatures such as specific differential phase (K_{DP}) drops and midlevel K_{DP} cores may aid in predicting low-level rotation or MV development and intensification. Here, we investigate the use of radar signatures as a predictive tool for QLCS MV tornadogenesis through two major efforts: (1) Development a radar-based dataset of QLCS MVs with automatically-classified storm segments and an extensive spatiotemporal range, and (2) comparison the radar characteristics of tornadic and nontornadic MVs to better understand the possible patterns that can indicate a MV’s tornadic potential.

The dataset is constructed using the GridRad-Severe archive, a high-resolution, multi-radar dataset with over ten years of single- and dual-polarization radar volumes. To properly isolate QLCS storm objects from the radar data, a seven-mode classification scheme is applied that differentiates convective objects based on composite

reflectivity and mid-level rotation (Potvin et al., 2022). Thousands of QLCS objects are objectively identified from 2013 to 2023 across the CONUS. The spatial and temporal distribution of the QLCS objects and the MVs embedded within them are analyzed and compared with previous climatologies, validating the identification and classification process. The storm objects are also tracked through time using an echo-top height tracking algorithm and linked to storm reports, yielding a comparative analysis of the radar signatures between tornadic and nontornadic MVs.

Assessment of the dataset distribution shows that the spatiotemporal behavior of the MVs follows the previously understood behaviors of QLCS objects very closely. Some of these behaviors include being most densely concentrated over the Deep South, occurring most frequently at night, and being most common during the spring and cool season. The radar patterns of tornadic and nontornadic MVs were examined through probability-matched composite means. Analyzing the radar patterns of both tornadic and nontornadic MVs, the discriminatory value of radar variables is mixed. For single-polarization variables, there appears to be significant discriminative utility in the strength of azimuthal shear throughout the vertical and low-level radial divergence. For polarimetric variables, the value is less clear; the distribution of differential reflectivity does not appear significantly different between tornadic and nontornadic populations, but low-level K_{DP} does show different structure between the two populations. Overall, these findings provide further insight into the radar characteristics of tornadic QLCS MVs and suggest that certain radar signatures may provide useful supplemental guidance for the warning decision process.

Chapter 1

Introduction

1.1 QLCS tornadoes

Tornadoes associated with quasi-linear convective systems (QLCSs) pose a significant threat to life and property across the U.S. QLCSs are a subtype of mesoscale convective systems (MCSs), characterized by a linearly organized area of convection that is much longer than it is wide. Although right-moving supercells are the leading producer of significant (EF2+) tornadoes, and tornadoes in general, QLCSs still account for roughly 21% of tornadoes in the U.S. (Ashley et al., 2019). This percentage increases even more when isolating tornado occurrence in the Southeast U.S. and particularly high-shear, low-CAPE environments within this region (Anderson-Frey and Brooks, 2019), an area of the country with noted high social vulnerabilities (Ashley, 2007; Ashley et al., 2008). Further, QLCS tornadoes occur at disproportionately high rates during the nocturnal hours and in the cool season compared to supercells, increasing hazard and fatality risk due to reduced awareness and responsiveness (Ashley et al., 2008; Anderson-Frey et al., 2016; Ashley et al., 2019; Strader et al., 2022).

Given the transient, short-lived, and relatively weak nature of many QLCS tornadoes, their development is often hard to predict and observe with the current meteorological toolkit, also limiting warning lead times. The current National Weather Service (NWS) baseline for supercellular tornadoes is a lead time of 16.8 minutes compared

to 11.9 minutes for nonsupercellular tornadoes (Brotzge et al., 2013). Similarly, the probability of detection (POD) for discrete supercell tornadoes is almost 40% higher than the POD for QLCS tornadoes (Brotzge et al., 2013; Anderson-Frey and Brooks, 2021).

1.2 Mechanisms behind mesovortexgenesis

It has long been theorized that low-level (LL), meso- γ -scale vortices (Orlanski, 1975), known as mesovortices (MVs), are largely responsible for the hazardous portions of QLCSs, including severe straight-line winds and tornadoes (Trapp and Weisman, 2003; Atkins et al., 2004; Wakimoto et al., 2006; Mahale et al., 2012). In an attempt to resolve the aforementioned gap in operational skill, substantial work has been done to investigate the physical mechanisms behind mesovortexgenesis. Trapp and Weisman (2003) initially proposed a mechanism by which baroclinically generated horizontal vorticity is tilted by downdrafts, producing a cyclonic-anticyclonic vertical vorticity (ζ) couplet. Later work reaffirmed this genesis mechanism (e.g. Wakimoto et al. (2006)), but additional and oftentimes conflicting theories have been proposed related to other types of MVs. From cyclonic-only MVs produced through updraft stretching of predominantly streamwise vorticity (Atkins and Laurent, 2009) to discrete, evenly-spaced MVs formed through the release of horizontal shearing instability (Conrad and Knupp, 2019), a range of precursors have been proposed to explain mesovortexgenesis. Additionally, studies have identified several possible airstreams and vorticity source regions for MVs (e.g., high θ environment inflow, storm-cooled air north of the MV, a rear-inflow jet (RIJ), or frictionally-induced horizontal rotors), further complicating the field’s conceptual understanding of their development (Atkins and Laurent, 2009; Schenkman et al., 2012; Xu et al., 2015; Flournoy and Coniglio, 2019; Schneider, 2025).

This difficulty in understanding mesovortexgenesis from a theoretical perspective has led to investigations into the kinematic and thermodynamic signals that may distinguish QLCS segments that are more likely to produce MVs and, in particular, damaging MVs. In particular, previous studies have found that the values of LL lapse rates, CAPE, LL shear, and deep-layer shear can significantly discriminate between tornadic and nontornadic MVs (Lovell and Parker, 2022; Chalmers and Parker, 2026). There are also key discriminatory signals in the baroclinic zones of QLCSs, notably that larger θ_v gradients correlate with rotating MVs and are a good proxy of MV strength (Ostaszewski et al., 2025). Although these along-line environmental heterogeneities may possess discriminatory value, they are difficult to capture in a nowcasting setting due to the spatial and temporal gaps in our current in-situ observational network, limiting their value in the warning-decision process (Lovell and Parker, 2022).

1.3 Mesovortex warning framework

Remote-sensing and particularly radar-based observations have been shown to provide useful discriminatory and predictive value for nowcasting QLCS tornadoes, warranting prioritization in the warning-decision process (Sandmæl et al., 2019). The current QLCS MV predictive framework used in the NWS is known as the Three Ingredients Method (3IM; Schaumann and Przybylinski, 2012). This tool provides three conditions that, if present in part of a linear system, indicate an increased likelihood for QLCS mesovortexgenesis. The three ingredients are as follows:

1. A near-balance or slightly shear-dominant relationship between the system cold pool and ambient LL shear
2. 0-3 km line-normal bulk shear greater than or equal to 30 knots

3. A surge or bowing segment caused by an RIJ or outflow

Once all these ingredients are met for a segment of a QLCS, the user can then reference additional radar signatures known as “confidence builders” and “nudgers” that help facilitate the forecast of a potentially tornadic MV. Although the 3IM has proven to be a relatively skillful tool for operational meteorologists and can provide a starting point in anticipating mesovortexgenesis, forecasting challenges associated with QLCS tornadoes still very much remain (Gibbs, 2021). In recent years, studies have posed critiques of this mesovortex warning system and/or proposed modifications and additional criteria for the framework (Gibbs, 2021; Ungar and Coniglio, 2023; Brown et al., 2024; Watson, 2025). Notably, many mesovortices have been observed when the line-normal shear is well below the threshold of 30 kts specified in the second ingredient (Ungar and Coniglio, 2023). Correspondingly, other work has shown that there may be a significant link between LL line-parallel shear and the development of intense MVs (Flournoy and Coniglio, 2019; Brown et al., 2024).

Aside from a potential reframing of how environmental information is viewed in the 3IM, other literature has proposed additions to the radar-aspect of the framework - notably the inclusion of dual-polarization variables. In its current state, the 3IM includes predictive radar signatures from single-polarization variables such as horizontal reflectivity (Z_H) and Doppler radial velocity (V_R), while only using dual-polarization to identify a tornadic debris signature using correlation coefficient (ρ_{hv}). The exclusion of dual-polarization variables has left a large gap in potential warning guidance since polarimetric variables can provide insight into features such as descending RIJs, updraft strength, and strong vertical wind shear (Mahale et al., 2012; Kuster et al., 2024; Healey and Broeke, 2025). Microphysical processes and storm structure evolution that are implied through polarimetric radar patterns and values could potentially serve as discriminatory thresholds between tornadic and null MVs (Kuster et al., 2024; Pardun

et al., 2025). However, these preliminary findings and hypotheses have yet to be explored on a robust spatiotemporal scale with a QLCS-focused dataset.

A handful of recent studies have substantially advanced radar-based investigations of nonsupercellular mesovortices. Pardun et al. (2025) conducted a comprehensive investigation of QLCS MVs using merged MRMS data, while Murphy and Homeyer (2023) utilized probability-matched composite means (PMMs) to examine the radar presentation of MCS MVs. These studies provide an important foundation for understanding the radar characteristics of tornadic and nontornadic MVs, particularly from a polarimetric perspective, and establish a basis for comparison with the present investigation. Despite their contributions, each study leaves opportunities for further investigation. Pardun et al. (2025) was limited to cases from 2019-2023, restricting both the temporal coverage and overall sample size. Additionally, Murphy and Homeyer (2023) examined the broad category of nonsupercellular MCS MVs rather than focusing exclusively on QLCSs.

More broadly, much of our understanding of QLCS theory and behavior stems from idealized simulations or case studies, limiting sample size and the applicability of findings to other environments (Schenkman et al., 2012; Flournoy and Coniglio, 2019; Lovell and Parker, 2022). In the context of radar-based investigations, smaller case studies are prevalent due to the reliance on manual radar interrogation, a time-intensive methodology that can limit the possibility of large-scale analysis (Smith et al., 2012; Ungar and Coniglio, 2023; Kuster et al., 2024). Furthermore, many investigations do not make robust attempts to separate truly linear systems from other hybrid storm modes, likely leading to a dataset with embedded cells or merger cases (Smith et al., 2012; Ashley et al., 2019; Kuster et al., 2024). Table 1.1 highlights and compares these characteristics of previous, larger-scale studies of QLCSs in the literature with those of the present investigation.

1.4 Project Overview

To address many of the aforementioned limitations of prior QLCS investigations and further analyze the role of polarimetric variables in signaling QLCS tornadogenesis, this study develops a novel dataset of QLCS MVs using an archive of merged radar mosaics and an objective storm-mode classification framework. The resulting dataset contains MVs over an 11-year period and their associated storm report information and radar fields, enabling a robust analysis of mesovortexgenesis and tornado production across the CONUS.

The first objective of this study is to explore and validate the climatological characteristics of the QLCS MVs within the dataset by comparing their seasonal, diurnal, and spatial patterns to previous studies (Ashley et al., 2019; Lyons et al., 2025). The second objective is to leverage the dataset to examine the differences in radar presentation between tornadic and nontornadic MVs in order to identify potential radar signatures associated with imminent tornado production and evaluate the consistency of these findings with previous investigations (Murphy and Homeyer, 2023; Kuster et al., 2024; Pardun et al., 2025).

Chapter 2 describes the creation of the dataset and the methodologies used for identifying and tracking MVs. Section 3.1 in Chapter 3 presents the spatial and temporal patterns of the QLCS MVs and compares the results to previous large-scale climatologies. Section 3.2 in Chapter 3 presents and compares the radar fields of tornadic and nontornadic MVs and evaluates the results in the context of previous radar-based investigations. Finally, Chapter 4 summarizes the study, discusses the primary findings, and highlights potential improvements to the current MV warning system.

Study	Cases	Automated Classifica- tion	Accounts for Embedded Cells	Date Range
Ashley et al. (2019)	3064	Y	N	1996-2017
Goodnight et al. (2022)	530*	N	Y	2016-2019
Murphy and Homeyer (2023)**	3252	Y	N	2010-2019
Ungar and Coniglio (2023)	50	N	Y	2010-2020
Kuster et al. (2024)	167*	N	N	2013-2022
Pardun et al. (2025)	274	N	N	2019-2023
Lyons et al. (2026)	4710	N	Y	2003-2023
This Study	1700*	Y	Y	2013-2023

Table 1.1: Comparison of previous large-scale QLCS studies and the present study. Studies marked with an asterisk indicate the number of cases is based on QLCS MVs rather than QLCSs as a whole. Studies marked with a double asterisk indicate investigations of MCSs rather than exclusively QLCSs.

Chapter 2

Data and Methods

The dataset presented herein combines radar volumes and storm tracks from the GridRad-Severe (GR-S; Murphy et al., 2023) archive with an automated storm-mode classification scheme to create an 11-year dataset of QLCS MVs and their associated radar characteristics.

2.1 GridRad

GridRad is a dataset of three-dimensional, high-resolution merged radar data from the CONUS NEXRAD network (Bowman and Homeyer, 2017). GridRad is well-suited for storm-scale analyses, mainly due to its sophisticated space- and time-weighting technique. This technique retains spatial and temporal scales that are properly sampled from a radar while conversely under-weighting observations from radars that are far away in either distance or time. Additionally, GridRad provides a broad range of radar variables available at all altitudes. Particular attention is given to the merging of polarimetric variables, and the aforementioned Gaussian space-time weighting scheme helps reduce noise.

The current version of GridRad, v4.2, contains gridded horizontal reflectivity and velocity spectrum width data with $1/48^\circ$ ($\sim 2km$) horizontal spacing and 0.5 km vertical spacing in the first 7 km above mean sea level (MSL), after which it decreases to 1 km vertical spacing above this level. In an effort to increase temporal resolution and

include additional radar-derived variables, the GR-S archive was created, becoming the only public version that contains both single- and dual-polarization variables (Murphy et al., 2023). Created as a subset of GridRad, GR-S stores data for approximately 100 severe weather days a year beginning in 2010. Severe weather days were chosen based on hazard reports pulled from the Storm Events Database (SED; National Centers for Environmental Information (1996)). Specifically, severe weather days are identified if tornado, hail, or wind reports exceed 8, 45, or 120, respectively (Murphy et al., 2023). GR-S data are available at 5-minute intervals and include azimuthal shear, radial divergence, and, beginning in 2013, the polarimetric variables differential reflectivity (Z_{DR}), specific differential phase (K_{DP}), and correlation coefficient (ρ_{hv}). These characteristics make GR-S particularly appropriate for a comprehensive investigation of the radar characteristics of QLCS MVs.

Along with the radar volumes, the dataset includes storm tracks defined by the echo-top height tracking technique of Homeyer et al. (2017) and extended by Lagerquist et al. (2020). At a specific time step, the tracking algorithm identifies the various point local maxima of 30-dBZ echo-tops (above 4 km MSL) and links them with cells in the next time step using a 15 km radius. Storm reports from the SED are linked with storms by interpolating the tracks to 1-minute intervals and matching reports within a 30 km radius of the nearest storm object.

GR-S additionally includes severe storm categorization, including a storm mode classification algorithm and a binary mesocyclone label. The three-mode classification scheme (single-cell, multicell, or mesoscale convective system (MCS)), is based on the overlap between composite reflectivity (CREF) and storm tracks. For each closed 30-dBZ CREF contour, its storm mode is determined from 1) the number of storm tracks within the contour, 2) the area of the contour (m^2), and 3) the maximum length in a single dimension (m). A reflectivity area threshold of 3000 km^2 per storm track is

used to identify single cells, while a maximum dimension of 100 km is used to delineate multicells from MCSs.

For mesocyclone identification, each individual track point is treated as a proxy for a storm updraft. Using various thresholds for shear and divergence based off of the right-moving supercell identification work of Sandmæl (2017), the presence of persistent mid-level rotation within the updraft is determined. The final storm mode classification and mesocyclone assignment are included as additional labels for each track file.

2.2 QLCS identification and classification

Although the 30-dBZ echo-top tracks within GR-S are helpful for object/updraft tracking, its storm classification system does not prove to be sufficient for QLCS analysis. Though QLCSs are a subtype of MCS, the broader MCS category also contains other clustered and disorganized storm modes that may dynamically and visually differ from squall lines (Parker and Johnson, 2000; Ashley et al., 2019). The distinction between QLCSs and other MCS storm modes is particularly important for analyzing radar fields, as Murphy and Homeyer (2023) found limited discriminatory value in polarimetric variables when comparing tornadic and nontornadic MVs across the broader MCS mode. Therefore, a more detailed classification framework was desired to properly isolate QLCSs from the broader MCS population.

To accomplish this objective, the seven-mode classification scheme from Potvin et al. (2022) was applied to GR-S tracks. Originally created to analyze QLCS objects produced by the Warn-on-Forecast System (Heinselman et al., 2024), the scheme uses CREF and mid-level rotation to classify storms into seven convective modes, including isolated cells, multicell convection, and embedded cells within linear systems. The storm object identification and classification processes are inherently intertwined

within the algorithm, as multiple iterative passes are performed and classification occurs during each stage of object identification.

Specifically, the algorithm employs an iterative, fixed-threshold method in which preliminary object identification and classification is performed using the minimum CREF contours along with 30-minute time-maximum mid-level rotation and other characteristics such as area, eccentricity, and length. Then, subsequent passes are made at progressively higher CREF thresholds to identify additional objects that may be embedded in the initial parent objects. These embedded objects within a parent QLCS are either labeled as an embedded cell lacking significant, sustained rotation ('QLCS_ORD') or an embedded cell containing significant, sustained rotation ('QLCS_MESO') based on the value of mid-level rotation. For further details on this identification and classification process, please refer to Figure 2.1 and Potvin et al. (2022).

2.3 Dataset creation

Utilizing the 3D radar volumes and storm tracks from GR-S as well as the storm identification and classification algorithm from Potvin et al. (2022), we created a novel database of QLCS storm objects and associated MVs. For every event stored in GR-S beginning in 2013, the corresponding 5-minute radar volumes are processed using the 7-mode classification scheme. The reflectivity and rotation variables for the classification scheme are CREF and 4-7 km MSL azimuthal shear, respectively. The minimum CREF threshold for preliminary storm objects is 40 dBZ, following the work of Britt et al. (2024), and the rotation threshold for identifying a mesocyclone is 0.004 s^{-1} 4-7 km MSL azimuthal shear.

Thereafter, the GR-S storm tracks aligning with the date and time are isolated

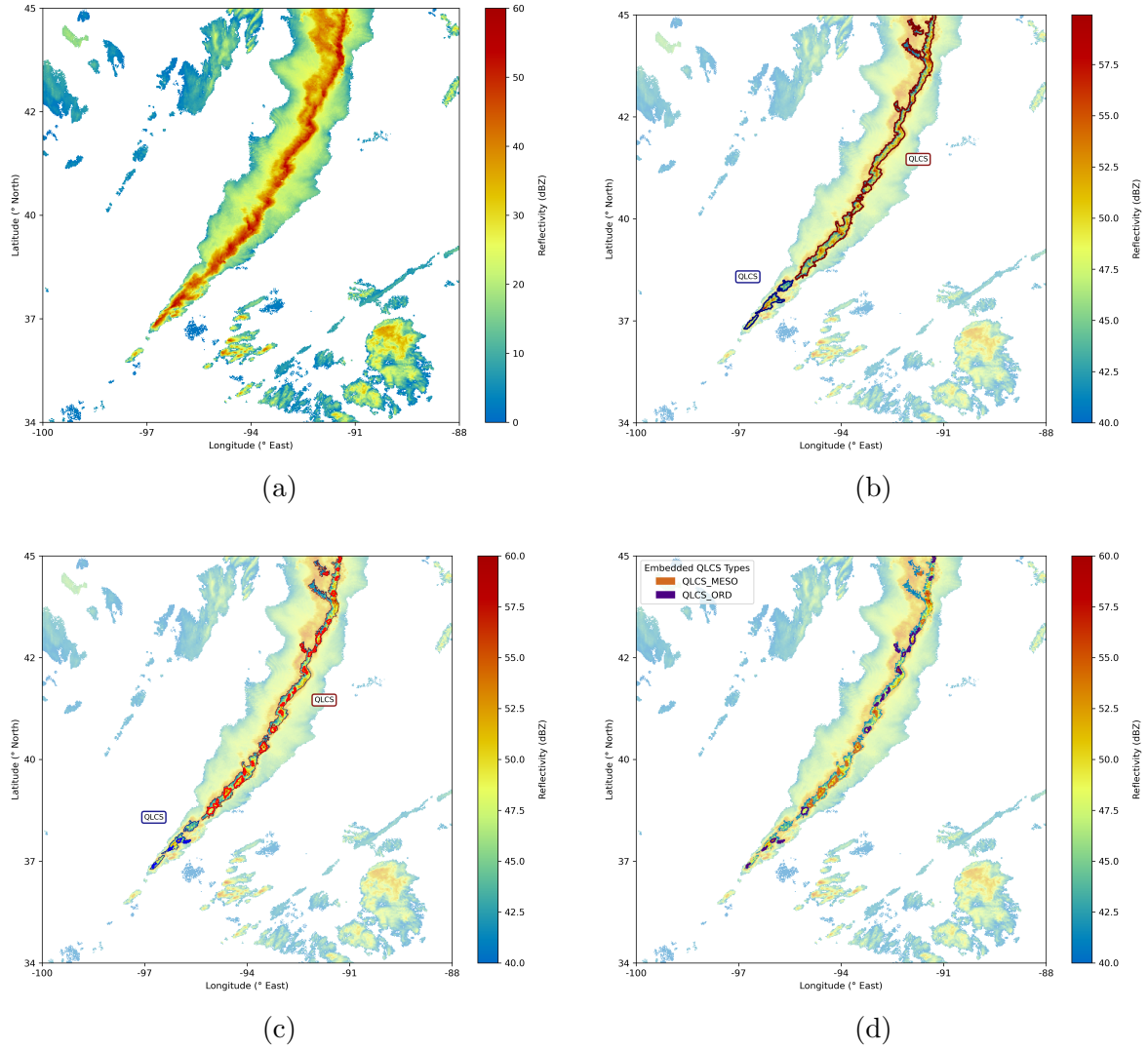


Figure 2.1: An example of how the storm identification and storm mode classification technique works on a single radar volume. (a) shows the composite reflectivity for the particular volume in dBZ. (b) has the same composite reflectivity with the contours separating the 40 dBZ values outlined. Within this contoured area, two distinct QLCS regions are identified. (c) contains the same information as (b), but additionally outlines all embedded cells within the two preliminary objects. (d) contains the same information as (c), but with the embedded cells colored by whether they are QLCS_MESO (orange) or QLCS_ORD (purple).

and matched with the newly identified and classified objects. If a track falls within a classified storm object, it is considered an updraft associated with that object. All tracks that match with a QLCS, QLCS_ORD, or QLCS_MESO object are retained and after all timesteps within a particular severe weather event are processed, the matched tracks are compiled into a dataframe. These tracks are then further subset using an instantaneous signal-to-noise threshold of 0.006 s^{-1} maximum LL (0.5-3.5 km MSL) azimuthal shear to specifically isolate MVs within QLCSs (Davis and Parker, 2014; Pardun et al., 2025). The resulting database contains all identified QLCS MVs along with their associated storm modes, storm reports, and radar attributes. Figure 2.2 provides a visual of how the tracks are matched with storm objects.

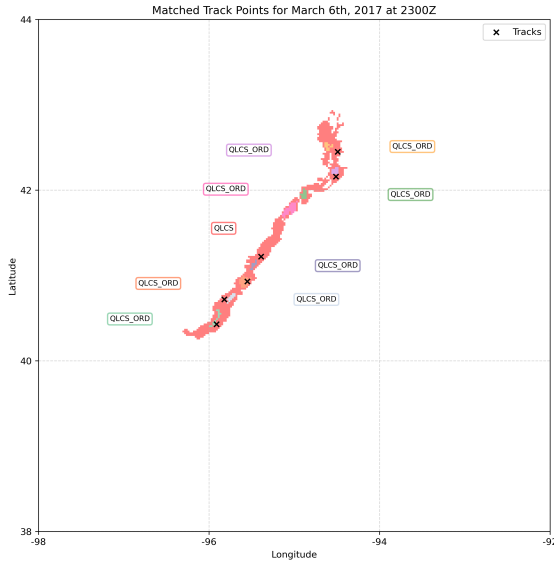
2.3.1 Parameter tuning and testing

To adapt the default classification scheme parameters from Potvin et al. (2022) to the GridRad dataset and the goals of this study, a series of case studies were conducted to evaluate the sensitivity of threshold values and object-merging parameters. For each case, parameter configurations were evaluated based on their ability to produce storm mode classifications consistent with visual assessments of the underlying radar structure. The final parameter values adopted in the dataset are listed in Table 2.1.

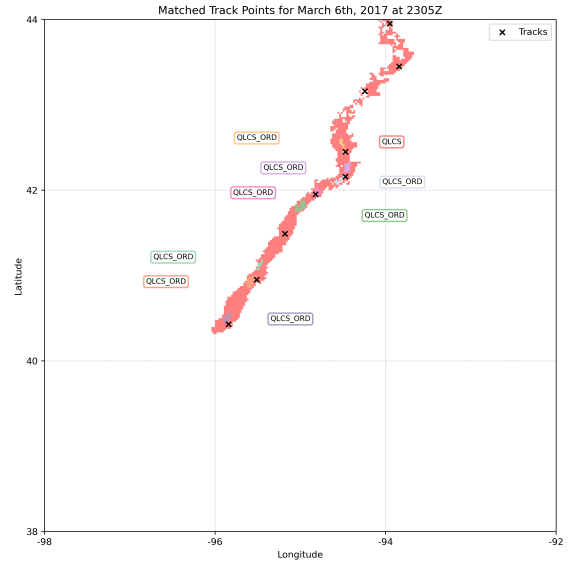
Parameters	Minimum reflectivity	Maximum reflectivity	Distance to merge objects	Minimum object area
Default (Potvin et al. 2022)	36.73 <i>dBZ</i>	40.73 <i>dBZ</i>	9 <i>km</i>	135 <i>km</i> ²
Final values (this study)	40.00 <i>dBZ</i>	45.00 <i>dBZ</i>	12 <i>km</i>	225 <i>km</i> ²

Table 2.1: List of parameters for the storm classification scheme used in this study as compared to the default values from Potvin et al. (2022).

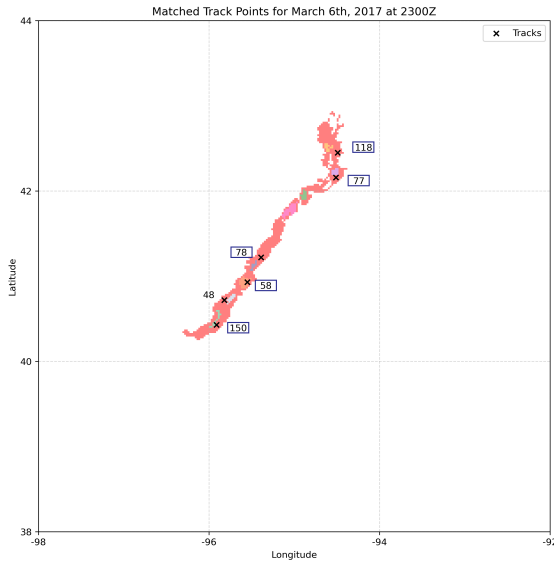
Figure 2.3 shows an example of one of these case studies with the final parameter set used for the labeling and classification. The event shown is the severe weather



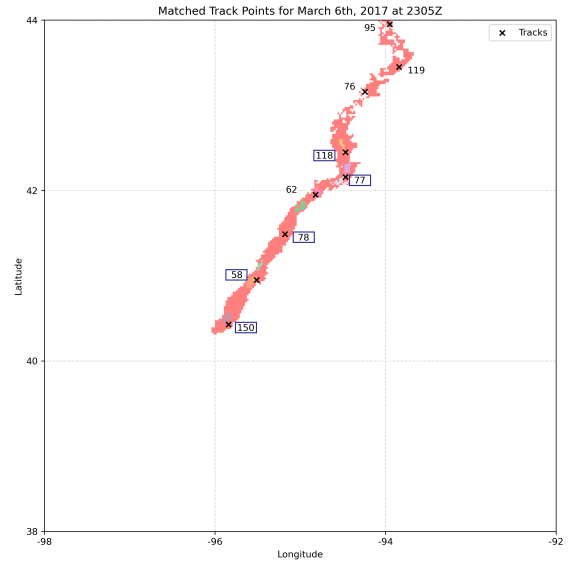
(a)



(b)



(c)



(d)

Figure 2.2: An example of how storm tracks are matched with identified and classified storm objects. (a) shows all classified storm objects with storm type labeled and track points overlaid (x, black). (b) shows the same as (a), but for the next timestep five minutes later. (c) shows the storm objects and track numbers for the same timestep as (a), but labels the storm numbers rather than storm type. (d) shows the same as (c), but for the timestep associated with (b).

outbreak that occurred during the evening and overnight hours of March 24-25, 2023, containing the long-track, EF-4 Rolling Fork, MS tornado. The system started out with a messier storm mode, resembling an MCS in the evening with a few discrete cells ahead of the line, as can be seen in figs. 2.3a and 2.3b. As the storm progressed eastward, the system started to grow into a more well-defined QLCS, but discrete cells persisted at the southern end of the line. One of these discrete supercells produced the Rolling Fork EF-4 and was classified as such by the framework (Figure 2.3d). Going into the overnight and morning hours of March 25th, almost all discrete cells grew upscale and a prominent QLCS was the dominating storm mode by 0600Z (figs. 2.3e and 2.3f).

When assessing the performance of the classification algorithm across the whole event, there are some limitations in the classification of stratiform precipitation regions, which are predominantly labeled in the “other” or “QLCS” category. In figs. 2.3d and 2.3f, there is a large area of trailing and parallel stratiform associated with the primary QLCS that is identified as a secondary QLCS object. Although this classification is likely incorrect and may appear in other cases, such objects are unlikely to contain a sustained updraft or be associated with a storm track and thus are not expected to be included in the final dataset. A similar limitation is evident in the classification of the Rolling Fork tornado-producing supercell. While the main updraft is properly classified as supercellular, the reflectivity associated with the forward flank downdraft is labeled as an ‘other’ storm object rather than being incorporated into the parent supercell. Despite this limitation, the only objects of interest for this study are the QLCS-related objects, which are well-resolved for this event. Overall, the classification output depicts the evolution of the system from a mixed convective mode containing many embedded, discrete cells into a more organized line of convection.

Another case study was conducted to directly compare our classification output

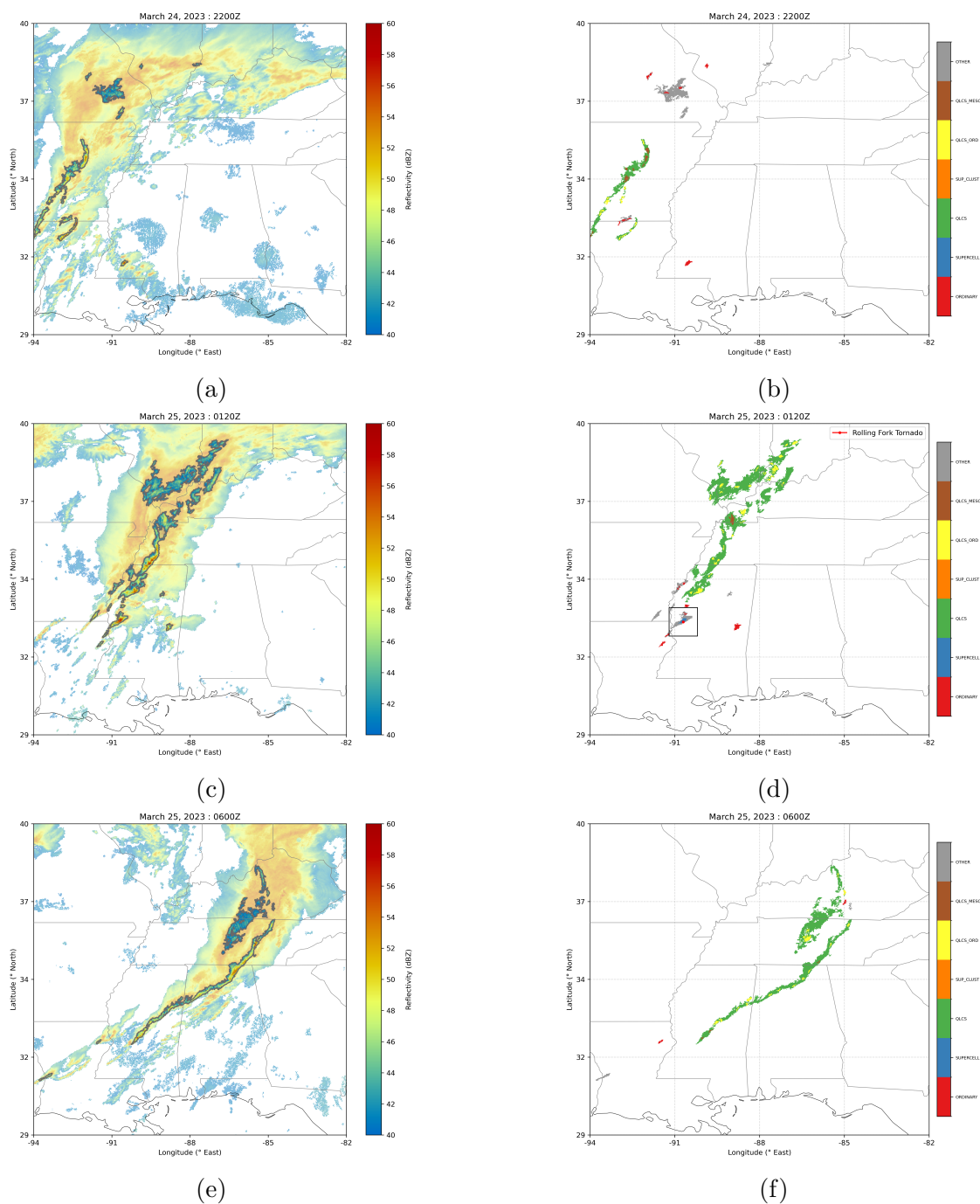


Figure 2.3: A depiction of the classification scheme output for three timesteps during a severe weather outbreak on March 24-25, 2023. Figures (a), (c), and (e) show the composite reflectivity (dBZ) at 2200Z, 0120Z, and 0600Z, respectively. Contours separating the 40 dBZ values are outlined. Figures (b), (d), and (f) visualize the storm mode classification for identified storm objects. The box in (d) highlights the storm that produced the EF-4 tornado that went through Rolling Fork, MS.

to the three-mode classification system within GR-S for a severe weather outbreak on April 14-15, 2011. At 2100 UTC, there are multiple cells forming along a stationary front that are still relatively discrete in nature, as noted in Figure 2.4a. The GR-S classification scheme identifies some of these cells as single-cellular, but already begins to cluster some of these storms into an MCS (Figure 2.4b). Conversely, our classification scheme maintains these reflectivity cores as discrete storm objects, labeling them as either ordinary cells or supercells (Figure 2.4c). As the convection begins to grow upscale, the classification system is able to resolve the larger MCS region while still highlighting the finer-scale features of stronger updrafts within the line and discrete cells at the southern end of the storm (Figure 2.4i). Due to the GR-S scheme's inability to represent embedded cells and more complex storm modes, several of these discrete features are not identified as distinct storm objects (Figure 2.4h). This distinction is particularly important for this study, as the improper inclusion of discrete cells within the broader MCS or QLCS category could suppress radar patterns preceding MV intensification and tornadic development.

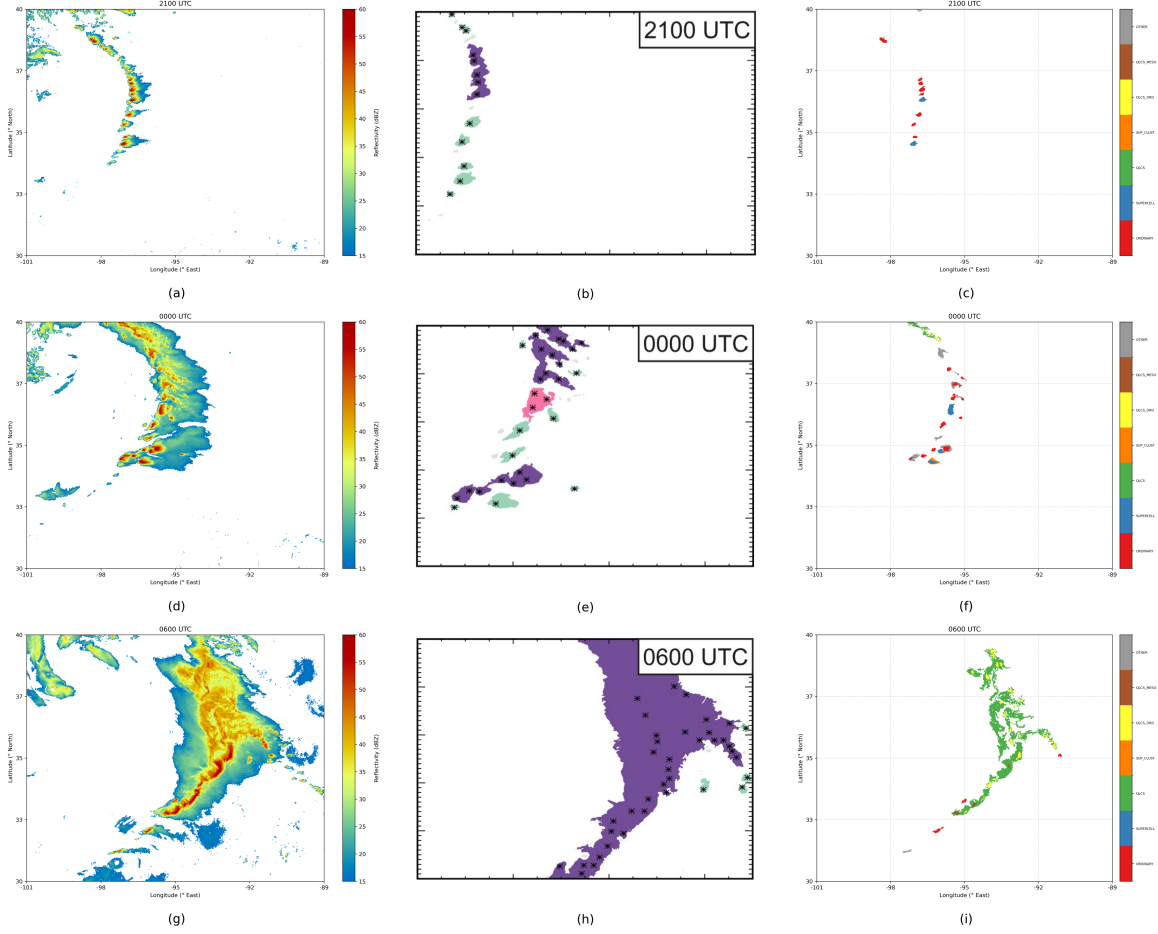


Figure 2.4: A comparison of the classification schemes from GR-S and this study for a severe weather event on April 14-15, 2011. Figures (a), (d), and (g) show the composite reflectivity values for 2100Z, 0000Z, and 0600Z respectively. Figures (b), (e), and (h) represent the classification of storms as either single-cell (green), multicell (pink), or MCS (purple) for the same timesteps. Figures (c), (f), and (i) represent the classification of storms made by this study's seven-mode classification scheme.

Chapter 3

Results

3.1 General dataset characteristics

The final dataset contains $\sim 30,000$ QLCS MVs across ~ 600 unique severe weather days. There are 886 tornado-producing mesovortices across 242 distinct severe weather days. To characterize the dataset and compare it to existing QLCS climatologies, spatial and statistical analyses were conducted.

3.1.1 Spatial patterns

Figure 3.1 illustrates the spatial distribution of all QLCS tornadoes within the dataset. Figure 3.1a highlights two prominent clusters of QLCS tornadoes: one over the Deep South and one over the Midwest. This pattern is consistent with the state-level tornado counts in Figure 3.1b, which shows the highest tornado counts in Mississippi/Alabama/Georgia followed by Illinois in the Midwest.

Another way to visualize the spatial distribution is through kernel density estimation (KDE), which estimates the spatial probability density of tornado occurrence. Figure 3.2a illustrates the KDE for the QLCS tornadoes, again confirming the highest density of tornadoes around Mississippi and the Midwest. This KDE plot highly resembles the plot from Lyons et al. (2025) in Figure 3.2b that illustrates the QLCS tornado KDE plot created from their dataset of QLCS-associated tornadoes from 2012-2023.

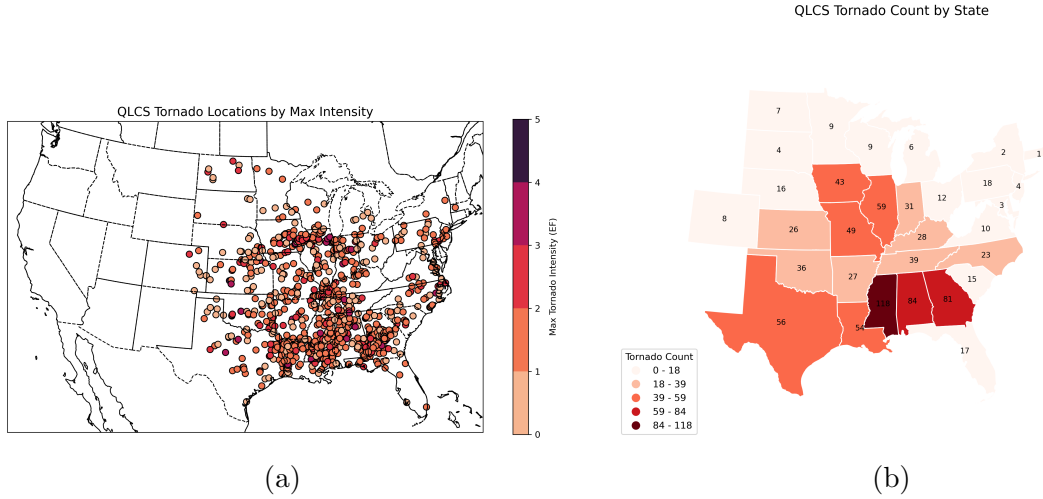


Figure 3.1: Spatial distribution of QLCS tornadoes across the CONUS. (a) shows the point locations of all tornadoes, color-coded by their associated maximum tornado intensity on the EF-scale. (b) shows the count of tornadoes for every state, with darker colors correlating to a higher count.

In an effort to understand the seasonal differences in QLCS tornado occurrence, seasonal KDE plots were also created, as shown in Figure 3.3. During winter, QLCS tornado density shifts eastward relative to the annual average, with the primary threat centered over south-central Georgia. Spring most closely resembles the annual KDE in Figure 3.2a, consistent with the known springtime peak in QLCS activity and with the distribution observed in this dataset (Figure 3.6; Ashley et al. (2019); Lyons et al. (2025)). Summer shows the highest probabilities over the Midwest and comparatively low values over the Southeast. In fall, two probability maxima are seen over Mississippi/Louisiana and the Ohio Valley.

Although tornadoes are a major focus of this study, the full QLCS MV dataset was also similarly analyzed to evaluate broader spatial patterns. Figure 3.4 shows the KDE plot for all QLCS mesovortices in the dataset. The spatial distribution is broadly similar to the KDE for solely tornadic cases with a slight western bias. Secondary centers of higher density are highlighted over Arkansas and the Kansas/Nebraska border.



Figure 3.2: Two KDE maps for QLCS tornadoes across the CONUS. (a) shows the KDE map for the data points within this dataset. Darker blue corresponds to a higher density. (b) KDE map of QLCS tornadoes from 2012-2023 from Lyons et al. (2025). Areas with lighter shading correspond to a higher density. Their Figure A2.e.

3.1.2 Temporal patterns

To assess the temporal distribution of QLCSs in the dataset, occurrences are examined on yearly, seasonal, monthly, and hourly scales. Figure 3.5 displays the empirical cumulative distribution functions (ECDFs) for all QLCSs (Figure 3.5a) and QLCS tornadoes (Figure 3.5b). For a year-long ECDF, values represent the proportion of events occurring prior to a given day of the year. For all QLCSs (Figure 3.5a), accumulation begins in mid-March and approaches 100% by August, indicating that most events occur during spring and early summer. A similar trend is observed for QLCS tornadoes (Figure 3.5b), though the steepest increase occurs slightly earlier, from late winter through midsummer. Interannual variability in the ECDF is also evident, with several years consistently deviating above or below the aggregate line. For both figures, the 2023 distribution is much earlier in the year, remaining above the aggregate line for most of the year. In contrast, the 2015 ECDF for all QLCSs is consistently below the aggregate curve, indicating a delayed and gradual increase throughout spring and summer. These deviations highlight significant interannual variability in the timing of

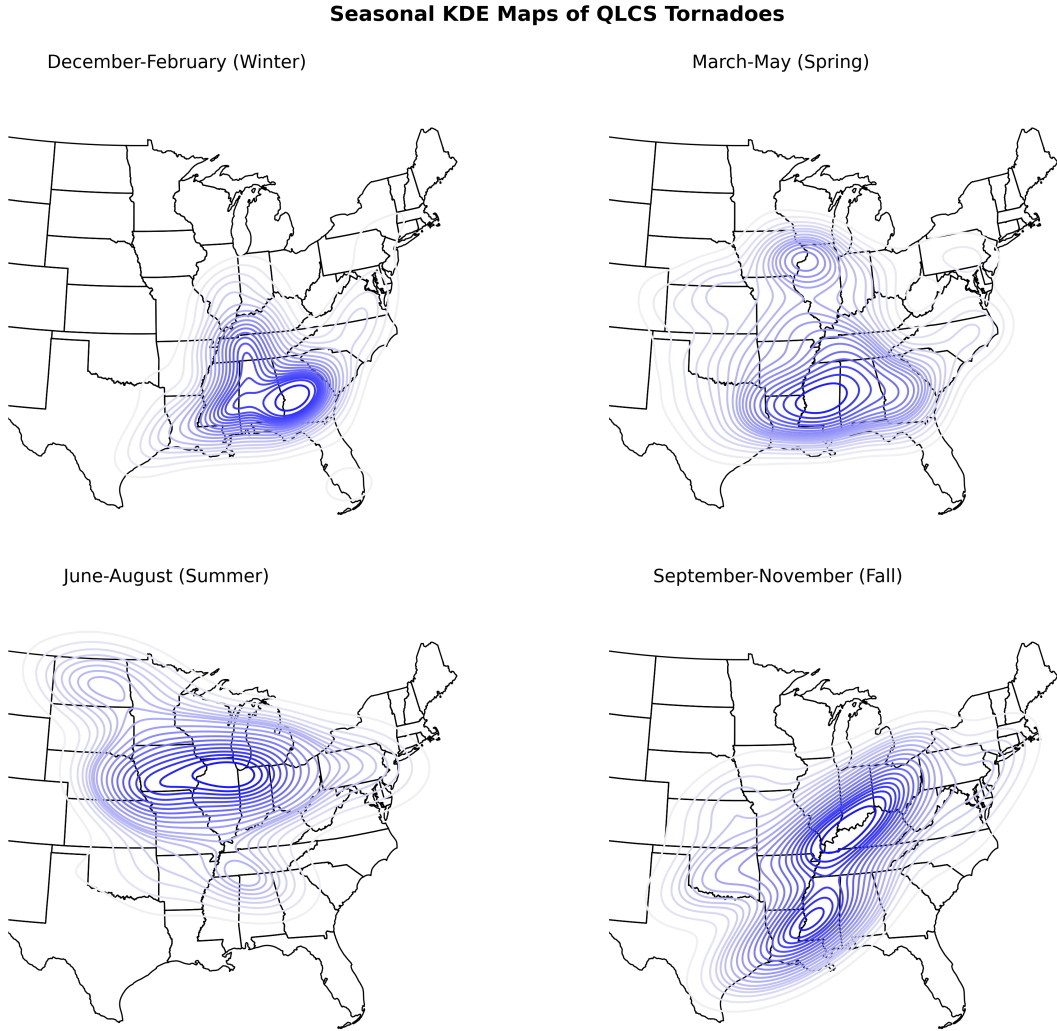


Figure 3.3: Same as 3.2a, but split across the four seasons.

QLCSs across the study period.

Figure 3.6 shows the seasonality of all QLCSs as well as just QLCS tornadoes as a function of their percentage occurrence. As aforementioned, the highest occurrence of both QLCSs and QLCS tornadoes occur during the springtime months, in alignment with Lyons et al. (2025) and Ashley et al. (2019). The summer months have approximately 30% of all QLCS MVs, but only around 10% of tornado reports. Conversely, winter accounts for 10% of all QLCSs, but almost 20% of QLCS tornadoes. These re-

KDE Map of All QLCSSs

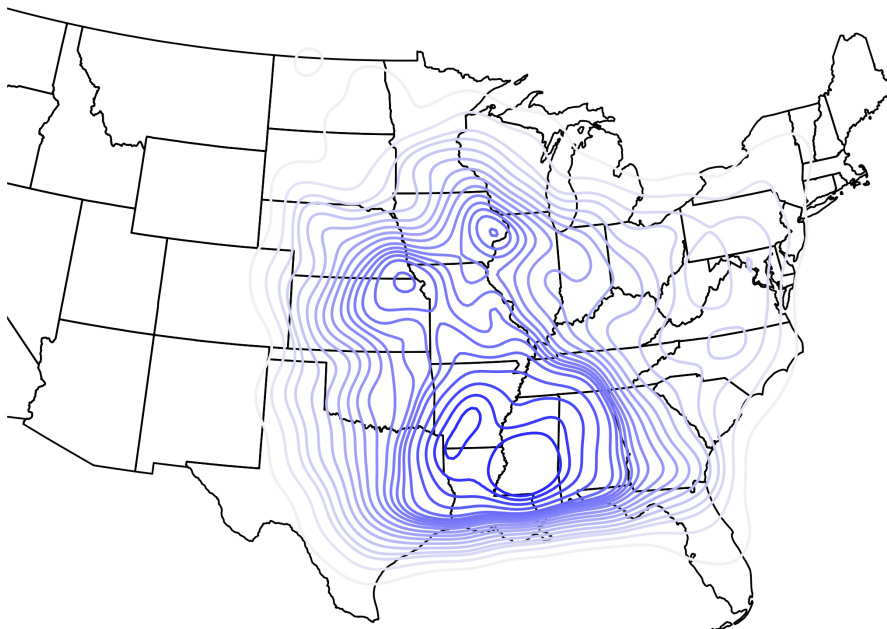


Figure 3.4: Same as 3.2a, but for all QLCSSs.

sults are in line with conclusions from previous literature that relative QLCS tornado production is highest during the cool and spring seasons (Ashley et al., 2019; Lyons et al., 2025).

Breaking down the seasons into a monthly scale, Figure 3.7 illustrates a similar comparison of the percentages of QLCS tornadoes and all QLCSSs for each month. Figure 3.7 shows that within the active spring season, the highest percentages are seen in April for both tornadoes and all. March and May unsurprisingly have the next highest percentages before a steep drop off into the summer months. In the cool season, January and February show a secondary peak with about 15% of QLCSS tornadoes occurring between the two months. As seen in Figures 3.5 and 3.6, the fall

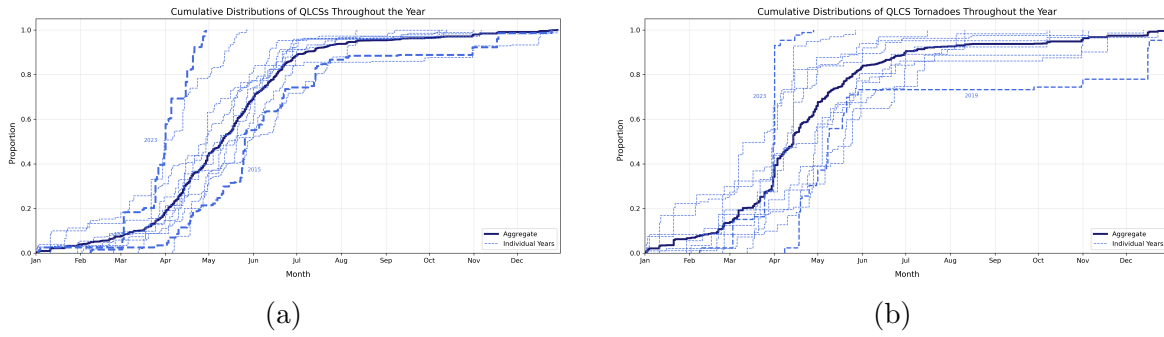


Figure 3.5: Empirical cumulative distribution functions (ECDFs) for all QLCSs and QLCS tornadoes. (a) shows the average ECDF for all QLCSs throughout the calendar year. Individual years are also plotted (light blue, dashed) and noteworthy years are labeled. (b) is the same as (a), but applies to only QLCS tornadoes.

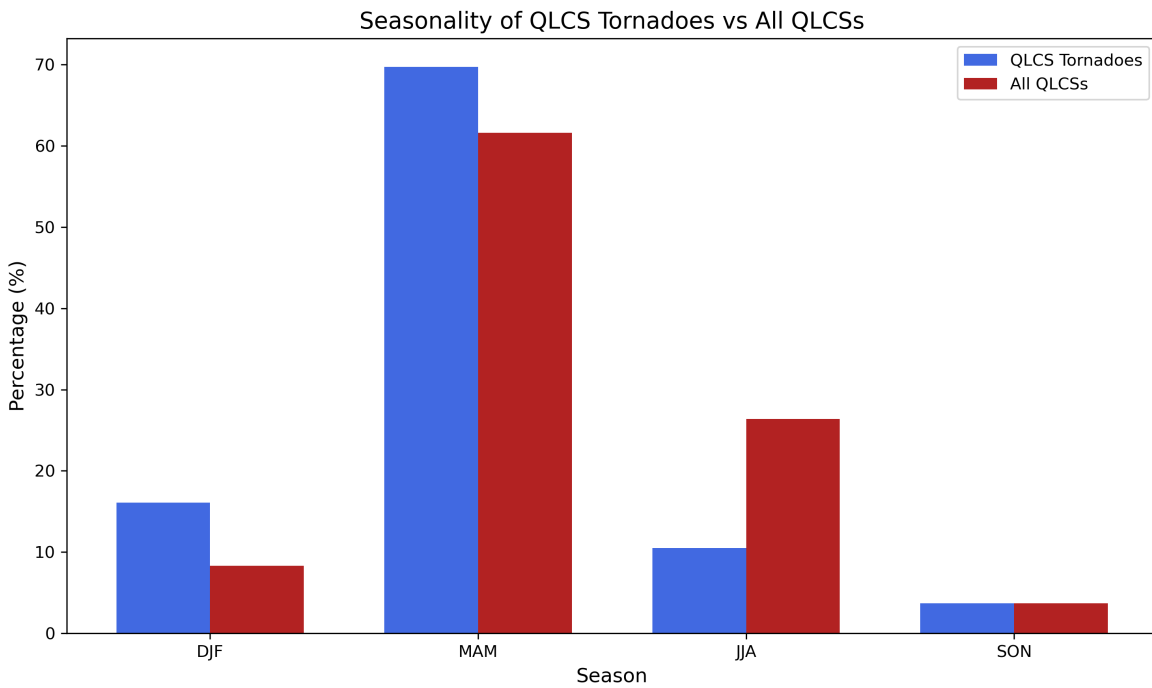


Figure 3.6: Bar charts displaying the seasonality of QLCS tornadoes (blue) and all QLCSs (red). Seasonality is expressed as percentages of the total amount of data points that are accounted for in that season.

months are the least active.

Lastly, Figure 3.8 demonstrates the hourly distribution of QLCS cases. The most notable pattern is the presence of a nocturnal cycle, with a significant peak in QLCS

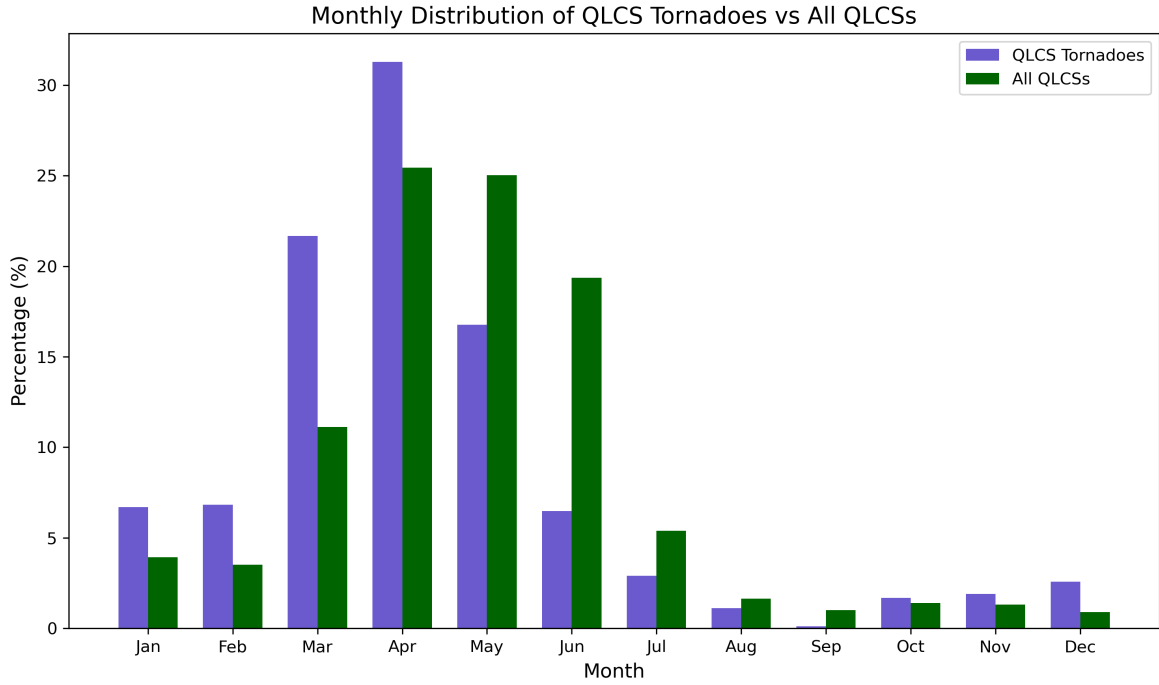


Figure 3.7: Bar charts displaying the seasonality of QLCS tornadoes (purple) and all QLCSs (green). Seasonality is expressed as percentages of the total amount of data points that are accounted for in that season.

occurrence between the hours of 2100-0300 UTC. This trend is in alignment with other climatologies and conclusions from previous literature that QLCS populations have a higher nocturnal tendency than other storm modes - likely a combination of the influence of the nocturnal low-level jet, general upscale growth, and self-organization (Trapp et al., 2005; Anderson-Frey et al., 2016; Ashley et al., 2019; Parker, 2021). Nocturnal tornadoes are associated with a high proportion of fatalities and have lower PODs as compared to daytime tornadoes, emphasizing the importance of understanding QLCS tornadoes and their unique societal impact (Ashley et al., 2008; Anderson-Frey and Brooks, 2021).

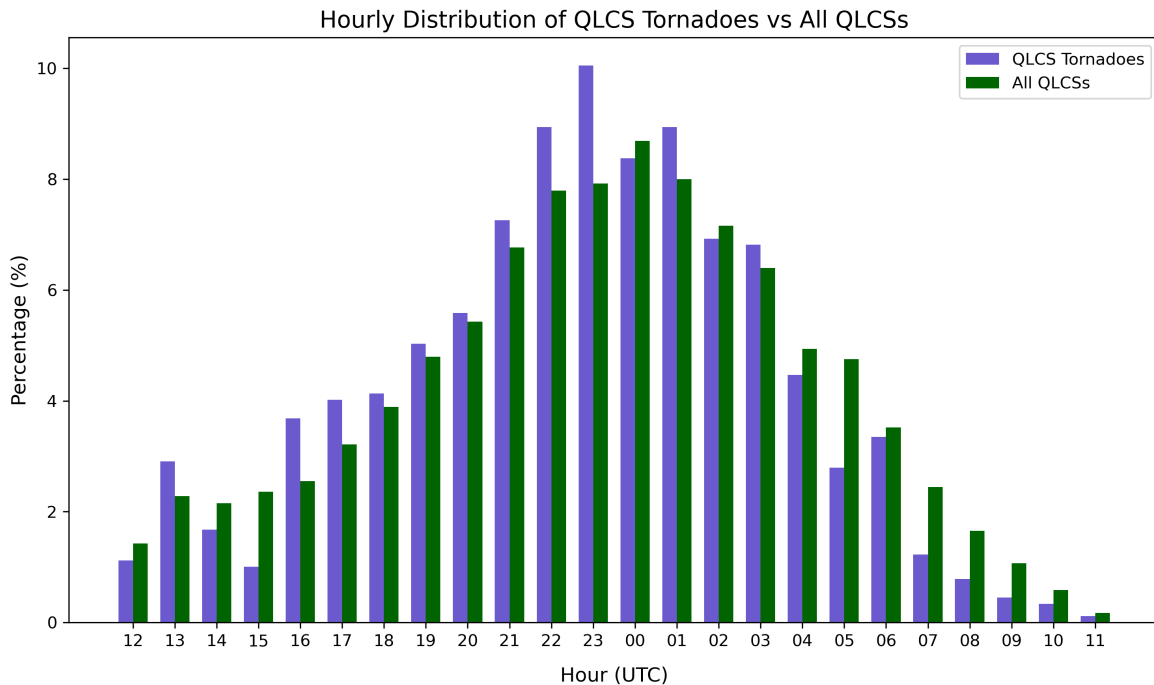


Figure 3.8: Same as 3.7, but for an hourly scale.

3.1.3 Storm mode and tornado intensity

As described in Chapter 2, the three storm modes included in this dataset are QLCSs, line-embedded cells with sustained, intense rotation (QLCS_MESOs), and line-embedded cells without sustained, intense rotation (QLCS_ORDs). A key objective of this study is to create a dataset that is truly representative of QLCS behavior with as little contamination from other storm modes as possible. Parameter tuning and case study analysis (see Section 2.3.1) revealed that many identified QLCS_ORD and QLCS_MESO objects are embedded convective elements whose evolution and behavior are governed by the parent QLCS rather than independent supercells. Given that these embedded circulations and discrete updrafts may also indicate portions of a QLCS that have a higher likelihood of tornado production, the decision was made to include both additional storm modes (Wolff et al., 2025; Trapp and Weisman, 2003).

To further verify that the additional storm objects were not potentially skewing the database, previously analyzed spatial and temporal patterns were stratified by storm mode type. Figure 3.9 illustrates the locations of all QLCS tornadoes broken down by storm type. Given that most MVs are classified as QLCS rather than QLCS_ORD or QLCS_MESO, it is unsurprising that the plot of solely QLCS tornadoes most closely resembles the overall pattern with a significant portion of tornadoes over the Deep South and Midwest. Looking to the line-embedded ordinary cells, the spatial distribution of tornadoes is a lot more scattered, with a slightly higher density over Mississippi/Alabama and up into the Ohio Valley. Lastly, the line-embedded rotating cells are also highly variable in location, but still mostly occur throughout the southern/central CONUS. Figure 3.10 compares the tornadoes associated with all three storm objects on a temporal scale, specifically on an hourly basis as in Figure 3.8. All three storm types show a drastic increase in occurrence during nighttime hours, consistent with the trend seen in Figure 3.8. Together, these figures and the classification case studies in Section 2.3.1 provide confidence in the inclusion of all three storm modes in this analysis.

The last metric of interest for this dataset is the distribution of tornado intensities. For the purposes of this investigation, tornado intensity was defined by the maximum EF-scale intensity that a tornado possessed during its entire lifetime. As can be seen in Figure 3.11, the most common EF rating for QLCS tornadoes is EF-1, followed by EF-0. After EF-1, the tornado counts significantly drop with only a few EF-4 tornadoes and no EF-5s. Lyons et al. (2025) found that from 2012-2023, 49% of QLCS tornadoes were EF-1 and 42% were EF-0 and in Thompson (2023), these percentages were 47% and 42%, respectively, for the same metrics from 2003-2021. These percentages differ in this dataset, where EF-0 tornadoes account for only 28% of cases (Figure 3.11). This dataset contains nearly 2000 fewer tornadoes than Lyons et al. (2025), despite a similar

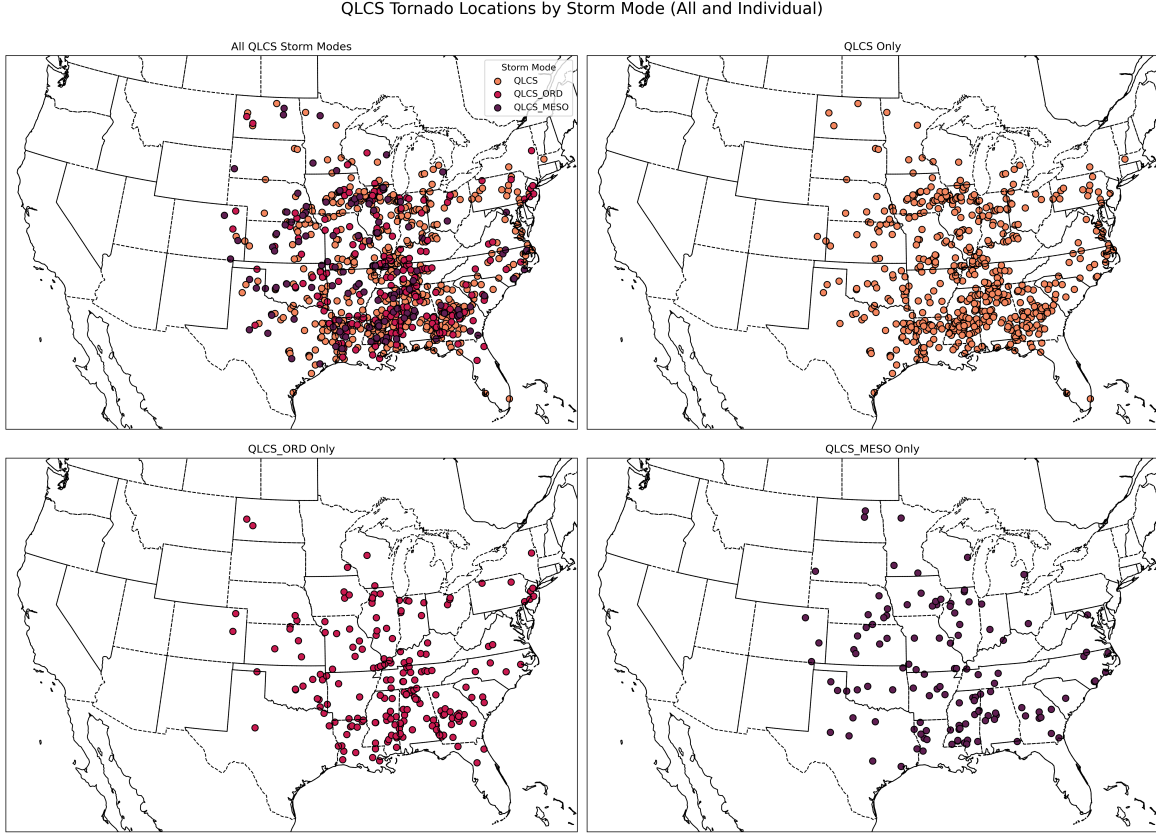


Figure 3.9: Geographical distribution of tornado locations stratified by storm mode. (a) is the same as (3.1a), but color-coded by storm mode. (b) only displays the points associated with QLCS objects, (c) QLCS_ORD objects, and (d) QLCS_MESO objects.

temporal range. Since GR-S is restricted to only ~ 100 severe days per year, the limited temporal sampling may contribute to differences in the observed EF distribution, as the omitted days may contain a higher proportion of weaker severe events. However, GR-S sampling alone likely does not fully account for this discrepancy, as it has been found that despite only including ~ 100 days per year, GR-S accounts for nearly 77% of tornado reports from the SED (Murphy et al., 2023). An additional explanation likely arises from the selection criteria of this dataset, which focuses on tornado-producing QLCS MVs rather than all reported QLCS tornadoes. Therefore, weaker tornadoes

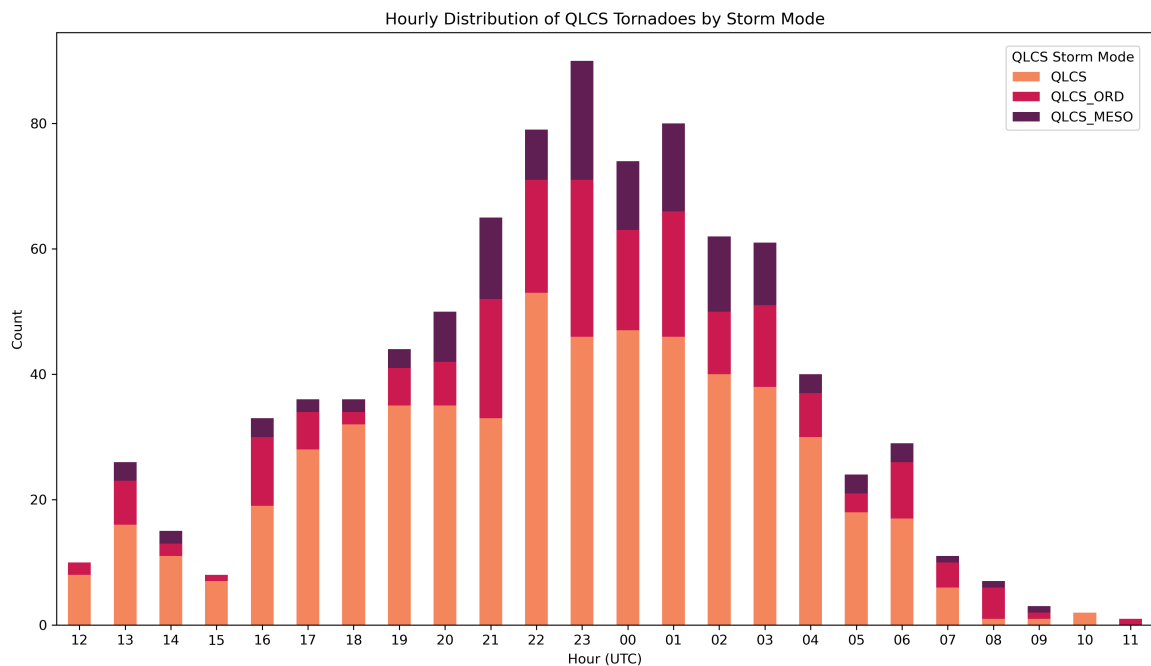


Figure 3.10: Hourly distribution of QLCS tornadoes color-coded by storm mode.

associated with less well-defined rotational signatures may be underrepresented in this dataset relative to other climatologies.

Looking briefly to the seasonal breakdown of tornadic intensity, Figure 3.12 shows that all tornado intensity ratings peak during the spring (MAM) season. The second most-frequent season for every tornado rating is the winter (DJF) months, in line with the findings of Figure 3.6. These results indicate limited variation in tornado intensity distribution across favorable tornadic environments.

3.2 Comparison of radar characteristics using probability-matched means

To assess the radar characteristics of the mesovortices within the dataset, storm-centered volumes are created in which the radar data surrounding an MV is interpolated

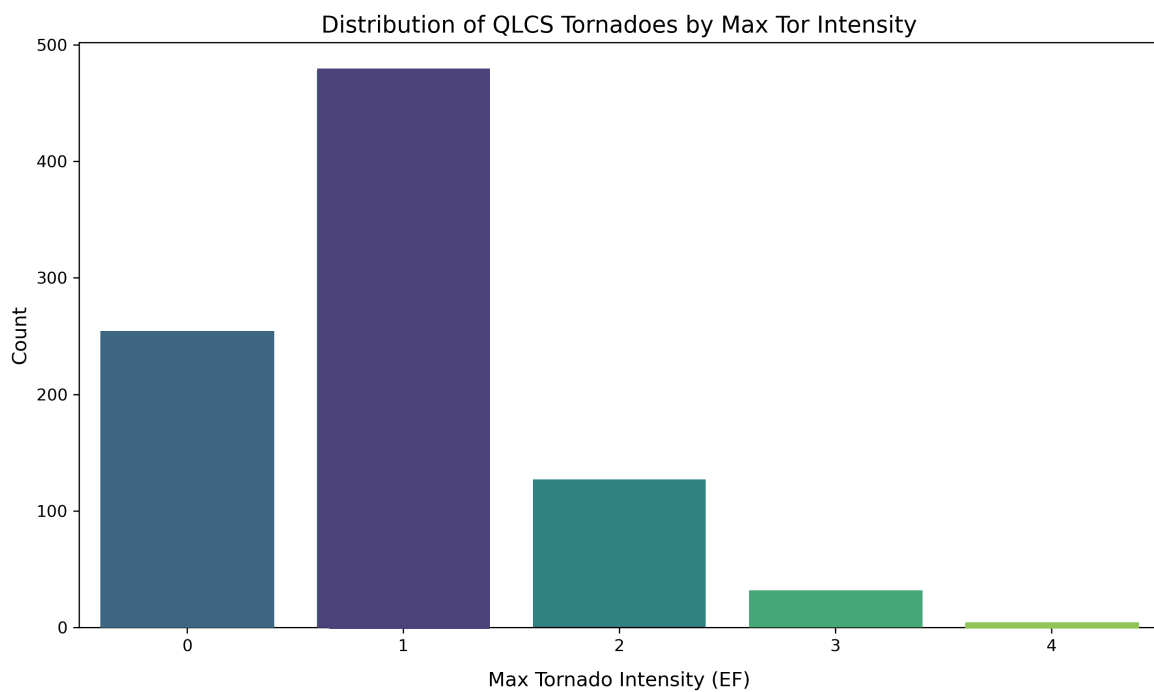


Figure 3.11: Bar chart of maximum tornado intensity for all QLCS tornadoes.

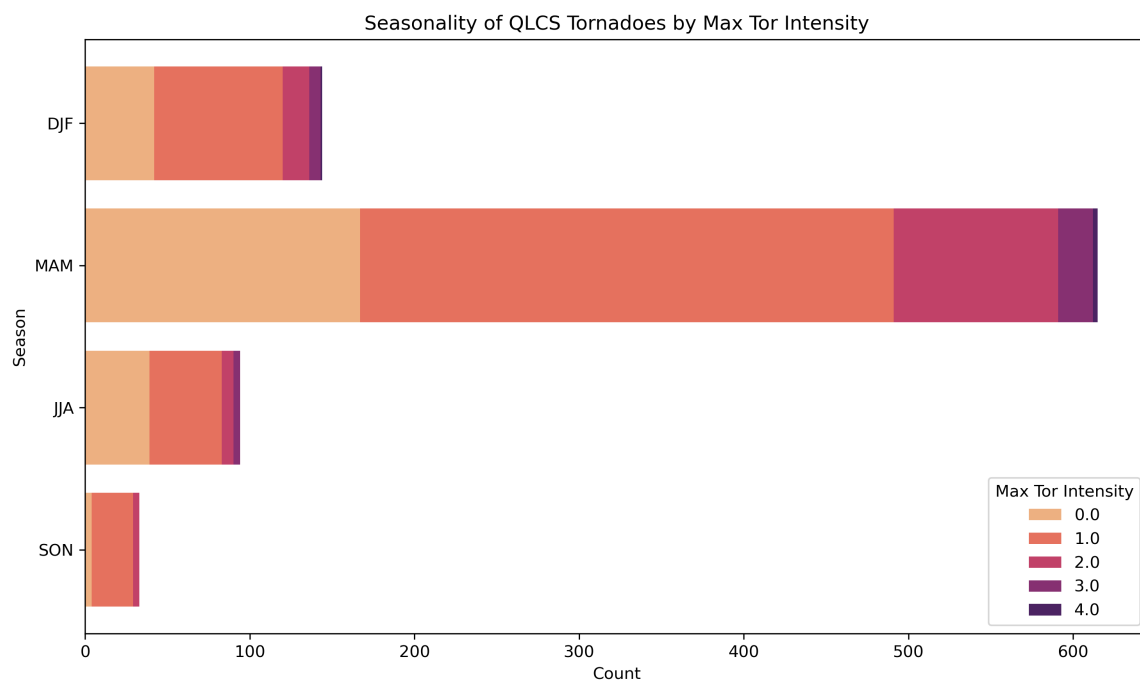


Figure 3.12: Seasonality of QLCS tornadoes clustered by maximum tornado intensity.

to a grid rotated to match the u- and v-motion of the storm track. This interpolation produces a storm-centered radar volume in which the u- and v-components of storm motion align with the positive direction of the x-axis and the echo-top center is located at the origin, providing an approximate center for the mesovortex. These storm-centered volumes are then aggregated across cases and analyzed using PMMs for all radar variables, including comparisons between tornadic and nontornadic cases and across lead times.

The PMM provides an alternative to the simple arithmetic mean by preserving the underlying distribution of values while retaining the spatial cohesion of the composite fields (Rosenfeld et al., 1993; Ebert, 2001). PMMs are created by matching cumulative distribution function (CDF) of the composite fields to the original CDF of the individual volumes. As a result, PMMs preserve extreme values and local structures that would otherwise be more heavily smoothed by a typical composite mean.

3.2.1 Single-polarization variables

3.2.1.1 Evolution of tornadic mesovortices

To investigate the progression of radar signatures that were affiliated with tornadogenesis in tornadic MVs, PMMs were calculated for the spatial fields of various single-polarization variables. For each variable, PMMs were calculated at tornadogenesis and at 5-minute time steps leading up to the time of tornadogenesis. As lead time is increased, fewer radar volumes are available, resulting in fewer observations contributing to the PMMs because some mesovortices are relatively short-lived and are therefore not present at longer lead times. To ensure that all PMMs have the same amount of samples underlying the mean, only a subset of all tornadic cases in the dataset were used for these plots (550 tornadic MVs).

First looking at azimuthal shear in Figure 3.13, the main feature that stands out is the presence of a strong area of positive azimuthal shear in the lowest few kilometers closest to the ground. As azimuthal shear is a proxy for rotation, this area of positive values near the storm center is likely a manifestation of the mesovortex. Going up in altitude, a vertical extension of the mesovortex into the mid-levels is seen as the bullseye of enhanced positive azimuthal shear is still prominent near storm center, consistent with previous PMM analyses of MCS MVs (Murphy and Homeyer, 2023). However, this region of positive azimuthal shear is also directly opposed by a negative area in the direction of storm motion at the higher altitudes. This negative region is likely a combination of the radial velocity field surrounding the main circulation, which can produce flanking regions of negative azimuthal shear, and broader shear associated with the leading edge of a QLCS. These features, although prominent, do not significantly change leading up to tornadogenesis, indicating a lack of utility from a predictive standpoint.

Radial divergence, Figure 3.14, tells a similar story to azimuthal shear. Within the lowest 5 km, a bullseye of strong convergence (negative divergence) is seen surrounding the center of the storm-centered PMMs. Conversely, the higher altitudes show stronger divergence near the storm-tops. The spatial structure of convergence and divergence remains consistent through the various lead times.

The last single-polarization variable examined is horizontal reflectivity, as seen in Figure 3.15. Unsurprisingly, the highest magnitude of reflectivity is around the center of the MV. At higher altitudes, the spatial distribution of reflectivity is circular in nature, reflecting the reflectivity cores that are associated with deep updrafts rather than broader storm structure. In contrast, the orientation of the field in the lower altitudes appears to be elongated along a lower-left to upper-right axis, better representing the linear presentation of QLCSs. Interestingly, a similar elliptical reflectivity distribution

Tornadic PMMs of Azimuthal Shear at Multiple Altitudes for Multiple Lead Times

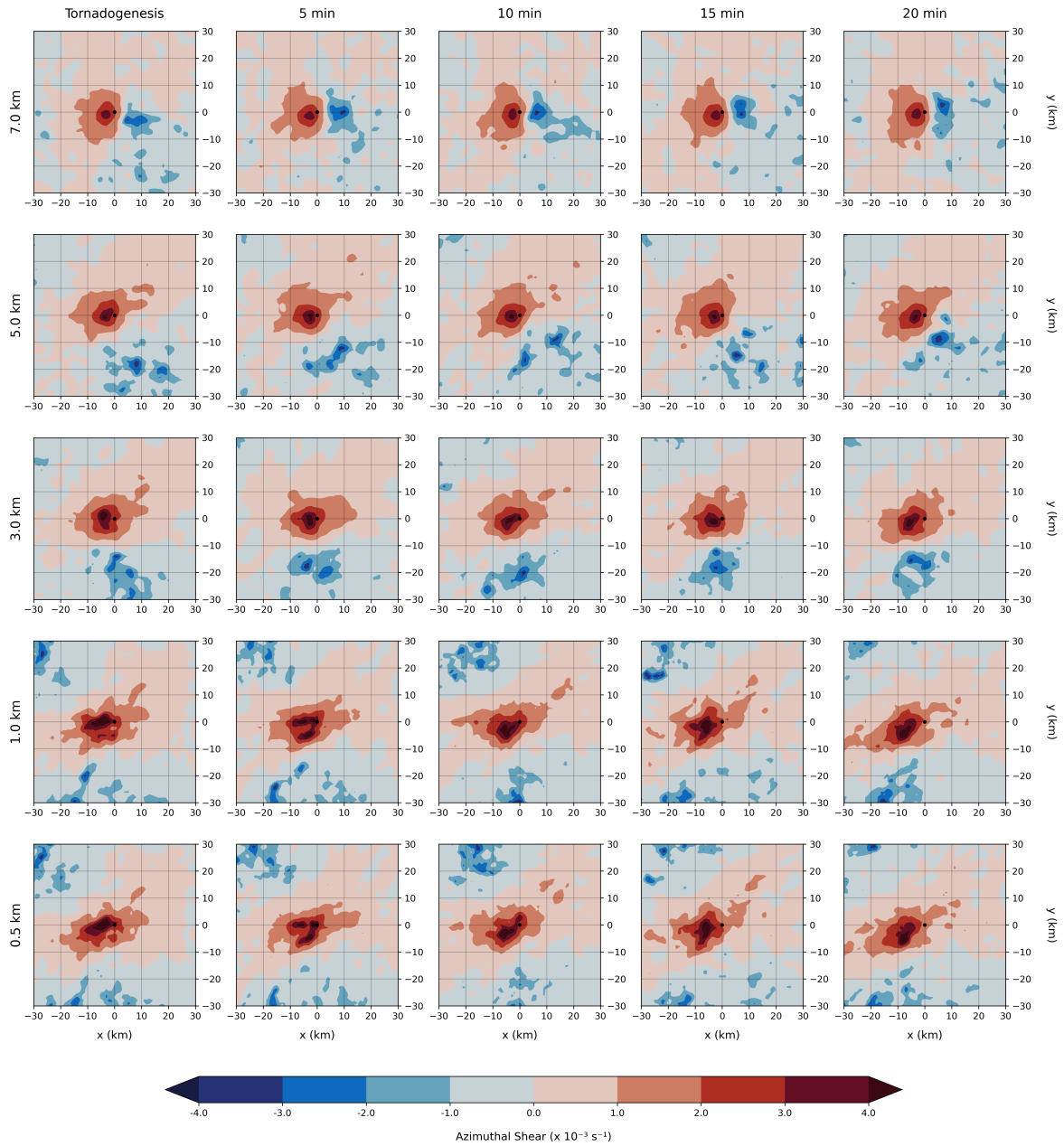


Figure 3.13: PMMs of azimuthal shear for tornadic MVs at constant altitudes of 0.5, 1.0, 3.0, 5.0, and 7.0 km above mean sea level (AMSL). The tornadic storms are represented at tornadogenesis and in five minute increments of lead time going up to 20 minutes.

Tornadic PMMs of Radial Divergence at Multiple Altitudes for Multiple Lead Times

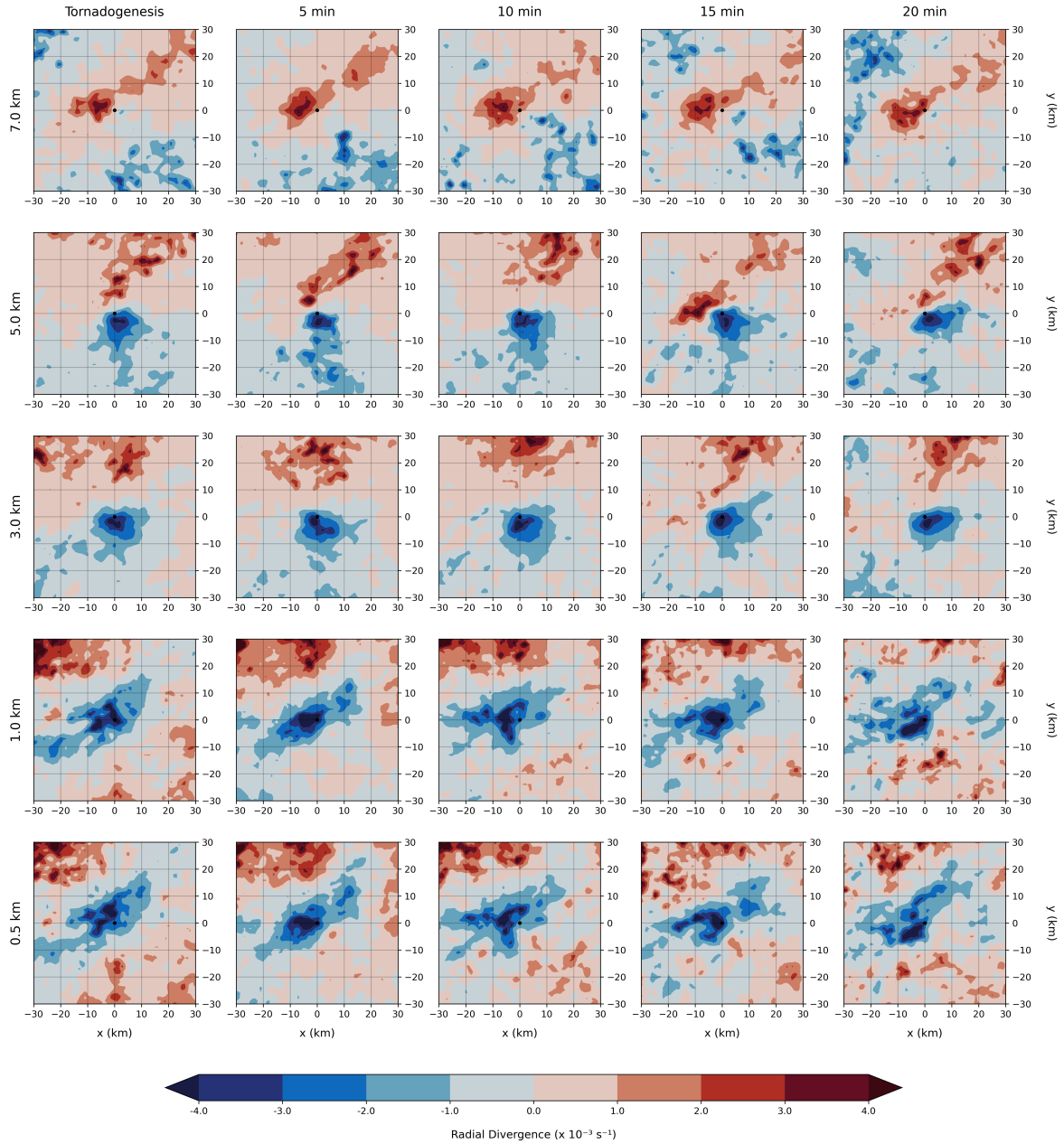


Figure 3.14: Same as 3.13, but for radial divergence.

was noted in Murphy and Homeyer (2023), who suggested that this pattern reflected a more consistent MCS line orientation in tornadic storms. Despite this unique pattern in the lower-levels, there is minimal evolution in the fields across lead times.

Across azimuthal shear, radial divergence, and horizontal reflectivity, the PMMs indicate that the spatial structure of tornadic MVs remains largely steady over the 20-minute lead time window.

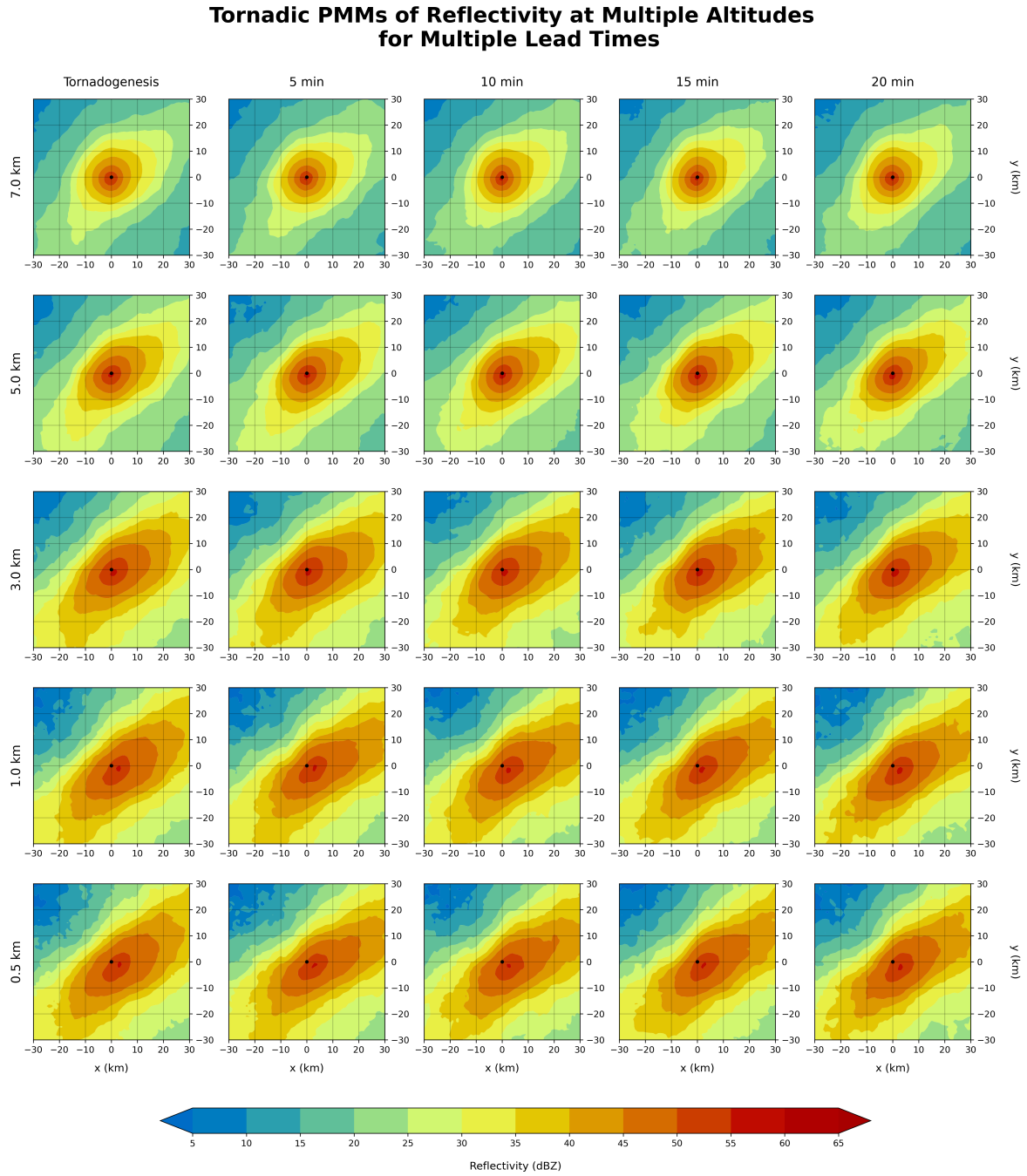


Figure 3.15: Same as 3.13, but for reflectivity.

3.2.1.2 Comparing tornadic and nontornadic mesovortex evolution

To compare tornadic and null MVs, the radar fields of both groups were compared at the time of tornadogenesis for tornadic cases and at the time of max LL azimuthal shear for null cases. Null MVs ($n = 850$) were selected by matching the distribution of maximum LL azimuthal shear derived from the tornadic population, ensuring comparable dynamic strength between the two groups (Murphy and Homeyer, 2023). The final dataset consisted of 850 tornadic and 850 strong, but nontornadic MVs.

Figure 3.16 illustrates this comparison for azimuthal shear at the same five altitudes previously examined. At higher altitudes, the azimuthal shear couplet can be seen in both tornadic and null cases. As aforementioned, the negative portion of this dipole likely results from the field surrounding the primary circulation, which produces flanking regions of negative azimuthal shear. Broader shear associated with QLCs and the leading edge may also contribute to this feature. Shifting the view to the lower-levels, the differences between the two sample populations become more apparent. Although positive azimuthal shear values take over as the primary feature at 0.5 and 1.0 km, this area is much more prominent and organized for the tornadic cases. This contrast suggests potential predictive value for identifying potentially tornadic MVs, as even strong, null MVs exhibit comparatively more diffuse and broad azimuthal shear fields, as also observed by Murphy and Homeyer (2023).

While a plan view of radar variables can illustrate the location and spatial distribution of values across a storm's 2D structure, some signatures and patterns are better understood through vertical cross sections through storms (Homeyer et al., 2023; Murphy and Homeyer, 2023). This view can provide a better depiction of a storm's structure and show some radar features that are best understood through their vertical evolution.

Following this understanding, Figure 3.17 displays PMMs for vertical cross sections taken perpendicular to storm motion for both null and tornadic MVs. Taking a holistic view of the evolution of the vertical azimuthal shear field in the tornadic cases, a prominent vertical column of rotation near the center of the MV maintains and intensifies leading up to the time of tornadogenesis. Simultaneously, a region of opposing negative azimuthal shear values develops in the low-levels on the right side of storm motion. Interestingly, the magnitude of positive azimuthal shear alone does not distinguish the two populations, as the null MVs actually exhibit stronger magnitudes of the variable at all times. Rather, the primary distinction is in the vertical alignment and continuity of the rotation. The null cases also exhibit a vertical column of positive azimuthal shear values, but the column is tilted with height in the storm-relative y-direction, resulting in a displacement of the mid-level rotation from the low-levels. Additionally, the null cases have stronger negative azimuthal shear in the higher altitudes whereas the tornadic cases contrarily have stronger negative values in the low-levels. From a predictive and discriminative standpoint, the vertical structure of rotation clearly has significant value. Even at a 20 minute lead time, the lack of collocation between the LL MV and its vertical extension in the mid-levels is clear in the null cases, yielding important insight into why these cases may not produce tornadoes.

The same analysis was performed for radial divergence, with Figure 3.18 comparing the constant altitude PMMs between tornadic MVs at the time of tornadogenesis and null MVs at the time of maximum LL azimuthal shear. Looking at the plots within the lowest kilometer, both MV groups display a strong region of convergence near the storm center. Although magnitude is roughly the same between both groups, the spatial distribution is in a much more organized fashion for the tornadic groups, a similar finding that was seen in Figure 3.16.

The area of strongest convergence is focused near the storm center in the tornadic

cases, whereas in the null cases it is more broadly distributed and displaced to the left of the storm-centered volumes. The groups become more alike above the lowest few kilometers, but this significant visual difference in the LL radial divergence distribution suggests potential discriminatory value for detecting tornadic MVs when tornadogenesis is suspected to be imminent.

To provide another perspective for comparing the two MV groups, especially from a predictive standpoint, Figure 3.19 illustrates PMMs of radial divergence for vertical cross sections through the center of the tornadic and null MVs. For the tornadic MVs, the vertical distribution of radial divergence looks roughly the same at the time of tornadogenesis, 10-minute lead time, and 20-minute lead time. In particular, the PMMs show an area of convergence near the storm center extending up to roughly 6.5 km before switching to divergence near the top of the storm. Although the null MVs display a similar pattern, the region of markedly high convergence tapers off near the surface, unlike the tornadic cases. Even with 20 minutes of lead time, an organized and enhanced region of convergence is seen for the tornadic PMM while the null PMM does not show such a region, consistent with Murphy and Homeyer (2023), who also noted near-zero LL convergence in their null MCS cases. This signal also substantiates the conclusion drawn from Figure 3.18.

The last of the single-polarization variables, Figure 3.20 shows the comparison between constant-altitude fields of horizontal reflectivity for null and tornadic MVs. The most significant difference between the two populations is that the reflectivity values are slightly higher in the tornadic population. At almost all plotted altitudes, the tornadic PMMs display a region of 55+ dBZ values near the storm center, which is almost nonexistent for the null cases. These slightly stronger reflectivity cores may be consistent with stronger updrafts in the tornadic cases as compared to the null MVs.

Looking at the vertical cross sections in Figure 3.21, both groups exhibit similar

reflectivity distributions, with the highest magnitudes right at the storm center and decreasing outward in both directions perpendicular to storm motion. As for the vertical structure of reflectivity, the null population interestingly exhibits a higher magnitude closer to the surface than the tornadic population. Although Figure 3.20 initially showed that there are small areas of comparatively higher values for the tornadic cases when looking at storms from a top-down view, Figure 3.21 indicates that this difference is negligible when examining storms directly through the MV center.

3.2.2 Dual-polarization variables

3.2.2.1 Evolution of tornadic mesovortices

The same PMM analysis for tornadic MVs was conducted for Z_{DR} and K_{DP} . Preliminary analysis of ρ_{hv} yielded limited discriminatory value and no notable differences between the tornadic and null populations; therefore, results for ρ_{hv} are omitted for brevity.

Looking at differential reflectivity in Figure 3.22, a region of enhanced values is present near the center of the MVs, extending up to 5 km. Although interpretative ability is limited without explicit knowledge of the freezing level, this structure may resemble a shallow Z_{DR} column. Such columns are typically representative of strong updrafts, which have been linked to QLCS segments that are more likely to produce damaging winds and/or tornadoes (Healey and Broeke, 2025; Wolff et al., 2025). The strength and orientation of these features remain relatively consistent leading up to tornadogenesis, but it could still signal potential predictive value when compared to null cases.

A similar pattern is observed for K_{DP} , with higher K_{DP} values concentrated near the storm center through the low to mid-levels (Figure 3.23). This feature is often

associated with a K_{DP} core, which has been linked to strong downdrafts within the RIJ. Such features are commonly thought to indicate an enhanced updraft and tilting and stretching of vorticity. The presence of a persistent LL K_{DP} core suggests that this signature may also provide useful information in the prediction of potentially tornadic MVs.

3.2.2.2 Comparing tornadic and nontornadic mesovortex evolution

A key motivation for this study is to evaluate whether polarimetric variables provide discriminative information for an MV's tornadic potential. While single-polarization signatures are commonly used in operational nowcasting settings, the value of dual-polarization signatures for distinguishing tornadic MVs remains uncertain and not fully integrated into warning operations. Thus, the same tornadic-null comparisons used for azimuthal shear, radial divergence, and horizontal reflectivity were extended to Z_{DR} and K_{DP} .

Figure 3.24 compares the spatial distribution of Z_{DR} between tornadic and null MVs for multiple altitudes throughout the low- and mid-levels. The Z_{DR} structures appear to be very similar between the two populations, with enhanced values near the storm center that extend through several altitudes, likely indicating large raindrops and wet hail. Magnitudes are largely indistinguishable between the two groups, suggesting limited discriminative ability for this variable.

Vertical cross sections highlight features such as Z_{DR} columns, reflectivity cores (seen in Figure 3.21), and areas of storm divergence and convergence (seen in Figure 3.19). Accordingly, Figure 3.25 compares vertical cross-sections of Z_{DR} for null and tornadic MVs over multiple time steps. Over the 20-minute period leading up to tornadogenesis, enhanced Z_{DR} magnitudes remain largely unchanged. The most notable difference is a slight change in orientation at the time of tornadogenesis, with a more

upright structure compared to the vertical tilt seen at previous time steps. In contrast, the null cases remain similarly upright at all times, and no consistent difference is evident between the two populations, in line with Murphy and Homeyer (2023), who likewise found that Z_{DR} magnitudes were largely similar between tornadic and null MCS MVs. It is also important to note that the areas of enhanced Z_{DR} in both groups extend slightly above the environmental freezing level (typically 3-5 km), suggesting the presence of a shallow Z_{DR} column. However, because this vertical enhancement is seen in both groups, the presence of a Z_{DR} column provides little discriminatory value, consistent with Kuster et al. (2024) and Pardun et al. (2025), who also found no significant differences in Z_{DR} column magnitude between tornadic and nontornadic QLCS MVs.

Following the same comparative analysis, Figure 3.26 shows that both tornadic and null populations exhibit similar magnitudes of K_{DP} at all altitudes. While tornadic cases show a slightly broader distribution, the overall structure and location of enhanced K_{DP} values are generally the same between the two.

Similar to Z_{DR} , depictions of vertical structure can provide additional insight into K_{DP} evolution. Figure 3.27 shows that both tornadic and nontornadic MVs exhibit increased values slightly beneath storm center, extending upward to approximately 6 km. However, tornadic cases maintain slightly higher magnitudes throughout the column, with differences on the order of ~ 0.5 deg/km. This contrast is most highlighted at peak strength for both tornadic and null cases, where a region of 3.0 deg/km extends from the surface to roughly 3 km in the tornadic composite, but is largely absent in the null composite, reinforcing the consistent enhancement in K_{DP} for tornadic cases. Previous work has established LL K_{DP} cores as a useful indicator for imminent microburst development, and this result provides additional evidence that they may also be associated with tornadogenesis. This result is consistent with Kuster et al. (2024),

who identified LL K_{DP} cores as a helpful predictor for the damage potential of a QLCS MV. However, this result contrasts with the findings of Murphy and Homeyer (2023), who found the K_{DP} fields of tornadic and null MCS MVs to be almost indistinguishable, suggesting that isolating QLCSs from the broader MCS storm mode may reveal radar signatures that are otherwise less apparent.

PMMs of Azimuthal Shear at Multiple Altitudes for Tornadoic and Null MVs

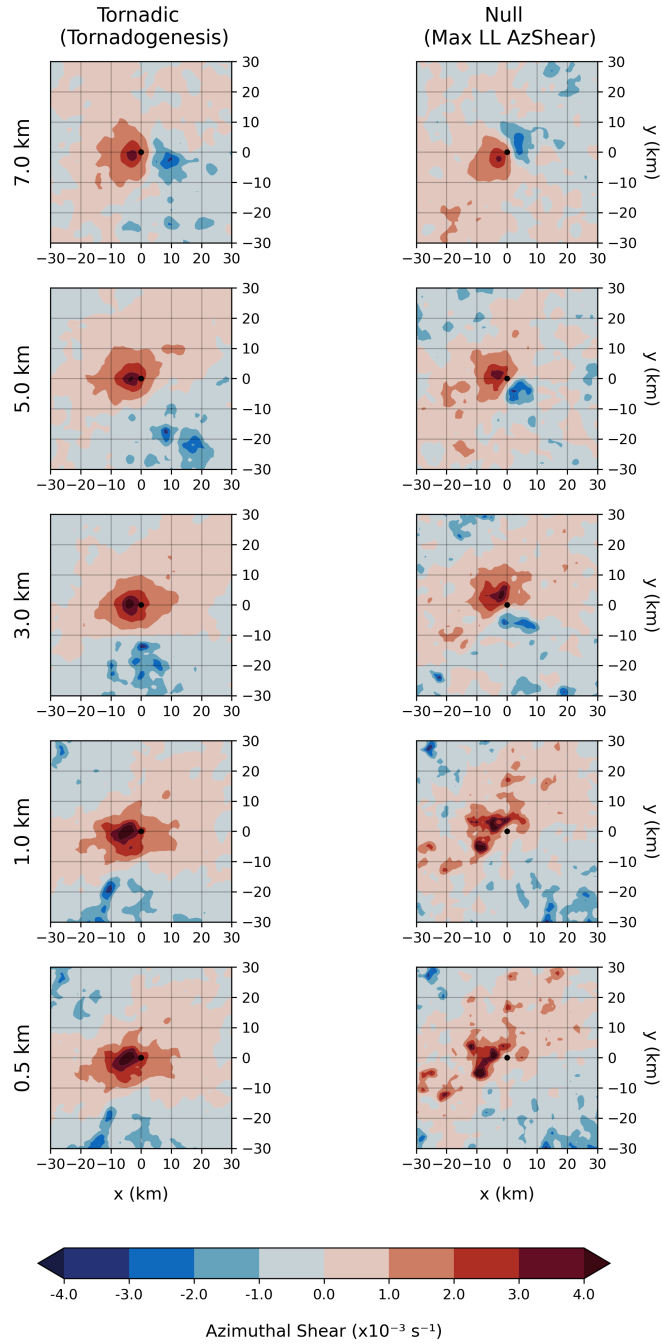


Figure 3.16: PMMs of azimuthal shear for tornadoic and null MVs at constant altitudes of 0.5, 1.0, 3.0, 5.0 km, and 7.0 above mean sea level (AMSL). The tornadoic storms are represented at the time of tornadogenesis and null storms are represented at the time during their entire lifetime where max LL azimuthal shear is the highest.

Vertical PMMs of Azimuthal Shear Perpendicular to Storm Motion

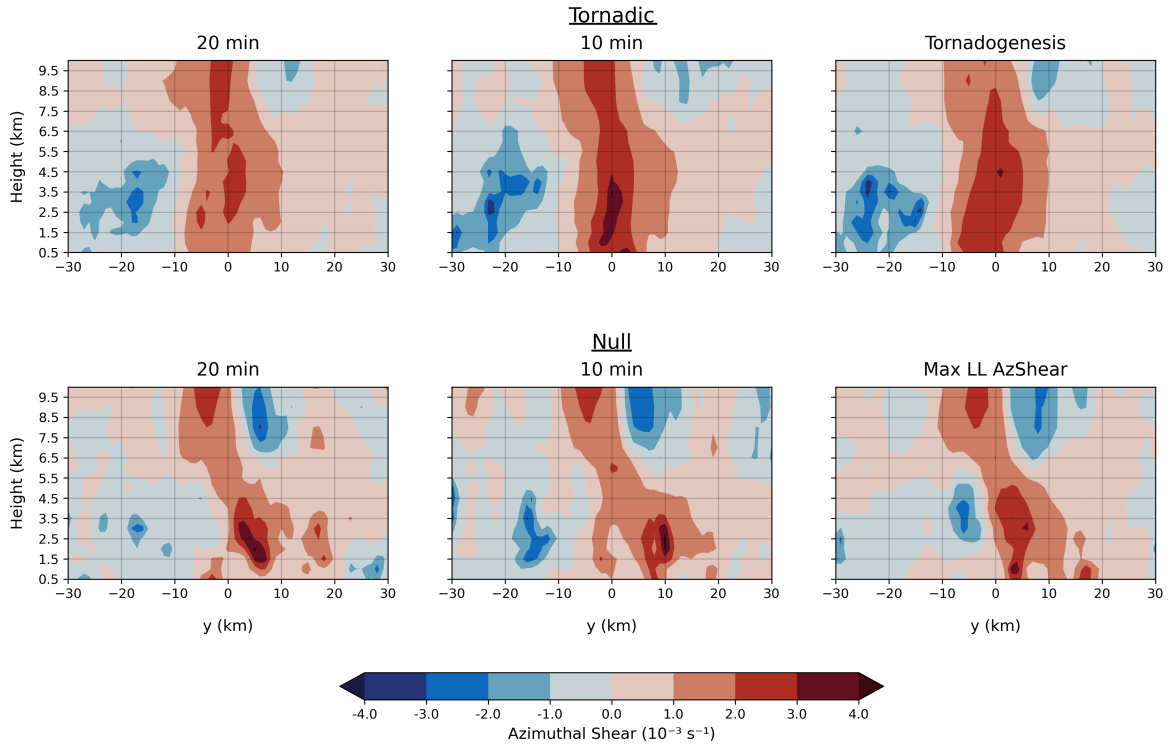


Figure 3.17: PMM vertical cross sections perpendicular to storm motion for azimuthal shear. The cross sections intersect the center of the MVs as was done in previous plots. Tornadic MVs are represented in three time steps: time of tornadogenesis, 10 minute lead time, and 20 minute lead time. Null MVs are also represented in three comparable time steps: time of maximum LL azimuthal shear, 10 minute lead time, and 20 minute lead time. Height is given in terms of kilometers AMSL.

PMMs of Radial Divergence at Multiple Altitudes for Tornadoic and Null MVs

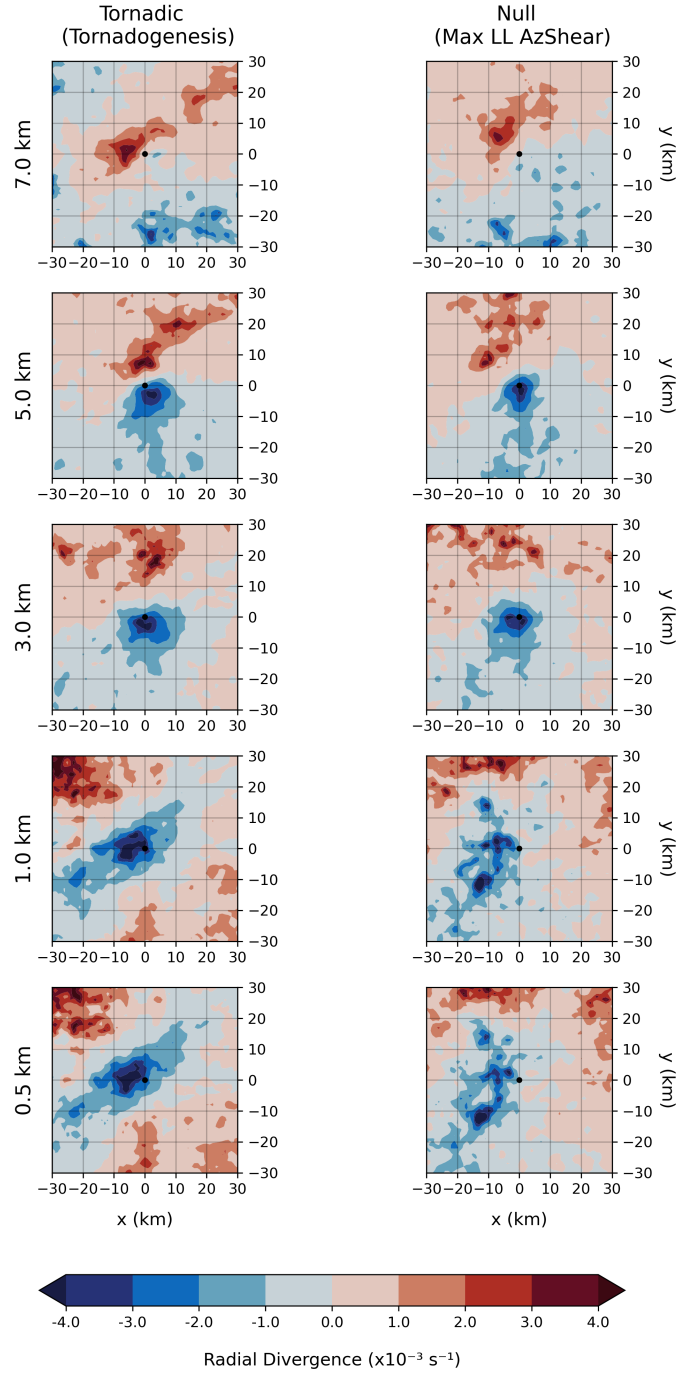


Figure 3.18: Same as 3.16, but for radial divergence.

Vertical PMMs of Radial Divergence Perpendicular to Storm Motion

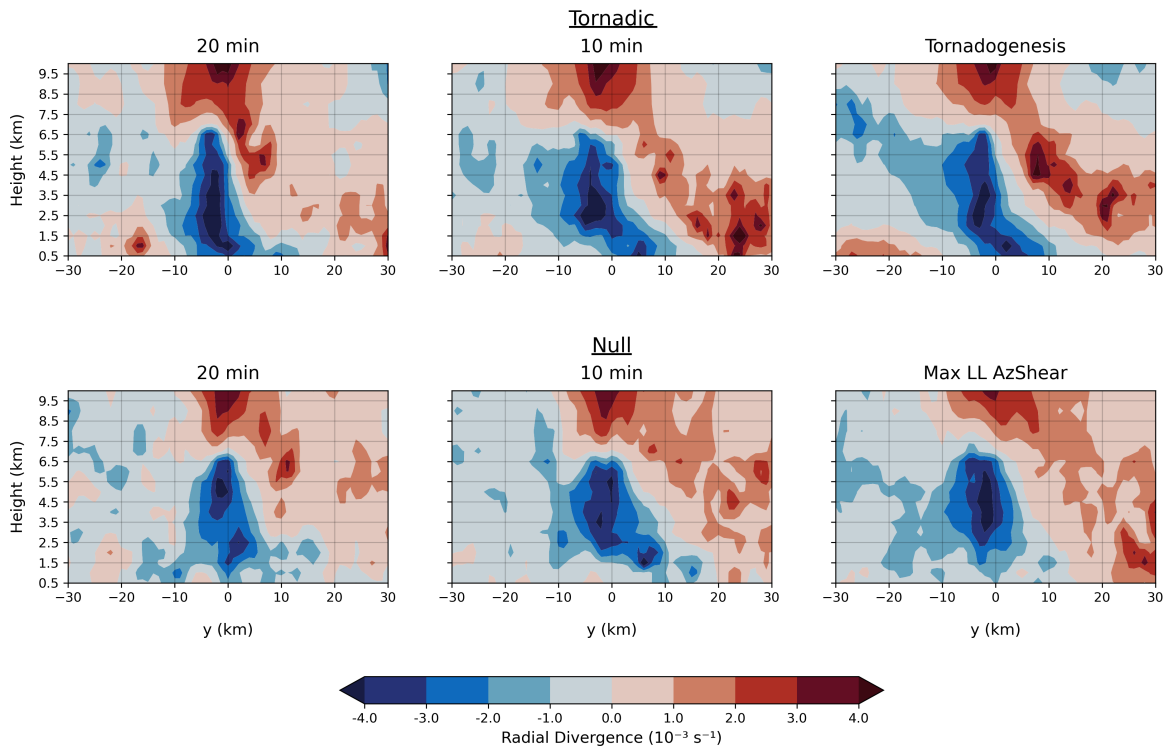


Figure 3.19: Same as 3.17, but for radial divergence.

PMMs of Reflectivity at Multiple Altitudes for Tornadoic and Null MVs

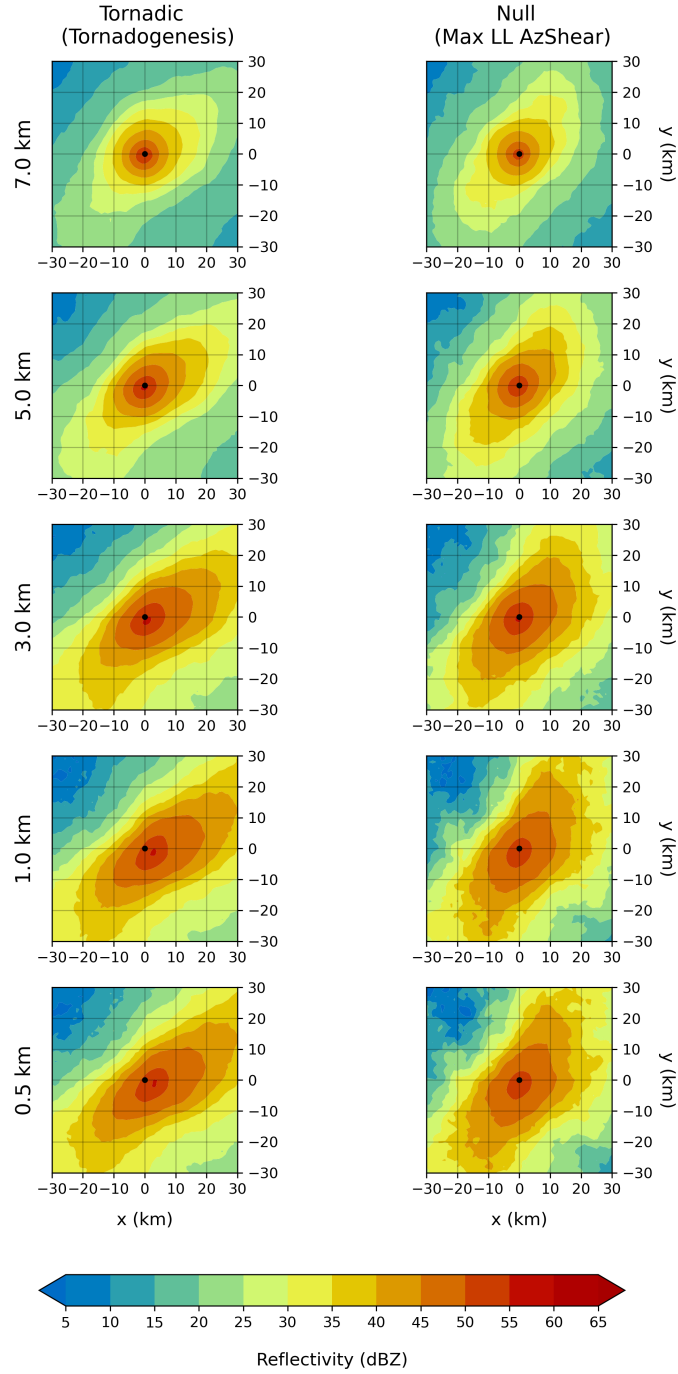


Figure 3.20: Same as 3.16, but for horizontal reflectivity.

Vertical PMMs of Reflectivity Perpendicular to Storm Motion

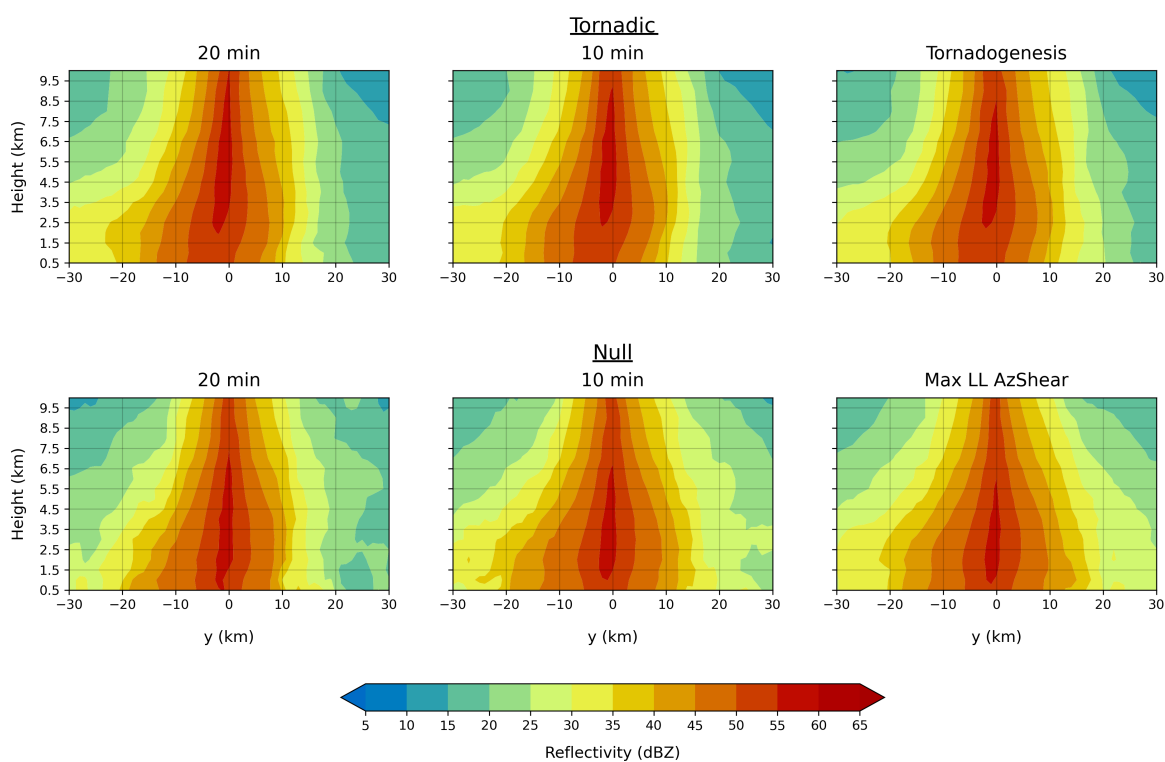


Figure 3.21: Same as 3.17, but for horizontal reflectivity.

Tornadic PMMs of Differential Reflectivity at Multiple Altitudes for Multiple Lead Times

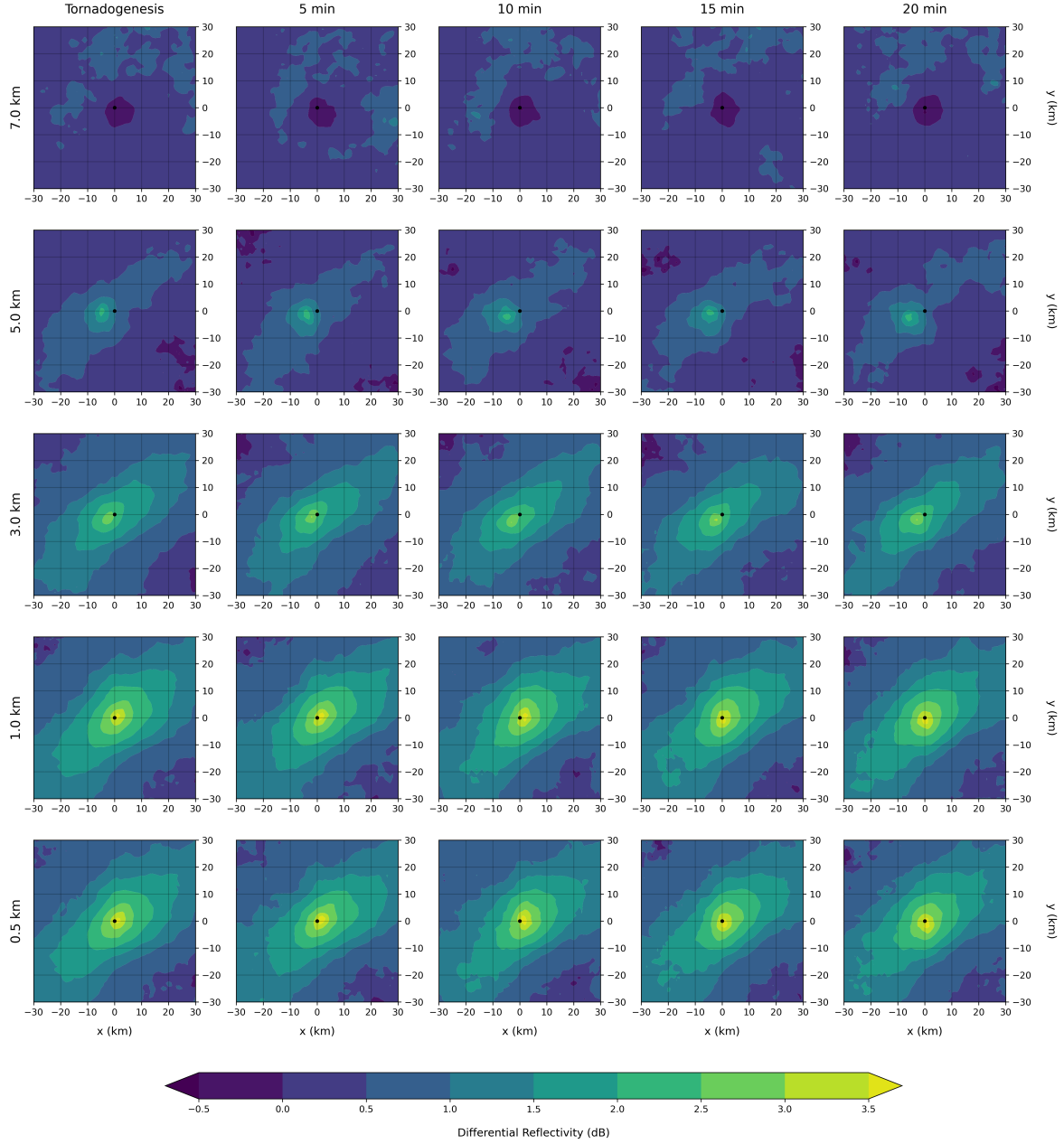


Figure 3.22: Same as 3.13, but for differential reflectivity.

Tornadic PMMs of Specific Differential Phase at Multiple Altitudes for Multiple Lead Times

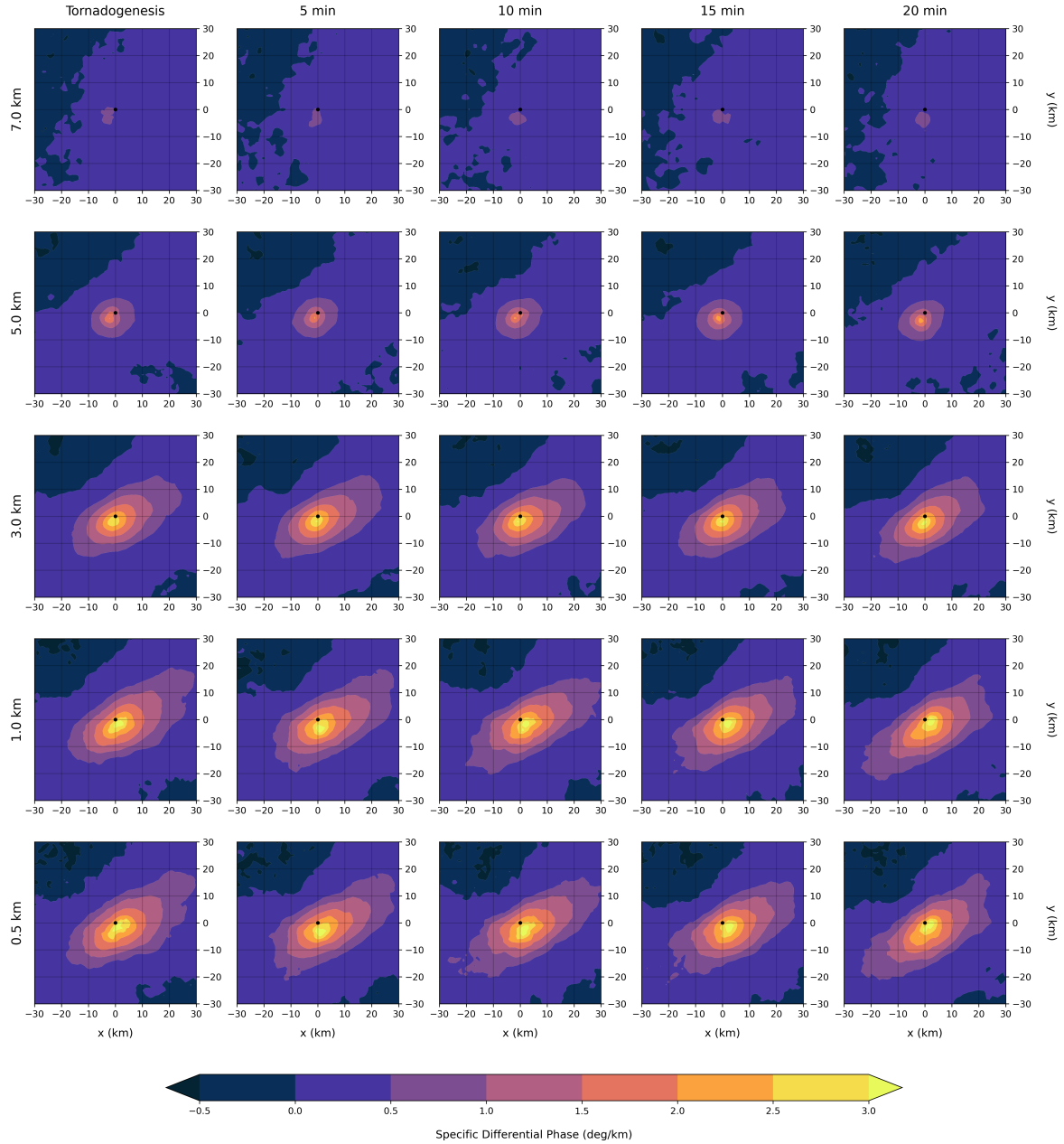


Figure 3.23: Same as 3.13, but for specific differential phase.

PMMs of Differential Reflectivity at Multiple Altitudes for Tornadoic and Null MVs

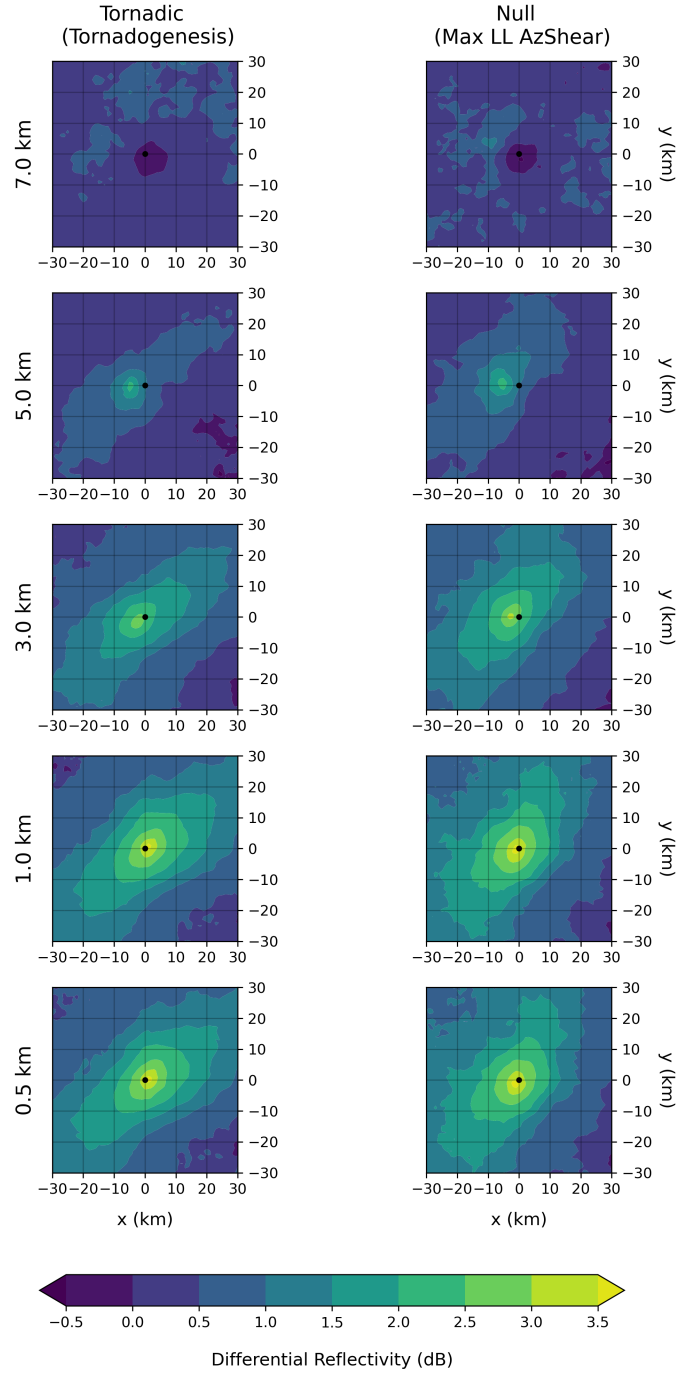


Figure 3.24: Same as 3.16, but for differential reflectivity.

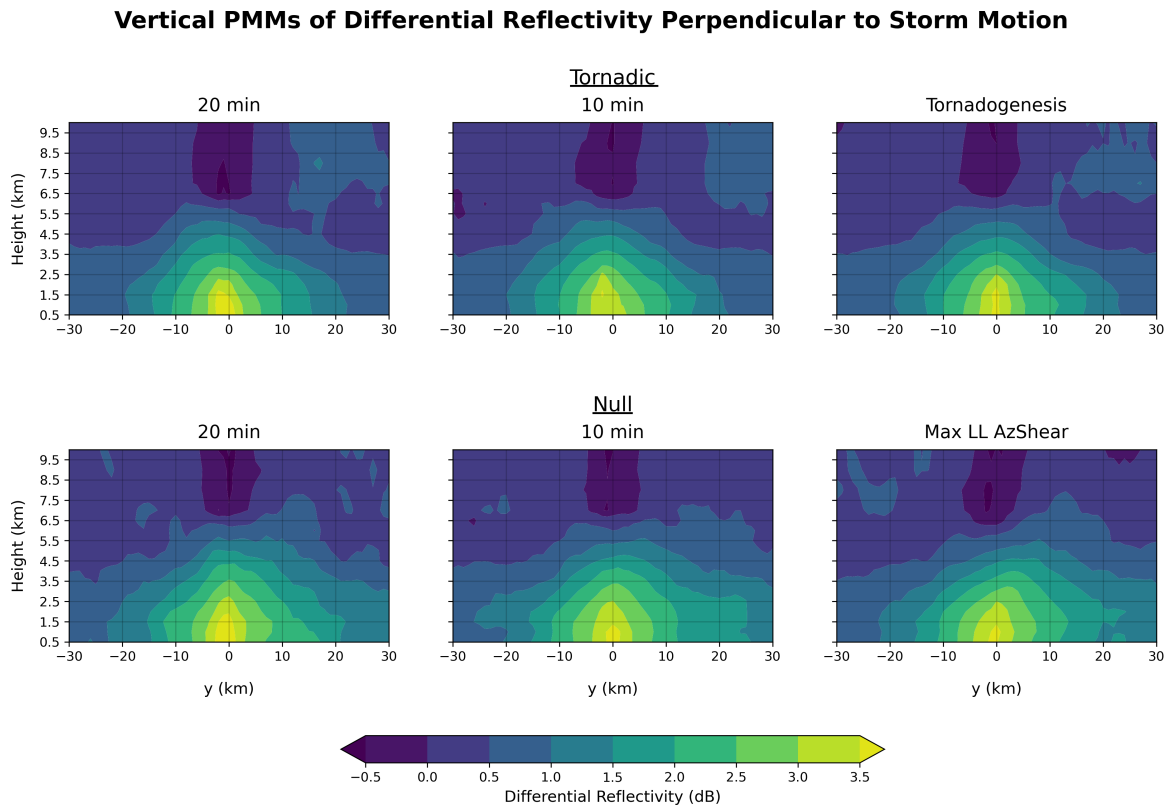


Figure 3.25: Same as 3.17, but for differential reflectivity.

PMMs of Specific Differential Phase at Multiple Altitudes for Tornadoic and Null MVs

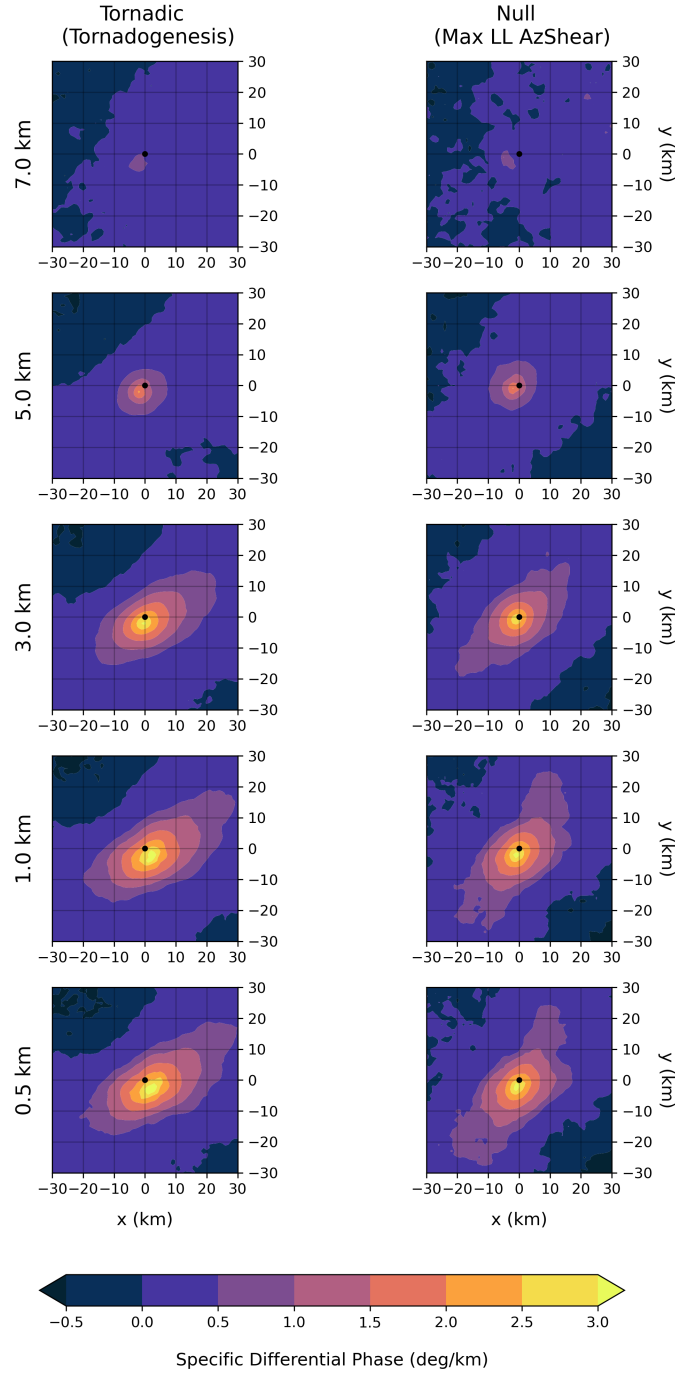


Figure 3.26: Same as 3.16, but for specific differential phase.

Vertical PMMs of Specific Differential Phase Perpendicular to Storm Motion

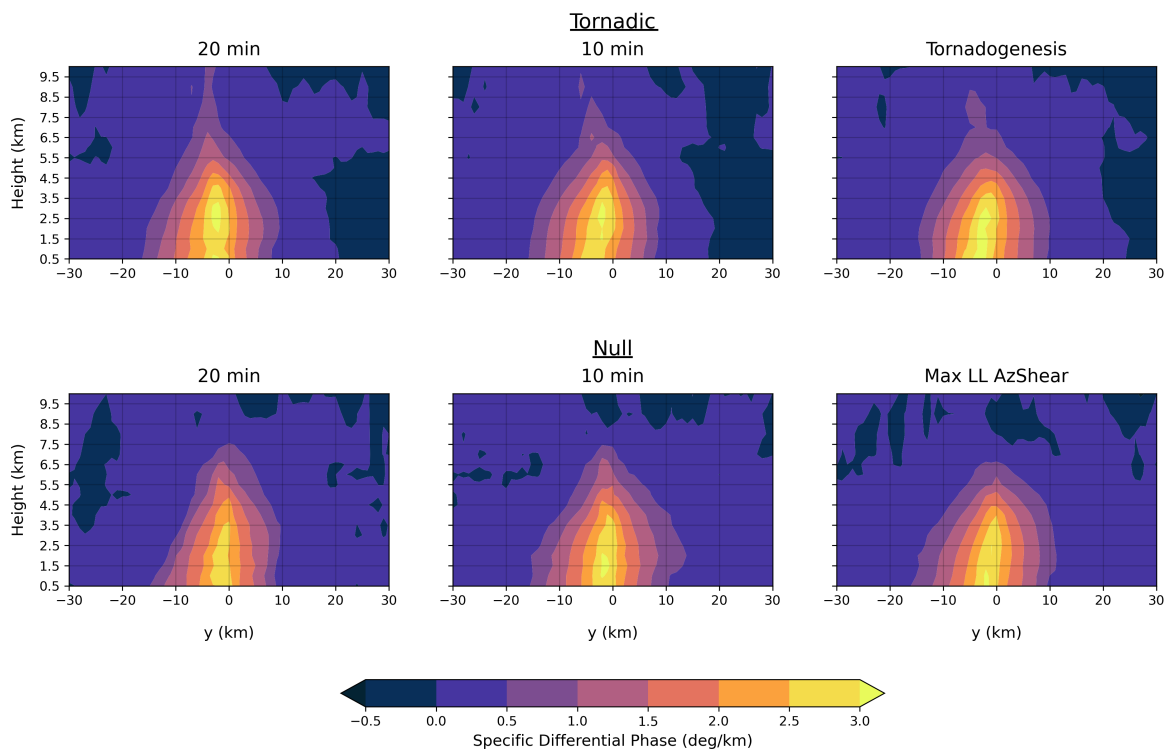


Figure 3.27: Same as 3.17, but for specific differential phase.

Chapter 4

Discussion and Conclusions

Previous literature has sought to understand the environmental, theoretical, and remote sensing-based factors behind damaging QLCSs and specifically, QLCS tornadoes. Many of these studies have explored samples that are limited temporally and/or spatially, and for the few that have larger sample sizes, limited focus is given to radar information or the specific characteristics of QLCSs.

To further explore the utility of radar signatures, particularly those derived from dual-polarization technology, for QLCS warning operations, we created a novel 11-year dataset of QLCS storm objects across the CONUS. The storm objects were detected using an adapted version of a seven-mode storm classification scheme from Potvin et al. (2022) that was applied to radar volumes from the GR-S database (Murphy et al., 2023). This automated classification scheme resulted in over 30,000 identified mesovortices across the 11 years, with approximately 900 being tornadic. This dataset allows for a broad, yet robust exploration of the climatological characteristics of QLCSs and the radar patterns associated with tornadic development.

The first objective of this study was to create a comprehensive radar-based dataset of QLCS MVs and assess its climatological characteristics. Analysis of the spatial patterns of QLCS objects reveals two main geographic areas with the highest likelihood of QLCS occurrence, the Deep South and the Midwest. In particular, Mississippi has the highest count of QLCS tornadoes, closely followed by Alabama and Illinois. From a temporal perspective, most QLCSs and QLCS tornadoes overwhelmingly occur

during the spring months. QLCS occurrence decreases through late summer and hits a minimum during the fall before increasing again during the cool season. On a diurnal scale, there is a dramatic increase in QLCSs during the nighttime hours. Specifically, most QLCSs and associated tornadoes take place between 2100 UTC and 0400 UTC. Lastly, around half of the tornadoes in our dataset rank as an EF-1 on the EF-scale. A significant portion of tornadoes are on the EF-0 scale as well, and major QLCS tornadoes are extremely rare.

Overall, the spatiotemporal characteristics of the dataset provide confidence in its ability to accurately represent the broader QLCS population. The general locations and timing of QLCSs align with the results of previous studies and follow the current theoretical understandings of QLCS evolution. Additionally, the dataset highlights the multi-faceted impact that QLCSs and their associated hazards have on the population. The combination of QLCSs frequently affecting the South, a region with a high proportion of vulnerable housing, and their tendency to occur overnight creates a particularly concerning societal risk (Ashley, 2007; Anderson-Frey and Brooks, 2019). However, given the consistency of these climatological characteristics with previous studies, we believe the dataset provides a valuable resource for future investigations of QLCS behavior and hazards. Further, the automated classification framework and explicit identification of embedded cells provide an efficient and reproducible approach to studying QLCSs.

The second half of the results aimed to explore the utility of radar variables to distinguish tornadic from nontornadic MVs, particularly from a predictive standpoint. Particular emphasis was placed on dual-polarization variables, given their growing role in tornado warning operations. PMMs were first used to examine the temporal evolution of radar signatures leading up to tornadogenesis. Although classic storm-scale features were evident, including signatures associated with strong updrafts and

storm-top divergence, these features exhibited little change leading up to the time of tornadogenesis. Consequently, the focus shifted to the comparisons between tornadic and nontornadic cases.

Comparison of tornadic and nontornadic MVs revealed several differences in radar presentation. For single-polarization variables, both the constant-altitude and vertical cross-section PMMs revealed that the strongest distinctions were found in LL azimuthal shear and radial divergence. In particular, the tornadic MVs showed more organized and concentrated regions of enhanced rotation and convergence. Horizontal reflectivity was largely similar between the two groups and any differences were comparatively small.

With the polarimetric variables, the results were variable. For Z_{DR} , the constant-altitude and vertical cross-sections both showed little distinction between the tornadic and null cases. K_{DP} , however, displayed somewhat greater discriminatory value. Specifically, the vertical cross sections revealed that tornadic MVs exhibited modestly larger magnitudes and a deeper vertical range of K_{DP} . While these differences were not dramatic, they still suggest that polarimetric signatures, particularly LL K_{DP} cores, may provide supplemental information regarding MV intensity and potential.

These findings both support and extend upon previous investigations of MVs. The vertical structures of both Z_{DR} and azimuthal shear are consistent with previous PMM analyses of MCS MVs as a whole (Murphy and Homeyer, 2023) and align with findings from recent QLCS-focused investigations examining the radar characteristics of tornadic and nontornadic MVs (Kuster et al., 2024; Pardun et al., 2025). The identification and visualization of enhanced LL K_{DP} differences between tornadic and null QLCS MVs is particularly notable, as it reinforces findings from smaller-scale QLCS studies while contrasting with the broader MCS-focused PMM analysis that motivated this work (Murphy and Homeyer, 2023).

Although none of the radar signatures identified in this study should be considered a significant indicator of tornadogenesis, several may serve as useful aids when used in conjunction with already-established frameworks for MV development and intensification, such as the 3IM. In particular, the enhanced LL convergence, stronger LL azimuthal shear, and larger K_{DP} values observed in the tornadic PMMs suggest that these signatures may provide additional guidance in QLCS nowcasting environments.

While these results provide insight into QLCS MV behavior, it is important to consider several limitations regarding the dataset and the methodology used herein. Firstly, QLCS MVs often have lifetimes on the order of only tens of minutes. With GR-S providing data at 5-minute intervals, only a handful of volumes may capture the entire genesis, intensification, and dissipation of an MV. Thus, radar signatures that are present for only one or two volume scans may be difficult to identify. Furthermore, although PMMs better preserve localized structures and extremes than traditional means, any compositing approach inherently smooths out case-by-case variability. Combined with the merged radar volumes of GR-S, this smoothing may obscure finer-scale features and reduce the apparent magnitude of signatures.

Additional uncertainty exists with the comparison of tornadic and nontornadic MVs. Tornadic cases were centered on the time of tornadogenesis whereas nontornadic cases were centered on the time of maximum LL azimuthal shear. This approach was chosen to create a population of MVs that were strong, but nontornadic that were comparable in intensity to the tornadic cases. However, these two times may not represent truly equivalent stages of MV intensity, as maximum LL azimuthal shear in a tornado does not always occur at the time of tornadogenesis. Furthermore, the identification of tornadoes in this dataset was based on storm reports from the SED, which are inherently subject to reporting biases and human error (Anderson et al., 2007; Edwards et al., 2013). Especially when dealing with tornadoes that are often

short-lived and nocturnal in nature, many tornadoes may go undocumented, potentially resulting in tornadic MVs being classified as nontornadic.

Lastly, many of the identified radar signatures that were different between tornadic and nontornadic MVs were located within the lowest one to two kilometers above the surface. Although these signatures are apparent within a curated dataset, this layer of the atmosphere is often poorly sampled in real-time operations by the current NEXRAD system due to beam height increasing away from the radar and limited radar coverage across the CONUS. Consequently, some of the signatures identified in this study may be more difficult to observe operationally than the composite analyses suggest.

Several opportunities for future work arise from this dataset and analysis. While PMMs provide a useful tool for assessing large populations of storms, they are inherently limited in their ability to capture transient and finer-scale features that may be important for assessing an MV's tornadic potential. Future studies focused on leveraging the storm-centered volumes on a storm-by-storm basis or other visualization techniques, such as self-organizing maps, may have better skill at identifying individual radar signatures. Additionally, the use of machine learning techniques can also reveal additional information as machine learning models can parse out and learn from small-scale features potentially missed by the human eye. Another interesting avenue for future projects is the application of this analysis and dataset creation to radar data taken from instrumentation with improved temporal resolution and LL coverage. For example, a phased-array radar provides a full volume scan a whole order of magnitude faster than a typical WSR-88D. With ample radar volumes available for the entire lifetime of an MV, unique features may be represented that are simply difficult to illustrate with the current radar network.

Overall, this project provides a comprehensive radar-based dataset of QLCS MVs

and their associated tornadoes with extensive spatiotemporal coverage. While the robustness of the dataset is validated through consistent climatological comparisons with previous large-scale studies, the radar-based analyses reveal that many distinctions between tornadic and nontornadic MVs are subtle and concentrated in the lowest levels of a storm’s structure. The ability of this large-scale QLCS-focused dataset to reproduce characteristics previously identified in smaller studies provides confidence that these signatures persist across a broad range of environments, highlighting their potential value for understanding tornadic MV behavior. These findings simultaneously highlight the potential and limitations of radar-derived variables for QLCS nowcasting applications.

Reference List

- Anderson, C. J., C. K. Wikle, Q. Zhou, and J. A. Royle, 2007: Population influences on tornado reports in the united states. *Weather and Forecasting*, **22** (3), 571 – 579, <https://doi.org/10.1175/WAF997.1>, URL <https://journals.ametsoc.org/view/journals/wefo/22/3/waf997.1.xml>.
- Anderson-Frey, A. K., and H. Brooks, 2019: Tornado fatalities: An environmental perspective. *Weather and Forecasting*, **34** (6), 1999 – 2015, <https://doi.org/10.1175/WAF-D-19-0119.1>.
- Anderson-Frey, A. K., and H. Brooks, 2021: Compared to What? Establishing Environmental Baselines for Tornado Warning Skill. *Bulletin of the American Meteorological Society*, <https://doi.org/10.1175/BAMS-D-19-0310.1>.
- Anderson-Frey, A. K., Y. P. Richardson, A. R. Dean, R. L. Thompson, and B. T. Smith, 2016: Investigation of Near-Storm Environments for Tornado Events and Warnings. *Weather and Forecasting*, <https://doi.org/10.1175/WAF-D-16-0046.1>.
- Ashley, W. S., 2007: Spatial and temporal analysis of tornado fatalities in the united states: 1880–2005. *Weather and Forecasting*, **22** (6), 1214 – 1228, <https://doi.org/10.1175/2007WAF2007004.1>.
- Ashley, W. S., A. M. Haberlie, and J. Strohm, 2019: A Climatology of Quasi-Linear Convective Systems and Their Hazards in the United States. *Weather and Forecasting*, <https://doi.org/10.1175/WAF-D-19-0014.1>.
- Ashley, W. S., A. J. Krmenec, and R. Schwantes, 2008: Vulnerability due to nocturnal tornadoes. *Weather and Forecasting*, **23** (5), 795 – 807, <https://doi.org/10.1175/2008WAF2222132.1>.
- Atkins, N. T., J. M. Arnott, R. W. Przybylinski, R. A. Wolf, and B. D. Ketcham, 2004: Vortex Structure and Evolution within Bow Echoes. Part I: Single-Doppler and Damage Analysis of the 29 June 1998 Derecho. *Monthly Weather Review*.
- Atkins, N. T., and M. S. Laurent, 2009: Bow Echo Mesovortices. Part II: Their Genesis. *Monthly Weather Review*, <https://doi.org/10.1175/2008MWR2650.1>.
- Bowman, K. P., and C. R. Homeyer, 2017: GridRad - Three-Dimensional Gridded NEXRAD WSR-88D Radar Data. NSF National Center for Atmospheric Research, Boulder, CO, URL <https://doi.org/10.5065/D6NK3CR7>, <https://doi.org/10.5065/>

D6NK3CR7.

- Britt, K. C., P. S. Skinner, P. L. Heinselman, C. K. Potvin, M. L. Flora, B. Matilla, K. H. Knopfmeier, and A. E. Reinhart, 2024: Verification of Quasi-Linear Convective Systems Predicted by the Warn-on-Forecast System (WoFS). *Weather and Forecasting*, **39** (1), 155–176, <https://doi.org/10.1175/WAF-D-23-0106.1>.
- 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. *Weather and Forecasting*, <https://doi.org/10.1175/WAF-D-12-00119.1>.
- Brown, M. C., G. R. Marion, and M. C. Coniglio, 2024: Influence of Low-Level Shear Orientation and Magnitude on the Evolution and Rotation of Idealized Squall Lines. Part I: Storm Morphology and Bulk Updraft/Mesovortex Attributes. *Monthly Weather Review*, <https://doi.org/10.1175/MWR-D-23-0262.1>.
- Chalmers, Z. A., and M. D. Parker, 2026: Variability in high-shear, low-cape qlcs environments in the southeastern united states. *Weather and Forecasting*, **41** (6), 1093 – 1117, <https://doi.org/10.1175/WAF-D-25-0137.1>.
- Conrad, D. M., and K. R. Knupp, 2019: Doppler Radar Observations of Horizontal Shearing Instability in Quasi-Linear Convective Systems. *Monthly Weather Review*, <https://doi.org/10.1175/MWR-D-18-0257.1>, URL <https://journals.ametsoc.org/view/journals/mwre/147/4/mwr-d-18-0257.1.xml>.
- Davis, J. M., and M. D. Parker, 2014: Radar climatology of tornadic and nontornadic vortices in high-shear, low-cape environments in the mid-atlantic and southeastern united states. *Weather and Forecasting*, **29** (4), 828 – 853, <https://doi.org/10.1175/WAF-D-13-00127.1>.
- Ebert, E. E., 2001: Ability of a poor man’s ensemble to predict the probability and distribution of precipitation. *Monthly Weather Review*, **129** (10), 2461 – 2480, [https://doi.org/10.1175/1520-0493\(2001\)129<2461:AOAPMS>2.0.CO;2](https://doi.org/10.1175/1520-0493(2001)129<2461:AOAPMS>2.0.CO;2).
- Edwards, R., J. LaDue, J. Ferree, K. Scharfenberg, C. Maier, and W. Coulbourne, 2013: Tornado intensity estimation: Past, present, and future. *Bulletin of the American Meteorological Society*, **94**, 641–653, <https://doi.org/10.1175/BAMS-D-11-00006.1>.
- Flournoy, M. D., and M. C. Coniglio, 2019: Origins of Vorticity in a Simulated Tornadoic Mesovortex Observed during PECAN on 6 July 2015. *Monthly Weather Review*, <https://doi.org/10.1175/MWR-D-18-0221.1>, URL <https://journals.ametsoc.org/view/journals/mwre/147/1/mwr-d-18-0221.1.xml>.

- Gibbs, J. G., 2021: Evaluating Precursor Signals for QLCS Tornado and Higher Impact Straight-Line Wind Events. *Journal of Operational Meteorology*, **9**, 62–75, <https://doi.org/10.15191/nwajom.2021.0905>.
- Healey, D. J., and M. S. V. D. Broeke, 2025: Connections Between ZDR Columns and Mesovortices in Quasi-Linear Convective Systems: Impacts of Low-Level Hodograph Curvature and Shear. *Monthly Weather Review*, <https://doi.org/10.1175/MWR-D-25-0103.1>.
- Heinselman, P. L., and Coauthors, 2024: Warn-on-forecast system: From vision to reality. *Weather and Forecasting*, **39** (1), 75 – 95, <https://doi.org/10.1175/WAF-D-23-0147.1>.
- Homeyer, C. R., J. D. McAuliffe, and K. M. Bedka, 2017: On the development of above-anvil cirrus plumes in extratropical convection. *Journal of the Atmospheric Sciences*, **74** (5), 1617 – 1633, <https://doi.org/10.1175/JAS-D-16-0269.1>.
- Homeyer, C. R., E. M. Murillo, and M. R. Kumjian, 2023: Relationships between 10 years of radar-observed supercell characteristics and hail potential. *Monthly Weather Review*, **151** (10), 2609 – 2632, <https://doi.org/10.1175/MWR-D-23-0019.1>, URL <https://journals.ametsoc.org/view/journals/mwre/151/10/MWR-D-23-0019.1.xml>.
- Kuster, C. M., K. D. Sherburn, V. N. Mahale, T. J. Schuur, O. F. McCauley, and J. S. Schaumann, 2024: Radar Signatures Associated with Quasi-Linear Convective System Mesovortices. *Weather and Forecasting*, <https://doi.org/10.1175/WAF-D-23-0144.1>.
- Lagerquist, R., A. McGovern, C. R. Homeyer, D. J. G. Li, and T. Smith, 2020: Deep Learning on Three-Dimensional Multiscale Data for Next-Hour Tornado Prediction. *Monthly Weather Review*, <https://doi.org/10.1175/MWR-D-19-0372.1>.
- Lovell, L. T., and M. D. Parker, 2022: Simulated QLCS Vortices in a High-Shear, Low-CAPE Environment. *Weather and Forecasting*, <https://doi.org/10.1175/WAF-D-21-0133.1>.
- Lyons, A. D., R. L. Thompson, B. T. Smith, H. G. Weinman, and A. R. Dean, 2025: Convective Mode Classification and Distribution of Contiguous United States Tornado Events from 2003–2023. *Weather and Forecasting*, <https://doi.org/10.1175/WAF-D-25-0034.1>, URL <https://journals.ametsoc.org/view/journals/wefo/aop/WAF-D-25-0034.1/WAF-D-25-0034.1.xml>.
- Mahale, V. N., J. A. Brotzge, and H. B. Bluestein, 2012: An Analysis of Vortices Embedded within a Quasi-Linear Convective System Using X-Band Polarimetric

- Radar. *Weather and Forecasting*, <https://doi.org/10.1175/WAF-D-11-00135.1>.
- Murphy, A. M., and C. R. Homeyer, 2023: Comparison of radar-observed tornadic and nontornadic mcs cells using probability-matched means. *Journal of Applied Meteorology and Climatology*, **62** (10), 1371 – 1388, <https://doi.org/10.1175/JAMC-D-23-0070.1>, URL <https://journals.ametsoc.org/view/journals/apme/62/10/JAMC-D-23-0070.1.xml>.
- Murphy, A. M., C. R. Homeyer, and K. Q. Allen, 2023: Development and investigation of gridrad-severe, a multiyear severe event radar dataset. *Monthly Weather Review*, **151** (9), 2257 – 2277, <https://doi.org/10.1175/MWR-D-23-0017.1>.
- National Centers for Environmental Information, 1996: Storm events database. National Oceanic and Atmospheric Administration (NOAA), <https://www.ncei.noaa.gov/stormevents/>.
- Orlanski, I., 1975: A rational subdivision of scales for atmospheric processes. *Bulletin of the American Meteorological Society*, **56** (5), 527–530.
- Ostaszewski, J. S., C. C. Weiss, J. M. McDonald, M. C. Coniglio, and S. M. Waugh, 2025: Surface Cold Pool Observations near Tornadic and Nontornadic QLCS Mesovortices during PERiLS. *Monthly Weather Review*, <https://doi.org/10.1175/MWR-D-24-0166.1>.
- Pardun, T. J., A. E. Reinhart, and M. C. Coniglio, 2025: A Comparison Between Tornadic and Non-Tornadic QLCS Mesovortices using a Multi-Radar Analysis of Operational and Experimental MRMS Products. *Weather and Forecasting*, <https://doi.org/10.1175/WAF-D-24-0050.1>.
- Parker, M. D., 2021: Self-organization and maintenance of simulated nocturnal convective systems from pecan. *Monthly Weather Review*, **149** (4), 999 – 1022, <https://doi.org/10.1175/MWR-D-20-0263.1>.
- Parker, M. D., and R. H. Johnson, 2000: Organizational modes of midlatitude mesoscale convective systems. *Monthly Weather Review*, **128** (10), 3413 – 3436, [https://doi.org/10.1175/1520-0493\(2001\)129<3413:OMOMMC>2.0.CO;2](https://doi.org/10.1175/1520-0493(2001)129<3413:OMOMMC>2.0.CO;2).
- Potvin, C. K., and Coauthors, 2022: An iterative storm segmentation and classification algorithm for convection-allowing models and gridded radar analyses. *Journal of Atmospheric and Oceanic Technology*, **39** (7), 999 – 1013, <https://doi.org/10.1175/JTECH-D-21-0141.1>.
- Rosenfeld, D., D. B. Wolff, and D. Atlas, 1993: General probability-matched relations

- between radar reflectivity and rain rate. *Journal of Applied Meteorology*, **32**, 50–72.
- Sandmæl, T. N., 2017: An evaluation of radar- and satellite-data based products to discriminate between tornadic and non-tornadic storms. M.S. thesis, University of Oklahoma.
- Sandmæl, T. N., C. R. Homeyer, K. M. Bedka, J. M. Apke, J. R. Mecikalski, and K. Khlopenkov, 2019: Evaluating the ability of remote sensing observations to identify significantly severe and potentially tornadic storms. *Journal of Applied Meteorology and Climatology*, **58** (12), 2569 – 2590, <https://doi.org/10.1175/JAMC-D-18-0241.1>.
- Schaumann, J. S., and R. W. Przybylinski, 2012: P9.10 OPERATIONAL APPLICATION OF 0-3 KM BULK SHEAR VECTORS IN ASSESSING QLCS MESOVORTEX AND TORNADO POTENTIAL. *26th Conference on Severe Local Storms*, URL <https://ams.confex.com/ams/26SLS/webprogram/Paper212008.html>.
- Schenkman, A. D., M. Xue, and A. Shapiro, 2012: Tornadogenesis in a Simulated Mesovortex within a Mesoscale Convective System. *Journal of the Atmospheric Sciences*, <https://doi.org/10.1175/JAS-D-12-038.1>.
- Schneider, M. E., 2025: Supercell-like Storm-Scale and Tornado-Scale Processes in Simulated and Observed Quasi-Linear Convective Systems. Ph.D. thesis, University of Oklahoma.
- 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. *Weather and Forecasting*, <https://doi.org/10.1175/WAF-D-11-00115.1>.
- Strader, S. M., W. S. Ashley, A. M. Haberlie, and K. Kaminski, 2022: Revisiting u.s. nocturnal tornado vulnerability and its influence on tornado impacts. *Weather, Climate, and Society*, **14** (4), 1147 – 1163, <https://doi.org/10.1175/WCAS-D-22-0020.1>.
- Thompson, R. L., 2023: A comparison of right-moving supercell and quasi-linear convective system tornadoes in the contiguous united states 2003–21. *Weather and Forecasting*, **38** (8), 1497 – 1513, <https://doi.org/10.1175/WAF-D-23-0006.1>.
- Trapp, R. J., S. A. Tessendorf, E. S. Godfrey, and H. E. Brooks, 2005: Tornadoes from squall lines and bow echoes. part i: Climatological distribution. *Weather and Forecasting*, **20** (1), 23 – 34, <https://doi.org/10.1175/WAF-835.1>.

- Trapp, R. J., and M. L. Weisman, 2003: Low-level mesovortices within squall lines and bow echoes. Part II: Their genesis and implications. *Monthly Weather Review*, **131** (11), 2084–2823.
- Ungar, M. D., and M. C. Coniglio, 2023: Using Radiosonde Observations to Assess the “Three Ingredients Method” to Forecast QLCS Mesovortices. *Weather and Forecasting*, <https://doi.org/10.1175/WAF-D-22-0176.1>.
- Wakimoto, R. M., H. V. Murphey, C. A. Davis, and N. T. Atkins, 2006: High winds generated by bow echoes. part ii: The relationship between the mesovortices and damaging straight-line winds. *Monthly Weather Review*, **134** (10), 2813 – 2829, <https://doi.org/10.1175/MWR3216.1>.
- Watson, K. E., 2025: Analysis of QLCS Three Ingredient Method Robustness using CM1. M.S. thesis, Texas Tech University.
- Wolff, E. C., R. J. Trapp, S. W. Nesbitt, M. D. Parker, K. A. Kosiba, and J. Wurman, 2025: On discrete convective updrafts and tornadoes in quasi-linear convective systems. *Weather and Forecasting*, **40** (7), 1065 – 1083, <https://doi.org/10.1175/WAF-D-24-0080.1>.
- Xu, X., M. Xue, and Y. Wang, 2015: Mesovortices within the 8 may 2009 bow echo over the central united states: Analyses of the characteristics and evolution based on doppler radar observations and a high-resolution model simulation. *Monthly Weather Review*, **143** (6), 2266 – 2290, <https://doi.org/10.1175/MWR-D-14-00234.1>.