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ROBERT A. SABA
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BY THE COMMITTEE CONSISTING OF

Dr. Michael C. Coniglio (Chair)

Dr. Stacey Hitchcock

Dr. Cameron Homeyer

Dr. Joshua Gebauer

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Abstract

While immense enhancements to meteorological observations and simulations have been made over the last several decades, two lingering questions continue to plague the community: (1) Why do some storms produce tornadoes while others do not, and (2) why do storms in seemingly identical environments go on to produce different hazards? Developing robust answers to these questions are critical as tornadoes continue to be a top cause for weather-related fatalities. Storm environment research through simulated storms, reanalysis products, and limited observations have guided the current understanding and have identified differences between environments supportive of tornadic and non-tornadic supercells. This work aims to use more detailed observations through Doppler wind lidars to capture the storm environment evolution in both time and space.

Since 2016, the National Severe Storms Laboratory has operated mobile scanning Doppler wind lidars within the inflow of supercell thunderstorms as part of collaborative field projects (mini-MPEX, TORUS, PERiLS, TORUS-LiTE, and LIFT). The research goal of this instrument is to observe the evolution of storm inflow properties to gain a better understanding of the storm environment surrounding an evolving supercell. Various scanning and post-processing techniques to capture the wind profile evolution via DWL observations have been used. Prior to 2022, a velocity azimuth display technique was used to retrieve a vertical wind profile every 3-5 minutes using 8 points 20 degrees off zenith. In 2022-23, a continuous scanning mode was implemented to retrieve wind profiles as frequent as every 5 seconds. Both of these scanning strategies yielded vertical profiles of derived horizontal winds about every 18 meters with the first usable data point around 75 meters AGL after filtering based on a signal-to-noise ratio threshold. A new optimal estimation technique was designed to incorporate co-located rawinsonde and surface observations into the wind retrievals that provide data between

the surface and 75 meters. These observations are used to validate the post processing techniques and output will be compared to previously used methods.

Focus will be placed on the evolution of the near-ground kinematic characteristics and the storm induced environmental modification in both tornadic and non-tornadic storms. To remove background trends from the environmental evolution, Rapid Refresh model-based analysis profiles are used. Full, surface-based wind profiles will allow for the quantification and time evolution of severe weather forecasting parameters, such as storm-relative helicity, storm-relative winds, etc. Implications of these results on recent studies discussing the relative importance of streamwise vorticity versus storm-relative winds on supercell properties and tornado production will be discussed.

Results show that differences in mesocyclone intensity between tornadic and non-tornadic supercells cause the downstream spatial variability of their environments. This is particularly true when quantifying storm-induced accelerations, which can lead to the length scales at which mesocyclone induced perturbations can be observed. Furthermore, low-level ground-relative winds tend to provide greater differences in the storm environment whereas storm-relative winds contain greater composite differences above 1 kilometer. Also explored are the vorticity trends in these storm environments in time and space, and the horizontal vorticity components (and associated differences) will be shown.

Chapter 1

Introduction

A better understanding of supercell thunderstorms and their hazards is critical towards saving a disproportionate number of lives lost compared to other weather-related events (Brotzge et al. 2013). Efforts continue in both modeling and observational research to decipher differences between various supercell environments and the downstream hazards associated with storms within them (e.g., Nowotarski and Jensen 2013; Parker 2014; Coffey et al. 2020; Coniglio and Parker 2020). Of note, predicting tornadic versus non-tornadic supercells has been particularly difficult (Brooks and Correia Jr 2018). These difficulties highlight the importance of storm environment research and developing a better understanding of storm environment variability.

1.1 Supercell Thunderstorms

The term 'supercell' is used to describe a thunderstorm with a rotating updraft, or mesocyclone (Browning 1962). An early distinction found between supercells and ordinary thunderstorms was their movement separate from the mean wind. Browning (1964) created a formal model of the now coined, 'right moving supercell'. As time and research progressed, a supercell was used to describe an anti-cyclonically rotating storm moving to the left or a cyclonically rotating storm moving right of the mean wind. In this study, only right-moving supercells are analyzed. Schematics for these storms were developed by Lemon and Doswell III (1979) who posed a two dimensional

view of supercell structure and its governing features (Fig. 1.1) as well as an evolutionary diagram of the supercell and its associated updraft and downdraft evolution (Fig. 1.2).

Early work aimed to address the impact that the updraft can have on supercell evolution. Browning (1964) established the critical role that vertical wind shear plays in developing a tilted updraft. With a tilted updraft, hydrometeors are displaced from the updraft, leading to the formation of the subsequent downdraft region. If these two are co-located, a storm cannot survive. Numerical simulations of storms and enhanced observations allowed for these hypotheses to be built upon. The impact of kinematics such as low-level vertical wind shear in the storms inflow region was found to be the primary driver of rotation (Lilly 1982; Davies-Jones 1984). While characteristics of the low-level mesocyclone often define a supercell's intensity, research uncovered that it was the mid-level mesocyclone that was formed first (Burgess and Lemon 1990). One key impact of the mesocyclone are the near-surface accelerations associated with the pressure gradient force (PGF) brought by the rotationally-induced low perturbation pressure (Rotunno and Klemp 1985). The strength of the mesocyclone can be tied directly to the strength of these accelerations, which can be impactful on the downstream hazards of the supercell.

Even with this deep understanding of supercell thunderstorm dynamics, one area of continued struggle in both the forecasting and research communities is the ability to differentiate between tornadic and non-tornadic supercells (Brooks and Correia Jr 2018). These struggles are the main motivator of storm environment research with the goal of finding high-skill parameters to separate tornadic and non-tornadic storm environments. This study emphasizes the use of various kinematic variables given the

unique set of observations collected over the past several years. The importance of these parameters are discussed hereafter.

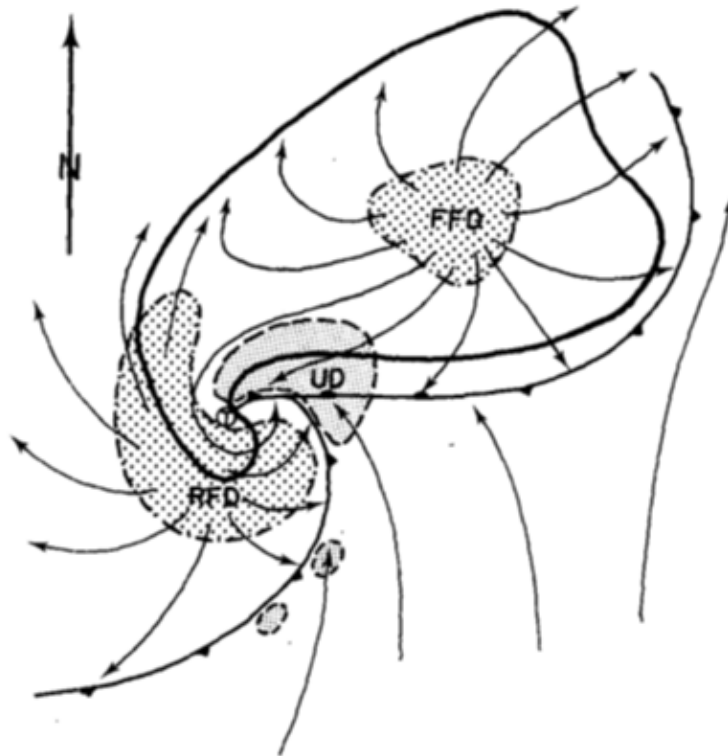


Figure 1.1: One of the first two dimensional views of a supercell and its primary regions. Regions include the forward and rear flank downdraft (FFD/RFD), updraft (UD), and a generalized flow pattern. Figure from Lemon and Doswell III (1979). Their figure 7.

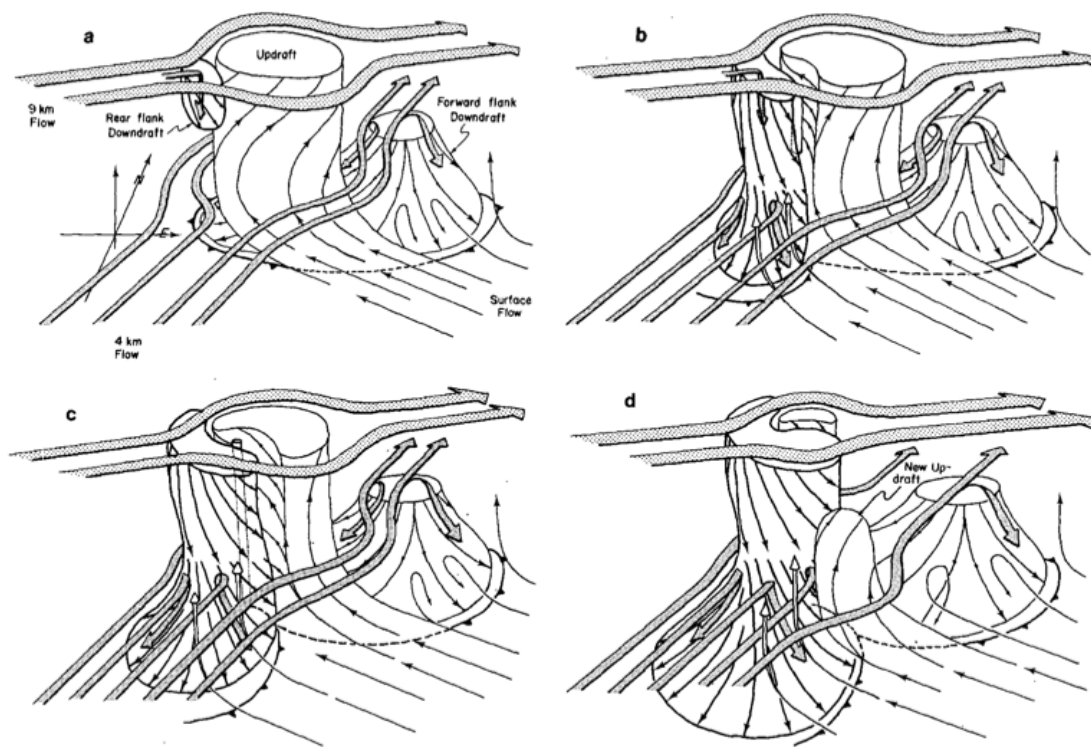


Figure 1.2: Updraft and downdraft evolution during the lifetime of a supercell thunderstorm including mid and upper level flow patterns and previously identified storm features. Figure from Lemon and Doswell III (1979). Their figure 9.

1.2 Kinematic Severe Parameters

1.2.1 Wind Shear

A necessary ingredient for supercell initiation is wind shear, or the change of wind speed and direction with height. The veering, or clockwise turning, of the shear vector with height allows for an updraft to acquire rotation about a vertical axis and a subsequent right-moving storm to develop (Rotunno and Klemp 1982). The importance of wind shear can be further demonstrated by Weisman and Klemp (1982, 1984, 1986) who found that too little shear within the convective environment would not support a long-lived supercell. Wind shear also has profound impacts in separating the distinct regions of a supercell (updrafts, downdrafts, precipitation) which if not done, creates unfavorable interactions within the storm system (Browning 1964).

The impacts of wind shear on supercell updrafts are not limited to their generation. We know that the vertical wind shear is the root cause for a supercell's rightward motion (Rotunno and Klemp 1982). Additional work has emphasized how the magnitude of vertical wind shear can effect the propagation speed of a supercell (Peters et al. 2019). The amount of low-level shear has also been related to the longevity of supercells (Davenport and Parker 2015), specifically how longer-lived supercells tend to have stronger low-level shear, likely supporting stronger dynamical lift for the storms. Evidently, shear present in a storm environment has immense impact on the dynamics of the supercell itself.

Several studies have highlighted the differences in the shear profile when comparing tornadic and non-tornadic storm environments. Using analyses from the Rapid Update Cycle (RUC) model, Markowski et al. (2003) separated cases into significantly tornadic, weakly tornadic, and non-tornadic datasets. It was found that low level shear (particularly in the lowest 500 meters) was about double in significantly tornadic cases

compared to non-tornadic or weakly tornadic cases. However, the shear profiles in weakly tornadic cases tended to be similar to that in the non-tornadic cases. These low level similarities highlight the need to better capture environmental differences between weakly tornadic supercells and non-tornadic supercells that may be in higher-end environments. Although shear is critical in supercell evolution and maintenance, other kinematics have found to be skillful as it relates to identifying tornadic storm environments.

1.2.2 Storm Relative Helicity

While its exact history is unknown, the term 'helicity' is believed to be introduced by Betchov (1961). When translated from the fluid dynamics field, the application of helicity to severe storms relates to its effects on energy lost due to dissipation (Lilly 1986). However helicity is not Galilean invariant, meaning that the frame of reference in which it is evaluated matters. Thus, using the storm-relative helicity (SRH) is good practice and is the best parameter to use regarding helicity in convective studies (Brandes et al. 1988).

By 1990, SRH was developed as a forecast parameter, particularly for tornadoes (Davies-Jones et al. 1990). This parameter was developed by the theory that quantifying the amount of streamwise vorticity (Davies-Jones 1984) over the inflow region of the storm environment could highlight the rotational characteristics of the storm and thus its tornadic potential (Woodall 1990). SRH can be evaluated in a particular layer by:

$$SRH = \int_{H_1}^{H_2} (\vec{V} - \vec{C}) \cdot \omega_h dz \quad (1.1)$$

where H_1 and H_2 are the height limits of the layer in which to evaluate the parameter, $(\vec{V} - \vec{C})$ is the storm-relative wind ($\vec{V}$: horizontal wind vector, $\vec{C}$: storm motion vector), and ω_h is the horizontal vorticity vector defined as:

$$\omega_h = \left(\frac{dw}{dy} - \frac{dv}{dz}, \frac{du}{dz} - \frac{dw}{dx} \right) \quad (1.2)$$

where u , v , and w are the horizontal and vertical components of the wind vector and x , y , and z the horizontal and vertical directions.

Numerous studies have focused on supercell storm environments and using parameters such as SRH to discriminate between tornadic and non-tornadic supercells (e.g., Rasmussen 2003; Esterheld and Giuliano 2008; Parker 2014; Coniglio and Parker 2020). Efforts were even made to incorporate SRH in various layers into pre-existing forecast parameters to evaluate the resulting skill. The energy helicity index (EHI) was developed on the idea that combining instability and SRH over the 0-3 kilometer layer was a better forecast parameter than each individually (Hart and Korotky 1991). However Rasmussen (2003) found that by incorporating surface to 1 kilometer SRH (SRH_{1km}) into EHI, a more valuable forecast parameter was created to discriminate between environments capable of producing significant tornadoes. While this low-level SRH was found to be a higher skilled parameter, it was discussed that an even lower level SRH quantification could enhance parameters' ability to portray environments capable of producing significant tornadoes (e.g., surface to 500m SRH (SRH_{500m}), Rasmussen (2003)). Esterheld and Giuliano (2008) aimed to address this hypothesis by using SRH_{500m} from radiosonde observations. Using a suite of launches in Oklahoma, it was discovered that SRH_{500m} provided more skill and better discrimination between environments with significant tornadoes and environments with no tornadoes. Discovering

the significance of SRH as a tornadic forecasting parameter continued as convective storm field efforts yielded much larger datasets to re-evaluate these early findings.

The Verification of the Origin of Rotation in Tornadoes Experiment (VORTEX) field project provided 134 observational profiles from various convective environments, motivating storm environment comparisons. Composite radiosonde profiles showed that there was nearly twice the amount of SRH_{500m} in the tornadic composite versus the non-tornadic composite (Parker 2014). From this finding, it was assumed that these greater values of SRH were found in the ambient storm environment, and not necessarily attributed to storm-induced accelerations. This supported the early-discovered correlation between mesocyclone intensity and environmental SRH (Davies-Jones 1984).

Coniglio and Parker (2020) analyzed a dataset of 902 field project soundings with a distinct goal of comparing tornadic and non-tornadic storm environments. While this study aims to identify trends in low-level parameters, variables such as SRH were evaluated in deeper layers such as surface to 3 kilometer SRH and effective SRH as thermodynamic profiles were provided. Results from this dataset included these deeper-layer parameters providing increased skill over quantities evaluated over shallower depths. In their compositing methods, Coniglio and Parker (2020) explored each component of SRH by defining the equation as:

$$SRH = \int_{H_1}^{H_2} |\vec{V} - \vec{C}| \times \left| \frac{\partial \vec{V}}{\partial z} \right| \times \sin(\theta), dz \quad (1.3)$$

where $(\vec{V} - \vec{C})$ is the storm-relative wind, $\frac{\partial \vec{V}}{\partial z}$ is the vertical wind shear, and θ is the critical angle. The critical angle represents the angle between the 10 meter storm-relative wind (SRW) vector and the 10-500 meter shear vector (Esterheld and Giuliano 2008). This angle can be used as a proxy for how much of the horizontal vorticity below 500 meters is streamwise, a skillful parameter when determining the tornadic

potential of a storm (Parker 2014). By using this equation, we can more clearly think about SRH as a parameter using two components: (1) the SRW component and (2) the ω_s component (the product of $\frac{\partial \vec{V}}{\partial z}$ and $\sin(\theta)$). Based on results shown in chapter 3, we decided to look at the streamwise vorticity directly. We can now explore the significance of other kinematics, including these two components.

1.2.3 Storm Relative Winds

There have been several studies highlighting the importance of SRW in regards to the characteristics of a storm’s mesocyclone (e.g., Droegemeier et al. 1993; Peters et al. 2019). These same studies hypothesized a minimum threshold of SRW was necessary to maintain a supercell, which was later confirmed in simulation studies by Peters et al. (2023). This threshold is needed as storm-relative flow that is too weak allows for a storm’s outflow to undercut the inflow, ceasing storm development (e.g., Klemp and Wilhelmson 1978; Brown and Nowotarski 2019). To better define these thresholds, Peters et al. (2020) ran a suite of simulations to further test a minimum SRW field of approximately 10 m s^{-1} in order to maintain a supercell originally suggested by Droegemeier et al. (1993). Parker and Dahl (2015) also hypothesized that this minimum must be met for tornadogenesis. While these simulated storms allowed for these conclusions to be drawn, there have been few studies exploring SRW in supercell environments directly from observations. In particular, limited observations have made analyzing the evolution of SRW over short time and space scales in storm environments particularly difficult, especially with detail in the lowest kilometer (Richardson 1993).

As reanalysis products evolved and data became more abundant, research surrounding the importance of SRW using these datasets ballooned accordingly. These newly available datasets allowed for a deeper dive into the differences in SRW characteristics between tornadic and non-tornadic storm environments. Early work using Eta

model (Black 1994) profiles uncovered insignificant differences in the SRW profile when comparing tornadic and non-tornadic supercells (Thompson 1998). Since these works, numerous model based studies have been conducted surrounding SRW and tornadic potential of storm environments (e.g., Nowotarski and Jensen 2013; Coffey et al. 2019). Results include SRW showing the most skill at predicting sub-severe and non-tornadic supercells rather than weakly or significantly tornadic storms (Nowotarski and Jensen 2013). Later simulations also show no evidence supporting the use of SRW as a forecast parameter with impacts on mesocyclone or tornadic attributes (Peters et al. 2023).

While the skill of SRW in forecasting applications has been discussed in previous work (Nowotarski and Jensen 2013), the role of SRW in SRH is lesser known. However, Peters et al. (2023) concluded through idealized simulations that the skill in SRH was from ω_s rather than the SRW. Although data source gaps exist in quantifying these storm-relative parameters, the impact on how they are quantified has been a notable problem. Where observed storm motion is not available, Bunkers storm motion (Bunkers et al. 2000) has been used widely. However, while it statistically improves upon use of simpler methods of estimating storm motion like mean wind or bulk wind shear vectors, the observed supercell motions can vary substantially from Bunkers motion (Bunkers et al. 2000). It has been shown that using observed storm motion can be a source of varying results in previous environment studies (Coniglio and Parker 2020; Homeyer et al. 2023; Coniglio and Thompson 2024). This study aims to use observed storm motion for increased accuracy in portrayal of storm-motion related variables for each case.

1.2.4 Vorticity

The importance of vorticity in the storm environment has been discussed to this point predominantly relating to storm-scale dynamics. This includes the importance of vorticity on processes such as the development of the mesocyclone and tornadogenesis (e.g., Davies-Jones et al. 2001; Markowski and Richardson 2009; Davenport and Parker 2015). Given its importance in these processes, it can be assumed that vorticity likely varies in tornadic storm environments compared to environments of non-tornadic storms. To better address these differences, the magnitude of horizontal vorticity (equation 1.2) in an environment can be broken down into two components: streamwise and crosswise horizontal vorticity. These can be defined as:

$$\omega_s = \frac{(\vec{V}(z) - \vec{C}) \cdot \vec{\omega}_h}{|\vec{V}(z) - \vec{C}|} \quad (1.4)$$

$$\omega_c = |\vec{\omega}_h| - \omega_s \quad (1.5)$$

The vorticity vector field provides critical information of the measure of rotation at any location within it. Breaking down each component, streamwise vorticity represents the directional shear of the SRW profile with height while the crosswise component is the speed shear of the SRW with height (Markowski and Richardson 2010). Focusing on streamwise vorticity, the component can be physically addressed as the component of the horizontal vorticity which is oriented in the direction of the storm-relative flow. Theory suggested that some component of streamwise vorticity is necessary in order to maintain a modest rotating updraft (Davies-Jones 2008, 2017, 2022). Given these ties, the use of streamwise vorticity as a forecast parameter for tornadic storms has been well documented (e.g., Davies-Jones 1984; Droegemeier et al. 1993; Coffey and Parker 2018).

In storm environments, various studies have found notable differences in the stream-wise vorticity in tornadic and non-tornadic storm environments (e.g., Davies-Jones 1984; Markowski et al. 2003; Wade et al. 2018). In more recent studies, the critical angle (Esterheld and Giuliano 2008), has been used as a parameter related to the amount of vorticity that is streamwise in the lowest 500 meters of a storm environment. Yet extreme dataset sensitivity leads to differing results in various storm environments. Simulated efforts have signified the importance of critical angle as it relates to the tornadic potential of supercells (Coffer and Parker 2017). However, later studies rooted in observed datasets continued showing differing results of critical angle significance. Parker (2014) showed notable differences between their tornadic and non-tornadic angles, while Wade et al. (2018) found much greater near-ground streamwise vorticity in non-tornadic cases compared to Parker (2014), with little differences in the critical angle. Because these previous studies show varying results, this work aims to use a more robust dataset to explore the differences in both streamwise and crosswise vorticity in tornadic and non-tornadic storm environments.

1.3 Storm Environment Variability

To this point, the importance of kinematic characteristics within the storm environment have been discussed at length. However the question still remains at how storms in seemingly identical environments go on to produce different hazards. This can be explained partly by the variability of a storm’s environment in both time and space. Past studies have attempted to quantify these variabilities as they relate to local storm reports from severe events. For example, Davenport (2021) found that tornadic reports were often preceded by rapid increases in the environmental wind shear. Although

retrospective studies can assess these variabilities, they may remain undetected in real-time. Therefore, a better understanding of these variabilities may be critical towards developing better forecasts.

Using observations from the VORTEX campaign, Markowski et al. (1998) found that SRH varied highly in both time and space in the near-storm environment. Given a limited set of observations, further analysis was needed to identify the variability trends in the wind profile itself. Efforts aimed at the low-levels (surface to 2 kilometers) found that although the mean wind remained relatively unchanged, the shear vector across the same layer changed by as much as 70° in time (Markowski and Richardson 2004). Additionally, enhanced curvature and elongation of the hodograph over the same layer was observed as distance to the storm decreased.

It has been covered at length the impact of the wind field on supercell characteristics. Thus, it can be expected that as a cell moves through a varying environment, the nature of the storm's intensity should change. Several simulated storm efforts aimed to address the effects of this variability on the storm environment. These simulated storms showed that horizontal variability in the shear profile can effect the convective evolution of the storm (Richardson et al. 2007). More specifically, if a cell were to move into a region of increased shear, that cell will likely intensify as there are new areas of enhanced vorticity due to the increase in wind shear. These heterogeneities can also have an impact on the longevity of a storm (Davenport and Parker 2015). Compared to enhancements of storms in higher shear environments, it can be expected for storms to dissipate quicker if shear were to decrease in the environment (e.g., prevention of hydrometeor displacement from the updraft; Browning (1964)). Using observations from the VORTEX 2 project, Klees et al. (2016) found that the wind profiles from tornadic storms displayed enhanced values of SRH and SRW. These enhanced values and downstream enhanced variability have also been linked to eventual tornadic production

(Flournoy 2020). A better understanding of these variabilities in storm environments would play a crucial role in not only our understanding of tornadic and non-tornadic storm environments, but allow for more robust simulations of severe storms through techniques such as base-state substitution (Letkewicz et al. 2013).

One lesser-explored topic is the storm’s impact on the environment and resulting perturbations from the base-state in time and space. A better understanding of these storm-induced modifications could also lend solutions to how similar storm environments can produce storms of differing intensities and hazards. The idea of storm-induced environmental variability has been in the literature for decades (e.g. Brooks et al. 1994). Hypotheses include that a storm likely has an impact on the low-level wind profile and that there is modification done on this profile as a storm moves through an environment (Markowski et al. 1998). It has been estimated that an environment undergoes most significant modification within 40 kilometers of the storm (Potvin et al. 2010). This finding was bolstered by Parker (2014) where wind profile modification appeared to be enhanced using the same distance threshold. It was also proposed that non-tornadic storms perturb their environments more than tornadic storms, with greater variability of the low-level wind profile and notably more low-level crosswise vorticity (Parker 2014). These variations in the shear vector was also hypothesized to be related to near-ground evaporative cooling (Parker 2014). Additional baroclinically-induced modifications have also been found in convective-allowing model storm environments (Kerr et al. 2019).

Although physical ties to storm-induced modification are supported, which supercell type (tornadic/non-tornadic) modifies their environment more is still relatively unknown. Differing from Parker (2014), Wade et al. (2018) found that tornadic supercells were responsible for enhanced modification of the wind profile. Noted were increased

values of SRH_{1km} . These changes to SRH_{1km} were related to vertical pressure gradient forces in the mesocyclone. Most notably, these enhancements were not found in non-tornadic supercells, likely attributed to the disorganization of non-tornadic mesocyclones compared to their tornadic counterparts. These data sources, however, do not allow for the fine-scale temporal evolution of the low-level wind profile that others profilers provide since the results were derived from radiosonde observations.

1.4 LiDAR

Doppler wind lidars (DWL) have been used in meteorological applications for decades, but began as airborne profilers (Schwiesow 1981). Their use of airborne lidar to analyze horizontal velocity profiles in waterspouts paved the way for further use of Doppler wind lidars for meteorological applications (e.g., Banta et al. 2006; Hill et al. 2010; Kühnlein et al. 2013). While DWL systems have been used extensively in boundary layer applications (e.g., Gal-Chen et al. 1992; Pearson et al. 2009; Manninen et al. 2018), little to no documented use of lidars for severe storms application had been conducted until the last few decades.

An effort in the VORTEX2 field project highlighted a use case for lidar observations in the severe convective storms community (Bluestein et al. 2014). Of note in the comparison of lidars and radar in severe storms application is the collimated beam which allows for consistent volume sample sizes in the direction of the scans. This is compared to radars which result in larger sample volumes as the wave moves away from the radar site. More recent work through VORTEX Southeast used a DWL to quantify the environmental fluxes in convective environments (Markowski et al. 2019).

Although the use of DWLs are limited within the severe storms community, the need for more robust observations within the storm environment is evident. Using a

DWL provides a much-needed, high-temporal look into the evolution of the low-level wind profile in supercell storm environments. This allows for new analysis techniques which are unable to be completed with previously used data sources, particularly from rawinsonde launches. More targeted deployment sites within the supercell inflow environment will also help to address the spatial heterogeneities discussed previously in this section. These data, supplemented with further observations, will allow for the most robust and complete analysis of observed wind profiles completed thus far in storm environment research. Methods to create these profiles will be discussed in the following chapter.

1.5 Motivation

The goal of this work is to use new observational methods to find potential differences in the environments between tornadic and non-tornadic supercells. This work aims to build at the efforts undertaken by prior research discussed in this section. Specifically, this project aims to address the following previous findings:

1. Kinematics vary more in non-tornadic storms in space, with drastic changes in SRH from the far-field to near-field not seen in tornadic composites (Parker 2014).
2. Low-level, inflow winds in non-tornadic supercell environments contain more crosswise vorticity compared to their tornadic supercell counterparts (Parker 2014).
3. SRW plays an insignificant role in tornado dynamics and thus, there are minimal differences in low-level SRW profiles in tornadic and non-tornadic environments (Peters et al. 2023).

4. Streamwise vorticity drives changes in SRH in the storm environment and provides the skill between SRH and tornado prediction (Peters et al. 2023).
5. Low-level parameters such as SRH_{500m} provide better discriminatory skill compared to deeper-layer parameters such as SRH_{1km} or SRH_{3km} (Coffer et al. 2019; Coniglio and Parker 2020).

Chapter 2

Data & Methods

This research analyzes mobile scanning DWL data from various deployments from 2017 through 2023. Instrumentation details, data collection strategies, and quality-control and post processing techniques will be provided in this section. In total, 36 supercells were observed over 50 deployments with co-located radiosondes launched throughout operating periods (Fig. 2.1).

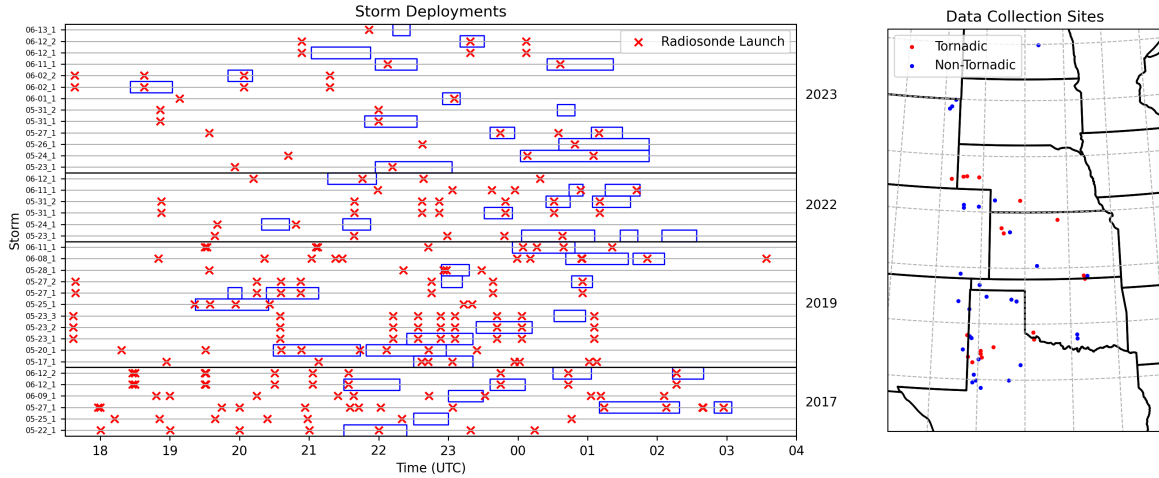


Figure 2.1: Timing of DWL deployments (blue rectangles) and co-located radiosonde launches (red marker) for each storm analyzed in this study (left). Deployment locations separated by tornadic (red) and non-tornadic (blue) storms (right).

2.1 Surface Observations

In 2017, the National Severe Storms Laboratory (NSSL) deployed a DWL as part of their Collaborative Lower Atmospheric Mobile Profiling System - CLAMPS. This system was outfitted with a Vaisala met station which collected surface observations valid approximately 1 meter above the trailer (approximately 5 meters above ground level). Surface observations were logged every 5 seconds with an accuracy of $\pm 0.1 m s^{-1}$ in wind speed observations and $\pm 2^\circ$ in wind direction (WIN 2022).

From 2019 to 2023, the NSSL operated a DWL (two DWLs in 2022) from the bed of a Ford pickup truck. Mounted on this truck was a mobile mesonet rack where an RM Young 05103 Wind Monitor was used to collect surface horizontal wind speed and direction information every 1 second. These observations have wind speed accuracy within $\pm 0.3 m s^{-1}$ and wind direction accuracy within $\pm 3^\circ$ (Waugh 2021). Collected surface observations were used to subjectively determine the passage of various boundaries indicative of no longer sampling inflow air (e.g., a gust front passage).

2.2 Rawinsonde Observations

Prior to 2019, Vaisala's RS92 radiosondes were used. From 2019 and later, the Vaisala RS41-SGP radiosonde was used. Both models of sondes resulted in wind speed and direction errors within $\pm 0.15 m s^{-1}$ and $\pm 2^\circ$ respectively. While there are temporal and spatial differences in the data, they are taken as a single proximity sounding representing an environment at the time the sonde was launched. These data were used initially to validate the lidar observation. In its early stages, the quality of DWL data and proper scanning methods to retrieve accurate vertical wind profiles was unknown,

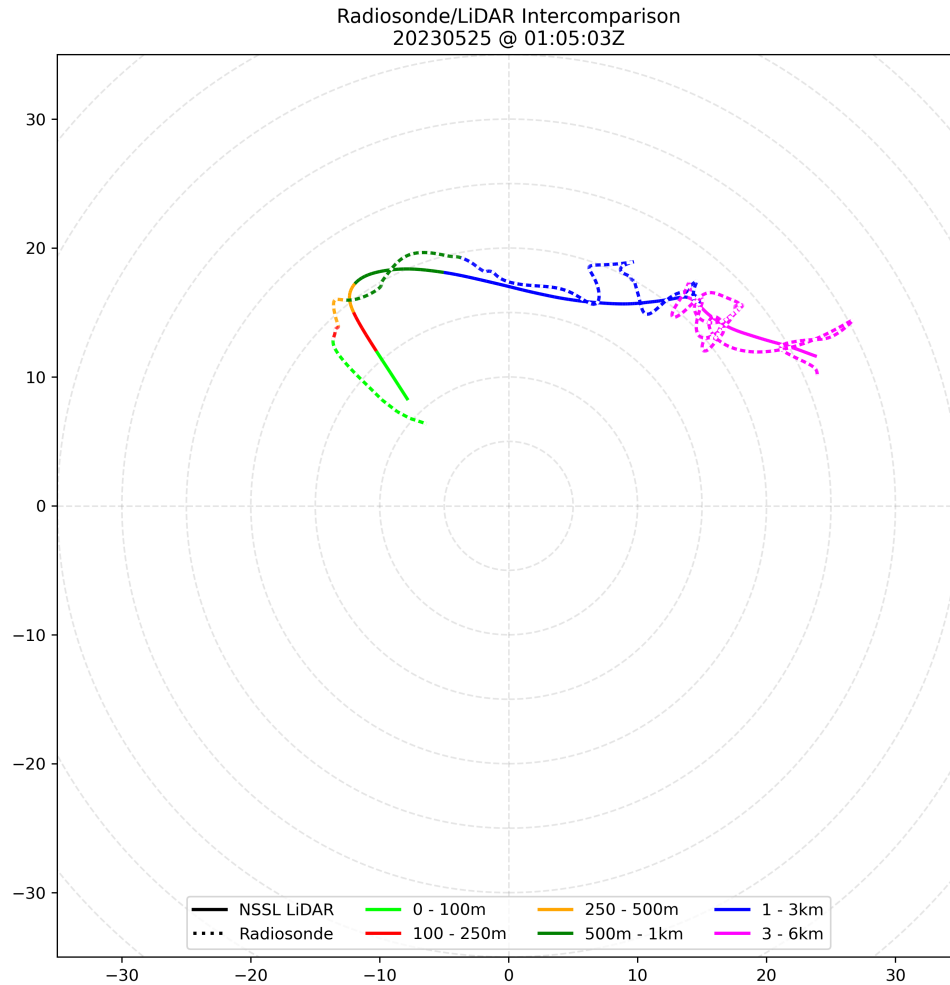


Figure 2.2: Inter-comparison between NSSL DWL (solid) and radiosonde (dashed) retrieved wind information. Comparison from 23 May 2024 Grady, NM tornadic supercell.

and was compared directly to these rawinsonde observations. Figure 2.2 highlights one of these comparisons.

In these comparisons, we average the available lidar data over the time frame it took the sonde to reach the maximum height of the lidar data in a given retrieval.

Differences in the radiosonde and DWL profiles are caused by (1) time differences when each retrieval was made by the respective instrument, (2) spatial differences (as the sonde moves vertically in the profile), and/or (3) general instrument uncertainty. Given these sources of error, overall similarity in the profiles validates the DWL data collected and used in this study.

Another potential use case of the sonde launches was to establish a base-state for the storm environment independent of the lidar observations. However, after a temporal analysis of launch times in relation to the lidar deployments was made (Fig. 2.1), too many inconsistencies arose preventing an accurate base-state estimation across all cases.

2.3 Lidar Observations

For all deployments, the NSSL operated Halo Streamline XR+ mobile Doppler lidars. This unique use-case for the instrument required the lidar to be truck mounted. These characteristics made the instrument nimble, which is critical for severe storms applications. A truck mounted lidar allowed for the deployment process to be completed in under two minutes. This granted the mobility required to redeploy on a quick-moving storm, maximizing sampling time. One downfall of the system in these applications is the Nyquist velocity of the instrument. These lidars operate at a wavelength of 1.5-microns with a Nyquist velocity of $38.8m\ s^{-1}$ (hal 2023). It is also important to note that wind speeds above the specified Nyquist velocity do not alias similar to radars. In the case of the Halo XR+, any wind speed over $38.8m\ s^{-1}$ appear as noise and cannot be deciphered.

An additional caveat of using a DWL for environmental studies such as this is the surface-layer limitations in data collection. Given the pulsed nature of the profiler, wind

speed information in the nearest 70 to 90 meters above ground level cannot be used. This could only be alleviated by running additional scans at extremely low elevation angles to retrieve horizontal wind speed information at these altitudes. However, this (1) limits the frequency of deeper profiles which is of particular interest in this study, (2) cannot be done effectively given the current instrument setup and protective measures in place, and (3) brings the horizontal homogeneity assumption into question as the cone covers a larger horizontal area. As discussed in Chapter 1, a large knowledge gap in observations remains regarding the near-ground kinematic environmental evolution. Therefore, new techniques must be developed to maintain quality data in the lowest 100 meters for the most robust analysis.

Where the lidar deployments are occurring must also be taken into consideration. The performance of the lidar is contingent on the aerosol distribution. Specifically, if there are minimal scatterers, the rays will not be able to reflect and return to the instrument itself. This problem is amplified in clear-air conditions, and was sometimes seen in high-Plains deployments, an example of which can be seen in Figure 2.3.

2.3.1 Scanning Strategies

The NSSL operated one DWL in the Rivers of Vorticity in Supercells field project in 2017. During this project, the lidar operated with a 60° elevation, completing a 360° plan position indicator scan with 8 regularly spaced azimuths. This method, referred to as step-stare hereafter, was conducted every 3 minutes and took roughly 30 seconds to complete; vertical stares were done in between the step-stare scans. Using the step-stare method, horizontal wind speed information can be collected at a much greater vertical depth compared to other methods discussed later in this section.

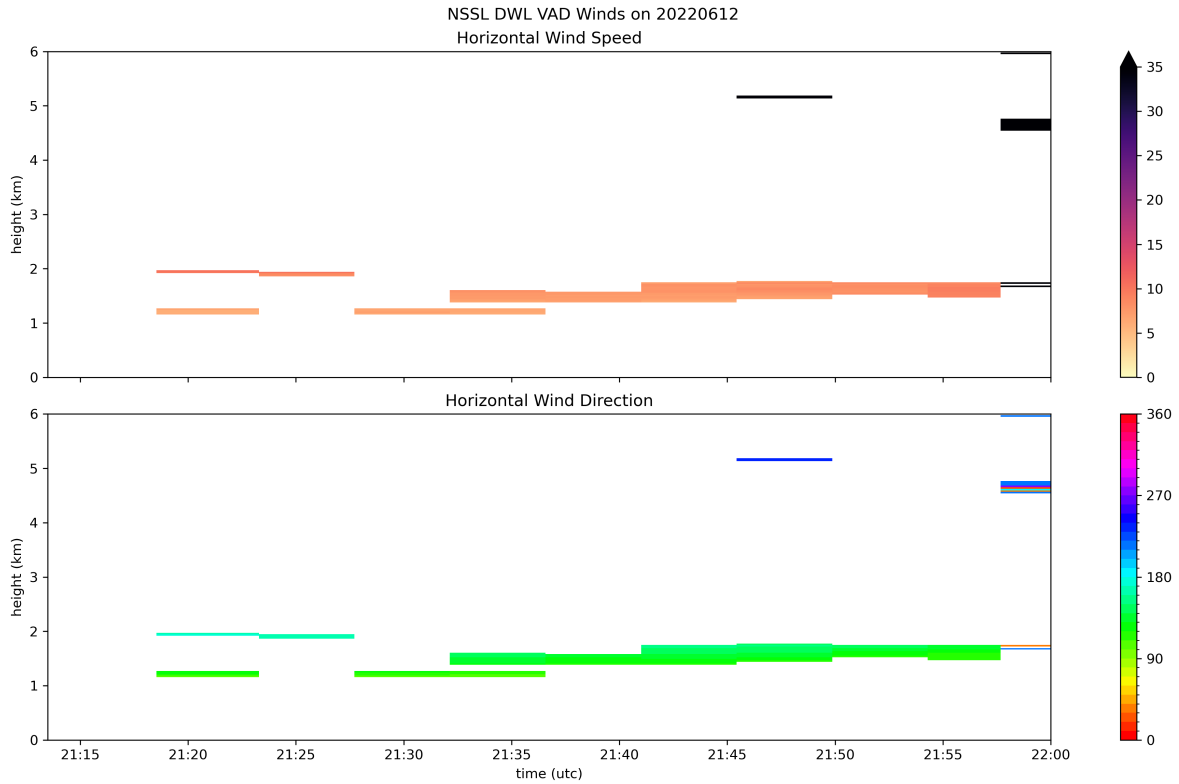


Figure 2.3: Horizontal wind speed (top) and direction (bottom) from 12 June 2022 Wyoming/South Dakota non-tornadic supercell after a signal-to-noise ratio filter.

In 2019 and beyond, the NSSL participated in the Targeted Observation by Radar and UAS of Supercells field campaign. The scanning strategy used by the single DWL in 2019 was similar to that used during the 2017 data collection period. Slight modifications include using an additional 4 azimuths and completing these scans every 2 minutes instead of every 3. These changes allowed for more reliable observations at a finer temporal scale.

In 2022 the NSSL adopted a new scanning strategy, referred to as continuous scanning mode (CSM; Steinheuer et al. (2022)). The use of the CSM scanning strategy allows for a finer temporal resolution of horizontal wind speed information compared to previously implemented strategies. Originally implemented to obtain turbulent kinetic energy information, data at the finest temporal resolution both measures turbulence

and is too noisy for this application (evolution of the mean wind). For this work, we average profiles over 1 to 3 minutes, resulting in reliable wind speed information.

Utilizing these different scanning strategies has direct impacts to the final observed profiles. These effects are most prevalent in the vertical range of quality data. When using the step-stare method, information can be collected through much deeper layers. However, when CSM is used, the number of rays used to comprise the velocity estimate are limited. This inherently limits the dwell time, reducing the vertical range of velocity data. We can better visualize these vertical height disparities through histograms of the highest data point passed through an signal-to-noise filter (Fig. 2.4).

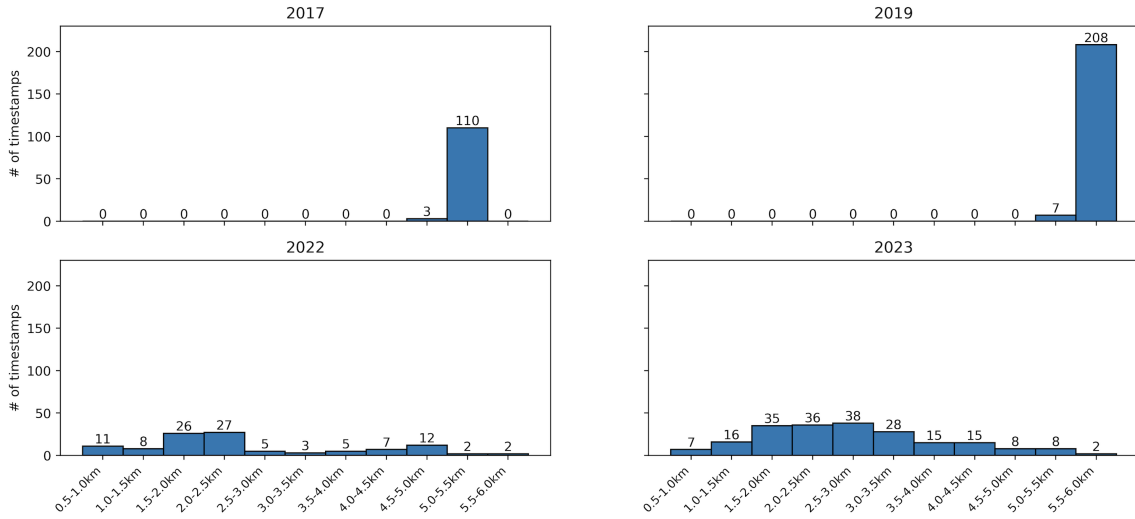


Figure 2.4: Histograms of the highest lidar observation which meets a particular uncertainty threshold. Data from 2017 (upper left), 2019 (upper right) consists of step-stare scanning retrievals while data from 2022 (lower left) and 2023 (lower right) are comprised of CSM retrievals.

Figure 2.4 shows the distribution of the highest lidar observations for every timestamp throughout all deployments. Separating these by scanning strategy, we can see in 2022 and 2023 that although we gain substantial temporal resolution by adopting the CSM scanning strategy, we sacrifice the vertical range of the reliable observations. This results in profiles (using only lidar observations), beginning at approximately 70 to 90

meters above ground level and reaching, depending on the scanning strategy, between about 2 and 5 kilometers above ground level. Although the highest data point passed through a filter may be about 5 kilometers above ground level, this does not guarantee there are valid horizontal wind speed and direction estimates at every range gate prior to this height. These drawbacks of using simply a signal to noise (SNR) filter to display and analyze lidar observations developed the need for a new post processing technique to extract more information from the lidar data than previously used through original post-processing techniques.

2.3.2 Post-Processing

To maximize the capabilities of the lidar observations, various post processing techniques were applied to the data. The traditionally used method, applying a velocity-azimuth display (VAD) technique (Liang 2007), is used amongst a majority of the field and provides reliable wind speed estimates. To filter the resulting profile, a basic SNR filter can be used. This filter is a measure of the signal strength compared to the background noise, and accounts for the thousands of data points making up the retrieved wind information. An example profile is provided in Figure 2.5.

The VAD technique has two apparent limitations. The first is it does not address the low-level data gap in the bottom 70-90m. The second is that profiles are not continuous. Although profiles may not have consistently 'good' data, there are different methods of handling these less-reliable data points (e.g., uncertainty information). A downstream effect of these non-continuous profiles is the ability (or lack thereof) to compute severe parameters such as SRH or other integrated/layer-averaged parameters that include the surface layer.

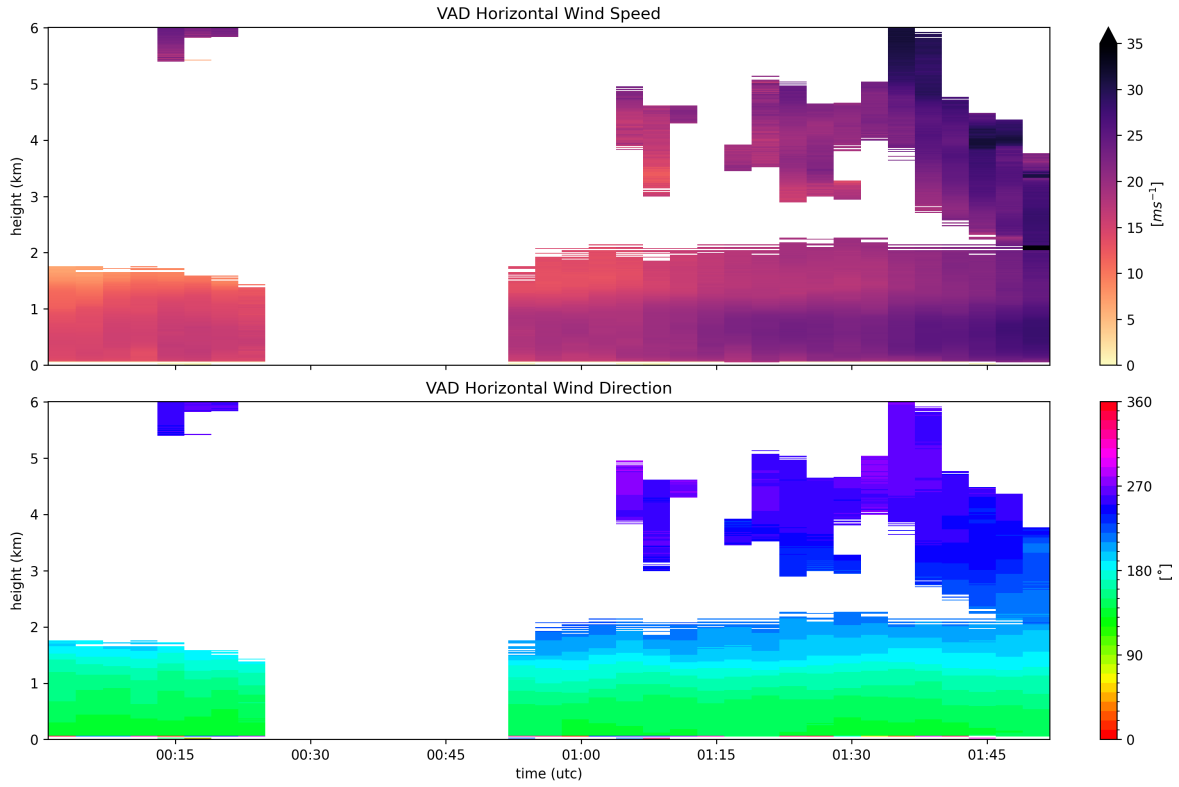


Figure 2.5: Horizontal wind speed (top) and direction (bottom) developed from the velocity-azimuth display post-processing method. Data from 24 May 2023 Grady, NM tornadic supercell.

Optimal estimation techniques have been used in the observational analysis of various atmospheric characteristics (e.g., Wunch et al. 2011; Turner and Löhnert 2014; Turner and Blumberg 2018). This technique is based on using a prior dataset of the desired variables (e.g., temperature, dew point, wind components), combined with observations, to create a more robust profile considered to be more representative of the actual environment. These retrievals also include uncertainties in the final estimates. Compared to other statistical methods, optimal estimation is used as a physical-based retrieval method, meaning a significant number of parameters are needed to create the final profile (Maahn et al. 2020). Previously developed techniques include using Doppler lidar VAD radial velocities to obtain more accurate and deeper profiles (Baidar et al. 2023).

Wind via optimal estimation (hereafter WINDoe) is a newly developed post processing technique used to extract more information from profiler and other observational data types (Gebauer and Bell 2024). The default implementation of WINDoe is based on prior information collected from the U.S. Department of Energy Atmospheric Radiation Measurement program Southern Great Plains site (ARM-SGP). Nominally, radiosondes were launched from this site every 6 hours for about 20 years (Keeler et al. 2022) and were used to develop a climatological background of wind profiles needed for the WINDoe method. Due to the number of profiles launched from the site and seasonal variability in the wind profile, WINDoe utilizes prior datasets for each month of the calendar year. Data from these priors can be visualized as seen in figure 2.6. In this study, the w-component of the wind will be negated.

The general structure of the wind profile, notably the weakness of winds aloft, signify the need to develop a prior dataset that encapsulates an environment more typically experienced when targeting severe convective storms. However, wind profiles in severe storm environments likely fall outside of the expected profiles when using prior information from stable atmospheres. Therefore, the need to leverage a preexisting convective environment dataset was apparent for this use case.

Over 20,000 near-storm environments were extracted from the Storm Prediction Center’s Surface Mesoscale Analysis product (SFCOA). These SFCOA profiles have been used in several recent peer-reviewed publications (e.g., Smith et al. 2012; Thompson et al. 2012; Coniglio and Jewell 2022), and can be used to estimate the environment near right-moving supercells across CONUS. Using these profiles, we can create a more representative prior dataset to be used in convective environments. Comparing this new convective prior (Fig. 2.7) to the default WINDoe prior shown in Figure 2.6, we note two distinctions. First, the mean wind profiles appear significantly different. The

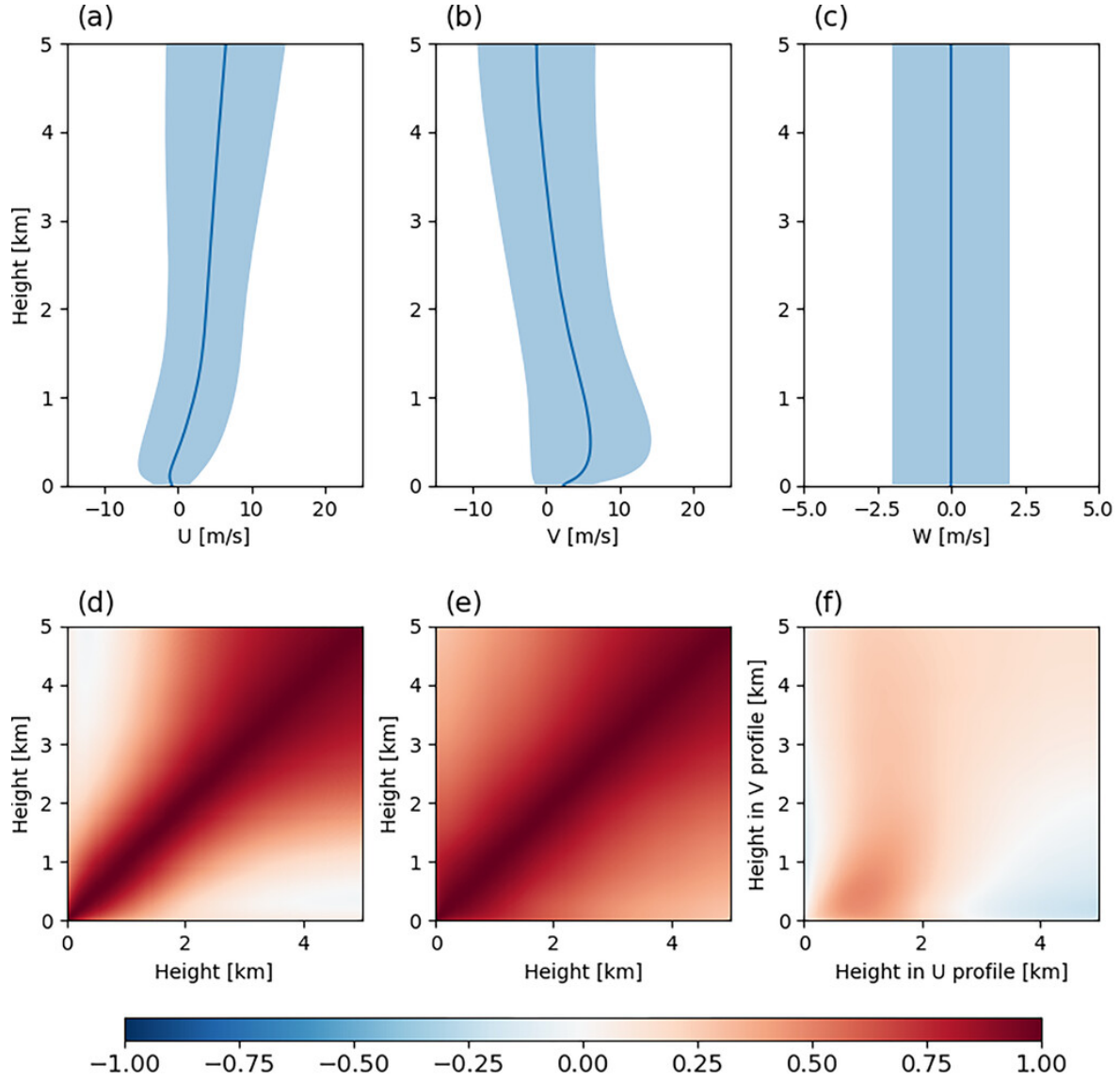


Figure 2.6: Example prior dataset information with the average u and v component profiles with associated one sigma uncertainties (a and b, respectively), and the covariances of u - u , v - v , and u - v (d, e, and f, respectively). From Gebauer and Bell (2024). Their figure 1.

profiles created in figure 2.7 appear much more representative of convective environments with enhanced shear clearly present with greater upper-level flow.

However, a key point regarding this application is that the mean u and v profiles for this prior are not what will be driving the wind speed estimations when ingesting

observations. While the mean profiles provide a first-guess for the retrieval, the amount of observations comprising these profiles (surface observations, rawinsondes, and DWL data) prevent the mean values from driving the output. This is because the prior profiles tend to have a large spread while the observations comprising the profiles have minimal spread at each height. Where there are fewer or more uncertain observations, it is the covariances of u and v with height that will drive the final profile. Related to these covariances is the second distinction of the convective prior, which are the generally strong covariances of u and v with themselves at greater heights above ground level. In supercell environments, we expect a continuously veering wind profile throughout much of the lowest 6 kilometers, and abrupt wind shifts are much less likely compared to clear-air days. Therefore, increased correlations with u and v aloft can be physically supported.

When creating a prior dataset, there must be enough profiles and covariance information to result in a 'stable' profile. To ensure that this prior is stable enough to use for the deployments from this work, we can run a test case. Using an unstable prior should be apparent immediately in data analysis, but as figure 2.8 shows, post-processed data appears reliable and realistic with the prior adequately handling covariances above where consistently reliable lidar observations end.

The use of WINDoe also addresses some of the previously discussed disadvantages of the lidar observations, where we can begin to improve upon the data gap between our surface observation and first usable lidar range gate. When using WINDoe, we can ingest the surface met tower or mesonet observations (year dependent) to be considered when creating the final profile. Each wind component (u and v) is manually assigned a conservative uncertainty of $3m\ s^{-1}$, and surface observations are constrained to only be used at the first range gate, allowing the covariances to guide the remaining data gaps

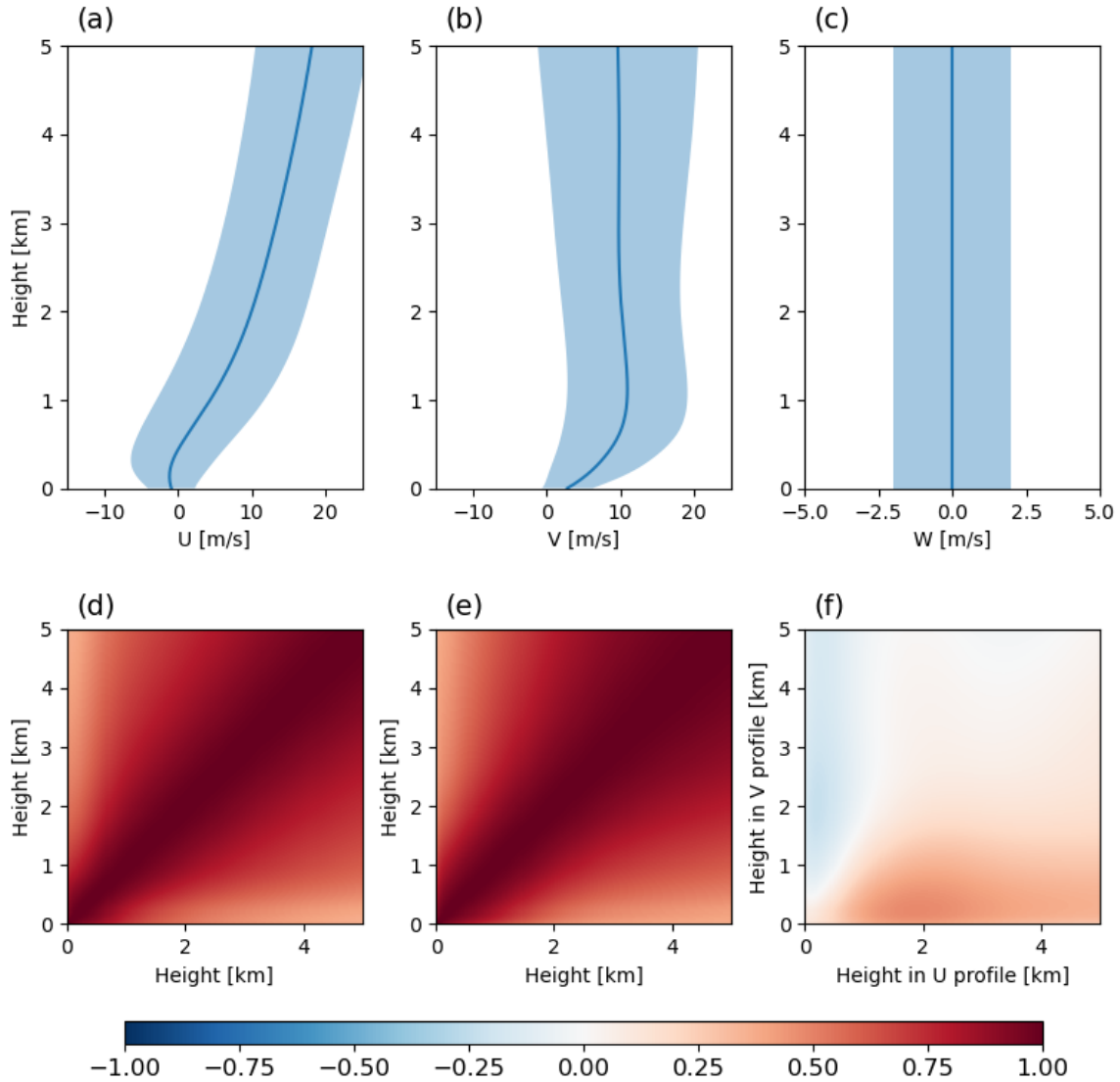


Figure 2.7: Identical prior dataset visualization as Figure 2.6 for the prior dataset developed from SFCOA storm environment profiles.

below the more consistent lidar observations. In addition to the surface observations, we can assimilate the co-located radiosonde observations into the final profile. These datasets were customized to assimilate only above 1.5 kilometers where the continuity of DWL data can become sparse. A relatively large value of uncertainty of $5m s^{-1}$ is used, so the radiosonde observations will only drive the final output where lidar data is

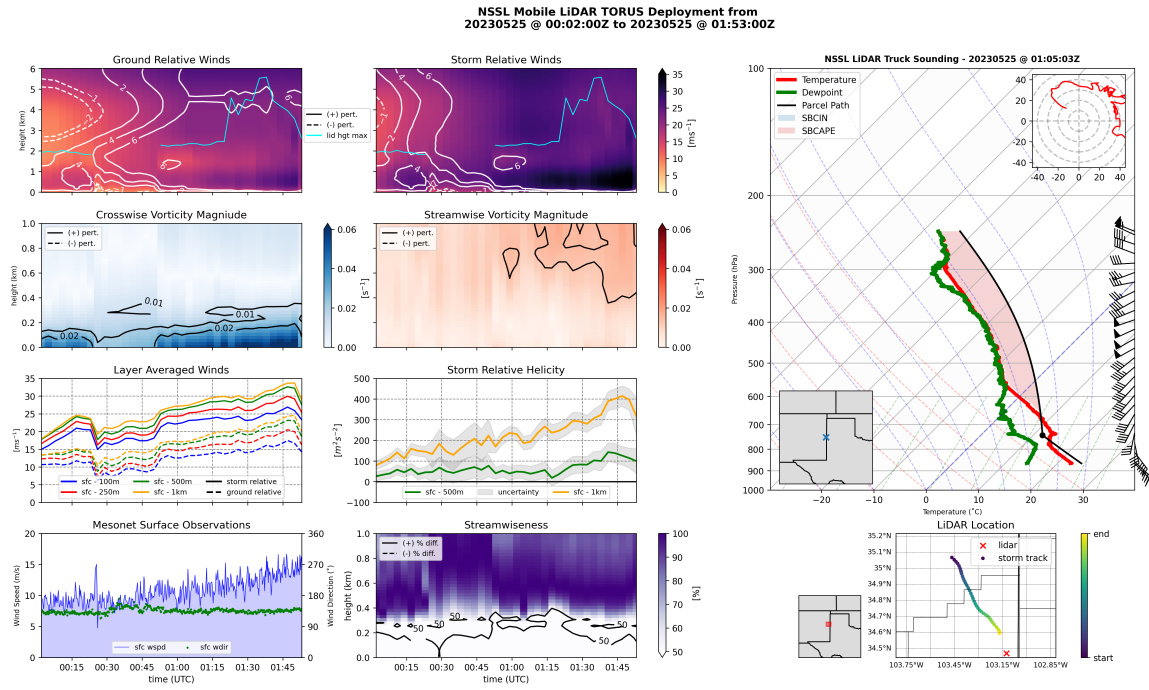


Figure 2.8: Quicklook graphic with WINDoe output data from 24 May 2023 Grady, NM tornadic supercell.

not present. Otherwise, the lower uncertainty in the DWL data will allow that dataset to carry more weight in the final output values.

A secondary fault of the purely lidar observations is the limited vertical continuity of the retrieved wind profiles. As previously mentioned, using the VAD post-processing technique often results in discontinuous profiles (Fig. 2.5). WINDoe takes into account the surrounding range gates of 'good' data and uses the covariances provided via the prior dataset to create an estimate of the winds at the previously blank range gate. This results in a more complete profile (Fig. 2.9), where WINDoe provided uncertainty can provide more meaningful data rather than noise from the VAD processed data.

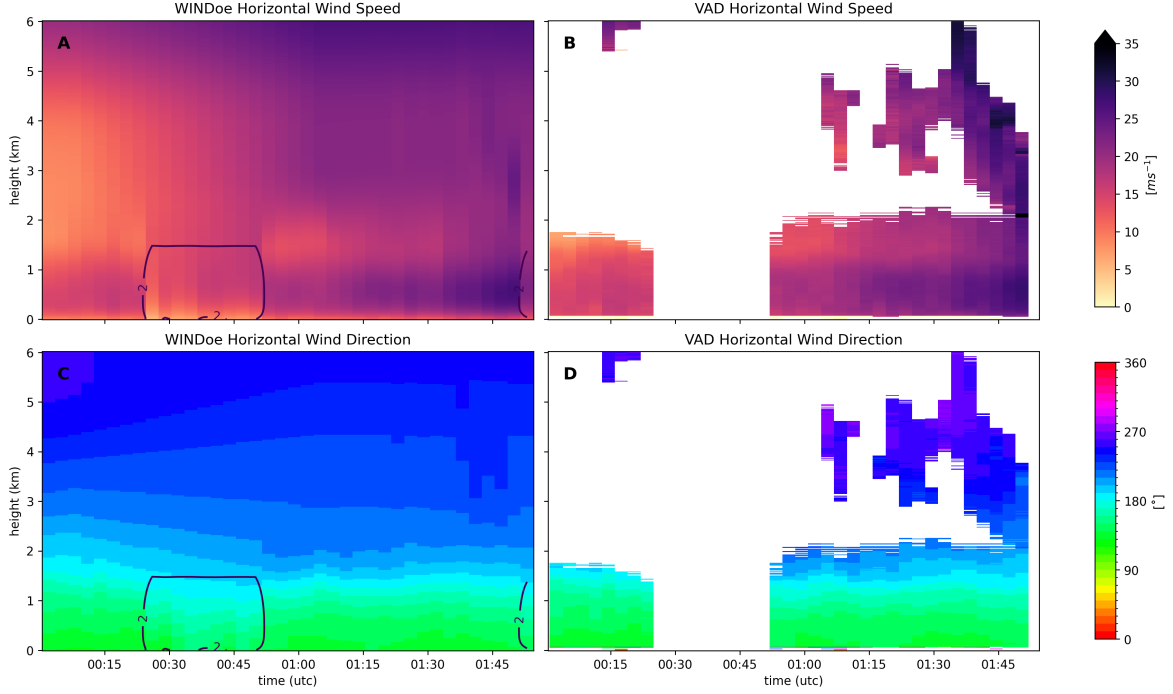


Figure 2.9: WINDoe processed horizontal wind speed (A) and direction (C), both with associated 2-sigma uncertainty contour (black). VAD processed horizontal wind speed (B) and direction (D), filtered by 1.01 intensity threshold (snr metric).

2.4 Base-State Environments

Given the lidar provides data on the storm environment, we can break down the storm environment into two components.

$$var = var_{bs} + var' \quad (2.1)$$

where var is the final measured variable from the lidar, var_{bs} is the base state quantity and var' can be referred to as the environmental perturbations. It was discussed at length in Chapter 1 how these environmental perturbations can be attributed to the impact the storm has on the surrounding environment. Quantifying these perturbations will provide valuable insight into how tornadic and non-tornadic supercells

modify their respective environments. Therefore, in order to isolate var' , we must quantify var_{bs} using a reliable and readily-available dataset.

To quantify these base-state environments, NOAA Rapid Refresh (RAP) analysis was used (Benjamin et al. 2016). When computing storm-relative quantities and parameters such as storm-relative winds and SRH, observed storm motion was used at the times of the profiles. This is an important distinction as the use of various storm motion methods has been found to have impacts on environmental analysis (Coniglio and Thompson 2024). Then, an area average profile is created using grid boxes centered around a point 50 kilometers from the storm location and 45° rotated clockwise from the storm motion vector (Fig. 2.10). Although it has been found that RAP struggles at times to accurately depict convective environments (Laffin 2013), a lack of finer-scale hourly reanalysis products makes using the RAP profiles the best choice for this use case. Using the previously discussed methodology, area-averaged profiles can be chosen at the hour on either end of the lidar deployments and time-interpolated (linearly) to establish a base-state throughout the data collection period.

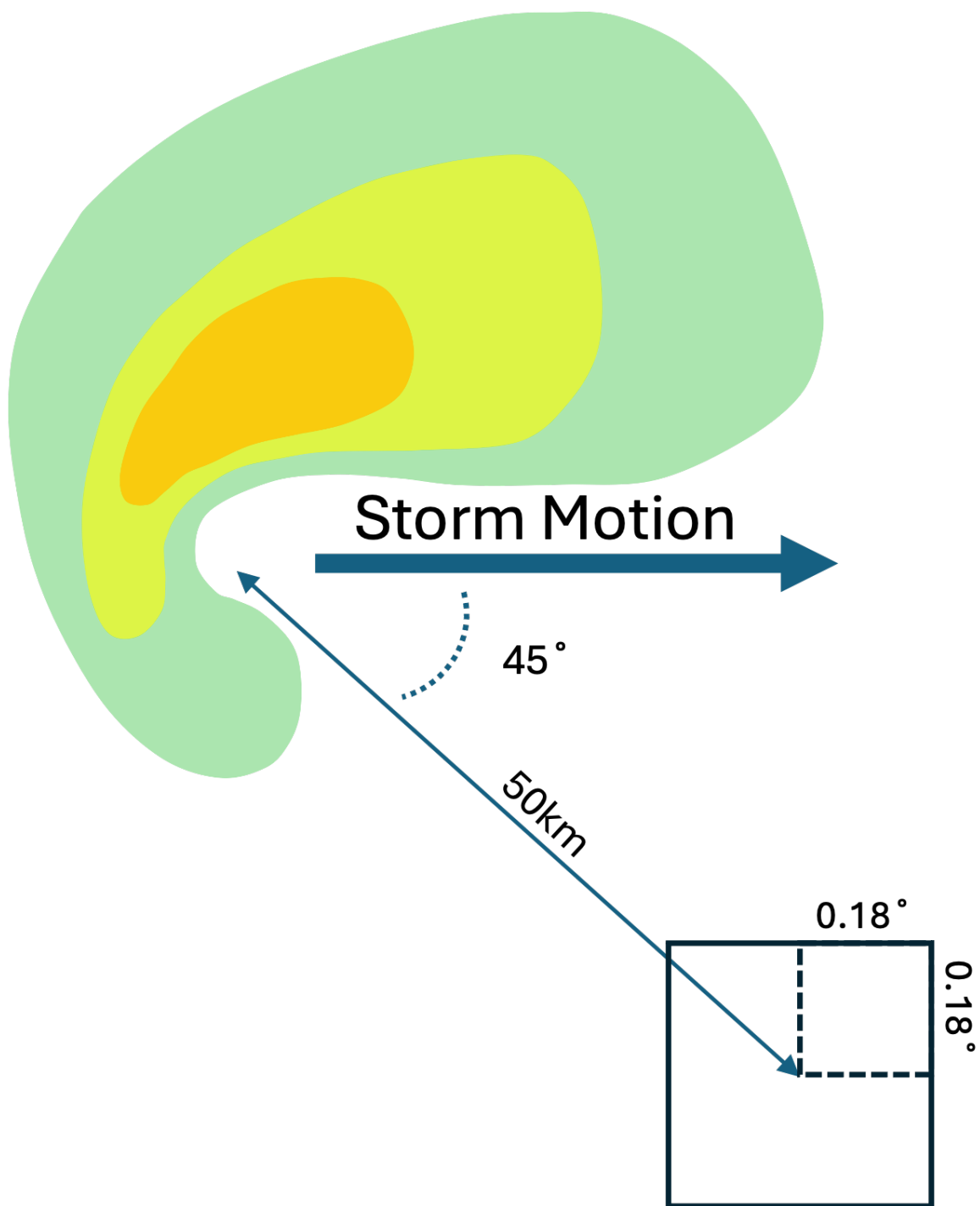


Figure 2.10: Visualization of storm-relative location of base-state environment quantification.

2.5 Compositing

In order to more robustly identify differences in tornadic and non-tornadic inflow environments, various compositing methods were done and are discussed herein. Before data were composited, additional quality-control measures were taken in addition to the boundary passage filter discussed previously. This included removing deployments that lasted less than 10 minutes.

2.5.1 Time Composites

Time based composites were done with profiles 30 minutes prior to a reference time and 30 minutes afterwards. For tornadic storms, this reference time was tornadogenesis. To determine the time of tornadogenesis for each storm, the Storm Prediction Center (SPC) OneTor dataset, SPC storm reports, and daily field reports were used. The daily field reports were completed by lidar operators at the end of each operation day for the respective field campaigns. These reports carried the most weight as uncertainty was lowest, and other datasets were used when these reports were not present.

For non-tornadic storms, compositing was referenced around the maximum rotational velocity (v_{rot}). These v_{rot} values were calculated using National Weather Service WSR-88D data from the nearest radar site. V_{rot} values are calculated using the lowest-elevation scan where there was an identifiable mesocyclone. For the deployments in environments of non-tornadic supercells, only those cases for which the maximum v_{rot} occurred during an active deployment are included in the time composites.

2.5.2 Space Composites

To compute spatial composites, the distance to the storm's mesocyclone at the time of each lidar profile was computed. Based on the resulting distance distribution, various bin sizes through 40km were used including profiles for any distance greater than 40km from the mesocyclone. A spatial plot of storm-relative locations can be visualized (Fig. 2.11), indicating profiles valid behind the mesocyclone. This led to an additional quality-control method of removing profiles that occurred with a negative zonal distance to the mesocyclone to further ensure that the data analyzed was from the inflow region of right-moving supercells.

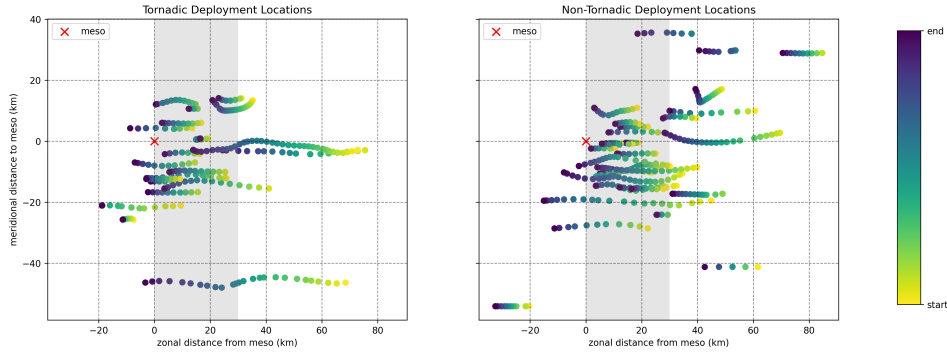


Figure 2.11: Storm relative lidar profile locations in tornadic (left) and non-tornadic (right) storms.

2.5.3 Uncertainty Information

Earlier in this section, the benefit of using WINDoe and the information it gives the user was discussed at length. One of these useful parameters is the uncertainty in the estimates of u and v throughout the profile in time and height. To maintain uncertainty information in the perturbation values, uncertainties must be assigned to the RAP profiles used to quantify the base-state. Using previously established RAP

errors in the wind profile from Coniglio and Jewell (2022), a generous uncertainty of $3m\ s^{-1}$ was used for both the u and v components of the RAP profiles.

For each parameter used in this study, uncertainty in the measurement was calculated. Using 1000 Monte Carlo (MC) simulations, u and v profiles were drawn between the uncertainty bounds and each parameter was calculated. The standard deviation of the distribution of variables was used as the uncertainty for that parameter at that time step. These uncertainties are critical in computing accurate composite uncertainties moving forward.

To maintain uncertainty information through the compositing process, additional statistical methods are needed. However, when compositing uncertainty, two uncertainty values portray the types of uncertainty in the estimate. The first is the uncertainty in the mean calculation which accounts for the uncertainties of each value making up the final composite. This uncertainty can be defined as:

$$\sigma_{mean} = \sqrt{\frac{\sum_{n=1}^N \sigma_n^2}{N^2}} \quad (2.2)$$

where σ_n is the uncertainty of each value coming from the WINDoe retrieval and N is the number of samples making up the composite. Although this value determines the uncertainty in the composite value calculation, this does not account for the variability in the distribution. To do so, we add to the estimated uncertainty as:

$$\sigma_{total} = \sqrt{\frac{\sum_{n=1}^N \sigma_n^2}{N^2} + \frac{s^2}{N}} \quad (2.3)$$

where in addition to the variables from equation 2.2, we introduce s as the standard deviation of the values making the composite. Thus, equation 2.3 accounts for the variance in the values as s^2 . When displaying uncertainty in the following sections, equation 2.3 is used to display the 1 sigma uncertainty bounds.

2.5.4 Statistical Significance

To highlight times and spatial bins where the differences between tornadic and non-tornadic profiles are statistically significant, additional MC simulations were done. 10000 simulations were used and tornadic and non-tornadic variables were chosen at random, with replacement. Differences were then computed and the actual composite difference was assigned a p-value based on the percentile at which the value falls within the MC distribution. Significance testing was done at the 15, 10, 5, and 1% levels and are shown in the figures shown in chapter 3.

Chapter 3

Results

This chapter addresses the results from this study as they relate to each of the hypotheses in chapter 1. Additional results as they were made apparent in the data will be discussed thereafter.

3.1 Hypothesis Driven Results

3.1.1 Environmental Spatial Variabilities

Previous observational based efforts have found greater spatial variability in non-tornadic inflow environments compared to tornadic storm environments (Parker 2014). Given their dataset of rawinsonde launches, these variances were displayed through SRH and composite wind profiles (Fig. 3.1). Using similar methodology, we can assess this dataset in a near and far-field perspective. First, an assessment of the number of profiles making up each spatial bin must be addressed (Fig. 3.2). Composite profiles can then be created showing near and far-field hodographs in tornadic and non-tornadic storms (Fig. 3.3). In this work, the near-field will be used to describe the inflow environment up to 30 kilometers away in the x-direction. Far-field will consist of data beyond the 30 kilometer threshold.

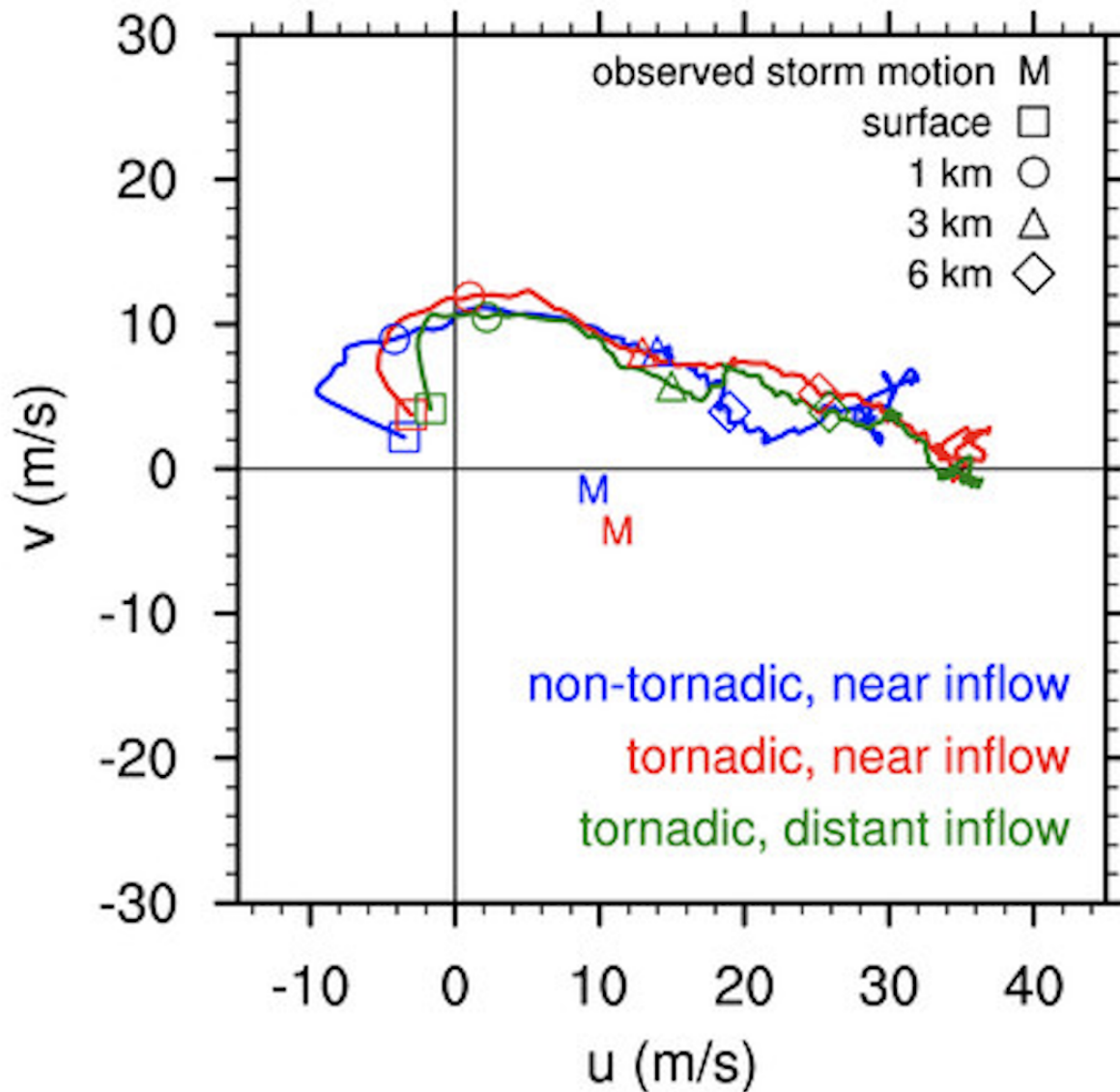


Figure 3.1: VORTEX-2 composite wind profiles, drawn from rawinsonde launches. From Parker (2014); their figure 12.

First, all of the near-field and far-field bins are composited into two mean profiles to facilitate a comparison to (Parker 2014, Fig. 3.1). More noticeable changes are seen in the tornadic wind profiles when transitioning from near to far field environments. Changes to the 3-6 kilometer wind profile are more uncertain with fewer DWL observations impacting the wind profile retrievals than in lower levels. Note that the spatial

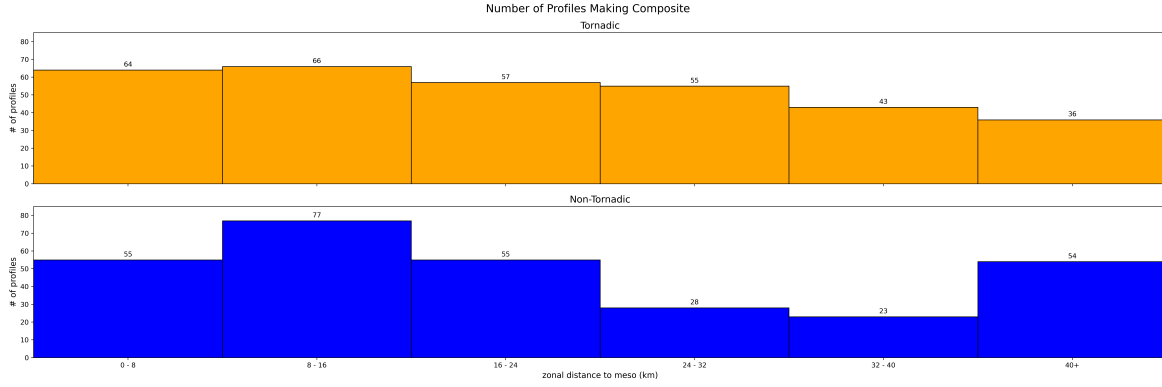


Figure 3.2: Histogram of the number of WINDoe profiles making up the spatial composites used in this section. Counts for tornadic (top, orange) and non-tornadic (bottom, blue) composites are shown.

coverage of the dataset used in Parker (2014) encompasses environments further from the storm (about 30-100 km) compared to this study (predominately 40 km or closer to the mesocyclone). Therefore, we are able to identify the spatial variability much closer to the storm with this dataset compared to rawinsondes from previous work. The findings from Fig. 3.3 pose the hypothesis that tornadic storms could be driving more significant environmental changes in the near-field than non-tornadic storms. This hypothesis could not be addressed using the Parker (2014) dataset, but a deeper look into these low-level variabilities in space is needed.

Observing SRH at different vertical depths, Fig. 3.4 shows how SRH_{500m} , SRH_{1km} , and SRH_{3km} vary with zonal distance to the mesocyclone. In the lower-levels (SRH_{500m} and SRH_{1km}), we see an overall decrease in the SRH as distance from the mesocyclone increases in non-tornadic storm environments. The same signal is not seen in tornadic environments where SRH_{500m} shows no changes and SRH_{1km} shows less of a decrease with increasing distance. However, when considering the SRH_{3km} , we note the most significant variability in space. This is consistent in both tornadic and non-tornadic environments, with the overall relationship between the two being reversed when transitioning from the near-field to far-field. To better address these patterns, we can create

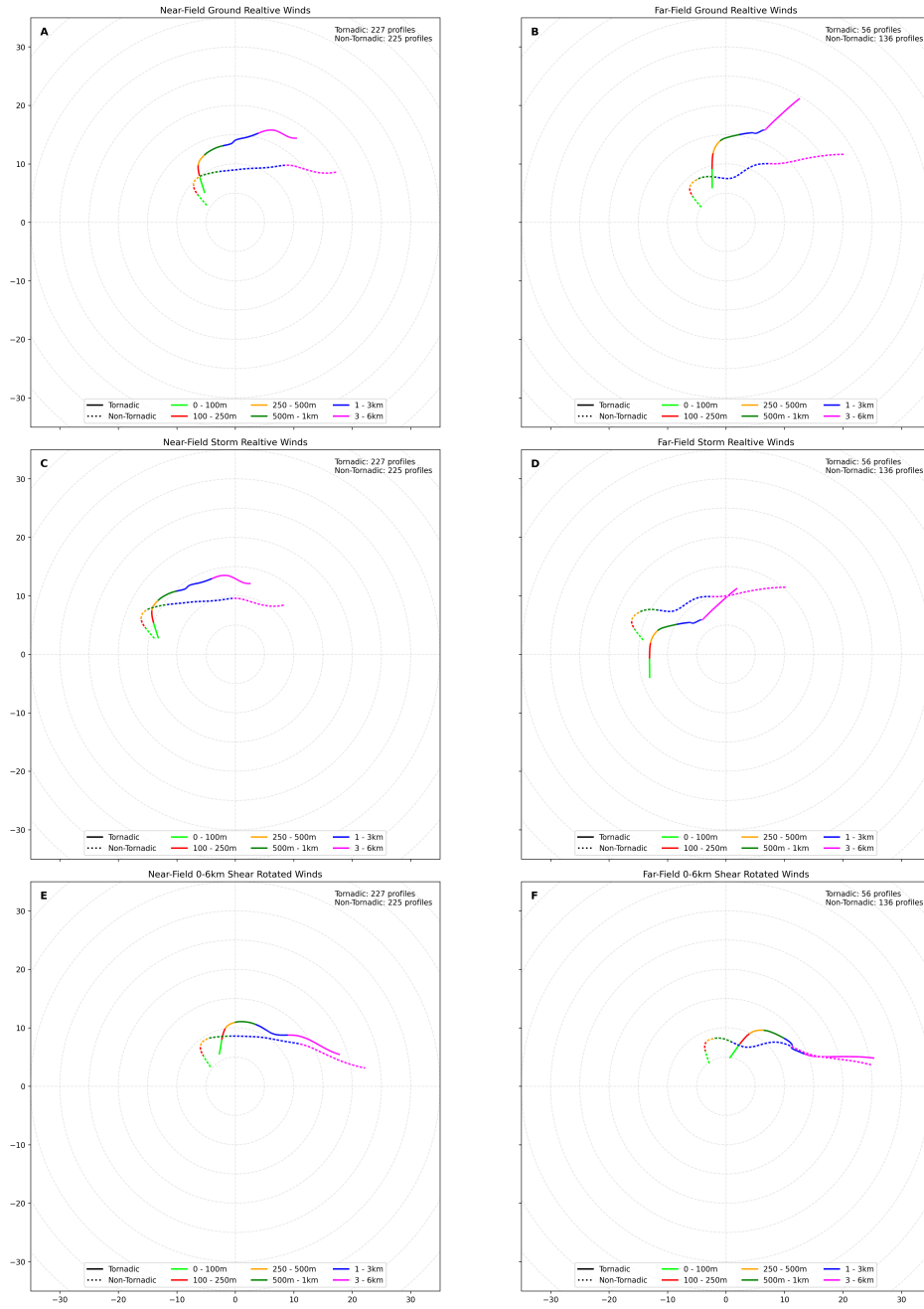


Figure 3.3: Composite ground relative (A,B; ms^{-1}), storm relative (C,D; ms^{-1}), and 0-6km shear vector rotated (E,F; ms^{-1}) hodographs for near-field and far-field inflow regions. Tornadic (solid) and non-tornadic (dashed) profiles are shown with the number of profiles comprising each composite shown in the respective panel.

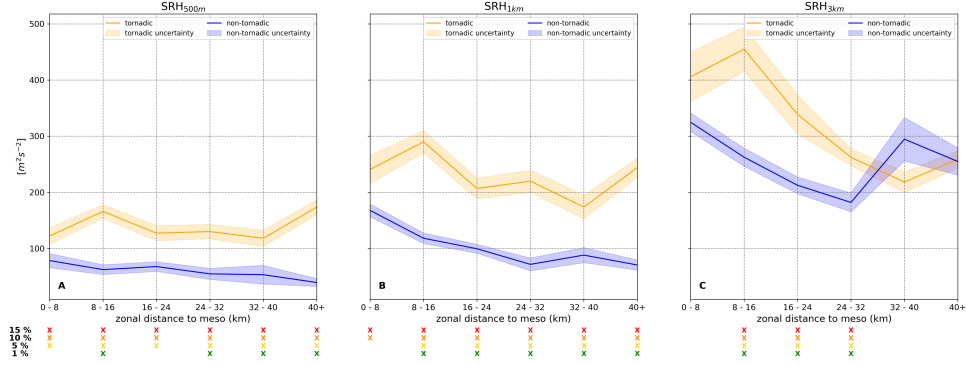


Figure 3.4: Spatial evolution of SRH_{500m} (A; m^2s^{-2}), SRH_{1km} (B; m^2s^{-2}), and SRH_{3km} (C; m^2s^{-2}). Tornadic (orange) and non-tornadic (blue) composites are shown along with the associated 1-sigma uncertainties in each (shaded). X-axis represents the zonal distance to the mesocyclone. 'X' markers indicate which bins contain significant differences between tornadic and non-tornadic environments at 15, 10, 5, and 1% confidence levels (indicated in red, orange, yellow, and green, respectively).

similar visualizations using bulk wind shear over the same vertical layers (Fig. 3.5) to assess if this signal is consistent between variables.

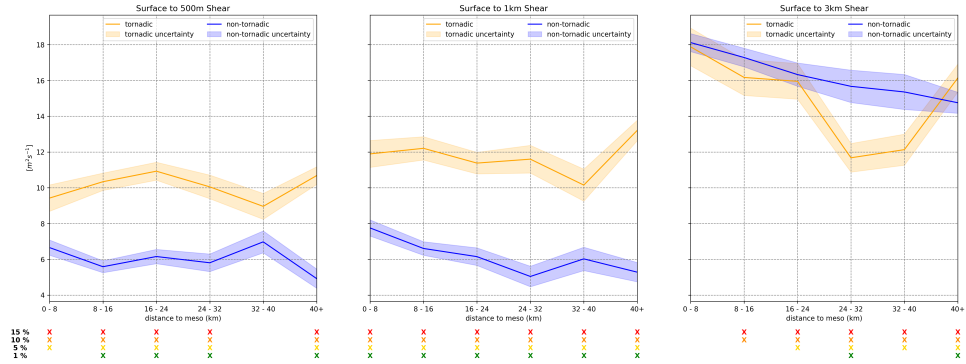


Figure 3.5: Spatial evolution of $shear_{500m}$ (A; ms^{-1}), $shear_{1km}$ (B; ms^{-1}), and $shear_{3km}$ (C; ms^{-1}). Tornadic (orange) and non-tornadic (blue) composites are shown along with the associated 1-sigma uncertainties in each (shaded). X-axis represents the zonal distance to the mesocyclone.

In Fig. 3.5, we note similar spatial evolution of shear as seen for SRH. In the low levels, we note significantly higher shear throughout all spatial bins in tornadic environments. Also similarly to SRH, we see a decline in shear with space in the non-tornadic

environments, which is not apparent in tornadic environments. Of note are the differences in the tornadic and non-tornadic shear_{3km} values. Although constantly declining with space, non-tornadic storm environments tend to have greater shear throughout this deeper layer, differences even being statistically significant at some spatial bins. This warrants a deeper dive into the ground-relative wind profile evolution, particularly in the 1-3 kilometer layer where we see notable changes in the shear relationships between tornadic and non-tornadic environments. To better quantify the variability of the aforementioned variables in the storm environment, we will use the coefficient of variation (CV), which can be defined as:

$$CV = \frac{\sigma}{\mu} \quad (3.1)$$

where σ is the standard deviation of the sample and μ is the mean of the sample across all spatial bins.

Variable	CV_{tor}	CV_{ntor}
SRH _{500m}	0.156	0.205
SRH _{1km}	0.156	0.324
SRH _{3km}	0.263	0.186
Shear _{500m}	0.068	0.113
Shear _{1km}	0.078	0.145
Shear _{3km}	0.152	0.071

Table 3.1: Coefficient of variation for SRH and shear evolution in space for tornadic and non-tornadic storm environments.

The values shown in Tab. 3.1 continue to highlight the variability of non-tornadic environments in space. These heightened variabilities are likely due to the general drop in the parameters with greater distance in the non-tornadic environments while

the tornadic spatial evolution appeared much more constant. However, we continue to see changes in the signal when incorporating deeper layer parameters as tornadic environments vary more in both SRH_{3km} and shear_{3km} .

The greater variability of non-tornadic storm environments from Parker (2014) was deemed due to the storm generated component of the environment. As previously indicated, tornadic storms could be perturbing their environments more, leading to the differences in SRH and shear. In space, we can quantify the storm generated component using RAP profiles as the base-state environment with the assumption that the trends in parameters related to the background environment are captured by the RAP analysis. The perturbations of the same parameters as used above (SRH and wind shear) can then be visualized as differences between the lidar profiles and the base-state environment (Fig. 3.6).

In the nearest 0-8 kilometers from the mesocyclone, we see that in both parameters, non-tornadic environments tend to be perturbed slightly more than tornadic environments. Total environmental quantities in Figs. 3.4 and 3.5 imply the tornadic cases have much more shear and SRH in the lowest kilometer. However, as distance from the mesocyclone increases, tornadic environments tend to be significantly more perturbed. This signal is evident from about 8 through 32 kilometers, supporting the findings from Potvin et al. (2010). Given the spatial coverage in this dataset, it remains unknown how the variability differs for greater zonal distances from the mesocyclone.

Digging deeper into these trends in perturbations, we note more statistically significant differences between tornadic and non-tornadic environments in low levels (Fig.

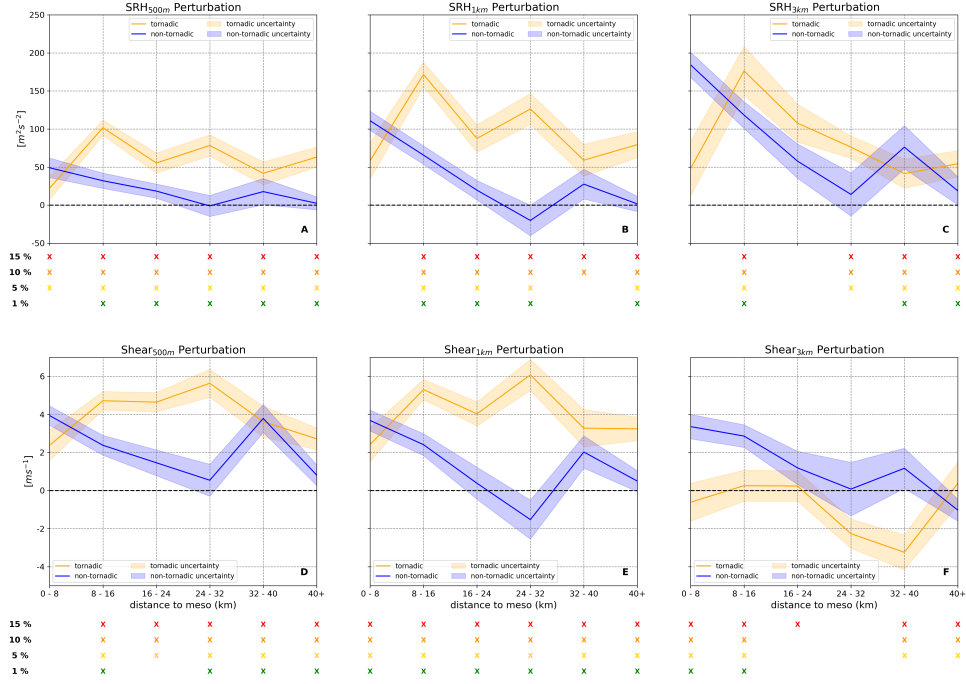


Figure 3.6: Base-state perturbations of SRH_{500m} (A; m^2s^{-2}), SRH_{1km} (B; m^2s^{-2}), SRH_{3km} (C; m^2s^{-2}), $shear_{500m}$ (D; ms^{-1}), $shear_{1km}$ (E; ms^{-1}), and $shear_{3km}$ (F; ms^{-1}) in space. Composites for tornadic (orange) and non-tornadic (blue) environments and the associated 1-sigma uncertainties (shaded) are shown.

3.6). Assuming these perturbations are due to flow accelerations from mesocyclone induced PGF, we are highlighting differences between the low-level and mid-level mesocyclones. We note that similar mid-level perturbations between the non-tornadic and tornadic environments could be due to similar mid-level mesocyclone characteristics, while greater differences in the low-level mesocyclones between tornadic and non-tornadic storms directly lead to significant differences in the perturbations at lower levels.

Overall, the DWL dataset allows for a more robust investigation into the variability of tornadic and non-tornadic environments in space. We find supporting evidence to suggest that the overall tornadic wind profile tends to vary more when transitioning from the near to far field inflow environments (Fig. 3.3). This was present in both

methods shown in the near-field/far-field hodographs and other spatial composites with numerous spatial bins over the inflow region. However, greater variability in non-tornadic environment severe parameters is seen very close to the storms and can likely be attributed to both smaller parameter values in the base state environments and weaker storm-induced perturbations that do not extend as far from the storm when compared to tornadic storm environments.

Aside from environmental spatial variability, Fig. 3.1 highlights another key difference in each composite: enhanced backing the low levels in non-tornadic environments. To explore these differences, composites in both time and space will be analyzed in a variety of reference frames.

Fig. 3.7 shows the evolution of the ground relative wind (GRW) profile as distance to the mesocyclone increases. Although these profiles vary significantly bin to bin, the non-tornadic profiles appear to have more backing in the lowest 200m. The enhanced backing in the lowest levels in non-tornadic storm environments, however, has not been studied at length. These signals are linked to ideas surrounding vorticity makeup in non-tornadic storm environments (increased crosswise vorticity; Parker (2014)). To confirm this signal is not dependent on the reference frame analyzed, storm-relative composite hodographs shown in Fig. 3.8 confirm enhanced low-level backing is again present throughout most spatial bins in the non-tornadic profiles. Furthermore, these results only highlight these signals composited in space (similar to Parker (2014)). Because this signal is seen in the storm-relative framework, this indicates the non-tornadic environments tend to display larger critical angles (farther from 90°) than the tornadic environments. However, it is not clear if these larger critical angles also correspond to larger crosswise vorticity since the magnitude of the shear and storm-relative winds

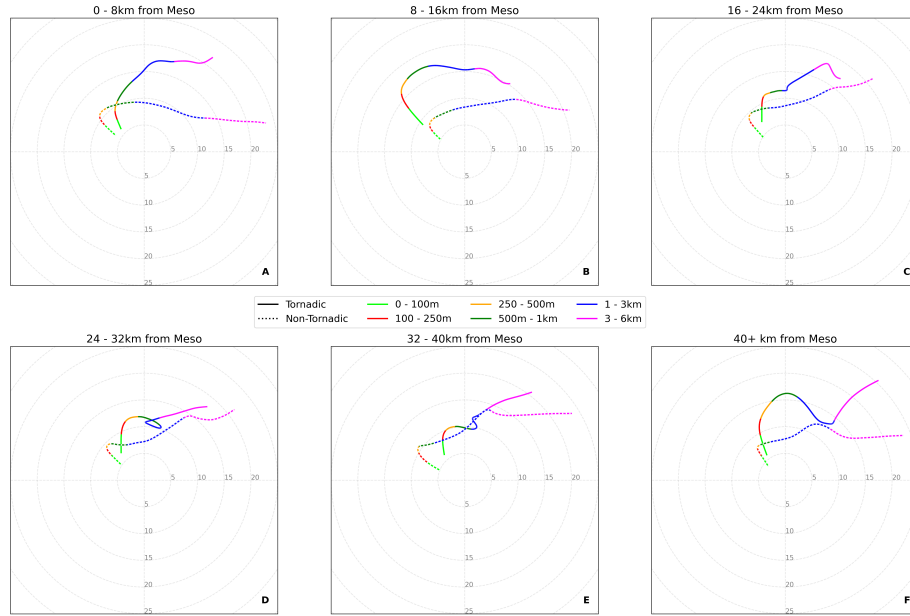


Figure 3.7: GRW profiles (ms^{-1}) for tornadic (solid) and non-tornadic (dashed) in 8 kilometers spatial bins ranging from 0 to 40+km zonally from the mesocyclone.

(SRW) are also different between the tornadic and non-tornadic environments. The differences in crosswise vorticity are discussed in a later section.

Next, we composite the wind profile at various times surrounding our reference times for tornadic and non-tornadic storms (10-minute bins; Fig. 3.9). Using these profiles, we can first note that the signal is muted and only present in 1-2 times. This is likely due to the fact that our non-tornadic mesocyclones are plausibly most intense in these time frames. Verifying these results with a second frame of reference, Fig. 3.10 visualizes the SRW profiles at the same reference times as Fig. 3.9. We note that this signal persists and the hypothesis of increased low-level backing is seen almost strictly in space, rather than time.

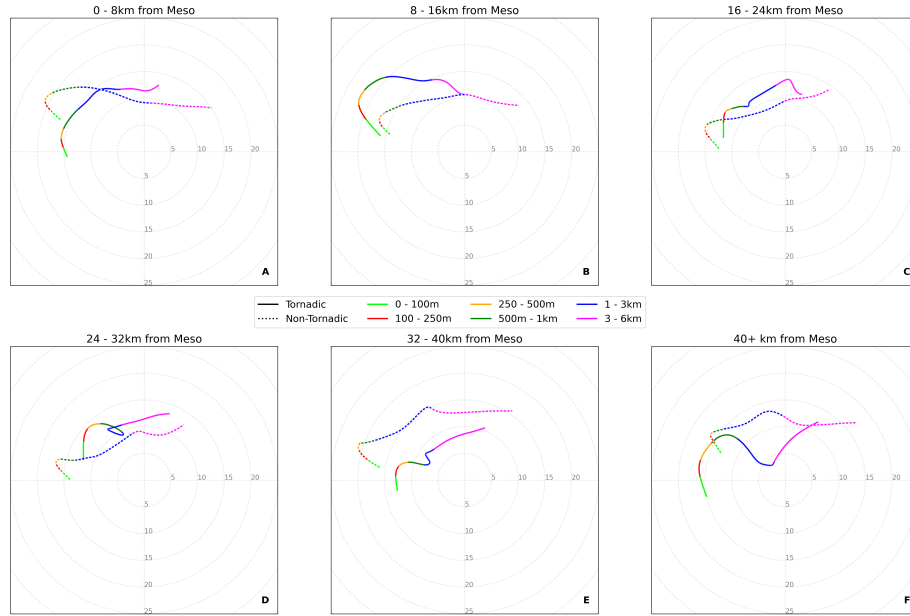


Figure 3.8: SRW profiles (ms^{-1}) for tornadic (solid) and non-tornadic (dashed) in 8 kilometers spatial bins ranging from 0 to 40+km zonally from the mesocyclone.

To summarize this subsection, we began identifying differences in tornadic and non-tornadic storm environments. In particular, we addressed the variability of the storm environments in space. We find that using a similar framework to Parker (2014), that our tornadic wind profiles tend to vary more between near and far-field inflow regions. This was found throughout most layers in the profile. However, differences in these results could be due to different spatial coverages of the datasets used in this study compared to that used in Parker (2014). Specifically how the Parker (2014) dataset encompasses much of the far-field (greater than 30 kilometers from the mesocyclone) while a bulk of this dataset is contained less than 30 kilometers from the mesocyclone.

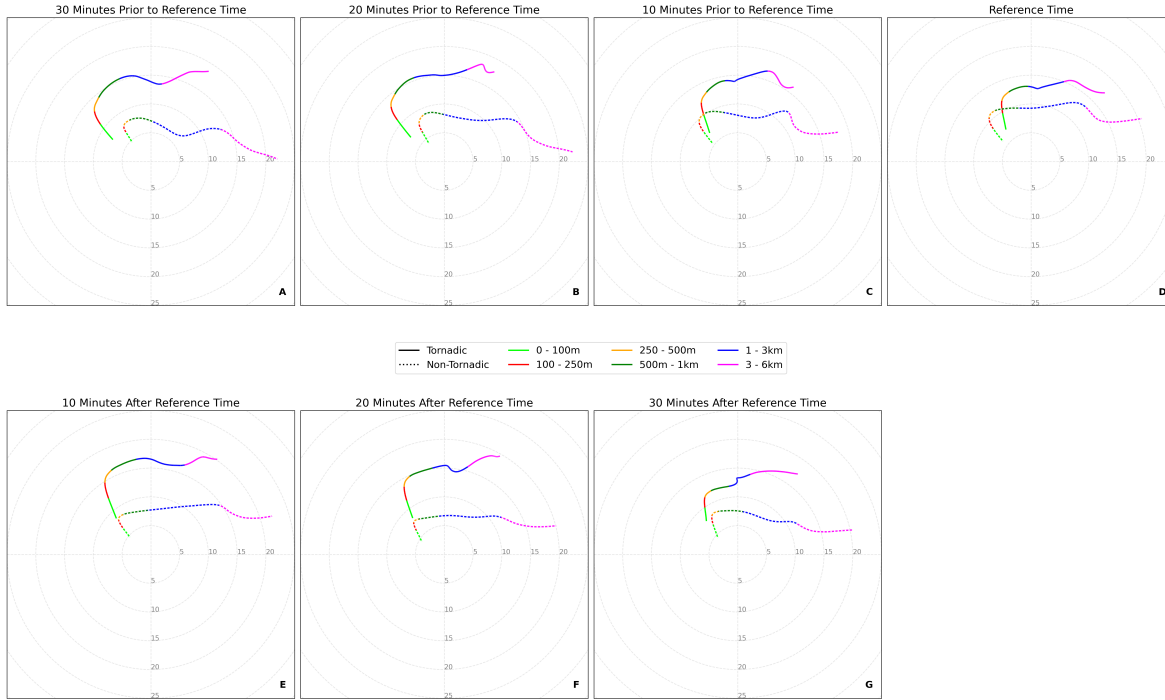


Figure 3.9: GRW profiles (ms^{-1}) for tornadic (solid) and non-tornadic (dashed) in 10-minute bins ranging from 30 minutes prior to 30 minutes after reference time.

Additional methods such as binning data by zonal distances also do not capture sensitivities in the storm environment that occur with greater meridional distance to the mesocyclone.

When an in-depth analysis is completed on various severe parameters such as SRH and bulk wind shear, we note that non-tornadic storm environments tend to vary more with distance from the mesocyclone. This is due to non-tornadic environments having comparable parameters to tornadic environments, although these parameters drop in magnitude significantly with increasing distance to the storm. This is particularly true for variables evaluated in layers from the surface to 1 kilometer. We also note that mid-level variables ($SRH_{3km}/shear_{3km}$) between tornadic and non-tornadic environments contain significant differences, with tornadic parameters varying more in space. These

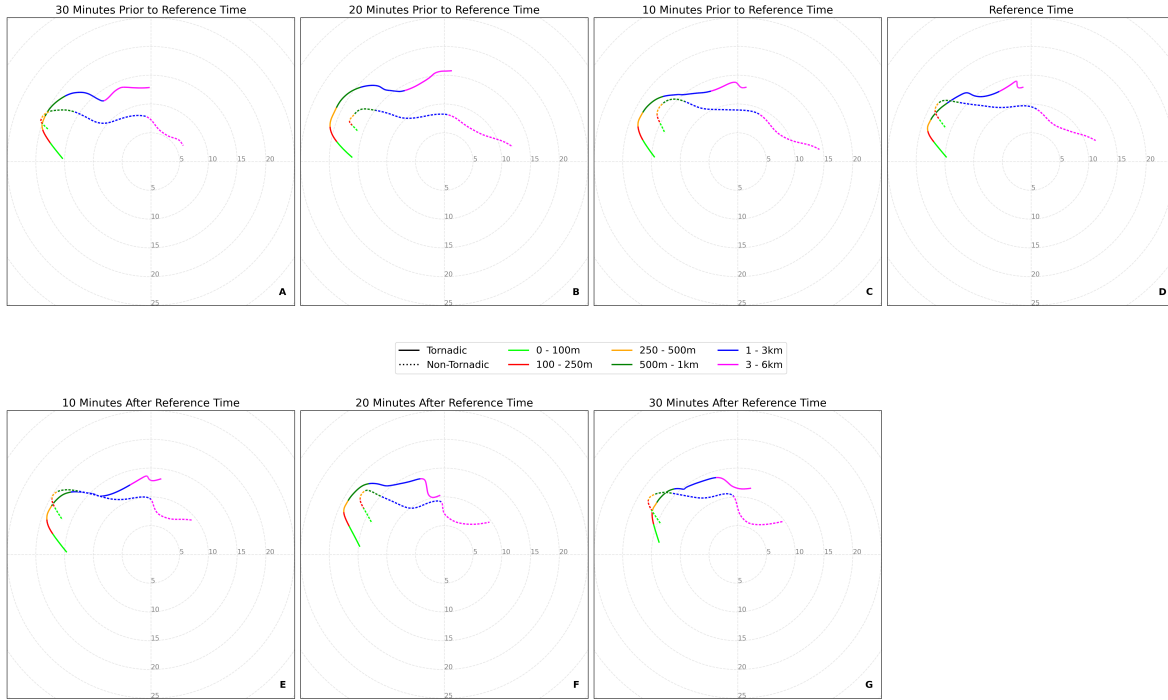


Figure 3.10: SRW profiles (ms^{-1}) for tornadic (solid) and non-tornadic (dashed) in 10-minute bins ranging from 30 minutes prior to 30 minutes after reference time.

variations are driven by overall weakening of SRH with increasing zonal distance to the mesocyclone, caused by lower perturbations from the base-state. Using $shear_{3km}$, we observe greater shear in non-tornadic cases in the 0-3 kilometer layer, with tendencies for non-tornadic storms to perturb this parameter more than tornadic storms. Finally, we address the backing present in the near-surface winds in each storm environment. In space, we find that non-tornadic environments tend to have more backing in the lowest levels throughout most of the spatial bins used in this work, corroborating the results from Parker (2014). Yet in time, this signal was not present likely due to the characteristics of the mesocyclones at the times of the profiles going into these composites.

3.1.2 Storm-Relative Flow in the Storm Environment

One key motivation of this work was to identify the role that SRW plays in storm behavior. Additionally, how the SRW profile varies in tornadic and non-tornadic storm environments is of high interest. Working from the ground up, we can analyze differences in low-level, layer-averaged SRW. Figure 3.11 shows layer averaged values from the surface to 100 (SRW_{100m}), 250 (SRW_{250m}), and 500 meters (SRW_{500m}). Evolutions at each level indicate minimal differences in the SRW profiles in these layers, particularly leading up to the reference time for each composite. This is further supplemented with minimal statistically significant time stamps. This includes only one time of significance at the 5% level combined amongst each plot, and no significant differences at the 1% level. However, a signal that is present in these layers is an enhancement to the storm-relative flow in the 10-20 minute time frame after tornadogenesis in the tornadic composite, one not seen in the non-tornadic composite. In space, we note similar SRW values in the extreme near-field environment (Fig. 3.12). In both environments similar trends with decreasing SRW as distance to the mesocyclone increases are found, directly related to the horizontal length scale at which storm-induced accelerations are felt. While trends supporting greater SRW in the far-field for non-tornadic are evident in Fig. 3.12, these values are associated with significantly higher uncertainty in the composite. These greater uncertainties are likely tied to the variability of values making up the composite mean, and the final value could be skewed to one outlier case. Considering the general weakening of SRW with zonal distance to the mesocyclone, we continue to note greater magnitudes of SRW in tornadic environments (Fig. 3.12). This is likely due to stronger PGF-related accelerations, which can be felt further from the mesocyclone compared to non-tornadic environments. Further analysis is

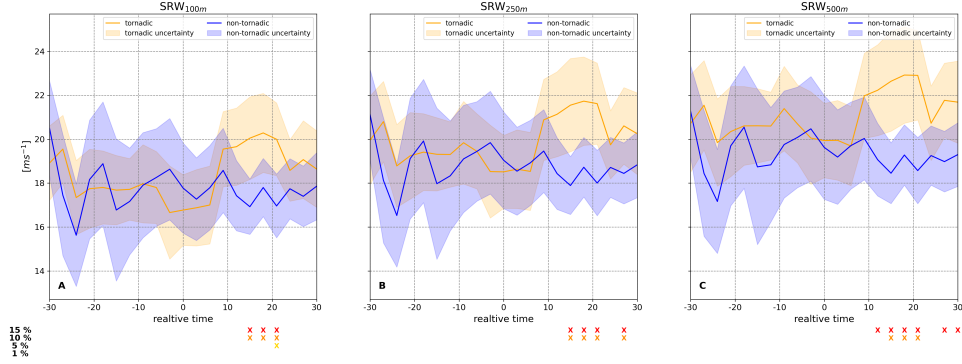


Figure 3.11: SRW_{100m} (A; ms^{-1}), SRW_{250m} (B; ms^{-1}), and SRW_{500m} (C; ms^{-1}) in time. Tornadoic (orange) and non-tornadoic (blue) composites are shown along with the associated 1-sigma uncertainties in each (shaded).

needed to support this works finding of greater low-level SRW in non-tornadoic, far-field environments.

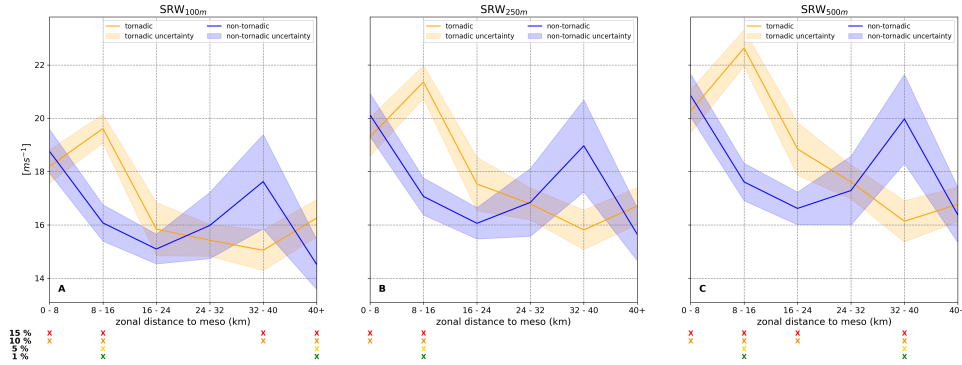


Figure 3.12: SRW_{100m} (A; ms^{-1}), SRW_{250m} (B; ms^{-1}), and SRW_{500m} (C; ms^{-1}) in space. Tornadoic (orange) and non-tornadoic (blue) composites are shown along with the associated 1-sigma uncertainties in each (shaded).

Moving vertically in the profile, Fig. 3.13 shows the layer-averaged SRW values in the mid-levels (1-2 kilometers; SRW_{1-2km} and 1-3 kilometers; SRW_{1-3km}). Greater differences are shown in each plot, signifying greater differences in the profiles in these layers. The previously discussed signal in the tornadoic SRW evolution continues to be

apparent through the mid-levels, although a second signal in the non-tornadic composite becomes evident in the mid-levels. Using both layers in Fig. 3.13, we find increases to the SRW leading up to the maximum v_{rot} in the non-tornadic composite resulting in slightly stronger flow at composite time compared to the tornadic composite. However, a steep decline in the SRW after this time in the non-tornadic composite paired with the increase in the tornadic composite results in significant differences in these profiles after the reference time. Spatial composites of the same parameters continue to highlight the effects of mesocyclone related accelerations in the near-field environment (Fig. 3.14). Non-tornadic SRW stays pretty constant, and increases after about 30 kilometers. Tornadic SRW peaks in the 8-16 kilometer bin, then decreases. Another continuous signal in the mid-level flow is stronger SRW in non-tornadic environments in the far-field environment. Next, time/height diagrams can be made to visualize the entire 0-6km profile for each composite.

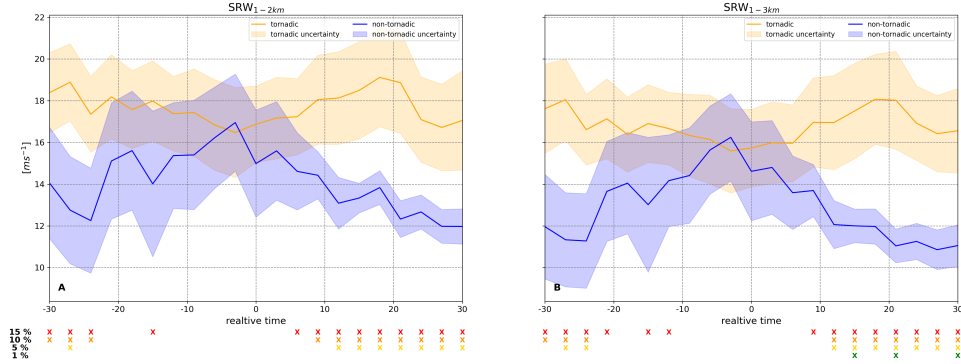


Figure 3.13: SRW_{1-2km} (A; ms^{-1}) and SRW_{1-3km} (B; ms^{-1}) in time. Tornadic (orange) and non-tornadic (blue) composites and the associated 1-sigma uncertainties (shaded) are shown.

Although SRW below 1 kilometer is somewhat larger for the tornadic environments, more notable differences in the profiles are seen above this layer (Figs. 3.15 & 3.16). When highlighting the low-levels in each profile, although tornadic magnitudes tend

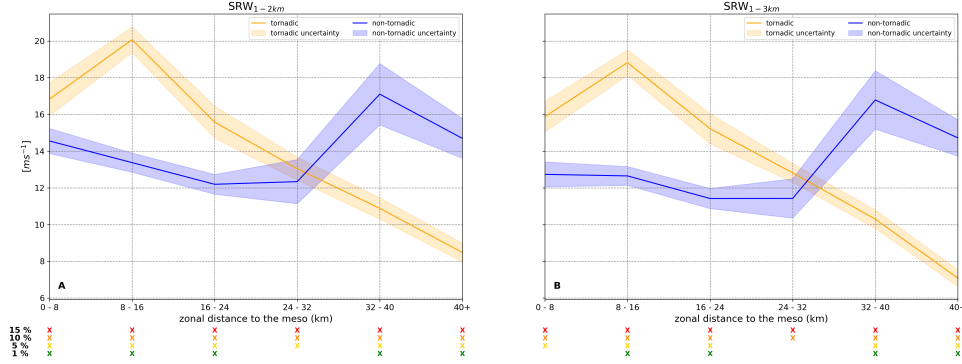


Figure 3.14: SRW_{1-2km} (A; ms^{-1}) and SRW_{1-3km} (B; ms^{-1}) in space. Tornadic (orange) and non-tornadic (blue) composites and the associated 1-sigma uncertainties (shaded) are shown.

to be slightly higher, they are not statistically significant at the 5% confidence level. Spatial composites show similar trends discussed previously in this section. To start, we note an overall decline in the SRW magnitude in the tornadic environment with zonal distance to the mesocyclone (Fig. 3.17). In the non-tornadic environment, we see generally weaker magnitudes of SRW, although Fig. 3.18 better highlights the stronger SRW in the far-field inflow region of non-tornadic environments. To better assess the impact the storms themselves are having on these environments, we can quantify the base-state perturbations for these aforementioned variables.

We can begin by analyzing perturbations of SRW_{100m} , SRW_{250m} , and SRW_{500m} in time. Although not statistically significant at most times, a signal for stronger perturbations in the tornadic environment about 10 - 20 minutes after tornadogenesis is apparent (Fig. 3.19). This is likely what is driving the notable differences in the total SRW discussed previously in this subsection. We also see a trend for increased perturbations in the non-tornadic dataset in the lowest levels leading up to the reference

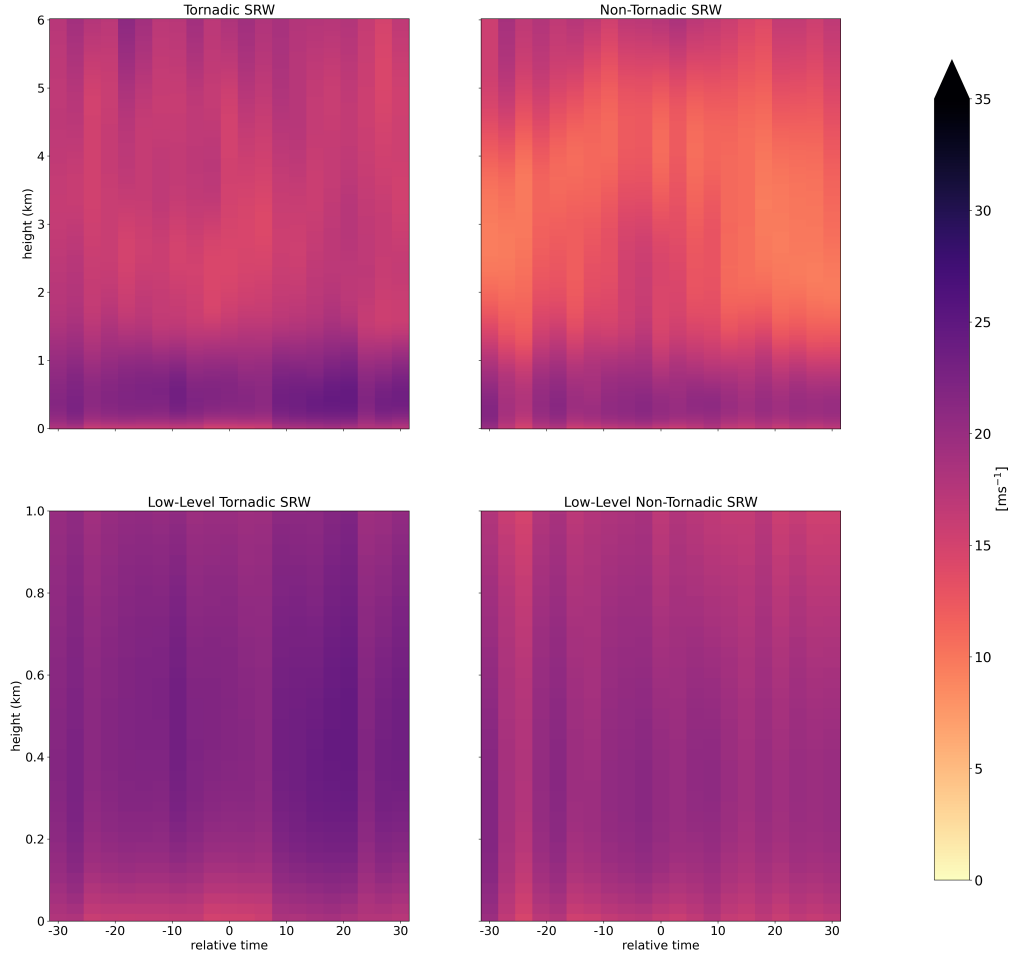


Figure 3.15: Shaded SRW magnitude (ms^{-1}) for tornadic (left) and non-tornadic (right) composites for the 0-6 (top) and 0-1km (bottom) layers in time.

time. These perturbations highlight the storm-induced variability in the storm environment rather than background environmental changes. Therefore in the near-surface layer, it can be hypothesized that the low-level differences in SRW between tornadic and non-tornadic environments leading up to the reference time are due primarily to

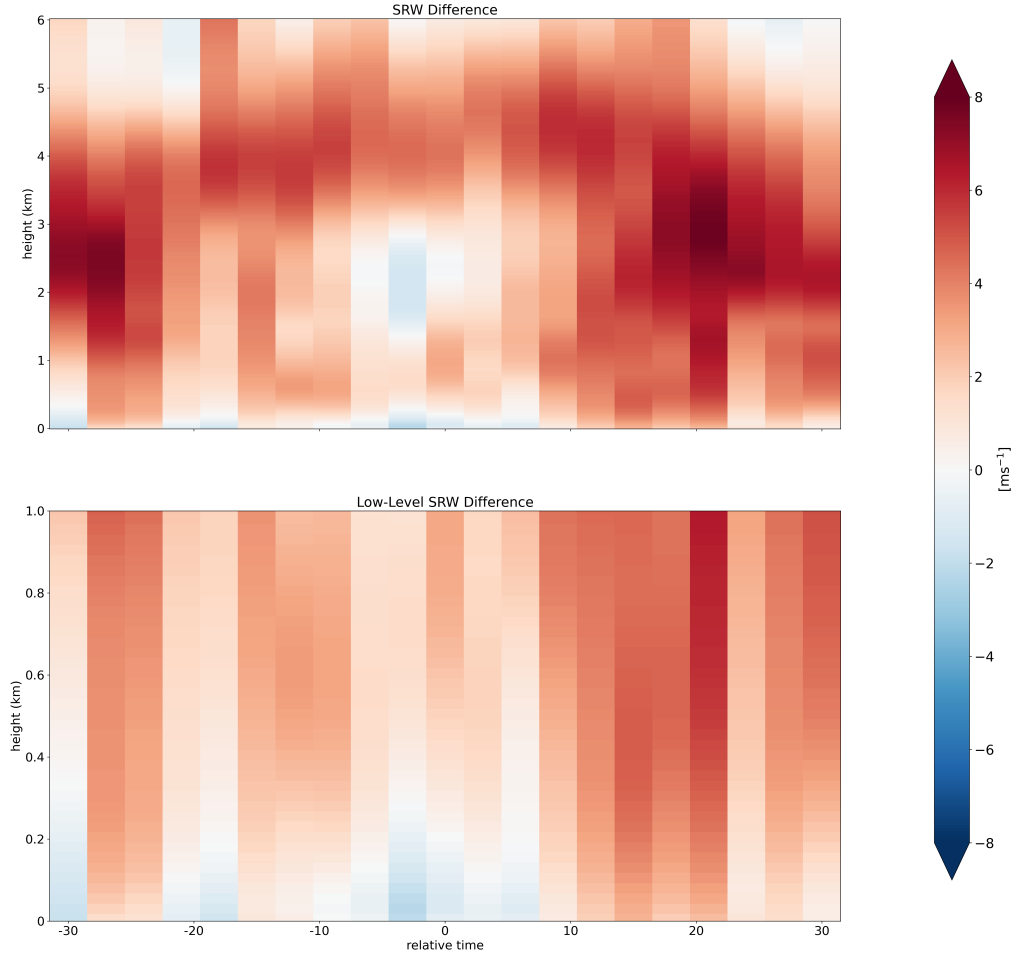


Figure 3.16: Differences in the SRW magnitude (ms^{-1}) between tornadic and non-tornadic composites for the 0-6 (top) and 0-1km (bottom) layers in time.

storm-induced accelerations, and that the base state environments for each are comparable. Moving to the mid-levels, Fig. 3.20 shows a similar story related to the differences in the 1-3 kilometer layer. Significant differences in the perturbations relate directly back to the highest differences in the SRW profile. Therefore these differences

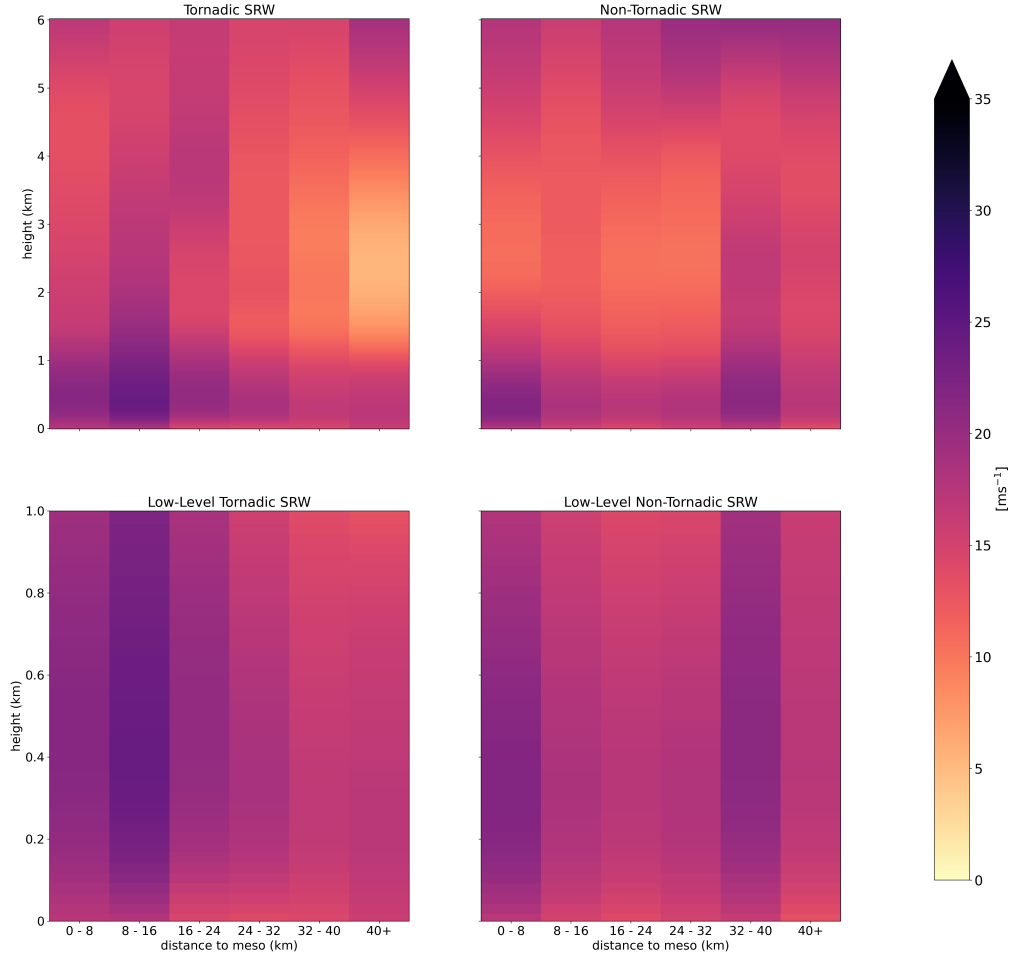


Figure 3.17: Shaded SRW magnitude (ms^{-1}) for tornadic (left) and non-tornadic (right) composites for the 0-6 (top) and 0-1km (bottom) layers in space.

are also likely due to the enhanced perturbations experienced in tornadic environments, and are not related to substantial differences in the base state environments.

Total perturbation profiles are shown in Fig. 3.21, while differences in these perturbations are shown in Fig. 3.22. Differences in perturbations appear more significant

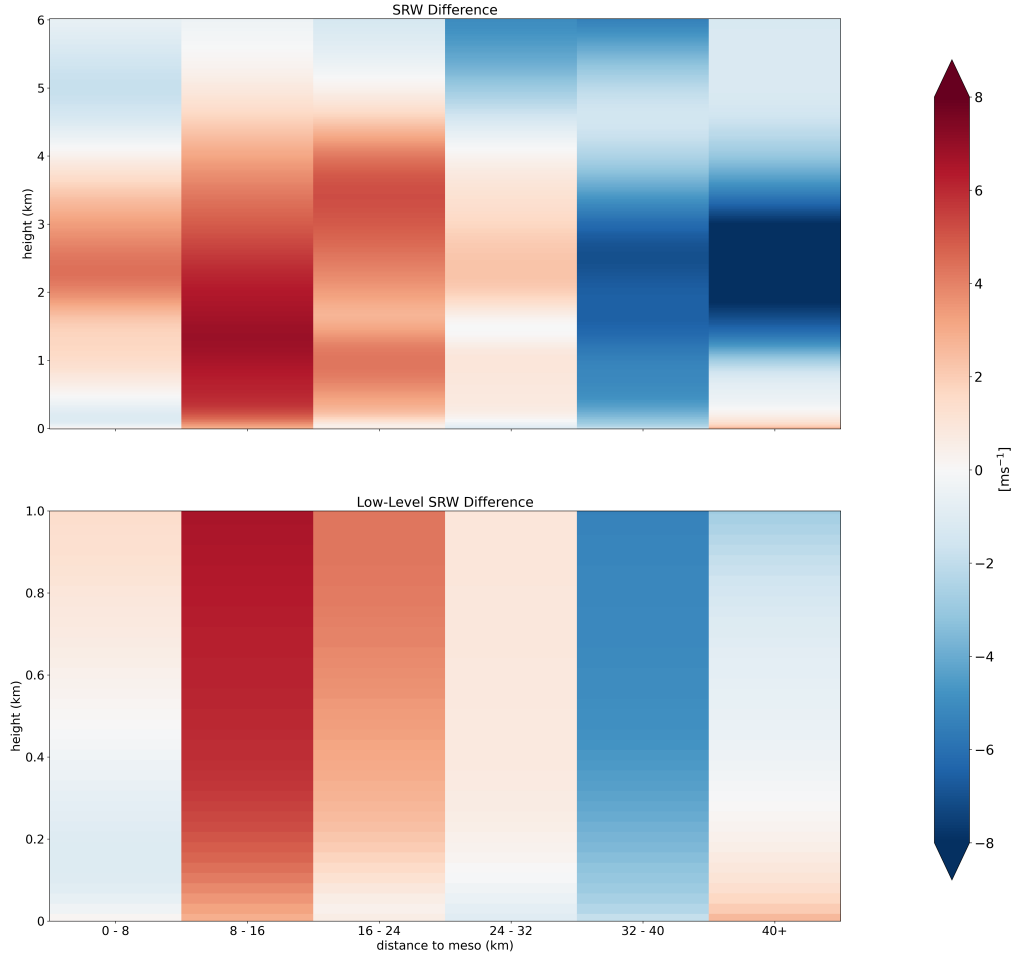


Figure 3.18: Differences in the SRW magnitude (ms^{-1}) between tornadic and non-tornadic composites for the 0-6 (top) and 0-1km (bottom) layers in space.

compared to the overall SRW magnitude, highlighting the driving factor between environmental differences in SRW. Although positive in the entire profile, perturbations 10-20 minutes after tornadogenesis are notable. Corroborating our signal from previous figures, we see greater SRW perturbations in the non-tornadic storm environment near the surface at our reference time. In these figures, we also continue to see the

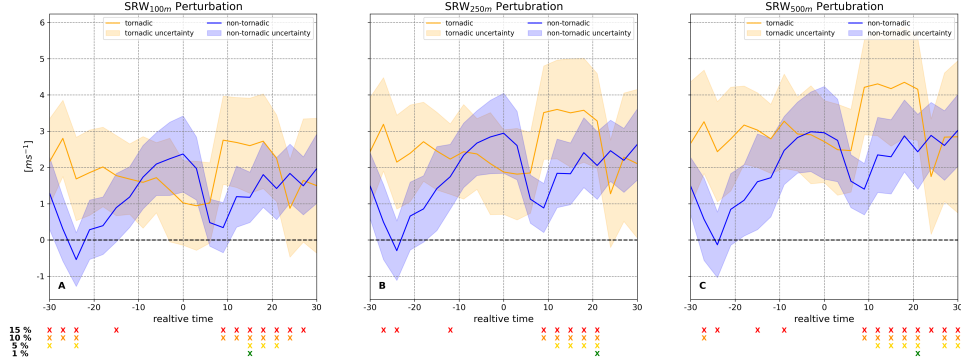


Figure 3.19: Base-state perturbations of SRW_{100m} (A; ms^{-1}), SRW_{250m} (B; ms^{-1}), and SRW_{500m} (C; ms^{-1}) in time. Tornadic (orange) and non-tornadic (blue) composites and the associated 1-sigma uncertainties (shaded) are shown.

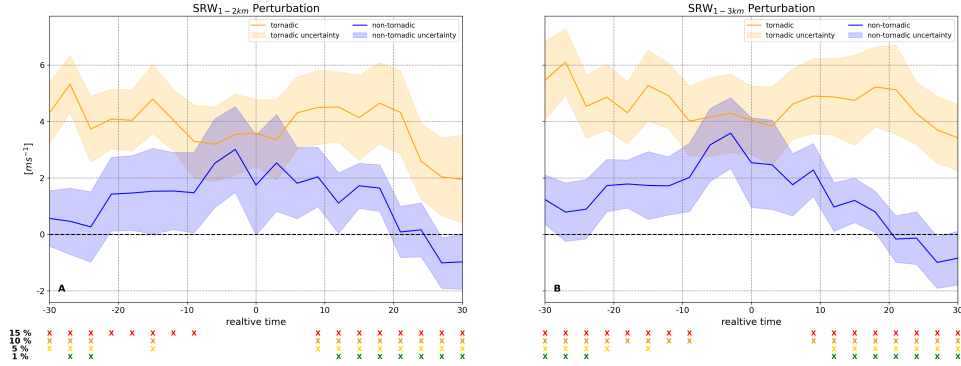


Figure 3.20: Base-state perturbations of SRW_{1-2km} (A; ms^{-1}) and SRW_{1-3km} (B; ms^{-1}) in time. Tornadic (orange) and non-tornadic (blue) composites and the associated 1-sigma uncertainties (shaded) are shown.

perturbations driving the overall environmental differences, highlighting the impact on storm-induced perturbations from discriminating between these environments. Observing spatial SRW perturbation differences, we can note that non-tornadic storms tend to perturb their environments more in the far-field where there has been found to be greater SRW magnitudes in the overall storm environment (Fig. 3.23). Greater tornadic perturbations throughout much of the near-field profile also exist, likely indicative to more intense mesocyclones driving greater flow accelerations felt over a larger spatial scale. In addition to quantifying SRW throughout the profile as well as

highlighting SRW in particular levels, we can assess the importance of SRW in other severe parameters such as SRH.

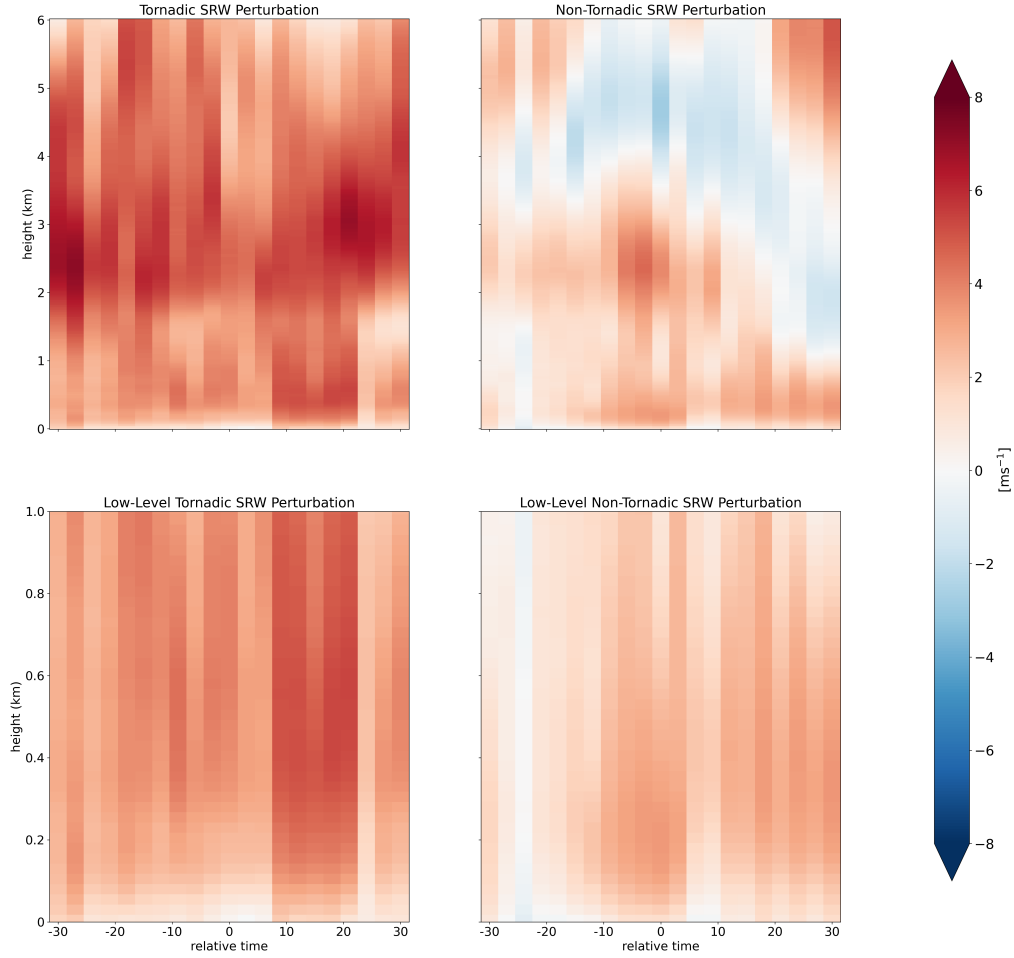


Figure 3.21: Perturbations in SRW (ms^{-1}) for tornadic (left) and non-tornadic (right) storm environments in time in the 0-6 (top) and 0-1 (bottom) kilometer layers.

To this point, differences in SRW between tornadic and non-tornadic environments have been addressed at length. However, it is believed that the forecasting skill in SRH

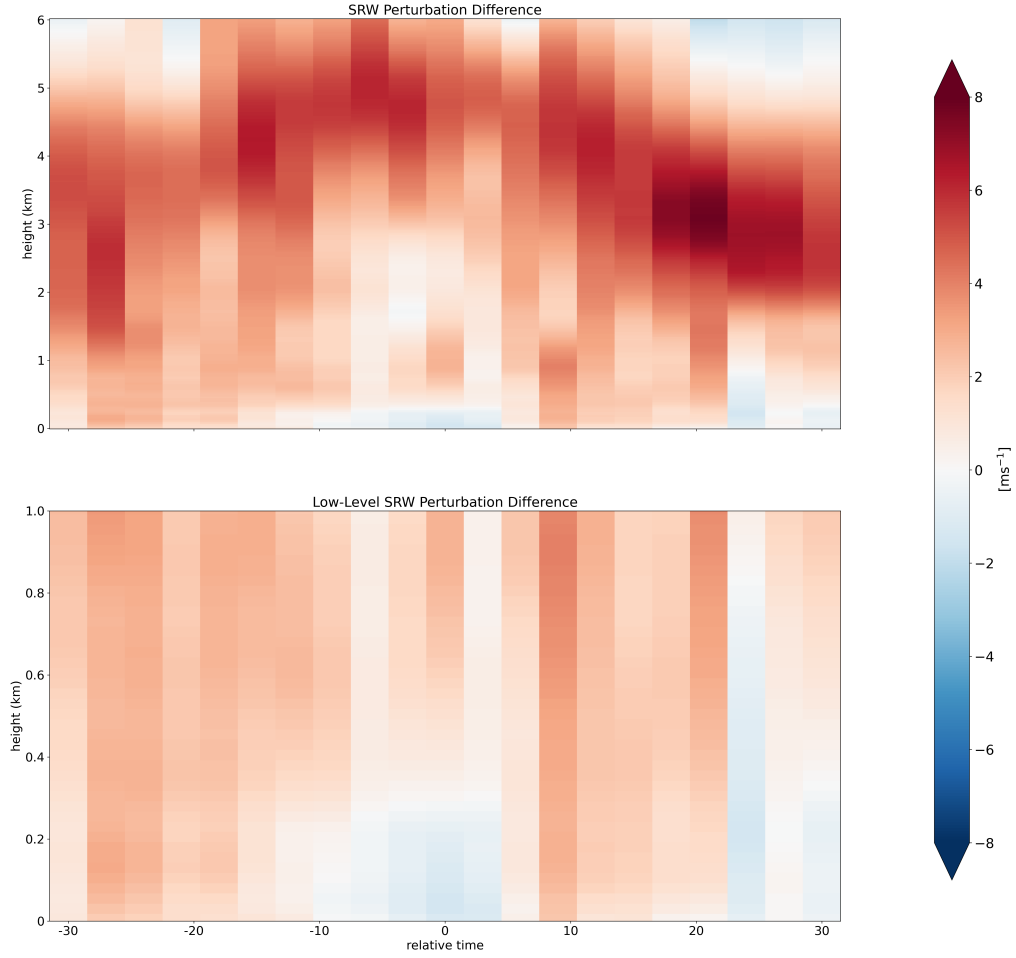


Figure 3.22: Perturbation differences in SRW (ms^{-1}) between tornadic and non-tornadic storm environments in time over the 0-6 (top) and 0-1 kilometer layers (bottom).

comes from streamwise vorticity (ω_s) versus SRW (Peters et al. 2023). To better address these differences, we can begin in the lowest 500 meters to find which parameter correlates higher with the SRH time series in the layer. Figure 3.24 breaks down the layer averaged ω_s and SRW in the surface to 500 meter layer ($\omega_{s:500m}$), along with the

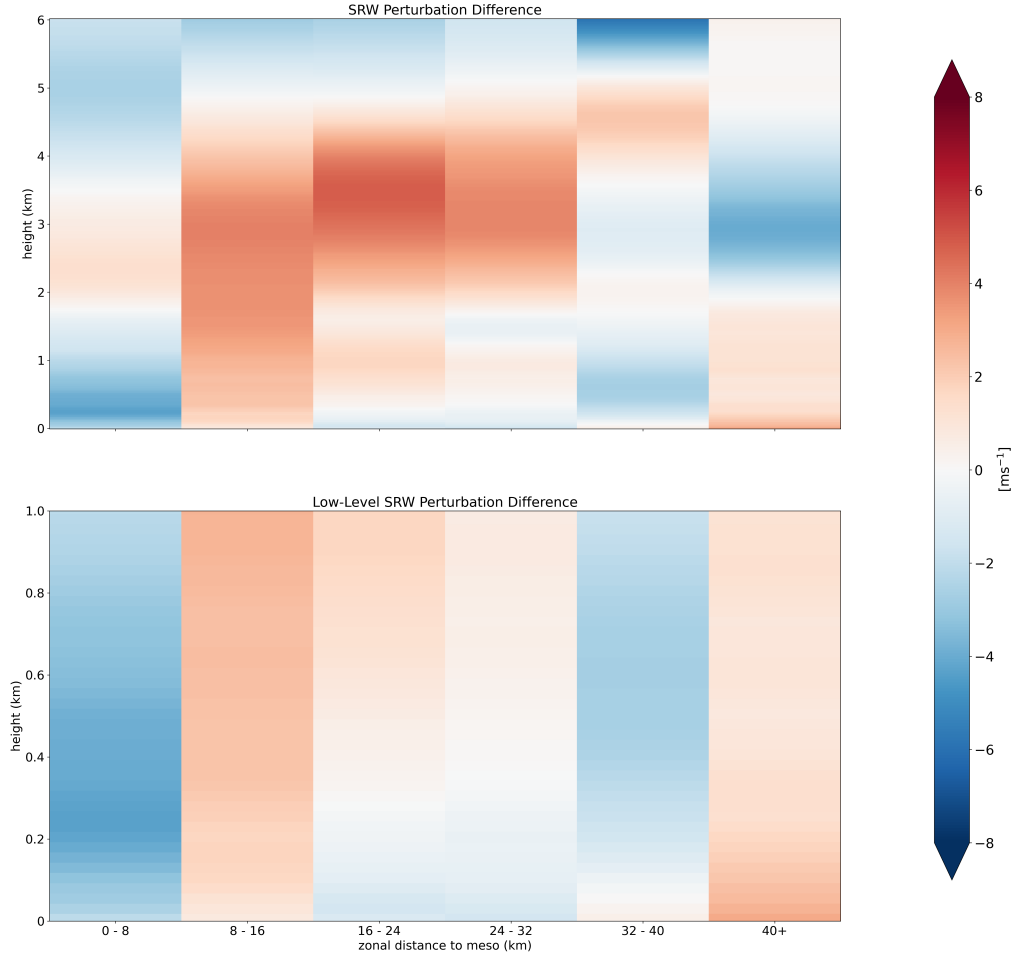


Figure 3.23: Perturbation differences in SRW (ms^{-1}) between tornadic and non-tornadic storm environments in space over the 0-6 (top) and 0-1 kilometer layers (bottom).

resulting SRH in the same layer. Initial analysis shows strong similarities in the SRW evolution, although the differences in final SRH are apparent and cannot be related solely to significant differences in the SRW. We note higher ω_s in the tornadic storm environment which presumably leads to the resulting differences in SRH. However, we

can more directly compare how each variable in the tornadic and non-tornadic environments correlate with the SRH time series by computing the correlation coefficients of each variable to the final SRH values:

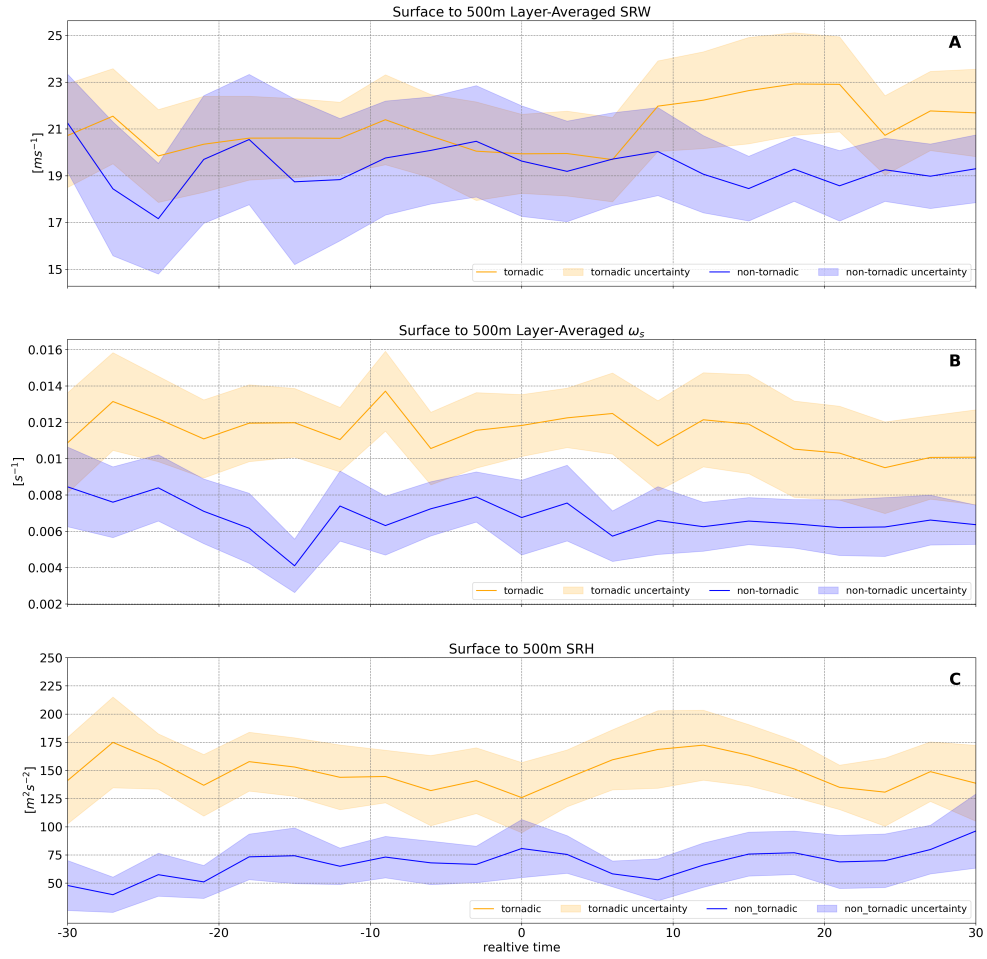


Figure 3.24: SRW_{500m} (A; ms^{-1}), $\omega_{s:500m}$ (B; s^{-1}), and SRH_{500m} (C; m^2s^{-2}) for tornadic (orange) and non-tornadic (blue) time composites with associated shaded one-sigma uncertainties.

Variable	Correlation
SRW _{500m}	0.304
$\omega_{s:500m}$	0.468

Table 3.2: Pearson correlation coefficients between SRH_{500m}, SRW_{500m}, and $\omega_{s:500m}$ in time within tornadic environments.

Variable	Correlation
SRW _{500m}	0.070
$\omega_{s:500m}$	0.424

Table 3.3: Pearson correlation coefficients between SRH_{500m}, SRW_{500m}, and $\omega_{s:500m}$ in time within non-tornadic environments.

In both tornadic and non-tornadic environments, the resulting SRH appears correlated higher with the streamwise vorticity in the same layer. However, increased correlation between SRH and SRW in tornadic environments (compared to the resulting correlation in non-tornadic environments) highlights the greater impact that SRW could be providing in these particularly intense environments. In non-tornadic environments, these correlation values are significantly different, showing the increased differences in ω_s in these scenarios. Table 3.4 further illustrates the improved correlation of ω_s and SRH when combining both tornadic and non-tornadic time series.

Variable	Correlation
SRW _{500m}	0.677
$\omega_{s:500m}$	0.882

Table 3.4: Pearson correlation coefficients between SRH_{500m}, SRW_{500m}, and $\omega_{s:500m}$ in time within tornadic and non-tornadic environments.

In summary, much remains unknown regarding the impact of the SRW profile on tornadic dynamics. However it is evident that there are notable differences between the SRW profiles in tornadic versus non-tornadic storm environments. Stronger magnitudes of SRW in much of the 0-6 kilometer profiles in tornadic storm environments with time are found, particularly above 1 kilometer. These differences are also apparent in the storm-induced component of the profile with greater perturbations to the SRW

profile in tornadic environments. What this analysis of SRW in time also provides is the possible relationships between storm-scale dynamics and the associated storm environments; in particular, the trends of SRW in and around reference time for tornadic and non-tornadic environments, which has not been documented in the literature. For tornadic environments, there appears to be an environmental response to an ongoing tornado in the SRW profile on a lag-time of 10-20 minutes. In both scenarios, these storm-induced accelerations are likely being driven by the PGF associated with low-level circulations whether that is a tornado or enhancements to the low-level mesocyclones in non-tornadic storms. In space, we find notable differences in the SRW profiles in the near-field with tornadic environments showing larger SRW. In the transition to the far-field environment, non-tornadic storms appear to have greater magnitudes of SRW. Using this compositing method, we can also quantify the length scale at which mesocyclone-induced flow accelerations are felt in the storm environment. In tornadic environments, we note larger perturbation values through the 24-32 kilometer bin compared to non-tornadic environments. This is compared to non-tornadic environments, where storm-induced perturbations are strongest in the 0-8 kilometer bin. These findings make the hypothesis that SRW carries little skill when differentiating tornadic from non-tornadic storm environments difficult to accept. Aside from environmental relationships to storm dynamics, we analyzed the relationship between SRH and the variables that make up the final quantity. This analysis confirmed via observations that the skill from SRH is provided primarily by the streamwise vorticity in the layer, with SRW being of secondary importance. An important note that this analysis was done in the lowest 500 meters, relationships in deeper layers could provide different findings and were not explored. A deeper dive into the evolution of vorticity in the storm environment will be discussed at greater lengths later in this section.

3.1.3 Extreme Low-Level Environmental Characteristics

One of the most unique aspects of this work is the dataset obtained in the lowest levels of the storm environment above the ground. Previous research efforts have surrounded identifying the skill in these low level parameters (e.g., Coffey et al. 2019; Coniglio and Thompson 2024), with varying results, given the lack of temporal or vertical spatial resolution in the underlying datasets. A goal of this work is to identify which parameters, and at which layers, provide the most statistically significant differences between tornadic and non-tornadic storm environments.

We first continue to explore with the evolution of SRH at various layers in both time and space. Figure 3.25 shows these time series plots, and initial analysis shows large disparities in the skill provided by SRH evaluated from the surface to 3 kilometer layer and the subsequently lower levels. Using the provided statistical significance information, we can quickly dismiss SRH_{3km} when establishing a layer which provides the most discrimination between tornadic and non-tornadic environments in this dataset. However we see roughly similar skill in using both SRH_{500m} and SRH_{1km} . In space, we can refer back to Fig. 3.4. Although SRH_{3km} appears to provide slightly better skill in space than in time, we note that SRH_{500m} and SRH_{1km} continue to provide the most skill. To this point, it appears as though each layer is similarly skillful, and that using SRH_{500m} does not add substantially more skill than SRH_{1km} in both time and space. Yet it is still unknown whether these SRH differences are present in the ambient environment or they are due to storm-induced perturbations.

Figure 3.26 addresses these differences. Similar to Fig. 3.25, we see significant differences in the perturbation evolution in both SRH_{500m} and SRH_{1km} whereas SRH_{3km} continues to show minimal significant differences even in the perturbation component.

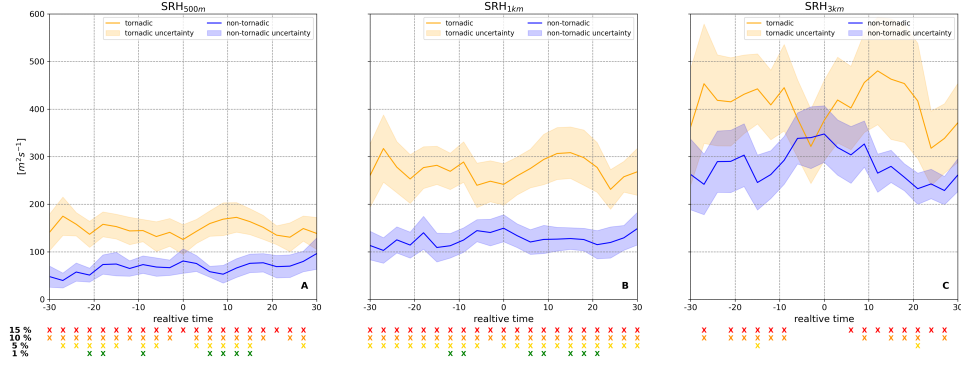


Figure 3.25: SRH_{500m} (A; m^2s^{-2}), SRH_{1km} (B; m^2s^{-2}), and SRH_{3km} (C; m^2s^{-2}) for tornadic (orange) and non-tornadic (blue) storm environments. Statistical significance markers at various levels are indicated below panels at the respective time stamp with associated one-sigma uncertainties (shaded).

Similar interpretations are made when viewing the SRH perturbations composited in space (Fig. 3.6).

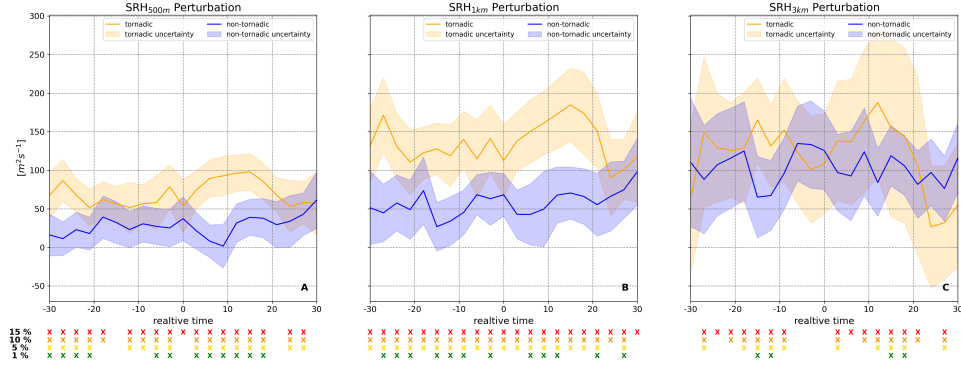


Figure 3.26: SRH_{500m} (A; m^2s^{-2}), SRH_{1km} (B; m^2s^{-2}), and SRH_{3km} (C; m^2s^{-2}) perturbations for tornadic (orange) and non-tornadic (blue) storm environments. Associated one-sigma uncertainties are shaded.

Overall, when using SRH to discriminate between tornadic and non-tornadic environments, both SRH_{500m} and SRH_{1km} seem to provide equitable skill; significantly more skill than deeper-layer SRH in this dataset. Differences in these results compared to Coniglio and Parker (2020), Coffey et al. (2019), and other environment studies are

due to many factors, including the datasets used and the quality of storms analyzed in this analysis (e.g., particularly strong non-tornadic storms are targeted in field project efforts). This layer-depth discrepancy can be further addressed using other severe parameters such as bulk shear. Coniglio and Thompson (2024) found that the surface to 1 kilometer bulk shear provided more skill compared to the same quantity over the surface to 500 meters and 6 kilometer layers. Shallower quantities were not evaluated in that work because of the lack of vertical resolution near the ground in the dataset used in that study, but will be in this work.

Figure 3.27 highlights the evolution of shear_{100m} , shear_{250m} , and shear_{500m} in time. Differences are seen between the two environments at all times, with larger shear in the tornadic environments. However, digging deeper into the statistically significant differences, using lower-layer averaged values does not add additional skill to that of the surface to 500 meter shear. Additionally, surface to 100 meter shear provides notably less skill compared to surface to 250 and 500 meter variables, specifically in and around the reference time for each composite. The differences in composite differences here could be due to the wind profile in the surface layer, and its tendency to follow the log-law relationship more closely compared to deeper layers. The differences of shear at various layers in space has already been discussed in prior sections (Fig. 3.5), with the spatial evolution of shear layers in Fig. 3.27 matching the same trends (not shown).

Moving up in the profile, we can observe surface to 1 and 3 kilometer shear values in Fig. 3.28. Similar to the SRH evaluation, we note that once the layer moves into the mid-levels through 3 kilometers, much of the previously provided skill is gone in this dataset. However, unlike in SRH, it is apparent that the surface to 1 kilometer shear is not the most skillful. Here, the differences in shear evaluated to 500 meters has notably more differences in the mean composites and uncertainties than shear evaluated to 1

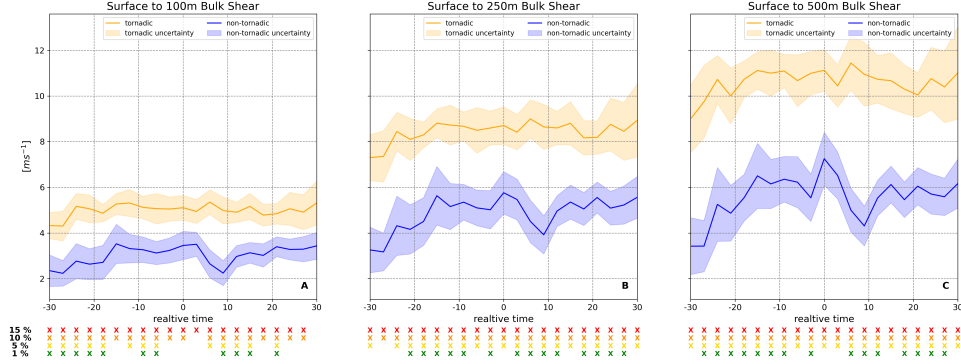


Figure 3.27: Shear_{100m} (A; ms^{-1}), shear_{250m} (B; ms^{-1}), and shear_{500m} (C; ms^{-1}) in time for tornadic (orange) and non-tornadic (blue) composite storm environments. One-sigma uncertainties are shaded for each composite at each level.

kilometer, especially with more significant bins at greater confidence levels. This is likely due to muted differences in the GRW above 500 meters, although a more in-depth look into the GRW evolution will take place later in this section. We can also identify whether these differences in shear at the lowest levels are due to storm-induced accelerations or differences in the overall wind profiles.

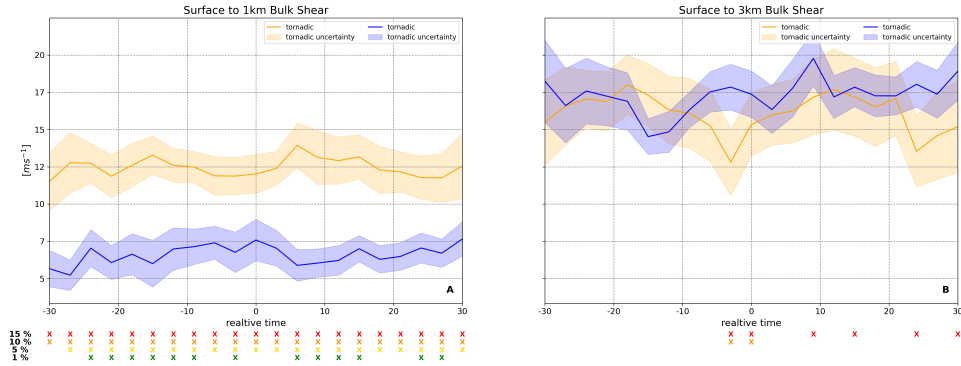


Figure 3.28: Bulk wind shear (ms^{-1}) evaluated from the surface to 1 (A), and 3 kilometers (B) for tornadic (orange) and non-tornadic (blue) composite storm environments. One-sigma uncertainties are shaded for each composite at each level.

Figure 3.29 addresses the perturbations in shear in the most skillful depths deemed by the previous plots, surface to 250 and 500 meters as well as surface to 1 kilometer

shear. In similar fashion to SRH, large perturbations are present in the shear profiles, with greater perturbations in the tornadic time series.

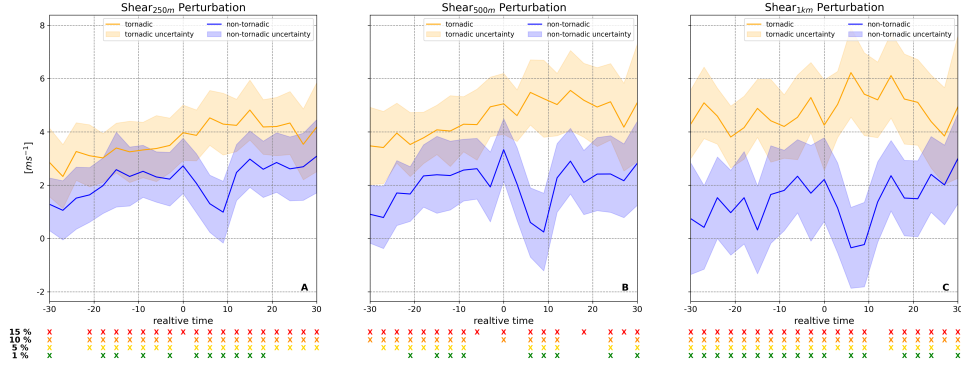


Figure 3.29: Bulk wind shear perturbations (ms^{-1}) evaluated from the surface to 250m (A), 500m(B), and 1km (C) for tornadic (orange) and non-tornadic (blue) composite storm environments. One-sigma uncertainties are shaded for each composite at each level.

To this point in the work, the value in low-level parameters has varied drastically depending on the variable. As discussed earlier in this section, the SRW profiles for both tornadic and non-tornadic environments contained smaller differences compared to other parameters and levels. SRW averaged over the 1-2 and 1-3 kilometer layers showed more differences than low-level SRW. However, SRH evaluated in the surface to 500 meter and 1 kilometer layers showed more skill compared to deeper layers. This latter result reflects the differences in ω_s in low levels while also supporting the findings from previous studies such as Coffey et al. (2019) and Coniglio and Thompson (2024). Throughout the rest of chapter 3, we will dive into variables such as GRW and horizontal vorticity to further evaluate this hypothesis.

3.2 Additional Findings

3.2.1 Ground Relative Winds

Although the ground-relative winds (GRW) have shown skill in discriminating between tornadic and non-tornadic environments (e.g., Nowotarski and Jensen 2013), it was not an initial motivator to this work. However, given some of the similarities and differences in GRW related parameters such as bulk shear, an in depth investigation into the GRW profiles is warranted. In a similar approach to the SRW analysis, we can begin with a bottom-up approach. Figure 3.30 addresses the GRW in the surface to 100, 250, and 500 meter layers in time.

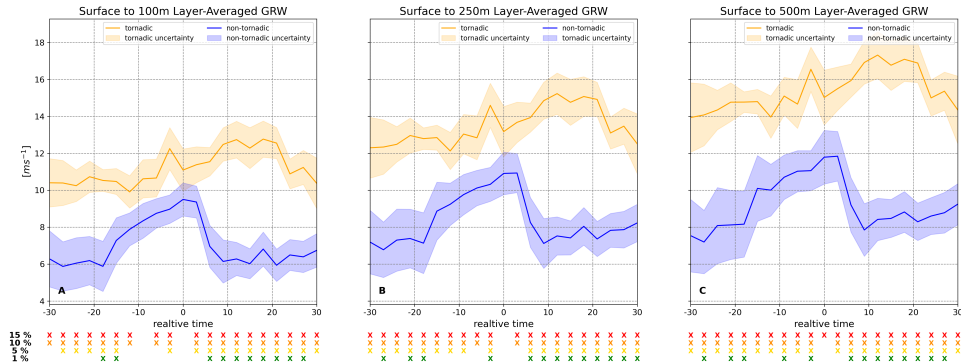


Figure 3.30: Layer-averaged GRW from the surface to 100 (A), 250 (B), and 500m (C) for tornadic (orange) and non-tornadic (blue) composite storm environments. One-sigma uncertainties are shaded for each composite at each level.

Compared to SRW (Fig. 3.11), we see notable differences in these layer-averaged values of GRW with significantly higher GRW in the tornadic storm environments in time. Using Figure 3.31, we can also gain confidence in the base state environmental differences. Although tornadic storms tend to perturb their GRW profiles more than non-tornadic storms, these perturbations do not address the total differences seen in

the overall environments. Therefore, it is sufficient to say that when evaluating low-level storm environments, the GRW profile provides more skill compared to flow in the storm-relative framework in this dataset.

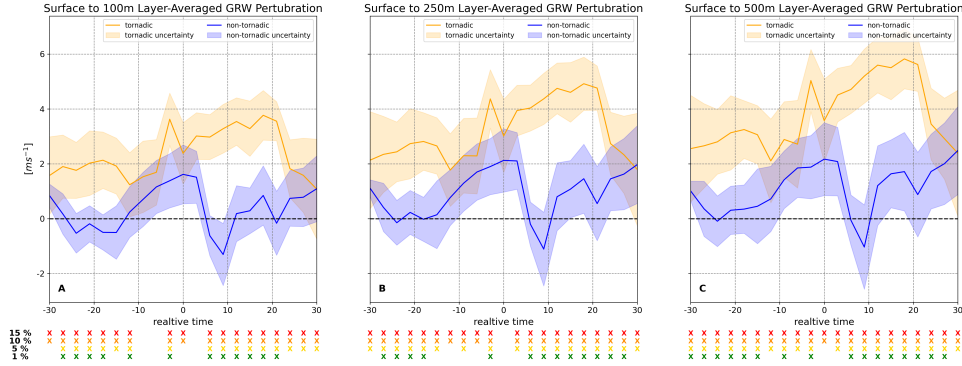


Figure 3.31: Layer-averaged GRW perturbations from the surface to 100 (A), 250 (B), and 500m (C) for tornadic (orange) and non-tornadic (blue) composite storm environments. One-sigma uncertainties are shaded for each composite at each level.

Moving up to the mid-levels (Fig. 3.32), we continue to see notable differences in the tornadic and non-tornadic values. This is significant as SRW differences were primarily in the mid-levels while GRW discriminatory skill is present throughout the surface to 3km layers. These layer-averaged parameters highlight the potential benefit of using GRW over SRW when it comes to forecasting the tornadic potential of a storm environment, a deeper look into the GRW over the entire 0-6km layer can uncover patterns and reasoning behind this skill.

Figure 3.33 shows the GRW magnitude, with stark differences, particularly in the low-levels. This matches our previously analyzed figures. However, we also note strong GRW in the 2+km level in non-tornadic cases (Fig. 3.34), greater than that in the

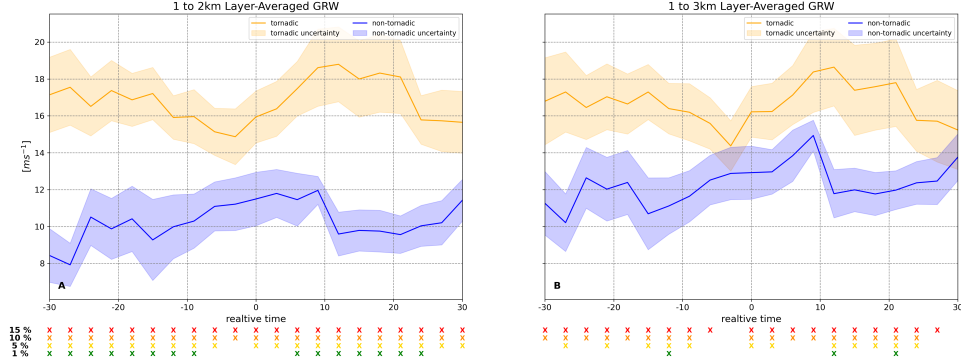


Figure 3.32: Layer-averaged GRW in the 1-2 (A) and 1-3km (B) layers for tornadic (orange) and non-tornadic (blue) composite storm environments. One-sigma uncertainties are shaded for each composite at each level.

tornadic composite. Isolating the perturbed component of these environments, we continue to see a signal for greater perturbations in the tornadic environments throughout much of the 0-6km profile (Fig. 3.35).

Unlike for SRW, much of the perturbations in GRW are focused in the lowest 2 kilometers in tornadic storm environments. For SRW, the larger perturbations were found above 2 kilometers. However, there is a continued signal for significant perturbations on a 10-20 minute lag time compared to tornadogenesis. This signal is not apparent in the GRW profile for non-tornadic environments. In addition to the added low-level skill, another signal unique to GRW is the trend of negative perturbations in the mid-upper levels in both tornadic and non-tornadic environments. In summary, we see added skill in using GRW as a discriminatory variable in forecasting between tornadic and non-tornadic supercells, particularly in the low-level profiles. When focusing on these layers below 500m, we find GRW provides the most skill out of all variables to this point.

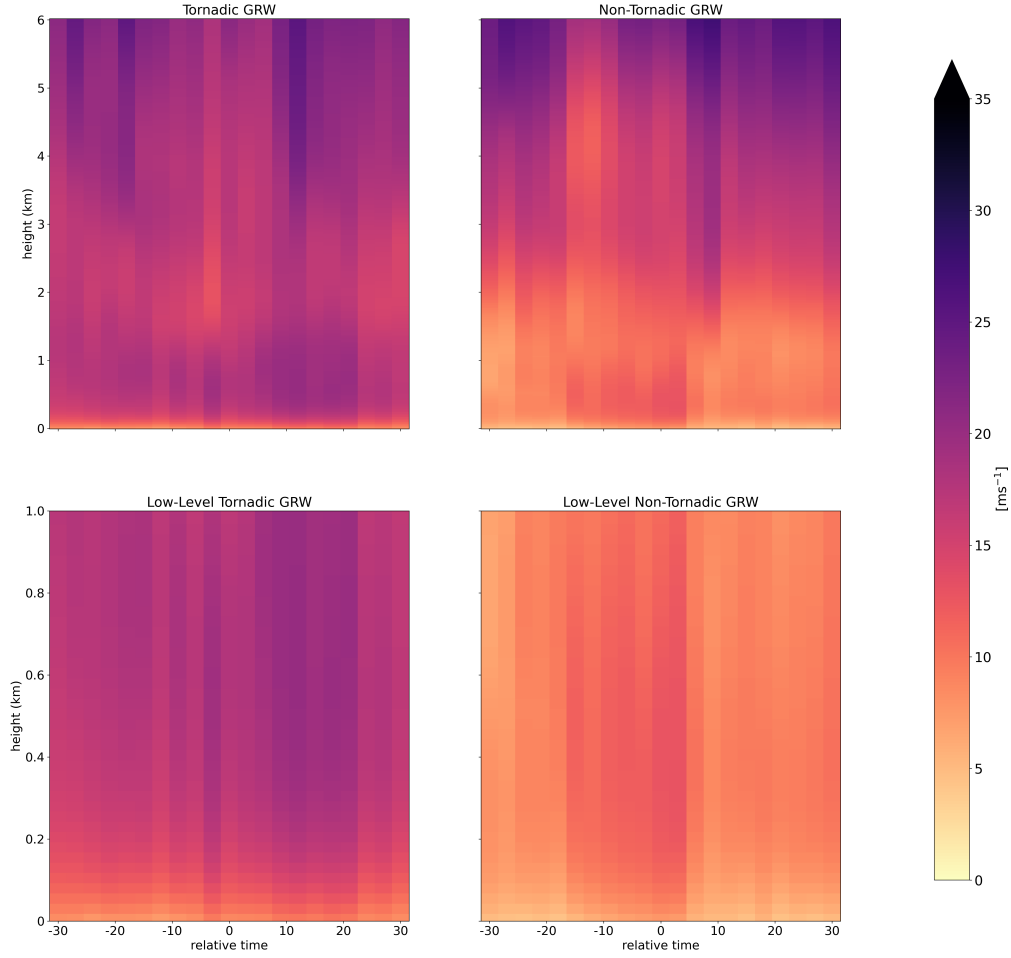


Figure 3.33: Time-height diagram of GRW (ms^{-1}) in the 0-6km layer in tornadic (left) and non-tornadic (right) storm environments.

3.2.2 Vorticity

To this point, the effects of vorticity as they relate to severe parameters such as SRH have been addressed. However the differences in overall quantified vorticity in each storm environment have not been discussed. Here, we aim to identify the differences in the horizontal vorticity present in tornadic and non-tornadic storm environments

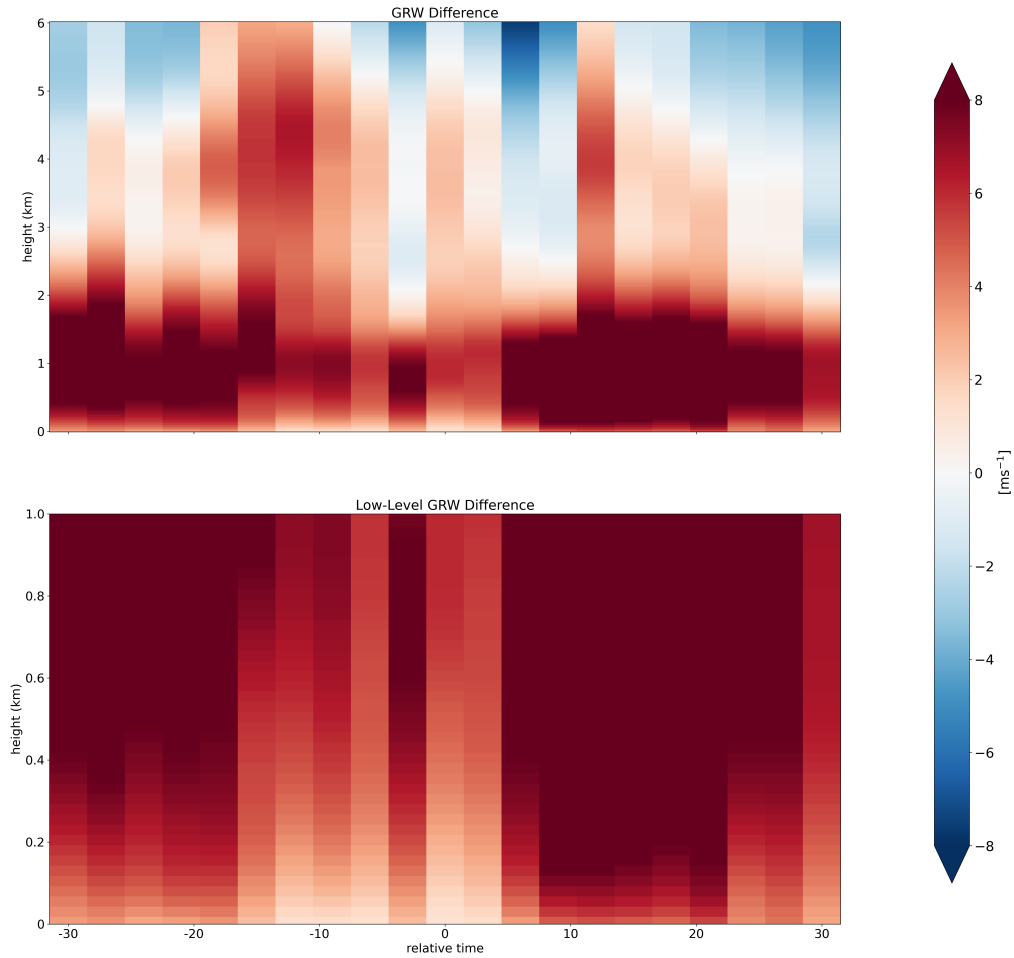


Figure 3.34: Time-height diagram of GRW (ms^{-1}) difference in the 0-6km layer between tornadic and non-tornadic storm environments.

while breaking down these quantities into their streamwise and crosswise components. In addition to the streamwise and crosswise components, the streamwiseness in the horizontal vorticity, or the percentage of vorticity that is streamwise, is shown.

Figure 3.36 shows each of these components throughout the entire 0 to 6 kilometer layer, while Fig. 3.37 highlights the differences in the tornadic and non-tornadic

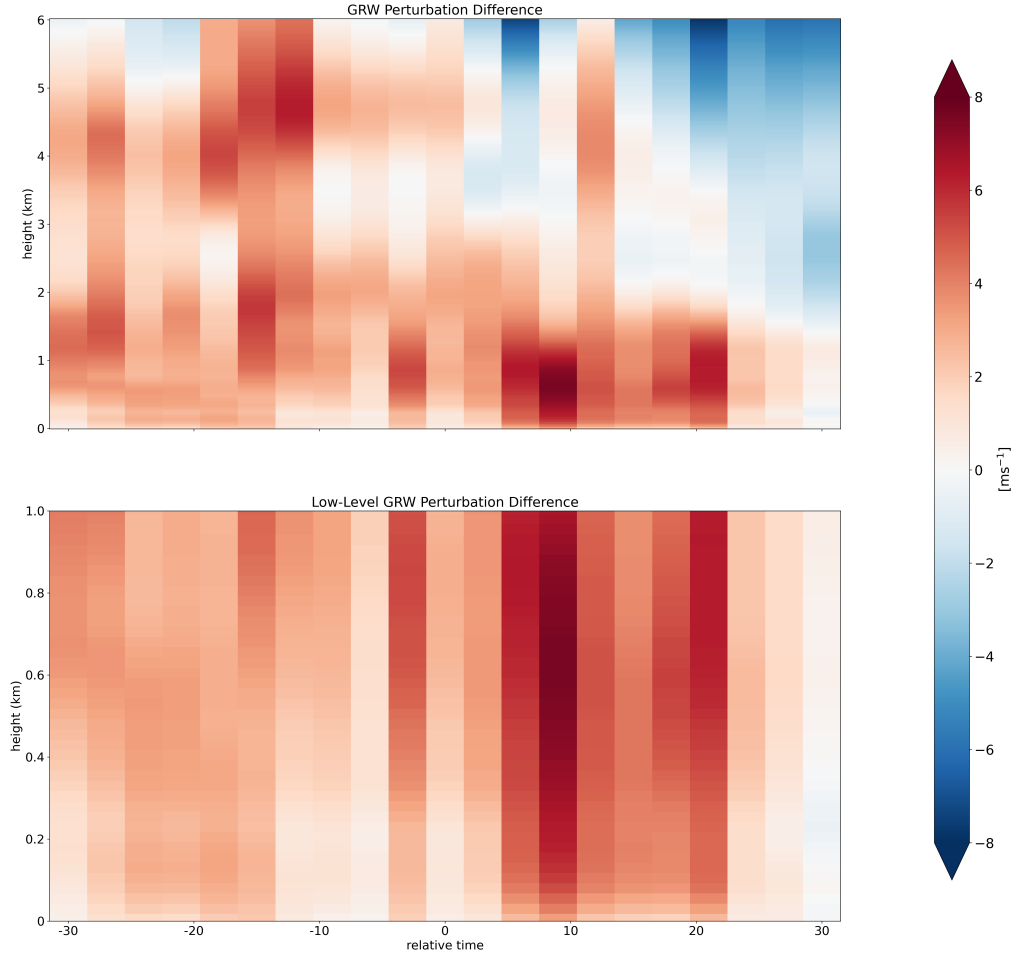


Figure 3.35: Time-height diagram of GRW (ms^{-1}) perturbation difference in the 0-6km layer between tornadic and non-tornadic storm environments.

environments. Before highlighting the lower levels, we note that a majority of the environmental vorticity appears to be concentrated in the surface layer. Differences also show the expected signal of larger streamwise vorticity in tornadic environments (e.g., Davies-Jones 1984; Davies-Jones et al. 1990; Coffer and Parker 2017). There is

also notably more crosswise vorticity in tornadic environments. This result is particularly novel as prior storm environment research has found conflicting results. Using RUC/RAP profiles, Markowski et al. (2003) found that there was more crosswise vorticity in non-tornadic storm environments while Esterheld and Giuliano (2008) and Coffey et al. (2019) concluded similarly through critical angles closer to 90° . This work is the first to highlight, through a longitudinal, observations study, that there is greater crosswise vorticity in tornadic environments.

It has been suggested that the ratio of streamwise to crosswise vorticity (Coffey et al. 2019), or the percentage of the vorticity that is streamwise (Nixon and Allen 2022) may be a discriminator of tornadic and non-tornadic environments. However, we can quantify the streamwiseness to see if the ratio of streamwise to crosswise vorticity is more skillful rather than the overall quantification of each vorticity component. Throughout the entire surface to 6 kilometer profile we note that over a vast majority of the time series, there are non-significant differences in the tornadic and non-tornadic streamwiseness values (Fig. 3.37). Figs. 3.36 & 3.37 show the clear importance of friction on generating the largest vorticity magnitudes in the column. Therefore, we now zoom in to investigate the evolution of vorticity in the lowest 1 kilometer.

Consistent for both streamwise and crosswise vorticity, we better see the concentration of the highest values in the lowest 250 meters (Fig. 3.38), or the surface layer. Figure 3.39 highlights this friction layer trend by showing the differences in magnitudes in tornadic and non-tornadic environments. We can relate the reasoning for the increased crosswise vorticity in the tornadic environment as the effect the increased GRW has on vorticity. Given surface friction, increased GRW very near to the ground

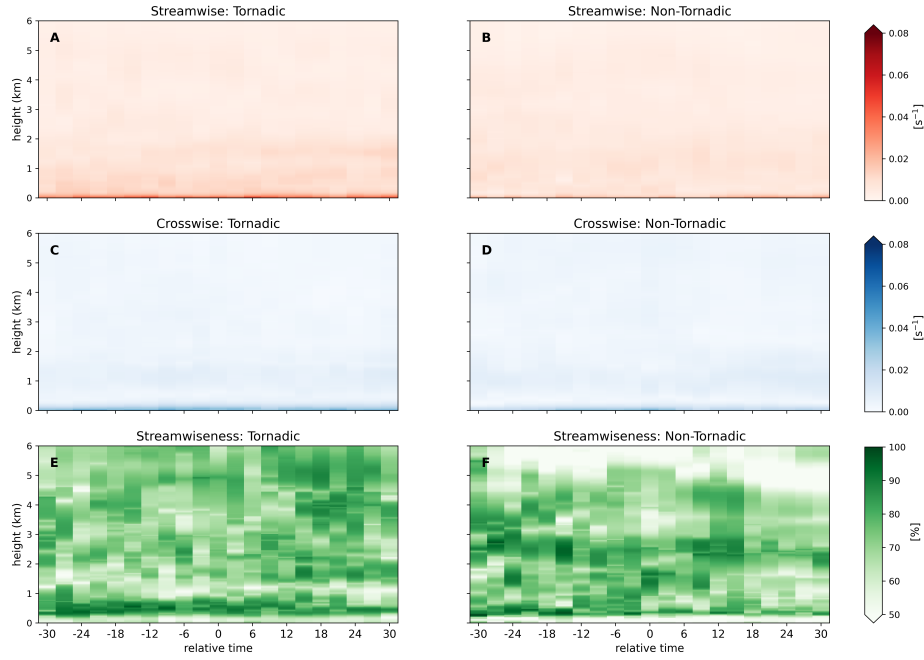


Figure 3.36: Streamwise (A, B) and crosswise (C, D) horizontal vorticity along with streamwiseness (E, F) for tornadic and non-tornadic storm environments, respectively. Profiles represent the 0-6km layer.

often results in greater crosswise vorticity Schenkman et al. (2014) and supports the findings from this dataset.

Of particular note with this data is the non-significant differences in the streamwiseness between tornadic and non-tornadic environments. Even in the lowest kilometer, Fig. 3.39 shows few significant differences at the 5% confidence level.

A slightly different story is seen when compositing streamwise and crosswise vorticity components in space rather than time. Both Fig. 3.40 and Fig. 3.41 continue to show the frictional effects on generating crosswise horizontal vorticity. This is particularly true in tornadic environments in which we note greater values of crosswise horizontal vorticity co-located with regions of stronger GRW. Additionally, a similar friction layer appears through much of the near-field environment. However in the



Figure 3.37: Differences in the streamwise (A) and crosswise (B) horizontal vorticity and streamwiseness (C) between tornadic and non-tornadic storm environments for the 0-6km layer.

far-field, there is more streamwise vorticity and less crosswise vorticity in tornadic environments in this layer, driving higher values of streamwiseness that were not apparent in the time composites.

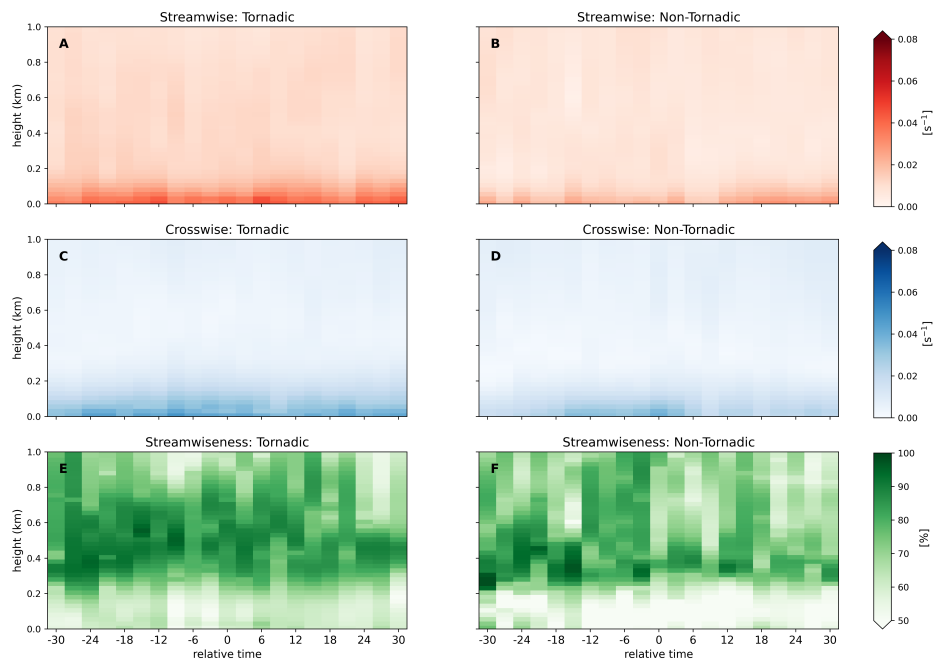


Figure 3.38: Streamwise (A, B) and crosswise (C, D) horizontal vorticity along with streamwiseness (E, F) for tornadic and non-tornadic storm environments, respectively. Profiles represent the 0-1km layer in time.

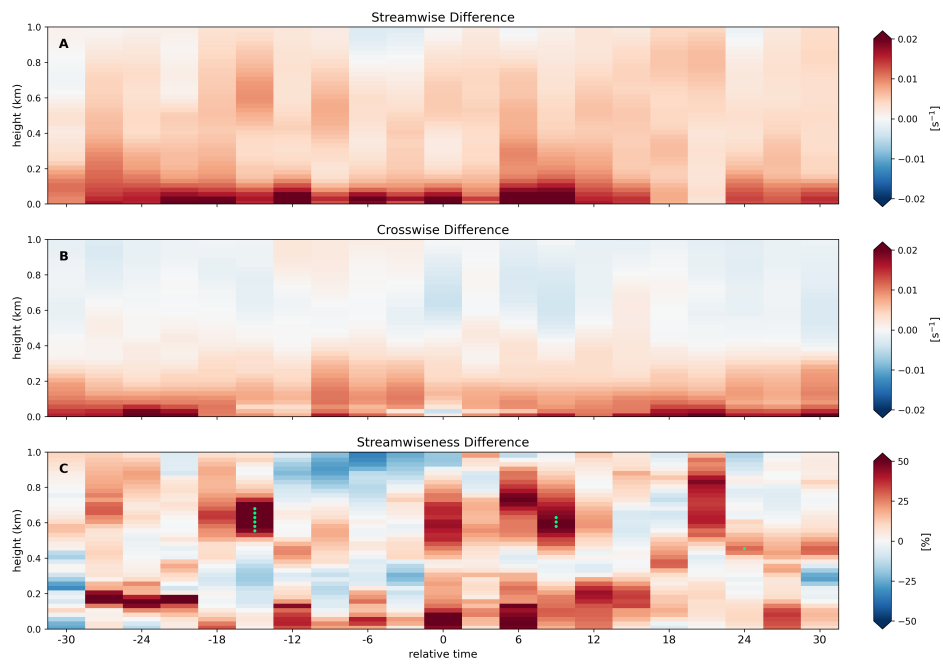


Figure 3.39: Differences in the streamwise (A) and crosswise (B) horizontal vorticity and streamwiseness (C) between tornadic and non-tornadic storm environments for the 0-1 kilometer layer in time.

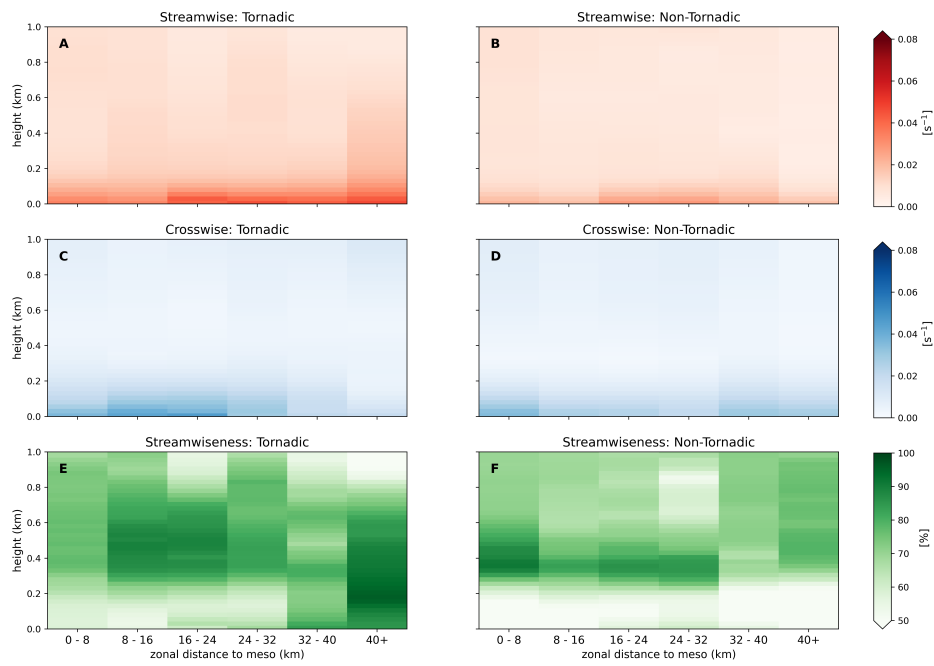


Figure 3.40: Streamwise (A, B) and crosswise (C, D) horizontal vorticity along with streamwiseness (E, F) for tornadic and non-tornadic storm environments, respectively. Profiles represent the 0-1 kilometer layer in zonal distance from the mesocyclone.

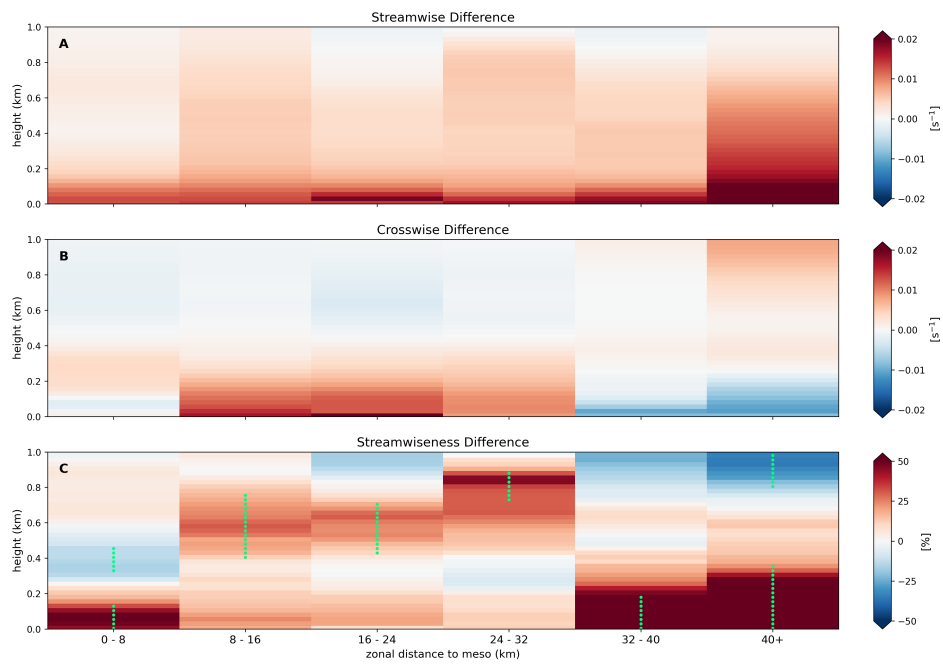


Figure 3.41: Differences in the streamwise (A) and crosswise (B) horizontal vorticity and streamwiseness (C) between tornadic and non-tornadic storm environments for the 0-1 kilometer layer in zonal distance from the mesocyclone.

Chapter 4

Summary and Conclusions

To this point in severe storms research, the use of DWL data in convective environments has been minimal. This work provides an atypical use case for the instrument and displays the benefits of using an instrument of this nature to observe severe convective storm environments, particularly in detailing the near-ground wind profiles. Although the main drawback of using DWLs for this purpose lies in their blind spot below about 60 to 80 meters, improvements to post-processing techniques have aided in alleviating this problem. In this study, we have explored the use of DWL wind retrievals and a wind estimation method (WINDoe) to quantify the evolution and variability of the low-level wind profile in storm environments. Specifically using the prior dataset created for use in this analysis, WINDoe provides an opportunity to combine DWL wind retrievals with other observational data sets to create a unified analysis of the wind profile over the lower troposphere in severe storm environments. Furthermore, WINDoe quantifies uncertainty in the retrievals, something missing from many observational based studies to this point in the science. Overall, the ability for this instrument to be nimble in operational settings, tied together with strides in data-analysis techniques should highlight the possibilities of utilizing DWLs in severe storms research.

This research provides an in-depth observation-based analysis into how supercell storm environment wind profiles evolve in time and space exploiting the ability of DWLs to retrieve wind profiles as frequently as every 5-10 seconds with high vertical resolution (about 18 meters). This includes the environmental differences between

tornadic and non-tornadic storm environments, building on a lengthy literature of storm environment research rooted in observations, reanalysis, and simulated storms. Many previous efforts have yielded conflicting results, so this work seeks to provide clarity through the use of real-world datasets while targeting the most intense non-tornadic storms, findings that could further inform the forecasting community. Based on previous efforts this work addressed the following hypotheses:

1. Kinematics vary more in non-tornadic storms in space, with drastic changes in SRH from the far-field to near-field not seen in tornadic composites (Parker 2014).
2. Low-level, inflow winds in non-tornadic supercell environments contain more crosswise vorticity compared to their tornadic supercell counterparts (Parker 2014).
3. SRW plays an insignificant role in tornado dynamics and thus, there are minimal differences in low-level SRW profiles in tornadic and non-tornadic environments (Peters et al. 2023).
4. Streamwise vorticity drives changes in SRH in the storm environment and provides the skill between SRH and tornado prediction (Peters et al. 2023).
5. Low-level parameters such as SRH_{500m} provide better discriminatory skill compared to deeper-layer parameters such as SRH_{1km} or SRH_{3km} (Coffer et al. 2019; Coniglio and Parker 2020).

with the following findings:

1. Enhanced spatial variability of severe parameters are noted in non-tornadic storm environments, and are enhanced in the low-levels. Although a more direct comparison to Parker (2014) shows that tornadic wind profiles vary more in a near-field/far-field framework. These variabilities are drawn from a tornadic storm's

ability to perturb its environment more than non-tornadic storms, greatly altering the wind profile. As a result of these enhanced perturbations, we note a negative shift in severe parameters as zonal distance to the mesocyclone increases, leading to enhanced variability in space.

2. Low-level winds in non-tornadic storms are more backed at various points in time and space compared to tornadic storm profiles. However, this is not consistent throughout all compositing methods and at all time/space bins. Increased backing in non-tornadic environments is more prevalent when accounting for spatial variability rather than in a time evolution framework. This agrees with previous storm environment efforts Parker (2014), and relates to the critical angle (angle between the surface SRW vector and the 0-500 meter shear) being larger, or more specifically, farther from 90° , for the non-tornadic soundings.
3. Overall differences in the 0-6 kilometer profile of SRW magnitude between tornadic and non-tornadic are found. In the lowest levels (up to 1 kilometer), differences are often inconsistent in magnitude and are smaller compared to that in other layers. Above 1 kilometer, tornadic environments tend to contain greater SRW, indicated by significant differences at the 1% level at many times. Also noted are significantly greater perturbations in tornadic environments, which was also found in previous parameters in both time and space. These greater perturbations are likely caused by more intense mesocyclones with greater PGF induced accelerations in time. In space, greater perturbations in tornadic environments with increasing distance to the mesocyclone can be attributed to the greater length scale at which the storm-induced accelerations can be felt.
4. Although limited to the surface to 500 meter layer, the root source of the skill behind SRH as a discriminator between tornadic and non-tornadic environments

is driven by differences in ω_s . However increased correlations between SRW and SRH is found in tornadic environments compared to non-tornadic environments, continuing to signal the possible ties between SRW and tornadic potential.

5. SRH and shear evaluated below 1 kilometer showed more skill than the same variables evaluated over deeper layers in this dataset. However, parameters evaluated from the surface to 1 kilometer tended to provide nearly identical skill between tornadic and non-tornadic environments as the same variable evaluated from the surface to 500 meters. This finding provides arguably the most benefit to the forecasting community as errors in wind-related variables in operational analysis systems may increase in the lowest 500 meters above ground level (Taszarek et al. 2021; Coniglio and Jewell 2022). Previous findings have suggested that these lowest-level parameters provide the most skill (e.g., Coffey et al. 2019), although this dataset finds otherwise. This can allow for more forecaster confidence when issuing forecasts based on analysis of parameters evaluated from the surface to 1 kilometer as it has been proven to provide ample skill in routine observations and analysis systems.

In addition to the previously discussed motivations/hypotheses, the dataset used in this study allowed for a careful examination of other important variables within the storm environment. We could then explore (1) the skill of GRW in the storm environment and how this skill compares to the skill provided by SRW at various layers, (2) the streamwiseness (percentage of vorticity that is streamwise) in tornadic and non-tornadic environments, and (3) if there are quantifiable differences between how much tornadic storms tend to perturb their environments away from the base-state compared to non-tornadic storms. The findings from these questions are as follows:

1. GRW tends to provide greater mean composite differences than SRW, particularly where the skill of SRW is limited. This is most notable in the lowest 500 meters where GRW provides statistically significant discriminatory skill between the two environments. This compared to SRW composites which contained less significant composite differences in both time and space. Given the recent storm environment research that highlights the importance on storm motion methodology on results, finding that GRW provides more skill in the low levels aids in eliminating biased results based on the storm motion used to compute variables such as SRW. We also find that GRW tends to provide skill throughout much of the profile (thorough the 3 kilometer layer) whereas the skill gained by using SRW was largest in the mid-levels (1-3 kilometers).
2. This work continued to highlight the importance of vorticity in the storm environment. Notably, a novel result of this work is that both streamwise and crosswise vorticity near the ground tend to be larger in tornadic environments compared to non-tornadic environments. This corroborates efforts from previous work behind the impact of friction on stronger ground-relative flow regimes Schenkman et al. (2014). The streamwiseness between tornadic and non-tornadic environments is not significantly different. These effects are seen from the surface to about 250 meters; above this level only the the streamwise component of horizontal vorticity is larger in tornadic environments.
3. Throughout chapter 3, we quantified the perturbations of various environmental characteristics in both a spatial and temporal framework. Nearly unanimously, the perturbations in tornadic environments were larger than the perturbations from non-tornadic storms. It is also important to note that much of the skill discussed in this work is reliant on the ability to capture and quantify these

perturbations. This emphasizes the continued difficulty in discerning between high-end non-tornadic storm environments and tornadic environments. While the DWL dataset used in this study is able to quantify the differences in these environments, more similar base states from the 13 kilometer resolution RAP continue to display the difficulty. Moving forward in observations, this highlights the need to wider coverage of instruments such as DWLs to better capture these perturbed components of storm environments in a more real-time framework.

While this work and these findings provide valuable insights, there are still limitations present that should be addressed:

1. Time of day constraints: the analyzed storms occurred mainly in the same time frame (predominately 18 - 03Z). It is likely that storm environment evolution varies in a time-of-day framework, although this could not be done using the field-collected data from the associated field efforts.
2. Spatial constraints: storm characteristics and storm environments are well documented to vary greatly in regions, notably the Southeastern U.S.. This work analyzed storm environments over a very small region of field project operations (predominately southern/central Plains). Therefore, these results should be taken as preliminary and likely do not apply directly to environmental evolution in other regions.
3. Compositing methods: in particular, the spatial compositing method used in this study is tied strictly to the zonal distance to the mesocyclone. There may be sensitivities tied to the meridional distance to the mesocyclone that are not uncovered in this work.

Previous campaigns have sought to mitigate these knowledge gaps (Plains Elevated Convection at Night: PECAN and VORTEX - Southeast), although the frequent timing of severe storms during the time-of-day present in this study and the heightened frequency of intense supercells over the Plains make these limitations nearly unavoidable.

Although the DWL dataset provides new perspectives and findings to decades long questions, questions still remain, prompting several possibilities for further storm environment research:

1. How do these results compare to a supercell environments in different regions?

Addressing a previously discussed limitation, recent field efforts in the Southeastern U.S. have provided datasets on storms environments not yet analyzed. Several intense tornadic and non-tornadic supercells have been analyzed and use of this data can highlight any differences in storm environments as well as different interactions between storms and their environments in this region.

2. Does the thermodynamic variability in a supercell environment vary in similar patterns to the wind profile? Given the lack observational platforms nimble and fit for these style of deployments, our thermodynamic sampling was limited to the rawinsonde and windsound launches conducted throughout the project. Analysis of these results could provide valuable thermodynamic relationships behind the results from this work.

Reference List

- , 2022: Vaisala, URL <https://docs.vaisala.com/v/u/B210917EN-M/en-US>.
- , 2023: Lumibird, URL <https://halo-photonics.com/lidar-systems/streamline-allsky-series/>.
- Baidar, S., T. J. Wagner, D. D. Turner, and W. A. Brewer, 2023: Using optimal estimation to retrieve winds from velocity-azimuth display (vad) scans by a doppler lidar. *Atmospheric Measurement Techniques*, **16** (15), 3715–3726.
- Banta, R. M., Y. L. Pichugina, and W. A. Brewer, 2006: Turbulent velocity-variance profiles in the stable boundary layer generated by a nocturnal low-level jet. *Journal of the atmospheric sciences*, **63** (11), 2700–2719.
- Benjamin, S. G., and Coauthors, 2016: A north american hourly assimilation and model forecast cycle: The rapid refresh. *Monthly Weather Review*, **144** (4), 1669–1694.
- Betchov, R., 1961: Semi-isotropic turbulence and helicoidal flows. *Physics of Fluids*, **4** (7), 925.
- Black, T. L., 1994: The new nmc mesoscale eta model: Description and forecast examples. *Weather and forecasting*, **9** (2), 265–278.
- Bluestein, H. B., J. B. Houser, M. M. French, J. C. Snyder, G. D. Emmitt, I. Pop-Stefanija, C. Baldi, and R. T. Bluth, 2014: Observations of the boundary layer near tornadoes and in supercells using a mobile, collocated, pulsed doppler lidar and radar. *Journal of atmospheric and oceanic technology*, **31** (2), 302–325.
- Brandes, E. A., R. P. Davies-Jones, and B. C. Johnson, 1988: Streamwise vorticity effects on supercell morphology and persistence. *Journal of Atmospheric Sciences*, **45** (6), 947–963.
- Brooks, H. E., and J. Correia Jr, 2018: Long-term performance metrics for national weather service tornado warnings. *Weather and Forecasting*, **33** (6), 1501–1511.
- Brooks, H. E., C. A. Doswell, and J. Cooper, 1994: On the environments of tornadic and nontornadic mesocyclones. *Weather and forecasting*, **9** (4), 606–618.
- 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*, **28** (5), 1261–1276.

- Brown, M., and C. J. Nowotarski, 2019: The influence of lifting condensation level on low-level outflow and rotation in simulated supercell thunderstorms. *Journal of the Atmospheric Sciences*, **76** (5), 1349–1372.
- Browning, K. A., 1962: Cellular structure of convective storms. *The Meteorological Magazine*, **91** (1085), 341–350.
- Browning, K. A., 1964: Airflow and precipitation trajectories within severe local storms which travel to the right of the winds. *Journal of Atmospheric Sciences*, **21** (6), 634–639.
- Bunkers, M. J., B. A. Klimowski, J. W. Zeitler, R. L. Thompson, and M. L. Weisman, 2000: Predicting supercell motion using a new hodograph technique. *Weather and forecasting*, **15** (1), 61–79.
- Burgess, D. W., and L. R. Lemon, 1990: Severe thunderstorm detection by radar. *Radar in Meteorology: Battan Memorial and 40th Anniversary Radar Meteorology Conference*, Springer, 619–647.
- Coffer, B. E., and M. D. Parker, 2017: Simulated supercells in nontornadic and tornadic vortex2 environments. *Monthly Weather Review*, **145** (1), 149–180.
- Coffer, B. E., and M. D. Parker, 2018: Is there a “tipping point” between simulated nontornadic and tornadic supercells in vortex2 environments? *Monthly Weather Review*, **146** (8), 2667–2693.
- Coffer, B. E., M. D. Parker, R. L. Thompson, B. T. Smith, and R. E. Jewell, 2019: Using near-ground storm relative helicity in supercell tornado forecasting. *Weather and Forecasting*, **34** (5), 1417–1435.
- Coffer, B. E., M. Taszarek, and M. D. Parker, 2020: Near-ground wind profiles of tornadic and nontornadic environments in the united states and europe from era5 reanalyses. *Weather and Forecasting*, **35** (6), 2621–2638.
- Coniglio, M. C., and R. E. Jewell, 2022: Spc mesoscale analysis compared to field-project soundings: Implications for supercell environment studies. *Monthly Weather Review*, **150** (3), 567–588.
- Coniglio, M. C., and M. D. Parker, 2020: Insights into supercells and their environments from three decades of targeted radiosonde observations. *Monthly Weather Review*, **148** (12), 4893–4915.
- Coniglio, M. C., and R. L. Thompson, 2024: Impacts of sampling and storm-motion estimates on ruc/rap-based discriminations of nontornadic and tornadic supercell environments. *Weather and Forecasting*.

- Davenport, C. E., 2021: Environmental evolution of long-lived supercell thunderstorms in the great plains. *Weather and Forecasting*, **36** (6), 2187–2209.
- Davenport, C. E., and M. D. Parker, 2015: Impact of environmental heterogeneity on the dynamics of a dissipating supercell thunderstorm. *Monthly Weather Review*, **143** (10), 4244–4277.
- Davies-Jones, R., 1984: Streamwise vorticity: The origin of updraft rotation in supercell storms. *Journal of Atmospheric Sciences*, **41** (20), 2991–3006.
- Davies-Jones, R., 2008: Can a descending rain curtain in a supercell instigate tornado-genesis barotropically? *Journal of the Atmospheric Sciences*, **65** (8), 2469–2497.
- Davies-Jones, R., 2017: Roles of streamwise and transverse partial-vorticity components in steady inviscid isentropic supercell-like flows. *Journal of the Atmospheric Sciences*, **74** (9), 3021–3041.
- Davies-Jones, R., 2022: Theory of parcel vorticity evolution in supercell-like flows. *Journal of the Atmospheric Sciences*, **79** (5), 1253–1270.
- Davies-Jones, R., D. Burgess, and M. Foster, 1990: Test of helicity as a tornado forecast parameter. preprints of sixth conf. on severe local storms. *Amer. Meteorol. Soc., Chicago IL*, 107–111.
- Davies-Jones, R., R. J. Trapp, and H. B. Bluestein, 2001: Tornadoes and tornadic storms. *Severe convective storms*, Springer, 167–221.
- Droegemeier, K. K., S. M. Lazarus, and R. Davies-Jones, 1993: The influence of helicity on numerically simulated convective storms. *Monthly weather review*, **121** (7), 2005–2029.
- Esterheld, J. M., and D. J. Giuliano, 2008: Discriminating between tornadic and non-tornadic supercells: A new hodograph technique. *E-Journal of Severe Storms Meteorology*, **3** (2), 1–50.
- Flournoy, M., 2020: Examining environmental conditions, storm-scale characteristics, and tornado potential in observed and simulated supercell thunderstorms. *ShareOK*.
- Gal-Chen, T., M. Xu, and W. L. Eberhard, 1992: Estimations of atmospheric boundary layer fluxes and other turbulence parameters from doppler lidar data. *Journal of Geophysical Research: Atmospheres*, **97** (D17), 18 409–18 423.
- Gebauer, J. G., and T. M. Bell, 2024: A flexible, multi-instrument optimal estimation retrieval for wind profiles. *Journal of Atmospheric and Oceanic Technology*.
- Hart, J., and W. Korotky, 1991: The sharp workstation v1. 50 users guide. *NOAA/National Weather Service*, **30**.

- Hill, M., R. Calhoun, H. Fernando, A. Wieser, A. Dörnbrack, M. Weissmann, G. Mayr, and R. Newsom, 2010: Coplanar doppler lidar retrieval of rotors from t-rex. *Journal of the Atmospheric Sciences*, **67** (3), 713–729.
- 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.
- Keeler, E., K. Burk, and J. Kyrrouac, 2022: Balloon-borne sounding system (bbss), wnpn output data. Tech. rep., Oak Ridge National Laboratory (ORNL), Oak Ridge, TN (United States
- Kerr, C. A., D. J. Stensrud, and X. Wang, 2019: Diagnosing convective dependencies on near-storm environments using ensemble sensitivity analyses. *Monthly Weather Review*, **147** (2), 495–517.
- Klees, A. M., Y. P. Richardson, P. M. Markowski, C. Weiss, J. M. Wurman, and K. K. Kosiba, 2016: Comparison of the tornadic and nontornadic supercells intercepted by vortex2 on 10 june 2010. *Monthly Weather Review*, **144** (9), 3201–3231.
- Klemp, J. B., and R. B. Wilhelmson, 1978: The simulation of three-dimensional convective storm dynamics. *Journal of the Atmospheric Sciences*, **35** (6), 1070–1096.
- Kühnlein, M., T. Appelhans, B. Thies, A. A. Kokhanovsky, and T. Nauss, 2013: An evaluation of a semi-analytical cloud property retrieval using msg seviri, modis and cloudsat. *Atmospheric research*, **122**, 111–135.
- Laffin, J. M., 2013: Verification of rap model soundings in preconvective environments. *Journal of Operational Meteorology*, **1** (6).
- Lemon, L. R., and C. A. Doswell III, 1979: Severe thunderstorm evolution and mesocyclone structure as related to tornadogenesis. *Monthly Weather Review*, **107** (9), 1184–1197.
- Letkewicz, C. E., A. J. French, and M. D. Parker, 2013: Base-state substitution: An idealized modeling technique for approximating environmental variability. *Monthly weather review*, **141** (9), 3062–3086.
- Liang, X., 2007: An integrating velocity–azimuth process single-doppler radar wind retrieval method. *Journal of Atmospheric and Oceanic Technology*, **24** (4), 658–665.
- Lilly, D., 1982: The development and maintenance of rotation in convective storms. *Intense Atmospheric Vortices: Proceedings of the Joint Symposium (IUTAM/IUGG) held at Reading (United Kingdom) July 14–17, 1981*, Springer, 149–160.
- Lilly, D. K., 1986: The structure, energetics and propagation of rotating convective storms. part ii: Helicity and storm stabilization. *Journal of Atmospheric Sciences*, **43** (2), 126–140.

- Maahn, M., D. D. Turner, U. Löhnert, D. J. Posselt, K. Ebell, G. G. Mace, and J. M. Comstock, 2020: Optimal estimation retrievals and their uncertainties: What every atmospheric scientist should know. *Bulletin of the American Meteorological Society*, **101** (9), E1512–E1523.
- Manninen, A., T. Marke, M. Tuononen, and E. O’Connor, 2018: Atmospheric boundary layer classification with doppler lidar. *Journal of Geophysical Research: Atmospheres*, **123** (15), 8172–8189.
- Markowski, P., C. Hannon, J. Frame, E. Lancaster, A. Pietrycha, R. Edwards, and R. L. Thompson, 2003: Characteristics of vertical wind profiles near supercells obtained from the rapid update cycle. *Weather and forecasting*, **18** (6), 1262–1272.
- Markowski, P., and Y. Richardson, 2004: P13. 1 multiple-doppler radar observations of vertical wind profile heterogeneity in convective boundary layers.
- Markowski, P., and Y. Richardson, 2010: *Mesoscale Meteorology in Midlatitudes*. John Wiley and Sons, <https://doi.org/10.1002/9780470682104>.
- Markowski, P. M., N. T. Lis, D. D. Turner, T. R. Lee, and M. S. Buban, 2019: Observations of near-surface vertical wind profiles and vertical momentum fluxes from vortex-se 2017: Comparisons to monin–obukhov similarity theory. *Monthly Weather Review*, **147** (10), 3811–3824.
- Markowski, P. M., and Y. P. Richardson, 2009: Tornadogenesis: Our current understanding, forecasting considerations, and questions to guide future research. *Atmospheric Research*, **93** (1–3), 3–10.
- Markowski, P. M., J. M. Straka, E. N. Rasmussen, and D. O. Blanchard, 1998: Variability of storm-relative helicity during vortex. *Monthly weather review*, **126** (11), 2959–2971.
- Nixon, C. J., and J. T. Allen, 2022: Distinguishing between hodographs of severe hail and tornadoes. *Weather and Forecasting*, **37** (10), 1761–1782.
- Nowotarski, C. J., and A. A. Jensen, 2013: Classifying proximity soundings with self-organizing maps toward improving supercell and tornado forecasting. *Weather and forecasting*, **28** (3), 783–801.
- Parker, M. D., 2014: Composite vortex2 supercell environments from near-storm soundings. *Monthly Weather Review*, **142** (2), 508–529.
- Parker, M. D., and J. M. Dahl, 2015: Production of near-surface vertical vorticity by idealized downdrafts. *Monthly Weather Review*, **143** (7), 2795–2816.
- Pearson, G., F. Davies, and C. Collier, 2009: An analysis of the performance of the ufam pulsed doppler lidar for observing the boundary layer. *Journal of Atmospheric and Oceanic Technology*, **26** (2), 240–250.

- Peters, J. M., B. E. Coffey, M. D. Parker, C. J. Nowotarski, J. P. Mulholland, C. J. Nixon, and J. T. Allen, 2023: Disentangling the influences of storm-relative flow and horizontal streamwise vorticity on low-level mesocyclones in supercells. *Journal of the Atmospheric Sciences*, **80** (1), 129–149.
- Peters, J. M., C. J. Nowotarski, and H. Morrison, 2019: The role of vertical wind shear in modulating maximum supercell updraft velocities. *Journal of the Atmospheric Sciences*, **76** (10), 3169–3189.
- Peters, J. M., C. J. Nowotarski, J. P. Mulholland, and R. L. Thompson, 2020: The influences of effective inflow layer streamwise vorticity and storm-relative flow on supercell updraft properties. *Journal of the Atmospheric Sciences*, **77** (9), 3033–3057.
- Potvin, C. K., K. L. Elmore, and S. J. Weiss, 2010: Assessing the impacts of proximity sounding criteria on the climatology of significant tornado environments. *Weather and Forecasting*, **25** (3), 921–930.
- Rasmussen, E. N., 2003: Refined supercell and tornado forecast parameters. *Weather and Forecasting*, **18** (3), 530–535.
- Richardson, Y. P., 1993: Verification of nmc short-range models using wind profiler data. Ph.D. thesis, University of Oklahoma.
- Richardson, Y. P., K. K. Droegemeier, and R. P. Davies-Jones, 2007: The influence of horizontal environmental variability on numerically simulated convective storms. part i: Variations in vertical shear. *Monthly weather review*, **135** (10), 3429–3455.
- Rotunno, R., and J. Klemp, 1985: On the rotation and propagation of simulated supercell thunderstorms. *Journal of Atmospheric Sciences*, **42** (3), 271–292.
- Rotunno, R., and J. B. Klemp, 1982: The influence of the shear-induced pressure gradient on thunderstorm motion. *Monthly Weather Review*, **110** (2), 136–151.
- Schenkman, A. D., M. Xue, and M. Hu, 2014: Tornadogenesis in a high-resolution simulation of the 8 may 2003 oklahoma city supercell. *Journal of the Atmospheric Sciences*, **71** (1), 130–154.
- Schwiesow, R., 1981: Horizontal velocity structure in waterspouts. *Journal of Applied Meteorology and Climatology*, **20** (4), 349–360.
- 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*, **27** (5), 1114–1135.

- Steinheuer, J., C. Detring, F. Beyrich, U. Löhnert, P. Friederichs, and S. Fiedler, 2022: A new scanning scheme and flexible retrieval for mean winds and gusts from doppler lidar measurements. *Atmospheric Measurement Techniques Discussions*, **2022**, 1–35.
- Taszarek, M., N. Pilgus, J. T. Allen, V. Gensini, H. E. Brooks, and P. Szuster, 2021: Comparison of convective parameters derived from era5 and merra-2 with rawinsonde data over europe and north america. *Journal of Climate*, **34** (8), 3211–3237.
- Thompson, R. L., 1998: Eta model storm-relative winds associated with tornadic and nontornadic supercells. *Weather and forecasting*, **13** (1), 125–137.
- Thompson, R. L., B. T. Smith, J. S. Grams, A. R. Dean, and C. Broyles, 2012: Convective modes for significant severe thunderstorms in the contiguous united states. part ii: Supercell and qlcs tornado environments. *Weather and forecasting*, **27** (5), 1136–1154.
- Turner, D., and U. Löhnert, 2014: Information content and uncertainties in thermodynamic profiles and liquid cloud properties retrieved from the ground-based atmospheric emitted radiance interferometer (aeri). *Journal of Applied Meteorology and Climatology*, **53** (3), 752–771.
- Turner, D. D., and W. G. Blumberg, 2018: Improvements to the aerioc thermodynamic profile retrieval algorithm. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **12** (5), 1339–1354.
- Wade, A. R., M. C. Coniglio, and C. L. Ziegler, 2018: Comparison of near-and far-field supercell inflow environments using radiosonde observations. *Monthly Weather Review*, **146** (8), 2403–2415.
- Waugh, S. M., 2021: The “u-tube”: An improved aspirated temperature system for mobile meteorological observations, especially in severe weather. *Journal of Atmospheric and Oceanic Technology*, **38** (9), 1477–1489.
- Weisman, M. L., and J. B. Klemp, 1982: The dependence of numerically simulated convective storms on vertical wind shear and buoyancy. *Monthly Weather Review*, **110** (6), 504–520.
- Weisman, M. L., and J. B. Klemp, 1984: The structure and classification of numerically simulated convective storms in directionally varying wind shears. *Monthly weather review*, **112** (12), 2479–2498.
- Weisman, M. L., and J. B. Klemp, 1986: Characteristics of isolated convective storms. *Mesoscale meteorology and forecasting*, Springer, 331–358.
- Woodall, G., 1990: Qualitative analysis and forecasting of tornadic activity using storm-relative environmental helicity. *NOAA technical memorandum*.

Wunch, D., and Coauthors, 2011: A method for evaluating bias in global measurements of co₂ total columns from space. *Atmospheric Chemistry and Physics*, **11** (23), 12 317–12 337.