

# Development and Investigation of GridRad-Severe, a Multiyear Severe Event Radar Dataset

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**ABSTRACT:** Many studies have aimed to identify novel storm characteristics that are indicative of current or future severe weather potential using a combination of ground-based radar observations and severe reports. However, this is often done on a small scale using limited case studies on the order of tens to hundreds of storms due to how time-intensive this process is. Herein, we introduce the GridRad-Severe dataset, a database including ~100 severe weather days per year and upward of 1.3 million objectively tracked storms from 2010 to 2019. Composite radar volumes spanning objectively determined, report-centered domains are created for each selected day using the GridRad compositing technique, with dates objectively determined using report thresholds defined to capture the highest-end severe weather days from each year, evenly distributed across all severe report types (tornadoes, severe hail, and severe wind). Spatiotemporal domain bounds for each event are objectively determined to encompass both the majority of reports and the time of convection initiation. Severe weather reports are matched to storms that are objectively tracked using the radar data, so the evolution of the storm cells and their severe weather production can be evaluated. Herein, we apply storm mode (single-cell, multicell, or mesoscale convective system storms) and right-moving supercell classification techniques to the dataset, and revisit various questions about severe storms and their bulk characteristics posed and evaluated in past work. Additional applications of this dataset are reviewed for possible future studies.

**KEYWORDS:** Hail; Severe storms; Tornadoes; Wind; Radars/Radar observations

## 1. Introduction

Severe weather, including tornadoes, severe hail, and severe wind, has substantial impacts across the United States each year. NOAA/NCEI (2023) reported that severe weather accounted for approximately \$8.5 billion (U.S. dollars; inflation adjusted) in annual losses and nearly 2000 deaths from 1980 to 2022. Additionally, there have been 163 severe weather events each totaling \$1 billion (inflation adjusted) in losses or more, including derechos, hail storms, and tornado outbreaks, and 38 events with 10 or more casualties over that same period. It remains important to analyze these, and other such high-end severe weather events, to further improve our resilience to them.

Examining a severe weather event is inherently multifaceted, and the data used depend primarily on the type of analysis. These data often include synoptic-scale and mesoscale data starting in the days to hours preceding an event (e.g., Rockwood and Maddox 1988; Coniglio et al. 2011; Hurlbut and Cohen 2014; Vaughan et al. 2017), radar and satellite data to examine storm-scale features and evolution during the event, and storm reports in the aftermath to evaluate impacts. Radar data can be incredibly useful to understand the physical and kinematic structure of severe versus non-severe storms.

In particular, such data have provided insight into the intensity of precipitation, horizontal and vertical extents, wind speeds, flow patterns, rotational velocities, and precipitation distributions associated with a storm (e.g., Byers and Braham 1949; Browning 1964; Brown et al. 1978; Lemon and Doswell 1979; Wurman et al. 1996; Parker and Johnson 2000). Radars have been used for several decades to understand tornadic storms and tornadogenesis (e.g., Lemon and Doswell 1979; Ryzhkov et al. 2002, 2005; Kumjian and Ryzhkov 2008; Kurdzo et al. 2017; Homeyer et al. 2020), estimate hail size in a storm (e.g., Witt et al. 1998; Murillo and Homeyer 2019), and better understand severe straight-line wind events (e.g., Fujita and Byers 1977; Fujita 1990; Wakimoto 2001; Klimowski et al. 2003). With the advent of dual-polarization radar and integration of such radars into the operational network of S-band radars in the United States (NEXRAD network) in 2013, a wealth of additional information can be inferred from these data including improved hydrometeor classification, detecting the presence and size of hail, convective updraft and vertical wind shear identification, and detection of tornadic debris (Kumjian 2013). Radar datasets therefore remain powerful tools to further understand the structure of severe storms and any unique identifying characteristics that can be used in real-time for warning decisions.

One such radar analysis technique that has been performed both manually and objectively is storm mode classification. Accurate identification of storm mode allows for further insight into the potential for various types of severe weather. Common storm classifications include single-cell storms, multicellular storms, and mesoscale convective systems (MCSs). For smaller-scale studies, subjective (manual) identification is often performed, as it is not prohibitively time intensive for so

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few samples. However, for studies using larger databases of storms, objective methods are a practical and often necessary solution for classification. Various studies use observed or simulated column-maximum reflectivity and a 30–40-dBZ threshold (e.g., Trapp et al. 2005; Snively and Gallus 2014; Thielen and Gallus 2019) to define contours encapsulating convective elements. Using radar data analyzed on the order of minutes to hours, these techniques often incorporate constraints for aspect ratio (i.e., the length to width ratio; e.g., Bluestein and Jain 1985; Fowle and Roebber 2003; Gallus et al. 2008; Smith et al. 2012; Snively and Gallus 2014; Thielen and Gallus 2019), maximum contour dimension (e.g., Bluestein and Jain 1985; Parker and Johnson 2000; Trapp et al. 2005; Gallus et al. 2008; Smith et al. 2012; Snively and Gallus 2014; Thielen and Gallus 2019), enclosed area (e.g., Fowle and Roebber 2003), and storm persistence/duration (e.g., Geerts 1998; Pinto et al. 2015; Feng et al. 2018, 2019).

Beyond determining a storm's mode, one common approach to analyzing their severe weather potential is through case studies, especially using radar observations and severe reports. Case studies of severe weather events and their radar presentations abound in the literature, providing valuable fine-scale insight into the inner workings of severe thunderstorms. For example, a case study examination of a tornadic supercell in Oklahoma on 3 May 1999 led to the discovery of the polarimetric radar tornadic debris signature (TDS) by Ryzhkov et al. (2002), prompting analyses of other supercells for potential analogous signatures in Ryzhkov et al. (2005) and the eventual inclusion of the polarimetric TDS in modern guides on polarimetric radar utility (e.g., Kumjian 2013). Additionally, Fujita and Byers (1977) examined the meteorological conditions surrounding an airplane crash and detected thunderstorm winds that were much stronger than anything previously observed, coining these winds a “downburst.” This observation prompted numerous field campaigns targeting downburst-producing storms (e.g., Fujita and Wakimoto 1982; McCarthy et al. 1982; Wilson et al. 1988), leading to a more comprehensive understanding of the phenomenon today and likely saving many lives (Wilson and Wakimoto 2001). Working with case studies allows for very detailed analyses of severe storms, but the conclusions from such studies are limited in generalizability given their relatively small sample sizes.

Large-scale studies of severe weather in the literature date as far back as the 1940s with the Thunderstorm Project (Byers and Braham 1949), and climatological studies have driven many of the scientific community's advances in severe weather knowledge. Tornadoes in the United States are most common in early summer (Brooks et al. 2003) and in the late afternoon to early evening (Ashley et al. 2008), mostly in the Great Plains and into the Southeast (Coleman and Dixon 2014; Gensini and Brooks 2018; Krocak and Brooks 2018). The majority of reported tornadoes are weak (EF0 to EF1; e.g., Brooks and Doswell 2001; Trapp et al. 2005) although the less frequent significant tornadoes (EF2+) are responsible for nearly 90% of fatalities (e.g., Anderson-Frey and Brooks 2019). Climatologies of severe hail like those by Cintineo et al. (2012), Murillo et al. (2021), and Wendt and Jirak (2021) are also typically built using reports, despite well-known reporting limitations

(see Allen and Tippett 2015, and references therein). Allen and Tippett (2015) examined a 60-yr record of over 260 000 hail reports and found that the majority of all hail reports occurred in the late afternoon to early evening primarily during the late spring, with a maximum in the Great Plains that is slowly shifting northward. Studies of severe winds often focus attention on MCSs, which can produce uniquely widespread and damaging severe winds, including and especially from derechos (Johns and Hirt 1987; Corfidi et al. 2016). Coniglio and Stensrud (2004) found that higher-end derecho events in their 16-yr climatology favor the southern plains and Midwest. Derechos in the eastern two-thirds of the CONUS tend to occur more in the summer months (Coniglio and Stensrud 2004) in the late evening to overnight (Bentley and Mote 1998). Recent work using machine learning to classify and track MCSs and quasi-linear convective systems (QLCSs) by Ashley et al. (2019) showed, using their developed MCS climatology, that nearly a third of all MCSs in their 22-yr dataset were also QLCSs, and QLCS storms were linked with 28% of all severe wind reports in the central and eastern United States. Climatological studies allow for a large-scale view of severe weather to develop mental models for how, when, and where severe hazards are likely to occur.

Several studies have investigated compelling scientific questions about severe storms beyond just their climatological distributions using a large record of observations. For example, studies such as Homeyer et al. (2020), Loeffler et al. (2020), and Van Den Broeke (2020) used radar data from tens to hundreds of tornadic and nontornadic supercells to examine tornadogenesis predictability; Blair et al. (2011) and Gutierrez and Kumjian (2021) examined radar signatures within tens to hundreds of giant and gargantuan hail-producing storms; and Bluestein and Jain (1985) and Schiesser et al. (1995) looked at mesoscale structures within radar data from dozens of severe MCSs. Past studies such as these, despite using larger datasets than the more numerous case study analyses, rarely contain more than a few hundred storms and are commonly limited in both their spatiotemporal extent and temporal resolution of observations. Furthermore, any larger-scale studies done before 2013 have limited to no access to polarimetric radar data, which further limits understanding of storm microphysics that may be relevant to severe events. Therefore, there exists a need to expand these studies using a longer temporal record and analyze a much larger population of storms that are more spatiotemporally diverse, have higher temporal resolution data, and that occurred within the observational range of one or more polarimetric radars.

Recognizing the contributions of the aforementioned prior work to our understanding of severe storms, and with the increasing record of observations and emergence of a national polarimetric radar network, a clear incentive exists to create a modern database of radar data and severe weather reports to evaluate the characteristics of storms that produce severe weather. This paper aims to fill the knowledge gaps outlined herein using the newly developed GridRad-Severe database (hereafter abbreviated GR-S): a database including gridded multiradar data covering the majority of the CONUS, objective storm tracks, and storm reports. Herein, we outline the

creation and utility of GR-S as well as how well it reflects the spatiotemporal distribution of all storm reports in the United States. Additionally, we introduce objective storm mode and supercell classification techniques to aid in data analysis, and examine initial findings of the GR-S dataset that complement and expand upon past studies. Finally, we directly compare GR-S findings with results from select seminal papers to demonstrate its ability to replicate and extend prior key findings.

## 2. The GR-S dataset

### a. Radar data

Radar data sourced from the nationwide NEXRAD network (NOAA/NWS/ROC 1991; Crum and Alberty 1993) were used to create GridRad data using version 4.2 of the public algorithm (Homeyer and Bowman 2022). GridRad data are merged volumes of individual radar observations across the CONUS, binned on a regular longitude–latitude grid. This includes single-polarization radar moments such as radar reflectivity at horizontal polarization ( $Z_H$ ) and radial velocity spectrum width ( $\sigma_v$ ) before 2013, and additional dual-polarization variables such as differential radar reflectivity ( $Z_{DR}$ ), copolar correlation coefficient ( $\rho_{hv}$ ), and specific differential phase ( $K_{DP}$ ) following the polarimetric upgrade of the radar network. Derived kinematic variables were also calculated on the native grid of each radar and binned into GridRad volumes, including radial divergence and azimuthal shear of the radial velocity. The spatial resolution of GridRad data is  $\sim 0.02^\circ \times \sim 0.02^\circ$  longitude–latitude (48 grid points per degree), and 0.5-km vertical resolution up to 7 km above mean sea level (MSL), after which the vertical resolution coarsens to 1-km up to 22 km MSL. Temporal resolution of the data is 5 min. More technical details about the creation of GridRad data can be found in Homeyer and Bowman (2022). GridRad is one of a few commonly used merged CONUS radar products [notable alternatives include NOAA’s Multi-Radar Multi-Sensor (MRMS) and Multi-Year Reanalysis of Remotely Sensed Storms (MYRORSS)] and is unique in its breadth of merged radar variables and merging methods that aim to provide high-fidelity echo-top heights and internal storm structure. Herein, we only create GridRad data for severe events within the CONUS (specifically, domains spanning  $24^\circ$ – $50^\circ$ N,  $125^\circ$ – $66^\circ$ W).

The GR-S database includes radar data from 2010 to 2019 inclusive, with future years expected to be added over time. This dataset starts in 2010 due to both good NEXRAD coverage and being after the NEXRAD transition to super resolution (Torres and Curtis 2007). Since the tornado rating scale changed from F to EF in 2007 (Doswell et al. 2009; Edwards et al. 2013) and the severe hail size threshold changed from 0.75" to 1.0" in early 2010 (before the first date in this dataset; Allen and Tippett 2015), all reports classified as severe herein are based on a uniform threshold for hail ( $\geq 1.0$  in.; 1 in. = 2.54 cm) and wind (gusts  $\geq 50$  kt; 1 kt  $\approx 0.51$  m s $^{-1}$ ) and a uniform damage rating scale for tornadoes (the enhanced Fujita or EF scale). Significant severe reports are those meeting or exceeding EF2

for tornadoes, 2.0 in. for hail, and 65-kt gusts for wind (Hales 1988).

### b. Storm report data

Storm report data are sourced from NOAA’s Storm Events Database (SED) hosted at the National Centers for Environmental Information (NOAA/NCEI 2022) from 2010 to 2019 inclusive, including tornado, hail, and wind report data. Each SED report includes a unique event ID, start and end date and time, initial and final event coordinates (longitudes and latitudes), and magnitude (EF rating for tornadoes, maximum diameter for hail, and maximum wind speed for severe wind). Tornado reports also include tornado pathlength and width.

### c. Event definition

Defining a GR-S event occurs in a few distinct steps. First, high-end severe days are identified using the tornado, hail, and wind reports from the SED. To be consistent with SPC severe days and most prior work, GR-S events begin at 1200 UTC on the event day and end at 1200 UTC on the following day. We identify days as high-end severe days if the number of tornado, hail, or wind reports exceeds 8, 45, or 120, respectively. These primary thresholds were chosen because they result in a nearly balanced dataset of high-end tornado, hail, and wind days each year, with approximately 100 days yr $^{-1}$  being labeled as high-end severe days (i.e., GR-S events). The thresholds also approximately correspond to the 85th percentile of daily report counts for each hazard. Once a day is included in the GR-S database (via the aforementioned primary threshold), secondary thresholds are used to determine what severe types will be used for domain definition on that day, roughly corresponding to the upper quartile of daily report counts. This is done to maximize the diversity and breadth of severe weather that is analyzed on the selected GR-S event days; if a day is already included in the dataset, it makes sense to analyze not only the severe hazard that happened enough times to warrant the day’s inclusion in the dataset, but also any other severe hazards that, while not prolific enough to pass that high primary threshold, still frequently occurred on that day. The secondary thresholds are roughly one-half of the primary thresholds: greater than 4 tornado reports, 22 hail reports, or 60 wind reports. Isolating data in these ways results in a large dataset focused solely on high-end severe weather events with a high level of spatiotemporal detail.

After high-end severe days are identified, the locations and times of the SED reports are used to constrain the spatiotemporal domains of each day’s GridRad data. Domain bounds are objectively determined using the latitudes, longitudes, and times of reports for each day’s selected report types (i.e., tornado, hail, and/or wind). These space and time bounds are independently created for each report type and the final domain results from retaining the extrema of each objective report domain. First, the mean latitude and longitude to the nearest half degree of a given report type is found. An initial box encompassing this point is created with bounds  $\pm 5^\circ$  longitude and latitude from the mean report location. This  $10^\circ \times 10^\circ$  box

then recursively expands by  $0.5^\circ$  in all directions until  $\geq 90\%$  of reports for that report type are encompassed. Using only those reports enclosed in the objectively identified box, time boundaries are created in a similar manner, starting with  $\pm 2$  h centered on the mean report time rounded to the nearest half-hour. The time boundaries expand recursively by half-hour increments in each direction until  $\geq 90\%$  of the reports within the spatial boundaries are captured (i.e.,  $\geq 81\%$  of the total number of reports). Note that the time bounds of a GR-S event (1200–1200 UTC) differ slightly from the SPC definition of a single day (1200–1159 UTC). Once these time boundaries are determined, they are trimmed such that the start time is no more than 30 min before the first report and the end time is no more than 30 min after the last report. This ensures that the GridRad data created are focused on the times when severe weather was occurring. Figure 1 shows how often a location was encompassed within a GR-S domain. Overall, the GR-S domains were generally focused on the region  $30^\circ$ – $45^\circ$ N,  $100^\circ$ – $80^\circ$ W, offset slightly southeast of the center of the CONUS. As the year cycles from spring through winter, the GR-S domains on average shift in a clockwise manner, consistent with seasonality in the SED report data (not shown).

As stated previously, this creation of space and time bounds is done independently and objectively for each report type that exceeds its secondary threshold. For days where more than one report type exceeds its secondary threshold, both a composite spatial domain and a composite temporal domain are created using the individual spatial and temporal domains for each report type, retaining the overall maximum and minimum latitudes, longitudes, and times to create a composite domain that encompasses all individual domains. Once these spatiotemporal bounds are determined, the time bounds are limited to begin no earlier than 1500 UTC on the event day and end no later than 1200 UTC the following day, to limit analyses to the 1200–1200 UTC period used for SED reports. We use 1500 UTC instead of 1200 UTC as the start time limit because all GR-S day temporal domains are then extended backward by 3 h to attempt to capture convection initiation (CI). This is motivated by prior work such as Bluestein and Parker (1993), which found in their dryline study in Oklahoma that the time between CI and the first tornado report for a storm was approximately 2–3 h (see their Table 2). A flowchart describing these methods is shown in Fig. 2, and an additional schematic showing an example GR-S case and spatiotemporal domain selection is available in the online supplemental material.

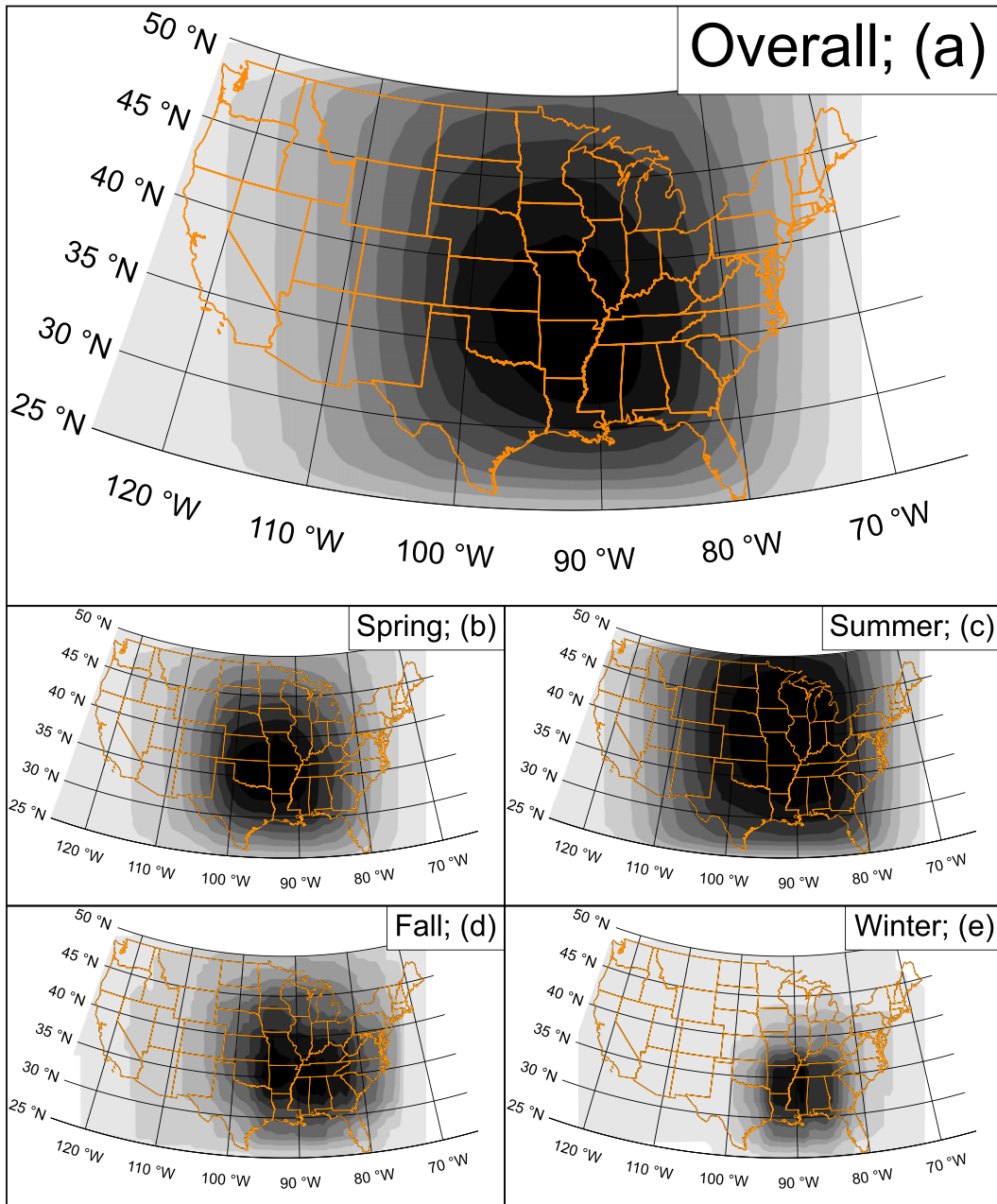
#### d. GR-S storm tracks

Each GR-S event includes the 5-min GridRad volumes outlined in section 2a and a comma-delimited storm track file that includes official storm reports matched with each storm. The storm tracks for each event are identified using an echo-top altitude-based tracking method from Homeyer et al. (2017), with modification to resolve premature termination of tracks during storm splits and mergers as outlined in Lagerquist et al. (2020). In summary, the GridRad storm tracking algorithm identifies point locations of  $Z_H = 30$ -dBZ echo-top altitude maxima and links them in time (5-min intervals for GR-S).

Echo-top maxima are required to reach at least 4 km MSL and be embedded within echoes classified as convection by the Storm Labeling in 3 Dimensions algorithm (SL3D; Starzec et al. 2017) to be tracked. Cells in subsequent time steps are linked in time if they are located within 15 km of each other (for neighboring 5-min volumes only). In cases where more than one echo-top maximum is located within 15 km of a previously defined storm, the closest one is matched during tracking. Finally, the tracking algorithm only retains tracks that are at least 15 min in duration—or, equivalently, are identified in at least three consecutive 5-min GridRad volumes. To resolve storm splits and storm mergers, colinear storm tracks with closely located or overlapping initial and final locations and times are combined into one track. This combination ensures that cyclic updraft cycles, as seen commonly in supercells, are not split into multiple short-duration storm tracks. Two passes are made in this attempt to combine broken storm tracks: (i) joining tracks with end and start times separated by one 5-min GridRad analysis (gap storms) so long as their end and start locations differ by  $\leq 15$  km, and (ii) joining storms with start and end times that fall within one 5-min GridRad analysis of each other, so long as the minimum distance between track locations during the overlapping period is  $\leq 15$  km. In the former, the location during the gap is determined using linear interpolation between the end and start locations of the combined tracks. In the latter, tracks are combined at the closest point of coincidence during overlap such that the point of the second (later) track through its remaining path is appended to the first (earlier) track. An illustration of the various track combination cases is included as supplemental material.

After the initial storm tracking and track combination algorithms are applied to each GR-S event, the resulting 5-min storm tracks are linearly interpolated to 1-min resolution for spatiotemporal collocation with SED reports. To match the SED reports to the storm tracks, the closest tracked storm to a report at the report time is matched, so long as it lies within 30 km of the report location. While a maximal 30-km radius for report matching may be considered generous, it is noted that nearly all matched reports fall within 10–15 km of the objectively tracked storm centers and manual validation efforts in the past have demonstrated broad reliability of this approach (e.g., Homeyer et al. 2020). Figure 3 shows how storm reports are matched to storm tracks for the 14 April 2011 GR-S event. Matching reports with storm tracks in this way allows for individual storms to be classified as sub-severe or severe, and their individual characteristics examined in a bulk sense. An important limitation to accurate report matching is the spatiotemporal accuracy of the reports themselves; many studies (e.g., Trapp et al. 2006; Allen and Tippett 2015, for severe wind and hail reports, respectively) have reported on the imperfect nature of human-reported severe weather. These limitations are an important consideration in any work using storm reports as a method of validation.

The final archived 1-min, comma-delimited storm track files contain information on storm location, motion, radar characteristics, and storm-matched severe reports (summarized in Table 1). In the case of severe hail or wind reports, the event information is linked to the midpoint time of the report so



Days with Overlapping Domain

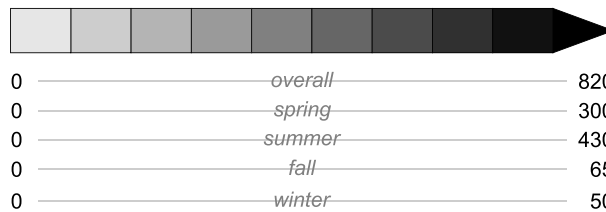


FIG. 1. Contour plots of the number of times a point was encompassed within a GR-S domain, gridded to an approximate 80 km × 80 km grid. Plots include (a) all GR-S days, (b) days in March–May (spring), (c) days in June–August (summer), (d) days in September–November (fall), and (e) days in December–February (winter). Color bar limits are individual to each panel, and listed below the color bar at the bottom. State borders are highlighted in orange.

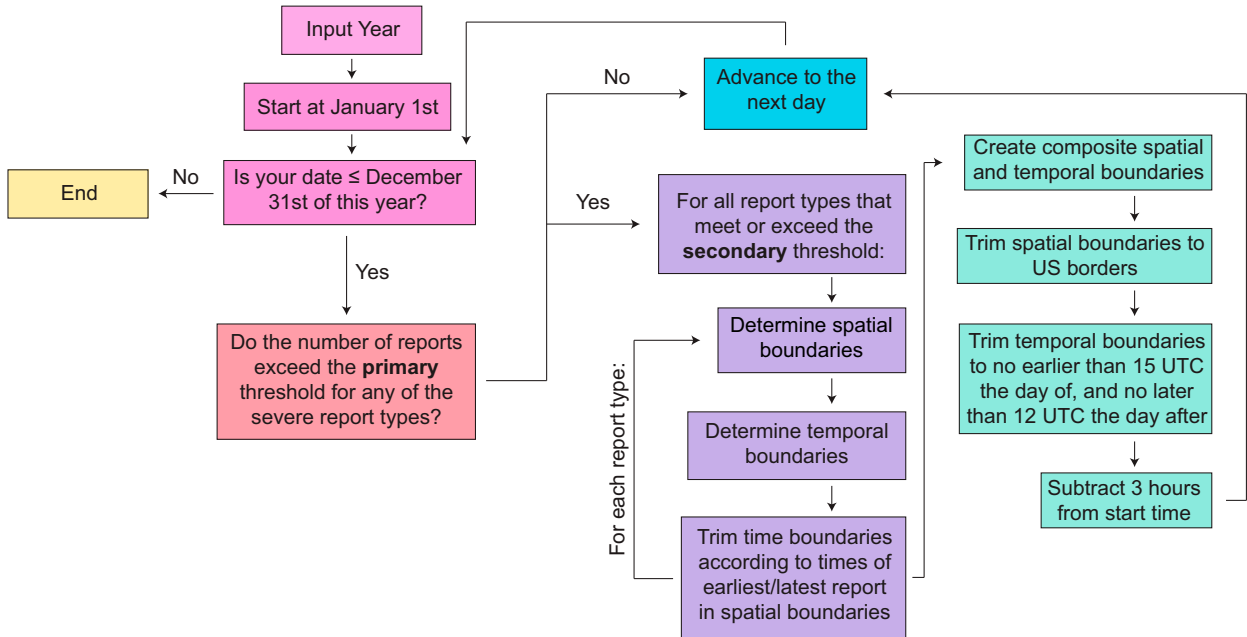


FIG. 2. Flowchart explaining the creation of GR-S data for a given year.

that no report gets counted more than once. For tornado reports, most of the report information is linked to the initial report time (i.e., tornadogenesis).

While enabling unique analyses of the GR-S data, limitations to the objective storm tracking methods do exist. Common drawbacks include unresolved storm splits and mergers and poorly tracked initiation phases of some storms (before  $Z_H = 30$  dBZ exists and/or before the 30-dBZ echo top exceeds 4 km MSL, which is typically <15 min in severe storms).

### 3. Analysis methods

#### a. Storm mode classification

Given that many past studies have classified storm mode subjectively, such efforts have often focused on small spatio-temporal domains. An objective method for storm mode classification is presented herein for use with the GR-S dataset. This storm mode classification relies on closed radar echo contours above a given  $Z_H$  threshold encompassing objectively tracked storms to be able to classify each track within a contour as a part of a single-cell storm, multicell storm, or an MCS. By classifying the mode of each objectively tracked storm, characteristics of each storm can be analyzed in concert with storm-matched SED reports to potentially link storm mode and storm-scale characteristics with the presence of (or lack thereof) severe weather.

To classify storm mode, 30-dBZ contours are identified using column-maximum reflectivity ( $Z_{Hmax}$ ) from each 5-min GridRad data file. For each closed contour, the area and maximum dimension are calculated, and the number of tracked storms within each contour is counted. Tracked storms are then identified as single cell (i.e., discrete) if either 1) only a

single tracked storm exists within a contour, or 2) a relatively small contour ( $<3000$  km<sup>2</sup>) encompasses no more than two tracked storms. Two tracked storms within a small contour are both classified as single-cell storms to account for storms with cyclic updraft generation (e.g., supercells) that can have more than one updraft at a single time, but do not persist as such. Homeyer et al. (2020) found in their composite analyses of supercells that the average supercell size for  $Z_{Hmax} = 30$  dBZ is approximately 3000 km<sup>2</sup> (their Fig. 3). The 3000 km<sup>2</sup> contour area threshold is therefore chosen to encompass the size of some of the largest single-cell storms expected. For larger contours ( $\geq 3000$  km<sup>2</sup>) containing two tracked storms or any contour containing 3 or more tracked storms, those storms are classified as either multicell or MCS. The delineation between the two is made using the contour maximum dimension; if the maximum dimension is  $\geq 100$  km, it is classified as an MCS (Houze 2004).

Since the storm mode classification algorithm is independently run on each time step, a tracked storm may have a complex, time-varying storm mode classification. We do not employ a minimum time that a tracked storm has to be identified as a consistent storm mode to retain such a classification. This is done because, instead of classifying a storm based on its mean storm mode, we want to enable investigation into how each storm evolves in time and, if possible, how changes in its severity accompany changes in storm mode. Figure 4 shows select times during the evolution of the 14 April 2011 GR-S event in the southern plains. Over time, many single-cell storms that initiated early in the event merge into what eventually becomes a large MCS. In concert with matched storm reports (e.g., Fig. 3), storm mode can be linked with a storm's severity for bulk analyses of the two characteristics.

## Storm Tracks for 14 April 2011 GridRad-Severe Event

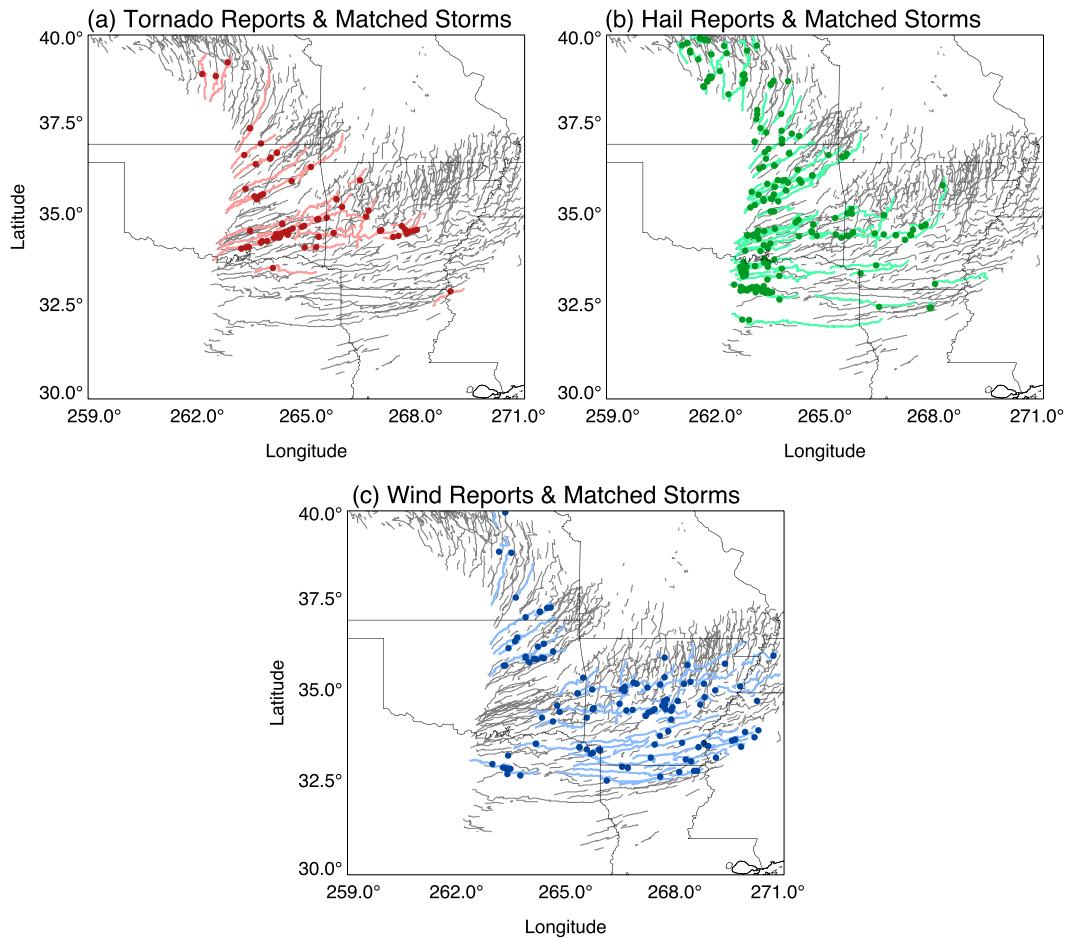


FIG. 3. GR-S storm tracks for the 14 Apr 2011 event, with severe reports superimposed as dark circles and storm tracks matched with reports in a lighter shade of the same color for (a) tornadoes, (b) hail, and (c) wind. Storm tracks not matched with a report are shown in gray.

### *b. Mesocyclonic updraft classification*

Another important severe storm characteristic is whether or not a storm's updraft was rotating when the storm produced a severe report. Updrafts that have sufficient persistent rotation are defined herein as mesocyclonic, and otherwise as non-mesocyclonic. Mesocyclonic updrafts are classified using the methods for right-moving supercell identification outlined in Homeyer et al. (2020), originally based on work by Sandmæl (2017). Namely, five criteria are used to objectively identify updrafts as mesocyclonic: 1) maximum midlevel (4–7 km MSL) azimuthal shear exceeds  $4 \times 10^{-3} \text{ s}^{-1}$  for at least 40 min; 2) maximum midlevel azimuthal shear meets or exceeds  $5 \times 10^{-3} \text{ s}^{-1}$ ; 3) maximum column-max azimuthal shear meets or exceeds  $7 \times 10^{-3} \text{ s}^{-1}$ ; 4) maximum column-max radial divergence meets or exceeds  $1 \times 10^{-2} \text{ s}^{-1}$ ; and 5) maximum column-max velocity spectrum width meets or exceeds  $13 \text{ m s}^{-1}$ . The sixth criterion used in Homeyer et al. (2020)—max 40-dBZ echo-top altitude meets or exceeds

11 km—was not applied in this study. This was done to enable reliable classification of wintertime convection, which often has lower echo tops.

It is important to note that the mesocyclonic updraft classification criteria were based on right-moving supercell identification criteria, so left-moving (meso-anticyclonic) storms are not independently examined herein. Both anecdotal evidence and prior research show a dearth of left-moving supercells compared to right-movers. Bunkers et al. (2006) examined long-lived supercells and found that, of 184 long-lived supercells in their dataset, only 4 were left-movers. An approximate ratio of left- to right-moving supercells is, to our knowledge, unknown. Future work may focus on classification of left-moving supercells using GR-S or an alternative dataset and further investigation of their characteristics compared to right-movers.

The result of these classification techniques is that each individual tracked storm has a time-varying storm mode classification and a binary mesocyclonic updraft classification. This

TABLE 1. Storm attributes included in GR-S event track files, separated for radar-based storm information (left column) and matched SED report information (right column).

Storm information	Report information <sup>a</sup>
Storm number	Binary report flag
Storm date and time	Report number
Storm longitude	Report longitude
Storm latitude	Report latitude
Eastward storm motion	Report magnitude
Northward storm motion	Instantaneous tornado count
Echo-top altitudes	Max instantaneous tornado rating
Column-maximum $Z_H$	Tornado end date and time
	Tornado width
	Tornado length

<sup>a</sup> Report flag (0 or 1), number, longitude, latitude, and magnitude are given for all report types (tornado, hail, and wind), where for tornadoes the report information is listed only at the time of tornadogenesis. The additional SED report information for tornado end time, width, and length are also only given at the time of tornadogenesis, while the instantaneous tornado count and maximum rating are based on all reports valid at each 1-min storm-track time.

can, and does, result in classifications such as multicell or MCS storms with mesocyclonic updrafts. Examples of these types of storms may include supercells that share the same 30-dBZ precipitation shield, mergers of a discrete supercell with a QLCS, supercells present in the early organizing stages of a QLCS (e.g., Weisman and Trapp 2003) or generation of vortices that meet mesocyclonic rotation criteria (e.g., DeWald and Funk 2002). The identification of multicells and storms within MCSs that meet mesocyclonic updraft criteria in GR-S data allow for filtering of these storms if desired. Herein, these storms and their attendant severe weather are retained and examined in section 4, but are removed in section 5 where GR-S MCS storms that produced severe weather are compared to objectively identified severe MCSs and QLCSs.

#### 4. Results

In order for conclusions in this study to be representative of the total climatology of severe weather and therefore broadly applicable, the distribution of GR-S storm matched reports must be representative of the complete SED database. Representativeness herein includes capturing not only the majority of SED reports, but also the correct spatiotemporal distribution. Looking at only the number of total SED reports versus GR-S storm-matched reports, Table 2 summarizes the percentage of severe and significant severe reports captured by GR-S for 2010–19. Of all SED reports during those 10 years, the GR-S data retains ~63%–77% of total reports and ~68%–91% of significant severe reports, with percentage matched highest for tornado reports and lowest for wind reports. Focusing only on SED reports that existed within the spatiotemporal bounds of the GR-S domains, the range of retained reports increases to ~88%–94% for all reports and ~91%–98% for significant severe reports, again with percentage matched highest for tornado reports and lowest for wind

reports. This means that for all SED reports within the spatiotemporal bounds of the GR-S domains, the GR-S storm tracking and report matching procedure matches approximately 9 out of every 10 reports to a storm. Examining the total number of reports captured, the GR-S database retains 164 748 out of the total 249 600 SED reports during the 10-yr period (~66%). This is expected since the GR-S database only includes ~100 days yr<sup>-1</sup>, with data only within limited spatiotemporal domains. However, it is encouraging that, if a report exists within a GR-S domain, it is highly likely that it will be matched with a GR-S tracked storm. Therefore, the domain selection criteria coupled with the matching algorithm are both capturing a majority of SED reports and effectively matching reports within GR-S bounds to objectively tracked storms.

Capturing the majority of severe reports is only one facet of examining the representativeness of the GR-S data. Equally important is the distribution of the reports—spatial and temporal, for both severe and significantly severe events – and whether those distributions match the full SED report climatology. Figure 5 shows the breakdown of total reports by month for both GR-S matched reports and SED reports, with lines showing the percentage contribution of tornado, hail, and wind reports to the total reports in each month. Tornado data in this figure and for all future analyses are focused on the time of tornado initiation. The difference in total data points represented on each plot is captured by the y axes, which show the mean 34% decrease in reports when comparing SED to GR-S data. The monthly distribution of reports is similar between the GR-S and SED data, although month-to-month variations in percentage of SED reports captured within GR-S are visible. Percentage differences between GR-S and SED reports per month range from 11% to 56%, with some of the lowest percentage differences in the late spring and early summer (below 19% from April to June, inclusive). This is potentially due to a preference for higher-end severe days to occur in the spring to early summer, so a higher percentage of all severe weather days in that period would be captured by the GR-S domain selection criteria. Notably, April through June alone make up 51.8% of all GR-S days in this dataset. If only SED reports within the GR-S bounds are considered (not shown), those percentage differences range from 8% to 28%, and are lowest in the spring and summer (8%–11%) and highest in fall and winter (11%–28%). Therefore, the storm tracking technique is most effective at tracking severe convection and matching reports to those storms during the maximum of the annual cycle in severe weather (the early–mid warm season) and least effective during the cool season. Despite these differences, the GR-S bar graph still closely resembles the SED bar graph, showing that GR-S is capturing the overall distribution of severe reports quite well. The percentage contribution of tornadoes, hail, and wind to each month's overall report count also show very similar values between the GR-S and SED data, demonstrating a monthly GR-S report type balance that is representative of the underlying SED report data. Overall, this analysis shows that the GR-S database captures the annual cycle of all SED reports well.



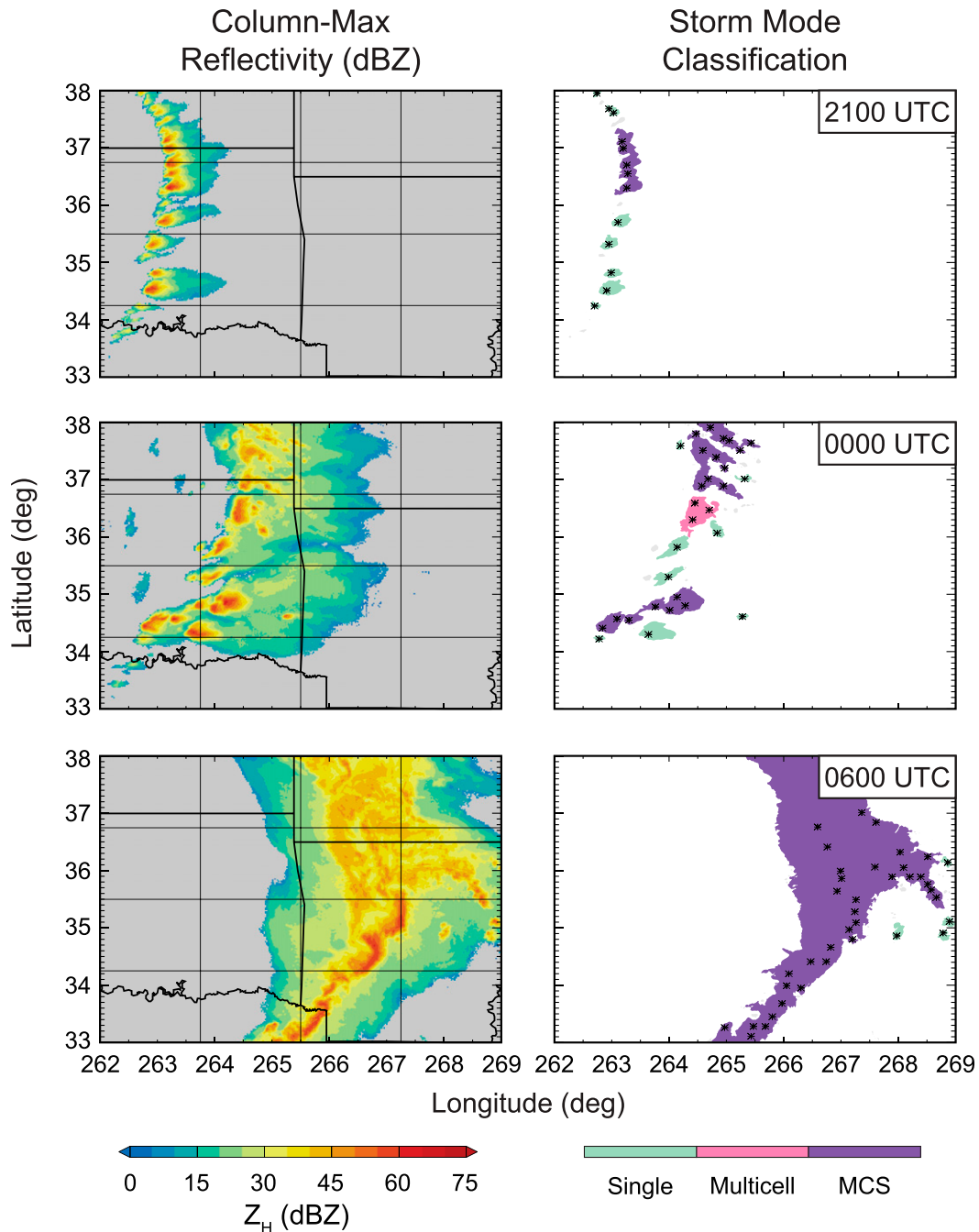


FIG. 4. Select images of (left) column-max reflectivity and (right) storm mode classification from a limited spatial domain within the 14 and 15 Apr 2011 GR-S case. For storm mode classification images, the interior of identified 30-dBZ contours are shaded in green, pink, or purple to denote single-cell, multicell, or MCS classification, respectively. Tracked storms within such contours are indicated by black asterisks. Identified 30-dBZ contours that do not encompass any storm tracks are shaded in light gray.

In addition to the annual cycle of reports, capturing the spatial distribution of reports is also very important. Figure 6 shows the gridded number of all SED reports from 2010 to 2019 for each severe report type juxtaposed with the gridded number of reports retained in the GR-S storm tracks. More

reports are expected on the SED maps, again since GR-S events only include  $\sim 100$  days  $\text{yr}^{-1}$  of severe weather. Qualitatively, maps of GR-S matched reports and SED reports have similar spatial distributions, confirming that the distribution of reported severe weather is well captured in the GR-S

TABLE 2. Comparison of SED and GR-S matched reports from 2010 to 2019. For each tornado, hail, and wind report, data include 1) percentage of GR-S matched reports compared to all SED reports of that type and over that period; 2) percentage of GR-S matched reports compared to SED reports of that type and over that period, confined within the corresponding day's GR-S spatiotemporal bounds; and 3) the total GR-S matched reports in the dataset. Data are also shown isolating significant severe reports.

Report type	Percentage of SED total	Percentage of SED within GR-S Bounds	Total GR-S reports
Tornado initiations	76.83%	94.16%	10 542
Hail reports	70.60%	94.33%	56 025
Wind reports	62.72%	87.81%	98 181
Significant tornado initiations	90.85%	97.69%	1608
Significant hail reports	79.85%	94.68%	5842
Significant wind reports	67.80%	90.56%	7179

database. In combination with Table 2, Fig. 6 gives confidence that GR-S is capturing the majority of reports in a consistent way across most of the CONUS. This can be more directly examined in Fig. 7, which shows both the total report difference between the GR-S database and the SED record and the

percentage difference between the two. These plots further demonstrate that reports are well matched across the eastern two-thirds of the country where reports are more frequent (Fig. 6). The areas with high percentage differences are commonly found in locations with low report counts for both GR-S and SED (e.g., compare total number of reports in Fig. 6f to percentage difference in Fig. 7f for severe wind in the western CONUS), meaning that while the percentage of reports missed in these regions may be quite high, the total number of reports missed is quite low. Therefore, based on the results shown in Figs. 5–7, we can confidently say that the storm-matched reports within the GR-S database are a representative sample of the total climatology within the SED dataset.

Confident that the GR-S database is representative of the seasonality and geographic distribution of SED reports, we can use GR-S data to examine other bulk aspects of storm severity. Identifying both the storm mode and updraft type (mesocyclonic or non-mesocyclonic) associated with each tracked storm and its matched reports can provide valuable insight into the types of storms that produce various severe phenomena. Figure 8 shows the average annual number of tornado, hail, and wind reports per month for 2010–19, broken into sub-significant and significant severe reports. Overlaid are lines showing the percentage of reports per month that were matched with storms classified as single-cell, multi-cell, or MCS storms, and whether or not the storm had a mesocyclonic updraft. Perhaps the most surprising result from this analysis is how often tornadoes are associated with MCS-classified cells throughout the year (Fig. 8a). However, the mesocyclonic classification reveals that many of the cells classified as MCS-type are dynamically consistent with supercell storms rather than the typical non-mesocyclonic cells often found in an MCS. We speculate that this may be driven by the reliance on a relatively low  $Z_H$  threshold to define storm contours during storm mode classification ( $Z_H = 30$  dBZ), which may encompass the precipitation shield of neighboring—and otherwise mostly discrete—storms (supercell or otherwise) and classify those storms as part of an MCS. The contribution of non-mesocyclonic (i.e., more traditional) MCS cells to tornado reports reaches a minimum in the spring and summer, when both the number of tornadoes peaks and the classical U.S. tornado season occurs. In contrast, the contribution of

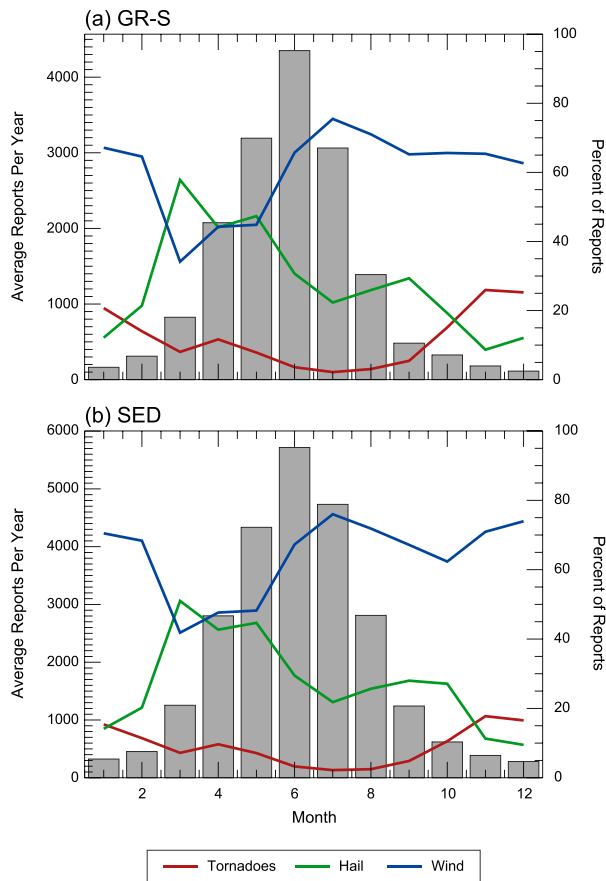


FIG. 5. Comparison of (a) GR-S and (b) SED average annual storm reports, broken down by month for 2010–19. Lines indicate the percentage contribution of various severe report types (tornado, hail, and wind) to the total number of reports in a given month. Pearson correlation coefficients comparing GR-S and SED lines for each severe hazard exceed 0.95.

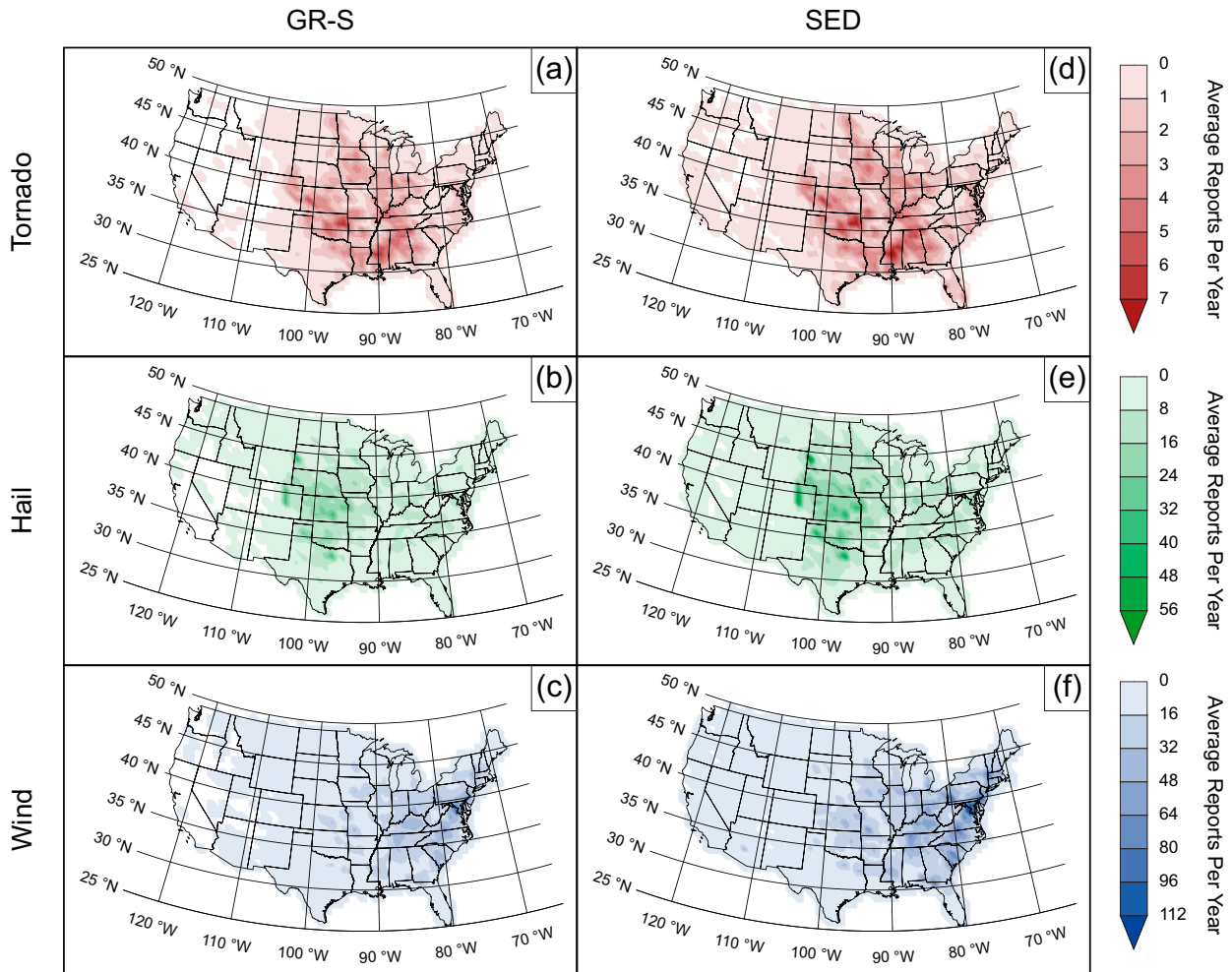


FIG. 6. Contour plots of average annual number of (a)–(c) GR-S and (d)–(f) SED reports for (a),(d) tornado; (b),(e) severe hail; and (c),(f) severe wind reports from 2010 to 2019, inclusive. Data are gridded on an approximately 80 km × 80 km grid. Areas not shaded indicate no (a)–(c) GR-S or (d)–(f) SED reports.

mesocyclonic storms to tornado reports, regardless of storm mode classification, peaks during this time.

Examining hail events (Fig. 8b), for much of the spring through fall, single-cell storms account for the largest fraction of reports by storm mode. However, while tornado and wind reports are fairly dominated by one storm mode (MCSs are associated with a majority of reports in 11 of 12 months for each tornado and wind), no one storm mode stands out as a consistent majority contributor to all hail reports. Single-cell storms account for slightly more than 50% of reports in July and August; multicellular storms are never associated with the majority (or even a relative majority) of reports per month; and MCS storms are never associated with the majority (or even a relative majority) of reports only in the winter months, where total matched reports are lowest. However, examining mesocyclonic versus non-mesocyclonic storms, mesocyclonic storms account for a majority of hail reports year-round. MCS storms contribute the most to wind reports year-round when compared to other storm modes (Fig. 8c), with a peak in single-cell and multicell

contribution in the late summer. This is when “severe weakly forced thunderstorms” (Miller and Mote 2017) are most common in the CONUS, which can cause downdraft-driven severe wind gusts (e.g., microbursts).

Similar to the annual cycle analysis, Fig. 9 reveals the average diurnal cycle of each hazard, relative to the reports’ local solar noon. Solar noon is the time the sun aligns with a location’s meridian, and using time relative to solar noon (as opposed to UTC time) eliminates the effect of time zones, providing a uniform representation of local time. Each severe report type has a pronounced diurnal cycle, with a peak in report frequency between approximately 2 and 8 h after solar noon. During local nighttime, severe weather is associated most with MCS storm cells. As tornado reports increase in frequency after solar noon, the overall fraction of reports associated with MCSs drops (Fig. 9a). From 2 to 12 h after solar noon, the majority of tornado reports for each of the three storm modes are produced from mesocyclonic storms. The hail data (Fig. 9b) show a more pronounced diurnal cycle

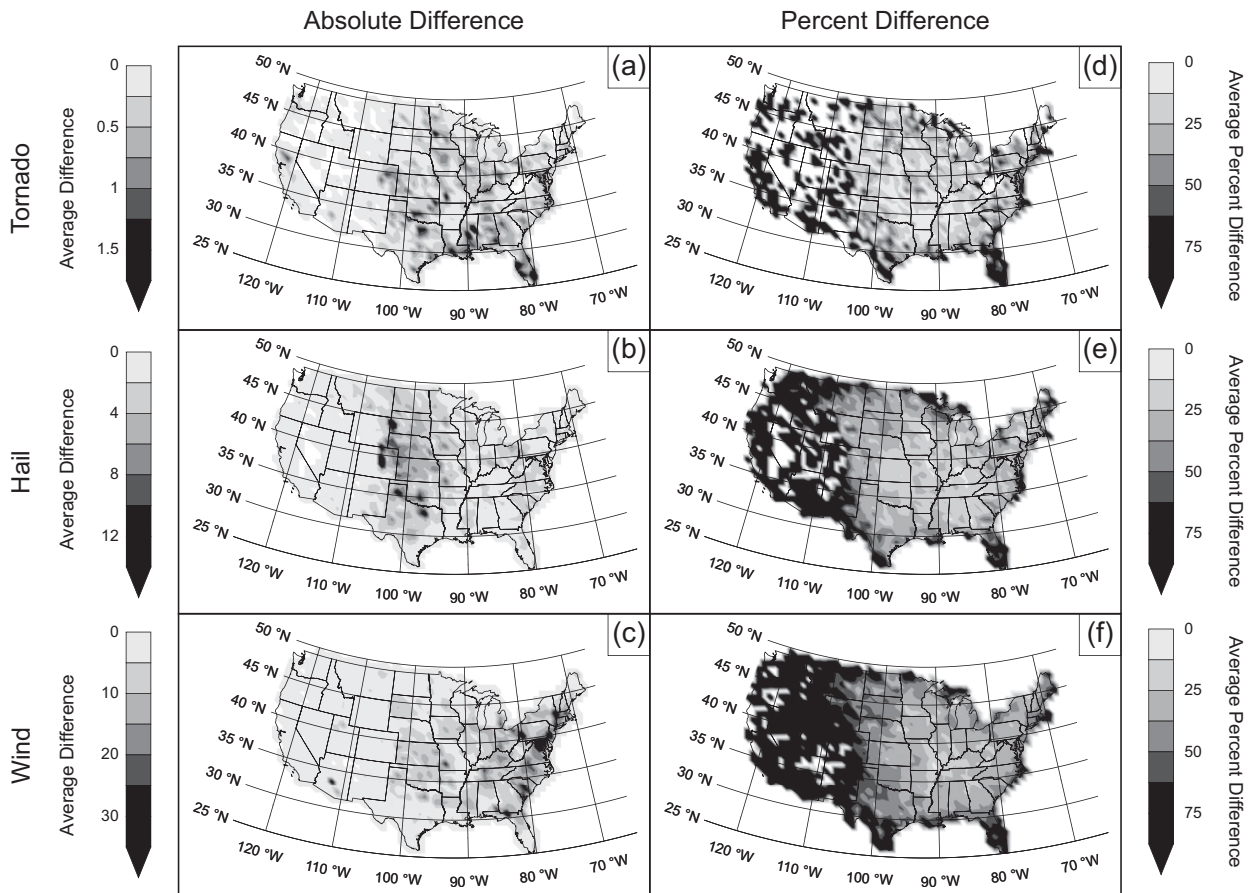


FIG. 7. Contour plots of average annual (a)–(c) absolute difference and (d)–(f) percentage difference between GR-S and SED reports for (a),(d) tornado; (b),(e) severe hail; and (c),(f) severe wind reports from 2010 to 2019, inclusive. Data are gridded on an approximately  $80 \text{ km} \times 80 \text{ km}$  grid. Areas not shaded indicate either no reports (both SED and GR-S) or an equal number of SED and GR-S reports.

when compared to tornadic and wind reports, with hail reports highly concentrated around their daily peak at 4–5 h after solar noon. Single-cell storms are the main contributor to hail reports in the first 7 h after solar noon, with the contributions of multicellular and MCS storms nearly equal during those hours ( $\sim 25\%$ ). Overall, mesocyclonic storms account for the majority of hail reports during 23 of the 24 total hours. As was true for the annual cycle, diurnal data show wind reports overwhelmingly associated with MCS storms throughout the majority of the day (Fig. 9c). MCSs are known to be prolific producers of damaging straight-line winds, so it is no surprise that these storms produce the most wind reports (a minimum of 48% of all wind reports each hour). Non-mesocyclonic single-cell and multicell severe wind-producing storms have a pronounced peak in the hours after solar noon, which, as previously mentioned, is likely attributable to down-draft-driven wind gusts from severe weakly forced thunderstorms that are common in the late summer and early afternoon. Notably, mesocyclonic storms never account for a majority of severe wind reports throughout the day ( $<39\%$  of reports per hour), in contrast to how often they contribute to severe hail and tornado reports during the peak tornado- and hail-producing hours. For all

analyses of the diurnal cycle of reports, note that the total number of reports may be lower during the overnight hours given that most people are asleep (e.g., Wendt and Jirak 2021).

Finally, we can examine how storms of various modes and mesocyclonic/non-mesocyclonic classifications contribute to reports of varying magnitude. Figure 10 shows histograms of the magnitude of each report type and the fractional contribution of storms of a given storm mode and mesocyclonic/non-mesocyclonic classification. The data show that the vast majority of reports ( $>90\%$ ) are sub-significant severe (i.e., below EF2, 2 in., or 65 kt for tornado, hail, and wind reports, respectively). As EF rating increases, the relative contribution of mesocyclonic storms also increases, to the point where they are responsible for 90.5% and 100% of all EF4 (84 total) and EF5 (12 total) tornado reports in the database, respectively. In fact, for any EF rating, mesocyclonic storms account for the majority of tornadoes. GR-S data also show that EF0, EF1, and EF2 tornadoes all predominantly come from cells embedded within MCSs (53.7, 73.4, and 65.6% of tornadoes, respectively). Focusing on significant tornadoes, the percentage of tornadoes linked to MCS-classified storms decreases from 65.6% to 33.3% as the percentage linked to single-cell

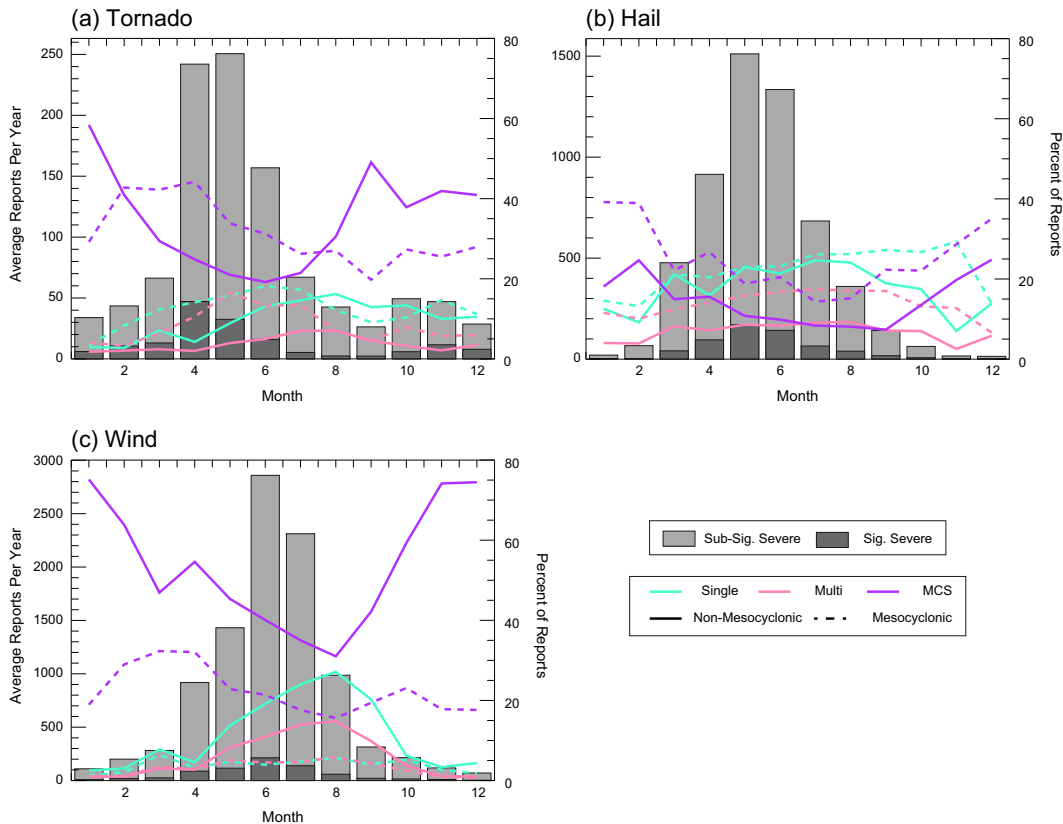


FIG. 8. Average annual number of GR-S matched (a) tornado, (b) severe hail, and (c) severe wind reports by month for 2010–19. Lines show the percentage of total reports that were matched to a storm of a given storm mode (single-cell, multicell, and MCS storms in green, pink, and purple, respectively) and with a given updraft type (non-mesocyclonic and mesocyclonic in solid and dashed lines, respectively). Bar charts are split into lighter and darker gray, which show sub-significant severe and significant severe reports, respectively. The vertical extent of these two bars combined is the total number of all reports, and the sum of all lines in a given month is 100%.

storms increases to a maximum of 58.3% for EF5 tornadoes. Mesocyclonic storms are also the main contributor to hail reports, and hailstones are more likely to be associated with mesocyclonic storms as hail size increases. As was evident in Figs. 8 and 9, no one storm mode clearly dominates hail production. Interestingly, single-cell storms account for a majority of hailstones in the lowest three bins, but contributions to 4-in.+ hailstones are relatively equal across storm modes. This comes with the caveat that the largest hailstone bin contains 0.7% of the total reports in the smallest hailstone bin. Wind reports become increasingly associated with mesocyclonic storms as wind speed increases, with the exception of the strongest winds in the dataset. These winds (95+ kt) are predominately from non-mesocyclonic storms (52.7%), in stark contrast with the strongest tornadoes and largest hail, which are overwhelmingly associated with mesocyclonic storms. Wind reports are largely dominated by storms embedded within MCSs, with 62.9%–81.3% of reports in each bin attributed to MCSs. As touched on in the discussion of hail-producing storms, it is important to recognize that as EF rating, hail size, and wind speed increase, the sample size of reports decreases. Therefore, interpretation of mode

and mesocyclonic–non-mesocyclonic breakdown must be done carefully, especially where sample sizes drop below a few hundred reports.

### 5. Comparison to past studies

Given that GR-S storm-matched reports were demonstrated to be a representative sample of SED reports from 2010 to 2019, we can also use GR-S data to revisit analyses and conclusions from prior papers to assess reproducibility. Herein, we focus on two studies, Trapp et al. (2005) and Ashley et al. (2019), which examined the prevalence of various storm modes and their propensity to produce severe weather. Table 3 lists basic information about data sources and methods employed in the papers, as well as a summary of those used in the present study.

For comparisons between GR-S data and prior results focusing on MCS or QLCS storms, we will compare the papers’ findings to only our non-mesocyclonic MCS cells. Comparing strictly our non-mesocyclonic MCS data to other studies’ full MCS datasets resulted in greater consistency, potentially pointing to mesocyclonic MCS cells being more dynamically

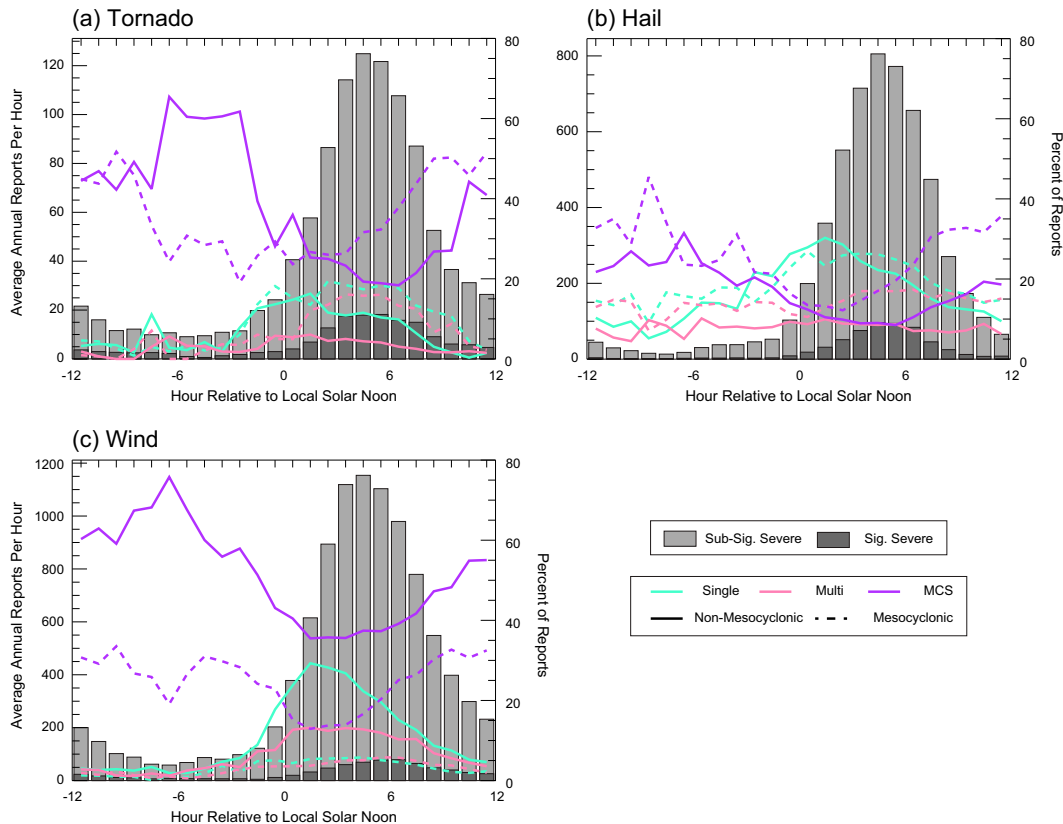


FIG. 9. Average annual number of GR-S matched (a) tornado, (b) severe hail, and (c) severe wind reports by hour relative to local solar noon for 2010–19. Lines show the percentage of total reports matched to a storm of a given storm mode (single-cell, multicell, and MCS storms in green, pink, and purple, respectively) and with a given updraft type (non-mesocyclonic and mesocyclonic in solid and dashed lines, respectively). Bar charts are split into lighter and darker gray, which show sub-significant severe and significant severe reports, respectively. The vertical extent of these two bars combined is the total number of all reports, and the sum of all lines in a given hour is 100%.

consistent with single-cell mesocyclonic storms than with non-mesocyclonic MCS storms. This result is relevant to any future work using GR-S MCS data with the storm mode classification employed here. Also important to note is the delineation between an MCS and a QLCS. As discussed in Schumacher and Rasmussen (2020), a QLCS is a subset of the MCS archetype. While MCSs are typically defined as convective complexes with a maximum dimension  $\geq 100$  km, a QLCS is an MCS further characterized by an aspect ratio around 3:1, meaning that the system has one long and one short dimension. Given that the terms MCS and QLCS are often conflated, it is important to keep in mind the true nature of MCS-classified cells herein and how they may or may not be a part of a QLCS-type convective complex.

GR-S data are first compared to select conclusions from Trapp et al. (2005). The study's main goal was to “estimate the percentage of U.S. tornadoes that are spawned annually by squall lines and bow echoes, or quasi-linear convective systems (QLCSs)” using subjectively classified radar echoes over a 3-yr period (1998–2000, inclusive). Classification was done for QLCS and individual cells near the time of tornadogenesis per Table 3. They delineated between QLCS and cell type echoes based on “dynamics unique to these phenomena” and

mentioned that, while tornadoes can form by mesocyclonic and non-mesocyclonic means, any distinction between cells producing tornadoes via these two different mechanisms was not investigated therein. Their final dataset included 3828 tornadoes.

Figure 11 shows reproductions of Trapp et al. (2005) Fig. 3b (Fig. 11a), Fig. 6 (Fig. 11b), and Fig. 8a (Fig. 11c) using GR-S data. Figure 11a shows the breakdown of the number of tornado reports by EF rating on a logarithmic scale for both single-cell and MCS storms. Crucially, both MCS mesocyclonic and non-mesocyclonic lines are shifted such that they have an equal number of EF2 reports per storm type; Fig. 11a therefore emphasizes the relative distributions of tornado intensity by storm type rather than absolute values. Trapp et al. (2005) found that there “appear to be disproportionately more F1 tornadoes from QLCSs, and more F3–F4 tornadoes from cells.” Figure 11a shows this as well, where the non-mesocyclonic MCS cell line is above the single-cell line for EF1 tornadoes and below the cell line for EF3–4 tornadoes. Here the mesocyclonic MCS curve more closely matches the single-cell curve, pointing again to their dynamical similarities. On the other end of the spectrum, data from Trapp et al. (2005) (GR-S) show no F5 QLCS (EF5 non-mesocyclonic MCS) tornadoes given they are quite rare, and

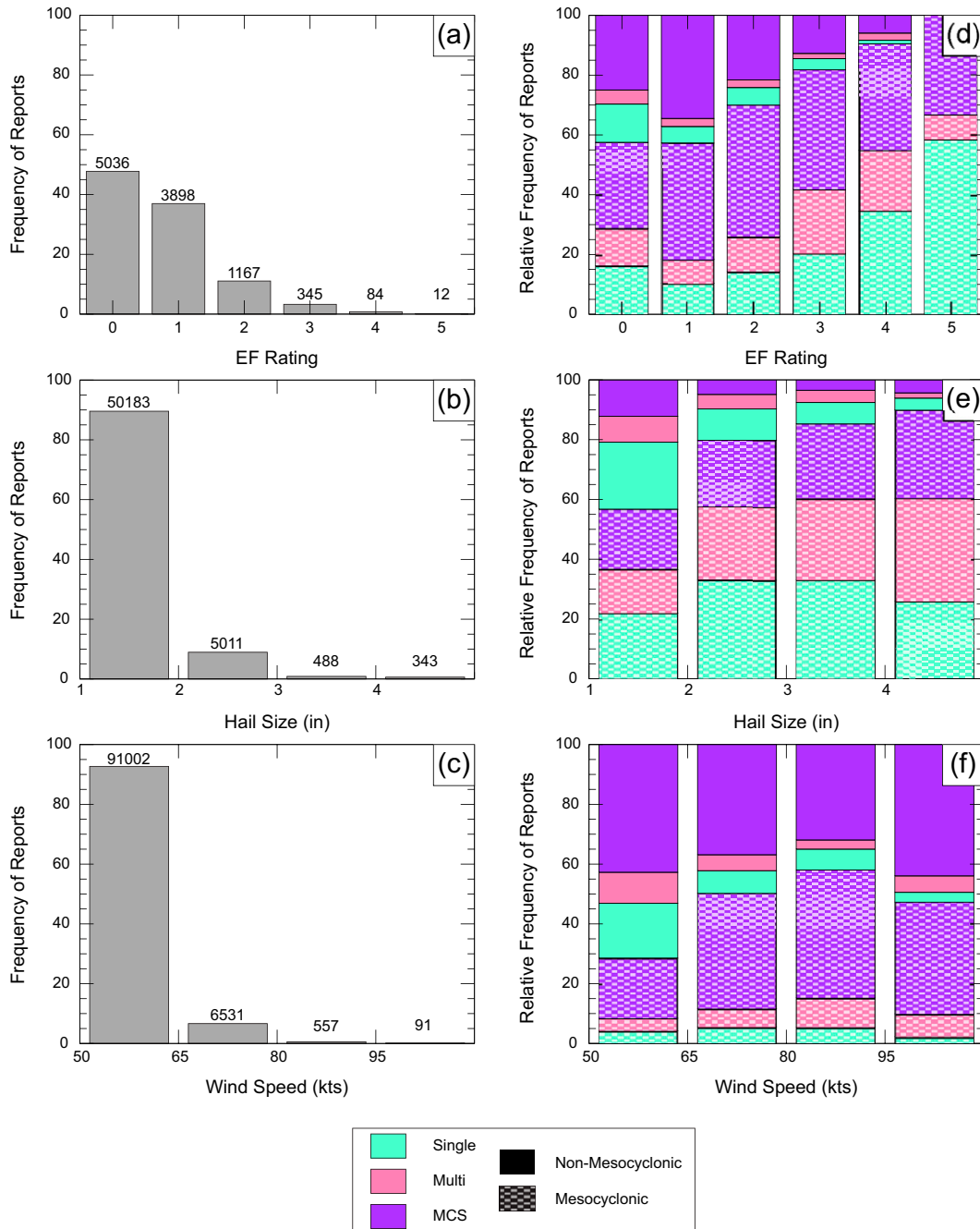


FIG. 10. Breakdown of (a)–(c) total frequency of reports by (a) EF rating, (b) hail size, and (c) wind speed; as well as (d)–(f) the percentage of reports associated with a given combination of storm mode and supercell classification by (d) EF rating, (e) hail size, and (f) wind speed. In (a)–(c), the total number of reports in each bin are listed on top of the individual bars.

also note that F5 (EF5) tornadoes only comprise 0.2% (0.11%) of the total dataset. [Trapp et al. \(2005\)](#) also noted that their QLCS curve was fairly log-linear except for F0 tornadoes, potentially attributable to underreporting of the weakest tornadoes. This same linear shape, along with relatively low EF0 tornado counts, is visible in the GR-S non-mesocyclonic MCS curve.

[Figure 11b](#) shows the cumulative distribution of all tornado reports broken down by month and storm type. [Trapp et al. \(2005\)](#) found that 32% of all QLCS tornado reports occurred within the first three months of the year, compared to just 14% of single-cell reports. The lower relative fraction of cell reports compared to QLCS reports is mirrored with the GR-S

TABLE 3. Comparison of techniques used to classify storm mode in past literature.

Field	Trapp et al. (2005)	Ashley et al. (2019)	This study
Years of data	1998–2000	1996–2017	2010–19
Classification technique	Hand analysis	Machine learning	Objective analysis
$Z_H$ data	Composite column-maximum images from NCDC (NCEI), other sources	NOWrad composite reflectivity data (Grassotti et al. 2003)	GR-S column-maximum data
Cell classification	Relatively isolated, circular, or elliptical in shape, with $Z_{Hmax} \geq \sim 50$ dBZ	—	One track in 30-dBZ $Z_{Hmax}$ contour or two tracks within 30-dBZ $Z_{Hmax}$ contour < 3000 km <sup>2</sup>
MCS classification	—	Region of $Z_{Hmax} \geq 40$ dBZ persisting for at least 3 h, with contiguous to semicontiguous 40 dBZ contour maximum dimension $\geq 100$ km	Two tracks within 30-dBZ $Z_{Hmax}$ contour $\geq 3000$ km <sup>2</sup> or three or more tracks within 30-dBZ $Z_{Hmax}$ contour; maximum dimension $\geq 100$ km
QLCS classification	Quasi-linear, $Z_{Hmax} \geq 40$ dBZ region with maximum dimension > 100 km	MCS with convective region aspect ratio $\geq 3$	—

data, with tornadoes in January–March making up 20% of non-mesocyclonic MCS tornadoes and just 8% of single-cell tornadoes. Therefore, with both datasets, a higher proportion of annual MCS tornadoes occurred in the first 3 months of the

year compared to the proportion of annual single-cell tornadoes. Finally, Fig. 11c shows the diurnal cycle of tornado reports, using time relative to local solar noon. Trapp et al. (2005) found that cell reports peaked close to 18 local

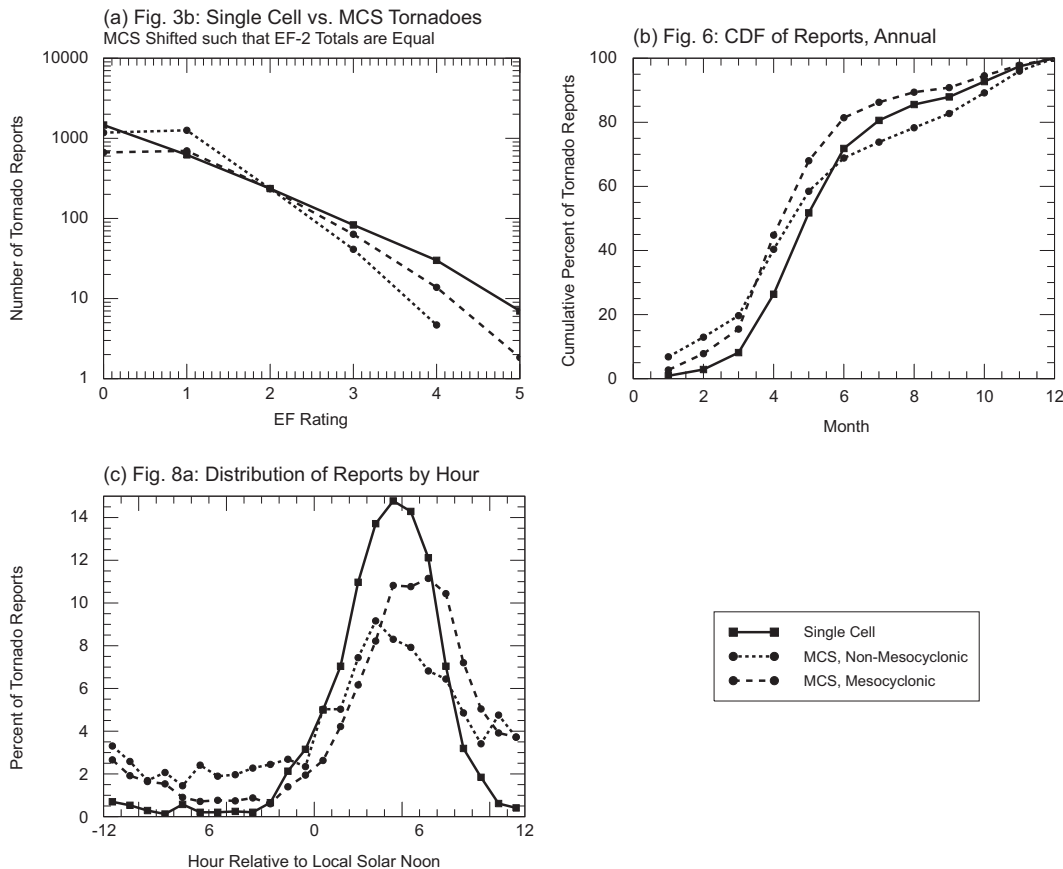


FIG. 11. Plots reproducing (a) Fig. 3b, (b) Fig. 6, and (c) Fig. 8a in Trapp et al. (2005) using GR-S data. Lines are broken into single-cell storms, non-mesocyclonic MCS storms, and mesocyclonic MCS storms. In (c), data within each 1-h bin are plotted at the 30-min mark of that hour.



TABLE 4. Comparison of percentage of reports attributable to MCSs for different report types and severity. Data shown are from Ashley et al. (2019) and GR-S data.

Report type and severity	GridRad-Severe MCS	Ashley et al. (2019) QLCS
Tornado, severe	27.54%	21%
Tornado, significant severe	18.72%	26%
Hail, severe	11.43%	10%
Hail, significant severe	4.74%	7%
Wind, severe	42.31%	28%
Wind, significant severe	36.61%	34%

standard time (LST), with a similar albeit smaller peak in QLCS data near 18 LST. GR-S data show similar trends, with peaks in single-cell and non-mesocyclonic MCS data between 3 and 5 h after solar noon, and a higher peak for single-cell than non-mesocyclonic MCS data (i.e., a more amplified diurnal cycle). Mesocyclonic MCS cells are again more consistent with single-cell storms, with a ~2-h offset in their diurnal cycle compared to the single-cell data.

GR-S data are additionally compared to the findings of Ashley et al. (2019), who used machine learning methods to classify storm mode using a 22-yr radar dataset. For training the model, QLCS storms were labeled by hand, and the model was trained on labeled QLCS and non-QLCS events. They defined an MCS per Table 3, with that definition motivated primarily by the work of Parker and Johnson (2000). A QLCS is defined as “an MCS that has instantaneous convective ( $\geq 40$  dBZ) regions that are longer than 100 km and must be at least 3 times as long as they are wide.” The major differences between their definition of an MCS and the definition used herein is the 30- versus 40-dBZ threshold for defining radar echoes for classification, and no temporal threshold versus a 3-h temporal threshold for GR-S and Ashley et al. (2019), respectively. Their paper focuses on the spatiotemporal distribution of both QLCSs and QLCS-matched tornado reports, and only the latter will be analyzed herein.

Table 4 shows the percentage contribution of severe reports attributable to QLCSs in Ashley et al. (2019) juxtaposed with storm-matched GR-S reports attributable to non-mesocyclonic MCS cells. In each category, the percentage of reports attributed to MCSs is fairly similar when comparing GR-S data to the results in Ashley et al. (2019). The greatest difference is with attribution of severe wind reports [28% of storms in Ashley et al. (2019) versus ~42% in GR-S]. Although trends in these data are similar, differences are no doubt the result of myriad differences in methods throughout the data analysis process. Both datasets show a high percentage of wind reports and a low percentage of hail reports attributed to QLCS/non-mesocyclonic MCS storms. Beyond examining total reports attributed to QLCSs, their Fig. 11 shows a breakdown of all severe reports by month and hour, with percentage attributed to QLCSs overlaid. Similar to Fig. 8 herein, they found tornado and hail reports peak in the late spring and wind reports peak in the early summer. They also found that QLCS contribution to total reports was maximized during the winter months

and minimized in late summer/early fall, which was similar to the summer/early fall minima and wintertime maxima seen in the non-mesocyclonic MCS GR-S data. Examining their hourly data, they found a minimum in QLCS contribution during times of peak reporting (~1800–0300 UTC), which, when examining GR-S data binned by local time (in UTC, not shown), non-mesocyclonic MCS contributions are minimized from 2000 to 0400 UTC for tornadoes and from 1700 to 0300 UTC for hail and wind reports. The average percentage contribution of QLCSs to hail reports in their study was lower than that for wind and tornado reports, which is also reflected in the GR-S data. Overall, the similarities between GR-S conclusions and those of Trapp et al. (2005) and Ashley et al. (2019) point to the efficacy of the GR-S techniques as a whole and the storm mode classification algorithms used herein.

## 6. Conclusions

In this study, the GR-S dataset was introduced, a dataset centered on CONUS-wide radar data for ~100 of the most severe days per year from 2010 to 2019, inclusive. After determining which days to include in the database, spatiotemporal domains for radar data are selected objectively, and all storms within the domain are tracked throughout their lifetimes. Storms are matched with severe reports and both storm mode classification (single-cell, multicell, and MCS storms) and supercell classification (mesocyclonic or non-mesocyclonic, for all three storm modes) are performed. Based on the analysis presented, the following conclusions can be drawn:

- 1) The GR-S dataset captures a majority of SED reports from 2010 to 2019 inclusive and captures ~90% of reports that exist within the spatiotemporal bounds of GR-S (Table 2). The reports captured are analogous in spatial and temporal distribution to the SED reports, and the relative contribution of tornado, hail, and wind reports to all reports per month also mirror that of the SED database quite well (Figs. 5–7). Therefore, the storm-matched reports within the GR-S database are a representative sample of the complete SED dataset.
- 2) Pronounced annual and diurnal variability was evident for tornado, hail, and wind reports: (i) MCS-classified cells produced the most tornadoes throughout the entire year when compared to other storm modes, and mesocyclonic storms were found to be the primary tornado contributors during peak tornado frequency in spring and summer (Fig. 8a). During the overnight and early morning when total number of reports is low, MCS contribution is maximized, and during the time of peak reports, mesocyclonic storms produce the majority of tornado reports (Fig. 9a). (ii) Single-cell storms account for the largest fraction of hail reports by storm mode for spring through fall, and mesocyclonic storms account for a majority of all hail reports both year-round (Fig. 8b) and throughout the day (Fig. 9b). Hail reports have the most pronounced diurnal cycle of the three report types, meaning that reports are highly concentrated around their time of peak occurrence

(~4–5 h after local solar noon). Unlike tornadoes and wind reports, there is no one storm mode that stands out as the primary producer of severe hail reports over the whole year or whole day. (iii) MCS-classified cells produce the most severe wind reports throughout the entire year (Fig. 8c) and day (Fig. 9c) when compared to other storm modes. There is a peak in non-mesocyclonic single-cell and multicell contribution to wind reports in the late summer and early afternoon, likely due to decay of severe weakly forced thunderstorms.

- 3) For both tornado and hail reports, as EF rating and hail size increase, so does the relative contribution of mesocyclonic storms to total reports (Fig. 10). Wind reports show a similar trend, but the contribution of mesocyclonic storms does not monotonically increase with increasing wind speed. However, due to small sample sizes at the highest intensities, such breakdowns should be interpreted carefully.
- 4) GR-S was found to broadly reproduce the findings of Trapp et al. (2005) (Fig. 11) and Ashley et al. (2019) (Table 4), lending credence to the usefulness of the GR-S dataset and quality of storm mode classification applied herein.

The GR-S database was created to facilitate robust studies of severe weather using radar data from a large sample of storms. Namely, the objective methods used to build the now-public dataset (School of Meteorology/University of Oklahoma 2021) provide an opportunity to easily investigate thousands of severe storms and over 1.3 million total storms with great detail. We believe these data can be used to examine several challenging and important science questions regarding severe weather and we encourage others to use GR-S to explore their own scientific questions as the dataset continues to grow.

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*Data availability statement.* Radar data are publicly accessible through the National Centers for Environmental Information (NOAA/NWS/ROC 1991), and storm reports can be accessed from the Storm Events Database (NOAA/NCEI 2022). Processed GR-S data are publicly available via the Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory (School of Meteorology/University of Oklahoma 2021).

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