1.5 26-YEAR CLIMATOLOGY OF SEVERE WIND-PRODUCING MESOSCALE CONVECTIVE SYSTEMS IN THE UNITED STATES

Andrew R. Wade*
University of Oklahoma, Norman, OK
NOAA/NWS/NCEP Storm Prediction Center, Norman, OK

Brian J. Squitieri
NOAA/NWS/NCEP Storm Prediction Center, Norman, OK

Israel L. Jirak
NOAA/NWS/NCEP Storm Prediction Center, Norman, OK

1. INTRODUCTION

Mesoscale convective systems (MCSs; e.g., Zipser 1977, Houze 1993, Parker and Johnson 2000) are a common mode of severe thunderstorms over the contiguous United States (CONUS), and are especially prone to producing severe (25.7 m s^{-1}/50 kt, or damaging) straight-line winds. The scope and severity of these winds varies widely across the spectrum of MCSs, from systems that produce no severe wind to derechos (Hinrichs 1888, Johns and Hirt 1987) that produce widespread significant severe (33.4 m s^{-1}/65 kt) wind over swaths that can exceed 1000 km in length.

Especially in the wake of high-profile, destructive events on 29 June 2012 and 10 August 2020, National Weather Service (NWS) Weather Forecast Offices as well as the NWS Storm Prediction Center (SPC) often receive questions from the media and the public about whether certain damaging wind events are derechos. The qualitative definition is mostly undisputed: “a widespread convectively induced straight-line windstorm” (American Meteorological Society 2023). However, the quantification of this definition to designate individual MCSs as derechos or not derechos has long posed a challenge (Squitieri et al. 2023a).

*Corresponding author: Andrew R. Wade, andrew.wade@noaa.gov

Quantitative criteria vary across at least nine major studies of derechos. SPC aims to unify these, resolving the conflicts among them, into a standard, operationally applicable set of criteria for derechos. This goal requires as comprehensive a sample of MCSs as possible to ensure that all major historical events widely recognized as derechos meet the operational criteria, as well as to estimate the climatological frequency and geographic distribution of MCSs meeting these criteria. Any attempt to find all MCSs in the CONUS over a long period and assign wind reports to each one must be automated to some extent. But this automation should not consist of a “black box”; forecasters must be able to apply the same method to a single MCS that has just occurred and understand why it was or was not identified as a derecho-producing MCS.

Haberlie and Ashley (2018a, 2018b, 2019) compiled a climatology of MCSs by extracting mesoscale features from radar reflectivity mosaics and training a machine learning model to distinguish MCSs from other features. While this dataset is likely very close to what is needed for a broad climatology of derechos and other severe MCSs, day-to-day operational use on individual MCSs may require interpretability, consistency, and tunability beyond that of the underlying model. So in this abstract, we describe an algorithm that identifies MCSs with explicit, fixed thresholds of certain radar reflectivity-based variables. The fields and thresholds used are primarily informed by

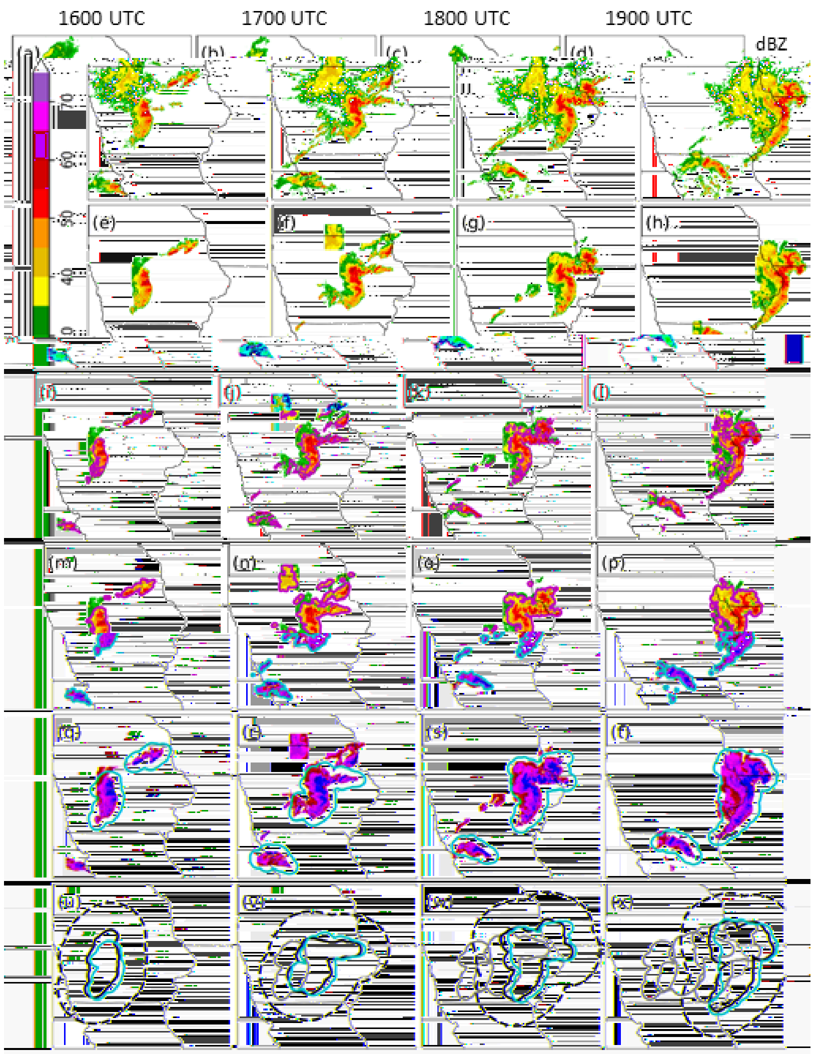

Fig. 1. Demonstration of MCS identification and tracking algorithm steps at 16, 17, 18, and 19 UTC 10 August 2020, including initial IEM reflectivity mosaics (a-d); remaining reflectivity after masking certain non-convective-line regions (e-h); identification of all 40-dBZ polygons, highlighted in magenta in panels (i-l); merging of nearby 40-dBZ polygons, with resulting convective areas highlighted in magenta in (m-p); identification of convective lines meeting length criterion, highlighted in magenta in (q-t); and tracking (u-x), in which the magenta polygon is the current MCS, the black polygon is the MCS at the prior 15-minute interval, the black dashed polygon represents the tracking radius whose area of intersection with new MCS polygons is used to prioritize matching, and the gray polygons are the MCS at the previous hours shown in this figure.

Haberlie and Ashley's (2018a, 2018b) most important predictors combined with the characteristic time and length scales of MCSs. Further tuning was done via trial and error on a varied set of historical derechos across regions and seasons to ensure their successful identification.

As intended, the resulting set of MCSs enables refinement of derecho criteria, described in more detail in the companion presentation Squitieri et al. (2023b). It also allows for a long-term climatology of wind production by severe but sub-derecho MCSs, which is relatively unexplored. We show basic climatological characteristics of the dataset, and demonstrate future work on the synoptic and mesoscale environments of different classes of MCSs.

2. DATA AND METHODS

2.1 *Identification of instantaneous MCS structures in radar reflectivity*

The algorithm begins with CONUS-wide radar reflectivity mosaics from the IEM archive (Iowa State University 2001), which have pixel dimensions on the order of 1 km. First, two types of non-MCS regions are masked: regions outside 81-pixel square neighborhoods of any 50-dBZ pixel, and regions with 21-pixel square neighborhood mean reflectivity less than 25 dBZ. The former criterion excludes features with only weak convective characteristics or none at all; the latter excludes small, isolated convective cells and most radar artifacts, like ground clutter, anomalous propagation, and sun spikes.

After masking these regions, all remaining polygons of 40 dBZ are given a 5-km buffer, and any that intersect as a result are merged. This closes small gaps in convective lines. For each remaining 40 dBZ polygon, the length of the diagonal of the bounding box is calculated. This must be at least 150 km [exceeding the 100 km length scale defining an MCS (Parker and Johnson 2000) because the long axis of the convective line often does not lie on the diagonal of the box]. Then, two intensity checks are performed: the polygon must contain at least 100 pixels of 50 dBZ or greater, and at least 0.01 such “intense” pixels per square kilometer of polygon area. The 50 dBZ area is an important predictor in Haberlie and Ashley’s (2018a) machine learning identification of MCSs. Any polygons that meet all of these criteria are given an additional 20-km buffer to attempt to capture gust fronts that may surge outside of MCSs’ main precipitation fields. Any individually qualifying polygons that intersect as a result of this buffer are merged.

2.2 *Temporal tracking and storm report matching*

A 15-minute step is used for tracking across time. MCS polygons at the previous timestep are sorted by area and, proceeding from largest to smallest, matches at the current timestep are sought. A 100-km tracking radius is added to the previous timestep’s polygon, and the current polygon with the largest intersection with it is matched to it. Matching is unique, so that post-merger or pre-split segments are not double-counted as part of two separate MCSs. In the case of a merger, the smaller MCS at the last pre-merger timestep is terminated; in the case of a split, the segment with the largest intersection with the previous timestep’s tracking radius is assigned to the existing MCS, and the other segment(s) may begin new MCS objects if they meet criteria. A one-timestep grace period is allowed to avoid terminating MCSs whose convective lines are briefly broken by radar artifacts/blockage. If an MCS cannot be matched to a new polygon for two consecutive timesteps, it is terminated. Only MCSs that have persisted for at least 3 h are stored. Fig. 1 demonstrates the identification and tracking process with an example case.

After each timestep, all thunderstorm wind local storm reports (LSRs) of 50 kt or greater in the past 15 minutes that fall within 10 km of the MCS polygon are assigned to the MCS. Each MCS object is saved as three lists: the reflectivity polygons with their coordinates, the times at which those polygons are valid, and the LSR objects assigned to the MCS. Each LSR object has attributes such as time, coordinates, magnitude, magnitude type (estimated or measured), etc.

Finally, after the tracking process is completed, MCSs within 500 km and 6 h of any tropical cyclone center are removed.

3. RESULTS

3.1 *MCSs*

20,400 MCSs were identified from 1 January 1996 through 31 December 2021. These MCSs were most common in a broad region including the Southern and Central Plains, the Ozarks, the Midwest, the lower Ohio Valley, the middle and lower Mississippi Valley, and the central Gulf Coast (Fig. 2). MCSs were seldom identified west of 104 degrees west longitude, owing to both the actual rarity of MCSs and the limitations of radar coverage. The spatial distribution and the local frequencies of MCSs are consistent with Haberlie and Ashley's (2019) machine learning-based climatology; the primary difference is a lower frequency of MCSs in the Gulf Coast states in the present study.

3.2 *Severe MCSs*

Severe MCSs (Fig. 3), defined for this study as MCSs matched to at least one report of severe wind, were a majority of all MCSs identified. In particular, in the most MCS-prone corridor from the Central and Southern Plains to the Tennessee Valley, roughly three-quarters of MCSs were severe. This increases confidence in the quality of MCSs identified.

By matching LSRs to MCSs, this dataset enables stratification of MCSs by severity. For example, arbitrary classes of "marginally severe" (1–10 LSRs and no significant severe, n = 2796) and "significantly severe" (5 or more significant severe, n = 405) warm-season [May–August, after Coniglio et al. (2004)] MCSs may be compared. A peak time and location for each MCS is determined using the maximum density of severe (significant severe for the latter class) reports. Then composites are created from SPC's objective analysis (SFCOA; Bothwell et al. 2002) valid at the peak times and centered on the peak locations. Composites of the derecho composite parameter (DCP; SPC 2023), which combines most-unstable convective available potential energy (CAPE), downdraft CAPE, 0–6-km bulk shear, and 0–6-km mean wind, reveal that the mean environments of these two sets of MCSs are dramatically different (Fig. 4). [Note that DCP was unavailable for a small minority of cases early in the study period.] This basic experiment suggests much deeper environmental analysis will be possible with the MCS dataset.

4. CONCLUSIONS

4.1 *Summary*

Automated radar reflectivity-based identification and tracking finds over 20,000 MCSs in 26 years. The spatial distribution is largely consistent with other literature, showing a maximum in MCS frequency from the Kansas-Oklahoma border to the lower Ohio and Tennessee Valleys. Most identified MCSs produced at least one severe wind report. In a simple demonstration of how the dataset may be applied, groups of significant severe and marginally severe MCSs appear to have markedly different characteristic environments.

4.2 *Future work*

Fine-tuning of algorithm features continues, particularly with respect to LSR matching, as using a tight spatiotemporal window can exclude MCS-related reports that are imprecisely timed relative to reflectivity, or that result from gust fronts surging unusually far from precipitation. 2022 MCSs will be added to the dataset after they are checked against tropical cyclone locations. Quality control is also ongoing among derecho and possible derecho cases by the proposed criteria of Squitieri et al. (2023b), which are themselves still under internal review. While it is possible that a few borderline events have been lost or divided into multiple MCSs by tracking failures, manual inspection confirmed reasonable tracking of all major historical derechos during the period. Of the current set of derecho candidates, fewer than 10 percent required manual corrections to tracking or report matching to meet the working criteria.

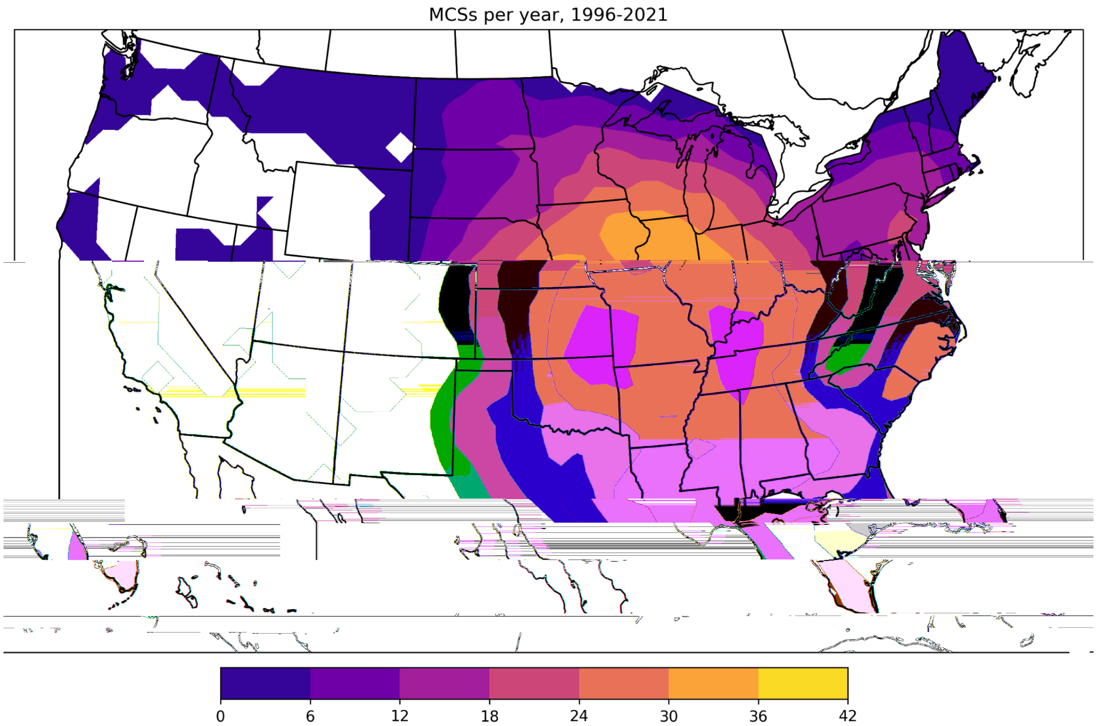

Fig. 2. Annual frequency of MCSs automatically identified from radar, 1996–2021 inclusive.

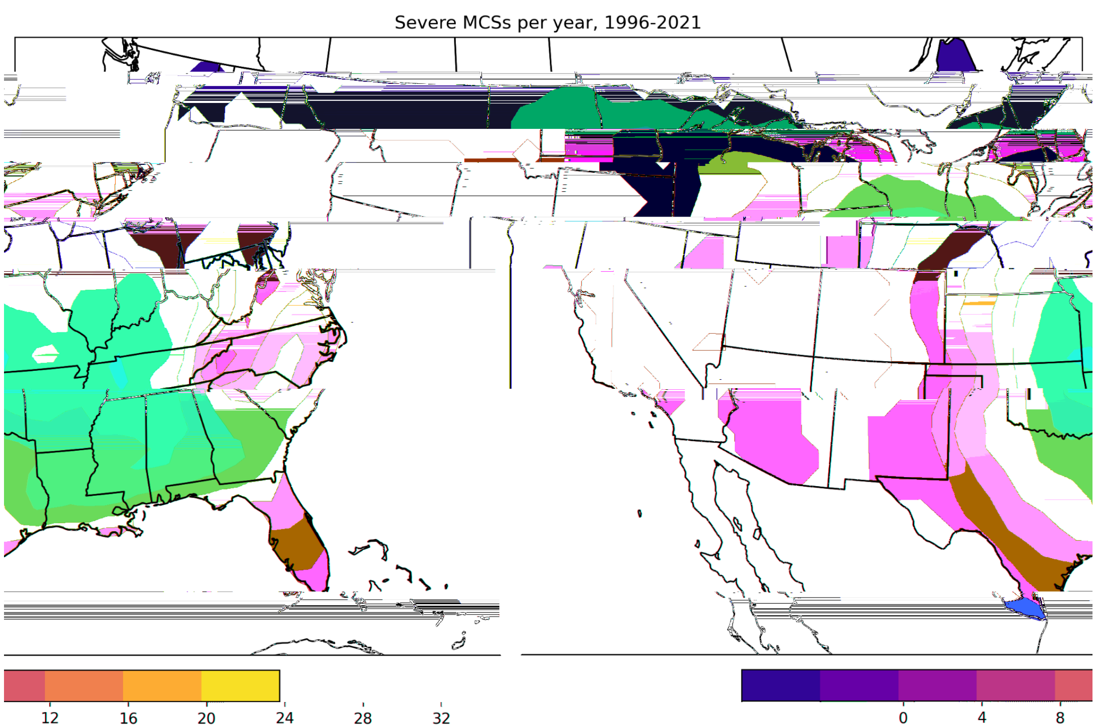

Fig. 3. As in Fig. 2, but for MCSs producing at least one severe wind report.

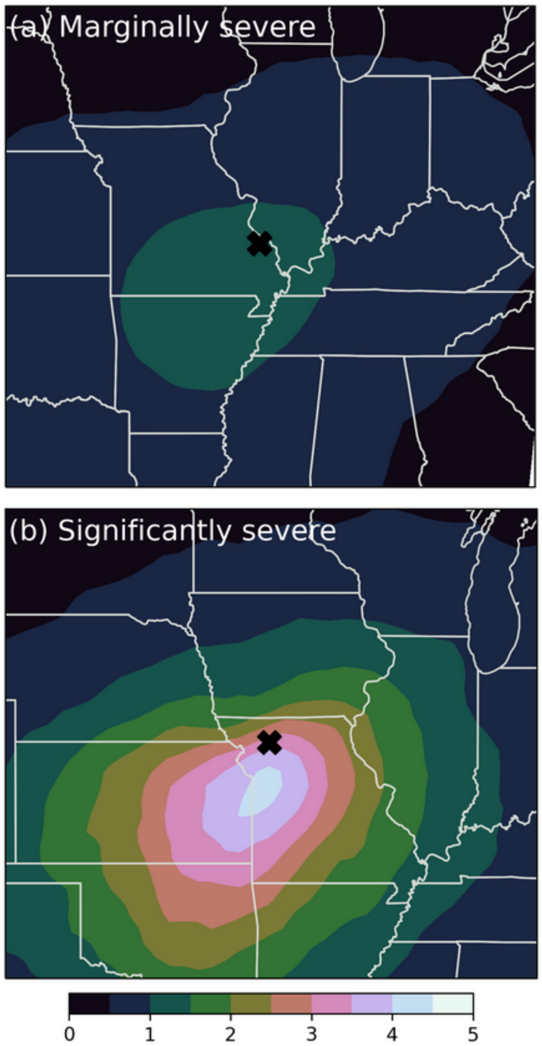

Fig. 4. Composites of DCP centered on the peak locations (X) of the (a) marginally and (b) significantly severe warm-season MCS sets described in section 3.2.

A comprehensive set of thousands of MCSs with matched wind reports offers many future research opportunities. Environmental compositing after the example in section 3.2 is promising. Objective clustering of derecho-producing MCSs by characteristics of the 500-hPa height field has been preliminarily successful, and wind probabilities in operational convection-allowing guidance for various classes of severe MCSs will also be explored. Though outside of SPC's focus, the dataset may have utility for studies of extreme rainfall. Finally, the MCS dataset continues to serve its original purpose of testing and refining operational criteria for derechos.

REFERENCES

American Meteorological Society, 2023: "Derecho". Glossary of Meteorology, http://glossary.ametsoc.org/wiki/derecho.

Bothwell, P., J. Hart, and R. Thompson, 2002: An integrated three-dimensional objective analysis scheme in use at the Storm Prediction Center. *Preprints, 21st Conf. on Severe Local Storms/19th Conf. on Weather Analysis and Forecasting/15th Conf. on Numerical Weather Prediction.*, San Antonio, TX, Amer. Meteor. Soc., JP3.1, https://ams.confex.com/ams/pdfpapers/47482.pdf.

Coniglio, M. C., and D. J. Stensrud, 2004: Interpreting the climatology of derechos. *Wea. Forecasting*, **19**, 595–605, doi:10.1175/1520-0434(2004)019<0595:ITCOD>2.0.CO;2.

Haberlie, A. M., and W. S. Ashley, 2018a: A method for identifying midlatitude mesoscale convective systems in radar mosaics. Part I: Segmentation and classification. *J. Appl. Meteor. Climatol.*, **57**, 1575–1598, doi:10.1175/JAMC-D-17-0293.1.

Haberlie, A. M., and W. S. Ashley, 2018b: A method for identifying midlatitude mesoscale convective systems in radar mosaics. Part II: Tracking. *J. Appl. Meteor. Climatol.*, **57**, 1599–1621, doi:10.1175/JAMC-D-17-0294.1.

Haberlie, A. M., and W. S. Ashley, 2019: A radar-based climatology of mesoscale convective systems in the United States. *J. Climate*, **32**, 1591–1606, doi:10.1175/JCLI-D-18-0559.1.

Hinrichs, G., 1888: Tornadoes and derechos. *Amer. Meteor. J.*, **5**, 306–317.

Houze, R. A., 1993: *Cloud Dynamics*., Academic Press, 573 pp.

Iowa State University, 2001: Iowa Environmental Mesonet. Department of Agronomy, Iowa State University, accessed 2023, https://mesonet.agron.iastate.edu/docs/nexrad_composites/.

Johns, R. H., and W. D. Hirt, 1987: Derechos: Widespread convectively induced windstorms. *Wea. Forecasting*, **2**, 32–49, doi:10.1175/1520-0434(1987)002<0032:DWCIW>2.0.CO;2.

Parker, M. D., and R. H. Johnson, 2000: Organizational modes of midlatitude mesoscale convective systems. *Mon. Wea. Rev.*, **128**, 3413–3436, doi:10.1175/1520-0493(2001)129<3413:OMOMMC>2.0.CO;2.

Squitieri, B. S., I. L. Jirak, and A. R. Wade, 2023a: A historical overview on the science of derechos. Part I: Identification, climatology, and societal impacts. *Bull. Amer. Meteor. Soc.*, in press.

Squitieri, B. S., I. L. Jirak, and A. R. Wade, 2023b: A damaging-wind based MCS classification system and formal definition of a derecho. *32nd Conf. on Weather Analysis and Forecasting*, Madison, WI, Amer. Meteor. Soc., 17.6.

Storm Prediction Center, 2023: Derecho composite parameter (DCP). Accessed 2023, https://www.spc.noaa.gov/exper/mesoanalysis/help/help_dcp.html.

Zipser, E. J., 1977: Mesoscale and convective-scale downdrafts as distinct components of squall-line circulation. *Mon. Wea. Rev.*, **105**, 1568–1589, doi:10.1175/1520-0493(1977)105<1568:MACDAD>2.0.CO;2.