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A derecho climatology (2004-2021) in the United States based on machine learning identification of bow echoes

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Abstract

Due to their persistent widespread severe winds, derechos pose significant threats to human safety and property, and they are as hazardous and fatal as many tornadoes and hurricanes. Yet, automated detection of derechos remains challenging due to the absence of spatiotemporally continuous observations and the complex criteria employed to define the phenomenon. This study proposes a physically based definition of derechos that contains the key features of derechos described in the literature and allows their automated objective identification using either observations or model simulations. The automated detection is composed of three algorithms: the Flexible Object Tracker algorithm to track mesoscale convective systems (MCSs), a semantic segmentation convolutional neural network to identify bow echoes, and a comprehensive algorithm to classify MCSs as derechos or non-derecho events. Using the new approach, we develop a novel high-resolution (4 km and hourly) observational dataset of derechos over the United States east of the Rocky Mountains from 2004 to 2021. The dataset is analyzed to document the derecho climatology in the United States. Many more derechos (increased by ~50-400%) are identified in the dataset (~31 events per year) than in previous estimations (~6-21 events per year), but the spatial distribution and seasonal variation patterns resemble earlier studies with a peak occurrence in the Great Plains and Midwest during the warm season. In addition, around 20% of damaging gust (≥ 25.93 m s^{-1}) reports are produced by derechos during the dataset period over the United States east of the Rocky Mountains. The dataset is available at https://doi.org/10.5281/zenodo.10884046 (Li et al., 2024).

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1 Introduction

A derecho is qualitatively defined as a widespread, long-lived straight-line windstorm associated with a fast-moving mesoscale convective system (MCS). Figure 1 shows two of the most destructive derechos in the United States: the June 2012 North American derecho and the August 2020 Midwest Derecho. Both events lasted for over 10 hours, with apparent bow echoes and extensive damaging wind gusts (≥ 25.93 m s^{-1}). Due to the persistent widespread damaging gusts, derechos can severely damage property and threaten human lives, as exemplified by the extensive power outages and more than ten fatalities caused by the two derechos. Ashley and Mote (2005) demonstrated that derechos could be as hazardous as and were comparable in magnitude to most hurricanes and tornadoes in the United States between 1986 and 2003.

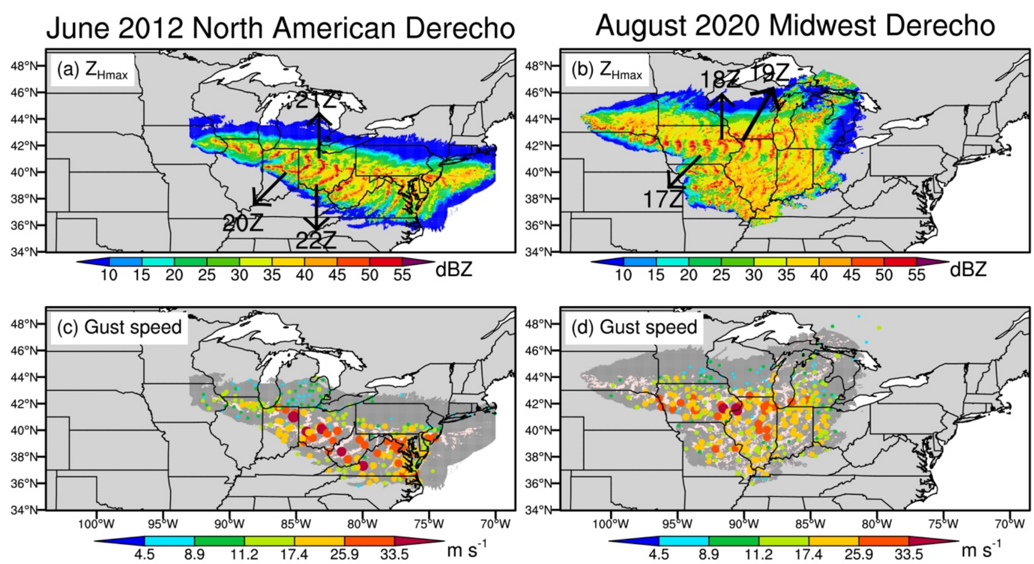

Figure 1. Spatial evolutions of the (a, b) composite (column-maximum) radar reflectivity (Z_{Hmax}) signatures and (c, d) surface gust speeds (colored dots) of two derechos. The first column is for the June 2012 North American derecho, which occurred on 29-30 June 2012, and the right column is for the August 2020 Midwest derecho, which occurred on 10-11 August 2020. Due to spatiotemporal overlapping, multiple Z_{Hmax} and gust speeds may exist for a given grid cell or weather station, in which case only the corresponding maximums are shown in the figure. The timings of some bow echo occurrences are labeled in (a) and (b). In (a), "20Z", "21Z", and "22Z" refer to 20:00, 21:00, and 22:00 UTC on 29 June 2012. In (b), "17Z", "18Z", and "19Z" refer to 17:00, 18:00, and 19:00 UTC on 10 August 2020. In (c) and (d), the misty rose shading corresponds to areas with Z_{Hmax} ≥ 40 dBZ, and the dark gray shading refers to derecho coverage with Z_{Hmax} < 40 dBZ. The dot

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sizes in (c) and (d) are proportional to the gust speed magnitudes. Notably, gust speed in (c) and (d) is based on the hourly maximum gust speed ($gust_{hourly\_max}$), which is the largest gust speed within one hour if multiple gust speed measurements are available.

A reliable derecho dataset is foundational for understanding the underlying physical mechanism of derecho initiation and development and their socioeconomic impacts. Johns and Hirt (1987) developed the first derecho climatology in the warm seasons of 1980-1983 in the United States by quantitatively defining a derecho as a family of downburst clusters produced by an extratropical MCS. Specifically, they required a derecho to satisfy the following six criteria. 1) There must be a concentrated area of reports with wind damage or convective gusts > 25.7 m s^{-1}, with a major axis length of at least 400 km. 2) These reports must show a pattern of chronological progression, either as a singular swath or a series of swaths. 3) The concentrated area must have at least three reports of either F1 damage (32.7-50.3 m s^{-1}) (Fujita, 1971) or convective gust of at least 33.4 m s^{-1} separated by ≥ 64 km. 4) At most 3 hours can elapse between successive reports of wind damage or gust > 25.7 m s^{-1}. 5) The associated convective system must have temporal and spatial continuity in surface pressure and wind fields. 6) If multiple swaths of wind damage or gust reports > 25.7 m s^{-1} exist, they must be from the same MCS event. Since then, several other studies have developed derecho climatologies during other periods using slightly different criteria (Bentley and Mote, 1998; Evans and Doswell, 2001; Bentley and Sparks, 2003; Coniglio and Stensrud, 2004; Guastini and Bosart, 2016). For example, Bentley and Mote (1998) removed the third requirement and reduced the elapsed time in the fourth condition from no more than 3 hours to no more than 2 hours in their derecho climatology from 1986 to 1996. In Coniglio and Stensrud (2004), the elapsed time was further changed to no more than 2.5 hours, and the gust reports of at least 33 m s^{-1} were used to separate derechos of different intensities.

Although the aforementioned derecho datasets were generated using different criteria and during different periods (Johns and Hirt, 1987; Bentley and Mote, 1998; Evans and Doswell, 2001; Bentley and Sparks, 2003; Coniglio and Stensrud, 2004; Guastini and Bosart, 2016), they showed many similar derecho climatological characteristics in the United States. For example, derechos occur more frequently

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in the warm than cold seasons; the Great Plains, Midwest, and Ohio Valley are regions most favorable for derecho development, and few derechos occur in the eastern and western coastal areas. Considering the inconsistent thresholds used in the above studies and the lack of physical mechanisms in their derecho definitions, Corfidi et al. (2016) proposed a stricter and more physically based derecho definition, which required the existence of sustained bow echoes with mesoscale vortices or rear-inflow jets and a nearly continuous wind damage swath of at least 100 km wide along most of its extent and 650 km long. In addition, the wind damage must occur after the convective system was organized into a cold-pool-driven forward-propagating MCS. Most derechos satisfying this definition would be classified as "progressive" but not "serial." A serial derecho typically originates in strongly forced environments and develops from a mature squall line with multiple embedded bow echoes. In contrast, progressive derechos generally originate from small convective clusters that grow upscale into large organized forward-propagating MCSs in synoptic environments with weak forcing (Squitieri et al., 2023).

It is difficult to develop a derecho climatology using the definition proposed by Corfidi et al. (2016) with current operational measurements, as it involves the identification of bow echoes, rear-inflow jets, and cold pools. However, rear-inflow jets and cold pools are generally associated with bow echoes (Weisman, 1993; Adams-Selin and Johnson, 2010). Once long-lived bow echoes are found in an MCS event, we can expect the simultaneous existence of rear-inflow jets and cold pools. Nevertheless, identifying bow echoes, a feature typically identified from radar observations, is still challenging for large volumes of data, such as the 30+ year National Oceanic and Atmospheric Administration (NOAA) Next Generation Weather Radar (NEXRAD) archive. The manual examination is time-consuming and sensitive to subjective biases. This study applies a semantic segmentation convolutional neural network (CNN) to detect bow echoes automatically from two-dimensional composite (column-maximum) reflectivity (Z_{Hmax}) data in the United States, which are then combined with an MCS tracking dataset and gust speed measurements from surface meteorological stations to identify derechos using criteria adjusted from Corfidi et al. (2016). After manual examination and validation, we produce a high-resolution (4 km and

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hourly) observational derecho dataset in the United States east of the Rocky Mountains from 2004 to 2021. As the first derecho climatology that utilizes a machine learning technique following physically based criteria and covers the recent decades, the dataset provides a reference for future derecho studies and can be used to investigate the underlying mechanisms for derecho initiation and development, the climatological impacts of derechos on hazardous weather, and the damage of derechos to infrastructure and human property.

The remainder of the paper is organized as follows. Section 2 introduces the MCS dataset and gust speed measurements used to generate the derecho dataset. Section 3 describes the machine learning (i.e., semantic segmentation CNN) methodology to detect bow echoes, including sampling, training, and evaluation. Section 4 explains our derecho identification criteria in detail. Section 5 evaluates our derecho dataset against the observational data from the NOAA Storm Prediction Center (SPC) in 2004 and 2005. Section 6 analyzes the derecho climatological characteristics. Section 7 shows how to access our derecho dataset, and the study is summarized in Section 8.

2 Source datasets

2.1 MCS dataset

Since previous MCS datasets only cover the period from 2004 to 2017 (Li et al., 2021; Feng et al., 2019), we use an updated version of the Python FLEXible Object TRacKeR (PyFLEXTRKR) software (Feng et al., 2023), which exploits collocated radar signatures, brightness temperature, and precipitation to identify robust MCS events (Feng et al., 2019), to produce an updated MCS dataset in the United States east of the Rocky Mountains from 2004 to 2021. Several source datasets are used in the generation of the MCS dataset, including the National Centers for Environmental Prediction (NCEP)/the Climate Prediction Center (CPP) L3 4 km Global Merged IR V1 brightness temperature dataset (Janowiak et al., 2017), the three-dimensional Gridded NEXRAD Radar (GridRad) dataset (Bowman and Homeyer, 2017),

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the NCEP Stage IV precipitation dataset (CDIACS/EOL/NCAR/UCAR and CPC/NCEP/NWS/NOAA, 2000), and hourly melting level heights derived from ERA5 (European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5) (Hersbach et al., 2023). The MCS definition criteria are almost the same as those in Feng et al. (2019), such as cold cloud shield (CCS) area > 60,000 km^2, precipitation feature (PF, which is a continuous convective or stratiform area with surface rain rate > 2 mm h^{-1}) major axis length > 100 km, the existence of 45-dBZ convective echoes, etc., except that the duration requirement is lowered to include those convective systems lasting for just 6 hours. This adjustment allows us to capture slightly shorter-lived MCSs that produce intense wind gusts but are missed in the previous MCS datasets. Convective and stratiform radar echo classification in PyFLEXTRKR follows the Storm Labeling in 3D (SL3D) algorithm (Starzec et al., 2017), which uses horizontal texture and vertical structure of radar reflectivity from the GridRad product. Notably, the GridRad data are available each month from 2004 to 2017 but only between April and August from 2018 to 2021. Since most derechos occur in the warm season (Ashley and Mote, 2005; Coniglio and Stensrud, 2004), missing the cold months between 2018 and 2021 does not affect our derecho climatological analyses in Section 6. For brevity, we do not mention the missing cold months between 2018 and 2021 in the following sections unless stated otherwise.

2.2 Surface gust speed observations

Surface gust speed measurements between 2004 and 2021 are from the Integrated Surface Database (ISD) (NOAA/NCEI, 2001), developed by the NOAA National Centers for Environmental Information (NCEI) in collaboration with several other institutions. ISD compiles global hourly and synoptic surface observations from numerous sources (e.g., the Automated Surface Observing System and the Automated Weather Observing System) into a single common format and data model. Besides internal quality control procedures conducted by the source datasets, ISD applies additional quality control algorithms to process each observation through a series of validity checks, extreme value checks, and internal and external

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continuity checks (Smith et al., 2011). This study uses measurements passing all quality control checks (NOAA/NCEI, 2018). Notably, there may be multiple measurements at different times within one hour for some stations. To keep the sampling consistency across different datasets used in the derecho identification, we calculate $gust_{hourly\_max}$, which is the largest gust speed of all available measurements within one hour, for each observational site, unless stated otherwise. A total of 4,260 observational sites provide gust speed measurements between 2004 and 2021 in the study domain, of which 3,954 are over land, and the rest are over the ocean or lakes (Figure S1). We have excluded one observational site (ISD station ID: 726130-14755) in the northeastern United States, which has an unrealistic number of damaging gust measurements (more than 1,000 hours), inconsistent with the surrounding sites. We note that although we only use measurements passing all the available quality control checks, spatial quality control is missing in the ISD (Smith et al., 2011). Figure S2a shows that some sites in the eastern United States have apparently more damaging gust occurrences than their surrounding sites, but the occurrence frequencies are less than those stations around the Rocky Mountains. We do not have enough evidence to exclude them from the study. However, the quality of the gust speed measurements will undoubtedly be a source of uncertainty for our derecho dataset. In addition, only 420 sites have continuous gust measurements from 2004 to 2021, while the rest have gust measurements only during part of the study period. The availability of observational sites is another source of uncertainty when identifying derechos.

3 Machine learning identification of bow echoes

A bow echo is a bow-shaped pattern on a radar image, but its vague definition makes it hard to identify them extensively and efficiently using traditional methods. Instead, we train a semantic segmentation CNN to identify bow echoes automatically from two-dimensional Z_{Hmax} images by performing pixel-level labeling of the bow echo extent. Compared to the manual examination of radar images, machine learning can save a tremendous amount of time and eliminate subjective bias.

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3.1 Bow Echo Samples

3.1.1 Initial manual sampling

Our initial bow echo samples are generated based on the named derechos on Wikipedia (https://en.wikipedia.org/wiki/List_of_derecho_events; last access: 19 March 2023). We identify 54 named derechos in the MCS dataset and manually label times with apparent bow echoes through visual inspection of Z_{Hmax} associated with the tracked MCSs. Each positive sample is a 384 × 384-pixel (~1536 km × 1536 km) Z_{Hmax} image centered at the corresponding derecho with a bow echo embedded (Figure 2). The number of bow echo samples varies among different derechos, and 566 positive samples are obtained in total. 5400 negative samples are also randomly selected from the radar reflectivity dataset.

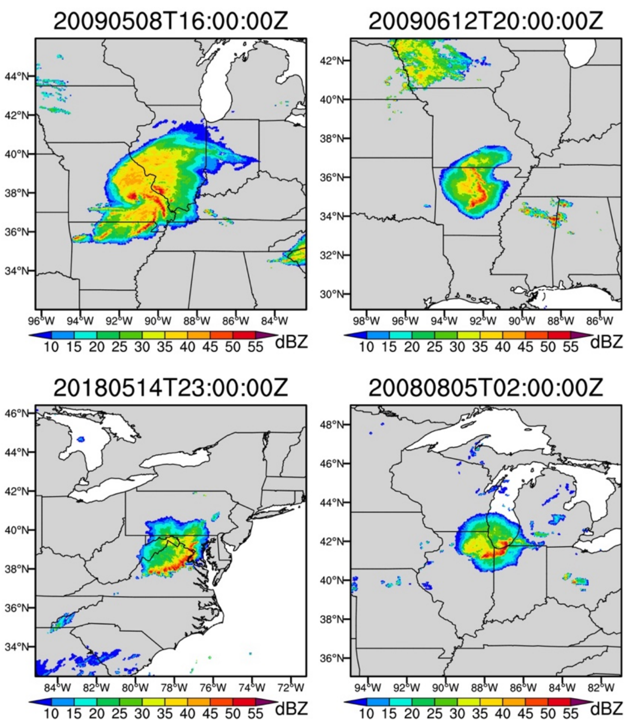

Figure 2. Four examples of bow echoes from the named derechos. The color shading is for Z_{Hmax}. The subplot titles indicate the bow echo timings. For example, 20130613T04:00:00Z represents 4:00 UTC on 13 June 2013.

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3.1.2 CNN-based selection of additional bow echo samples

Our initial attempt at developing an automated bow echo detection scheme is to train a classifier CNN — "Dense Net" (Huang et al., 2019) that ingests 384×384-pixel single-channel Z_{Hmax} images and outputs a single classification indicating the presence of a bow echo. Dense Nets are notable for their large number of skip connections, and they can achieve comparable performance to very large classifier CNNs with only a fraction of the trainable parameters. Unfortunately, a Dense Net trained on the aforementioned initial samples has a very high false positive rate when applied to the full radar dataset (determined by manual inspection). Although this Dense Net is unsuitable for deployment, the collection of new positive samples it successfully identifies allows us to supplement the list of known bow echoes and develop a more diverse training set for the following segmentation model.

3.1.3 Pseudo-labeling

By combining the initial samples and the manually selected true positives from the low-quality Dense Net model, we build a semantic segmentation training dataset of 500 unique bow echo snapshots and corresponding hand-drawn bow echo masks. While 500 positive samples are relatively small for a deep learning application, these samples have higher diversity than the initial bow echoes generated from the named derechos on Wikipedia because they are drawn from more distinct events, and, in general, semantic segmentation CNNs can be successfully trained with far fewer samples than image classification CNNs (Bardis et al., 2020).

A relatively low-skill version of the semantic segmentation CNN is trained using the 500 hand-labeled radar images and then applied to the entire Z_{Hmax} dataset. We manually review the bow echo masks produced by this segmentation model and add some of the high-quality masks to a new training dataset. We also collect some of its false positive masks as new negative samples in the new training dataset. This is a semi-supervised learning approach known as "pseudo-labeling" or "bootstrapping" (Van

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Engelen and Hoos, 2020; Ouali et al., 2020) and is commonly applied to semantic segmentation problems because of the high expense of hand-drawn labels (Peláez-Vegas et al., 2023). The pseudo-labels and hand-labels are combined into a final training dataset with 3677 samples, including 1699 bow echoes and 1978 negative samples, which is used to train the much more skillful semantic segmentation model in Section 3.2.

3.1.4 Data augmentation

To combat the limited training data further, we use several data augmentation strategies when constructing training batches. During training, positive and negative samples are selected with equal probability, and a batch size of 8 is used. First, random salt and pepper noise is added to 10% of the pixels in each sample with a probability of 0.1. Second, weak random Gaussian noise with a standard deviation of 5 dBZ is added to all the pixels in each sample with a probability of 0.1. Third, samples are flipped in up-down and left-right directions, each with a likelihood of 0.5. Fourth, samples are rotated by 0, 90, 180, or 270 degrees, each with a probability of 0.25. Fifth, samples are randomly shifted vertically and horizontally by -5 to 5 pixels. Sixth, the brightness of the sample image is adjusted by a random factor of -0.6 to +0.2, and the image contrast is randomly adjusted by -0.2 to 0.2. Seventh, the binary target bow echo masks are multiplied by 0.9, and random noise drawn from a uniform distribution between 0 and 0.1 is added. This is known as “soft labels.” Lastly, both positive and negative samples are blended with randomly selected negative samples by taking the pixel-wise maximum reflectivity values of the two samples with a 0.5 likelihood. This last data augmentation is unusual but works well in our application because a) reflectivity features typically occupy only a fraction of the sample area, with most pixels being clear-sky and b) bow echoes are high-reflectivity features. When the last data augmentation is applied to a positive sample, the resulting image will typically still contain a bow echo that matches the target mask well.

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3.2 Training of U-Net 3+ CNN

Our final semantic segmentation CNN model (Figure 3) uses the U-Net 3+ architecture (Huang et al., 2020). U-Net 3+ is a modern variant of the U-Net architecture (Ronneberger et al., 2015) and differs from the U-Net primarily in the addition of many more skip connections and its multi-resolution loss, which computes loss on rescaled classification masks generated from feature representations at various model levels.

U-Net models were originally developed for the segmentation of biomedical imagery but have been applied to image segmentation problems in other fields and are broadly useful for any image-to-image mapping tasks where the input and target data are the same (or similar) size and shape and merging multi-resolution information from the input data is important. U-Net CNNs have been applied to a myriad of problems in the atmospheric sciences, such as segmentation (Galea et al., 2024; Kumler-Bonfanti et al., 2020), super resolution (Geiss and Hardin, 2020; White et al., 2024), physics parameterization (Lagerquist et al., 2021), downscaling (Sha et al., 2020), and weather forecasting (Weyn et al., 2021). Perhaps most closely related to this study is Mounier et al. (2022), who used a U-Net to detect bow echoes in simulated radar reflectivity images from a forecast model. A U-Net is an appropriate choice for the segmentation of bow echoes because merging multi-resolution information is crucial for identifying the feature. For example, bow echoes have high reflectivity at the pixel scale, strong reflectivity gradients in the transverse direction at the mid-scale (tens of pixels), and the characteristic bow shape at the large scale (hundreds of pixels).

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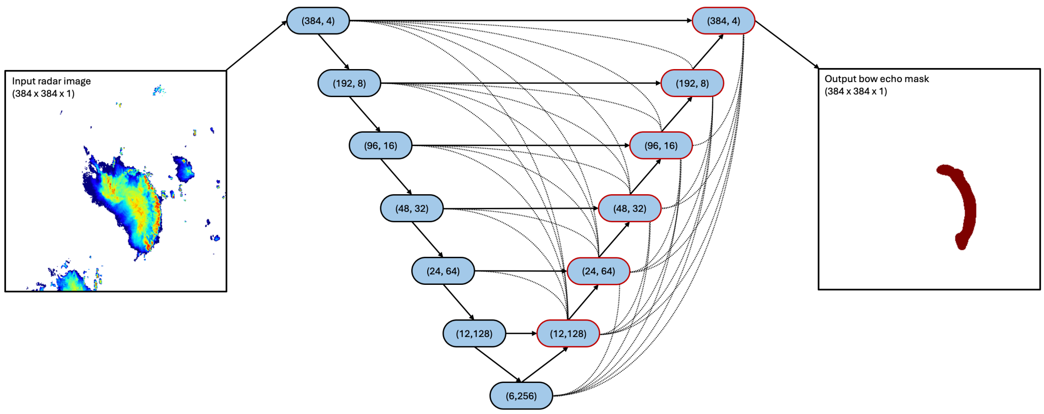

Figure 3. A diagram of our semantic segmentation CNN architecture. The CNN inputs a 384×384-pixel radar image (Z_{Hmax} scaled to 0-255) and outputs a bow echo mask of the same size. The blue ovals represent 3×3 convolutional layers, each followed by a batch normalization layer and a leaky rectified linear unit (ReLU) activation function. The first number in each blue oval indicates the spatial size (for both the width and height) of the output tensor, and the second represents the number of output channels. The solid arrows indicate connections in a standard U-Net architecture, with the downward arrows corresponding to 2×2 max-pooling and the upward arrows corresponding to 2×2 bilinear upsampling operations. The dashed lines represent the skip connections introduced in the U-Net 3+ architecture. These skip connections use max-pooling for spatial downsampling and bilinear interpolation for upsampling, followed by a 16-channel 3×3 convolutional layer with a linear activation. Layers with multiple inputs use channel-wise concatenation to combine those inputs. During training, the output tensors from the layers in the upsampling branch (blue ovals with red boundaries) are scaled to the output spatial resolution and passed through a 1-channel 1×1 convolutional layer with sigmoid activation. Training loss is computed on all 6 of the resulting masks. At inference time, only the mask outputted from the upper-rightmost layer is used.

Our U-Net 3+ CNN ingests 384×384-pixel Z_{Hmax} images where Z_{Hmax} have been clipped to a 0-50dBZ range and then linearly mapped to a range of 0-255. It is trained using binary cross entropy loss on masks generated from its 384, 192, 96, 48, 24, and 12-pixel resolution feature representations (Huang et al., 2020), though only the full-resolution (384×384-pixel) output mask is used at inference time. A detailed diagram of the model architecture is shown in Figure 3. Notably, although the model is trained using 384×384-pixel samples, it is a fully convolutional model and can process inputs of variable sizes.

We use the Adam optimizer (Kingma and Ba, 2014) with the Keras default settings (Ketkar, 2017) and an initial learning rate of 0.001 for training. The U-Net 3+ CNN is first trained for 60 epochs composed of 1000 randomly generated training batches of 8 samples each. Then, we decrease the learning

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rate to 0.0001 and train the CNN for an additional 20 epochs. The training duration is determined by performing an initial 5 rounds of training with 5-fold cross-validation and approximating the epoch numbers to reduce the learning rate and stop training when the mean intersection over union metric plateaus for the validation set. Instead of random shuffling, the validation sets are separated from the training dataset in temporally contiguous chunks to avoid any overlap because, sometimes, multiple samples may be drawn from different times of the same convective system.

3.3 Evaluation of the Semantic Segmentation CNN

We apply the trained U-Net 3+ CNN to the entire Z_{Hmax} dataset and obtain potential bow echo masks over the United States between 2004 and 2021 (Figure 4). As a final post-processing step, we ignore "bow echo" masks with less than 20 pixels (~320 km^2), which are too small to be classified as bow echoes.

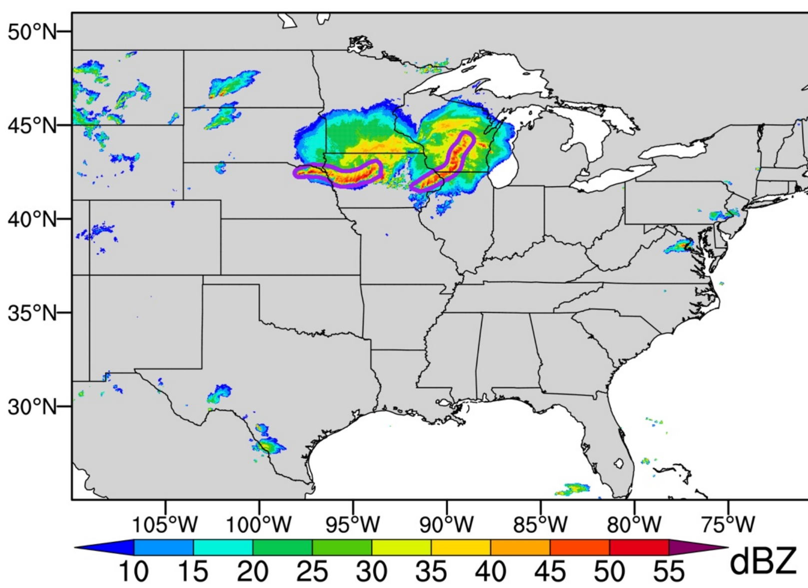

Figure 4. Examples of the U-Net 3+ CNN identified bow echoes (purple contours) based on Z_{Hmax} (color shading) at 5:00 UTC on 17 June 2014.

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Instead of validating our segmentation model at a pixel scale, as during the training stage, we prefer evaluating its performance in detecting bulk bow echo features. In other words, we care about whether the segmentation model can recognize the existence of bow echoes and capture their rough locations. Minor spatial biases in bow echo coverage do not affect our below derecho identification, which contains various flexible criteria to minimize their impacts, such as the buffer zone within 100 km of bow echoes. We also choose to validate the segmentation CNN specifically on MCS events where high reflectivity features are present. Identifying low-reflectivity and clear-sky images as non-bow echoes is desirable for our segmentation model but trivial and not of particular interest for creating a derecho climatology.

To build a testing dataset, we randomly select 217 MCS-associated Z_{Hmax} images in 2010 based on the following requirements. Each image is from a different MCS event. The images have variable sizes and contain the full spatial extents of the MCSs at the selected times; however, they must be at least 192x192 pixels and cannot be drawn from a day that also has a sample in the training dataset. Three of the authors independently assessed the presence of bow echoes in each image, the results of which are then compared to the segmentation CNN (Table 1). Overall, the CNN model identifies 57 bow echoes, while human labelers 1, 2, and 3 identify 46, 76, and 66, respectively. The average human-human agreement and F_1 scores are 82% and 0.69, while the average human-CNN agreement and F_1 scores are 82% and 0.67 (Table 1). The test indicates that, on the one hand, the detection of bow echoes in radar images is prone to subjective bias; on the other hand, the performance of the segmentation CNN is comparable to that of a human in identifying bow echoes. We emphasize that the CNN bow echo identification is only one component in our following derecho detection criteria, and the adverse impact of this uncertainty is mitigated by other constraints (e.g., almost continuous bow echo existence and strong gusts in proximity with bow echoes).

Table 1 Evaluation of the performance of the segmentation CNN in the bow echo identification[1]

	CNN (57[2])	Person 1 (46)	Person 2 (76)	Person 3 (66)
CNN		84%	79%	83%
Person 1	0.66		77%	88%

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Person 2	0.66	0.59		81%
Person 3	0.70	0.77	0.70	

[1]The upper part of the table shows agreement between two independent identifications ($Agreement = \frac{TP+TN}{TP+TN+FP+FN}$), and the lower part shows F_1 scores ($F_1 = \frac{2TP}{2TP+FP+FN}$), which is a better indication of the ability to agree on positives when positives are a minority (Taha and Hanbury, 2015). Here, *TP* denotes true positive, *TN* refers to true negative, *FP* is false positive, and *FN* is false negative. Notably, for the comparison between any two independent identifications, we consider one as "true" and evaluate the other against it (and which set of classifications are considered true does not impact these two metrics).
[2]The number of identified bow echoes from the 217 images.

We match the segmentation CNN detected bow echoes with MCS events from the MCS dataset and identify those MCS-associated bow echoes, which are used to identify derechos in the following section. Figure 5 shows the spatial distribution of MCS-associated bow echo occurrences from 2004 to 2021, which is similar to the MCS spatial distribution with more occurrences in the Great Plains (Li et al., 2021).

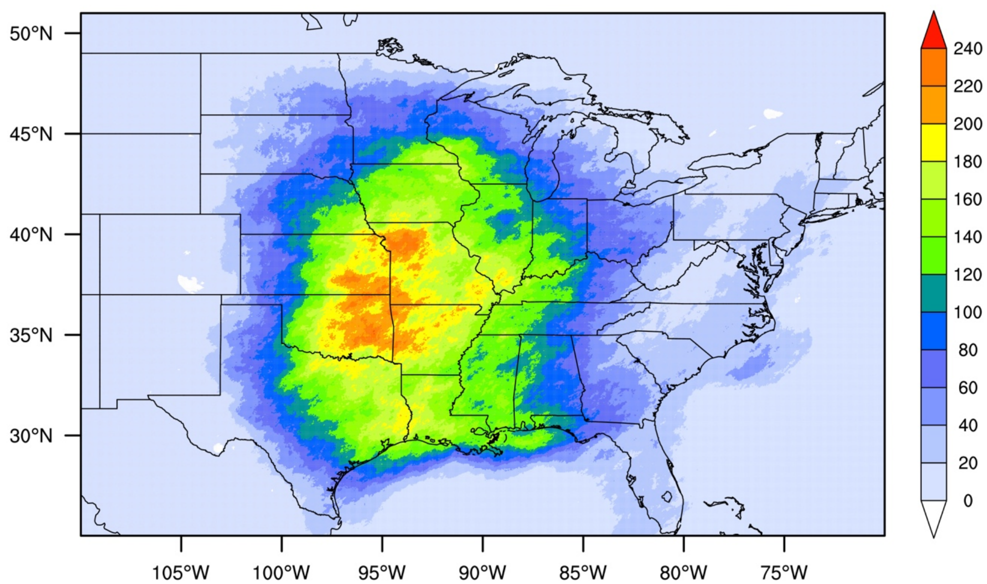

Figure 5. Spatial distribution of the number of MCS-associated bow echoes from 2004 to 2021. Here, we use bow echo masks produced by the segmentation CNN and exclude bow echoes that do not overlap with MCS events. Notably, the PyFELXTRKR-generated MCS dataset contains tropical cyclones (TCs). This figure excludes bow echoes from those non-derecho MCS events that overlap with TCs from the International Best Track Archive for Climate Stewardship (IBTrACS) Version 4 data over the North Atlantic basin (Knapp et al., 2010) following the approach of (Feng et al., 2021).

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4 Derecho identification

As mentioned above, we adopt the derecho definition proposed by Corfidi et al. (2016) but revise some criteria based on previous studies (Johns and Hirt, 1987; Bentley and Mote, 1998) and the limitation of the observational datasets used in this study so that they can be used in the objective identification of derechos. Our detailed definition criteria are summarized below.

1) A derecho must be attached to an MCS from the MCS dataset. This is the most straightforward requirement and one of our advantages. Due to the lack of a reliable MCS dataset, most previous studies spent much effort identifying spatiotemporally continuously propagating convective systems (Squitieri et al., 2023).
2) At least one derecho feature (DF) exists in the MCS lifetime. A DF is defined as a continuous period satisfying the following criteria (Figure 6).

   2.1) The DF must last for at least 2 hours, and bow echo occurs during ≥ 80% of the DF period. For example, if the DF lasts for 10 hours, it must have bow echoes in at least 8 hours. In addition, no more than 2 hours can elapse between successive bow echo occurrences. In other words, bow echo must exist for at least one hour in any two consecutive hours. The above two thresholds consider the segmentation CNN identification uncertainty and the diversity of MCS events. Moreover, a DF requires these bow echoes to be from the same bow echo series. Due to merging or splitting or the complex nature of some convective systems, a bow echo at one hour may be far from the bow echoes right after or before that hour or another bow echo during that hour (Figure 6). In such a rare situation, these bow echoes are unlikely caused by the same physical process and, therefore, do not belong to the same bow echo series. We separate different bow echo series in two steps. First, a distance criterion categorizes multiple bow echoes in the same hour into different series. Any bow echoes more than 100 km from each other belong to different series. Second, we temporally connect bow echoes from the same series using another distance threshold. The distance between two successive bow echoes (no more than 2 hours can elapse between their occurrences) from the same series must be no more than 200 km. Notably, the second step can overwrite the first step. For example, two bow echoes at hour *t* belong to different series in the first step, but in the second step, they are close enough (≤ 200 km) to the same bow echo at hour *t*-1. If so, they are considered from the same bow echo series.

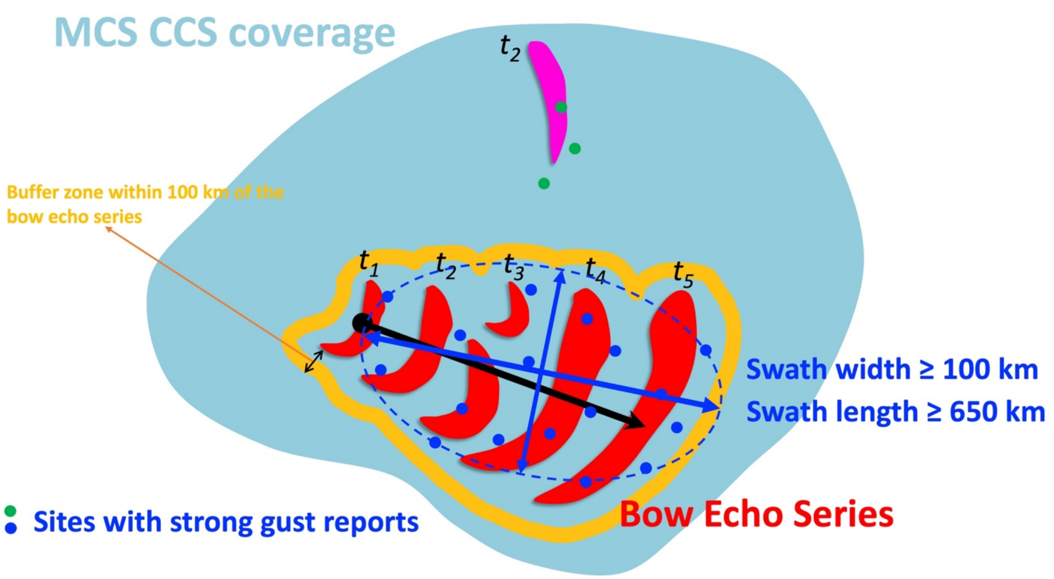

Figure 6. Schematic of the automated detection algorithm. Red and pink contours represent bow echoes. At time t_2, there are two bow echoes belonging to different bow echo series due to their great distance from each other. In contrast, the two bow echoes at t_3 are from the same bow echo series since they are close to each other. The pink bow echo at t_2 is far from the bow echoes at t_1 and t_3. Therefore, they belong to different bow echo series. The sites (green dots) with strong gust reports outside the 100-km buffer zone of the bow echo series (i.e., the DF area) are excluded from the strong gust swath calculation. The black arrow indicates the propagation direction of the bow echo series.

2.2) We calculate the DF-associated maximum gust speed for each land observational site during the DF period. Within 100 km of the DF bow echoes, which we name the DF area, there must be ≥ 10 sites with strong gusts (gust speed ≥ 17.43 m s^{-1}) and ≥ 1 site with damaging gusts (gust speed ≥ 25.93 m s^{-1}). In addition, the fraction of sites with strong gusts should be ≥ 20%. This fraction criterion is intended to exclude potential MCSs associated with extratropical cyclones, which could produce strong or damaging gusts over limited observational sites but weaker gusts

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at most other sites. Besides, a DF requires that no more than 2 hours can elapse between successive strong gust reports. Then, we calculate the major and minor axis lengths of the fitted ellipse swath using the locations of those sites with strong gust reports (Figure 6). As a DF, the major and minor axis lengths must be at least 650 km and 100 km, respectively. We emphasize that our gust speed criteria are weaker than those of previous studies (Squitieri et al., 2023; Bentley and Mote, 1998; Johns and Hirt, 1987), which estimated the gust swath based on damaging gusts. Moreover, previous studies often required a few reports of gust speed ≥ 33 m s^{-1}. Notably, many gust speeds in earlier studies were from post-disaster estimates, while this study uses ISD surface station measurements. Post-disaster estimates can capture damaging gust occurrences over a much larger area. In contrast, due to the limited coverage of observational sites, real-time measurements may miss substantial damaging gust occurrences in nearby regions. Therefore, we lower the gust speed criteria to capture potential derechos.

2.3) If no DF is identified for a given MCS using the above procedures, we can relax the distance requirement in (2.2) to be within 200 km of the DF bow echoes that satisfy the condition that there is no bow echo from the same bow echo series an hour ago or later during the DF period. If the bow echo is in the first hour of the DF period and there are no CNN-identified bow echoes for the MCS event an hour ago, we can also extend the distance threshold to 200 km. This is similar to the bow echo in the last hour of the DF period but without any CNN-identified bow echoes an hour later. Notably, the distance extension is optional. For the bow echoes satisfying the above conditions, the distance threshold can be either 100 or 200 km. Using 100 km is superior to using 200 km until we find a DF if it exists. The distance extension is also intended to minimize the impacts of the bow echo identification error. If a bow echo is missed in the semantic segmentation procedure, extending the distance threshold can include strong gusts associated with the missed bow echo, thus slightly reducing the derecho detection error.

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We identify 537 derechos between 2004 and 2021 using the above objective detection criteria, with an example of the June 2012 North American derecho shown in Figure 7. Figure 7a displays the CNN-identified bow echoes, and Figure 7b shows the DF area and associated gust speeds. As expected, the derecho produced extensive strong gusts during its DF period.

Although we have considered the segmentation CNN bow echo identification uncertainties in the above derecho definition criteria, there is no guarantee that every specific situation is considered. Therefore, we carefully examine all the identified derechos and remove 32 events that are possibly false detections primarily due to the false identification of bow echoes (Figure S3). In addition, we manually examine all MCS events (808 in total, excluding the aforementioned 537 automatically identified derechos) that produce extensive strong (≥ 10 observational sites) and damaging (≥ 1) gusts over land areas with a strong gust swath of at least 650 × 100 km^2. Our manual examination focuses on bow echo identification errors but does not change any of the above derecho definition thresholds or parameters. For those MCSs (55 events in total) that are potential derechos based on our visual inspection, we manually label their bow echo occurrences that fail the segmentation identification during potential DF periods (Figure S4) and rerun the automated derecho detection algorithm. Finally, 51 events meet the derecho detection criteria described above.

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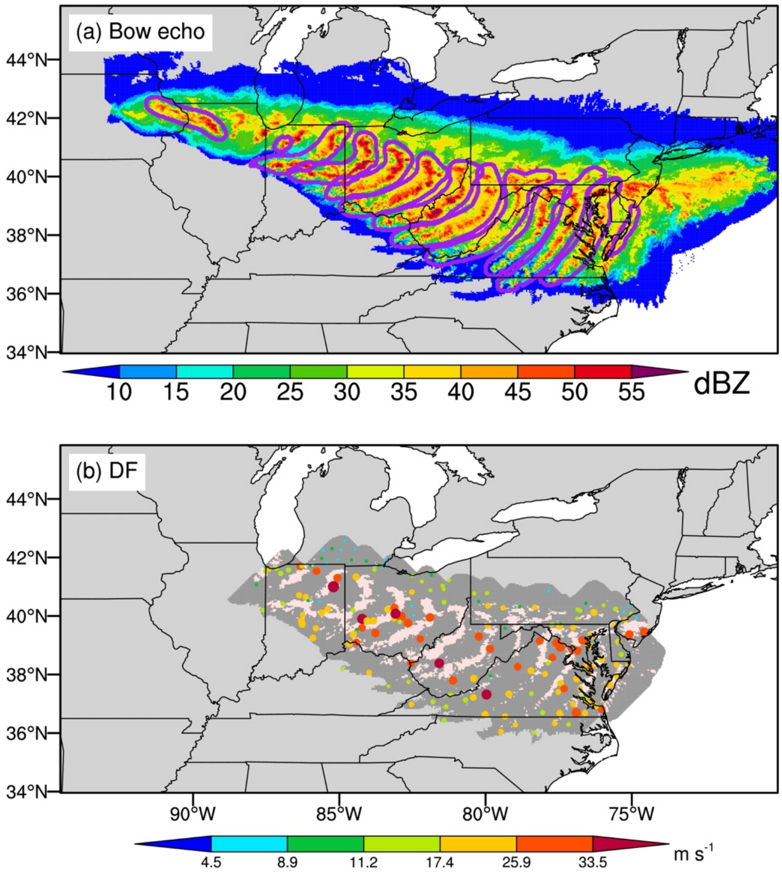

Figure 7. (a) Spatial evolution of Z_{Hmax} (color shading) and CNN-identified bow echoes (purple contours) from the June 2012 North American derecho. (b) Spatial evolution of the corresponding DF. The DF lasted from 17:00 UTC on 29 June to 6:00 UTC on 30 June 2012. The misty rose shading in (b) corresponds to $Z_{Hmax} \geq 40$ dBZ, while the gray shading refers to the DF area. Colored dots are the same as those in Figure 1c, except only the DF-associated gust measurements are shown.

5 Dataset evaluation and uncertainty

Finally, we obtain 556 derechos between 2004 and 2021, 505 of which are identified automatically and 51 of which are added manually. The number of derechos (30.9 per year) is much larger than previous estimations (6.1-20.9 per year) using a major axis length threshold of 400 km (Squitieri et al., 2023; Johns and Hirt, 1987; Bentley and Mote, 1998; Evans and Doswell, 2001; Guastini and Bosart, 2016; Ashley and Mote, 2005). The number is also much larger than the result of Corfidi et al. (2016), which identified only 25 derechos in the warm seasons during 2010-2014 using a major axis length

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threshold of 650 km. The large discrepancies are likely related to our usage of strong gusts but not damaging gusts to calculate wind damage swath and other definition criteria. However, the diverse observational datasets used in the derecho detections also play a critical role. Previous studies did not have an available MCS dataset; as a result, many of their definition criteria were intended to capture MCS events. In contrast, we have developed a high-quality, high-resolution MCS tracking dataset using PyFLEXTKR and many coincident ground-based and remote-sensing observations. Our definition criteria purely focus on the derecho properties and generation mechanism. Previous studies may underestimate the derecho number due to missing MCS events. We confirm this by comparing the derechos from the NOAA SPC with our derecho dataset in 2004 and 2005 (Table 2). The NOAA SPC data (https://www.spc.noaa.gov/misc/AbtDerechos/annualevents.htm; last access: November 17, 2023). provide more detailed timings and locations of derechos in 2004 and 2005 than previous studies (Squitieri et al., 2023), which is the only available dataset that we can use to evaluate our derecho dataset at the event scale. Notably, the NOAA SPC data contains not only derechos but also convective windstorms of near-derecho size, and we do not know which event is a derecho or a convective windstorm of near-derecho size. In addition, the data is based on gust speed measurements and post-disaster estimations. There is not an underlying MCS dataset for the NOAA SPC data.

The NOAA SPC data contains 50 derechos and convective windstorms of near-derecho size, 22 of which are directly captured by the automated detection procedure, and 2 of which can be captured after we manually correct the segmentation CNN bow echo identification errors. Five of the 50 events are entirely missed in the MCS dataset, possibly because they move too fast and do not meet the PyFLEXTRKR > 50% areal overlap tracking criterion using the hourly combined satellite and NEXRAD dataset, or they break other MCS requirements in PyFLEXTRKR (Feng et al., 2019). We emphasize that 10 of the 50 NOAA SPC events are not derechos based on the actual gust speed measurements since we do not find any land damaging gust reports associated with the MCS events. Seven of the 50 events are not derechos using the major axis length threshold of 650 km and the minor axis length threshold of 100

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km, even if we consider all the observational sites associated with the events, regardless of whether they are in proximity with the bow echoes. One event is an extratropical cyclone. These 18 events are excluded from derechos using more objective or consistent criteria as NOAA SPC. The remaining three of the 50 events are missed in our derecho dataset due to the criteria used in our derecho definition, two of which are due to too few sites with strong gusts, and one is due to the violation of the bow echo and gust speed criteria. In summary, after excluding those 18 non-derechos and the five missed events in the MCS dataset, the identification accuracy of our automated detection approach is $\frac{22}{50-18-5} = 81\%$ (Table 2). Even if we consider the five missed MCS events, the accuracy can reach up to $\frac{22}{50-18} = 69\%$. For the final derecho dataset with the 51 manually added events, the accuracy is $\frac{22+2}{50-18} = 75\%$. Finally, our derecho dataset identifies 14 derechos that are entirely missed by NOAA SPC, confirming the underestimation of derecho numbers in previous studies due to the lack of a reliable MCS dataset (Squitieri et al., 2023).

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Table 2. Evaluation of our derecho dataset against the NOAA SPC data in 2004 and 2005

	Year 2004	Year 2005	Sum
NOAA SPC[1]	24	26	50
Captured by our dataset	10	12	22
Events missed in the MCS dataset[2]	2	3	5
No land damaging gust, strong gust swath too small, no bow echo, or extratropical cyclone[3]	10	8	18
Bow echo identification error[4]	1	1	2
Other criteria not satisfied[5]	1	2	3
Our identified derechos not listed by NOAA SPC	5	9	14
Identification accuracy if excluding those missed MCS events[6]	83%	80%	81%
Identification accuracy if including those missed MCS events[7]	71%	67%	69%

[1]NOAA SPC provides the tracks of derechos and other convective systems of near derecho size in 2004 and 2005.

[2]Some events were moving so fast that the PyFLEXTRKR algorithm, which tracks storms with spatial overlapping > 50%, could not track the systems with the hourly combined satellite and NEXRAD dataset, while some may not meet other MCS criteria.

[3]Here, "strong gust swath too small" refers to those MCS events with the largest strong gust swath of less than 650 km × 100 km, even if we include those strong gusts not associated with bow echoes.

[4]It refers to those MCS events with bow echoes not captured by the segmentation CNN. If we manually label the missed bow echoes, they would be identified as derechos.

[5]It refers to MCS events that do not meet any other criteria (e.g., too few sites with strong gusts) and cannot be classified as derechos.

[6]$Accuracy = \frac{Captured\ by\ our\ dataset}{Captured\ by\ our\ dataset + Bow\ echo\ identification\ error + Other\ criteria\ not\ satisfied}$

[7]$Accuracy = \frac{Captured\ by\ our\ dataset}{Captured\ by\ our\ dataset + Bow\ echo\ identification\ error + Other\ criteria\ not\ satisfied + MCS\ events\ missed\ in\ the\ MCS\ dataset}$

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Although the evaluation against the NOAA SPC data indicates the high quality of our derecho dataset, we must acknowledge its uncertainties caused by several sources.

The first uncertainty source is from the MCS dataset, as mentioned in the evaluation against the NOAA SPC data. The areal overlap threshold, which is set to 50% and used to connect consecutive CCSs in the current PyFLEXTRKR configuration, cannot capture those very fast-moving convective systems with the hourly satellite and NEXRAD datasets. Reducing the threshold will undoubtedly increase the "MCS" and then the "derecho" number, but it may also increase the number of false tracks that do not belong to the same type of storm. The threshold of 50% is widely used in the different versions of the FLEXTRKR algorithms (Li et al., 2021; Feng et al., 2023; Feng et al., 2019) and other tracking algorithms based on overlap (e.g., (Whitehall et al., 2015)). Therefore, we would like to keep the overlap threshold as is, but users should realize the uncertainties of the MCS dataset caused by many adjustable parameters (e.g., area overlap threshold, MCS duration, and major axis length) and the limitations of the observational datasets used in PyFLEXTRKR (Feng et al., 2019; Li et al., 2021).

The second uncertainty source is related to the segmentation CNN identification of bow echoes. Although the evaluation in Section 3.3 shows the high accuracy of our bow echo identification and we consider the bow echo identification uncertainties in the automated derecho detection procedure, we still miss a small fraction of derechos and falsely classify some non-derechos as derechos due to the bow echo identification error. To alleviate the CNN identification errors, we spend much effort manually examining the derecho events identified by the automated algorithm and other MCS events that produce widespread strong gusts. However, the manual examination is susceptible to subjective biases, and it is difficult to completely eliminate the bow echo identification uncertainties.

The third uncertainty source is from the gust speed measurements. Although we only use gust measurements passing the ISD quality control, it is not guaranteed that all gust speeds are reliable and have the same quality, such as the site we exclude in Section 2.2 due to its unrealistic number of

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damaging gust reports. Moreover, we cannot qualitatively evaluate the impact of the gust measurement uncertainty on the derecho dataset, but users should be aware of the limitations of the gust speed observations.

The last uncertainty source is related to the derecho definition criteria. Many adjustable parameters and procedures are used in our algorithm to detect derechos. There is no doubt that changing these parameters will alter the identified derecho number. For example, if we change the major axis length threshold of the strong gust swath to 400 km, the derecho number will increase to 654 (a 29.5% increase). As the first climatological derecho dataset that utilizes bow echoes in the derecho identification and provides detailed tracking for each event, evaluating the uncertainties of the tunable parameters is unfeasible and not our priority either. However, based on our sensitivity tests, the derecho spatial distribution and seasonal variation patterns in Section 6 generally stay mostly the same with different parameters (e.g., reducing the strong gust fraction threshold to 10% or the threshold of the number of sites with strong gust reports to 5). The exception is that when we calculate the gust swath length and width using sites (requiring ≥ 10 sites) with damaging gusts as in previous studies (Squitieri et al., 2023), the derecho number is significantly reduced to 19, highlighting the spatial limitation of ISD gust measurements. We emphasize that although our derecho definition follows Corfidi et al. (2016), we exclude the “forward propagating” criterion they proposed. We try several methods to calculate the angles between the derecho orientations and their propagation directions but cannot obtain satisfying and accurate results for some events with complex structures. Figure 8 shows the probability density function (PDF) of the angles between “derecho propagation directions” and “bow echo orientations” for all derechos from the final derecho dataset. Based on this type of calculation, 78% of derechos have an angle ≥ 30°, and 58% of derechos have an angle ≥ 45°. For those derechos with angles < 30°, it does not mean that they are not forward propagating systems, but it is more likely that this type of angle calculation does not reflect their actual propagation direction. In total, even though we do not use the “forward

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propagating" criterion in the derecho definition, most of the identified derechos are indeed forward propagating systems.

Finally, users should acknowledge the high quality of our derecho dataset but understand its limitations due to various uncertainties during its generation.

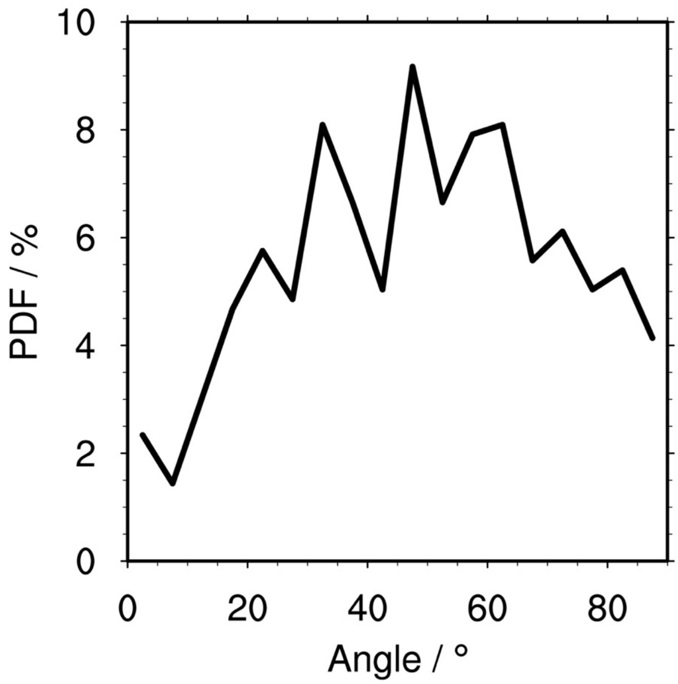

Figure 8. The probability density function (PDF) of the angles between derecho propagation directions and bow echo orientations. For any derecho, we calculate all the bow echoes' orientations during its DF period and use the median orientation in the angle calculation. Propagation direction is also based on bow echoes during the DF period. We select any two distinct bow echoes during the period and use their centroid points to derive a direction. If there are n bow echoes, we can obtain $C_n^2 = \frac{n\times(n-1)}{2}$ directions. Similarly, we use the median direction as the derecho's propagation direction to calculate the angle. The angle is initially in the range of -180° to 180°, and we adjust them to be between 0° and 90° to reflect the minimum angle between the derecho's orientation and propagation direction.

6 Derecho climatological characteristics

We use the final derecho dataset with 556 derechos to conduct the following climatological analyses.

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6.1 Annual statistics

Figure 9 displays the annual derecho numbers from 2004 to 2021. There is an apparent jump in the derecho number before (~20 derechos per year) and after 2007 (~30 derechos per year), which may be partially related to the general increase in the number of gust speed observational sites from 2004 to 2010 (Figure S5). Figure 10 shows the spatial distribution of yearly averaged annual derecho numbers between 2004 and 2021, and the derecho paths during their DF periods are displayed in Figure S6. The central Great Plains has the most frequent derecho occurrences, extending to Oklahoma in the south, Iowa in the north, Kansas in the west, and Illinois in the east. The areas with frequent derecho occurrences are generally consistent with previous studies (Coniglio and Stensrud, 2004; Guastini and Bosart, 2016; Johns and Hirt, 1987; Ashley and Mote, 2005), although some differences are identified. For example, several studies identified a northwest-southeast axis with frequent derecho occurrences extending from southern Minnesota to Ohio, which is not apparent in our spatial distribution (Johns and Hirt, 1987; Coniglio and Stensrud, 2004; Guastini and Bosart, 2016). The differences can be caused by many factors, such as distinct derecho definitions and observational datasets used in these studies. We make a sensitivity test by calculating the gust swath using ≥ 10 sites with damaging gusts as mentioned in Section 5, which identifies 19 derechos. The corresponding spatial distribution in Figure S7 well captures the aforementioned west-east axis, although the occurrence frequency is much smaller than in previous studies with more than one derecho occurrence per year (Johns and Hirt, 1987; Coniglio and Stensrud, 2004; Guastini and Bosart, 2016). The sensitivity test seems to indicate that the most intense derechos prefer to occur in the northern Great Plains and Midwest, while weaker derechos occur preferably in central Great Plains around the junction of Oklahoma, Kansas, Missouri, and Arkansas.

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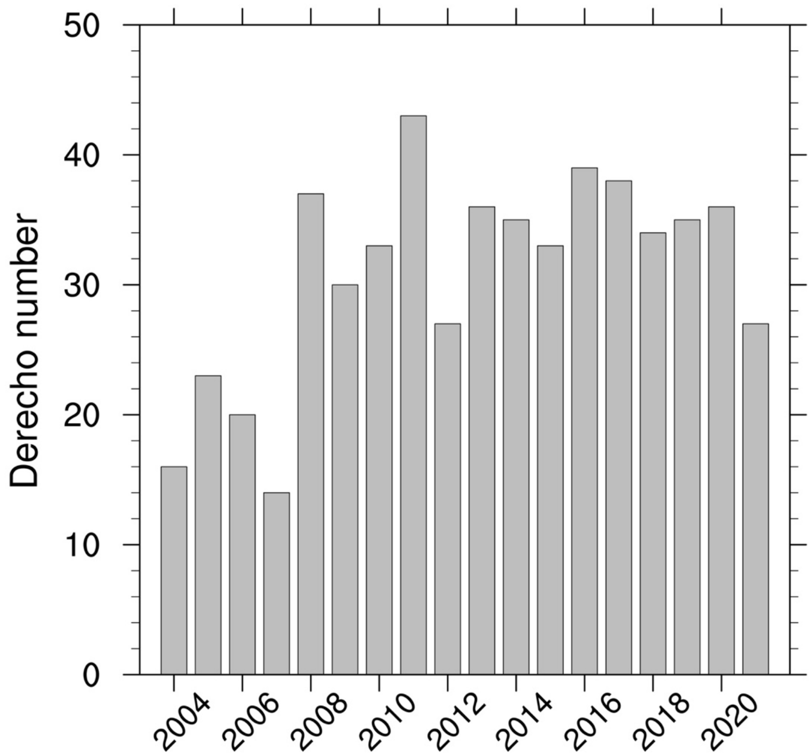

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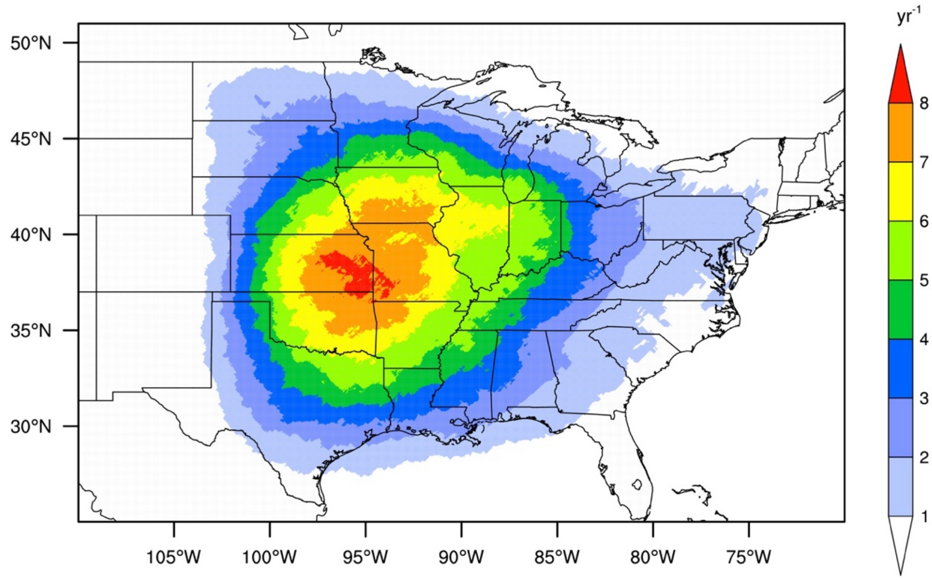
562 Figure 9. Bar chart of the annual derecho numbers from 2004 to 2021.



563
564 Figure 10. Spatial distribution of yearly averaged annual derecho numbers over the United States east of the
565 Rocky Mountains between 2004 and 2021. Here, we use derecho DF areas as derecho spatial coverages.

6.2 Monthly statistics

Figure 11 displays the yearly averaged seasonal variations in the derecho number, with remarkably more derechos in the warm than cold seasons, a feature widely captured by previous studies (Ashley and Mote, 2005; Squitieri et al., 2023; Bentley and Sparks, 2003). The derecho seasonal variation resembles that of the MCS events (Feng et al., 2019), similar to the derecho annual spatial distribution (Figure 10 and Feng et al. (2019)).

Figure 12 shows the spatial distributions of the yearly averaged monthly derecho numbers between 2004 and 2021. On the one hand, many more derechos occur in the warm than cold months. On the other hand, we find remarkable shifts in the areas with the most frequent derecho occurrences from April to August. The region with the most derechos moves northward during the warm season but shrinks zonally. The northward shifts also resemble the MCS events (Li et al., 2021). We can identify two axes with frequent derecho occurrences. One is in the south-north direction along the Great Plains, and the other is in the west-east direction along the northern Great Plains and Midwest, which are consistent with the derecho paths in Figure S6. The axes may represent the two types (serial and progressive) of derechos mentioned in Squitieri et al. (2023). A follow-up study will be conducted to investigate the large-scale environmental conditions associated with different types of derechos based on the developed derecho dataset. Notably, derechos are concentrated in the Lower Mississippi Valley in the cold season, which is also consistent with previous studies (Squitieri et al., 2023).

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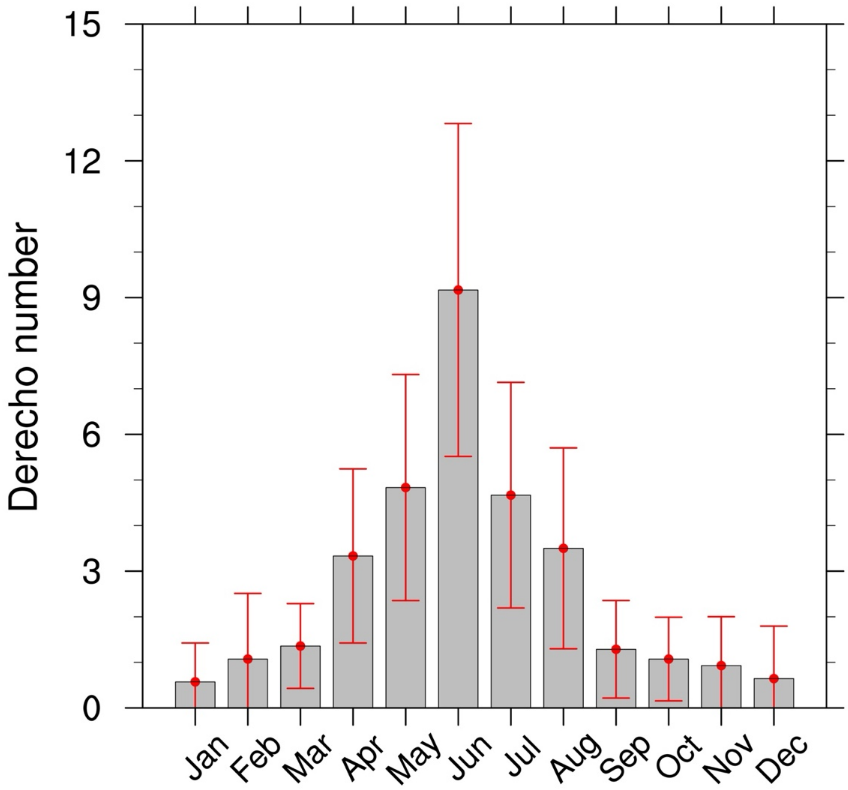

Figure 11. Yearly averaged monthly variations of the derecho numbers between 2004 and 2021. The error bars denote standard deviations.

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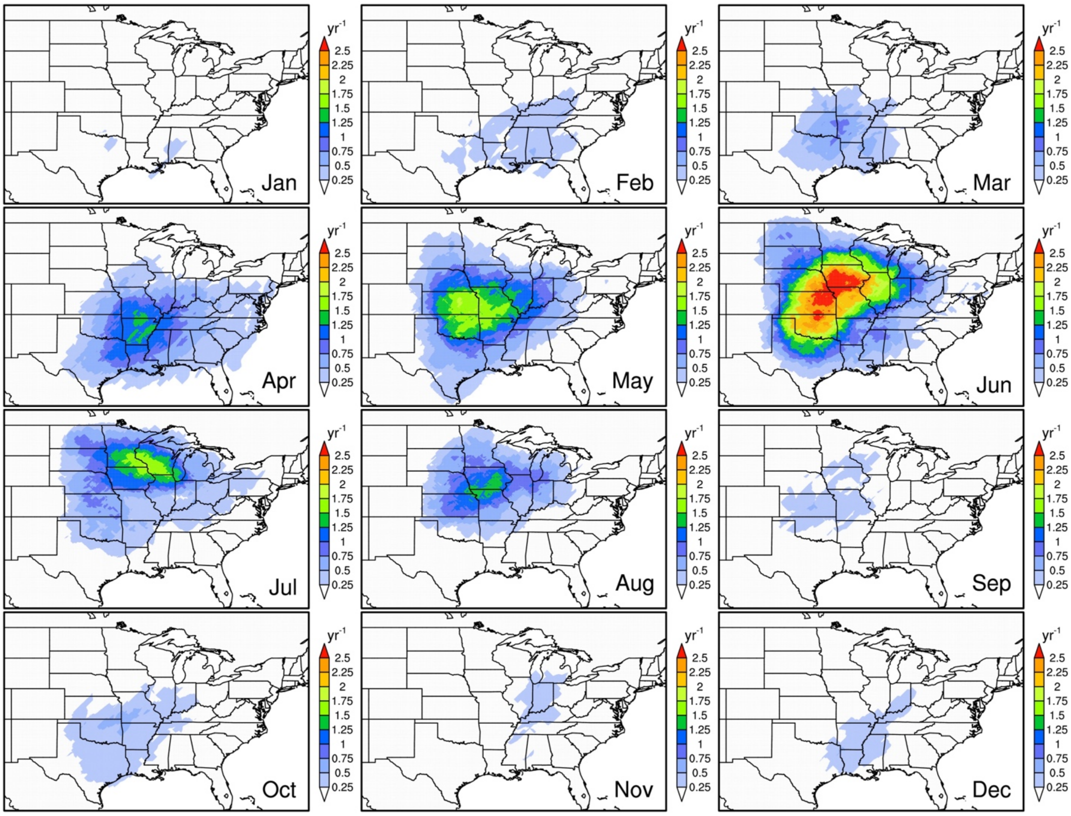

Figure 12. Same as Figure 10 but for yearly averaged monthly derecho numbers over 2014-2021.

6.3 Wind damage characteristics

We examine the contributions of derechos and DFs to all the damaging gust reports in the United States area of the dataset domain between 2004 and 2021 in Figures 13, S2, and S8. MCSs contribute about 36.8% of the damaging gust reports, but most occur east of the Rocky Mountains. On average, derechos and DFs contribute 19.2% and 16.5% of the damaging gust occurrences, respectively. In other words, about half of the damaging gusts associated with MCS events are related to derechos. Understanding the underlying mechanisms will be our focus in a follow-up study. In addition, most (> 80%) derecho-generated damaging gusts occur during the DF periods, justifying using DF in our derecho definition, consistent with the larger probabilities of extreme gusts in the gust speed PDF of DFs than that

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of derechos in Figure S9. The gust speed PDFs for MCSs and derechos indicate that derechos are more favorable for producing extreme gusts than MCSs (Figure S9). Moreover, as expected, the contributions of derechos to damaging gust reports are the highest in the Great Plains, Midwest, and Lower Mississippi Valley (Figure 13).

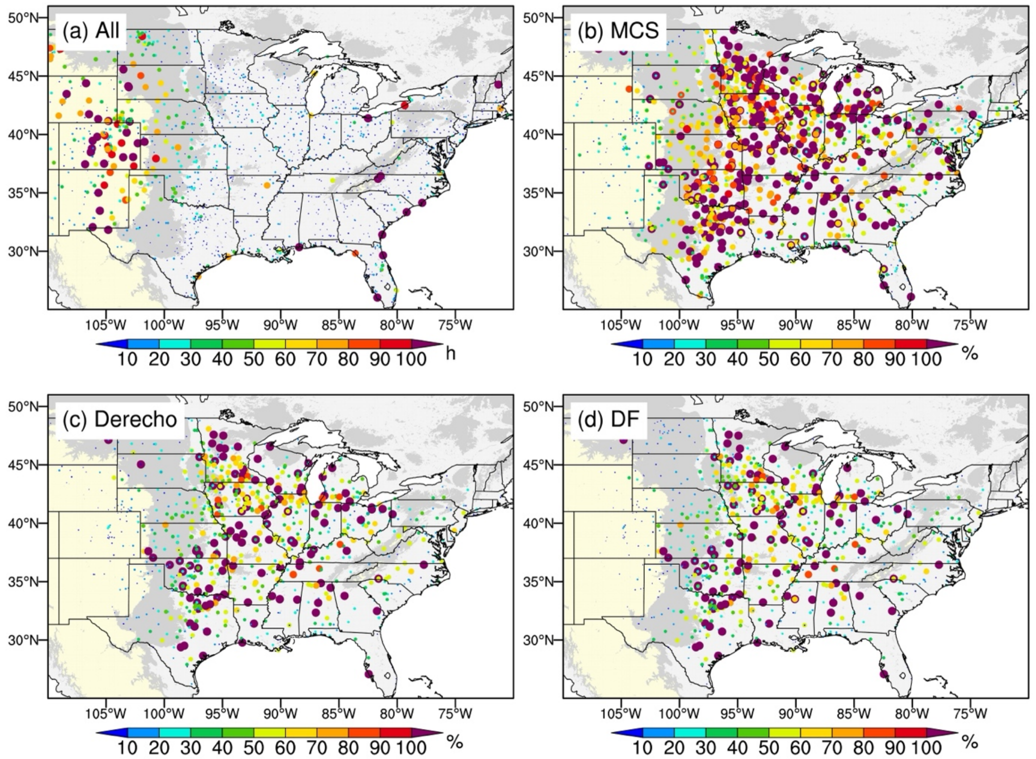

Figure 13. (a) The total numbers of damaging gust occurrences between 2004 and 2021 at weather stations over the United States east of the Rocky Mountains. (b) Relative contributions of MCS events to the damaging gust occurrences in (a). (c) is the same as (b) but for relative contributions of derechos. (d) is the same as (c), but we only consider the DF periods when counting the derecho-associated damaging gust occurrences. Similar to Figure 5, we exclude non-derecho MCS events overlapping with TCs in (b). The dot sizes are proportional to the corresponding values. Light-yellow shading denotes an elevation greater than 1000 m; light-gray shading denotes an elevation between 400 m and 1000 m; and smoke-white shading denotes an elevation less than 400 m. Background white is for oceans and lakes.

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7 Data availability

The final derecho dataset and the corresponding user guide are available at https://doi.org/10.5281/zenodo.10884046 (Li et al., 2024). The original format of the data files is NetCDF-4, and we compress them for each year so that the dataset is easily accessible. The user guide contains a detailed description of the data files to help users understand the dataset. For each derecho, the dataset provides two figures displaying the temporal evolutions of Z_{Hmax}, precipitation, wind speed, and gust speed during its entire lifetime and DF period (e.g., Figures 14 and S10). The figures are helpful for users to understand the basic characteristics of the derechos immediately. Notably, the dataset contains all the derecho-associated gust speed measurements, so users can further separate the derechos into different intensities, as in Coniglio and Stensrud (2004).

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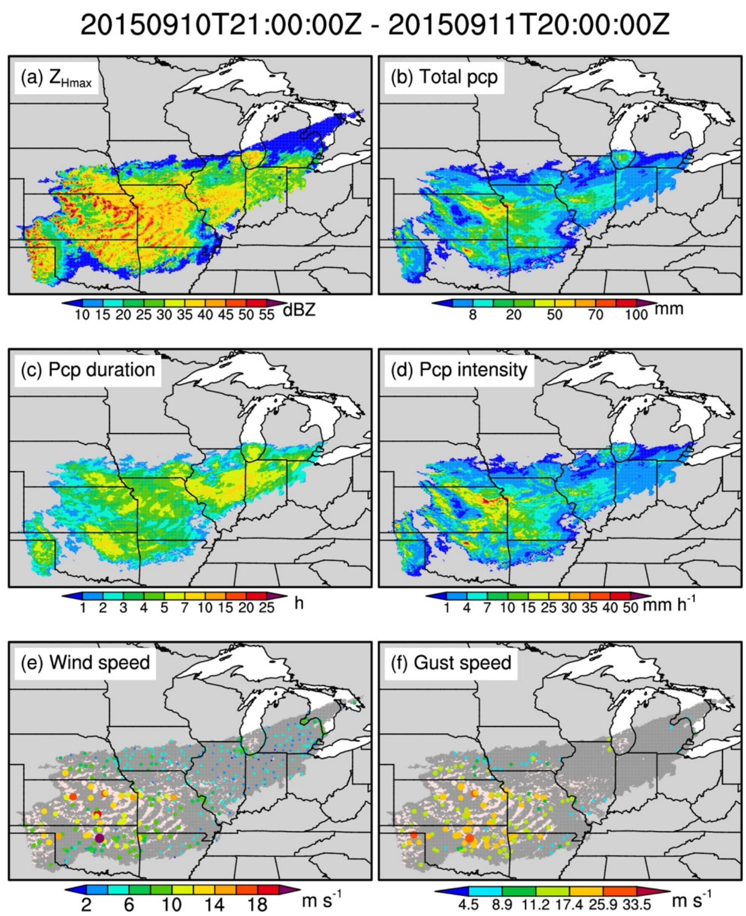

Figure 14. Similar to Figure 1 but for the spatial evolutions of (a) Z_{Hmax}, (b) total accumulated precipitation, (c) precipitation duration, (d) mean precipitation intensity, (e) hourly maximum wind speed, and (f) hourly maximum gust speed during the entire lifetime of a derecho that occurred on 10-11 September 2015. In (e) and (f), the misty rose shading corresponds to areas with $Z_{Hmax} \geq 40$ dBZ, and the dark gray shading refers to derecho coverage with $Z_{Hmax} < 40$ dBZ. The figure title refers to the derecho timing range.

8 Conclusions

This study presents a high-resolution (4 km and hourly) observational derecho dataset covering the United States east of the Rocky Mountains from 2004 to 2021. We develop the dataset using an MCS dataset generated by the PyFLEXTRKR software, a machine-learning-based identification of bow echoes, ISD hourly gust speed measurements, and physically based identification criteria. The evaluation and potential uncertainties of the dataset are discussed. The dataset contains 556 derechos, most of which are

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in the warm season (April-August). Analyses indicate that derechos preferably occur in the Great Plains and Midwest. Areas with the most frequent derechos show a northeastward shift from April to August. Derechos contribute 19.2% of land damaging gusts over the United States between 2004 and 2021. About half of MCS-associated damaging gusts are produced by derechos. As the first derecho dataset that uses machine-learning identification of bow echoes, physically based definition criteria, and surface station measured gust speeds, it provides an independent reference for derecho climatology compared to previous studies. In addition, the derecho dataset can be used to investigate the derecho initiation and development mechanisms, the environments that facilitate the formation and intensification of derechos, and the damage of derechos to human security and property. Moreover, due to its high spatiotemporal resolutions, the dataset can be used to select specific derecho events for case studies and evaluate the numerical model simulations.

Author Contributions

JL, ZF, and LRL designed the study. JL prepared the input files for PyFLEXTRKR, and ZF ran PyFLEXTRKR to generate the MCS dataset. JL and ZF generated the initial positive and negative bow echo samples. AG trained and validated the CNN model. AG applied the trained semantic segmentation CNN to identify bow echoes from the MCS dataset with discussions with JL and ZF. JL defined and identified derechos with discussions with ZF. JL evaluated the derecho dataset and manually examined the data. JL analyzed the derecho climatology with discussions with ZF. JL wrote the manuscript except for the machine-learning part which was written by AG. All co-authors reviewed the manuscript.

Competing Interests

The authors declare that they have no conflict of interest.

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The NOAA SPC derechos and near-derechos are available at https://www.spc.noaa.gov/misc/AbtDerechos/annualevents.htm (last access: November 17, 2023). The named derechos we use to generate bow echo samples are from https://en.wikipedia.org/wiki/List_of_derecho_events (last access: 19 March 2023). The elevation data is from http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NGDC/.GLOBE/ (last access: March 7, 2024). The IBTrACS Version 4 TC data over the North Atlantic basin is from https://doi.org/10.25921/82ty-9e16 (Knapp et al., 2018). Thank Drs. Israel L. Jirak, Brian J. Squitieri, and Andrew R. Wade from NOAA SPC for discussing the derecho definition criteria with us.

The bow echo segmentation code and datasets are available at https://doi.org/10.5281/zenodo.10822721 (Geiss et al., 2024). This repository includes the trained CNN weights and instructions for use. A video supplement showing the bow echo segmentation scheme in use can be viewed at https://youtu.be/iHWY_OhaVUo and is permanently archived in the above Zenodo repository.

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