Python-Based Supercell Tracking for Coarse Temporal and Spatial Resolution Numerical Model Simulations

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ABSTRACT: Deep convective thunderstorm tracking methodologies and software have become useful and necessary tools across many applications, from nowcasting to model verification. Despite many available options, many of these preexisting methods lack a customizable, fast, and flexible methodology that can track supercell thunderstorms within convective-allowing climate datasets with coarse temporal and spatial resolution. This project serves as one option to solve this issue via an all-in-one tracking methodology, built upon several open-source Python libraries, and designed to work with various temporal resolutions, including hourly. Unique to this approach is accounting for varying data availability of different model variables, while still sufficiently and accurately tracking specific convective features; in this case, supercells were the focus. To help distinguish supercells from ordinary cells, updraft helicity and other three-dimensional atmospheric data were incorporated into the tracking algorithm to confirm its supercellular status. Deviant motion from the mean wind was also used to identify supercells. The tracking algorithm was tested and performed on a dynamically downscaled regional climate model dataset with 4-km horizontal grid spacing. Each supercell was tracked for its entire lifetime over the course of 26 years of model output, resulting in a supercell climatology over the central United States. Due to the tracking configuration and dataset used, the tracking performs most consistently for long-lived and strong supercells compared to weak and short-lived supercells. This tracking methodology allows for customizable open-source tracking of supercells in any downscaled convective-allowing dataset, even with coarse temporal resolution.

KEYWORDS: Supercells; Algorithms; Regional models; Software

1. Overview and motivation

Over the last several decades, many methods and approaches have been developed for algorithmically tracking deep convective cells in observed and simulated data for both research and operational uses (e.g., Rinehart and Garvey 1978; Dixon and Wiener 1993; Wilson et al. 1998, 2004; Johnson et al. 1998; Pinto et al. 2007; Han et al. 2009; Caine et al. 2013; Prein et al. 2017). Many of these methods arose from the need for nowcasting cell motion for operational forecasting purposes. For example, the Thunderstorm Identification, Tracking, Analysis, and Nowcasting (TITAN; Dixon and Wiener 1993) and the Storm Cell Identification and Tracking Algorithm (SCIT; Johnson et al. 1998) identify and track high reflectivity deep convective cells within the operational Weather Surveillance Radar-1988 Doppler (WSR-88D) network. These efforts have recently been extended to cell tracking within convective-allowing numerical models as a result of increased computing capacity and associated increase in model resolution that realistically resolves individual deep convective cells (e.g., Pinto et al. 2007; Caine et al. 2013; Prein et al. 2017; Picel et al. 2018).

The algorithmic techniques used for object tracking can vary, but generally use one or both of two approaches: overlapping and centroid tracking, or cross correlation. Overlapping and centroid tracking, usually conducted based on the reflectivity field, involves comparing consecutive images and assessing any overlap between images to assume motion (i.e., Han et al. 2009). Cross-correlation tracking estimates the object motion by calculating the displacement in pixels between consecutive images. From the displacement and time between images an estimated velocity vector is then used to predict object motion and locations (e.g., Leese et al. 1971; Rinehart and Garvey 1978; Li et al. 1995; Fridlind et al. 2019). Typically, the benefit of the overlapping and centroid tracking is that individual cells are readily tracked, while the cross-correlation method instead measures the general flow field and does not necessarily track individual cells (Han et al. 2009). Thus, a combination of these two methodologies would provide an optimal framework for tracking convective systems ranging in size from mesoscale convective systems to individual cells; the Enhanced TITAN (ETITAN) tracking software (Dixon and Wiener 1993; Han et al. 2009) is an example of blending overlapping, cross correlation, and centroid tracking. For more details on these methods, the reader is encouraged to refer to comprehensive discussions in Wilson et al. (1998, 2004), Johnson et al. (1998), and Han et al. (2009).

Notably, object tracking options such as overlapping and centroid tracking or cross correlation were designed to be primarily used in datasets with high temporal resolution, allowing for tracking of all deep convective cells or systems. While powerful, the preexisting tracking methodologies are not easily scalable for large datasets, nor are they easily tuned when using data with coarse temporal resolution or for tracking of specific deep convective morphologies, such as supercell thunderstorms. For example, downscaled climate

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model datasets are stored with sufficient spatial resolution to reasonably resolve (e.g., via horizontal grid spacing of 4 km or less) smaller convective features, such as supercell thunderstorms, but insufficient temporal resolution (e.g., in comparison to observed radar data) due to the extensive simulated periods. This combination makes previous tracking methods inappropriate or extremely inconvenient. The explicit tracking of supercells amplified this issue as atmospheric wind fields are required; previous methodologies have no direct way of incorporating these with simulated model data. Thus, this project fills the gap in open-source and versatile thunderstorm tracking software by creating a flexible tracking tool with open-source Python. Identification and tracking of all simulated isolated and discrete (e.g., as defined in Bunkers et al. 2006) thunderstorm types, including supercells, are possible with this approach. The methodology described herein was developed particularly for simulations with poor temporal resolution, such as downscaled climate models. It should be noted that poor temporal resolution is relative to the feature of interest; in the case of rapidly evolving convective storms examined in this study, hourly resolution is considered “poor.”

To help achieve the goal of tracking discrete thunderstorms in models with poor temporal resolution, we use a combination of flexible Python libraries, Python ARM Radar Toolkit (PyART), and TiNT is not TITAN (TiNT; Helmus and Collins 2016; Picel et al. 2018). TiNT (Picel et al. 2018; Fridlind et al. 2019) is an open-source and flexible tracking software that uses a combination of centroid tracking and cross-correlation principles to track both isolated and nonisolated thunderstorms based on reflectivity signatures. The TiNT software is inspired by the cell tracking software and algorithm, TITAN (Dixon and Wiener 1993), and loosely follows its approach in its tracking methodology. TiNT requires specific input radar formats and can be especially cumbersome in the context of large or long iteration datasets due to extensive preprocessing (e.g., Caine et al. 2013). Each element of the tracking is highly customizable where TiNT identifies cells based on adjustable reflectivity thresholds. The tracking itself is performed via cross correlation between temporally consecutive images in a customizable window around each object of interest, in this case, deep convective cells. As with TITAN, an optimization algorithm is implemented to select the most optimal tracks for cells based on their relative motions; a concise example is seen in Fig. 3 of Dixon and Wiener (1993). More on the specifics of TiNT are found in section 3 here and in Fridlind et al. (2019).

In this study, we identify two novel components. First, we implement new tools and approaches to aid in supercell tracking in the challenging scenario of coarse temporal resolution relative to the rapid evolution that supercells sometimes undergo. Second, we explicitly focus on identification and tracking of supercells within regional climate model data with coarse spatial resolution; this has not yet been previously explored. The result is an efficient tool combined with new tracking techniques to allow for supercell tracking in long-iteration regional climate simulations.

The paper is outlined as follows. First, the data used in formulating and building the tracking tool will be described, as well as the specific Python tools that were created, utilized, or implemented. Next, the details of the tracking approach and methods focused on supercellular deep convective morphology will be summarized. This will be followed by identifying the various testing used to optimize the tracking, as well as a brief discussion of sample results. Last, the known errors and assumptions of the software and methodologies are discussed.

2. Data

This project is part of a larger study on the connection between climate and supercell thunderstorms, thus necessitating the development of a supercell tracking algorithm within large downscaled regional climate model datasets (Gropp and Davenport 2020). To achieve this, the Rasmussen and Liu (2017) dataset of downscaled regional Weather Research and Forecasting (WRF; Skamarock and Klemp 2008) Model simulations of a modern and future climate over the continental United States (CONUS) was utilized. The goal of Rasmussen and Liu (2017), also described in Liu et al. (2016), was to identify differences between a modern and future climate via convective-allowing simulations (4-km horizontal grid spacing) forced with global climate model data; this dataset was tailored to assess impacts of changing land surface features like soil moisture and snow coverage on convective-scale weather and precipitation. The dataset has been shown to reasonably reproduce deep convective morphologies, convective intensity, and temporal and geographic frequency (Rasmussen et al. 2017; Prein et al. 2017). Each simulation was 13 years in duration, with the future simulation following the pseudo–global warming methodology (Rasmussen et al. 2011; Lackmann 2013). Given the extensive nature of the dataset, only surface variables and reflectivity (composite and lowest level) were saved hourly, while full three-dimensional fields (e.g., x, y, and z dimensions for u and v wind) were saved every three hours. Though the temporal resolution of this simulation was not ideal for capturing all details of deep convective morphology, the spatial resolution with 4-km horizontal grid spacing is adequate to resolve supercell-like thunderstorms, as this grid spacing has been shown to resolve the pressure perturbations produced by supercells and thus reasonably capture supercell behavior (Vandenberg et al. 2014). In the vertical, 51 levels were used from the surface to 50 hPa. Each simulation had a 13-yr duration, which allows for increased confidence due to the robust sample size and significant year to year variability. More information on the specifics of these simulations can be found in Liu et al. (2016) and Rasmussen et al. (2017). It is important to note that the Liu et al. (2016) dataset was used out of convenience of dataset availability and convective allowing resolution; however, this tracking approach could be tuned to other downscaled climate datasets, such as those used in Hoogewind et al. (2017) and Gensini and Mote (2015).

3. Approach and methods

This project provides a Python-based identification and tracking tool for deep convective cells, including supercells, in convective-allowing climate datasets. Preexisting Python libraries were utilized, connected, and adapted for this task with feature tracking based on TiNT. This tracking approach
provides a flexible, customizable, and “all-in-one” algorithm that can take any convective-allowing model and track simulated supercells within the dataset. The identification and tracking code breaks down into three parts: 1) building the interface that is able to read in WRF gridded reflectivity, 2) modifying the TiNT tracking code such to interact with the WRF 4-km hourly, simulated, and single-level radar data, and 3) integrating the WRF gridded atmospheric information (e.g., three-dimensional wind fields) with the TiNT cell tracks to identify supercells. Importantly, this code needed to be parallelizable to ensure reasonable run times.

The first part of the identification and tracking process included the creation of a tool to convert WRF gridded reflectivity data into a Py-ART data object (Helmus and Collis 2016). Py-ART is an object-oriented Python based package of radar specific subroutines, algorithms, and plotting software that provides a concise tool for most radar related tasks. Most applications of Py-ART have been used for observed radar data, rather than simulated model radar data. Py-ART objects have become a common standard for radar reflectivity data and related metadata when using Python but did not previously interface with WRF data directly. The WRF Py-ART objects are then passed into the tracking software. TiNT was the primary object tracking system used for the tracking of supercell-like thunderstorms in the two datasets (Picel et al. 2018). TiNT was chosen for its flexibility and customizable software structure that blended well with this project’s intent to be a Python-based and open-source tracking algorithm despite TiNT’s original intention for observed reflectivity data. The TiNT code is flexible such that the thresholds and tolerances used to identify and track objects can be adjusted based on the dataset; this flexibility thus allowed for hourly tracking of cells.

The default settings in TiNT were not appropriate given the coarse temporal nature of the dataset. The parameters that can be readily tweaked within the tracking setup in TiNT include controlling the windows over which the phase cross correlation (flow margin) is calculated, as well as thresholds for tracking objects in time (search margin). Figure 1 shows an example of the flow margin and search margin parameter; these control the area over which the phase cross correlation is calculated and the region where the predicted cell is assumed to be based on the motion vector, respectively. In the case of Fig. 1, the flow margin of 160 km × 160 km in the two images describes the area where the phase correlation calculation is performed. A circle of radius 25 km is centered on where the flow vector (derived from the phase correlation) estimates the cell to be at that hour. Control of these parameters were based on realistic speeds and motions of the cells and on the hourly temporal resolution. See section 5 for the thorough descriptions of the parameters and how they were tuned.

Compared to the parameter settings for observed radar with high temporal resolution, the settings for TiNT were larger and less stringent. Due to the generally robust nature of this tracking methodology, scaling to hourly temporal resolution and the coarser spatial grid spacing was fairly straightforward. The necessary changes to the phase correlation tracking approach were increasing the search window around the suspected cell, increasing the size of the window where the correlation was performed, and allowing for a greater shift between images than one would expect to occur over 1 h.

4. Tracking process for a coarse resolution downscaled climate simulation

The availability of reflectivity and surface data every hour, as well as three-dimensional data only every 3 h, made the tracking process for supercells more complicated. Despite their
unique reflectivity signatures, supercells cannot be unambiguously identified solely from reflectivity data, particularly in a simulation with 4-km horizontal grid spacing. Even when tracking via operational radar data with much finer spatial and temporal resolution, Doppler velocity fields are used to concretely identify a supercell’s rotating updraft (mesocyclone); in the case of simulated storms, 2–5-km updraft helicity (UH) provides a reasonable proxy for identifying the supercellular nature of a deep convective cell (Kain et al. 2008; Trapp et al. 2010). In this study, only positive UH values were considered, so all convective cells are cyclonic and “right moving.” However, while useful, UH is problematic in the present dataset since three-dimensional wind data are only available every three hours. As a remedy, deviant motion of convective cells (described in more detail below) was used to infer supercellular thunderstorms when UH was not available. The entire workflow of the tracking process that combines reflectivity, UH, and deviant cell motion is shown in Fig. 2. The following are the justifications for each portion of the tracking process.

The first step in the tracking process was identifying each potential deep convective cell via 1 km above ground level hourly reflectivity data with TiNT. The output of the TiNT tracking was the reflectivity centroid of every cell with a minimum reflectivity of 45 dBZ with its corresponding location(s), time(s), maximum reflectivity, size (based on the contiguous area above 45 dBZ), and isolation status; a cell was assumed to be isolated if the reflectivity maximum was bounded by reflectivity values of 20 dBZ or less. The corresponding cell was additionally required to have an area greater than 30 km². Based purely on the reflectivity and at least one hour of isolation, this initial tracking yielded 831 817 candidate cells in the 13-yr control simulation for March–June; for brevity, only the modern WRF (control) simulation is discussed. With the candidate cells tracked, collocation of UH with each associated cell was performed by assuming the cell occurred at a three-dimensional data hour; for example, a cell that existed at 0000 UTC had its corresponding UH collocated. The UH value was then added to the candidate cell data frame; if the cell occurred between times when three-dimensional data were not available, the UH was listed as unknown. Therefore, it should be noted that some short-lived supercells (<2-h lifetime; Bunkers et al. 2006) would be listed with unknown UH.

If a cell either had low UH (see Fig. 2) or unknown UH, the candidate cell’s motion was used to infer if it was indeed a
supercell or not. Due to the pressure perturbations that occur within a supercell, the motion of a supercell deviates from other deep convective features (e.g., Rotunno and Klemp 1982); in contrast, more common ordinary thunderstorms are advected by the mean wind throughout the thunderstorm’s depth. Thus, any cell with motion that deviates from the mean wind is potentially a supercell [e.g., see discussion of identifying and tracking deviant motion in Bunkers et al. (2000)]. To verify this assumption, it was found that cells with confirmed $U_H > 75 \text{ m}^2\text{s}^{-2}$ also tracked closer to the Bunkers right-moving storm motion vector in 80% of the cases; while several $U_H$ thresholds were tested, 75 m$^2$s$^{-2}$ confidently represents a supercellular storm (at least when using 4-km horizontal grid spacing). Last, even if a cell tracked closer to the Bunkers motion vector, it was also required to fall within a mean error margin of 30 km, a distance based on the typical errors associated with 4-km simulated supercells (Vandenberg et al. 2014).

Initially, any candidate cell that had the required deviant motion and error margin was considered a supercell; however, this produced unrealistic “supercells” over the Intermountain West, possibly due to terrain influences (not shown). Therefore, only candidate cells that displayed greater than 25 m$^2$s$^{-2}$ but less than 75 m$^2$s$^{-2}$ were used for deviant motion. This strategy captures supercells that likely had sufficient $U_H$ at the interhour periods. While this does inherently exclude some supercells, it provides a more realistic and confident dataset.

The Bunkers motion estimation process was performed by comparing the tracked cell motion to the calculated 0–6-km mean wind and Bunkers motion locations from the previous hour. Therefore, a cell was assumed to be supercellular if it either had sufficient deviant motion (i.e., the cell tracks closer to the Bunkers motion estimation than the mean wind). To assess whether the cell had deviant motion, the mean wind and Bunkers storm motion predicted locations were calculated. The Bunkers mean motion and storm motion predicted locations were then recorded for each candidate cell yielding all the required information to infer whether the candidate cell was indeed a simulated supercell based on proximity to the mean wind and Bunkers motion estimated tracks. Figure 3 shows an example of a supercell with corresponding Bunkers motion predicted track and predicted mean wind track.

The above process was performed twice for supercell categorization, once using the default 75 m$^2$s$^{-2}$ threshold (as described above) and then using a lower 25 m$^2$s$^{-2}$ threshold. This repetition was done due to the uncertainties with 3-hourly wind data; using the default threshold of 75 m$^2$s$^{-2}$ provided a high-confidence sample of supercells while the 25 m$^2$s$^{-2}$ threshold increased the sample size but reduced confidence. Cells that met the default threshold of $U_H > 75 \text{ m}^2\text{s}^{-2}$ were considered supercells, while cells with deviant motion plus $U_H > 25 \text{ m}^2\text{s}^{-2}$ were considered inferred supercells. Cells with $U_H$ less than 25 m$^2$s$^{-2}$ but still showed deviant motion were considered marginal supercells.

5. Testing and results

To ensure that the tracking parameters were tuned optimally, 324 combinations of parameter sets were tested; the
combinations tested each varied the search margin, flow margin, and maximum flow speeds incrementally, using ranges based on typical supercell behavior. Vandenberg et al. (2014) found that all supercells in their 4-km WRF simulation sample had translational velocities less than 28 m s\(^{-1}\), providing a starting point for the tuning of parameters. In the present study, the search margin varied from 10 to 35 km every 5 km, the flow margin shifted between 70 and 120 km every 10 km, and the maximum translational velocity between images shifted from 10 to 20 m s\(^{-1}\) every 5 m s\(^{-1}\); the idea was to test both conservative and liberal thresholds, but with a starting point based on realistic motions of supercells.

Following the testing described above, the final settings of a 25-km search margin, 80-km flow margin, and maximum translational velocity between images of 15 m s\(^{-1}\) were selected based on visual inspection of the number and shape of the tracks produced. Each of 324 cell tracking settings were used to track supercells for a single month (May 2008) in the modern simulation; the visual inspection was done only using the raw hourly tracks of each supercell. As an initial check, all the settings that showed physically realistic tracks were then saved. With the most appropriate 1-month settings selected, further testing of that tracking setting was performed by hand on a random subset of 200 supercell tracks (representing \(~3\%\) of the total simulated supercells in each simulation) with the track and reflectivity overlaid for each of those settings (from the modern and future simulations). The hand testing was done to ensure that the cell tracks were behaving in a physically realistic manner and that no physically unrealistic tracks were seen. Figure 3 is an example of a “well-behaved” simulated supercell and its corresponding track indicating a correct track setting. Figure 4 shows an example of a case with an “unusual” or unrealistic track, thus, indicating a failure in the tracking setting; this specific error was a too-wide search margin.

Table 1 notes the counts of supercells and marginal supercells for the control simulation based on a modern-day climate (2001–13). The final tracking settings yielded 6818 supercells for the 75 m\(^2\) s\(^{-2}\) UH threshold and 34,335 marginal supercells and supercells using the 25 m\(^2\) s\(^{-2}\) UH threshold; given the initial candidate cells, this equates to a supercell occurrence of 4\% for marginal supercells and 0.8\% for only supercells. Figure 5 shows an example of a typical supercell season (March–June) of tracked supercells, including marginal supercells, from a single year of the control simulation. The geographic and seasonal

![Figure 4](image-url)
distribution of the supercells follows expected patterns in the
modern simulation (Smith et al. 2012). The geographic distri-
bution of the modern simulation also includes topographic
influences, such as the lee side of the Sierra del Burro moun-
tains in Mexico and Texas, where observed supercells com-
monly occur (Weiss and Zeitler 2008).

6. Limitations and biases

There are several uncertainties, limitations, and biases that
should be noted with this tracking approach. The majority of the
limitations arise from the use of an hourly resolution for reflec-
tivity, combined with 3-hourly resolution for three-dimensional
wind data. For example, the TiNT tracking software is not
designed to be used with hourly reflectivity data, as there is no
“perfect” setup for the flow and search margins that works ideally
for all storm speeds at that temporal resolution. Additionally,

<table>
<thead>
<tr>
<th>Simulation</th>
<th>All candidates</th>
<th>Marginal threshold</th>
<th>Supercell threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Total</td>
<td>UH only</td>
</tr>
<tr>
<td>Control</td>
<td>831 817</td>
<td>34 335</td>
<td>14 891</td>
</tr>
</tbody>
</table>

TiNT does not explicitly handle mergers and splits of cells; if a cell
splits, TiNT will assign one of the new cells the same identification
number as the original, and merged cells will take on one of
previous cell identification numbers. However, this issue is less
significant given the already coarse hourly resolution.

A similar issue arises when upscale growth from an isolated
cell to a larger mesoscale convective system occurs. In this
situation, the cell tracks can appear erratic even with proper
settings since the system centroid can shift dramatically. Thus,
an isolated cell growing upscale would cause the cell track to
shift to the upscale system center. To avoid this type of track
anomaly, the hourly isolation status can be used and all track
hours after a switch from isolated to nonisolated could be
omitted; for example, the tracks shown in Fig. 5 show the hours
at which cells were discrete. This would allow the tracking to
only follow discrete or isolated supercells and avoid any up-
scale growth contamination.

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**Table 1.** Tracking statistics for the March–June 2001–13 modern climate downscaled WRF simulation. “All candidates” refers to all
cells that were isolated for at least 1 h and had maximum reflectivity > 45 dBZ. The “marginal threshold” column represents all cells that
meet the supercell criteria (either UH or via deviant motion) based on a 25 m$^2$/s$^2$ UH threshold. The “supercell threshold” column
represents all cells that meet the supercell criteria based on a 75 m$^2$/s$^2$ UH threshold (see Fig. 2).

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**Fig. 5.** Example tracks from the modern climate downscaled simulation for March–June 2009. Solid lines indicate
confirmed supercells based solely on UH with the black dot indicating the initial location, dashed lines indicate
supercells confirmed by Bunkers motion, and the $\times$ symbol indicates a cell that only existed for a single hour. Panels
show all cells following the (left) 75 and (right) 25 m$^2$/s$^2$ UH criteria. All cells are shown up until the hour they
transition from isolated to nonisolated or dissipate.
The nature of the dataset used in this study also introduces some sampling biases. In general, the assumptions and techniques used herein bias the supercells that are tracked toward longer-lived, right-moving, and stronger supercells. As a result, short-lived, left-moving, and weaker supercells are not tracked. Since the Bunkers motion method, the alternative to UH confirmation, required a lifetime of two or more hours, cells that had a lifetime of only 1 h that did not specifically have a UH > 75 m$^2$s$^{-2}$ are not included in this study. Thus, any cell that had a lifetime of 1 h that did not occur at a 3-hourly data point was not included; only cells with a lifetime of one hour that are included are those that occurred at a 3-hourly output time and had UH > 75 m$^2$s$^{-2}$. As part of the deviant motion assessment, the estimated Bunkers motion prediction is only for right movers; thus, left movers would not be included in the tracking. Notably, the Bunkers and 0–6-km mean wind motion estimations were interpolated and averaged over a grid box around the cell, meaning that convective contamination of the grid box could cause uncertainty in the mean wind and Bunkers motion vectors produced from this field; measuring the storm’s convective wind field rather than the mean surrounding environment is considered convective contamination in this case. Last, the 4-km horizontal grid spacing of the downscaled climate simulations does not perfectly resolve supercell thunderstorms and all the associated pressure perturbations. Even so, the 4-km grid spacing produces realistic enough supercell features to be useful for the purposes of this study (Vandenberg et al. 2014).

7. Summary

A supercell tracking algorithm was developed for use in coarse spatial or temporal resolution convective-allowing numerical model output. The algorithm herein was developed for and applied to a downscaled convective-allowing regional climate model simulation containing 4-km horizontal grid spacing over the central United States (Rasmussen and Liu 2017). Using the TiNT Python package, tracking of supercells first used hourly reflectivity maximum and cell isolation, followed by collocating UH to each cell (Fig. 1); since the UH was only available every 3 h, this was only possible when a cell occurred on that hour. Figure 2 shows the entire workflow of this methodology. Due to the temporal constraints of data availability, the deviant right-moving motion relative to the mean wind was used as a proxy to determine whether a cell was indeed a supercell, despite not necessarily having large UH (Fig. 3). This approach allowed for a confident collection of supercells within the dataset despite the resolution issues. Even so, it should be noted that the coarse hourly resolution combined with 3-hourly atmospheric data can result in biases and uncertainties, including an undersampling of the actual total number of supercells, as well as preferential tracking of strong, long-lived, and right-moving supercells.

Importantly, this approach was designed to be universal so that the code and algorithm structure could be adapted to another dataset, with either the same temporal and spatial resolution or higher. This work is part of a larger study on the impacts of climate change on supercell thunderstorms, but we envision the methodology developed as part of the project could be readily applied to any large-scale deep-convective-resolving datasets with hourly or higher temporal resolution.

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Data availability statement. The downscaled dataset used in this project can be found in the National Center for Atmospheric Research’s Research Data Archive (Rasmussen and Liu 2017) with additional model configuration information available in Liu et al. (2016). Readers interested in accessing the code used for this project can go to https://github.com/wxmatt/Supercell-Tracking.

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