

Projection of future tornado activity in the United States with convection-permitting dynamical downscaling

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Abstract

An ensemble of high-resolution dynamical model simulations is used to offer the first projection of future tornado activity in the United States for the upcoming decades. The simulations are performed at 3-km grid spacings and are forced by initial and lateral boundary conditions provided by eight different GCMs sourced from CMIP6 archive. Two bi-decade epochs, 1995–2014 (historical) and 2040–2059 (SSP585), are considered. Tornado occurrence is approximated from attributes of the explicitly resolved thunderstorms. The historical simulations reproduce the geospatial distribution of EF1+ tornado reports well. Geospatially, tornado proxy occurrences and outbreaks increase in the future in the region extending northward from the southeast U.S. region into the Midwest. Temporally, the inter-annual variability in proxy occurrences is larger in the future. And seasonally, spring (March–April–May) contributes to the largest future increase, with a seasonal cycle that peaks one to two weeks earlier. The results from this study provide insights into the shifting geographical and seasonal risks of tornadoes and hazardous convective weather, offering a reference for emergency management, infrastructure resilience, and long-term climate adaptation strategies in the most vulnerable regions of the United States.

1. Introduction

To date, the response of tornado activity to future anthropogenic climate change remains an open question. It is possible that hints about the future may be revealed by a consideration of the past. Mindful of the caveats of the historical tornado database¹, we note that: the annual number of tornado occurrences in the United States rated as (E)F1+, i.e., “tornado reports”, exhibit a positive trend over the past multiple decades; the annual number of days with at least one (E)F1+ tornado, i.e., “tornado days”, exhibit a negative trend; and the annual number of days on which large numbers of tornadoes occur, i.e., “tornado outbreak days”, exhibit a positive trend^{2,3}, even when an additional decade of tornado reports is taken into consideration³ (see Extended Data Figure 1). An increase in the inter-annual variability of reported tornadoes, quantified as an increase in volatility⁴, has also been found.

These temporal trends appear to have geospatial manifestations. Evidence of a geospatial shift is provided in the analysis by ref⁵, which displays statistically significant positive trends in tornado reports — and supporting meteorological conditions — in a zone extending from Gulf of Mexico northward into the Midwest, and statistically significant negative trends in southern Texas northward into Oklahoma. Such trends are similarly depicted by ref⁶. When further stratified by season, the trend of tornado days in southeast U.S. is positive during the cool season (November through February) and negative during the warm season (April through July)³.

One could simply project – linearly or otherwise – these trends into the future. However, this approach does not account for the range of future greenhouse gas emission scenarios and associated range of nonlinear climatic responses⁷. In this regard, a more reliable projection would be based on physics-constrained numerical models. Even though the effective grid resolution of typical global and regional climate models (GCMs and RCMs, respectively) is too coarse to explicitly represent tornadic thunderstorms, implicit representations are possible through analyses of the meteorological conditions that support their existence. Such conditions can be quantified using environmental parameters including convective available potential

energy (CAPE), bulk vertical wind shear (VWS), and storm-relative helicity (SRH), as well as combinations of these parameters, especially the significant tornado parameter (STP)^{8–11}; higher values generally imply a greater probability of tornado occurrence. Although environment-based projections^{12–23} are foundational, they still have a fundamental limitation: environments alone cannot explicitly represent thunderstorm initiation, implying that projected frequencies are outer bounds²⁴.

Convection-permitting dynamical downscaling (CPDD) of relatively coarse GCM, RCM, or reanalysis data to kilometer-scale resolution provides such explicit representations^{24,25} but when used for regional climate applications is computationally expensive. Accordingly, the relevant CPDD studies to date have only downscaled a single GCM^{26–29}, implying a susceptibility of their associated projections to model bias³⁰. This motivates our use herein of kilometer-scale simulations from an ensemble of downscaled GCMs, as generated through a prescreening, filtering, and random-sampling process termed environment-informed CPDD (EICPDD)³¹. Of equal motivation is that no CPDD study to date has specifically pursued projections of tornado occurrence. We use this EICPDD ensemble to develop such a projection for the United States.

2. Results

We first assess the EICPDD over the historical period (1995–2014) by comparing tornado reports from the NOAA Storm Prediction Center database to tornado proxy occurrences resulting from the downscaled GCMs. Despite the inherent differences between human-based reporting¹ and simulated storm-based detection (see section 4), the GCM-forced ensemble proxy occurrences in each season and region (see Extended Data Figure 2a) has a similar percentage to that of tornado reports (Figure 1a). In addition, the geospatial distributions of the reports and the modelled proxies are well aligned (Extended Data Figure 3a): both show a maximum in the southeast (SE) U.S. extending westward into the southern Great Plains (SGP) and northward into the Midwest (MW). This correspondence demonstrates the capability of our EICPDD ensemble to represent the historical tornado climatology, at least in a bulk sense.

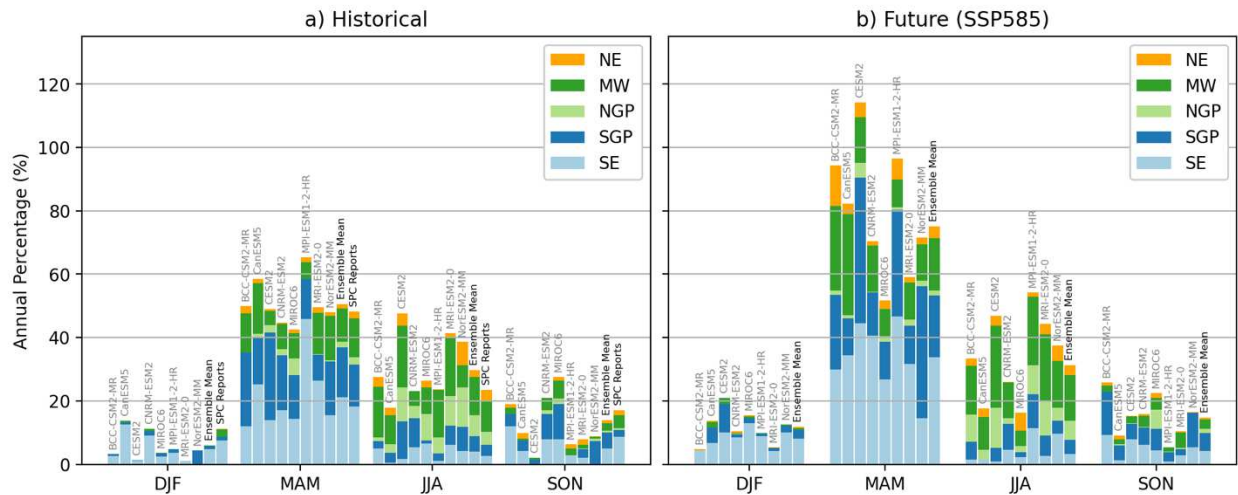


Figure 1. Frequency of tornado proxy occurrences by season [winter: December-January-February (DJF), spring: March-April-May (MAM), summer: June-July-August (JJA), and fall: September-October-November (SON)] and region (defined in Extended Data Figure 2a) for the EICPDD over (a) the historical period, and (b) the future (SSP585) period. Frequencies are represented as a percentage of historical annual occurrence for each GCM. Individual bars show

frequencies from each GCM that was downscaled. SPC reports here refer to the tornado reports rated EF1 or higher during 1995–2014), based on data from the NOAA Storm Prediction Center.

The ensemble mean of seasonal and annual tornado proxy occurrence is presented in Figure 2 for the historical as well as future (2040-2059; SSP585) periods. In both periods, proxies are maximized during boreal spring in the southeast U.S. Proxy maxima of lesser amplitudes are shown during: summer in the upper Midwest, fall in the southern Great Plains, and winter in the southeast. This implied cycle, which is also represented in Figure 1 as well as in geospatial analyses of tornado proxy *days* (Extended Data Figure 4), corresponds to the known seasonal migration of tornadic storm forcing in the United States³².

The future minus historical differences (right column of Figure 2) are considered to be the response of tornado proxies to anthropogenic climate change. Annually there is a future increase of approximately 16.4 (95% CI: 4.7–29.5) proxies per $1^{\circ}\times 1^{\circ}$ grid box in the region from Gulf of Mexico extending through the Midwest, and around 7.1 (95% CI: 3.9–10.0) in the northeast U.S., which represent increases of 46.2% and 93.9%, respectively, relative to the local historical occurrences. Decreases of up to 5.7 (95% CI: -2.1–13.6) proxies per $1^{\circ}\times 1^{\circ}$ grid box occur in western Texas (Figure 2c), which is 24.6% decrease relative to the local historical occurrence. The response in spring contributes most to the changes in annual frequency in areas south of $\sim 40^{\circ}\text{N}$ latitude, including the statistically significant increases in the southeast and Midwest, and the decreases over Texas (Figure 2f). For summer and fall the response lacks significant signals over large areas (Figure 2i&l). In winter, the response is positive and statistically significant along the Gulf coast (Figure 2o). Such regional responses can also be confirmed by Figure 1. The overall conclusion is that tornado occurrence is projected to increase in the future, especially during the spring and winter seasons, over a broad area extending to 45°N latitude, and generally east of 95°W longitude.

Within both the historical and future periods the seasonal and regional distribution of proxy occurrences for all ensemble members (Figure 1) show that the percentages of proxy occurrences are clearly different across the GCMs. This is especially reflected in larger differences within the future period for spring and summer; the numbers of proxy occurrences per season and region also have a large deviation across the GCMs (Extended Data Figure 2b&c). The season and region of largest future increase depend on the individual GCMs. For example, in spring the largest increase for CanESM5 is in the Midwest, while for CNRM-ESM2 this signal is found in the southeast U.S., despite being of similar magnitudes. As computed from all GCMs, the largest standard deviations of proxy occurrences are found in the southeast during the spring season (Extended Data Figure 5). Such variability across GCMs testifies to the utility of a multi-model ensemble approach.

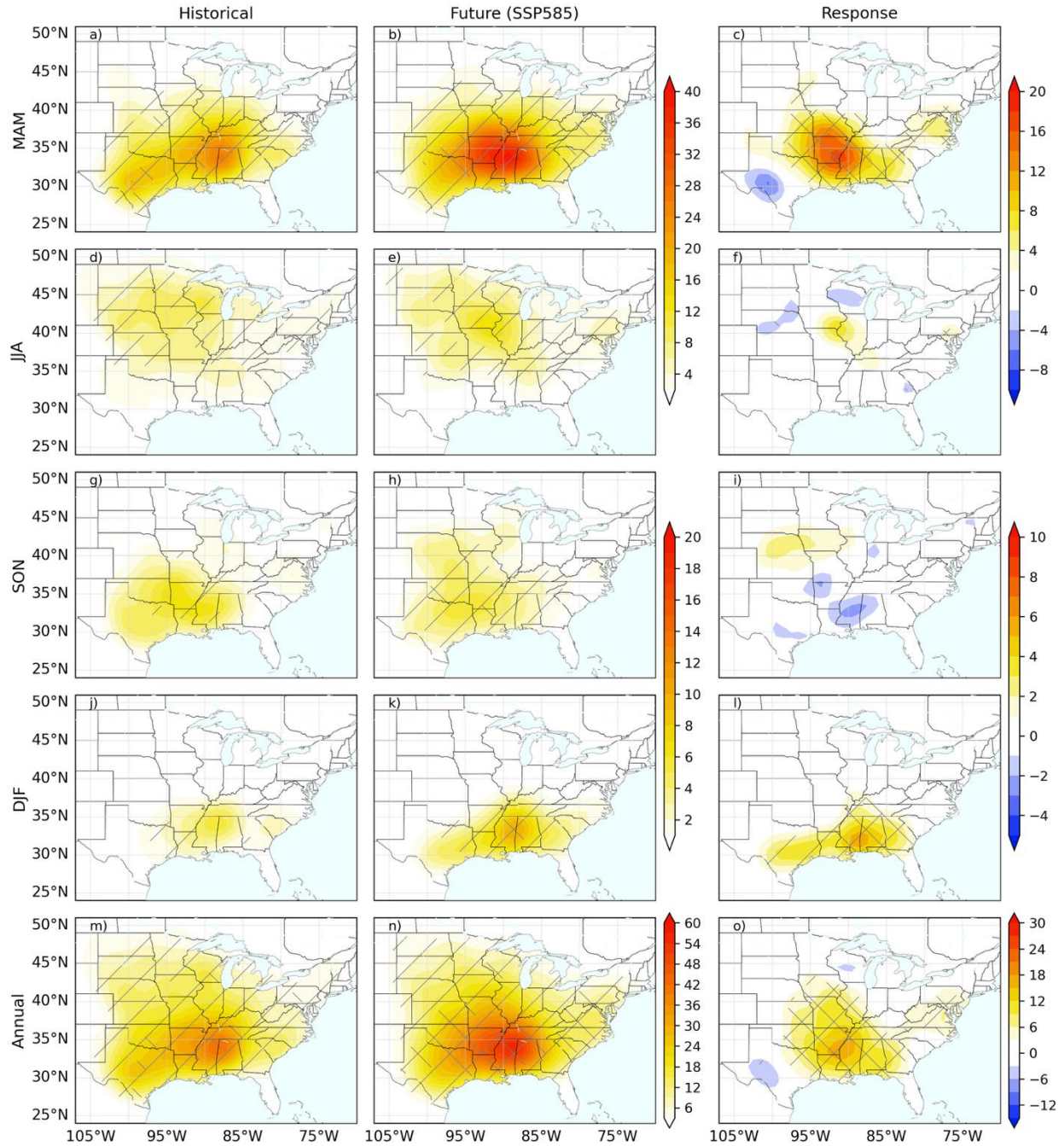


Figure 2. Ensemble mean tornado proxy occurrences (smoothed by a two-dimensional Gaussian filter with $\sigma=1.5$) for spring (MAM, a–c), summer (JJA, d–f), fall (SON, g–i), winter (DJF, j–l), and the year (m–o). Historical occurrences are represented in the left column, future occurrences in the middle column, and the response (difference) in the right column. The hatching in the historical and future panels indicates robustness: ensemble mean $>$ ensemble std is marked with ‘/’ slashes; ensemble mean $>$ twice ensemble std is marked with ‘\’ slashes. The hatching in the response plots indicates the significance of a t-test: p-value < 0.10 is marked with ‘/’ slashes; and p-value < 0.05 is marked with ‘\’ slashes. Note that the color scale is not the same for different panels due to large variations in seasonal frequency. The unit of the scale is the average number of proxy occurrences per season (or year).

Over the eastern contiguous United States (ECONUS; see Extended Data Figure 2a), the timeseries of ensemble mean tornado proxy occurrences within the 20-year historical and future periods exhibit positive trends, but with low significance (Figure 3a). However, the one-sided two-sample t-test between historical and future period has a p-value of 0.00076, providing evidence that the proxy occurrences are significantly greater in the future period. In addition, the volatility⁴ of the occurrences in the future is also larger, which means there is more inter-annual variability of the tornado proxy in the future period.

The increase in global mean temperature during the historical period (1995–2014) and future period (2040–2059) is $\sim 0.5^{\circ}\text{C}$ and $\sim 1^{\circ}\text{C}$ respectively, for the GCMs downscaled in this study²³. Over these two periods, the occurrence frequency of tornado proxies increases annually by $\sim 12\%$ and $\sim 8\%$ respectively, over the ECONUS. Acknowledging the lack of statistical significance with the associated trends (Figure 3a), the rate of proxy increase per degree of global warming would appear to be relatively less in the future, which is consistent with the rate of increase in the frequency of days with tornado-supportive environments (0.6 days/year in historical period and 0.3 days/year in the future period).

As suggested in Figures 1–2, the seasonal cycle of the tornado proxies (Figure 3b; see also Extended Data Figure 3b) is amplified in the future, especially during spring. Embedded within this amplification is a shift of annual peak from 10 May (day 130; 129–133, 95% CI) to 29 April (day 119; 118–123, 95% CI). Mean occurrences from June to the end of the year remain approximately the same for the future, but the start of the tornado season, characterized by 10% of annual occurrences^{2,28}, shifts from 12 March (day 71; 61–79, 95% CI) to 4 March (day 63; 61–76, 95% CI) (see Extended Data Figure 6a).

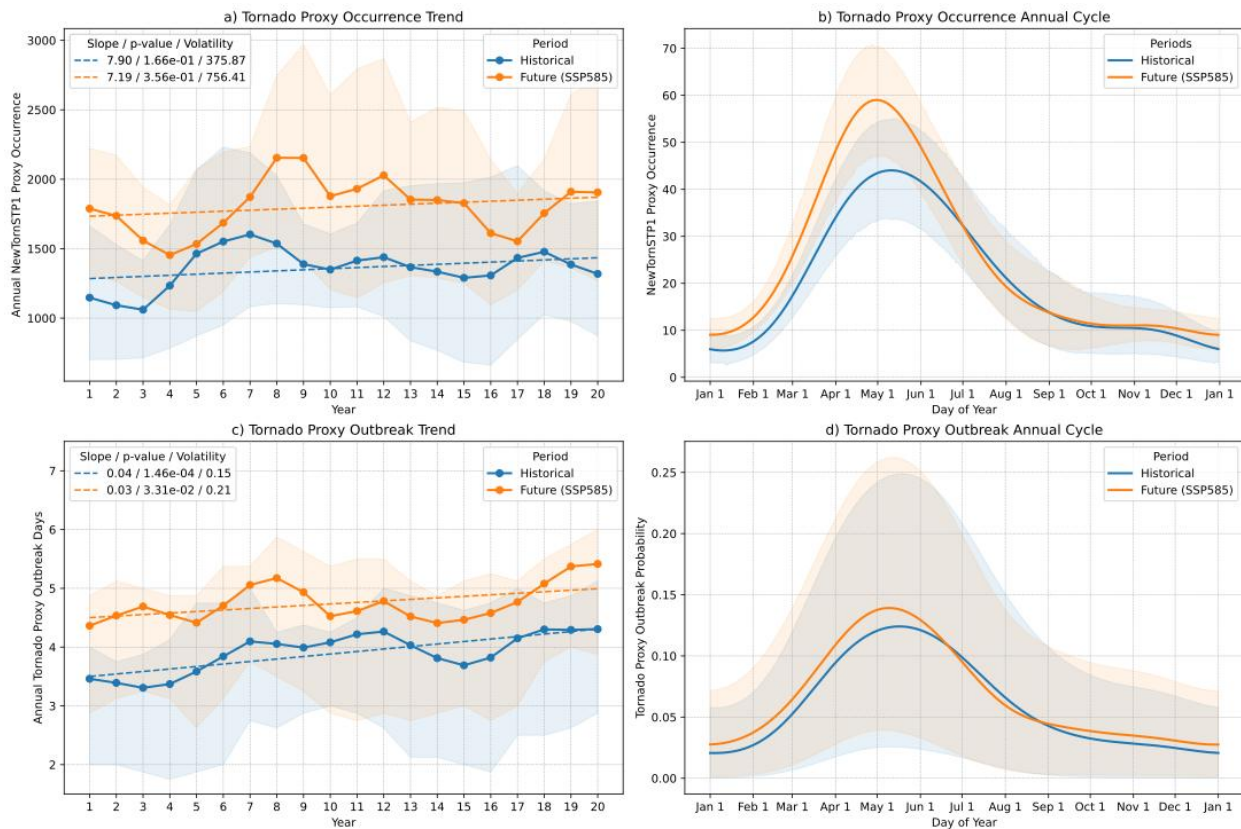


Figure 3. Ensemble mean timeseries (solid line; data smoothed by a Gaussian filter with $\sigma=1$) for a) tornado proxy occurrence and c) tornado proxy outbreaks; annual cycle (smoothed by a Gaussian filter with $\sigma=30$) of ensemble mean b) tornado proxy occurrences and d) tornado proxy outbreaks. Shading shows the 95% confidence interval. Dashed lines in a) and c) indicate linear fits. The calculations apply to land points over an eastern contiguous United States (ECONUS) domain (see Extended Data Figure 2a).

Instances of relatively large numbers (> 50 th percentile) of tornado proxies on given days are quantified as outbreaks (see section 4). As shown in the timeseries of tornado proxy outbreaks (Figure 3c), the annual trend is significantly positive during the historical period (Figure 3c), which is consistent with the trend of observed outbreaks in the United States^{2,3}. The trend in the future is also significantly positive, but with a slope that is less steep than in the past (Figure 3c, Extended Data Figure 7a&b). Thus, the rate of proxy outbreaks per degree of global warming would also appear to be relatively less in the future ($\sim 11\%/1^\circ\text{C}$), compared to that in the historical period ($\sim 23\%/0.5^\circ\text{C}$). Nevertheless, on average, there are more outbreak days in the future period, as supported by a p-value of 0.00016 from a one-sided two-sample t-test. The less significance of the trend and larger volatility in the future period compared to the historical period indicates that the future tornado outbreak activity is more uncertain.

A shift and amplification in the seasonal cycle of tornado proxy outbreaks are also observed (Figure 3d). The annual peak shifts from 16 May (day 136; 130–138, 95% CI) to 9 May (day 129; 125–131, 95% CI). The uncertainty of outbreak seasonal cycle is, however, much larger than that of the proxy occurrences, likely due to the lower number of outbreak events.

The geospatial distribution of tornado proxy outbreaks (Figure 4) is quite similar to that of tornado proxy occurrence (Figure 2) and proxy days (Extended Data Figure 4). Likewise, the seasonal migrations of areas affected by outbreaks in historical and future period are similar, as are the future expansions of outbreak areas, especially in fall and winter (Figure 4j, 4k, 4m, & 4n). The overall conclusion is that outbreaks are projected to increase in the future, especially during the spring and winter seasons, over a broad area generally south of 40°N latitude, and east of 100°W longitude. Accompanying this conclusion is an uncertainty for outbreaks that is relatively higher than that for tornado occurrence alone.

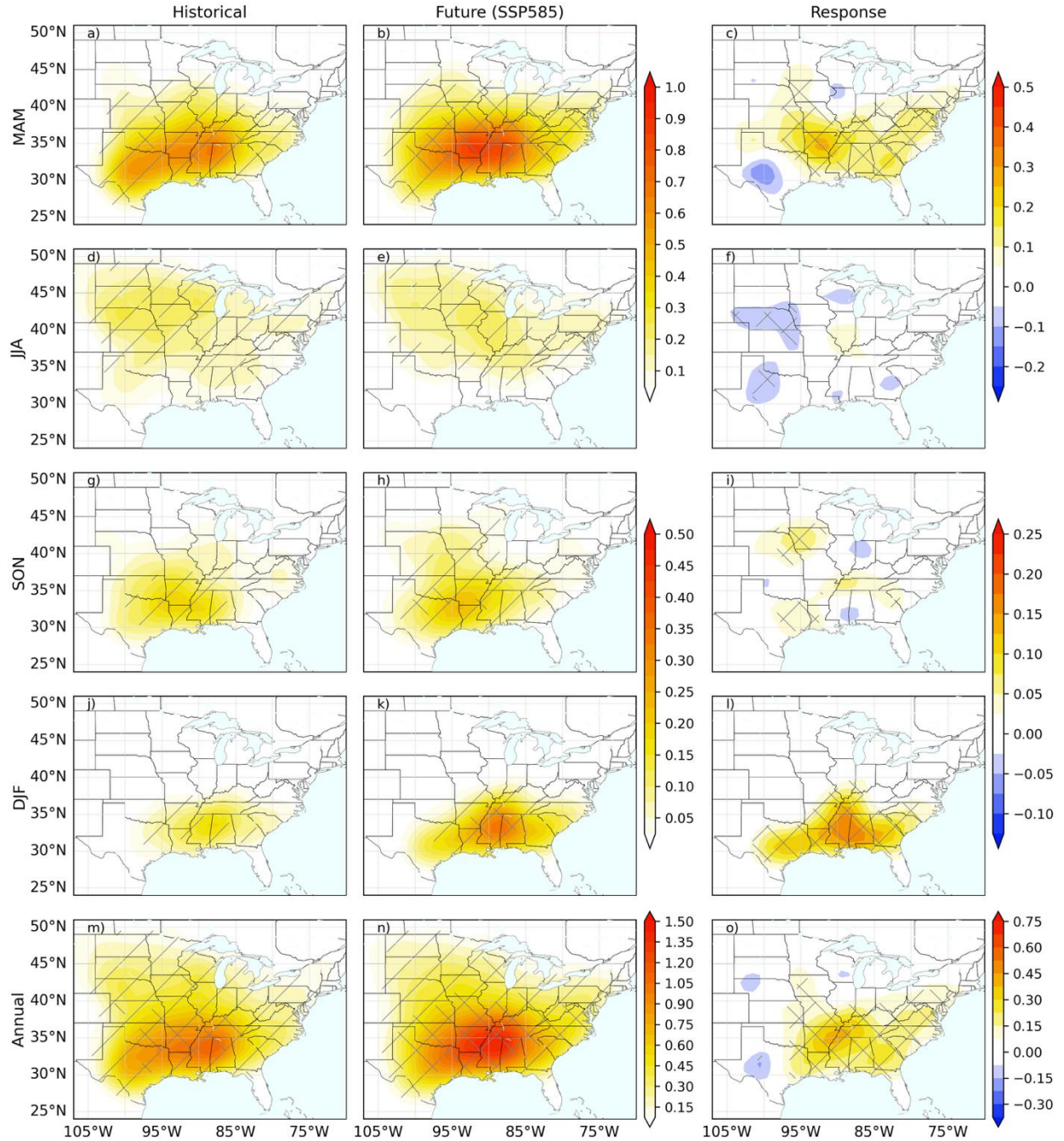


Figure 4. As for Figure 2. but for tornado proxy outbreaks. The unit of the scale is the average number of outbreak days per season (or year).

3. Discussion

Our CPDD-based projection of future tornado activity highlights an increase in occurrence and in outbreaks over a broad geographical area centered on approximately 35°N, 90°W, which is inclusive of the southeast U.S. Although applicable specifically for a midcentury (2040-2059) time period under SSP585, this conclusion is consistent with historical trends in reported tornadoes^{3,5,33}. It is also consistent with trends in observed environmental conditions

supportive of tornadoes ^{5,34,35}. In this regard, the past does indeed reveal the future, at least for tornadoes.

For insight beyond midcentury, we can again return to environmental conditions evaluated using GCM data. As a function of bi-decade periods, exceedances of the multivariate parameter STP clearly indicate a progressive increase in the frequency of days of tornado-supportive environments to the end of the 21st Century (Figure 5). Although we have already argued that such environment-based information lacks the details generated by CPDD, especially related to where and when tornadic storms are realized ²⁴, it nonetheless adds to the evidence indicating a regional increase in U.S. tornado activity during boreal spring. Indeed, an ECONUS-wide increase is likewise indicated in annual counts of STP exceedances over 2015-2099 (Figure 5e). This outer bound estimate of an approximately 18% increase in annual days with tornado-favorable environments under SSP585 contrasts with the long-term negative trend of annual tornado days based on reports over 1990-2025 (Extended Data Figure 1b). The projected increase is consistent, however, with the positive trend and associated 15% increase in tornado days over the last decade (2015-2025) of the report database (Extended Data Figure 1b). Trend confirmation awaits additional years of data as well as the next generation of GCM simulations ³⁶.

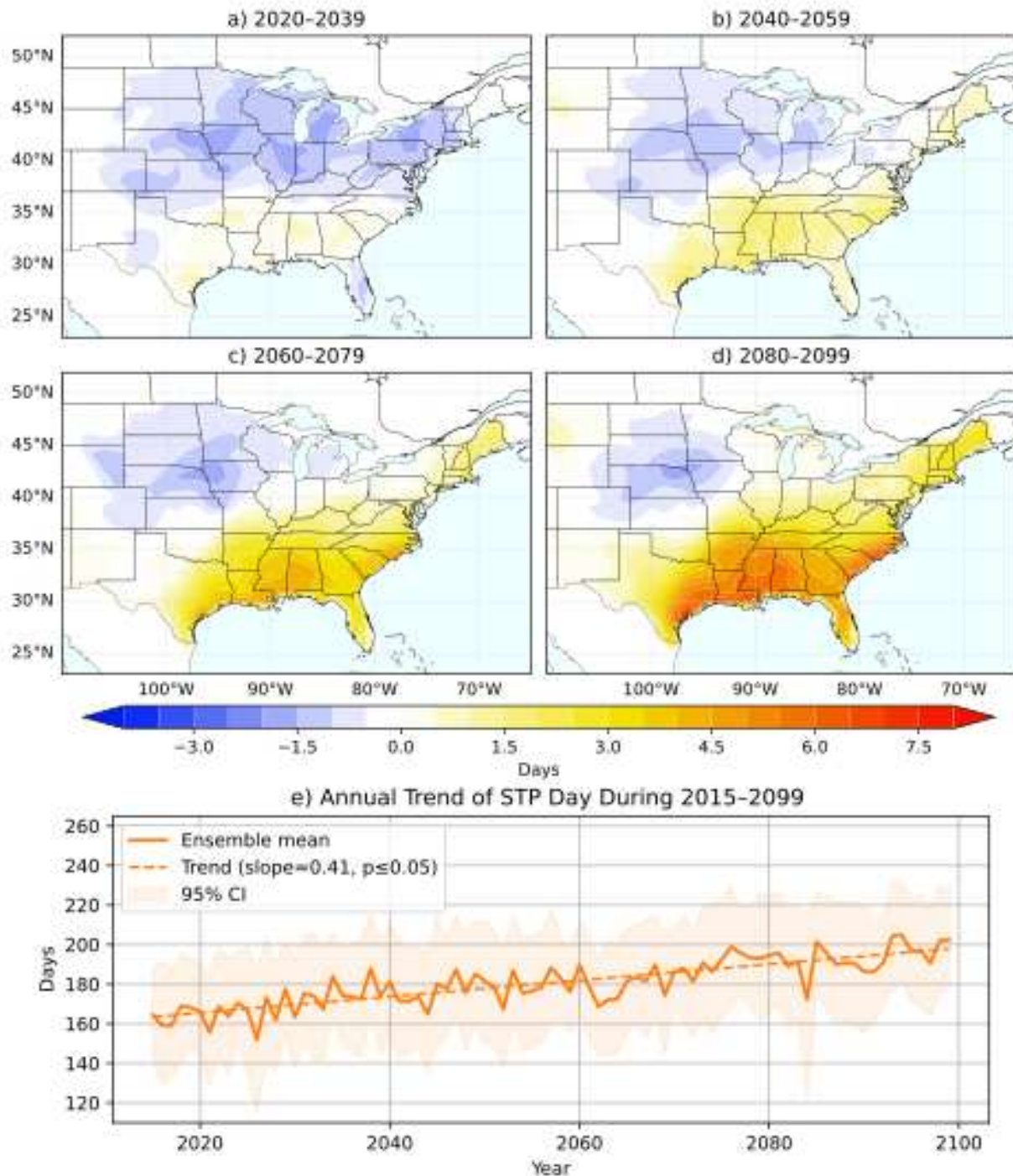


Figure 5. Ensemble mean change (future minus historical) of the number of days with environments supportive of tornadoes (STP > 1), for future periods of a) 2020–2039, b) 2040–2059, c) 2060–2079 and d) 2080–2099 relative to the historical period of 1995–2014; and the e) ensemble mean time series of annual days over ECONUS with STP > 1.

The driver of this increase is CAPE, as can be deduced from a separation of the environmental contributions to STP. Perhaps unsurprisingly given the narrative introduced in early studies^{12,15}, the generally negative contributions from the wind shear parameters are more

than offset by the positive contributions from CAPE (Extended Data Figure 8). Also consistent with the narrative in early studies is that the increase in the frequency of tornado-supportive CAPE is primarily a response to increases in temperature and water vapor within the atmospheric boundary layer (Extended Data Figure 8).

An important caveat is that the projection herein does not differentiate occurrences by intensity. By invoking theoretical reasonings applied to environmental parameters³⁷, stronger tornadoes would be expected under future conditions. In fact, a tendency for cool-season tornadoes to be disproportionally strengthened in the future relative to warm-season tornadoes has been shown³⁸. Further research involving the use of climate modeling approaches at much higher resolution, e.g., from ~100 m to ~10 m mesh lengths, will be needed to more fully address the physical drivers of future intensity.

Indeed, grid resolution is an ever-present limitation that must be balanced with other methodological choices, including computational domain size, temporal period of consideration, numbers of experiments, etc.³¹. Our choice of 3-km mesh lengths allowed for an explicit representation of thunderstorms and their attributes such as updraft core rotation, which were used to diagnose likely tornado occurrence. Support for this approach, including a theoretical analysis, is provided by ref³⁸. We do acknowledge, in the vernacular of forecast verification, the possibility both of “false alarms” and “misses” with our proxies. The geospatial and seasonal correspondences between our proxy occurrences and observed tornadoes during the historical period (Extended Data Figure 3a&b) argue that our modelled proxies provide both an acceptable reference state and a basis for an assessment of future changes relative to it.

4. Methodology

4.1. Kilometer-scale simulation ensemble via the environment-informed CPDD approach

This study employed the ensemble of kilometer-scale simulations generated by ref.³¹ via the environment-informed convection permitted dynamical downscaling (EICPDD) approach. In essence, EICPDD is targeted downscaling, wherein all potential “targets” – in this case, days – were identified in each GCM using an environmental-parameter threshold. A large (300) sample of days per GCM, per period, was randomly selected and then simulated using Weather Research and Forecasting (WRF) model version 4.4.1³⁹. The choice of the sample size is supported by ref.³¹. Of note is the use of 3-km horizontal grid point spacings over regional computational domains with dimensions 1,500 km (east-west) by 900 km (north-south). Additional information about the WRF model configuration and implementation can be found in ref.³¹.

The following eight GCMs were downscaled using this approach, as applied over two bi-decade epochs, 1995–2014 (historical) and 2040–2059 (SSP585),: BCC-CSM2-MR^{40,41}, CanESM5^{42,43}, CESM2^{44,45}, CNRM-ESM2^{46,47}, MIROC6^{48,49}, MPI-ESM1-2-HR^{50,51}, MRI-ESM2-0^{52,53}, and NorESM2-MM^{54,55}.

4.2. Proxies of tornado occurrence and outbreaks

We follow the well-established practice of using thunderstorm-scale attributes to approximate the occurrence of attendant hazardous convective weather^{24,27–29,38,56}. The specific justification for a tornado proxy is provided in ref.³⁸, which includes a theoretical analysis in their Supporting Information. As is the practice, proxies are based on exceedance thresholds of attribute quantifications. Of particular relevance to tornado occurrence are quantifications of rotating updraft cores over near-ground and mid-altitude layers (0–2 km and 2–5 km updraft

helicity, respectively)⁵⁷, as well as evidence of a precipitating convective storm (simulated radar reflectivity). To ensure that these attributes relate to tornadic storms, we additionally adapt the procedure of ref. ⁵⁷ and require storm occurrence in a tornado-favorable environment, as quantified by the condition of significant tornado parameter (STP) > 1; the surface-based (SB) formulation of STP is defined as a variation of the original formula ¹¹:

$$\text{STP} = \begin{cases} \left(\frac{\text{SBCAPE}}{1500 \text{ J kg}^{-1}} \right) \left(\frac{2000\text{m} - \text{SBLCL}}{1000\text{m}} \right) \left(\frac{0 - 1 \text{ km SRH}}{150 \text{ m}^2 \text{ s}^{-2}} \right) \left(\frac{\text{S06}}{20 \text{ m s}^{-1}} \right), & \text{SBCIN} \leq 125 \text{ J kg}^{-1} \\ 0, & \text{SBCIN} > 125 \text{ J kg}^{-1} \end{cases} \quad (1)$$

where SBCIN is expressed with positive values. The LCL term is set to 0 when LCL is higher than 2000 m and 1 when LCL is lower than 1000 m; and the S06 term is set to 0 when S06 is smaller than 12.5 m/s and 1.5 when S06 exceeds 30 m/s.

The exceedance thresholds were determined using NOAA Storm Prediction Center tornado reports and corresponding data from CPDD simulations forced by ERA5 ³¹. For each of 300 simulation days during the historical period of 1995-2014, model grid points with a simulated radar reflectivity greater than or equal to 30 dBZ were considered matched to a report if they occurred within a search radius of approximately 30 km (about 300 nearest grid points) centered at each report's location (Extended Data Figure 3c&d). About 95% of the reports on the 300 simulation days were successfully matched to at least one model grid point. The maximum values of the updraft helicity in 0–2 and 2–5 km layers within the search region for each matched report were catalogued and then averaged across all matched reports. It is noteworthy that these averaged values (25.76 m² s⁻² for 0–2 km updraft helicity, 115.13 m² s⁻² for 2–5 km updraft helicity), which are thus the exceedance thresholds, are consistent with those used in CP model-based weather forecasting of tornadoes⁵⁷, as are the thresholds of column-maximum radar reflectivity (≥ 30 dBZ) and STP (> 1). Accordingly, the exceedance of updraft helicity, radar reflectivity, and STP thresholds at a grid point in the WRF simulations were regarded as a tornado proxy occurrence.

Here we clarify that because simulated thunderstorms meeting our criteria are typically composed of multiple grid points, the expectation is that our tornado proxy occurrences are some multiplicative factor of tornado reports. In this light, we consider an outbreak of tornado proxies to have occurred when the number of proxies within a simulation day exceeds the 50th percentile value of the daily proxy distribution among all historical EICPDD simulations (Extended Data Figure 7c). A test of the sensitivity of proxy outbreak trends to this threshold shows that the trends are similar for thresholds based on a 30–70th percentile range (Extended Data Figure 7a&b). We also consider a tornado proxy day to be one on which the number of proxies exceeds the 10th percentile value (as shown in Extended Data Figure 7c).

4.3. Result compilations

The proxy occurrences are summed within 1°×1° grid cells over eastern contiguous United States (110°W–60°W, 20°N–55°N) for each GCM and period. Trends, annual cycles, and seasonal and regional analyses are based on these 1°×1° grid cell compilations. Since only selected candidate cases informed by the convective environment are dynamically downscaled, we “inflated” the number of occurrences by multiplying the ratio of the number of candidate cases to the simulated cases (300), for each GCM and period. Tornado proxy outbreak values are also inflated with the same factors.

311
312 5. Data Availability

313 All CMIP6 model outputs can be obtained from Earth System Grid Federation (ESGF,
314 <https://esgf-node.llnl.gov/projects/cmip6/>). ERA5 data can be obtained from ECMWF Climate
315 Data Store (<https://cds.climate.copernicus.eu/datasets/reanalysis-era5-complete>).
316

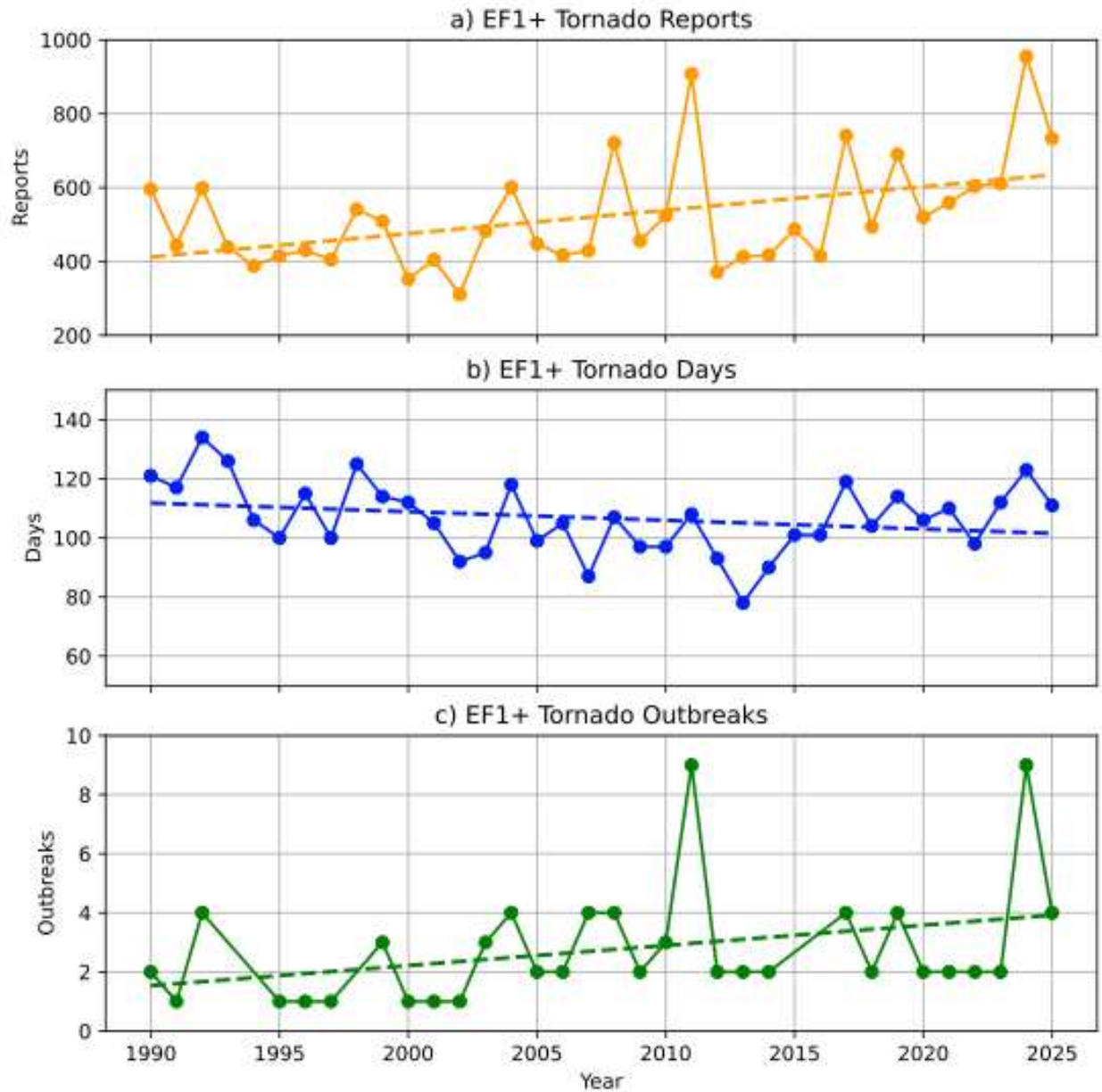
317 6. Code Availability

318 The source code of WRF model can be accessed on
319 https://www2.mmm.ucar.edu/wrf/users/download/get_source.html. Other information including
320 namelist files for WRF simulations, case lists, and the modification to WRF to calculate 0–2 km
321 updraft helicity can be accessed through <https://github.com/Songningw99/EICPDD-info>⁵⁸.
322

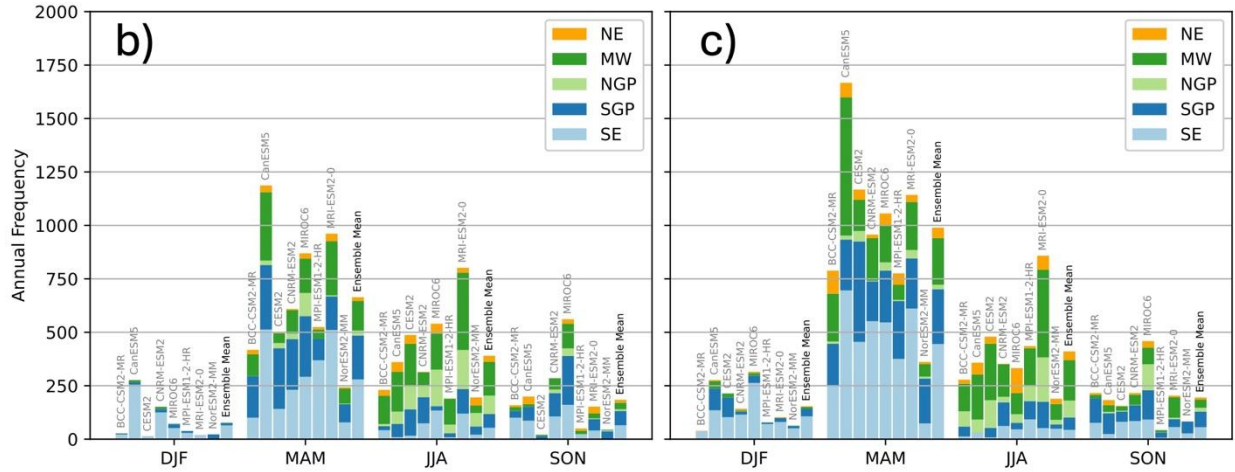
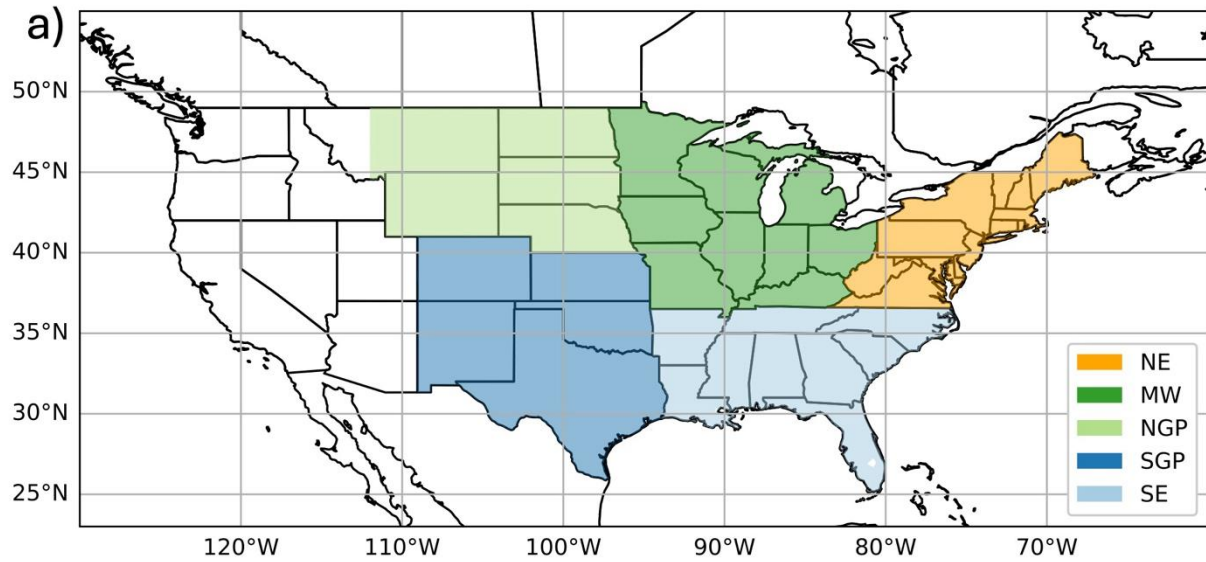
323 7. Funding statement

324 All authors disclose partial support for the research of this work from Aon Ltd.
325

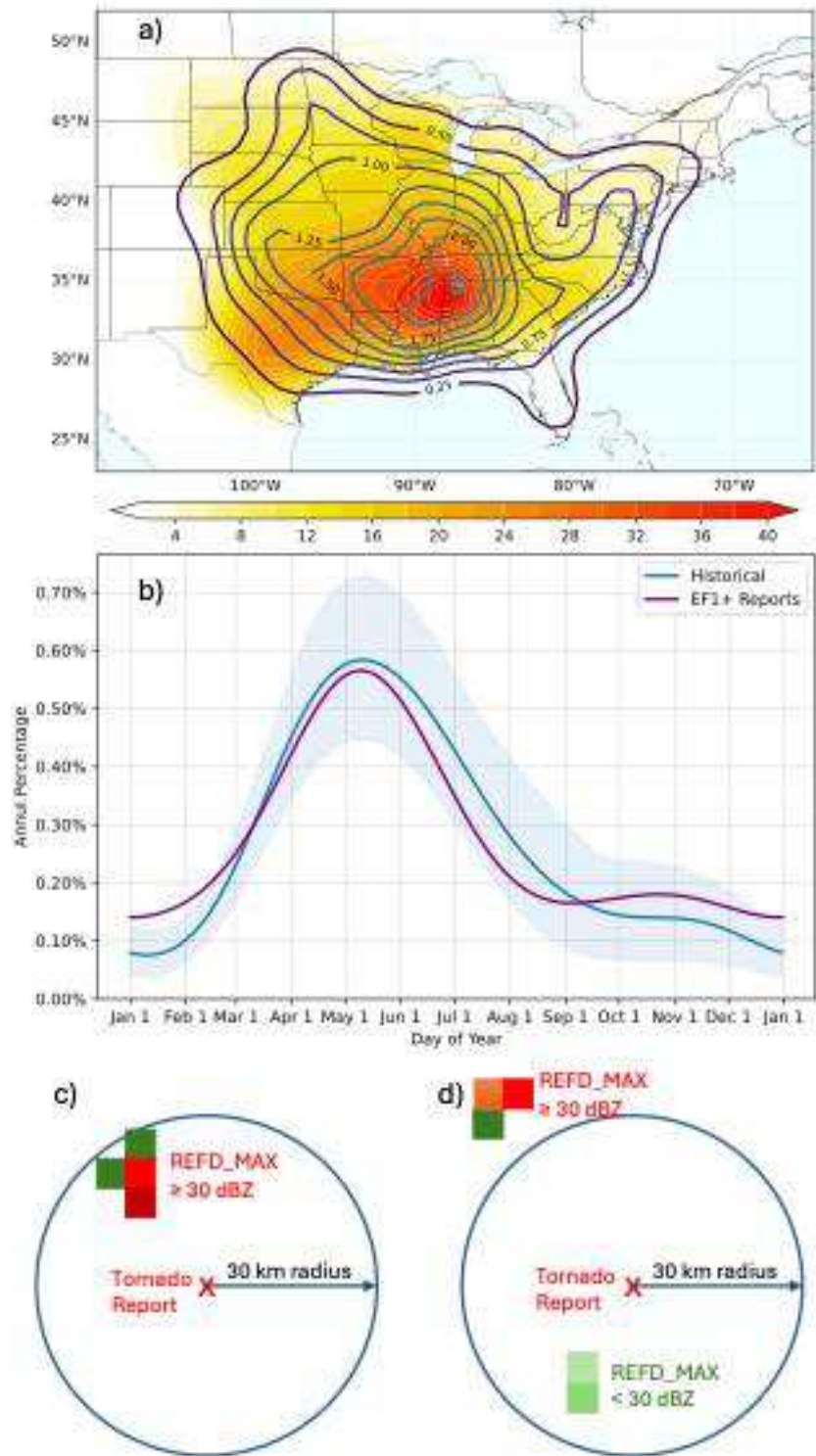
326 8. Extended Data Figures



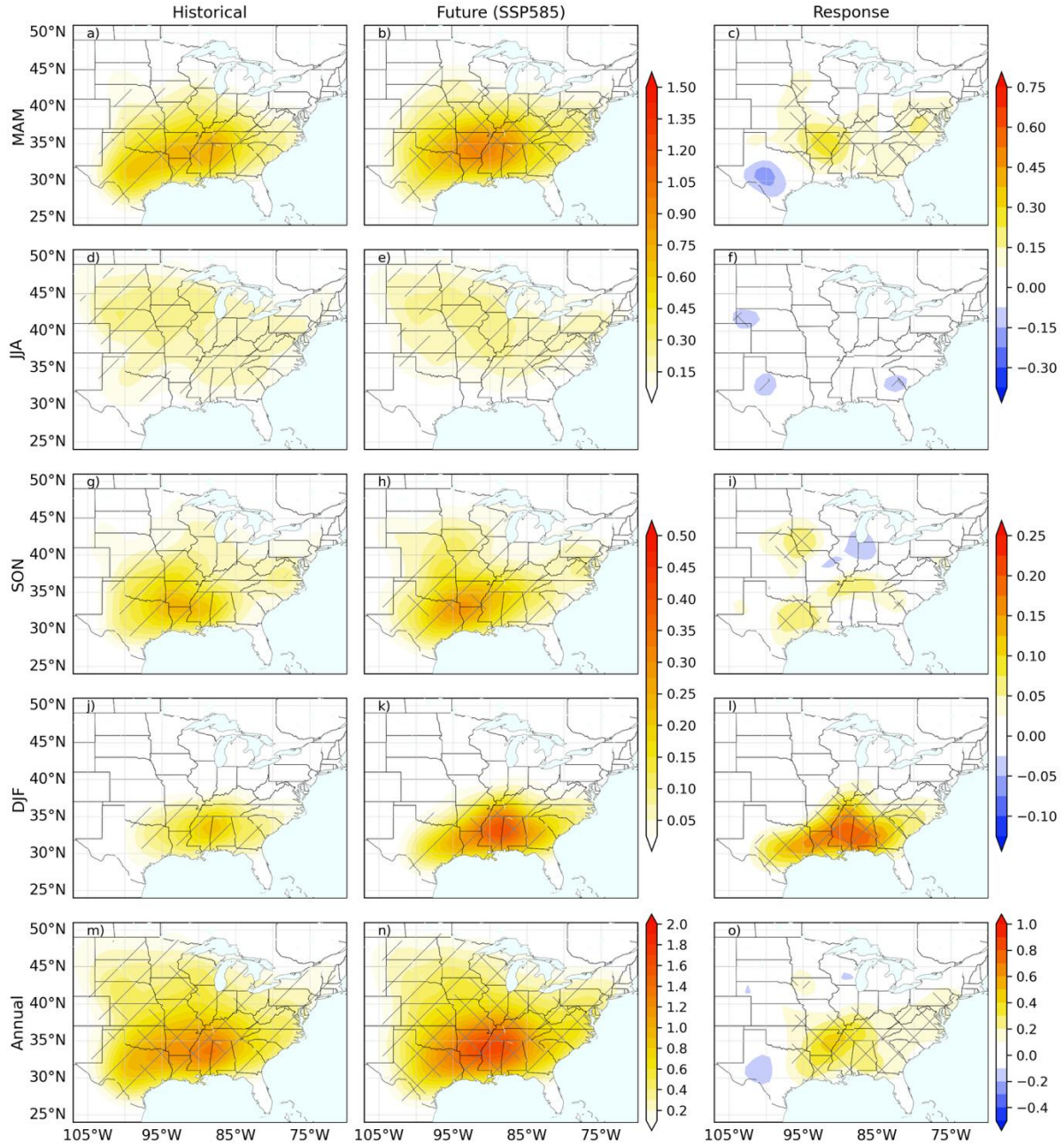
Extended Data Figure 1. Timeseries of annual a) EF1+ tornado reports, b) EF1+ tornado days, and c) tornado outbreaks (with 30 or more EF1+ tornadoes), based on data from the NOAA Storm Prediction Center (SPC). Dashed lines represent linear fits.



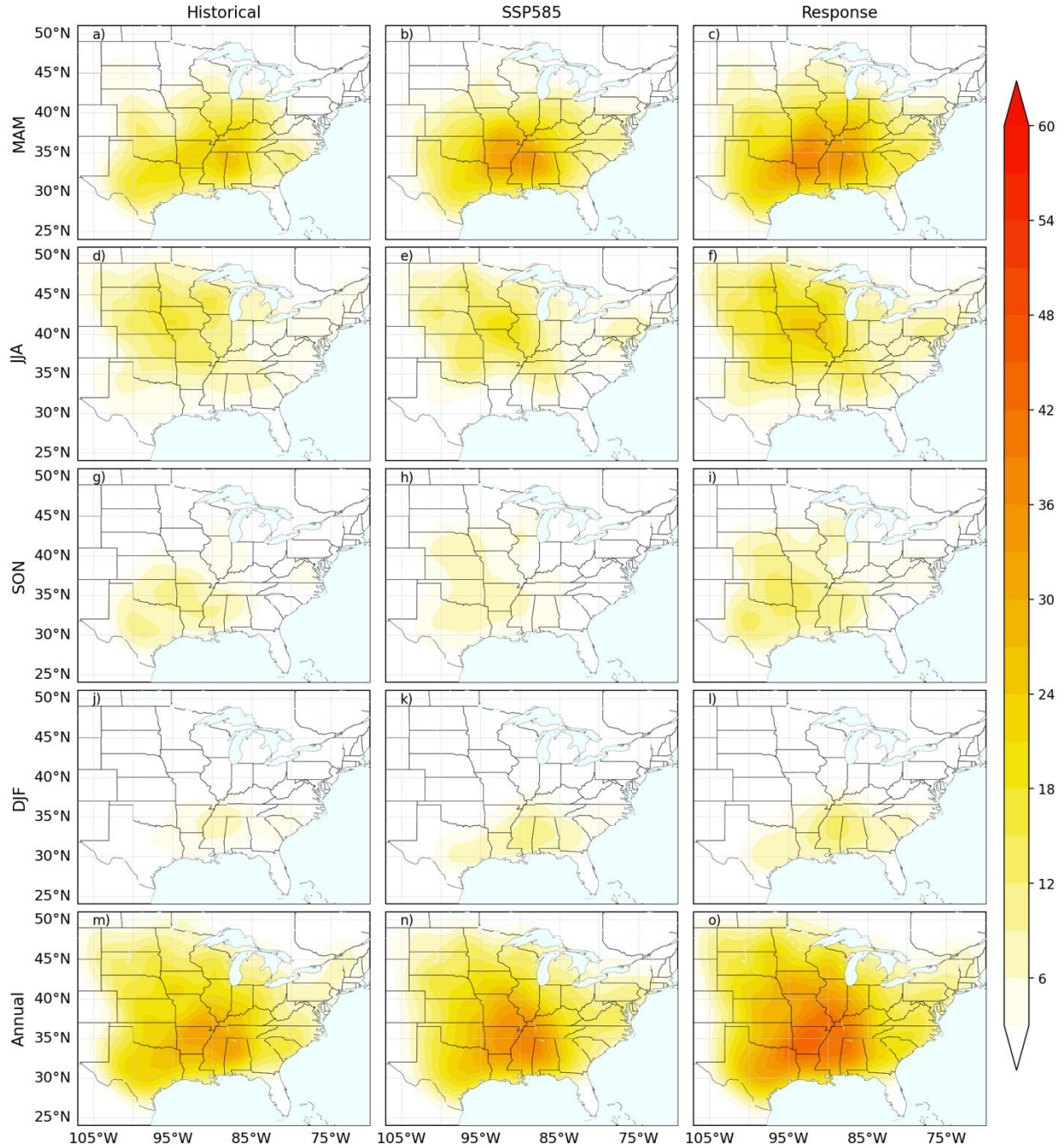
Extended Data Figure 2. a) Graphical depiction of the U.S. regions for the regional analysis; and the regional number of tornado proxy occurrences by season for the CPDD over b) the historical period (1995-2014), and c) the future (2040-2059; SSP585) period. (NE: northeast U.S.; MW: Midwest U.S.; NGP: Northern Great Plains; SGP: Southern Great Plains; SE: southeast U.S.; the west-most boundary of all WRF simulations is 112°W.)



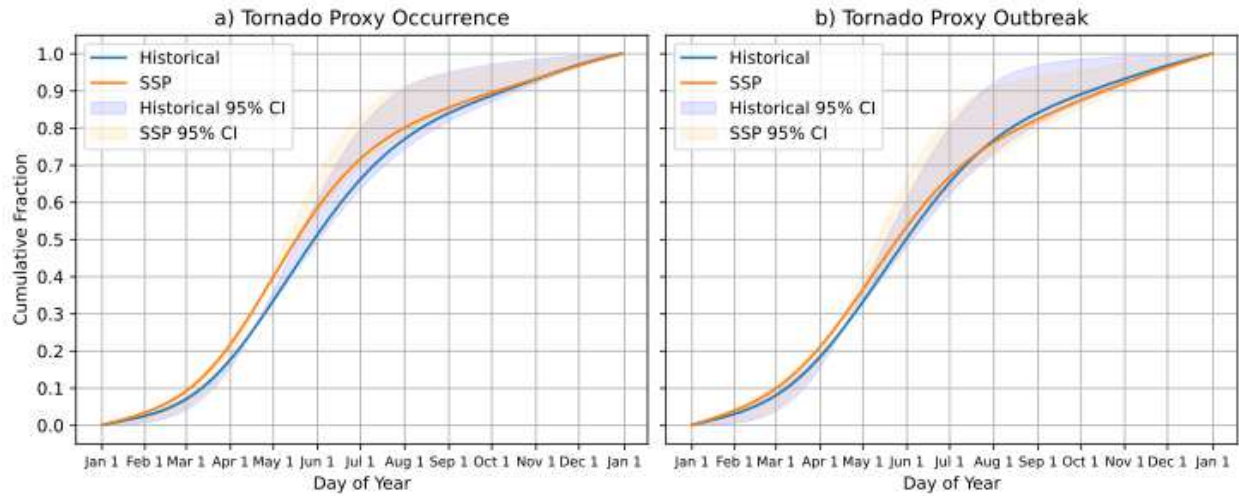
Extended Data Figure 3. a) Geospatial distribution of tornado proxy occurrences (color fill) and NOAA SPC EF1+ reports (lines); b) annual cycle (smoothed by a Gaussian filter with sigma=30) of the annual percentage of EF1+ tornado reports and CPDD proxy occurrence during 1995–2014; and the illustration of storm searching with examples of c) matched tornado report and d) unmatched tornado report.



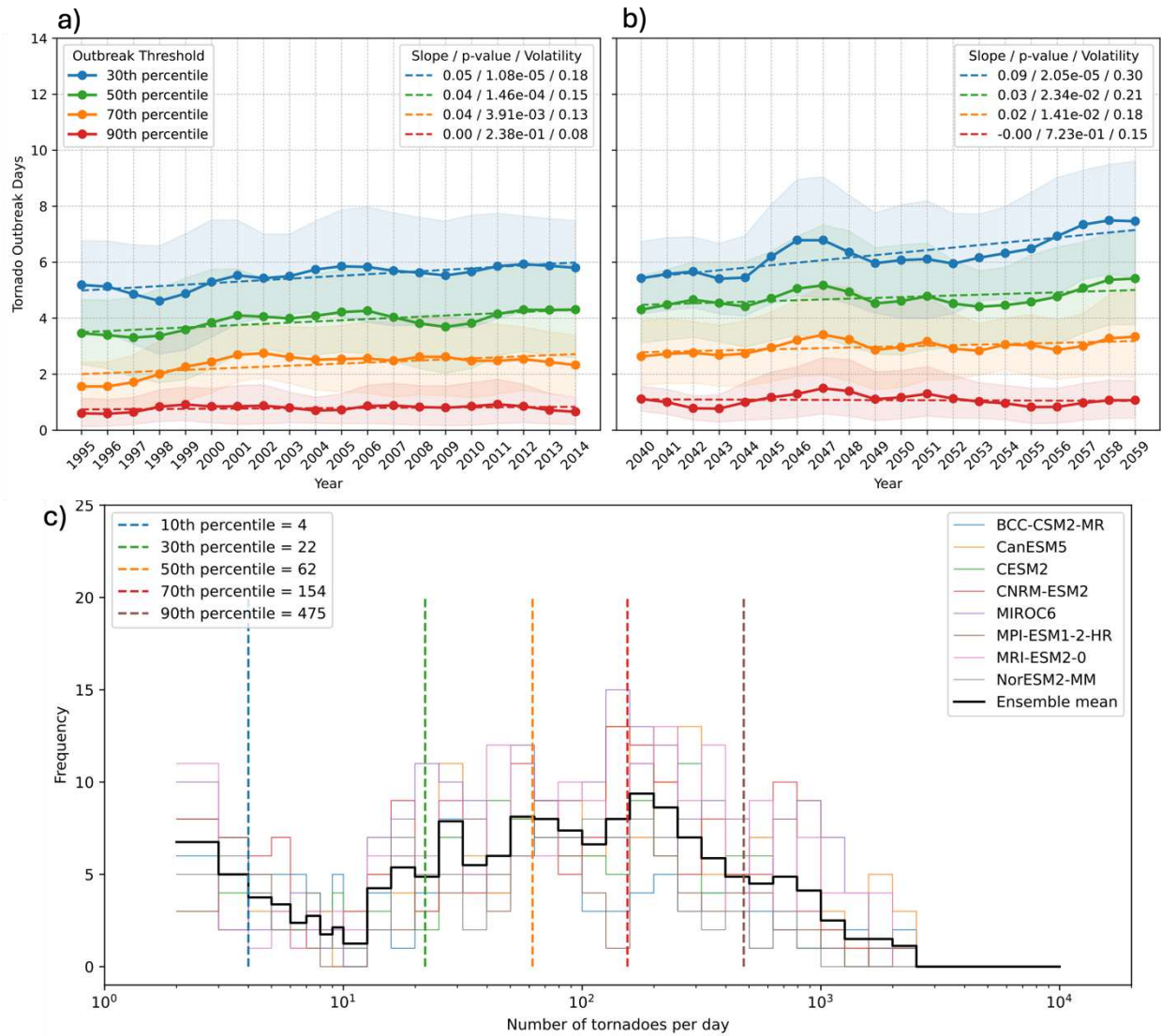
Extended Data Figure 4. Ensemble mean tornado proxy days (smoothed by a two-dimensional Gaussian filter with $\sigma=1.5$) for spring (MAM, a–c), summer (JJA, d–f), fall (SON, g–i), winter (DJF, j–l), and the whole year (m–o). Historical occurrences are represented in the left column, future occurrences in the middle column, and the response (difference) in the right column. The hatching in the historical and future panels indicates robustness: ensemble mean $>$ ensemble std is marked with ‘/’ slashes; ensemble mean $>$ twice ensemble std is marked with ‘\’ slashes. The hatching in the response plots indicates the significance of a t-test: p-value < 0.10 is marked with ‘/’ slashes; and p-value < 0.05 is marked with ‘\’ slashes. Note that the color scale is not the same for different panels due to large variations in seasonal frequency. The unit of the scale is average number of tornado proxy days per season (or year).



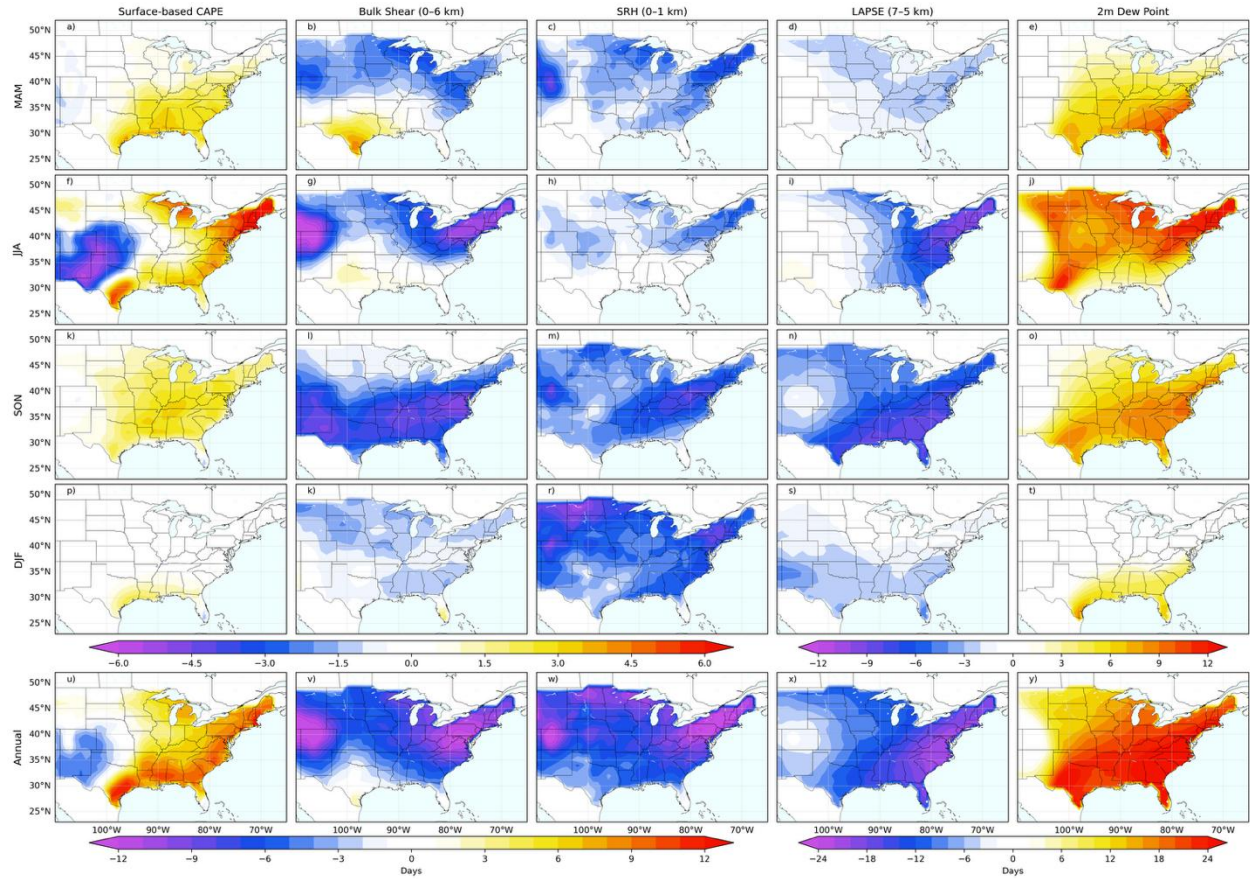
Extended Data Figure 5. Annual and seasonal ensemble standard deviation of tornado proxy occurrences (smoothed by a two-dimensional Gaussian filter with $\sigma=1.5$) for spring (MAM, a–c), summer (JJA, d–f), fall (SON, g–i), winter (DJF, j–l), and the whole year (m–o). Standard deviation of historical occurrences are represented in the left column, future occurrences in the middle column, and the response (difference) in the right column. The unit of the scale is average number of tornado proxy occurrences per season (or year).



Extended Data Figure 6. Cumulative fraction of a) tornado proxy occurrences and b) tornado proxy outbreaks in an annual cycle.



Extended Data Figure 7. Ensemble mean tornado outbreak trend (smoothed by a Gaussian filter with $\sigma=1$) with different percentile thresholds (as defined in panel c) for a) historical and b) future time periods; the percentile thresholds are determined by c) the distribution of daily tornado proxy occurrences during historical period.



Extended Data Figure 8. Annual (u–y) and seasonal ensemble mean number of days with daily maximum environmental parameters exceeding certain thresholds (smoothed by a two-dimensional Gaussian filter with $\sigma=1.5$) for spring (MAM, a–e), summer (JJA, f–j), fall (SON, k–o), and winter (DJF, p–t). Threshold for daily max CAPE (first column) is 1500 J/kg, daily max 0–6 km bulk shear (second column) is 20 m/s, daily max 0–1 km SRH (third column) is 150 m^2/s^2 , daily max 700–500 hPa lapse rate (fourth column) is 6°C/km, and daily max 2m dew point (right column) is 60°F.

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