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Tornado damage in forest ecosystems of the United States

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ABSTRACT

Changing climate dynamics have been forecasted worldwide, including in some regions of the United States (U.S.), leading to potentially significant damage to forest ecosystems. To better understand how natural disturbances may affect forests, we analyzed trends in frequency and area of tornado damage for 1995–2021, damage area within forested ecosystems, and assessed data limitations for the contiguous U.S. for 1950–2021. We found that recent, more uniform data collection periods from 1995-present showed stable to declining numbers of tornadoes nationally. However, our results indicate that the southeastern U.S. has experienced significant increases in total and forest area damaged by tornadoes as compared to other regions over the last three decades. The northeastern U.S. also showed a slight increase in damage, while all other regions showed no significant trends. This indicates a potential shift in the geographic location of tornadic events from the Midwest towards the Southeast, which has a larger area of commercial timberland. Additionally, forest area damage has increased 36 %, as estimated by total tornado track area, over the most recent 20 years. Increased tornado damage in forests suggests increased financial risks for the wood products sector and landowners in recent decades, and we recommend that large, institutional landowners monitor and assess natural disturbances (occurrence, extent, severity, and financial consequences). These findings highlight the need to improve risk assessment methodologies and support research that informs both pre- and post-disturbance forest management practices.

1. Introduction

Tornado disturbances have a marked effect on economic systems, public health, infrastructure frameworks, agricultural viability, and the ecological resilience of forested landscapes (Simmons and Sutter, 2013). Forests, in particular, play a crucial role in rural economies by supporting jobs, providing recreation, conserving biodiversity, regulating water cycles, and mitigating climate change by acting as natural carbon sinks (Brockerhoff et al., 2017). Alterations in storm dynamics (i.e., frequency, intensity, outbreak dynamics, and spatial distribution) due to climatic changes surrounding temperature, moisture, and windshear can influence these ecosystem services (Dale et al., 2001; Elsner et al., 2015; Etkin, 1995; Lee, 2012; Lindroth et al., 2009). Investigating the complex interactions among extreme weather events and forests is critical for developing appropriate mitigation and adaptation strategies.

The contiguous United States (CONUS) experiences between 800 and 1400 tornadoes per year as reported by the National Oceanic and Atmospheric Administration (NOAA) and National Weather Service (https://www.spc.noaa.gov/), which is significantly higher than most other countries (approximately <30/year/country) (Phillips et al., 2015). Tornadic activity is projected to increase in North America and every other continent except for Antarctica due to climate change, particularly for higher intensity storms (Chernokulsky et al., 2022; Dube and Chikodzi, 2021; Etkin, 1995; Goliger and Milford, 1998; Hosen and Jubayer, 2016; Silva Dias, 2011; Vicencio et al., 2021). Trends in tornado frequency have been difficult to study using currently available data and technologies, particularly in sparsely populated geographic areas (Allen and Allen, 2016; Cheng et al., 2013; Dotzek, 2001; Shikhov and Chernokulsky, 2018). This is partly because consistency in data collection has not been a priority, as noted by Diffenbaugh et al. (2008), and due to technological limitations during the early part of the record (<1990 or so). There was likely a bias (see Gall et al., 2009) against detecting low severity tornadoes [i.e., Enhanced Fujita Scale (EF), EF0 and EF1] prior to Doppler radar and satellite coverage, which may

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account for much of the observed event increases prior to 2000.

Historical concerns have largely focused on tornado effects on human health and infrastructure rather than forests and commercial timber. Tornadoes, however, can have a profound effect on forest ecosystems by reducing basal area and altering forest dynamics and communities (Ford et al., 2018; Fraver et al., 2017; Glitzenstein and Harcombe, 1988; Peterson and Rebertus, 1997). The Mississippi Forestry Commission estimated economic losses exceeding $400,000 for private landowners because of a single EF3 tornado that occurred in 2017 (https://www.mfc.ms.gov/2017/01/forestland-economic-impact-assessment-for-ef-3-tornado/). To elucidate the economic dimensions of this trend, the Georgia Forestry Commission reported >$3 million in timber damages from a series of tornadoes that affected >2000 ha in Georgia in April 2020 (GFC, 2020). These tornadoes ranged from EF0-EF3, with timber damage primarily located in areas affected by >EF1. Damage ranges from localized leaf removal or broken branches from less severe tornadoes (e.g., EF0–1) to tree mortality through either snapping of boles or uprooting in more extreme tornadoes (>EF2) (Phillips et al., 2008). This leads to a reduction in tree biomass and carbon storage and transfers of carbon among pools (e.g., living to dead

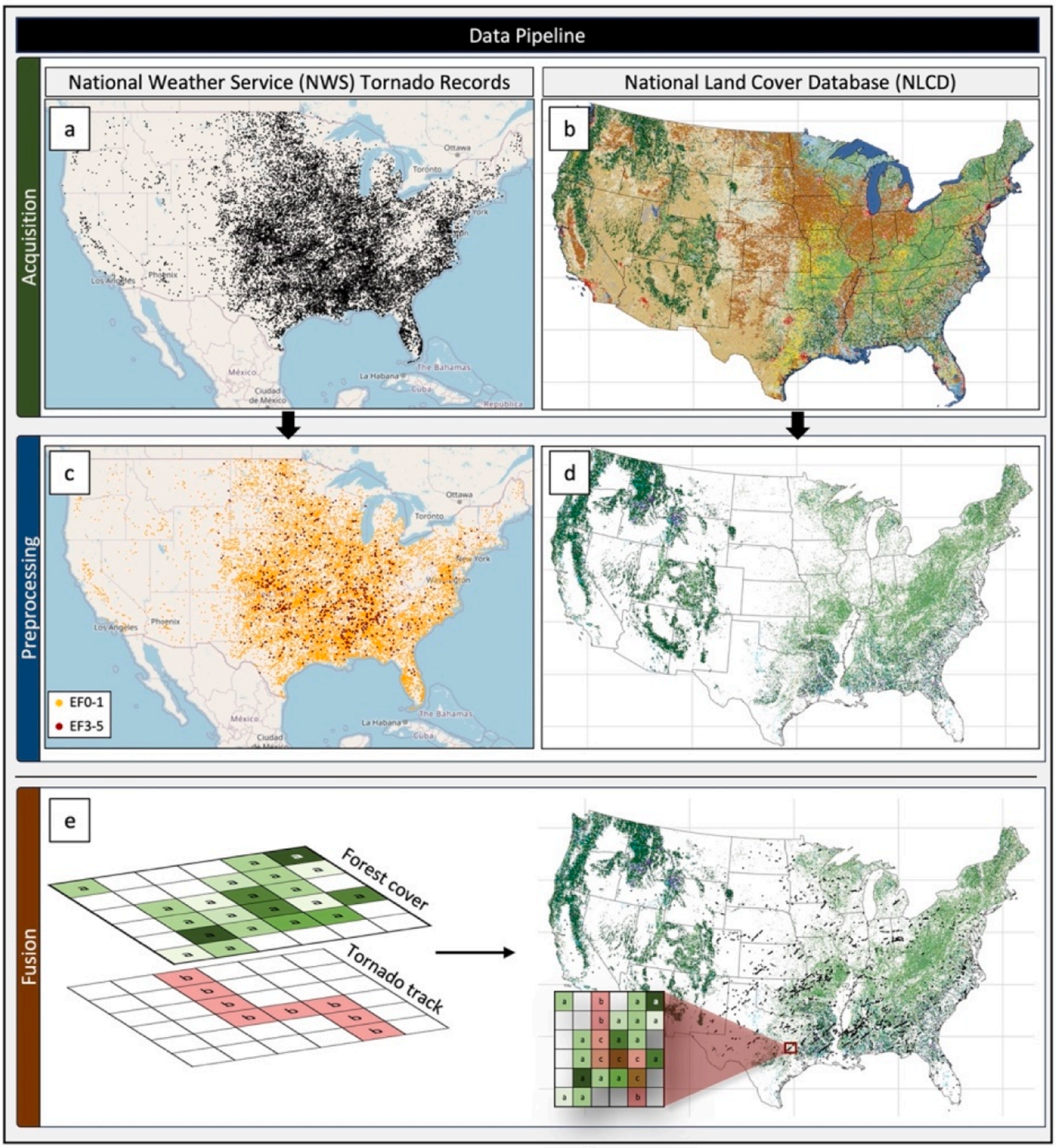

Fig. 1. Pipeline for data acquisition, preprocessing and fusion to assess the trends in tornado frequency, and total damage, forest damage, and relative forest damage area in the continental United States (CONUS). Data were obtained from the (a) National Weather Service (NWS) and (b) National Land Cover Database (NLCD). (c - d) Preprocessing for NWS data included unknown EF rating removal and development of discrete categories of low (EF0–1) and high severity groups for 1950–2021, while the NLCD data were converted to a binary feature (forest vs non-forest land cover) for each year available. (e) Tornado record and land cover were fused to estimate forest damage area where tornadoes for each year were paired with the closest available NLCD year. Trends in tornado frequency were assessed using simple linear regression for NWS data (a, c). Trends in total path area (path area = length x maximum width), forest area (path area = length x maximum width within pixels identified as forest), and relative forest area per tornado (forest damage area divided by total damage area) were assessed using Mann-Kendall trend analysis and Theil-Sen Slope estimator for CONUS and regionally using NWS and NLCD. Discrete tornado rating categories were only used for frequency trends, as these were pooled for area estimates.

wood) (Thom and Seidl, 2016). Forest recovery post-disturbance can take several years to decades depending on forest composition, storm severity, and post-tornado management (Peterson and Rebertus, 1997; Skłodowski and Garbalińska, 2011). Different ecological (e.g., organismal to ecosystem), spatial (e.g., local to stand and landscape), and temporal (e.g., days to decades) scales will likely show varying relationships between the extent of tornado damage and forest recovery. Forest areas hit by tornadoes may be inaccessible or may be too damaged to salvage, which results in further biomass and carbon losses and leads to higher timber salvage costs, expensive removal and clean-up, and decreased local stumpage prices due to excess supply locally (Dickens et al., 2016; Rousseau, 2011).

Assessing changes in tornado dynamics in forests over time and across regions is critical for risk and damage assessments, guiding pre- and post-disturbance forest management practices, and reporting on biomass and carbon losses. Yet, the stochasticity in tornadic activity, complex interacting endogenous and exogenous factors, and potential biases in currently available data makes it difficult to assess historical trends and predict future events and their ecological and economic effects in forest ecosystems (Fischer et al., 2013; Holmes et al., 2008; Peterson, 2007). Hence, the objectives of this study were to assess trends and data limitations in tornado frequency and size and to investigate how these dynamics have changed in forested ecosystems. Specifically, we assessed trends in frequency of tornadoes from 1950 – 2021, and tornado damage for all land area, and total and relative forest area for 1995 – 2021. While prior work has assessed trends (e.g., tornado frequency, power, and spatial distribution) and/or data limitations (Broyles and Crosbie, 2004; Elsner et al., 2015, 2019; Gall et al., 2009; Nouri et al., 2021), our study adopts a novel approach by stratifying tornado events according to the extremes of the EF Scale, thereby helping clarify trends by focusing on groups where severity assessments are more consistently discernible. This data quality assessment shaped our data selection for the second objective, thereby enhancing the precision and dependability of our forest area damage quantification.

2. Methods

2.1. Data pipeline

To highlight trends and data limitations surrounding tornado frequency and size and how these trends have changed in forested ecosystems, we analyzed tornado data for the U.S. using the National Weather Service (NWS) (https://www.spc.noaa.gov/wcm/#data) data and the National Land Cover Database Science Research Products (NLCD) (Fig. 1). We used the NWS dataset to assess tornado frequency and damage area. This dataset is maintained by the U.S. Storm Prediction Center (SPC) and provides the location, fatalities, Enhanced Fujita Scale (EF0–5) or Fujita Scale (F0-F5), length, and width of tornadoes in the U.S. from 1950 to 2021. The Fujita Scale (F-Scale) ratings are based on damage, relying heavily on damage to human structures, but vegetation is used when those metrics are absent (Peterson, 2003). This rating system was modified and is now called the Enhanced Fujita scale (EF) and is the standard for rating the intensity of tornadoes (Fujita, 1971; McDonald et al., 2010). The EF system connects the Beaufort wind scale and the Mach speed scale and ranges from EF0 (weak winds with minimal damage) to EF5 (strong winds and significant damage) (Canham et al., 2001; Fujita, 1971). The NWS data used the F-Scale prior to 2007 and changed to the EF-Scale from 2007-present, but this modification does not influence the validity of these ratings (i.e., only the wind speeds associated with each category have changed (McCarthy et al., 2006).

We used the National Land Cover Database (NLCD) to identify forested land. This is a 30 m^2 Landsat-based geospatial dataset that provides information about land cover across CONUS for 2001, 2004, 2006, 2008, 2011, 2013, 2016, and 2019 (Dewitz, 2021; Homer et al., 2012). The U.S. Geological Survey (USGS) and the Multi-Resolution Land Characteristics (MRLC) Consortium developed the NLCD from composite Landsat satellite imagery paired with ancillary information to classify land cover. NLCD includes eight classes (water, developed, barren, forest, shrubland, herbaceous, planted/cultivated, and wetlands) and 20 subclasses. Forest subclasses included in the NLCD are deciduous, evergreen, and mixed forests. Researchers expanded the NLCD to include additional classes that better captured transitional forest ecosystems (i.e., Herbaceous-Forest, Shrub-Forest, and Young-Forest). However, we converted these forest type classifications to binary indicators (e.g., forest vs non-forest land) for our analyses. The NLCD accuracy has improved over time and typically exceeds 80 % (Wickham et al., 2017). The NLCD data and methodology is further described in Jin et al. (2023); Jin et al. (2019).

We performed data preparation, analyses, and visualizations in Mathematica (Wolfram Research, 2022) and RStudio (RStudio Team, 2016) using the following packages: dplyr (Wickham et al., 2021), ggplot2 (Wickham, 2016), raster (Hijmans et al., 2019), sf (Pebesma, 2018), terra (Hijmans, 2023), and trend (Pohlert, 2023).

2.2. Assessing tornado frequency and data limitations

To estimate trends in tornado frequency and assess data limitations, we partitioned tornado counts by intensity. A few tornadoes did not have a severity rating (−9 code) and were dropped. We excluded EF2 tornadoes to create more distinct groupings due to some subjectivity inherent in the rating system: low (EF0 + EF1) and high severity groups (EF3 + EF4 + EF5) were created. Prior work has analyzed overall trends (i.e., all severities combined) and trends by individual severity classification, and potential data limitations. However, we took a unique approach that was designed to focus on the extremes of the tornado rating scale. This stratification by severity excludes the moderate-intensity tornadoes, which could introduce a wider range of damage severity due to the subjective nature of the damage assessment. Differentiating between EF1 and EF2 or between EF2 and EF3 may not be consistent across different events and observers. By analyzing overall trends within these low-intensity (EF0 and EF1) and high intensity (EF3 to EF5) groupings, we enhanced the sensitivity of our analyses. Additionally, forest damage indicators are largely absent or need improvements in both the F-Scale and EF-Scale system and the complexity of forest dynamics that contribute to damage risk makes their inclusion difficult (Blanchard, 2013; Diffenbaugh et al., 2008; Peterson, 2003). This potentially introduces some bias towards higher ratings in urban areas. It is also important to note that Doppler radar (WSR-88D), introduced in the early 1990s (Agee and Childs, 2014; Nouri et al., 2021), increased the ability to detect tornadoes. However, Doppler implementation was not instantaneous and was slowly integrated over the subsequent decade. To account for this, we compared trends in CONUS using simple linear regression for the full period, post-1989 (Doppler introduced) and post-1999 (Doppler widespread). Regional analyses were precluded due to insufficient sample size arising from the rarity of high-severity storms, which rendered trend analysis methodologically unreliable.

2.3. Quantifying tornado area

It is possible to get an estimate of total damage area from a tornado where path area (km^2) for a single storm is roughly a long rectangle of dimensions width x length. We defined Total Area as this metric summed over all storms for that year. This will be an over-estimate for smaller storms, which may not stay on the ground during the entire storm event. There was a switch in 1995 from reporting mean path width (m) to maximum path width, which is easier to determine (Agee and Childs, 2014). The summary analysis here used data post-1994 to avoid this discontinuity in methods and also avoids potential biases introduced due to poor detection of lower severity tornadoes, particularly in unpopulated forested areas, prior to Doppler radar. Maximum path width introduces another upward bias in total area estimates, but the bias was constant over time. The significance of this consistent bias lies in it enabling dependable trend analysis over the study period, even while the bias itself persists. Forest damage area was calculated as the damage area located in forests within a year as identified using the NLCD database, where the tornado year was paired with the closest available NLCD database year. The relative forest area damaged was calculated by dividing the forest area damaged by the total area damaged, providing an indication of whether the proportion of forest area damaged is increasing at a greater rate compared to the total damage area.

Trends in total path area, forest area, and relative forest area per tornado were assessed using Mann-Kendall trend analysis ($\alpha = 0.05$) and Theil-Sen Slope estimator (Sen, 1968; Theil, 1950). Mann-Kendall trend analysis is a non-parametric statistical method that can be used to detect trends in time series data, where Kendall's tau (τ) values range between -1 (strong negative correlation) and 1 (strong positive correlation) or is zero when no correlation is detected. Theil-Sen Slope test is a non-parametric analysis to assess magnitude and direction of change. These methods make no assumptions regarding data distributions and are robust to outliers (Wilcox, 2010), and have been used in prior tornado trend analyses (Gensini and Brooks, 2018). In addition to assessing trends, the record was divided into two periods (1995–2007 and 2008–2021, roughly in half) to analyze the damage area data due to an apparent discontinuity in the mean. Means of the two periods were compared for difference using the LocationTest function in Mathematica, which computes the Mann-Whitney, T and Z tests for difference. Analyses were performed for CONUS and regionally. Regions in the analyses included Mountain (Colorado, Idaho, Montana, Nevada, Utah, Wyoming), Midwest (Illinois, Indiana, Iowa, Kansas, Michigan, Missouri, Minnesota, Nebraska, North Dakota, Ohio, South Dakota,

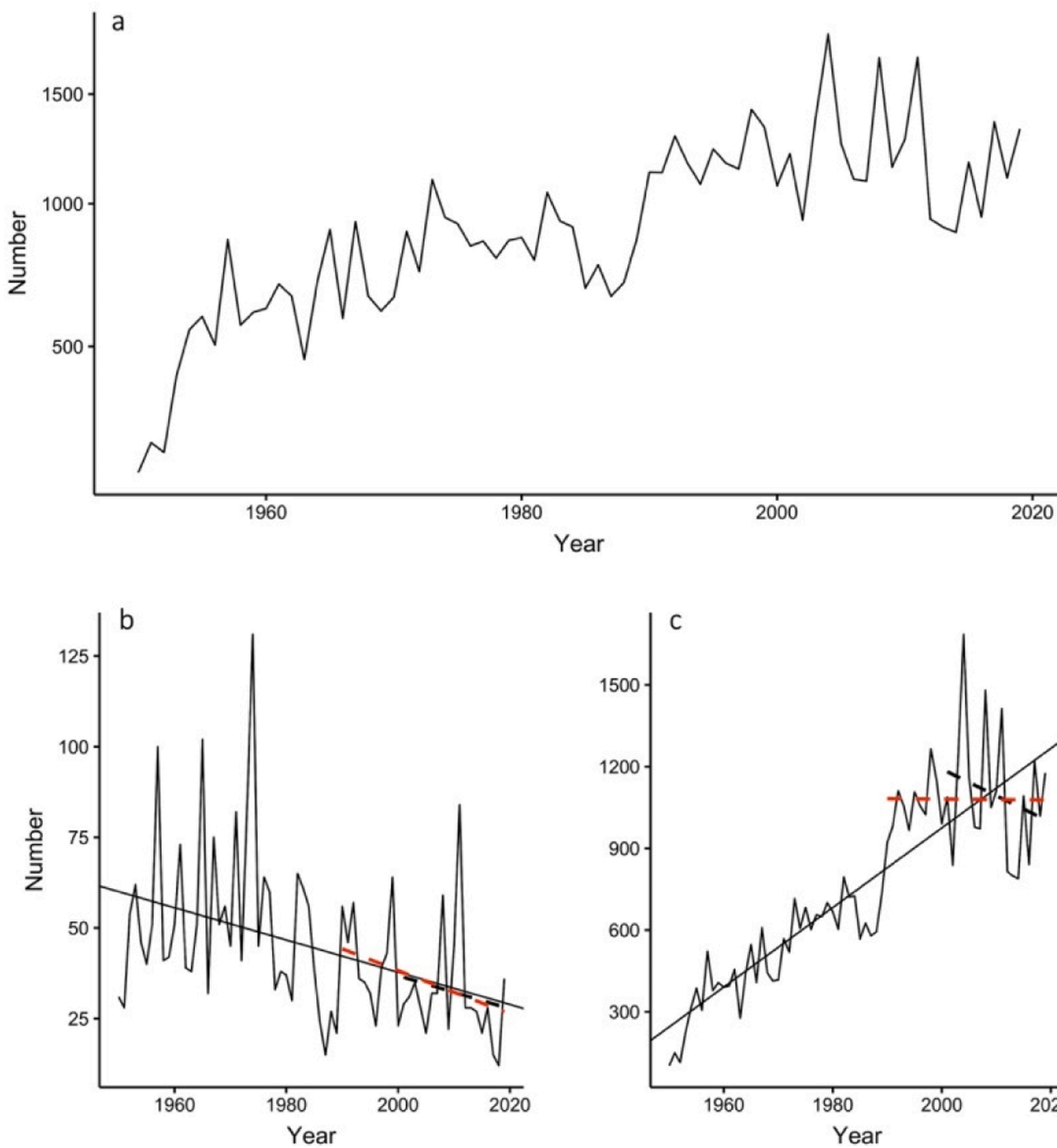

Fig. 2. (a) Tornado trends for the United States for 1950–2021. Number of tornadoes by year. Database limitations are reviewed by Gall et al. (2009). Rise is likely dominated by increasing detectability of EF0 events over time. (b) Regressions of high severity storm counts (sum for EF3+EF4+EF5) versus time for the full period (1950–2021) (black line), 1990–2021 (red dashed line), and 2000–2021 (black dashed line). (c) Like 1b, but for low severity tornadoes (EF0+EF1). Regression estimates presented in text.

Wisconsin), North (Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, West Virginia), Pacific (California, Oregon, and Washington), Southeast (Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Virginia), and Southwest (Arizona and New Mexico).

3. Results

3.1. Trends in tornado frequency and data limitations

Total tornado counts (Fig. 2a) appeared to show a strong upward trend. However, most of this was likely due to the increasing detectability of EF0 and EF1 tornadoes over time. For stronger tornadoes (EF3 + EF4 + EF5), there was a clear downward trend in the number per year (-0.51/y, $p < 0.01$) over the 70-year record (Table 1; Fig. 2b). However, the high variability led to only modest degree of fit (adj $R^2 = 0.16$). We can safely assume that strong storms were equally detectable over the entire period and certainly not less detectable in the satellite era. Since 1990 or 2000, the best fit trend lines were visually concordant with the 1950–2019 trend line, but were not statistically significant (i.e., slope was not different from zero) due to noise ($p = 0.13$ and $p = 0.60$, respectively) (Table 1). However, the slopes for all, post-1989, and post-1999 (-0.44, -0.57, -0.36), each had confidence intervals (CI) that encompassed the other two slopes. This suggests a constant rate of decline over the entire period. In contrast, the EF0 + EF1 storms had a strong positive trend over the full period (+14.2/y, $p < 0.001$) (Table 1; Fig. 2c). After the beginning of adequate satellite and radar coverage, the trend switched to a modest decline (-0.98/y and -8.2/y for post-1989 and post-1999 periods, both $p > 0.10$). There was no overlap in CI ranges for all and post-1989 slopes (Table 1), suggesting a significant change in the pattern. The all vs. post-1999 slopes barely overlapped but this was strongly influenced by post-1999 variability and a short record. The observed divergent trends – increasing counts of weaker tornadoes (EF0–1) and decreasing counts of stronger tornadoes (EF3–5) – can be reconciled through a historical detection bias framework. It is plausible that initial technological limitations led to a systematic undercount of lower-intensity tornadoes, a shortcoming progressively ameliorated with the advent of advanced satellite and Doppler radar systems. Upon reaching this technological milestone, the data can be regarded as approaching a state of minimal detection bias, thereby allowing for a more accurate interpretation of meteorological trends. It is difficult to imagine a meteorological change that could otherwise produce these contrasting trends with storm size.

3.2. Trends in tornado area

The U.S. experienced an estimated 64,367 km^2 of tornado damage during 1995–2021. Over this same period, total area damaged by tornadoes increased ($\tau = 0.49$; $p < 0.001$) (Table 2; Fig. 3a). These data indicated two distinct groupings from 1995 to 2007 and 2008–2021, which had average annual summed damage of 1378 km^2 and 3318 km^2, respectively. The second half of the tornado record had 2.4 times more tornado damage than the first half of the record. Increases were primarily concentrated in the southeastern U.S. ($\tau = 0.62$; $p < 0.001$), where 43,870 km^2 were damaged over the last three decades with an increase of approximately 60.5 km^2/year (Fig. 4a). This region experienced uncharacteristically high damage in 2011 (damage > 7900 km^2) [also see Simmons and Sutter (2012)]. However, similar trends were observed even with the removal of this year. The northeastern U.S. had a slight increase in damage area of 1.68 km^2/year ($\tau = 0.27$; $p = 0.05$), but this was still < 30 times than the Southeast region. In contrast, other regions experienced relatively constant levels of tornado damage (Fig. 4a).

Approximately 22,328 km^2 of forest area (35 % of total damage area) was damaged during 1995–2021 for the CONUS. Annual forest damage was 357 km^2 during 1995–2007 and 1264 km^2 during 2008–2021 (Fig. 3b). The Theil-Sen test estimated an increase of around 32.3 km^2/year (Table 2). Regional trends in forest area damaged were only detected in the southeastern U.S. ($\tau = 0.58$; $p < 0.001$), and this region had an increase of 32.9 km^2/year in damage (Table 2; Fig. 4b). Forest area damage in other regions remained relatively stable over time (Table 2; Fig. 4b).

Slight trends were observed when assessing relative forest area damage ($\tau = 0.36$; $p = 0.01$), but this trend was not identified at the regional scale (Table 2). This indicates that the increases in forest area damage were comparatively proportional to the increases observed in total area damaged, meaning total and forest area damage changed by approximately the same ratio over the three decades analyzed (Fig. 3c). However, the relative area estimates (Fig. 3c) appeared to show two distinct periods. For 1995–2007, relative damage area had a mean

Table 1
Linear regression trends over three different intervals for the frequency of weak (EF0 and EF1) and strong (EF3 to EF5) tornadoes in the United States. Three intervals were selected due to varying levels of detectability pre- and post-remote sensing.

F-Scale	Time interval	Slope	95 % CI	P-value
EF0 + EF1	1950–2019	14.6	12.5, 16.7	<0.001
	1990–2019	−0.15	−9.0, 8.7	0.97
	2000–2019	−6.9	−26.6, 12.8	0.47
EF3 + EF4 + EF5	1950–2019	−0.44	−0.685, −0.205	<0.001
	1990–2019	−0.60	−1.25, 0.05	0.07
	2000–2019	−0.26	−1.59, 1.07	0.69

Table 2
Mann-Kendall and Theil-Sen Slope estimator results to assess trends in tornado damage area (km^2) in the contiguous United States over three decades (1995–2021).

Region	Mann-Kendall Tau (τ)	Theil-Sen slope estimator	95 % CI	P-value
Total damage area				
Midwest	0.111	6.32	−9.29, 24.4	0.428
Mountain	0.083	0.320	−0.543, 1.24	0.559
Northeast	0.271	1.64	−0.063, 3.03	0.050
Pacific	0.046	0.017	−0.059, 0.112	0.758
Southeast	0.618	60.5	32.7, 114	<0.001
Southwest	0.134	0.025	−0.040, 0.171	0.338
All	0.487	84.1	39.4, 137	<0.001
Forest damage area				
Midwest	0.202	1.99	−0.565, 5.56	0.145
Mountain	0.057	0.001	−0.015, 0.046	0.692
Northeast	0.191	0.626	−0.258, 1.23	0.169
Pacific	0.147	0	0, 0.003	0.321
Southeast	0.579	32.9	15.9, 53.3	<0.001
Southwest	0.238	0.001	0, 0.005	0.097
All	0.578	32.3	17.6, 60.4	<0.001
Relative forest damage area				
Midwest	0.179	0.002	−0.001, 0.005	0.196
Mountain	0.063	0	−0.001, 0.002	0.662
Northeast	−0.002	−0.117	−0.008, 0.005	0.404
Pacific	0.153	0	0, 0.001	0.300
Southeast	0.225	0.004	−0.001, 0.008	0.104
Southwest	0.220	0	0, 0.002	0.126
All	0.356	0.006	0.002, 0.009	0.010

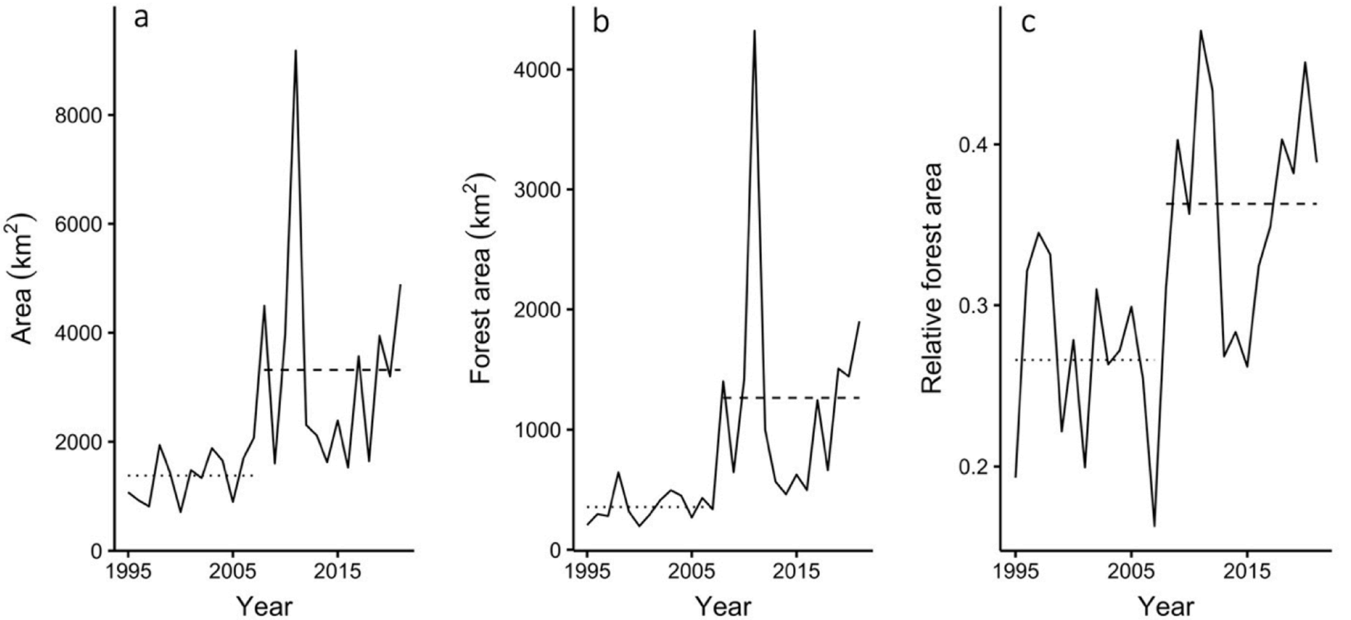

Fig. 3. Trends in forest area damaged by tornadoes in the contiguous United States from 1995 to 2021. The start date of 1995 was chosen because this was when maximum storm path width was introduced, replacing mean width. All area metrics indicated two distinct periods: 1995–2007 (dotted line) and 2008–2021 (dashed line). Means of the two periods in all three figures are significantly ($p < 0.01$) different by Mann-Whitney, T and Z tests. (a) Total area (km^2) was calculated as the summation of area (length x width) for all tornadoes each year. The period 1995–2007 had an average summed width of 1377.6 km^2 and 2008–2021 was 3318.4 km^2, 2.4 times as great. (b) Forest area (km^2) was calculated as the area of damage in forests as identified by the National Land Cover Database (NLCD). The first period had an average summed width of 356.6 km^2, while the second was 1263.7 km^2. (c) Relative forest area damaged is the area of forest damage divided by the total area of damage. The first part of the period had an average relative forest area damage of 26.6 %, and 36.3 % in the second period, a 36 % increase in the percent forested.

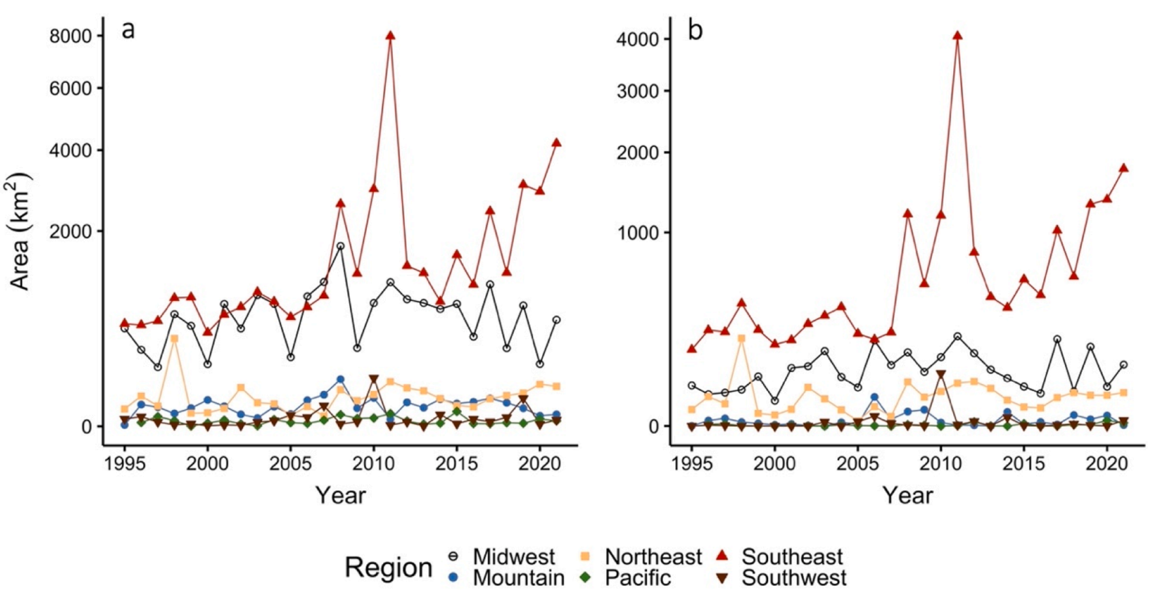

Fig. 4. Regional trends in total (a) and forest (b) tornado damage area (km^2) in the contiguous United States over three decades (1995–2021). Area of damage is the sum of length times width for all storms. The start date of 1995 was chosen because this was when maximum storm path width was introduced, replacing mean width. A square root transformation was applied to the y-axis to allow for differentiation between the Mountain, Northeast, Pacific, and Southwest regions.

difference of 26.6 % per year for 1995–2007 and 36.3 % for 2008–2019 (difference significant $p < 0.01$). This suggests an increase that may not have been identified in these analyses, perhaps due to the response between the periods being so nonlinear. A 36 % increase in the percent of damage area that is forested is a major discontinuity. This increase is likely due to a shift toward more forested regions, namely the southeastern U.S.

4. Discussion

Our results indicate that the frequency of tornadoes in the U.S. has remained relatively stable for low severity storms and has likely decreased for high severity storms in recent decades, despite growing concern surrounding effect of climate change on the frequency and intensity of tornadoes globally (Chernokulsky et al., 2022; Etkin, 1995; Silva Dias, 2011). Considering climate change, these 70-year results imply that warming has had nominal, if not decreasing, effects on the counts of strong tornadoes. This discrepancy invites a more nuanced consideration of regional climatic conditions, such as variations in wind shear (i.e., variation or change in wind speed and/or direction over a short geographic distance), which are integral to tornado genesis but may be impacted differently by climate change than previously understood (Trapp et al., 2009). Because wind shear is projected to decrease (Trapp et al., 2009) and tornadoes occur when air masses of very contrasting temperature meet (Diffenbaugh et al., 2008), the decrease in tornado frequency found in our study is plausible. Additionally, documented regional and/or national increases in tornadic activity and occurrence variability (Brooks et al., 2014) could be due to potential data limitations such as reduced detectability of low severity tornadoes (Boruff et al., 2003). Therefore, we recommend that future work on tornado modeling efforts investigate potential solutions, such as limiting data use to post-1990 or accounting for the potential biases in the early part of the record for low severity storms through simulation or the elimination of low severity storms from analyses (Elsner et al., 2015; Verbout et al., 2006).

While no evidence was found indicating an increasing frequency of tornadoes, the up bias in all estimates due to the use of maximum path width was constant over the period examined. This uniformity in bias allows for the reliable analysis of trends over time, despite the presence of the bias itself. Hence, there seems to have been a large increase in damage area over the last three decades, particularly in the Southeast. This is, in part, in line with prior findings that this region had the highest risk for tornadic activity and increased high-frequency tornadic days (i.e., confirmed multiple tornadoes on the same day) (Coleman and Dixon, 2014; Moore, 2017). Elsner et al. (2019) also found that tornado power increased from 1994 to 2016, which was calculated through a composite function that incorporated tornado area (length x width), air density, midpoint windspeed, and EF ratings. It stands to reason that this increase in tornado power would parallel our observation of an increase in the overall area of tornado-affected landscapes, thereby underscoring the potential severity and broad-ranging ecological and socio-economic implications of this phenomenon. These findings may also be indicative of the southeastern shift documented in prior work (Moore, 2018; Moore and DeBoer, 2019). For instance, Gensini and Brooks (2018) observed that the spatial distribution of tornadoes in the U.S. has shifted with fewer storms in the traditional "tornado alley" but an increase in the Upper Midwest and Southeast regions. While we did not observe an increase in the Midwest, this could have been due to the scale used in our analyses (i.e., partitioning the Midwest into a smaller subregion vs assessing the region as a whole). Similarly, Moore (2018) reported increased tornadic activity in the southeastern U.S. since 1960, but also noted changes in seasonality with a decrease during summer and an increase during fall. While this geographic shift of tornadoes toward the Southeast took place and is reflected in our data, damage area has also increased, suggesting a regime change in tornado climatology. The interplay of multiple meteorological factors (e.g., ENSO) is complex (Diffenbaugh et al., 2008; Nouri et al., 2021), and thus an explanation for increased damage, should this trend continue, remains to be determined.

This regime shift has brought more tornadoes into timber-producing states such as Alabama and Mississippi, increasing recovery costs for commercial forestry. The southeastern U.S. has been termed the “wood basket” of the nation, due to its extensive forests and focus on timber production (> 200 million acres of forest land) (Oswalt et al., 2019). For example, the 2021 USDA Forest Service, Forest Inventory Analysis (FIA) for Alabama, a state that has seen increased tornadic activity, estimates that this state is 69 % forested (>9 million hectares of forest land) (USDA, 2022). This far exceeds the forest area for states in historical tornado-prone areas, such as Oklahoma (26 % forested), Kansas (5 % forested), and Nebraska (3 % forested). Our findings relative to FIA estimates on area of southeastern forest land suggest an uptick in commercial timber damage in recent decades.

Parallel to these economic concerns is the necessity to improve our tornado damage assessment systems. Currently, the EF system is the standard for rating the intensity of tornadoes (Fujita, 1971; McDonald et al., 2010), but other scales have also been described [e.g., Tornado and Storm Research Organization (TORRO) scale; described by Kirk (2014)]. EF-scale ratings are described in terms of damage and rely primarily on damage to human structures, but vegetation damage is used when those metrics are absent (Peterson, 2003). There are potential issues with this rating system (Blanchard, 2013), such as subjectivity of the F-scale rating criteria and complexity of forest dynamics that contribute to damage risk (Diffenbaugh et al., 2008; Peterson, 2003). As such, it will be important to refine the EF system, especially given our results that point to a trend of rising forest area damage in the southeastern U.S., a region whose dense forests challenge the efficacy of the existing rating system.

5. Conclusions

Changes in forest disturbance regimes such as the ones we report on tornadic activity can have negative effects on the environment and society through alterations forest ecosystem services due to reductions in live tree biomass and carbon shifts from living to dead pools (Amiro et al., 2010; Thom and Seidl, 2016). Our findings contribute to a growing body of evidence of changes in tornado dynamics, highlighting the need for forest management strategies that are specifically designed to enhance resistance and resilience to tornado disturbances, particularly in the southeastern U.S. where forest area damage has increased. As this study reveals a noticeable increase in tornado-related forest damage and possibly to commercial timber, targeted interventions such as optimizing forest stand structure and composition, can play a crucial role in mitigating both ecological and economic effects. Understanding the complexities of how tornadoes influence forest ecosystems in this region becomes indispensable for developing adaptive management plans that safeguard both the ecological integrity and economic viability of these forests, particularly in an era of changing climate and disturbance regimes.

Our assessment also opens avenues for a more granular analysis that could factor in damage severity with respect to forest characteristics and improve the current EF rating system. Susceptibility of forests to tornado damage is not uniform due to site-dependent characteristics (e.g., slope, valley depth, soil characteristics, species composition and age) (Fortuin et al., 2022; Gardiner, 2021). Currently, comprehensive data encapsulating these factors at a resolution congruent with tornado paths are lacking, and addressing this gap would require a concerted effort to compile or model high-resolution forest attribute data that can be spatially and temporally matched with tornado tracks. Such detailed analysis could yield insights into the nuanced interactions between tornadoes and forests, informing management practices tailored to the resilience and recovery of these ecosystems post-disturbance.

6. Data statement

Tornado records used to assess trends in frequency and damage area were obtained from the National Weather Service (NWS) (https://www.spc.noaa.gov/wcm/#data) This dataset is maintained by the U.S. Storm Prediction Center (SPC) and provides the location, fatalities, Enhanced Fujita Scale (EF0–5) or Fujita Scale (F0-F5), length, and width of tornadoes in the U.S. from 1950 to 2021. The National Land Cover Database (NLCD) used to identify forested land is Landsat-based geospatial dataset that provides information about land cover for CONUS (Dewitz, 2021; Homer et al., 2012). The NLCD was developed from composite Landsat satellite imagery paired with ancillary information to classify land cover. This database was expanded to include additional classes that better captured transitional forest ecosystems (i.e., Herbaceous-Forest, Shrub-Forest, and Young-Forest) in their research product. The NLCD is available at https://doi.org/10.5066/P9JZ7AO3.

CRediT authorship contribution statement

Holly L. Munro: Conceptualization, Methodology, Formal analysis, Resources, Writing – original draft, Visualization, Project administration. **Craig Loehle:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Visualization. **Bronson P. Bullock:** Conceptualization, Writing – review & editing, Project administration, Funding acquisition. **Dan M. Johnson:** Conceptualization, Writing – review & editing, Funding acquisition. **James T. Vogt:** Conceptualization, Writing – review & editing, Funding acquisition. **Kamal J.K. Gandhi:** Conceptualization, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data are publicly available and access is detailed in the data availability statement in the paper.

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