Increasingly powerful tornadoes in the United States

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ABSTRACT

Storm reports over the past few decades show a clear trend toward more powerful tornadoes from longer and wider paths and higher damage ratings. Quantifying the magnitude of this increase is important for understanding its possible connection to climate change but doing so is difficult given strong diurnal and seasonal influences on tornado activity embedded within large natural variations. The problem is made worse by changes in procedures for rating storm damage. Here we solve this problem by fitting a statistical model to a metric of power using all tornado reports since 1994. We find a substantial increase of 5.5% [(4.6, 6.5%), 95% CI] per year in power controlling for the diurnal cycle, seasonality, natural climate variability, and the switch to a new damage scale. Further we find that a portion of the trend is statistically attributable to rising ocean temperatures across the Gulf of Mexico and western Caribbean Sea. Results support the hypothesis that with added instability from more heat and moisture in a warming world tornadoes are becoming more powerful qualitatively consistent with climate models showing increasingly favorable conditions for stronger tornadoes with higher concentrations of greenhouse gases.

Introduction

Tornadoes are nature's most violent storms with winds that can exceed 120 m s^{-1}. A mobile Doppler radar estimated a near-ground-level wind speed of 135 m s^{-1} in the Bridge Creek/Moore/Oklahoma City, Oklahoma tornado of May 3, 1999. How global warming will affect tornadoes remains an open question. It has been argued that with low data adequacy and low to medium physical understanding of the processes that cause tornadoes it is difficult to find significant trends related to climate change[1]. However these arguments are based on studies that are at least five years old, focus exclusively on tornado occurrences, and use methods that lack ways to include intervening factors at multiple levels. Here instead we focus on tornado power and use a hierarchical statistical model that controls for the known behavior of tornado activity.

We start by noting that while the annual number of strong and violent tornadoes (EF2 or worse) has remained relatively consistent from year to year, the number of days with many tornadoes is on the rise[2–4]. An increase in the number of big tornado days implies a larger threat of damaging tornadoes[5] with the percentage of violent tornadoes (EF4 or worse) increasing with increasing outbreak size. Less than 4% of tornadoes occurring on days with between 16 and 31 tornadoes are rated EF3 or higher while more than 8% of tornadoes occurring on days with more than 63 tornadoes are rated similarly (Table 1). Increases occur for the percentage of violent (EF4 and EF5) tornadoes as well. This leads us to hypothesize that tornadoes have become more powerful.

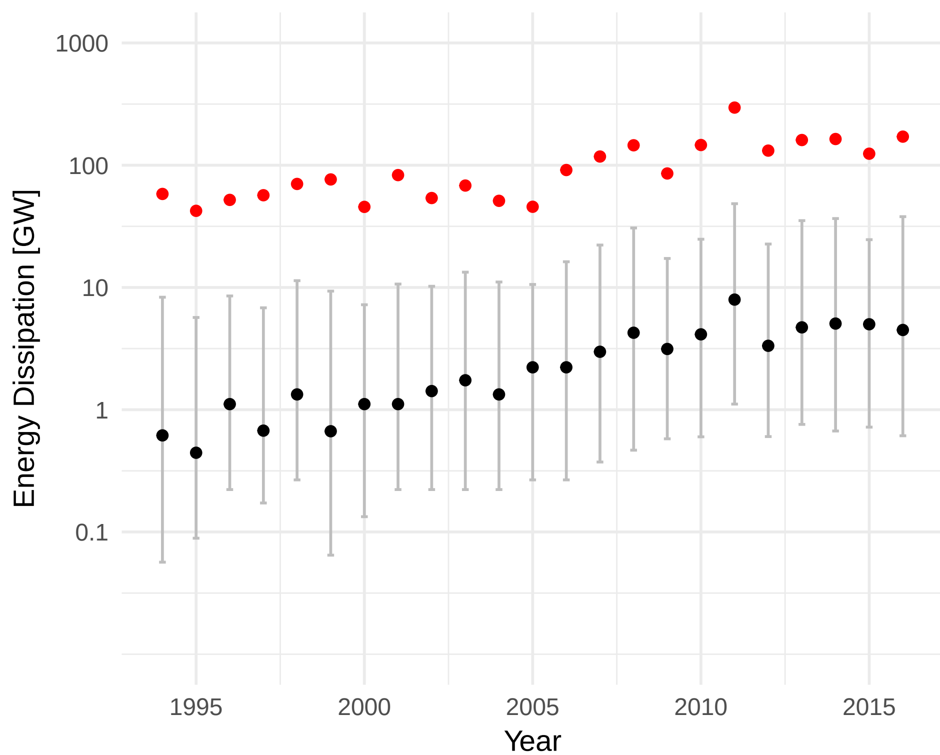
Table 1. Tornadoes by outbreak-day size. Numbers are based on all tornado reports over the period 1994–2016. Data are from the Storm Prediction Center.

Outbreak Day Size (No. Tor.)	Number of Cases	Total Number of Tor.	% Tor. Rated Intense (EF3+)	% Tor. Rated Violent (EF4+)
1	1088	1088	0.37	0.00
2-3	1068	2581	0.39	0.00
4-7	874	4521	0.82	0.09
8-15	644	6921	1.99	0.38
16-31	295	6466	3.34	0.57
32-63	103	4355	5.49	1.08
>63	25	2018	8.18	2.23

Results

Tornado power is metered by the energy dissipated near the ground[6]. On average the longest lasting tornadoes generate the most extreme wind speeds[7–9]. And indeed damage paths are getting longer and wider (see Supplemental Fig. S1). Multiplying path area, air density, and wind speed gives an estimate of the total energy dissipated by a tornado[6] (See §Methods). For the set of 27,950 tornadoes during the period 1994–2016, the median energy dissipation is 2.22 gigawatts (GW) with an inter-quartile range between .27 and 17.0 GW. Tornado power is highly correlated with the destructive potential index[9] and the number of casualties when people are present[6]. The Tallulah-Yazoo City-Durant tornado (Louisiana and Mississippi) of 24 April 2010 that killed ten and injured 146 had an estimated power of 66,200 GW. Annual statistics of tornado power show clear upward trends with the median, quartiles, and 90th percentile all on the rise since 1994 (Fig. 1).

Figure 1. Annual energy dissipation by year. The black dot is the median and the red dot is the 90th percentile value each year. The vertical bar extends from the lower to upper quartile numbers.

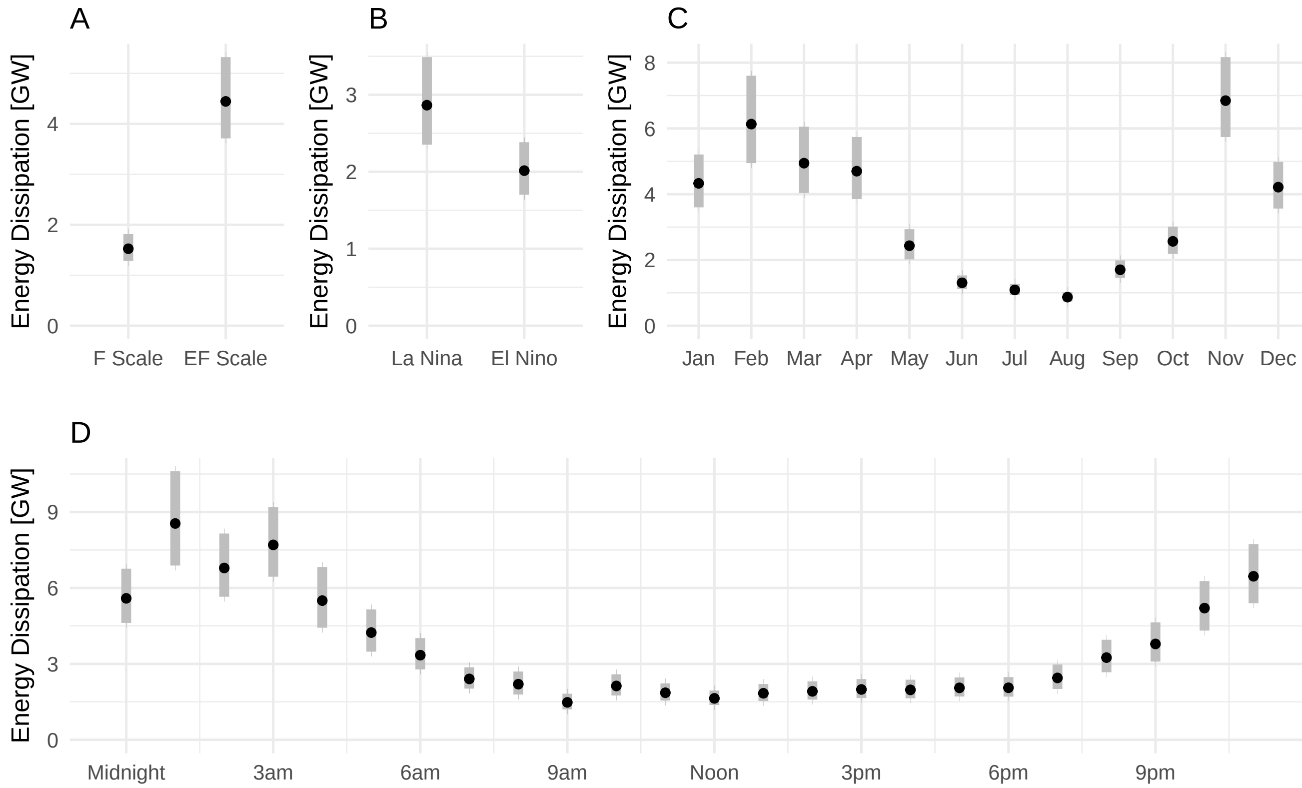


The observed increase in power might be the result of shifts in when and where tornadoes occur[10]. Also, at least a portion of the rise is very likely due to a change in the procedures to rate the damage left behind. The EF damage rating scale was revised from the original F scale (and put into operational use in 2007) with better standards for determining what was previously subjective including additional structures and vegetation, expanded degrees of damage, and a better accounting of variables such as construction quality. Figure 2 shows tornado power grouped by the change in the EF rating scale, El Niño/La Niña, month of occurrence (genesis), and by time of day (in hours). Mean energy dissipation is relatively higher at night, during La Niña, in the cooler months, and after the implementation of the EF rating procedure.

To test the hypothesis of an upward trend, after accounting for these known influences, we fit a hierarchical regression model to the per-tornado power using all available tornado reports over the period 1994–2016. The model has a log-normal distribution for the likelihood on the per-tornado power where a lower bound is set at 444 kW; a value just below the least powerful tornado in the record. Fixed effects in the model include the bivariate index for ENSO and an indicator variable to mark the year when the switch to the new damage rating procedures were put in place (2007). Random effects include month and hour to capture the cyclic change in energy at these respective time scales. A term indexing the year of occurrence is included as a fixed effect to test our hypothesis and to quantify the residual trend per annum (see §Methods Summary).

As expected the model shows the cycle of alternating ocean-atmosphere conditions in the equatorial Pacific, known as ENSO, is an important and significant influence on tornado power with a regression coefficient expressed as a multiplicative decrease of .93 [(.90, .96), 95% CI] for every one standard deviation increase (going from La Niña to El Niño) in the bivariate

Figure 2. Energy dissipation grouped by EF change, ENSO, month, and hour. The dot is the geometric mean for each subgroup and the gray bars extend one standard deviation from the mean.



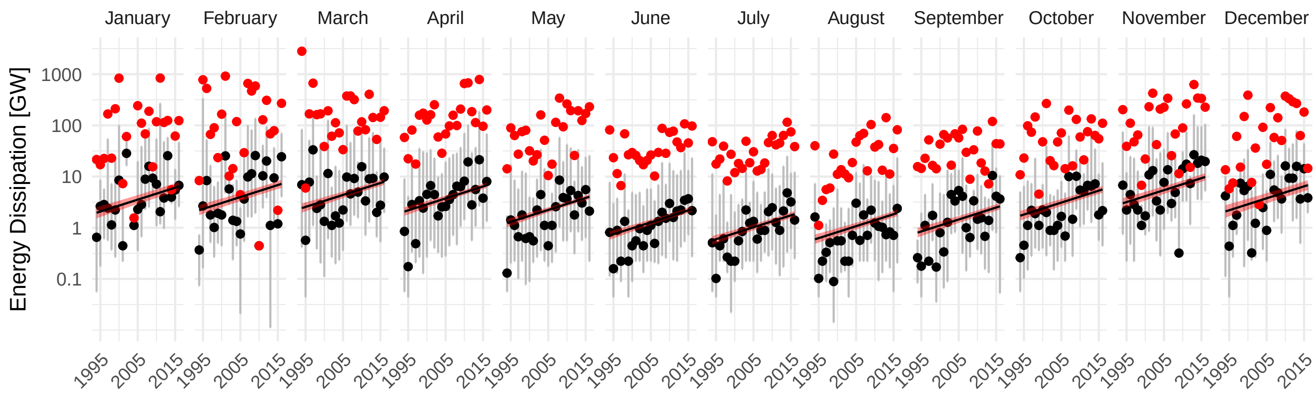
ENSO index (exponentiating the coefficient in Table 2). This is consistent with the fact that under La Niña conditions (especially during winter) amplified upper-air troughs move across North America with warmer than normal temperatures in the Southeast and cooler than normal temperatures in the Northwest, which sets the stage for severe weather outbreaks that are intensified by a strong jetstream[11–13]. The model also shows that the procedures put in place following the adoption of the EF damage rating scale results in an increase in power by a factor of 1.41 [(1.24, 1.59), 95% CI]. This increase is expected given the improvements in damage surveys including more precise and inclusive damage indicators.

Table 2. Fixed effects. Estimated coefficients on the fixed effects terms in the model. The Error is one standard deviation. The lower and upper 95% credible intervals are given.

	Estimate	Error	l-95% CI	u-95% CI
α	21.298	0.023	21.253	21.344
β_{Year}	−0.068	0.016	−0.101	−0.036
$\beta_{\text{EF?}}$	0.341	0.063	0.217	0.462
β Year	0.054	0.005	0.045	0.063

Most importantly for this study the model shows a significant upward trend in tornado power at a rate of 5.5% [(4.6, 6.5%), 95% CI] per year. The magnitude of the increase depends on the data and the model that controls for diurnal and seasonal variability, the ENSO cycle, and implementation of the EF rating scale. The model quantifies the increasing ferocity of tornadoes independent of the other factors considered and lends support to our hypothesis that as outbreaks are becoming larger tornadoes are becoming more powerful. The base rate from which the upward trend is estimated depends on the time of the year through the random-effect term, but the modeled monthly trends appear to track the data well (Fig. 3).

Figure 3. Upward trends in tornado power by month. The black dot is the median and the red dot is the 90th percentile value each year. The vertical bar extends from the lower to upper quartile numbers. The black line is the modeled trend with a 95% CI band shown in red shading.



Discussion

The study is retrospective but our hierarchical model can help better understand what is likely happening as the earth warms. Convective available potential energy (CAPE) and wind shear are the two environmental factors needed for tornadoes. Climate models show CAPE should increase with warming[14,15] because of the extra water vapor a warmer atmosphere can hold but wind shear should decrease due to the slowing of the polar jet associated with a weaker temperature gradient between the Arctic and lower latitudes[16]. The upward trend in tornado power we find here suggests that increasing CAPE is winning the battle between the these two competing environmental controls; a conclusion that coincides with climate modeling studies examining the occurrence of severe convection in a future warmer world[14,17–21].

If increasing CAPE is responsible for some of the upward trend over the past few decades then the hierarchical model should be improved by adding monthly SST averaged across the Gulf of Mexico and adjacent waters of the western Caribbean (the source region for the heat and moisture) as a fixed effect. Indeed, we find the SST effect (using numbers averaged monthly over the region bounded by 10 and 35° N, and -97 and -70° E) is positive as anticipated and statistically important. The improved model estimates that tornado power increases by a factor of 1.35 [(1.23, 1.47), 95% CI] for every one degree increase in average SST. Importantly, the SST effect reduces the upward trend by 16% lending credence to the idea that warming seas over this region are causally linked to more powerful tornadoes likely through a pathway that involves more heat and moisture consistent with recent pseudo global warming experiments showing stronger convective updrafts and enhanced vertical rotation with higher CAPE[22].

Further, if increasing CAPE is more than offsetting decreasing shear, the upward trend should be most pronounced during winter when the jet stream is strongest. That is, during winter the limiting environmental factor for severe thunderstorms is CAPE rather than shear since shear is always (nearly) present during winter. To test this hypothesis we add a random slope term to the model and find that the largest trends are found between November through April with the largest trend of 8.5% per annum occurring with December tornadoes. This understanding is consistent with results from a suite of climate models that show decreases in shear tend to be concentrated on days with low CAPE and therefore do not lessen the chance that environments will be conducive to strong tornadoes[15].

More definitive answers will need to wait for a better theoretical understanding of tornado processes and how they are linked to climate variability. But the large number tornadoes that occur each year provides a generous sample of events allowing us to separate signal from noise with hierarchical models. And, as demonstrated here, these models help us begin addressing these important questions.

Methods

Energy dissipation (power)

Energy dissipation (power) for each tornado is computed as:

$$E = A_p \rho \sum_{j=0}^{5} w_j v_j^3,$$

where the summation is over the six possible EF ratings (0, 1, 2, 3, 4 and 5), A_p is the area of the tornado's path [units of square meters], ρ is air density [1 kg m^{-3}], v_j is the midpoint wind speed [m s^{-1}] for each damage rating (EF scale) j, w_j is the corresponding fraction of path area by damage rating, and J is the maximum damage rating. Path area is the product of path width and path length. Path length is known to a relatively high degree of accuracy[23]. Multiplying the units from the individual terms results in E being measured in a unit of power [kg m^2 s^{-3} = Joule/s = Watt (W)]. Path length and width and maximum EF rating are listed in the Storm Prediction Center's tornado database. The database is compiled from the National Weather Service's (NWS) *Storm Data*, and includes all known tornadoes dating back to 1950. Here we focus on the available period of this record since 1994. The fraction of path area is that recommended by the U.S. Nuclear Regulatory Commission[9]], which combines a Rankine vortex with empirical estimates derived from detailed storm surveys[24]. Threshold wind speeds for the EF ratings are a three second gust. With no upper bound on the EF5 wind speeds, the midpoint wind speed is set at 97 m s^{-1} (7.5 m s^{-1} above the threshold wind speed consistent with the EF4 midpoint speed relative to its threshold). Tornado energy is highly correlated with the destructive potential index[25]. Additional details and justification for energy dissipation as a valid measure of tornado strength are given in[6]. Tornado power by EF rating is given in Table 3.

Table 3. Tornado power by EF rating. Numbers are in gigawatts (GW) and are based on the 27,950 tornadoes over the period 1994–2016.

(E)F Rating	n	Median	Total	Arithmetic Mean	Geometric Mean
0	17182	0.5	73329.6	4.3	0.6
1	7735	12.5	364162.5	47.1	10.8
2	2224	91.4	609230.8	273.9	77.5
3	650	615.7	827474.3	1273.0	495.4
4	145	1631.0	511177.8	3525.4	1427.6
5	14	6458.5	130239.0	9302.8	5622.7

Statistical model

For each tornado a log-normal distribution is assumed for its energy dissipation with a lower bound set to 444 kW. The geometric means of the distributions are logically related to the fixed effects and their coefficients (β's) including year of occurrence, the bivariate ENSO index, and an indicator variable to mark the year when the switch to the new damage rating procedures were put in place. Variations in energy dissipation by month and hour are modeled as smoothed (spline) random effects [s()]. Mathematically the multivariate regression model is expressed as:

$$\mathrm{ln(E|E > 444000)} = \alpha + \beta_{\mathrm{Year}}\mathrm{Year} + \beta_{\mathrm{ENSO}}\mathrm{ENSO} + \beta_{\mathrm{EF?}}\mathrm{EF?} + \mathrm{s(Month)} + \mathrm{s(Hour)}$$

Code and data

Analysis and modeling are performed using the software environment R (`http://www.r-project.org`). The model is fit using Bayesian simulations in the Stan computational framework (`http://mc-stan.org/`) accessed with **brms** package[26]. To improve convergence and guard against over-fitting, we specified mildly informative conservative priors. The code and data to reproduce the results from this are available here (`https://github.com/jelsner/IncreasingTornadoPower`).

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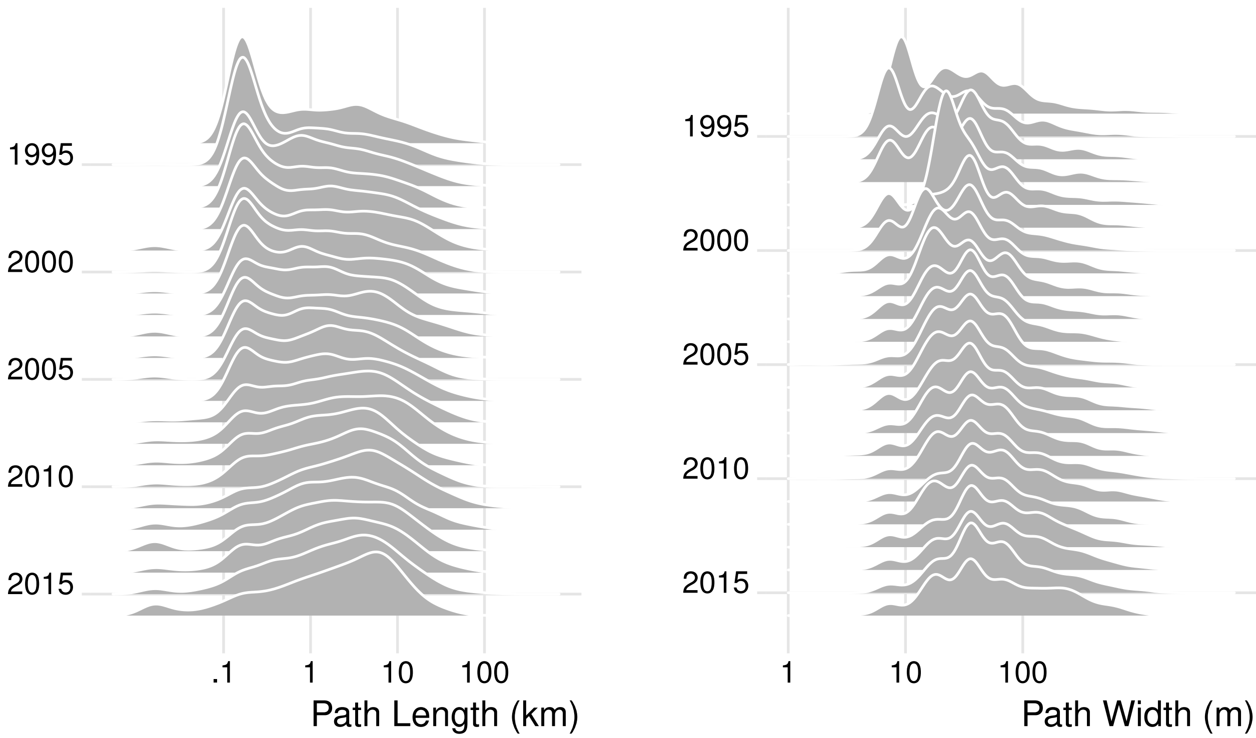
Figure S1. Distributions of path length and path width by year. Path widths narrower than 1 meter are not plotted.



Author contributions statement

J.B.E. and T.F. conceived the idea and designed the study, J.B.E. coded the model and conducted the analysis, J.B.E. and T.F. wrote and reviewed the manuscript.

Additional information

Competing financial interests The authors received no funding for this work and have no competing financial interests.

Supplementary Information