Increasingly powerful tornadoes in the United States

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ABSTRACT

Storm reports over the past decades show a clear trend toward more powerful tornadoes from longer and wider damage paths and higher 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 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 hierarchical 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 the 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 more instability from additional heat and moisture in a warming world tornadoes are becoming more powerful and are 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/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 more than five years old, focus 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 for 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 the hypothesis that tornadoes have become more powerful.

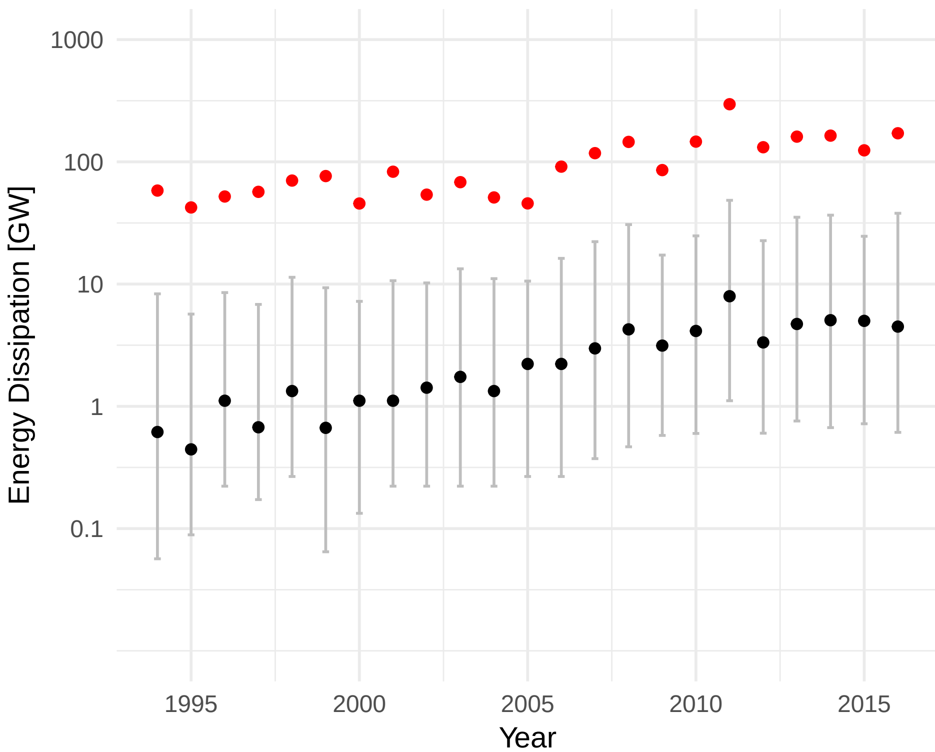
Table 1. Tornadoes by outbreak-day size. Values are based on all tornado reports over the period 1994–2016. Data are from the Storm Prediction Center.

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 total energy dissipated near the ground[6]. On average longer lasting tornadoes generate the most extreme winds[7,8]. The combination of 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 strongly correlated with 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 values.

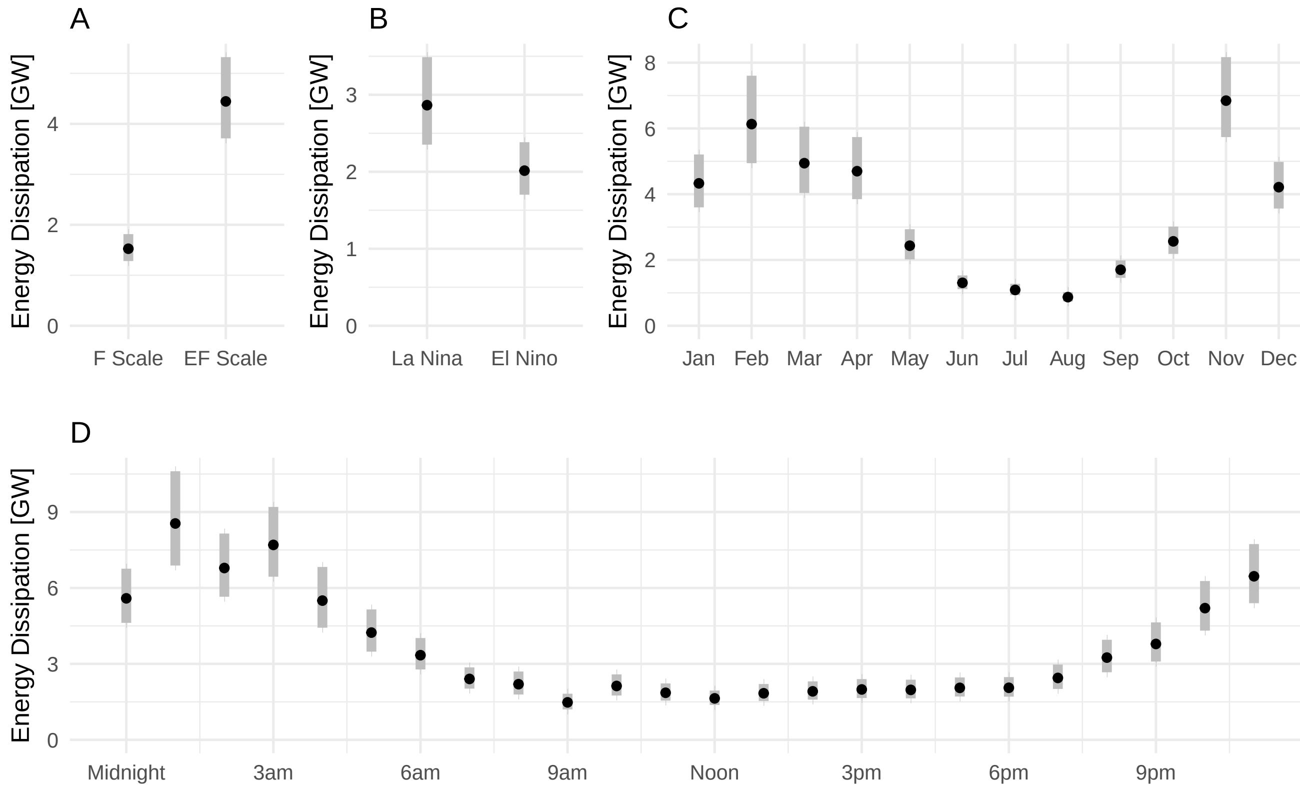


The observed increase in power might be the result of shifts in when and where tornadoes occur[9]. Also, at least a portion of the rise is very likely due to a change in the procedures to rate the damage left behind. The EF damage rating scale was revised from the original F scale (and put into operational use in 2007) with better standards for determining what was previously subjective including additional structures and vegetation, expanded degrees of damage, and better accounting for variables such as construction quality differences. 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 while 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 truncated log-normal distribution for the likelihood on the per-tornado power where the lower bound is set to 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). Smoothed 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 directly test the hypothesis and to quantify the residual trend per annum (see §Methods Summary).

As expected the model shows that the cycle of alternating ocean-atmosphere conditions in the equatorial Pacific has 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 ENSO index (exponentiating the coefficient in Table 2). This is consistent with the fact that under La Niña conditions (especially

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.



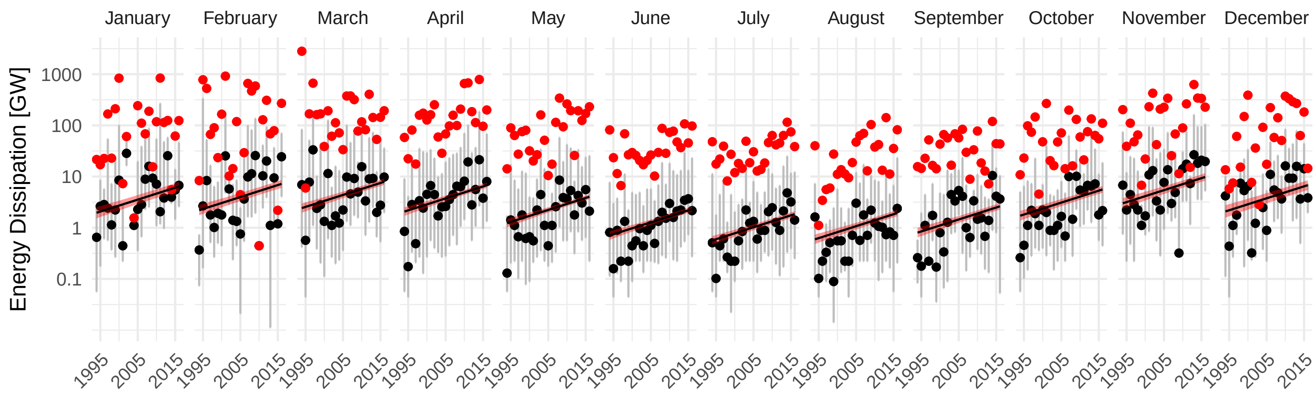
during winter) amplified upper-air troughs cross North America with warmer than normal temperatures in the Southeast and cooler than normal temperatures in the Northwest setting the stage for severe weather outbreaks enhanced by an invigorated jetstream[10–12]. The model also shows that the procedures put in place following the adoption of the EF damage rating scale resulted in an increase in power by a factor of 1.41 [(1.24, 1.59), 95% CI]. This 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
Intercept	21.298	0.023	21.253	21.344
ENSO	−0.068	0.016	−0.101	−0.036
EF Scale	0.341	0.063	0.217	0.462
Year	0.054	0.005	0.045	0.063

Importantly 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. This result quantifies the increasing ferocity of tornadoes independent of the other factors considered and lends credence 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 but the modeled monthly trends 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 values. 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 happening as the climate warms. Convective available potential energy (CAPE) and wind shear are the two environmental factors necessary for tornadoes. Climate models have shown that CAPE should increase with warming[13,14] because of the extra water vapor a warmer atmosphere can hold but that wind shear should decrease due to the slowing of the polar jet associated with a weaker temperature gradient between the Arctic and lower latitudes[15]. The upward trend in tornado power we find here suggests that increasing CAPE is already winning the battle between the these two environmental controls; a conclusion that coincides with climate modeling studies examining the occurrence of severe convection in a future warmer world[13,16–20].

If increasing CAPE is responsible for at least some of the upward trend then the hierarchical model will 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 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 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[21].

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 almost always 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 showing that decreases in shear are concentrated on days with low CAPE and therefore do not decrease the total occurrence of environments conducive to strong tornadoes[14].

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 to 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. Values of path length are known to a relatively high degree of accuracy[22]. 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)]. Values for 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[23]], 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). 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. Values 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 truncated 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:

$$\ln(\mathrm{E}|\mathrm{E} > 444000)_t = \alpha + \beta_1 \mathrm{Year}_t + \beta_2 \mathrm{ENSO}_t + \beta_3 \mathrm{EF?}_t + \mathrm{s(Month)} + \mathrm{s(Hour)} + \varepsilon_t$$

Code and data

All analysis and modeling is 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[25]. 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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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

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