Increasingly powerful tornadoes in the United States

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Key Points:

- Tornadoes in the U.S. appear to be getting more powerful
- The trend is independent of occurrence time and changes to the damage scale
- Part of the trend is linked to increases in convective inhibition and to CAPE conditional on increasing shear.

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Abstract

Storm reports show an upward trend in the power of tornadoes from longer and wider paths and higher damage ratings. Quantifying the magnitude of the increase is difficult given diurnal and seasonal influences on tornadoes embedded within natural variations and made worse by changes for rating damage. Here the authors solve this problem by fitting a statistical model to a metric of power during the period 1994–2016. They find an increase of 5.5% [(4.6, 6.5%), 95% CI] per year in tornado power controlling for the diurnal cycle, seasonality, natural climate variability, and the switch to a new damage scale. A portion of the trend is attributed to long-term changes in convective storm environments involving dynamic and thermodynamic variables and their interactions. Increasing tornado power is occurring in environments where the effect of convective available potential energy is enhanced by increasing vertical wind shear.

1 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 tornado of May 3, 1999. How global warming will affect tornadoes remains an open question. It has been argued that because of data inadequacy and limited physical understanding of the processes that cause tornadoes it is difficult to find trends related to climate change (Kunkel et al., 2013). 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 (e.g., hourly and seasonal). Here we focus on tornado power and use a hierarchical statistical model that controls for the known behavior of tornado activity.

We note 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 (Brooks, Carbin, & Marsh, 2014; Elsner, Elsner, & Jagger, 2015; Tippett, Lepore, & Cohen, 2016; Tippett, Sobel, Camargo, & Allen, 2014). An increase in the number of big tornado days implies a larger threat of damaging tornadoes (Elsner, Jagger, Widen, & Chavas, 2014) 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.

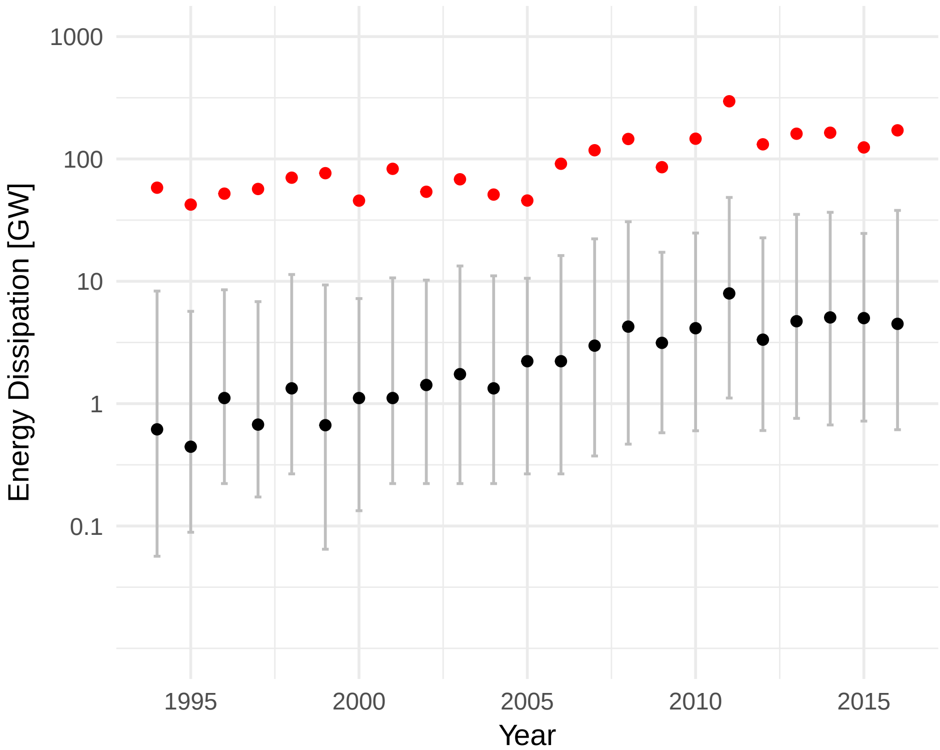
Table 1. Tornado statistics by tornado-day size. Numbers are based on all tornado reports over the period 1994–2016. Data are from the Storm Prediction Center.

Tornado 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

2 Results

Tornado power is metered by the energy dissipated near the ground (Fricker, Elsner, & Jagger, 2017). On average the longest lasting tornadoes generate the most extreme wind speeds (Brooks, 2004; Elsner, Jagger, & Elsner, 2014; Fricker & Elsner, 2015). And indeed damage paths are getting longer (see Appendix Fig. A1). Multiplying path area, air density, and wind speed gives an estimate of the total energy dissipated by a tornado (Fricker et al., 2017) (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 GW. Tornado power is highly correlated ($r > .9$) with the destructive potential index developed at the U.S. Storm Prediction Center (SPC) (Fricker & Elsner, 2015) and with the number of casualties when people are present (Fricker et al., 2017). 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 over the period 1994–2016 (Fig. 1).

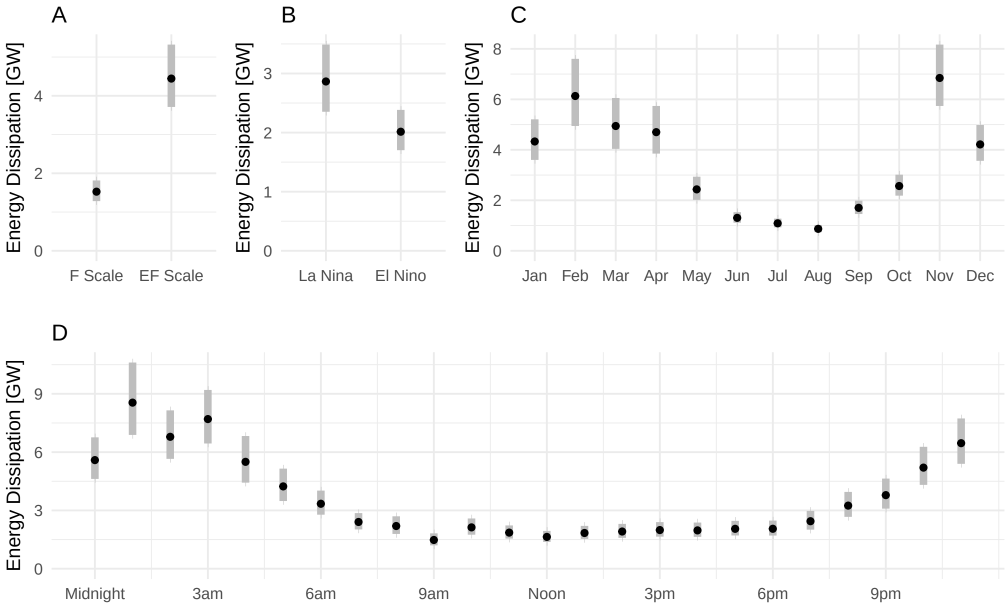
Figure 1. Annual energy dissipation by year. The black dot is the median and the red dot is the 90th percentile value each year. The vertical bar extends from the lower to upper quartile numbers.



The observed increase in power might be the result of shifts in when and where tornadoes occur (Agee, Larson, Childs, & Marmo, 2016). Also, at least a portion of the rise is 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 was 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 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 a 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).

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.



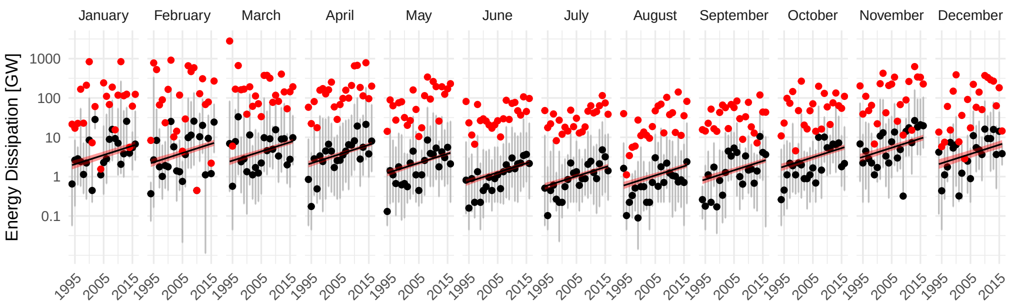
As expected the model shows the cycle of alternating ocean-atmosphere conditions in the equatorial Pacific, known as ENSO, is an important and significant influence on tornado power with a regression coefficient expressed as a multiplicative decrease of .93 [(.90, .96), 95% CI] for every one standard deviation increase (going from La Niña to El Niño) in the bivariate 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 (Allen, Tippett, & Sobel, 2015; Cook, Leslie, Parsons, & Schaefer, 2017; Cook & Schaefer, 2008). 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 after adoption 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_{ENSO}	−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 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 tornado-days become larger the tornadoes themselves are becoming more powerful. The base rate from which the upward trend depends on the time of the year through the random-effect term, but the 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.



3 Discussion

The study is retrospective but our hierarchical modeling strategy can help uncover clues about what might be happening as the earth warms. We conjecture that at least a portion of the upward trend in tornado power is related to long-term changes in regional environments associated with severe thunderstorms. Modeling studies project increases in convective available energy (CAPE) with a warmer climate (DelGenio, Yao, & Jonas, 2007; Diffenbaugh, Scherer, & Trapp, 2013; Trapp, Diffenbaugh, & Gluhovsky, 2009), and we previously hypothesized that climate change and increases in CAPE could be leading to more active areas of severe convection on days with tornadoes (Elsner, Jagger, & Elsner, 2014). Increases in CAPE with global warming are documented in both climate models (Sobel & Camargo, 2011) and cloud-system-resolving models (Romps, 2011), and these increases have theoretical support (Seeley & Romps, 2015; Singh & O'Gorman, 2013).

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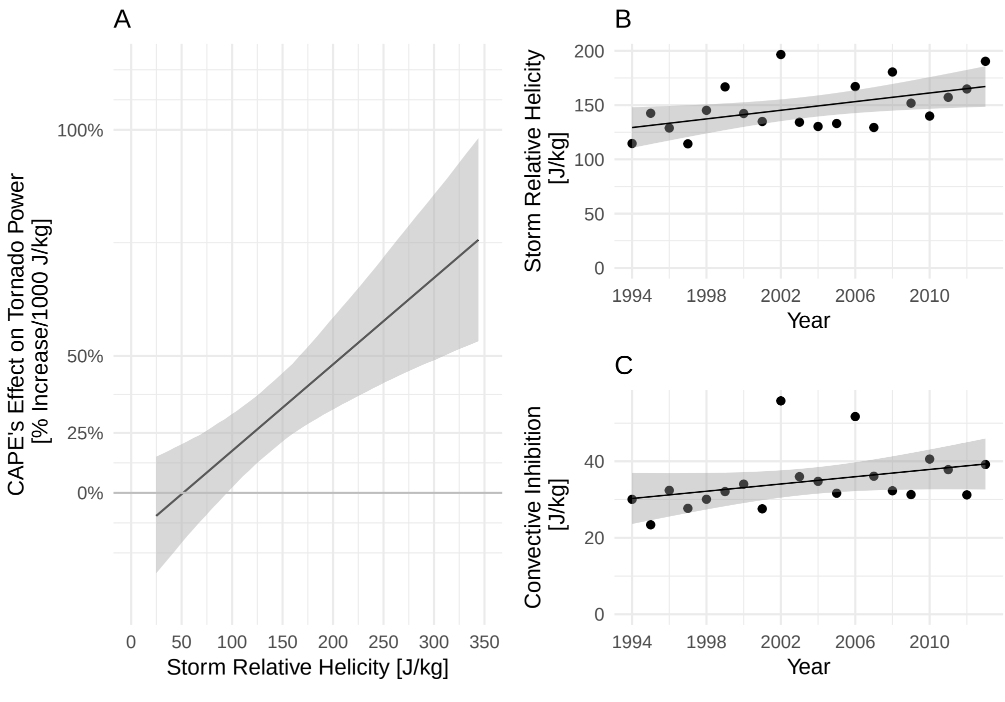
Here we examine how regional environmental factors including CAPE, convective inhibition (CIN), and storm relative helicity (SRH) are related to the trend in tornado power. We use gridded reanalysis data at 1800 UTC on (outbreak) days with at least ten tornadoes (there are 748 such days in the period January 1994 through September 2014). We spatially average values for each of the three environmental variables separately over all grids within the domain defined by the tornado genesis locations for that day. Averages over all outbreak days by year show upward trends in SRH (Tippett et al., 2016) and SRH (Fig. 4[B & C]). We include the environmental variables in models for average tornado power (averaged over all tornadoes in the outbreak and scaled by the area of the domain) and find the best model when CAPE and SRH are used as an interaction term. In other words, the model indicates that CAPE's effect on tornado power is significantly enhanced with increasing SRH (Fig. 4[A]). For example, with average SRH values at 100 J/kg tornado power increases by 18% per 1000 J/kg of CAPE but with average SRH values of 250 J/kg power increases by 55% for the same 1000 J/kg of CAPE. Importantly the magnitude of the trend in a model that includes the environmental variables is 24% lower compared with the magnitude of the trend in a model that excludes the variables. Thus we conclude that increasing tornado power is occurring in environments with increasing CIN and in environments where the effect of CAPE is being enhanced by increasing SRH.

Figure 4. Upward trends in storm relative helicity (SRH), convective inhibition (CIN), and the conditional effect of convective available potential energy (CAPE). The sloping black lines denote point estimates of the trends and the gray ribbons indicate the 95% uncertainty bound around the point estimates.



In summary, we identified an upward trend in tornado power after accounting for known factors and then demonstrated that a portion of the trend is statistically related to CAPE conditional on SRH. More definitive answers to important questions concerning climate change and tornadoes will need to wait for a better theoretical understanding of tornado processes. But the large number tornadoes that occur each year provides a generous sample that allows researchers to use hierarchical model to separate potential climate-change signals from noise.

4 Methods

4.1 Energy dissipation (power)

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

$$E = A_p \rho \sum_{j=0}^{5} w_j v_j^3, \tag{1}$$

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 5 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 (Doswell, Edwards, Thompson, Hart, & Crosbie, 2006). 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 recent period of this record from 1994–2016. The fraction of path area is that recommended by the U.S. Nuclear Regulatory Commission (Fricker & Elsner, 2015), which combines a Rankine vortex with empirical estimates derived from detailed storm surveys (Ramsdell & Rishel, 2007). 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 (Thompson & Vescio, 1998). Additional details and justification for energy dissipation as a valid measure of tornado power are given in Fricker et al. (2017). 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

4.2 Statistical models

For each tornado a log-normal distribution is assumed for its power 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 power by month and hour are modeled as random intercept effects so the corresponding coefficients are vectors of length 12 and 24, respectively. Mathematically the regression model is expressed as:

$$
\begin{aligned}
\ln(\mathrm{E}|\mathrm{E} > 444000) = \alpha + \beta_{\mathrm{Year}}\mathrm{Year} + \beta_{\mathrm{ENSO}}\mathrm{ENSO} + \beta_{\mathrm{EF?}}\mathrm{EF?}+ \\
\boldsymbol{\beta}_{\mathrm{Month}}(1|\mathrm{Month}) + \boldsymbol{\beta}_{\mathrm{Hour}}(1|\mathrm{Hour})
\end{aligned}
$$

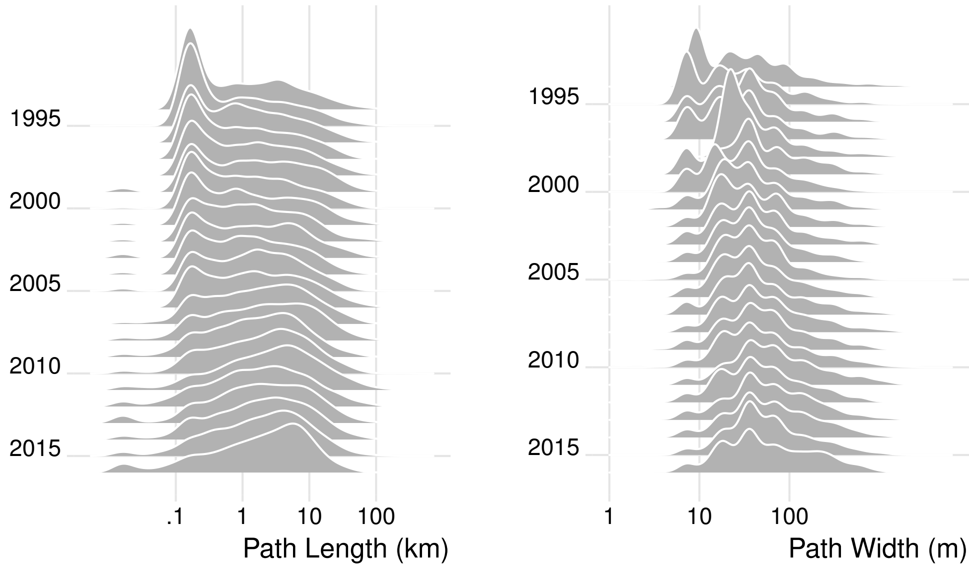
To examine the influence environmental variables including CAPE, CIN, and SRH have on reducing the upward trend, a similar regression model is fit to power per unit area averaged over all tornadoes on a day with at least ten tornadoes. A model using outbreak-level data (rather than tornado-level data) is needed because the scale of individual tornadoes is much smaller than the scale at which the environmental variables are resolved. Here values for the environmental variables on a regular grid are averaged over a convex polygon domain enclosing all the tornado genesis locations for that day. The best model (lowest Akaike information criterion (AIC) value) includes CIN and an interaction between CAPE and SRH.

4.3 Code and data

Analysis and modeling are performed using the software environment R (`http://www.r-project.org`). Models are fit using maximum likelihood procedures with functions in the **lme4** package Bates, Mächler, Bolker, and Walker (2015) and using Bayesian simulations in the Stan computational framework (`http://mc-stan.org/`) accessed with the **brms** package Bürkner (2017). To improve convergence and guard against over-fitting with the Bayesian procedures, we specified mildly informative conservative priors. The codes and data to reproduce the results from this study are available here `https://github.com/jelsner/tor-pwr-up` and here `https://github.com/jelsner/get-NARR`.

A Distributions of path length and path width by year

Figure A1. Distributions of path length and path width by year. Path widths narrower than one meter are not plotted.



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The code and data to reproduce the results from this study are available from `https://github.com/jelsner/tor-pwr-up` and `https://github.com/jelsner/get-NARR`.

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