More tornadoes in the most extreme U.S. tornado outbreaks

Michael K. Tippett,[1,2]* Chiara Lepore,[3] Joel E. Cohen[4,5,6]

[1]Department of Applied Physics and Applied Mathematics, Columbia University, New York, NY, USA. [2]Center of Excellence for Climate Change Research, Department of Meteorology, King Abdulaziz University, Jeddah, Saudi Arabia. [3]Lamont Doherty Earth Observatory, Columbia University, Palisades, NY 10964, USA. [4]Laboratory of Populations, Rockefeller University, New York, NY 10065, USA. [5]The Earth Institute and Department of Statistics, Columbia University, New York, NY 10027, USA. [6]Department of Statistics, University of Chicago, Chicago, IL 60637, USA.

*Corresponding author. E-mail: mkt14@columbia.edu

Tornadoes and severe thunderstorms kill people and damage property every year. Estimated U.S. insured losses due to severe thunderstorms in the first half of 2016 were 8.5 billion USD. The largest U.S. impacts of tornadoes result from tornado outbreaks, which are sequences of tornadoes that occur in close succession. Here, using extreme value analysis, we find that the frequency of U.S. outbreaks with many tornadoes is increasing and is increasing faster for more extreme outbreaks. We model this behavior by extreme value distributions with parameters that are linear functions of time or of some indicators of multidecadal climatic variability. Extreme meteorological environments associated with severe thunderstorms show consistent upward trends, but the trends do not resemble those currently expected to result from global warming.

In the United States, tornado outbreaks have the largest impacts on human lives and property. Tornado outbreaks are sequences of six or more tornadoes rated F1 and greater on the Fujita scale, or rated EF1 and greater on the Enhanced Fujita scale, that occur in close succession (*1*, *2*). 79% of tornado fatalities during the period 1972–2010 occurred in outbreaks (*1*), and 49 people died in U.S. tornado outbreaks in 2015. No significant trends have been found in either the annual number of reliably reported tornadoes (*3*) or of outbreaks (*1*). However, recent studies indicate increased variability in large normalized economic and insured losses from U.S. thunderstorms (*4*), increases in the annual number of days on which many tornadoes occur (*3*, *5*) and increases in the annual mean and variance of the number of tornadoes per outbreak (*6*). Here, using extreme value analysis, we find the frequency of U.S. outbreaks with many tornadoes is increasing, and is increasing faster for more extreme outbreaks. We model this behavior by extreme value distributions with parameters that are linear functions of time or of some indicators of multidecadal climatic variability. Extreme meteorological environments associated with severe thunderstorms show consistent upward trends, but the trends do not resemble those currently expected to result from global warming.

Linear trends in the percentiles of the number of tornadoes per outbreak (Fig. 1a) are positive, statistically significant and increase exponentially faster with percentile probability (Fig. 1b). This behavior is consistent with the positive trends in mean and variance (*6*) which suggested that the distribution of the number of tornadoes per out-

break is shifting to the right (increasing mean) and that higher percentiles of the distribution are shifting faster than the mean (increasing variance). The increase of percentile trends with percentile probability is consistent with trends in the frequency of tornado days with many tornadoes increasing with threshold (*5*).

Nonstationary generalized extreme value (GEV) distributions with trends in their parameters do not reproduce the observed upward trend in the slopes of percentiles as a function of percentile probability (Supplementary Materials and fig. S1). Therefore we use the Generalized Pareto (GP) approach with a threshold of 12 E/F1+ tornadoes [(*2*) and fig. S2)]. We refer to outbreaks with 12 or more E/F1+ tornadoes as "extreme outbreaks" (*2*). There were 435 extreme outbreaks 1965-2015, no statistically significant trends in the annual number of extreme outbreaks (P = 0.66) (Fig. 2a), and no statistically significant autocorrelation in the numbers of tornadoes per extreme outbreak (fig. S2c). The GP distributions found here have shape parameter around 0.3 (finite mean and variance) and are lighter-tailed distributions than was found considering tornadoes per day (rather than outbreaks) and a threshold of one (Pareto shape parameter of 0.61, infinite mean and variance) (*7*).

The percentiles of the number of tornadoes per extreme outbreak (Fig. 2b) also have upward trends that are statistically significant (above the 30th percentile) and depend approximately exponentially on the percentile probability (Fig. 2c). Allowing a trend as a function of time in the GP threshold u would give percentile trends (slopes) that are the same for all percentiles, contrary to observation. Permitting a lin-

ear trend as a function of time in the scale $\tilde{\sigma}$ improves the fit to the data statistically significantly. According to this model, the scale parameter and the percentiles increase linearly with time (Table 1), and higher percentiles increase faster. The standardized quantile-quantile plot in fig. S3 shows fairly good agreement between the data and the GP distribution with a linear trend in its scale parameter as a function of time. Data quantiles exceed those of the model at high percentiles (standardized model quantile values of 3-4 in fig. S3), meaning that the model predicts outbreaks with many tornadoes would occur more often than is observed. The difference between model and data quantiles falls within the range expected from sampling variability (fig. S3). We cannot reject the model on this basis.

The slopes of the percentiles of the GP distribution with a linear trend in its scale parameter are approximately exponential in the percentile probability and match well those estimated by quantile regression (Fig. 2c). The trends from quantile regression and from the nonstationary GP distribution deviate from exponential dependence on the percentile probability near the endpoints of 0% and 100% probability. Adding a trend to the scale parameter ξ results in a marginally statistically significant (P = 0.04) (Table 1) upward trend that is statistically insignificant when the largest value (in 2011) is withheld (P = 0.1) (table S2). The scale trends change little when the outbreak value from 2011 is withheld (table S2). Return levels for 2, 5 and 25-year return periods are shown in Fig. 2d along with 90% bootstrap confidence intervals (5000 bootstrap samples with bias correction and acceleration). The estimated number of tornadoes in the 5-year most extreme outbreak roughly doubles from 40 in 1965 to nearly 80 in 2015.

The outbreak trends in the tornado report database may reflect changes in reporting rather than real properties of tornadoes (8). The environments associated with tornadoes and severe thunderstorms provide valuable evidence that is independent of report data for assessing the variability of severe convective storms (4, 9–13). We use a two-part environmental proxy for the number of tornadoes per outbreak (2, 6). Here we define extreme environments as those with values of the outbreak proxy greater than 12, matching the extreme outbreak definition. The proxy is computed using reanalysis data (2) and depends on two factors, convective available potential energy (CAPE) and a measure of vertical wind shear, storm relative helicity (SRH). Modeling studies project that CAPE will increase in future warmer climates (14, 15), and Ref. 5 hypothesized that climate change and increases in CAPE could already be leading to more active areas of severe convection on days with tornadoes.

However, we find no statistically significant trends in the percentiles of CAPE conditional on extreme environments (Fig. 3a) nor in the percentiles of CAPE conditional on CAPE

> 1 J kg^{-1} (not shown). On the other hand, there are statistically significant upward trends in the percentiles of SRH conditional on extreme environments (Fig. 3b), and these trends are the source of the trends in the percentiles of the outbreak number proxy (Fig. 3c). The linear growth rates (slopes) of the proxy for the number of tornadoes per extreme outbreak are approximately exponential in the percentile probabilities, like those for the number of tornadoes in extreme outbreaks, and have roughly the same range of values. Percentiles of environments (not extreme) conditional on the environmental occurrence proxy show the same qualitative behavior (fig. S5). Therefore we cannot at present associate previously identified features of a warmer climate with the observed changes in our environmental proxy, and by extension, with the changes in tornado outbreak statistics.

The observed trends in the statistics of outbreaks and extreme environments may be related to low-frequency climate variability other than climate change. Multidecadal variability in U.S. tornado activity has been compared with sea-surface-temperature (SST)-forced variability (16). We explore the connection between multidecadal climate signals and outbreak statistics using a nonstationary GP distribution whose scale parameter is a linear function of the climate signal rather than time.

The Atlantic Multidecadal Oscillation (AMO) (17) affects North American climate, is characterized by variations in North Atlantic SST and can be explained as an oceanic response to mid-latitude atmospheric forcing (18). The AMO shows multidecadal variability, increasing from about 1970 though the mid-2000s (fig. S4a). The GP distribution whose scale parameter is a linear function of the AMO index fits the data significantly better than the stationary GP distribution, but not better than a linear time trend (Table 1).

Another important pattern of climate variability is the Pacific Decadal Oscillation (PDO) (19) (fig. S4b). The GP distribution whose scale parameter is a linear function of the PDO index does not fit the data significantly better than the stationary GP distribution (Table 1).

Contiguous U.S. (CONUS) annual average temperature is increasing and that change has prompted investigations of changes in the U.S. tornado climatology (20). Taking the GP scale parameter to depend linearly on CONUS temperature gives a significantly better fit to the data than does the stationary GP distribution, but not a better fit than the GP distribution with a scale parameter that depends linearly on either time or the AMO index (Table 1).

Many changes in U.S. tornado report statistics have been ascribed to changes in reporting practices, technology and other nonmeteorological factors (8). However, recent findings point to increases in the number of tornadoes per event, whether events are defined as days when tornadoes

occur (*3*, *5*) or as tornado outbreaks (*6*). Here we found statistically significant upward trends in the higher percentiles of the number of tornadoes per outbreak. We modeled these trends using extreme value distributions with a time-varying scale parameter. Similar behavior in an environmental proxy suggested that the behavior of the tornado reports is not due simply to changes in reporting practice or technology.

Climate change has been proposed as contributing to changes in tornado statistics (*5*, *20*). Climate model projections indicate that CAPE, one of the factors in our environmental proxy, will increase in a warmer climate leading to more frequent environments favorable to severe thunderstorms in the U.S. (*14*, *15*). However, the proxy trends here are not due to increasing CAPE but instead due to trends in storm relative helicity, a quantity related to vertical wind shear which was previously identified as a factor in increased year-to-year variability of U.S. tornado numbers (*11*). Therefore we cannot at present associate the observed changes in our environmental proxy, and by extension the changes in tornado outbreak statistics, with previously identified features of a warmer climate. This conclusion is, of course, subject to revision by the discovery of other implications of a warmer climate for severe thunderstorm environments.

The question of which climatic factors have driven the observed changes in tornado activity has important implications for the future. If global warming is changing tornado activity, then we might expect to see either continued increases in the number of tornadoes per outbreak or at least no return to earlier levels. On the other hand, if multidecadal variability, anthropogenic or natural, is responsible, then a return toward earlier levels might be possible in the future. Further clouding the future, many of the outbreak measures (annual maximum and higher percentiles of the number of tornadoes per outbreak) reached their lowest values in more than a decade in 2015. As a final caveat, inferring tornadic actively solely from the environment has considerable uncertainty even in the current climate and at least as much in projected climates (*21*).

REFERENCES AND NOTES

1. C. M. Fuhrmann, C. E. Konrad II, M. M. Kovach, J. T. McLeod, W. G. Schmitz, P. G. Dixon, Ranking of tornado outbreaks across the United States and their climatological characteristics. *Weather Forecast.* **29**, 684–701 (2014). doi:10.1175/WAF-D-13-00128.1
2. Materials and methods are available as supporting material on *Science* Online.
3. H. E. Brooks, G. W. Carbin, P. T. Marsh, Increased variability of tornado occurrence in the United States. *Science* **346**, 349–352 (2014). doi:10.1126/science.1257460 Medline
4. J. Sander, J. F. Eichner, E. Faust, M. Steuer, Rising variability in thunderstorm-related U.S. losses as a reflection of changes in large-scale thunderstorm forcing. *Weather Clim. Soc.* **5**, 317–331 (2013). doi:10.1175/WCAS-D-12-00023.1
5. J. B. Elsner, S. C. Elsner, T. H. Jagger, The increasing efficiency of tornado days in the United States. *Clim. Dyn.* **45**, 651–659 (2015). doi:10.1007/s00382-014-2277-3
6. M. K. Tippett, J. E. Cohen, Tornado outbreak variability follows Taylor's power law of fluctuation scaling and increases dramatically with severity. *Nat. Commun.* **7**, 10668 (2016). doi:10.1038/ncomms10668 Medline
7. J. B. Elsner, T. H. Jagger, H. M. Widen, D. R. Chavas, Daily tornado frequency distributions in the United States. *Environ. Res. Lett.* **9**, 024018 (2014). doi:10.1088/1748-9326/9/2/024018
8. S. M. Verbout, H. E. Brooks, L. M. Leslie, D. M. Schultz, Evolution of the U.S. tornado database: 1954-2003. *Weather Forecast.* **21**, 86–93 (2006). doi:10.1175/WAF910.1
9. H. E. Brooks, N. Dotzek, in *Climate Extremes and Society*, H. F. Diaz, R. Murnane, Eds. (Cambridge Univ. Press, New York, 2007), pp. 35–54.
10. E. D. Robinson, R. J. Trapp, M. E. Baldwin, The geospatial and temporal distributions of severe thunderstorms from high-resolution dynamical downscaling. *J. Appl. Meteorol. Climatol.* **52**, 2147–2161 (2013). doi:10.1175/JAMC-D-12-0131.1
11. M. K. Tippett, Changing volatility of U.S. annual tornado reports. *Geophys. Res. Lett.* **41**, 6956–6961 (2014). doi:10.1002/2014GL061347
12. J. T. Allen, M. K. Tippett, A. H. Sobel, Influence of the El Niño/Southern Oscillation on tornado and hail frequency in the United States. *Nat. Geosci.* **8**, 278–283 (2015). doi:10.1038/ngeo2385
13. M. Lu, M. Tippett, U. Lall, Changes in the seasonality of tornado and favorable genesis conditions in the central United States. *Geophys. Res. Lett.* **42**, 4224–4231 (2015). doi:10.1002/2015GL063968
14. R. J. Trapp, N. S. Diffenbaugh, A. Gluhovsky, Transient response of severe thunderstorm forcing to elevated greenhouse gas concentrations. *Geophys. Res. Lett.* **36**, L01703 (2009). doi:10.1029/2008GL036203
15. N. S. Diffenbaugh, M. Scherer, R. J. Trapp, Robust increases in severe thunderstorm environments in response to greenhouse forcing. *Proc. Natl. Acad. Sci. U.S.A.* **110**, 16361–16366 (2013). doi:10.1073/pnas.1307758110 Medline
16. S. J. Weaver, S. Baxter, A. Kumar, Climatic role of North American low-level jets on U.S. regional tornado activity. *J. Clim.* **25**, 6666–6683 (2012). doi:10.1175/JCLI-D-11-00568.1
17. D. B. Enfield, A. M. Mestas-Nuñez, P. J. Trimble, The Atlantic Multidecadal Oscillation and its relation to rainfall and river flows in the continental U.S. *Geophys. Res. Lett.* **28**, 2077–2080 (2001). doi:10.1029/2000GL012745
18. A. Clement, K. Bellomo, L. N. Murphy, M. A. Cane, T. Mauritsen, G. Rädel, B. Stevens, The Atlantic Multidecadal Oscillation without a role for ocean circulation. *Science* **350**, 320–324 (2015). doi:10.1126/science.aab3980 Medline
19. N. J. Mantua, S. R. Hare, Y. Zhang, J. M. Wallace, R. C. Francis, A Pacific interdecadal climate oscillation with impacts on salmon production. *Bull. Am. Meteorol. Soc.* **78**, 1069–1079 (1997). doi:10.1175/1520-0477(1997)078<1069:APICOW>2.0.CO;2
20. E. Agee, J. Larson, S. Childs, A. Marmo, Spatial redistribution of USA tornado activity between 1954 and 2013. *J. Appl. Meteorol. Climatol.* **55**, 1681–1697 (2016). doi:10.1175/JAMC-D-15-0342.1
21. R. J. Trapp, K. A. Hoogewind, The realization of extreme tornadic storm events under future anthropogenic climate change. *J. Clim.* **29**, 5251–5265 (2016). doi:10.1175/JCLI-D-15-0623.1
22. NOAA, National Weather Service, Storm Prediction Center, Warning Coordination Meterologist; http://www.spc.noaa.gov/wcm/.
23. F. Mesinger, G. DiMego, E. Kalnay, K. Mitchell, P. C. Shafran, W. Ebisuzaki, D. Jović, J. Woollen, E. Rogers, E. H. Berbery, M. B. Ek, Y. Fan, R. Grumbine, W. Higgins, H. Li, Y. Lin, G. Manikin, D. Parrish, W. Shi, North American regional reanalysis. *Bull. Am. Meteorol. Soc.* **87**, 343–360 (2006). doi:10.1175/BAMS-87-3-343
24. NOAA, Earth System Research Laboratory, Climate Indices: Monthly Atmospheric and Ocean Time Series; http://www.esrl.noaa.gov/psd/data/climateindices/list/.
25. NOAA, National Centers for Environmental Information, National Temperature Index, Time Series; http://www.ncdc.noaa.gov/temp-and-precip/national-temperature-index/time-series.
26. R. Koenker, G. Bassett, Regression quantiles. *Econometrica* **46**, 33–50 (1978). doi:10.2307/1913643
27. P. Huybers, K. A. McKinnon, A. Rhines, M. Tingley, U.S. daily temperatures: The

meaning of extremes in the context of nonnormality. *J. Clim.* **27**, 7368–7384 (2014). doi:10.1175/JCLI-D-14-00216.1

28. J. Machado, J. Silva, Quantiles for counts. *J. Am. Stat. Assoc.* **100**, 1226–1237 (2005). doi:10.1198/016214505000000330

29. S. Coles, *An Introduction to Statistical Modeling of Extreme Values* (Springer, 2001).

ACKNOWLEDGMENTS

SUPPLEMENTARY MATERIALS
www.sciencemag.org/cgi/content/full/science.aah7393/DC1
Materials and Methods
Figs. S1 to S5
Tables S1 and S2
References (*22–29*)

4 August 2016; accepted 17 November 2016
Published online 1 December 2016
10.1126/science.aah7393
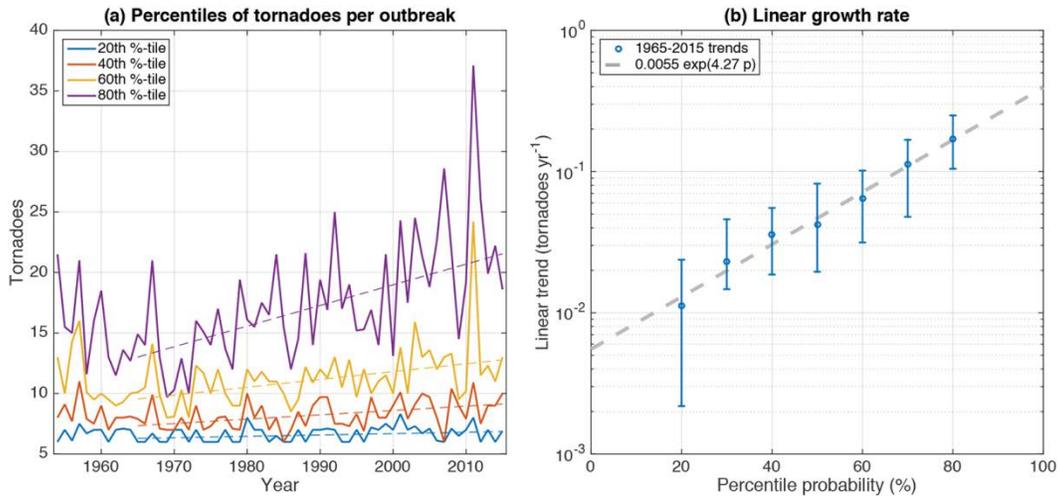
Fig. 1. Numbers of tornadoes per outbreak. (a) Annual 20th, 40th, 60th and 80th percentiles of the number of E/F1+ tornadoes per outbreak (6 or more E/F1+ tornadoes), 1954-2015 (solid lines), and quantile regression fits to 1965-2015 assuming linear growth in time (dashed lines). (b) Linear growth rates as a function of percentile probability. Error bars are 95% bootstrap confidence intervals and indicate linear trends that are statistically significantly different from zero.
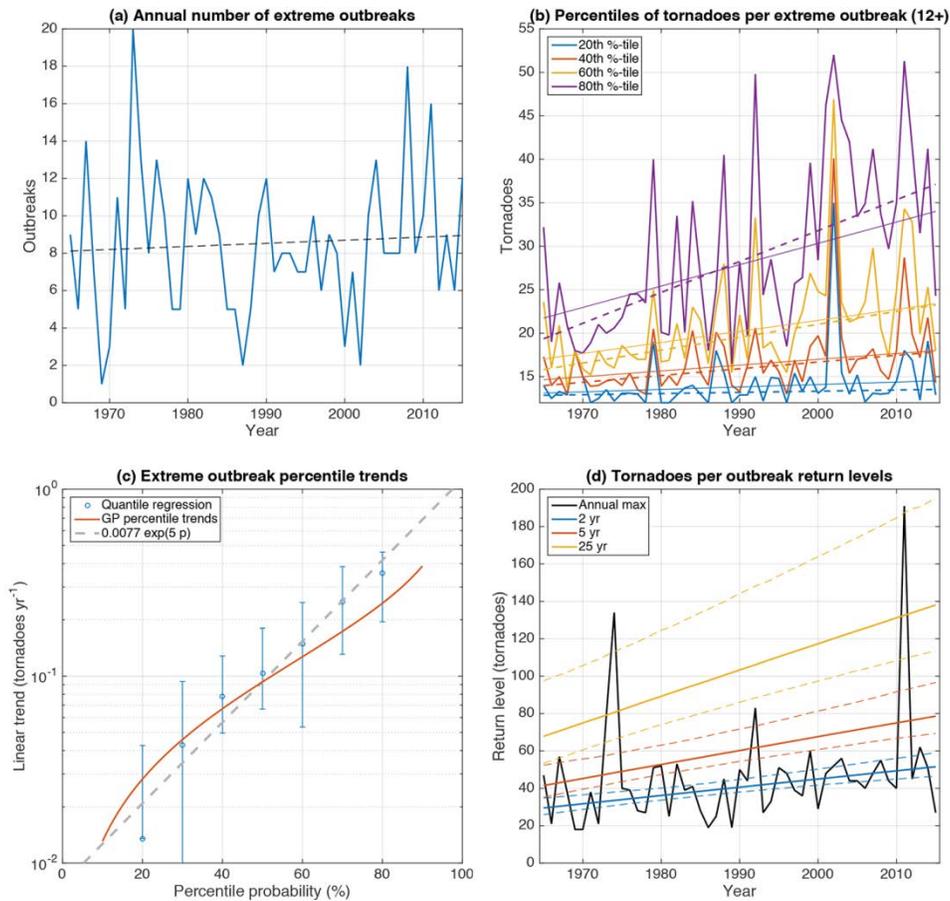
**Fig. 2. Extreme outbreaks.** (**a**) Annual number of extreme outbreaks (12 or more E/F1+ tornadoes). (**b**) Annual 20th, 40th, 60th and 80th percentiles of the number of E/F1+ tornadoes per extreme outbreak 1965-2015 (jagged solid lines) along with quantile regression lines (dashed lines) and percentiles of the GP distribution with a linear trend in the scale parameter (solid lines). (**c**) Quantile regression linear growth rates (slopes) along with 95% confidence intervals (blue) and corresponding growth rates of a GP distribution with linear trend in the scale parameter as functions of percentile probability (solid red line). (**d**) Annual maxima (black line) along with GP return levels as functions of year for return periods of 2, 5, and 25 years (solid colored lines), and 90% bootstrap confidence intervals (dashed lines).
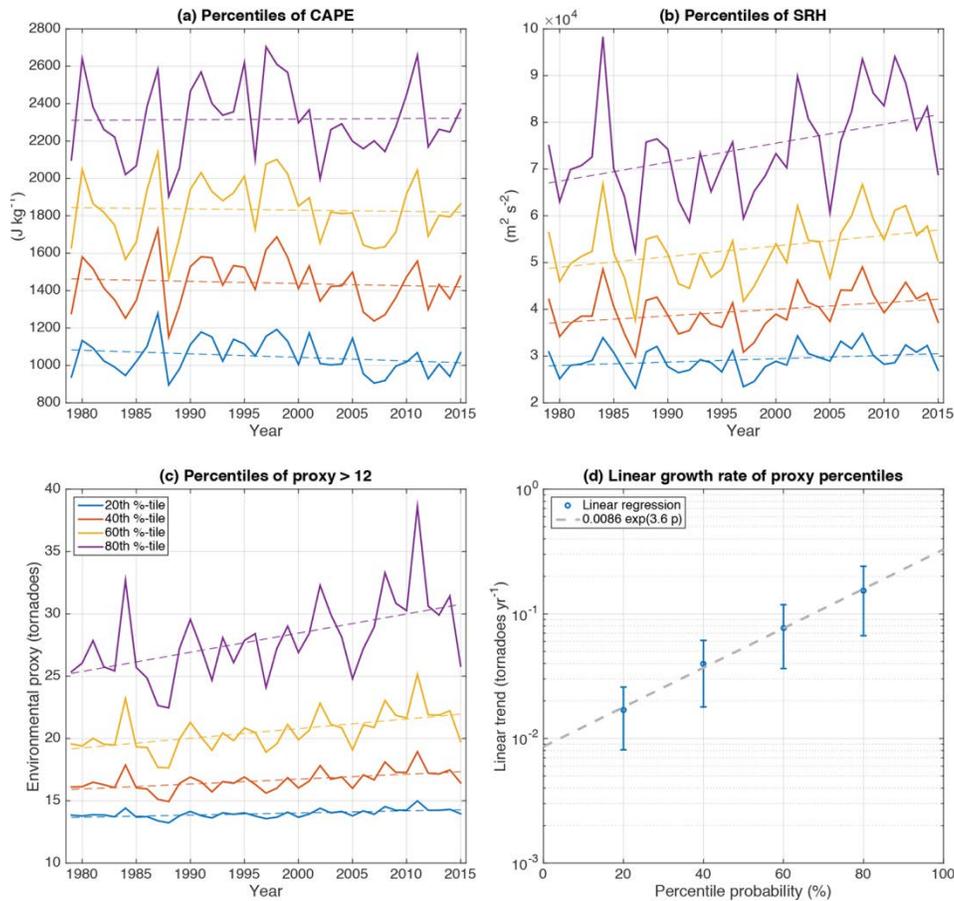
Fig. 3. Extreme environments. Percentiles of (**a**) CAPE and (**b**) SRH conditional on the proxy for the number of E/F1+ tornadoes per outbreak (see Methods for definition) exceeding 12. (**c**) Percentiles of the proxy for the number of tornadoes per extreme outbreak. (**d**) Linear growth rate (ordinary least squares estimates of slope and 95% confidence intervals) of the extreme outbreak proxy percentiles as a function of percentile.

	$\widetilde{\sigma}_0$	$\widetilde{\sigma}_1$	ξ_0	ξ_1
Stationary (NLL=1449)				
Maximum likelihood estimates	7.6	–	0.3	–
Standard error estimates	0.621	–	0.067	–
$\tilde{\sigma} = \widetilde{\sigma}_0 + \widetilde{\sigma}_1 t$ (NLL=1440)				
LR p-value $=2\times10^{-5}$				
Maximum likelihood estimates	4.73	0.12	0.26	–
Standard error estimates	0.736	0.029	0.062	–
$\xi = \xi_0 + \xi_1 t$ (NLL=1447)				
LR p-value = 0.04				
Maximum likelihood estimates	7.48	-0.13	0.0066	–
Standard error estimates	0.61	–	0.088	0.0031
$\tilde{\sigma} = \widetilde{\sigma}_0 + \widetilde{\sigma}_1 \times$ AMO (NLL=1442)				
LR p-value = 2×10^{-4}				
Maximum likelihood estimates	8.18	8.48	0.28	–
Standard error estimates	0.6531	2.2009	0.0626	–
$\tilde{\sigma} = \widetilde{\sigma}_0 + \widetilde{\sigma}_1 \times$ PDO (NLL=1449)				
LR p-value = 0.3				
Maximum likelihood estimates	7.71	-0.52	0.29	–
Standard error estimates	0.63	0.54	0.067	–
$\tilde{\sigma} = \widetilde{\sigma}_0 + \widetilde{\sigma}_1 \times$ CONUS temperature (NLL=1444)				
LR p-value = 0.001				
Maximum likelihood estimates	8.31	1.62	0.28	–
Standard error estimates	0.70	0.52	0.065	–

Table 1. Generalized Pareto distribution parameters. Distributions are fitted to the number of E/F1+ tornadoes per outbreak for outbreaks with 12 or more E/F1+ tornadoes. The negative log likelihood (NLL), maximum likelihood estimates and their standard errors are indicated for each model. The likelihood ratio (LR) test p-value compares non-stationary models with the stationary distribution.

More tornadoes in the most extreme U.S. tornado outbreaks

Michael K. Tippett, Chiara Lepore and Joel E. Cohen (December 1, 2016)
published online December 1, 2016

Editor's Summary

Article Tools	Visit the online version of this article to access the personalization and article tools: http://science.sciencemag.org/content/early/2016/11/30/science.aah7393
Permissions	Obtain information about reproducing this article: http://www.sciencemag.org/about/permissions.dtl

Supplementary Materials for

More tornadoes in the most extreme U.S. tornado outbreaks

Michael K. Tippett,* Chiara Lepore, Joel E. Cohen

*Corresponding author. Email: mkt14@columbia.edu

This PDF file includes:

Materials and Methods
Figs. S1 to S5
Tables S1 and S2
References

Materials and Methods

Tornado data
    U.S. tornado report data come from NOAA's Storm Prediction Center *(22)*. We consider only reports of tornadoes within the contiguous United States (CONUS) rated F1 and greater on the Fujita scale, or rated EF1 and greater on the Enhanced Fujita scale, and denoted here as E/F1+ tornadoes. There are no significant trends or apparent discontinuities in the annual number of tornadoes rated F1 or EF1 and greater *(3)*. We make no further distinctions according to rating. Tornado start times are sorted in chronological order (accounting for time zone), and clusters of tornado reports are formed consisting of those tornadoes whose start time is no more than 6h after that of the previous tornado. Clusters with 6 or more E/F1+ tornadoes are defined as *outbreaks (1)*. We define *extreme outbreaks* as outbreaks with 12 or more E/F1+ tornadoes. The tornado reports begin in 1950, but have known problems of quality prior to 1954 *(8)*, and most of the analysis here is restricted to the 51-yr period 1965-2015.

Environmental data
    Daily averages of 0-180 hPa convective available potential energy (CAPE) and 0-3km storm relative helicity (SRH) interpolated to a $1° × 1°$ lat-lon grid are taken from the North American Regional Reanalysis *(23)* for the period 1979-2015. We use a two-part (occurrence and number of tornadoes) environmental proxy for outbreaks *(5)*. The environmental proxy for occurrence is that the daily value of the product of CAPE and 0-3km SRH exceeds 160,000 $m^2 \, s^{-2} \, J \, kg^{-1}$. The environmental proxy for number of tornadoes conditional on the environmental occurrence proxy is $CAPE × SRH^2/(3.6 × 10^6 \, m^4 \, s^{-4} \, J \, kg^{-1})$, a unitless quantity normalized to match approximately the average number of outbreaks per year. We define extreme environments as ones where the environmental proxy for number of tornadoes exceeds 12, though the main results are not sensitive to this choice.

Climate indices
    Annual averages are computed from monthly values of the Pacific Decadal Oscillation (PDO) and the Atlantic Multidecadal Oscillation (AMO; unsmoothed) indices taken from NOAA's Earth System Research Laboratory *(24)*. The CONUS annual average temperature anomaly (based on the nClimDiv dataset) comes from NOAA's National Centers for Environmental Information *(25)*.

Quantile regression
    The median minimizes the sum of the absolute value of differences between itself and the data, while the mean minimizes the sum of the squares of differences between itself and the data. Analogously, quantile regression estimates conditional percentiles by minimizing weighted absolute residuals rather than squared residuals *(26)*. Quantile regression uses the data from all years, in contrast to the alternative procedure of fitting a linear trend to percentiles computed separately for each year, though the results from the two approaches should be similar given sufficient data *(27)*. Since the numbers of tornadoes per outbreak are integers, the quantile regression loss function being minimized

is discontinuous, and uniformly distributed random "jitter" on the interval [−0.5, 0.5] are added to smooth the data *(28)*. Bootstrap confidence intervals (with bias correction and acceleration) for the quantile regression coefficients are computed from 5000 bootstrap samples. Independent jitter samples are used for each bootstrap sample.

Extreme value analysis: Annual maxima

Extreme value theory indicates that the generalized extreme value (GEV) distribution is asymptotically appropriate for modeling block maxima *(29)*. Here we use the GEV distribution to approximate the distribution of the annual maxima of the number of tornadoes per outbreak. The location μ, scale σ and shape ξ parameters of the GEV distribution are found by maximum likelihood (ML) estimation, and approximate standard errors and confidence intervals follow from the asymptotic normality of the ML estimates. The return level z_p of the GEV distribution for return time $\frac{1}{p}$ is

$$z_p = \mu - \frac{\sigma}{\xi}\left(1 - y_p^{-\xi}\right), \quad \xi \neq 0, \tag{1}$$

where $y_p = -\log(1-p)$. Equivalently, z_p is the $100(1-p)$-th percentile of the distribution of annual maxima. We introduce nonstationarity in the GEV distribution by allowing its parameters to be functions of the year t. For instance, we allow the location parameter to have linear trend in time by taking

$$\mu = \mu_0 + \mu_1 t.$$

Again we estimate the constants μ_0 and μ_1 by ML. Approximate standard errors and confidence intervals follow from the asymptotic normality of the ML estimates. The model with no trend ($\mu_1 = 0$) is a special case of the general model. A likelihood ratio (LR) test can be used to decide if the improvement in fit from having a nonzero trend parameter is statistically significant.

Annual maxima of the number of tornadoes per outbreak

The annual maxima of tornadoes per outbreak in 1974 and 2011 are at the edge and outside, respectively, of the 95% confidence intervals for the return levels of a GEV distribution fitted to outbreak data 1965-2015 (Fig. S1a). The annual maximum for 2011 has an estimated return period of several hundred years. The shape parameter is positive and less than 0.5 indicating unbounded heavy tails, but finite mean and variance. Including a trend in the GEV location parameter μ improves the fit to the data and the improvement is statistically significant according to the likelihood ratio test. Estimated GEV parameters, their standard errors and the results of the likelihood ratio test comparing stationary and nonstationary distributions are given in Table S1. However, a trend in the location parameter results in a nonstationary distribution with percentile trends that are independent of percentile probability, or equivalently, with return levels that have the same trends for all return periods (see Eq. S1 and Fig. S1b). This behavior is not consistent with that of the data in Fig. 1.

Allowing a linear trend in the scale parameter σ gives percentile trends that depend on percentile probability, but the estimate of the trend in the scale parameter is negative

3

with 95% confidence intervals that include zero (Table S1), and the improvement in fit is not statistically significant by the likelihood ratio test. A negative trend in the scale parameter means that return levels decrease with time (Fig. S1c), which is not realistic. Allowing a linear trend in the shape parameter ξ gives percentile trends that increase with percentile probability (Fig. S1d), but the 95% confidence interval of the trend estimate includes zero (Table S1), and the improvement in fit is not statistically significant by the likelihood ratio test. Including trends in either the scale or the shape parameters, in addition to the trend in the location parameter, neither improves the overall performance nor is the improvement statistically significant according to the likelihood ratio test (not shown). We conclude that none of these GEV distributions adequately describes the data.

Extreme value analysis: Peaks over threshold

The "peaks over threshold" (POT) approach is an alternative to the analysis of block maxima. It considers exceedances over some large threshold, here outbreaks with more tornadoes than some specified value. An advantage of the POT method is that more data enter the analysis than in the analysis of annual maxima. Asymptotic theory says that for a large enough threshold u, the generalized Pareto (GP) distribution approximates the distribution of exceedances $(Y − u)$ conditional on $Y > u$ *(29)*. The GP distribution parameters are the threshold u, a scale parameter $\tilde{\sigma}$ and a shape parameter ξ. These parameters are related (at least asymptotically) to those of the GEV distribution because the shape parameters ξ are the same and the scale parameters are related by $\tilde{\sigma} = \sigma + \xi(u − \mu)$. For the GP, the N-year return level z_N is

$$z_N = u + \frac{\tilde{\sigma}}{\xi}\left[\left(Nn_y\right)^{-\xi} - 1\right],$$

where n_y is the average number of exceedances per year. Linear trends in the GP parameters (as functions of time or climatic indices) are introduced and estimated as for the GEV distribution. The analysis of peaks over threshold requires choosing a threshold that is large enough that the asymptotic theory applies and small enough that sufficient data remain for estimation. We consider integer thresholds and make a so-called continuity correction by adding 0.5 to the observed number of tornadoes per outbreak. The results are similar if random numbers uniformly distributed on the interval zero to one are added. The GP estimated scale (reparameterized as $\sigma^* = \tilde{\sigma} − \xi u$ so that it is not intrinsically a function of threshold) and shape parameter ξ are shown as functions of the threshold in Figs. S2a and b, respectively. For thresholds ≥ 8, both quantities show little variation relative to their uncertainty. Overall, point estimates of the shape parameter decrease as the threshold increases. For thresholds in the range of 8-12, the GP shape parameter is around 0.3 and consistent with the GEV estimated shape parameter. None of the main results is particularly sensitive to this choice. Thresholds ≥ 8 give similar results.
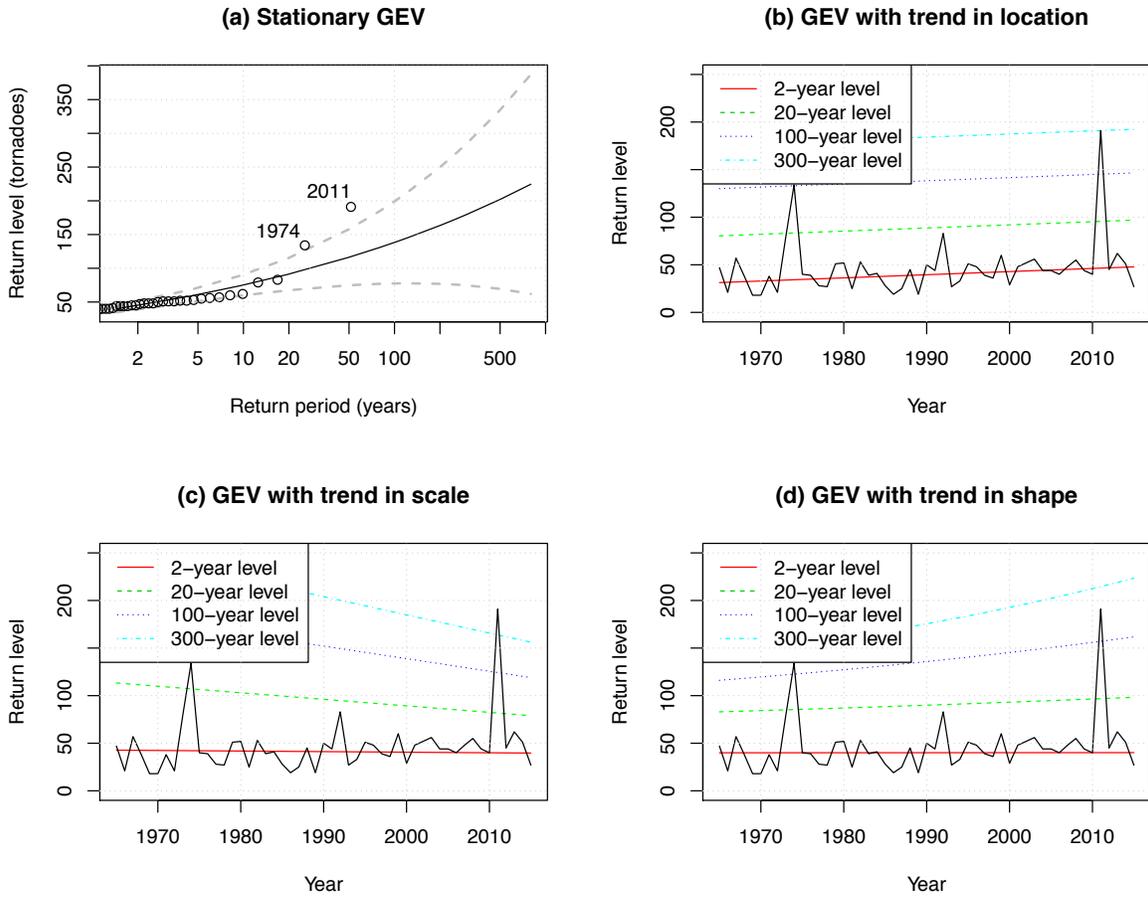
Fig. S1.

GEV return levels. Number of tornadoes per outbreak for a GEV distribution with (a) constant parameters (the circles show the observed annual maximum number of tornadoes per outbreak, one circle per year), (b) a linear trend in the location parameter, (c) a linear trend in the scale parameter and (d) a linear trend in the shape parameter. The dashed lines in (a) are 95% confidence intervals for the return level estimated by the delta method.
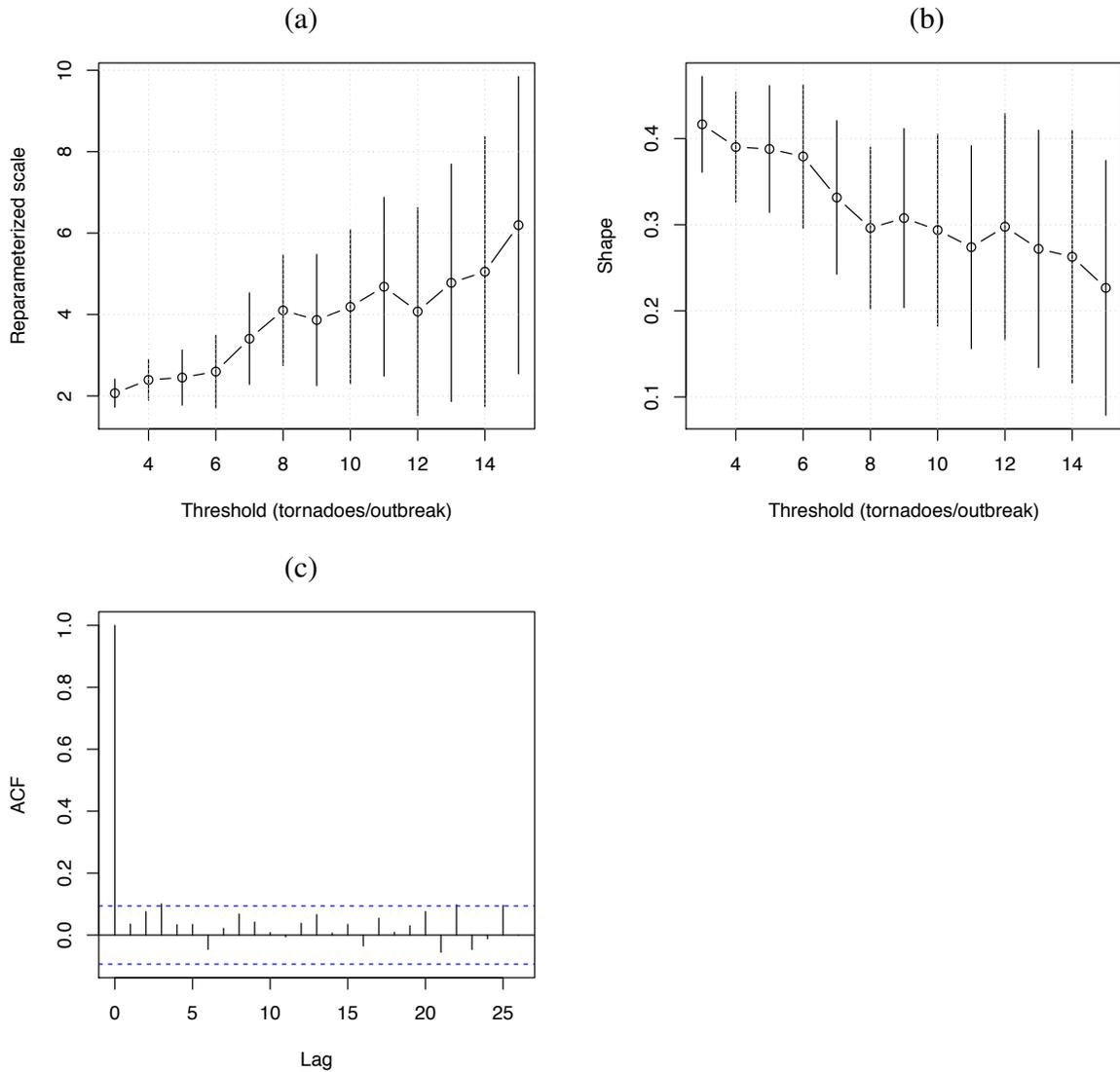
Fig. S2

Threshold selection. (a) Reparameterized scale and (b) shape parameters of the generalized Pareto distribution fitted to the number of tornadoes per outbreak as a function of threshold. Vertical lines indicate 95% confidence intervals; open circles indicate medians of bootstrap estimates. (c) The autocorrelation function for the number of tornadoes per extreme outbreak (outbreaks with 12 or more E/F1+ tornadoes) as a function of the lag between extreme outbreaks measured in number of extreme outbreaks, not in chronological time. Dashed lines indicate the 95% significance level.
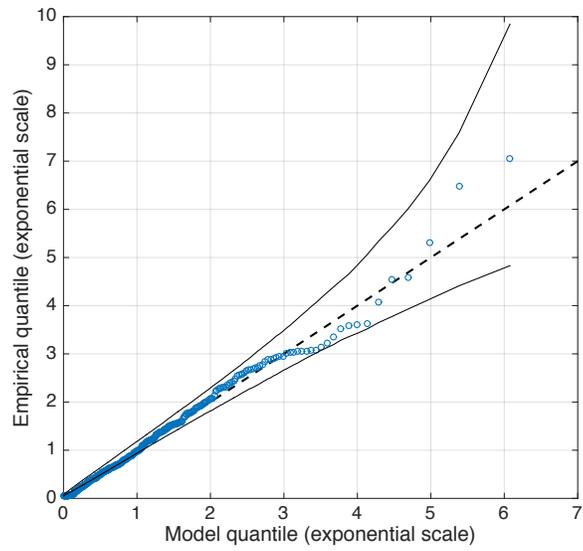
Fig. S3

Quantile-quantile plot. Standardized (exponential) quantiles of the data and the generalized Pareto distribution with a linear trend in the scale parameter. Solid lines show 2.5 and 97.5 percentiles of the data quantiles of 5000 samples of the fitted distribution.
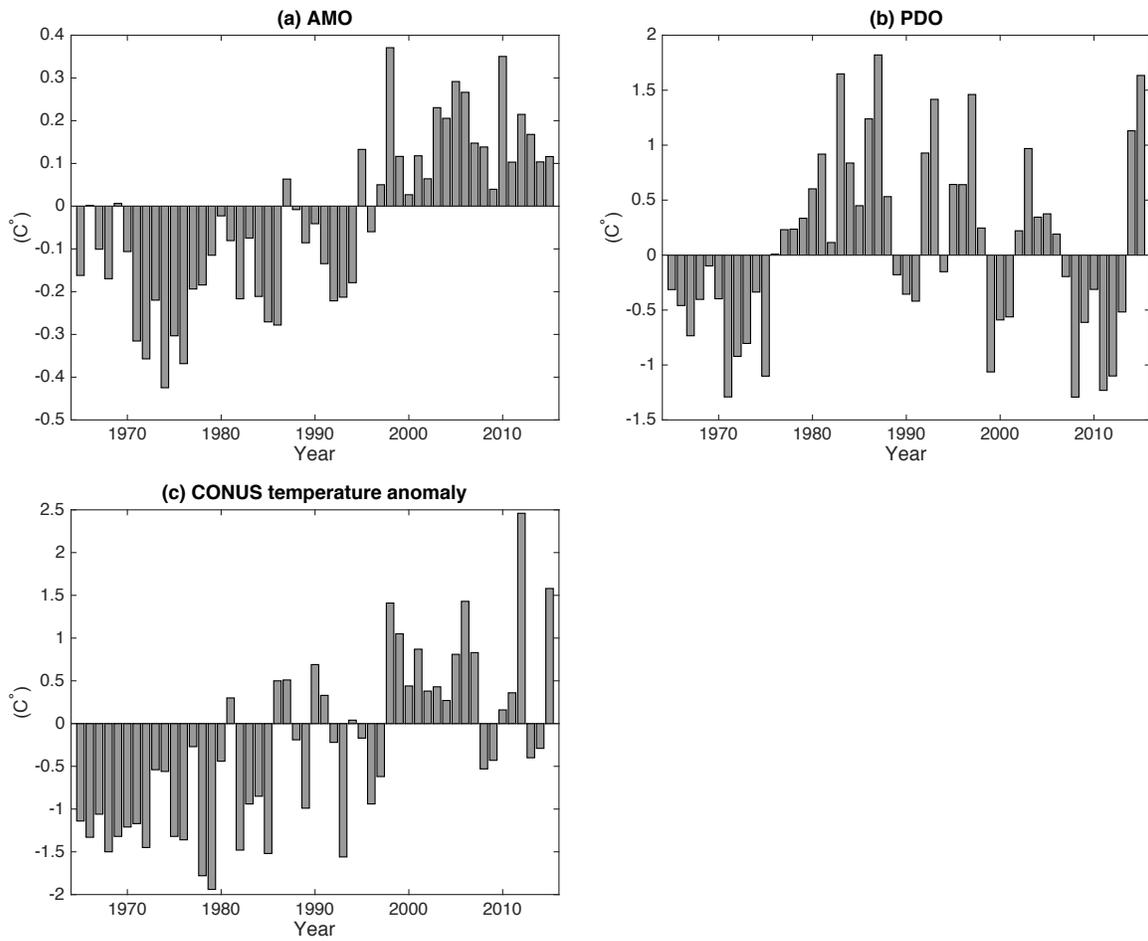
Fig. S4

Indices of multidecadal climatic variability. Annual time series 1965-2015 of (a) the Atlantic Multidecadal Oscillation (AMO), (b) the Pacific Decadal Oscillation (PDO) and (c) the contiguous United States (CONUS) temperature anomaly.
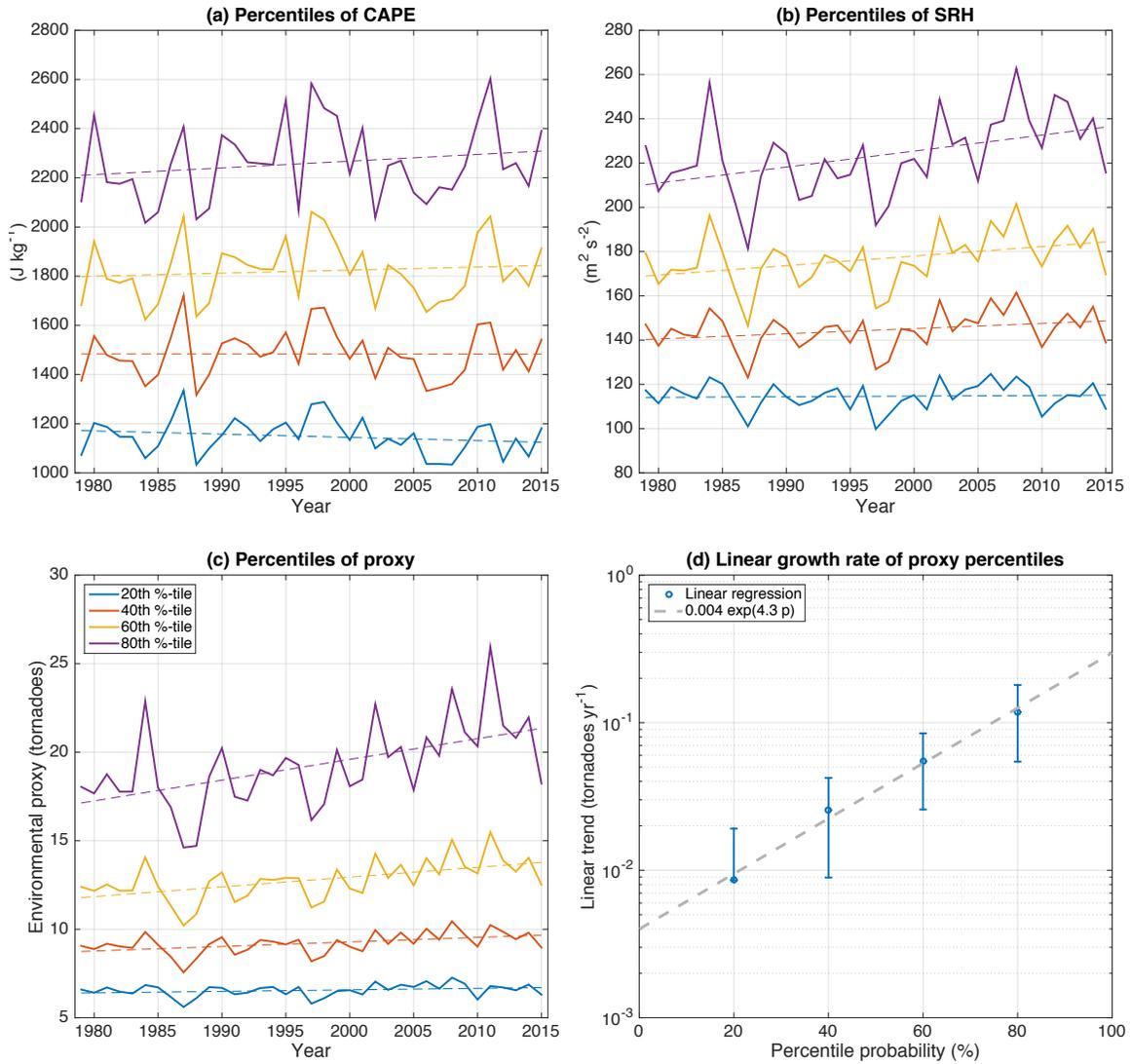
Fig. S5

Environments. Percentiles of (a) CAPE and (b) SRH conditional on the environmental occurrence proxy (see Methods for definition). (c) Percentiles of the proxy for the number of tornadoes per outbreak. (d) Linear growth rate (ordinary least squares estimates of slope and 95% confidence intervals) of the proxy for the number of tornadoes per outbreak as a function of percentile. The 95% confidence interval of the 20th percentile linear growth rate includes zero and is omitted.

Table S1.

Generalized Extreme Value distribution parameters. Parameters are estimated from the annual maxima of the number of tornadoes per outbreak 1965-2015. For each model the negative log likelihood (NLL) is indicated. The likelihood ratio (LR) test p-value is shown for models with trends, comparing that model to the stationary GEV distribution.

	μ_0	μ_1	σ_0	σ_1	ξ_0	ξ_1
Stationary (NLL=221)						
Maximum likelihood estimates	34.44	–	14.12	–	0.19	–
Standard error estimates	2.23	–	1.74	–	0.11	–
$\mu = \mu_0 + \mu_1 t$ (NLL=217)						
LR p-value=0.004						
Maximum likelihood estimates	26.13	0.33	12.66	–	0.23	–
Standard error estimates	3.24	0.10	1.60	–	0.11	–
$\sigma = \sigma_0 + \sigma_1 t$ (NLL=220)						
LR p-value=0.2						
Maximum likelihood estimates	35.81	–	18.23	-0.16	0.23	–
Standard error estimates	2.27	–	3.57	0.10	0.12	–
$\xi = \xi_0 + \xi_1 t$ (NLL=221)						
LR p-value=0.6						
Maximum likelihood estimates	34.75	–	13.98	–	0.095	0.0034
Standard error estimates	2.30	–	1.74	–	0.18	0.0061

Table S2.
Outlier sensitivity. As in Table 1 but withholding the maximum value in 2011.

	$\widetilde{\sigma_0}$	$\widetilde{\sigma_1}$	ξ_0	ξ_1
Stationary (NLL=1449)				
Maximum likelihood estimates	7.83	–	0.26	–
Standard error estimates	0.65	–	0.068	–
$\tilde{\sigma} = \widetilde{\sigma_0} + \widetilde{\sigma_1}t$ (NLL=1440)				
LR p-value =2×10^{-5}				
Maximum likelihood estimates	4.95	0.12	0.23	–
Standard error estimates	0.764	0.02	0.062	–
$\xi = \xi_0 + \xi_1 t$ (NLL=1447)				
LR p-value = 0.04				
Maximum likelihood estimates	7.62		0.14	0.0048
Standard error estimates	0.63	–	0.089	0.0032

References

1. C. M. Fuhrmann, C. E. Konrad II, M. M. Kovach, J. T. McLeod, W. G. Schmitz, P. G. Dixon, Ranking of tornado outbreaks across the United States and their climatological characteristics. *Weather Forecast.* **29**, 684–701 (2014). doi:10.1175/WAF-D-13-00128.1

2. Materials and methods are available as supporting materials on *Science* Online.

3. H. E. Brooks, G. W. Carbin, P. T. Marsh, Increased variability of tornado occurrence in the United States. *Science* **346**, 349–352 (2014). doi:10.1126/science.1257460 Medline

4. J. Sander, J. F. Eichner, E. Faust, M. Steuer, Rising variability in thunderstorm-related U.S. losses as a reflection of changes in large-scale thunderstorm forcing. *Weather Clim. Soc.* **5**, 317–331 (2013). doi:10.1175/WCAS-D-12-00023.1

5. J. B. Elsner, S. C. Elsner, T. H. Jagger, The increasing efficiency of tornado days in the United States. *Clim. Dyn.* **45**, 651–659 (2015). doi:10.1007/s00382-014-2277-3

6. M. K. Tippett, J. E. Cohen, Tornado outbreak variability follows Taylor's power law of fluctuation scaling and increases dramatically with severity. *Nat. Commun.* **7**, 10668 (2016). doi:10.1038/ncomms10668 Medline

7. J. B. Elsner, T. H. Jagger, H. M. Widen, D. R. Chavas, Daily tornado frequency distributions in the United States. *Environ. Res. Lett.* **9**, 024018 (2014). doi:10.1088/1748-9326/9/2/024018

8. S. M. Verbout, H. E. Brooks, L. M. Leslie, D. M. Schultz, Evolution of the U.S. tornado database: 1954-2003. *Weather Forecast.* **21**, 86–93 (2006). doi:10.1175/WAF910.1

9. H. E. Brooks, N. Dotzek, in *Climate Extremes and Society*, H. F. Diaz, R. Murnane, Eds. (Cambridge Univ. Press, New York, 2007), pp. 35–54.

10. E. D. Robinson, R. J. Trapp, M. E. Baldwin, The geospatial and temporal distributions of severe thunderstorms from high-resolution dynamical downscaling. *J. Appl. Meteorol. Climatol.* **52**, 2147–2161 (2013). doi:10.1175/JAMC-D-12-0131.1

11. M. K. Tippett, Changing volatility of U.S. annual tornado reports. *Geophys. Res. Lett.* **41**, 6956–6961 (2014). doi:10.1002/2014GL061347

12. J. T. Allen, M. K. Tippett, A. H. Sobel, Influence of the El Niño/Southern Oscillation on tornado and hail frequency in the United States. *Nat. Geosci.* **8**, 278–283 (2015). doi:10.1038/ngeo2385

13. M. Lu, M. Tippett, U. Lall, Changes in the seasonality of tornado and favorable genesis conditions in the central United States. *Geophys. Res. Lett.* **42**, 4224–4231 (2015). doi:10.1002/2015GL063968

14. R. J. Trapp, N. S. Diffenbaugh, A. Gluhovsky, Transient response of severe thunderstorm forcing to elevated greenhouse gas concentrations. *Geophys. Res. Lett.* **36**, L01703 (2009). doi:10.1029/2008GL036203

15. N. S. Diffenbaugh, M. Scherer, R. J. Trapp, Robust increases in severe thunderstorm environments in response to greenhouse forcing. *Proc. Natl. Acad. Sci. U.S.A.* **110**, 16361–16366 (2013). doi:10.1073/pnas.1307758110 Medline

16. S. J. Weaver, S. Baxter, A. Kumar, Climatic role of North American low-level jets on U.S. regional tornado activity. *J. Clim.* **25**, 6666–6683 (2012). doi:10.1175/JCLI-D-11-00568.1

17. D. B. Enfield, A. M. Mestas-Nuñez, P. J. Trimble, The Atlantic Multidecadal Oscillation and its relation to rainfall and river flows in the continental U.S. *Geophys. Res. Lett.* **28**, 2077–2080 (2001). doi:10.1029/2000GL012745

18. A. Clement, K. Bellomo, L. N. Murphy, M. A. Cane, T. Mauritsen, G. Rädel, B. Stevens, The Atlantic Multidecadal Oscillation without a role for ocean circulation. *Science* **350**, 320–324 (2015). doi:10.1126/science.aab3980 Medline

19. N. J. Mantua, S. R. Hare, Y. Zhang, J. M. Wallace, R. C. Francis, A Pacific interdecadal climate oscillation with impacts on salmon production. *Bull. Am. Meteorol. Soc.* **78**, 1069–1079 (1997). doi:10.1175/1520-0477(1997)078<1069:APICOW>2.0.CO;2

20. E. Agee, J. Larson, S. Childs, A. Marmo, Spatial redistribution of USA tornado activity between 1954 and 2013. *J. Appl. Meteorol. Climatol.* **55**, 1681–1697 (2016). doi:10.1175/JAMC-D-15-0342.1

21. R. J. Trapp, K. A. Hoogewind, The realization of extreme tornadic storm events under future anthropogenic climate change. *J. Clim.* **29**, 5251–5265 (2016). doi:10.1175/JCLI-D-15-0623.1

22. National Oceanic and Atmosphere Administration (NOAA), National Weather Service, Storm Prediction Center, Warning Coordination Meterologist; http://www.spc.noaa.gov/wcm/.

23. F. Mesinger, G. DiMego, E. Kalnay, K. Mitchell, P. C. Shafran, W. Ebisuzaki, D. Jović, J. Woollen, E. Rogers, E. H. Berbery, M. B. Ek, Y. Fan, R. Grumbine, W. Higgins, H. Li, Y. Lin, G. Manikin, D. Parrish, W. Shi, North American regional reanalysis. *Bull. Am. Meteorol. Soc.* **87**, 343–360 (2006). doi:10.1175/BAMS-87-3-343

24. NOAA, Earth System Research Laboratory, Climate Indices: Monthly Atmospheric and Ocean Time Series; http://www.esrl.noaa.gov/psd/data/climateindices/list/.

25. NOAA, National Centers for Environmental Information, National Temperature Index, Time Series; http://www.ncdc.noaa.gov/temp-and-precip/national-temperature-index/time-series.

26. R. Koenker, G. Bassett, Regression quantiles. *Econometrica* **46**, 33–50 (1978). doi:10.2307/1913643

27. P. Huybers, K. A. McKinnon, A. Rhines, M. Tingley, U.S. daily temperatures: The meaning of extremes in the context of nonnormality. *J. Clim.* **27**, 7368–7384 (2014). doi:10.1175/JCLI-D-14-00216.1

28. J. Machado, J. Silva, Quantiles for counts. *J. Am. Stat. Assoc.* **100**, 1226–1237 (2005). doi:10.1198/016214505000000330

29. S. Coles, *An Introduction to Statistical Modeling of Extreme Values* (Springer, 2001).