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SUPPLEMENTARY MATERIALS

www.sciencemag.org/content/354/6318/1414/suppl/DC1
Materials and Methods
Figs. S1 to S13
Tables S1 and S2
References (*37–39*)

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TORNADOES

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

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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 (US). The largest U.S. effects 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 that it 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 substantial effects on human lives and property. Tornado outbreaks are sequences of six or more tornadoes that are rated F1 and greater on the Fujita scale or rated EF1 and greater on the Enhanced Fujita scale and that occur in close succession (*1*, *2*). About 79% of tornado fatalities during the period 1972 to 2010 occurred in outbreaks (*1*), and 35 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 that the frequency of U.S. outbreaks with many tornadoes is increasing and that it 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

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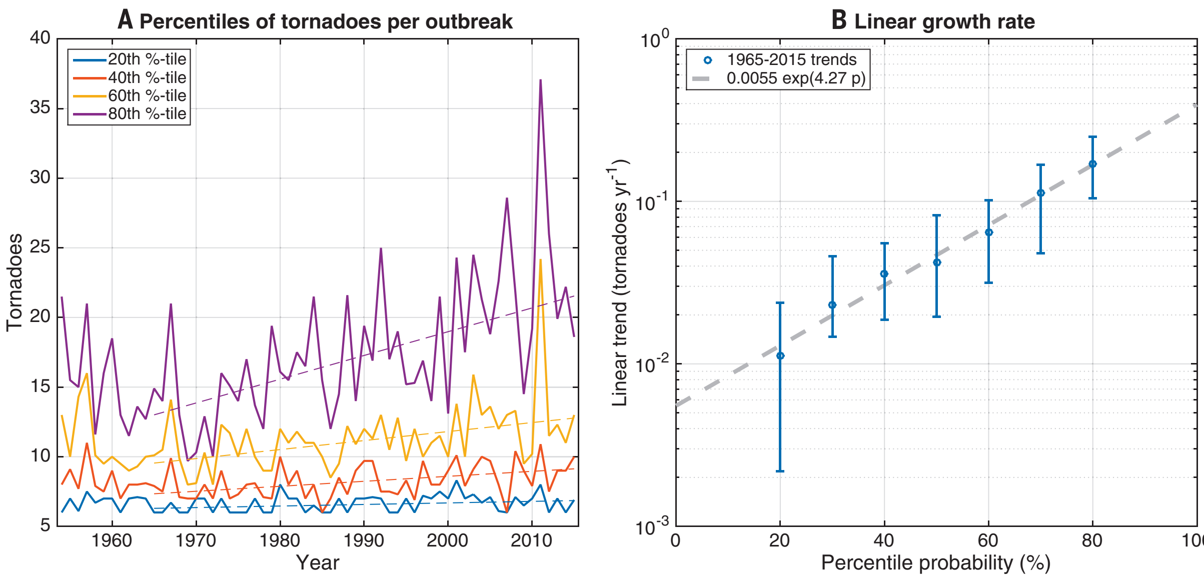

Fig. 1. Numbers of tornadoes per outbreak. (**A**) Annual 20th, 40th, 60th, and 80th percentiles of the number of E/F1+ tornadoes per outbreak (6 or more E/F1+ tornadoes), 1954 to 2015 (solid lines), and quantile regression fits to 1965 to 2015, assuming linear growth in time (dashed lines). (**B**) 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.

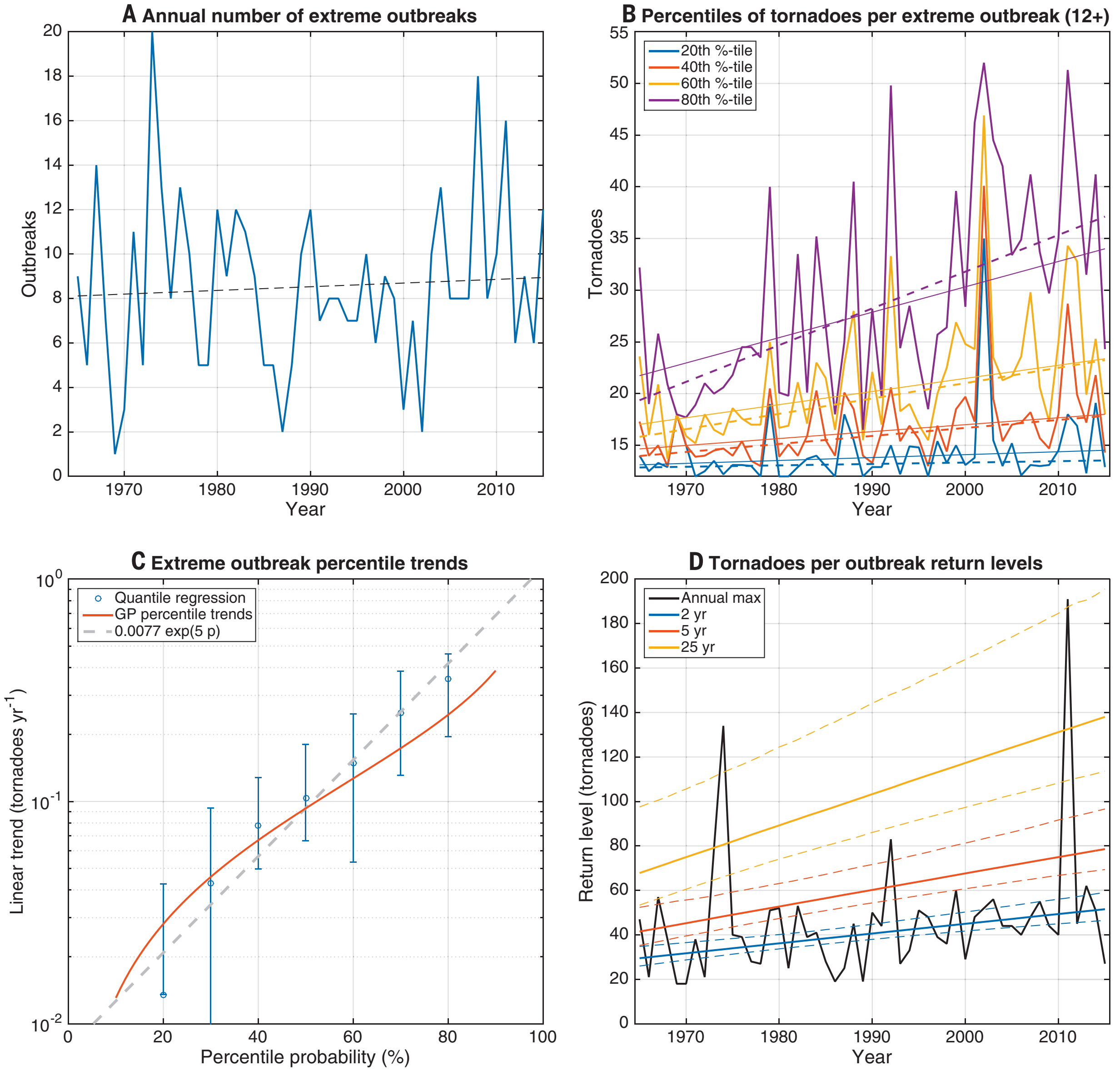

Fig. 2. Extreme outbreaks. (**A**) Annual number of extreme outbreaks (12 or more E/F1+ tornadoes). (**B**) Annual 20th, 40th, 60th, and 80th percentiles of the number of E/F1+ tornadoes per extreme outbreak, 1965 to 2015 (jagged solid lines), along with quantile regression lines (dashed lines) and percentiles 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).

mean and variance (*6*), which suggested that the distribution of the number of tornadoes per outbreak 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 from 1965 through 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 linear 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

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 nonstationary models with the stationary distribution.

	$\tilde{\sigma}_0$	$\tilde{\sigma}_1$	ξ_0	ξ_1
Stationary (NLL = 1449)				
Maximum likelihood estimates	7.6	–	0.3	–
Standard error estimates	0.621	–	0.067	–
$\tilde{\sigma} = \tilde{\sigma}_0 + \tilde{\sigma}_1 t$ (NLL = 1440)				
LR *P* value = 2×10^{-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
$\tilde{\sigma} = \tilde{\sigma}_0 + \tilde{\sigma}_1 \times$ 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	–
$\tilde{\sigma} = \tilde{\sigma}_0 + \tilde{\sigma}_1 \times$ 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	–
$\tilde{\sigma} = \tilde{\sigma}_0 + \tilde{\sigma}_1 \times$ 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	–

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 to 4 in fig. S3), meaning that the model predicts that 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 end points 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 Elsner *et al.* (*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 midlatitude 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

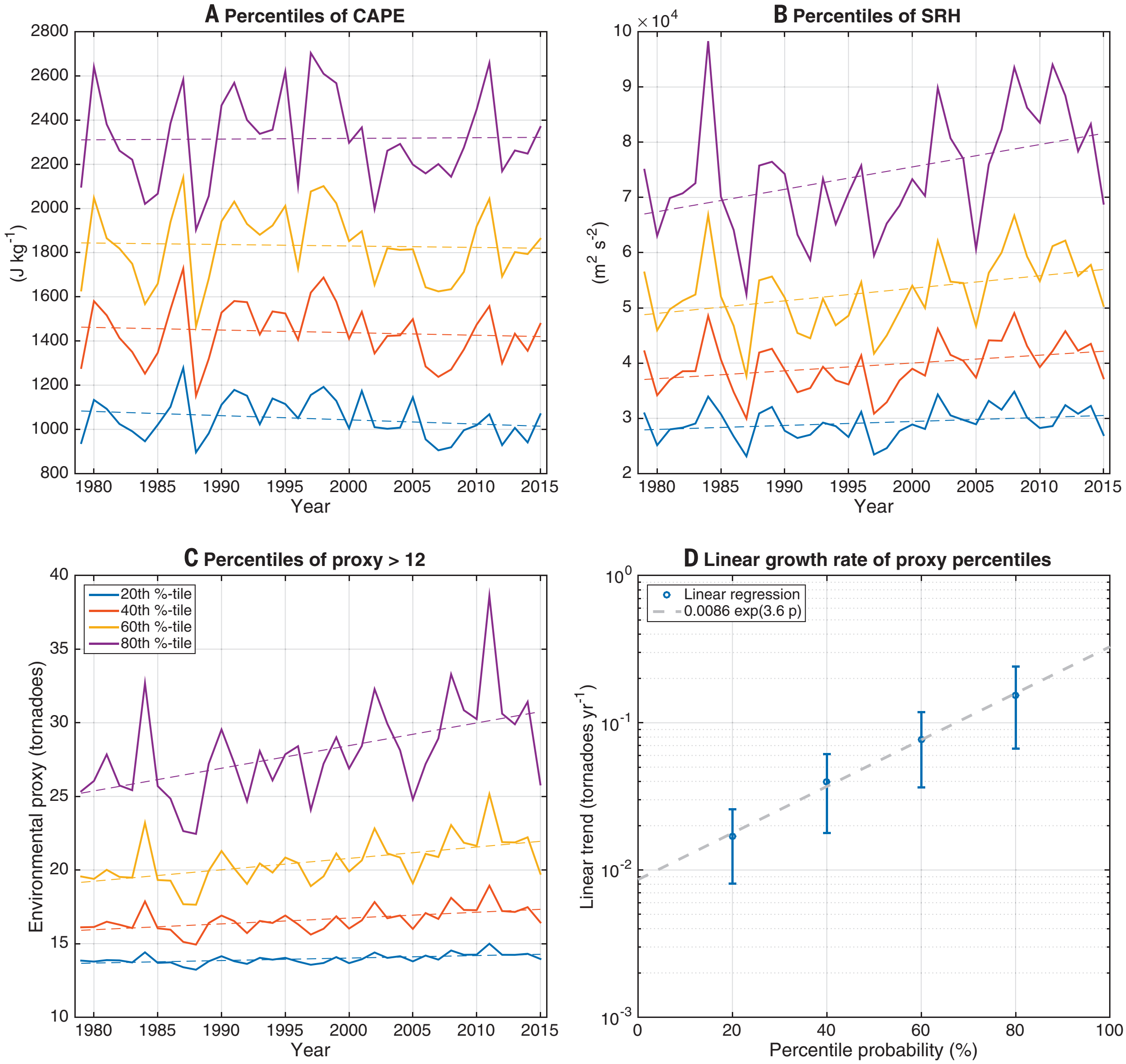

Fig. 3. Extreme environments. Percentiles of (**A**) CAPE and (**B**) SRH conditional on the proxy for the number of E/F1+ tornadoes per outbreak (see methods for definition) exceeding 12. (**C**) Percentiles of the proxy for the number of tornadoes per extreme outbreak. (**D**) Linear growth rate (ordinary least-squares estimates of slope and 95% confidence intervals) of the extreme outbreak proxy percentiles as a function of percentile.

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 United States (*14*, *15*). However, the proxy trends here are not due to increasing CAPE but instead due to trends in SRH, a quantity related to vertical wind shear that 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*).

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SUPPLEMENTARY MATERIALS

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Tables S1 and S2
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CONSERVATION

A global map of roadless areas and their conservation status

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Roads fragment landscapes and trigger human colonization and degradation of ecosystems, to the detriment of biodiversity and ecosystem functions. The planet's remaining large and ecologically important tracts of roadless areas sustain key refugia for biodiversity and provide globally relevant ecosystem services. Applying a 1-kilometer buffer to all roads, we present a global map of roadless areas and an assessment of their status, quality, and extent of coverage by protected areas. About 80% of Earth's terrestrial surface remains roadless, but this area is fragmented into ~600,000 patches, more than half of which are <1 square kilometer and only 7% of which are larger than 100 square kilometers. Global protection of ecologically valuable roadless areas is inadequate. International recognition and protection of roadless areas is urgently needed to halt their continued loss.

The impact of roads on the surrounding landscape extends far beyond the roads themselves. Direct and indirect environmental impacts include deforestation and fragmentation, chemical pollution, noise disturbance, increased wildlife mortality due to car collisions, changes in population gene flow, and facilitation of biological invasions (*1*–*4*). In addition, roads facilitate "contagious development," in that they provide access to previously remote areas, thus opening them up for more roads, land-use changes, associated resource extraction, and human-caused disturbances of biodiversity (*3*, *4*). With the length of roads projected to increase by >60% globally from 2010 to 2050 (*5*), there is an urgent need for the development of a comprehensive global strategy for road development if continued biodiversity loss is to be abated (*6*). To help mitigate the detrimental effects of roads, their construction should be concentrated as much as possible in areas of relatively low "environmental values" (*7*). Likewise, prioritizing the protection of remaining roadless areas that are regarded as important for biodiversity and ecosystem functionality requires an assessment of their extent, distribution, and ecological quality.

Such global assessments have been constrained by deficient spatial data on global road networks. Importantly, recent publicly available and rapidly improving data sets have been generated by crowd-sourcing and citizen science. We demonstrate their potential through OpenStreetMap, a project with an open-access, grassroots approach to mapping and updating free global geographic data, with a focus on roads. The available global road data sets, OpenStreetMap and gROADS, vary in length, location, and type of roads; the former is the data set with the largest length of roads (36 million km in 2013) that is not restricted to specific road types (table S1). OpenStreetMap is more complete than gROADS, which has been used for other global assessments (*7*), but in certain regions, it contains fewer roads than subglobal or local road data sets [see the example of Center for International Forestry Research data for Sabah, Malaysia (*8*); table S1]. Given the pace of road construction and data limitations, our results overestimate the actual extent of global roadless areas.

The spatial extent of road impacts is specific to the impact in question and to each particular road and its traffic volume, as well as to taxa, habitat, landscape, and terrain features. Moreover, for a given road impact, its area of ecological influence is asymmetrical along the road and can vary among seasons, between night and day, according to weather conditions, and over longer time periods. We conducted a comprehensive literature review of 282 publications dealing with "road-effects zones" or including the distance to roads as a covariate, of which 58 assessed the spatial influence of the road (table S2). All investigated road impacts were documented within a distance of

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

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Blowing harder and more often

The frequency of tornado outbreaks (clusters of tornadoes) and the number of extremely powerful tornado events have been increasing over nearly the past half-century in the United States. Tippett *et al.* found that tornado outbreaks have become more common since the 1970s. This increase seems to have been driven by consistent changes in the meteorological environment that make tornadoes more likely to form. However, the changes are not necessarily those that one would expect from climate change, which makes it difficult to predict whether this trend will continue.

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