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Key Points:

- The economic concept of elasticity compares casualty relationships at the tornado level
- Casualties increase by 21% with a doubling of the population under the path
- Casualties increase by 33% with a doubling of energy dissipation

Supporting Information:

• Supporting Information S1

Correspondence to:

T. Fricker, tfricker@fsu.edu

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Population and energy elasticity of tornado casualties

Tyler Fricker¹, James B. Elsner¹, and Thomas H. Jagger¹

¹Department of Geography, Florida State University, Tallahassee, Florida, USA

Abstract Tornadoes are capable of catastrophic destruction and mass casualties, but there are yet no estimates of how sensitive the number of casualties are to changes in the number of people in harm's way or to changes in tornado energy. Here the relationship between tornado casualties (deaths and injuries), population, and energy dissipation is quantified using the economic concept of "elasticity." Records of casualties from individual tornadoes over the period 2007–2015 are fit to a regression model. The coefficient on the population term (population elasticity) indicates that a doubling in population increases the casualty rate by 21% [(17, 24)%, 95% credible interval]. The coefficient on the energy term (energy elasticity) indicates that a doubling in energy dissipation leads to a 33% [(30, 35)%, 95% credible interval] increase in the casualty rate. The difference in elasticity values show that on average, changes in energy dissipation have been relatively more important in explaining tornado casualties than changes in population. Assuming no changes in warning effectiveness or mitigation efforts, these elasticity estimates can be used to project changes in casualties given the known population trends and possible trends in tornado activity.

1. Introduction

Tornadoes are storms of high-energy wind capable of catastrophic destruction and mass casualties. They account for nearly one fifth of all natural hazard fatalities in the United States [National Oceanic and Atmospheric Administration, 2015]. A tornado's potential for destruction is tied to the wind energy dissipated as the vortex moves across the landscape. The potential magnitude of destruction can vary widely; weak tornadoes typically have winds of 29 m s⁻¹ (65 mph) near the ground, while the most violent have winds that can exceed 100 m s⁻¹ (224 mph) and are powerful enough to destroy concrete structures. For example, the Sawyerville-Eoline, Alabama, tornado on 27 April 2011 had an estimated total kinetic energy of 123 TJ [Fricker et al., 2014].

Strong tornadoes have the potential to cause mass casualties and to severely disrupt economic productivity. Whether that potential is realized depends on a number of factors including how many people are affected and the extent of the property in the path. Population growth implies a greater potential for casualties. Recent research shows that as population increases and the built environment disperses, so does the chance that a tornado impacts developed land, resulting in more damage and a higher number of casualties [Ashley and Strader, 2016]. This concept, known as the expanding bull's-eye effect [Ashley et al., 2014], explains changes in tornado destruction (and thus the potential for casualties) using housing units and households. But other factors beyond population and structural changes might play a role in the potential for casualties in the future.

How climate change will impact human mortality from severe convective storms remains an open and challenging question [*Brooks*, 2013; *Diffenbaugh et al.*, 2013; *Tippett et al.*, 2015]. First, any link between climate change and tornado activity remains tenuous. The rising number of tornado reports over the past several decades is largely explained by increasing population, better observing technology, and greater interest in these events [*Doswell et al.*, 1999; *Brooks*, 2004; *Verbout et al.*, 2006; *Diffenbaugh et al.*, 2008; *Doswell et al.*, 2009; *Simmons and Sutter*, 2011; *Elsner et al.*, 2013]. Yet there is evidence that the risk of tornado outbreaks is on the rise [*Tippett et al.*, 2014; *Elsner et al.*, 2015]. This increasing threat is hard to explain through better reporting practices. Second, the relationship between casualties and tornado strength has yet to be largely quantified [*Simmons and Sutter*, 2008, 2009]. Although it is well understood that stronger tornadoes pose the greatest risk, advances in methods to quantify by how much casualty counts increase with increases in population and with increases in energy are needed to address this important question.

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The goal of this study is to better understand the relationship between energy, population, and tornado casualties. The objective is to establish statistical estimates (including uncertainties) on how sensitive casualties are to changes in population and on how sensitive casualties are to changes in tornado strength. This study uses the economic concept of "elasticity" to quantify these changes for the first time. Quantification is done at the tornado level over the period 2007 through 2015. Additional effort is spent estimating the elasticity values using various subsets of the tornado record. All analyses and modeling are done using the R project for statistical computing [R Core Team, 2016].

2. Data and Methods

2.1. Tornado and Population Data

The Storm Prediction Center's (SPC) database is the most readily available set of tornado records in the world. $Records \ are \ obtained \ from \ http://www.spc.noaa.gov/gis/svrgis/zipped/tornado.zip. The \ database \ is \ compiled$ from the National Weather Service's (NWS) Storm Data and includes all known tornadoes dating back to 1950. Tornado records contain information on initiation point (latitude and longitude), date, length and width of the damage path, and maximum damage rating on a scale from 0 to 5 (Enhanced Fujita (EF) damage scale). They also contain the number of direct injuries and fatalities. Reports in the database are compiled by the NWS offices and reviewed by the National Centers for Environmental Information (formerly known as the National Climate Data Center) [Verbout et al., 2006].

The database is available in a shapefile format with each tornado represented as a straight line track. The tornado track is the great circle line (no width) between the estimated start (initiation point) and end locations. Locations in the attribute table are recorded with two-digit decimal precision prior to 2009 and four digits afterward. Locations have greater precision later in the record when estimates are made with Global Positioning System (GPS). This study considers all tornadoes in the database over the period 2007 - 2015. The start year coincides with the period when the EF scale was officially adopted by the NWS, signaling more consistent data collection, better documentation, and the inclusion of more damage indicators (and associated degrees of damage) [Doswell et al., 2009]. The end year is the most currently available for this study.

Population data are obtained from the Gridded Population of the World, version 4 (GPW, v4) from the Socioeconomic Data and Applications Center at Columbia University, USA. The database contains density estimates from 2010 represented as people per square kilometer. Densities are based on residential, or estimated evening, population. The native cell resolution is 0.0083° latitude/longitude, which at 36°N latitude means a cell having the dimension of 0.9 km in the north-south direction and 0.7 km in the east-west direction.

2.2. Casualties

The United States experiences more tornadoes than any other country in the world [Grazulis, 1990]. As a result, it is unique in the potential risk of casualties due to these severe convective storms. "Casualty" refers to either human death or injury as a direct consequence of a tornado according to the NWS Storm Data. Tornadoes threaten lives because of a number of factors including the short time between warnings and impact, the quality of building materials in structures, and the fast winds associated with the vortex [Greenough et al., 2001]. Flying debris is the major determinant of casualties. Soft tissue injuries are the most common [Bohonos and Hogan, 1999] (Table S1 in the supporting information) including lacerations, contusions, abrasions, punctures, and musculoskeletal strain. Other types of injuries include fractures (open or closed), head injuries (scalp lacerations, concussions, etc.), and blunt trauma. The most common cause of death is severe head injuries from airborne objects (either objects located in the building of shelter or incoming objects) [Carter et al., 1989; Bohonos and Hogan, 1999; Brown et al., 2002; Chiu et al., 2013].

Over the conterminous United States during the period 2007 – 2015 there were 10,807 tornadoes. Of these, 872 are linked to 12,972 casualties. Only 8% of all casualties resulted in death. Most casualty-producing tornadoes have only a few casualties, while relatively few casualty-producing tornadoes have many casualties (Figure 1). The tornado with the most casualties was the 2011 Tuscaloosa-Birmingham (AL) tornado with 1564. Half of the casualty-producing tornadoes resulted in less than three casualties. Over two thirds (72%) of all casualty-producing tornadoes resulted in less than six casualties, while only 5% of all casualty-producing tornadoes resulted in 50 or more casualties. The relationship between casualties and the number of tornadoes on a log-log scale shows a straight line suggesting a power law. Power law behavior has been noted in daily tornado frequency [Elsner et al., 2014a] and in outbreak variability [Tippett and Cohen, 2016].

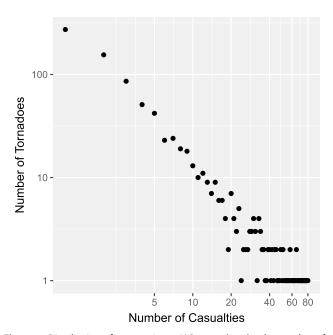


Figure 1. Distribution of conterminous U.S. tornadoes by the number of resulting casualties over the period 2007-2015.

Tornado casualties during the period 2007 - 2015 are concentrated across the Southeast (Figure S1), consistent with prior research [Ashley, 2007; Ashley et al., 2008; Dixon et al., 2011; Coleman and Dixon, 2014]. Even the least damaging tornadoes can cause casualties. However, on average tornadoes resulting in the most damage are those that tend to have the most casualties (Table S2). In total, the 67 EF4 tornadoes have resulted in the most casualties by EF rating at 4844. The 269 EF3 tornadoes result in the second most casualties by EF category with a total of 3248, followed by the nine EF5 tornadoes with a total of 2298. The 6161 EF0 tornadoes result in the fewest casualties by EF category with only 128. While intense tornadoes (EF3+) make up less than 5% of all tornadoes, they account for 80% of all casualties. On average a casualty-producing EF0 tornado results

in 1.9 casualties, a casualty-producing EF1 tornado results in 2.7 casualties, and a casualty-producing EF2 tornado results in 5.7 casualties. The big jumps in the expected number of casualties occur for the highest-rated tornadoes. On average a casualty-producing EF3 tornado results in 18 casualties, a casualty-producing EF4 tornado results in 90 casualties, and a casualty-producing EF5 tornado results in 255 casualties. Alabama had the most casualties (2749) followed by Missouri (1521), Oklahoma (1399), Texas (962), and Mississippi (942). Rounding out the top 10 are Arkansas (717), Georgia (618), North Carolina (594), Tennessee (526), and Illinois (408). Eight of the top 11 are states in the Southeast including Kentucky with 404 casualties. Massachusetts, ranked fourteenth, stands out in New England with 205 casualties from two tornadoes. Due to the limited period of record, these rankings could change with a single event or outbreak.

2.3. Population Density

Tornado paths are created using a buffer on the straight line track (a first-order approximation used in many studies) in accordance with recorded path width. Path area is track length multiplied by path width. Since the path width represents the maximum width anywhere along the path, the path area is an upper bound on the actual area impacted by the tornado. The average population density (people per square kilometer) under the path is computed for each tornado. For the set of 872 tornadoes with at least one casualty the median population density per tornado is 27.1 people per square kilometer with an interquartile range between 8.38 and 104 people per square kilometer (Figure S2). It is estimated that as many as 30,000 people were in the path of the Queens, New York, EF1 tornado on 16 September 2010 resulting in one injury and one death.

Although average tornado path area increases with EF rating [Brooks, 2004; Elsner et al., 2014b; Ashley and Strader, 2016], population density within the tornado path generally decreases with increasing EF rating (Table 1). The 68 EFO tornadoes result in the highest population density value at 545 people per square kilometer followed by the 253 EF1 tornadoes at 378 people per square kilometer. The nine EF5 tornadoes result in the lowest population density value at 78.2 people per square kilometer. One reason for this inverse relationship is likely due in part to the fact that the greater the EF rating of a tornado, the larger its area, making it more likely that the storm will pass through undeveloped/underdeveloped landscapes [Strader et al., 2014]. Another reason is likely due to the fact that the strongest tornadoes with the potential for producing the most damage tend to occur farther to the west where population density is lower relative to the distribution of all tornadoes. For example, the average tornado genesis latitude for the 951 EF2 tornadoes is 90.8°W longitude, while the average genesis longitude for the nine EF5 tornadoes is almost 2° west at 92.7°W longitude.

Table 1. Total Casualties, Average Surface Energy Dissipation, and Average Population
Density by EF Rating

EF Rating	Total Casualties (Number of People)	Energy Dissipation (TW)	Population Density (People per Square Kilometer)
0	128	0.016	545
1	687	0.133	378
2	1767	0.582	176
3	3248	2.50	78.3
4	4844	7.18	96.7
5	2298	14.2	78.2

2.4. Energy Dissipation

Tornadoes generate and dissipate a tremendous amount of atmospheric energy [Schielicke and Névir, 2011; Fricker et al., 2014]. The energy dissipated at the surface is the destructive potential. Similar to what is done to quantify destructive potential in hurricanes [Emanuel, 2005], here we multiply the path area by the cube of the wind field to estimate the surface energy dissipation. The wind field is a weighted average of the midpoint wind speed from the corresponding EF rating, where the weights are the fraction of total damage area by each EF rating [Fricker et al., 2014]. Thus, the surface energy dissipation (E) is given by

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

where A_p is the area of the approximate path (width times length), ρ is the air density (assumed to be 1 kg/m³ at the surface), v_i is the midpoint wind speed for each damage rating j, and w_i is the corresponding fraction of path area. 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). Since path area fractions by EF rating are not available in the much larger SPC database, the U.S. Nuclear Regulatory Commission (NRC) model for the fractions (Table S3) can be used [see Fricker and Elsner, 2015]. The NRC model combines a Rankine vortex with empirical estimates to estimate the percentage of path area associated with each EF rating [Ramsdell and Rishel, 2007]. Energy dissipation has units of power.

The distribution of energy dissipation on a log scale over all casualty-producing tornadoes is shown in Figure S2. For this set of 872 tornadoes the median energy dissipation is 0.155 terawatts (TW) with an interquartile range between 0.032 and 0.906 TW. The tornado with the largest energy dissipation is the 2010 Tallulah-Yazoo City-Durant (LA/MS) tornado that resulted in 66.2 TW. The average energy dissipation of a casualty-producing tornado is 1.4 TW. This compares with 1.4 petawatts (PW) for the average energy dissipation of a category 1 hurricane [Emanuel, 1999].

Average energy dissipation increases by EF category (Table 1). The nine EF5 tornadoes have the highest average energy dissipation at 14.2 TW. The 54 EF4 tornadoes had the second highest average energy dissipation at 7.18 TW, followed by the 176 EF3 tornadoes at 2.50 TW. While EF5 tornadoes make about 1% (1.03%) of all tornadoes with at least one casualty, they account for 10.9% of total energy dissipation. Conversely, while EFO and EF1 tornadoes make up 37% of all tornadoes with at least one casualty, they account for only 2.95% of total energy dissipation.

2.5. Population and Energy Elasticity

Tornado casualties are statistically related to population and energy dissipation (energy) using the economic concept of elasticity. This is an efficient way to compare changes in casualties by focusing on the ratios of the percentage changes in population and energy to the percentage change in casualties. Elasticity has the advantage of being a dimensionless ratio that is independent of the type of quantities being varied. This simplifies the analysis. Parameter uncertainty on the elasticity is a by-product of the approach.

The number of casualties is related to the estimated population at risk and to the energy of the tornado. With no energy or no people the casualty count is zero. For the set of tornadoes with at least one casualty, the mean and variance of the counts are 14.9 and 5850, respectively, suggesting a negative binomial model for counts expressed as

$$C \sim \text{NegBin}(\hat{\mu}, n)$$
 (2)

$$\log(\hat{\mu}) = \hat{\alpha} \log(P) + \hat{\beta} \log(E) + \hat{\nu}$$
(3)

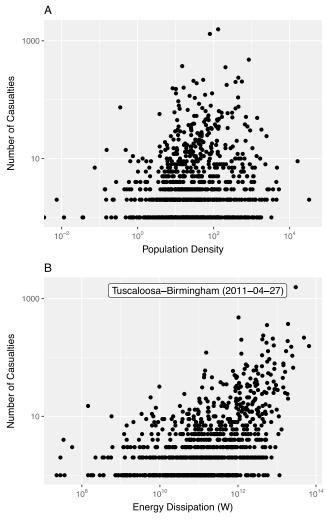


Figure 2. Casualties versus (a) population density and (b) energy dissipation.

where $NegBin(\hat{\mu}, n)$ indicates that the conditional casualty counts are described by negative binomial distributions with mean (rate) $\hat{\mu}$ and size n. The negative binomial distribution has been used in modeling tornado casualty counts [Simmons and Sutter, 2005] and is preferable to a normal distribution, which leads to nonnormal residuals. The logarithm of casualty rate (given at least one casualty) is linearly related to the logarithm of population density (P) and the logarithm of energy dissipation (E). The coefficient $\hat{\alpha}$ is the population elasticity, and the coefficient $\hat{\beta}$ is the energy elasticity, and \hat{v} is the intercept parameter. The population elasticity of tornado casualties measures the change in casualty potential in response to a change in population holding energy dissipation constant. A 1% increase in P leads to an α % increase in the rate of casualties. For $\hat{\alpha} > 1$ the population-casualty relationship is unbounded (elastic) and for $0 < \hat{\alpha} < 1$ the relationship is bounded (inelastic). To complete the model, a log-gamma prior is assigned to the logarithm of the size (n) and log-Gaussian priors are assigned to the elasticity parameters.

3. Results

3.1. Bivariate Relationships

The number of casualties increases with the number of estimated people in harm's way. On a log-log scale the points arrange in a tent shape (Figure 2) with the highest number of casualties occurring over the populated, but not the most populated, areas. The lack of mass casualties (exceeding 1000) for the most densely populated areas is a consequence of small sample size (luck) [Wurman et al., 2007], the fact that the more densely populated areas (the Northeast corridor) tend to be outside the main tornado regions of the Great Plains and

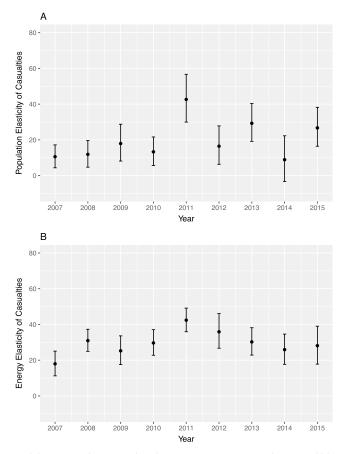


Figure 3. (a) Population and (b) energy elasticity values by year. Mean (points) and 95% credible intervals (vertical bars) are computed from the posterior density of the regression model coefficients using all tornadoes producing at least one casualty during the year.

the Southeast and the fact that the most densely populated areas generally coincide with higher incomes, leading to better adaptive capacity and resiliency [*Cutter et al.*, 2003].

The number of casualties also increases with energy dissipated (Figure 2). The point labeled in the upper right of the distribution is the 2011 Tuscaloosa-Birmingham (AL) tornado. Tornado casualties are limited by the amount of energy dissipated. With low-energy dissipation only relative few casualties tend to occur. In contrast with high-energy dissipation casualty counts can be high, low, and every number in between. Energy dissipation is a necessary but not sufficient cause of tornado casualties. High-energy tornadoes occurring in regions with relatively few people result in relatively few casualties. A bubble plot of the casualty counts jointly dependent on population density and energy dissipation conditional on EF rating is shown in Figure S3.

3.2. Regression Model

Application of Bayes rule using the method of Integrated Nested Laplace Approximation (INLA) [Rue et al., 2009, 2014] results in posterior densities for the regression model parameters. The correlation between the logarithm of the casualties and the modeled rates is 0.67 indicating a reasonably good fit of the model to the data. The coefficient on the population term is 0.272 [(0.232, 0.311), 95% credible interval (CI)] (Table S4). This indicates that a doubling of population (100% increases) increases the casualty rate by 21% (($2^{.272}-1$) × 100%). The coefficient on the energy term is 0.411 [(0.384, 0.438), 95% CI]. This indicates that a doubling of energy increases the casualty rate by 33%. As anticipated from the bivariate relationships, both population and energy are important in explaining casualty rates at the tornado level. The model shows that the energy elasticity of tornado casualties exceeds the population elasticity of tornado casualties on average.

The largest overprediction of the casualty rate by the model is the 2013 Weldon Spring-Northern St. Louis County (MO) EF3 tornado. Based on the estimated number of people in harm's way and the estimated energy dissipation, the model predicts upward of 75 casualties. Only eight were reported. The largest underprediction



by the model is the aforementioned Tuscaloosa-Birmingham (AL) tornado. Again, based on the number of people in harm's way and the energy dissipation, the model predicts 91 casualties. The official report has 1564 casualties. Removing these two tornadoes and refitting the model drop the population elasticity to 20% and the energy elasticity to 32% indicating that they are not overly influential to the fit. Removing all tornadoes during 2011 lowers the population elasticity to 17% and the energy elasticity to 28%, but no single year dominates the elasticity values although there is large year-to-year variation (Figure 3). Also, there are no large differences in elasticity values when length of study period, distance to nearest city, time of day, and past population densities are considered (Table S4).

More than 80% of the casualties during the study period occurred in tornadoes rated 3 or higher on the EF damage rating scale. These are the tornadoes that are on average longer and wider exposing more people to the damaging winds. Thus, we refit the model keeping only tornadoes with a damage rating EF3 or higher. The population elasticity increases to 38%, and the energy elasticity increases to 57% for this subset of the most damaging tornadoes in these data using this model. Considering only deaths over all EF ratings, the population elasticity is 12%, while the energy elasticity is 32%.

4. Discussion

How climate change will influence tornado activity remains an open and challenging question. Recent studies [Brooks et al., 2014; Elsner et al., 2015; Tippett et al., 2015] find upward trends in the interannual frequency variability and patterns of clustering over the past several decades. If the warming climate enhances hazardous convective weather, then it is important to understand how a change in tornado activity will affect the risk to human life. The goal of this study was to better understand the relationship between energy, population, and tornado casualties by establishing statistical estimates on how sensitive casualties are to changes in population and on how sensitive casualties are to changes in tornado strength.

The expanding bull's-eye effect is one reason used to describe a potential increase in future tornado casualties and losses due to an increase in population and a dispersal of the built environment. Another reason is potential changes in tornado energy. Here a multiplicative regression model quantifies these two effects (population and energy) in tandem. Results show that on average, a doubling of the population under the path of a tornado leads to a 21% increase in the casualty rate, while a doubling of the energy dissipated by the tornado leads to a 33% increase in the casualty rate. For the subset of the most damaging tornadoes, which cause more than 80% of all casualties, the energy elasticity is 19 percentage points higher than the population elasticity. Similarly, the tornado death rate is also more sensitive to changes in energy than to changes in population. Concerning future changes in casualties, while it is likely that population will continue to increase, with estimates as much as 30% over the current population by 2060 [Colby and Ortman, 2015], it is still uncertain as to whether or not tornado energy will increase.

The study is limited by the quality of the tornado reports, but there are no trends in the elasticity values over the 8 years considered. Random errors in path length and width are amplified by the definition of energy dissipation, which ultimately limits the amount of variance in per-tornado casualties explained by the model. This suggests that the model fit to the tornado records earlier than 2007 will result in somewhat lower values of elasticity. The influence of potential systematic errors are more difficult to anticipate. However, the large year-to-year variability suggests that such errors are not large relative to the natural variability associated with where and at what magnitude tornadoes occur in proximity to population centers. The influence on the results of assuming a straight line path (all researchers assume this with these data) is a topic for future research when more data on the path characteristics become available.

The model explains 45% of the variation in casualty counts as determined by the correlation between the predicted mean rate and the logarithm of the number of casualties. Additional factors not considered that could improve this fit include differences in the quality of the built environment and differences in social factors such as a willingness to take shelter and a sense of community across areas prone to tornadoes [Boruff et al., 2003; Ashley, 2007; Baker et al., 2007; Collins and Kapucu, 2008; Simmons and Sutter, 2008, 2009; Sutter and Simmons, 2009]. Adding these factors will require the model be fit to data locally and at various spatial resolutions. In this regard, spatial regression models can be used to highlight regional differences in population and energy elasticity values. These estimates are made at the tornado level. Results will likely be different at the level



of individuals. That is, for an individual exposed to a tornado the chance of getting hurt or killed might actually be lower for stronger tornadoes due to better warnings and preparedness. Lastly, using an exposure variable such as housing units [Strader et al., 2017] rather than population will likely lead to different results.

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References

Ashley, W. (2007), Spatial and temporal analysis of tornado fatalities in the United States: 1880 – 2005, Weather Forecasting, 22, 1214 – 1228. Ashley, W. A., A. J. Krmenec, and R. Schwantes (2008), Vulnerability due to nocturnal tornadoes, Weather Forecasting, 23, 795-807.

Ashley, W. S., and S. M. Strader (2016), Recipe for disaster: How the dynamic ingredients of risk and exposure are changing the tornado disaster landscape, Bull. Am. Meteorol. Soc., 97, 767-786.

Ashley, W. S., S. Strader, T. Rosencrants, and A. J. Krmenec (2014), Spatiotemporal changes in tornado hazard exposure: The case of the expanding bull's-eye effect in Chicago, Illinois, Weather Clim. Soc., 6(2), 175-193, doi:10.1175/wcas-d-13-00047.1.

Baker, S. M., D. M. Hunt, and T. L. Rittenburg (2007), Consumer vulnerability as a shared experience: Tornado recovery process in Wright, Wyoming, J. Public Policy Mark., 26(1), 6–19, doi:10.1509/jppm.26.1.6.

Bohonos, J. J., and D. E. Hogan (1999), The medical impact of tornadoes in North America, J. Emergency Med., 17(1), 67 - 73.

Boruff, B., J. Easoz, S. Jones, H. Landry, J. Mitchem, and S. Cutter (2003), Tornado hazards in the United States, Clim. Res., 24, 103 – 117,

Brooks, H. E. (2004), On the relationship of tornado path length and width to intensity, Weather Forecasting, 19, 310-319.

Brooks, H. E. (2013), Severe thunderstorms and climate change, Atmos. Res., 123, 129-138.

Brooks, H. E., G. W. Carbin, and P. T. Marsh (2014), Increased variability of tornado occurrence in the United States, Science, 346(6207), 349-352, doi:10.1126/science.1257460.

Brown, S., P. Archer, E. Kruger, and S. Mallonee (2002), Tornado-related deaths and injuries in Oklahoma due to the 3 May 1999 tornadoes, Weather Forecasting, 17, 343-353.

Carter, A. O., M. E. Millson, and D. E. Allen (1989), Epidemiologic study of deaths and injuries due to tornadoes, Am. J. Epidemiol., 130(6),

Chiu, C. H., A. H. Schnall, C. E. Mertzlufft, R. S. Noe, A. F. Wolkin, J. Spears, M. Casey-Lockyer, and S. J. Vagi (2013), Mortality from a tornado outbreak, Alabama, April 27, 2011, Am. J. Public Health, 103(8), e52 – e58, doi:10.2105/aiph.2013.301291.

Colby, S. L., and J. M. Ortman, (2015), Projections of the size and composition of the US population: 2014 to 2060, Tech. Rep., United States Census Bureau, Washington, D. C.

Coleman, T. A., and P. G. Dixon (2014), An objective analysis of tornado risk in the United States, Weather Forecasting, 29(2), 366-376. Collins, M. L., and N. Kapucu (2008), Early warning systems and disaster preparedness and response in local government, Disaster Prev. Manage. Int. J., 17(5), 587-600, doi:10.1108/09653560810918621.

Cutter, S. L., B. J. Boruff, and W. L. Shirley (2003), Social vulnerability to environmental hazards, Soc. Sci. Q., 84(2), 242-261, doi:10.1111/1540-6237.8402002.

Diffenbaugh, N. S., R. J. Trapp, and H. Brooks (2008), Does global warming influence tornado activity, Eos Trans. AGU, 89(53), 553 – 560. Diffenbaugh, N. S., M. Scherer, and R. J. Trapp (2013). Robust increases in severe thunderstorm environments in response to greenhouse forcing, Proc. Natl. Acad. Sci. U.S.A., 110, 16361-16366, doi:10.1073/pnas.1307758110.

Dixon, P. G., A. E. Mercer, J. Choi, and J. S. Allen (2011), Tornado risk analysis: Is Dixie Alley an extension of tornado alley?, Bull. Am. Meteorol. Soc., 92, 433-441.

Doswell, C. A., A. R. Moller, and H. E. Brooks (1999), Storm spotting and public awareness since the first tornado forecasts of 1948, Weather Forecasting, 14, 544-557.

Doswell, C. A., H. E. Brooks, and N. Dotzek (2009), On the implementation of the enhanced Fujita scale in the USA, Atmos. Res., 93, 554-563. Elsner, J. B., R. J. Murnane, T. H. Jagger, and H. M. Widen (2013), A spatial point process model for violent tornado occurrence in the U.S. Great Plains, Math. Geosci., 45, 667-679.

Elsner, J. B., T. H. Jagger, H. M. Widen, and D. R. Chavas (2014a), Daily tornado frequency distributions in the United States, Environ. Res. Lett., 9(2), 024018.

Elsner, J. B., T. H. Jagger, and I. J. Elsner (2014b), Tornado intensity estimated from damage path dimensions, PLoS One, 9(9), e107571.

Elsner, J. B., S. C. Elsner, and T. H. Jagger (2015), The increasing efficiency of tornado days in the United States, Clim. Dyn., 45(3-4), 651-659. Emanuel, K. (2005), Increasing destructiveness of tropical cyclones over the past 30 years, Nature, 436, 686 – 688.

Emanuel, K. A. (1999), The power of a hurricane: An example of reckless driving on the information superhighway, Weather, 54(4), 107 - 108, doi:10.1002/j.1477-8696.1999.tb06435.x.

Fricker, T., and J. B. Elsner (2015), Kinetic energy of tornadoes in the United States, PLoS One, 10, e0131090.

Fricker, T., J. B. Elsner, P. Camp, and T. H. Jagger (2014), Empirical estimates of kinetic energy from some recent U.S. tornadoes, Geophys. Res. Lett., 41, 4340-4346, doi:10.1002/2014GL060441.

Grazulis, T. P. (1990), Significant Tornadoes, 1880 – 1989: Discussion and Analysis, Significant Tornadoes, 1880 – 1989, Environmental Films, St. Johnsbury, Vermont.

Greenough, G., M. McGeehin, S. M. Bernard, J. Trtanj, J. Riad, and D. Engelbert (2001), The potential impacts of climate variability and change on health impacts of extreme weather events in the United States, Environ, Health Perspect., 109, 191 – 198.

National Oceanic and Atmospheric Administration (2015), National Weather Service Weather Fatality, Injury, and Damage Statistics, Natl. Weather Ser., Silver Spring, Md.

R Core Team (2016), R: A Language and Environment for Statistical Computing, R Found. for Stat. Comput., Vienna, Austria.

Ramsdell, J. V., Jr., and J. P. Rishel, (2007), Tornado climatology of the contiguous United States, Tech. Rep. NUREG/CR-4461, PNNL-15112, Pac. Northwest Natl. Lab., Richland, Wash.

Rue, H., S. Martino, and N. Chopin (2009), Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations, J. R. Stat. Soc., Ser. B. 71, 319-392.

Rue, H., S. Martino, F. Lindgren, D. Simpson, A. Riebler, and E. T. Krainski (2014), INLA: Functions which allow to perform full Bayesian analysis of latent Gaussian models using Integrated Nested Laplace Approximation, R package version 0.0-1417182342.

Schielicke, L., and P. Névir (2011), Introduction of an atmospheric moment combining Eulerian and Lagrangian aspects of vortices: Application to tornadoes, Atmos. Res., 100(4), 357-365, doi:10.1016/j.atmosres.2010.08.027.

Simmons, K. M., and D. Sutter (2005), WSR-88D radar, tornado warnings, and tornado casualties, Weather Forecasting, 20(3), 301 – 310, doi:10.1175/waf857.1.



- Simmons, K. M., and D. Sutter (2008), Tornado warnings, lead times, and tornado casualties: An empirical investigation, Weather Forecasting, 23(2), 246-258, doi:10.1175/2007waf2006027.1.
- Simmons, K. M., and D. Sutter (2009), False alarms, tornado warnings, and tornado casualties, Weather Clim. Soc., 1(1), 38-53, doi:10.1175/2009wcas1005.1.
- Simmons, K. M., and D. Sutter (2011), Economic and Societal Impacts of Tornadoes, 282 pp., Am. Meteorol. Soc., Boston, Mass.
- Strader, S. M., W. Ashley, A. Irizarry, and S. Hall (2014), A climatology of tornado intensity assessments, Meteorol. Appl., 22(3), 513-524, doi:10.1002/met.1482.
- Strader, S. M., W. S. Ashley, T. J. Pingel, and A. J. Krmenec (2017), Projected 21st century changes in tornado exposure, risk, and disaster potential, Clim. Change, 141(2), 301-313, doi:10.1007/s10584-017-1905-4.
- Sutter, D., and K. M. Simmons (2009), Tornado fatalities and mobile homes in the United States, Nat. Hazards, 53(1), 125-137,
- Tippett, M. K., and J. E. Cohen (2016), Tornado outbreak variability follows Taylor's power law of fluctuation scaling and increases dramatically with severity, Nat. Commun., 7(10), 668, doi:10.1038/ncomms10668.
- Tippett, M. K., A. H. Sobel, S. J. Camargo, and J. T. Allen (2014), An empirical relation between U.S. tornado activity and monthly environmental parameters, J. Clim., 27, 2983-2999.
- Tippett, M. K., J. T. Allen, V. A. Gensini, and H. E. Brooks (2015), Climate and hazardous convective weather, Curr. Clim. Change Rep., 1(2), 60-73, doi:10.1007/s40641-015-0006-6.
- Verbout, S. M., H. E. Brooks, L. M. Leslie, and D. M. Schultz (2006), Evolution of the U.S. tornado database: 1954-2003, Weather Forecasting, 21, 86-93.
- Wurman, J., P. Robinson, C. Alexander, and Y. Richardson (2007), Low-level winds in tornadoes and potential catastrophic tornado impacts in urban areas, Bull. Am. Meteorol. Soc., 88(1), 31-46, doi:10.1175/bams-88-1-31.