Unusually Devastating Tornadoes in the United States: 1995–2016

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Previous research has identified a number of physical, socioeconomic, and demographic factors related to tornado casualty rates. There remain gaps in our understanding of community-level vulnerabilities to tornadoes. Here a framework is provided for systematically identifying the most unusually devastating tornadoes, defined as those where the observed number of casualties far exceeds the predicted number. Results show that unusually devastating tornadoes occur anywhere tornadoes occur in the United States, but rural areas across the Southeast appear to be most frequented. Seven examples of unusually devastating tornadoes affecting six communities are examined in more detail. In addition, results highlight that cities and towns affected by unusually devastating tornadoes have their own socioeconomic and demographic profiles. Identifying geographic clusters of unusually devastating tornadoes builds a foundation to address community-level causes of destruction that supports ethnographic and qualitative—in addition to quantitative—studies of place-based vulnerability. *Key Words: statistics, tornado, vulnerability.*

过往的研究已指认与龙捲风死伤率有关的诸多环境、社会经济与人口因素，但我们对社区层级之于龙捲风的脆弱性之理解仍有缺口。本文提供一个架构，系统性地指认破坏力极不寻常的龙捲风，并定义为观测到的死亡数远远超过预测数的案例。研究结果显示，破坏力极不寻常的龙捲风，在美国任何遭遇龙捲风之处皆会发生，但东南方的乡村地区似乎最频繁。本研究仔细检视影响六座社区的七个破坏力极不寻常之龙捲风案例。此外，研究结果强调，受到破坏力极不寻常的龙捲风所影响的城市与乡镇，具有自身的社会经济和人口特徵剖析。指认破坏力极不寻常的龙捲风之地理集群，建立了应对社区层级破坏导因的基础，该基础在量化研究之外，支持根据地方的脆弱性之民族志与质性研究。*关键词：统计，龙捲风，脆弱性。*

En investigaciones anteriores, se han identificado un número de factores físicos, socioeconómicos y demográficos relacionados con las tasas de víctimas causadas por tornados. Subsisten vacíos en nuestro entendimiento de las vulnerabilidades frente a los tornados a nivel de comunidad. Aquí suministramos un marco para identificar sistemáticamente los tornados devastadores más atípicos, que se definen como aquellos donde el número observado de víctimas excede ampliamente el número pronosticado. Los resultados muestran que tornados devastadores pueden ocurrir en cualquier parte donde se presenta este fenómeno extremo en los Estados Unidos, aunque las áreas rurales a través del Sudeste parecen ser las más frecuentadas. Se examinaron con mayores detalles varios ejemplos de tornados devastadores atípicos que afectaron a seis comunidades. Además, los resultados destacan que las ciudades y pueblos afectados por tornados devastadores extraordinarios tienen sus propios perfiles socioeconómicos y demográficos. Identificar agrupamientos geográficos de tornados devastadores extraordinarios construye la base para abocar causas de destrucción a nivel de comunidad que le de soporte a estudios etnográficos y cualitativos—además de cuantitativos—de vulnerabilidad basada en lugar. *Palabras clave: estadística, tornado, vulnerabilidad.*

Tornadoes are one of the deadliest weather-related hazards in the United States. Wind energy and population density statistically explain a large portion of tornado casualty rates (Ashley et al. 2014; Ashley and Strader 2016; Fricker, Elsner, and Jagger 2017; Elsner, Fricker, and Berry 2018), but socioeconomic and demographic factors also play a role (Bohonos and Hogan 1999; Mitchem 2003; Simmons and Sutter 2005, 2008, 2009; Ashley 2007; Donner 2007; R. W. Dixon and Moore 2012; Donner, Rodriguez, and Diaz 2012; Lim et al. 2017; Strader and Ashley 2018). For example, Simmons and Sutter (2005, 2008, 2009) found that casualties increase with an increase in the percentage of mobile homes in an area affected. Other known factors include time of day (Simmons and Sutter 2005, 2008, 2009; Ashley, Krmenec, and Schwantes 2008) and day of

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occurrence (workday or weekend; Zahran, Tavani, and Weiler 2013).

Identifying the physical, socioeconomic, and demographic factors related to tornado casualty rates is critical for understanding human vulnerability to these potentially devastating events. There remains a gap, however, in our knowledge around why some communities are particularly vulnerable to tornadoes. For example, why was the Spencer, South Dakota, tornado of 30 May 1998 that resulted in six deaths and 150 injuries—nearly half of the town's population—so impactful?

In an effort to fill this knowledge gap, in this article a framework is provided for systematically identifying the most unusually devastating tornadoes. We begin by defining unusually devastating tornadoes. This is done with the help of a statistical model for predicting per tornado casualty rates. Next, the set of unusually devastating tornadoes since 1995 is identified by examining the difference between what is predicted from the statistical model and what was observed on the ground. More specifically, after statistically conditioning on the known physical and socioeconomic determinants of casualties, we identify what tornadoes were unusual in producing more casualties than expected based on where they hit. Our interest—for this work—is in tornadoes that caused far more casualties than expected rather than in tornadoes that caused far fewer casualties than expected. In addition, we discuss examples of locations that were hit with unusually devastating tornadoes and synthesize the community profiles of these places.

Factors Related to the Number of Casualties

Tornadoes kill and injure nearly 1,000 people, on average, in the United States each year. Previous research has identified physical factors that affect the rate of tornado casualties. These include the maximum damage rating (Fujita/Enhanced Fujita [F/EF] scale), the tornado damage path length, and the strength, or energy dissipation, of the tornado. For example, Ashley (2007) found that tornadoes categorized with a high maximum damage rating (F scale) produce the vast majority of tornado fatalities, and Fricker, Elsner, Mesev, and Jagger (2017) showed that tornadoes with a high maximum damage rating (EF scale) represent a disproportionate number of casualty-producing tornadoes relative to the total number of tornadoes. In addition, Simmons and Sutter (2005, 2008, 2009) and Lim et al. (2017) found that as tornado damage path length increases, so does the number of tornado casualties. Quantitatively, Fricker, Elsner, and Jagger (2017) noted that a doubling of tornado strength, represented as an estimate of energy dissipation, leads to a 33 percent increase in the rate of tornado casualties.

Previous research has also identified a number of socioeconomic and demographic factors that affect the rate of tornado casualties. These include the number of people in harm's way, the type of housing stock present (permanent or mobile), and the age and income of the population within the damage path. For instance, Simmons and Sutter (2008, 2009) and Fricker, Elsner, and Jagger (2017) found that the number of tornado casualties increases with population density. Similarly, Simmons and Sutter (2005, 2008, 2009) found that the number of tornado casualties increases with the percentage of mobile homes within an area. This result is further supported by Ashley (2007) and Strader and Ashley (2018), who noted that more than half of all housing-related tornado fatalities between 1985 and 2017 occurred in mobile homes. Bohonos and Hogan (1999) posited that the number of tornado casualties might increase with age due to the elderly being less likely to receive warning and being less mobile and more likely to have health issues (Kilijanek and Drabek 1979; Bolin and Klenow 1983; Cutter, Mitchell, and Scott 2000; R. W. Dixon and Moore 2012).

Additional factors such as race, poverty, education, and sex of household head have been linked to the rate of tornado casualties as well. Donner (2007) hypothesized that African Americans are likely more vulnerable to tornado casualties, in part because they might have more difficulty understanding warning messages (Mitchem 2003). Lim et al. (2017) found that wealthier communities experience fewer tornado casualties and that female-headed households are more vulnerable to tornado casualties than two-parent households or male-headed households, both of which are consistent with previous natural hazard research (Bosworth 1999; Anbarci, Escaleras, and Register 2005; Kahn 2005; Enarson, Fothergill, and Peek 2007).

Multiple regression models are used to determine what factors are important in statistically explaining casualties and to quantify the effect that a single factor has on casualties while conditioning on the other factors. For example, using county-level socioeconomic and demographic data with a straight-line model for the tornado footprint, Simmons and Sutter (2014) predicted per tornado fatalities of events during the active 2011 season. Masoomi and van de Lindt (2018) used a more detailed footprint model to produce tornado-level estimates of population and housing units from census block–level data and improve on the predictive skill of Simmons and Sutter (2014) using the maximum damage rating, path length, and number of people within the damage path as fixed effects. Fricker, Elsner, and Jagger (2017) used a similarly detailed model for the tornado footprint and produced tornado-level estimates of energy dissipation and population with a dasymetric approach on grid-level data. They found that the rate of tornado casualties increases with population and energy dissipation and labeled the regression coefficients the population and energy elasticity, respectively. More recently, Elsner, Fricker, and Berry (2018) improved on the Fricker, Elsner, and Jagger (2017) model by including an interaction between energy dissipation and population density. They found that the energy elasticity increases significantly with population density and that the population elasticity increases significantly with energy dissipation.

Unusually Devastating Tornadoes

Definition

Knowing the physical, demographic, and environmental factors that influence casualty rates provides guidance on how to communicate the risk across a broad segment of society. For example, the regression model of Elsner, Fricker, and Berry (2018) predicts a casualty rate of twenty people (per casualty-producing tornado) for a 100- GW tornado affecting an area with a population density of 1,500 people per square kilometer. This predicted rate represents the average, or expected, count given specific values for the factors without regard to where the tornado occurs. Local, place-based factors are also important, however, in mitigating or amplifying casualty rates. To locate places where local factors might be particularly important, we examine the residuals from a regression model and define an unusually devastating tornado (UDT) as one where the observed number of casualties substantially exceeds the predicted rate.

More formally, let C_T be the observed casualty count for tornado T and $\hat{C}_T$ be the predicted casualty rate for the same tornado from a regression model f involving known tornado-level factors $\mathbf{X}_T$ (e.g., population density, energy dissipation, number of mobile homes, etc.). We then define a UDT as one in which the difference between C_T and $\hat{C}_T$ exceeds some large value (L) (see Equation 1).

$$UDT_T = C_T - \hat{C}_T > L \quad (1a)$$

$$\hat{C}_T \sim f(\mathbf{X}_T). \quad (1b)$$

In what follows, we fit a regression model to the casualty counts and examine the differences between what the model predicts and what actually occurred. Again, we are particularly interested in where the tornadoes occurred that resulted in a large difference between the observed count and the predicted count.

Model and Data

We fit a log-linear regression model to the casualty count of all casualty-producing tornadoes occurring in the United States between 1995 and 2016. The model is described in detail in Elsner, Fricker, and Berry (2018) and includes energy dissipation and population density as the two most important factors that statistically explain casualties. Energy dissipation (power) in units of watts is defined as the product of path area, air density, and the weighted sum of the velocity cubed. The summation is over the six possible damage ratings and the weights are the fractions of path area by damage rating. Velocities are set as the midpoint wind speed defined by the EF scale (Fricker et al. 2014; Fricker and Elsner 2015; Fricker, Elsner, and Jagger 2017; Elsner, Fricker, and Berry 2018). Population density is the number of people per square kilometer within the damage path of the tornado.

Here the model of Elsner, Fricker, and Berry (2018) is expanded to include the number of mobile homes within the path and the year of occurrence as additional fixed effects and month and hour of occurrence as random effects. Month and hour of occurrence are included as random effects to capture the cyclic change in energy at these respective time scales (Figure 1). The coefficients on month and hour of occurrence are elements of vectors of length

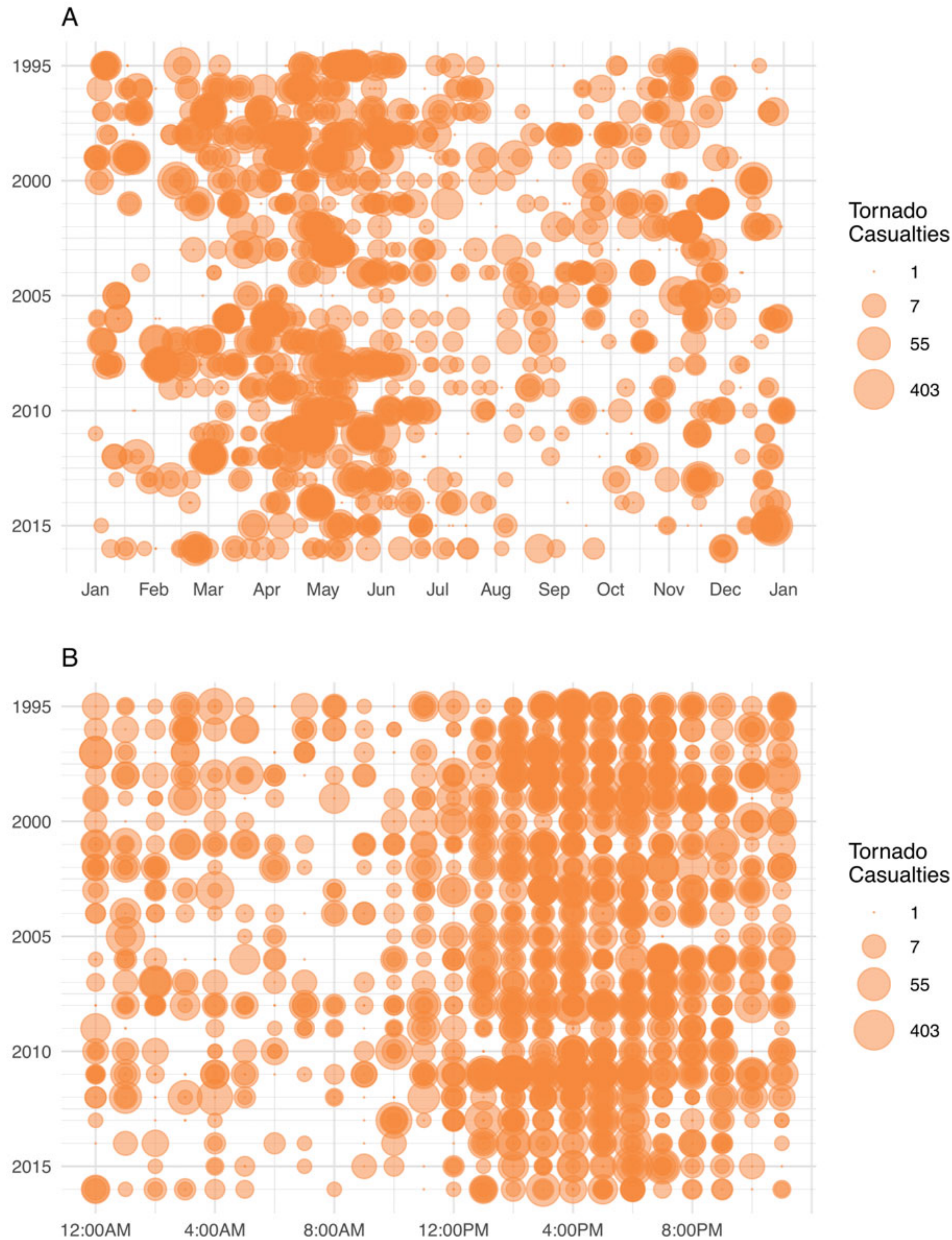

Figure 1. The number of tornado casualties by (A) month and (B) hour. The size of the circle is proportional to the number of casualties.

12 and 24, respectively. The number of mobile homes is estimated using a dasymetric method similar to the procedure used in Fricker, Elsner, Mesev, and Jagger (2017), where weighted estimates of mobile homes are made for each fraction of the tornado path and summed for the entire tornado path.

Formally, the model is given by

$$\begin{aligned}\ln(\mathrm{C}) = {} & \ln(\beta_0) + \beta_P \ln(\mathrm{P}) + \beta_E \ln(\mathrm{E}) \\ & + \beta_{P\ x\ E}\left[\ln(\mathrm{P})\ \times\ \ln(\mathrm{E})\right] + \beta_Y \mathrm{Y} \\ & + \beta_{MH}\mathrm{MH} + \beta_{MO}(1|\mathrm{MO}) + \beta_{HR}(1|\mathrm{HR}),\end{aligned} \tag{2}$$

where P is the population density in people per square kilometer, E is energy dissipation in watts, Y is the year of occurrence, MH is the estimated number of mobile homes, and MO and HR are the month and hour of occurrence, respectively.

Our modeling approach is similar to that of recent work that examines factors related to tornado casualties (Donner 2007; Simmons and Sutter 2008, 2011; Zahran, Tavani, and Weiler 2013; Lim et al. 2017). Here, though, we use tornado power (energy dissipation) rather than EF rating or total damage as an indicator of tornado strength and we focus on factors influencing the casualty rate among those tornadoes producing at least one casualty. In addition, we include a multiplicative term, which creates a statistical interaction between environmental (tornado power) and demographic (population density) factors and implies that the tornado casualty rate is related to values of tornado power and population density conditional on one another.

Tornado report information is from the Storm Prediction Center's (SPC) historical tornado database, which is compiled from the National Weather Service (NWS) Storm Data and reviewed by the National Centers for Environmental Information (NCEI; Verbout et al. 2006). The start year for this study coincides with the period of record where maximum path width was adopted by NWS. The end year for this study is the most currently available to us at the time of analysis. A casualty is defined by the NWS as a direct injury or fatality directly attributable to the tornado event itself. Population and mobile home data are obtained from the U.S. Census Bureau and American Community Survey (ACS), which is a nationwide survey that collects and produces information on demographic, social, economic, and housing characteristics each year. Population and mobile home estimates are made at the tract level.

The Pearson correlation coefficient between the observed count and predicted rate of casualties for all casualty-producing tornadoes in the study is 0.5, indicating a moderately good relationship. When a subset of the largest casualty-producing tornadoes—tornadoes causing twenty-five or more casualties—is considered, the relationship strengthens to 0.63 (Figure 2). These correlation coefficients are higher than the relationships between observed counts and predicted rates from other tornado casualty models (Simmons and Sutter 2014; Lim et al. 2017; Masoomi and van de Lindt 2018). Note that the model predicts a casualty rate (not a count), so the highest possible correlation will be less than one. Therefore, we are confident that the model is adequate for identifying UDTs.

Where UDTs Occur

For the set of casualty-producing tornadoes (2,198 tornadoes) over the period, the model underpredicted the observed count for 491 tornadoes. Of these 491, 101 were underpredicted by ten or more casualties and 43 (90th percentile) were underpredicted by twenty-two or more casualties. A tornado that results in an underprediction at the 90th percentile is defined here as a UDT. For example, given the storm's power and the demographic profile in its path, the 26 December 2015 Garland–Rowlett, Texas, tornado has an expected casualty rate of 81. The tornado produced 478 casualties, which is a difference of 397 casualties. Nine of the top ten UTDs ranked by the difference in predicted and observed casualty rates resulted in more than 100 casualties (Table 1). The Joplin, Missouri, tornado of 22 May 2011 stands out as the most UDT. Given estimates of physical and socioeconomic factors, the model predicts a casualty rate of 131 people, but the tornado produced 1,308 casualties—a difference of 1,177 casualties. The choice of the 90th percentile for defining a UDT is arbitrary, but it focuses our attention to the most destructive tornadoes.

UDTs can occur anywhere in the United States where a tornado affects a populated area (Figure 3). Rural areas across the Southeast, however, appear to be where we find more UDTs. Six of the top ten UDTs ranked by the difference in predicted and observed casualty rates occurred in the Southeast (Arkansas, Alabama, Georgia, Mississippi, and North Carolina). Two of the top ten occurred in Texas, and one of the top ten occurred in both Missouri and South Dakota. It is likely that the disproportionate distribution of UDTs across portions of the rural Southeast is driven by a combination of physical and social vulnerabilities, including an increased risk of significant and long-track tornadoes (P. G. Dixon

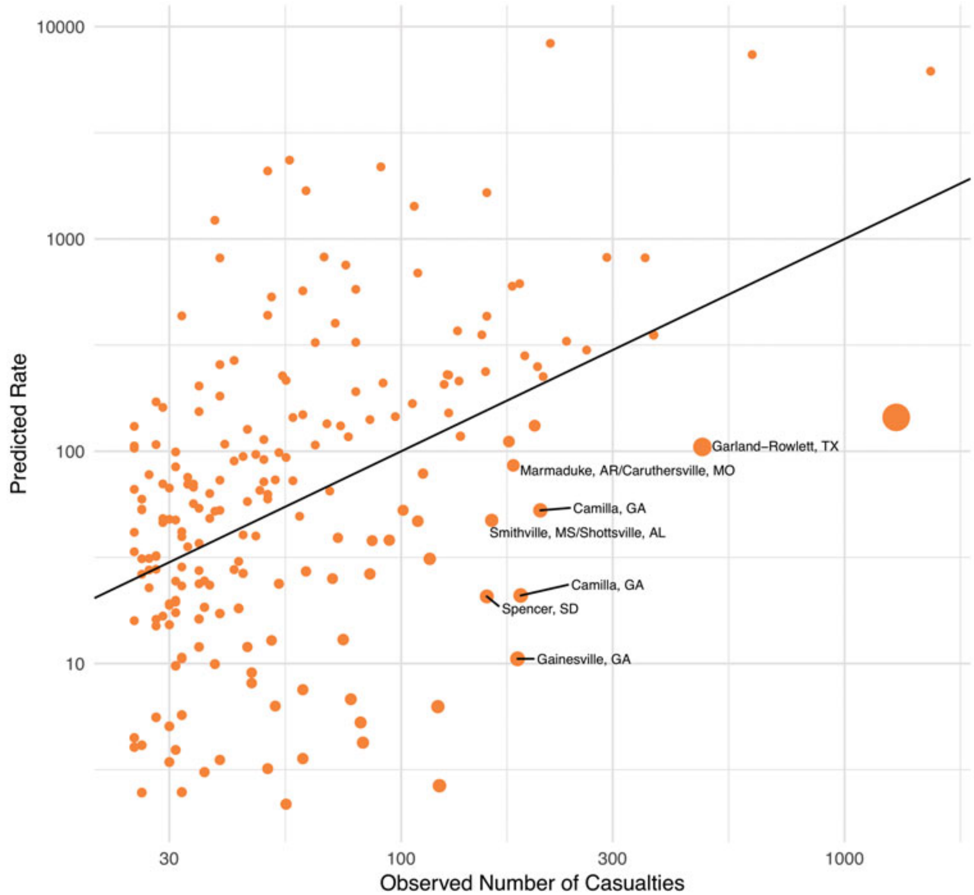

Figure 2. Predicted casualty rate versus observed casualty count. Points are shown only for tornadoes with at least twenty-five casualties. Values below the black line indicate tornadoes with more casualties than predicted using the regression model and the size of the circle is proportional to the number of underpredicted casualties.

Table 1. Top ten unusually devastating tornadoes ranked by the difference in predicted and observed casualty rates

Location	Date (Day-Month-Year)	Observed	Predicted	Difference (observed – predicted)
Joplin, MO	22-05-2011	1,308	131	1,177
Garland–Rowlett, TX	26-12-2015	478	81	397
Gainesville, GA	20-03-1998	183	10	173
Camilla, GA	13-02-2000	186	20	166
Camilla, GA	20-03-2003	206	46	160
Spencer, SD	30-05-1998	156	22	134
Smithville, MS/Shottsville, AL	27-04-2011	160	41	119
Columbus County, NC	07-11-1995	122	3	119
Copeville, TX	26-12-2015	121	6	115
Marmaduke, AR/Caruthersville, MO	02-04-2006	179	90	89

et al. 2011; Coleman and Dixon 2014), as well as higher percentages of persons and households that are black (or minority), unemployed, in poverty, on disability, part of the Supplemental Nutrition Assistance Program, or headed by a single female (Cutter, Boruff, and Shirley 2003; Emrich and Cutter 2011; Strader and Ashley 2018).

Examples of UDTs

Highlighting examples of UDTs underscores the fact that they can occur anywhere in the United States. Here seven examples of UDTs affecting six communities are investigated: (1) the 1998 Spencer, South Dakota, tornado; (2) the 2015 Garland–Rowlett,

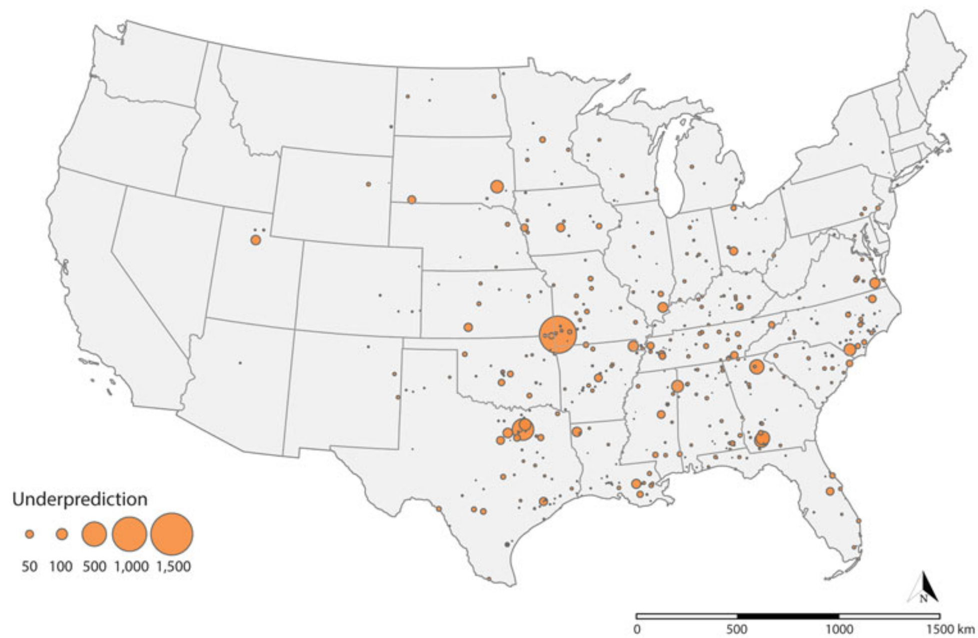

Figure 3. Unusually devastating tornadoes. The size of the circle is proportional to the number of underpredicted casualties.

Texas, tornado; (3) the 2000 and 2003 Camilla, Georgia, tornadoes; (4) the 2011 Smithville, Mississippi/Shottsville, Alabama, tornado; (5) the 1998 Gainesville, Georgia, tornado; and (6) the 2006 Marmaduke, Arkansas/Caruthersville, Missouri, tornado. The examples were chosen to provide a wide spatial distribution of affected communities. The cities range from a small rural town in the northern Great Plains, to small cities and towns in the Southeast, to midsize urban and suburban cities in the southern Great Plains. These cities have their own individual socioeconomic and demographic profiles, yet all were hit by tornadoes that caused more casualties than expected given a model for tornado casualties. The purpose of highlighting these examples is to bring attention to the complexity and potential uniqueness of each case of a UDT. It is not to find the specific reason or set of reasons for the high rate of tornado casualties—because there might never be an easily identifiable reason or set of reasons for high casualty rates.

Spencer, South Dakota

Spencer is a rural town in southeast South Dakota (Figure 4). As of the 2010 Census, Spencer had a population of 154 people, including sixty households and forty-seven families. The age structure of the city is 30 percent under the age of eighteen, 2 percent from eighteen to twenty-four, 19 percent from twenty-five to forty-four, 25 percent from forty-five to sixty-four, and 24 percent over the age of sixty-five years. The racial makeup of the city is 97 percent white and 1 percent African American. About 7 percent of families and 11 percent of the total population are below the poverty line. The median household income in the city is $21,250 and 7 percent of families and 11 percent of the total population are below the poverty line.

Spencer was hit by a violent tornado (EF4) on 30 May 1998. The tornado killed six people and injured more than one third of the city's residents. It also destroyed most of the 190 buildings in town and resulted in $18 million in property damage. The tornado was part of a supercell thunderstorm that produced five tornadoes during a one-hour period.

The 1998 Spencer, South Dakota, storm started at approximately 7:35 p.m. Eastern Standard Time (EST) southwest of Wessington Springs, South Dakota—about sixty miles west-northwest of Spencer. The storm almost immediately split into left and right moving cells with the right moving cell becoming a midlevel mesocyclone at 9:26 p.m. EST. By 9:28 p.m. EST, Sioux Falls radar (WSR-88D) had indicated a hook echo and well-defined rotation. From 9:23 p.m. to 9:37 p.m. EST, the Spencer tornado tracked through farmland, within one mile of the town of Farmer, before striking the town of Spencer. The city of Spencer experienced violent tornado conditions from 9:38 p.m. to 9:39 p.m. EST, before the storm dissipated at 10:10 p.m. EST.

Figure 4. Spencer, South Dakota; Garland–Rowlett, Texas; Camilla, Georgia; Smithville, Mississippi/Shottsville, Alabama; Gainesville, Georgia; and Marmaduke, Arkansas/Caruthersville, Missouri. The orange circle indicates the location of the city or town and the size of the circle is proportional to the number of underpredicted casualties (see Figure 3).

Garland–Rowlett, Texas

Garland and Rowlett are two midsize cities in the Dallas–Fort Worth metroplex in north Texas (Figure 4). As of the 2010 Census, Garland had a population of 226,876 people, including 75,696 households and 56,272 families. The age structure of the city is 29 percent under the age of eighteen, 10 percent from eighteen to twenty-four, 28 percent from twenty-five to forty-four, 25 percent from forty-five to sixty-four, and 9 percent over the age of sixty-five. The racial makeup of the city is 58 percent white, 15 percent African American, and 9 percent Asian. The median household income in the city is $52,441, and 11 percent of families and 14 percent of the total population are below the poverty line.

As of the 2010 Census, Rowlett had a population of 56,310 people, including 22,875 households and 17,275 families. The age structure of the city is 34 percent under the age of eighteen, 6 percent from eighteen to twenty-four, 37 percent from twenty-five to forty-four, 19 percent from forty-five to sixty-four, and 5 percent over the age of sixty-five. The racial makeup of the city is 78 percent white, 9 percent African American, and 4 percent Asian. The median household income in the city is $100,872, and only 2 percent of families and 3 percent of the total population are below the poverty line.

Garland and Rowlett were hit by a violent tornado (EF4) on 26 December 2015. The tornado killed ten and injured more than 400 people, while producing $26 million in property damage. It was part of the north Texas tornado outbreak of 26 December 2015 that produced twelve tornadoes, causing thirteen fatalities across eight north and central Texas counties.

The 2015 Garland–Rowlett, Texas, tornadic storm formed near Hillsboro around 7:00 p.m. EST. The storm strengthened as it moved north-northeast through Waxahachie at 7:45 p.m. EST, spawning two tornadoes just south of Dallas. As the storm moved north of Dallas, it again became tornadic near Sunnyvale passing through the cities of Garland and Rowlett between 8:46 p.m. and 9:02 p.m. EST, before dissipating around McKinney at 9:30 p.m. EST.

Camilla, Georgia

Camilla is a small city in southwest Georgia (Figure 4). As of the 2010 Census, Camilla had a population of 5,360. The age structure of Camilla is

30 percent under the age of eighteen, 11 percent from eighteen to twenty-four, 27 percent from twenty-five to forty-four, 19 percent from forty-five to sixty-four, and 13 percent over the age of sixty-five. The racial makeup of the town is 70 percent African American and 25 percent white. The median household income in the town is $22,485, and 35 percent of families and 38 percent of the total population are below the poverty line.

Camilla was hit by two significant tornadoes in the early 2000s, both occurring in the early morning and both traveling through the southeast side of town. The first tornado (EF3) occurred on 13 February 2000 and resulted in 186 casualties. According to the American Red Cross (ARC) and Federal Emergency Management Agency (FEMA), 200 homes were destroyed and 250 homes were damaged, resulting in $20 million in property damage. The second tornado (EF3) occurred on 20 March 2003 and resulted in 206 casualties. It took a similar path to the 2000 tornado and according to the ARC and FEMA destroyed sixty-six homes while damaging another 200.

The 2000 Camilla, Georgia, tornado was part of the larger southwest Georgia tornado outbreak of 13 and 14 February 2000. Beginning Sunday evening, and continuing into the early morning hours of Monday, the NWS Tallahassee issued fifty-two severe weather warnings, including twenty-five tornado warnings. During the outbreak, three deadly tornadoes caused nineteen fatalities across three Georgia counties.

The 2000 Camilla tornadic storm came ashore in extreme southeast Walton County, Florida, at around 8:30 p.m. EST. The storm weakened as it crossed Lake Seminole, the dividing line between Florida, Alabama, and Georgia, around 11:00 p.m. EST, before strengthening near the boundary of Seminole County, Georgia. The storm became tornadic around 11:42 p.m. near Branchville, remaining tornadic as it passed just south of Camilla before dissipating east-northeast of the city around 12:05 a.m. EST.

The 2003 Camilla, Georgia, tornado was part of the larger 20 March 2003 outbreak in northern Florida and southwestern Georgia, which included two deadly tornadoes. These two tornadoes caused six fatalities, hundreds of injuries, and a path of destruction that extended from the Florida Panhandle coast all the way into central Georgia.

The 2003 Camilla tornadic storm initially came ashore in extreme southwest Bay County, Florida, at approximately 2:30 a.m. EST. The cell rapidly developed circulation and might have become tornadic in the northern part of the county. The storm destroyed a home in Fountain, Florida, around 3:07 a.m. EST before continuing across the northeastern Florida Panhandle into Jackson County, Florida, where the first confirmed tornado occurred. The parent storm again became tornadic as it crossed into Mitchell County, affecting the city of Camilla at around 5:12 a.m. EST, before dissipating east-northeast of the city around 5:30 a.m. EST.

Smithville, Mississippi/Shottsville, Alabama

Smithville, Mississippi, and Shottsville, Alabama, are two rural towns near the northern Mississippi–Alabama border (Figure 4). As of the 2010 Census, Smithville had a population of 942 people, including 365 households. The age structure of the city is 24 percent under the age of eighteen, 10 percent from eighteen to twenty-four, 25 percent from twenty-five to forty-four, 25 percent from forty-five to sixty-four, and 16 percent over the age of sixty-five. The racial makeup of the city is 96 percent white and 2 percent African American. The median household income in the city is $32,583, and 7 percent of families and 11 percent of the total population are below the poverty line.

As of the 2010 Census, Shottsville was an unincorporated town in Marion County, Alabama, which had not participated in any census or other population survey. If we assume Marion County as a representative sample of Shottsville, the age structure of the town is 22 percent under the age of eighteen, 8 percent from eighteen to twenty-four, 24 percent from twenty-five to forty-four, 28 percent from forty-five to sixty-four, and 18 percent over the age of sixty-five. The racial makeup of the town is 94 percent white and 4 percent African American. The median household income in the town is $32,769, and 13 percent of families and 18 percent of the total population are below the poverty line.

Smithville and Shottsville were hit by a violent tornado (EF5) on 27 April 2011. The tornado killed twenty-three and injured 137 people. It was part of the Super Outbreak of 25 to 28 April 2011 that produced 360 tornadoes, causing 324 fatalities and more than 3,100 injuries.

The 2011 Smithville, Mississippi/Shottsville, Alabama, tornado formed a few miles west-southwest of Smithville along the Tennessee–Tombigbee Waterway at 3:42 p.m. EST. The storm strengthened as it moved toward and through Smithville, reaching EF5 intensity. It continued northeast across the Alabama state line into Marion County, where it weakened as it moved near the small town of Bexar. The storm again strengthened as it struck the town of Shottsville around 4:00 p.m. EST, before dissipating near Hodges at 4:23 p.m. EST.

Gainesville, Georgia

Gainesville, Georgia, is a city in northern Georgia (Figure 4). As of the 2010 Census, Gainesville had a population of 33,804, including 11,273 households and 7,165 families. The age structure of the city is 34 percent under the age of eighteen, 10 percent from eighteen to twenty-four, 29 percent from twenty-five to forty-four, 17 percent from forty-five to sixty-four, and 10 percent over the age of sixty-five. The racial makeup of the city is 54 percent white, 15 percent African American, and 23 percent other. The median household income in the city is $38,119, and 25 percent of families and 29 percent of the total population are below the poverty line.

Gainesville was hit by a significant tornado (EF3) on 20 March 1998. The tornado killed twelve and injured 171 people. It was part of the Gainesville–Stoneville tornado outbreak of 20 March 1998 that produced twelve tornadoes, causing fourteen fatalities and 205 injuries across the states of Georgia, North Carolina, and Virginia.

The 1998 Gainesville, Georgia, tornado formed in northwestern Hall County at around 6:25 a.m. EST. The storm strengthened as it moved through rural areas outside of Gainesville, reaching EF3 intensity. It continued into southern White County before weakening and dissipating at around 6:40 a.m. EST.

Marmaduke, Arkansas/Caruthersville, Missouri

Marmaduke, Arkansas, and Caruthersville, Missouri, are two rural towns near the Arkansas–Missouri border (Figure 4). As of the 2010 Census, Marmaduke had a population of 1,111 people, including 487 households and 323 families. The age structure of the city is 25 percent under the age of eighteen, 8 percent from eighteen to twenty-four, 28 percent from twenty-five to forty-four, 23 percent from forty-five to sixty-four, and 17 percent over the age of sixty-five. The racial makeup of the city is 97 percent white and 3 percent other. The household median income is $23,300, and 18 percent of families and 20 percent of the total population are below the poverty line.

As of the 2010 Census, Caruthersville had a population of 6,168 people, including 2,454 households, and 1,567 families. The age structure of the city was 30 percent under the age of eighteen, 9 percent from eighteen to twenty-four, 23 percent from twenty-five to forty-four, 24 percent from forty-five to sixty-four, and 14 percent over the age of sixty-five. The racial makeup of the city is 64 percent white and 33 percent African American. The household median income is $24,821, and 28 percent of families and 36 percent of the total population are below the poverty line.

Marmaduke and Caruthersville were hit by a significant tornado (EF3) on 2 April 2006. The tornado killed two and injured 177 people. It was part of the larger tornado outbreak of 2 April 2006 that produced sixty-six tornadoes, causing twenty-eight fatalities and injuring hundreds more—making it both the most active and deadliest tornado outbreak in 2006.

The 2006 Marmaduke, Arkansas/Caruthersville, Missouri, tornado began in Randolph County just south of the town of Pocahontas around 7:00 p.m. EST. The tornado first affected the community of Shannon at EF1 intensity before intensifying to EF3 strength as it crossed into Greene County, where it went through the town of Marmaduke at 7:37 p.m. EST. The tornado then crossed the St. Francis River into Dunklin and Pemiscot counties, where it struck the town of Braggadocio with EF2 intensity before intensifying to EF3 strength as it went through the town of Caruthersville before dissipating outside of the town at around 9:00 p.m. EST.

Synthesizing the Results of Communities Affected by UDTs

The preceding survey of examples of communities affected by UDTs makes it clear that no single socioeconomic or demographic variable will explain high casualty rates across all tornadoes (Table 2). For example, although having a low median household income or high rate of poverty will, on average, exacerbate the number of tornado casualties experienced by a community, these factors cannot be blamed for the high casualty count of the 2015 Garland–Rowlett, Texas, tornado. Similarly,

Table 2. Socioeconomic and demographic profiles for the six communities chosen as examples of unusually devastating tornadoes

Variable	Spencer, SD	Garland–Rowlett, TX	Camilla, GA	Smithville, MS/ Shottsville, AL	Gainesville, GA	Marmaduke, AR/ Caruthersville, MO
Age (under 18)	30%	30%	30%	23%	34%	29%
Age (18–24)	2%	9%	11%	9%	10%	9%
Age (25–44)	19%	29%	27%	25%	29%	24%
Age (45–64)	25%	24%	19%	26%	17%	24%
Age (over 65)	24%	8%	13%	17%	10%	15%
Race (white)	97%	62%	25%	95%	54%	69%
Race (black)	1%	14%	70%	3%	15%	28%
Race (other)	2%	24%	5%	2%	31%	3%
Median household income	$21,250	$76,657	$22,485	$32,676	$38,119	$24,061
Poverty (total family)	7%	9%	35%	10%	25%	26%
Poverty (total population)	11%	12%	38%	15%	29%	34%

Notes: Age is given as a percentage of total population, race is given as a percentage of total population, household median income is given in 2010 U.S. dollars, and poverty is given as a percentage of total population.

although having a relatively large number of elderly residents will, on average, lead to an increased number of tornado casualties felt by a community, this factor is not what caused the high casualty counts of the 2000 and 2003 Camilla, Georgia, tornadoes.

For the few socioeconomic factors considered in this study, it is obvious that many of the communities affected by UDTs suffer from limited resources, in part due to a lack of disposable income. For example, the average median household income for these six communities is $35,875, which is well below the median U.S. household income of $61,822. When Garland and Rowlett, Texas, are removed from consideration, the average household median for the remaining five communities (Spencer, South Dakota; Camilla, Georgia; Smithville, Mississippi/Shottsville, Alabama; Gainesville, Georgia; and Marmaduke, Arkansas/Caruthersville, Missouri) is $31,968, which is roughly half of the median U.S. household income. That said, poverty rates only seem to be a driving force in the rate of tornado casualties for half of these communities (Camilla, Georgia; Gainesville, Georgia; and Marmaduke, Arkansas/Caruthersville, Missouri). In fact, the average rate of poverty for both families and population in the other half (Spencer, South Dakota; Garland–Rowlett, Texas; and Smithville, Mississippi/Shottsville, Alabama) affected by UDTs is consistent with the U.S. average of 9 percent and 12 percent, respectively.

For the few demographic factors considered in this study, it is more difficult to tease out reasons for why these communities were affected by UDTs. There is no large difference in the percentage of people over the age of sixty-five in these communities and the U.S. average. Perhaps the number of young people (under the age of eighteen) contributed to the rate of tornado casualties in these communities. Indeed, the average percentage of people under the age of eighteen in these six communities is 29 percent, which is slightly higher than the U.S. average of 24 percent. Race does not appear to make a large difference, because these six communities range from predominantly white (Spencer, South Dakota; Smithville, Mississippi/Shottsville, Alabama; and Marmaduke, Arkansas/Caruthersville, Missouri) to predominantly black (Camilla, Georgia).

In summarizing the socioeconomic and demographic profiles of the communities hit by UDTs, it is apparent that establishing causal relationships between descriptive variables and the rate of tornado casualties requires a bespoken approach. Although indexes like the Social Vulnerability Index (SoVI; Cutter, Boruff, and Shirley 2003) and the Socioeconomic and Demographic Vulnerability Index (SEDVI; Strader and Ashley 2018) are useful in understanding the broad-scale patterns of factors that influence physical, social, and human vulnerability, they have limited utility at smaller scales. This is especially true of research that relies on statistical analysis, because many of the variables included in the vulnerability indexes are confounding (e.g., median household income and race, family structure and education, renters and occupation). As such, for work with the goal of intervening—reducing the number of tornado casualties—in the tornado casualty problem, it does not help to simply add more variables to a model and interpret the coefficients. There are likely systems in place (e.g., institutionalized poverty, wealth inequality, distrust of government, etc.) at various scales in many of these communities that contribute to the presence of UDTs. Additionally, it is likely that unique situations—cultural events—contribute to the presence of UDTs. For example, the 2011 Joplin, Missouri, tornado took place on the same day as a high school graduation and the 2015 Garland–Rowlett, Texas, tornado took place on the day after Christmas. Accounting for these factors statistically is difficult but should be considered in more detail moving forward.

Summary

Broad-scale factors that contribute to the number of tornado casualties are well understood. These factors range from physical variables, such as wind energy and EF category (Ashley 2007; Fricker, Elsner, and Jagger 2017), to socioeconomic and demographic variables, such as population and the number of mobile homes (Simmons and Sutter 2008, 2009). Place-based factors that contribute to the number of tornado casualties have yet to be systematically examined. For example, no research committed to uncovering the shared histories—both archival and oral histories—of communities (McCreary 2018) at risk for high rates of tornado casualties exists. Neither does work centered around connecting the lines of labor (e.g., labor displacements) and housing (e.g., postreconstruction housing) to the susceptibility of these areas to tornadoes.

In this article, a model for tornado casualties is used to define UDTs and to identify where they cluster. The model builds on the work of Fricker, Elsner, and Jagger (2017) and Elsner, Fricker, and Berry (2018) but is similar to that of recent work that examines factors related to tornado casualties (Donner 2007; Simmons and Sutter 2008, 2011; Zahran, Tavani, and Weiler 2013; Lim et al. 2017). Given the Pearson correlation coefficient between the observed and predicted rate of casualties at 0.5, the model appears adequate for assessing UDTs and is therefore useful in identifying where UDTs occur most often.

Adding variables will certainly increase the explanatory power of the model, but it is not clear that doing so would bring us closer to answering questions about why some communities are more prone to high tornado casualty rates. Put another way, although other socioeconomic and demographic variables (median household income, poverty rates, race, ethnicity, etc.) exist in aggregated data sets, it is unlikely that new causative reasons for casualties will be found given the lack of quantification for potentially important aggravating factors (segregation, redlining, etc.). One way to attack questions about why some communities are more prone to high tornado casualty rates than others is to ground future work in the communities in which UDTs tend to cluster or reappear. This can be done, in part, through research using ethnographic and other qualitative methodologies (Sherman-Morris 2009; Senkbeil, Rockman, and Mason 2012; Senkbeil et al. 2013; Klockow, Peppler, and McPherson 2014; Ash 2016; Ellis et al. 2018; Mason et al. 2018).

Although UDTs can occur anywhere in the United States, there appears to be a consistent presence of UDTs across rural portions of the Southeast. In fact, six of the top ten UDTs ranked by the difference in predicted and observed casualty rates occurred in the Southeast (Arkansas, Alabama, Georgia, Mississippi, and North Carolina), in small cities and towns not known as urban centers. Two of the top ten occurred in Texas, and one of the top ten occurred in Missouri and South Dakota. Although it is likely that a combination of physical and social vulnerabilities influence this disproportionate spatial distribution of UDTs, it is uncertain that the number of people or the number of mobile homes within the tornado's path are to blame for the casualty numbers—because the modeled rates are conditioned on these variables.

Seven examples of UDTs affecting six communities were further examined. These include (1) the 1998 Spencer, South Dakota, tornado; (2) the 2015 Garland–Rowlett, Texas, tornado; (3) the 2000 and 2003 Camilla, Georgia, tornadoes; (4) the 2011 Smithville, Mississippi/Shottsville, Alabama, tornado; (5) the 1998 Gainesville, Georgia, tornado, and (6) the 2006 Marmaduke, Arkansas/Caruthersville, Missouri, tornado. After investigating the demographic and socioeconomic profiles of these communities, it is clear that no one factor is consistently to blame for the high casualty rates found in UDTs. Although median household income and rates of poverty are likely to increase the rate of tornado casualties, they did not largely influence the number of tornado casualties found in the 2015 Garland–Rowlett, Texas, tornado. Similarly, although a higher percentage of young people in a community is likely to increase the rate of tornado casualties, it did not largely influence the number of tornado casualties found in the 2011 Smithville, Mississippi/Shottsville, Alabama, tornado.

After investigating the demographic and socioeconomic profiles of communities affected by tornadoes where predicted rates of tornado casualties were high but observed casualties were low (Figure 2), it is also clear that no one factor consistently dictates low vulnerability and that communities can have similar physical or social vulnerabilities yet have different casualty outcomes. Examples of these tornadoes on the opposite side of UDTs include (1) the 1997 Detroit, Michigan, tornado; (2) the East Nashville, Tennessee, tornado; (3) the 1999 Bridge Creek–Moore, Oklahoma, tornado; and (4) the 2011 Hackleburg–Phil Campbell, Alabama, tornado. Surprisingly, many of these affected communities also suffer from low median household income and high rates of poverty (e.g., Eight Mile Road/Hamtramck, Michigan; Hackleburg/Phil Campbell, Alabama). Thus, if the goal is to successfully intervene in the tornado casualty problem, it remains important to move beyond—but not necessarily in place of—statistical or systematic indexes (e.g., SoVI, SEDVI) that define vulnerabilities, because no single variable or group of variables will easily define a causal relationship between tornado casualties and vulnerability, resiliency, or adaptive capacity.

By identifying clusters of UDTs, this research provides a foundation to address community-level causes of destruction. These factors might include the history of tornado occurrence (physical risk), the NWS county warning area, lines of labor (e.g., labor displacements), lines of housing (e.g., history of mobile homes), or other critical structures. Although it is unlikely that all areas affected by UDTs have the same shortcomings in public safety or in other potential causes of vulnerability, it is possible that some areas, particularly those communities experiencing multiple UDTs, suffer from more systematic issues. By recognizing these communities throughout the United States, this research stands to confront the current paradigm of responsibilization in the hazards—particularly tornado—and vulnerability literature (Begg et al. 2016).

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