Unusually devastating tornadoes in the United States: 1995–2016

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ABSTRACT

Previous research has identified a number of physical, socioeconomic, and demographic factors related to tornado casualty rates. However, there remains gaps in the understanding of community-level vulnerabilities to tornadoes. Here a framework for systematically identifying the most unusually devastating tornadoes, defined as those where the observed number of casualties far exceeds the predicted number, is provided. Results show that unusually devastating tornadoes occur anywhere tornadoes occur in the United States, but rural areas across the Southeast appear most to be most frequented. Four examples of unusually devastating tornadoes are examined in more detail. Results highlight that cities and towns impacted 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 and that supports ethnographic and qualitative studies of place-based vulnerability.

1. Introduction

Tornadoes are one of the deadliest weather-related hazards in the United States. Wind energy and population density explain a large portion of the casualty rates (Ashley et al. 2014; Ashley and Strader 2016; Fricker et al. 2017a; Elsner et al. 2018), but socioeconomic and demographic factors also play a role (Bohonos and Hogan 1999; Mitchem 2003; Simmons and Sutter 2005, 2008, 2009; Donner 2007; Ashley 2007; Dixon and Moore 2012; Donner et al. 2012; Lim et al. 2017). For example, Simmons and Sutter (2005, 2008, 2009) find 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 et al. 2008), and day of occurrence (workday or weekend) (Zahran et al. 2013).

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

In an effort to fill this knowledge gap, here a framework for systematically identifying the most unusually devastating tornadoes is provided. 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 are identified by examining the difference between what is predicted from the statistical model and what was observed on the ground. More specifically, after statistically controlling for 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. In addition, we discuss examples of locations that were hit with unusually devastating tornadoes.

The paper is organized as follows. Section 2 reviews the factors related to tornado casualties that past researchers have identified as important in explaining the rates. It describes how statistical regression models have recently been used in this regard. Section 3 defines an unusually devastating tornado (UDT) as one where there is a large difference between how many casualties occurred and what the statistical model predicts given the physical and demographic factors. It describes the model and data used to identify UDTs and then examines their spatial distribution. Section 4 provides examples of unusually devastating tornadoes, and Section 5 summarizes the work.

2. Factors Related to the Number of Casualties

Tornadoes kill and injure around one thousand people, on average, in the United States each year. Previous research has identified physical factors that impact 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) finds that tornadoes categorized with a high maximum damage rating (F scale) produce the vast majority of tornadoes fatalities, while Fricker et al. (2017b) find 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) find that as tornado damage path length increases, so does the number of tornado casualties. Quantitatively, Fricker et al. (2017a) show that a doubling of tornado strength, represented as an estimate of energy dissipation, leads to a 33% increase in the rate of tornado casualties.

Previous research has also identified a number of socioeconomic and demographic factors that impact 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 et al. (2017a) find that the number of tornado casualties increases with population density. Similarly, Simmons and Sutter (2005, 2008, 2009) find that the number of tornado casualties increases with the percentage of mobile homes within an area. This result is further supported by Ashley (2007), who notes that nearly half of all tornado fatalities between 1985–2005 occurred in mobile homes. Bohonos and Hogan (1999) posit that the number of tornado casualties may 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 et al. 2000; Dixon and Moore 2012).

Additional factors such as race, poverty, education, and the number of female headed households have been linked to the rate of tornado casualties as well. Donner (2007) hypothesizes that African-Americans are likely more vulnerable to tornado casualties, in part, because they may have more difficulty understanding warning messages (Mitchem 2003). Lim et al. (2017) find 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 et al. 2005; Kahn 2005; Enarson et al. 2007).

Multiple regression models are used to determine what factors are important in statistically explaining casualties and to quantify the effect a single factor has on casualties while controlling for the effect of other factors. For example, using county-level socioeconomic and demographic data with a straight line model for the tornado 'footprint' Simmons and Sutter (2014) predict per-tornado fatalities of events during the active 2011 season. Fricker et al. (2017a) use a more detailed model for the tornado footprint and produce tornado-level estimates of energy dissipation and population with a dasymetric approach on grid-level data. They find that the rate of tornado casualties increases with population and energy dissipation and label the regression coefficients the population and energy elasticity, respectively. Masoomi and van de Lindt (2018) use a similar 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 the number of people within the damage path as fixed effects. More recently, Elsner et al. (2018) improve on the Fricker et al. (2017a) model by including an interaction between energy dissipation and population density. They find that the energy elasticity increases significantly with population density and that the population elasticity increases significantly with energy dissipation.

3. Unusually Devastating Tornadoes

a. 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 et al. (2018) predicts a casualty rate of 20 people (per casualty-producing tornado) for a 100 GW tornado affecting an area with a population density of 1500 people per square kilometer. This predicted rate represents the average, or expected, count given specific values for the factors without regards to where the tornado occurs. However, local, place-based, factors are also usually important 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 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 an unusually devastating tornado as one in which the difference between C_T and $\hat{C}_T$ is large (L) (see Eq.1).

$$\mathrm{UDT}_T = C_T - \hat{C}_T > L \tag{1a}$$

$$\hat{C}_T \sim f(\mathbf{x}_T), \tag{1b}$$

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. We are particularly interested in where the difference between the observed count and the predicted count is large.

b. 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 1995–2016. The model is described in detail in Elsner et al. (2018) and includes energy dissipation and population density as the two most important factors that statistically explain casualties. Energy dissipation (in 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 et al. 2017a; Elsner et al. 2018). Population density is the number of people per square kilometer within the damage path of the tornado.

Here the model of Elsner et al. (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 (Fig. 1). The coefficients of month and hour of occurrence are vectors of length 12 and 24, respectively. The number of mobiles homes are estimated using a dasymetric method similar to the procedure used in Fricker et al. (2017b), 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

$$\ln(C) = \ln(\beta_0) + \beta_P \ln(P) + \beta_E \ln(E) + \beta_{P \cdot E}[\ln(P) \cdot \ln(E)] + \beta_Y Y + \beta_{MH} MH + \beta_{MO}(1|MO) + \beta_{HR}(1|HR) \tag{2}$$

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 et al. 2013; Lim et al. 2017). However, here we use tornado energy 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.

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 the authors at the time of analysis. Population and mobile home data are obtained from the United States 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.

The Pearson correlation coefficient between the observed and predicted rate of casualties for all casualty-producing tornadoes in the study is .50, indicating a moderately good relationship. When a subset of the largest casualty-producing tornadoes—tornadoes causing 25 or more casualties—is considered, the relationship becomes stronger (Fig. 2). This suggests that the model is adequate for assessing UDTs.

c. Where UDTs occur

For the set of casualty-producing tornadoes (2198 tornadoes) over the period, the model under predicted the observed count for 491 tornadoes. Of these 491, 101 were under predicted by ten or more casualties, while 43 (90th percentile) were under predicted by 22 or more casualties. A tornado that results in an under prediction at the 90th percentile is defined here as an UDT. For example, given the storm's energy 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 so it is categorized as an UDT. Nine of the top ten UTDs ranked by the difference in predicted and observed casualty rates (Table 1) resulted in more than 100 casualties. 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. In fact, the tornado produced 1308 casualties—a difference of 1177 casualties.

Unusually devastating tornadoes can occur anywhere in the United States where a tornado impacts a populated area (Fig. 3). However rural areas across the Southeast appear to be where we find more unusually devastating tornadoes. Indeed, six of the top ten UDTs ranked by the difference in predicted and observed casualty rates occur 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 in South Dakota.

4. Examples of Unusually Devastating Tornadoes

Highlighting examples of unusually devastating tornadoes provides further evidence that UDTs can occur anywhere in the United States. Here four examples of unusually devastating tornadoes are investigated: (1) the 1998 Spencer, South Dakota tornado, (2) the 2015 Garland-Rowlett, Texas tornado, (3) the 2000 and 2003 Camilla, Georgia tornadoes, and (4) the 2011 Smithville, Mississippi/Shottsville, Alabama tornado. The impacted cities range from a small rural town in the northern Great Plains, to small cities and towns in the Southeast, to mid-size urban/suburban cities in the southern Great Plains. These cities have their own individual socioeconomic and demographic profiles, yet were all hit by tornadoes that caused more casualties than expected given a model for tornado casualties.

a. Spencer, South Dakota

Spencer is a rural town in southeast South Dakota (Fig. 4). As of the 2010 Census, Spencer had a population of 154 people, including 60 households, and 47 families. The age structure of the city is 30% under the age of 18; 2% from 18 to 24, 19% from 25 to 44, 25% from 45 to 64, and 24% over the age of 65 years. The racial makeup of the city is 97% White and 1% African American. About 7% of families and 11% 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 5 tornadoes during a one hour period.

The 1998 Spencer, South Dakota storm started at approximately 7:35pm Eastern Standard Time (EST) southwest of Wessington Springs, South Dakota—about 60 miles west-northwest of Spencer. The storm almost immediately split into left and right moving cells with the right moving cell becoming a mid-level mesocyclone at 9:26pm EST. By 9:28pm EST, Sioux Falls radar (WSR-88D) had indicated a hook echo and well-defined rotation. From 9:23pm–9:37pm EST, the Spencer tornado tracked through farmland, within 1 mile of the town of Farmer, before striking the town of Spencer. The city of Spencer experienced violent tornado conditions from 9:38pm–9:39pm EST, before the storm dissipated at 10:10pm EST.

b. Garland-Rowlett, Texas

Garland and Rowlett are two mid-size cities in the Dallas-Fort Worth metroplex in north Texas (Fig. 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% under the age of 18, 10% from 18 to 24, 28% from 25 to 44, 25% from 45 to 64, and 9% over the age of 65. The racial makeup of the city is 58% White, 15% African American, and 9% Asian. The median household income in the city is \$52,441, and about 11% of families and 14% 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% under the age of 18, 6% from 18 to 24, 37% from 25 to 44, 19% from 45 to 64, and 5% over the age of 65. The racial makeup of the city is The racial makeup of the city is 78% White, 9% African American, and 4% Asian. The median household income in the city is $100,872, and only about 2% of families and 3% 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 10 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 12 tornadoes, causing 13 fatalities across eight north and central Texas counties.

The 2015 Garland-Rowlett, Texas tornadic storm formed near Hillsboro around 7:00pm EST. The storm strengthened as it moved north-northeast through Waxahachie at 7:45pm 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 8:46pm–9:02pm EST, before dissipating around McKinney at 9:30pm EST.

c. Camilla, Georgia

Camilla is a small city in southwest Georgia (Fig. 4). As of the 2010 Census, Camilla had a population of 5360. The age structure of Camilla is 30% under the age of 18, 11% from 18 to 24, 27% from 25 to 44, 19% from 45 to 64, and 13% over the age of 65. The city's median property value is $81,600 and 28% of all housing units in the city are low income properties. The racial makeup of the town is 70% African American and 25% White. The median household income in the town is $22,485, and about 35% of families and 38% 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 66 homes while damaging another 200.

The 2000 Camilla, Georgia tornado was part of the larger southwest Georgia tornado outbreak of 13–14 February, 2000. Beginning Sunday evening, and continuing into the early morning hours of Monday, the National Weather Service (NWS) Tallahassee issued 52 severe weather warnings, including 25 tornado warnings. During the outbreak, three deadly tornadoes occurred, causing 19 fatalities across three Georgia counties.

The 2000 Camilla tornadic storm came ashore in extreme southeast Walton County, Florida at around 8:30pm EST. The storm weakened as it crossed Lake Seminole, the dividing line between Florida, Alabama, and Georgia, around 11:00pm EST, before strengthening near the boundary of Seminole County, Georgia. The storm became tornadic around 11:42pm near Branchville, remaining tornadic as it passed just south of Camilla before dissipating east-northeast of the city around 12:05am 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 2:30am EST. The cell rapidly developed circulation and may have become tornadic in the northern part of the county. The storm destroyed a home in Fountain, Florida around 3:07am 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 impacting the city of Camilla at around 5:12am EST, before dissipating east-northeast of the city around 5:30am EST.

d. Smithville, Mississippi/Shottsville, Alabama

Smithville, Mississippi and Shottsville, Alabama are two rural towns near the northern Mississippi-Alabama border (Fig. 4). As of the 2010 Census, Smithville had a population of 942 people, including 365 households. The age structure of the city is 24% under the age of 18, 10% from 18 to 24, 25% from 25 to 44, 25% from 45 to 64, and 16% over the age of 65. The racial makeup of the city is 96% White and 2% Africa American. The median household income in the city is $32,583, and about 7% of families and 11% 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% under the age of 18, 8% from 18 to 24, 24% from 25 to 44, 28% from 45 to 64, and 18% over the age of 65. The racial makeup of th town is 94% White and 4% African American. The median household income in the town is $32,769, and about 13% of families and 18% of the total population are below the poverty line.

Smithville and Shottsville were hit by a violent tornado (EF5) on April 27, 2011. The tornado killed 23 and injured 137 people. It was part of the Super Outbreak of 25–28 April, 2011 that produced 360 tornadoes, causing 324 fatalities and over 3100 injuries.

The 2011 Smithville, Mississippi/Shottsville, Alabama tornado formed a few miles west-southwest of Smithville along the Tennessee-Tombigbee Waterway at 3:42pm 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 4:00pm EST, before dissipating near Hodges at 4:23pm EST.

5. 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 et al. 2017a), 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, research committed to uncovering the shared histories—both archival and oral histories— of communities (McCreary 2018) at risk to high rates of tornado casualties does not exist. Neither does work centered around the lines of labor (e.g. labor displacements) and housing (e.g. post-reconstruction housing) that exist and potentially influence the susceptibility of these areas to large counts of tornado casualties.

Here a model for tornado casualties is used to define unusually devastating tornadoes and to identify where they cluster. The model builds on the work of Fricker et al. (2017a) and Elsner et al. (2018), but is similar to that of recent work that examines factors related to tornado casualties (Donner 2007; Simmons and Sutter 2008, 2011; Zahran et al. 2013; Lim et al. 2017). Given the Pearson correlation coefficient between the observed and predicted rate of casualties at .50, the model appears adequate for assessing UDTs and is useful for identifying where UDTs occur most often.

Adding variables to the model 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. One way to attack this question is to ground future work in the communities in which unusually devastating tornadoes tend to cluster or reappear. This can be done, in part, through research using ethnographic and other qualitative methodologies (Sherman-Morris 2009; Senkbeil et al. 2012, 2013; Klockow et al. 2014; Ash 2016; Ellis et al. 2018; Mason et al. 2018).

While unusually devastating tornadoes 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 occur 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 in South Dakota.

Four examples of unusually devastating tornadoes are 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, and (4) the 2011 Smithville, Mississippi/Shottsville, Alabama tornado. The impacted cities range from a small rural town in the northern Great Plains, to small cities and towns in the Southeast, to mid-size urban/suburban cities in the southern Great Plains. These cities have their own individual socioeconomic and demographic profiles, yet are similar in that they were hit by tornadoes that caused more casualties than expected given a model for tornado casualties.

By identifying clusters of unusually devastating tornadoes, 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), or lines of housing (e.g. history of mobile homes). Though it is unlikely that all areas impacted by UDTs have the same shortcomings in public safety or in other potential causes of vulnerability (e.g. poverty rates, etc.), it is possible that some areas, particularly those communities experiencing multiple UDTs suffer from more systematic issues.

Acknowledgments. The code used to produce the tables and graphs is available at `https://github.com/tfricker/Casualty-Risk-Model`.

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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	1308	131	1177
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

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

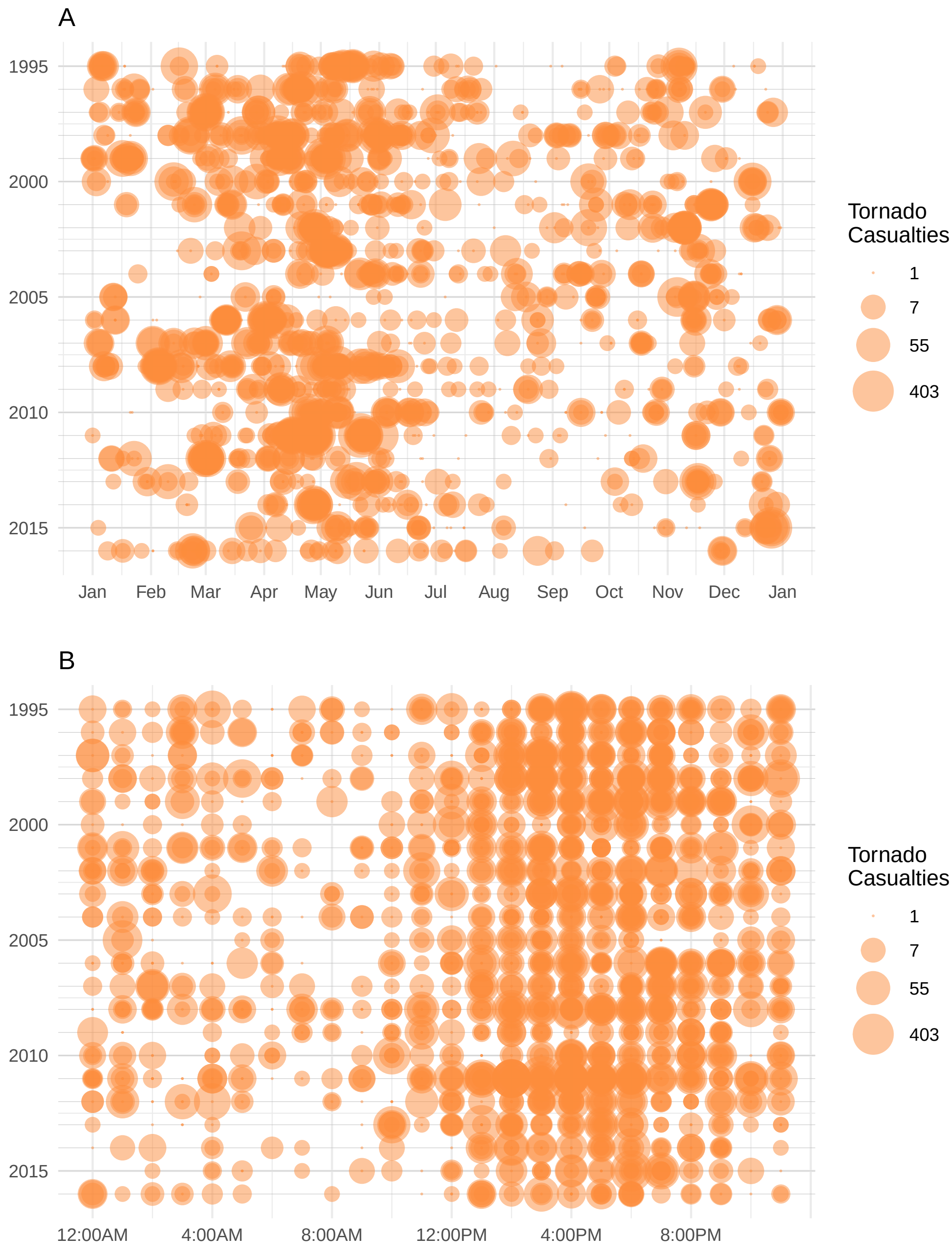

FIG. 2. Predicted casualty rate versus observed casualty count. Points are shown only for tornadoes with at least 25 casualties. Values below the black line indicate tornadoes with more casualties than predicted using the regression model and the size of the circle is proportional to the number of underpredicted casualties.

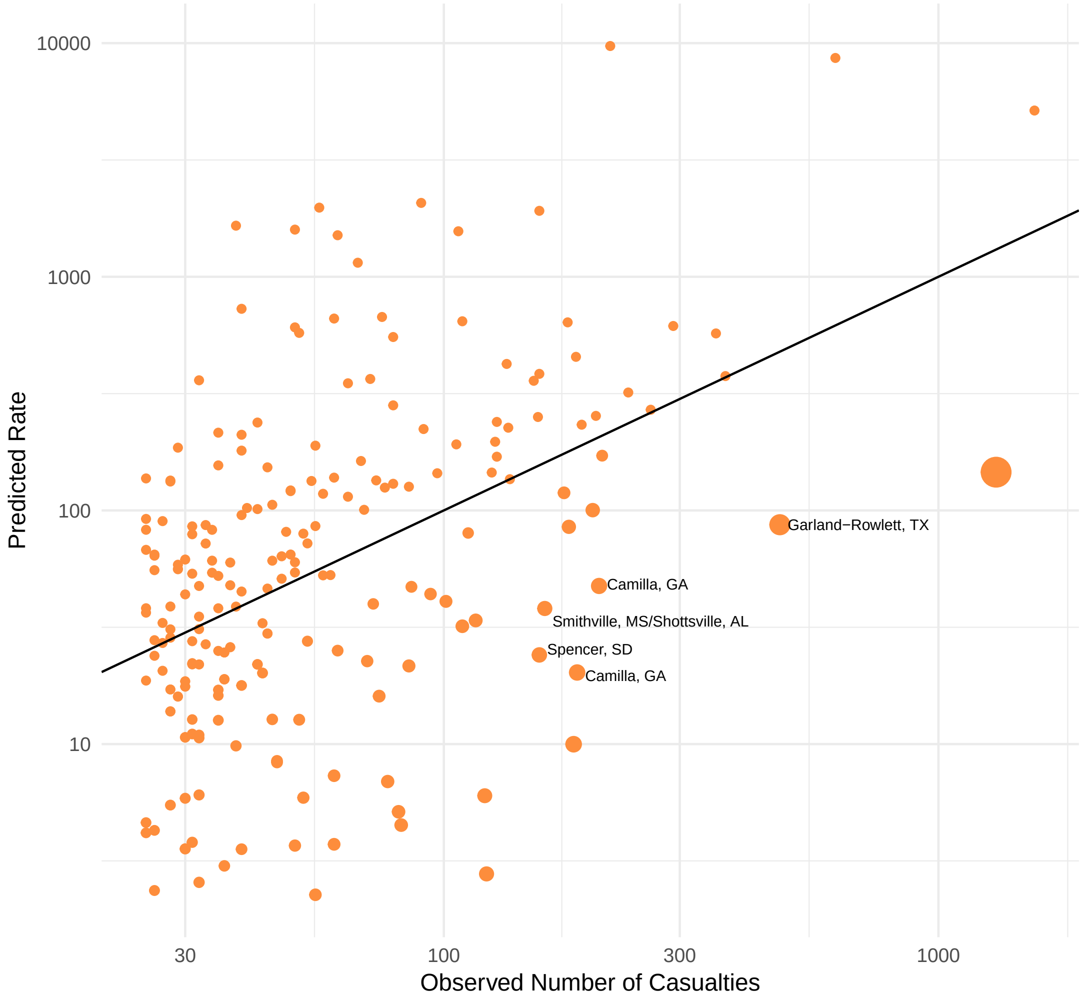

FIG. 3. Unusually devastating tornadoes. The size of the circle is proportional to the number of underpredicted casualties.

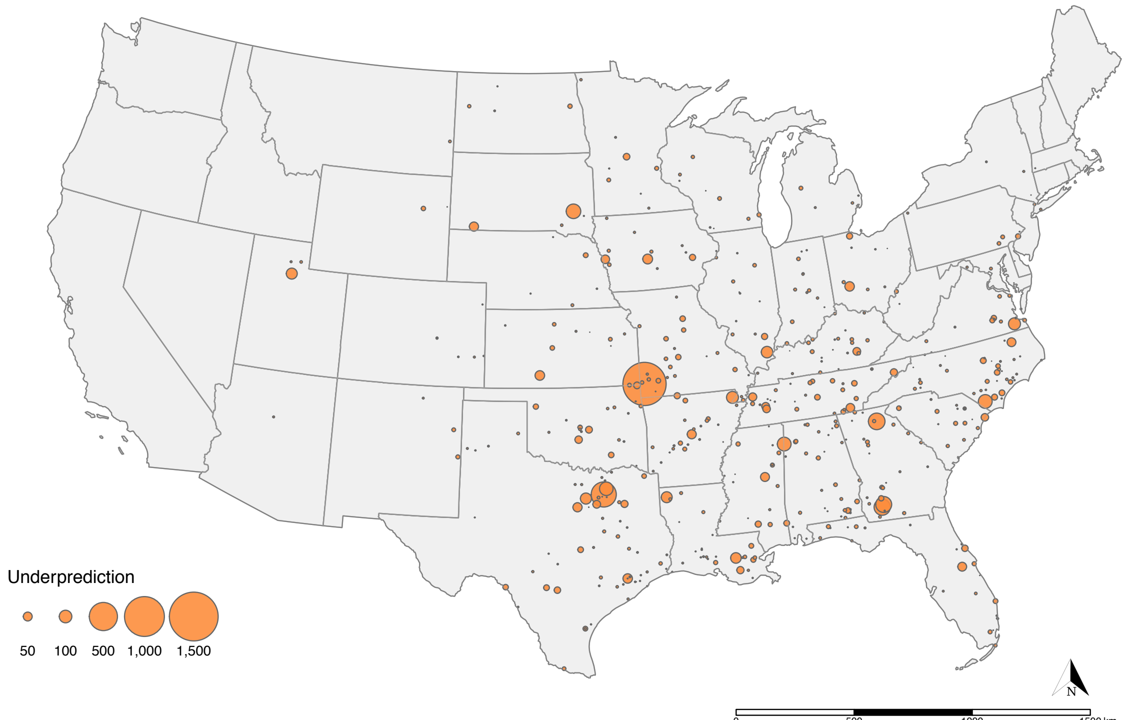

FIG. 4. Spencer, South Dakota, Garland-Rowlett, Texas, Camilla, Georgia, and Smithville, Mississippi/Shottsville, Alabama. The orange circle indicates the location of the city or town and the size of the circle is proportional to the number of underpredicted casualties (see Fig. 3).