Geography Compass 9/4 (2015): 157–168, 10.1111/gec3.12205

New Methods in Tornado Climatology

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Abstract

How climate change might affect tornadoes remains an open scientific question. Climatological studies are often contested due to inconsistencies in the available data. Statistical methods are used to overcome some of the data limitations. A few of these methods including using the proportion of tornadoes occurring on big tornado days, estimating tornado energy from the damage path, and modeling counts spatially are described here. The methods move beyond analyses of occurrences by damage ratings and spatial smoothing. Applications of these and related methods will help grow the nascent field of tornado climatology.

1. *Introduction*

Climate change and the recent high-impact tornado events have bolstered interest in the field of tornado climatology (Agee and Childs, 2014; Dixon et al., 2011; Farney and Dixon, 2014; Simmons and Sutter, 2012; Standohar-Alfano and van de Lindt, 2014). There is much to learn about how tornadoes might collectively change as the earth continues to warm. For example, new research shows more tornadoes on fewer days (Brooks et al., 2014; Elsner et al., 2014a), perhaps related to the combination of additional moisture and warming aloft (Elsner et al., 2014a). Yet there is greater uncertainty surrounding the interpretation of such results owing to the nature of the dataset (Kunkel et al., 2013). Methods are needed to model the data that allow more confident physical interpretations.

The Storm Prediction Center (SPC) contains the most readily available tornado database in the world. The dataset provides information on occurrence time, location, damage rating, width, length, injuries, fatalities, property loss, and other characteristics from individual tornado reports since 1950. The history of official reporting of tornadoes in the USA is relatively brief compared to that of other meteorological phenomena but encompasses significant changes to the collection procedures (Figure 1).

The collection of tornado reports began in 1916, and the US Weather Bureau started issuing public tornado forecasts in 1952 (Galway, 1977; Grazulis, 1990). The Tornado Watch and Warning Program together with its network of tornado spotters were implemented in 1953 (Galway, 1977). The Fujita Scale (F Scale) was adopted by the National Weather Service (NWS) in the late 1970s to rate tornadoes based on damage severity (McCarthy et al., 2006). To make the dataset more complete, earlier tornadoes were retroactively rated using accounts of damage found in newspapers and photographs. Incomplete and exaggerated news articles may have resulted in the overrating of some events (Schaefer and Edwards, 1999; Verbout et al., 2006). On the other hand, the lowest rating was used as default when the amount/extent of damage was unknown (Doswell et al., 2009).

The discovery of microbursts (downbursts that can produce damage similar to tornadoes) led to a decrease in tornado reports starting around 1973 (Fujita, 1981). In retrospect, decreases are

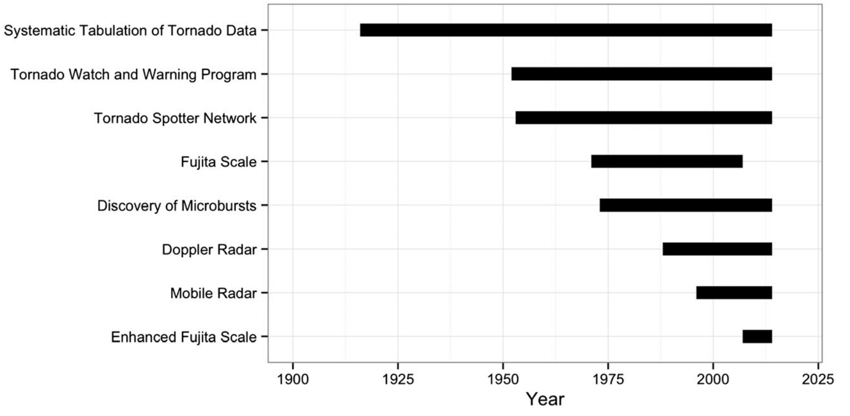

Fig. 1. Timeline of milestones influencing tornado reporting in the USA.

also apparent in reports of F2+ tornadoes after the early 1970s due to changes in F Scale rating assignments (Kelly et al., 1978; Verbout et al., 2006). Damage ratings began to include structural integrity assessments around this time (Doswell, 2007). However, a tornado in a rural area is unlikely to receive an extreme damage rating due to a lack of damage indicators and weak structures (Doswell and Burgess, 1988; Schaefer and Galway, 1982).

Implementation of Weather Surveillance Radar Doppler radar (WSR-88D), enhanced emphasis on tornado warning verification statistics, and a jump in the number of storm chasers resulted in more F0 tornado reports beginning in the late 1980s (Doswell, 2007). This upward trend in reports continued into the 1990s as mobile radars or "Doppler on Wheels" (DOWs) were used in the field to improve radar data collection (Bluestein et al., 1993; Wurman et al., 1996). Recently, the Enhanced Fujita Scale (EF Scale) was developed to include more damage indicators to improve ratings (Potter, 2007).

The effect of improved technology and greater public awareness on reporting consistency is large (Brooks, 2004; Doswell et al., 2009; Etkin et al., 2001; Simmons and Sutter, 2011; Verbout et al., 2006). Reports of tornadoes reach the database only if a manual observation of damage is made and verified. The National Climatic Data Center organizes the reports by county segments with multiple entries for a tornado crossing jurisdictions. The tornado segments are merged into a whole-tornado track in the SPC database (Edwards et al., 2013). Tornadoes that cause little or no damage may go unreported, and it is reasonable to assume that not all tornadoes were reported particularly early in time and outside the normal season (Galway, 1977). Thus, the number of tornadoes in the dataset is a lower bound on the true number, especially early on and in rural areas.

There is little doubt that the difference between the observed and the actual number of tornadoes is diminishing due to technology, public awareness, and population growth (Doswell et al., 1999; Verbout et al., 2006). A recent factor influencing tornado reports in rural areas is the increased number of storm chasers (Diffenbaugh et al., 2008; Elsner et al., 2013). In fact, the movie Twister featuring storm chasers was released in 1996, and the Discovery Channel's *Storm Chasers* series premiered in 2007. Verbout et al. (2006) mention the possibility of overreporting weak tornadoes in recent decades due to changes in the methods and technology used to collect the data. Furthermore, Doswell (2007) maintains the procedures involved in data collection vary substantially among NWS offices, as there is no consistent oversight mechanism. Additional details on the history of the SPC tornado dataset are available in Edwards et al. (2013).

Inhomogeneities in the SPC dataset create a challenge for researchers. New statistical methods are needed to overcome this challenge. In this article, we overview some of them focusing largely on our research at Florida State University. Section 2 shows how we move beyond count data by using proportional measures. Section 5 shows how we move beyond the EF Scale by using path characteristics to estimate total kinetic energy as a physics-based metric of tornado power. Section 8 shows how we move beyond exploratory tools by using contiguous polygons for aggregating tornado activity. Section 9 provides an outlook of some research we feel will facilitate understanding of the complex link between tornadoes and climate. This overview represents a point of view on what is innovative in this emerging field of study.

2. *Beyond Annual Tornado Counts*

A recent report concerning extreme storms and climate change (Kunkel et al., 2013) states there is little evidence of trends in tornado frequency for the most reliable subset (F1+ starting from 1954). However, frequency is only one component of tornado climatology. Examining the number of days with tornadoes and the spatial density of tornadoes can yield new insight into changes over time.

A. INCREASING PROBABILITY OF BIG TORNADO DAYS

As one example, Elsner et al. (2014a) examine temporal and spatial changes in the efficiency of tornado days since 1954. The authors remove tornadoes rated (E)F0 (Doswell et al., 2009; Verbout et al., 2006) to examine the frequency of tornadoes and tornado days (Figure 2). They find large variation in frequency from year to year but no long-term trend. However, they also find the number of tornado days has been decreasing since the 1970s (Brooks et al., 2014).

Since the total number of tornadoes is not trending—although regional trends in frequency are likely (Coleman and Dixon, 2014)—the authors find the atmosphere is producing more tornadoes on fewer days (Elsner et al., 2014a). They show this by computing the proportion of all tornadoes occurring on "big" tornado days (Figure 3). Each panel in Figure 3 displays an upward trend in proportion (blue lines). Statistical significance of the trends is assessed with

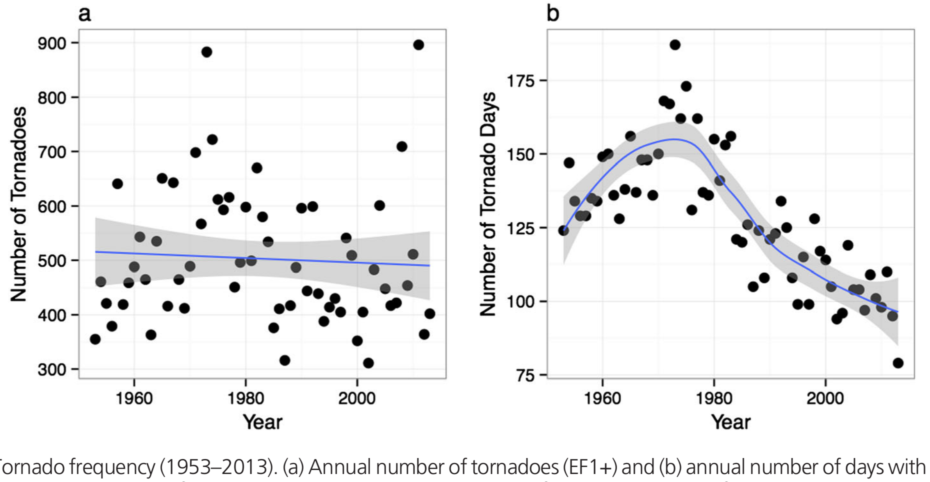

Fig. 2. Tornado frequency (1953–2013). (a) Annual number of tornadoes (EF1+) and (b) annual number of days with at least one tornado. The choice of trend line is made based on the low-frequency pattern of activity. Gray bands indicate confidence interval. Redrafted from Figure 1 (Elsner et al., 2014a).

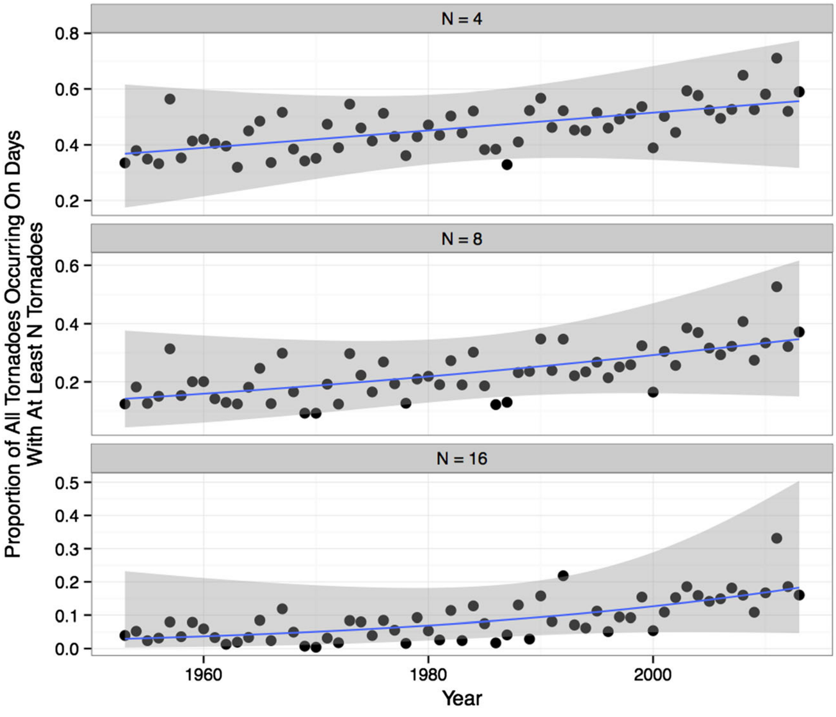

Fig. 3. Annual proportion of all tornadoes occurring on days with at least N tornadoes. Gray bands indicate prediction interval. Redrafted from Figure 4 (Elsner et al., 2014a).

a statistical model assuming the counts are adequately described by a negative binomial distribution (Elsner and Widen, 2014).

These results can be interpreted as increasing climatological "efficiency." There are fewer days with tornadoes, but on days that tornadoes occur, there are more of them. A portion of the increase could be due to changes in data collection procedures as discussed in Doswell et al. (2009); however, the growing efforts to improve data collection would most likely lead to an increase in tornado days with few tornadoes, thereby decreasing the proportion of tornadoes occurring on big tornado days.

Analyzing daily tornadoes can also give new insights. For example, Elsner et al. (2014c) show that daily tornado counts in the US follow a power-law relationship in the distribution of frequency. The authors also find the total number of tornadoes by damage category on days with at least one violent tornado to follow an exponential rule. Thus, on average, the daily number of tornadoes in the preceding damage category is about twice that of the current category. Similar power-law behavior appears with the number and length of consecutive tornado days (Farney and Dixon, 2014). These findings are important and appropriate for tornado hazard models and for predictions of seasonal and sub-seasonal tornado activity.

B. THE INCREASING SPATIAL DENSITY OF TORNADOES

The increasing efficiency of tornadoes might be due to a greater area favorable for tornadogenesis. Elsner et al. (2014a) examine this hypothesis by assessing changes in spatial dimensions of tornadoes. They first define a tornado cluster as a set of touchdown locations within the same general area using cluster analysis. They then examine clusters for each tornado day by grouping the touchdown points determined by a partitioning around the medoids (Reynolds et al., 2006). A medoid is a touchdown point that has the shortest average distance to all other points in the cluster.

Elsner et al. (2014a) place a convex hull around the touchdown points to delineate cluster areas and a 40 km buffer around the hull (Figure 4). The results show that clusters across much of the country are of similar size (number of tornadoes), albeit clusters across the Ohio and Tennessee Valleys tend to be somewhat larger (more tornadoes). The authors find an average of approximately two clusters per day and an average daily total cluster area of 1.5 million square kilometers. They also find a significant upward trend in the number of tornadoes per cluster; thus, the upward trend in the proportion of tornadoes occurring on big days is related to an increasing spatial density of tornado touchdowns. These results are similar to findings showing a greater percentage of annual precipitation occurring in heavy downpours resulting from an enhanced hydrologic cycle (Groisman et al., 2004).

3. Beyond the EF Scale

Whether tornadoes are getting stronger cannot be answered directly with tornado counts, but tornado wind speed measurements are difficult to obtain due to the extreme velocities and short duration of most tornadic events. Presently, wind speed is related to observed damage (Dotzek et al., 2005). Surveyors categorize damage using the EF Scale. Historically, only a single maximum EF rating is used to describe the worst damage. The rating is limited to the available damage indicators, so the maximum EF rating is a lower bound on the highest tornado intensity.

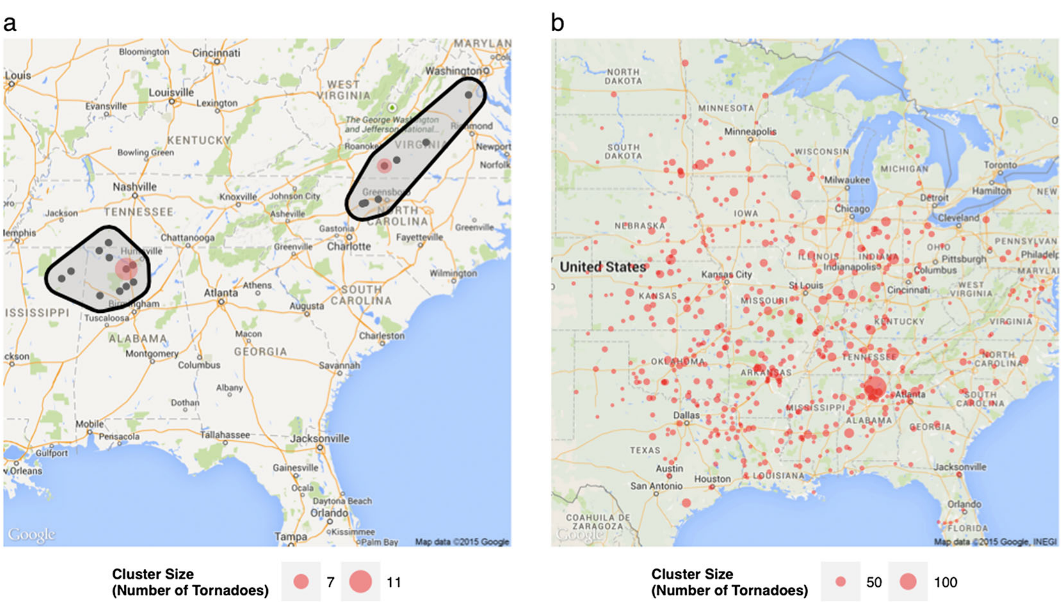

Fig. 4. Tornado clusters. (a) An example from May 8, 2008 showing the touchdown locations (black dots), the medoids (red circles), and the cluster area (gray shading). (b) Medoids of all clusters over all days with at least 16 tornadoes (1953–2013). The size of the circle is proportional to the number of tornadoes in the cluster. Redrafted from Figure 6. (Elsner et al., 2014a).

A. LENGTH AND WIDTH

Statistically, damage path length and width are directly related to EF Scale (Brooks, 2004). On average, longer and wider paths are associated with higher damage ratings (Abbey and Fujita, 1975; Kelly et al., 1978) (Figure 5). Elsner et al. (2014b) find that length and width each explain greater than 30% of the variability in damage rating across all tornadoes over the period 2007-2013. They also discover that the relationship between length and width is strongest for the widest tornadoes.

The authors do this by treating the wind speed on the EF scale as interval censored data and regressing wind speed onto damage path dimensions and fatalities. The resulting model exhibits a 25% increase in expected intensity (wind speed) over a threshold intensity of 29 m/s for a 100 km increase in path length and a 17% increase in expected intensity for a 1 km increase in path width (Elsner et al., 2014b). In addition, the model shows a 43% increase in the expected intensity when fatalities are observed while controlling for path dimensions. Using a sample of tornado wind speeds estimated independently from Doppler radar calibration, they find the model-estimated wind speeds correlate at .77 (.34, .93) [95% confidence interval–CI].

B. KINETIC ENERGY

While some research has investigated tornado intensity (Elsner et al., 2014b; Ramsdell and Rishel, 2007; Reinhold and Ellingwood, 1982; Standohar-Alfano and van de Lindt, 2014), less has been conducted to evaluate tornado power. Thompson and Vescio (1998) create a destructive potential index (DPI) by multiplying damage area by EF rating. Agee and Childs (2014) reformulate the DPI by multiplying the wind speed associated with the EF Scaling rating by the squared path width and squared wind speed. Others evaluate the distribution of tornado intensities (Brooks, 2004; Dotzek et al., 2003, 2005) and mass-specific kinetic energy (Schielicke and Névir, 2009).

Total damage area, damage area by EF rating, and storm duration are now available in the NWS Damage Assessment Toolkit (DAT) (Edwards et al., 2013). Fricker et al. (2014) determine the percent damage area for each of the 18 tornadoes in the DAT to estimate total kinetic energy (TKE). They calculate it using the midpoint wind speed of the damage rating while assuming constant air density and tornado height. The authors find the Sawyerville-Eoline,

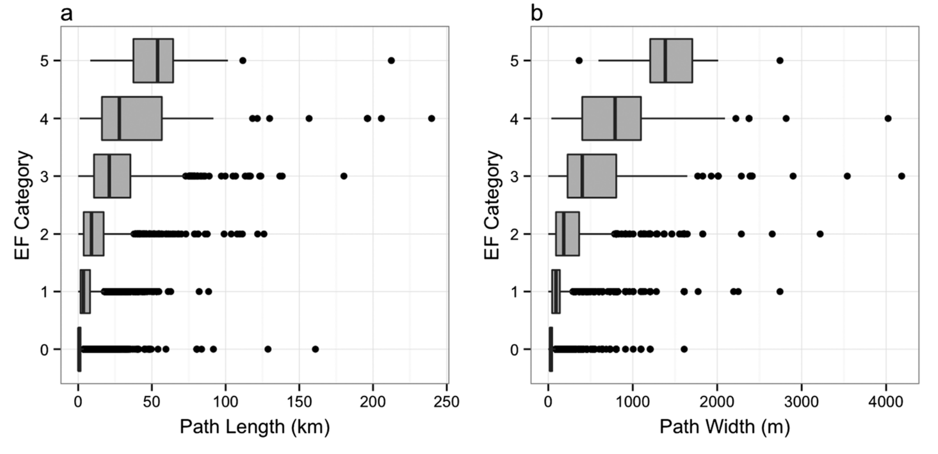

Fig. 5. Relationship between tornado (a) path length and (b) path width using data over the period 1994–2013. Redrafted from Figure 1 (Elsner et al., 2014b).

AL tornado to be the most energetic storm of the past few years (2011–2013) with an estimated total kinetic energy (TKE) of 123 TJ. They find the next most energetic storms to be the Hackleburg-Phil Campbell, AL tornado with an estimated energy of 93 TJ, and the Argo-Shoal Creek-Ohatchee-Forney, AL/GA tornado with an estimated energy of 88 TJ.

It is possible to estimate an energy of individual tornadoes using the SPC dataset by extending the work of Fricker et al. (2014). For instance, we can assume a model for the highest intensity of a tornado using path length and width together with a model for the spatial distribution of winds by damage rating (Ramsdell and Rishel, 2007). This is done for the most recent set of tornadoes in the SPC dataset since 2007 (Figure 6). The year 2011 stands out clearly as the most energetic season of the past 7 years. Energy estimates allow comparisons to be made between individual tornadoes that go beyond the single EF rating, and they allow climatologies to be done by day, season, year, and so on.

4. *Beyond Exploratory Analysis*

Exploratory analysis of tornado activity often relies on kernel smoothing (Brooks et al., 2003; Dixon et al., 2011; Shafer and Doswell, 2011), which is a way to average tornado occurrences spatially. The resulting maps show regions of high and low frequency useful for delineating patterns of tornado activity. For example, Dixon et al. (2011) use kernel density smoothing on tornado tracks to redefine "tornado alley." In addition, Coleman and Dixon (2014) use kernel smoothing to assess regional frequency and severity of tornadoes.

One drawback of kernel smoothing is the need to choose a bandwidth. Dixon et al. (2014) show ways to do this objectively, but they also show that bandwidth depends on the spatial

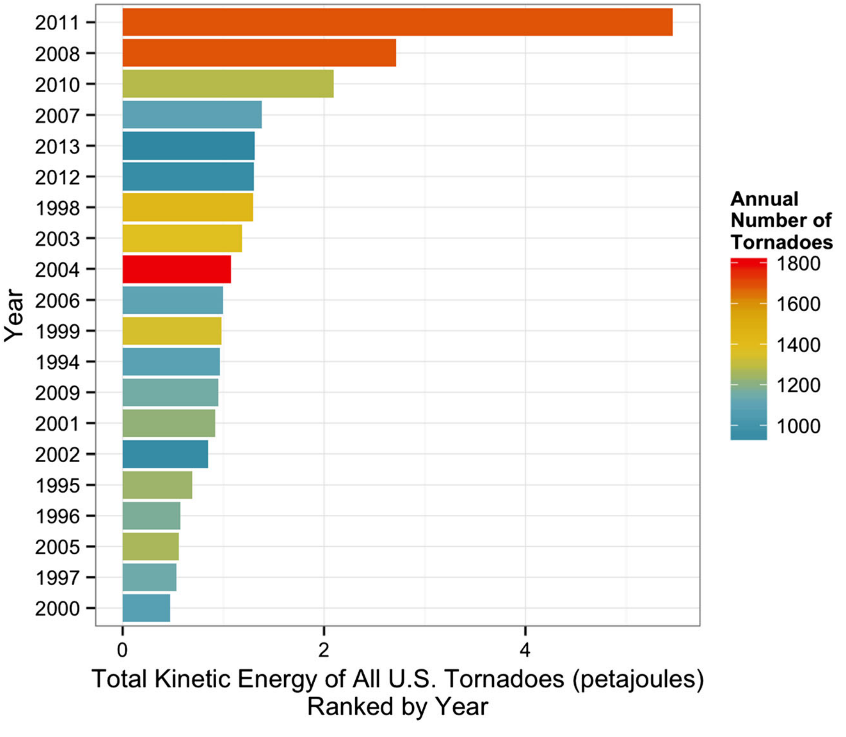

Fig. 6. Tornado kinetic energy ranked by year using data over the period 1994–2013. The bar colors correspond to the annual number of tornadoes. Redrafted from Figure 3 (Fricker et al., 2014).

scale. Another drawback is the assumption that tornado occurrences are independent. This might not always be the case as a single supercell thunderstorm can generate a family of tornadoes (Doswell and Burgess, 1988).

As an alternative to smoothing, here we aggregate tornadoes within the boundaries defined by the state counties of Kansas. This allows us to statistically control for variables (including population density, terrain, area, distance to radar, etc.) and to estimate the amount of clustering. Kansas is chosen here as a test case because of the relatively large number of tornadoes it receives each year. Additionally, the county-level maps are directly relevant to decision makers. More details on the analysis and models are given in Jagger et al. (2015).

We overlay the tornado paths across the county boundaries and tabulate the number of tornadoes and the number of tornado days by county (Figure 7). This results in a spatial dataset containing attributes that include county area and tornado frequency. County area is given in units of square kilometers, and the tornado rate per county is expressed as the number of tornadoes per 10,000 square kilometers per year. Tornado report frequency is highest across the central counties of Kansas. Large areas tend to have more tornado reports although statistically, the relationship is not strong [r = .27 (.08, .44) 95% CI]. Regional hotspots include Sedgwick County (which contains the city of Wichita) and the northeast counties near Kansas City.

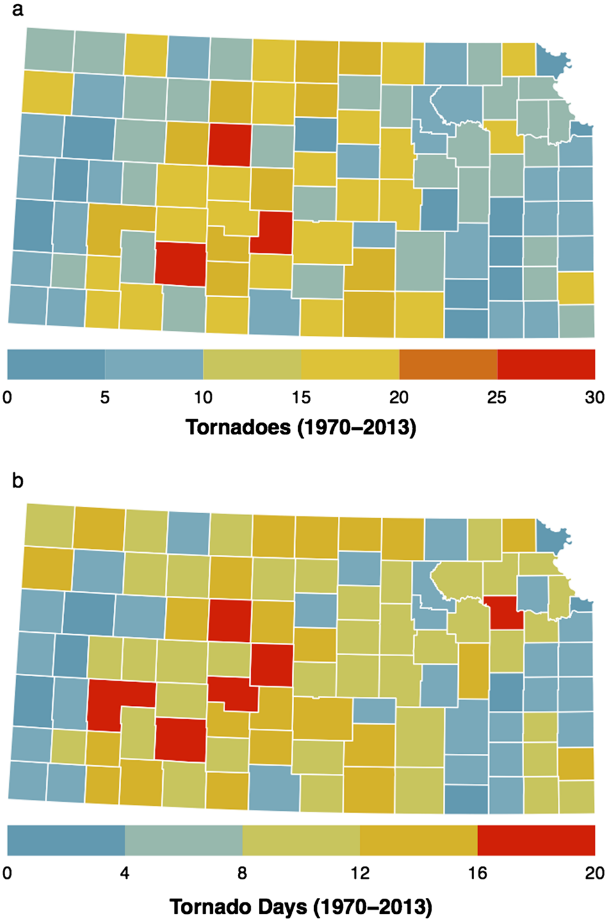

Fig. 7. County aggregated EF1+ (a) tornadoes and (b) tornado days across Kansas over the period 1970–2013.

In addition to county area and tornado frequency attributes, we add county population estimates from the ⋆American Fact Finder⋆ to the spatial dataset. Population estimates for the year 2013 range from a minimum of 1298 in Greeley County in western Kansas to a maximum of 559,913 in Johnson County in northeast Kansas (southwest of Kansas City). Sedgwick County, which includes the city of Wichita, is ranked second with a population of 503,889. The correlation between county population and the number of tornado reports is positive as expected, yet the bivariate relationship is weak [$r = .18$ (−.01, .36) 95% CI].

With the tornado and environmental data aggregated to fixed counties, spatial models can be used to test hypotheses about what factors are important for occurrence rates independent of population, area, and other non-meteorological factors. For example, the number of tornado reports in each county can be treated as the response variable with county area and population used as explanatory variables. Then the spatially correlated residuals from the regression model provide a climatology independent of the non-meteorological factors (Figure 8).

Here, tornado report values are expressed as a percent difference from the statewide average. The map features a north–south axis of above average activity across the west central part of the state with lower activity to the west (as found in Brooks et al., 2003). Barton, Edwards, Pawnee, and Stafford counties in south central Kansas have tornado activity that exceeds the average by at least 25%.

The map simplifies physical interpretation. Roughly three quarters of Kansas tornadoes occur between April and June. During this time, surface low pressure to the lee of the Rockies, forced by westerly winds aloft, produces veering southeasterly surface winds across the state. These winds transport moisture upslope with deep convection initiating in western Kansas along the dryline (Carlson, 1991). Thunderstorms initially organize as discrete supercells roughly along a northeast-southwest axis. The discrete cells tend to merge into a mesoscale convective system over eastern Kansas after sunset, reducing the threat for tornadoes there.

5. *Looking Ahead*

The outlook for new discoveries in tornado climatology is promising. As one example, the method of delineating tornado clusters suggests a way to aggregate tornado information and collate it with environmental data. An extended SPC dataset can be created to include cluster membership and associated cluster-averaged shear and instability measures. The dataset could

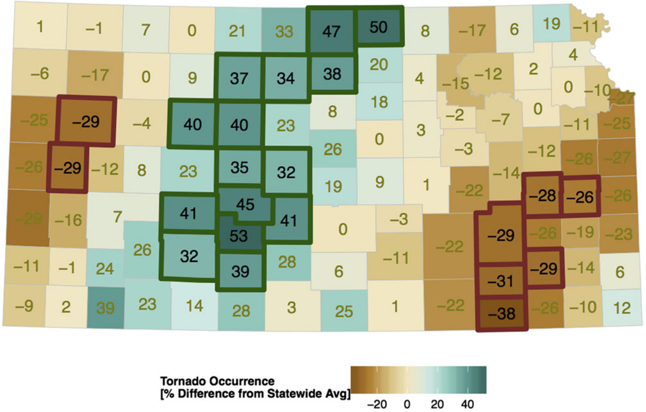

Fig. 8. Correlated residuals of a regression of per county tornado occurrence onto county area and population. The values are expressed as a percent difference from the statewide average. Outlined counties demonstrate significant differences. Details are given in Jagger et al. (2015).

also include per tornado and per cluster estimates of tornado energy. This extended dataset would aid climatologists in making discoveries about tornado outbreak size/intensity and their related environmental factors.

Aggregating tornado occurrences to counties (or grids) makes it easy to control for differences in area and population density. A flexible way to do this is to use Bayesian methods with the integrated nested Laplacian approximation (INLA) to solve the integrals (see Elsner and Widen, 2014, for an example). The setup facilitates a spatially correlated residual. A choropleth map of the residuals illustrates where tornado activity is high relative to the statewide average after statistically controlling for non-meteorological factors including variations in terrain elevation and land cover type. Maps like this will be an important step toward making new discoveries concerning the physical mechanisms responsible for local-scale tornado climatology.

The USA has the largest and most freely accessible record of tornado events in the world. However, the dataset contains inconsistencies and biases that have materialized over time due to changes in data collection procedures, rating assignment, technology, population, and so on. The inconsistencies make climate research challenging.

This paper exposes several analytical methods for overcoming some of the data inconsistencies, including using the proportion of tornadoes, estimating tornado energy from the damage path, and aggregating and modeling counts spatially. Interpreting the results always requires care, but the methods show ways to control for the systematic biases and the lurking non-meteorological factors at least in some instances. The nascent field of tornado climatology will certainly grow as more researchers become familiar with these techniques. We hope this article will inspire more research on this important topic.

Short Biographies

Holly M. Widen is currently in the PhD program in the Geography Department at Florida State University. Her research interests include tornado climatology, risk assessment, climate change, and spatial statistics. Her most recent publication is "Adjusted Tornado Probabilities" in the Electronic Journal of Severe Storms Meteorology. Holly obtained a Master's of Science in Geography at Ball State University and a Bachelor's of Science in Geography at Indiana University.

Tyler Fricker is currently in the Master's program in the Department of Geography at Florida State University. His research interests include tornado climatology, biogeography, and climate change. His most recent publication is "Empirical estimates of kinetic energy from some recent U.S. tornadoes" in Geophysical Research Letters. Tyler obtained a Bachelor of Science degree in Environment and Natural Resources from The Ohio State University.

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