Spatiotemporal Analysis of Near-Miss Violent Tornadoes in the United States

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ABSTRACT

In the hazards literature, a near-miss is defined as an event that had a nontrivial probability of causing loss of life or property but did not due to chance. Frequent near-misses can desensitize the public to tornado risk and reduce responses to warnings. Violent tornadoes rarely hit densely populated areas, but when they do they can cause substantial loss of life. It is unknown how frequently violent tornadoes narrowly miss a populated area. To address this question, this study looks at the spatial distribution of possible exposures of people to violent tornadoes in the United States. We collected and replicated tornado footprints for all reported U.S. violent tornadoes between 1995 and 2016, across a uniform circular grid, with a radius of 40 km and a resolution of 0.5 km, surrounding the centroid of the original footprint. We then estimated the number of people exposed to each tornado footprint using proportional allocation. We found that violent tornadoes tended to touch down in less populated areas with only 33.1% potentially impacting 5000 persons or more. Hits and near-misses were most common in the Southern Plains and Southeast United States with the highest risk in central Oklahoma and northern Alabama. Knowledge about the location of frequent near-misses can help emergency managers and risk communicators target communities that might be more vulnerable, due to an underestimation of tornado risk, for educational campaigns. By increasing educational efforts in these high-risk areas, it might be possible to improve local knowledge and reduce casualties when violent tornadoes do hit.

1. Introduction

Tornadoes are one of the most destructive forces on Earth and present a substantial threat to both life and property. Each year approximately 1200 tornadoes are reported in the United States and while the majority (~98.0%) cause no fatalities (SPC 2017), a single tornado can result in a large number of fatalities (e.g., Joplin, Missouri, on 22 May 2011; Paul and Stimers 2012). High-fatality tornadoes (hereafter any tornado causing 100 or more fatalities) are extremely rare, with only 14 occurring since 1880 (Grazulis 1993, 1997), and of those only 3 occurring after the advent of the first tornado forecasts in 1948 (Doswell et al. 1999). While major improvements in tornado detection and warning dissemination systems, building technology, and general public awareness have dramatically reduced the likelihood of the occurrence of a high-fatality tornado, the 2011 tornado season proved that they can and still do occur (Paul and Stimers 2012; Simmons and Sutter 2012).

High-fatality tornadoes tend to occur when a violent tornado [rated (E)F4 or higher on the (enhanced) Fujita scale] hits a densely populated area, but this is a rare occurrence given that between 1995 and 2016 there were, on average, only seven violent tornadoes per year (SPC 2017), and densely populated areas are relatively small targets (Ashley and Strader 2016). Many studies have investigated these "worst-case scenarios," where violent tornadoes track through the central business district or urban core of a major city by transposing historical (Rae and Stefkovich 2000; Hall and Ashley 2008; Ashley et al. 2014) or synthetic (Wurman et al. 2007; Ashley et al. 2014) tornado footprints over urban areas. Some studies have focused on specific external influences on these impacts including urban growth and expansion (Ashley et al. 2014), and daily mobility patterns (Paulikas 2015). While tornadoes have hit major

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cities in the past (e.g., St. Louis, Missouri; Waco, Texas; Nashville, Tennessee; Galway 1981; Grazulis 1993; Edwards and Schaefer 2012), the odds of a violent tornado hitting the urban core of a major city are minimal and thus worst-case scenario events are extremely unlikely to occur (Doswell et al. 2012).

While direct hits have been historically rare, there appears to be an increase in the potential for high-impact tornadoes with the expansion of the urban environment (Ashley et al. 2014; Ashley and Strader 2016; Strader et al. 2018), increased traffic along the interstate (Blair and Lunde 2010), and the influence of climate change (Trapp et al. 2007; Gensini and Ashley 2011; Gensini et al. 2014; Gensini and Mote 2015; Strader et al. 2017b). The exact role that climate change may have on tornado risk (here defined as the probability of the occurrence of a tornado) is unclear. However, there have already been changes in the interannual variability of tornadoes (Brooks et al. 2014; Elsner et al. 2015) and many studies have projected that there will be increases in the number of days with environments favorable for tornado development (e.g., Trapp et al. 2007; Diffenbaugh et al. 2008; Gensini and Ashley 2011; Gensini et al. 2014; Gensini and Mote 2015).

True tornado risk includes both direct hits and near-misses. The latter are tornadoes that come close to hitting densely populated areas or potentially tornadic storms that pass over a densely populated area without producing a tornado. The hazards literature defines a near-miss as an event that had some nontrivial probability of causing a disaster, but by chance it did not (Dillon et al. 2011). Examples would include a tornado that ends just before entering a populated area or a hurricane that suddenly curves away from the coast (Tinsley et al. 2012). Near-misses are important because they could have caused a disaster and they can influence risk perception and future disaster preparedness (Dillon et al. 2014).

Risk perception is a key component of public safety during a tornado. If a person does not believe themselves to be at risk, they are unlikely to seek shelter if a tornado warning is issued (Biddle 1994; Ashley 2007). Frequent false alarms due to near-misses can erode public confidence in the warning dissemination systems making people less likely to seek shelter (Barnes et al. 2007; Brotzge et al. 2011; Simmons and Sutter 2011). Simmons and Sutter (2009) showed a direct causal link between the average tornado false-alarm rate of an area and the average rate of casualties. Paul and Stimers (2012) found that 27% of respondents to a survey, given to tornado survivors after the 2011 Joplin, Missouri, tornado, received a warning about the tornado but did not act because of how frequently the city sounded the tornado sirens. Frequent near-misses can also prompt the development of tornado myths and folklore that can lead people to assume they are safe and thus not seek shelter or seek shelter in the wrong location (Hoekstra et al. 2011). Some examples of these myths include the following: when on the road, it is safest to seek shelter under an overpass (Hoffman 2013); tornadoes will not cross rivers; tornadoes will not stay on the ground for many miles (Klockow et al. 2014); and tornadoes will not hit large cities (Hoekstra et al. 2011; Hoffman 2013; Klockow et al. 2014). Near-misses can influence disaster preparedness in two ways: 1) if a person interprets a near-miss as a nonevent, they may underestimate their risk; and 2) if a person interprets it as a lucky break, they may prepare more for future events as if they had been hit (Tinsley et al. 2012; Dillon et al. 2014).

Studies on near-miss severe weather events often focus on the impacts of a singular event without formally defining the parameters of a near-miss. Prosser (1976) studied the unusual characteristics of a tornado that nearly hit Denver, Colorado, on 18 May 1975 and Sherman-Morris (2010) studied sheltering behavior during a near-miss tornado at Mississippi State University on 10 January 2008. However, the authors are aware of no large-scale study on near-miss tornadoes that provides a clear definition of a near-miss. One such study on *hurricanes* defined near-misses as hurricanes that were forecast to make landfall but did not, and used this definition as a part of an analysis on the accuracy of tropical cyclone forecasts in the Atlantic Ocean between 1976 and 2000 (Powell and Aberson 2001). The authors propose to fill in this gap in the literature by developing a methodology to define near-miss violent tornadoes as a function of the population surrounding the tornado footprint, and to apply this definition to all violent tornadoes in the United States between 1995 and 2016.

The purpose of this study is to determine the frequency with which violent tornadoes in the United States are near-misses and to assess any spatiotemporal patterns that exist for near-miss violent tornadoes in the United States. To answer these questions, we use replicates of historical violent tornado footprints and gridded representations of historical census data to determine possible exposure (here defined as the number of people residing in the footprint of the tornado) scenarios for violent tornadoes.

2. Data and methods

The track that a tornado takes is primarily dependent upon the atmospheric environment during its life cycle

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with small changes potentially shifting a track toward or away from a populated area (Kurdzo et al. 2015). While the environment typically dictates tornado tracks, there is a certain level of randomness to when and where a tornado forms (Klockow et al. 2014). As such, there are many potential tracks a tornado could take and since risk includes all events that did or could have happened (Kaplan and Garrick 1981) it is of interest to know the potential distribution of tornado exposure if a tornado took a different, yet reasonable, track through the area. To determine this potential distribution, we replicated historical tornado footprints throughout their respective surrounding areas and estimated the number of people exposed for each replicate.

The bounds of historical violent tornado activity between 1995 and 2016 closely match the four study regions used by Gensini and Ashley (2011) in their study on severe convective environment climatology. Since the regions are representative of environments favorable for violent tornado development, they were replicated for this study (Fig. 1). In this study, we define a tornado track as a line from the point of touchdown for the tornado to the point of dissipation and a footprint as the total area experiencing tornadic winds. We started our analysis by updating the violent tornado climatology of Concannon et al. (2000) and conducting a sensitivity test to determine whether the error in the exposure estimates, introduced by using linear tornado footprints, could be minimized by careful selection of the census resolution.

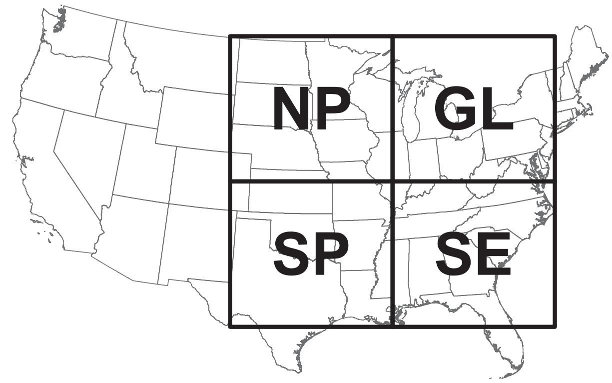

FIG. 1. Four regions used in this study: Northern Plains (NP), Southern Plains (SP), Great Lakes (GL), and Southeast (SE).

a. Data and data accuracy

We collected population data from the U.S. Census Bureau at multiple levels between 1880 and 2010 from the University of Minnesota's National Historical Geographic Information System (NHGIS; Manson et al. 2017). We used county-level data from 1880 to 2010 for the violent tornado climatology and sensitivity test, tract-level and block group–level data from 2000 for the sensitivity test, and block-level data from 1990 to 2010 for the sensitivity test as well as for our primary analysis. We obtained historical violent tornado data for 1880–2016 from two sources: tornado reports from a long-term study of U.S. tornadoes by Tom Grazulis, hereafter referred to as the Grazulis dataset (1880–1994; Grazulis 1993, 1997), and tornado tracks from the U.S. Storm Prediction Center's (SPC) Severe Weather GIS (SVRGIS) database, hereafter referred to as the SPC dataset (1995–2016; SPC 2017). The starting year was selected as 1880 as this is the period after which John Park Finley started collecting regular tornado reports (Ashley 2007; Brooks and Doswell 2002). These reports and tracks were collected from both amateur and professional observers and included information on the time and location, size and intensity, and the damage and casualties caused by each tornado. Many articles discuss the quality problems inherent in this data, including errors in report accuracy and consistency (Doswell and Burgess 1988; Grazulis 1993), limits of using damage to assess tornado intensity (Verbout et al. 2006), and changes in reporting methodology (Agee and Childs 2014; Strader et al. 2016).

Two of these quality problems are particularly relevant for this analysis: changes in width reporting and use of damage-based intensity ratings. In 1995, the Storm Prediction Center switched from reporting tornado widths as the mean width of the path to the maximum width (Brooks 2004; Ashley et al. 2014). This switch resulted in significantly larger widths after 1994 (Agee and Childs 2014; Strader et al. 2015) and introduced a source of error in estimating tornado exposure. Previous studies have resolved this inconsistency by using only tornadoes after 1995 (Ashley et al. 2014; Strader et al. 2015) or adjusting the widths before 1995 by adding the difference in the mean width between the two periods (Agee and Childs 2014) or defining a standard width to use for all tornadoes based on the intensity (Ashley and Strader 2016). We chose to employ the prior method and started our analysis in 1995 since the required block-level population data were only available nationally after 1990 (Ashley et al. 2014).

Tornado intensity was estimated using the Fujita or enhanced Fujita scale, which measures the degree of damage (DoD; i.e., magnitude of damage to an object) a tornado causes to various damage indicators (DIs; e.g., mobile homes, trees) and relates it, empirically, to a wind speed. The original scale was devised by T. Theodore Fujita and colleagues in the 1970s, after the completion of many detailed tornado damage surveys, in reference to the damage caused to ''well built''

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one- and two-family homes (Fujita 1971; Fujita and Pearson 1973; Abbey 1976). Many flaws were noticed in the F scale including too few DIs, especially in rural areas, (Doswell and Burgess 1988; Doswell et al. 2009), the fact that maximum intensity rating was limited by the presence of DIs and the wind speed required to cause the maximum DoD [e.g., double-wide manufactured homes have their maximum DoD at 134 mph ($\sim$60 m s^{-1}) while one- and two-family residences have their maximum DoD at 200 mph ($\sim$89 m s^{-1}); McDonald and Mehta 2006; Edwards et al. 2013], and, according to wind engineers, the fact that the maximum wind speeds for each intensity category were generally too high (McDonald et al. 2003). These concerns led to the development and adoption of the enhanced Fujita (EF) scale, which provided 28 DIs, a number of which are common in rural areas (e.g., small barns, hardwood and softwood trees), as well as a more engineering-based understanding of the wind speeds required to cause damage/failure to various DIs (Edwards et al. 2013). In the EF scale each DI has a maximum possible DoD, associated with an expected wind speed, so each DI has a maximum intensity rating associated with that wind speed that it can indicate [e.g., double-wide manufactured homes are expected to be destroyed in 134-mph winds (EF2 range), so they cannot be used to indicate intensities over EF2].

The adoption of the EF scale helped alleviate some of the concerns with using the F scale to rate tornado intensity; however, for tornadoes that hit in rural areas, it is still very easy to either not hit any damage indicators or to not hit damage indicators with DoDs allowing for a rating of EF4–5. This implies that, historically, especially before the adoption of the EF scale in 2007, rural tornadoes may have been underrated and there may have been more violent tornadoes than the records currently indicate (Strader et al. 2015). A good example of a tornado that was likely underrated was the tornado that hit El Reno, Oklahoma, on 31 May 2013. This tornado tracked over mostly rural areas and did not hit many DIs, resulting in a rating of only EF3. However, a mobile Doppler unit (RaXPol) recorded multiple wind speed measurements exceeding 100 m s^{-1} (maximum recorded wind speed was 135 m s^{-1}), which is in the EF5 range (Snyder and Bluestein 2014). Despite these quality issues, this database is the best record of tornado occurrence currently available and is considered suitable for climatological studies (Verbout et al. 2006; Ashley 2007; Brooks et al. 2014).

We obtained official tornado footprints from the U.S. National Weather Service (NWS) offices in Norman (Oklahoma), Birmingham (Alabama), and Springfield (Missouri) for select tornadoes during the Great Plains Outbreak of 3 May 1999 (NWS 1999), the Super Outbreak of 27 April 2011 (NWS 2011), and the tornado that hit Joplin, Missouri, on 22 May 2011 (NWS 2017). The Great Plains Outbreak tornadoes were used in the sensitivity test while the others were used to compare the accuracy of synthetic versus observed tornado footprints.

b. *Violent tornado climatology*

Concannon et al. (2000) produced a spatial and temporal climatology of violent tornadoes for the period from 1921 to 1995 using the database of Grazulis (1993, 1997). We propose an update to the climatology to include the period from 1880 to 2016. To extend our period of record from 1880 to 2016 we combined the Grazulis and SPC datasets. Since the Grazulis dataset only had the name of the counties impacted by each tornado, we chose to follow the method of Concannon et al. (2000) and assigned each tornado (for both datasets) a location based on the coordinates of the centroid of the county where it touched down. Once each tornado has coordinates we create an 80 km $\times$ 80 km grid (corresponding to the Storm Prediction Center's practice of using 40 km as a proximity distance for severe weather events; Hitchens et al. 2013) over the continental United States and calculated the number of days where a violent tornado touched down in each grid cell (''violent tornado days''). We used ''tornado days'' instead of actual tornado reports to reduce the influence of changes in reporting frequency (Concannon et al. 2000; Brooks et al. 2003). We are interested in changes in the violent tornado climatology over time, so we break the record into three 30-yr periods (1880–1909, 1930–59, and 1987–2016) and calculated the mean number of violent tornado days per millennium. Since we are only interested in large-scale patterns, we smooth the data using a Gaussian low-pass filter with a 120-km standard deviation following Concannon et al. (2000). We test for trends in both the number of violent tornadoes and violent tornado days during this period using the nonparametric Mann–Kendall test ($\alpha = 0.05$; Mann 1945; Kendall 1975). We chose Mann–Kendall because our data were nonnormal and Mann–Kendall is commonly used to test for trends in climate research (Fraedrich et al. 2001; Yue et al. 2002; Sayemuzzaman and Jha 2014; Westra et al. 2013). All subsequent trend testing was done using the same Mann–Kendall test.

c. *Sensitivity test for grid resolution*

Three main methodologies exist for creating tornado footprint polygons for exposure analysis: 1) digitizing postevent damage surveys by government agencies,

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consulting meteorologists and others (Ashley et al. 2014); 2) digitizing observed (radar generated) or modeled wind field data for a tornado (Wurman et al. 2007; Strader et al. 2015); and 3) synthesizing tornado footprints by buffering a tornado track, in a geographic information system (GIS), to a distance corresponding to the reported tornado width (Strader et al. 2015). Of these three methods, the most accurate is the first as observations constrain the footprints. However, post-event surveys are mostly only available for recent high-end events (Ashley et al. 2014; NWS 2018). Radar-based wind fields can be unrealistically large (e.g., Wurman et al. 2007) due to the angle and height at which the radar samples the tornado and can lead to overestimations of exposure (Ashley et al. 2014; Strader et al. 2015); additionally, tornadoes rarely pass close enough to radar to obtain wind field data (Wurman et al. 2007; Simmons and Sutter 2011). While synthetic footprints must by definition be (unrealistically) linear and constant width they can be produced for most tornadoes in the Storm Events Database, and thus are frequently used in ''worst-case scenario'' work for tornado hazards (Wurman et al. 2007; Ashley et al. 2014; Strader et al. 2016). Hence, we chose to buffer the collected tornado tracks in a GIS using the reported width to create synthetic footprints for all violent tornadoes between 1995 and 2016.

Since tornadoes frequently have curved tracks and their widths vary over the lifetime of the storm, it is of interest to note how accurately tornado exposure can be estimated using a synthetic footprint. It is also of interest to analyze the error in exposure (here defined as the difference between the exposures calculated for an observed and synthetic footprint) to determine if it can be minimized by carefully choosing the resolution of the census data to use in the exposure calculations. We required the finest-resolution census data available (blocks) for our analysis because we were interested in the influence of small-scale variations in population on tornado exposure. However, it was unclear if census blocks provided the most accurate estimate of the population in a synthetic tornado footprint. To validate our choice, we conducted a sensitivity test to determine which census resolution yielded the smallest error in exposure.

In this study, we define tornado exposure as the number of persons residing in the footprint of the tornado based on data from the U.S. Census Bureau. The census data are effectively nighttime estimates of population, in a given area, as many people leave home for certain periods during the day to work or run errands (Paulikas 2015; Ashley and Strader 2016). We chose this measure instead of the more conservative housing units used by many studies (Ashley et al. 2014; Strader et al. 2015; Ashley and Strader 2016; Strader et al. 2016) because we were interested in relating the people potentially exposed to a tornado with potential fatalities (Merrell et al. 2005; Simmons and Sutter 2011). Tornado exposure was estimated using proportional allocation based on the intersection between a tornado footprint and the census population data. We allocated each section of the tornado a population, based on the proportion of the area of each census unit that is in that section of the tornado. For example, if the tornado footprint covered 70% of a census unit, we would assign 70% of that census unit's population to that segment of the tornado. The total population exposure for the tornado footprint was then the sum of the population in each segment (Ashley et al. 2014).

To determine how changes in population distribution might influence the error in exposure between observed and synthetic tornado footprints, we replicate selected tornadoes from the 3 May 1999 Great Plains Outbreak over the entire study area. We paired each of the 28 selected observed tornado footprints with the corresponding synthetic footprints generated from the SPC SVRGIS database (see section 2a). We then created a 10-km-resolution replication grid over the entire study area and replicated and shifted the paired footprints to the center of each grid cell maintaining the size and distribution of the tornadoes within the original outbreak (Fig. 2). The tornado footprints were intersected in a GIS with the population data (2000 census) at each census level (county, tract, block group, and block) for each region in the study area. During the intersection procedure, we split the tornado footprint into many small segments, one for each census unit it crossed. We assigned each segment a population, based on the proportion of the original census unit it covered (proportional allocation; Ashley et al. 2014). For each cell in the replication grid, we calculated the root-mean-square error (RMSE) of the exposure. For our RMSE calculation, we compare the exposure for the synthetic footprint, intersected with the population data for each census level, to the observed footprint, intersected with only the block-level population data. We only use the block-level population data for the observed footprint since we want an exact measure of the people residing in the actual footprint. We also calculated the RMSE at the region and study area level. To determine which resolution performed best we selected the resolution that yielded the lowest RMSE value at each level (cell, region, and study area).

d. *Exposure distributions*

To simulate many possible tornado footprints, we first created a uniform circular replication grid with a

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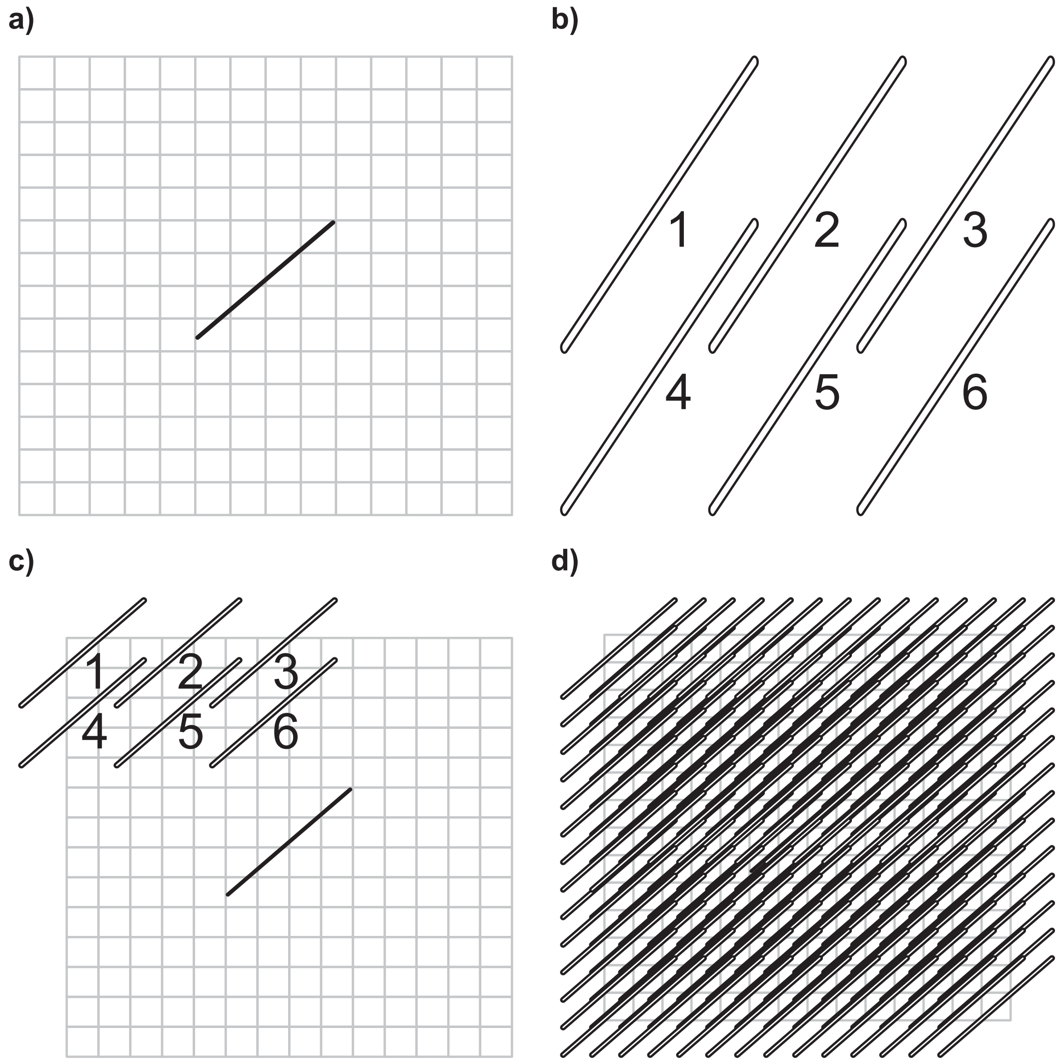

FIG. 2. Simplified workflow for the replication procedure: (a) Create a uniform grid surrounding the tornado footprint to be replicated; (b) make copies of the tornado footprint maintaining the size and orientation of the original footprint; (c) move each copy to the center of its corresponding grid cell; and (d) repeat steps (b) and (c) until all grid cells have a copy of the original footprint. This example is not to scale; the actual grid is a uniform circular grid with a radius of 40 km and a resolution of 0.5 km for a total of 20 140 grid cells.

40-km radius and a resolution of 0.5 km surrounding the centroid of the synthetic footprint. We define the extent of the area occupied by all tornado replicates as the potential impact zone. We then created replicates of the synthetic footprint (maintaining the size and orientation of the original) and shifted each one to the centroid of each of the 20 140 grid cells in the replication grid (Fig. 2). We chose a 40-km radius following the Storm Prediction Center's practice of using 40 km as a proximity distance for severe weather events (Hitchens et al. 2013). We used block-level population data in our analysis since we aim to assess small-scale changes in exposure and those required the finest resolution possible. Since census blocks vary in size and shape both in space and time, we followed the method of Ashley et al. (2014) to interpolate census blocks onto a fixed grid using proportional allocation. As in Ashley et al. (2014), we used a grid resolution that corresponded to the mean resolution of the census blocks located within the grid. We then linearly interpolated the population grids to the year of the tornado using the preceding and succeeding census data. Finally, we calculated exposure for each replicate as above by intersecting the tornado footprint and the population grid.

We subset our replicate exposures into those within 10 km (the upper range for mesocyclone size; Adlerman et al. 1999) and 40 km (SPC's proximity radius; Hitchens et al. 2013) of the original footprint and calculated

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summary statistics for the following variables: footprint area (AREA), observed tornado exposure (OBS), median (PPEMED) and maximum (PPEMAX) number of persons potentially exposed to the tornado (from the distribution of all replicate exposures), and the probability that a tornado hitting within 10 (40) km of the original footprint would exceed the observed exposure (EPOBS), 5000 persons (EP5K), or 20 000 persons (EP20K). The probability of exceedance (EP) was calculated as follows:

$$\mathrm{EP} = 1 - F(t),$$

where t is the threshold (e.g., 5000 persons) and $F(t)$ is the empirical cumulative distribution function derived from the set of all replicate exposures within the specified radius (10 or 40 km), calculated as

$$F(t) = \frac{1}{n}\sum_{i=1}^{n} \mathbf{I}_{[x_i \le t]},$$

where n is the number of exposures within the specified radius and $\mathbf{I}$ is the indicator function (1 if $x_i \le t$ and 0 otherwise). The likelihood related to the EP is defined as very likely ($\mathrm{EP} > 75\%$), likely ($50\% < \mathrm{EP} \le 75\%$), unlikely ($25\ \% < \mathrm{EP} \le 50\%$), or very unlikely ($\mathrm{EP} \le 25\%$).

Using the exposure distributions, we defined a hit as a tornado where OBS $\ge$ 5000 persons, a near-miss where OBS $<$ 5000 persons and PPEMAX $\ge$ 5000 persons within 10 km, and a far-miss where OBS $<$ 5000 persons, PPEMAX $<$ 5000 persons within 10 km, and PPEMAX $\ge$ 5000 persons within 40 km. We chose 5000 persons as the threshold as Brooks et al. (2008) report a 0.1%–1.9% fatality rate for select violent tornadoes and this range was supported by fatality estimates from the 27 April 2011 Tuscaloosa–Birmingham, Alabama (1.9%), and the 22 May 2011 Joplin, Missouri tornadoes (0.9%). These estimates were derived by following the methodology of Brooks et al. (2008), using the number of homes destroyed as reported by Prevatt et al. (2012) and assuming the national average of 2.64 persons per home (U.S. Census Bureau 2015). A threshold of 5000 persons would yield an expected fatality total from 5 to ~100 and only 10.4% of all violent tornadoes occurring between 1995 and 2016 had fatality totals exceeding five (SPC 2017). We used a similar procedure as that used to produce the violent tornado climatology to determine the high-risk areas for violent tornadoes and for all tornadoes with observed or potential exposures exceeding 5000 persons (hits or near-misses) during the period of 1995–2016. We used the reported coordinates of tornado touchdown to place each tornado on an 80 km × 80 km grid. We then proceeded to calculate the mean number of days when a violent tornado touched down in each grid cell during the study period. As in the violent tornado climatology we were only interested in large-scale trends so we smoothed the data using a Gaussian low-pass filter with a standard deviation of 120 km (Concannon et al. 2000). We arbitrarily defined high-risk areas as all areas estimated to have had at least two violent tornado days per century as the one violent tornado day per century area covered most of the middle part of the country. We tested for trends in the number of hits, near-misses, far-misses, observed exposure, median and maximum potential exposure, and the probability that a tornado would impact at least 5000 persons. We used a quadrat analysis with a chi-squared test ($\alpha = 0.05$; Griffith and Haining 2006; Arnold et al. 2017) to determine which regions had more hits, near-misses, and far-misses. We also used global (Moran 1950; Legendre and Legendre 2012) and local Moran's I tests (Anselin 1995) to determine the degree of spatial autocorrelation in the tornado locations and the locations of clusters with reference to large metropolitan statistical areas. To perform the Moran's I tests we first counted the number of tornadoes in each county during the whole study period and then defined our neighborhood using the county boundaries with the standard "queen's case" contiguity rule (Greenbaum 2002).

e. *Comparing exposures using synthetic and observed damage paths*

We selected 10 violent historical tornadoes with both synthetic and observed footprints available (Table 1) and reran the replication analysis to calculate the observed exposure (OBS) and maximum replicate exposure (PPEMAX) within 10 and 40 km for each footprint type for each tornado. We used these results to classify each footprint as a hit, near-miss, or far-miss to determine if the use of synthetic footprints affects the classification of the tornado.

3. Results

a. *Violent tornado climatology*

Risk occurs when a hazard (i.e., tornado) and a vulnerable population/structure are collocated. An understanding of the violent tornado climatology is thus key in determining violent tornado risk (Dixon et al. 2011; Coleman and Dixon 2014; Ashley and Strader 2016). A large body of literature has discussed tornado climatology (Abbey 1976; Concannon et al. 2000; Doswell and Burgess 1988; Grazulis 1993; Ashley 2007; Doswell et al. 2012; Brooks et al. 2014; Strader et al. 2015;

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TABLE 1. Comparison of exposure, potential exposure, and type between synthetic and observed tornado footprints for select violent tornadoes between 1995 and 2016. Variables include the date (Date) and location (Location) of the tornado, its exposure (OBS), and maximum potential exposure within the specified radius (PPEMAX) and whether the tornado is a near-miss, far-miss, or hit (TYPE).

		Synthetic footprint				Observed footprint			
			r = 10 km	r = 40 km			r = 10 km	r = 40 km	
Date	Location	OBS	PPEMAX	PPEMAX	TYPE	OBS	PPEMAX	PPEMAX	TYPE
3 May 1999	Bridge Creek–Moore, OK	23 649	37 617	47 503	Hit	10 057	16 810	42 282	Hit
3 May 1999	Cimarron City–Mulhall, OK	1209	3749	38 478	Far-miss	440	3582	39 048	Far-miss
3 May 1999	Dover, OK	62	1783	6112	Far-miss	229	1026	5832	Far-miss
27 Apr 2011	Cullman, AL	4162	4825	16 255	Far-miss	2662	3666	11 313	Far-miss
27 Apr 2011	Hackleburg–Phil Campbell, AL	22 784	63 522	63 645	Hit	6722	20 303	33 835	Hit
27 Apr 2011	Cordova, AL	5712	10 413	40 943	Hit	2445	5032	46 434	Near-miss
27 Apr 2011	Tuscaloosa–Birmingham, AL	39 231	102 942	114 368	Hit	18 690	37 900	46 454	Hit
27 Apr 2011	Shoal Creek–Ohatchee–Argo, AL	7887	17 661	57 974	Hit	2278	7766	12 546	Near-miss
27 Apr 2011	Lake Martin, AL	1199	3205	17 455	Far-miss	500	1392	9662	Far-miss
22 May 2011	Joplin, MO	4474	14 449	14 579	Near-miss	17 292	18 119	18 119	Hit

and many more). We update the violent tornado climatologies of Concannon et al. (2000) and Doswell et al. (2012) to include the period from 1880 to 2016 during which there were 1255 violent tornadoes reported in the United States, occurring over 786 days (SPC 2017; Grazulis 1993, 1997). During this period violent tornadoes were most common in an L-shaped pattern over Iowa, Oklahoma, and Alabama, similar to

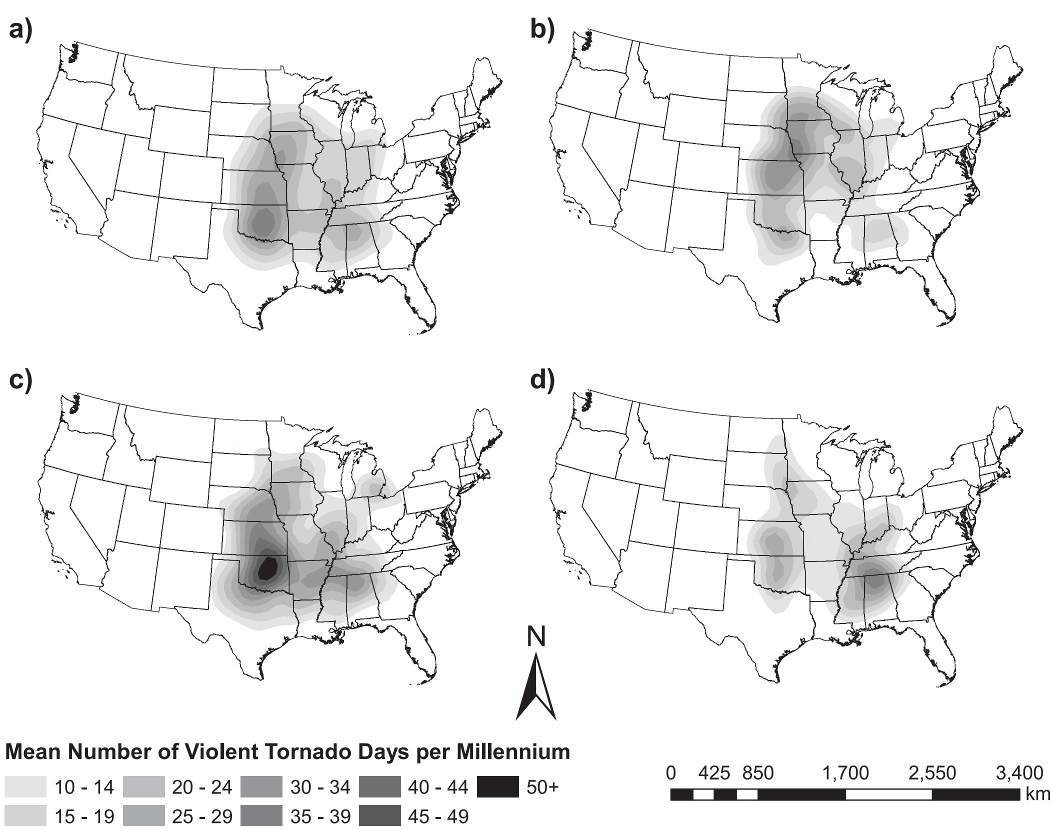

FIG. 3. Mean number of violent tornado days in the United States per millennium for the period of (a) 1880–2016 and select 30-yr periods: (b) 1880–1909, (c) 1930–59, and (d) 1987–2016. Figure created following the methods of Concannon et al. (2000).

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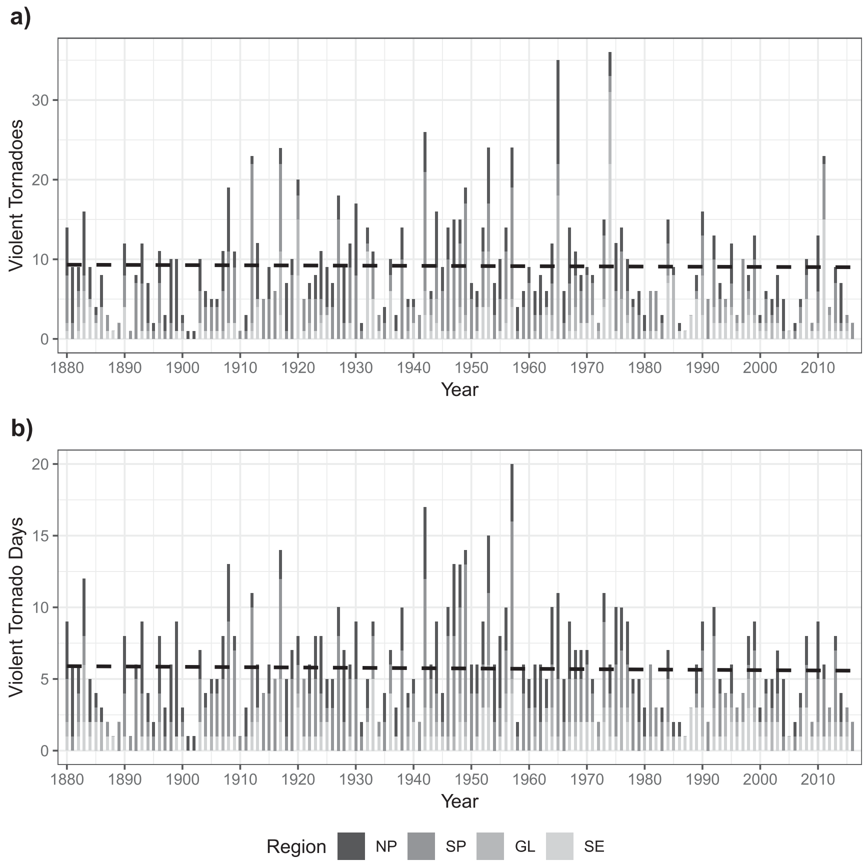

FIG. 4. (a) Violent tornado counts and (b) days with a violent tornado per year from 1880 to 2016. Stacked bars are colored by region. Dashed line is the best fit using a linear model.

the patterns found by Concannon et al. (2000) and Doswell et al. (2012) for the period of 1921–1995 (2010). The greatest number of mean violent tornado days (35–39 days per millennium) was found in central Oklahoma. The 1880–1909 period saw peak activity (35–39 days per millennium) in the central Great Plains whereas the 1930–59 and 1987–2016 periods saw peak activity shift to the southern Great Plains (50+ days per millennium) and Southeast (35–39 days per millennium) respectively (Fig. 3). While there was no significant temporal trend nationally for either annual violent tornado counts ($p = 0.57$) or tornado days ($p = 0.63$) between 1880 and 2016, we found a small but significant decrease in annual counts the Northern Plains ($p = 0.02$) and a corresponding increase in the Southeast ($p = 0.05$; Fig. 4). With regard to tornado days, only the increase in the Southeast was significant ($p = 0.04$). As in Concannon et al. (2000) and Ashley and Strader (2016) we found a high degree of interannual variability in violent tornado occurrence and location resulting in some periods where certain regions are more active than others. It is unclear if the long-term significant increasing (decreasing) trend for violent tornado counts in the Southeast (Northern Plains) is due to overall changes in tornado favorable environments or to other nonmeteorological factors such as a short period of record or changes in reporting frequency over time (Trapp et al. 2007; Diffenbaugh et al. 2008, 2013; Ashley and Strader 2016).

b. *Population distribution in potential impact zones*

The character of the population distribution over the study area showed significant changes during the period of our study. The regions with the highest (Great Lakes) and lowest (Northern Plains) population densities remained the same. However, the mean population density (per census block) decreased over time as more people moved from rural to urban areas, as found by Ashley and Strader (2016).

We defined the potential impact zone for each violent tornado as the extent of the area surrounding all of its replicates. We found that the potential impact zones were largest in the Southeast (Table 2), due to larger tornado footprints (Ashley 2007; Strader et al. 2015;

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TABLE 2. Population distributions and violent tornado recurrence intervals for each region in the study area. For the potential impact zones the data were interpolated to a grid with a resolution equivalent to the mean census block size in each impact zone while for the other tables the data are in the original census blocks for each decennial census (1990–2010). Variables include region name (Region), area of impact zone or total land area for census blocks (km^2; AREA), percentage of blocks or grid cells with a population density exceeding 386 persons per square kilometer (one definition of an urban area; Ratcliffe et al. 2016; PCTURB), percentage of blocks or grid cells that are populated (PCTPOP), mean grid cell or census block population density (persons per square kilometer; POPDEN), number of violent tornadoes (NTOR), and recurrence interval for the period 1995–2016 (months; RECUR).

Region	AREA	PCTURB	PCTPOP	POPDEN	NTOR	RECUR
Potential impact zones						
GL	14 697.3	7.5	96.6	125.3	11	24.0
NP	15 743.4	1.2	96.5	19.3	41	6.4
SE	20 750.9	2.2	96.3	41.2	44	6.0
SP	18 046.8	2.6	94.9	43.8	58	4.6
1990 census blocks						
GL	774 146.9	4.1	87.0	2014.0		
NP	1 324 138.8	0.5	76.2	504.4		
SE	1 002 375.1	2.0	82.8	699.6		
SP	1 390 897.1	1.2	78.0	769.1		
2000 census blocks						
GL	773 830.4	4.5	87.5	1793.9		
NP	1 322 642.4	0.6	74.1	523.2		
SE	1 001 832.1	2.4	84.1	613.9		
SP	1 385 149.3	1.3	70.1	740.4		
2010 census blocks						
GL	773 680.3	4.9	86.0	1442.5		
NP	1 322 228.1	0.6	71.1	453.5		
SE	1 001 024.5	2.9	82.4	510.4		
SP	1 385 004.2	1.5	67.5	623.6		

Ashley and Strader 2016). The greatest risk for violent tornadoes (defined here as the shortest recurrence interval) was in the Southern Plains and Southeast (Ashley 2007; Ashley et al. 2008; Dixon et al. 2011; Strader et al. 2015; Ashley and Strader 2016), while the greatest population density was in the Great Lakes (Table 2). Relative to the mean population density in each region, the population density in each potential impact zone was very small, indicating that most violent tornadoes were hitting in less populated areas. The percentage of the areas that were ''urban'' (here defined following one of the U.S. Census Bureau's criteria for urban area classification; population density exceeds 386 persons per square kilometer; Ratcliffe et al. 2016) or populated were generally greater in the potential impact zones than in the regions themselves. This is an interesting finding, but given that most of the developable area in the study area is populated (Table 2), it is not surprising that populated areas are more frequently hit (Ashley and Strader 2016). The probable explanation is a reduction in the number of reported violent tornadoes in unpopulated areas due to a combination of the underreporting of tornadoes in unpopulated regions (Brooks et al. 2003; Simmons and Sutter 2011; Elsner et al. 2013; Strader et al. 2015) and the underrating of tornadoes in rural areas because of a lack of people/structures to impact (Doswell and Burgess 1988; Doswell et al. 2009; Strader et al. 2015).

c. Sensitivity test

At the gridcell level, we found that no one census resolution significantly outperformed the others in terms of providing the lowest RMSE. The block-level resolution yielded the lowest RMSE in the most grid cells (greatest area) for the study area as a whole as well as for each individual region. However, the remaining census levels only performed marginally worse (Fig. 5). In regions with higher population densities (Great Lakes and Southeast; Table 2), the difference in performance was very low, while in areas with lower population densities (Northern and Southern Plains) the differences were greater but still not significant (Table 3). At the regional level, we found that the RMSE did not significantly vary by census level for each region, but the lowest RMSE was produced using the county-level resolution for all regions except the Northern Plains. Similar results were found at the level of the study area with the county-level resolution outperforming the others (Table 3).

The difference in the performance of the block-level resolution between the gridcell level and the regional and

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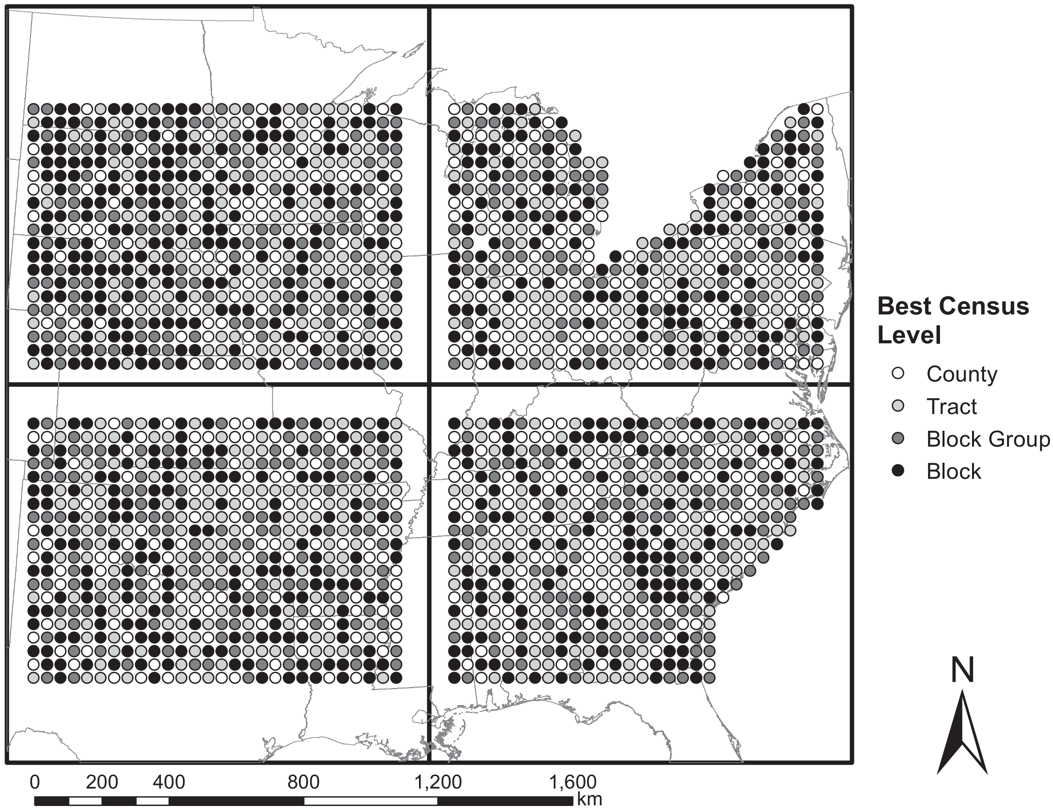

FIG. 5. Results of the sensitivity test for best census resolution at the gridcell level over the study area. The best census level was the one that yielded the lowest root-mean-square error for the estimation error between the observed and synthetic footprint exposures. The sensitivity test involved replicating the 3 May 1999 Oklahoma tornado outbreak in each grid cell over a uniform rectangular grid with a resolution of 10 km spanning the entire study area.

study-area levels is likely due to the mismatch between the observed and synthetic footprints. When the observed footprint closely matches the synthetic footprint the finest resolution (block level) typically yields the lowest RMSE, while this is not always the case when the footprints are mismatched. When the observed footprint curves significantly it can hit a nearby population center that the synthetic footprint missed, yielding a large RMSE. These large differences can be most pronounced when block-level population data are used since coarser resolutions (census level) typically result in fewer variations in population over the length of the footprint. In aggregate, these large differences appear to result in larger RMSEs for the block level than the county level. Based on these results it is evident that tornado exposure is only marginally sensitive to the selection of the census resolution. Each resolution has its weaknesses and no one resolution works significantly better than the others.

d. *Potential exposure to violent tornadoes*

Because of the lack of block-level census data prior to 1990 (Ashley et al. 2014) and a shift in tornado width reporting in 1994 (Brooks 2004; Agee and Childs 2014; Strader et al. 2015), our analysis was limited to the period of 1995–2016. This 22-yr period is small and thus is likely influenced by small-sample bias due to the rarity of violent tornadoes (Doswell 2007; Ashley and Strader 2016). While the characteristics of individual tornadoes during this period might be biased (Doswell 2007), the climatology during this period is in general agreement with the long-term climatology from 1880 to 2016 (Fig. 3; Ashley 2007; Doswell et al. 2012; Ashley and Strader 2016), implying that the spatial trends may be reliable. In spite of the potential bias, the data can still provide some information about violent tornadoes.

Between 1995 and 2016, there were 154 violent tornadoes in the United States with most of them occurring between the Rocky and Appalachian Mountains. The greatest number occurred in the Southern Plains, but the Northern Plains and Southeast also had significant numbers of violent tornadoes (differences between regions were significant based on a Pearson chi-square test; $p = 0.002$; Fig. 6a). The high-risk area for violent tornadoes (area expected to have at least two violent

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TABLE 3. Results of sensitivity test for selection of the best census level. At the gridcell level, each grid cell is assigned a best census level that corresponds to the census level yielding the lowest root-mean-square error (RMSE) between the synthetic and observed population exposures. The overall best census level to use for each region (and for the whole study area) corresponds to the census level that is the best in the greatest number of grid cells. At the regional level, the RMSE is calculated for each census level for the entire region (study area) and the best census level corresponds to the census level with the lowest RMSE for the region.

Region	County	Tract	Block group	Block	Best level
Gridcell level (values are gridcell count)					
GL	104	95	79	110	Block
NP	90	138	135	197	Block
SE	117	114	106	127	Block
SP	107	150	136	167	Block
Study area	418	497	456	601	Block
Regional level (values are RMSE)					
GL	2006.4	2158.3	2194.5	2230.3	County
NP	687.6	596.7	636.9	650.5	Tract
SE	987.7	1130.4	1163.9	1239.6	County
SP	870.4	916.5	968.8	1011.5	County
Study area	1170.1	1246.7	1282.9	1322.4	County

tornado days per century) covered approximately 483 788 km^2 and extended in a broken L shape between Iowa, Oklahoma, and Alabama (Fig. 7), following the pattern found by Concannon et al. (2000) and Doswell et al. (2012). These violent tornadoes had a median area, observed exposure, potential exposure (within 10 km), and probability of impacting 5000 persons or more (within 10 km) of 22.9 km^2, 564 persons, 311 persons, and 30.3% respectively. As found by Ashley (2007) and Ashley and Strader (2016), the tornadoes were largest and had the greatest observed and potential exposure in the Southeast (Table 4), due to greater rural population densities (Table 2) and larger damage areas. Observed and potential exposure were lower in the Northern Plains due to lower rural population densities.

Within 10 (40) km of the original footprint 33.1% (57.8%) of all violent tornadoes between 1995 and 2016 had a potential exposure of at least 5000 persons while only 8.4% (24.7%) had an exposure of at least 20 000 persons. The high-risk area for violent tornadoes with observed or potential exposures of at least 5000 persons (within 10 km) covered approximately 35 663 km^2 and was located primarily in central Oklahoma and northern Alabama (Fig. 7). This area matches where major metropolitan areas (Oklahoma City, OK, and Birmingham, AL) meet the areas with the greatest risk of violent tornadoes (Concannon et al. 2000; Ashley 2007; Doswell et al. 2012; Ashley and Strader 2016).

Approximately 10.4% of the violent tornadoes were likely to very likely to be hits (EP5K > 50% within 10 km), with all of these occurring in the Southern Plains and Southeast (Fig. 8). There were no significant temporal trends in median annual observed ($p = 0.61$), maximum ($p = 1.00$), or median ($p = 1.00$) potential exposure (within 10 km) or in the median annual probability of impacting 5000 persons or more (within 10 km; $p = 0.54$) between 1995 and 2016.

e. Near-misses and far-misses

Near-misses (far-misses) were defined as violent tornadoes where OBS < 5000 persons and PPEMAX ≥ 5000 persons within 10 km (OBS < 5000 persons, PPEMAX < 5000 persons within 10 km, and PPEMAX ≥ 5000 persons within 40 km). Figure 9 shows an example of a near-miss to the City of Norman, Oklahoma, on 10 May 2010 (Fig. 9b) and a far-miss for the cities of Canton and Pekin, Illinois, on 13 May 1995 (Fig. 9c). Between 1995 and 2016 there were 30 near-misses and 38 far-misses. Near-misses and far-misses occurred in all regions with their distribution being similar to the distribution of violent tornadoes in general. Near-misses (far-misses) occurred most frequently in the Southern Plains (Southeast) but the regional differences were not significant ($p = 0.09$ and $p = 0.13$ respectively; Figs. 6c,d). The median maximum potential exposure was similar between near-misses and far-misses (9415 and 9234 persons respectively) with the highest value for near-misses (far-misses) in the Southern Plains (Great Lakes) (Table 5). The median probability of being a hit was 8.1% (1.9%), indicating that it is very unlikely that any near-misses or far-misses could have been hits. In fact, no near-miss was likely to very likely to have been a hit (Table 6). However, the median probability of impacting more persons than was observed was 47.8%, indicating it was nearly likely that near-misses could have impacted more persons (Table 5). There was no significant temporal trend found for either near-misses ($p = 0.38$) or far-misses ($p = 0.60$) between 1995 and 2016 for the entire United States or for any subregion.

f. Hits

Hits were defined as violent tornadoes where OBS ≥ 5000 persons. There were 21 reported hits, between 1995 and 2016, occurring in all regions, except the Great Lakes. They were most common in the Southern Plains and Southeast and rare in the Northern Plains (regional differences were significant; $p = 0.008$; Fig. 6b). These locations match the findings of Ashley and Strader (2016), who found the high rural population density in the Southeast combined with the high risk of tornadoes

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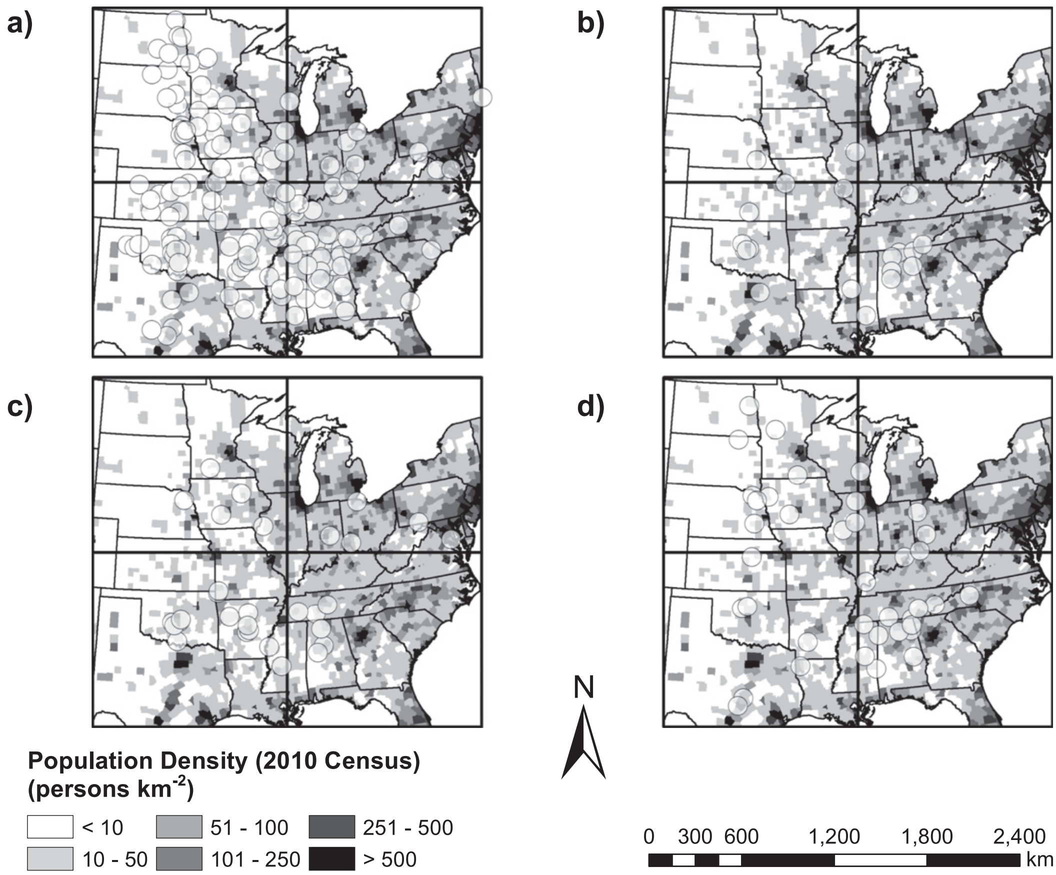

FIG. 6. Centroids of (a) violent tornadoes, (b) hits, (c) near-misses, and (d) far-misses between 1995 and 2016. Population density, at the county level, from the 2010 census is included for reference.

resulted in significant potential impacts. The Northern Plains have high tornado risk but low population density while the Great Lakes have high population density but low tornado risk (Ashley and Strader 2016). Figure 9d shows an example of a hit on the city of Cleveland, Tennessee, on 27 April 2011. Hits had a median observed exposure of 8848 persons with the highest value in the Southern Plains and lowest in the Northern Plains (Table 5). They had a median maximum potential exposure (within 10 km) of 19 534 persons with the greatest maximum potential exposure in the Southern Plains. Hits that occurred in the Northern Plains were unlikely to actually be hits whereas hits in the Southern Plains and Southeast were very likely to be hits. All but five of the hits were either likely or very likely to be hits (Table 7). Hits in the Southeast were likely to have impacted more persons than they did while they were very unlikely to do so in the Northern Plains (Table 5). Similarly to the near-misses and far-misses, we found no significant temporal trend for hits ($p = 0.92$) between 1995 and 2016 for the entire United States or for any subregion.

g. Characteristics of select violent tornadoes

A total of 13 violent tornadoes had a maximum potential exposure (within 10 km) exceeding 20 000 persons; of these 10 were hits and 3 were near-misses. Three of these were likely to very likely to have had an exposure of at least 20 000 persons and another seven were very unlikely to have had such an exposure. Only five were likely to impact more people than was observed (Tables 6 and 7).

h. Comparison of synthetic and observed damage paths

Tornado footprints come in all shapes and sizes (Wurman et al. 2007; Ashley et al. 2014; Strader et al. 2015) with some taking a relatively straight track (Ashley et al. 2014), others curving significantly (Paul and Stimers 2012), and some even moving in a loop (Wurman et al. 2014). The width of the footprint can also change significantly throughout the life of the tornado as it weakens or strengthens (Burgess et al. 2014). Wind speed also varies throughout the tornado

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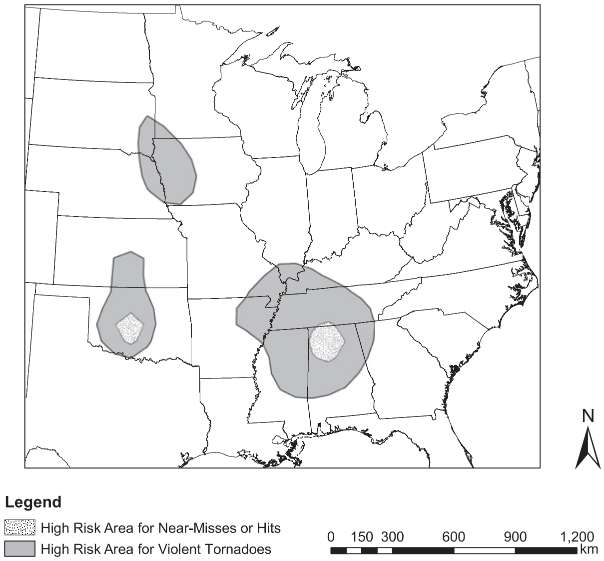

FIG. 7. High-risk area for all violent tornadoes (gray) and near-misses or hits (stippled) between 1995 and 2016. High-risk area is defined as the area expected to have had at least two violent tornado days per century. High-risk areas were calculated after the data had been smoothed with a Gaussian low-pass filter with a standard deviation of 120 km (Concannon et al. 2000).

footprint with only a small fraction of the total area experiencing EF4–5 wind speeds and damage (Wurman et al. 2007; Ashley et al. 2014; Strader et al. 2015). These variations in footprint shape and area can result in large departures from the linear synthetic footprint produced by buffering the SPC tornado tracks (SPC 2017). To test if these variations affected the classification of a violent tornado as a hit, near-miss, or far-miss, we ran our replication analysis on the observed footprints of 10 violent tornadoes and compared the exposures to those from the matching synthetic footprints. We found substantial differences between synthetic and observed tornado footprints in terms of both observed exposure and maximum potential exposure (within 10 km). The largest difference in observed exposure was 16 062 persons for Hackleburg–Phil Campbell, AL, while the smallest difference was 167 persons for Dover, OK. The largest difference in maximum potential exposure was 65 042 persons for Tuscaloosa–Birmingham while the smallest difference was 167 persons for Cimarron City–Mulhall, OK. These differences in exposure arose from both curvature in the observed footprints and differences in footprint area between observed and synthetic footprints. The latter finding was in agreement with a study by Strader et al. (2015) that found a mean overestimation of significant tornado footprint area of 39% for synthetic footprints between 1995 and 2013. While most of the synthetic and observed tornado footprints were classified the same (e.g., near-miss), three (Joplin, MO; Cordova, AL; and Shoal Creek–Ohatchee–Argo, AL) had large enough differences to result in different classifications. All three of the misclassifications were the result of tornado footprints with significant curvature. The Joplin tornado curved into a densely populated area, resulting in a hit, while the others curved away from densely populated areas, resulting in near-misses (Table 1).

i. Spatial autocorrelation of violent tornadoes

Violent tornadoes typically form as a result of the presence of key ingredients in the atmosphere: low-level moisture, increases in wind speed with height, rapid change in temperature with height, and the presence of a thunderstorm. It is rare to get all of these ingredients together to produce violent tornadoes (Doswell et al. 2012); however, there are certain regions where these ingredients are more common (e.g., ‘‘Tornado Alley’’ and ‘‘Dixie Alley’’; Dixon et al. 2011; Gensini and Ashley 2011; Ashley and Strader 2016). Because of the spatial dependence of tornado-favorable environments, there is spatial clustering (spatial autocorrelation) in the tornado climatology. Spatial clustering also exists in population data with a significant proportions of the population living in clustered urban areas (Ashley et al. 2014; Ashley and Strader 2016). We tested for spatial autocorrelation in all tornadoes, near-misses, far-misses, and hits using a global and local Moran's I test. For the global Moran's I test, we found positive spatial autocorrelation (clustering) in all cases ($p \leq 0.05$) as expected. At the local level, for all violent tornadoes, we found significant clustering scattered throughout the traditional Tornado Alley and Dixie Alley (Dixon et al. 2011; Gensini and Ashley 2011). For near-misses, far-misses, and hits, we found significant clustering in or near large metropolitan statistical areas (population of 500 000 persons or more; Fig. 10). This was also expected as, by definition, near-misses, far-misses, and hits require significant populations living within the potential impact zone.

4. Discussion

The risk of tornado exposure is typically measured as a function of the number of tornadoes hitting an area during a specified time period (Boruff et al. 2003; Ashley et al. 2014; Strader et al. 2016). These risk assessments rarely include tallies of tornadoes that narrowly missed a populated area; however, near-misses are equally likely events and thus are an important part of the true exposure risk (Dillon et al. 2011; Tinsley et al. 2012; Dillon et al. 2014). In addition to impacting exposure risk,

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TABLE 4. Characteristics of violent tornadoes and the regions they struck in the United States between 1995 and 2016. Tornado footprint area (AREA) refers to the area of the tornado footprint polygon (km^2). Persons exposed (OBS) refers to the residential population (based on the U.S. census data at the time of each tornado) within the tornado footprint. Median persons potentially exposed (PPEMED) refers to the median value of the residential population within the footprint of all replicate tornadoes within the specified distance radius r. Probability that a replicate tornado within the specified distance from the original footprint will have a potential exposure of at least 5000 persons (EP5K) is also shown. Statistics included are minimum (MIN), median (MED), interquartile range (IQR), and maximum (MAX) values for all tornadoes within each region.

Region	MIN	MED	IQR	MAX	MIN	MED	IQR	MAX
	AREA				OBS			
GL	1.1	7.8	19.4	68.4	41	993	1375	3907
NP	0.4	16.1	36.7	349.6	0	112	364	5815
SE	0.1	39.8	49.4	427.3	4	1232	3760	39 231
SP	0.9	28.2	39.2	675.2	0	782	2955	24 130
US	0.1	22.9	48.9	675.2	0	564	2441	39 231
PPEMED								
	r = 10 km				r = 40 km			
GL	59	554	1068	3166	39	404	821	3027
NP	0	40	261	4408	0	52	231	3116
SE	2	967	3258	41 949	1	659	2,110	17 807
SP	1	346	2496	23 508	0	215	1,547	8415
US	0	311	1891	41 949	0	251	1206	17 807
EP5K								
	r = 10 km				r = 40 km			
GL	0.2	2.9	7.5	17.4	0.1	6.2	4.7	34.1
NP	2.3	6.0	17.1	42.0	0.0	2.0	10.7	36.7
SE	4.1	49.5	51.8	100.0	0.4	12.4	25.2	100.0
SP	1.1	39.8	60.8	100.0	0.0	14.3	34.9	62.8
US	0.2	30.3	57.2	100.0	0.0	9.2	26.2	100.0

near-misses can also influence vulnerability via their effect on risk perception and shelter-seeking behavior (Dillon et al. 2014). This study represents a first attempt to determine the frequency of near-misses for violent tornadoes by replicating and translating each original tornado footprint across the area surrounding the potential impact zone. This method allows us to consider scenarios where a tornado struck a more or less populated area nearby the original footprint. We chose this methodology since it enables us to test many possible exposure scenarios throughout the area surrounding the potential impact zone and also because it has the advantage of ease of use.

We first updated the U.S. violent tornado climatology of Concannon et al. (2000) to include the period of 1880–2016. We found that the general pattern over the 137-yr period was the same (Fig. 3) as has been found by others (Concannon et al. 2000; Ashley 2007; Doswell et al. 2012; Ashley and Strader 2016). However, there was a small but statistically significant increase (decrease) in the number of violent tornadoes in the Southeast (Northern Plains; Fig. 4) over the period as found by Ashley and Strader (2016). The climatology shows that the general pattern has not changed (with regular peaks in the Southern Plains and Southeast); however, during some periods certain regions are more active than others (Concannon et al. 2000; Doswell et al. 2012; Ashley and Strader 2016). It is unclear if the increasing trend for violent tornadoes in the Southeast is due to nonmeteorological factors, such as small-sample bias (Doswell 2007; Ashley and Strader 2016) or population bias (Brooks et al. 2003; Simmons and Sutter 2011; Elsner et al. 2013; Strader et al. 2015), or to climate change (Trapp et al. 2007; Diffenbaugh et al. 2008; Gensini and Ashley 2011; Gensini et al. 2014; Gensini and Mote 2015). If this increase in violent tornado activity in the Southeast is due to climate change it is a major concern given that the population growth in the Southeast has been rapid (Ashley 2007; Ashley and Strader 2016) and the highly vulnerable mobile/manufactured home market continues to grow there (Merrell et al. 2002; Ashley 2007).

We tested the sensitivity of the error in exposure estimates between synthetic and observed tornado footprints to the selection of census level. Most studies that estimate tornado exposure tend to ignore the error generated by using synthetic tornado footprints since the focus is on scenario work and exact historical exposure values are unnecessary (Wurman et al. 2007; Ashley et al. 2014; Ashley and Strader 2016). This error can become important for historical estimates of tornado exposure, however, since it is possible for exposure

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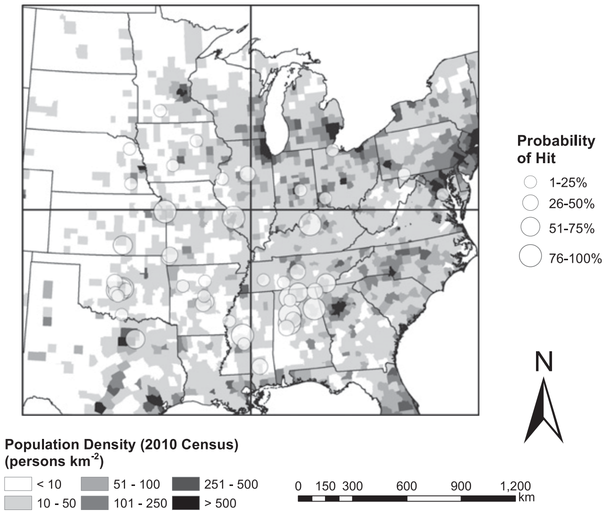

FIG. 8. Probability that a violent tornado hitting within 10 km of its original footprint would have resulted in a hit between 1995 and 2016. Population density, at the county level, from the 2010 census is included for reference. The sizes of the dots relate to the probability category with higher probabilities represented by larger circles.

estimates to be highly inaccurate if the observed footprint curves into or away from a densely populated area (e.g., Joplin, MO, 22 May 2011; Paul and Stimers 2012). Our finding that the error between synthetic and observed footprints is large is not surprising as tornado widths change over the lifetime of the tornado and tracks frequently curve (Strader et al. 2015). It is noteworthy that the differences in error between the different census levels for each region, as well as for the whole study area, are relatively small, indicating a lack of sensitivity to the selection. The finding that the block-level census data perform best at the replication level while the county-level data perform best in aggregate is interesting as it shows that the error generated when a curved tornado footprint travels through a densely populated area is large enough to overcome the local inaccuracies in county-level data. It is also noteworthy that the error is sensitive to the regional population with more densely populated areas (e.g., Great Lakes) having a much higher error than more sparsely populated areas (e.g., Northern Plains). The overall findings of the sensitivity test indicate that the error in exposure (relative to a nonlinear, width-changing footprint) cannot be minimized through the selection of the census level. This implies that if a study does not require fine-resolution census data (Ashley et al. 2014; Ashley and Strader 2016; Strader et al. 2016, 2017b), it is reasonable to use county-level data (Boruff et al. 2003; Merrell et al. 2005; Simmons and Sutter 2011, 2012). This is highly relevant since it allows the use of county-level census data to study historical tornado exposure going back to the beginning of the tornado record in the 1880s (Grazulis 1993; Ashley 2007).

Many studies have shown that tornadoes rarely hit densely populated areas due to both the rarity of violent tornadoes and the comparatively small amount of developed area that exists in the United States (Rae and Stefkovich 2000; Wurman et al. 2007; Ashley and Strader 2016; Strader et al. 2016, 2017b, 2018). Our findings that violent tornadoes typically hit sparsely populated areas with median observed and potential exposures under 1000 persons (in all regions except the Southeast; Table 4) were thus unsurprising. Most tornado-prone regions (Concannon et al. 2000; Doswell et al. 2012) have low population densities (Table 2), and thus low exposure, while the Southeast is the exception with greater rural population densities, longer tornado tracks, and more fatalities (Ashley 2007; Strader et al. 2015; Ashley and Strader 2016). While densely populated areas are rarely hit, contrary to folklore, cities are no safer from tornadoes than rural areas (Hoekstra et al. 2011; Klockow et al. 2014). In fact, there have been many tornadoes that have even hit the downtown areas (central business districts) of major cities (Edwards and Schaefer 2012).

We found that only 33.1% of all violent tornadoes had observed or potential exposures of at least 5000 persons (within 10 km; i.e., were near-misses or hits) and the high-risk area for such tornadoes only covered 7.4% of the total high-risk area (area expected to have at least two violent tornado days per century). The high-risk area was primarily located in central Oklahoma and northern Alabama, matching the areas of peak violent tornado activity (Concannon et al. 2000; Doswell et al. 2012) and killer tornado activity (Ashley 2007), respectively. It was interesting that no near-miss was likely to be a hit (Table 6) while several hits were very unlikely to have been hits (Table 7). This is likely because the near-miss definition only required the maximum potential exposure to be 5000 persons. We chose to use a maximum potential exposure due to the small sample size of violent tornadoes, but future work looking at near-misses for all tornadoes could include a more stringent definition by, for example, using a median potential exposure of 5000 persons. If we had used such a measure for our small sample we would have found no near-misses.

The primary goal of this study was to understand the spatiotemporal patterns of near-miss violent tornadoes and their relation to population distributions in the area surrounding the potential impact zone. We found that the likelihood of hits, near-misses, and far-misses were a function of the underlying population

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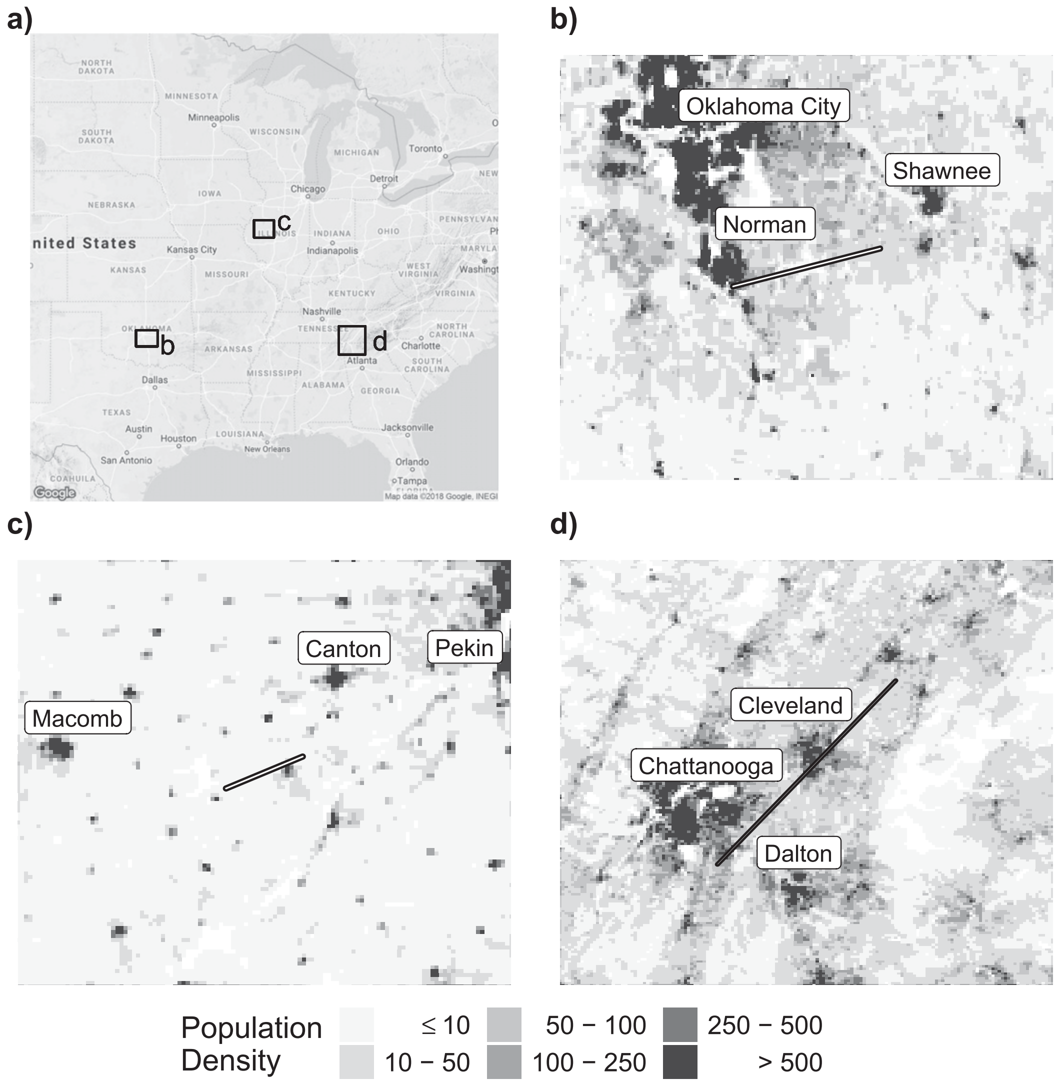

FIG. 9. Examples of the tornado footprints for a near-miss, far-miss, and hit. (a) A reference map of the United States displaying the extent for each example. (b) A near-miss on the city of Norman, OK, on 10 May 2010. (c) A far-miss for the cities of Canton and Pekin, IL, on 13 May 1995. (d) A hit on the city of Cleveland, TN, on 27 Apr 2011. The population grids (for each potential impact zone) were generated following the method of Ashley et al. (2014) and use the block-level census data from the 1990 and 2010 censuses and a grid resolution matching the mean block size in the potential impact zone. The population was linearly interpolated to the year of the tornado.

distribution (Table 2) as well as the climatology of violent tornadoes (Fig. 6). The spatial distribution of near-misses, far-misses, and hits was similar to the general distribution of all violent tornadoes with peak occurrence in the Southern Plains and Southeast (Concannon et al. 2000; Ashley 2007; Doswell et al. 2012; Ashley and Strader 2016). The differences in the spatial patterns between the three types of violent tornadoes is primarily evident in the differences in population density. The results indicate that hits were relatively more common in the Southeast where the rural population density is higher and less common in the less populated areas (e.g., Northern Plains; Table 2; Ashley and Strader 2016). The results also indicate that near- and far-misses were relatively highest in the Great Lakes, likely due to the expansion of the urban areas into the countryside as well as the rarity of violent tornadoes in this region (Ashley and Strader 2016). We also found significant spatial autocorrelation (clustering) for counties with hits, near-misses, and far-misses near large metropolitan areas (Fig. 10). The clustering implies that the risk for near-misses is low outside large urban areas. As urban expansion continues, the vulnerable areas will likely see an increase in

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TABLE 5. Characteristics of violent tornadoes by type and region. Characteristics include the median value for each region of persons exposed (OBS), tornado footprint area (AREA; km^2), maximum persons potentially exposed (PPEMAX), probability (%) that the persons potentially exposed exceeds the persons exposed (EPOBS), 5000 persons (EP5K), or 20 000 persons (EP20K) within the specified distance radius r. An asterisk denotes the sample size for the probability calculation was less than 3.

				r = 10 km				r = 40 km			
Region	n	OBS	AREA	PPEMAX	EPOBS	EP5K	EP20K	PPEMAX	EPOBS	EP5K	EP20K
Far-misses											
GL	4	1100	10.3	4226	38.0	—	—	15 488	43.3	5.9	1.4*
NP	12	206	17.7	1433	27.0	—	—	8872	37.3	1.2	1.4*
SE	14	1198	55.1	3565	38.9	—	—	13 337	43.7	8.4	1.3
SP	8	492	26.3	3386	30.9	—	—	7677	30.1	0.5	1.1*
US	38	647	37.5	3142	31.8	—	—	9234	40.0	1.9	1.3
Near-misses											
GL	5	1969	7.8	10 012	31.1	2.9	—	14 123	33.6	7.2	11.7*
NP	5	813	103.0	6394	69.6	5.1	7.0*	21 130	58.2	8.2	6.4
SE	6	2699	38.1	8915	40.8	19.8	9.2*	11 190	26.2	10.1	5.6*
SP	14	2412	45.5	11 144	51.1	17.5	16.6*	23 617	40.5	13.6	2.1
US	30	2182	49.2	9415	47.8	8.1	9.2	19 611	36.3	12.3	2.6
Hits											
GL	0	—	—	—	—	—	—	—	—	—	—
NP	2	5631	204.8	12 327	22.7	30.3*	—	59 941	26.8	29.6*	18.0*
SE	9	7887	87.1	18 144	52.2	82.5	63.3	40 943	27.6	42.5	15.2
SP	10	10 873	34.9	23 698	42.1	82.6	30.1	41 431	18.5	43.7	10.7
US	21	8848	70.6	19 534	43.0	82.5	34.6	40 943	27.3	42.5	16.8

population, making it more likely that tornadoes will pass close by or hit densely populated areas (Ashley et al. 2014; Ashley and Strader 2016; Strader et al. 2017a,b).

The methodology used in this study is a first attempt at determining the frequency of near-miss violent tornadoes and as such we employed a definition that made use of existing tornado footprint data. The definition appears reasonable as small shifts in environmental conditions have been known to shift the footprints of violent tornadoes (Bluestein et al. 2015). Our study was limited to a 22-yr period due to a lack of block-level census data prior to 1990 and a change in tornado width reporting in 1994. This short period is likely subject to small-sample bias due to the extreme rarity of violent tornadoes (Doswell 2007; Ashley and Strader 2016). However, the distribution of violent tornadoes was found to match the long-term climatology (Fig. 3; Concannon et al. 2000; Doswell et al. 2012), implying that the distribution observed was reasonable. Likewise, the high-risk area for near-misses and hits (Fig. 7) was located where the highest risk for violent tornadoes met large metropolitan areas in central Oklahoma (Oklahoma City) and northern Alabama (Birmingham–Hoover). Given that hits and near-misses require large populations, by definition, this distribution also makes sense (Ashley and Strader 2016; Strader et al. 2017b).

Near-misses do not only result from tornadoes that dissipated before, shifted away from, or just narrowly missed a densely populated area. Some cyclic tornadic supercells pass over populated areas without producing a tornado (e.g., Nashville, TN, on 5 February 2008; Murphy and Knupp 2013), resulting in a near-miss. Future work on this topic could include creating synthetic tornado tracks and translating them along and about the track of tornadic supercells (identified via radar; Trapp et al. 2005) to determine the likelihood of near-misses for tornadoes that did not happen.

The use of synthetic tornado footprints to estimate exposure also creates a source of error for this analysis as true tornado footprints often curve and change strengths and widths over the life of the tornado (Paul and Stimers 2012; Strader et al. 2015). The error introduced by using synthetic footprints can be significant. As an example, the official footprint from the NWS for the EF5 tornado which hit Joplin, Missouri, on 22 May 2011 had an exposure of 17 292 persons while the synthetic footprint from the SPC only had an exposure of 4474 persons. The reason for the difference is that the SPC used a linear footprint that passed south of the highest population areas in Joplin. Conversely the NWS footprint for the EF4 tornado that hit Tuscaloosa–Birmingham, Alabama, on 27 April 2011 had an exposure of only 18 690 persons while the SPC footprint had an exposure of 39 231 persons. As a result of errors such as these 3 of the 10 tornadoes tested (Joplin, MO; Cordova, AL; and Shoal Creek–Ohatchee–Argo, AL) were misclassified as a near-miss,

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TABLE 6. Characteristics of all near-misses from 1995 to 2016. Characteristics include the date and location of the tornado, its magnitude on the EF scale (MAG), tornado footprint area (AREA; km^2), fatalities (FAT), persons exposed (OBS), median (PPEMED) and maximum (PPEMAX) persons potentially exposed, and the probability (%) that the persons potentially exposed exceeds the persons exposed (EPOBS), or 5000 persons (EP5K) within 10 km. Table is sorted by the probability that the near-miss would have been a hit. Boldface rows have a maximum potential exposure (within 10 km) of 20 000 persons or more.

Date	Location	MAG	AREA	FAT	OBS	PPEMED	PPEMAX	EPOBS	EP5K	EP20K
10 May 2008	Picher, OK	4	195.6	21	3076	4651	10 888	87.8	44.9	—
1 Mar 1997	**Little Rock, AR**	**4**	**22.8**	**5**	**3269**	**3420**	**34 315**	**52.5**	**44.5**	**16.6**
22 May 2011	Joplin, MO	5	50.9	158	4474	3851	14 449	46.7	44.5	—
8 Apr 1998	**Oak Grove–Rock Creek, AL**	**5**	**58.9**	**32**	**4251**	**4227**	**32 927**	**49**	**40.3**	**9.2**
1 Mar 1997	Vimy Ridge–Shannon Hills, AR	4	29	10	3625	2806	17 352	42.8	35.2	—
10 Apr 2009	Murfreesboro, TN	4	25.7	2	4996	4592	8168	32.7	32.6	—
16 Dec 2000	Tuscaloosa, AL	4	19.9	11	2558	2423	9662	49.6	30.3	—
27 Apr 2014	Mayflower–Vilonia, AR	4	79.8	16	2697	2923	12 313	67.4	23.7	—
25 May 2008	**Parkersburg–New Hartford, IA**	**5**	**126.6**	**9**	**1665**	**2498**	**25 321**	**85.4**	**23.1**	**7.0**
10 May 2010	Norman–Little Axe, OK	4	28.8	1	2985	1522	14 480	27.2	18.4	—
24 May 2011	Chickasha–Oklahoma City, OK	4	43.1	1	2564	2057	11 401	40	18.1	—
2 Jun 1998	Frostburg, MD	4	64.5	0	2095	3166	13 766	70.5	17.4	—
24 Nov 2001	Madison, MS	4	14.9	2	2259	2173	15 674	46.5	16.9	—
4 May 2003	Jackson, TN	4	50.5	11	2780	1846	6988	30.5	9.3	—
5 Feb 2008	Atkins–Clinton, AR	4	236.7	13	2184	2456	5874	56.1	8.2	—
28 Apr 2002	La Plata, MD	4	36.3	3	3907	2348	10 633	25.2	8	—
16 Apr 1998	Lawrence County, TN	5	179.7	3	2619	1941	11 639	32.1	7.1	—
8 Apr 1999	Creston–Granger, IA	4	103	0	813	1103	6395	69.6	6	—
4 Oct 2013	Wayne, NE	4	65.6	0	624	341	5401	38.8	5.1	—
19 May 2013	Lake Thunderbird–Shawnee, OK	4	50.8	2	2179	2128	6988	44.8	4.5	—
6 Feb 2008	Moulton-Decatur, AL	4	21.6	4	944	949	7377	50.4	4.1	—
24 Nov 2001	Winterville, MS	4	39.2	0	349	379	8241	57.8	3.8	—
5 Jun 2010	Millbury, OH	4	5.2	7	937	498	10 012	31.1	2.9	—
13 May 1995	Niota, IL	4	73.6	0	195	447	7391	98.4	2.4	—
29 Mar 1998	Comfrey, MN	4	162.2	1	1021	783	5337	29.5	2.3	—
24 May 2011	Washington–Goldsby, OK	4	29.9	0	284	474	9168	82.6	1.8	—
10 Feb 2009	Lone Grove, OK	4	47.9	8	791	788	5071	49.6	1.2	—
24 May 2011	Etna–Denning, AR	4	148	4	1660	1914	6408	69.8	1.1	—
9 Apr 1999	Blue Ash, OH	4	4	4	1969	1499	6143	28	0.5	—
11 Jun 1998	Greenfield–Maxwell, IN	4	7.8	0	993	579	5449	35.3	0.2	—

hit, and hit respectively (Table 1). Since the sensitivity test showed that changing the census resolution used in the analysis had minimal effect on the accuracy of the exposures using the SPC footprints, this represents a distinct limitation of this methodology. However, we believe our methodology justified given that 70% of the tested tornadoes were classified correctly (Table 1).

Since we found no temporal trend in near-misses, farmisses, or hits since 1995, it is unclear if either climate change or urban expansion have influenced their occurrence but it seems likely that urban expansion has had at least some effect since various scenario studies have showed exposures increasing over time (Ashley et al. 2014; Ashley and Strader 2016). We limited our analysis to violent tornadoes because they cause the most fatalities (Ashley 2007), but it would be of interest to rerun this analysis on all historical U.S. tornadoes since 1995 to see if a temporal trend could be found with a larger sample size. Additionally, by limiting our analysis to only those tornadoes that were classified as violent we could have missed many tornadoes that might have had winds on the level of a violent tornado but did not hit any damage indicators capable of receiving (E)F4- or 5-level damage (e.g., El Reno, OK on 31 May 2013; Snyder and Bluestein 2014). Our findings that the percentage of urban and populated areas were generally higher, in the potential impact zone than in the surrounding region, could be an indicator of an underrating problem for tornadoes in unpopulated areas (Table 2). While it is not possible to know exactly how many violent tornadoes were underrated due to a lack of damage indicators (Doswell and Burgess 1988; Doswell et al. 2009; Edwards et al. 2013; Strader et al. 2015), including all, or at least all significant [(E)F2+], tornadoes would allow for a much better picture of the risk strong tornadoes pose to populated areas

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TABLE 7. As in Table 6, but for hits.

Date	Location	MAG	AREA	FAT	OBS	PPEMED	PPEMAX	EPOBS	EP5K	EP20K
22 Apr 2011	**St. Louis, MO**	**4**	**27.6**	**0**	**24 130**	**23 508**	**38 957**	**45.5**	**100**	**71.5**
27 Apr 2011	**Hackleburg–Phil Campbell, AL**	**5**	**427.3**	**72**	**22 784**	**22 678**	**63 522**	**43**	**100**	**63.3**
27 Apr 2011	**Tuscaloosa–Birmingham, AL**	**4**	**308.7**	**64**	**39 231**	**41 949**	**102 942**	**52.2**	**100**	**80.8**
27 Apr 2011	Shoal Creek–Ohatchee–Argo, AL	4	252.1	22	7887	10 969	17 661	88.9	100	—
3 May 1999	**Bridge Creek–Moore, OK**	**5**	**77.9**	**36**	**23 649**	**18 992**	**37 617**	**30.6**	**94.7**	**45.5**
10 May 2010	**Moore–Choctaw, OK**	**4**	**70.6**	**2**	**10 582**	**11 710**	**55 020**	**53**	**90.5**	**30.1**
4 May 2003	Franklin, KS	4	15.5	2	8848	8286	14 277	41.2	89.6	—
27 Apr 2011	Cordova, AL	4	264.8	13	5712	5961	10 414	58.5	83.9	—
24 Apr 2010	Tallulah–Yazoo City–Durant, MS	4	675.2	10	5628	7337	13 533	74.6	82.6	—
20 May 2013	**Moore, OK**	**5**	**38.7**	**24**	**19 181**	**17 548**	**42 244**	**43**	**82.6**	**39.0**
28 May 1996	**Pioneer Village–Hillview, KY**	**4**	**37.5**	**0**	**7877**	**8340**	**32 553**	**54.4**	**82.5**	**9.3**
3 May 1999	**Wichita–Haysville, KS**	**4**	**31.1**	**6**	**15 361**	**9074**	**21 860**	**21**	**73.2**	**5.5**
26 Dec 2015	**Sunnyvale–Garland, TX**	**4**	**10.6**	**10**	**7399**	**7197**	**25 536**	**49.2**	**63.7**	**4.0**
18 May 1995	Deerfield–Campbellsville, AL	4	74.6	1	6173	6383	19 534	52.6	63.6	—
27 Apr 2011	Apison–Cleveland, TN	4	56.5	20	9833	8680	13 696	33.9	63.6	—
8 May 2003	**Moore–Oklahoma City, OK**	**4**	**17.8**	**0**	**11 163**	**7586**	**20 620**	**32.6**	**59.9**	**1.7**
10 Feb 2013	Hattiesburg, MS	4	42.1	0	16 491	4947	18 144	5.6	49.5	—
27 Apr 2011	Pisgah, AL–Trenton, GA	4	87.1	14	5293	4968	17 380	43.4	49.3	—
17 Nov 2013	Washington, IL	4	60	3	5815	4408	18 304	30.6	42	—
24 May 2011	El Reno–Piedmont, OK	5	163.4	9	5123	2566	14 352	24.1	26.1	—
22 May 2004	Hallam, NE	4	349.6	1	5446	2658	6350	14.8	18.5	—

(Ashley et al. 2014; Ashley and Strader 2016; Strader et al. 2017b, 2018).

5. Conclusions

This study has represented a first large-scale attempt to determine the frequency of near-miss violent tornadoes by replicating and translating each original tornado footprint across the area surrounding the potential impact zone. Not surprisingly, we found that tornadoes tended to hit in less populated areas and that hits, near-misses, and far-misses had spatial distributions that matched the violent tornado climatology. The primary difference we noted in the distributions was related to rural population density, with locations with higher rural population densities (e.g., Southeast) favoring hits and areas with lower rural population densities (e.g., Southern Plains) favoring near-misses. Our analysis also found that the error introduced by using synthetic tornado footprints is not sensitive to the selection of the level of census data used. This finding is important because 1) it allows a user to select the census level that best fits their tornado hazard assessment and 2) it enables analysis of tornadoes going back to the late 1800s (Grazulis 1993, 1997) when county-level census data were the only census data available.

Emergency managers require an in-depth understanding of tornado hazard risk to help mitigate tornado disasters, but they often ignore near-miss tornadoes when assessing risk due to a lack of direct impacts. Near-misses are important because in addition to representing realistic outcomes they can also influence risk perception and sheltering behavior (Dillon et al. 2011; Tinsley et al. 2012; Dillon et al. 2014). Tornado warnings do not always reach the entire population at risk, due to factors such as language barriers or lack of television/radio/TV/Internet access (Brotzge and Donner 2013). However, often the warning is received and not heeded (Sherman-Morris 2010; Paul and Stimers 2012) due to a lack of personalization of the risk. Studies have shown that frequent false alarms, due to near-misses, can desensitize the public to tornado risk and reduce the likelihood of response to a warning (Barnes et al. 2007; Simmons and Sutter 2009; Brotzge et al. 2011; Simmons and Sutter 2011; Paul and Stimers 2012). Frequent near-misses can also prompt the development of tornado folklore that can lead people to assume they are safe and thus not seek shelter or seek shelter in the wrong location (Hoekstra et al. 2011; Klockow et al. 2014). Knowledge about the location of frequent near-misses can help emergency managers and risk communicators target communities that might be more vulnerable, due to an underestimation of tornado risk, for educational campaigns (Brotzge and Donner 2013). Expert-led town halls could be conducted to combat tornado myths and better explain the true nature of local tornado risk (Stewart et al. 2018). By increasing educational efforts in these high-risk areas, it might be possible to improve local knowledge and reduce casualties when violent tornadoes do hit.

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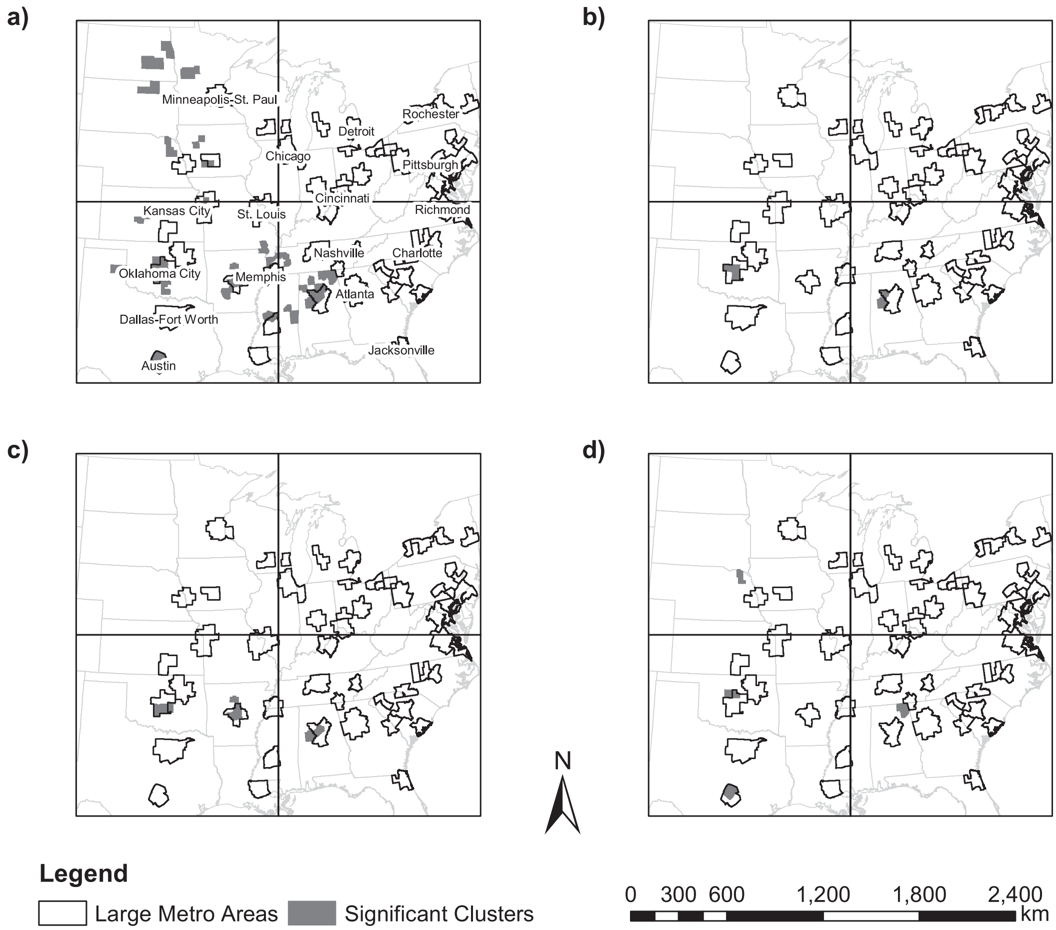

FIG. 10. Counties with clusters of (a) violent tornadoes, (b) hits, (c) near-misses, and (d) far-misses. Counties are identified as clusters based on a local Moran's I test with $\alpha = 0.05$. Metropolitan statistical areas with populations greater than or equal to 500 000 persons are also plotted for reference.

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