TJ18.1 EXAMINING VULNERABILITY TO TORNADOES USING CENSUS TRACT-LEVEL DEMOGRAPHIC DATA AND TORNADO DAMAGE SURVEY PATHS

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ABSTRACT

Tornadoes pose a substantial risk to life and property and while advancements in understanding of hazard evolution and forecast communication increases community resiliency, better understanding and quantification of social vulnerability to tornadoes at high spatial resolutions is also needed to increase preparedness and resiliency. To expand this understanding of vulnerability, relationships were examined between census tract-level demographic data, land-use land-cover data, and specific fatality locations for 13 deadly tornadoes where tornado damage path shapefiles were available. These spatially precise datasets were used to examine what demographic variables might be most connected to tornado fatalities and to build a linear predictive statistical model that quantifies relative social vulnerability to tornadoes. The predictive model was then used to create a map of Oklahoma showing relative vulnerability on a census tract-level scale that could be used by decision makers to prepare for, respond to, and recover from tornadoes. Key results of this pilot study include: 1) social vulnerability to tornadoes is higher in urban areas than in rural areas, 2) incorporating as many demographic variables as possible into the predictive statistical model appears to result in more accurate vulnerability maps, 3) vulnerability maps can add useful information to other tools, such as radar-based tornado track estimation products, and 4) the area of developed land within a tornado track is likely related to fatalities.

1. INTRODUCTION

Meteorologists, engineers, and public safety officials have made significant advancements in terms of preparing for and warning the general public about tornadoes over the past several decades, yet tornadoes can still cause significant impacts including fatalities. In addition to research leading to increased understanding of tornado formation (e.g., Lemon and Doswell 1979; Markowski et al. 2003; Houser et al. 2015) and improvements to National Weather Service (NWS) tornado warnings (e.g., Coleman et al. 2011; Brotzge and Donner 2013), vulnerability assessments and indices can also provide important information used in preparing for and responding to tornadoes (e.g., Cutter et al. 2003; Ashley 2007; Donner 2007).

Vulnerability is the susceptibility of any given system to be impacted and disrupted by a disaster (e.g., Cutter et al. 2003; Flanagan et al. 2011) and is different from resilience in that resilience relates to the ability of a system to successfully plan for and recover from a disaster (e.g., Mileti 1999; Cutter et al. 2010; Bakkensen et al. 2017). To create useful indices for

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planning and response purposes, previous studies have quantified community-level vulnerability and resilience by examining various demographic variables (e.g., Cutter et al. 2003; Peacock et al. 2010; Flanagan et al. 2011). The Social Vulnerability Index (Cutter et al. 2003) is one of the more well-known indices that uses 11 normalized factors based on 42 demographic variables to provide information about social vulnerability on a county-by-county basis. This information allows decision makers to target communities in need of increased hazard mitigation activities and better understand factors that affect disaster recovery. Other indices, such as the Baseline Resilience Index for Communities (Cutter et al. 2010) and the Community Disaster Resilience Index (Peacock et al. 2010), are also calculated on a county-by-county basis (i.e., county scale).

To quantify vulnerability at finer scales, some studies have used census tracts or census block groups, which are smaller subdivisions of counties (U.S. Census Bureau 2010), to examine vulnerability and disaster impacts. For example, Flanagan et al. (2011) used census tract-level demographic data relating to socioeconomic status, household composition, minority status, and housing characteristics to create a social vulnerability index specifically for disaster management. The authors also demonstrated the potential predictive power of the tool by comparing it with measures of recovery in New Orleans, Louisiana after Hurricane Katrina. They found that census tracts with higher vulnerability were more likely to experience slow recovery. Wilhelmi and Morss (2013) conducted hazard-specific vulnerability research by mapping radar estimated rainfall and flash-flood impacts relative to social vulnerability for census block groups in Fort Collins, Colorado. Their goal was to provide decision makers with a tool that would enable targeted preparation, response, and recovery actions for extreme precipitation events.

Hazard-specific research has also been conducted for tornadoes especially with respect to what demographic variables and physical characteristics of the tornado (e.g., width, intensity, etc.) might most impact fatalities and injuries (e.g., Ashley 2007; Donner 2007; Fricker et al. 2017). Using county-level demographic data, tornado line (i.e., line connecting tornado start and end points) data, and regression models, Simmons and Sutter (2005) found that time of day in which a tornado occurred and the number of mobile homes within an affected county had a significant effect on expected fatalities. Specifically, for every 1% increase in mobile homes, expected fatalities increased by 6%. Donner (2007) used census tract-level demographic data and tornado start and end points to build a predictive model for fatalities. Analysis suggested that fatalities were related to factors such as percentage of mobile homes present and spatial area impacted by a tornado, but not to population density and poverty. This later result was unexpected and also differed somewhat from the results of other studies (e.g., Wurman et al. 2007; Ashley and Strader 2016; Fricker et al. 2017).

One potential limitation of much of the existing research deals with the precision and resolution of the data. A single line connecting tornado start and end points does not fully capture factors such as width or nonlinear motion, while county-level demographic data represents a scale much larger than any single tornado. These limitations are important, because tornadoes are small-scale events with widely varying path characteristics and the degree of damage and fatalities depends on these path characteristics as well as specifics of the population and built environment within the tornado's path (e.g., Wurman et al. 2007; Burgess et al. 2014; Paul and Stimers 2014). It can therefore be challenging to precisely determine which communities might be most vulnerable to and thereby most impacted by a tornado.

Therefore, the purpose of this study is to use tornado path data, census tract-level demographic data, and location-specific tornado fatality information to explore relationships between various demographic variables and tornado fatalities. The ultimate goal is to use these relationships to produce maps of relative social vulnerability—specifically to tornadoes—that can be used by decision makers to prepare for and respond to tornadoes. Decision-maker knowledge of local communities is vitally important and useful in disaster planning and our intent is not to replace the need for this information, but to supplement it with information based on a quantitative analysis of social vulnerability (hereafter referred to as vulnerability) to tornadoes.

2. TORNADO-RELATED DATA AND DEMOGRAPHIC VARIABLES

To be as precise and accurate as possible when examining tornado fatalities relative to demographic data, we leveraged three different datasets with relatively high spatial resolution. We selected tornadoes for analysis based on two factors: 1) the availability of damage survey path shapefiles through the NWS Damage Assessment Toolkit (available at https://apps.dat.noaa.gov/stormdamage/damageviewer/) and 2) fatality location descriptions within the National Center for Environmental Information's Storm Events Database (available at https://www.ncdc.noaa.gov/stormevents/) that were specific enough to determine which census tract each fatality occurred in. Using these factors ensured that each considered census tract was actually impacted by a tornado and that census tracts with fatalities were not left out of the analysis—both of which are possible if using tornado line data (Fig. 1). Based on these criteria, we selected 13 tornadoes for analysis (Table 1) that impacted 156 census tracts and caused 128 fatalities.

Census tract-level data were then downloaded for 10 different demographic variables (Table 2) using data from the U.S. Census Bureau's 2010 American Community Survey 5-year estimates (available at https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml). These data were chosen based on previous studies (e.g., Cutter et al. 2003; Donner 2007; Hall and Ashley 2008) and to ensure that all demographic data were collected prior to the occurrence of any tornado in our dataset. All variables, other than median age and home value, were then normalized based on census tract area and represent density (units per km^2) of each variable.

3. RELATING DEMOGRAPHIC VARIABLES TO TORNADO FATALITIES

After matching tornado paths and fatalities to census tract-level demographic data, we began examining how each demographic variable might impact fatality numbers by primarily using linear and negative binomial models. Using the slope and y-intercept parameter output by each model, we calculated how fatality numbers changed across each variable's distribution between the 10th and 90th percentiles. We also examined p values output by these models, linear correlations, and Monte Carlo simulations (n = 1000) to see which demographic variables were most connected to the observed tornado fatalities. From this analysis, we determined the top 5 demographic variables to be, in no particular order, population density, mobile home density, under age 10 density, over age 65 density, and median age (Table 2).

Since we are not suggesting that the aforementioned top 5 variables are the best or only variables to consider when examining vulnerability to tornadoes, we used all 10 demographic variables to build a predictive linear statistical model. This model used the relationships between the demographic variables and the observed fatalities for all tornadoes in the dataset to predict fatalities for every census tract in Oklahoma if it were impacted by a tornado. These fatality predictions were then normalized by calculating z-scores for each census tract that were then used to create maps of relative vulnerability in Oklahoma (Fig. 2). For comparison, we also produced relative vulnerability maps using the top 5 demographic variables (Fig. 3).

4. MAPS OF RELATIVE VULNERABILITY AND THEIR POTENTIAL APPLICATIONS

The relative vulnerability maps for Oklahoma show that the highest vulnerability generally exists in urban areas, while lower vulnerability exists in rural areas (Fig. 2). This pattern likely occurs due to our normalization of each demographic variable by census tract area—except for median age and median home value—and resulting focus on each variable's density characteristics. Previous studies (e.g., Donner 2007; Hall and Ashley 2008; Fricker et al. 2017) corroborate this idea since tornadoes

Table 1. Tornadoes used in the analysis.

Tornado Location	Date	Fatalities	Census Tracts Affected
Cordova, AL	27 April 2011	13	22
Cullman, AL	27 April 2011	6	11
Jefferson County, AL	27 April 2011	22	20
Chickasha, OK	24 May 2011	1	7
El Reno, OK	24 May 2011	9	8
Henryville, IN	2 March 2012	11	10
Granbury, TX	15 May 2013	6	2
Moore, OK	20 May 2013	24	15
Vilonia, AR	27 April 2014	16	10
Rowlett, TX	26 December 2015	10	11
Hattiesburg, MS	21 January 2017	4	12
Albany, GA	22 January 2017	5	18
Northwest WI	16 May 2017	1	10

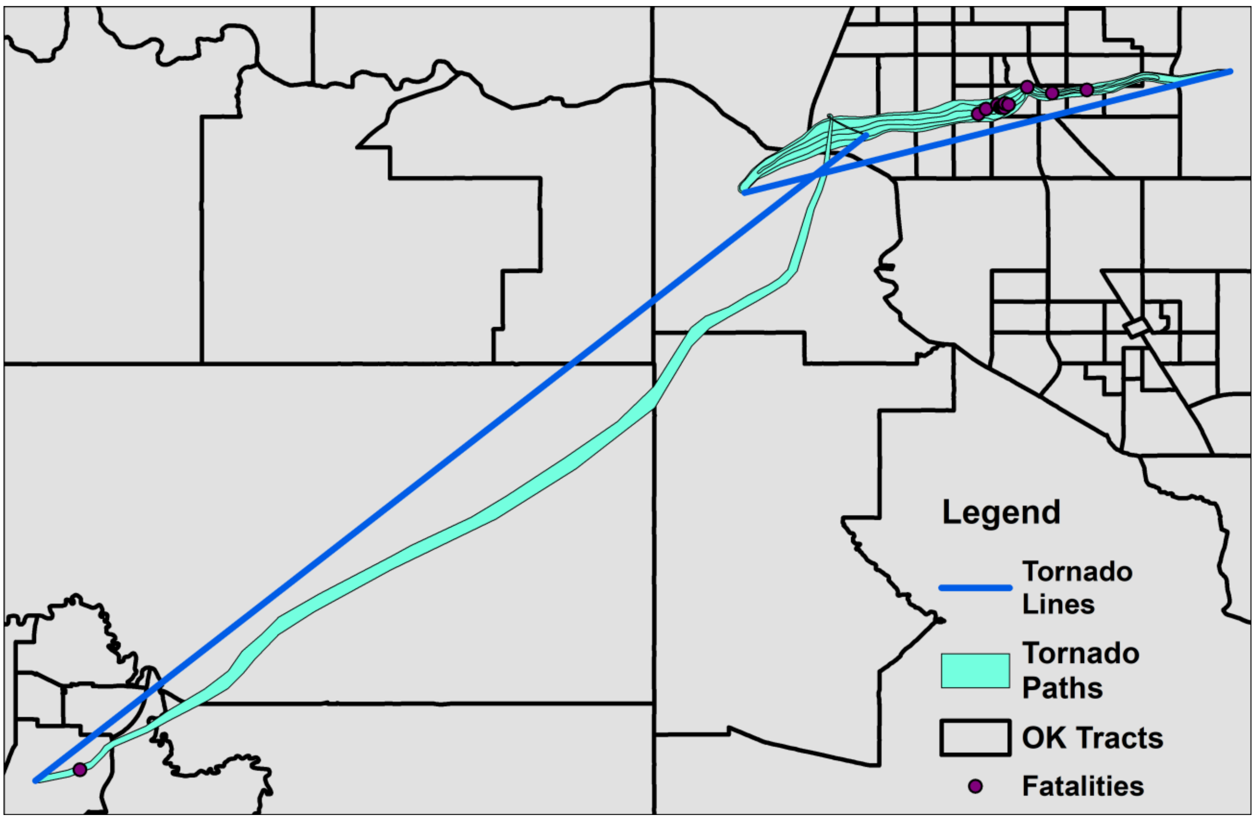

Fig. 1. Example of tornado line (dark blue lines) and path (light blue polygons) data for two different tornadoes in central Oklahoma. Tornado line data can miss census tracts (black outlines) actually affected by a tornado or include census tracts not actually affected by a tornado. Fatality locations are indicated by purple circles.

Table 2. Demographic variables used in the analysis. Top five variables are indicated by a **+**.

Demographic Variable Name	Description
+Over age 65 density	Number of people per km^2 over age 65.
+Under age 10 density	Number of people per km^2 under age 10.
+Population density	Number of people per km^2.
+Median age	Median age of population (years).
+Mobile home density	Number of mobile homes per km^2.
Median home value	Median value of all homes (dollars).
New population density	Number of people per km^2 who moved to their current location from a different county, state, or country.
No English speaking household density	Number of households per km^2 where no one over age 14 speaks English very well.
Poverty density	Number of people per km^2 below the poverty level.
Minority population density	Number of people per km^2 who identified as an ethnicity other than white.

that occur in rural, sparsely populated areas are typically less likely to impact human development, thereby lowering the vulnerability of rural areas regardless of the population's characteristics.

Some differences did exist between maps created using the top 5 and all 10 demographic variables (Fig. 3). The most notable differences occurred in southwest Oklahoma City, where maps created using all 10 demographic variables showed above average vulnerability in this area (Fig. 3a), while maps created using the top 5 demographic variables showed below average vulnerability (Fig. 3b). This difference likely occurred because poverty and minority densities tend to be high in this area but these two variables are not considered in maps created using only the top 5 variables (Table 2). Based on previous research (e.g., Cutter et al. 2003), we expect that including as much demographic information as possible will produce more accurate and realistic results. In addition, since there is no statistical reason to exclude any demographic variable from the predictive model and because relative vulnerability maps created using all 10 demographic variables showed consistent results across the state and above average vulnerability in southwest Oklahoma City, which is expected, maps shown here are created using all 10 demographic variables unless otherwise stated.

4.1 USING MAPS FOR EMERGENCY PREPAREDNESS AND RESPONSE

Knowing the precise location of vulnerable populations within a community can help decision makers, such as emergency managers, plan for and respond to natural disasters through refined hazard mitigation planning, identifying communities in need of additional assistance after an event, and efficient allocation of disaster resources (e.g., Cutter and Finch 2008; Flanagan et al. 2011). Author conversations with local emergency managers about the produced tornado relative vulnerability maps supported this idea. Uses identified for the maps included targeting vulnerable areas for additional education campaigns, weather radio distribution, and long-term recovery assistance, informing hazard mitigation plans, and focusing resource deployment on areas potentially most in need.

4.2 USING MAPS WITH RADAR-BASED TORNADO TRACK ESTIMATION PRODUCTS

Research is also ongoing to refine and distribute weather radar-based products that can estimate the location and intensity of a tornado in near real time (e.g., Manross et al. 2008; Snyder and Ryzhkov 2015; Kuster et al. 2017). Specifically, in Kuster et al. (2017), analysis of survey responses from 183 public safety officials found that these products were viewed as useful and could provide valuable information regarding what may have been affected by a

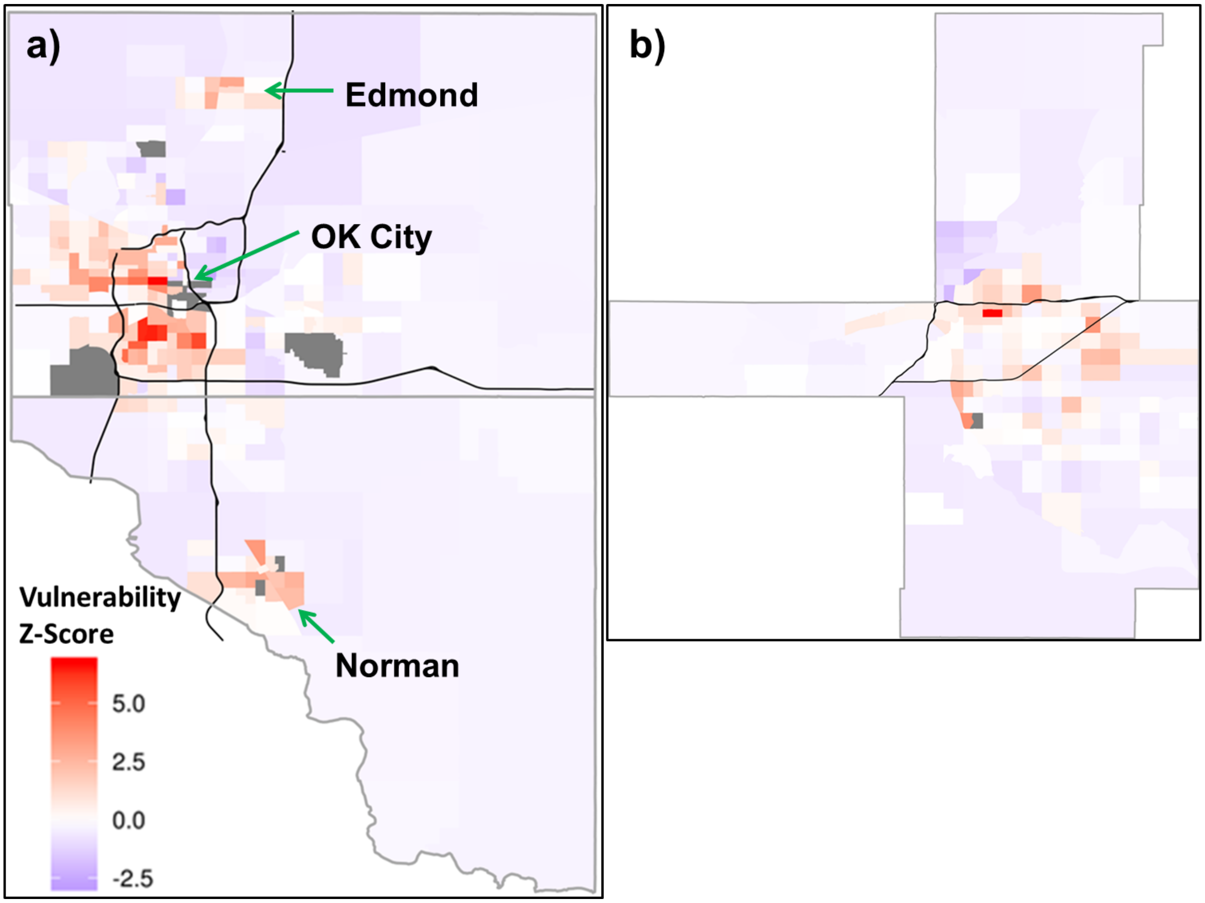

Fig. 2. Example of relatively vulnerability maps for a) central Oklahoma (i.e., Oklahoma and Cleveland County) and b) Tulsa County, Oklahoma. Warmer colors indicate census tracts with above average vulnerability z-scores and cooler colors indicate census tracts with below average vulnerability z-scores. Thin black lines are Interstate highways. Gray census tracts indicate incomplete data. In a), several cities have been annotated and in b) the Tulsa metro area is located in the center of the county near the Interstate highways.

tornado and the overall scope of the disaster. Relative vulnerability maps could provide an important background layer for these tornado track products (Fig. 4). Providing emergency managers with both products could quickly show what vulnerable communities were impacted. Additional resources could then be sent to these areas in the immediate aftermath of the tornado as well as during the long-term recovery efforts. Overlaying the tornado track with vulnerability maps could also increase ability to quickly determine overall scope of the disaster since greater and longer-lasting impacts might be expected if many census tracts with above average vulnerability are affected (e.g., Flanagan et al. 2011).

4.3 USING MAPS WITH LAND-USE LAND-COVER DATA AND ANALYSES

Relative vulnerability maps may also help inform analyses of tornado fatalities using other datasets, such as the National Land Cover Dataset (NCLD; USGS 2012). As part of this study, we sought to quantitatively relate tornado fatalities to the area (i.e., spatial extent) of human development impacted by a tornado. We therefore used the NCLD and NWS surveyed damage paths of 23 deadly tornadoes to determine the area of developed land (low, medium, and high intensity development) within

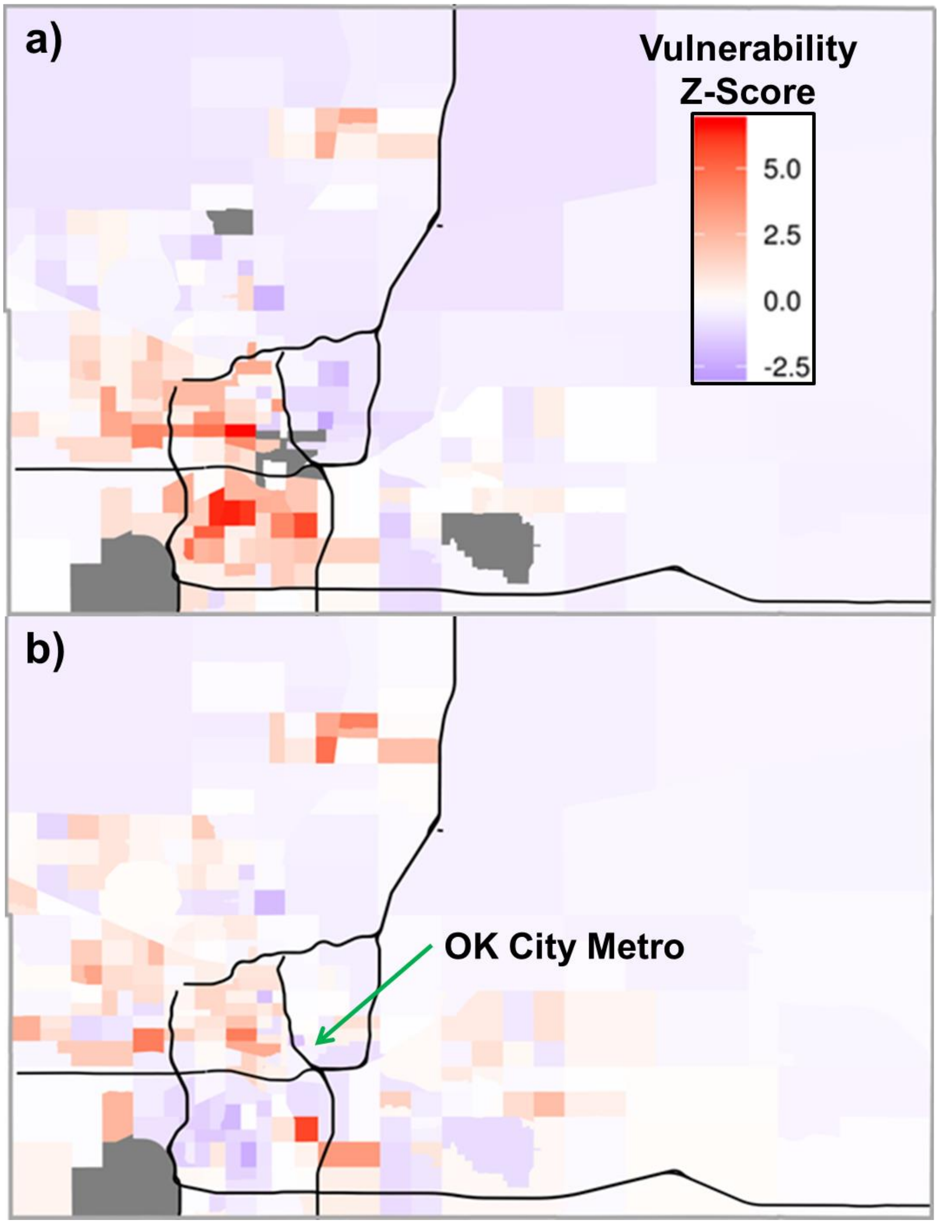

Fig. 3. Relative vulnerability map created using a) all 10 demographic variables and b) top 5 demographic variables. Approximate center location of Oklahoma City metro area is indicated in b). Figure convention is the same as in Fig. 2.

each tornado's damage path (Fig. 5a). This area, which provides an idea of how many homes, businesses, etc. were within the tornado damage path, was then compared to the number of fatalities associated with each tornado (Fig. 5b).

It is not surprising that in general as the area of developed land within a tornado path increases, so does the number of fatalities (e.g., Hall and Ashley 2008). However, there are instances where two tornadoes affect similar areas of developed land but have very different fatality counts (Fig. 5b). For example, the 19 May 2013 Shawnee tornado affected 8.4 km^2 of developed land and caused 2 fatalities. The next day, the 20 May 2013 Moore tornado affected 7.8 km^2 of developed land and caused 24

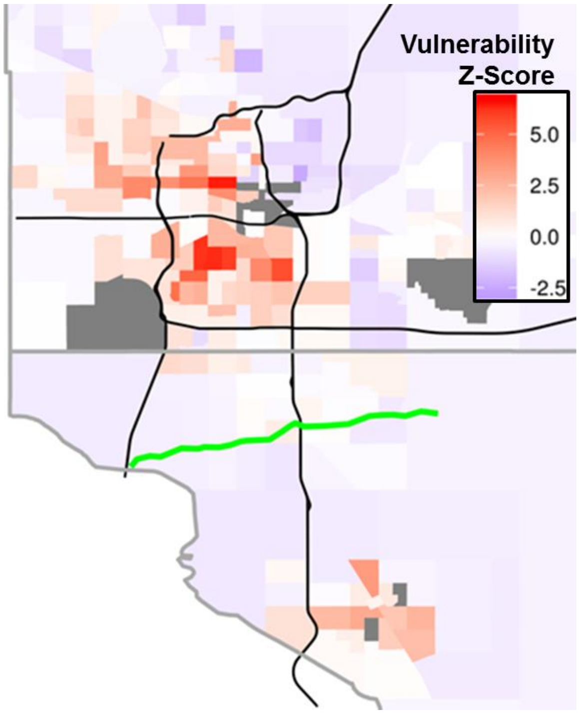

Fig. 4. Example of relative vulnerability map overlaid with a radar-based tornado track estimation product (green line). This product represents the radar estimated center location of the 20 May 2013 Moore, OK tornado over time and was created using rapid-update (~1 min volume scans) phased-array radar data. Figure convention is the same as in Fig. 2.

fatalities. There are likely several factors that led to this large difference in fatalities, but looking at maps of relative vulnerability could provide insight into how small-scale vulnerability differences may have influenced fatalities (Fig. 6). Indeed, the census tracts affected by the Moore tornado had slightly higher average and maximum vulnerability z-scores than those tracts affected by the Shawnee tornado (0.06 and 0.79 respectively). It is reasonable to expect that more fatalities would have occurred with either tornado if they had occurred in areas with higher vulnerability z-scores.

From the NLCD dataset, we also examined the effect of developed land within a tornado's damage path on fatalities using our sample of 13 tornadoes, 156 census tracts, and 128 fatalities (section 2). For each census tract, we calculated the areal extent and percentage of developed land affected by the tornado. Similarly to the demographic variables, we used correlations, linear and negative binomial models, and Monte Carlo simulations to explore relationships between tornado fatalities and the area of developed land affected. Both area and percentage of developed land affected appeared to be related to tornado fatalities—more so than any of the demographic variables. Once again, this result is not surprising since fatalities are generally expected to increase as more human development is affected (e.g., Donner 2007), but incorporating some measure of developed land affected in each census tract into predictive statistical models may help create a clearer picture of potential tornado impacts and fatalities.

5. SUMMARY

This work aims to build upon existing work by examining vulnerability specifically to tornadoes by using datasets that allow for precise spatial relationships between tornado fatalities and demographic variables. By looking at tornado damage paths, census tract-level demographic data, and precise fatality locations, we were able to identify demographic variables most related to tornado fatalities and build a linear predictive statistical model based on those relationships. The model was then used to create maps of relative vulnerability to tornadoes in Oklahoma. From that analysis we observed the following:

1) The methods described here produced realistic looking maps of relative vulnerability to tornadoes in Oklahoma with generally higher vulnerability in urban areas and lower vulnerability in rural areas.

2) There appeared to be no advantage in only considering the top 5 variables potentially most connected to tornado fatalities when producing maps of relative vulnerability. Since including as much demographic information as possible is likely beneficial, we plan to incorporate all 10 demographic variables when creating products for potential use by decision makers.

3) Using relative vulnerability maps with radar estimated tornado tracks can be helpful for coordinating response efforts and determining

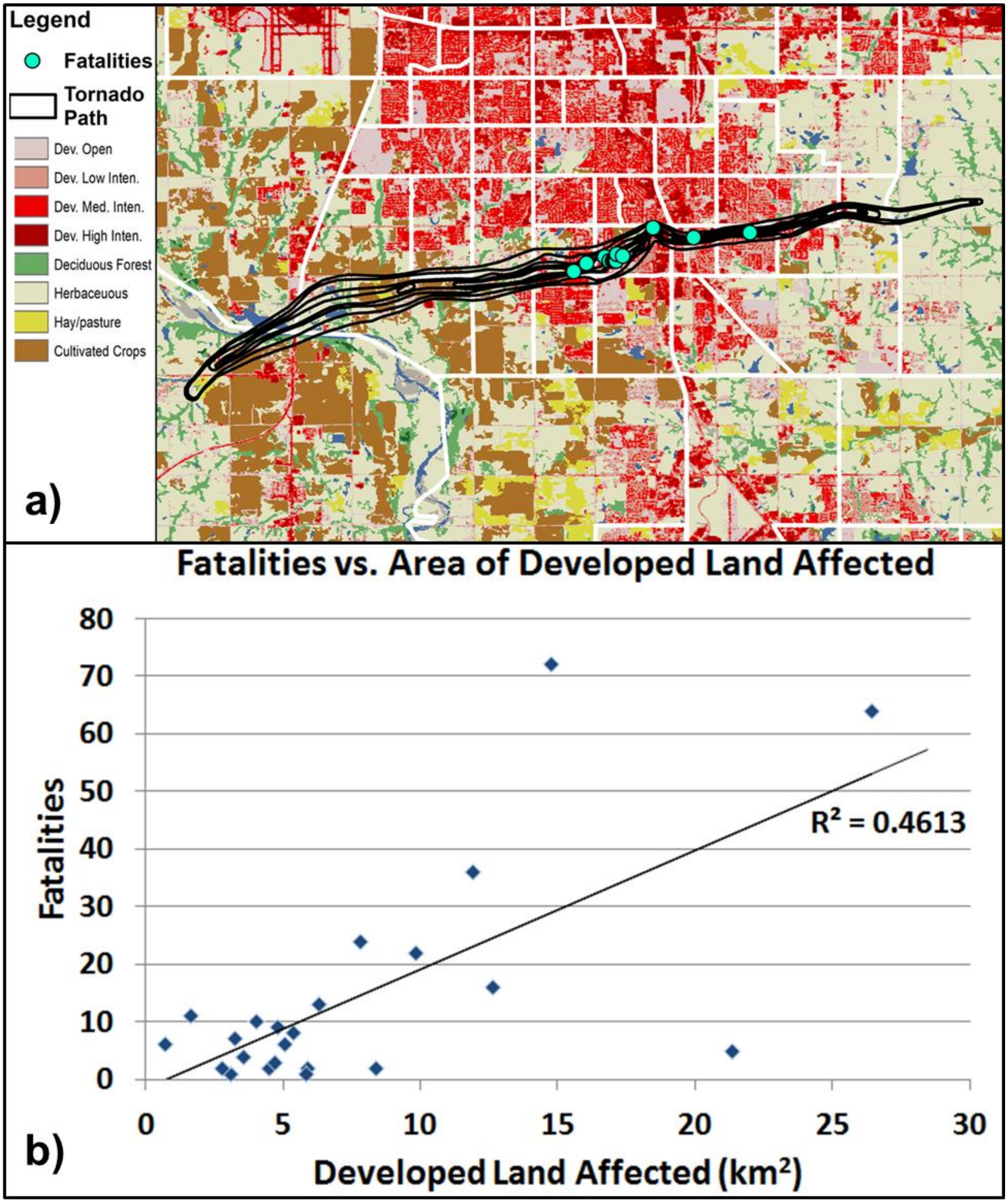

Fig. 5. Land-use land-cover data showing a) map of the 20 May 2013 Moore, OK tornado damage path (black outlines) and fatalities (light blue dots) relative to land-use land-cover and b) scatter plot of developed land area affected by a tornado compared with fatalities. In a), white outlines are the individual census tracts and red colors indicate developed land with deeper reds indicating a higher intensity of development.

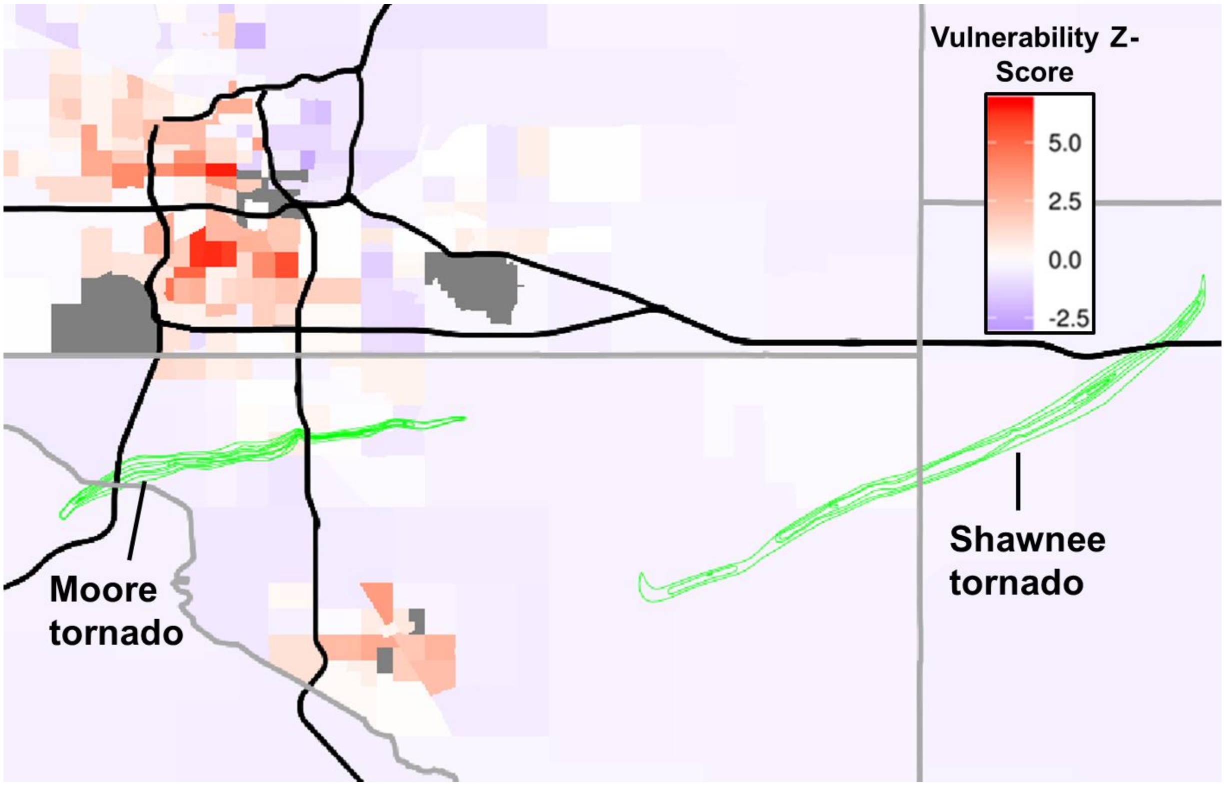

Fig. 6. Vulnerability maps with NWS damage paths (green outlines) for the 19 May 2013 Shawnee, OK tornado and the 20 May 2013 Moore, OK tornado. Figure convection is the same as in Fig. 2.

disaster scope based on what vulnerable populations were affected.

4) A relationship existed between the area of developed land affected by a tornado and the associated fatalities, and examining vulnerability can provide additional insight into this relationship.

There are some important limitations to consider when applying the results of this study. The statistical relationships used in the predictive model are based on a relatively small sample size of 13 tornadoes and 156 census tracts. Most of the considered tornadoes fortunately did not impact urban areas, which could affect the performance of the predictive statistical model, especially in densely populated census tracts that have very different demographic characteristics than most of the census tracts used to build the model. The predictive model is also a linear model that may not capture the complex and non-linear relationships between demographic variables and tornado fatalities. Any errors in the collected census data could also affect results. This analysis also does not consider factors such as time of day, season, or geographic region, that likely influence tornado fatalities (e.g., Simmons and Sutter 2005; Ashley 2007). In our models, the max R^2 value was only 0.175 indicating that demographic variables alone can only explain a relatively small amount of the variance observed with tornado fatalities. Therefore, we only aim to examine a small piece of the overall tornado fatality puzzle. Additionally, relative vulnerability maps were sensitive to methods of transforming the fatality and demographic data (e.g., taking the natural log), suggesting that more refinement and work is needed in terms of determining the most appropriate statistical model and methods for analyses of vulnerability to tornadoes.

Despite the limitations, this work can serve as a pilot study of a potentially valuable tool for use during hazard planning and response (Fig. 2). Future studies can build upon this foundation by refining the demographic variables and statistical analyses used, expanding the sample size to include more deadly tornadoes and tornadoes that hit communities without producing fatalities (i.e., null events), and comparing these vulnerability maps to other vulnerability maps and tools, such as the Brief Vulnerability Overview Tool (e.g., Flanagan et al. 2011; Friedman 2019). Experiments within the Hazardous Weather Testbed may also be appropriate to test this and other vulnerability tools with NWS forecasters and emergency managers to ensure the tool is useable and helpful to decision makers. Interactive maps and tools should also be provided to decision makers to maximize potential use and application.

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