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Public perception of climatological tornado risk in Tennessee, USA

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Abstract The southeastern United States experiences some of the greatest tornado fatality rates in the world, with a peak in the western portion of the state of Tennessee. Understanding the physical and social characteristics of the area that may lead to increased fatalities is a critical research need. Residents of 12 Tennessee counties from three regions of the state (N=1804) were asked questions about

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their perception of climatological tornado risk in their county. Approximately half of participants underestimated their local tornado risk calculated from 50 years of historical tornado data. The percentage of participants underestimating their climatological risk increased to 81% when using model estimates of tornado frequencies that account for likely missed tornadoes. A mixed effects, ordinal logistic regression model suggested that participants with prior experience with tornadoes are more likely to correctly estimate or overestimate (rather than underestimate) their risk compared to those lacking experience ($\beta = 0.52, p < 0.01$). Demographic characteristics did not have a large influence on the accuracy of climatological tornado risk perception. Areas where more tornadoes go unreported may be at a disadvantage for understanding risk because residents' prior experience is based on limited observations. This work adds to the literature highlighting the importance of personal experiences in determining hazard risk perception and emphasizes the uniqueness of tornadoes, as they may occur in rural areas without knowledge, potentially prohibiting an accumulation of experiences.

Keywords tornado · risk · climatology · population bias · prior experience

1 Introduction

Each year, tornadoes destroy lives and property in the southeastern United States (SEUS), and the unique physical and social characteristics surrounding tornadoes in the region are evolving, critical research areas. In 2015, the National Oceanic and Atmospheric Administration (NOAA) launched the Verification of the Origins of Rotation in Tornadoes EXperiment-Southeast (VORTEX-SE) with the ultimate goal to save lives in the SEUS. Similar to the original VORTEX (Rasmussen et al, 1994) and VORTEX2 (Wurman et al, 2012) projects in the Great Plains of the USA (the area traditionally known as "tornado alley"), VORTEX-SE aims to understand the atmospheric conditions favorable for tornadogenesis, but specifically in the SEUS. VORTEX-SE is different, however, in that it integrates social science research, recognizing that such research is essential to determine the best way to communicate tornado threats to the public and understand public behavior during tornado events in order to reduce tornado fatalities in the region (Rasmussen, 2015).

Recent research highlights the frequency of (Coleman and Dixon, 2014) and fatalities from (Ashley, 2007) tornadoes in the region. The SEUS has the greatest exposure to significant ((E)F2–(E)F5) tornadoes in the country, because of both the frequency and path length of tornadoes that occur there (Coleman and Dixon, 2014). The region also hosts the largest proportion of nocturnal tornadoes (those that occur during the night) in the country. Ashley et al (2008) found that the maximum of nocturnal tornadoes occurred in Tennessee, with 45.8% of Tennessee tornadoes occurring at night. Nocturnal tornadoes are 2.5 times more likely to kill than those that occur during daylight hours (Ashley et al, 2008), leading to heightened tornado vulnerability in Tennessee and the SEUS. Therefore, it is not surprising that a bull's eye of killer tornado events is centered in southwest Tennessee and extends to the northwest and southeast (Ashley, 2007). Other factors that may lead to fatalities there are socioeconomic characteristics, such as high mobile home density, poverty incidence, and elderly population; and physical characteristics, such as speed of the storm and unusual seasonal timing (Ashley, 2007). The seasonality of tornado outbreaks in the SEUS does not coincide with national tornado activity, and instead peaks in early April with a second peak during late fall (Fuhrmann et al, 2014). Because the climatology of the tornado threat is unique in the region, it leads to the questions: How do residents of the SEUS perceive their climatological risk to tornadoes? What variables contribute to the accuracy of their perception?

Slovic (1987) describes risk perception as the intuitive judgments that citizens rely on to assess their risk. Information guiding these judgments is gathered by directly experiencing a hazard, or through indirect experiences, for example hearing about a hazard on the news (Wachinger et al, 2013). For this work, we define risk as the likelihood of occurrence, and risk perception as public perception of their local risk. More specifically, we refer to “climatological” risk, meaning the frequency of past tornado events, instead of risk of future events, which is the more traditional approach in risk research. The literature referenced here within may use different definitions of risk perception, and we focus on those explaining the causes of, and effects on, the perception of the likelihood of a hazardous event rather than the likelihood of harm. We evaluate the perception of climatological tornado risk using phone surveys, but we do not use the word “risk” in the survey itself, as to many non-scientists the term corresponds to the catastrophic potential of a hazard (Slovic, 1987), which we mostly attribute to vulnerability. It is important to note that risk and vulnerability do overlap, as the inability to anticipate risk and prepare for future hazards is a contributor to one’s vulnerability (Blaikie et al, 1994), highlighting the importance of risk perception in public safety.

A major factor contributing to risk perception is direct experience of the hazard (Greening and Dollinger, 1992; McClure et al, 2015), but the relationship is complicated, especially for tornadoes (Silver and Andrey, 2014). A direct experience with a tornado, including having one’s home damaged or knowing people who were injured, has been found to heighten a person’s risk perception (Greening and Dollinger, 1992). On the other hand, if a hazard did not result in negative consequences, a person may perceive the hazard as less severe (Wachinger et al, 2013). The characteristics of tornadoes—most commonly being short in time and small in area—may lead them to be forgotten more quickly than a long-duration hazard, stifling any encouragement to be better prepared for the next event (Burton et al, 1993). The effect of a direct experience on risk perception changes over time, lasting as long as seven years for a single lightning strike (Greening and Dollinger, 1992), and may be complicated by a perception of hazard cycles (Wachinger et al, 2013). The most recent event someone has experienced has been shown to affect their perception more than earlier events (Shao et al, 2017).

The degree to which socioeconomic factors affect risk perception is debated (Fothergill and Peek, 2004; Wachinger et al, 2013). Some studies indicated that women, people with lower incomes, less-educated individuals, and others that have or believe they have less control over their own lives have greater concern about natural hazards and heightened risk perception (Pilisuk et al, 1987; Flynn et al, 1994; Palm and Carroll, 1998; Shavit et al, 2013). On the other hand, people of lower socioeconomic status are often employed in more hazardous occupations, which may lead them to be less concerned with day-to-day hazards (Beach and Lucas, 1960). Regardless of impact on risk perception, socioeconomic factors can affect the ability to respond to, or prepare for, a dangerous event (Fothergill and Peek, 2004). Women have been specifically linked to greater perceived risk to environmental hazards, for example hurricanes (Peacock et al, 2005) and climate change (Brody et al, 2008).

How residents perceive their risk may affect how they prepare for (Miceli et al, 2008) or respond to a particular hazard (Dash and Gladwin, 2007). For example, some studies have found that if a person believes a hazard is not likely in their area, they may be less likely to prepare for it (McClure et al, 2015), thus increasing their vulnerability (Messner and Meyer, 2006). Schultz et al (2010) found that survey participants who had plans for tornado events were more likely to believe they would experience a tornado in their lifetime than those who did not have plans. Miceli et al (2008) found that not only risk perception, but worry about the impending hazard, encourages preparedness. However, the relationship is not always that simple. Wachinger et al (2013) note common explanations for why there is sometimes a weak relationship between risk perception and behavior, for example, when benefits outweigh risks and when individuals have little resources or agency to affect the situation or their own actions. Thus, while people with lower socioeconomic status may have heightened risk perception, the feeling of powerlessness that led to that perception, plus fewer resources, may make them less inclined to prepare for hazards (Vaughan, 1995).

We aim to understand the perceived risk to tornadoes by Tennessee, USA, residents as compared to their climatological risk. Residents from three regions of the state were asked via a phone survey about their perceived tornado risk, and results are compared to their climatological risk calculated using historical tornado data. Descriptive statistics and a predictive model for accuracy of tornado risk perception are presented and discussed. Tornado risk perception has not been well studied (Klockow et al, 2014), and while this study focuses on a single state, results can provide meaningful insight into tornado perception in the SEUS and beyond. Our focus on climatological risk and the importance of prior experience in perceiving that risk adds to the literature emphasizing how the history of events someone experiences affects how they shape their views of local risk.

2 Data and Methods

This study focuses on counties containing and surrounding three major Tennessee cities (Figure 1). The western Tennessee region (Memphis and surrounding area) includes Fayette, Haywood, Shelby, and Tipton counties; the middle Tennessee region (Nashville and surrounding area) includes Davidson, Robertson, Rutherford, and Williamson counties; and the eastern Tennessee region (Knoxville and surrounding area) includes Anderson, Knox, Loudon, and Union counties. The regions and counties differ in socioeconomic characteristics and tornado risk. Brown et al (2016) showed that, of the three regions in Tennessee, the Nashville area has the most reported tornadoes in the modern record, more than twice as many as the Knoxville area. The Memphis area has had the most days with tornadoes and by far the most casualties during the same period (Brown et al, 2016).

Basic socioeconomic characteristics of each county are provided in Table 1. Counties were selected for their varying population densities, percent of residents living in poverty, and percent of residents (age 25 years and older) with a bachelor's degree or higher, among other socioeconomic differences. Comparisons of county demographics with our sample are given later in this section.

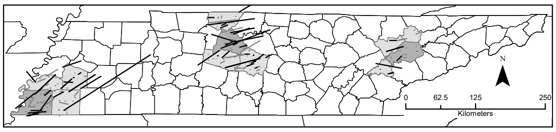

Fig. 1 Observed tornadoes within the selected counties (shaded) from 1965–2014. Counties with darker shading contain the city center (Memphis, Nashville, or Knoxville). Black tracks signify significant tornadoes.

Table 1 Characteristics of Tennessee counties used in this study; bachelor's degree is the percentage of residents 25 years and older that have received at least that degree. Data: U.S. Census Bureau, American Community Survey, Population estimates, 1 July 2014.

Region	County	Population	Population per km ^{2}	Poverty (%)	Bachelor's degree (%)	65 yrs+ (%)
West	Fayette	39,011	33.9	14.7	21.5	18.7
	Haywood	18,185	21.9	23.1	11.4	16.1
	Shelby	938,803	755.3	21.6	29.0	11.6
	Tipton	61,623	82.8	14.4	15.1	13.1
Middle	Davidson	668,347	772.6	17.8	35.9	11.1
	Robertson	68,079	86.5	12.1	17.1	13.5
	Rutherford	288,906	263.5	12.3	28.3	9.6
	Williamson	205,226	195.4	5.5	52.8	11.6
East	Anderson	75,528	138.4	19.7	23.5	18.9
	Knox	448,644	528.5	16.3	34.3	14.5
	Loudon	50,771	131.6	14.2	25.2	16.3
	Union	19,113	53.1	22.1	8.2	24.5

2.1 Tornado Data and Risk Estimates

Climatological tornado risk was quantified using 50 years (1965–2014) of tornado data from the Storm Prediction Center (SPC). The SPC database contains information for tornadoes observed since 1954, including the date and time of the event, its intensity, the number of injuries and fatalities, and its start and end location. We selected tornadoes that occurred within or intersected one or more of the 12 counties (Figure 1) and calculated mean annual frequencies per county.

There are well-known, inherent spatial and temporal biases in the database (Verbout et al, 2006; Elsner et al, 2013; Kunkel et al, 2013), with more tornadoes being observed in places with more people and in more recent years. We recalculated risk based on model estimates that account for some of these issues. The mean annual frequency of tornadoes was calculated for each county and a regression model fit to these counts. The model includes a term that estimates the under-reporting bias in less populated areas. It also includes a term that accounts for improvements in the procedures to rank tornadoes by the amount of damage. Details of the model and the fitting procedure are presented in Elsner et al (2016).

2.2 Survey Data and Sample

Residents' perceptions of tornado activity were assessed via phone survey between February and July 2016, after approval by an Institutional Review Board for research with human subjects. Participants were asked 51 questions, including classification, behavioral, knowledge, and perception questions (Patton, 1990). Specifically, participants were asked about their socioeconomic status, risk perception, beliefs related to tornadoes, and hypothetical behavior during tornado warnings, among other items relating to their tornado risk and intended behavior during events. Questions that were asked regarding prior experience, perception of risk, and beliefs are listed in Table 2. Surveys lasted approximately 15 minutes each, and participants received a ten-dollar (USD) gift card for their time. Quota sampling was used to gain near-equal participation among counties. Within counties, random sampling of land-line and cell phone numbers was used. For questions with a set of possible answers the answers were read aloud to participants in the order give in Table 2. This result in a limitation of the data, as previous research suggests that the category order (Dillman et al, 1995) and direction of response (Liu and Keusch, 2017), for example, least to most tornado risk, may affect the

Table 2 Survey questions regarding prior experience with tornadoes, beliefs, and perceived risk.

Question	Response options
Has a tornado ever hit your home?	Yes or no
Has a tornado ever hit a building while you were inside?	Yes or no
Has a tornado ever hit near where you live?	Yes or no
How often would you say tornadoes hit _____ county?	Never, Once every 50 years or longer, Once every 25 years, Once every 10 years, Once every few years, Once a year, or More than once a year
To what extent do you think hills protect nearby places from tornadoes, if at all?	Not at all, Somewhat, Very much, Completely
To what extent do you think bodies of water, such as rivers and lakes, protect nearby places from tornadoes, if at all?	Not at all, Somewhat, Very much, Completely
To what extent do you think tall buildings protect nearby places from tornadoes, if at all?	Not at all, Somewhat, Very much, Completely

participant's answer. Another study found participants will select a middle option to avoid the extremes of a scale (Moors, 2008), so an optimal organization is not always clear.

There were 131–175 participants per county for a total of 1804 survey participants. All questions used for analysis had at least a 95% response rate. Among participants, 63% identified as female. The majority of participants reported having completed some college or more (71%), and 36% reported having earned a college degree. This is higher than most of the 12 county averages, as only two had 36% or more college graduates. The proportion of participants over 65 years old (34%) is also greater than the county averages. Thus, our participants, on average, are more highly educated and older than the county means, and responses are biased toward females.

We also collected information about housing types from participants. Approximately 10% of the housing units in Tennessee are mobile homes. Union County in East Tennessee is one of the top 10 counties by mobile home percentage (35% of housing stock), while three of the Middle Tennessee and one of the West Tennessee

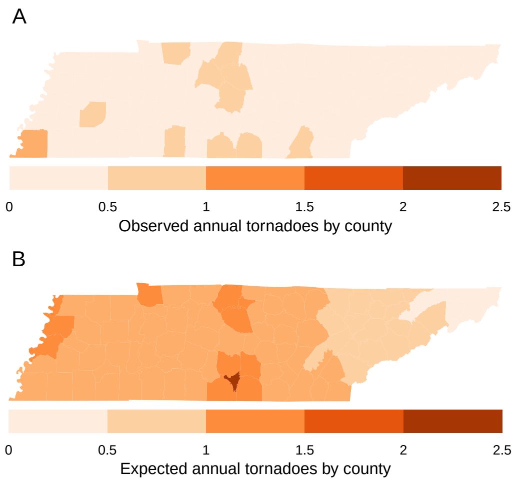

Fig. 2 Average annual number of tornadoes per county in Tennessee from 1965–2014 based on (a) raw observations, and (b) a model incorporating population bias.

counties make up four of the five lowest Tennessee counties in mobile-home percentage, with Shelby county only having 1% mobile homes (Nelson, 2012). In our study, Union County had nearly twice the percentage of participants from mobile homes than the next county (26.3% of participants). In most counties 5–13% of participants reported living in mobile homes. While these are not comparing the same statistic (% housing stock versus % people), the housing of the study sample well represents the population.

2.3 Measures and Analyses

We created a risk perception accuracy (RPA) measure, which quantifies how accurately a participant perceived their climatological risk. Their perceived climatological risk was their answer to the question "How often would you say tornadoes hit [your county]," and the climatological risk was the survey response most closely representing the previous 50 years of tornado reports (Figure 2). Of the 1804 participants, 1720 answered the risk perception question.

Participants are considered to have correctly estimated their risk if their perceived risk category equals their county's climatological risk. Participants are considered to have moderately underestimated or moderately overestimated their risk if their perceived risk is one survey category lower or higher than their county's climatological risk; for example, they perceived their county to be hit "once every 25 years" on average, but they are actually hit "once every 10 years," or vice versa. Participants are considered to have extremely underestimated or extremely overestimated if their perceived risk is at least two categories lower or higher than climatological risk; for example, they perceive their county to be hit "once every 25 years" on average, but they are actually hit "once every few years," or vice versa. There was no category two steps above three of the counties' climatological risk, therefore there is no possible way for participants from these counties to extremely overestimate their risk.

Bivariate tests of demographic, belief, and prior experience variables were used to determine what variables meaningfully influence RPA. Several of the variables were collapsed for analyses. Significant variables from the bivariate analyses were used in a mixed effects, ordinal logistic regression model to quantify the odds of a participant being in a higher RPA category given their characteristics. We recategorized the participant's RPA based on modeled tornado estimates to demonstrate the influence of the population bias in tornado reports. Responses with missing data were removed, resulting in an analysis sample of 1675.

3 Results and Discussion

3.1 County-wide tornado risk

Climatological tornado risk for each county was calculated using 50 years of tornado reports (Figure 2a). For scientific purposes risk per unit area is more appropriate, but for the public to estimate their risk a county may be more meaningful than an area of a given size. Of the 12 counties studied here, a county in West Tennessee (Shelby) observed the most tornadoes, averaging one per year, while a county in East Tennessee (Union) observed the least tornadoes, averaging one

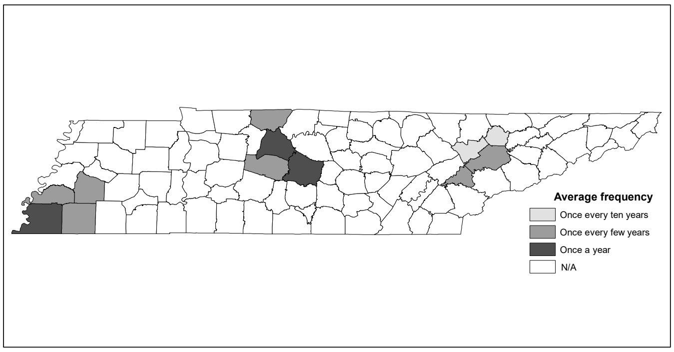

Fig. 3 Correct survey categories for each county in the study. Categories reflect average county-wide tornado frequency.

tornado approximately every 17 years. East Tennessee counties made up four of the five counties with the least risk.

When comparing each county's historical tornado risk to possible survey answers, the corresponding answer for most counties was "once every few years" (Figure 3). This answer represents counties with historical return periods around every three years, specifically, those closer to 3 years than the two surrounding options (1 or 10 years). Two counties (Anderson and Union in East Tennessee) experienced tornadoes "once every ten years," meaning their return periods are closer to 10 years than any other options. The final three counties (Davidson and Rutherford in Middle Tennessee and Shelby in West Tennessee) were designated as having tornadoes occur "once a year," meaning their return period is closer to one than the less risky option (three), but their mean annual frequency was closer to 1 than the next risky option (more than once per year). It is important to note that we treated each tornado as a separate event to calculate climatological risk, but tornadoes often occur on the same day. While the number of historical tornadoes may equal an average of one tornado every ten years, actual occurrences may be three tornadoes with a thirty-year break in between. This may skew the perception of how many tornadoes hit an individual county, as a person may group a day or two of tornadoes in their area as one tornado event.

3.2 Risk perception accuracy

Among all participants, "Once every few years" was the most frequent response (33%) for risk perception, followed by "Once every 10 years" (22%) and "Once every 25 years" (15%). By county, "Once every few years" was the most frequent response in all counties except Union, where "Once every 25 years" was the most common. For RPA (Table 3), 54% of participants underestimated their risk, with over half of those extremely underestimating their risk.

For bivariate and regression analyses, we grouped participants who moderately and extremely underestimated their risk, and participants who moderately and extremely overestimated their risk, creating three total RPA categories: underestimated, correctly estimated, and overestimated. Chi-square results indicate that the category a participant belongs to is independent of region ($\chi^2 = 1.7$, $p = 0.79$), but not independent of county ($\chi^2 = 200.2$, $p < 0.01$). This could be in part because of the categories not allowing for participants from some counties to have extremely overestimated their risk, and also because of cultural differences that may make participants more aware of their risk in a particular county, for example, varying media coverage of events. For this reason, county is used as a random effect in the final regression model.

3.3 Factors contributing to risk perception accuracy

First, we tested demographic variables. Education was tested using four categories: did not finish high school, graduated high school, attended some college, and graduated from college. The chi-square tests indicated RPA was independent of education ($\chi^2 = 7.04$, $p = 0.32$) and gender ($\chi^2 = 3.08$, $p = 0.21$). Ordinal logistic regression indicated RPA is significantly influenced by age ($p = 0.03$), therefore age was included as an independent variable in the final regression model.

Next, we tested belief variables, including whether the participant believes hills, water bodies, or tall buildings may protect places from tornadoes. We created

Table 3 RPA by county, % of participants. N/a indicates that category was not an option for the given county.

Region	County	Extremely underestimated	Moderately underestimated	Correctly estimated	Moderately overestimated	Extremely overestimated
West	Fayette	22.9	26.0	32.8	10.7	7.6
	Haywood	14.5	23.4	33.1	12.1	17.0
	Shelby	39.4	36.0	12.4	12.4	n/a
	Tipton	27.6	22.1	38.0	9.0	3.8
Middle	Davidson	39.0	28.8	14.4	11.0	n/a
	Robertson	11.8	22.0	37.0	14.2	15.0
	Rutherford	30.3	41.5	22.5	5.6	n/a
	Williamson	11.0	20.7	40.7	18.6	9.0
East	Anderson	19.6	20.3	25.7	27.0	7.4
	Knox	39.1	21.7	23.6	9.3	6.2
	Loudon	42.0	20.3	31.1	4.3	2.2
	Union	28.7	27.3	23.1	14.7	6.3

two categories by grouping together participants that answered “not at all” or “somewhat” and “very much” or “completely.” Chi-square tests indicated RPA was independent of the belief of protection from hills ($\chi^2 = 1.76$, $p = 0.41$), water bodies ($\chi^2 = 0.58$, $p = 0.75$), or buildings ($\chi^2 = 1.09$, $p = 0.58$), therefore these variables are not included in the final regression model.

Finally, we tested the prior-experience variable. Prior experience was grouped into two categories. If the participant said yes to any of the three questions about tornado experience (Table 2), then they were counted as having prior experience, while the remaining participants were said to have no prior experience. The chi-square test indicated that RPA was not independent of prior experience ($\chi^2 = 55.21$, $p < 0.01$), therefore prior experience was included as an independent variable in the final regression model.

The model was completed with the **ordinal** package in the R-project for statistics using the `clmm2` function. The **ordinal** package makes estimations via maximum likelihood and is capable of incorporating random effects and variables with partial proportional odds (Christensen, 2015). An assumption in ordinal logistic regression is that of proportional odds, which means an independent variable’s effect

Table 4 Characteristics of mixed effects model, where prior experience and age are modeled as having a fixed effect and county as a random effect.

Variable	Coef	p	SE	var
Prior Experience	0.52	<0.01	0.08	–
Age	-0.01	<0.01	<0.01	–
County	–	–	–	0.37

on an event occurring in every subsequent category is the same for every category. The **ordinal** package allows a test of this assumption using the `nominal_test` function. Results here suggested that there is no evidence against proportional odds for the prior experience ($p = 0.87$) or age ($p = 0.40$) variables, therefore ordinal regression can be used to model these relationships.

The resulting mixed effects model predicts RPA (three categories) using age and prior experience (two categories) as independent variables with a fixed effect, and county as a random effect (Table 4).

The coefficient for prior experience is positive, indicating that participants were more likely to correctly estimate or overestimate their risk with prior experience, compared to participants with no prior experience. The odds ratio of 1.7 ($OR = exp(\beta); \beta = 0.52$) suggests that participants were nearly twice as likely to correctly estimate or overestimate (rather than underestimate) their risk with prior experience. Age has a negative coefficient, but the effect size is small; the odds of correctly estimating or overestimating (rather than underestimating) risk increase by 1% for every year decrease in age.

It is important to note that the statistics presented here represent the perceptions of the participants, but may not represent views of their entire county or region. Our data are biased toward those who responded to the survey, which favors older, well-educated females. Additionally, it is understandable if participants struggled to estimate risk across their entire county; however, we needed to use a large enough area to capture a representative sample of historical tornadoes. The model presented in this section is also biased toward those participants that answered all of the questions required by the model.

3.4 Accounting for population bias in tornado reports

Tornado reports are biased toward populated areas, resulting in missed tornadoes, especially in rural locations. We recalculated risk using a model that accounts for population bias (Figure 2b). Mapped estimated tornado frequencies show a gradient of risk across the eastern half of the state, which increases until Middle Tennessee. When ranking the counties by expected annual frequencies, the riskiest area remained the central corridor of the state and the most western counties. The four East Tennessee counties were the four least risky, while Middle and West Tennessee counties were well mixed in the most risky counties. Some counties could expect as many as two more tornadoes per year according to model estimates.

We calculated the percentage of "missed tornadoes," or the percentage of tornadoes that went unobserved over the 50-year period, per county based on the number of observed tornadoes versus the model estimates (Table 5). The model assumes that areas in each region have relatively the same risk, so areas with fewer observed tornadoes and lower populations in each region of Tennessee must have missed more than their surrounding areas. It is likely that more tornadoes were missed earlier in the period, and the percentage of missed tornadoes is not evenly distributed over time. The range of percentages are in the same ballpark as those estimated across Kansas and surrounding areas (Elsner et al, 2013) where it is was found that over the 62-yr period from 1950–2011 reports near cities and towns exceeded those in the country by 70% with a 95% uncertainty interval on these percentages of between 54 and 87%.

In general, East Tennessee counties missed the most tornadoes. It is important to understand the population bias in tornado reports in an area, as missing tornadoes may influence RPA. When tornadoes go unobserved, the public does not know they existed. Since the location of a tornado touchdown within a single county is mostly random, people are spared by chance, and missed tornadoes present a missed opportunity to raise public awareness of their local tornado risk.

Table 5 The estimated percent of tornadoes that went unobserved in each county ("missed tornadoes"), and RPA by county (% of participants) based on modeled risk.

Region	County	Missed tornadoes	Extremely underestimated	Moderately underestimated	Correctly estimated	Moderately overestimated
West	Fayette	73.6	74.0	30.5	8.4	12.2
	Haywood	83.2	78.2	32.3	8.9	12.9
	Shelby	27.3	57.1	23.5	6.5	9.4
	Tipton	72.7	66.9	27.6	7.6	11.0
Middle	Davidson	55.3	66.4	27.4	7.5	11.0
	Robertson	72.9	76.4	31.5	8.7	12.6
	Rutherford	53.2	68.3	28.2	7.7	11.3
	Williamson	66.8	66.9	27.6	7.6	11.2
East	Anderson	84.7	65.5	27.0	7.4	0.0
	Knox	55.8	60.2	24.8	6.8	9.9
	Loudon	81.9	70.3	29.0	8.0	11.6
	Union	89.8	67.8	28.0	7.7	11.2

We recategorized participant RPAs based on modeled risk (Table 5). The lowest risk was in Union County in East Tennessee (0.59 tornadoes per year) and the greatest risk was in Tipton County in West Tennessee (1.47 tornadoes per year). The closest appropriate survey answer for both of these is "once a year," which puts all counties in the same risk level and removes the option for participants to extremely overestimate their risk. Using these new categories, 81% of participants underestimated their county's tornado risk. The broad survey categories grouping all counties in the same risk category makes additional analyses on these results inconsequential.

The issue with missed tornadoes is not unique to Tennessee or the SEUS; however, the relationship between population and tornado observations has been changing differently across the country. In areas of the Great Plains, where tornadoes are more easily observed and there are networks of spotters and storm chasers, there are now minimal differences in the number of tornado reports in urban and rural areas (Elsner et al, 2013). In other words, the population bias of tornado reports in this area is near zero. In the SEUS, where tornadoes are hidden by darkness, hills, rain, and trees, and where storm chasing is unsafe and not commercialized, the population bias is still as great as ever, contributing to many missed tornadoes (Elsner et al, 2013). Additionally, weaker tornadoes are more likely to be missed (Brooks, 2004), which are common in Tennessee. While we did not expect the public to have memory of these tornadoes, the recalculated RPA reiterates that participants are more at risk than perceived.

4 Conclusion

How the public perceives local tornado frequency may affect how they prepare for and behave during tornado events. Therefore, it is important to understand how people perceive their climatological risk, and what factors may contribute to this perception. We aimed to assess perceptions of tornado risk in counties surrounding three Tennessee cities through data gathered from a phone survey.

By comparing a participant's perception of tornado frequency to that of the historical database, we found about half of participants underestimated their climatological tornado risk. This is concerning, since the historical tornado record is based on observed tornadoes, and is documented as missing tornadoes in rural areas, weaker tornadoes, and those earlier in the record. When accounting for potentially missed tornadoes, eight of ten participants underestimated their risk.

The most important predictor of RPA was prior experience with tornadoes, whether a participant was directly impacted or it was a "close call," meaning it hit somewhere else in their neighborhood. Prior experience with disasters has been identified as an important contribution to risk perception in other studies (Greening and Dollinger, 1992; McClure et al, 2015). Our study adds to this literature, and emphasizes the significance of experience over socioeconomic characteristics for perceiving risk. In addition to influencing risk perception, Blanchard-Boehm and Cook (2004) found that prior experience with tornadoes motivated survey participants to prepare for future events, and Silver and Andrey (2014) found that both direct and indirect experience of a local tornado affect behavior during subsequent tornado events. Sattler et al (2000) note that the influence of prior experience on preparation changes over time, but we did not collect information about the length of time since the participant experienced a tornado.

Other unidentified county-wide characteristics contributed to RPA. The survey mechanism may introduce some of these differences because in some counties there was no opportunity for participants to extremely overestimate their risk as a result of the provided survey categories. Real-world county variability in climatological risk perception could be a function of cultural differences, imbalances in media coverage, different patterns of built environments that lead to differences in exposure rates (Ashley et al, 2014), or beliefs about their local space tied to prior experiences (Klockow et al, 2014). County differences could also stem from recent tornado events the participants have experienced. Perhaps those that have not been affected in a longer time period, or those not recently affected by a significant tornado, perceive lower climatological risk. Meanwhile, a person recently affected by a significant tornado may perceive tornadoes as more frequent. Overall, it may be that the climatology of significant tornadoes may be closer to participants' perceived climatology. We could not test this with our data because of the low sample size of significant tornadoes. We would have also liked to assess complacency in participants to determine if the amount of time elapsed since the last event is a factor contributing to their perceptions, but this is challenging in a large-scale phone survey. Both of these concepts may be better addressed through individual interviews with residents.

Demographic variables including age, gender, and education, were not important predictors of RPA, adding more contradictory results to the already discordant risk perception literature (Fothergill and Peek, 2004; Wachinger et al, 2013). Age was significantly related to RPA, but had a small effect. Our work adds to others finding demographic variables are not the leading factor contributing to risk perception, although one potential explanation for our findings is that our work focuses more on past events and not beliefs of future events. While we found no demographic variables had a strong influence on RPA, they may be important variables contributing to preparation. Senkbeil et al (2012) found that age and education contributed to preparation for a tornado, specifically the elderly and educated were more likely to have shelter plans, and Blanchard-Boehm and Cook (2004) found that formal education encouraged preparation for future tornadoes. It is somewhat surprising that gender was not a significant contributor to risk perception, as literature suggests that women perceive greater risk, specifically environmental risk (Gustafsod, 1998); however, this greater perceived risk may result from a sense of worry or vulnerability, not event frequency as addressed in this study.

In rural areas where the random behavior of tornadoes means there is a good chance no one is affected by one that touches down, or perhaps it goes completely unnoticed, it may be likely for residents to be complacent or to underestimate their local risk. Since prior experience plays such an important part in RPA, each missed tornado is a missed opportunity for informing residents of their local risk. In areas of East Tennessee, where tornadoes are less frequent than other parts of the SEUS, and where rural hillsides render tornadoes hidden from the population, residents may be at a greater risk of not developing a personal sense of tornado risk.

An important next step is to determine if climatological risk perception affects behavior during tornado events. Does an underestimation of past risk correspond to less safe behavior during a tornado? Are there other factors that contribute more to preparation and behavior? Continued research in these areas may identify groups that are not likely to respond safely to tornado warnings, and find ways to encourage safe behavior and reduce fatalities and injuries resulting from tornadoes.

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