The Role of Geographic Context in Tornado Risk, Risk Perception, and Protective Action Behavior

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THE ROLE OF GEOGRAPHIC CONTEXT IN TORNADO RISK, RISK PERCEPTION, AND PROTECTIVE ACTION BEHAVIOR

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ABSTRACT

Our current understanding of tornado risk, risk perception, and protective action behavior lacks proper spatial consideration of local physical and social geographic contexts. This investigation asks how the conceptual drivers of tornado risk (geographic context, risk perception, and response) interact to create the spatiality of tornado risk. The study proposes that the inclusion of geographic context and its influence on perception and behavior produces differential tornado risk and seeks to determine which factors contribute to such variability. A novel, researcher-designed Tornado Risk of Place (TROP) conceptual model guides the methodological framework, incorporating statistical and geospatial analytics in an Illinois State case study. The study first develops quantifiable indicators of physical and social domains at the Illinois county level to measure the geographic context of tornado risk. The questionnaire data from a representative sample of Illinois residents provide individualized assessments of risk perception and response behavior. Community knowledge is incorporated into tornado risk understanding and adaptation by employing individual-level survey construct data alongside the county-level context indices. A Structural Equation Model framework assesses the existence and strength of the linear relationships between tornado context, perception, and behavior. An evaluation of the variability captured by the TROP conceptual drivers across the study area determines the spatiality of tornado risk. Geographic assessments of tornado risk...
outcomes among formal and functional regions include urban-rural counties, National Weather Service County Warning Areas, emergency management regions, and more. Results of the study indicate tornado risk drivers included in the TROP model vary statistically and spatially throughout Illinois. County-level local and physical risk context significantly influence individuals' risk perceptions, directly determining tornado risk responses. The spatial assessment results find significantly different tornado risk outcomes in urban areas, Northern Illinois, StormReady® counties, and the Chicago region, highlighting the need for targeted emergency management strategies to reduce societal tornado risk. Enhanced tornado risk assessments may decrease disproportionate impacts and protect vulnerable populations commonly bearing the brunt of hazard risk burdens. The findings of this investigation can thus help inform policy decisions to mitigate vulnerabilities and improve severe weather preparedness, response, and recovery.
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# LIST OF SYMBOLS

- **®** Registered Trademark.
- **$** U.S. Dollar.
- **z** $z$-score representing how many standard deviations above or below the mean sample the score derived from a $z$-test is.
- **x** Observed value.
- **x̅** Sample mean, or the average of the values of a variable in a sample.
- **s** Sample standard deviation, or the root-mean square of the differences between observations and the sample mean.
- **n** Sample size.
- **N** Population size.
- **p** Probability value or statistical significance level.
- ***** Statistically significant probability level.
- **+** Positive or plus.
- **-** Negative or subtract.
- **=** Equals.
- **%** Percent.
- **r** Pearson’s correlation coefficient, or measure of closeness of association between variables.
- **r²** Coefficient of determination, or the proportion of the variation in the dependent variable that is predictable from the independent variable.
- **β** Standardized regression coefficient, or the average amount by which the dependent variable increases when the independent variable increases.
\begin{itemize}
  \item \textit{F} \quad \text{Ratio of variances calculation used in ANOVA to determine if two sample variances are equal.}
  
  \item \textit{t} \quad \text{Standardized value used to compare the average values of two samples in difference of means testing.}
  
  \item \textit{U} \quad \text{Measure of difference in central tendencies in two sample groups used in the Mann-Whitney \textit{U} test.}
  
  \item \textit{MD} \quad \text{Mean difference, or the absolute difference between the mean value in two different groups.}
\end{itemize}
# LIST OF ABBREVIATIONS

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>ACS</td>
<td>American Community Survey</td>
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<tr>
<td>ADJ</td>
<td>Adjusted</td>
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<tr>
<td>AGFI</td>
<td>Adjusted Goodness-of-Fit Statistic</td>
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<tr>
<td>AMOS</td>
<td>Analysis of Moment Structures</td>
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<td>ANOVA</td>
<td>Analysis of Variance</td>
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<td>CEMHS</td>
<td>Center for Emergency Management and Homeland Security</td>
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<tr>
<td>CFI</td>
<td>Comparative Fit Index</td>
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<tr>
<td>CWA</td>
<td>County Warning Area</td>
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<td>EFA</td>
<td>Exploratory Factor Analysis</td>
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<tr>
<td>ESRI</td>
<td>Environmental Systems Research Institute</td>
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<tr>
<td>F/EF</td>
<td>Fujita/Enhanced Fujita</td>
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<tr>
<td>FIPS</td>
<td>Federal Information Processing Standards</td>
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<tr>
<td>GFI</td>
<td>Goodness-of-Fit Statistic</td>
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<tr>
<td>GIS</td>
<td>Geographic Information Systems</td>
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<td>GWR</td>
<td>Geographically Weighted Regression</td>
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<tr>
<td>HOP</td>
<td>Hazards of Place</td>
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<tr>
<td>HS</td>
<td>Home Safety</td>
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<tr>
<td>HSD</td>
<td>Honestly Significant Difference</td>
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<td>HVRI</td>
<td>Hazards Vulnerability and Resilience Institute</td>
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<tr>
<td>IBM</td>
<td>International Business Machines Corporation</td>
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<tr>
<td>ID</td>
<td>Identification</td>
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<tr>
<td>Abbreviation</td>
<td>Full Form</td>
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<tr>
<td>IEMA</td>
<td>Illinois Emergency Management Agency</td>
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<td>IRB</td>
<td>Institutional Review Board</td>
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<tr>
<td>LISA</td>
<td>Local Indicators of Spatial Association</td>
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<tr>
<td>MAUP</td>
<td>Modifiable Areal Unit Problem</td>
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<tr>
<td>MLE</td>
<td>Maximum Likelihood Estimation</td>
</tr>
<tr>
<td>MSA</td>
<td>Metropolitan Statistical Area</td>
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<tr>
<td>NASEM</td>
<td>National Academies of Sciences, Engineering, and Medicine</td>
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<tr>
<td>NCEI</td>
<td>National Centers for Environmental Information</td>
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<tr>
<td>NHC</td>
<td>Natural Hazards Center</td>
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<tr>
<td>NOAA</td>
<td>National Oceanic and Atmospheric Administration</td>
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<td>NWS</td>
<td>National Weather Service</td>
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<tr>
<td>OMB</td>
<td>Office of Management and Budget</td>
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<tr>
<td>PA</td>
<td>Protective Action</td>
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<tr>
<td>PADM</td>
<td>Protective Action Decision Model</td>
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<tr>
<td>PCA</td>
<td>Principal Components Analysis</td>
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<td>PCM</td>
<td>Physical Context Metric</td>
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<td>RMSEA</td>
<td>Root Mean Square Error of Approximation</td>
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<td>RP</td>
<td>Risk Perception</td>
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<td>RQ1</td>
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<td>RQ2</td>
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<tr>
<td>RUCC</td>
<td>Rural-Urban Continuum Code</td>
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<tr>
<td>SEM</td>
<td>Structural Equation Model</td>
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<tr>
<td>SHELDUS</td>
<td>Spatial Hazards and Events Loss Database</td>
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<tr>
<td>SoVI®</td>
<td>Social Vulnerability Index</td>
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</table>
SPC ................................................................. Storm Prediction Center
SPSS ......................................................... Statistical Package for the Social Sciences
SV ................................................................. Social Vulnerability
TE ................................................................. Tornado Experience
TK ................................................................. Tornado Knowledge
TR ................................................................. Tornado Response
TROP ......................................................... Tornado Risk of Place
U.S ............................................................... United States
UHI ............................................................... Urban Heat Island
UGCoP ....................................................... Uncertain Geographic Context Problem
USCB ........................................................ United States Census Bureau
USDA ........................................................ United States Department of Agriculture
USDC ........................................................ United States Department of Commerce
CHAPTER 1
INTRODUCTION

Tornadoes are a type of extreme weather event that can pose severe threats to life and property in the United States, where they occur more frequently than anywhere on Earth (Mileti 1999; Lim et al. 2017). In the U.S., an average of 1,200 tornadoes strike annually, resulting in roughly 65 deaths and 1,500 injuries (USDC, NOAA, and NWS 2010, 1). Additionally, reported loss data between 1990-2019 reveals that total annual economic damages (i.e., property and crop) caused by tornadoes averaged 1.67 billion U.S. dollars (ADJ 2019) (CEMHS 2021). Tornadoes are a unique hazard in that they generally occur at the local level (Bluestein 2013), and their potentially catastrophic damage can be very limited in aerial extent (Thomas and Mitchell 2001). As such, populations must take proper mitigative action relative to their local geographic context in the event of a tornado to adequately reduce risk and potential negative impacts. However, tornado risk is a dynamic, interconnected system that evolves alongside individuals’ exposure, vulnerability, risk perceptions, and protective action decisions when faced with a threat like a tornado (Morss et al. 2017). Not to mention, tornadoes are among the most difficult hazards to predict and warn the public about promptly. Advancements in tornado detection and warning technologies have significantly improved tornado awareness over the past few decades (Boruff et al. 2003; Ashley 2007; Schumann, Ash, and Bowser 2018;
Despite these developments and the implementation of a variety of other tornado disaster risk reduction strategies, tornado fatalities have increased since the 1990s. The current state of tornado risk underscores the need for further research advancements to reduce the risk and vulnerability associated with tornadic events (Stokoe 2016).

A recent report by the National Academies stressed the urgent need for enhanced data collection relating to social and behavioral sciences within the weather enterprise (NASEM 2018). Research is recommended on the effects of geospatial tornado risk judgments and protective actions since they are relatively unknown (Klockow 2013; Ripberger et al. 2020), and a recent call for small research proposals confirms such interest (NHC 2020). For example, investigations into the factors driving people’s tornado risk, risk perception, and protective action have primarily focused on individual-level socio-demographic variables, past experiences, and elements of warning communication (Paul, Stimers, and Caldas 2015; Demuth 2018; Schumann, Ash, and Bowser 2018). Unfortunately, research pays little attention to the role of local physical and social geographic contextual factors in tornado risk (Klockow 2013). The human and physical characteristics of places (e.g., geographic context) are significant in communities when such area-based contextual variables are proven drivers of individuals’ decision-making and outcomes (Kwan 2012). Geographic differences in exposure are essential in risk and vulnerability assessments, especially due to community demographic changes and how location creates non-random exposure to tornado hazards (Lim et al. 2017). Research can uncover how these
contextual place-based characteristics impact tornado risk perceptions and protective action decisions across space. An improved empirical understanding of place-based societal tornado risk based on a holistic analysis of geographic context, risk perceptions, and response actions is necessary to strengthen disaster risk reduction strategies. The results have practical implications for emergency management approaches, including warnings designed to protect life and property, minimize population exposure, and mitigate the social vulnerability of marginalized communities.

1.1 Purpose and Research Questions

Our current social scientific understanding of tornado risk, risk perception, and protective action behavior lacks proper spatial consideration of the physical and social geographic contexts within which they operate. No conceptual model currently exists that incorporates these influential risk variables and is specific to tornado hazards. This study proposes that including geographic context and its influence on perception and behavior produces differential tornado risk. It also seeks to determine which factors are the most significant contributors to such variability. Little is known about the role of space-time activity in tornado risk perception and behavioral response. Additionally, few studies attach tornado risk to the societal context or compare the current level(s) of social vulnerability to geographic context. Expanding the research base on the physical and social contextual influence on individuals’ responses to tornado threats and uncovering ways to improve tornado preparedness and mitigation is crucial. This dissertation research aims to determine how geographic context elements influence place-
based tornado risk experiences in a U.S. state case study. Ultimately, the results help uncover how the nature of ‘place’ plays a role in tornado risk perception and protective action decision-making and help determine whether spatial context or risk perception is the more influential driver of mitigative action in the event of a tornado. In turn, this advanced empirical understanding of societal tornado risk can aid practical strategies for disaster risk reduction.

This investigation addresses three research questions:

(1) How does the physical and social geographic context of community-level tornado risk vary across space?

(2) How do the conceptual drivers of tornado risk (geographic context, risk perception, and protective action decision-making) interact to create the spatiality of tornado risk?

(3) Does tornado risk vary across different geographic areas within a U.S. state (i.e., formal urban-rural and Northern-Central-Southern regions or by functional state emergency management regions, National Weather Service County Warning Areas, and StormReady® counties)?

This investigation utilizes the following approaches to answer these questions:

(1) Measures the geographic context (both physical and social) of tornado risk and determines its variability in the landscape.

(2) Measures individuals’ tornado risk perceptions and protective action behaviors within the study area.
(3) Measures the direct and indirect relationships between the driving factors (i.e., physical context, social context, risk perception, and protective action) forming the tornado risk of place.

1.2 Study Area

One state was chosen as the study area to test the conceptual relationships proposed in this investigation by binding the analytics as a place-based analysis and controlling for broad-scaled tornado risks. Additionally, U.S. public emergency management operations occur at the state and county levels, with various contextual organizational structures that influence the culture of each state’s emergency management system. It is also crucial that the state selected as the case study is big enough to contain a large number ($n > 100$) of counties to ensure statistical validity in factor analyses. The central unit of analysis employed in this research approach is at the county level, commonly selected as the unit of analysis in socio-environmental variable-based studies due to widespread data availability, accessibility, and ease of spatial aggregation. The county-level locality is also essential in measuring community dynamics in geographic or place-based empirical investigations.

Illinois (Figure 1.1) is the selected study area location due to its wide-ranging urban-rural environments, high tornado risk, and recent history of extreme tornadic events. Illinois has a population of 12,716,164 within 102 counties (USCB n.d.b.). The State of Illinois spans nearly 56,000 square miles, with an average of 544 square miles of land per county (USCB n.d.c.). While many counties contain rural farmland, the state includes many metropolitan
areas, including Chicago, Peoria, Springfield, Champaign-Urbana, East St. Louis, and more (USCB n.d.b.). Concerning tornado risk, a national tornado assessment ranked Illinois as the fifth highest state for tornado rates per 10,000 square miles (Simmons and Sutter 2011). A recent severe weather event in August 2020 resulted in fifteen tornadoes that devastated many communities in Illinois, Iowa, and Indiana (USDC, NOAA, and NWS 2020a). In December 2021, a significant tornado outbreak across six states also included a severe tornado that killed six people at an Amazon warehouse in Southwestern Illinois (Ford 2021).

Figure 1.1 Map of Illinois Study Area (Nations Online 2023).
1.3 Document Structure

Following this introduction, six additional chapters make up this dissertation. Chapter Two (Literature Review) outlines the conceptual basis of this investigation before proposing a new framework to assess tornado risk geospatially, the Tornado Risk of Place model. Then, the chapter synthesizes the existing literature on the driving factors in the geographic context of tornado risk perception and protective action. Chapter Three (Tornado Risk Context Assessment) details the methodological approach and analytical results to research question one. Chapter Four (Implementing the TROP Model Framework) presents the methods and results of the second research question. Chapter Five (Regional Assessment of the TROP Model Outcomes) describes the methodology and analysis outcomes for the third research question. Chapter Six (Discussion) provides a detailed discussion of the main findings from this investigation. Chapter Seven (Conclusion) summarizes the research question results, as well as the contributions and limitations of the study.
CHAPTER 2
LITERATURE REVIEW

The background research that informs this investigation includes inter-and intra-disciplinary approaches based on existing literature. Overall, this study is rooted in the academic field of geography, the subfield of human-environmental interaction, and the hazards-disasters research paradigm (Cutter 2001). A place-based, spatial perspective of social science elements is applied based on the human ecology of hazards perspective (i.e., the mutual relationship between the environment and humans) (Boruff et al. 2003). In addition to social science perspectives, geospatial methods of risk determination and the nature of tornadic exposure based on weather and climate research play a significant role in measuring the tornadic risk of places.

2.1 Conceptual Background

Risk perception and protective action behavior are inevitably related, creating differential hazard risks across space. Social science research on risk perception (i.e., the intuitive judgments people make about potential risks) is critical to understanding why people respond to communicated hazard threats (Mileti and Sorenson 1990), particularly in tornado contexts (Golden and Adams 2000). Scholars have developed a few critical models for understanding place-based risk, vulnerability, and decision-making. Social scientists first systematically modeled hazard warning response as a set of five complex
behavioral stages (i.e., receive, understand, believe, confirm, and personalize warnings) that individuals undergo sequentially before appropriate protective actions occur (Mileti and Sorenson 1990). A more recent behavioral response framework, the Protective Action Decision Model (PADM), comprises multistage pre-decision processes and outcomes regarding typical societal responses to environmental hazards (Figure 2.1). The PADM design incorporates risk communication, threat perceptions, and response options availability (Lindell and Perry 2004; 2012). A significant component of the PADM is its iterative nature and feedback loop processes that can occur when additional environmental and social cues are received and processed. Not everyone progresses sequentially through every step of the PADM and may skip steps due to the speed of hazard onset. The more PADM stages ignored often equates to increased ambiguity in response decisions, which is more likely in sudden-onset hazards like tornadoes (Lindell and Perry 2012).

Figure 2.1 Protective Action Decision Model (Lindell and Perry 2012, 617).
No response model yet found in the literature is specific to tornadoes, leaving intuitive judgments largely unknown for these short-term, dynamic events. While the PADM is the primary framework applied to understanding tornado risk and behavior, the model addresses an all-hazards experience despite existing variations in risk and response between hazard types. Many scholars have implemented the PADM model in empirical studies of natural hazard response (Huang, Lindell, and Prater 2017; Strahan and Watson 2019; Scovell et al. 2021), but only a few are specific to tornadoes. One analysis of household preparedness for tornadoes only assessed demographics, previous experience, and locus of control, failing to account for any contextual influences (Chaney et al. 2013). Another PADM-rooted study found place-based drivers to be very influential in the spatiality of tornado response but focused on forecasting and warning elements (Klockow 2013). The PADM framework considers a few societal and environmental factors of influence (Lindell and Perry 2004; 2012), but it is still aspatial in approach. The model's process is inherently geographical, as the first steps involve evaluations of environmental signals (i.e., what you see, hear, and smell) and social cues (i.e., observations of peers and warning communication). Still, it fails to fully incorporate the significance of place uniqueness or underlying social vulnerability. The PADM also lacks validation of spatial variability in hazard outcomes, and the model's fit is not assessed based on differences in geographic location or scale of analysis. The model's incorporation of situational factors merely refers to a narrow range of societal conditions that impede or facilitate response action. Additionally, the PADM does
not account for geographic context’s direct or indirect influence through variable measurement or differences in each variable’s impact on overall risk, providing no risk assessment as it varies across space.

Research is ambiguous about what “context” means when investigated as a possible influential element in risk management, and very few do so in tornado-specific investigations. These pitfalls lead to dangerous ambiguity in the indicators controlling tornado perception and response (Severtson and Burt 2012; Klockow 2013). Geography inherently associates the spatial dimensions of risk, dictating that all places are unique and experience different levels of exposure to hazards. Two elements of geographic context, the physical and social environment, can be generally categorized and associated with hazard risk (Lindell and Perry 2012). These area-based dynamics of “site” (i.e., intrinsic physical characteristics), “situation” (i.e., relative social and geophysical factors that set the context), and “connection” (i.e., the spatial relationship between people and their environment) exert contextual influence on risk. Due to known spatial differences in exposures and outcomes, it is necessary to incorporate geographic context in hazard vulnerability research and risk management decision-making (Pine 2009; Müller-Mahn, Everts, and Doevenspeck 2012). While context is an essential element to consider in empirical research and risk/vulnerability assessments, actual contextual influence can easily be overlooked and ignored through the measurement or spatial aggregation of data in analyses and cartographic representations (Fekete 2012). How area-based contextual factors are geographically delineated can differ from the truly causally
relevant nature of individual behaviors and outcomes. This Uncertain Geographic Context Problem (UGCoP) can result in hidden contextual variable influences if the individual-based behaviors or outcomes examined occur at a different scale than what is observable in the data. However, the UGCoP may not be a significant problem in analyses of area-based variables or outcomes (Kwan 2012).

A framework commonly applied to understand place-based risk and vulnerability is the geographically rooted Hazards-of-Place (HOP) model (Cutter 1996), a multi-scale approach to measuring overall place vulnerability (i.e., potential for loss) to environmental hazards (Figure 2.2). Risk and mitigation serve as initial predictors of hazard potential, while the existing geographic context (e.g., site, situation, elevation, proximity), social fabric (e.g., community characteristics and demographics), and social-biophysical vulnerabilities alter hazard potential (Cutter 1996; Wisner 2016; Burton, Rufat, and Tate 2018). In this context, social vulnerability is a pre-existing, multi-dimensional condition defined as “the susceptibility of social groups or society at large to potential losses (structural and nonstructural) from hazard events and disasters” (Cutter 1996, 530), which impacts the ability to respond and recover. Since its inception, various studies have implemented the HOP model to measure and map vulnerability indicators (Cutter, Mitchell, and Scott 2000; Cutter, Boruff, and Shirley 2003; Boruff, Emrich, and Cutter 2005), but few target tornadic social vulnerability explicitly (Chaney 2004; Mitchem 2004; Ashley 2007; Bright et al. 2018). Additionally, while the HOP model is applicable at multiple spatial scales,
it is conceptually abstract and does not assess risk perception or decision-making in the framework.

Figure 2.2 The Hazards-of-Place Conceptual Model (Cutter 1996, 536).

The HOP model’s inclusion of geographic context as a casual element addresses an important missing PADM variable. Unfortunately, the HOP framework never specifically defines or empirically measures geographic context. Overall, the HOP and PADM are restrictive in their conceptual ambiguity, generalization for all hazard types, unaddressed spatial differences in risk outcomes, and unclear geographic context, risk perception, or decision-making elements. The limitations of these commonly applied approaches to modeling tornado-specific response drivers and place-based vulnerability underscore the critical need for a refined model to fully understand the complex interactions in conceptualizing spatial tornado risk.

2.2 Tornado Risk of Place Model

The PADM (Lindell and Perry 2012) and the HOP model (Cutter 1996) guide the development of this investigation's conceptual framework. Due to the
PADM and HOP shortcomings, as noted above, a conceptual framework called the Tornado Risk of Place (TROP) model is introduced to bridge the gap between the missing elements in the previous conceptual models. The TROP model displays the relationships between geographic context, risk perception, and mitigative action that require inclusion in research evaluations of place-based tornado risk (Figure 2.3). The block model boxes show the observed and latent variables explaining the factors influencing tornado risk. The solid lines and arrows indicate their direct and indirect (mediated) orientations of influence and existing feedback loops. The model theoretically assumes that the overall risk comes back to influence the context, delineated by the dashed lines, but this study will not investigate this outer model relationship.

![Figure 2.3 The Tornado Risk of Place (TROP) Conceptual Model.](image)

2.3 Factors Influencing Tornado Risk Perception and Behavioral Decision-Making

The following sections synthesize the main interacting drivers (i.e., geophysical context, social context, risk perception, and behavior) in the geography of tornado risk. In the current research literature, these drivers are the
main contributors to the spatial variability of tornado risk and guided the
development of this study’s research design.

2.3.1 Geophysical Tornado Exposure and Risk

Contextual changes in geography can increase tornado exposure and risk
(Ashley and Strader 2016). Hazard exposure is the level at which individuals,
infrastructure, and other environmental features intersect hazard-prone areas
(Burton, Rufat, and Tate 2018; UNDRR 2023a). Risk is generally defined in
hazards geography as the likelihood of hazard impacts, which is a product of the
potential for loss or harm caused by the physical hazard occurrence and
amplified by the underlying vulnerabilities that increase susceptibility to the event
consequences (Kunreuther and Useem 2010; Burton, Rufat, and Tate 2018;
UNDRR 2023b). Understanding and measuring changes in tornado risk and
exposure, as well as their influence on risk perception and response across
space, is essential to holistic assessments of tornado hazards.

Previous research on geophysical tornado risk and exposure drivers
provides crucial information for trend assessments and explorations of causal
factors. Weather records from the U.S. National Weather Service (NWS) provide
vital temporal and spatial data on U.S. climatological trends in tornado
occurrence, intensities, impacts, and geographic risk areas. Consequences from
tornadic activity, commonly measured in economic losses, injuries, and fatalities,
contribute to the record of tornado occurrence and the physical context of risk
(Simmons and Sutter 2011). Studies have explored longitudinal changes in
fatalities (Ashley 2007), economic losses (Boruff et al. 2003; Reeves 2015), and
broad societal implications by analyzing statistical and spatial trends in tornado occurrence. Assessments of tornado incidence, or the likelihood of event occurrence, are a standard method of analyzing exposure (Simmons and Sutter 2011).

The U.S. regions experiencing the highest tornado incidence (Hyndman and Hyndman 2011; Abbott 2012) and contributing the most to increasing tornado incidence over time are the Great Plains, Midwest, and Southeast (Guo, Wang, and Bluestein 2016). However, within a region of potential tornadic activity, the local geographic scale of exposure (e.g., state, county, or sub-county level) is ever-changing and unpredictable (Bluestein 2013). Over the past several decades, developments in radar coverage, storm spotter networks, and public tornado awareness alongside urbanizing populations have presumably led to increased reporting of tornado occurrences (otherwise known as the population or reporting bias). Reporting bias is more common in smaller magnitude events (e.g., F/EF 0 or 1 tornadoes) that may be undetected in rural geographies (Simmons and Sutter 2011; Kunkel et al. 2013; Elsner et al. 2013; Widen, Fricker, and Elsner 2015; Ellis et al. 2018). Scholars attempt to combat this bias in the methodological design of empirical studies, but research still points to increased tornado risk and exposure in metropolitan areas (Rosencrants and Ashley 2015).

Geographic variations in tornado impacts are also driven by population increases in expanding metropolitan environments (Ashley and Strader 2016) and urban-rural dynamics that alter the tornado landscape (Strader et al. 2015;
The urban-rural makeup of the U.S. population has changed dramatically over the last 70 years, with urban populations increasing alongside nationwide growth (USCB 2012). According to the USCB (2023), roughly 80% of the U.S. population lives in an urban area. The demographic shift into U.S. metropolitan areas that resulted in escalating population and building densities should be considered in tornado vulnerability assessments (Hall and Ashley 2008) and analyses of tornado risk, exposure, and incidence (Boruff et al. 2003). Research shows that individuals perceive urban areas to be less vulnerable to tornadoes (Mitchem 2003; Schultz et al. 2010; Klockow 2013), which can decrease warning response rates (Jauernic and Van Den Broeke 2016). Incorporating urban-rural variables in tornado research is thus crucial, especially when underrated tornado risk assessments in urban-rural areas may result in less protective action measures based on perceived reduction in risk (Simmons and Sutter 2011).

The built environment level developed from land-use/land cover modifications influences the increase in tornado exposure and risk in urbanized areas. Land-use/land cover alters the tornado landscape, making the built environment's impact a key component in differences between urban and rural tornado incidence and exposure (Strader et al. 2018). Research examining the urban variable influence finds increasing geophysical tornado exposure in metropolitan areas between 1960-2011 (Rosencrants and Ashley 2015). Assessments exploring the relationship between tornado impacts and intensity also find that incorporating land-use/land cover is crucial in accurately evaluating tornado exposure (Strader et al. 2015). One analysis examined regional societal
tornado exposure and found the Midwest to have the highest exposure based on the high built environment levels (Strader et al. 2017). Urban sprawl, a significant component of land use/land cover change in the U.S., is an important consideration when analyzing tornado exposure. An investigation of the impacts of urban sprawl on tornado exposure in Northeastern Illinois found increased levels of high-value housing units in the study area that contribute to expanding physical exposure in Chicago’s suburbs (Hall and Ashley 2008). Other research has indicated the potential for tornado exposure to increase alongside rising, sprawling populations due to higher rates of trapped heat and pollution in the developing built environment (Gildemeyer 2019).

Studies of tornado occurrence in rural versus urban areas have taken many different analytical approaches since Aguirre et al. (1993) found an increase in tornado incidence in metropolitan counties between 1950-1990. Cities are known to impact local weather systems due to the Urban Heat Island effect (UHI), which occurs when concrete, asphalt, and stone landcover surfaces absorb heat during the day to release and radiate it throughout the night. The increased warm air created by a UHI can create low-pressure cells that can form thunderstorms by rising, cooling, and condensing (Abbott 2012; Shourd 2015; Gildemeyer 2019). A few scholars have specifically examined the impact of a UHI on tornado genesis and exposure in the United States. UHIs can increase storm severity in metropolitan areas and those directly downwind (Cusack 2014), resulting in higher numbers of stronger urban tornadoes (Shourd 2015; Lim et al. 2017) and higher urban tornado incidence probabilities (Gildemeyer 2019).
Additionally, research has indicated that increases in low-level wind shear caused by surface roughness in urban areas create ideal conditions for tornado formation (Cusack 2014). Overall, research on U.S. tornado exposure and risk has been necessary for incidence, impact, and geographic trend detection due to the increased growth of sprawling populations, the UHI effect, and the densities of built environments.

Structural housing characteristics of the built environment also influence tornado outcomes, particularly in structural collapse and human fatality risk. The increasing numbers of housing units affected by tornadic events and land-use changes are directly related to more significant rates of risk and exposure (Ashley and Strader 2016). Structural collapse is common during tornadoes of higher intensity, highlighting the importance of shelter availability in areas with unsafe housing units. Two-story homes, newer buildings, and brick homes are more at-risk than one-story, older, and wooden structures (Boruff et al. 2003). However, mobile and manufactured homes have the highest levels of tornado exposure of any home type. These structures are known for the highest percentages of tornado-induced deaths due to their increased susceptibility to damage and destruction based on structural weakness (Ash 2017; Ash et al. 2020). Unfortunately, individuals sometimes do not have a choice in reducing their tornado exposure by living in mobile homes (Sutter and Poitras 2010) due to their low-costs and housing availability (Simmons and Sutter 2007). Additionally, statistical and geographical analyses of mobile and manufactured home residents’ risk perceptions and protective actions during tornado warnings find
many individuals believed their homes to be safe, did not execute proper protective measures, or lacked the resources to evacuate (Ash 2017; Ash et al. 2020).

2.3.2 Social Contextual Tornado Risk Drivers

Critical social context indicators influence tornado risk, perception, and response literature. The connection between societal context and existing social vulnerability is essential as the two can create feedback loops that alter community vulnerability to tornadoes. Vulnerability is the potential for loss or harm (Hill and Cutter 2001) as controlled by physical-environmental features and social fabric (Cutter, Boruff, and Shirley 2003). Vulnerability is a multidimensional, preexisting condition that varies over space and time (Hill and Cutter 2001; Cutter 1996). Attempts to model, measure, and explain vulnerability have changed over time and discipline (Cutter, Boruff, and Shirley 2003; Wisner et al. 2004; Birkmann 2006; Wisner 2016) but generally include exposure and sensitivity elements and adaptive capacity (Smit and Wandel 2006). Social vulnerability (SV) is of primary concern here, which refers to a population's susceptibility to harm or loss that influences their ability to respond, cope with, and recover from environmental hazard impacts (Wisner et al. 2004; Cutter and Finch 2008; Wisner 2016). In the geographic discipline, SV is applied as a tool and measurable concept for place-based analysis using the HOP framework (Cutter 1996). Socio-demographic, economic, and political indicators can lead to differential hazard impacts and variance in SV among communities. Population characteristics impacting SV have included race, ethnicity, socio-economic
status, gender, age, migration, and housing tenure (Cutter and Finch 2008), with areas of higher SV commonly associated with more significant loss potential (Mileti 1999).

Calls for further research have sought to determine how the public perceives disaster risk science and vulnerability assessments (Fekete 2012). Primary research objectives in emergency management and disaster risk reduction are identifications and assessments of SV (International Council for Science 2008; FEMA 2023a) with spatial mapping and analysis via Geographic Information Systems (GIS) to target high-risk populations (Fekete 2012; Wisner 2016; FEMA 2023b). These methods require spatial planning at the local level through integrated risk and vulnerability mapping (Sutanta, Rajabifard, and Bishop 2010). Unfortunately, research finds emergency managers underutilize these approaches (Wood, Sanders, and Frazier 2021). Mapping SV requires measuring dynamic latent factors adequately using quantitative or qualitative methods (Wisner et al. 2004; Dunning and Durden 2013; Burton, Rufat, and Tate 2018), which may be difficult without adequate funding or training.

The most widely accepted geospatial measurement of SV is the Social Vulnerability Index (SoVI®), a comparative metric drawn from aggregate socio-demographic variables to quantify place-based vulnerability based on the HOP model framework (Cutter 1996; Cutter, Boruff, and Shirley 2003; HVRI n.d.). SoVI® can be continually updated with U.S. Census Bureau (USCB) American Community Survey (ACS) data releases and calculated at the U.S. county or census tract level(s). The most recent version of SoVI® developed by the
Hazards Vulnerability and Resilience Institute (HVRI n.d.) comprises 29 variables supported in the empirical literature as accurate indicators of community vulnerability to environmental hazard risks, which include socio-demographic, economic, housing, and healthcare related information. SoVI®’s statistical construction applies principal component analysis, a data reduction technique to produce groupings of correlated variables based on their factor loadings. Grouped factors are assessed for their cardinality (i.e., positive or negative influence on social vulnerability) and combined to produce a total social vulnerability value for each geographic unit (e.g., county/tract) in the dataset. Scholars can map and comparatively assess the resulting total SoVI® scores and underlying factors scores to determine high/low vulnerability areas within a specified study area (HVRI 2016; n.d.).

Violent tornadoes occurring in open spaces without subsequent damage produces little risk, but weaker tornadoes passing through a densely populated environment may pose a significant risk to populations with high SV (Donner and Rodríguez 2011). SV also impacts the tornado perception and response process through sheltering availability, language barriers impeding communication, disabilities reducing mobility, and missing capital for warning technology and recovery (Lindell and Perry 2012; Brotzge and Donner 2013; Trainor et al. 2015; Cappelli et al. 2020; Martins et al. 2020). Tornado risk assessments find risk and vulnerability to be a function of physical and social factors, including income disparities, per capita income, and mobile home households (Lim et al. 2017). Highly socially vulnerable individuals (e.g., disabled, poor) are likelier to live in
mobile or manufactured homes and experience higher rates of tornado-induced fatalities (Lim et al. 2017). One spatial analysis of tornado vulnerability explored social, physical, and mitigative factors (Mitchem 2004) but ignored influential geographic contextual variables (e.g., urban-rural location, prior consequences, cultural beliefs, community engagement, or residency length) across differential spatial contexts. Evaluating SV as an aggregate, comparative measurement of social context alongside physical exposure elements is essential in tornado risk assessments.

The role of specific socio-demographic variables and past experiences in hazard risk perception and response are well known, even in a tornado-specific context. Ethnic and racial variables can impact tornado perception (Senkbeil et al. 2014), while age and gender may influence risk (Stokoe 2016). Education level emerges as a primary indicator of understanding warning information (Liu et al. 1996) and reductions in warning response (Liu et al. 1996; Balluz et al. 2000; Blanchard-Boehm and Cook 2004). Research finds individual socio-demographic variables are not sufficient in fully explaining risk perception and behavior (Lindell and Perry 2012; Kox and Thieken 2017), particularly during tornadoes (Silver and Andrey 2014; Ellis et al. 2018; Miran, Ling, and Rothfusz 2018). The role of past experiences is significant in tornado risk awareness (Klockow 2013; Paul, Stimers, and Caldas 2015; Demuth 2018) and response (Silver and Andrey 2014; Paul, Stimers, and Caldas 2015; Schumann, Ash, and Bowser 2018), but the effect can vary depending on the amount of time since the hazard experience and its level of severity (Paul 2011). Shared tornado experiences may also
influence risk perception, particularly in rural communities (Wallace, Keys-Matthews, and Hill 2015). Individuals’ everyday place-based risk perceptions and heuristics constantly evolve and can be tied to community place dependence. As a result, reductions in risk perceptions can occur when individuals grow comfortable or settled in with the functions provided by their geographic space (Manzo and Perkins 2006; Masuda and Garvin 2006; Klockow 2013), indicating residency length is another potential variable of influence in tornado risk.

Normative social influence (i.e., external social forces that motivate behavior) is a compelling persuading factor for tornado warning perception and comprehension (Parker 2017), and local disaster culture is directly influential in tornado response (Schumann, Ash, and Bowser 2018). Community members report a shared social understanding of localized tornado risk based on cultural values, beliefs, and customs. People generally turn to their community when tornadoes occur to process the event (Klockow 2013). Friend/kinship and social/community networks are essential in hazard response (Lindell and Perry 2004). Regular voluntary work, strong community involvement, and frequent family interaction can improve community tornado warning reception (Brotzge and Donner 2013).

Religious belief is an attributable contextual factor in hazard response due to the increased support provided by adherents to cope, respond, and recover, resulting in a shared social identity and network to enhance community involvement (Schipper 2010; Sun, Deng, and Qi 2018). Prayer is a typical
protective action during disasters (Mitchell 2003). The fatalistic attitude (i.e., God will provide adequate protection or that disasters are God’s will) can occur when people acknowledge the risk but feel protection is out of their control (Jauernic and Van Den Broeke 2016). Regional disparities in tornado fatalities were found in early research, with the Southern U.S. region containing higher fatality risk due to human behavior characteristics like fatalistic attitudes (Sims and Baumann 1972). However, updated analyses have revealed that fatalism does not explain the elevated fatality risk in Southern states (Biddle et al. 2020). Few scholars have accounted for fatalism in recent geographic tornado risk research (Mason et al. 2018) due to its lack of usefulness in predicting tornado fatalities (Key 2015).

2.3.3 The Role of Risk Perception and Protective Action Response

Risk perception, or the judgments people make about potential risks (Paul 2011), is important to understand within the context of the tornado warning process because it is the first cognitive step to initiate a protective response (Brotzge and Donner 2013). Geographers began to analyze risk perceptions toward natural and technological hazard threats (Sims and Baumann 1972; Burton, Kates, and White 1978; Slovic 1987) after earlier scholars developed a spatial perception approach to studying differences in human behavior (i.e., psychology) based on their environments (Wood 1970). The psychometric paradigm is a hazard risk taxonomy applied to understand and predict public risk response (Slovic 1987; 2000). This paradigm is a metric to assess risk perception comprised of a two-dimensional factor analysis that categorizes and evaluates individual risk by what is observable and dreaded based on intuition,
experience, and emotions. Perceived risk declines as perceived benefit increases, known as the affect heuristic, which is predictable and quantifiable. The paradigm further expanded the study of risk perception by examining the factors influencing risk assessment and risk response decision-making (Slovic 1987; 2000). The public employs multidimensional assessment strategies to evaluate risks that incorporate many psychological and cultural factors alongside scientific hazard risk information provided by experts (Klockow 2013). An improved understanding of intuitive risk judgments to evaluate hazardous environmental conditions is necessary for risk assessments and policymaking to aid disaster risk reduction strategies (Slovic 1987).

Risk perception drives response decisions, which can indirectly mold tornado risk. Research investigating the factors driving protective action decision-making to natural hazards helps outline key influential drivers, many relating to elements of geographic context. Effective warning dissemination is the first component driving successful public responses to tornadoes, which relies on proper risk communication within one’s social context. The milling process is a crucial step of protective action decision-making, which occurs when individuals receive the warning information, intuitively search for confirmation of the warning (e.g., check sources and examine cues), and then respond (Lindell and Perry 2012). When the NWS issues a public tornado warning, the information is diffused through multiple public and private communication channels (e.g., broadcast media, outdoor siren networks, mobile devices, and social media), varying by location (Trainor et al. 2015). Individuals and formal and informal
organizations operate within a network of social contexts to diffuse tornado warnings, significantly impacting risk perceptions and behavior (Lindell and Perry 2012). Formal warning channels, like those provided by the NWS or emergency managers, are more successful at reaching individuals of higher socioeconomic status. Informal channels, or information sources from family members, friends, or coworkers, better communicate tornado warnings to populations that are recent migrants, racial/ethnic minorities, and of lower economic status (Aguirre 1988; Schmidlin and King 1995; Donner 2007).

Public belief in the source of a tornado warning plays a vital role in initiating public protective action measures. Trust in the NWS and the false alarm effect, which occurs when tornado warnings are issued without an actual tornado event preceding, impact the public trust and perceived credibility in warnings (Ripberger et al. 2015a). Areas with high false alarm frequencies correlate with lower rates of mitigative action (Trainor et al. 2015). Research shows that NWS warnings possessing real-time tornado confirmations (i.e., when the tornado is confirmed live in person) increase trust and a sense of urgency regarding the event (Blair and Leighton 2014). Additionally, receiving warnings from more sources significantly increases the likelihood of executing protective action (Luo, Cong, and Liang 2015; Miran, Ling, and Rothfusz 2018).

Tornado warning receipt through environmental cues triggers evacuation behavior (Durage et al. 2014) and primarily motivates mitigative behavior (Silver and Andrey 2014). Cues like changing pressure in the ear and seeing debris or the tornado itself prompt protective action behavior (Donner, Rodriguez, and Díaz
as does hearing the iconic, roaring freight train sound (Lindell and Perry 2012). Environmental cues are an unofficial warning source (Durage et al. 2014), as people tend to go outside when aware of a tornado warning (Sherman-Morris 2009). However, cues are challenging for the public to interpret accurately (Klockow 2013). Evaluation of cloud formations is also a common approach to evaluating tornado risk. Still, laypersons commonly misinterpret tornadic versus non-tornadic clouds (Dewitt et al. 2015), and everyday distractions may divert attention from storm clouds (Lindell and Perry 2004). Physical landscape features influence tornado risk awareness and response, but they require understanding the hazard and its physical elements (Lindell and Perry 2004; Klockow 2013). Poor visibility due to hills or trees can impede the tornado response process, as the second most frequently assessed source of information is the outdoors (Klockow 2013). Studies reveal that individuals perceive tornado-modifying characteristics of landscape features, meaning that hills, waterways, and mountains are thought to influence tornado paths and occurrence (Donner, Rodriguez, and Diaz 2012; Klockow 2013; Klockow, Peppler, and McPherson 2014), and individuals sometimes believe tornadoes follow similar paths (Klockow, Peppler, and McPherson 2014).

Spatial disparities in preparedness and protection from weather hazards exist across the country. Research shows that warning systems integrating social design into their approaches maximize public protective action behavior (Sorenson 2000). Tornado warnings serve as spaces of risk and thus grounded in cognitive geography typology (Peuquet 2008; Klockow 2013), making
geographic context an influential element in the thought processes guiding protective response. As such, geographic context inherently drives mitigative action in tornado hazards. However, we still lack a comprehensive empirical understanding of the direct and indirect role of physical and social contextual factors in tornado risk perception and response. Research shows that geographic visualizations of hazard risks help create mental maps for more accurate locational relation to risk (Bass and Blanchard 2011). To correctly interpret risk tornado warnings utilizing maps rely on individuals having a prior spatial understanding of their location (Klockow 2013). Map graphics must be easy for the public to understand spatially, especially when they play a primary role in comprehension and response to tornado warnings (Ash, Schumann, and Bowser 2014; Drost et al. 2016; Schumann, Ash, and Bowser 2018). Place-based knowledge is critical to effective risk communication, education, and public outreach regarding severe weather to initiate proper protective behavior (Ripberger et al. 2020).
CHAPTER 3
TORNADO RISK CONTEXT ASSESSMENT

Quantifiable indicators were developed as computational metrics of both physical and social context domains at the county level to measure the geographic context of tornado risk. These observed indicator metrics were then adjusted as inputs for the geographic context indices, completing this study’s first required research input. The variability captured by these physical and social tornado risk context indicators is then statistically and spatially assessed across Illinois counties to address the investigation’s first research question.

3.1 Measuring Geographic Context Indicators: Data

Six primary data sources were employed to create observable metrics of physical and social context indicators, as summarized in Table 3.1. Most data applied in this investigation originate from U.S. federal agencies, including the National Weather Service (NWS), the U.S. Census Bureau (USCB), and the U.S. Department of Agriculture (USDA). Other than the Spatial Hazards and Events Loss Database (SHELDUS) from the Arizona State University’s Center for Emergency Management and Homeland Security (CEMHS 2022), all geographic context indicator datasets source from publicly available, open-access sources. The USCB Cartographic Boundary files for state and county areas are also key inputs for geospatial analytics and data visualizations in GIS (USCB 2022).
Table 3.1 Input Data Sources for County Measurements of Geographic Context Indicators (Physical and Social).

<table>
<thead>
<tr>
<th>Indicator</th>
<th>County-Level Metric</th>
<th>Data Source(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tornado Occurrence</td>
<td>Weighted and Adjusted Tornado Frequency</td>
<td>Storm Prediction Center (SPC et al. 2022) and USCB (2021a) Land Area</td>
</tr>
<tr>
<td>Exposure</td>
<td>Urban-Rural Classification Rank</td>
<td>USDA (2020b) Rural-Urban Continuum Codes</td>
</tr>
<tr>
<td>Prior Tornado Losses</td>
<td>Annualized Tornado Property and Crop Losses</td>
<td>SHEL DUS (CEMHS 2022)</td>
</tr>
<tr>
<td>Warning Incidence</td>
<td>Annualized Tornado Warning Rate</td>
<td>Iowa Environmental Mesonet (2022)</td>
</tr>
<tr>
<td>Structural Housing Risk</td>
<td>Percentage of Mobile Home Housing Units</td>
<td>USCB (n.d.a.) 2020 ACS 5-year estimates</td>
</tr>
</tbody>
</table>

Social

Social Vulnerability

SoVI® Score (29 input variables)

USCB (n.d.a.) 2020 ACS 5-year estimates

3.1.1 Physical Context Data

Based on the variables of tornado risk contextual influence deduced from the research literature, five geophysical context indicators transform into county-level metric inputs. The first indicator, tornado occurrence, originates from climatological data as a measurement of physical context to assess objective tornado risk. The most widely utilized source for long-term tornado data in the U.S. is the NWS Storm Prediction Center (SPC) historical tornado archive (Widen, Fricker, and Elsner 2015; SPC et al. 2022). The dataset includes over 67,000 tornado records for the contiguous U.S. from 1950 through 2021 (SPC et al. 2022). The SPC historical tornado archive contains occurrence records for complete tornado storm tracks that cross county boundaries, allowing for accurate aggregated tornado frequency value calculations among Illinois counties. Most tornado records in the dataset include starting/ending
coordinates of the event, length, width, time/date, injuries, fatalities, Fujita/Enhanced Fujita (F/EF) scale rating of severity, and more (SPC et al. n.d.a.). The F scale was in place for classifying tornado magnitude from the late-1970s until February 1, 2007, when replaced by the EF scale (Edwards et al. 2013). However, the EF scale was designed for continuity with the F scale rating system to allow for long-term analysis of tornado climatology data (SPC et al. n.d.b.). Both scales delineate magnitude using estimated wind speeds from the impact damage caused by the tornado event, ranging from F/EF 0-5 (F/EF 0 being the least severe and destructive and F/EF 5 being the most severe and destructive). Some tornado events are classified as unrated when failing to meet the minimum wind speed and damage threshold of a F/EF 0 by the NWS. An additional dataset, land area (in square miles) per county based on the 2010 U.S. Decennial Census (USCB 2021a), adjusts tornado frequencies by county sizes.

To adjust for well-documented differences over time in the SPC dataset (Gall, Borden, and Cutter 2009; Widen, Fricker, and Elsner 2015) and avoid the reporting bias (Simmons and Sutter 2011), the period of tornado occurrence for this study ranges from 1992-2021 to encompass the most recent thirty-year climatological range of available data. While this limits the study's longitudinal extent, this approach considers the most accurate portion of the historical tornado record without removing lower-rated (F/EF 0 or 1) tornadoes. Increased tornado detection and reporting beginning in the early 1990s (McCarthy and Schaefer 2003) due to Doppler radar and storm spotter networks also justifies the removal of the tornado occurrence record before 1990 in this investigation, as
this has presumably resulted in increased reporting of lower-rated tornadoes (Elsner et al. 2013; Kunkel et al. 2013; Coleman and Dixon 2014; Nouri et al. 2021).

The built environment indicator data originates from the U.S. Department of Agriculture’s (USDA 2020b) 2013 Rural-Urban Continuum Codes (RUCCs). RUCCs are ranked and delineated in codes one (more urban) through nine (more rural) based on population size, metropolitan area adjacency and proximity, and degree of urbanization (USDA 2020b). The U.S. White House Office of Management and Budget (OMB 2010) applies information regarding population and urban core socio-economic influences to assign Metropolitan Statistical Areas (MSAs) and micropolitan statistical areas. An MSA includes the central counties of an urbanized area and the adjacent counties that contain socio-economic linkages to the urban core. Smaller urban clusters form micropolitan statistical areas outside MSAs, sometimes including outlying counties with individuals who commute into the micropolitan nucleus (Ingram and Franco 2014). The OMB delineations of MSAs and micropolitan statistical areas are combined to form core-based statistical areas of county spatial groupings. The remaining unclassified areas outside core-based statistical areas are rural/nonmetropolitan. Federal agencies like the USDA apply OMB metropolitan or nonmetropolitan designations as a starting point in their development of urban-rural schemes (OMB 2010; USCB 2019). The USDA RUCCs designate each county with a code based on a nine-level urban-rural continuum scale in which codes are also grouped into a metro or nonmetro category (codes 1-3 assigned
as metro counties and codes 4-9 as nonmetro counties), as delineated in Table 3.2. The USDA Economic Research Office is responsible for creating the county-level rural-urban continuum, arguing that counties are the national standard for socio-economic analyses (USDA 2020a).

Table 3.2 USDA 2013 Rural-Urban Continuum Codes.

<table>
<thead>
<tr>
<th>Category</th>
<th>Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Metro</td>
<td>1</td>
<td>Counties in metro areas of 1 million population or more</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Counties in metro areas of 250,000 to 1 million population</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Counties in metro areas of fewer than 250,000 population</td>
</tr>
<tr>
<td>Nonmetro</td>
<td>4</td>
<td>Urban population of 20,000 or more, adjacent to a metro area</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>Urban population of 20,000 or more, not adjacent to a metro area</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>Urban population of 2,500 to 19,999, adjacent to a metro area</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>Urban population of 2,500 to 19,999, not adjacent to a metro area</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Completely rural or less than 2,500 urban population, adjacent to a metro area</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>Completely rural or less than 2,500 urban population, not adjacent to a metro area</td>
</tr>
</tbody>
</table>

Source: USDA 2020b.

The prior consequence indicator is measured based on SHELDUS data (CEMHS 2022), which provides direct economic (i.e., crop and property) and human (i.e., injuries and fatalities) loss estimates caused by tornadic events in all U.S. counties and territories since 1960. The dataset only contains event reports for events that result in monetary or human losses, and total event losses are divided equally amongst the impacted counties. The data source for direct tornado losses within the SHELDUS database is the National Centers for Environmental Information (NCEI). Loss data is downloaded in county aggregations for the State of Illinois covering the 1991-2020 30-year period, with all monetary amounts adjusted to 2020 U.S. dollars ($). The SHELDUS data was
accessed utilizing the University of South Carolina Geography Department’s subscription to the database, meaning no monetary payments were required to access the data that is normally behind a paywall.

Historical tornado warning data from the Iowa Environmental Mesonet (2022) measures the physical context indicator for warning incidence for the entire 37-year period of available data (1986-2022). The warning data downloads as geospatial shapefiles, which include a record for each NWS-issued tornado warning. Before October 2007, all NWS tornado warnings conformed to county boundary geometry, meaning that a tornado warning polygon consists of the entire county where a tornado was potentially occurring. Starting in October 2007, the NWS switched to storm-based warning geometry, meaning warnings no longer conform precisely to county boundaries. As a result, most storm-based tornado warnings overlap multiple counties or occur in only parts of a county. Additionally, tornado warning data includes separate records for each stage of a warning cycle (e.g., warning issuance, extension, expiration, etc.).

The final physical context indicator, structural housing risk, is based on the county-aggregated mobile home housing unit data from the USCB 2020 ACS 5-year estimates (USCB n.d.a.). The ACS estimates sources from data collected via a nationwide survey conducted each year, combined over five years to produce 5-year estimates (2016-2020). Each annual sample is roughly 3.5 million households and includes a margin of error with each data estimate. Data collected via the ACS relates to social, economic, housing, and demographic characteristics and provides more up-to-date information regarding these
population dynamics between the decennial census collection periods (USCB 2021b).

3.1.2 Social Context Data

To measure the social context of tornado risk among Illinois counties, a Social Vulnerability Index (SoVI®) is calculated based on the USCB 2020 ACS 5-year estimates (USCB n.d.a.). Input data for the SoVI® include 29 variables influencing community vulnerability to environmental hazard threats (Table 3.3). The SoVI® inputs have been updated in recent years, no longer including median gross rent, median housing value, percent children living in married-couple families, and hospitals per capita. Instead, variables now include percent children living in single-parent families, percent of the population with a disability, and percent mortgage or rent burden. The variable input data originates from the USCB data table portal, accessible in 24 separate ACS data sheets in county-level aggregations. The SoVI® applied here removes the percent mobile home data variable typically included in the SoVI® formula input due to its inclusion in the physical context metric. In place of the mobile home variable removed from this customized SoVI®, a variable measuring the number of households without broadband internet is applied as an input variable due to the influence of broadband internet on the reception of tornado warnings.

3.1.3 Processing Geographic Context Indicator Datasets

The indicator metrics for the physical context of tornado risk variables first require calculations into a metric via conversion of the raw data into a percentage, average, ranking, or rate before analyses (Figure 3.1). Each metric's
cardinality (i.e., positive or negative direction of influence on final model) orients to assign higher values to those that lead to increased tornado risk based on their known contextual influence justified in the research literature.

Table 3.3 Input Variables for the Social Vulnerability Index Construction.

<table>
<thead>
<tr>
<th>Input Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MEDAGE</td>
<td>Median Age</td>
</tr>
<tr>
<td>PERCAP</td>
<td>Per Capita Income</td>
</tr>
<tr>
<td>PPUNIT</td>
<td>People per Unit</td>
</tr>
<tr>
<td>QAGEDEP</td>
<td>Percent Population under 5 years or 65 and over</td>
</tr>
<tr>
<td>QASIAN</td>
<td>Percent Asian</td>
</tr>
<tr>
<td>QBLACK</td>
<td>Percent Black</td>
</tr>
<tr>
<td>QCVLUN</td>
<td>Percent Civilian Unemployment</td>
</tr>
<tr>
<td>QDISABLE</td>
<td>Percent Population with a disability</td>
</tr>
<tr>
<td>QED12LES</td>
<td>Percent with Less than 12th Grade Education</td>
</tr>
<tr>
<td>QESL</td>
<td>Percent Speaking English as a Second Language with Limited English Proficiency</td>
</tr>
<tr>
<td>QEXTRCT</td>
<td>Percent Employment in Extractive Industries</td>
</tr>
<tr>
<td>QFEMALE</td>
<td>Percent Female</td>
</tr>
<tr>
<td>QFEMLBR</td>
<td>Percent Female Participation in Labor Force</td>
</tr>
<tr>
<td>QFHH</td>
<td>Percent Female-Headed Households</td>
</tr>
<tr>
<td>QHISP</td>
<td>Percent Hispanic</td>
</tr>
<tr>
<td>QMORTBRDN</td>
<td>Percent Households Spending 30%+ Income on Mortgage</td>
</tr>
<tr>
<td>QNATAM</td>
<td>Percent Native American</td>
</tr>
<tr>
<td>QNOAUTO</td>
<td>Percent of Housing Units with No Car</td>
</tr>
<tr>
<td>QNOBRDBND</td>
<td>Percent of Households without Broadband Internet</td>
</tr>
<tr>
<td>QNOHLTH</td>
<td>Percent Without Health Insurance</td>
</tr>
<tr>
<td>QNRRRES</td>
<td>Nursing Home Residents Per Capita</td>
</tr>
<tr>
<td>QPOVTY</td>
<td>Percent Poverty</td>
</tr>
<tr>
<td>QRENTER</td>
<td>Percent Renters</td>
</tr>
<tr>
<td>QRICH</td>
<td>Percent Households Earning over $200,000 annually</td>
</tr>
<tr>
<td>QRNTBRDN</td>
<td>Percent Households Spending 30%+ Income on Rent</td>
</tr>
<tr>
<td>QSERV</td>
<td>Percent Employment in the Service Industry</td>
</tr>
<tr>
<td>QSNGLPAR</td>
<td>Percent Children Living in Single Parent Families</td>
</tr>
<tr>
<td>QSSBEN</td>
<td>Percent Households Receiving Social Security Benefits</td>
</tr>
<tr>
<td>QUNOCCHU</td>
<td>Percent Unoccupied Housing Units</td>
</tr>
</tbody>
</table>
For the first physical context variable, tornado frequency calculations as raw and weighted counts are based on the F/EF magnitude originating from the SPC occurrence dataset. The SPC tornado record data (SPC et al. 2022) are preprocessed in Microsoft Excel to eliminate any events occurring before 1992 or outside Illinois. Those events touching down in neighboring states and tracking into Illinois remain in the dataset for analytics. After removing any tornado events with missing geospatial information (i.e., starting latitude and longitude), each tornado record is weighted to account for tornado severity based on the event F/EF magnitude reported by the NWS (Table 3.4). Nonrated, F/EF 0, and F/EF 1 tornadoes count as one weighted event. Each subsequent higher magnitude event (2-5) weight equates to the E/EF value of the event (e.g., a F/EF 4 rated event equates to a weighted count of four). As a result, higher magnitude (more severe) tornado events represent an increased value for tabulation in the total
tornado counts per county. No F/EF 5 magnitude events occurred throughout the
30-year study period in Illinois.

Table 3.4 Weighting Scheme for Tornado Occurrence Metric.

<table>
<thead>
<tr>
<th>F/EF Rating</th>
<th>Weighted Tornado Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 or Unrated</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

A geospatial processing (geoprocessing) analysis of the tornado event
data accurately counts the weighted tornadoes per county. A tornado
identification (ID) field provides a unique ID to each tornado event for joining
event attribute information. The resulting tornadoes split events between those
with only touchdown point data and those with complete tornado path geometry
(polylines). Many tornadoes were missing ending latitude and longitude
information and could only map as touchdown points, not polyline tracks. Point
mapping in Environmental Systems Research Institute (ESRI) ArcGIS Pro
version 3.0.2 utilizes the Display XY Data tool. The tornadoes with complete
ending geometry information spatially map as paths using the XY to Line tool.
These paths join to their attribute information using the tornado ID field as a final
step in the geoprocessing analysis. The tornado points and paths map features
graduated symbols based on the tornado magnitude (F/EF ranking). The Spatial
Join tool executes a data match on the point and polyline tornado layers to join
the county name in which the tornado occurred to the tornado record. The USCB
Cartographic Boundary File layer provides the county boundary geometry for this
geoprocessing analysis (USCB 2022). The join output produces a new layer for each tornado record with an attribute column for the county name(s) of each tornado event occurrence. Summary statistics calculations on the weighted tornado attribute column sum the weighted tornado occurrence totals per county. The county tornado frequencies adjust for differences in county sizes by dividing the weighted frequencies by the county land area and multiplying the result by 1,000. The resulting final value tornado occurrence metric equates to the county’s total number of weighted tornadoes per 1,000 square miles. This final metric information is spatially matched to the county geospatial data layer using an attribute join based on the county Federal Information Processing Standards (FIPS) codes.

The remaining physical context indicators required relatively minimal processing. The RUCC measurements of the built environment indicator are re-coded to assign the urban counties higher tornado risk based on their increased exposure and lower perceived vulnerability. The investigator reverses the coding of each county’s 1-9 (urban-to-rural) indicator values to rank 1-9 (rural-to-urban) for appropriate cardinality influence. The metric for the prior consequence indicator, annualized economic losses in U.S. Dollars (USD), is calculated by adding together the county values of property and crop losses (ADJ 2020 USD) and creating an annualized loss metric (i.e., total economic county losses divided by 30 years). The final physical indicator, structural housing risk, is calculated as the percentage of mobile home units within each county (i.e., the number of
mobile home housing units divided by the total number of all housing units in the county).

Processing the average annual rates of tornado warnings per county requires counts of warnings issued per county based on geospatial polygon warning data and the USCB Cartographic Boundary File layer (USCB 2022). The only warnings which remain in the dataset when tabulating total county warnings counts are those with the assigned status of “New,” “Corrected,” or “Continued.” The Spatial Join tool (one to many) in ESRI ArcGIS Pro provides a new output layer with an attribute column summing the number of times a warning polygon overlaps that county’s geometry. The resulting number of tornado warnings occurring within each county’s boundaries throughout the data record (1986-2022) provides inputs for calculating the average annual tornado warning rate (i.e., the number of total warnings divided by 37 years) for each Illinois county.

Within the social context domain, a SoVI® analysis calculation for the 102 Illinois counties based on the Cutter and Emrich (2021) analytical workflow (Figure 3.2) uses the International Business Machines Corporation (IBM®) Statistical Package for the Social Sciences (SPSS®) statistical software version 28. The ACS input variables’ descriptive statistics estimates ensure no data entry errors or missing values existed in the dataset. The input variable z-score transformations provide a normalized metric for data reduction analysis. In the z-score formula equation (Equation 1), the mean of the sample (\( \bar{x} \)) is subtracted from the observed value (x) before being divided by the sample’s standard deviation (s). The raw input variable is re-calculated based on its relationship to
the variable groups’ mean value (i.e., the measurement transforms to a calculation based on its standard deviations from the group mean).

\[ z = \frac{(x - \bar{x})}{s} \]  
(Equation 1)

Figure 3.2 Flow Diagram for the SoVI® Development (Cutter and Emrich 2021).
The standardized SoVI® input variable z-scores provide principal components analysis (PCA) input using a varimax rotation based on 100 iterations. The Kaiser Criterion rule is applied to retain components with Eigenvalues greater than one based on 100 iterations, which helps ensure that variables do not load highly on more than one factor. The multi-dimensional factor loadings examine where variables loaded higher than .500 and less than -.500. The factors (or components) are then named based on the most substantially loading factors (generally greater than .700 or less than -.700) and listed in order of the highest explained variance percentage on the total model. The final retained factor components cardinality assessment provides the directional influence of each factor on increasing (+) or decreasing (-) vulnerability. The resulting component summed values create an Illinois county-level index value equating higher vulnerability to a higher SoVI® score. Equal weighting is assigned to each component, meaning the factors are assumed to have equal influence on the total model in the summation of the resulting social vulnerability component scores (HVRI 2016).

3.2 Geographic Context Analytical Approach

A case study of Illinois counties evaluates the geographic contextual elements of tornado risk by assessing the statistical and spatial variability captured by these physical and social tornado risk context indices (RQ1). Each of the five separate physical context input metrics is normalized as z-scores (Equation 1) to create a comparable reference value. The five physical subindices' z-scores summation creates a combined physical context metric for
each of the 102 Illinois counties. The researcher determines a total social context value per county using the retained factor calculation from the PCA. After assessing factor cardinality, the social geographic context value is created by summating the retained factors from the SoVI® results. A combined spatial dataset in ESRI ArcGIS Pro links all county-level geographic context variable metrics using the FIPS codes assigned to U.S. states and counties. The 2020 USCB Cartographic Boundary File layer (USCB 2022) spatially matches each county’s social and physical context values and input factors. The total social and physical context choropleth map visualizations apply a five-class categorization that classifies high/low context based on standard deviations from the mean. Lower risk context values (negative deviations from the mean) equate to lower context values (e.g., lower vulnerability), and higher values (positive deviations from the mean) to higher context values.

The variability in each separate contextual influence variable undergoes statistical evaluation using Microsoft Excel among the physical and social context indices to evaluate the geographic context of community-level tornado risk. Descriptive statistics are executed on each separate observed variable indicator value to ensure no data input errors exist based on inconsistent frequency distributions. Descriptive statistic assessments also provide measures of context value averages, standard deviations, and ranges for the physical, social, and total geographic context indices to test the existence of any statistical variability. Correlation analysis based on Pearson’s $r$ then calculate the physical and social context index relationships among the 102 counties to determine if these
measurements contain statistically significant correlations (p-value less than 0.05).

Spatial variability assessments employ ESRI ArcGIS Pro to map each physical and social contextual indicator at the county level, visually evaluate each metrics’ distribution, and test for spatial autocorrelation. All geospatial-based studies must consider spatial dependence (autocorrelation) and spatial heterogeneity (variability) (Negreiros et al. 2010). According to Tobler’s First Law of Geography, “Everything is related to everything else, but near things are more related than distant things.” (Tobler 1970, 236). Spatial autocorrelation is a product of Tobler’s Law and is a property of random variables at given locations that are more or less similar than expected for randomly associated spatial variables (Legendre 1993; Andrienko et al. 2010). In other words, it is a concept of spatial dependence of environmental/socioecological variables where those nearer are more similar than those further away. Statistically, spatial autocorrelation measures the degree of linear dependency between a variable’s origin error and its spatial neighbors (Páez and Scott 2005). Spatial autocorrelation deals with the spatial influence of neighboring environmental values on those nearby. Positive autocorrelation results in spatial clusters of geographies with similar values, while negative autocorrelation produces areas where variable values differ from their neighbors. Spatial autocorrelation is implicit in social science studies in human ecology, urban sociology, rural/applied demography, and more (Chi and Zhu 2008).
The degree to which features are clustered or dispersed over Earth’s surface can be identified by spatial autocorrelation and non-stationarity assessments (Negreiros et al. 2010), which take various forms. The primary methods for assessing spatial autocorrelation include Global and Local autocorrelation statistics (Anselin 1995; Grubesic, Wei, and Murray 2014). Global measures (e.g., Anselin’s Moran’s $I$, Geary’s $C$, and the general $G$) summarize the overall similarity of neighboring areas in the entire (global) dataset. The Moran’s $I$ statistic, the most popular global statistic, measures the overall correlation of each observation within a specified distance to capture the degree of covariance within an entire dataset (Grubesic, Wei, and Murray 2014; Negreiros et al. 2010). Moran’s $I$ statistic is applied in this study to assess the spatial autocorrelation of the areal (polygon) vector data (Rogerson 2015) based on inverse distance spatial relationships, Euclidean distance, and row standardization. Global Moran’s $I$ testing uncovers any overall underlying geographic data clustering or dispersion for the physical, social, and total geographic context values. The Global Moran’s $I$ result for each evaluates a measurement of the covariances of units (attributes) to the overall mean. Neighbors compare spatial unit values, and if above/below the mean, there is positive spatial autocorrelation of high-high or low-low values. If the value of two mean deviations is negative, there is a negative correlation (high–low and low–high). Results range from a 1.0 (positive) to -1.0 (negative) correlation coefficient value, and a value closest to zero reveals a random pattern (Negreiros et al. 2010). However, these are global diagnostic tools for an entire study region, are
suitable in homogeneous areas (Chi and Zhu 2008) and cannot identify specific areas of detected spatial autocorrelation (Grubesic, Wei, and Murray 2014). These global indices only summarize complete spatial distribution into a single value, posing limitations to large datasets that hide spatial heterogeneity and local spatial clustering patterns (Negreiros et al. 2010).

Local measures complement global measures of spatial autocorrelation by measuring and detecting local pockets of spatial association, as measured with the Local Moran’s $I$ statistic (Anselin 1995; Páez and Scott 2005). Anselin’s Local Moran’s $I$, also known as Cluster and Outlier Analysis or LISA (Local Indicators of Spatial Association), is also conducted in this analysis to precisely identify areas of significant high and low clustering among county context indicators (ESRI n.d.). The LISA calculation measures spatial associations as a covariance measurement between variable values at spatially relative locations based on inverse distance spatial relationships, Euclidean distance, and row standardization. Positive spatial autocorrelation occurs when values are significantly similar at nearby neighbor locations (cluster), and negative autocorrelation occurs in areas with significantly different values than spatially neighboring locations (outlier). No association results in a value that is closest to zero. The Local Moran’s $I$ statistic uses a normalized z statistic based on the mean and variance of the Moran’s $I$ statistic. Interpreting the standardized statistic is in four patterns of high-high (cluster), low-low (cluster), high-low (outlier), and low-high (outlier) associations of values above or below the mean (Páez and Scott 2005). Counties nearer to one another with positive spatial
autocorrelation mean their context values are statistically similar and significant. In contrast, negative autocorrelation values mean counties have statistically different context values than those farther away (ESRI n.d.). The researcher investigated these total spatial variations, then examined the more detailed differences in underlying drivers of high or low contextual influence.

3.3 Results: The Geographic Context of Tornado Risk

The physical and social metrics of tornado risk result in differential spatial-statistical distributions throughout Illinois counties. Once combined into a total geographic context indicator, the physical and social metrics both influence the tornado risk context. The result descriptions include tabular and map outputs to visualize these findings more clearly.

3.3.1 Physical Context Results

For the first physical risk context input, tornado occurrence, 1,652 total tornado events took place throughout the 1992-2021 climatological period (Figure 3.3). Figure 3.3. shows both the tornado touchdown points (circles) and tornado paths (lines), but not all events include a path. Of the 1,652 tornado events, 1,145 include the full path geometry with starting and ending latitude and longitude. The majority of total tornado events were Unrated or F/EF 0 (973 or 58.9%), followed by F/EF 1 (489 or 29.6%), F/EF 2 (142 or 8.2%), F/EF 3 (37 or 2.2%), and F/EF 4 (11 or 0.7%) events. The delineation of the number of tornadoes per county results in 1,836 combined tornado events, with county values ranging from 2 to 48 and an average of 18 events per county. Converting the raw tornado occurrence counts to a county-level metric weighted by the event
F/EF scale magnitude and adjusted by county area results in tornado frequencies ranging from 5 to 97 with an average of 40 (rounded). The counties with the highest weighted and adjusted tornado frequencies include Massac (97), Tazewell (85), and Logan (83). The counties with the lowest weighted and adjusted tornado frequency metric are Lawrence (5), Clark (10), and Hamilton (14). Each county’s weighted and adjusted tornado occurrence z-score ranges from -2.07 to 3.39 in value. Among the 102 Illinois counties, 58 contain z-score values below the mean (i.e., negative) and 44 above the mean (i.e., positive). Figure 3.4 displays the mapped standard deviation distribution of the physical context occurrence metric, with three categories for high (greater than 1.5 standard deviations from the mean), medium (between 0.5 to -0.5 standard deviations), and low (less than -1.5 standard deviations) ranked values.

The second physical risk context metric input for exposure ranks Illinois counties from codes one (rural) through nine (urban) based on a reversed order of the USDA RUCCs. Table 3.5 displays the distribution of these county count assignments. The highest number of counties (23 of 102) are populations of 2,500 to 19,999 adjacent to a metro area. The smallest number of counties (3 of 102) have populations of 20,000 or more not adjacent to a metro area. Based on the USDA (2020b) RUCC assignments, 62 counties are rural (61%), and 40 are urban (39%). Hardin County contains the smallest population of 3,890, and Cook County has the largest population of 5,169,517 (USCB n.d.a.). The exposure metric z-score calculation ranges from -1.77 to 1.44, with 53 county values falling
below the mean and 49 above the mean. Figure 3.5 displays the mapped standard deviation distribution of the physical context exposure metric.

Figure 3.3 Illinois Tornado Occurrence by Magnitude (1992-2021).
Figure 3.4 Physical Context Occurrence Metric z-score Distribution Map.
### Table 3.5 Exposure Metric Distribution in Illinois Counties.

<table>
<thead>
<tr>
<th>Inverted Code</th>
<th>County Count</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rural</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>5</td>
<td>Completely rural or less than 2,500 urban population, not adjacent to a metro area</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>Completely rural or less than 2,500 urban population, adjacent to a metro area</td>
</tr>
<tr>
<td>3</td>
<td>17</td>
<td>Urban population of 2,500 to 19,999, not adjacent to a metro area</td>
</tr>
<tr>
<td>4</td>
<td>23</td>
<td>Urban population of 2,500 to 19,999, adjacent to a metro area</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
<td>Urban population of 20,000 or more, not adjacent to a metro area</td>
</tr>
<tr>
<td>6</td>
<td>9</td>
<td>Urban population of 20,000 or more, adjacent to a metro area</td>
</tr>
<tr>
<td>Urban</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>13</td>
<td>Counties in metro areas of fewer than 250,000 population</td>
</tr>
<tr>
<td>8</td>
<td>10</td>
<td>Counties in metro areas of 250,000 to 1 million population</td>
</tr>
<tr>
<td>9</td>
<td>17</td>
<td>Counties in metro areas of 1 million population or more</td>
</tr>
</tbody>
</table>

**Description Data Source:** USDA 2020b.

The third physical risk context input data for prior consequence includes $2,052,465,312 in total property and crop damages (ADJ 2020 USD) over the 1990-2019 period. The average amount of losses per county is $20,731,973. The counties experiencing the highest reported losses include Tazewell ($1,100,458,601), Christian ($130,856,447), and Peoria ($104,419,254). Clinton, Hardin, Jo Daviess, and Jersey Counties did not report any tornado losses during this period. The adjusted rate of annualized tornado losses per county over the 30 years ranges from $0 to $36,681,953 annually, with an average of $670,740 in losses per year. The tornado consequence z-score metric calculation for average annual losses ranges from -0.18 to 9.84, with 88 county values falling below the mean and 14 above the mean. Figure 3.6 displays the mapped standard deviation distribution of the physical consequence metric.
Figure 3.5 Physical Context Exposure Metric $z$-score Distribution Map.
Figure 3.6 Physical Context Loss Metric z-score Distribution Map.
The fourth physical risk context input, warning incidence, includes 6,277 tornado warnings across Illinois from 1986 to 2022. In converting the overlapping raw warning counts to the total number of warning experiences in each county, a total of 26,999 warnings occurred. The average number of warnings issued per county throughout the thirty-seven-year period is 265, with a total count ranging from 37 to 533. The counties with the highest number of warnings include Logan (533), McLean (531), and Tazewell (514). The counties with the lowest number of warnings are Lake (37), McHenry (85), and Jo Daviess (87). The adjusted annualized warning rate per county over the 37 years ranges from 1 to 14, with an average of 7 warnings per year. The z-score normalization for average annual warnings per county ranges from -2.23 to 2.63, with 45 county values falling below the mean and 57 above the mean. Figure 3.7 displays the mapped standard deviation distribution of the physical context warning incidence metric.

The final physical risk context variable, structural housing, equates to the percentage of mobile home housing units per county. Of the 5,373,385 housing units in Illinois, 129,855 are mobile homes (2.4%). The average amount of mobile home housing units in all Illinois counties is 7.8%, with the three highest rates in Wayne (22.6%), Gallatin (21.9%), and Johnson (21.6%) Counties. Five counties contain less than 0.01% mobile home housing units, including Cook, DuPage, Kane, Kendall, and McHenry Counties. This mobile home metric's z-score normalization measurement ranges from -1.34 to 2.56, with 59 county values falling below the mean and 45 above the mean. Figure 3.8 displays the mapped standard deviation distribution of the physical context structural housing metric.
Figure 3.7 Physical Context Warning Metric $z$-score Distribution Map.
Figure 3.8. Physical Context Mobile Home Metric z-score Distribution Map.
The total physical context measurement, which sums the total $z$-score values of all five input metrics, results in county values ranging from -4.33 to 14.96 throughout Illinois (range = 19.29). The counties with the highest physical context score include Tazewell (14.96), Logan (4.03), and Woodford (3.92), while the lowest ranking are Jo Daviess (-4.33), Carroll (-4.14), and Crawford (-3.66) Counties. In examining the $z$-score distribution, 53 counties rank below the mean (i.e., negative) physical context value and 49 above the mean (i.e., positive). Figure 3.9 displays the distribution of the final physical context metric using standard deviation data classifications ($s = 2.43$). Visual evaluation of the map shows clustering of high (dark red) total physical context values (greater than 1.5 standard deviations from the mean) in 4 Central Illinois counties. Medium-high (light red) physical context values (0.5 to 1.5 standard deviations) are seen throughout the state in 22 counties, although most are within Central and Southwestern Illinois. Medium (white) physical context values (0.5 to -0.5 standard deviations) in 41 counties display the highest dispersion of the five data classifications, although few large clusters exist in West-Central and Southern Illinois. Medium-low (light blue) physical context values (-0.5 to -1.5 standard deviations) within 32 counties display clusters in Northern, Western, and Eastern Illinois. Low (dark blue) physical context values (less than -1.5 standard deviations) occur in only three counties, one of which is in Southeastern Illinois (Crawford County) and the remaining two in Northwestern Illinois (Jo Daviess and Carroll Counties).
Figure 3.9 Total Physical Tornado Risk Context Map.
3.3.2 Social Context Results

In assessing social context, the SoVI® analysis results in six retained factors (i.e., components) from the PCA that explain 75.82% of the variance in the model (Table 3.6). Component one explains 24.59% of the model variance and represents the elderly, disabled, unemployed, and populations lacking broadband internet. Component two explains 13.97% of the variance in the model and represents housing size (large), ethnicity (Hispanic), and race (Asian). Component three explains 13.72% of the model variance and represents single-parent, female-headed, and impoverished households, as well as race (African American) and service industry workers. Component four explains 8.54% of the model's variance and represents uninsured people with no automobile access and who rent their homes. Component five explains 7.78% of the model variance and represents females (low), low education level (i.e., less than high school), and unemployment. Component six explains 7.23% of the model variance and represents the female labor force. All components contain positive cardinality, meaning they have an increasing contribution to the total social vulnerability score. The total county SoVI® values are the sum of the final component scores.

The total social context measurement, which equates to the county SoVI® score, results in county values ranging from -4.35 to 9.99 throughout Illinois (range = 14.34). The counties with the highest social context score include Pope (9.99), Pulaski (8.33), and Alexander (6.37), while the lowest ranking is Monroe (-4.35), Menard (-4.18), and Washington (-3.45) Counties. Overall, 56 counties rank below the mean social context value and 46 above the mean. Figure 3.10
Table 3.6 Component Results for the 2020 SoVI® PCA for Illinois Counties.

<table>
<thead>
<tr>
<th>Component</th>
<th>Cardinality</th>
<th>Name</th>
<th>% Variance Explained</th>
<th>Dominant Variables</th>
<th>Component Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>+</td>
<td>Elderly, Disabled, and Lack of Broadband Access</td>
<td>24.59%</td>
<td>QSSBEN</td>
<td>0.881</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>QUNOCCHU</td>
<td>0.825</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>QNOBRDBND</td>
<td>0.802</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>QDISAB</td>
<td>0.784</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>QAGEDEP</td>
<td>0.776</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>MEDAGE</td>
<td>0.766</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>QEXTRCT</td>
<td>0.676</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>QCVLUN</td>
<td>0.532</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>PERCAP</td>
<td>-0.684</td>
</tr>
<tr>
<td>2</td>
<td>+</td>
<td>Housing Size (Large), Ethnicity (Hispanic), and Race (Asian)</td>
<td>13.97%</td>
<td>PPUNIT</td>
<td>0.835</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>QHISP</td>
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<td></td>
<td>QESL</td>
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<tr>
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<td></td>
<td></td>
<td></td>
<td>QMORTBRDN</td>
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</tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>QRICH</td>
<td>0.660</td>
</tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>QASIAN</td>
<td>0.519</td>
</tr>
<tr>
<td>3</td>
<td>+</td>
<td>Single Parent, Female-Headed Households, Race (African American), and Poverty</td>
<td>13.72%</td>
<td>QSGNELPAR</td>
<td>0.889</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>QFHH</td>
<td>0.885</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>QPOVRY</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>QSERV</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>QBLACK</td>
<td>0.590</td>
</tr>
<tr>
<td>4</td>
<td>+</td>
<td>Uninsured, No Automobile Access, and Renters</td>
<td>8.54%</td>
<td>QNOAUTO</td>
<td>0.770</td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td>QNOHLTH</td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>QRENTER</td>
<td>0.570</td>
</tr>
<tr>
<td>5</td>
<td>+</td>
<td>Female (Low), Education Level (Low), and Unemployed</td>
<td>7.78%</td>
<td>QED12LES</td>
<td>0.704</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>QCVLUN</td>
<td>0.531</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>QFEMALE</td>
<td>-0.869</td>
</tr>
<tr>
<td>6</td>
<td>+</td>
<td>Female Labor Force</td>
<td>7.23%</td>
<td>QFEMLBR</td>
<td>0.786</td>
</tr>
</tbody>
</table>

displays the distribution of the final social context metric using standard deviation data classifications ($s = 2.50$). Visual evaluation of the map shows clustering of high (dark red) total social context values (greater than 1.5 standard deviations from the mean) in 7 Illinois counties, with the majority (5) along Illinois' Southern border. The remaining high social risk locales are Cook County in the Chicago urban area and Brown County, a rural area of East-Central Illinois.
Figure 3.10 Total Social Tornado Risk Context Map.
The factors driving high SoVI® scores vary amongst these seven locations, manifesting different spatial patterns between urban and rural counties. Unlike the other six counties with the highest SoVI® scores, factors two (i.e., large housing size, Hispanic, and Asian) and four (i.e., uninsured, no automobile access, and renters) are the main drivers of high social vulnerability in Cook County, which is the only county of these seven ranked in the most urbanized RUCC category. The remaining six high SoVI® ranked counties all contain a population of less than 12,500 and are driven by different factors than those in Cook County. Brown County loads strongly on factor five (i.e., low females, low education level and unemployment). In the five Southern Ohio Valley counties, there are variations in social vulnerability drivers. Pope, Pulaski, and Hardin are most heavily influenced by factor one (i.e., elderly, disabled, and no broadband internet). At the same time, Pope and Pulaski load strongly in factor six (i.e., female workforce). Alexander loads strongest in factor three (i.e., single-parent, female-headed, and impoverished households, along with African Americans), followed by factors one and two. Alexander is also the only other high county with an urban RUCC ranking (code 3, or counties in metro areas of fewer than 250,000 population) because it lies in the Cape Girardeau metropolitan area. On the other hand, Johnson County is highly rural and strongly driven by factors five and six, which represent female vulnerability components and employment circumstances.

Medium-high (light red) social context values (0.5 to 1.5 standard deviations) are in 19 counties throughout the state, with most in Southern Illinois.
and a few sporadically distributed throughout the rest of the state. Medium (white) social risk context values (0.5 to -0.5 standard deviations) occur in 44 counties and vary across space, although few large clusters exist in Northern, Central, and Southern/Southwestern Illinois. Medium-low (light blue) social context values (-0.5 to -1.5 standard deviations) within 30 counties are primarily in a large cluster along the Western/Northwestern border. Low (dark blue) social context values (less than -1.5 standard deviations) occur in only two counties. One low value of social risk context is Menard County, which is in Central Illinois, and the second is Monroe County, which is on the Southwestern Missouri border near the St. Louis metropolitan area.

3.3.3 Total Geographic Context Results

Pearson's correlation between the physical and social context values in all 102 counties results in an $r = 0.064$ value and is insignificant ($p = 0.525$). The combined geographic risk context measurement sums the total physical and social context values per county, resulting in values ranging from -6.09 to 12.59 (range = 18.68). The counties with the highest total geographic context score include Tazewell (12.59), Alexander (10.71), and Pulaski (9.87), while the lowest ranking are Jo Daviess (-6.09), Clark (-5.90), and Carroll (-5.83) Counties. Overall, 54 counties rank below the mean geographic context value and 48 above the mean. Figure 3.11 displays the distribution of the combined geographic context metric using standard deviation classifications ($s = 3.56$). Visual evaluation of the map shows the distribution of high (dark red) total geographic context values in 5 Illinois counties, with the majority clustered along
Figure 3.11 Total Geographic Tornado Risk Context Map.
Illinois’ Southern border. However, Tazewell County in Central Illinois contains the highest total value, and its neighbors contain either medium-high or medium total geographic context values. Medium-high (light red) total geographic context values occur throughout the state in 27 counties. Although, most medium-high ranked counties are in Central Illinois and the Northeastern Chicago area. Medium (white) geographic context values are within 34 counties and spread widely throughout each Illinois region. Medium-low (light blue) geographic context values within 32 counties are more densely concentrated in Northern and Western clusters. Low (dark blue) geographic context values occur in only four counties, with three in Northwestern Counties and the remaining in Clark County on the Central Illinois border with Indiana.

3.3.4 Spatial Autocorrelation Results

The spatial autocorrelation assessment of the physical, social, and total geographic context output values highlights statistically significant clustering utilizing the Global Moran’s I statistic (Table 3.7). The physical context test produces in a Moran’s I value (i.e., correlation coefficient) of 0.468 and a z-score (i.e., standard deviation) of 5.950. The social context assessment results in a Moran’s I value of 0.356 and a z-score of 4.321. The total geographic context metric contains a Moran’s I value of 0.441 and a z-score of 5.275. All three context measurements’ global spatial autocorrelation results contain a significant (p-value < 0.0001) and positive z-score value. In other words, the overall spatial distribution of context values includes more spatial clustering than expected by chance, and significant spatial autocorrelation is present in all three datasets.
Table 3.7 Global Moran's / Summary Statistics for Context Inputs.

<table>
<thead>
<tr>
<th></th>
<th>Physical Context</th>
<th>Social Context</th>
<th>Total Geographic Context</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moran's I Value</td>
<td>0.468</td>
<td>0.356</td>
<td>0.441</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt;0.0001</td>
<td>&lt;0.00001</td>
<td>&lt;0.00001</td>
</tr>
</tbody>
</table>

The Local Indicators of Spatial Autocorrelation (LISA) assessment for the physical, social, and total geographic context values mainly results in convergent patterns of high-high and low-low value clusters throughout the state. In all three LISA analyses, only five counties are divergent outliers and four out of these five result from the social context metric. The physical context measurement produces statistically significant (p-value less than 0.05) county clusters and outliers, representing localized pockets of spatial autocorrelation convergence or divergence (Figure 3.12). Overall, 20 counties contain a significant physical context LISA result, and 82 counties are not significant clusters or outliers (shown in white). Clusters of high physical context values surrounded by counties with high values exist in 7 counties in Central Illinois (dark red). One outlier of high physical context surrounded by counties with significantly lower physical context values exists in Boone County on the Northern Wisconsin border (light red). Clustering of low physical context values surrounded by counties with low values exists in 12 counties in both Northwestern and Eastern Illinois (dark blue). No significant outliers exist for low physical context value counties surrounded by high physical context counties.

The LISA assessment of the social context measurement produces statistically significant (p-value less than 0.05) county clusters and outliers throughout the state (Figure 3.13). Overall, 15 counties contain significant social
context results, and 87 counties are not significant clusters or outliers (shown in white). Convergent clusters of high social context values surrounded by counties with high values exist in 7 counties in Southern Illinois near the confluence of the Ohio and Mississippi Rivers (dark red). Two high social context outliers (Macon and St. Clair Counties) surrounded by counties with significantly lower social context values exist in Central and Southwestern Illinois pockets (light red). Clustering of low social context values surrounded by counties with low values exists in four counties in Central and North-Central Illinois (dark blue). Two outliers (Williamson and DuPage) of low social context value counties surrounded by high-value social context counties (light blue) exist in the data. The DuPage outlier lies in the Chicago metropolitan area, while Williamson County sits adjacent to the high-high cluster on the state's Southern border.

The LISA assessment of the combined geographic context measurement produces statistically significant ($p$-value less than 0.05) county clusters throughout the state (Figure 3.14). Overall, 17 counties contain a significant total geographic context LISA result, and 85 counties are not within significant clusters (shown in white). Clusters of high geographic context values surrounded by counties with high values converge in 7 counties in Southern Illinois near the confluence of the Ohio and Mississippi Rivers (dark red). Clustering of low geographic context values surrounded by counties with low values exists in 10 counties in East-Central and Northwestern Illinois (dark blue). No significant county outliers exist for high-low or low-high total geographic context values, meaning no divergent patterns result.
Figure 3.12 Physical Context LISA Map.
Figure 3.13 Social Context LISA Map.
Figure 3.14 Total Geographic Context LISA Map.
CHAPTER 4

IMPLEMENTING THE TROP MODEL FRAMEWORK

The researcher estimates the interactions between all measured conceptual drivers of tornado risk (i.e., physical context, social context, risk perception, and protective action decision-making) to uncover the spatiality of tornado risk via implementing the novel TROP model framework (RQ2). Metrics of tornado risk perception and protective action behavior among a sample of Illinois residents combined with the county contextual measures from Chapter 3 allow for analysis of the TROP model variables.

4.1 Measuring Perception and Protective Action Behavior Constructs

The State of Illinois study area population of 12,716,164 averages 125,000 people per county (USCB n.d.b.; 2021a). The state has a total population density of 229 people per square mile but a county average of 195 people per square mile (USCB n.d.b.; 2021a). For the questionnaire data collection, the sample targets are representative of the 2020 census demographics of Illinois residents aged 18-85. The targeted gender distribution of respondents is 50% male and 50% female. The targeted racial distribution of respondents is 74% White, 15% African American, 6% Asian/Pacific Islander, 1% American Indian/Alaskan Native, and around 4% mixed race. The targeted ethnic distribution of respondents is 18% Hispanic and 82% non-Hispanic. The targeted
age distribution is 30% of respondents aged 18-34, 32% aged 35-54, and 38% aged 55-85.

To gain a representative sample of the Illinois population regarding age, ethnicity, and gender, the Qualtrics\textsuperscript{\textregistered} survey company accessed the sample and distributed the survey virtually to respondents. The minimum sample size needed based on the state population, a 95% confidence interval, and a 5% margin of error equated to 385 respondents. A higher confidence interval of 99% at a 5% margin of error required a 664 respondent sample. Qualtrics\textsuperscript{\textregistered} provided the 664 total sample size for $4,156.25 (~$6.25 per completed response), including all incentives to respondents and fees to the company. Qualtrics\textsuperscript{\textregistered} collaborates with panel providers like airlines, credit cards, market research panels, and social media to recruit a representative sample for the study. Hard-to-reach groups are targeted through specialized recruitment campaigns to ensure their representation in the sample. Reliability and validity assurance occurs through internal checks of IP addresses and third-party verification measures. The researcher only pays for quality responses filtered for possible speed responders by removing any respondents who completed the survey in less than half the median sample completion length.

The questionnaire sample assessment of population representativeness uses the USCB (n.d.a.) 2020 ACS 5-year estimates. Descriptive statistics estimates of the primary demographic categories relating to gender, age, race, ethnicity, income, education level, employment status, and disability status compare the sample to the ACS estimates for the State of Illinois. Additionally, a
difference of proportions independent samples $Z$-test (PSU 2023) on each demographic categorization determines if the sample percentages are significantly different ($p$-value less than 0.05) from those of the Illinois population.

### 4.1.1 Questionnaire Design and Deployment

Self-reported, online survey questionnaire data assess tornado risk perception and protective action behavior constructs among the population sample. Given the COVID-19 pandemic, the virtual deployment is appropriate for accessing a quality sample for this investigation (Singh and Sagar 2021) while proving effective for quick response coding. Questionnaires can collect important individual-level information regarding tornado experiences, risk perception, warning communication and reception, and protective action behavior. Surveys have been used in many social scientific tornado studies (Durage et al. 2014; Luo, Cong, and Liang 2015; Paul, Stimers, and Caldas 2015; Ripberger et al. 2015a; Ripberger et al. 2015b; Jauernic and Van Den Broeke 2016; Kox and Thieken 2017; Demuth 2018; Miran, Ling, and Rothfusz 2018; Schumann, Ash, and Bowser 2018; Ripberger et al. 2020), which served as guides in the development of this study’s instrument. Widespread and large-scale population surveys do not always collect enough responses in small geographic areas or at the appropriate geographic scale to analyze and understand local communities’ spatial dynamics (Ripberger et al. 2020). The questionnaire collects information at a refined spatial scale (city and county) for aggregation to formal and functional regional levels to combat this potential limitation.
The self-administered online questionnaire (i.e., the Tornado Risk Survey; See Appendix A) included 74 items relating to respondents' socio-demographics, aggregated residence location information, perceptions of tornado risk, and protective action response (Table 4.1). Nearly all item responses are closed-ended categories with Likert interval, ordinal, and categorical response options. One open-ended item concludes the survey and asks respondents to provide any other information they would like about their tornado perceptions and experiences without any identifying information.

Table 4.1 Questionnaire Content Based on Information Category.

<table>
<thead>
<tr>
<th>Category</th>
<th>Information Collected and Example Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>Socio-Demographics</td>
<td>Age, sex, gender, income, ethnicity/race, education level, children, disability, access to a vehicle, homeowner/renter, residency length, home structure type</td>
</tr>
<tr>
<td>Location</td>
<td>County and City of residence, perceived urbanity/rurality of residence</td>
</tr>
<tr>
<td>Perception of Risk</td>
<td>Evaluation of tornado risk (e.g., 5-scale Likert disagree-agree responses to “Tornadoes are a threat where I live,” “Thinking about a tornado makes me feel worried,” and “I feel fearful when issued a tornado warning at my home”)</td>
</tr>
<tr>
<td></td>
<td>Knowledge (e.g., 5-scale Likert disagree-agree responses to “I understand what I should do when a tornado warning is issued where I live,” “I understand the science behind what causes tornadoes,” and “I understand the damage potential if a tornado struck my home”)</td>
</tr>
<tr>
<td></td>
<td>Previous tornado experiences (e.g., Yes, No, or Unsure responses to “Have you ever lived in an area that experienced a tornado warning?” and “Has the area your current home is located been under a tornado warning?”)</td>
</tr>
<tr>
<td>Behavioral Response</td>
<td>Response Action (e.g., 5-scale Likert disagree-agree responses to “Until I see a tornado funnel, I do not respond to tornado warnings,” and “I trust my instinct to help decide if I should respond to a tornado warning”)</td>
</tr>
<tr>
<td></td>
<td>Preparedness (e.g., 5-scale Likert disagree-agree responses “I feel prepared to respond to a tornado warning” and check all that apply responses to “Which sources do you use to receive tornado warnings: outdoor sirens, cable/TV news, automated phone messages, Internet/social media, family/neighbors, local radio stations, NOAA weather radio, and other (please list).”)</td>
</tr>
<tr>
<td></td>
<td>Home Safety (e.g., 5-scale Likert disagree-agree responses “My home would be safe during a tornado,” and “I feel safe seeking shelter in my home during a tornado.”)</td>
</tr>
</tbody>
</table>
The survey instrument design includes a group of questions (~10 items each) assessing three different subconstruct factors for individuals’ risk perception and three groups of questions (~10 items each) for protective action behavior. Questions for the risk perception constructs measure respondents’ evaluation of tornado risk, knowledge, and previous tornado experience subconstructs. Protective action construct questions involve the three subcontracts of tornado response action, preparedness, and home safety. Some repetitive questions assess instrument validity by asking the inverse of a previously included question, assuming the individual's response would be the opposite of the earlier question. For example, one question asked respondents how strongly they agreed with “Tornadoes are a threat where I live,” while another asked a near opposite question of “I do not worry about tornadoes where I live.” Spearman’s Rank correlation analysis on these items can confirm instrument validity, expecting that these item responses would negatively and significantly correlate at the 95% confidence level (p-value less than 0.05).

The virtual instrument was pilot tested throughout early March 2022 to twenty Illinois residents the researcher sourced from their hometown social network in Collinsville, Illinois. The researcher implemented minor item wording and clarity adjustments based on the pilot test feedback. Institutional Review Board (IRB) exempt approval was gained on April 6th, 2022, through the University of South Carolina IRB office (Study ID PRO00119797), ensuring the study protects human subjects’ rights. The questionnaire employed informed consent forms to notify respondents of the study's purpose and ensure the
anonymity of respondents before they agree to participate. The survey does not collect any personally identifiable information. The online instrument was deployed from May 5th through May 24th, 2022 (20 days). A total of 1,174 respondents accessed the survey, but only 700 responses were fully complete and adequate for inclusion in the analysis (60% response rate). The average response completion time for the 700 fully completed responses was fourteen minutes.

4.1.2 Developing Construct Inputs

First, Qualtrics™ automatically codes each item’s response as a ranked value based on their response scale option order. For example, the five Likert-ranked response categories (i.e., strongly disagree, somewhat disagree, neither disagree nor agree, somewhat agree, and strongly agree) receive a response code ranging from one (strongly disagree) to five (strongly agree). The directional influence of each subconstruct indicator assigns appropriate cardinality to ensure the responses measured low-to-high perceptions and decreased-to-increased protective action responses. The cardinality evaluation requires item response categories re-coding as the inverse value from the original coding scheme (e.g., strongly agree coded as one and strongly disagree coded as five). Items with the response options of (a) yes, (b) no, or (c) unsure are assigned codes of one (response selected unsure or no) or two (response selected yes). For “check all that apply” questions relating to protective actions (e.g., “What tornado sheltering options do you have available in or near your home?”), the response options codes range from zero, one, or two based on the
decreased-to-increased level of protective action response. For example, no shelter options are available is coded as zero, and a basement with no windows is coded as two since it is the best sheltering place option when under a tornado warning. Any instances of an “Other: (please list)” response selection choice by respondents for a “check all that apply” question undergo individual researcher evaluation to assign an appropriate response code. A data column within the code sheet for these “check all that apply” questions sum the total responses based on their coded values. For example, suppose a respondent selected the two sheltering options available: a basement with windows (coded as one) and a detached storm shelter (coded as one). In that case, their total sheltering options summed score is two. Upon completion of questionnaire item re-coding, item responses are evaluated with descriptive statistics estimates (e.g., frequencies, means, and standard deviations) to ensure no data errors exist in the re-coded dataset. In calculating each item’s descriptive statistics using IBM® SPSS®, the item response scores are normalized as z-scores (Equation 1) to allow for comparable values among the variables in the TROP model assessment.

Exploratory Factor Analyses (EFA) on the normalized input items determine which latent subconstruct questions best represent the risk perception and protective action response metrics separately. An EFA is a common data reduction technique for survey constructs in social and behavioral sciences to identify the smallest number of factors that explain the variance in observed variables (Watkins 2018). The Pearson r correlation coefficient is applied in EFA using IBM® SPSS® to measure the linear relationship between the input
variables. In this investigation, the Maximum Likelihood Estimation (MLE) common factor analysis method extracts the number of factors the model represents (i.e., estimates the relationships between the observed variables of factors). The MLE approach mathematically determined the underlying structure, or the number of factors, to measure the risk perception and protective action response constructs via a matrix of variables’ correlation coefficients. Based on these coefficients, items are grouped into related factors, deducing the dataset into the underlying factor-variable relationships. The Promax rotation method, an oblique rotation designed for when correlations between factors exist, applies 500 maximum iterations for convergence. The Kaiser rule of retaining factors with Eigenvalues greater than one also employs 500 maximum iterations for convergence. A visual examination of the scree plot confirms the appropriate number of factors to include.

Multiple EFAs on each risk perception and protective action grouped variables provide the best model configuration for the two separate constructs. With each iteration, individual variable items (i.e., questions) failing to load on any factor are removed from the next EFA run until a resulting factor solution results in an insignificant (95% confidence interval) Chi-square Goodness-of-Fit statistic value. The Chi-square test is a global model fit index that tests Goodness-of-Fit of the hypothesized model. The null hypothesis states that the hypothesized model is a good fit, so the goal is to have an insignificant test statistic (i.e., fail to reject the null hypothesis). The Chi-square test statistic value also assessed the model fit based on the ratio of the test statistic value to the
model’s degrees of freedom. The hypothesized model fit is superior when the proportion is greater than or equal to the value of two (i.e., the lower the chi-square test statistic value, the better) (Alavi et al. 2020).

The researcher assesses the multidimensional constructs based on the final EFA retained factors, with each factor’s definitive identification and naming based on the strongest factor loadings. The factor loadings examination for each variable analyzes where variables loaded higher than .500 and less than -.500. The factors are then named based on the strongest loading variables (generally greater than .700 or less than -.700) and listed in order of the highest explained variance percentage. Cardinality assessment’s final retained factor components rank increasing (+) or decreasing (-) risk perception and protective action. The resulting factor scores assess Pearson’s r correlation with IBM® SPSS® to confirm that the oblique rotation method is appropriate for the EFAs. Final construct values of perception and response are created by summatcing the z-scores for each input factor relating to both perception and response indicators and ultimately used to create a total conceptual latent construct measurement for each variable (Figure 4.1). The final retained factors from the EFA are then added to the dataset for application as input metrics in assessing this study’s second research question.

Multicollinearity testing for internal consistency (i.e., reliability) of the construct variable indicators resulting from the final EFAs utilizes IBM® SPSS® Cronbach’s alpha assessment (Goforth 2023). Constructs’ item design assumes responses to be correlated, so the more significant the correlations (i.e., multicollinearity) among the retained items, the stronger the representation of the
construct based on the retained variables. Cronbach’s alpha values with significant multicollinearity ($p$-value less than 0.05) are acceptable if greater than 0.600 (Hajjar 2018).

![Survey Construct Development Flow Diagram](image)

Figure 4.1 Survey Construct Development Flow Diagram.

4.1.3 TROP Model Assessment Approach

Implementing the TROP model framework (Figure 2.3) uncovers the direct and indirect relationships between the main drivers of community tornado risk. A statistical examination of the observed and latent input variable influence on the tornado risk of the place addresses this study’s second research question. First, the respondents’ state-level perception and response scores are combined with the county-level physical and social contextual indices to create one input dataset for all Illinois counties. The questionnaire dataset is linked in Microsoft Excel to the county-level context indices using the self-reported county of residence by the respondents. By employing individual-level survey data based
on latent variable metrics alongside the county-level indices of geographic context, differences in risk perception, mitigation actions, and the totality of contextual tornado risk of place are more accurately represented across space.

A Structural Equation Model (SEM) framework assesses the existence and strength of the linear relationships between the context, perception, and behavior concepts. The SEM method, a helpful technique when examining complex conceptual drivers, investigates covariance patterns among variables based on a general linear model. An SEM allows for the testing of direct causal variable relationships and through variables indirectly by applying a set of multivariate statistical methodologies (e.g., multiple regression, correlation, chi-square testing, and factor analysis) designed for social and behavioral sciences analyses (Hox and Bechger 1998; Bollen and Noble 2011). An SEM is a primary method of executing path analyses using latent variables, or those variables that are latent within people that drive attitude and behavior. Latent variables cannot be observed directly, making it difficult to measure these conceptual influences using most statistical methods. However, SEM approaches can measure these latent variable relationships based on observable indicators (i.e., caused by underlying latent constructs). The IBM® SPSS® Analysis of Moment Structures (AMOS) Graphics (v. 28) statistical software develops, visualizes, and runs the SEM, which includes the model output statistical assessments.

A path diagram visualizes the SEM and its multiple measures of concepts alongside their error measurements (Hox and Bechger 1998) directly based on the TROP model framework model specifications. The SEM inputs include the
calculated metrics from the individual-level, self-reported latent (risk perception and mitigative action) and county-level observed (physical and social context) variables. These research inputs are then applied in the assessment of research question two to determine how risk perception directly influences protective action behavior and how geographic context, directly and indirectly, influences protective action behavior. The EFA assessment deduces the latent constructs of risk perception and protective action behavior measurements from the item responses in the Tornado Risk Survey. The total perception and behavior construct score measurements sum the $z$-score values of the retained questionnaire item responses. The physical context total score input calculation is the sum of the $z$-score values of the five sub-metrics, while the social context total score input is a total SoVI® score summing the PCA retained factors.

The SEM analysis assesses how the context and construct inputs are directly and indirectly linked by examining their model’s regression coefficients, covariances, factor loadings, error terms, and overall model fit. Regression analysis execution in the SEM (see detailed model equation in Bollen and Noble 2011, 15640) employs MLE (see MLE equation in Bollen and Noble 2011, 15641). The regression estimates determine any strong or weak positive or negative relationships among data variables (i.e., physical context to perception, social context to perception, and perception to behavior). Additionally, these regression relations evaluate for statistically significant relationships at the 95% confidence level. The SEM path diagram delineates these relationships with a solid line with a single-headed arrow pointing from the independent to the
dependent variable. Examining the standardized regression coefficients between variables traces the quantitative relationship between physical context, social context, risk perception, and behavioral response. The correlation assessment between the physical and social contexts is based on the model output and evaluated at the 95% confidence level. This covariance relationship is visualized in the SEM path diagram using a curved line and double-headed arrow.

Finally, the TROP fit is assessed based on the SEM output statistics of five model fit statistics calculated by AMOS from the path model. The first assessment of the overall model fit applies the model’s degrees of freedom ($df$) and the Chi-square test statistic value. The $df$ in the SEM calculation subtracts the number of parameters needing to be estimated (unknowns) from the total number of model parameters (knowns) (Hooper, Coughlan, and Mullen 2008). As previously discussed with this study’s construct EFA approach (Section 3.3.3), a good fitting model will have an insignificant Chi-square test result (alpha value greater than 0.05) with a low Chi-square value (Alavi et al. 2020). Next, the Goodness-of-Fit (GFI) and Adjusted Goodness-of-Fit (AGFI) statistics further examine the model fit. The GFI determines the variance accounted for by the estimated population covariance, while the AGFI adjusts that calculation based on the model’s degrees of freedom. The resulting GFI and AGFI values range from zero to one, with a good-fitting model obtaining a value no lower than 0.95. Another SEM Goodness-of-Fit index assessed in this analysis is the Comparative Fit Index (CFI), with a better-fitting model approaching a value closest to one (no lower than 0.95) (Hooper, Coughlan, and Mullen 2008). A final fit assessment is
the Root Mean Square Error of Approximation (RMSEA) statistic, which assesses how well the model approximates the population covariance matrix. If the approximation is good, the RMSEA value is near zero and no greater than 0.05 (Hox and Bechger 1998). All five model fit indicators (i.e., Chi-square, GFI, AGFI, CFI, and RMSEA) assess the specified SEM TROP model output.

4.2 Results: Tornado Risk Survey

The Tornado Risk Survey analysis results include assessments of instrument validity and evaluations of respondents’ geographic and demographic representation. Then, the EFA results for the risk perception and protective action constructs outline the chosen items representing these latent variables.

4.2.1 Tornado Risk Survey Validity and Representation

The instrument’s validity is confirmed with a correlation assessment of two sets of inversely worded items to ensure responses oppositely correspond between these items. The first two items assessing risk perceptions (RP2 and RP3) ask respondents how strongly they agree or disagree with the statements “Tornadoes are a threat where I live” and “I do not worry about tornadoes where I live.” The Spearman’s Rank correlation value of $r = -0.380$ between these risk perception item responses is significant at the $<0.001$ level. As expected, the moderate negative correlation shows that respondents who agree with one item disagree with the other. However, this relationship is not very strong, possibly because one asks about object threat and the other is more about psychological feelings of worry. The second set of items related to response behavior (HS4 and HS6) asks respondents the level at which they agree or disagree with the
statements “My home is sturdy enough to protect me during a tornado” and “My home is not a safe place during a tornado warning.” The Spearman’s Rank correlation value of \( r = -0.460 \) between these protective action item responses is significant at the <0.001 level. The moderate negative correlation shows that respondents who disagree with one item agree with the other, as expected.

The 700 completed questionnaire responses from the Tornado Risk Survey represent 72 of the 102 Illinois counties (Figure 4.2). The counties with the largest number of respondents are in the Northeastern Chicago urban area counties with the largest populations in the state, including Cook \((n = 317)\), DuPage \((n = 49)\), Will \((n = 36)\), and Lake \((n = 35)\) Counties. Of the 700 survey respondents, 618 live in counties with an urban designation and 82 in rural areas. Of the 30 counties without a survey response, 23 are rural, and 7 are urban, so the sample underrepresents rural geographies.

Examining the demographic representation of the survey sample to the total Illinois population compares respondents to the 2020 ACS 5-year estimates (USCB n.d.a.). Table 4.2 compares the Tornado Risk Survey respondents to all Illinois residents’ gender, age, race, ethnicity, education level, employment status, and disability status. Overall, the demographic representation aligns when comparing these percentages. The difference of proportions testing finds most of the demographic categories considered in the sample are not significantly different than the state population. Statistical assessment of the proportions between the 24 categories of these demographic variables (excluding “other” genders not measured in ACS), only 10 are significantly different (indicated by a
* in Table 4.2). While these are statistically different, the overall composition of the sample closely mirrors the state demographic profile.

Figure 4.2 Tornado Risk Survey Respondent Counts in Illinois Counties.
Table 4.2 Demographic Comparisons between Respondents and Illinois Residents.

<table>
<thead>
<tr>
<th>Demographic</th>
<th>Respondent Frequency</th>
<th>Respondent Distribution</th>
<th>Illinois Resident Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18-34</td>
<td>201</td>
<td>28.7%</td>
<td>30.6%</td>
</tr>
<tr>
<td>35-54</td>
<td>235</td>
<td>33.6%</td>
<td>34.2%</td>
</tr>
<tr>
<td>55-85</td>
<td>264</td>
<td>37.7%</td>
<td>35.2%</td>
</tr>
<tr>
<td><strong>Gender (Age 18 and up)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Woman</td>
<td>358</td>
<td>51.1%</td>
<td>51.4%</td>
</tr>
<tr>
<td>Man</td>
<td>333</td>
<td>47.6%</td>
<td>48.6%</td>
</tr>
<tr>
<td>Other</td>
<td>9</td>
<td>1.3%</td>
<td>---</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than high school*</td>
<td>23</td>
<td>3.3%</td>
<td>10.5%</td>
</tr>
<tr>
<td>High school graduate*</td>
<td>154</td>
<td>22.0%</td>
<td>26.1%</td>
</tr>
<tr>
<td>Some college or Associate's</td>
<td>225</td>
<td>32.1%</td>
<td>30.4%</td>
</tr>
<tr>
<td>Bachelor's or higher*</td>
<td>298</td>
<td>42.6%</td>
<td>33.0%</td>
</tr>
<tr>
<td><strong>Race</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White*</td>
<td>516</td>
<td>73.7%</td>
<td>69.8%</td>
</tr>
<tr>
<td>Black/African American</td>
<td>103</td>
<td>14.7%</td>
<td>14.1%</td>
</tr>
<tr>
<td>American Indian or Alaska Native</td>
<td>2</td>
<td>0.3%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Asian</td>
<td>43</td>
<td>6.1%</td>
<td>5.6%</td>
</tr>
<tr>
<td>Native Hawaiian or Pacific Islander</td>
<td>1</td>
<td>0.1%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Other*</td>
<td>19</td>
<td>2.7%</td>
<td>6.0%</td>
</tr>
<tr>
<td>Mixed Race*</td>
<td>16</td>
<td>2.3%</td>
<td>4.2%</td>
</tr>
<tr>
<td><strong>Hispanic Ethnicity</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>126</td>
<td>18.0%</td>
<td>17.2%</td>
</tr>
<tr>
<td>No</td>
<td>574</td>
<td>82.0%</td>
<td>82.8%</td>
</tr>
<tr>
<td><strong>Employment Status</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed*</td>
<td>378</td>
<td>54.0%</td>
<td>61.3%</td>
</tr>
<tr>
<td>Unemployed*</td>
<td>65</td>
<td>9.3%</td>
<td>3.9%</td>
</tr>
<tr>
<td>Not in the labor force</td>
<td>257</td>
<td>36.7%</td>
<td>34.8%</td>
</tr>
<tr>
<td><strong>Disability</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes*</td>
<td>134</td>
<td>19.1%</td>
<td>11.2%</td>
</tr>
<tr>
<td>No, or Prefer not to say*</td>
<td>566</td>
<td>80.9%</td>
<td>88.8%</td>
</tr>
</tbody>
</table>

*Significantly different proportions ($p < 0.05$)

The age representation contains the highest distribution in the 55-85 category (37.7% of respondents and 35.2% of Illinois residents) and the lowest distribution in the 18-34 category (28.7% of respondents and 30.6% of Illinois residents)
residents). The gender representation is split nearly in half for respondents and total residents ages 18 and up, with 51.1% women and 47.6% male respondents compared to the 51.4% women and 48.6% male Illinois resident distribution. The distribution of education level is highest for those with Bachelor’s degrees for both respondents (42.6%) and Illinois residents (33%), followed by those with some college or Associate’s degree (32.1% and 30.4%), high school graduates (22% and 26.1%), and less than a high school education (3.3% and 10.5%). The racial representation aligns closely between respondents and residents, with the highest distribution being White (73.7% and 69.8%), followed by African American (14.7% and 14.1%) and Asian (6.1% and 5.6%). The representation of Hispanic ethnicity is nearly identical, with 18% of respondents and 17.2% of residents identifying as Hispanic or Latino/a/x. The employment status distribution is very similar, with 54% of respondents and 61.3% of residents employed. Disability status is somewhat similar in distribution, with 19.1% of respondents and 11.2% of residents having a disability.

A comparison between respondents’ and Illinois residents’ income levels is shown in Table 4.3, although the two are measured using different income range categories. Difference of proportions testing is inappropriate for the income categories since they measure different income ranges. However, the broad distribution is closely aligned, with the highest percentages observed in income levels averaging around $30,000.
Table 4.3 Income Level Comparisons between Respondents and Illinois Residents.

<table>
<thead>
<tr>
<th>Respondent Income Category</th>
<th>Respondent Frequency</th>
<th>Respondent Distribution</th>
<th>Census Income Category</th>
<th>Illinois Resident Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than $10,000</td>
<td>55</td>
<td>7.9%</td>
<td>Less than $10,000</td>
<td>1.4%</td>
</tr>
<tr>
<td>$10,000 to $19,999</td>
<td>66</td>
<td>9.4%</td>
<td>$10,000 to $14,999</td>
<td>2.2%</td>
</tr>
<tr>
<td>$20,000 to $39,999</td>
<td>156</td>
<td>22.3%</td>
<td>$15,000 to $34,999</td>
<td>23.6%</td>
</tr>
<tr>
<td>$40,000 to $59,999</td>
<td>121</td>
<td>17.3%</td>
<td>$35,000 to $49,999</td>
<td>18.3%</td>
</tr>
<tr>
<td>$60,000 to $79,999</td>
<td>107</td>
<td>15.3%</td>
<td>$50,000 to $74,999</td>
<td>23.2%</td>
</tr>
<tr>
<td>$80,000 to $99,999</td>
<td>79</td>
<td>11.3%</td>
<td>$75,000 to $99,999</td>
<td>12.9%</td>
</tr>
<tr>
<td>$100,000 or more</td>
<td>116</td>
<td>16.6%</td>
<td>$100,000 or more</td>
<td>18.3%</td>
</tr>
</tbody>
</table>

4.2.2 Risk Perception Construct

The risk perception construct assessment from the EFA results in ten retained items from the Tornado Risk Survey (Table 4.4). The EFA model for the risk perception construct explains 74.29% of the data variance in the initial principal components estimation before MLE accounts for common variance. The Chi-square Goodness-of-Fit test in the MLE model results in a test statistic of 15.404 at 11 degrees of freedom and a 0.165 significance level. The insignificant Chi-square test statistic fails to reject the null hypothesis stating that the model is a good fit, meaning that the model is indeed well-fitting. The Cronbach’s alpha test of reliability results in a value of 0.694, which is an acceptable level for the construct items.

Four factors result from the ten-variable input EFA model for risk perception (Table 4.5). Factor one represents the overall perception of risk, with items RP4 (Fear of tornado warning), RP5 (Property damage worry), and RP6 (Human damage worry) loading the strongest. Factor two represents personal tornado experiences, with items TE2 (5-year tornado experiences) and TE3 (1-
year tornado experiences) loading the strongest. Factor three represents tornado knowledge, with items TK7 (Tornado watch versus warning meaning), TK8 (Warning Understanding), and TK9 (Understand Tornado Science) loading the strongest. Factor four represents tornado experiences of those known personally, with items TE8 (Know individual experiencing injury) and TE9 (Know individual experiencing property damage) loading the strongest.

Table 4.4 Retained Risk Perception Questions Resulting from the EFA.

<table>
<thead>
<tr>
<th>Risk Perception Construct Question</th>
<th>Response Options</th>
<th>Item ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>I am fearful when a tornado warning is issued for my home’s location</td>
<td>5-point Likert Scale: Strongly Disagree to Strongly Agree</td>
<td>RP4</td>
</tr>
<tr>
<td>When there is severe weather in my area that could result in a tornado, I worry my property will be damaged</td>
<td>5-point Likert Scale: Strongly Disagree to Strongly Agree</td>
<td>RP5</td>
</tr>
<tr>
<td>When there is severe weather in my area that could result in a tornado, I worry I will suffer injury or death</td>
<td>5-point Likert Scale: Strongly Disagree to Strongly Agree</td>
<td>RP6</td>
</tr>
<tr>
<td>I understand the difference between a tornado watch and a tornado warning</td>
<td>5-point Likert Scale: Strongly Disagree to Strongly Agree</td>
<td>TK7</td>
</tr>
<tr>
<td>I understand what I should do when a tornado warning is issued where I live</td>
<td>5-point Likert Scale: Strongly Disagree to Strongly Agree</td>
<td>TK8</td>
</tr>
<tr>
<td>I understand the science behind what causes tornadoes</td>
<td>5-point Likert Scale: Strongly Disagree to Strongly Agree</td>
<td>TK9</td>
</tr>
<tr>
<td>Thinking about the last 5 years, what is your level of experience with tornadoes?</td>
<td>5-point Likert Scale: None to A Great Deal</td>
<td>TE2</td>
</tr>
<tr>
<td>Thinking about the last year, what is your level of experience with tornadoes?</td>
<td>5-point Likert Scale: None to A Great Deal</td>
<td>TE3</td>
</tr>
<tr>
<td>Has someone you know personally been injured by a confirmed tornado?</td>
<td>3-point Scale: Yes, No, or Unsure</td>
<td>TE8</td>
</tr>
<tr>
<td>Has someone you know personally ever had their property damaged (home, vehicle, crops, etc.) by a confirmed tornado?</td>
<td>3-point Scale: Yes, No, or Unsure</td>
<td>TE9</td>
</tr>
</tbody>
</table>

The total risk perception construct value (i.e., the sum of the z-score value for each of the ten retained items) ranges from -13.50 to 16.41 (range = 29.92).
The risk perception construct value of 338 respondents is above the mean value (i.e., positive) and 362 below the mean (i.e., negative), meaning most respondents have a lower risk perception value than average. The respondent with the highest risk perception score is a resident of Naperville in DuPage County, while the lowest-scoring respondent is a resident of Chicago in Cook County.

Table 4.5 Factor Loadings for the Risk Perception Construct EFA.

<table>
<thead>
<tr>
<th>Questionnaire Item and Description</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>Factor 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>RP4 - Fear of Tornado Warning</td>
<td>0.799</td>
<td>-0.007</td>
<td>-0.015</td>
<td>-0.016</td>
</tr>
<tr>
<td>RP5 - Property Damage Worry</td>
<td>0.804</td>
<td>-0.034</td>
<td>0.070</td>
<td>0.042</td>
</tr>
<tr>
<td>RP6 - Human Damage Worry</td>
<td>0.752</td>
<td>0.054</td>
<td>-0.065</td>
<td>-0.037</td>
</tr>
<tr>
<td>TK7 - Watch versus Warning meaning</td>
<td>-0.025</td>
<td>-0.028</td>
<td>0.778</td>
<td>-0.022</td>
</tr>
<tr>
<td>TK8 - Warning Understanding</td>
<td>0.028</td>
<td>-0.005</td>
<td>0.787</td>
<td>-0.015</td>
</tr>
<tr>
<td>TK9 - Understand Tornado Science</td>
<td>-0.016</td>
<td>0.083</td>
<td>0.452</td>
<td>0.022</td>
</tr>
<tr>
<td>TE2 - 5-year Tornado Experience</td>
<td>-0.008</td>
<td>0.994</td>
<td>0.030</td>
<td>0.013</td>
</tr>
<tr>
<td>TE3 - 1-year Tornado Experience</td>
<td>0.020</td>
<td>0.803</td>
<td>0.004</td>
<td>0.038</td>
</tr>
<tr>
<td>TE8 - Know Individual Injured</td>
<td>-0.025</td>
<td>0.152</td>
<td>-0.046</td>
<td>0.422</td>
</tr>
<tr>
<td>TE9 - Know Individual with Property Damage</td>
<td>0.008</td>
<td>-0.046</td>
<td>0.020</td>
<td>1.009</td>
</tr>
</tbody>
</table>

4.2.3 Protective Action Construct

The protective action construct assessment from the EFA also results in ten retained items from the Tornado Risk Survey (Table 4.6). The model for the protective action construct explains 71.22% of the data variance in the initial principal components estimation before MLE accounts for common variance. The Chi-square Goodness-of-Fit test in the MLE model results in a test statistic of 14.089 at 11 degrees of freedom and a 0.228 significance level. The insignificant Chi-square test statistic fails to reject the null hypothesis and thus finds the
model well-fitting. The Cronbach’s alpha test of reliability results in a value of 0.687, which is an acceptable level for construct reliability.

Table 4.6 Retained Protective Action Questions Resulting from the EFA.

<table>
<thead>
<tr>
<th>Protective Action Construct Question</th>
<th>Response Options</th>
<th>Item ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>In the event of a tornado watch, I would... (check all that apply)</td>
<td>Do nothing, Pray, Go outside, Go to an indoor sheltering place, Go to an underground sheltering place, Check for environmental cues, Check to see what family or neighbors do, Bring children or pets inside, Seek more info about the storm, Gather supplies around the house, Evacuate the tornado warning area, Other</td>
<td>TR1</td>
</tr>
<tr>
<td>In the event of a tornado warning, I would... (check all that apply)</td>
<td>&quot;...&quot;</td>
<td>TR2</td>
</tr>
<tr>
<td>I feel prepared to adequately respond to a tornado approaching my home</td>
<td>5-point Likert Scale: Strongly Disagree to Strongly Agree</td>
<td>HS9</td>
</tr>
<tr>
<td>I feel prepared to respond to a tornado warning</td>
<td>5-point Likert Scale: Strongly Disagree to Strongly Agree</td>
<td>PA1</td>
</tr>
<tr>
<td>My residential community is adequately prepared for a tornado</td>
<td>5-point Likert Scale: Strongly Disagree to Strongly Agree</td>
<td>PA2</td>
</tr>
<tr>
<td>Which sources do you use to receive tornado warnings? (check all that apply)</td>
<td>Outdoor sirens, Cable/TV News, Automated phone or text message alerts, Internet News Social media, Local radio stations, NOAA weather radio, Family/neighbors, I use none of these sources to receive tornado warnings, Other</td>
<td>PA6</td>
</tr>
<tr>
<td>What tornado sheltering options do you have available in or near your home? (check all that apply)</td>
<td>Basement with no windows, Basement with windows, Detached storm shelter, Shared/community shelter, Inside room with no windows, Inside room with windows, No sheltering options are available to me, Other</td>
<td>HS1</td>
</tr>
<tr>
<td>When you are at home, where is the first place you would take shelter from an approaching tornado?</td>
<td>&quot;...&quot;</td>
<td>HS2</td>
</tr>
<tr>
<td>My home is sturdy enough to protect me during a tornado</td>
<td>5-point Likert Scale: Strongly Disagree to Strongly Agree</td>
<td>HS4</td>
</tr>
<tr>
<td>My home is sturdy enough to withstand tornado damage</td>
<td>5-point Likert Scale: Strongly Disagree to Strongly Agree</td>
<td>HS5</td>
</tr>
</tbody>
</table>
Four factors result from the ten-variable input EFA model for protective action (Table 4.7). Factor one represents the personal and community preparedness level, with items HS9 (Prepared to respond in one’s home), PA1 (Personally prepared to respond), and PA2 (Community prepared to respond) loading the strongest. Factor two represents tornado watch and warning response, with items TR1 (Tornado watch response) and TR2 (Tornado warning response) loading the strongest. Factor three represents home structure safety, with items HS4 (Home will protect me) and HS5 (Home sturdiness to physical damage) loading the strongest. Factor four represents sheltering and warning options, with items PA6 (Count of warning sources), HS1 (Count of sheltering options), and HS2 (Final sheltering choice) loading the strongest.

Table 4.7 Factor Loadings for the Protective Action Construct EFA.

<table>
<thead>
<tr>
<th>Questionnaire Item and Description</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>Factor 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>TR1 - Tornado Watch Response</td>
<td>-0.067</td>
<td>0.752</td>
<td>0.081</td>
<td>-0.022</td>
</tr>
<tr>
<td>TR2 - Tornado Warning Response</td>
<td>-0.019</td>
<td>0.875</td>
<td>-0.047</td>
<td>-0.020</td>
</tr>
<tr>
<td>HS9 - Prepared to Respond in my Home</td>
<td>0.596</td>
<td>0.036</td>
<td>0.126</td>
<td>0.040</td>
</tr>
<tr>
<td>PA1 - Personally Prepared to Respond</td>
<td>0.927</td>
<td>0.018</td>
<td>-0.132</td>
<td>-0.048</td>
</tr>
<tr>
<td>PA2 - Community Prepared to Respond</td>
<td>0.575</td>
<td>-0.039</td>
<td>0.135</td>
<td>0.026</td>
</tr>
<tr>
<td>PA6 - Count of Warning Sources</td>
<td>0.139</td>
<td>0.469</td>
<td>-0.034</td>
<td>0.074</td>
</tr>
<tr>
<td>HS1 - Count of Sheltering Options</td>
<td>-0.008</td>
<td>0.013</td>
<td>-0.021</td>
<td>0.909</td>
</tr>
<tr>
<td>HS2 - Final Shelter Choice</td>
<td>0.008</td>
<td>0.001</td>
<td>0.016</td>
<td>0.452</td>
</tr>
<tr>
<td>HS4 - Home will Protect Me</td>
<td>0.080</td>
<td>0.023</td>
<td>0.799</td>
<td>-0.019</td>
</tr>
<tr>
<td>HS5 - Home Sturdiness to Physical Damage</td>
<td>-0.029</td>
<td>-0.014</td>
<td>0.932</td>
<td>0.012</td>
</tr>
</tbody>
</table>

The total protective action construct value (i.e., the sum of the z-score value for each of the ten retained items) ranges from -13.53 to 14.55 (range = 28.08). A total of 340 respondents received a protective action construct score
above the mean score value. In comparison, 360 respondents’ values fell below
the mean, meaning most respondents have a lower-than-average protective
action construct value. The respondent with the highest protective action score is
a resident of Rockford in Winnebago County, while the lowest scoring is a
resident of Arlington Heights in Cook County.

4.3 Results: TROP Model SEM Implementation

The SEM output from the TROP model implementation uncovers the
direct and indirect relationships between this study’s tornado risk input metrics.
The TROP SEM produces a well-fitting model and significant statistical
relationships for the calculated input variables. The input data includes a sample
size of 700, representing each Tornado Risk Survey respondent. Ten distinct
sample moments makeup the model with eight parameters requiring estimation,
resulting in two df (10 - 8 = 2). The model is well-fitting according to all five fit
statistics (Table 4.8). The Chi-square statistic value of 1.3 at two df (1.3 / 2 =
0.65) is insignificant at the 0.522 probability level, indicating an overall well-fitting
model. The GFI statistic results in a value of 0.999, AGFI is 0.995, and CFI is 1,
all above the 0.95 acceptable model fit levels. The RMSEA value is less than
0.000, which indicates a well-fitting model (less than 0.05). The RMSEA can
equate to zero when the Chi-square statistic results in a value less than the
model’s df (1.3 < 2).

The final SEM path model diagram shown in Figure 4.3 displays the
standardized regression coefficients, correlation, and squared multiple
correlations. Those estimates with a *** symbol indicate significant results at a p-
value less than 0.001. The six main variables in the SEM display include the physical context, social context, risk perception, risk perception measurement error term (e1), protective action, and the protective action measurement error term (e2).

Table 4.8 SEM Fit Statistics

<table>
<thead>
<tr>
<th>Fit Estimate</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-square / df</td>
<td>1.300 / 2 = 0.65</td>
</tr>
<tr>
<td>p-value</td>
<td>0.522</td>
</tr>
<tr>
<td>GFI</td>
<td>0.999</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.995</td>
</tr>
<tr>
<td>CFI</td>
<td>1.000</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Figure 4.3 Path Diagram of the SEM Output.

Table 4.9 displays the SEM correlation and regression estimates alongside their standard error calculations. An $r = -0.329$ significant correlation between the physical and social context indicates that increased physical risk among respondents’ county of residence is significantly related to lower social context or vice versa. In other words, as one value increases, the other
decreases at a weak but significant level. The squared multiple correlation for risk perception ($r^2 = 0.05$) indicates that physical and social contexts account for 5% of the variance in risk perception. The squared multiple correlation for protective action ($r^2 = 0.09$) finds that 9% of the variance in protective action is accounted for by risk perception (and indirectly by physical and social context).

Table 4.9 SEM Correlation and Regression Estimates.

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Context ↔ Social Context Correlation</td>
<td>-0.329</td>
</tr>
<tr>
<td>Risk Perception Squared Multiple Correlation</td>
<td>0.050</td>
</tr>
<tr>
<td>Protective Action Squared Multiple Correlation</td>
<td>0.092</td>
</tr>
<tr>
<td>Physical Context → Risk Perception Std. Regression Coefficient</td>
<td>0.129</td>
</tr>
<tr>
<td>Social Context → Risk Perception Std. Regression Coefficient</td>
<td>-0.146</td>
</tr>
<tr>
<td>Risk Perception → Protective Action Std. Regression Coefficient</td>
<td>0.303</td>
</tr>
<tr>
<td>Physical Context → Protective Action Indirect Std. Regression Coefficient</td>
<td>0.039</td>
</tr>
<tr>
<td>Social Context → Protective Action Indirect Std. Regression Coefficient</td>
<td>-0.044</td>
</tr>
</tbody>
</table>

The three direct standardized regression coefficient calculations from the MLE all result in significant relationships. The county-level physical context has a weak positive influence on individuals’ risk perceptions with a $\beta = 0.129$ value, meaning the higher the physical context value, the higher the risk perceptions. The county social context has a weak negative influence on individuals’ risk perceptions with a $\beta = -0.146$ value, meaning the higher the social vulnerability value, the lower the risk perceptions. Individuals’ risk perceptions have a moderate positive relationship with protective actions with a $\beta = 0.303$ value, meaning that the protective action metric increases significantly with higher risk perceptions. The standardized regression coefficient for physical context’s indirect effects on protective action results in a $\beta = 0.039$ value, meaning that increased physical context values correspond to increased
protective action. The standardized regression coefficient for social context’s indirect effects on protective action results in a $\beta = -0.044$ value, meaning that social vulnerability values increase with lower higher protective action values (and vice versa). Risk perception is thus a mediator in the SEM, creating an indirect relationship between context and response. However, risk perception has a more substantial direct effect on protective action than the indirect effects from physical and social contexts.
CHAPTER 5
REGIONAL ASSESSMENT OF THE TROP MODEL OUTCOMES

Statistical and geospatial methodologies based on the geographic contextual indices alongside latent construct metrics derived from the Tornado Risk Survey provide a framework for assessing TROP model outcomes among the questionnaire respondents. The geographic variability of the tornado risk outcome metric is evaluated and mapped across five different regional groups (both formal and functional geographic area delineations) within Illinois to address this study’s third and final research question.

5.1 Approach to Assessing TROP Model Outcomes

To fully understand the totality of statistical interactions between the conceptual drivers of tornado risk (i.e., physical context, social context, risk perception, and protective action behavior), a combined final output metric of the TROP relationships is calculated (Figure 5.1). In other words, the metrics for the four conceptual drivers applied as inputs to the SEM combines to create one tornado risk outcome measure for each survey respondent. The total TROP value calculation first sums the positively oriented physical and social constructs measures of respondents’ respective counties of residence. Each respondent’s summed geographic context score then subtracts the risk perception and protective action construct score to create the final TROP value. The negative cardinality assignment of the constructs is due to increased perception and
protective response decreasing overall tornado risk.

Figure 5.1 Flow Diagram of the TROP Model Outcome Analytics.

5.1.1 Regional Delineations

Multiple geographic regional delineations within the study area are defined and measured at the county level, including urban-rural assignment, Northern, Central, or Southern region, emergency management region, and NWS County Warning Area (CWA) assignments. Urban-rural county analysis coding applies a binary metric based on the USDA RUCCs (Table 3.2), which split codes one to three (1-3) as urban/metro and codes four to nine (4-9) as rural/nonmetro (USDA 2020a). Illinois counties classified as urban are assigned a code of one (1), while rural counties received a code of zero (0) (Figure 5.2). The Illinois Nature Conservancy delineates the three Northern, Central, and Southern regions of the state (Figure 5.3) based on landform features and land use (Wuebbles et al. 2021). These three regions conform to county boundaries, and analysis coding for this investigation equates these geographic areas to a value of one (Northern), two (Central), or three (Southern). Geospatial data for NWS CWAs, the boundaries of the multi-county zones that NWS forecast offices are
responsible for, are also applied as functional regions tested for spatial variability (USDC, NOAA, and NWS 2020b). The State of Illinois includes five separate CWAs, some of which include forecasting responsibilities for adjacent states (Figure 5.4). The analytical coding for the CWAs for this investigation’s regional analysis equates to a value of one (Chicago), two (Quad Cities), three (Lincoln), four (St. Louis), or five (Paducah). Practical emergency management regions within Illinois apply the Illinois Emergency Management Agency’s (IEMA) eight functional regions (Figure 5.5), which conform to county boundaries (State of Illinois 2023). For this study’s analytics, the IEMA region assignments retain their original numerical value identification codes (i.e., 2, 3, 4, 6, 7, 8, 9, or 11).

An additional regional variable included in the spatial analysis of the tornado risk outcome measure consists of a proxy metric representing practical community tornado preparedness. A county-level indicator of tornado preparedness measures involvement in the NWS StormReady® program, which trains and prepares communities to strengthen their local weather safety. For a county to officially become StormReady®, it must adhere to specific emergency management guidelines that ensure proactive hazardous weather operations. The StormReady® requirements include establishing a twenty-four-hour emergency operations center and having at least two methods of disseminating severe weather warning alerts to the public (USDC, NOAA, and NWS n.d.a).

Data for StormReady® involvement in Illinois counties tabulates the participant certification listing from the NWS website documentation (USDC, NOAA, and NWS n.d.b.). Each county receives a value of one (1) for total participation and a
value of zero (0) for no involvement in the program (Figure 5.6).

Figure 5.2 Urban-Rural Binary Delineations for Illinois Counties.
Figure 5.3 Northern, Central, and Southern Illinois Regional Delineations.
Figure 5.4 National Weather Service County Warning Areas in Illinois.
Figure 5.5 Illinois Emergency Management Agency Regions.
Figure 5.6 StormReady® Participation of Illinois Counties
5.1.2 Regional Assessment Analytical Approach

An assessment of the five regional delineations across the Illinois study area examines the difference in mean values of the TROP model outcome measure calculation (Figure 5.1) for each survey respondent. Independent sample t-tests (i.e., the difference of means) among respondents in urban-rural and StormReady®/non-StormReady® counties assesses any statistically significant differences between these delineated geographies’ TROP outcome mean values. Levene’s testing for unequal variances (Rogerson 2015) determines if the non-parametric Mann-Whitney U test is necessary for the independent samples (McKnight and Najab 2010). Analysis of Variance (ANOVA) testing for the respondents in geographic regions with three or more groupings (i.e., Northern-Central-Southern Illinois, IEMA regions, and NWS CWAs) then analyzes the difference of means (Mishra et al. 2019) of respondents TROP outcome values in the remaining regional subsets of the data. Levene’s testing for unequal variances determines if the non-parametric Kruskal-Wallis test is necessary for these regional ANOVA assessments (Rogerson 2015). For significant ANOVA outputs, the post hoc Tukey’s Honestly Significant Difference (HSD) test compares the group means to specifically determine which pairwise matches are significantly different (Williams and Abdi 2010). The null hypothesis tested in the independent samples t-tests and ANOVA analyses stated that the populations within the study areas do not have significantly different mean TROP outcome values. The researcher expects analysis results to reject the null hypothesis due to anticipated geographic-based
tornado risk differences. The IBM® SPSS® program executes the difference of means and ANOVA testing evaluating the significance outcomes at a 95% confidence level.

5.2 Validating the TROP Model

A final step in this investigation is the validation of the TROP outcome values based on tornado damages within the Illinois study area. Tornado event economic loss data (i.e., combined property and crop losses) and human losses (i.e., injuries and fatalities) per county from SHELDUS (CEMHS 2022) create three practical measures for model validation. The two human loss measure calculations equate to the total number of injuries and fatalities for the 61-year data period covered by the SHELDUS database. The total amount of monetary loss is adjusted for inflation to 2020 U.S. dollars based on the entire historical record of loss data (1960-2020). The model validation assessment assumes the TROP outcome values positively correlate with increasing monetary damages, injuries, and fatalities, indicating a well performing model. Correlation analyses uncover the linear relationships (i.e., dependence) between the TROP outcome measure and the damage variables utilizing Pearson’s r. IBM® SPSS® conducts the validation assessment and significance testing at a 95% confidence level.

5.3 Results: Spatial Variability of the TROP Model Outcomes

The final TROP value calculations (i.e., = physical context + social context - risk perception construct - protective action construct) for the 700 respondents range from -25.36 to 28.79 (range = 54.15). The average TROP value per respondent is 1.75, with a standard deviation of 8.94 and a variance of 79.90.
The respondent with the highest TROP score is a resident of Chicago in Cook County, while the lowest-scoring respondent is a resident of Naperville in DuPage County (i.e., Chicago suburban area).

5.3.1 Urban-Rural Variability

The first spatial variability assessment tests the null hypothesis that the urban-located respondents' TROP outcome value means are not significantly different from the rural-located respondents. The independent samples t-test between urban and rural respondents results in statistically significant mean differences for the two groups ($t = 4.52, p = <0.001$). The significant t-tests thus rejects the null hypothesis, and the alternative hypothesis, that the urban respondents' means are significantly different than rural respondents' means, is accepted. Table 5.1 shows the final TROP value means are higher among urban county respondents ($n = 618; \bar{x} = 2.30; s = 8.94$) than among rural county respondents ($n = 82; \bar{x} = -2.36; s = 7.81$). The Levene’s test for equality of variances is insignificant ($F = 1.16, p = 0.283$), so the non-parametric Mann-Whitney $U$ test is unnecessary.

Table 5.1 Independent Samples T-Tests Results for Urban and Rural County Respondents.

<table>
<thead>
<tr>
<th>Region</th>
<th>Number of Respondents ($n$)</th>
<th>Mean ($\bar{x}$)</th>
<th>Standard Deviation ($s$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>618</td>
<td>2.30</td>
<td>8.94</td>
</tr>
<tr>
<td>Rural</td>
<td>82</td>
<td>-2.36</td>
<td>7.81</td>
</tr>
</tbody>
</table>

5.3.2 StormReady® Variability

The second spatial variability assessment tests the null hypothesis that residents in StormReady® counties have no significant difference in TROP...
outcome value means than those in non-StormReady® designated counties. The independent samples t-test between the two groups results in statistically significant mean differences for residents in StormReady® and non-StormReady® counties ($t = -6.29, p < 0.001$). The significant t-test thus rejects the null hypothesis, and the alternative hypothesis, that the StormReady® respondents' means are significantly different than non-StormReady® means, is accepted. Table 5.2 shows the final TROP value means are higher among StormReady® county respondents ($n = 503; \bar{x} = 2.96; s = 9.09$) than for non-StormReady® county respondents ($n = 197; \bar{x} = -1.35; s = 7.75$). The Levene’s test for equality of variances is significant ($F = 5.13, p = 0.024$), but the non-parametric Mann-Whitney U test confirms the group means' significant difference ($U = 63232, Z = 5.69, p = <0.001$).

Table 5.2 Independent Samples T-Tests Results for StormReady® and non-StormReady® County Respondents.

<table>
<thead>
<tr>
<th>Region</th>
<th>Number of Respondents ($n$)</th>
<th>Mean ($\bar{x}$)</th>
<th>Standard Deviation ($s$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>StormReady®</td>
<td>503</td>
<td>2.96</td>
<td>9.09</td>
</tr>
<tr>
<td>Non-StormReady®</td>
<td>197</td>
<td>-1.35</td>
<td>7.75</td>
</tr>
</tbody>
</table>

5.3.3 Northern-Central-Southern Illinois Variability

The third spatial variability assessment tests the null hypothesis that residents in the three Illinois Nature Conservancy regions have no significant differences in their TROP outcome value means. The one-way ANOVA results in significantly different means for respondents' TROP values between the three groups ($F = 3.39; p = 0.034$). Table 5.3 shows the highest TROP value means result in the Northern region ($n = 541; \bar{x} = 2.22; s = 9.14$), followed by the
Southern \((n = 40; \bar{x} = 0.40; s = 7.84)\) and Central regions \((n = 119; \bar{x} = 0.05; s = 8.14)\). The significant ANOVA result thus rejects the null hypothesis, and the alternative hypothesis, that respondents' TROP outcome value means are significantly different among the three Nature Conservancy regions, is accepted.

The Levene’s test for unequal variances is insignificant \((F = 1.32, p = 0.269)\), meaning the assumption of homogeneity of variances is met for the ANOVA test, and the nonparametric Kruskal-Wallis test is unnecessary.

Table 5.3 ANOVA Results for Respondents in the Three Nature Conservancy Regions.

<table>
<thead>
<tr>
<th>Region</th>
<th>Number of Respondents ((n))</th>
<th>Mean ((\bar{x}))</th>
<th>Standard Deviation ((s))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northern</td>
<td>541</td>
<td>2.22</td>
<td>9.14</td>
</tr>
<tr>
<td>Central</td>
<td>119</td>
<td>0.05</td>
<td>8.14</td>
</tr>
<tr>
<td>Southern</td>
<td>40</td>
<td>0.40</td>
<td>7.84</td>
</tr>
</tbody>
</table>

The ANOVA post hoc Tukey HSD test allows for comparing each group’s pairs of means to determine which Illinois Nature Conservancy regional matches contain significantly different respondent TROP outcome values. Table 5.4 shows the Northern and Central regional respondents include the only pair match of significantly different TROP means \((MD = 2.17; p = 0.043)\). The remaining regional pair matches do not have statistically significant differences in respondents' TROP outcome values.

Table 5.4 Significant Tukey HSD Post Hoc Results for Respondents in the Illinois Nature Conservancy Regions.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Mean Difference ((MD))</th>
<th>Significance ((p))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northern – Central</td>
<td>2.174</td>
<td>0.043</td>
</tr>
</tbody>
</table>
5.3.4 NWS Forecasting Area Variability

The fourth spatial variability assessment tests the null hypothesis that residents in the five NWS forecasting areas have no significant differences in their TROP outcome value means. The one-way ANOVA results in significantly different means for respondents’ TROP values between the five groups ($F = 4.40; p = 0.002$). The significant ANOVA result thus rejects the null hypothesis, and the alternative hypothesis, that respondents’ TROP outcome value means are significantly different among the five NWS forecasting areas, is accepted.

Table 5.5 shows the highest TROP value means result in the Chicago forecast area ($n = 533; \bar{x} = 2.35; s = 9.07$), followed by Lincoln ($n = 79; \bar{x} = 1.28; s = 7.91$) and Paducah ($n = 24; \bar{x} = 1.06; s = 8.64$). The forecast areas with the lowest mean values are Quad Cities ($n = 23; \bar{x} = -3.44; s = 7.89$) and St. Louis ($n = 41; \bar{x} = -1.87; s = 8.24$). The Levene’s test for unequal variances is insignificant ($F = 0.677, p = 0.608$), meaning the assumption of homogeneity of variances is met for the ANOVA test, and the nonparametric Kruskal-Wallis test is unnecessary.

Table 5.5 ANOVA Results for Respondents in the National Weather Service Forecasting Areas.

<table>
<thead>
<tr>
<th>Region</th>
<th>Number of Respondents (n)</th>
<th>Mean (\bar{x})</th>
<th>Standard Deviation (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chicago</td>
<td>533</td>
<td>2.35</td>
<td>9.07</td>
</tr>
<tr>
<td>Lincoln</td>
<td>79</td>
<td>1.28</td>
<td>7.91</td>
</tr>
<tr>
<td>Paducah</td>
<td>24</td>
<td>1.06</td>
<td>8.64</td>
</tr>
<tr>
<td>St. Louis</td>
<td>41</td>
<td>-1.87</td>
<td>8.24</td>
</tr>
<tr>
<td>Quad Cities</td>
<td>23</td>
<td>-3.44</td>
<td>7.89</td>
</tr>
</tbody>
</table>

The ANOVA post hoc Tukey HSD test allows for comparing each group’s pairs of means to determine which NWS forecasting area matches contain
significantly different respondent TROP outcome values. Table 5.6 shows the two pair matches of significantly different TROP means: Chicago – Quad Cities \((MD = 5.80; p = 0.019)\) and Chicago – St. Louis regions \((MD = 4.22; p = 0.028)\).

The remaining regional pair matches do not have statistically significant differences in respondents' TROP outcome values.

Table 5.6 Significant Tukey HSD Post Hoc Results for Respondents in the National Weather Service Forecasting Areas.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Mean Difference ((MD))</th>
<th>Significance ((p))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chicago – Quad Cities</td>
<td>5.795</td>
<td>0.019</td>
</tr>
<tr>
<td>Chicago – St. Louis</td>
<td>4.224</td>
<td>0.028</td>
</tr>
</tbody>
</table>

5.3.5 IEMA Regional Variability

The fifth spatial variability assessment tests the null hypothesis that residents in the eight IEMA regions have no significant differences in their TROP outcome value means. The one-way ANOVA results in significantly different means for respondents' TROP values between the eight groups \((F = 8.93; p < 0.001)\). The significant ANOVA result thus rejects the null hypothesis, and the alternative hypothesis, that respondents' TROP outcome value means are significantly different among the eight IEMA Regions, is accepted. Table 5.7 shows the highest TROP value means result in the IEMA Region 4 \((n = 401; \bar{x} = 3.81; s = 8.97)\), which includes the Chicago area counties of Cook, DuPage, and Lake. Region 11, which makes up the southernmost counties of the state, possesses the second highest means \((n = 21; \bar{x} = 1.51; s = 8.75)\). The respondents in the Northwestern counties included in Region 2 contain the lowest mean TROP values \((n = 47; \bar{x} = -3.28; s = 8.65)\). The second lowest
respondent TROP values are among those in Region 3 \((n = 101; \bar{x} = -1.64; s = 7.55)\), which includes the Northeastern counties outside of the Chicago urban area. The Levene’s test for unequal variances is insignificant \((F = 1.07, p = 0.384)\), meaning the assumption of homogeneity of variances is met for the ANOVA test, and the nonparametric Kruskal-Wallis test is unnecessary.

Table 5.7 ANOVA Results for Respondents in the Eight Illinois Emergency Management Regions.

<table>
<thead>
<tr>
<th>Region</th>
<th>Number of Respondents ((n))</th>
<th>Mean ((\bar{x}))</th>
<th>Standard Deviation ((s))</th>
</tr>
</thead>
<tbody>
<tr>
<td>IEMA 2 – Northwest</td>
<td>47</td>
<td>-3.28</td>
<td>8.65</td>
</tr>
<tr>
<td>IEMA 3 – Northeast sans Chicago</td>
<td>101</td>
<td>-1.64</td>
<td>7.55</td>
</tr>
<tr>
<td>IEMA 4 – Chicago Urban Area</td>
<td>401</td>
<td>3.81</td>
<td>8.97</td>
</tr>
<tr>
<td>IEMA 6 – West Central</td>
<td>37</td>
<td>-0.08</td>
<td>7.96</td>
</tr>
<tr>
<td>IEMA 7 – East Central</td>
<td>42</td>
<td>1.04</td>
<td>8.49</td>
</tr>
<tr>
<td>IEMA 8 – Southwest</td>
<td>33</td>
<td>-1.62</td>
<td>8.42</td>
</tr>
<tr>
<td>IEMA 9 – Southeast</td>
<td>18</td>
<td>-0.12</td>
<td>7.07</td>
</tr>
<tr>
<td>IEMA 11 – Far South</td>
<td>21</td>
<td>1.51</td>
<td>8.75</td>
</tr>
</tbody>
</table>

The post hoc Tukey HSD test allows for comparing each group's pairs of means to determine which IEMA region matches contain significantly different TROP outcome values. Table 5.8 shows the three pair matches of significantly different respondent TROP outcome value means. All three matches involve IEMA Region 4 (Chicago urban area), which has significantly different mean values than respondents in Regions 2 \((MD = 7.09; p = <0.001)\), 3 \((MD = 5.44; p = <0.001)\), and 8 \((MD = 5.42; p = 0.012)\). Region 8 includes the Southwestern Illinois counties in the St. Louis metropolitan area and beyond, which contains the third lowest TROP outcome means after Regions 2 and 3. The remaining regional pair matches do not have statistically significant differences in respondents' TROP outcome values.
Table 5.8 Significant Tukey HSD Post Hoc Results for the IEMA Regional Differences in Respondents' TROP Value Means.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Mean Difference (MD)</th>
<th>Significance (p)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IEMA 4 - 2</td>
<td>7.086</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>IEMA 4 - 3</td>
<td>5.441</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>IEMA 4 - 8</td>
<td>5.425</td>
<td>0.012</td>
</tr>
</tbody>
</table>

5.4. Results: TROP Model Validation

The final TROP model evaluation helps to determine the performance and accuracy of the model with a test dataset evaluation. A Pearson correlation assessment verifies the model outcomes’ direct relationship to local tornado loss estimates. The model validation assessment results include statistically significant correlations for the questionnaire respondents' TROP outcome values and the historical tornado loss estimates in their counties of residence (Table 5.9). The three loss measures contain a moderately positive correlation with the respondent’s TROP outcome values, all significant at the $p < 0.001$ level. First, economic losses per county (i.e., combined property and crop losses from 1960 to 2020) significantly correlate with individuals' TROP model outcomes at a $r = 0.214$ value. Second, tornado-caused human injuries per county from 1960 to 2020 correlate with TROP outcomes at a $r = 0.366$ value. Last, tornado-caused fatalities per county from 1960-2020 correlate with TROP outcomes at a $r = 0.367$ value. As the losses increase for all three historical measures, the TROP outcome values also increase significantly. In other words, a higher total tornado risk value correlates with increasing economic and human losses. However, human losses correlate more strongly to TROP outcomes than monetary losses.
Table 5.9 Correlation of TROP Outcome Values to Historic Tornado Losses (1960-2020).

<table>
<thead>
<tr>
<th>Loss Measure</th>
<th>TROP Outcome Correlation Coefficient (r)</th>
<th>Significance (p)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Economic Losses</td>
<td>0.214</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Injuries</td>
<td>0.366</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Fatalities</td>
<td>0.367</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>
CHAPTER 6
DISCUSSION

This dissertation holistically evaluates tornado risk in a U.S. case study of Illinois, binding quantitative and geospatial methodologies in a place-based analysis. The investigation employs various input datasets and modes of analysis to address each research question and evaluates community-level tornado risk within the specified study area and sample. The first research question assesses the statistical and spatial variability captured by Illinois counties’ physical and social tornado risk context indices. The second research question estimates the interactions between all measured conceptual drivers of tornado risk, uncovering the main drivers of tornado risk by implementing the novel TROP model framework. The third research question evaluates the geographic variability in the tornado risk outcome metric, which is then assessed and mapped across five different regional groups within Illinois. The following discussion explains and interprets the study results in the context of these three research questions. The research provides insights into Illinois's community exposure and vulnerability that influence tornado risk, risk perceptions, and protective actions. The straightforward methodology and new TROP model provide empirical and practical contributions for future place-based tornado risk research applications. Overall, the study demonstrates the importance of analyzing the geographical context of tornado risk, risk perception, and behavioral response,
which can help inform disaster management policies and address hazard vulnerability.

6.1 Context Matters

Research shows that changes in geographic context can increase tornado exposure (Ashley and Strader 2016), and tornado risk is dynamic down to the county or sub-county level (Bluestein 2013). The contextual assessment confirms these place-based differences in tornado risk among local geographies concerning geophysical and socio-environmental variables. The study first develops quantifiable indicators to measure Illinois counties’ physical and social tornado risk context as inputs for the geographic context indices to conduct statistical and spatial assessments across the study area. The study evaluates the geospatial clustering of these factors separately and as a combined total geographic context measurement.

The study uses Global and Local autocorrelation statistics to extend the visual choropleth mapping evaluation that categorizes the tornado risk levels based on standard deviation data classifications. The Global Moran's I testing uncover significant overall spatial autocorrelation for all three physical, social, and total geographic context values throughout Illinois counties. The Local Moran's I LISA assessment identifies significant county clusters and outliers throughout the state for each contextual measurement. The autocorrelation assessment adds valuable insight into the appropriate allocation of resources for the environmental management of tornado risk by uncovering the underlying spatial relationships of the physical and social context metrics. Few studies
account for spatial autocorrelation in tornado risk assessments, with many limiting their studies to evaluations of tornado frequency without social context variables (Dixon et al. 2014; Reeves 2015; Potvin et al. 2022). Others assess spatial trends in tornado frequency without including autocorrelation analyses (Gensini and Brooks 2018). As such, this dissertation study adds to the current geographic tornado risk literature by assessing spatial autocorrelation of the county context indices.

6.1.1 Physical Tornado Risk Context

Each of the five individual physical risk context inputs (i.e., tornado occurrence; urban exposure; prior consequence; warning incidence; and mobile home structural housing risk) contains unique spatial distributions throughout Illinois counties. In other words, the results of the study’s physical context input metric development find that Illinois counties vary in their levels of geophysical tornado risk. No previous studies have developed a geophysical tornado risk metric using this methodology and instead commonly assess tornado occurrence frequency as an objective measure of spatial risk (Coleman and Dixon 2014). Yet, a plethora of empirical literature indicates that geophysical tornado risk is a more dynamic process influenced by many variables. This study provides an easy-to-follow research design for future scholars and practitioners to create a physical tornado risk metric in their study area, which is designed to accommodate the unique datasets that complicate tornado risk analyses.

The study finds that the spatial distribution of 1992-2021 tornado occurrence across Illinois counties was uneven, with the counties of Massac,
Tazewell, and Logan having the highest weighted and adjusted tornado frequency metric, while Lawrence, Clark, and Hamilton contain the lowest. Counties across Central Illinois experienced higher densities of tornado events, but these occurrences vary in magnitude. These results are consistent with earlier Illinois tornado climatology mapping by the Illinois State Climatologist (Angel 2022) for both the 1950-2010 and 1995-2020 periods that find Central Illinois to have a denser concentration of events. The study adds to the available literature on spatial-statistical assessments of tornado incidence by developing an occurrence metric weighted by event magnitude and adjusted based on county size. This occurrence metric provides a standardized value rather than a simplified measurement derived from a raw occurrence count commonly employed in many U.S. state and county hazard mitigation plans. Since tornado incidence directly impacts risk potential (Simmons and Sutter 2011), this occurrence evaluation’s application of the most recently available 30-year climatological data provides up-to-date information for tornado incidence assessments since the reduction of the reporting bias (Elsner et al. 2013; Kunkel et al. 2013; Coleman and Dixon 2014; Nouri et al. 2021).

In the second geophysical tornado metric development for urban exposure, the study finds an uneven distribution of counties based on the USDA RUCCs. Chicago's Cook County contains the most urban population and is adjacent to highly urbanized counties throughout the Northeast region. Recognition of the built environment’s influence on the potential for increased tornado impacts, particularly in Illinois, where a stark contrast in urban-rural
county designations exists, is necessary for accurate risk assessments. Compared to the rest of the country, Illinois has previously ranked in the top ten states for tornado catastrophes due to its density of at-risk properties prone to economic losses (Changnon 2009). Due to high levels of urban sprawl, the Chicago metropolitan area is at higher risk for monetary loss from tornado disasters (Ashley et al. 2014). The increased risk of tornado-producing thunderstorm genesis and severity potential due to the Urban Heat Island effect (Shourd 2015; Lim et al. 2017; Gildemeyer 2019) may also help inform the Illinois Emergency Management Agency’s (IEMA) current understanding of urban tornado risk. Additionally, these findings can increase Illinois residents' awareness of urban tornado risk, which influences their risk perceptions and protective action decisions, to correct the misunderstanding that metropolitan areas are less vulnerable to tornadoes (Schultz et al. 2010; Klockow 2013).

This dissertation study finds that the annualized average of tornado economic losses per county from 1990-2019 is $670,740, with Tazewell, Christian, and Peoria counties experiencing the highest reported losses. Of note, Tazewell and Peoria Counties are designated as urban, while Christian is a rural county with a total population of around 33,000 (USCB n.d.a.). However, this study’s economic losses include property and crop damages to help account for rural-specific economic impacts. Additionally, Christian County experienced a major EF-3 tornado in December 2018 that damaged over 500 homes (USDC, NOAA, and NWS n.d.c.) and contributed to the $127.7 million (ADJ 2020 USD) in tornado losses and 22 injuries reported that year (CEMHS 2022). Tazewell
County has a long tornado history, with economic losses reported from tornadoes in 15 out of the 30 years of record, including some significant deadly events. In 2013, an EF-4 tornado moved through a mainly suburban area of Washington, Illinois (USDC, NOAA, and NWS n.d.d.). The event caused just over a billion dollars in economic damages, 131 injuries, and three fatalities in Tazewell County alone (CEMHS 2022). The development of this loss metric shows that a few major events over a 30-year record can lead to significant outliers in tornado loss data. For example, a total of $2.05 billion in losses are recorded throughout the state, but the 2013 Tazewell County event accounts for half of that (CEMHS 2022). The types of losses reported can also offset the perception that a geographic area with a denser built environment will always result in higher economic losses.

For the prior tornado warning metric, an average of 265 warnings per county and an average annualized county rate of 7 warnings per year occurred from 1986-2022, with Logan, McLean, and Tazewell Counties experiencing the highest warning rates. High and low county warning rate distribution is similar to past tornado occurrences throughout Illinois counties, but the patterns are not identical. Counties with high warning incidences are visibly clustered in Central Illinois, while low warning incidences occur in the Northern and Southeastern regions of the state. However, there are many instances of warning issuance during severe weather without a subsequent tornado occurrence. This false alarm effect is proven to impact protective action behavior (Trainor et al. 2015) and is thus an essential contributor to the TROP framework. Additionally, there
are instances when tornadoes occur without warning issuance (i.e., missed event) (Ripberger et al. 2015a), so the two metrics are important to retain as separate measurements of physical risk. For example, a five-year study found that 26% of reported U.S. tornadoes occurred without an NWS warning issuance (Brotzge and Erickson 2010). Further, the NWS change in the tornado warning geometry from county to storm-based warning polygons in 2007 (Iowa Environmental Mesonet 2022) may influence the distribution of counts throughout the period of record.

Finally, the fifth physical tornado context metric in this study finds that while 2.4% of all housing units in Illinois are mobile homes, the average amount of mobile home housing units per county was 7.8%. Mobile home housing units are spatially concentrated throughout Illinois, with the northern half of the state displaying low rates and the southern half clustering most counties with high mobile home housing unit rates. Due to the increased risk of structural collapse of mobile and manufactured homes in tornado events, alongside the high rates of associated fatalities, the stark spatial clustering of these households is alarming. Research in the Southeastern U.S. also shows that residents of these structures believe their homes to be safe and do not execute proper protective action (Ash 2017; Ash et al. 2020), but further research is needed to determine if this belief extends to Midwestern residents. Regardless, residents occupying these households and counties with higher rates of mobile home housing units require access to nearby, safe sheltering options and targeted tornado communication and awareness campaigns to increase these residents’ risk perceptions (Liu,
While the reduction in mobile home housing units could reduce their associated losses, it is not always possible for these households to avoid mobile home housing altogether due to their low costs. Unfortunately, those occupying these housing units are also commonly associated with other social vulnerabilities that exacerbate their tornado risk (Lim et al. 2017) and resource availability for recovery (Strader and Ashley 2018).

Mapping and visually evaluating the physical context values using standard deviation classifications reveal counties with high physical risk contexts cluster in the state’s Central region. Overall, the geographic distribution of high, medium, and low physical context closely resembles that of the tornado occurrence input metric map, meaning that tornado occurrence may be the most accurate sub-indicator of the overall spatiality of the physical risk context. However, additional research in other states may be needed to confirm this is an actual pattern, not a research outlier for this study area. Ultimately, the autocorrelation assessment statistically confirms the visual clustering observed in the raw index mapping, with high physical context clusters in Central/East-Central Illinois. The highest-ranking counties of Tazewell, Logan, and Woodford are all adjacent neighbors and appear in a high-high cluster together due to their high and medium-high occurrence rates, exposure, losses, and warnings. All three of these counties contain a low rate of mobile home housing units compared to the rest of the state. Nevertheless, the lower mobile home unit rates are not influential enough to reduce their overall physical context values. Also of note, the Boone County outlier of high physical context surrounded by counties
with significantly lower physical context values is apparent in the tornado occurrence map but does not appear as an outlier in the exposure, loss, warnings, or mobile home input metrics.

6.1.2 Social Tornado Risk Context

In the social tornado risk context assessment, a Social Vulnerability Index (SoVI®) analysis (HVRI 2016) on 29 input variables contributing to community hazard vulnerability results in six retained components that explain the variables contributing to high vulnerability across Illinois counties. The distribution of social context values shown in standard deviation classification mapping uncovers high social vulnerability scores clustering in seven counties, including five counties along Illinois' Southern border, Chicago's Cook County, and Brown County in rural East-Central Illinois. These results demonstrate the dynamic structure of high social vulnerability across space driven by the level of urbanization and variables relating to race and ethnicity, class, gender, age, employment, and housing. The Southern Ohio Valley region counties consist of diverse populations, mainly rural, with variations in vulnerability drivers. Those counties with the highest social context scores, Pope, Pulaski, and Alexander, are strongly influenced by factor one (i.e., those who are elderly, disabled, or lacking broadband internet). Pope and Pulaski Counties are classified as rural and also load strongly in factor six (i.e., the female labor force). However, in addition to factor one, Alexander County loads strongly in factor three (i.e., single-parent, female-headed, and impoverished households, along with African Americans) seemingly due to its urban status. Chicago's Cook County loads strongest on
factors two (i.e., large housing size, Hispanic ethnicity, and Asian) and four (i.e., uninsured people, no automobile access, and renters), all typical characteristics of highly urbanized environments. On the other hand, Brown County contains one of the lowest populations in the state \((N = 6,599)\) and loads almost exclusively on factor five (i.e., low females, low education levels, and unemployment). Brown County has experienced a recent decline in employment and contains a large female population living in poverty, which could derive from the lack of work opportunities in rural geographies (Data USA n.d.). Overall, the SoVI\(^\circledast\) factor loadings provide insight into which vulnerable people greatly need future disaster risk reduction strategies.

Only two counties have low social vulnerability scores, Menard County in Central Illinois and Monroe County in the St. Louis metropolitan area. Both Menard and Monroe Counties are primarily suburban areas in their respective Metropolitan Statistical Areas of Springfield and St. Louis (USCB n.d.a.), which could contribute to lower levels of social vulnerability. The social context LISA assessment identifies a dominant high-high cluster of social risk values results in Southern Illinois. In contrast, a few smaller low social risk value clusters occur in the Central/North-Central region. The two outliers of high social risk counties (i.e., Mason and St. Clair Counties) surrounded by low social vulnerability are essential to note. Macon is adjacent to the low social context value cluster in Logan and Sangamon Counties, contributing to its outlier significance. St. Clair County is in the St. Louis metropolitan area and adjacent to Monroe County, which has very low levels of social vulnerability. St. Clair County also contains
East St. Louis, a historically marginalized city in St. Clair County with a 96% African American population and 29% persons in poverty (USCB n.d.d.). These two locations are significantly more vulnerable than their nearby county neighbors. As a result, they may be missing key targeted strategies for vulnerability reduction that are regionally focused since they are an outlier.

The resulting six factors from the SoVI® provide insight into the specific social vulnerabilities faced by different populations (e.g., older adults, those with disabilities, or populations lacking broadband internet), which may require targeted interventions to address their increased risk. Highly vulnerable people are more likely to live in mobile or manufactured homes, the housing structure type with the highest rates of tornado-induced fatalities (Lim et al. 2017). Research also shows that tornado risk is also affected by gender (Stokoe 2016), which is incorporated in multiple influential variables in the SoVI® results for the female-dominated variables in factors one, three, five (inverse), and six. In addition, education level drives understanding of warning information and response to warnings (Liu et al. 1996; Balluz et al. 2000; Blanchard-Boehm and Cook 2004), which appears in factor five as a dominant variable representing individuals with less than a high school education. This variable can directly contribute to the possibility of lower economic capital from decreased employment opportunities and decreased scientific understanding of tornado science that could impede risk processing.

Social vulnerability can directly impact tornado perceptions and response decisions, particularly in households with language barriers, disabilities, and of
low-income who lack appropriate communication, mobility, and monetary capital (Lindell and Perry 2012; Brotzge and Donner 2013; Trainor et al. 2015). For example, language barriers or a lack of access to media sources may hinder some minorities from receiving adequate warning information. Research has shown that ethnic and racial minorities perceive tornado risk differently from other groups. In this study, the Hispanic ethnicity variable in factor two is essential to social tornado risk influence and is a primary driver of high social vulnerability in Cook County. Additionally, racial variables are important drivers in factors two (Asian) and three (African American), contributing to high social context scores in Cook and Alexander Counties. These variables can impact tornado perception, possibly due to cultural differences in experiences with severe weather or access to information about tornadoes. So, it is vital to consider and address these differences in risk perception to improve the effectiveness of tornado preparedness and preparedness response efforts (Senkbeil et al. 2014).

Social vulnerability to tornado risk is a critical inclusionary variable lacking consideration in many other spatial assessments that may only focus on the geophysical risk or simplified vulnerability measures. Existing biophysical context and the social fabric of a community are known predictors of environmental hazard risk potential (Cutter 1996; Wisner 2016; Burton, Rufat, and Tate 2018), but previous geospatial conceptual models fail to clearly define or measure both elements of geographic context for tornado hazard risk (Cutter 1996; Mitchem 2004). Empirical approaches are steering toward the inclusion of geophysical and social vulnerabilities in tornado risk modeling. Recent research from Mishra
et al. (2023) expands tornado risk assessments to include vulnerability alongside exposure to predict tornado outcomes in terms of human losses. However, this approach only applies tornado occurrence data from 2005-2014 (not a full 30-year climatological period) and models vulnerability based on the less robust Social Vulnerability Index from the Centers for Disease Control (Rufat et al. 2019).

6.1.3 The Total Geographic Context of Tornado Risk

Combining the physical and social context measures results in a total geographic tornado risk context value per county that slightly differs from the variable inputs in spatial distribution. The highest total geographic risk values occur in Tazewell, Alexander, and Pulaski counties, while the lowest occur in Jo Daviess, Clark, and Carroll Counties. The total geographic context LISA assessment identifies a large high-risk total geographic context cluster resulting in Southern Illinois counties, which is heavily influenced by the high social vulnerability values in those counties. Low total context value clusters in the Northwest and East/Southeast are consistent with the low clusters resulting from the physical context LISA assessment. Interestingly, no significant county outliers existed for the total geographic context values. If only measuring the geographic context as a combination of physical and social variables, analyses will fail to uncover each metric’s unique spatial patterns and outliers.

Due to the physical and social context measures containing low-value concentrations in similar regions (i.e., Northwest and Southeast), the total physical risk values mirrored those low-value spatial patterns. However, the
differences in high-risk values among counties in the physical and social context indices influenced which counties display high total geographic risk. The high social context values attributed to Cook County and the Southern Ohio Valley counties increase the total geographic tornado risk context values when combining the indices. The high physical context values in Central and Southwestern Illinois counties also increase the total geographic tornado risk values. Tazewell County in Central Illinois contains the highest physical and total geographic tornado risk values but medium-low social vulnerability. The results of this study thus indicate that the Central Illinois region is an important location for structural mitigation interventions to reduce geophysical exposure. Improved wind load and vortex flow-based building codes for new residential and commercial buildings are crucial (Prevatt et al. 2013; Huang et al. 2016), as well as retrofitting existing structures. While many of these techniques are cost-effective, a significant hurdle exists in convincing policymakers and construction personnel of their immense benefits (Henderson, Huff, and Bouton 2021). Additionally, homeowner support for mandatory structural mitigation for tornadoes using building codes is challenging due to opposing public views on government regulation from conservative populations (Ripberger et al. 2018).

6.2 The TROP Model Effectiveness

To successfully address this study's second research question, the TROP model assessment evaluates the relationships between an individual's tornado risk perceptions, protective action behavior, and local physical and social geographic context. Creating risk perception and protective action constructs
from Exploratory Factor Analyses (EFAs) utilizing the Tornado Risk Survey responses determines the subconstructs best representing these latent variables. The assessment of the multidimensional constructs based on the final EFA retained factors is an appropriate data reduction technique for survey constructs in social and behavioral sciences to identify the smallest number of factors that explain the variance in observed variables (Watkins 2018). This methodological approach is proven helpful in hazard perception and response construct development and may inform future researchers conducting similar studies in other locations or analyzing different hazard types.

The Tornado Risk Survey assessment provides valuable insights into how people perceive and act upon tornado risks in Illinois. The risk perception EFA model was more robust than the protective action model, representing a higher percentage of variance in the data and a larger Cronbach's alpha value. However, both construct model results meet the acceptability level for social science analytics. Ten items measuring perceptions of tornado risk and ten items measuring tornado response behavior result from the EFAs. The EFA results show that personal/loved ones' tornado experiences, the extent of tornado knowledge, and perceived risk factors such as fear of warning, property damage worry, and life loss or injury worry significantly influence respondents' risk perceptions. These results confirm previous research finding past experiences are significant in increasing tornado risk awareness (Klockow 2013; Paul, Stimers, and Caldas 2015; Demuth 2018) and response (Silver and Andrey 2014; Paul, Stimers, and Caldas 2015; Schumann, Ash, and Bowser 2018). The
protective action EFA finds that individuals' personal and community levels of preparedness, home structure safety, and sheltering and warning options significantly influence their behavioral responses to tornado risks. The resulting factors from both EFAs can inform policies and interventions to improve risk management by targeting influential drivers of risk perceptions and protective actions. For example, Cook County may be a prime location for targeted tornado awareness campaigns since residents of Cook County hold the lowest risk perception and protective action construct scores. Hazard response depends on friend/kinship and social/community networks (Lindell and Perry 2004), with research showing that strong community involvement improves community tornado warning reception (Brotzge and Donner 2013). Since normative social influence is proven to influence tornado warning perception and comprehension (Parker 2017), and local disaster culture directly affects tornado response (Schumann, Ash, and Bowser 2018), strengthening these community systems could be beneficial in reducing overall tornado risk.

6.2.1 TROP Model Relationships

Implementing the TROP model framework employs an SEM to assess the direct and indirect relationships between the main drivers of community tornado risk, which would be difficult to measure using most statistical methods. The SEM method is helpful when examining complex conceptual drivers and investigates covariance patterns among variables based on a general linear model. It allows for the testing of direct causal variable relationships and through variables indirectly by applying a set of multivariate statistical methodologies designed for
social and behavioral sciences analyses (Hox and Bechger 1998; Bollen and Noble 2011). The SEM examines the relationships between physical context, social context, risk perception, protective action, and their measurement error terms, utilizing data from the 700 respondents of the Tornado Risk Survey. Each respondent's perception and protective action construct values resulting from the EFAs are linked to their county of residence physical and social context values for multi-scalar analysis, which helps adjust for the Modifiable Areal Unit Problem (MAUP) common in geographic research (Openshaw 1984).

The SEM of the TROP conceptual model is well-fitted to the input data and results in significant relationships between all four input variables. The SEM results find that physical context has a weak positive effect on individuals' tornado risk perception. Physical contexts' significant positive influence on risk perceptions is inherently understandable, as the increased level of past tornado occurrences or damages, for example, would increase individuals' awareness of the potential future risk. Studies have shown that individuals living in areas with a higher frequency of recent, intense tornadoes increase their risk perceptions (Johnson et al. 2021) and protective actions (Silver and Andrey 2014). However, the SEM's weak effect could result from the urban exposure, mobile homes, and tornado warning metric inputs mediating the total strength of the relationship. Landscape features that are manufactured or urban can be perceived as less vulnerable to a tornado (Mitchem 2003; Schultz et al. 2010; Klockow 2013), and tornado risk assessments in urban areas find a reduction in perceived risk (Simmons and Sutter 2011). However, research shows that urban exposure to
tornadoes is higher (Aguirre et al. 1993; Rosencrants and Ashley 2015), particularly in the Midwest (Strader et al. 2017) and Northeastern Illinois (Hall and Ashley 2008). Another potential mediator to the total physical context impact on risk perceptions is high rates of tornado warning issuance, causing the false alarm effect that influences public trust in warnings (Ripberger et al. 2015a). Research shows that high false alarm rates impact perception and response to tornadoes (Trainor et al. 2015), indicating that over-warning counties may manipulate individuals' total physical context effect on the model. Regardless, the SEM analysis confirms the proposed TROP model relationship of the physical context influence on risk perception.

Social context's resulting significant but weak negative effect on tornado risk perception provides a noteworthy discussion area. Overall, those with increased social vulnerabilities may have more pressing things to worry about (e.g., paying their bills, taking care of family, etc.) than natural hazard risks. The SEM relationship indicates that the higher the social vulnerability levels, the lower the risk perception levels. Inversely, the association is that lower levels of social vulnerability are significantly related to higher levels of risk perception. Many streams of research support this result, especially when considering a few specific social context input variables assessed in the empirical literature on hazard risk perception and response. Those populations with specific highly socially vulnerable characteristics relating to ethnicity and race (i.e., Hispanic and African American) are more likely to make incorrect tornado response decisions based on their lower levels of risk perception (DeWinter 2021). Differences in
linguistic communication barriers among Hispanic populations and those speaking English as a second language decreases risk perceptions (Senkbeil et al. 2014), and these individuals are less likely to trust and comply with tornado warnings if they receive them from fewer sources (Luo, Cong, and Liang 2015; Miran, Ling, and Rothfusz 2018). Age can also significantly influence the relationship between social context and perception, as children may not fully understand the danger and generally require adult assistance in emergencies. Additionally, elderly individuals are less likely to use smartphones or other recent technologies that would supply multiple sources of warnings in real time (Stokoe 2016), and they may have physical limitations that make the response to warnings difficult.

Individuals with disabilities are another critical variable in high social vulnerability to tornado hazards and is a characteristic commonly associated with elderly individuals who already possess increased vulnerability (Martins et al. 2020; Cappelli et al. 2020). Those with disabilities may find it challenging to read environmental cues based on limited mobility, which is essential when environmental cues are a primary motivator of mitigative behavior (Silver and Andrey 2014) by visually seeing the tornado or related debris (Donner, Rodriguez, and Diaz 2012; Jauernic and Van Den Broeke 2016). Additionally, environmental cues are proven to trigger evacuation decisions (Durage et al. 2014), which may be difficult when a physical disability limits mobility. The mobility issue from a disability is highlighted explicitly by a respondent to the Tornado Risk Survey, stating in the open-ended response, "My wife is
handicapped and has [a] mobility issue, so it takes me a while to get her down into the basement when we get a warning."

Lower-income individuals also possess increased social vulnerabilities to tornadic hazards, as they have less access to resources or capabilities to purchase emergency supplies and commonly have compound vulnerabilities. Research shows that lower-income individuals are disproportionately exposed to extreme weather hazards, experiencing higher rates of tornado-induced fatalities (Lim et al. 2017), and are less prioritized in tornado disaster recovery (Smart and Prohaska 2017). Education level is another significant social context contributor to the inaccuracy of risk perceptions as it influences one's understanding of warning information (Liu et al. 1996) and can lead to reductions in warning response (Liu et al. 1996; Balluz et al. 2000; Blanchard-Boehm and Cook 2004). These socio-economic variables are critical contributors to the SEM results of this investigation, and existing research supports their influence on decreasing tornado risk perception and response.

The resulting weak effect of social context on risk perceptions may be a product of specific demographic characteristics that research shows can increase perceptions or mitigation, even though they are known to increase overall social vulnerability to environmental hazards. One key example of this is the gender variable. Research shows that females have increased trust and reliance on tornado warnings, are more risk-averse (Stokoe 2016), and are more likely than males to take protective action when receiving a tornado warning (Silver and Andrey 2014). One critical tornado perception and response study utilizing an
SEM approach confirms this factor in finding females perceive fear at higher rates than their male counterparts (Schumann, Ash, and Bowser 2018). Reductions in risk perceptions can also occur when individuals live in the same geographic space for extended periods (Manzo and Perkins 2006; Masuda and Garvin 2006; Klockow 2013), so some respondents’ residency length could also be contributing to the weak result between social context and perception. Overall, respondents’ length of residency at their current home ranged from less than a year to 30 years or more. Over 60% of residents lived in their current homes for at least five years, around 43% for more than ten years, and 25% for more than twenty years. While longer home residency could positively influence local awareness of tornado risk, it can contribute to overall reductions of risk perceptions and mediate the resulting weak effect of social context in the SEM.

Unsurprisingly, risk perception has a moderate, positive effect on protective action, indicating that individuals are significantly more likely to take protective action if they perceive a higher risk. Research shows that risk perception is necessary to understand within the tornado mitigation process because it is the first cognitive step in the behavioral response process (Brotzge and Donner 2013). The psychometric paradigm (Slovic 1987; 2000) supports the TROP model results, finding that risk perceptions are a significant driver of response decision-making based on what is observable and dreaded. Individuals evaluate risk using multidimensional assessments based on these critical cultural and psychological factors alongside experts’ scientific hazard risk information, like tornado warnings (Klockow 2013). Further, SEM-based research on tornado
perception and response finds the visual interpretation of the warning graphic a critical predictor of warning response (Schumann, Ash, and Bowser 2018). The role of mass media must be explored further, as past research finds that individuals' tornado perceptions can increase when they trust their local weathercaster (Sherman-Morris 2005). However, contemporary advancements in warning dissemination and social media proliferation are changing how the public receives and interprets warnings (Ripberger et al. 2014; Finch et al. 2016), and fewer people watch cable news or broadcast television in the modern era. This investigation incorporates different warning sources, including those from social media and online outlets, in designing and assessing the latent construct inputs. These warning variables ultimately influence the significant EFA factor results for protective action response relating to respondents' warning options.

Overall, risk perception mediates the relationship between context and response, with indirect effects from physical and social contexts. The results also include an unexpectedly significant negative correlation between respondents' physical and social context. This correlation means either: (1) the higher the physical risk context, the lower the social vulnerability of the individual's county of residence; or (2) the higher the social vulnerability, the lower the physical risk context value. However, this statistic results from the 700 individual respondents' context values in the 72 counties represented, and some respondents occupy the same counties. As an alternative means to assess the connection between these two variables, Pearson's $r$ correlation between the physical and social context values in all 102 counties results in an $r = 0.064$ value and is insignificant, and
the correlation in only the 72 counties with a survey response is also insignificant at an \( r = -0.024 \) value. This result better represents the relationship of the calculated physical and social geographic context values in the study area, which are not linearly related and should thus remain separate measurements. Notably, the variance accounted for by physical and social contexts in the risk perception and protective action variables is relatively low \( (r^2 = 5\% \text{ and } 9\%, \text{ respectively}) \). These low \( r \)-squared values mean the model is weak because the contextual predictor variables explain a small percentage of the perception and response variables’ variation. The small \( r \)-squared values alone do not indicate a bad fitting model, though, as it is impossible to include all relevant predictors to explain an outcome variable in a social scientific study. Regardless, this SEM analysis proves helpful when examining the complex conceptual drivers of tornado risk outcomes that cannot be directly observed, allowing for successful empirical assessment of the TROP model framework.

This investigation proves the effectiveness of a novel conceptual paradigm, the TROP model, in assessing the geographic context of tornado risk and its influence on risk perceptions and protective actions. The TROP model addresses the shortcomings of the currently employed conceptual models assessing hazard risk and place-based vulnerability, bridging the gaps between their missing elements to understand their complex interactions. The two standard conceptual models for understanding place-based environmental risk and vulnerability, namely the Protective Action Decision Model (PADM) (Lindell and Perry 2004; 2012) and the Hazards-of-Place (HOP) model (Cutter 1996),
have been widely applied in empirical studies of natural hazards, but they have certain limitations. The PADM model focuses on all-hazard experiences and fails to account for geographic context and social vulnerability. The HOP model considers geographic context as a casual element but lacks practical measurement, and the model does not include perceptions and responses. The TROP model incorporates influential physical and social context variables into the perception and response risk equation. By empirically testing the TROP model, this study provides a valuable addition to the existing literature on hazard perceptions and responses specifically designed for place-based tornado risk.  

6.2.2 Tornado Risk Survey Open-Ended Responses

A few key discussion points are worth noting in a post-analysis review of respondents' text responses to the one open-ended questionnaire item asking if there is anything else they would like the researcher to know about their perception, response, and understanding of tornado risks. While only 64 respondents (9%) answered the open-ended item, their responses still provide some valuable insights into the contributions of the research design to increasing awareness, preparedness, and overall tornado response behavior. Overall, many respondents voiced concerns over the need for better risk awareness, safer sheltering locations, or how their experiences impact their current perspectives on tornado preparedness and protective actions. A few respondents specifically detail past tornado experiences or those of their loved ones, which directly contributed to increased risk perceptions and protective action behavior. Two respondents specifically cite the 2013 Washington EF-4 tornado (USDC, NOAA,
and NWS n.d.d.), which occurred nine years before the completion of the survey.

One respondent is a Tazewell County resident who suffered damage from the event. She specifically highlights the extra measures her household now takes after living through the event. She writes,

A devastating EF4 tornado hit our town in 2013 and our house was damaged along with about 1000 others that were destroyed or damaged. Prior to that, we always heeded tornado warnings by going to the basement, but now we do extra things like make sure we are fully dressed; gather money, phones and chargers, water, flashlights, etc. to take to the basement with us; and have a transistor radio with us for updates. We stay awake if severe weather is predicted at night.

The other is a resident of a nearby town (about 15 minutes away from Washington) who reports how their perceptions and responses have changed since the 2018 tornado event. They also cite their increased vulnerabilities due to living in an apartment complex, a circumstance unavoidable at the time due to their budget. They explain the following:

I live in an apartment that doesn't have any tornado shelter. You'd think living in tornado alley that all apartments would have some form of tornado shelter but they do not. I grew up in houses with basements so this has been a huge shock to me and I get considerably more frightened during tornado warnings now cause the best place we can shelter is in the inner bathrooms in our second floor apartment. I lived 15 minutes away from the devastating Washington tornado and I know what a tornado can do to an apartment complex. It's terrifying but I do not have the option to move right now.

A few individuals discuss the proliferation of tornado awareness information, or the need for it, in shaping their perspectives. One Cook County resident noted, "People who are prone to tornadoes activities should receive tornadoes' handbook." Another Cook County resident discussed how their child learned about tornadoes in school and brought that knowledge home to the rest of the family. He states,
My daughter is in third grade. At the beginning of the school year, they taught her about tornado watches and warning, what to do in school as well as at home. She shared this new information with the rest of her family, even though she admitted she knew most of it. So, if my family wasn't knowledgeable before October 21, we most certainly are now!

A key takeaway from this response is that educational campaigns for school-aged children may successfully alter the perceptions and behaviors of their families at large. As such, tornado hazard education must continue in locations where it currently occurs and be implemented in areas where it is not yet taking place. Interestingly, only one individual discussed their general acceptance of the risk because tornadoes are unavoidable in the study area, stating, "I live in the Midwest. Tornadoes happen." This response closely aligns with the fatalistic attitude that occurs when people acknowledge risk but believe they have little control over the outcome of an event (Jauernic and Van Den Broeke 2016).

Respondents also mention the lack of adequate tornado sheltering availability and how mitigative improvements to current structures are a concern in the study area. A handful of respondents specifically explain the need for better sheltering options: (1) "A safe place should be available in every area for people that don't have a basement or safe area in their homes"; (2) "I wish that there was a real tornado shelter near me"; and (3)

I live in a small apartment with no really good sheltering options. There is one little spot in the basement, but it has windows to the outside and is also right next to the boilers, so it's hardly the best place to hide, but it's all I've got. I am worried that a decent-sized tornado could rip the entire building out of the ground and us with it, but there's nothing I can do.

These statements highlight the need for further research on sheltering availability, especially concerning highly vulnerable populations. One resident explicitly emphasizes the need for improved structural mitigation for tornado
risks, stating, "Homes should be built with stronger materials." Intriguingly, this Cook County resident took the time to advocate for a change in the current standard practice of home construction despite research showing that homeowner support for mandatory structural mitigation for tornadoes is challenging to obtain (Ripberger et al. 2018).

Many respondents are grateful for being informed or reminded to be more aware and prepared for the next event: (1) "Good reminder with this survey. Always being prepared to be prepared if needed"; (2) "This survey was interesting. It let me know I could be more aware and continue with education and research of tornadoes"; (3) "Recounting this with you has made me consider being better prepared in the event of impending danger"; (4) "Thanks for your survey. It made me think and be better prepared for the next warning"; (5) "Thanks for a survey like this to keep me better prepared for a tornado"; (6) "What a different but excellent survey, and the importance of this survey is crucially important to awareness and safety during bad weather! Thank You So Much!" and (7) "Great informative survey. I hope people are prepared after taking this survey. Thanks." These responses provide validation regarding the added value of this dissertation work by mere participation in the Tornado Risk Survey and are an unexpected bonus contribution of this investigation.

6.3 TROP Model Outcomes Differ by Region

The TROP model outcome assessment allows for regional comparisons of survey respondents’ total risk measurement within the Illinois state study area and empirical validation of the TROP model. The study examines differences in
TROP outcome values among residents in urban-rural counties, Northern-Central-Southern Illinois Nature Conservancy regions, IEMA regions, NWS County Warning Areas (CWAs), and StormReady® designated counties. Statistical analyses, including t-tests, ANOVA, and post hoc tests, assess whether the mean TROP outcome values differ significantly across these regions. The investigation's null hypotheses for each regional assessment state that the populations within the study areas do not contain significantly different mean TROP outcome values. However, all five regional assessments reject the null hypothesis due to significant geographic-based differences in tornado risk outcomes. The results find significant differences in TROP outcomes among all regional classifications, reflecting place-based variances in tornado risk evident in the preceding phases of the dissertation analyses.

The study finds statistically significant mean differences between the TROP outcome values of urban and rural respondents, with urban respondents having higher TROP means. There were also significant differences in TROP outcome values between residents of StormReady® and non-StormReady® counties, with StormReady® county respondents having higher TROP outcome means. Furthermore, there were significant differences in TROP outcome values between respondents in the three Illinois Nature Conservancy regions, five NWS CWAs, and eight IEMA regions. The Northern region holds higher TROP outcomes across all three of these delineations. The Northern Nature Conservancy Region contains significantly higher TROP outcome means. The Chicago CWA holds significantly higher TROP outcome means than the
remaining four regions. The IEMA regions with significantly higher TROP outcome means are IEMA 4 (i.e., Chicago region) and 11 (i.e., Southern Illinois). However, the results of this assessment could stem from higher questionnaire response rates in Chicago-area counties. The disproportionate number of respondents in these counties potentially impacts the statistical analysis results in the regional assessment. Nonetheless, the proportion of the population in the state is much higher in the Chicago metropolitan area, and the survey sample design sought a representation of the state population.

Overall, the present study applies a comprehensive approach to examine the statistical interactions between the conceptual drivers of tornado risk and assess regional differences in the tornado risk outcome measure. The study's findings could have implications for policymakers and emergency management agencies in developing effective strategies to mitigate tornado risks in different geographic regions. For instance, the conclusion that urban residents have higher TROP outcome values than rural residents suggests that emergency management agencies should prioritize tornado awareness and preparedness campaigns in urban areas. Similarly, the finding that StormReady® county residents have higher TROP outcome values than non-StormReady® county residents suggests that the StormReady® designation doesn't imply reduced risk. Nonetheless, communities should still seek StormReady® certification to improve their tornado preparedness. Those counties seeking StormReady® involvement might be doing so because they possess higher risk and may need additional guidance and support to strengthen response capabilities. Becoming
StormReady® may also increase tornado education and preparedness programs, but the effectiveness of the StormReady® campaign requires further empirical evaluation. Finally, the study’s finding that TROP outcome values vary across Nature Conservancy regions, NWS forecasting areas, and IEMA regions can inform targeted tornado preparedness resources in these Northern Illinois geographies. The study underscores the importance of understanding spatial variability in tornado risk variables to tailor effective outreach campaigns and mitigation approaches.

Tornado risk and exposure vary greatly by spatial scale (Ashley and Strader 2016), and perceptions and responses are a product of risk proximity and place attachment (Peppler, Klockow, and Smith 2017). Many previous regional assessments of tornado risk fail to examine finer-scale regional differences within a state and instead focus on larger continental U.S. regional delineations (e.g., North, South, Southeast, Great Plains, Midwest, etc.) in objective climatology-focused analyses (Trapp and Brooks 2013; Strader et al. 2017; Moore 2018; Biddle et al. 2020). Macro-scale regional assessments are less valuable when tornadoes generally transpire in a localized environment (Bluestein 2013) with spatially limited impacts (Thomas and Mitchell 2001), and emergency management operations occur locally in state and county areas. A few assessments examine localized regional risk differences among CWA delineations, assessing tornado vulnerability differences in Texas CWAs (Dixon and Moore 2012), tornado climatology between states in the Memphis CWA (Gonteski 2022), or tornado occurrence in Kansas CWAs (Jagger, Elsner, and
Widen 2015). Others evaluate educational institutions’ preparedness, perceptions, and responses (Hoekstra, Nichols, and Gruntfest 2014) or students (Jauernic and Van Den Broeke 2016) at universities enrolled in the StormReady® program. This investigation adds to the current literature in assessing the totality of tornado risk between multiple localized regions of a study area, not just CWAs or those at StormReady® designated schools, to determine multivariate high-risk regions based on a holistic metric of geographic context, perceptions, and protective action behavior.

6.4 TROP Model Sensitivity

Creating a TROP outcome measure for each survey respondent provides a value to conduct a sensitivity analysis on the total tornado risk measurement with historical tornado loss estimates in their counties of residence. The TROP model validation applies three practical measures of tornado losses as aggregate counts from 1960-2020: economic loss (i.e., property and crop adjusted for inflation to 2020 USD), human injuries, and fatalities. The results find the TROP outcome values significantly and positively correlate with increasing monetary damages, injuries, and fatalities, which confirms that the TROP model outcomes directly relate to local tornado loss outcomes. These results support previous spatial tornado modeling for the continental U.S., validating their findings based on human injuries and fatalities (Shen and Hwang 2015). However, this earlier study did not validate their model using monetary damages nor incorporate social risk variables, and the study only assessed tornado records up to 2012. The findings of this investigation suggest that the TROP model effectively predicts the
tornado risk in the recent climatological era and can be utilized to evaluate potential economic and human damages from future tornado events based on both physical and social context influences. The results of this study are applicable in disaster management and preparedness by providing a valuable tool for decision-makers to allocate resources and prepare for tornado losses at the local level.
CHAPTER 7

CONCLUSION

There are many vital considerations in geographic analyses of physical and social contextual influences on population risk perception and behavior related to tornadoes. Due to tornado hazards’ spatially limited nature, it is essential to assess geographic differences in risk, as all places are unique and experience different levels of exposure to these hazards. This study’s rigorous geospatial and statistical research approach controls for broad-scaled tornado risks to measure the TROP model inputs, assess their interactions, and test the conceptual relationships proposed between physical context, social context, risk perception, and protective action response. This study proposed that including geographic context and its influence on perception and behavior produces differential tornado risk and sought to uncover which factors are the most significant contributors to such variability. This dissertation research successfully determined how geographic context elements influence place-based tornado risk experiences in a U.S. case study of Illinois. Ultimately, the results uncover how the nature of ‘place’ plays a role in tornado risk perception and protective action decision-making and that risk perception is the more influential driver of mitigative action. However, physical and social contexts also have a role to play as driving elements of tornado risk. The significant relationships uncovered in the analysis are directly relevant to empirical advancements in tornado risk.
assessments, as well as practical emergency management and policy approaches to reduce the impacts of these severe weather events. Based on these results, future hazard research and mitigation approaches that consider geophysical context, underlying social vulnerabilities, risk perceptions, and protective action decision-making can be designed and implemented.

7.1 Research Question One

The first research question in this investigation asks how the physical and social geographic contexts of community tornado risk vary across space. The geospatial and statistical methods applied in this study analyze the spatiality of tornado risk and identify areas with high and low levels of geographic risk context utilizing relevant socio-environmental data. Quantifiable indicators measure Illinois counties' physical and social tornado risk context and produce aggregate context metrics across the study area. The study evaluates the geospatial clustering of these factors separately and a combined total geographic context measurement employing spatial autocorrelation statistics as an extension of the visual choropleth mapping evaluation that categorizes risk levels based on standard deviations from the mean.

The study's findings reveal that the spatial distribution of tornado risk based on the physical and social geographic context in Illinois counties is uneven, with varying values across counties. The study finds that Central Illinois counties have higher physical tornado risk when considering five input metrics: tornado occurrence; urban exposure; prior consequence; warning incidence; and mobile home housing risk. These results directly apply to policymakers,
engineers, and construction personnel to design and implement effective structural mitigation interventions to reduce geophysical exposure in high-risk areas like Massac, Tazewell, and Logan Counties. The research study results are also essential for Illinois's policymakers, emergency managers, and the public to better understand the spatial distribution of geophysical tornado risk in the state, and its findings can aid in the development of non-structural mitigation and response strategies to reduce the potential for economic and human losses. The study adds to the available literature on spatial-statistical assessments of tornado incidence by developing an occurrence metric weighted by event magnitude and adjusted based on county size, providing up-to-date data for tornado exposure assessments since the reduction of the reporting bias. Future work could consider a moving period of climatological data to continue diminishing the reporting bias in risk modeling by repeating the analysis from 1993-2022, 1994-2023, 1995-2024, and so on as data becomes available. Additionally, future research should address the limitation of storm-based tornado warning polygon counts by developing an advanced method to adjust warning counts to account for this data discrepancy.

Compared to physical context risk concentrations in Central Illinois, Southern Illinois along the Ohio Valley and the Chicago urbanized area contain higher social vulnerability as a measure of social tornado risk context. The SoVI® analysis of tornado risk identifies six retained components contributing to community tornado hazard vulnerability. The six factors include variables related to socio-economic characteristics like age, ethnicity, housing size, gender,
education level, and employment. Since social vulnerability can directly impact tornado perceptions and response decisions, particularly in households with language barriers, disabilities, and lower income, aiding these socially vulnerable populations is crucial. The findings of this investigation provide insight into the specific drivers of social vulnerabilities faced by different people, which may require targeted interventions to address their increased risk. The geospatial clustering of high social context values in certain counties (e.g., Pope, Pulaski, and Alexander) suggests that these areas may require more resources and attention to address the specific social vulnerabilities of their populations. SoVI® is a valuable tool for assessing the social context and identifying vulnerable populations, providing a critical contribution to holistic research on tornado risk assessments at the local level for improving disaster preparedness and informing policy decisions to mitigate vulnerabilities. Future research could focus on enhancing tornado risk assessments to include vulnerability alongside exposure, which adheres to current FEMA hazard mitigation planning requirements.

The study’s geographic context assessment allows for accurately measuring tornado risk in Illinois counties based on physical and social context indicators. By mainly utilizing publicly available open-access sources, the study ensures its methodology is transparent and replicable. The only cost-prohibitive data source originates from SHELDUS, but the NWS Storm Events Database provides a free dataset for aggregate losses per county as an open-access replacement. The study’s statistical and spatial data assessment also permits identifying spatial patterns and trends in tornado risk across Illinois counties that
are expandable to other geographic areas. Including geographic contextual elements in tornado risk and vulnerability research is crucial for informed mitigation decision-making (Pine 2009; Müller-Mahn, Everts, and Doevenspeck 2012), particularly for the spatial differences in tornado exposures and outcomes. Ignoring geographic contextual influence can be easy due to spatial data aggregations or inappropriate cartographic representations (Fekete 2012). When this information is applied to inform policy or emergency management decisions, it can have detrimental results if inaccurate. The spatial differences in high physical and social risk underscore the importance of measuring these contextual variables separately to understand tornado risk drivers across geographic areas holistically. The underlying social and physical clusters can be easily overlooked when combining the two measures and creating one metric for the total geographic context. As a result, targeted emergency management strategies and policy initiatives may be ineffective or focused on the wrong locations by failing to uncover critical information necessary for effective mitigation interventions.

Overall, the case study contextual analysis results uncover the specific geophysical and social vulnerabilities different populations face and their spatial variation across the study area, answering this investigation’s first research question. The results find that changes in geographic context variables can increase tornado exposure and risk at the community level. These findings contribute to the tornado risk literature by providing insights into the geographic context of tornado risk and its differential distribution in Illinois counties. Future
research could expand the study to other states to provide a broader evaluation of tornado risk at the county level and compare results to the Illinois case study. However, future work must consider full 30-year climatological periods for objective tornado occurrence variables and evaluate the effectiveness of different social vulnerability metrics in methodological design choices.

7.2 Research Question Two

This study’s second research question asks how the conceptual drivers of tornado risk (physical context, social context, risk perception, and protective action behavior) interact based on the TROP model. The investigation successfully executes the TROP model assessment to uncover the statistical strength of the relationships between these tornado risk drivers utilizing the individual-level responses from the Tornado Risk Survey and the county-level geographic context metrics developed to answer research question one. The EFAs determine which factors measured in the Tornado Risk Survey best represent the latent variable constructs of risk perception and protective action. The EFA results demonstrate that personal tornado experiences or those of loved ones, level of tornado knowledge, and fear of damage significantly influence respondents’ risk perceptions. The protective action EFA indicates that individuals' personal and community levels of preparedness, home structure safety, and sheltering and warning options significantly affect their behavioral responses to tornado risks. Both EFA models’ resulting factors can inform policies and interventions to improve risk management by targeting influential drivers of risk perceptions and protective actions. This methodological approach
is helpful in hazard perception, and response construct development and provides valuable guidance for future researchers.

The SEM estimates the interactions between all measured conceptual drivers of tornado risk, uncovering the differential variable influences of tornado risk via implementing the TROP model framework and addressing this study’s second research question. Physical and social risk context significantly drives risk perceptions, while perceptions directly drive protective action decisions. In turn, physical and social risk contexts indirectly contribute to individuals’ protective action decision-making relating to tornadoes. Physical context has a weak positive effect on individuals’ tornado risk perception, while social context negatively impacts tornado risk perception. Both contextual relationships with risk perceptions are consistent with findings in current literature but contribute to the knowledge base in enumerating the strength of these variable influences. The most robust statistical relationship is risk perceptions’ direct influence on protective action behavior, supported by the psychometric paradigm and previous tornado empirical studies consistently finding individuals’ prior experiences to be a significant driver of perception and response. Overall, risk perception mediates the relationship between context and response, with indirect effects from physical and social contexts. However, the variance accounted for by physical and social contexts in the risk perception and protective action variables was relatively low, indicating that the contextual predictor variables explain only a small percentage of the variation in the perception and response variables. These results emphasize the importance of considering and
addressing differences in risk perception to improve the effectiveness of tornado preparedness and response efforts.

This study's successful use of the TROP model assessment and its associated survey instrument provides an effective approach to evaluating the relationships between tornado risk perceptions, protective action behavior, and local physical and social geographic context. The study's methodology and data analysis approaches also offer practical guidance for future social and behavioral sciences hazard research via a spatial assessment framework. The assessment of multidimensional constructs based on the final EFA retained factors and the SEM analysis uncover the conceptual drivers of tornado risk outcomes that cannot be directly observed. The findings of this study also provide a valuable contribution to the literature on geographic tornado risk assessments that incorporates all known variables of influence into one conceptual model. Nevertheless, future research should continue to explore the role of space-time factors in shaping individuals' tornado perceptions and response behavior in other study areas to build upon these results. For example, empirical studies should critically explore the changes in warning dissemination to online formats and how perceptions or response behavior adapt to these new sources.

Future scholars can also adapt and apply the Tornado Risk Survey for their study area population but must consider sample representation of the total population demographics. The demographic representation in this study sample suggests that the survey's results are generalizable to the larger population of Illinois and thus practically employable. Empirical studies employing survey
methodologies must also consider open-ended or more qualitative-based approaches to holistically understand individuals’ perspectives and experiences. The handful of written responses in this investigation provides valuable insights into the contributions of the research design of the Tornado Risk Survey to increasing awareness, preparedness, and overall tornado response behavior. Those respondents answering the open-ended item expressed concerns about the need for better risk awareness, safer sheltering locations, or how their experiences impacted their current perspectives on tornado preparedness and response. Most impactfully, many respondents articulate gratitude for being informed or reminded to be more conscious and prepared for the next event, underscoring the value of their mere participation in the study in increasing tornado risk awareness and appropriate protective action behavior.

7.3 Research Question Three

The third and final research question asks if tornado risk varies across different geographic regions within a U.S. state, which was answered in this investigation via the Illinois case study. The regional assessment of the Tornado Risk Survey respondents’ TROP model outcomes offers a better understanding of local spatial variability in the combined tornado risk variables. The study’s approach of examining finer-scale regional differences within a state is valuable, as tornadoes generally occur in a localized environment with spatially limited impacts, and emergency management operations occur locally in state and county areas. The study examines five different regional delineations in the Illinois study area to determine whether there are differences in mean values of
the TROP model outcome measurement for each survey respondent. The TROP outcome calculation derives from the four conceptual drivers of tornado risk: physical context (+), social context (+), risk perception (-), and protective action behavior (-). The study finds statistically significant differences in the mean TROP outcome values across five regional delineations of Illinois, with urban respondents, residents of StormReady® counties, and respondents in the Northern Illinois Nature Conservancy region, Chicago CWA, and Chicago IEMA region possessing higher TROP outcome values than those in other regions.

The TROP model outcome assessment highlights the importance of understanding geographic variability in tornado risk variables to tailor effective outreach campaigns and mitigation approaches. The study results have implications for policymakers and emergency management agencies in developing effective strategies to reduce tornado risks in different localized regions. The finding that urban residents have higher TROP outcome values than rural residents suggests that emergency management agencies should prioritize tornado awareness and preparedness campaigns in urban areas like Chicago. The result that StormReady® county residents have higher TROP outcome values than non-StormReady® county residents suggests that the StormReady® designation does not necessarily imply reduced risk and future research on StormReady® effectiveness on tornado risk reduction is needed. The study's finding that TROP outcome values vary across Illinois Nature Conservancy regions, NWS CWAs, and IEMA regions can also inform targeted tornado preparedness resources in Northern Illinois. Additionally, these types of
campaigns will reach more people in a densely populated area, resulting in an increased value of the investment.

The TROP model output sensitivity analysis confirms that respondents’ tornado risk outcomes relate directly to local tornado economic and human losses. The TROP model effectively predicts tornado risk and can be used to evaluate potential damages from future tornado events based on physical and social context influences and differences in perceptions and behavior. This study contributes to the literature on validating tornado risk assessment models utilizing the TROP framework. It also provides a valuable tool for decision-makers to assess the potential risks and damages from tornado events and better allocate resources in areas with a high loss potential. Future research can expand on this study by testing and validating the TROP model in other geographic regions or assessing its effectiveness in future disaster events.

7.4 Overall Contributions

This study's transparent methodology and open-access data sources allow for replication in other states and regions to evaluate tornado risk in different contexts, thereby contributing to a broader understanding of the spatial distribution of TROP variables. The employment of the county-level unit of analysis for the contextual risk analysis is appropriate due to its widespread data availability, ease of spatial aggregation, practical emergency management operation structure, and representativeness in measuring community dynamics in geographic empirical investigations. A sample of Illinois residents at the individual level that demographically represents the broader study population
also allows for multi-level analytics of tornado risk perceptions and protective actions. The Tornado Risk Survey is also directly transferable for utilization in other study areas to measure latent constructs like perception and response. However, scholars must consider sample representation of the total population demographics to generalize survey analysis results. The open-ended responses to the survey also underscore its practical contributions to increasing awareness and response behavior of those participants involved in the study. Future work utilizing the Tornado Risk Survey could also incorporate more qualitative-based methodological design to expand upon this study’s findings via an in-depth investigation of the open-ended responses.

7.4.1 Intellectual Merit

Overall, the present study empirically contributes to the literature by providing insights into the complex relationships between context, risk perception, and protective action and has implications for disaster risk management. This investigation first adds critical intellectual contributions to the field of geography, specifically in the hazards-disasters subfield. The methodological and conceptual approach applied in this investigation contributes to geography literature on environmental hazards and Geographic Information Science, particularly in attributing social science phenomena to the spatial characteristics of place. The study’s findings also contribute to the literature on tornado risk and exposure, which vary significantly across space. This research also addresses the empirical gap related to community-specific effects on tornado action responses that incorporate local measurements of social
vulnerability, a critical area of study in social science research that continues to expand alongside the Environmental Justice movement.

Conceptual advancements of the study include the development of a researcher-designed framework and effective conceptual model (i.e., TROP) to refine the current intellectual understanding of place-based tornado risks. While there are theoretical and conceptual underpinnings to hazard response processes among the public, fewer are specific to tornadoes. The new TROP lens is designed explicitly for tornado hazards rather than an all-hazards assessment that is conceptually abstract and does not account for hazard-specific variable influence. Ultimately, this research addresses a critical gap in understanding the variability in drivers of tornado risk perception and spatial context influences on protective action behavior that is empirically validated. Enhanced intellectual contributions to social science based on geographic risk drivers are crucial to strengthening tornado risk assessments that inform strategies for disaster risk reduction.

7.4.2 Broader Impacts

Practical contributions of this research include key results for targeting improvements in emergency management decision-making and hazard mitigation assessments. Emergency managers conducting government-mandated mitigation assessments require up-to-date knowledge of natural hazard risks like tornadoes to make appropriate decisions on preparing for, responding to, and mitigating hazard threats. Overall, the study provides valuable contributions to tornado risk assessments by developing quantifiable metrics of
physical and social context indicators at the county level. The study’s results help uncover influential variables in risk perception and protective action response to tornadoes so more accurate risk assessments can occur based on geographic contextual elements. Enhanced risk assessments can help protect those socially vulnerable populations who commonly bear the brunt of hazard risk burdens and help to decrease the societal impacts of tornadoes.

The Illinois county-level SoVI® analysis findings could help inform mitigation approaches and policy decisions to address social vulnerabilities and improve disaster preparedness. The creation of this investigation’s SoVI® indicator also addresses calls for local spatial planning improvements for disaster risk reduction through integrated risk and vulnerability mapping (Sutanta, Rajabifard, and Bishop 2010). Since social vulnerability is a multidimensional, preexisting condition that varies over space and time (Cutter 1996; Hill and Cutter 2001), this study’s metric of local vulnerability is based on the most recently-available data and empirically validated indices like SoVI® (Rufat et al. 2019). Since SoVI® applies open-access USCB data and ACS 5-year estimates are released annually, it is possible for emergency managers to continually update social vulnerability metrics and account for dynamic population changes (HVRI n.d.). Fortunately, recent updates for state hazard mitigation planning requirements from the Federal Emergency Management Agency (FEMA 2023a) include social vulnerability components in the hazard identification and risk assessment component of mitigation plans.
The statistical and spatial evaluation allows for identifying spatial patterns and trends in tornado risk across Illinois counties, which IEMA can immediately apply in strategic approaches to tornado risk reduction. The results can assist Illinois policymakers and planners in identifying areas of high tornado risk and allocating resources for disaster preparedness and response efforts. For example, they can help improve the design and implementation of early warning systems for tornadoes for at-risk populations and aid in developing more effective building codes and land-use policies. Stakeholders can target these applications to communities containing higher physical and social risk based on the results of the geographic context assessment to address local drivers of tornado risk and reduce losses. The findings of this investigation can thus help inform policy decisions to mitigate vulnerabilities and improve severe weather preparedness, response, and recovery.

The results of this investigation lead to several practical implications for severe weather disaster risk management holistically based on the TROP model framework assessment. The finding that risk perception is a moderate mediator of the relationship between context and response suggests that disaster risk communication programs should focus on increasing risk perception to promote protective action. Moreover, the weak effects of physical and social contexts on risk perception highlight the importance of considering individual characteristics (e.g., age, income, and education) alongside community-level socio-environmental variables in tornado risk perception and response research. The study’s findings also suggest that tornado risk management programs across the
U.S. should incorporate physical and social context variables separately into their planning, as these geographic contextual variables indirectly contribute to variations in tornado response. Identifying areas of significant spatial clustering and outliers of tornado risk drivers can also inform decisions regarding the placement of sustainable public infrastructure and allocating resources to promote equitable disaster outcomes. The study underscores the importance of understanding spatial variability in tornado risk variables to tailor effective outreach campaigns and risk-reduction approaches to those most in need. As such, the study’s findings can inform NWS’s communication strategies relating to locational and scalar influences on public response to tornado risks. These results also aid in validating the StormReady® program and modernizing NWS tornado warning approaches via up-to-date research investigations.

7.5 Noteworthy Limitations

In discussing this investigation’s scientific and practical merits, it is important to recognize limitations to the study’s research design. Common survey limitations include the participants’ ability to recall information, otherwise known as the recall bias. Reductions in recall bias include the employment of the instrument during tornado season, which may also introduce an awareness bias. Future work could consider deploying the Tornado Risk Survey in the winter months to the same sample population and evaluate any changes in their construct results. Online surveys and recruitment can be complex due to issues like retaining engagement and survey fatigue. Attempts to combat this problem include a costly survey sample and applying Qualtrics’ quality control methods,
resulting in a high response rate (60%). Regardless, the study relies on self-reported data that may be subject to response biases that are difficult to avoid. An additional data limitation is that only 71% of Illinois counties hold at least one survey respondent, and most unrepresented counties are rural. However, the questionnaire sampling design targeted population representation, so most respondents come from an urban designated county (88%). However, not all researchers or practitioners have the funds to access a representative sample. Alternatively, they may rely on other sampling methods and extended data collection periods to obtain a larger sample size (Hendra and Hill 2019).

Other potential limitations of this study include the lack of sensitivity to questionnaire constructs because latent variables like tornado perceptions mitigation are only self-reported. SEMs provide a quantified way of analyzing latent variables that can be hard to capture or accurately measure, so the model fit evaluation and inclusion of error measurements minimize this limitation. Unfortunately, the TROP SEM model is weak regarding explained variance in the perception and response variables. Future research should attempt to improve the variance explained by these variances in the squared multiple correlations without sacrificing model fit. Another weakness of this study is that the regression analysis does not include spatial weighting like in geographically weighted regression (GWR) techniques. This investigation’s dataset, which incorporates latent variables and multi-scalar inputs, is inappropriate for this type of analysis. There are also no known current software capabilities for running a GWR-based SEM. In the coming years, there is hope for developments of GWR SEM
approaches with techniques for spatial weighting that can integrate multi-scale datasets. Spatial lag/spatial error regression models are additional geographically weighted methods of assessing TROP variable relationships that may help remove randomness influence and dramatically improve the low explained variance. Unfortunately, the type of data employed in this study is not appropriate for spatial lag or spatial error models, which require non-overlapping polygon inputs.

Geographic assessments provide a unique perspective to explorations of the influence of geographic context on tornado risk perception, response, and overall risk distribution, but they contain inherent spatial data limitations. Spatial models of tornado risk at the state level alone are inefficient, requiring smaller spatial units to be more practical in policy applications. The spatial scale of any place-based assessment will never be perfect, but the research design did consider scale throughout the analyses to avoid the MAUP. The MAUP dictates that a study’s unit of analysis/geographic scale choice must accurately represent the data or population, which can impact the results of empirical analyses when changing the level of analysis (Openshaw 1984). This study’s multi-scalar data collection and analysis techniques help combat this inherent issue to geospatial analyses, collecting open-access context data at the smallest unit that aligns with practical emergency management approaches (i.e., county) to combine with individual-level latent constructs. However, future work could assess contextual tornado risk variables at a different spatial scale (e.g., census tract) and compare results to validate this investigation. Future survey data collection could also
collect refined spatial location information of respondents (e.g., address or nearest intersection), but must be careful of methods for protecting personally identifiable information. These approaches may also help evaluate the impact of the UGCoP (Kwan 2012) on this study’s geographic context variables. Unfortunately, this may be difficult due to current socio-environmental data aggregations for the input metric datasets, and research may have to wait until finer-scale data becomes available.

Researchers and practitioners should exercise caution when applying this investigation’s results to explain spatial-statistical patterns in other study areas or for different hazard types. For instance, the study’s focus on Illinois may limit its generalizability to other regions like the South or Southeast. The investigation also focuses only on tornado risk, and the results may not generalize to other natural hazards such as hurricanes, earthquakes, or floods. However, while the TROP model framework specifically incorporates the influential drivers of tornado risk responses, the dynamic interactions between geographic context, risk perception, and protective action exist for many environmental hazards. As a result, the TROP model design allows for easy conversion for conceptual applications and future research exploring other hazards by employing alternative metrics representing that unique event type. Replacing measurements of physical context (i.e., past occurrence, impacts, warnings, exposure, and housing risk) with data corresponding to another hazard type is straightforward, and a plethora of open-access data is available. For example, researchers can assess flood risk utilizing geographic proximity to coastal areas or riverine
floodplains using FEMA, NCEI, and USCB datasets. Variable inputs for evaluating social vulnerability are already based on all-hazards vulnerability to environmental hazards and would not require much alteration when applying to another hazard type. Additionally, questionnaire-based assessments of perceptions and protective actions for other hazard types are possible by reviewing the current literature on its influential response dynamics and evaluating existing instruments employed for that event type. Future work can reuse many items from the Tornado Risk Survey (Appendix A) by simply replacing the word “tornado” with a different hazard type (e.g., “When there is severe weather in my area that could result in a tornado-flood, I worry my property will be damaged”).

A few additional limitations are worth noting. The study's use of the NWS Storm Prediction Center historical tornado archive dataset in the most recent climatological period may also limit its longitudinal extent. However, this methodological choice is seemingly justified due to reporting bias reductions since the 1990s. Furthermore, the study’s use of the USDA's 2013 RUCCs may not capture all relevant aspects of the current built environment that could affect tornado risk. Future research could address this limitation by reevaluating the physical context metric when the updated RUCC codes are released, which is currently planned for mid-2023 (USDA 2020a). In addition, this study’s social vulnerability metric assigns equal weighting to each factor when calculating the total SoVI® score. While this is a reasonable assumption, it is essential to note that some factors may significantly impact social vulnerability more than others.
(Beccari 2016; Rufat et al. 2019), which requires future research in the tornado risk context.

In conclusion, the dissertation results provide insights into the relationships between physical context, social context, risk perception, and protective action in the context of tornado risk to help reduce disproportionate economic and human losses to future events. However, the study is not without limitations, and future research should attempt to address these weaknesses to provide a more comprehensive understanding of disaster risk perception and protective action. Hopefully, this investigation will catalyze future studies of tornado disaster mitigation and vulnerability. The present study can be scaled up into a wide-ranging evaluation of the TROP framework throughout all U.S. regions. Future work extending from this analysis could also evaluate the Chicago-area counties as a separate case study or specifically examine Illinois' urban residents in the TROP framework due to their overrepresentation in the survey. Nonetheless, the study's findings provide empirical contributions to hazard geography with the TROP conceptual framework and practical implications for equitable disaster risk management programs relating to acute severe weather hazards.


Dear Resident,

My name is Sarah Jackson, and I am a doctoral graduate student in the Geography Department at the University of South Carolina. I am conducting a research study as part of my degree requirements and would like to invite you to participate. This study is partially funded from the University of South Carolina Office of the Vice President for Research. If you participate, you will be compensated according to your agreement with your online survey provider.

The research study asks you to complete a survey about your perspective on tornado hazards impacting the area in which you live in Illinois. You will be asked questions about your perceptions of tornado risk, the actions you take to prepare and respond to tornadoes, and basic socio-demographic and housing information. There are no personal risks to your participation in this study. Participation is anonymous, which means that no one will know what your answers are. So, please do not write your name or other directly identifying information in your responses. Study information will be kept in a secure location at the University of South Carolina. The results of the study may be published or presented at professional meetings, but your response will remain anonymous.

You may contact me at SJ36@email.sc.edu or my faculty advisor, Dr. Susan Cutter, at scutter@mailbox.sc.edu to answer any questions you have about the study. You can also contact the University of South Carolina Office of Research Compliance at 803-777-6670 with questions, concerns or complaints about your rights as a research participant, or if you don’t want to talk to the researcher. The study has been approved by the University of South Carolina Institutional Review Board (#Pro00119797).

Thank you for your consideration. You have the right to withdraw at any point during the study, for any reason, and without any prejudice. If you would like to participate, please begin completing the survey. The survey will take around 10-15 minutes to complete. When you are done, please submit your responses.

With kind regards,
Sarah Jackson
University of South Carolina, Department of Geography
SJ36@email.sc.edu

*Consent Confirmation*
Do you consent to begin the study?
- Yes
- No

*D1 – State*
Do you live in Illinois?
- Yes
- No

*D2 – Age*
How old are you?
- 17 or under
- 18-24 years old
- 25-34 years old
- 35-44 years old
- 45-54 years old
- 55-64 years old
- 65-74 years old
- 75-85 years old
- Over 85

*D3 – Gender*
What gender do you identify as?
- Woman
- Man
- Nonbinary
- Transgender
- Intersex
- Prefer not to say
- Other (Please List):

*D4 - Ethnicity*
Are you Spanish, Hispanic, or Latino/a/x?
- Yes
- No

*D5 - Race*
Choose one or more races that you consider yourself to be: (Check all that apply)
- White
- Black or African American
• American Indian or Alaskan Native
• Asian
• Native Hawaiian or Pacific Islander
• Other (Please List):

D6 – County
In which County do you Currently reside?

D7 – City
In which city do you currently reside?

D8 – Urban/Rural
Please select which best describes the area you live:
• Urban (in densely populated area)
• Suburban (neighborhood near densely populated area)
• Rural (in sparsely populated area)

D9 – Location
Can you find your home’s location on a map without GPS?
• Yes
• No

D10 – Structure
What type of housing Structure do you currently live in?
• Single Family Detached Home
• Townhome/Duplex
• Apartment Complex
• Mobile/Trailer/Manufactured Home
• Boat/Floating Structure
• Other (Please List):

D11a – Residency Length
How long have you lived at your current residence?
• Less than a year
• 1-2 years
• 3-4 years
• 5-9 years
• 10-19 years
• 20-29 years
• 30 years or more

D11b – Previous Residence
If answered Less than a year, 1-2 years, or 3-4 years to D11a:
Where was your last residence located? (City, State)
D12 – Housing Status
What is your current housing status?
- Homeowner
- Rent/Lease
- Live with others and do not pay rent
- Homeless
- Other (Please List):

D13 – Vehicle
Is there a vehicle available to your household?
- Yes – Own/Lease a vehicle
- Yes – Can borrow a vehicle from family/friend/neighbor
- No

RP1 – Risk Perception 1
What do you feel is the risk of a tornado occurring where you presently live?
- No Risk
- Slight Risk
- Moderate Risk
- High Risk
- Extreme Risk

RP2 – Risk Perception 2
How strongly do you agree/disagree with the following statement - Tornadoes are a threat where I live.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

RP3 – Risk Perception 3
How strongly do you agree/disagree with the following statement – I do not worry about tornadoes where I live.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

RP4 – Risk Perception 4
How strongly do you agree/disagree with the following statement – I am fearful when a tornado warning is issued for my home's location.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**RP5 – Risk Perception 5**
How strongly do you agree/disagree with the following statement - When there is severe weather in my area that could result in a tornado, I worry my property will be damaged.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**RP6 – Risk Perception 6**
How strongly do you agree/disagree with the following statement - When there is severe weather in my area that could result in a tornado, I worry I will suffer injury or death.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**RP7 – Risk Perception 7**
How strongly do you agree/disagree with the following statement - I feel I am in control of my safety when a tornado threatens me in my home.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**RP8 – Risk Perception 8**
How strongly do you agree/disagree with the following statement - When a tornado threatens me in my home, the outcome is in God’s hands.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**TK1 – Tornado Knowledge 1**
On average, how many tornadoes occur every year in the county where you live?
- 0
TK2 – Tornado Knowledge 2
Have you ever heard of the Fujita/Enhanced Fujita Scale (sometimes just called the F/EF-scale)?
• Yes
• No

TK3 – Tornado Knowledge 3
Which of the following is more violent and could produce greater damage:
• An F/EF 2 rated tornado
• An F/EF 4 rated tornado
• Unsure

TK4 – Tornado Knowledge 4
In the past 10 years, have you heard/read any public safety information on how to prepare for a tornado?
• Yes
• No
• Unsure

TK5 – Tornado Knowledge 5
If the National Weather Service issues a tornado warning for your area, how much time do you have before the tornado arrives?
• Less than 15 minutes
• 15-45 minutes
• 1-2 hours
• 24 hours
• 2-3 days

TK6 – Tornado Knowledge 6
How strongly do you agree/disagree with the following statement - Tornadoes can occur at any time of the day/night.
• Strongly Disagree
• Somewhat Disagree
• Neither Agree nor Disagree
• Somewhat Agree
• Strongly Agree
**TK7 – Tornado Knowledge 7**
How strongly do you agree/disagree with the following statement - I understand the difference between a tornado watch and a tornado warning.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**TK8 – Tornado Knowledge 8**
How strongly do you agree/disagree with the following statement - I understand what I should do when a tornado warning is issued where I live.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**TK9 – Tornado Knowledge 9**
How strongly do you agree/disagree with the following statement - I understand the science behind what causes tornadoes.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**TK10 – Tornado Knowledge 10**
How strongly do you agree/disagree with the following statement - Hills and mountains can provide protection from tornadoes.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**TK11 – Tornado Knowledge 11**
How strongly do you agree/disagree with the following statement - I understand how to interpret severe weather radar maps.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree
**D14 – Marital Status**
What is your current Marital Status?
- Married
- Living with a partner
- Widowed
- Divorced/Separated

**D15 – Children**
Do you have children?
- Yes
- No

**D16 Children at home**
How many children under 18 live with you?

**D17 – Education**
What is the highest level of school you have completed or the highest degree you have received?
- Less than high school diploma
- High school graduate (high school diploma or GED)
- Some college but no degree
- Associate’s degree in college (2-year)
- Bachelor’s degree in college (4-year)
- Master’s degree
- Doctoral degree
- Professional degree (JD, MD)

**D18 - Employment**
What best describes your primary employment status over the last three months?
- Working full-time
- Working part-time
- Unemployed and looking for work
- A stay-at-home parent or caregiver
- Student
- Retired
- Other (Please List):

**D19 – Income**
Please indicate your entire household income in 2021 before taxes.
- Less than $10,000
- $10,000 - $19,000
- $20,000 - $39,000
- $40,000 - $59,000
- $60,000 - $79,000
- $80,000 - $99,000
• $100,000 - $149,000
• $150,000 - $200,000
• More than $200,000

_D20 – Disability_
Do you identify as a person with a visual, hearing, mobility, psychiatric, intellectual and/or other disability?
• Yes
• No
• Prefer not to say

_TE1 – Tornado Experience 1_
Thinking about your lifetime, what is your level of experience with tornadoes?
• None at all
• A little
• A moderate amount
• A lot
• A great deal

_TE2 – Tornado Experience 2_
Thinking about the last 5 years, what is your level of experience with tornadoes?
• None at all
• A little
• A moderate amount
• A lot
• A great deal

_TE3 – Tornado Experience 3_
Thinking about the last year, what is your level of experience with tornadoes?
• None at all
• A little
• A moderate amount
• A lot
• A great deal

_TE4 – Tornado Experience 4_
Please answer the following question about your tornado experiences - Have you ever lived in an area that experienced a tornado warning?
• Yes
• No
• Unsure
TE5 – Tornado Experience 5
Please answer the following question about your tornado experiences - Has the area where your current home is located been under a tornado warning in the past year?

- Yes
- No
- Unsure

TE6 – Tornado Experience 6
Please answer the following question about your tornado experiences - Have you ever been injured by a confirmed tornado?

- Yes
- No
- Unsure

TE7 – Tornado Experience 7
Please answer the following question about your tornado experiences - Have you ever had your property damaged (home, vehicle, crops, etc.) by a confirmed tornado?

- Yes
- No
- Unsure

TE8 – Tornado Experience 8
Please answer the following question about your tornado experiences - Has someone you know personally been injured by a confirmed tornado?

- Yes
- No
- Unsure

TE9 – Tornado Experience 9
Please answer the following question about your tornado experiences - Has someone you know personally ever had their property damaged (home, vehicle, crops, etc.) by a confirmed tornado?

- Yes
- No
- Unsure

TR1 – Tornado Response 1
"In the event of a tornado watch, I would..." (check all that apply to you)

- Do nothing
- Go to an indoor sheltering place
- Go to an underground sheltering place
- Go outside
- Check for environmental cues (cloud formations, hail, roaring sound)
• Check to see what family or neighbors do
• Pray
• Bring children or pets inside
• Seek more information about the storm
• Gather supplies around the house
• Evacuate the tornado warning area
• Other (please list):

TR2 – Tornado Response 2
"In the event of a tornado warning, I would...." (check all that apply to you)
• Do nothing
• Go to an indoor sheltering place
• Go to an underground sheltering place
• Go outside
• Check for environmental cues (cloud formations, hail, roaring sound)
• Check to see what family or neighbors do
• Pray
• Bring children or pets inside
• Seek more information about the storm
• Gather supplies around the house
• Evacuate the tornado warning area
• Other (please list):

TR3 – Tornado Response 3
How often do you take protective action when a tornado warning occurs?
• Never
• Sometimes
• About half the time
• Most of the time
• Always

TR4 – Tornado Response 4
How strongly do you agree/disagree with the following statement - During a tornado warning, I check outdoor conditions before taking protective action
• Strongly Disagree
• Somewhat Disagree
• Neither Agree nor Disagree
• Somewhat Agree
• Strongly Agree

TR5 – Tornado Response 5
How strongly do you agree/disagree with the following statement - Until I see a tornado funnel, I do not respond to tornado warnings
• Strongly Disagree
• Somewhat Disagree
• Neither Agree nor Disagree
• Somewhat Agree
• Strongly Agree

**TR6 - Tornado Response 6**
How strongly do you agree/disagree with the following statement - Tornado warnings happen so often that I do nothing when they occur.
• Strongly Disagree
• Somewhat Disagree
• Neither Agree nor Disagree
• Somewhat Agree
• Strongly Agree

**TR7 - Tornado Response 7**
How strongly do you agree/disagree with the following statement - I trust my instinct to help decide if I should respond to a tornado warning.
• Strongly Disagree
• Somewhat Disagree
• Neither Agree nor Disagree
• Somewhat Agree
• Strongly Agree

**TR8 - Tornado Response 8**
How strongly do you agree/disagree with the following statement - I have taken protective action for a tornado without receiving a warning.
• Strongly Disagree
• Somewhat Disagree
• Neither Agree nor Disagree
• Somewhat Agree
• Strongly Agree

**PA1 – Protective Action 1**
How strongly do you agree/disagree with the following statement - I feel prepared to respond to a tornado warning.
• Strongly Disagree
• Somewhat Disagree
• Neither Agree nor Disagree
• Somewhat Agree
• Strongly Agree

**PA2 – Protective Action 2**
How strongly do you agree/disagree with the following statement - My residential community is adequately prepared for a tornado.
• Strongly Disagree
• Somewhat Disagree
• Neither Agree nor Disagree
• Somewhat Agree
• Strongly Agree

**PA3 – Protective Action 3**
How strongly do you agree/disagree with the following statement - If severe weather that could result in a tornado is occurring, I seek out more information before responding.
• Strongly Disagree
• Somewhat Disagree
• Neither Agree nor Disagree
• Somewhat Agree
• Strongly Agree

**PA4 – Protective Action 4**
How strongly do you agree/disagree with the following statement - If severe weather that could result in a tornado is occurring, I wait for information to come to me before responding.
• Strongly Disagree
• Somewhat Disagree
• Neither Agree nor Disagree
• Somewhat Agree
• Strongly Agree

**PA5 – Protective Action 5**
Please check whether you own/have prepared each of the following for your home: (check all that apply)
• Emergency kit
• Weather radio
• A practiced tornado safety plan
• A tornado sheltering place
• Backup generator
• Non-perishable food
• 3-day supply of water
• First aid kit
• Flashlight
• Batteries
• Emergency cash
• Instructions for turning off water, electric, and/or gas
• I have none of these items prepared for my home

**PA6 – Protective Action 6**
Which sources do you use to receive tornado warnings? (check all that apply)
• Outdoor Sirens
• Cable/TV News
• Automated phone or text message alerts
• Internet News
• Social Media
• Local radio stations
• NOAA weather radio
• Family/neighbors
• I use none of these sources to receive tornado warnings
• Other (please list):

**PA7 – Protective Action 7**
In the last 5 years, have you taken any first aid/CPR training?
• Yes
• No
• Unsure

**PA8 – Protective Action 8**
In the last 5 years, have you and your household members practiced a tornado drill?
• Yes
• No
• Unsure

**HS1 – Home Safety 1**
What tornado sheltering options do you have available in or near your home? (check all that apply)
• Basement with no windows
• Basement with windows
• Detached storm shelter
• Shared/Community shelter
• Inside room with no windows
• Inside room with windows
• No sheltering options are available to me
• Other: (Please List)

**HS2 – Home Safety 2**
When you are at home, where is the **first place** you would take shelter from an approaching tornado?
• Basement with no windows
• Basement with windows
• Detached storm shelter
• Shared/Community shelter
• Inside room with no windows
• Inside room with windows
- No sheltering options are available to me
- Other: (Please List)

**HS3 – Home Safety 3**
Do you live close enough to an outdoor tornado siren to hear it inside your home?
- Yes
- No
- Unsure

**HS4 – Home Safety 4**
How strongly do you agree/disagree with the following statement - My home is sturdy enough to protect me during a tornado.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**HS5 – Home Safety 5**
How strongly do you agree/disagree with the following statement - My home is sturdy enough to withstand tornado damage.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**HS6 – Home Safety 6**
How strongly do you agree/disagree with the following statement - My home is not a safe place during a tornado warning.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

**HS7 – Home Safety 7**
How strongly do you agree/disagree with the following statement - Hills, mountains, and trees near my home create poor visibility for severe storms.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree
HS8 – Home Safety 8
How strongly do you agree/disagree with the following statement - During a tornado warning, I move outdoor belongings (vehicles, lawn furniture, etc.) to a safer location.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

HS9 – Home Safety 9
How strongly do you agree/disagree with the following statement - I feel prepared to adequately respond to a tornado approaching my home.
- Strongly Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Strongly Agree

Open Response 1
Is there anything else you would like to share with me about your perception, response, and understanding of tornado risks?
- No
- Yes (please share below with no identifying information):

End of Survey Message:
“We thank you for your time spent taking this survey
Your response has been recorded.”