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A SPATIAL ANALYSIS OF SIMULATED TORNADO WARNING DECISIONS IN THE UNITED STATES

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ABSTRACT

The work presented in this thesis uses theories from risk perception and decision making to examine spatial variations of tornado warning decision making across the U.S. Decision-making as it relates to tornado warnings is heavily researched, yet many of these studies do not incorporate a spatial analysis of tornado warning decisions that compare individual responses across different geographical locations and populations. To address this research gap, this study uses data from a simulated tornado warning decision experiment, implemented nationwide, to examine demographic attributes that may influence incorrect decision making, how these attributes contribute to decision making across the U.S., and if there are broader regions in the U.S. that are hot spots for incorrect decision making. First, multilevel regression analysis and poststratification is used to (1) determine if there are certain demographic commonalities in people who are more prone to make incorrect decisions and (2) estimate what National Weather Service County Warning Areas are most associated with these populations. Second, the results of the multilevel regression analysis and poststratification are analyzed using spatial autocorrelation to identify if there are hot spots or regions where people tend to make more incorrect decisions in the decision experiment. Findings from this study show that gender, race, and ethnicity are important factors that influence incorrect decision making. Findings also consistently show that, though not statistically significant in most cases, the people across the southern U.S. tend to make more incorrect decisions, as defined in this work. This region tends to have high relative exposure to tornadoes. This study's results have important implications because the demographic groups identified as making more incorrect decisions are also those groups that typically have higher social vulnerability than those who make fewer incorrect decisions. This work concludes

with a summary of findings, avenues for future work, and recommendations for risk communicators.

Chapter 1. Introduction

The United States experiences, on average, more than 1000 tornadoes per year (National Centers for Environmental Information). Large-scale and/or violent tornado outbreaks (Ćwik et al. 2021), though rare, account for a majority of the deaths and injuries (Simmons and Sutter 2011). Relatively recent major tornado events such as the 25 April 2011 Super Outbreak across the southern United States, the EF-5 tornado on 22 May 2011 in Joplin, Missouri, and the EF-5 tornado on 20 May 2013 in Moore, Oklahoma, caused 316, 158, and 47 direct fatalities, respectively (National Oceanic and Atmospheric Administration 2011a,b, 2014). Despite that these events were well forecasted with adequate lead-times, one common theme emerged in the National Weather Service (NWS) post-event assessments: residents were reluctant to personalize threat and seek appropriate shelter (National Oceanic and Atmospheric Administration 2011a,b, 2014). Thus, The National Oceanic and Atmospheric Administration (NOAA) and its NWS have since voiced the need for better understanding of the public's risk perception and decision making in the face of tornado events (National Oceanic and Atmospheric Administration and National Weather Service 2019; Uccellini and Ten Hoeve 2019).

The research community has responded with studies on tornado risk perception, risk communication, and decision making under uncertainty. However, just as tornado climatology varies across the United States, people's perceptions of tornado risk and decision-making processes may vary as well. It is important then to understand and acknowledge these differences so that local NWS forecasters, media, and emergency responders can effectively communicate the threat and associated risks to the public to elicit appropriate responses. Thus, the goal of this project is to analyze the variations of tornado warning decision-making across the United States and provide weather communicators with useful audience characteristics.

With this goal in mind, this thesis begins with a discussion of the background and literature relevant to decision-making in the face of tornado warnings (Chapter 2). First, the concepts and theories behind risk perception are discussed alongside associated factors such as the role of experience, false alarms, fear, communication, space and time, and place-based attachment. Next, decision-making is discussed in terms of how it is influenced by space and uncertainty and how it is conceptualized in models and design visualizations. Finally, regional comparisons of tornado warning decision making and behavior are examined in addition to hazard exposure and social vulnerability mapping.

In Chapter 3, the research question and sub-questions are identified followed by an explanation of the datasets utilized for this thesis. The methods are then discussed and address what they are and why they were chosen. Chapter 4 highlights the results of the analysis, and Chapter 5 presents a discussion and conclusion.

Chapter 2. Past Research and Research Gaps

Given accurate tornado warnings that are disseminated with sufficient lead time, ultimately the choice to protect oneself is an individual choice. An individual's decision to protect depends on many factors, mainly, their risk to a particular threat, such as a tornado. Risk itself is broadly defined as the multiplication between the probability a specific event will occur and the magnitude of the event's consequences (Kasperson et al. 1988). Risk from a tornado, then, equates to the probability a tornado will occur times the potential consequences a tornado could have, such as destruction, injury, or death. The decision to protect oneself depends on how an individual views, or perceives, the risk, which is also influenced by various factors such as personal experience, false alarms, and fear, among others. This chapter highlights many of the theories, models, and studies that relate to how a person chooses to protect (or not) themselves during a tornado warning or similar hazard alert.

2.1 Risk Perception

An individual's decision-making in response to a threat, such as a tornado, is influenced by how they perceive that threat or risk. Risk perception broadly defined is the way in which people evaluate or judge their risk to a threat and then act upon that evaluation (Slovic 1987). However, when people are asked to evaluate a risk they are not an expert in, they rely on something about the risk they remember hearing in the past (Slovic et al. 1979). This recall may lead to skewed judgments or a reliance on what Slovic et al. (1979) call "heuristics." There are several types of heuristics that individuals use to judge a risk. These include availability, overconfidence, and the desire for certainty (Slovic et al. 1979). The availability heuristic relies on information that can be recalled quickly, which usually relates to knowledge of frequent rather than rare events. For instance, tornadoes are rare events so people may apply the availability heuristic to downplay a tornado warning. However, the availability heuristic can be skewed by exposure to a particular risk. Slovic et al. (1979) provide the example of the movie "Jaws" and how it heightened people's perception of the risk of shark attacks. Exposure also is seen to heighten risk perception during tornadoes. On 31 May 2013, just 11 days after the Moore, Oklahoma EF5 tornado, many people recalled that prior day's devastating events and acted out of fear to the tornado warnings on the 31st, such as attempting to drive away from the storm instead of sheltering at home (National Oceanic and Atmospheric Administration 2014).

The overconfidence heuristic refers to how people tend to be confident of their own judgements and decisions, or in built or environmental systems. This level of confidence can be dangerous as it may skew the actual risk of a particular event. For instance, people believe they can accurately estimate failure rates, which is not the case (Slovic et al. 1979). This belief can lead to overconfidence in a particular system and decrease risk perception. For example, people may be overconfident in the ability of a dam or levee to protect them from flood risk. Many people, for example, were confident that the levees in New Orleans would hold during Hurricane Katrina; however, those structures were not able to hold, resulting in catastrophic flooding and many people were caught unaware. Overconfidence can manifest with experts as well, such as in human error, overconfidence in scientific knowledge, insensitivity to technological systems, and a failure to anticipate human response (Slovic et al. 1979). In the case of tornadoes, experts may be overconfident in their issuance of warnings. For instance, once a warning is issued, forecasters might anticipate that people will take immediate action; however, a warning issued does not necessarily mean a warning is received. There may be several technological or social systems preventing or delaying the information. For example, a storm can interrupt power, and therefore people may have more difficulty receiving the warning.

The desire for certainty is the final heuristic mentioned by Slovic et al. (1979). People want to have a yes or no answer and a certainty for a particular outcome. Certainty is often not the case, however, especially when it comes with the risks associated with natural hazards. The weather is inherently uncertain, and although weather forecasting has become more accurate, it is not perfect. Probability estimation is one method meteorologists use to provide uncertainty information so people can make better decisions. While some may argue against probabilities, there are benefits of its use for weather-related risks (e.g. Nadav-Greenberg and Joslyn 2009; Joslyn and LeClerc 2012; Rothfusz et al. 2018). For instance, probability-of-precipitation forecasts provide more detailed information on how much precipitation is predicted to occur, but they are difficult to understand, which is why some argue against more widespread application of probabilities to weather forecasts (Joslyn and LeClerc 2012). (The use of probabilities and uncertainty information will be discussed in detail later.)

In addition to heuristics, the characteristics of the individual influence risk perception rather than simply a factor of quantifiable measures such as fatality rates or risk estimates (Slovic et al. 1979; Slovic 1987). For example, people may be aware that shark attacks are very rare, but thanks to pop culture and the gruesome nature of an attack, people may believe swimming in the ocean where there may be sharks is a high-risk activity. The discrepancy between actual and perceived risk also can be seen in the risks posed in flying and driving. Flying is perceived as higher risk even though people are more likely to die or get injured from driving (Slovic 1987). These perceptions can be influenced by external features, such as pop culture and media, as well as individual features, such as personal experience or worldviews. For example, someone who does not know how to swim will perceive snorkeling as a higher risk activity than someone who does because they have a higher perceived risk of drowning.

Individual characteristics can extend beyond experience and worldviews to one's identity. For example, gender may influence the perceived risk of a similar activity. A woman might find walking around a city, alone, at night riskier than a man would. It is the same activity, but gender and hearing about unfortunate incidents when women were attacked result in different levels of perceived risk (Masuda and Garvin 2006).

In addition to individual characteristics, risk is a social construct and is influenced by factors such as culture and sense of place. Therefore, risk perception can be intensified via social networks. Kasperson et al. (1988) developed a conceptual framework for this phenomena called "the social amplification of risk" (Fig. 1), defining it as the social structures that influence individual and group perceptions of risk, as well as how these perceptions influence society. In this framework, there are seven steps in amplifying risk: filter risk signals, decode signals, process risk information, attach social values, social interactions to interpret and validate information, form intent, and engage in group or individual action to accept, ignore, tolerate, or change their risk. The authors identified several factors that influence their model: mental perception of the risk, individual attitudes, local environmental impacts, political/social presence, changes in the physical nature of the threat, and attributes of the information itself, such as the volume and degree the information can be debated and how the information is communicated (Kasperson et al. 1988).

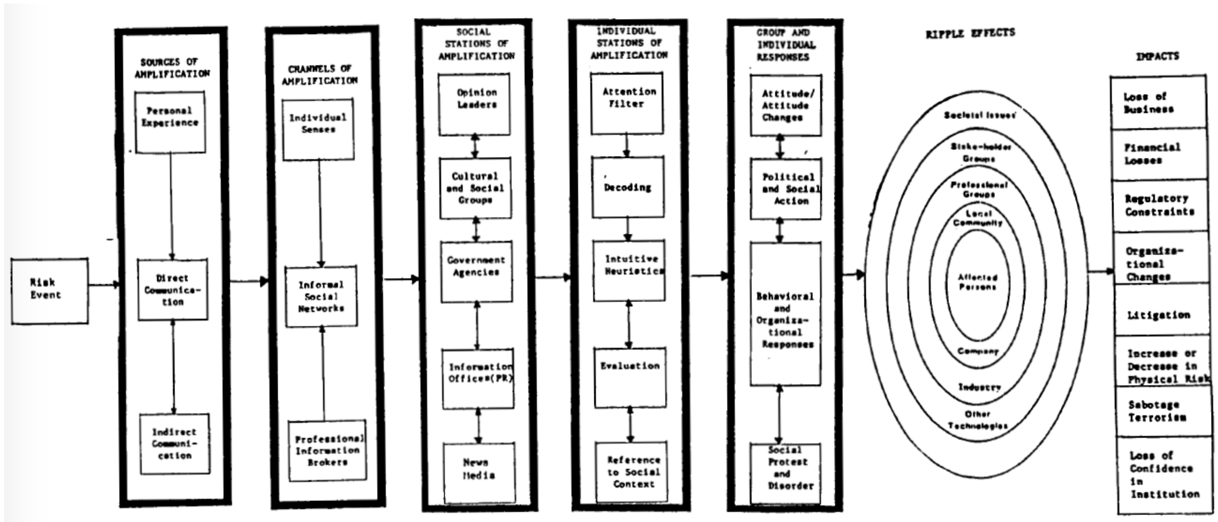

Figure 1. The “social amplification of risk” conceptual framework from Kasperson et al. (1988). First, a risk or event occurs followed by amplifications of the even by different means. The risk could be amplified via different sources or channels. The risk can then be amplified by secondary impacts, such as social amplifications, individual amplifications, or group and individual responses. The third level is where the risk amplification can spread or “ripple” to other people or places. Finally, the event concludes with impacts on society.

Sjoberg (2000) described how culture, attitude, risk sensitivity, and fear affect a person’s risk perception. Sjoberg argued that attitude, risk sensitivity, and fear play a larger role than culture, heuristics, and biases. Attitude, sometimes called affect, is developed from beliefs and values, but can also inform belief and be influenced by a risk. For example, if an individual does not believe that tornadoes are possible in their location, they are less likely to view tornadoes as posing a high risk to them. Risk sensitivity is the amount of anxiety or feelings of worry people have towards a risk. This element can vary from person to person and is therefore based on individual preference. Finally, fear of impacts from a hazard influences risk perception. Sjoberg (2000) provided the examples of flying and nuclear power. People may define these industries as risky because they are afraid of falling, in the case of flying, or the negative health impacts of nuclear radiation, in the case of nuclear power. Even though airplane crashes and nuclear explosions are extremely rare, people still view them as risky because of the fear surrounding potential disasters and the devastating consequences.

Just as risk perceptions vary from person to person, they also vary across different hazards (Slovic 1987; Sherman-Morris 2013). Tornadoes pose significant threat of bodily harm and structure damage, and people evaluate their risk based on the tornado itself, or, more likely, warning messages about the tornado. Risk perception of tornadoes is influenced by the factors listed above as well as some identified as being particular to tornadoes. These additional factors include prior experience with tornadoes, false alarms, fear, the communication of the threat, the effects of space and time, and place-related beliefs. These factors are important to consider when thinking about risk perception and how that influences decision-making.

2.1.1 Experience

The effects of prior experience with tornadoes or tornado warnings on risk perception are mixed. Some studies indicate that prior experience has little effect (e.g. Wallace et al. 2015), others that it increases risk perception and protective action (e.g., Comstock and Mallonee 2005; Drost 2013; Schumann et al. 2018), and others that have mixed results on the role of experience on risk perception (e.g., Silver and Andrey 2014; Walters et al. 2020). These differences may result from how the researchers designed their study, especially if they equated risk perception with taking precautionary measures versus the evaluation of their risk to a threat.

Wallace et al. (2015) administered an online survey to residents in two rural Alabama towns to see if experiencing the 27 April 2011 tornado outbreak influenced their perception of risk to tornadoes. The towns were chosen because the residents had never experienced a tornado prior to this event. The researchers found that even though almost half of their 195 participants noted a change in their risk perception shortly after the event took place, there were no strong correlations between experiencing the tornadoes and their perceived risk. However, Wallace et al. (2015) did find that prior experience with tornadoes made participants more aware of their risk to tornadoes even though it did not change their overall risk perception.

On the other hand, Comstock and Mallonee (2005) compared protective action (the actions taken to protect themselves) of those who experienced both the 3 May 1999 and 8 May 2003 tornadoes in Moore, Oklahoma. The authors administered questionnaires to 324 residents of Moore shortly after the 2003 tornado and discovered that the residents' protective action increased in response to the 2003 tornado since experiencing the 1999 tornado. Drost (2013) looked at whether experience with and knowledge of tornadoes improved protective action. Forty-nine non-science, undergraduate students participated in a classroom experiment to assess how the students responded under a risk scenario. Drost's results showed that those with more experience and higher knowledge of tornadoes were more likely to take shelter. Likewise, Schumann et al. (2018) found that those with more experience with tornadoes were more likely to take shelter after analyzing surveys of 501 university students in South Carolina.

There also are studies where results are mixed, however, when it comes to the role of experience on risk perception. Silver and Andrey (2014) studied a town in Canada where two tornado events occurred three days apart to see if experiencing the first tornado had any effect on responding to the second. The authors found that there was a significant increase in overall awareness and sheltering for the second event, but there was not a significant difference in sheltering for those who directly experienced the first tornado. They concluded that it was difficult to tell if the increase in sheltering was due to experience or social amplification of risk. Walters et al. (2020) likewise had mixed results in their interviews with Tennessee residents' response to tornado warnings. After experiencing a tornado warning, some participants had higher risk perception while others had lower. Those who had reported lower risk perception had an "optimism bias" mentality, or "it won't happen to me", while those whose risk perception increased reported more caution to tornadoes.

Walters et al. (2020) noted, however, that it is complicated to define "tornado experience", as it may mean being directly impacted by the tornado (such as suffering from bodily harm or a destroyed home), hearing about the tornado on the television, or knowing someone who suffered damage from the tornado. Therefore, it is likely because of this vague definition that the results of experience on perception of risk to tornadoes is not clear.

2.1.2 False Alarms

In this context, false alarms are defined as tornado warnings without a verified tornado or when a tornado that occurred in a different location or time than the warning predicted (Trainor et al. 2015; Lim et al. 2019). Mathematically, the false alarm ratio (FAR) is the ratio between unverified and verified forecasts (Barnes et al. 2007) and is an indicator that has been used for quantitative analysis of tornado forecasts in the United States. Brotzge et al. (2011) did just that in an analysis of a five-year climatology of tornado false alarms. The authors used tornado warning and event information provided by the Performance Division of the NWS for the United States between 2000 and 2004. Their analysis revealed three aspects about tornado detection and warning. First, FAR increased during certain time periods, such as at night, during the winter, and during marginally severe weather events. This result indicates that these are periods of time when tornado detection is more challenging. The second case found that as distance from the weather radar increased, FAR decreased; but so did the probability of detection. This result means that forecasters were more hesitant to issue tornado warnings because of limitations in the radar technology. Finally, FAR increased as the warning polygon size decreased. The change in the size of the warning polygon was attributed to the change from county-based warnings (tornado warnings encompassing entire counties) to the current storm-based warning system in 2007 (Brotzge and Donner 2013). Brotzge et al. (2011) noted that although there were more false alarms after this change, only people in the immediate vicinity of the storm were warned rather than an entire county, decreasing the total amount of people who would be warned unnecessarily.

One difficulty in researching the relationship between false alarms and risk perception is that the definition of false alarms becomes more flexible when it is applied to human perception (Barnes et al. 2007). That is, a person may consider an event to be a false alarm when they were not impacted by the event, even though a tornado occurred. Tornado sirens also heavily impact people's perception of false alarms, as people often hear them but do not experience a tornado (they are unaware that a tornado occurred, or a tornado did not impact their particular location; Barnes et al. (2007)).

Ripberger et al. (2015) administered an online survey to over 4,000 residents of tornado-prone states in the United States to analyze the relationship between false-alarm ratio and people's experiences of false alarms to determine their trust in tornado warnings. Ripberger et al. (2015) determined that local experience of false alarms had significant influence on trust in the warning. The more trust an individual had, the more likely they properly evaluated their risk and took appropriate safety actions. The researchers also found that people had varying perceptions of warning system accuracy. For example, those who did not know the difference between a tornado watch and a tornado warning were more likely to over-estimate false alarms. Thus, those individuals with adequate knowledge and trust in forecasters correctly perceived their risk and responded appropriately.

Similar to Ripberger et al. (2015), Trainor et al. (2015) utilized telephone interviews with 800 residents in tornado-prone states and also discovered that people were less likely to take appropriate action when they perceive a higher frequency of false alarms. Trainor et al. (2015) found that the term “false alarm” had a negative connotation and was often associated with blame. They also found, like Barnes et al. (2007), that there were a host of individual factors that played into how an individual perceived a false alarm. Donner et al. (2012) agreed and added that individual value judgements, past experience, and socializing with others influenced how people perceive false alarms and their respective risk. Donner et al. (2012) used purposive sampling to interview residents in Louisiana, Tennessee, and Missouri to assess public response to tornado warnings. They added that evaluating whether a warning is a false alarm delays participant response. Therefore, false alarms appeared to influence an individual’s personalization of the risk and delayed their decision to action.

Contrary to Ripberger et al. (2015) and Trainor et al. (2015), Lim et al. (2019) administered over 2000 online surveys in the southern United States (Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia) and found that the actual false-alarm ratio did not predict protective action. In fact, Lim et al. (2019) found that higher perceived false alarms led to a higher likelihood of taking protective action. They also found that people had a lower perceived false-alarm ratio compared with the actual false-alarm ratio. The researchers took a positive approach; instead of associating false alarms with negative emotions, they noted that people tended to feel more relief and gratitude that the tornado warning turned out to be false.

Regardless of these mixed findings of the influence of false alarms, there is still a wide body of literature that mentions the negative impacts of excessive use of television coverage (e.g.

Sherman-Morris and Brown 2012; Sherman-Morris 2013; National Oceanic and Atmospheric Administration 2014; Sanders et al. 2020), outdoor warning sirens (e.g. National Oceanic and Atmospheric Administration 2011a,b; Donner et al. 2012; Paul and Stimers 2012; Brotzge and Donner 2013; Klockow et al. 2014; Paul et al. 2015; Lim et al. 2019), and weather radios (Walters et al. 2020), which may lead some to perceive false alarms. Many times, people tend to ignore these alerts, especially outdoor sirens, because they have heard them many times before without any tornado occurrence, therefore, viewing these situations as other false alarms. These perceived false alarms may lead people to ignore tornado sirens, which was detrimental during some violent tornado events, including the 2011 EF5 tornado in Joplin, Missouri. The NOAA NWS service assessment of the Joplin event noted that people mentioned how they were "bombarded with sirens" and ignored them believing the threat was no different than any prior events (National Oceanic and Atmospheric Administration 2011b).

To avoid these negative consequences, weather forecasters do their best to avoid the "cry wolf" effect. They do not want to overuse warnings, but they also do not want to miss an event (Durage et al. 2016; Lim et al. 2019; Walters et al. 2020). Emergency managers are also cautious of this effect (League et al. 2010). Both types of experts attempt to balance between warning the correct amount and over warning, but there is still debate on what the threshold is so that people can evaluate their risk and respond appropriately.

2.1.3 Fear

Much of the research on the false-alarm effect is because the effect is thought to reduce fear, therefore reducing risk perception to the point of inaction. Fear is another factor of risk perception because people who are afraid of a threat often associate higher risk with that threat, such as flying (Sjoberg 2000). Ruiter et al. (2001), however, stated that risk perception may arouse fear, but does not require it. The authors discussed how it is the precautionary information given, not the message's ability to arouse fear, that influences people's behavior. Fear can cause some to ignore the threat rather than take it seriously, but fear arousal may help people to process the information. That is, when people are afraid, they are more likely to do something about it.

Perreault et al. (2014) administered 168 online surveys to undergraduate students at a midwestern university to assess their fear in the face of disaster warnings. The researchers noted that there must be both fear and efficacy, or the belief that an individual can do something about the risk, to perceive the correct amount of risk. Sometimes warning messages can be too "scary" and people do not act. Perreault et al. (2014) compared current disaster warnings with warnings that included threat information worded to arouse fear and found that "scary" messages were least credible compared with regular disaster warning messages. They also found that messages that included information on the threat and what they could do about it were most effective.

2.1.4 Communication

In addition to fear, the way in which the threat is communicated also influences risk perception. If the message does not communicate the correct amount of fear and efficacy, then the threat is not perceived accurately. As a result, NWS forecasters struggle with how to word warnings, geographic specificity, and immediacy of a threat (Walters et al. 2020). There is also a growing body of literature that addresses the issue of how and what to include when communicating risk.

Ash et al. (2014) distributed 501 online surveys to University of South Carolina students to look at different visualizations of tornado warnings as well as how different locations in the warning may influence risk perception. They found that message intent was not always received and acted upon. Specifically, the participants' interpretation of their position and the tornado warning location resulted in different interpretations of fear and action than what the message intended. Figure 2 depicts all 352 possible positions participants could find themselves in during the survey. It was at these different locations that the authors found participants various reactions to the same warning message. Participants who were located near the centroid of the tornado warning polygon had the highest fear and protective action responses. The lowest fear and response rates were located near the warning's boundary or outside the warning. Different interpretations of risk means that the warning message needs to be clearer and more consistent. This task is difficult to accomplish and raises the question of what to communicate to create consistent risk perception.

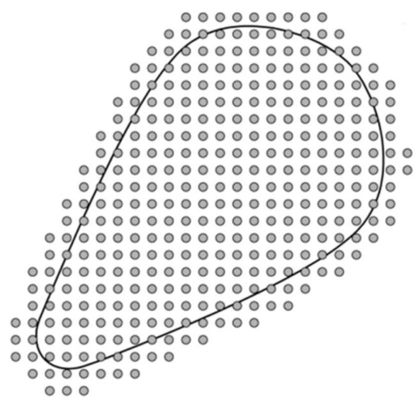

Figure 2. Ash et al. (2014) survey locations. Gray circles represent potential participant locations, the black boundary represents the edges of the tornado warning. Participants were randomly assigned a point and then the authors measured their fear and protective action decisions at that point.

Mileti and Sorensen (1990) wrote a report on the communication of warning messages to the public. They found that people do not perceive risk the same way and that this problem can be avoided by creating more realistic and understandable warning messages. They described four features in communicating risk in warning messages: whom to notify, the ability to describe the hazard, physical abilities to communicate, and conflicting information. Uncertainties in these features can delay public response as well as confuse risk messaging. For example, when Hurricane Alicia occurred in 1983, there was conflicting information about landfall from the local NWS offices and the National Hurricane Center, resulting in confusing risk signals for the public (Mileti and Sorensen 1990). Similarly, the NOAA NWS Service Assessment for the May 2013 tornadoes and flash flooding event in central Oklahoma also indicated issues with conflicting messaging. In this case, there was conflicting sheltering information when tornado warnings recommended sheltering low or underground while flash flood warnings recommended seeking higher ground (National Oceanic and Atmospheric Administration 2014). People were confused about which hazard was more of a risk to them and did not know what to do. With more media coverage of the tornadoes, many considered this threat more of a risk and sought shelter underground only to be forced out due to flash flooding.

In a more recent example, Liu et al. (2020) studied the communication practices between the Nashville NWS office and a local storm spotting group called Nash Severe Weather. The authors employed rapid ethnography and nine semi-structured interviews with meteorologists from the Nashville NWS office and three members of Nash Severe Weather, finding that it was beneficial to have a citizen science group knowledgeable about weather to help translate and spread the NWS warning messages. The storm spotting group helped risk communication because they understood the local culture and places, were able to help translate the NWS' warning messages in a way the local population could understand, and more easily share storm reports with the NWS. The combination of local knowledge and communication resulted in a population that was more informed and confident in the warning messages they received.

In addition to studies on how to communicate current risk messages, several studies have explored different ways of sharing risk information. Drost et al. (2016) experimented with three different types of warnings using eye-tracking technology to see if the warnings had an effect on how people retained and used the information. They recruited 90 participants from a midwestern university, including undergraduate students, graduate students, faculty, and staff – none of whom were science majors. They studied traditional warning messages with words only, animated warnings, and audio-only warnings and found that there was not a statistically significant difference in information retention between the traditional and audio messages, but people had greater retention with animated messages. Communication that included a visual element had greater success with retention and understanding of the risk information than other mediums.

2.1.5 Spatial and Temporal Considerations

In addition to communicating the risk itself, tornado warnings depict space and time considerations that also influence risk perception and, in turn, an individual's decision-making processes. For instance, tornado-warning polygons occupy a certain amount and configuration of space while the storm itself travels through time and space. People must make decisions throughout this spatiotemporal context and determine where they are relative to the storm, how far away it is from them, what direction it is moving, how fast it is moving, how much time they have to shelter, etc.

As one considers this space-time context, questions are asked about how much lead time the warning provides, the effects of near-miss events, the size of the warning polygon, and the proximity of people to the warning and/or tornado, and geographic specificity. For example, Hoekstra et al. (2011) discussed the effects of warning lead time on risk perception. In their survey, they asked 320 people visiting the National Weather Center in Norman, Oklahoma, what their preferred amount of lead time would be and what would be the absolute minimum amount of time to shelter. The authors found that the average minimum time to shelter was 10.2 minutes while the preferred lead time was 34.4 minutes. Additionally, too much lead time could decrease risk perception and action; lead times between one and two hours were too long for participants who took the survey to take the threat seriously.

Klockow (2011, 2013) and Klockow-McClain et al. (2019) discussed spatial awareness, geospatial risk, location, and boundary effects on risk perception. Klockow (2011, 2013) interviewed residents in Mississippi and Alabama and discussed how people understood space differently by assessing geospatial awareness of individuals after the 27 April 2011 tornado outbreak. This event was chosen because there were many tornadoes in a short time span and small region during the event. Klockow (2011, 2013) found there was confusion with television and radio broadcasts because, while the live footage was helpful, it did not provide maps or the location of the tornado. The author also noted that those interviewed had difficulty in interpreting map scale, familiar locations, and interpreting trajectory because the radar loops were either not shown or were too short in duration. Radio broadcasts completely lacked a visual element that many people used to estimate their spatial or temporal risk, therefore rendering radio broadcasts as difficult to understand. When asked about scale in general, many respondents noted confusion with map scale or conceptualizing what a large, almost mile wide, tornado looked like. Klockow (2011) found that the usage of landmarks was important for people to understand where the threat was located, which helped to personalize the risk. For them to accurately perceive their risk, residents had to know where they were located relative to the tornado and the tornado's trajectory (Klockow 2013).

Sherman-Morris and Brown (2012) explored spatial risk perceptions and effects of the tornado warning polygon of residents of Smithville, Mississippi, after the 27 April 2011 tornado outbreak. Their 29 interviews revealed that participants actively sought more information, and the most common information searched for was the tornado's location. The authors reasoned that the participants might not perceive that every area in the tornado warning polygon was at equal risk. The location most often cited by participants as the area most at risk (i.e., tornado most likely) was the center of the polygon while others indicated the whole area. The authors concluded that the participants added their own spatial uncertainty to the warning polygon.

Walters et al. (2020) also discussed the question of proximity to the warning and tornado location in their assessment of the public's perception of risk, shelter seeking, and attitudes about NWS communications. One of the most cited factors influencing risk and shelter seeking was a person's proximity to a tornado. They found that people took shelter at different distances from the storm, indicating that they have different perceptions of their risk from the storm depending on their distance from it. When asked about their attitudes towards NWS communications, there was overall satisfaction but a desire for more information on the proximity of the risk and estimated time-of-arrival.

Nagele and Trainor (2012) examined spatial effects of warnings including geographic specificity and the location of the risk compared to the warning polygons, storm tracks, and household location. In telephone interviews with 1038 residents of tornado-prone states, the authors found a "proximity heuristic" whereby people tended to evaluate their risk by judging their distance to the storm based on spatial, temporal, or conceptual distance. They also discovered that geographic specificity (specific mentioning of landmarks or locations) led to greater warning response. They also assessed sheltering responses at different locations of participants to the warning polygon: inside, home inside, smaller polygons, and proximity. While being inside the polygon did not increase action, having one's home inside the polygon did somewhat. Smaller polygons did not increase action either; however, proximity did—as the proximity decreased, protective action increased. Thus, distance to a warning matters in an individual’s perception of that risk but being inside or outside of the warning polygon had little effect.

2.1.6 Place and Place Attachment

Similar to the spatial component of warnings, there are also place-based considerations. Place is not only a location, or point on the earth’s surface, but a location that has shape and meaning (Cresswell 2013, p. 112). Place is related to space as it can be a particular location, can take up space, and comprise space. But what makes it a “place” rather than just “space” is that it is a realized space, i.e., a space with meaning (Agarwal 2018). Cresswell (2013, pp. 112–113) discussed “sense of place” – the process of attaching meaning to a place. He explained how sense of place referred to both individual and shared aspects of meaning that can be attached to a place. These attachments of meaning are a combination of location and landscape across a variety of different scales, such as a community or favorite chair. Cresswell explained that a “place” can be fixed or moving, such as a ship, which is a center of meaning for fishermen even though it moves.

Meaning also can be attached through the experience of a place. Tuan (1975, p. 152) defined place as a “center of meaning constructed by experience.” He defined experience as the way in which a person knows the world, which can be experienced through sensory means, such as sight, hearing, touch, etc. In addition to sensory modes of knowing, Tuan (1975) added that understanding a place means that one knows that place, and understanding can only be accomplished through experiencing that place on various temporal and spatial scales. He discussed the experience of place at different spatial scales: places within the home, home (as a place of shelter, rest, and safety), city, neighborhood and region, state, and nation. Tuan then explained that the experience and attachment of place is made visible through art, education, and politics. Therefore, a place that has meaning is formed by individual and shared experiences. Finally, Tuan (1975) concluded that experience of a place takes time, but time itself does not guarantee a sense of place. Thus, the way an individual experiences and attaches meaning to the place where they live or work can alter and be altered by the physical environment, such as tornadoes. The safety of “home” (i.e., someone’s house, neighborhood, or community) may give someone a false sense of security or may enhance feelings of risk because they do not want home destroyed by a tornado (Tuan 1975).

Manzo and Perkins (2006) expanded on community ties to place through the perspectives of place attachment and community development. They added to Tuan’s concept of place attachment through experience with the concepts of rootedness and bondedness. Rootedness is similar to Tuan’s concept of “home” and refers to one being imbedded in their community. Bondedness refers to the feelings one has being a part of their community. These concepts are both internal and external social processes that influence place attachment to a community. These factors provide a sense of community and the emotional ties an individual has with that community. Manzo and Perkins (2006) explained that these attachments can be disrupted by many factors, including crime, relocation, and environmental disasters. Hence, attachments to communities or a place are impacted by different risks, such as tornadoes. For instance, a tornado impacting one’s community might cause them to question their risk to tornadoes and disrupt the secure feelings they have of “home.” Alternatively, the security of “home” also may lessen their risk perception of tornadoes because they feel safe and therefore misinterpret the severity of the risk.

Masuda and Garvin (2006) discussed how place attachment influences the social amplification of risk. They described that different meaning is attached to places by people with different social and cultural backgrounds, leading to unique place attachments that, in turn, influence the social construction of risk. The authors identified four main social constructs that influence the social amplification of risk – all with underlying themes in place attachment: life, home, prosperity, and community. The first construct, life, refers to the threats that people perceive on their lives and how that helps them to identify a "safe" place to live versus a "risky" place to live. Home refers to their attachment to their lifestyle. More risk is perceived when they feel that there is more threat to their lifestyle. Prosperity refers to economic risks, with possible damage to their finances leading to an increased perception of risk. Finally, community refers to how the broader community may be affected by a particular threat. All four factors influence risk perception, as a threat to any or all of these factors may increase risk perception. Finally, Masuda and Garvin (2006) found that place attachment was embedded in the family, traditions, and lifestyles. Thus, risk can be socially amplified by many factors, and each place has a unique set of factors for each person. The authors summed these ideas as: "risk communication is a cultural process that operates in place" (Masuda and Garvin 2006 p. 452).

Place attachment and its influence on risk perception is also found in tornado risk literature. Klockow et al. (2014) discussed the effects of place and place attachment on tornado risk perception through interviews with 71 residents of Mississippi and Alabama after the 27 April 2011 tornado outbreak. During these interviews, they continuously heard themes of place attachment and how it influenced the participant's perception of risk. For example, the participant's local knowledge of the place where they lived influenced their perceived risk of the tornadoes that day; the geography of the landscape around them could either enhance or attenuate their perception of risk. Many times, people felt lower risk due to the perceived protection from waterways. They had never experienced a tornado crossing the river, so they believed they were safe from the tornado. In another instance, the local landscape increased perceived risk, as the clearing of trees for highway construction led people to believe that the tornado could more easily move through the area and affect them. They felt at greater risk because of this belief. Hence, their connection with and knowledge of their local community influenced how they perceived their risk from the tornadoes. Their connection of "home" also may have influenced their risk perception as "home" often is regarded as a place of safety that can influence the degree of risk they feel (Klockow 2013).

Peppler et al. (2018) also discussed how place attachment affected risk perception. They conducted town hall meetings with 35 residents from towns in central Oklahoma to discuss their perceptions of risk from tornadoes. They followed these meetings with a survey whereby 63 additional people responded and supported the findings from the town hall meetings. The data collected revealed that risk perception varies greatly even over short distances. These differences are influenced by both place-based knowledge and optimism bias, or the belief that "it won't happen to me," from past events. Like those interviewed in Mississippi and Alabama in Klockow et al. (2014), Peppler et al. (2018) also found evidence of perceptions of place. Residents of Norman, Oklahoma, believed they were safer due to protective features of the Canadian River, higher elevation, or Native American burial grounds. Residents of Newcastle, Oklahoma, felt more at risk from tornadoes for three reasons. First, the residents thought that the southwest-to-northeast orientation of Interstate-44 made an "easy path" for tornadoes to follow, as that was also the prevailing path of many tornadoes. Second, they also noted that because they were southwest, or upstream, of Moore, Oklahoma, they were more at risk because Moore had historically been hit by many tornadoes. Finally, they believed that because they were west of

Oklahoma City, they were "unprotected" by the urban heat island, which they believed disrupted tornadoes.

Jauernic and Van Den Broeke (2016) also discussed the effects of physical geography on risk perception. They found in their survey of 613 undergraduate students in Nebraska that 90% of the respondents believed features of the landscape, such as hills, rivers, and snow cover, had some effect on tornado formation. Twenty-one percent believed that the local city was protected, and therefore less at risk, from tornadoes because of its lower elevation. The authors also noted that this perception also resulted from people who did not know the local tornado risk. Thus, local geography and knowledge of the place where they reside influenced how they perceived their risk from tornadoes.

Place attachment and local knowledge indeed affect how tornado risk is perceived. Rather than passively receiving a tornado warning, people are interacting with the information, the environment, and their knowledge of local areas to evaluate their risk and inform their decision-making. Whether it is through their experience of tornadoes, false alarms, fear, how the information was communicated, their perception in space, time, or place, individuals perceive their risk uniquely. These factors affect risk perception, which in turn affects how an individual makes decisions.

2.2 Decision Making

There are many factors that influence risk perception of tornadoes; however, an individual perceiving that they are at risk is only one part of responding to the threat. Not only do they have to believe that they are at risk, they need to believe that they can do something about it and then decide to take action (Perreault et al. 2014). In the case of tornadoes, the warning must convey enough risk for an individual to decide to respond. There are several factors that influence decision-making, and many stem from the same factors that influence risk perception such as experience, false alarms, and how risk is communicated.

Brotzge and Donner (2013) discussed the tornado warning process, including tornado warning detection, decision, dissemination, and public response. They noted that false alarms and experience influence the decision-making process, and similar to risk perception research in these two areas, results are mixed. Brotzge and Donner (2013) also discussed how communication of the tornado warning influences decision-making. Specifically, that a key challenge of warning communication is the need to communicate scientific and risk information to the public effectively. In addition to perceiving accurate risk from the warning, people need to understand it and be able to apply the recommended actions. Therefore, proper communication and understanding of risk information is important to make informed decisions.

Some literature suggests that experiencing a tornado warning leads people to make proper sheltering decisions because they understand what they should do. Silver and Andrey (2014) conducted 35 semi-structured interviews and distributed 304 questionnaires to residents of Goderich, Ontario, Canada, and discovered that there was an increase in sheltering in this town after it experienced tornado warnings three days apart. The researchers were unable, however, to determine if experience caused the residents to take shelter or if it changed their risk perception.

In addition to the public, other decision makers have been studied. For instance, Hoss and Fischbeck (2018) examined how emergency managers used weather data to make decisions. They distributed about 2000 online surveys to emergency managers across the United States asking them how they use weather information. The results showed that those with more work experience, and therefore more experience with tornado events, were more likely to use weather data and use their experiences to make the best decision.

In addition to experience, communication practices, effects of false alarms, ground truth, confidence, and knowledge are also discussed. Durage et al. (2016) analyzed the probabilities of false warning and detection of tornadoes and how that may influence decision-making in the Canadian Prairies. Their analysis of historical tornado warnings in the Canadian Prairies showed a high probability of false alarms and low probability-of-detection. They then conceptualized decision-making with a decision tree and found through quantitative decision analysis that the best decisions were made when the tornado warning system is viewed as reliable. The researchers concluded that although there was a high probability of false alarms and low probability-of-detection of tornadoes, decision-makers needed to factor the difficulty of detecting tornadoes into their decision-making processes, but still respect the validity of the warning.

McCarthy (2002) discussed the role of ground-truth in his study of reports from storm spotters and live broadcasts of tornadoes during the 3 May 1999 F5 tornado in Moore, Oklahoma. He found that real-time storm reports from spotters and live broadcasts of tornadoes were crucial to help people confirm the tornado and act. He also noted that providing timely and credible ground-truth information helped people respond to the warning than they otherwise would have. Therefore, more information about the tornado, such as location, size, estimated intensity, increased people's belief and personalization of the warning so they would act.

An individual's confidence in their ability to respond and decide to take action is another factor that is discussed. Schultz et al. (2010) surveyed 519 residents of Austin, Texas about their confidence in responding to tornado warnings and found that those who were more confident in their abilities were more likely to report the wrong sheltering decision while those who were less confident were more likely to report taking the correct sheltering action. The sheltering options also varied from place to place, such as at home or while driving. The survey also asked if false alarms reduced the participant's confidence in their decision-making and found that they do not, adding to the mixed results found in false alarm literature.

Jauernic and Van Den Broeke (2016) discussed college students' tornado knowledge and how it affects their sheltering decisions. They surveyed 613 undergraduate students at the University of Nebraska and found that residents of the U.S. Great Plains states scored higher on tornado knowledge and safety procedures than those from other parts of the country or international students. Additionally, students who learned tornado knowledge from their parents scored higher on safety decisions than those who did not. In addition, those who used their parents as their primary knowledge source had a higher response rate, making better decisions.

2.2.1 Models of Disaster Decision-Making

These factors discussed have been incorporated into various decision-models to describe how they influence individual choices to act when under threat. Two noteworthy decision models in the field of disaster decision-making are the Mileti-Sorensen sequence developed by Mileti and Sorensen (1990) and the Protective Action Decision Model (PADM) developed by Lindell and Perry (2012). These models sum the decision-making process during hazards, both natural and man-made, and are discussed here in context of how individuals choose to respond to a tornado warning.

The Mileti-Sorensen sequence comprises six steps: Hearing, Understanding, Believing, Personalizing, Deciding, and Responding. Figure 3 depicts the Mileti-Sorensen sequence with "receiver factors" indicating the process an individual receiving the warning goes through, which is what is discussed here (Mileti and Sorensen 1990).

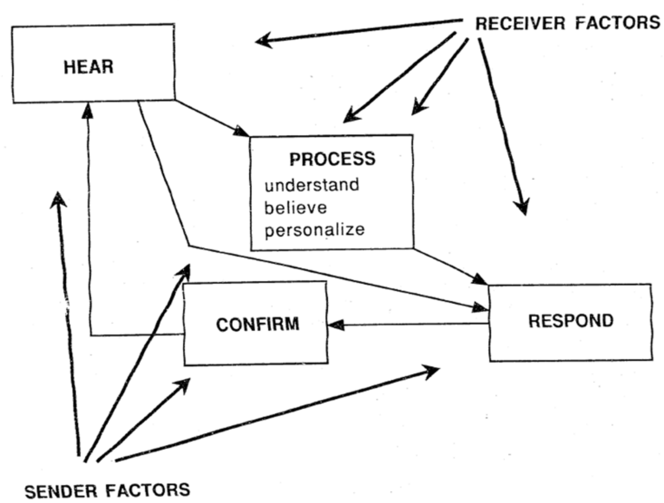

Figure 3. Mileti-Sorensen (1990) sequence. Bolded arrows indicate Sender and Receiver Factors influencing an individual. The remaining arrows outline the sequence an individual goes through when they receive risk information.

Hearing refers to physically hearing the tornado warning, which can take place via various information sources and at various points in time during the warning's duration. The understanding step refers to the individual understanding the contents of the warning message and how it applies to them. Or, as Mileti and Sorensen put it, "personal attachment of meaning to the message" (Mileti and Sorensen, 1990, p.5-2), meaning that they acknowledge what the tornado warning message says and understand that it is important. Believing means the individual has acknowledged that the warning is valid and a threat indeed exists. Mileti and Sorensen (1990) noted that this stage of the sequence often is hindered by the "cry wolf," or false alarm, effect, whereby people have experienced tornado warnings before without a tornado occurrence, so the threat is not acknowledged. The next step, Personalization, means the individual believes the warning and existence of the threat *and* they believe the threat can happen *to* them. This step is often hindered by optimism bias, or the thought that "it won't happen to me." Once the threat is personalized, the individual then decides to do something about it.

Importantly, Mileti and Sorensen (1990) noted that even if a decision were made, it does not mean that it is immediately acted upon. Therefore, the final step is to respond and carry out their decision. The Mileti-Sorensen sequence is a linear decision model whereby each step is completed before the next step begins. Additionally, the process can be stopped at any time if one of the steps is not made and therefore a decision to act is not made. For instance, if a tornado warning is not believed to be true, the individual may not decide to take shelter.

In contrast to this linear decision model, Lindell and Perry's PADM provides a non-linear, iterative model. PADM suggests that individuals do not necessarily go through a sequential, step-by-step process, but rather progress through each step multiple times with new information each time (Lindell and Perry 2012). Figure 4 depicts the model from this study. The model starts with different types of inputs: Environmental Cues, Social Cues, Information Sources, Channel Access and Preferences, Warning Messages, and Receiver Characteristics. Note that many of these inputs can have spatiotemporal components, including place attachment. An individual experiences some or all inputs before moving into the next part of the model: the Pre-decision Process. This process is affected by Exposure, Attention, and Comprehension which, in turn, affect perceptions of the threat, protective actions, and relevant stakeholders. Once these factors are considered, Protective Action Decision Making begins.

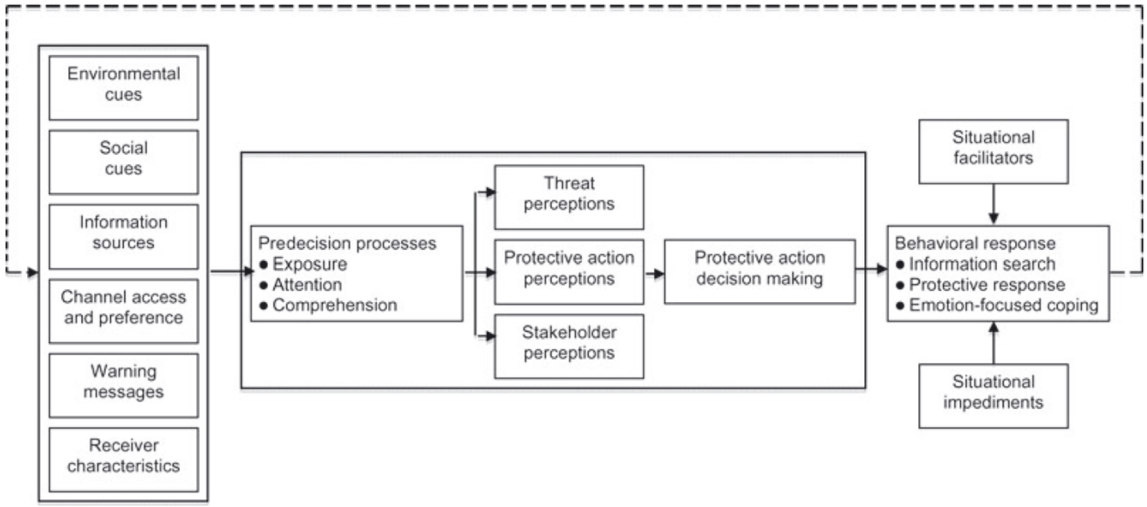

Figure 4. Lindell and Perry (2012) protective action decision model (PADM). Solid black arrows indicate the flow of information and decision making. The model ends with either a behavioral response (decision) or a feedback loop (dotted arrow) and the decision maker goes through the process again.

Decision-making in PADM (Fig. 4) is influenced by Information Search (e.g., risk identification and assessment), Protective Response (e.g., evaluating actions from memory or others' actions, evaluating the best course of action), and Emotion-Focused Coping (e.g., emotional responses to stress). Decision-making can also be aided or hindered by the condition of the physical or social environment. For example, physical separation between family members, such as between work and school, can hinder the process while a parent is seeking their child's safety. The PADM is interlinked and, many times a feedback loop develops when new information, such as environmental or social cues, is inputted back into the model. While PADM is more complex than the Mileti-Sorensen sequence, the intricacies help to model the complex system of information that people process once a tornado warning is received and acted upon.

The Mileti-Sorensen sequence and PADM provide frameworks of how people make decisions during tornado warnings. Many studies apply both models to describe decision making. For example, Ash et al. (2014) utilized both models to evaluate people's decision-making in various risk visualizations. Ripberger et al. (2019) used both models as well to create a generalizable system to understand tornado reception, comprehension, and response. Applying both models, Klockow (2013) examined tornado risk perception and response in space and time, and Sanders et al. (2020) assessed public perceptions of severe weather forecasts after the 2011 tornado outbreak in Tuscaloosa, Alabama. Also, Silver and Andrey (2014) studied how experiencing previous disasters influenced decision-making, and Walters et al. (2020) explored how the public responds to tornado warnings.

Many studies use just one of the two models in their applications to tornado warnings. For instance, the Mileti-Sorensen sequence has been used to study the tornado warning process, from both the forecaster and public perspectives (Brotzge and Donner 2013), tornado warning decision-making among undergraduate students (Jauernic and Van Den Broeke 2016), public response patterns (Donner et al. 2012), decision-making in response to tornado sirens (Drost et al. 2016), decision-making in response to the false alarm effect (Trainor et al. 2015), and creation of a continuum of information in the Forecasting a Continuum of Environmental Threats (FACETs) program (Rothfusz et al. 2018). Additionally, the sequence has helped to describe decision-making during specific tornado events, such as the 3 May 1999 tornado in Moore, Oklahoma (Hammer and Schmidlin 2002; McCarthy 2002), the 22 May 2011 tornado in Joplin, Missouri tornado (Paul et al. 2015), and a violent tornado in Colorado (Schumacher et al. 2010). This list is not exhaustive, but it demonstrates the prevalence and breadth of application of the Mileti-Sorensen sequence to tornado-warning response.

Several researchers applied the PADM alone, though its use has not been as extensive as that of Mileti and Sorensen's, which was developed years earlier. Like the Mileti-Sorensen sequence, the PADM was used to explore different aspects of decision-making during tornadoes. Chaney et al. (2013) used PADM to assess household preparedness among residents in Alabama. Klockow-McClain et al (2019) applied PADM as a framework to analyze decision-making in response to different tornado warning visualizations. Similarly, Miran et al. (2020) used PADM to discuss people's decision-making given probabilistic tornado warnings.

The Mileti-Sorensen sequence and PADM are effective models to discuss decision-making; however, the models do not specifically consider three important concepts: spatial decision-making, decision-making under uncertainty, and decision-making given different threat visualizations. These decision models and their underlying concepts are important because they provide a foundation to understanding decision-making. This foundation is key when asking more specific questions about decision-making, such as how decision-making varies for different people in different places.

2.2.2 Place-Based Decision Making and Geographic Specificity

Research into specific events provide context for how decision-making can unfold depending on place, including prior tornado experiences in a place. Brown et al. (2002), for example, studied public response to tornado warnings and compared that to the death and injury rate of the 3 May 1999 F5 tornado in central Oklahoma with the goal to reduce overall injuries and fatalities in future events. Most of the deaths occurred in Bridge Creek, an unincorporated town southwest of Moore. The authors theorized that the high death toll was due to lack of place-based specificity in the communication of the tornado warning. Since Bridge Creek had no sirens and was not labeled on maps displayed by local television broadcasters, many residents were unaware of the danger posed to them by the tornado. Brown et. al.'s (2002) results demonstrate that geographic-specificity is important for people to make protective decisions. Hammer and Schmidlin (2002) also considered public response in the same event, interviewing 190 residents whose homes received F4 or F5 damage about their decision process to either evacuate or shelter in place. They found that street-level tornado path information provided by local television broadcasters, the appearance outdoors, and phone calls from loved ones influenced people's safety decisions. For those with longer lead times, individuals were able to assess the information provided by these sources and their knowledge of the local landscape to determine that there was enough time and distance between them and the storm to evacuate. Hammer and Schmidlin's (2002) results show that knowledge of place and geographic information is important when making sheltering decisions. McCarthy (2002) examined the effects of ground-truth reports on decision-making and response during the 3 May 1999 tornado and found that ground-truth reports were critical to decision makers. The reports provided information about the tornado's location and intensity that decision makers were able to use to make informed decisions. Comstock and Mallonee (2005) also reviewed this tornado event, by comparing survey results from the same community (Moore, Oklahoma) after an F3 tornado struck on 8 May 2003 to determine if experiencing the first tornado had any influence over the decision-making process and response for the second tornado. They concluded that there was an increase in protective action decisions following the second tornado, indicating that prior tornado experience prompted Moore residents to take more protective action.

Studies also examine the 27 April 2011 outbreak across the southeastern U.S. (e.g., the aforementioned Klockow et al. (2014)). Chaney et al. (2013) surveyed 109 residents of DeKalb County, Alabama about their household preparedness and decisions to shelter during this event and found that residents with safety plans in place were more likely to seek shelter, apart from mobile home residents. Mobile home residents responded that they would likely shelter in place because they did not know or were unaware of the nearest shelter. Therefore, not knowing places of safety influenced the residents' decision to take an unsafe course of action. Sanders et al. (2020) considered the 2011 outbreak as well and used focus groups of residents in Alabama to study public perceptions of warnings, individual responses to the warnings, and what gaps may exist between warning dissemination and public response. Many of the participants noted being aware of the tornado warnings, but they were not concerned it would impact them because they had never experienced a tornado. Certain environmental cues, such as hail or strong winds, prompted them to act. Thus, local knowledge prompted them to initially ignore the warnings, but interactions with the environment finally convinced them to act. Interviewing 29 residents in Smithville, Mississippi, after the outbreak, Sherman-Morris and Brown (2012) examined information seeking and actions taken after receiving a warning. They found that the tornado's location was the most common searched for piece of information, suggesting that location is important when making decisions.

The record high fatality rate during the 2011 Joplin, Missouri, tornado prompted Paul and Stimers (2012) to evaluate possible reasons for the fatalities, such as the magnitude and size of the tornado, its path through town, size, and the desensitized attitude some of the residents had towards tornado warnings. Continuing this work, Paul et al. (2015) studied how people complied with the tornado warnings – specifically, how residents received the information, their attitudes towards the warnings, their effectiveness at sheltering, and their response rate of sheltering. The authors found that many residents noted how there had never been a tornado in Joplin before, so they were less likely to believe the warnings based on this experience. These results show that place-based knowledge, such as knowledge or experiences of local tornado exposure, influence protective decisions. In the case of Joplin, there was a tendency not to take protective action.

In addition to place-based studies after specific, large-scale events, there are studies that examine place-based decisions after smaller-scale events. For instance, Monfredo and Tiefenbacher (2003) and Tiefenbacher et al. (2001) both assessed an F3 tornado that took place in Siren, Wisconsin on 18 June 2001. Both studies analyzed Siren residents' decision-making, behavior, and response to this event and found that some residents acted because they believed Siren was located in a "mini–Tornado Alley" (Tiefenbacher et al. 2001). The studies did not expand upon this observation, but it appears that local knowledge and experiences residents had with Siren's location prompted them to believe they were more at risk to tornadoes and therefore seek shelter. Schultz et al. (2010) studied decision-making during a hypothetical tornado warning with residents who lived in floodplains in Austin, Texas. They found that, even though the residents were more accustomed to flooding threats, they were aware of the dangers of tornadoes. However, many responded that they would take unsafe sheltering decisions, such as sheltering under overpasses if driving. This result may indicate that experience with hazards specific to a place, in this case flooding being more common than tornadoes in Austin, may influence decision-making. Schumacher et al. (2010) discussed public response from an EF3 tornado event that took place in northern Colorado by interviewing 15 decision makers (emergency managers, school administrators, university officials, school teachers, small business owner, and broadcast meteorologist). Like many of the aforementioned studies, they also found that experience with local climatology affects decision making. Since the area researched in Colorado had never experienced a tornado, many respondents were either unsure how to act or if the warning was real.

Some studies assess broader regions, but the results are not directly compared. Donner et al. (2012) investigated public response in the southern United States by interviewing residents in Louisiana, Missouri, and Tennessee about their sheltering responses after tornadoes occurred in these states in February and April of 2006. Like studies of specific locations, the residents in the region stated that the tornado's location was important in their decision-making processes. They also used towns and landmarks, such as street names, to help them make decisions. Interestingly, residents in Missouri noted that local churches were helpful as they were able to translate warning messages into Spanish for the local population. The Missouri residents were able to make better decisions because they felt connected to the churches and their local community and were able to understand the warnings better.

2.2.3 Spatial Decision-Making

Spatial decision-making is an important area of research in the field of geography and much of the prior work can be applied to natural hazards. For example, Klockow (2011, 2013) and Klockow-McClain et al. (2019) studied decision-making given different tornado warning designs. Klockow (2011) examined geospatial awareness during tornado warnings, explaining that geospatial awareness, or how well and individual understands the area around them, is a function of how they interpret the warning. She employed in-depth interviews with 71 people in Alabama and Mississippi after the 27 April 2011 tornado outbreak. In these interviews, she found usage of maps, scale, and landmarks influenced how people became spatially aware of the tornado threat and acted upon that information. She also noted that spatial reasoning was different for every individual.

Klockow (2011, 2013) discovered that maps were often cited as a source of warning information, but participants were confused when they were used by television broadcasters. The participants noted that while live footage of a tornado or storm was shown, it was not aligned with a map showing tornado location, maps or map scales were difficult to interpret, and the trajectory of the tornado was difficult to interpret because radar loops were either not shown or too short. As for the scale of map information, participants noted that they preferred the county-level scale because they could personalize the risk as a tornado passed through familiar towns. For this event, a scale problem arose; many individuals did not understand or could not conceptualize how large a one-mile-wide tornado was. This complication reduced response time because many people thought the tornado would hit one landmark at a time rather than multiple locations because of the width. Those without landmark information had even more difficulty. Landmarks were found to be useful for communication because, when used, the reports were trusted by participants almost without question. The usage of landmarks helped the participants to understand where the tornado was located and more quickly personalize the risk. This result agreed with that of Drost et al. (2016), who noted that geographic specificity and mention of landmarks led to greater response to warnings.

Klockow-McClain et al. (2019) evaluated different spatial warning graphics and their influence on how people made decisions. Specifically, they studied how people made decisions given three geospatial framing effects: boundary inclusion and exclusion (i.e., whether a person was inside or outside the warning area), distance from the storm, and symbolic spatial representations of risk (e.g., different color palettes). They administered an online tornado warning decision experiment to 5,564 participants across the United States and found that under deterministic warnings, participants inferred uncertainty based on their distance from the storm. When given a probabilistic tornado warning, people made better decisions and their decisions were more based on the probabilities more than on the distance from the storm.

Nagele and Trainor (2012) also explored geographical dimensions of tornado warnings in their study of storm-based tornado warnings and public response. Specifically, they considered effects of the warning polygon, proximity of the participant to the warning, and geographic specificity of tornado warnings by interviewing 1038 people from across the United States. The researchers discovered that when participants were located inside the polygon, their response did not increase, but being told their home was located inside the warning polygon correlated with higher rates of sheltering. Nagele and Trainor (2012) also found that using smaller polygons increased response and participants inside the polygon were less likely to seek information. Additionally, those who were closer to the storm and had a family emergency plan were more likely to take shelter. Also, geographic specificity, or specifying the location of the tornado, led to increased sheltering, but not necessarily information seeking.

Likewise, Sherman-Morris and Brown (2012) and Walters et al. (2020) noted the importance of the warning polygon, location of the tornado, and proximity of the individual to the warning. The former researchers interviewed 29 people in Mississippi shortly after the 27 April 2011 tornado outbreak to examine public perception of the NWS warning polygons and found that most people suggested that the middle of the polygon was the most likely location of the tornado and therefore the location most at risk. Sherman-Morris and Brown (2012) also discovered that the most commonly desired piece of information was the tornado’s location. Walters et al. (2020) interviewed 11 NWS forecasters from Tennessee about their perceptions of public response and what information they believe the public wants. Their results showed that the forecasters believed that proximity of a community to the warning was the most important piece of information.

Jankowski (2018) discussed spatial decision-making models. Five broad spatial decision models were discussed: descriptive models (analyzing empirical observations), normative models (assuming perfectly rational and utility-maximizing agents), exploratory models (simulating agents' behavior based on rational or bounded rational agents), prescriptive models (making decisions given limitations), and cognitive models (simulating behavior under explicit tasks). These models can be used in the context of making decisions during tornado warnings as they form a basis of how to view the decision maker. For instance, under a normative model, a decision-maker always knows what the best course of action is to take during a tornado warning. This behavior might not necessarily reflect real-world scenarios, since it is impossible to know exactly what the outcome is and be able to make the correct decision accordingly. Therefore, more exploratory models, such as a bounded rational decision-maker, are more realistic because they view the decision-maker as having limitations, i.e., not knowing the outcome(s) of every tornado event. It is also important to consider how the environment influences the decision-maker. Taylor et al. (2018) discussed that the physical attributes of environment influence how people make decisions. In the case of tornadoes, the storm environment may influence their decisions. For instance, a person may experience hail, which may prompt them to take the tornado warning more seriously and decide to shelter. Like the decision-models discussed previously, these models provide a foundation for how to treat decision-making across wider concepts, such as decision-support services. Ultimately, disseminators of tornado warnings want the warnings to convey the correct amount of information to support people's decisions. It is therefore important to understand how decision-makers think.

2.2.4 Uncertainty

In natural hazards, outcomes are inherently uncertain. In the context of tornado warnings, the question arises of how people make protective decisions given uncertainty. Joslyn and LeClerc (2012) discussed the use of uncertainty information in warnings and forecasts, noting that there is reluctance by forecasters to provide uncertainty information rather than current deterministic forecasts out of concern that it will be misused. Yet, in their study of 304 University of Washington psychology students, they found that the participants inferred uncertainty from deterministic forecasts anyway and that participants made better decisions when given the uncertainty information (e.g., precautionary information and descriptions of the risks involved). Joslyn and LeClerc (2012) also discovered that just telling people what to do without giving them uncertainty information was not convincing enough for participants to respond. The researchers surmised that giving uncertainty information allows people to make better decisions and they make the decisions when the conditions are sufficiently motivating.

Nadav-Greenberg and Joslyn (2009) also discussed the use of uncertainty information and how the resulting decision-making changes. They administered surveys to two different populations: (1) 251 Internet users who were recruited through a news website, and (2) 173 psychology students from the University of Washington. Like Joslyn and LeClerc (2012), Nadav-Greenberg and Joslyn (2009) found that decision-making improved when the participants received the uncertainty information, even though there was some reluctance to use this information. They theorized that it might be because uncertainty guidance is unfamiliar to use or that they do not know its potential advantages. Regardless, decision-making improved after using the information.

Klockow-McClain et al. (2019) examined how decision-making changed given different types of tornado warnings with and without verbal uncertainty information included (a high or low chance of a tornado occurring). Klockow-McClain et al. (2019) found that, much like the participants in Joslyn and LeClerc's (2012) study, the 5,564 participants from across the United States inferred uncertainty into deterministic forecasts in the online experiment. They also found that participants made fewer errors when the participant was given the verbal information and when given probability information rather than deterministic information.

Human decision making also is influenced by the design and visualization of the hazard information. In addition to providing uncertainty information verbally, many studies examine different warning graphics that depict uncertainty information – typically displays of deterministic versus probabilistic products.

Montello et al. (2018) discussed how cartography and geographic information visualizations are communicated, influence cognition, and are interpreted, including how uncertainty information should be used. They noted several processes that influence map usage such as perception, spatial memory, map reasoning, and emotion, as well as that the type of map (e.g., three-dimensional maps, moving maps, non-visual, interactive, and customizable maps) influences how people apply information. These factors impact how people interpret and make use of maps and geographic information.

Given these factors, researchers have attempted to develop new ways to present uncertainty and geographic information contained within tornado warnings. Drost et al. (2016) evaluated current warning visualizations or audio messages, such as through television, online animation, radio, and how people pay attention to and retain the information presented through these mediums. The results showed that the visual warnings were more helpful than the audio warnings, and that the latter were only helpful when location and movement information were given. Visual warning messages that contained information about location, town names, road names, movement, etc. best helped people understand and respond to a warning message.

Ash et al. (2014) studied response rates given deterministic and probabilistic tornado warnings in a survey of 501 students at the University of South Carolina. The authors found that probabilistic warnings were better than deterministic warnings at helping participants understand their proximity to the storm as well as helping the participants to perceive the appropriate amount of risk and take protective action. Using the same survey, Schumann et al. (2018) examined people's risk perception and response to tornado warnings given different visual designs and found that people perceived more risk with graphics that contained visual information. Additionally, people who personally sought out this information and had more experience with tornadoes were more likely to decide to shelter, indicating that obtaining visual information was helpful in making decisions.

Klockow-McClain et al. (2019) also discovered that probabilistic information led to better sheltering decisions being made in their decision experiment given different designs of tornado warning graphics. They also examined different color schemes of probabilistic warnings including black and white, sequential (red gradient), divergent (red to blue), and spectral (rainbow). They found that the divergent and sequential color schemes significantly reduced protective action at low probabilities (10-25% chance of a tornado) which, in turn, reduced subjective estimates of risk. Therefore, not only color, but the absence of color influenced how people perceived the tornado risk and made decisions under uncertainty.

Miran et al. (2020) conducted an experiment similar to Klockow-McClain et al. (2019). They recruited 109 participants from random classes at the University of Akron in Ohio to complete an online experiment that tested uncertainty information in the form of probabilistic tornado warnings on people's decision-making. Miran et al. (2020) found that probability played a significant role in decision-making and that people made better decisions.

These studies show that people can use probabilistic information to make better decisions in response to tornado warnings; however only a select few compare decision-making across a large region, such as the entire United States. In most cases, the studies are limited to particular populations, such as students at a single university. Other studies are specific case studies, restricted geographically and many times resulting from a damaging tornado event. Events that have been studied most include the 3 May 1999 F5 tornado in central Oklahoma (National Oceanic and Atmospheric Administration 1999), the 27 April 2011 outbreak across the southeastern United States (National Oceanic and Atmospheric Administration 2011a), the 22 May 2011 EF5 tornado in Joplin, Missouri (National Oceanic and Atmospheric Administration 2011b), and the 20 May 2013 EF5 tornado in Moore, Oklahoma (National Oceanic and Atmospheric Administration 2014). The NOAA NWS Service Assessments also provide rich detail for these events but are intended to overview the event, assess how the forecast office handled the situation, and recommend potential improvements; they are not intended to research public decision-making practices. Although case studies cannot be generalized to larger regions, they have provided insightful and detailed analyses.

2.3 Spatial Perspectives on Tornado Safety

Although individuals perceive risk and decide how to respond, their broader social vulnerability and exposure to the hazard climatologically also play roles in their susceptibility to harm and ability to recover from tornadoes. Many of the attributes noted in prior research have a spatial dimension (e.g., place attachment, people's proximity to storms, etc.) and even with growing understanding about how individuals respond, tornado warnings are issued for regions, not individual people. Therefore, it is important to understand better how people in different locations experience tornado warnings.

Studies in the United States that explore tornado hazard exposure include Boruff et al. (2003) who assessed the frequency and location tornado hazards across the United States; Brotzge et al. (2011), who analyzed a five-year climatology of tornado false alarms; Hatzis et al. (2019), who conducted a spatiotemporal analysis of near-miss violent tornadoes; and Ashley (2007), who provided a spatial and temporal analysis of tornado fatalities. In addition, Ashley and Strader (2016) examined the physical characteristics of tornado-prone regions to quantify risk, including physical attributes of tornadoes, tornado exposure, differences in tornado mortality, and different scales. Emrich and Cutter (2011) similarly conducted a spatial assessment of hazards in the southern United States, but added the element of social vulnerability, defined as socioeconomic and demographic characteristics, such as age, gender, race, income, education, that make an individual or group more susceptible to hazards.

Social vulnerability studies focus primarily on socioeconomic information, usually obtained from census data. These studies do not examine individual risk perception and response, and instead attempt to pinpoint populations that may be vulnerable to hazards so that hazard planning can reduce potential harm as much as possible. For example, Cutter et al. (2000, 2003) and Cutter and Finch (2008) used census data to construct a Social Vulnerability Index (SoVI) for the United States.

The SoVI was generated by performing a Principal Component Analysis (PCA), a type of factor analysis, on county-level census data obtained from the U.S. Census Bureau. Based on prior hazards literature review, Cutter and others identified and collected more than 250 variables from the census data that contributed to social vulnerability to environmental hazards. The PCA identified 11 variables that accounted for 76.4% of the variance in the county-level data. These 11 variables represented the most important variables that contribute to social vulnerability to environmental hazards at the county level: personal wealth, age, density of built environment, single-sector economic dependence, housing stock and tenancy, race- African American, Hispanic ethnicity, Native American ethnicity, Asian, occupation, and infrastructure dependence (Cutter et al. 2003). The SoVI score was generated by summing all factor loadings per county (Cutter and Finch 2008). Figure 5 shows SoVI for each county in the U.S. In general, rural U.S. and inner-city counties have higher values of social vulnerability. Cutter and Finch (2008) found that the most vulnerable county was New York County, New York, and other areas with high SoVI were associated with Native American reservations (such as North Dakota, South Dakota, and Montana), and counties along the U.S.- Mexico border.

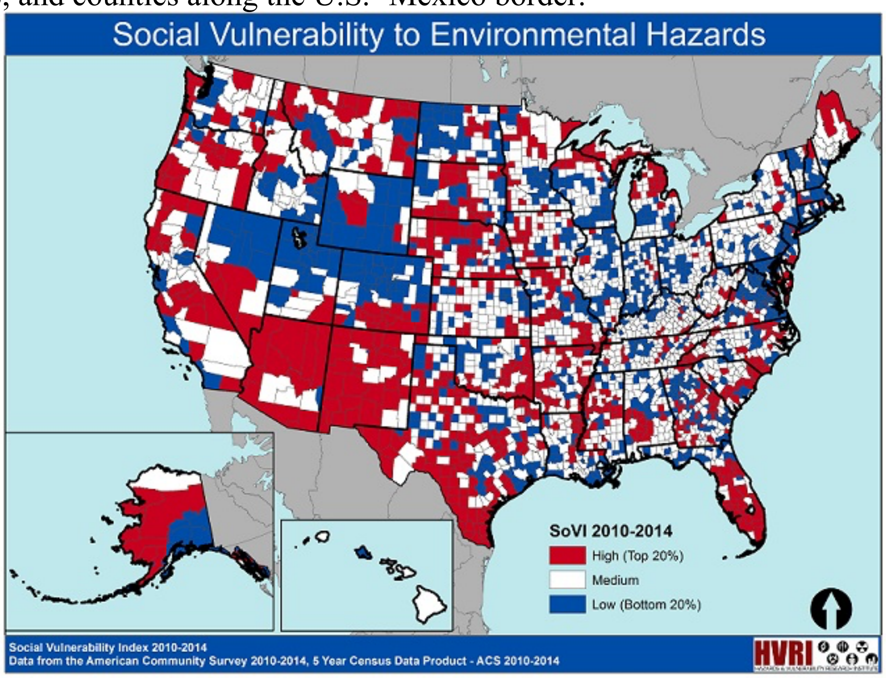

Figure 5. The Social Vulnerability Index scores for all counties in the United States as calculated by Cutter and others at the Hazards and Vulnerability Research Institute (http://artsandsciences.sc.edu/geog/hvri/sovi%C2%AE-0). Counties in red (blue) represent the top (bottom) 20% of SoVI values. SoVI values were computed using U.S. Census data from 2010-2014.

Stewart et al. (2012) gave an online survey to 1465 participants across the U.S. to compare weather salience (perceptions and attitudes toward weather). The participants were sorted by their locations across different U.S. climate regions, including dry/arid, temperate, and continental. Participants from dry climates, such as the southwestern U.S., had lower weather salience than those who lived in temperate and continental climates. Participants from temperate and continental climates also emphasized precipitation forecasts and overall usage of weather information. Stewart et al.'s results indicated that people from different parts of the United States observe weather differently.

Ripberger et al. (2020) and Allan et al. (2020) used the Severe Weather and Society Survey (WxSurvey) from the Center for Risk and Crisis Management at the University of Oklahoma to examine geographic distributions of risk reception, perception, and response to tornadoes across the United States. WxSurvey is an annual survey that began in 2017 and asks both recurring questions that measure tornado warning reception, comprehension, and responses and one-time questions addressing specific interests of individual researchers (Ripberger et al. 2019). Ripberger et al. (2020) and Allan et al. (2020) compared their results with tornado occurrence and found that exposure to and experience with the hazard likely resulted in populations that are more knowledgeable and responsive to tornado warnings. For instance, Ripberger et al. (2020) found that, on average, reception, comprehension, and response to tornadoes was lowest in the western United States, slightly below average in the eastern United States, and above average in the central United States. This spatial pattern aligned generally with tornado climatology, as tornadoes have been more prevalent in the central United States.

Allan et al. (2020) analyzed numerous weather hazards and found that risk perception and response correlated with hazard climatology. For instance, they found that risk perception for hurricanes was highest along the eastern and southern coasts of the United States, matching the areas with highest exposure to a hurricane threat. When comparing risk perception and hazard exposure, they determined that risk perceptions of hurricanes, tornadoes, and drought were highest among a set of climate hazards. There were more moderate relationships between risk perception and exposure to snow/ice, wildfire, and extreme cold, and a weak relationship with flood and heat risk and exposure. Allan et al. (2020) offers unique insights and comparisons of risk across the United States.

Sims and Baumann (1972) administered a survey to 57 people to compare weather responses and coping styles (e.g., feeling lucky, reliance on religion, reliance on technology) between residents in Illinois and Alabama. They found Alabamans to be more fatalistic than Illinois residents and concluded that this tendency was perhaps why more tornado fatalities occurred in the south as compared to the north. Their conclusion was quite bold, which is why Cohen and Nisbett (1998) responded to this result by creating a similar study to examine fatalistic attitudes more broadly, including more states to compare the Midwest and the South. Cohen and Nisbett (1998) found that fatalism was not only concentrated in the South; many people in the Midwest displayed this attitude as well. They found that, if anything, youth were more positively correlated with risk-taking than being from one of these locations.

2.4 Research Gap

In combining tornado climatology and social vulnerability, one can find great insight into areas that are more vulnerable to tornadoes, may suffer greater social or economic loss, and can use more work in mitigation and resilience. But these studies do not account for spatial differences in how people respond to and make safety decisions in response to tornado warnings. Although risk perception (e.g., Allan et al. 2020), tornado warning reception, comprehension, and response (e.g., Ripberger et al. 2020), and weather salience (e.g., Stewart et al. 2012) have been analyzed geographically, these studies have not examined *decision making* spatially. These analyses did find geographical variations that may indicate that decision making varies by geography, and other research has demonstrated that place-based knowledge can be important in the decision process (e.g., Klockow et al. 2014, Peppler et al. 2018).

The research that follows addresses these gaps in knowledge about whether there are geographic variations in decision making in response to tornado warnings. These variations may result from similar experiences of all residents within a common NWS Forecast Office may have resulting from the office's unique set of features, such as false-alarm rates, communication practices, etc. The analysis can help risk communicators identify locations of higher risk so they can hone their communication efforts as well as serve locations that may need extra help or education in preparing for and becoming more resilient to tornadoes.

Chapter 3. Research Questions, Data, and Methods

As a result of prior research, this study asks: How does decision-making during tornado warnings vary spatially across the United States by National Weather Service County Warning Area (CWA). A CWA is the jurisdiction of a single NWS Weather Forecast Office that comprises multiple counties. Generally, CWAs are smaller than states and, in the contiguous U.S., can overlap multiple state boundaries. NWS forecasters from a single office produce the tornado warnings for their CWA according to their office policies, forecaster skill, local data, and other input; hence, it is expected that the processes to produce tornado warnings may vary by CWA and, as a result, response decisions by the public may vary by CWA. In addition, people's response decisions within each CWA may vary based on local characteristics, such as place attachment, experiences with tornado warnings, or familiarity with tornado warnings.

To determine how public decision making may vary across CWAs, I ask the following questions:

- Are there particular demographic attributes that contribute to incorrect decision making (i.e., sheltering when there is no tornado or not sheltering when there is one)?
- Do these attributes contribute to decision making that varies geographically across the United States?
- Are there regions of the United States where people are more prone to making incorrect decisions?

Although there are a variety of ways to answer these questions, this study uses data from a nationwide, online experiment because it provides a consistent dataset of decisions made during simulated tornado warnings from a large sample across the U.S. as well as demographic and geographic information for each participant.

3.1 Data

3.1.1 Simulated Tornado Response

This project uses an existing dataset developed and provided by Dr. Klockow-McClain of the University of Oklahoma's Cooperative Institute of Severe and High-Impact Weather Research and Operations/NOAA National Severe Storms Laboratory. Klockow-McClain et al. (2019) detail that these data were collected from a nationwide survey of 5,564 participants with approximately 100 people from each of the 50 U.S. states. The purpose of the original experiment was to analyze how people make decisions given deterministic (i.e., current products) and probabilistic (i.e., future products) warnings as well as to examine how different probabilistic cartographic designs influenced decision making. Survey participants provided demographic and socioeconomic information including gender, age, household income, employment status, and education, as well as state and county of residence.

To gather these data, each participant engaged in a web-based decision experiment to evaluate risk estimates derived from different tornado warning displays. A single experiment consisted of 96 total decision trials whereby a participant was hypothetically in charge of sheltering aircraft at one of four airport locations using three ranges of probability of a tornado occurring, with eight trials for each pair of airport locations and tornado probabilities (4 locations x 3 probability ranges x 8 trials = 96 total trials). They were given the following cost-loss scenario (Table 1): 1) discontinuing airport operations and sheltering aircraft cost $3,000, 2) failing to shelter and a tornado struck cost $6,000, and 3) not sheltering and no tornado occurred acquired no cost or loss. Each trial ended after they chose to protect or not protect the aircraft.

Table 1. Cost-loss scenario used for decision experiments that resulted in the dataset developed by Klockow-McClain et al. (2019). The 2x2 matrix displays the cost or loss result from the participant's decision (protect or not) and a computer-generated event (tornado or not tornado).

		Tornado	
		Yes	**No**
Protect	**Yes**	-$3,000	-$3,000
	No	-$6,000	$0

During each trial, participants were randomly and evenly assigned verbal guidance conditions (i.e., they received verbal guidance for zero trials or all 96 trials) and one of six warning displays for all trials, resulting in 12 possible combinations of guidance and graphics. Verbal guidance contained one of two messages, either a "high chance" that a tornado will strike (i.e., probability of tornado occurrence was greater than 50%) or a "low chance" (i.e., probability of tornado occurrence was less than 50%).

The six possible warning graphics included two deterministic warnings and four probabilistic warnings (Fig. 6). The deterministic graphics contained no color fill within the polygon with one graphic representing a "short" lead-time (30 minutes; Fig. 6A) and the other representing a "long" lead-time (1 hour; Fig. 6B). All probabilistic warnings explicitly included the numerical probability of a tornado occurrence in each of four segments of the graphic. The probabilistic warning graphics were the following: 1) without color filled in the polygon (only text probability values for four sections of the graphic; Fig. 6C), 2) a sequential color-scheme (red gradient; Fig. 6D), 3) a divergent color-scheme (blue low-end probabilities transitioning to red high-end probabilities; Fig. 6E), and 4) a spectral color-scheme (rainbow, with red indicating higher probabilities; Fig. 6F). The four probability values increased by 15% for each segment closer to the tornado location (e.g., Fig. 6C). Finally, each participant was randomly assigned a location, A-D, within or near the warning boundary for any given warning graphic. After the participant selected a protection response, the computer would determine whether a tornado occurred using the probability at the participant's assigned location (using random sampling without replacement). For example, a participant might be located at point C with a sequential color scheme that equated to a 55% chance that a tornado would occur. They would decide whether to shelter given this information. The computer then computed whether a tornado occurred, given the 55% chance. Verbal guidance, if they received it, did not change how the computer generated a tornado or not; it only highlighted whether the participant was at a location with a higher or lower than 50% probability of tornado occurrence.

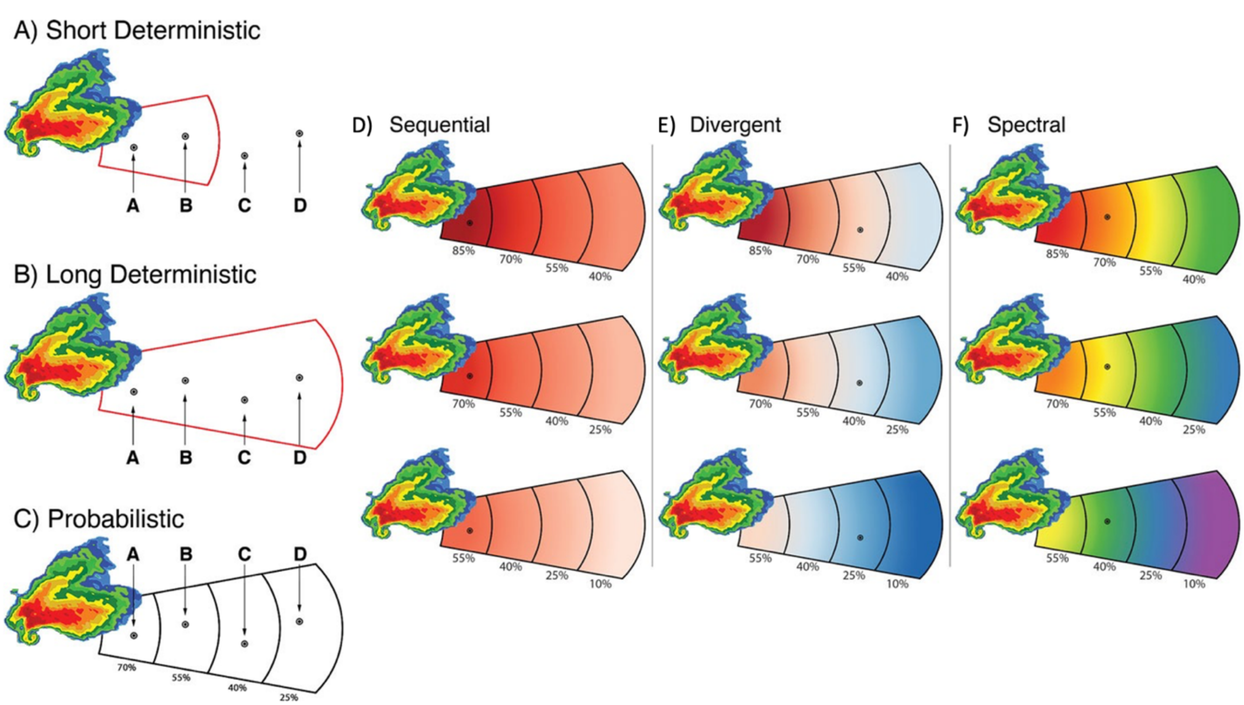

Figure 6. Tornado warning cartographic designs used for decision experiments developed by Klockow-McClain et al. (2019). The data from these decision experiments are used for the study herein.

During each trial, a tornado could strike their location (or not) and they had the choice to protect/shelter (or not). Therefore, there were four possible results a participant could obtain: hit, miss, false alarm, or null (Table 2). A hit (H) occurred when a participant chose to protect and the computer generated a tornado from the probabilities (which were generated internally but not shown in the deterministic graphics); a false alarm (F) occurred when they protected but no tornado occurred; a miss (M) happened when they did not protect and a tornado occurred, and a null (N) occurred when they did not protect and there was not a tornado.

Table 2. Four decision results possible after each trial in the decision experiments developed by Klockow-McClain et al. (2019). The 2x2 matrix, similar to the cost-loss matrix (Table 1), displays the participant's result after they chose to protect (or not) and if there was a tornado (or not).

		Tornado	
		Yes	**No**
Protect	**Yes**	Hit (H)	False Alarm (F)
	No	Miss (M)	Null (N)

For this study, I defined a "correct" decision as either H or N and an "incorrect" decision as either M or F. Although a false alarm is not a mistake in reality (perhaps indicating a "better safe than sorry" motto indicating higher risk aversion), I included it in the definition of an "incorrect" decision because the project is meant to examine whether or not a warning conveyed the correct amount of risk to prompt the participant to take necessary action or not at the least cost to them. Thus, it is important to note that my definition of an incorrect decision does not necessarily imply a "bad" or "wrong" decision.

From the original 5,564 participants, Dr. Klockow-McClain retained only 4,461 participants who had complete results from all 96 trials, who did not have any missing information, and who took enough time on the experiment to be taken seriously. For my study using CWA-level data, I filtered the dataset through additional steps. First, I paired each participant with their CWA using the *merge* command in R, merging the CWA shapefile from the NWS AWIPS Basemap Shapefile webpage (https://www.weather.gov/gis/AWIPSShapefiles) with county Federal Information Processing System (FIPS) codes listed for each participant.

Twenty people did not provide county information, reducing the participants to 4,436. CWAs in Alaska and Hawaii then were removed, resulting in a total of 4,331 participants. Alaska and Hawaii were removed because they receive minimal tornado exposure, and their results were difficult to compare alongside the contiguous United States.

<u>3.1.2 Tornado Frequency</u>

NOAA's Storm Events Database provided the tornado frequency data, including the mean number of tornadoes per year by CWA (personal communication, accessed 2/11/21). These data were used to determine if tornado climatology, or exposure, had any relationship to decision making during the simulated tornado warnings. Figure 7 depicts tornado event frequency per CWA in the United States. The events are displayed in percentiles to show how each CWA ranks in tornado events compared to others. Note that the central and southern U.S. have the highest percentile rank for tornado frequency, meaning that CWAs in these areas have an above average number of tornadoes per year compared to other CWAs.

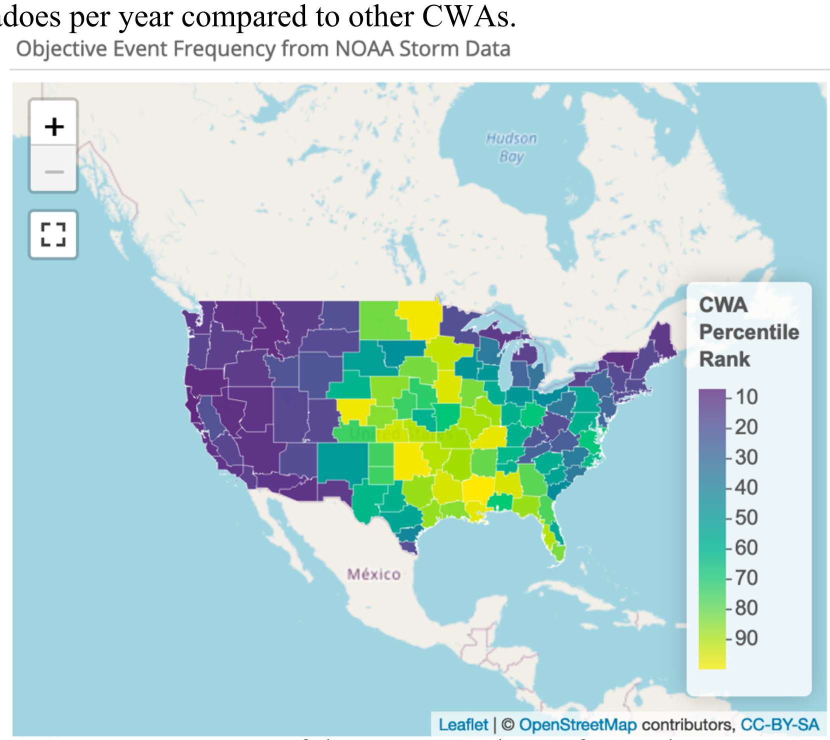

Figure 7. NOAA Storm Event Data of the mean numbers of tornadoes per CWA by percentile rank. Greens and yellows (blues and purples) indicate higher (lower) percentiles.

3.1.3 U.S. Census Data

Finally, United States census data aggregated by CWA was provided by Dr. Joseph Ripberger from the Center for Risk and Crisis Management and the National Institute for Risk and Resilience at the University of Oklahoma (personal communication, 2/11/21). The census data originated from the United States Census Bureau website for the years 2010-2018 – the latest years with complete census data records available. The dataset included county resident population estimates by age, gender, race, and Hispanic ethnicity, and it was aggregated to CWA scale by Dr. Ripberger.

3.2 Methods

In this study, Multilevel Regression Analysis and Poststratification (MRP) and spatial autocorrelation were used to examine (1) the characteristics of the participants who were more prone to make incorrect decisions during the tornado warning experiment, (2) where these participants were likely to be located, and (3) if there were spatial patterns where incorrect decision making was most prevalent. Questions 1 and 2 utilize MRP; question 3 applies spatial autocorrelation.

3.2.1 Multilevel Regression Analysis and Poststratification (MRP)

Multilevel Regression Analysis and Poststratification (MRP) is a type of small-area estimation (SAE) that is used to downscale data from larger to smaller population characteristics (Lax and Phillips 2009; Ripberger et al. 2020). SAE "is a statistical technique used to produce statistically reliable estimates for smaller geographic areas than those for which the original surveys were designed" (Zhang et al. 2015). For instance, SAE techniques are used to predict voting patterns in relatively small areas (e.g., states or voting districts) from data obtained through political opinion surveys that are administered nationally. Likewise, a nationwide decision experiment can be downscaled to the CWA scale.

There are two primary techniques to conduct a SAE: disaggregation and MRP. Disaggregation is commonly used because of its simplicity, as it pools many survey results and then calculates the proportion of responses per geographic unit based on those results (Lax and Phillips 2009). For example, 20% of people in state X hold opinion Y while 42% of people in state Z hold this opinion. In contrast, MRP estimates responses across geographic units, such as states or counties, from individual characteristics and responses based on location (Buttice and Highton 2013). In this way, MRP retains spatial characteristics within the dataset where the region's sample size is sufficient and draws information from other data in the broader sample where the region's sample size is too small. MRP is more complex than disaggregation because it models responses (e.g., from a survey, opinion poll, etc.) as a function of both demographic and geographic variables (Lax and Phillips 2009). MRP models responses by creating a multilevel regression model to produce a preference estimate for each type of person in the dataset and then weights those preferences by population frequency at a particular geographic unit (Buttice and Highton 2013).

Thus, MRP uses experiment data to predict the types of people who have certain responses and where they may be located in pre-defined geographic units, such as states, counties, or CWAs. MRP has been used primarily in the political sciences, such as election forecasting and voting patterns (Hanretty 2020), but recently has been applied to study people's responses to climate change and extreme weather, such as geographic distributions of climate change opinions (Howe et al. 2015); climate change messaging (Zhang et al. 2018); extreme heat risk perceptions (Howe et al. 2019); tornado warning reception, comprehension, and response (Ripberger et al. 2020); and extreme weather risk perceptions (Allan et al. 2020).

The study herein applies MRP to examine geographic distributions of incorrect decision making by using each participant's proportion of incorrect decisions during the 96 trials of the simulated tornado warning decision experiment (Klockow-McClain et al. 2019). A participant's proportion of incorrect decisions (i.e., the independent variable) is calculated by dividing their number of incorrect decisions (Table 2) by the total number of decision trials, i.e., (M + F) / 96.

The two steps in a MRP analysis are a multilevel regression and a poststratification. First, a multilevel regression generates a model that estimates the influence each dependent variable has on the independent variable. For this study, a participant's proportion of incorrect decisions varies as a function of their demographic attributes (gender, age group, ethnicity, and race) and geographic area (CWA) as follows:

$$y_i = \beta^0 + \alpha_{j[i]}^{gender} + \alpha_{k[i]}^{age} + \alpha_{l[i]}^{ethnicity} + \alpha_{m[i]}^{race} + \alpha_{s[i]}^{area} \tag{1}$$

where

$$\alpha_j^{gender} \sim N(0, \sigma_{gender}^2), j = 0 \; or \; 1$$

$$\alpha_k^{age} \sim N(0, \sigma_{age}^2), k = 1, 2, or \; 3$$

$$\alpha_l^{ethnicity} \sim N(0, \sigma_{ethnicity}^2), l = 0 \; or \; 1$$

$$\alpha_m^{race} \sim N(0, \sigma_{race}^2), m = 1, 2, or \; 3$$

$$\alpha_s^{area} \sim N(tornado\ exposure_s, \sigma_{area}^2), s = 1, \dots, 116$$

In equation 1, β_0 is the intercept, and α is the offset (Buttice and Highton 2013). Each α represents individual characteristics at *j, k, l, m, n,* and *s* levels, or categories. For instance, α_j^{gender} represents gender at two categories in the decision experiment: female (level 0) and male (level 1). Age has three categories: ages 18-34 (level 1), ages 35-59 (level 2), and ages 60-110 (level 3) — the same age groups used in the U.S. Census. In addition, ethnicity is either non-Hispanic (0) or Hispanic (1); race is White (1), African American (2), and Other (3). Finally, the CWA variable has 116 levels that represent each CWA in the U.S., numbered alphabetically, from ABQ (1) to VEF (116), excluding Alaska, Hawaii, and U.S. territories.

The combinations of demographic variables and CWAs from equation 1 were used to predict the proportion of incorrect decisions that people in each CWA will make. In other words, the regression model assessed how much influence each demographic and geographic combination had on the proportion of incorrect decisions to predict the types of people who are more prone to making incorrect decisions.

The next step is poststratification, which applies both the model predictions and CWA-level census data to estimate the average proportion of incorrect decisions made by the entire population of each CWA. The multilevel regression model applies only the data from the experiment's participants to predict the average proportion of incorrect decisions by CWA; the poststratification uses the actual demographics of the CWA to make a prediction. In poststratification, predictions are weighted (θ) for each demographic-geographic combination (r) (Buttice and Highton 2013; Allan et al. 2020; Ripberger et al. 2020). The frequencies (N) and the weights (θ) are used to calculate the MRP estimates for each CWA:

$$Y_{CWA}^{MRP} = \frac{\sum_{r \in CWA} N_r \theta_r}{\sum_{r \in CWA}} \tag{2}$$

where θ_r are the weighted predictions from the multilevel regression model output for each demographic-geographic combination, and N_r are the population frequencies (from U.S. census data) for each demographic-geographic combination.

3.2.2 Spatial Autocorrelation

One way to identify if spatial patterns exist is to examine the spatial autocorrelation of a dataset. Spatial autocorrelation is the process whereby a datum from one spatial location, such as a latitude/longitude pair, CWA, census block, or school district, is compared to the datum from its "nearest neighbor" to determine if they are related to each other (e.g., to compare two adjacent CWAs). Spatial autocorrelation has been applied across different fields to assess a variety phenomena, such as epidemiology and the study of disease patterns, economic geography and the study of crime patterns, and ecology and the study of migration (Ord and Getis 1995, 2001). In this study, I apply spatial autocorrelation to identify patterns of incorrect decision making across the U.S. by comparing the average proportion of incorrect decisions for each CWA with its neighbor.

There are several ways to test for spatial autocorrelation, but the Moran's I statistic is the most popular (Ord and Getis 1995; Anselin 1995). Moran's I tests the null hypothesis that spatial autocorrelation is zero, i.e., a datum in one location is not related (correlated) to its neighbor. Rejection of the null hypothesis means that the data are spatially autocorrelated (Ord and Getis 1995). The Moran's I statistic can be calculated "globally," demonstrating whether spatial autocorrelation exists, and "locally," uncovering where and what kind of spatial autocorrelation exists. The local Moran's I statistic is a type of local indicator of spatial association (LISA) statistic, meaning the global statistic can be decomposed into each individual observation's contribution (Anselin 1995). There are two primary assumptions for LISA statistics, including local Moran's I: "a) the LISA for each observation gives an indication of the extent of significant spatial clustering of similar values around that observation; b) the sum of LISAs for all observations is proportional to a global indicator of spatial association" (Anselin 1995 p. 94).

Thus, while global Moran's I gives an overall indicator of spatial autocorrelation, the local Moran's I statistic will identify which CWAs are similar/dissimilar to the CWAs surrounding it.

Global and local Moran's I do not, however, identify clusters (or hot spots) of high/low values. Getis-Ord statistics are used to distinguish areas with statistically significant spatial autocorrelation and identify hot spots in the data. In this study, Getis-Ord statistics are used to identify hot spots of high values of incorrect decisions, or CWAs where people make more incorrect decisions than surrounding CWAs.

First, I created a spatial-weights matrix by defining the CWA's neighbor and how to weight "close" CWAs from "far" CWAs. There are four primary methods to define nearest neighbor: Rook, Queen, k-nearest neighbors, and inverse distance (Getis and Aldstadt 2004). K-nearest neighbors and inverse distance weighted matrices are defined a priori based on user defined distances, such as centroids of geographic units (i.e., the center point of the CWA). These two techniques typically are used when the data are continuous across all units, such as air temperature across the contiguous U.S. (Esri ArcGIS Pro). Rook and Queen neighbors are more useful with discrete data, or one value per geographic unit, and can be visualized as how their namesakes can move on a chess board. Rook neighbors are neighbors to the front, back, and sides; queen neighbors are the same as rook, but also include neighbors diagonally. Figure 8 visualizes a CWA (blue square), its neighbors (green squares), and non-neighbors (orange squares). Neighbors (non-neighbors) carry a value of 1 (0). Because this study's data are discrete (i.e., each CWA has one predicted proportion of incorrect decisions score), rook or queen neighbors are best to use. Queen was chosen because CWAs will likely be related to other CWAs located diagonally from them as they would from CWAs directly to either side.

Rook Neighbors

0	0	0	0	0
0	0	1	0	0
0	1		1	0
0	0	1	0	0
0	0	0	0	0

Queen Neighbors

0	0	0	0	0
0	1	1	1	0
0	1		1	0
0	1	1	1	0
0	0	0	0	0

Figure 8. Visualization of rook and queen neighbors, with a CWA (blue square), its neighbors (green squares), and non-neighbors (orange squares). Neighbors (non-neighbors) carry a value of 1 (0).

Second, after computing the spatial weights matrix, I applied global Moran's I to each CWA, testing whether the proportions of incorrect decisions are spatially correlated with any its nearest neighbors. Global Moran's I uses the spatial weights matrix to determine whether spatial autocorrelation exists:

$$I = \frac{N \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{X})(x_j - \bar{X})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\right) \sum_{i=1}^{n} (x_i - \bar{X})^2} \tag{3}$$

where N is the number of observations, in this case CWAs; $\bar{X}$ is the mean of the proportion of incorrect decision scores; x_i is the value of the proportion of incorrect decision score at a particular CWA; x_j is the value of the proportion of incorrect decision score at a different CWA; and w_{ij} is the spatial weight from CWA_i to CWA_j (Cao 2014).

The resulting Moran's I statistic returns a single value between -1 and 1, where 1 (-1) indicates perfect positive (negative) spatial autocorrelation. Positive (negative) spatial autocorrelation signifies areas where similar (dissimilar) values are clustered together. A value of 0 indicates no spatial autocorrelation (i.e., the values are random). The I statistic can be thought of similarly to a correlation coefficient, where the magnitude of the statistic indicates the strength of the relationship.

Local Moran's I uses a similar process to Global Moran's I, except it can determine where there is positive or negative spatial autocorrelation and if each location's I statistic is significantly different from that expected. In other words, it provides a measure *I* at each location *i* (i.e., the "ith" CWA):

$$I_i = z_i \sum_j w_{ij} z_j \tag{4}$$

where z_i is $x_i - \bar{X}$; w_{ij} is the spatial weight from CWA_i to CWA_j; and Σ_j is the sum across each row of the spatial weights matrix (Cao 2014). The local I statistic can be interpreted the same way as the global I statistic, except now it can be mapped to visually show where spatial autocorrelation exists on a map. Like the global I statistic, the local I statistic is a value ranging from -1 to 1, where positive (negative) values indicate positive (negative) spatial autocorrelation at every location (CWA). Therefore, the local I will denote which CWAs have similar (dissimilar) values related to neighboring CWAs based on the positive (negative) local I statistic.

After local Moran's I is identified, Getis-Ord statistics are calculated to identify spatial clusters. Getis-Ord statistics include the G_i and G_i^* statistics and they measure the degree of association across all values at all locations (Getis and Ord 1992). G_i only includes values in its neighborhood, not x_i itself while G_i^* includes both x_i and its neighbors:

$$G_i = \frac{\sum_{j \neq i} w_{ij} x_j}{\sum_{j \neq i} x_j} \tag{5}$$

$$G_i^* = \frac{\sum_j w_{ij} x_j}{\sum_j x_j} \tag{6}$$

where w_{ij} is the spatial weight from CWA_i to CWA_j and x_j is the value of a neighboring CWA. A positive (negative) G_i and G_i^* indicate local clustering of high (low) values, i.e., a hot (cold) spot (Anselin 2021). Since both G_i and G_i^* provide almost identical results, either can be used in practice (Anselin 2021). Both are calculated and compared in this research, however.

Chapter 4. Results

This study's first research question asks if there are demographic attributes that contribute to incorrect decision making. To answer this question, I apply the first step in MRP, creating a multilevel model. If the model shows significant differences among demographic groups, then it indicates that there are certain types of people who are more prone to making incorrect decisions. The second research question determines if these attributes contribute to decision making that varies geographically across the U.S. The poststratification step in MRP is used to map predicted proportion of incorrect decision scores across the U.S. according to census data. The map highlights where there are CWAs with populations that are prone to making more incorrect decisions. The final research question asks if there are regions of the U.S. where people are more prone to making incorrect decisions. To answer this question, I assess the spatial autocorrelation of the predicted proportion of incorrect decision scores. If spatial autocorrelation occurs and patterns exist, then it indicates that there are broader regions in the U.S. that are more prone to making incorrect decisions.

4.1 Demographic Attributes and Geographic Variations

First, applying MRP, I developed a national model that pooled the proportion of incorrect decisions for all participants, regardless of graphic type (see section 3.1.1; Fig. 6). Table 3 displays the estimate of the amount each demographic group varied in their likelihood to get more incorrect decisions, the standard of error of this estimate, and the t-value from a t-test. Positive (negative) values indicate that the proportion of incorrect decisions increase (decrease), and the magnitude of the estimate describe how much a category differs from one category to the next. Larger values indicate large differences while values close to zero indicate little difference. As you transition from one demographic group to another (by category; Table 3), the estimate reflects how the proportion of incorrect decisions change. The *t*-value indicates which relationships are significant. I established a 95% confidence interval for significance; thus, if the absolute value of *t* is greater than 1.96, then the result is significant.

Table 3. Summary Statistics for the Multilevel Regression Analysis – National Model

Mean Change in the Ratio of Incorrect Decisions to All Decisions from the Intercept (0.3970586)			
	Estimate	Standard Error	t-value (95% CI → $\|t\| > 1.96$ is significant)*
Gender: Group 1 (Female) to Group 2 (Male)	–0.0098091	0.0018537	–5.292*
Age: Group 1 (18-34) to Group 2 (35-59)	0.0013624	0.0020660	0.659
Age: Group 1 (18-34) to Group 3 (60-110)	–0.0043660	0.0025925	–1.684
Ethnicity: Group 1 (Non-Hispanic) to Group 2 (Hispanic)	0.0087245	0.0032489	2.685*
Race: Group 1 (White) to Group 2 (African American)	0.0189956	0.0032998	5.757*
Race: Group 1 (White) to Group 3 (Other)	0.0079366	0.0029720	2.670*
Tornado Exposure	0.0002845	0.0009193	0.310

The mean proportion of incorrect decisions by the 4,331 participants in the study was 0.397; hence, without accounting for graphic type, verbal conditions, demographics, or location, all participants averaged 39.7% in combined misses and false alarms over their 96 trials. Males tended to make fewer incorrect decisions (i.e., more correct decisions) than did females (Table 3). Although this finding is significant ($t = –5.292$), the difference between female and male decisions was only –0.0098, amounting to less than one trial out of the 96 (0.0104) per person.

This result contrasts with that of Klockow-McClain et al. (2019), who found that females made fewer errors than males using ordinary least squares regression on the same data plus Alaska and Hawaii. It is unknown why this discrepancy occurs with the same dataset. I also performed ordinary least squares regression on my data subset and still concluded that females had a higher proportion of incorrect decisions. More detailed analysis may be needed to account for this discrepancy between the two studies.

In terms of age group, participants who were 35-59 years old made more incorrect decisions (i.e., 0.00136), in general, than did participants ages 18-34. Participants who were 60-110 years old made fewer (–0.00437) combined misses and false alarms than did participants ages 18-34. This result indicates that participants ages 35-59 made more incorrect decisions than both other age groups, but the results were not significant ($t = 0.659$ for younger group; $t = -1.684$ for older group).

For ethnicity, participants of Hispanic ethnicity had more combined misses and false alarms than participants of Non-Hispanic ethnicity (0.0087). This finding was both significant ($t = 2.685$) and it is consistent with Klockow-McClain et al. (2019), who found that Hispanic participants were likely to incur more errors.

The final demographic category, race, also yielded in statistically significant results. Participants who identified as African American made more incorrect decisions than their White counterparts (0.0019, $t = 5.757$). Additionally, participants of the Other race category also made more incorrect decisions than those of White race (0.0079, $t = 2.67$). Klockow-McClain et al. (2019) looked at the effects of race on decision making, also finding that African Americans had higher error rates. They did not, however, look at the effects of other races.

Finally, tornado exposure was analyzed to see if having a lower frequency of tornadoes in a participant's local CWA was associated with them making more incorrect decisions. The estimate for tornado exposure indicated that tornado exposure had little impact on the proportion of incorrect decisions, and the result was statistically insignificant (estimate = 0.0003, $t = 0.31$). This result indicates that being exposed to tornadoes had little impact on participants' ability to protect within this decision experiment.

In sum, the multilevel model revealed that participants who were female, Hispanic, African American, or of Other race were more likely to make more incorrect decisions as compared to male, Non-Hispanic, White participants. Age did not play a statistically significant role in influencing the proportion of incorrect decisions. Therefore, in terms of demographics, gender, ethnicity, and race were the major influencers on incorrect decision making according to this dataset.

After poststratification into CWAs, it was clear that there were geographic differences in tornado warning decision making, but these differences appeared minimal. Figure 9 shows the predicted proportion of incorrect decision for the National Model across the United States, highlighting locations with a higher proportion of incorrect decisions, such as the southern and eastern coasts of the United States and CWAs with major cities associated with them. For instance, the CWAs encompassing Chicago, Detroit, New York City, and Los Angeles had higher proportions of incorrect decisions than nearby CWAs. This result is consistent with higher racial and ethnic diversity, as African American and Hispanic were forecasted by the National Model to have more incorrect decisions.

Although the results highlighted areas that may be more likely to make incorrect decisions, the differences appeared comparatively minor. The minimum mean predicted proportion of incorrect decisions is 0.391 and the maximum is 0.401 – a difference of only 0.01(or about one decision during the 96 trials). The predicted proportion of incorrect decision scores also is not significant compared to the median (p = 0.08789), meaning that predicted scores are not significantly different from each other. The small difference in the results indicates that although there are differences among geographic locations, they appear to be small, and it appears that location does not play a large role when it comes to making decisions during simulated tornado warnings. This result seems unexpected, as prior research (see sections 2.2.2 and 2.3) indicates that geography does matter when it comes to risk perception, reception, comprehension, and response to tornadoes.

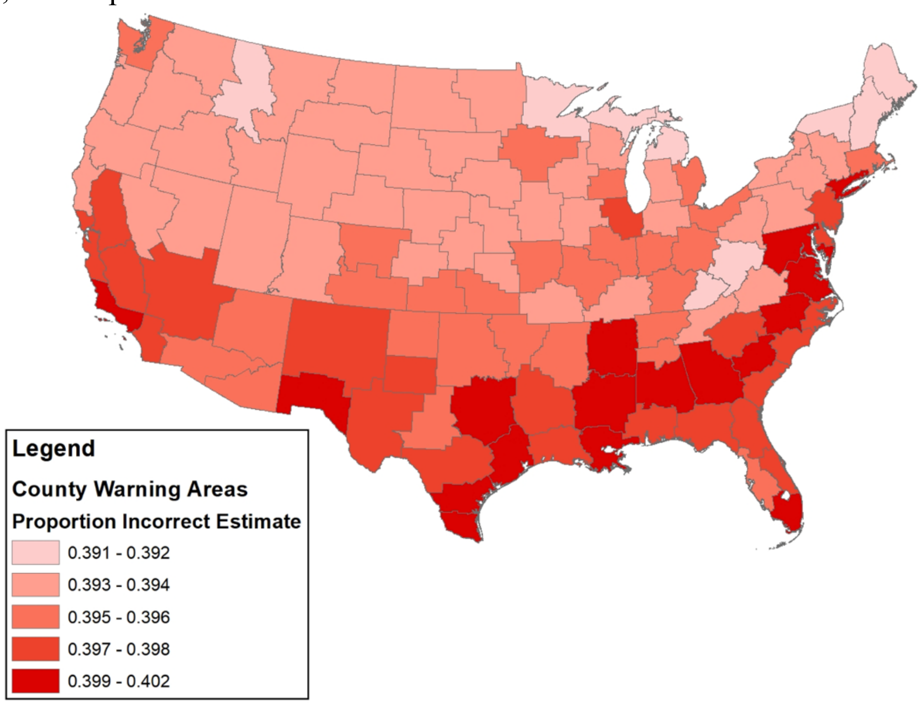

Figure 9. Predicted proportion of incorrect decision estimates for the National Model. Darker reds represent a higher predicted proportion of incorrect decision scores.

4.2 Discussion of Geographic Variations of Hazard-related Decision Making

As of the writing of this thesis, I have found no studies that directly analyze decision-making during tornado warnings and how decisions vary geographically, but my results can be compared to studies of risk perception of other natural hazards. Based on these studies, I would expect more noticeable differences between people's behaviors towards the weather and their geographic location. For example, Ripberger et al. (2020) used MRP at the CWA level to analyze differences in people's reception (i.e., how they received the warning), comprehension (i.e., how they understood the warning), and response (i.e., how they acted in response to the warning) to tornado warnings across the United States using data from an ongoing survey project administered by the Center for Risk and Crisis Management called the Severe Weather and Society Survey, or Wx Survey. The authors applied MRP and found that there was significant, nonrandom variation across the country for tornado warning reception and comprehension as well as a slight variation geographically for tornado warning response. Figure 10 shows that tornado warning reception, comprehension, and response are lowest in the western United States, slightly below average in the far eastern United States, and above average in the central United States. The authors noted that because this pattern reflected that of tornado climatology, experience and exposure to tornadoes might enhance people's reception, comprehension, and response to the warnings.

Figure 10 also shows that there are noticeable geographic differences in all concepts Ripberger et al. (2020) examined. For instance, response patterns were above average in the southern and central United States and lower in the western and eastern United States while Figure 9 shows that the southern U.S. has the highest proportions of incorrect decisions. This result may indicate that although the southern U.S. has the hightest response rate, the sheltering actions taken may not be correct according to my dataset and definition of an incorrect decision. This finding is interesting and one that requires further research.

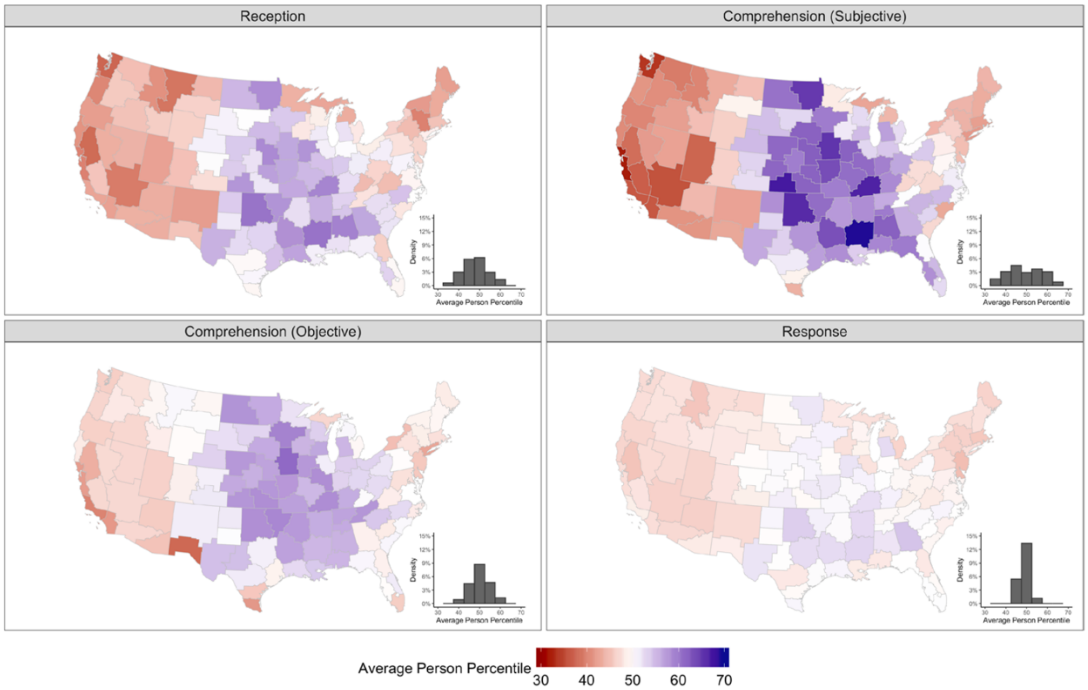

Figure 10. Average person percentile estimates from Ripberger et al. (2020) with tornado warning reception (top left), subjective comprehension (top right), objective comprehension (bottom left), and response (bottom right) for the contiguous U.S. Frequency distributions of average person percentile estimates across CWAs are included in the insets.

Based on the results of Ripberger et al. (2020), I would expect larger differences in my own results because reception, comprehension, and response could influence decision-making. It also should be noted that response and decision making are similar. Ripberger et al. (2020) defined response as the participant's intent to action in a given scenario. For example, "If a tornado WARNING were issued for your area tomorrow at [RANDOM TIME], how confident are you that you would take protective action in response to the warning" (Ripberger et al. 2020, p. E939). Similarly, I defined decision making as the protective action the participant took in response to a tornado warning in the online experiment. I examined their actions in the experiment rather than their intents, and I checked whether the response was correct while

Ripberger et al.'s (2020) only assessed if the participant stated they would act. The response patterns in Figure 10 (bottom, right) indicate values relatively close to the 50th percentile.

It is interesting that Ripberger et al.'s (2020) response results and my results both show relatively weak spatial patterns in response and decision making. One reason may be that response or decision making are difficult to capture through online surveys or experiments. Studies have shown that there are differences between participant intent versus action in real life because experiments cannot account for situational factors (see Lindell and Perry 2012; Ash et al. 2014). Lindell and Perry (2012) explained that a person's actions in a situation depend on intent *and* environmental conditions. Thus, a person may intend to do something in a controlled environment, but that action may differ given the circumstances or obstacles of real life. For instance, a person may intend to shelter, but physical or social environmental factors such as mobility, lack of shelter, or separation from family members may hinder an individual from taking shelter. The storm itself may also act as an obstacle to decision making in real life, as tornado-warned storms are rarely "textbook", isolated supercells often depicted in online experiments, but rather clustered within larger storm complexes with multiple types of warnings that could add confusion. Therefore, there are many factors that may influence an individual's decision that cannot be easily accounted for in online decision experiments, and it is unknown how intent in a simulated tornado warning may translate to a real-life situation (Ash et al. 2014).

In addition to geographic distributions of tornado warning reception, comprehension, and response, risk perception also has been examined in relation to geographical differences in respondent locations. Using Wx Survey data (Ripberger et al. 2020), Allan et al. (2020) analyzed geographic distributions of risk perceptions to various weather and climate hazards, including tornadoes. The survey asked participants to rate the amount of risk they felt for the following hazards during all four seasons (winter, spring, summer, fall): extreme heat and cold, drought, snow or ice storms, tornadoes, floods, hurricanes, and wildfires. Their results showed that risk perceptions to tornadoes were highest in the central United States, including the Plains, Midwest, and southeastern portions of the United States. They also found that these risk perceptions aligned with geographic patterns of tornado exposure. Thus, the authors surmised that tornado exposure influences how people perceive their risk to tornadoes. While my study does not analyze or describe decision making, previous literature shows that risk perceptions influence decision making. Therefore, given the results of Allan et al. (2020), one would assume there may be some geographic variation of decision-making during tornado warnings.

Howe et al. (2019) also utilized MRP to assess extreme-heat risk perceptions across the United States. The authors issued a survey to 9,217 people across the nation and then analyzed the results at the census tract, county, and state levels. Their results showed that risk perceptions to extreme heat varied geographically and demographically. Broadly, those who live in the south have higher perceptions of heat risk than those from the northern U.S. – consistent with the climatological temperature pattern from the north (cooler) to south (warmer). They also found that urban areas had higher levels of extreme-heat risk perception than suburban or rural areas. At the county and census tract level, demographics played a larger role than climatology. Demographics linked with higher social vulnerability, such as women, minority groups, and low income, had higher levels of extreme-heat risk perception. Although Howe et al. (2019) studied extreme-heat risk perceptions rather than tornadoes, their results show that there are significant geographic variations in how people perceive the weather, indicating that their perceptions and behaviors towards other extreme weather events, such as tornadoes, may vary as well. Although risk perception influences decision making, the degree to which it does is less understood and does not guarantee spatial variation.

4.2.1 Discussion

One reason as to why the MRP analysis does not show a significant spatial variation may be that the format of the experiment detached participants from "place." Recall that place is a geographical concept that roots an individual's experiences and worldviews to a particular location (see section 2.1.6). Therefore, a person's perception of a place, or location, will be influenced by what they have experienced there, which in turn will shape their behaviors and decisions. The original experiment of Klockow-McClain et al. (2019) used graphics of simulated tornado warnings and simulated locations, labeled A-D. It was therefore an arbitrary, virtual place where participants had no prior experience or perception of. To complete the decision experiment, they pulled themselves out of their "home place" and pretended they were a decision maker in the virtual location.

As they had no prior knowledge of the virtual location, such as tornado exposure or perceived influences of geography, they made decisions based on the information provided in the experiment. Although they may have inferred some of their own individual experiences into their decisions, the lack of place specificity may have led them to rely more heavily on the information provided rather than their own experiences. The goal of the original decision experiment was to analyze participant decision making given different types of tornado warning risk information, not whether their geographical home location influenced their decision making. Therefore, the dataset was not created to answer the specific questions posed in this thesis.

Although there does not appear to be large spatial variations, there are significant differences in decision making among female, Hispanic, African American, and other races.

Klockow-McClain et al. (2019) noted that this difference may be attributed to higher risk aversion. These groups had higher proportions of overall sheltering than other groups, which means they protected more often and incurred more false alarms than other groups. Since these are more vulnerable groups, they may be more risk averse and more likely to accept false alarms than other groups (Klockow-McClain et al. 2019). It is important to note, then, that false alarms are not necessarily mistakes and are only considered incorrect in this experiment based on my definition (see section 3.1.1). Therefore, a portion of the higher proportions of incorrect decisions may be attributed to higher risk aversion, not necessarily "wrong" decisions. This notion is important to consider because it means that these demographic groups might not be "bad" at making decisions but would rather choose to accept the costs associated with false alarms (time, safety, money) than risk a hit from a tornado. Thus, an incorrect decision does not equal a bad decision in this study.

Another reason for the spatial variation might lie in quantitative methods that tend to generalize information. Generalization can help provide quick and meaningful summaries of complex information; however, generalization has limitations when applied to people. Each individual is unique and has different characteristics that influence who they are and the decisions they make. Not only is a female, Non-Hispanic, 18–34-year-old, white person from the Norman, OK, CWA (OUN) different from a female, Non-Hispanic, 18–34-year-old, white person from the Milwaukee, WI, CWA (MKX), but they may be different within the same CWA. For instance, Peppler et al. (2018) found that people in Moore, Oklahoma, and Norman, Oklahoma, have very different perceptions of their own risk to tornadoes even though the neighboring cities are located within the same CWA (OUN). Thus, quantitative analyses have limitations in that they often cannot account for this level of detail because there is not enough data.

Therefore, this MRP analysis has its own limitations in how it generalizes the data from participants from a subset of the population and applies the data to the entire population using census statistics. The process assumes that the subset is representative of the entire population, which may not be the case. For instance, a particular CWA may have participants whose demographics is proportional to the census, but it is possible that some of the participants may be more weather aware and knowledgeable about tornadoes than is normal within a CWA. In other words, there is a chance that the results can be biased. Although Klockow-McClain et al. (2019) administered the survey in such a way as to be representative, it is never guaranteed that it is accomplished. Therefore, assuming the participants behave in the exact same way as their neighbors is not realistic and limits the generalizability of the results. Additionally, it is difficult to apply these results to every person in the U.S., as everyone's personal situations and experiences are different. For example, the results of this study showed that white people tended to make fewer incorrect decisions. This statement could be generalized to say that most white people make better decisions during tornado warnings, but this may not be the case for every individual. Despite these limitations, however, this quantitative analysis offers insights into phenomenon that can be further explored in future studies.

4.3 Subsets of Decision Results: Trials and Graphic Type

In addition to looking at overall decisions, I investigated two subsets of the data to determine whether they affected the estimated means of proportions of incorrect decisions in CWAs. The first subset was extracted to determine if learning occurred as participants progressed through the trial; the second subset was used to see if different decisions were made based on graphic type. Learning was assessed by exploring if participants' decisions got better as the trials progressed, if they began to play the experiment like a game rather than making objective decisions based on the information given, or if their decisions were consistent throughout.

4.3.1. First-and-Last-48 Trials

To do test whether learning occurred, I followed the procedure of Nadav-Greenberg and Joslyn (2009) and separated the first and second halves of the decision trials into distinct subsets. Using 120 repeated trials, Nadav-Greenberg and Joslyn (2009) found that outcomes in online experiments improved by comparing the difference in the proportion of incorrect decisions between the first and second halves of their decision trials. For my research, I split the 96 decision trials into the first and last 48 trials and compared the medians of each subset to examine whether decisions improved as the trials progressed, i.e., if learning occurred. If learning occurred, then it would be more realistic to examine the first half of the trials because they are more representative of participants' initial decisions and may paint a more realistic picture of decision making across the United States.

I tested whether the distribution of trials 1-48 and trials 49-96 were normal using the Shapiro-Wilks test; they were not. Hence, I calculated medians for each subset and compared them to each other and to all 96 trials using the Mann-Whitney test, defining significance at the 95% confidence interval. The median for trials 1-48 was 0.375 and for trials 49-96 was 0.396, with the difference not being statistically significant ($p = 0.1319$). This result indicates that decision making did not improve as the participants made their decisions over the 96 trials. The median for all 96 trials was 0.385 and was not statistically significant when compared to the first and last 48 trials ($p = 0.1039$ and $p = 0.8861$, respectively). Therefore, I confirmed that it was sufficient to use the proportion of incorrect decisions across all 96 trials to understand each participant's overall decision making.

4.3.2 Different Graphic Designs

Next, I selected two graphic types to examine if they resulted in better or worse decisions. Recall that the data were from a simulated tornado warning experiment that utilized six different tornado warning graphic types: short-deterministic (half-hour lead time), long-deterministic (one-hour lead time), probabilistic with no color scheme, probabilistic with a sequential color scheme, probabilistic with a divergent color scheme, and probabilistic with a spectral color scheme. The short-deterministic and sequential probabilistic warning graphics were selected here because they represent tornado warning graphics currently in use by the NWS and proposed future tornado warning graphics, such as the new FACETs paradigm (see Rothfusz et al. 2018), respectively. The sequential color scheme also was shown by Klockow-McClain et al. (2019) to have the best performance (most correct decisions) and more positive feedback among participants in the study. Data from participants who received either of these two graphic types were segregated according to graphic type and the MRP analysis was conducted on each type individually.

The median of the proportion of incorrect decisions was about 0.396 for participants given the short deterministic graphic and 0.365 for the sequential warning graphic. This result indicates that those who received the sequential warning graphic made fewer incorrect decisions than those who received the short deterministic warning thus making more correct decisions when provided with probabilistic information. This difference was statistically significant ($p <$ 2.2e-16). This result agreed with that of Klockow-McClain et al. (2019), as they found that participants had fewer false alarms and therefore more correct decisions when given probabilistic information rather than our current deterministic warning paradigm. Given these results, the proposed shift towards probabilistic information may result in people being able to perform better decision making.

Because the difference between the medians of the short deterministic decisions and the sequential probabilistic was significant, I modeled these subsets (as in section 4.1) independently using MRP to see if there were significant differences in how people make decisions given the current and future NWS warning paradigms. Tables 4 and 5 summarize the MRP statistics using the proportion of incorrect decisions from participants who only received the short deterministic (n = 746) and sequential probabilistic (n = 739) warning graphics, respectively.

Table 4. Summary Statistics for the Multilevel Regression Analysis – Short Deterministic

Mean Change in the Ratio of Incorrect Decisions to All Decisions from the Intercept (0.412464)			
	Estimate	Standard Error	t-value (95% CI → $\lvert t \rvert > 1.96$ is significant)*
Gender: Group 1 (Female) to Group 2 (Male)	–0.011719	0.004960	–2.646*
Age: Group 1 (18-34) to Group 2 (35-59)	–0.001650	0.004428	–0.336
Age: Group 1 (18-34) to Group 3 (60-110)	–0.009191	0.005865	–1.567
Ethnicity: Group 1 (Non-Hispanic) to Group 2 (Hispanic)	0.010806	0.008126	1.330
Race: Group 1 (White) to Group 2 (African American)	0.018411	0.007610	2.419*
Race: Group 1 (White) to Group 3 (Other)	–0.002499	0.007320	–0.341
Tornado Exposure	0.002706	0.002307	1.173

Table 5. Summary Statistics for Multilevel Regression Analysis – Sequential Probabilistic

Mean Change in the Ratio of Incorrect Decisions to All Decisions from the Intercept (0.374810)			
	Estimate	Standard Error	t-value (95% CI → $\|t\| > 1.96$ is significant)*
Gender: Group 1 (Female) to Group 2 (Male)	–0.001641	0.004788	–0.390
Age: Group 1 (18-34) to Group 2 (35-59)	0.005345	0.004652	1.149
Age: Group 1 to Group 3 (60-110)	0.006391	0.005899	1.083
Ethnicity: Group 1 (Non-Hispanic) to Group 2 (Hispanic)	–0.004126	0.007263	–0.568
Race: Group 1 (White) to Group 2 (African American)	0.035405	0.007482	4.732*
Race: Group 1 (White) to Group 3 (Other)	0.018396	0.006720	2.738*
Tornado Exposure	–0.003807	0.002400	–1.586

The estimated mean values of the subset models for the short deterministic and sequential probabilistic graphics were 0.412 and 0.375, respectively. This result indicates that participants made more incorrect decisions when given the short deterministic warning graphic, a finding that agrees with Klockow-McClain et al. (2019). In terms of demographics, the model for the short deterministic warning had similar results with the National Model (section 4.1), with a few differences in the significance testing. For gender, the proportion of incorrect decisions decreased among males (–0.00641), indicating that females made more incorrect decisions than males. Like the National Model, this result was also significant (t = –2.646). For age, the proportion of incorrect decisions increased as age increases, but these results were not significant

(t = –0.336 and –1.567). The short deterministic graphic model also showed that Hispanic participants made more incorrect decisions than Non-Hispanics (0.010806), but unlike the National Model, the results were not significant (t = 1.330). Both models agreed that African Americans made more incorrect decisions than Whites (0.018411) and the results were significant (t = 2.419). Unlike the National Model, the model for the short deterministic warning graphic found that those of Other races made fewer incorrect decisions than Whites (–0.002499); however, this result was not significant (t = –0.341). In terms of short deterministic warnings, it appeared that females and African Americans were more likely to make incorrect decisions, indicating that these groups may be more risk averse.

The model for the sequential probabilistic warning graphic also had some similarities to and differences from the National Model. Like the National Model, it also revealed that males made fewer incorrect decisions than females (–0.001641), though not significantly (t = –0.390). Unlike the National Model, age and ethnicity were not significant for the sequential probabilistic warning graphic. Results from the model for the sequential probabilistic graphic indicated that more incorrect decisions occurred as the age group increased and that the proportion of incorrect decisions was lower among Hispanics (–0.004126) than among Whites. In terms of race, results from the model for the sequential probabilistic warning graphic were similar to those of the National Model, showing that those of African American and Other races make significantly more incorrect decisions (0.035405, t = 4.732, and 0.018396, t = 2.738, respectively) than Whites. Therefore, for sequential probabilistic warnings, those who are of African American or Other races are more likely to make incorrect decisions.

After these models were post stratified with the census data, the predicted average proportions of incorrect decisions for each CWA were slightly different (p < 2.2e-16) between the short deterministic and sequential probabilistic groups. These models predicted that people made more incorrect decisions when given short deterministic versus sequential probabilistic information. This finding suggests that probabilistic information and the inclusion of a sequential color gradient provide a better candidate product than the current short deterministic warnings for helping people to make more correct decisions.

Figures 11 and 12 show the estimated proportion of incorrect decisions for each CWA, as calculated by the MRP models for both the short deterministic and sequential probabilistic warning graphics, respectively. The maps show that, like the National Model, the model for the short deterministic graphic predicted the southeastern, south-central, and north-central U.S. to have higher ratios of incorrect decision making. Interestingly, the estimations for the sequential probabilistic graphic (Fig. 12) depicts a completely different spatial pattern. The ratios of incorrect decision making are lower in the central U.S. and higher along the western and eastern coasts. Interestingly, the estimations for each warning graphic are almost the reverse of each other. The highest ratios of incorrect decision estimates for the short deterministic graphic are in the southeastern and south-central U.S., but these locations have some of the lowest ratios of incorrect decision making for the sequential probabilistic graphic. Similarly, CWAs in the Midwest region, such as Wisconsin, Michigan, Minnesota, Illinois, Iowa, and CWAs along the U.S.-Canadian border had somewhat lower ratios of incorrect decision estimates for the short deterministic graphic and higher for the sequential probabilistic graphic. Further investigation needs to be performed to understand this difference.

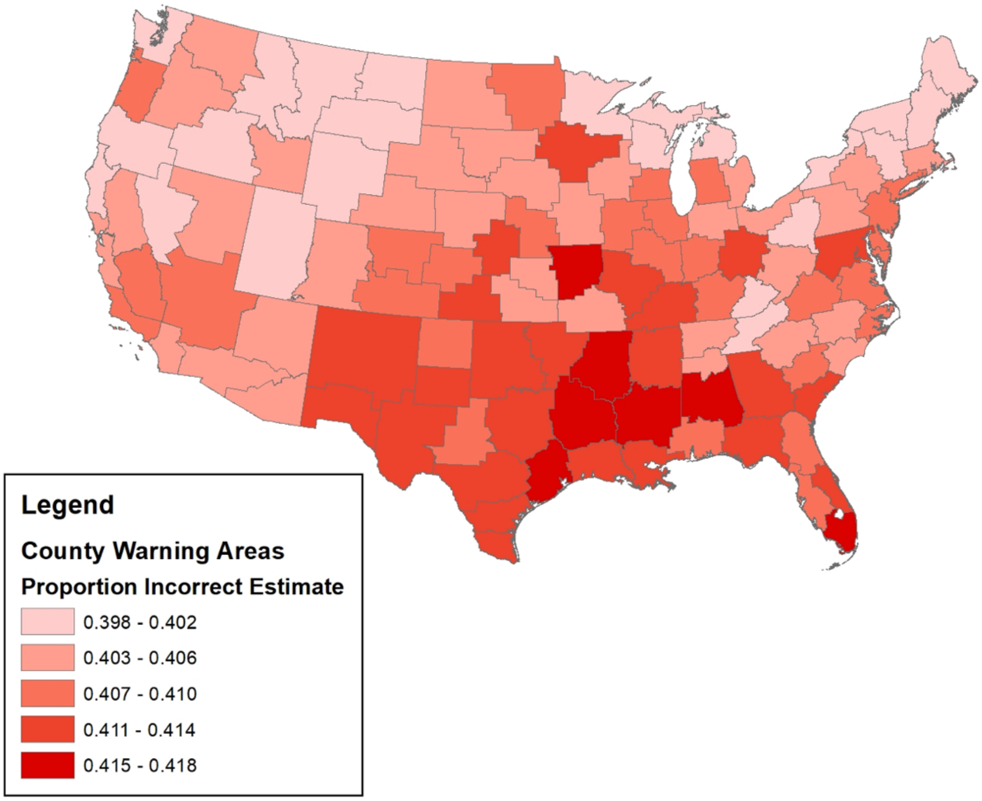

Figure 11. Predicted proportion of incorrect decision estimates for the short deterministic graphic. Darker reds represent a higher predicted proportion of incorrect decision scores.

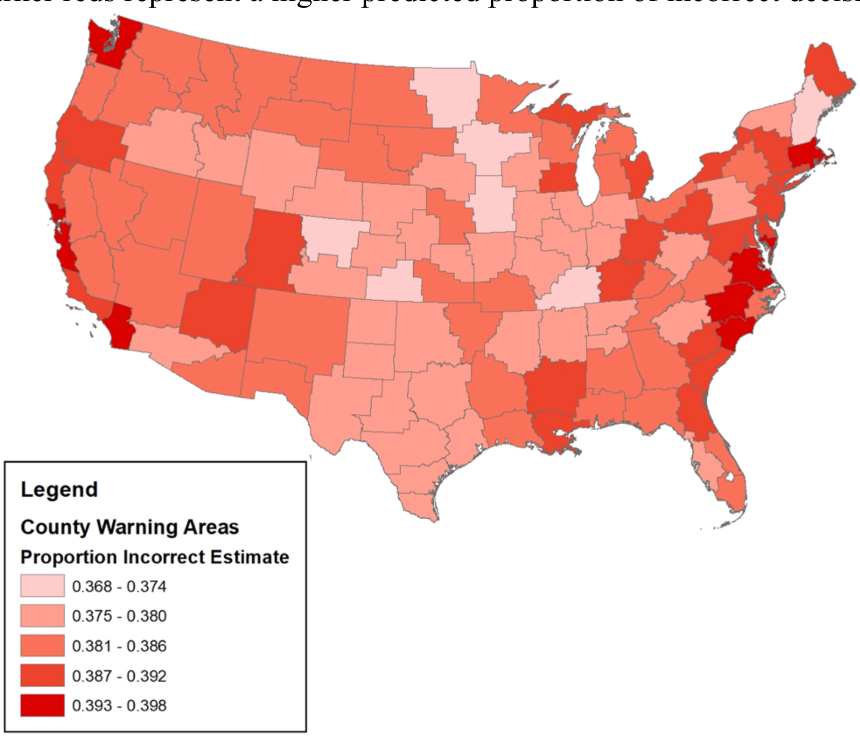

Figure 12. Predicted proportion of incorrect decision estimates for the sequential graphic. Darker reds represent a higher predicted proportion of incorrect decision scores.

4.4 Spatial Autocorrelation of National Model with its CWAs

My third research question examined whether there were regions where people are more prone to making incorrect decisions. I used spatial autocorrelation to help answer this question, focusing on the Global Moran's I statistic to determine whether the data are spatially autocorrelated. I applied the Local Moran's I statistic to determine where any significant spatial autocorrelation occurs and the local G_i^* statistic to determine if there are hot (cold) spots of incorrect decision making, thus locating regions of incorrect (correct) decision making.

Using the National Model's predictions of the proportion of incorrect decisions for each CWA (Fig. 13), the Global Moran's I statistic revealed a moderate positive spatial autocorrelation among the CWAs ($I = 0.608$, $p < 2.2\text{e-}16$). Positive spatial autocorrelation means that high (low) values, or proportions of incorrect decisions, are clustered near other high (low) values.

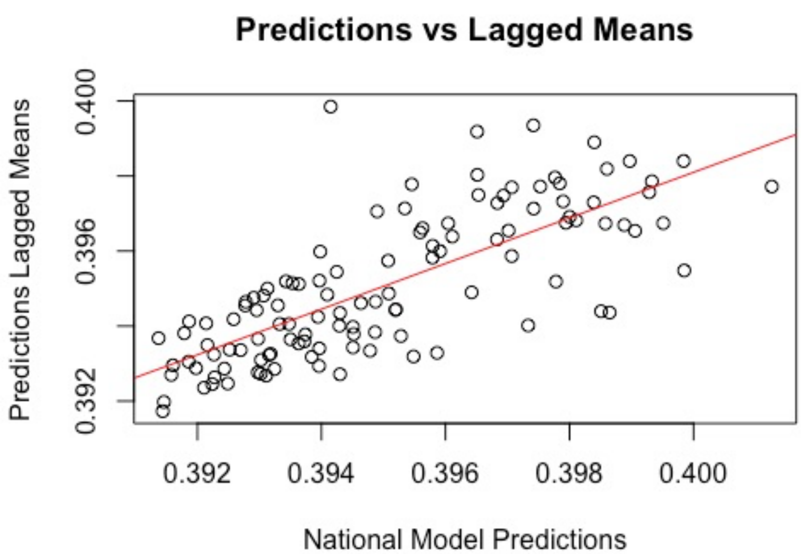

Figure 13. National model predictions versus spatially lagged means and global Moran's I statistic (i.e., line of best fit ($R^2 = 0.5667$), red). The upper-right quadrant indicates that high values are clustered near high values and the lower-left quadrant represents low values that are clustered near other low values.

To demonstrate how the National Model's prediction for a given CWA is spatially correlated with its neighboring CWA(s), I examined the local Moran's I statistic (Fig. 14). Just as the global Moran's I predicted, there is spatial autocorrelation, with large swaths of the U.S. displaying values over 0.34 (Fig. 14). Interestingly, a few CWAs are dissimilar to their neighbors (Fig. 14): Denver, Chicago, Detroit, Blacksburg, Sterling, and New York. These CWAs are associated with large cities, potentially indicating that the Local Moran's I statistic may be highlighting higher diversity between cities and their surrounding areas. However, other CWAs associated with large U.S. cities, such as Los Angeles, Seattle, Houston, Boston, are not dissimilar from their surrounding CWAs.

One reason for this dissimilarity may be that the Denver, Chicago, Detroit, etc. CWAs are *more* dissimilar to their surrounding CWAs than other cities are. For instance, the Chicago CWA may have more diversity as compared to the Lincoln, Quad Cities, and Milwaukee CWAs than does the Los Angeles CWA compared to the San Diego, Las Vegas, Harford, and San Francisco CWAs. For example, there may be more Hispanic and non-white populations living in Chicago than in surrounding suburbs whereas there are likely large Hispanic and non-white populations both in and surrounding Los Angeles. However, this scenario may not be the case everywhere, and higher resolution demographic data are likely needed to understand this difference.

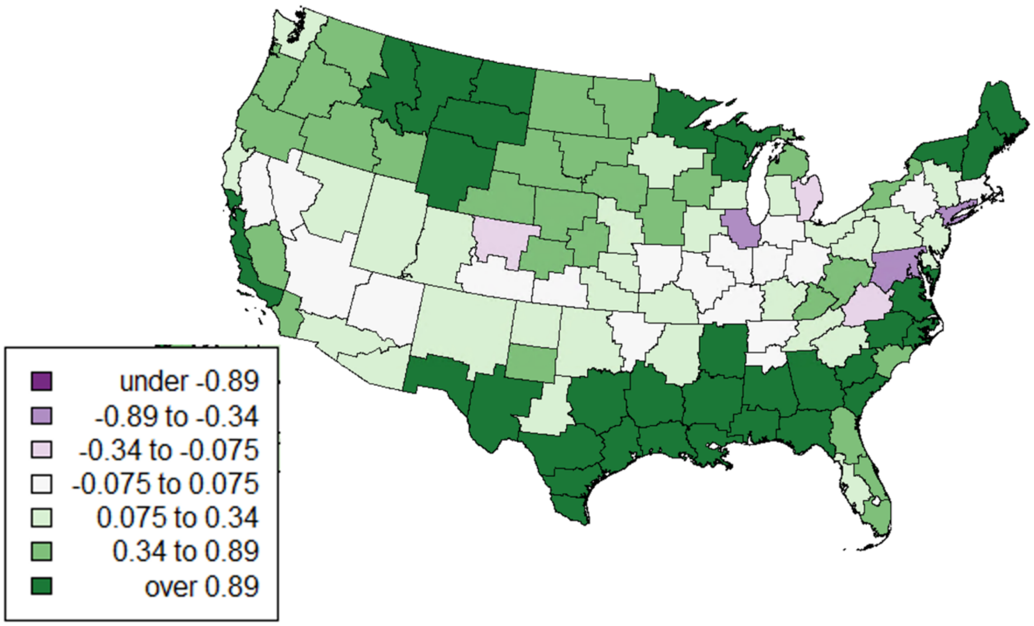

Figure 14. Local Moran's I statistic for model predictions. Greens indicate positive values of the local Moran's I (similarity) and purples indicate negative values of the local Moran's I (dissimilarity). If *I* were positive (negative), then it is surrounded by CWAs with similar (different) values. The closer *I* is to 1 or -1 indicates the magnitude of the relationship, just like R-squared indicates the strength of a linear relationship.

The four prominent regions that are spatially similar are 1) the Intermountain West and far northwest Great Plains, 2) the Lake Superior region, 3) northern New England, and 4) much of the southern United States. Within each "region," the CWAs are alike (e.g., Duluth, Marquette, and Green Bay CWAs), but distinct regions with similar values of the local Moran's I statistic (e.g., Lake Superior and the southern U.S. regions) are not necessarily similar to one another. Each region may be spatially autocorrelated because they have similar demographics, cultural values and experiences that may influence decisions, or similarities in NWS forecast operations. Before drawing conclusions, however, the statistical significance of the spatially correlated clusters must be assessed. Figure 15 shows the *p*-values for the local Moran's I statistic across all CWAs, indicating that those CWAs with positive spatial autocorrelation are statistically significant. This result means that the people living in those CWAs make similar decisions as their neighboring CWAs.

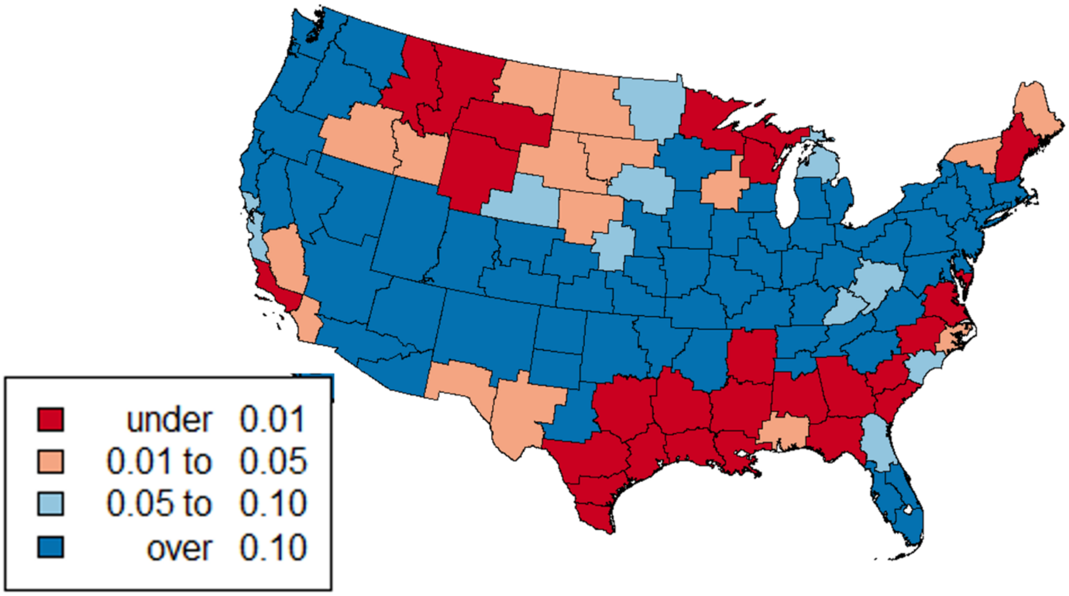

Figure 15. *P*-values for local Moran's I at the 95% confidence interval. Reds (blues) indicate significant (insignificant) *p*-values.

The next question asks whether spatially autocorrelated CWAs have spatially similar good or poor decision making, i.e., lower (higher) proportions of incorrect decisions. G_i and G_i^* statistics are used to determine hot and cold spots, or clustering, of similar values in data. Figures 16 and 17 depict the G_i and G_i^* statistics, respectively, for the predicted proportion of incorrect decisions. Although the values of the G_i and G_i^* statistics are different, the overall patterns are almost the same, as suggested by Anselin (2021). An interesting feature in both figures is a clear divide between the northern and southern United States. The most notable feature is the cluster, or hot spot, of high incorrect decision making in the southern United States that extends from CWAs in Texas eastward to the Atlantic coast.

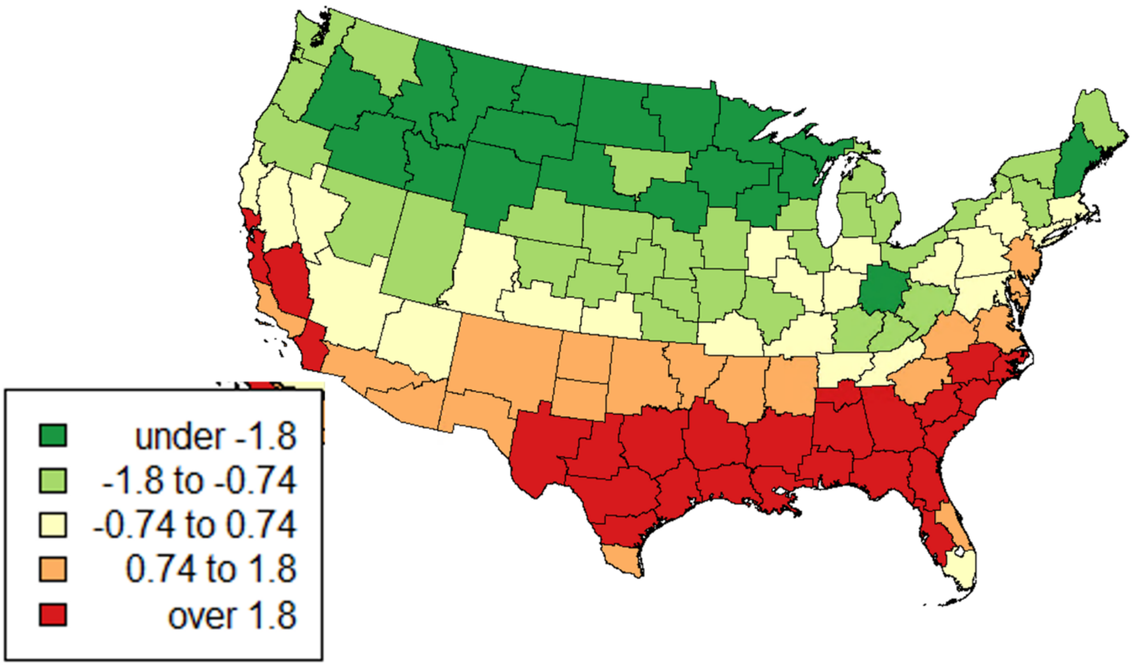

Figure 16. G_i statistic indicating hot spots and cold spots of incorrect decision making. Reds indicate hot spots, greens indicate cold spots, yellows indicate little or no correlation.

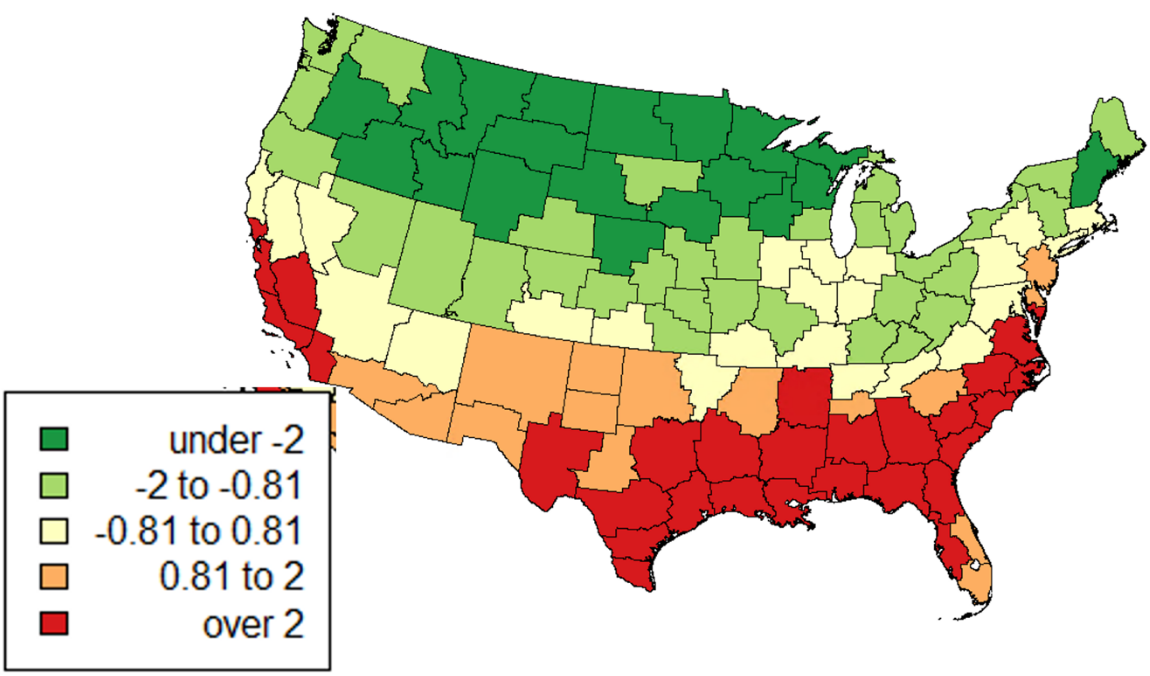

Figure 17. G_i^* statistic indicating hot spots and cold spots of incorrect decision making. Reds indicate hot spots, greens indicate cold spots, yellows indicate little or no correlation.

Even though there does not appear to be large or significant differences in decision making across CWAs when looking at them individually (e.g., sections 4.1–4.3), it appears that there may be broad regions that can be identified as having more incorrect decisions when compared to their neighbors. The difference, as the predicted proportion of incorrect decision scores show, is not huge, but the southeastern U.S. is consistently highlighted. The National Model predicted scores, while not being statistically significantly different from each other, still highlighted the southern U.S. as having more incorrect decisions (Fig. 9). Spatial autocorrelation also identified the southern U.S. with decision scores similar to their CWA neighbors, and the Getis-Ord statistics confirmed that this area is a hot spot for higher proportions of incorrect decision making. Even though the scores might not be significantly different, the analyses show that the southern U.S. is an area of concern.

The southern United States has been identified as an area vulnerable to extreme hazards, such as tornadoes (Boruff et al. 2003; Ashley 2007; Emrich and Cutter 2011; Allan et al. 2020), as well as an area that is socially vulnerable (Cutter et al. 2003; Cutter and Finch 2008; Emrich and Cutter 2011). The collocation of higher proportions of incorrect tornado warning decision making, exposure to tornadoes, and high social vulnerability in the southern United States is alarming. Figures 5 and 7 show social vulnerability and tornado exposure in the United States, respectively. Not only is the southern region more exposed to tornadoes, but the people living there may not have adequate resources to deal with the threat or the knowledge to make the best decision when tornadoes occur. The totality of these issues may make the people in this region more susceptible to disaster from tornadoes.

Chapter 5. Conclusion

Tornado decision-making is well studied on an event-by-event or region-by region basis, but there has been a gap in the literature regarding spatial variability of decision making under tornado threats across the United States. This study uses existing data from a simulated tornado decision experiment (Klockow-McClain et al. 2019) to examine how decision making varies across the National Weather Service's county warning areas in the United States.

I first asked if there were certain demographic attributes that contribute to incorrect decision making. To answer this question, I created a multilevel regression model using simulated tornado warning decision experiment results from the aforementioned Klockow-McClain et al. (2019) study. The results for the National Model, i.e., the MRP model using all participants' decisions regardless of cartographic tornado warning design, revealed that there were demographic characteristics that contributed to higher proportions of incorrect decision making. Participants who were female, Hispanic, African American, or Other race (i.e., not African American or White) were more likely to make more incorrect decisions compared to male, Non-Hispanic, White participants. Therefore, gender, ethnicity, and race are important indicators for incorrect decision making, successfully answering my study's first research question (see Chapter 3).

These results are consistent with previous literature (see Chapter 2) and Klockow-McClain et al.'s (2019) results using the same data (see section 4.1). Klockow-McClain et al. (2019) also noted that a higher proportions of incorrect decisions by a given population could be due to that population having higher risk aversion, therefore sheltering more frequently, resulting in some incorrect decisions, i.e., they sheltered when a tornado did not occur (false alarm). Therefore, it is important to note that my definition of an incorrect decision does not necessarily imply a wrong decision or that a population is bad at making decisions. My results may show that these populations are sheltering more frequently regardless of the outcome, which is recommended by the National Weather Service and should be encouraged. One avenue of future work could be to compare the proportion of incorrect decisions with false alarms and misses and investigate if the high proportion incorrect decisions were due risk aversion or missed protections.

Although false alarm decisions are not necessarily mistakes, there are costs associated with them that could impact these populations. For example, there is the cost of sheltering itself. For most individuals, sheltering can be as simple as going to a basement or ground-level bathroom. For others, sheltering could cost time, money, or safety. For instance, mobile home residents need more time to shelter because they must travel to a different location. The second cost is the “false alarm” or “cry wolf” effect (see section 2.1.2), whereby people begin to discount future warnings because forecasters have been wrong in the past. The “better safe than sorry” mentality, therefore, may have future costs because people may tire of sheltering. These costs, coupled with populations with high social vulnerability, could put these populations at future risk.

Other factors may contribute to higher proportions of incorrect decisions as well, such as not understanding the warning due to lack of knowledge or experience with tornadoes, language barrier, or misunderstanding the warning message. These reasons were not assessed in the given study, however, and will require further investigation. Importantly, the demographic groups listed here are those groups also identified as having high social vulnerability (see Cutter et al. 2003 and Cutter and Finch 2008). Higher proportions of incorrect decision making may therefore increase their vulnerability to tornadoes.

The results for the National Model were post-stratified using U.S. census data to estimate proportions of incorrect decisions for each CWA across the contiguous U.S. The results revealed that there did not appear to be large, significant differences in decision making among CWAs, indicating that people across the United States, regardless of demography, made a similar proportion of incorrect decisions during tornado warnings. However, despite the lack of significance across CWAs, the southern U.S. appears to have higher proportions of incorrect decision making compared to the rest of the U.S.

The lack of significant geographic differences is surprising, as many studies have found that geography tends to make a difference in people's attitudes and responses towards hazardous weather. While these studies did not assess decision making directly, they researched attitudes and behaviors towards tornadoes and other types of hazardous weather, such as risk perception (Allan et al. 2020; Ripberger et al. 2020), tornado warning reception, comprehension, and response (Ripberger et al. 2020), extreme-heat risk perception (Howe et al. 2019), opinions on climate change (Howe et al. 2015), and effects of climate change messaging (Zhang et al. 2018), and how these vary geographically. The studies found that there are geographical differences in people's attitudes and behaviors towards hazardous weather. Given the results of these studies and previous literature, one would expect that there should also be geographical differences in decision making, as attitudes and behaviors influence decision making.

Ripberger et al. (2020) investigated tornado warning response, defining it as the participant's intent to shelter during a tornado warning, and is similar to my definition of a decision. It is interesting that Ripberger et al.'s response results and my decision results both show relatively weak spatial patterns, indicating that tornado warning response or decision making are difficult to capture through online surveys or experiments. The online format situates participants in a virtual place where they are cut-off from real-world social or physical environmental factors. A person may intend to do something in a controlled environment, such as a survey or decision experiment, but their resulting decision may differ given the obstacles of real life. For instance, social factors such as separation from a family member may hinder an individual taking immediate shelter. Environmental factors such as the storm itself may impede or enhance an individual taking shelter as well. For instance, a storm in real life may not be an isolated supercell often depicted in online experiments, but a cluster with multiple warnings that may add confusion to the sheltering decision, thus delaying response. The storm itself may also enhance sheltering due to environmental cues, such as rain, hail, or lightning that may lead to personalization of the warning and therefore a sheltering decision. These environmental factors cannot be easily depicted in online surveys and experiments, and it is unknown how intent in a simulated tornado warning may translate to a real-life situation. Thus, a reason for weak spatial variation in decision making may be due to the complexities of intent in online formats versus real-world decision making.

Another reason for weak spatial variation in decision making may be due a limitation of using multilevel models for detecting spatial patterns. Multilevel models tend to ignore potential between-neighbor correlations, treating each CWA as its own unit and not comparing it to its neighboring CWAs (Xu 2014). This process is effective when comparing each CWA individually, but not necessarily in examining broader regions of decision making. In order to assess between-neighbor correlations and broader patterns of decision making, the predictions from the National Model were analyzed for spatial autocorrelation. The Global and Local Moran's I analyses indicate that there was indeed spatial autocorrelation in the data and that high (low) proportions of incorrect decision making were located near other high (low) proportions.

This result indicates that even if the differences in decision making was not significant, there still appears to be broader regions in the United States that have higher proportions of incorrect decisions. The G_i and G_i^* statistics were calculated and mapped to show where these "hot spots" of higher proportions of incorrect decision making occur. The results revealed that there is a distinct north-south divide, with the southern United States identified as a hot spot for higher proportions of incorrect decisions. The reason behind the north-south divide is not directly assessed in this study, however, it is an interesting finding that requires further research.

On all analyses performed, the southern United States is consistently highlighted as an area that makes more incorrect decisions. This finding is concerning because the southern United States has a relatively high exposure to tornadoes (i.e. Boruff et al. 2003; Ashley 2007) and is an area that is more socially vulnerable to extreme hazards (i.e. Cutter et al. 2003; Cutter and Finch 2008). Thus, people in the southern U.S. are more exposed to tornadoes and may not have adequate resources to cope with tornadoes and may suffer more greatly from their impacts than others who are less socially vulnerable. These factors coupled with higher proportions of incorrect decision making may make the population in the southern U.S. even more vulnerable to tornadoes and their impacts. It is important for decision makers and risk communicators to be aware of the vulnerabilities in the populations that they serve so they can provide adequate resources and information. Therefore, the colocation of areas of people with higher proportions of incorrect decisions during tornado warnings, higher exposure to tornadoes, and higher social vulnerability should be addressed in future research.

In addition to examining overall decisions, I also investigated two subsets of the data to see if participants' decisions in these subsets impacted the estimated means of proportions of incorrect decisions in CWAs. The first subset assessed if learning occurred as participants progressed through the trials and found that that participants' decisions did not significantly change from the first half of trials to the second half, indicating that they did not learn over the 96 trials. I then selected two tornado warning graphic types to determine if they prompted participants to make better or worse decisions. Short deterministic and sequential probabilistic warnings were used because they represent the current and future NWS tornado warning paradigms. Overall, the analysis showed that there was a significant difference between short deterministic and sequential probabilistic decisions; participants made better decisions with the sequential probabilistic warning graphic, agreeing with Klockow-McClain et al. (2019). This result indicates that sequential probabilistic warning information may be a better candidate for helping people make correct decisions during tornado warnings than the current short (30-minute) deterministic warnings.

Like the National Model, the results from the short deterministic and sequential probabilistic graphic type models also showed that those who identified as African American or Other races had higher proportions of incorrect decisions, confirming that race is an important factor influencing decision making. Though not significant, gender and ethnicity also impacted decision making, as females and Hispanic participants had higher proportions of incorrect decision making, also agreeing with the National Model. Thus, overall, participants made better decisions given the sequential probabilistic warning graphic, but minority and socially vulnerable groups still make more incorrect decisions than their counterparts. However, as discussed with the National Model, these groups may be more risk averse and shelter more often, resulting in incorrect decisions based on my definition (see section 3.1.1).

In terms of spatial patterns of short deterministic and sequential probabilistic graphics, the results are interesting compared to the National Model results and the spatial autocorrelation of the National Model. The short deterministic model estimates showed that, like the National Model, the southern U.S. had higher ratios of incorrect decision making. The sequential probabilistic warning graphic, however, depicted that the southern U.S. had some of the lowest ratios of incorrect decision making while higher ratios were in the Midwest region and along the U.S.-Canada border. The reason for the difference between these warning graphics requires further investigation, but the spatial patterns further support that sequential probabilistic tornado warning graphics performed better (lower overall ratios of proportion of incorrect decisions) across the U.S. than the short deterministic tornado warning graphic and may be a better candidate for future tornado warning paradigms.

In sum, three research questions were posed: 1) are their demographic attributes that contribute to incorrect decision making, 2) do these attributes contribute to decision that varies geographically across the U.S., and 3) are there regions of the U.S. where people are more prone to making incorrect decisions? Using MRP on the full dataset regardless of graphic type and subsets of short deterministic and sequential probabilistic, four demographic groups were consistently identified as being more prone to making incorrect decisions: female, Hispanic, African American, and Other race (i.e., not African American or White). The poststratification of the results of the National Model, short deterministic model, and sequential probabilistic model revealed that, though not statistically significant, CWAs in the southern U.S. have higher ratios of incorrect decision making. This result was confirmed through spatial autocorrelation of the National Model, showing that the southern U.S. is a hot spot of higher ratios of incorrect decision making. Although my results were not statistically significant in some cases, the consistency of the results and the colocation of the demographic groups and geographic location identified have high social vulnerability and tornado exposure show that further research is needed.

5.1 Limitations

Limitations always exist in research, as it is not realistic to obtain the perfect dataset or method. Likewise, this study had limitations with the research questions posed, dataset, and methods that are worth noting. The dataset collected by Klockow-McClain et al. (2019) was collected to assess decision making given different cartographic designs. The dataset provided both high quality and high-resolution information, but the virtual nature of the experiment may have been a weakness for my study. The virtual space in which participants were making decisions in may have disassociated them from how they would make decisions in a real-life place with real external influences (see Klockow et al. 2014; Peppler et al. 2018; Lindell and Perry 2012). It is also difficult to assume participants take personal experience into account in the virtual environment. It is also important to note that just because geographic information was given for each participant, it does not mean they were drawing on local knowledge or sense of place while they were participating in the experiment. Therefore, decisions taken out of place-based contexts may not provide understanding of the real nature of decision making and how decision making may vary across different places and people.

Additionally, the study method had limitations in how it was conducted for this research. One unique aspect of MRP that is that it can perform cross-tabulations. That is, if a certain demographic group is missing in a CWA, MRP can apply the same demographic group from another CWA to account for that missing data (see Lax and Phillips 2009). While this process is useful for some studies, it may have affected my results. Since this study specifically examined geographic location, applying information from one CWA to another may have produced unrealistic decisions for a particular CWA because it may be unrepresentative of the actual population. Therefore, ensuring adequate sample sizes of demographic groups across CWAs is needed to produce more realistic results, though this is often difficult to achieve.

Another limitation might be the geographic scale that was used. Data aggregation was conducted on CWAs because the results may be useful to inform NWS forecasters about their CWA's population, and because it was the sufficient scale for MRP to work effectively (see section 3.2.1). It is possible that the CWA scale is too large to capture the nuances of decision making at the local level. For instance, Peppler et al. (2018) found that residents of Central Oklahoma had drastically different views of their risk and response to tornadoes, even within the same county. Residents of Moore and Norman, Oklahoma are neighboring cities in Cleveland County, but residents viewed their risk differently to tornadoes even though they are at equal risk. Residents of Moore felt they were more prone to tornadoes and took warnings more seriously than those who live in Norman. If views on people's risk and responses to tornadoes varies so significantly at the county level, perhaps the CWA scale is too large to assess variations in decision making. Therefore, future work using higher resolution data to discover if there are spatial variations at more local scales, such as county-level.

5.2 Future Work

This project provided interesting results with several avenues for future work. First, it would be interesting to compare my model results quantitatively with the Social Vulnerability Index to see if higher proportions of incorrect decision making correlates with pre-identified locations of social vulnerability. Likewise, these maps could also be correlated with tornado exposure maps to see if there is another layer of vulnerability for certain populations or locations. High correlations would suggest that these populations might be more at risk if they are not only vulnerable, but also less likely to make the correct decision. I visually compared the estimation maps with the Social Vulnerability Index map, but this process could be done in more intentionally and in detail through spatial correlation, which can be calculated in GIS software.

It would also be interesting to further investigate geographic variations of decision through a combination of both quantitative and qualitative methods. For instance, designing a tornado warning decision experiment that specifically addresses place rather than cartographic design would be more beneficial for the questions posed in this thesis. Rather than an arbitrary virtual place, the experiment could somehow draw on their own sense of place. For instance, the experiment could provide an inset map of their state depicting where the tornado warning is occurring or asking them to imagine the tornado warning is for their hometown. Qualitative data, such as a follow-up survey or interviews, would be beneficial to collect, asking them why they decided to shelter or not. The quantitative data could provide an overview of what happened, but the qualitative data could offer more detail to the decision-making process and how that might differ in place-based contexts.

5.3 Relevance to Society and to the Discipline of Geography

Despite the limitations and subtleties of the results of this study, they are still relevant for decision makers and risk communicators. First, three demographic groups were identified as being more prone to making incorrect decisions: females, Hispanic, African American, and Other races. These are also groups that are identified as having higher social vulnerability compared to their male, Non-Hispanic, White counterparts. This result is important for risk communicators, such as NWS forecasters or local emergency managers, to know so they can help the populations they serve. For instance, if a risk communicator serves a large Hispanic population, they should take more care in disseminating the message or educating the public about tornado safety. It also may be pertinent to take care in working with experts to effectively translate the message into Spanish so their population can understand the message better and make better decisions.

Second, the southern U.S. was consistently identified as a region with higher proportions of incorrect decision making, even if the results were not always statistically significant. This result is important because the southern U.S. is more prone to getting tornadoes and has been identified as more socially vulnerable. Risk communicators in the south-central and southeastern U.S. should be aware that the populations they serve are vulnerable to tornadoes and may not know how to make the best decision during a tornado warning. Risk communicators should educate the public about tornadoes and tornado warnings and take care to clearly communicate the risk information. Risk communicators should also be aware that their populations may not necessarily make bad decisions but are more risk averse. They should continue to encourage sheltering behavior but also make sure there are adequate resources in place to help these populations since they may intend to shelter but do not have the means or resources available to them.

Third, the weak spatial variation in decision making may indicate that decision making is a complex, place dependent, and individual process. It likely has more to do with the individual, their experiences with tornadoes, and their interactions with place and their environment rather than simply with their location on a map or demographics. It is inappropriate, then, to make assumptions or generalizations about people in broader geographic regions. Risk communicators should pay attention to their local environment as it has the potential to impact local decision making. The exact implications of local knowledge and the local environment are beyond the scope of this study, however, and should be further explored in future studies.

Finally, this research is also relevant to the field of geography. Previous research in geography and other fields in the social and behavioral sciences have not examined spatial patterns in decision making in detail. This research filled that gap by providing different spatial analysis methods that identified consistent patterns of decision making across the U.S. My research also showed that virtual tornado warning decision experiments may not be ideal when examining people's real-world location alongside their decisions. It is likely that place-based attachment and experiences influence people's decisions in ways that cannot be fully captured in an online format. Spatial patterns in decision making as well as the influence of place-attachment are both topics of interest in geography and have ample room for future research.

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