THESIS

A RHETORICAL STORM: LINGUISTIC ANALYSIS OF UNCERTAINTY IN SEVERE WEATHER COMMUNICATION

Submitted by

Zoey Rosen

Department of Journalism and Media Communication

In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Summer 2019

Master's Committee:

Advisor: Marilee Long

Julie Demuth
Russ Schumacher

ABSTRACT

A RHETORICAL STORM: LINGUISTIC ANALYSIS OF UNCERTAINTY IN SEVERE WEATHER COMMUNICATION

Weather forecasts are a product with inherent uncertainty and a wide audience (Compton, 2018). Known as an example of prediction rhetoric (Morss, Demuth, & Lazo, 2008), weather forecasts have been found to be influenced by linguistic and cultural factors in case studies (Pennesi, 2007). However, forecasts are still rarely studied as articles of rhetoric (Compton, 2018). This study analyzed patterns amongst the linguistics of uncertainty expressions in Twitter forecasts during a cluster of tornadoes in March 2018 through a content analysis. Tornado hazard messaging, due to tornadoes' short-term threat and overarching potential for damage (Ripberger, Jenkins-Smith, Silva, Carlson, & Henderson, 2014), provides an opportunity to study uncertainty language during short-term hazardous scenarios. Across a five-day period, there were N = 2,459 severe weather forecast tweets from 146 Twitter users located in Alabama, Mississippi, Tennessee, and Georgia. Results indicate there were significant relationships between the source of a forecast (i.e., weather media, weather government, and non-weather government) and uncertainty expression. Weather media sources were significantly less likely than government sources (both weather and non-weather) to use uncertainty expressions in their forecast tweets. The state the Twitter source was located also influenced the amount of uncertainty expressed within a forecast. For example, tweets from areas with a greater number of tornadoes were significantly less likely to contain uncertainty expressions than were areas with fewer threats. Also, time (measured as the number of days before tornado touchdown) was shown to have a

significant relationship with uncertainty expression, as the amount of uncertainty expressed decreased the closer in time the messages were to the tornadic event. Due to the large amount of uncertainty in weather prediction, meteorological forecasts during severe events provide a unique, fascinating area for future research on risk communication and public safety messaging.

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1. INTRODUCTION

A concept with many definitions, uncertainty takes on different forms depending on the context in which it is discussed. Scientific uncertainty arises from measurement limitations and epistemic gaps in knowledge, meaning that not all information is known, nor knowable. As these limitations are common, it is widely accepted that uncertainty is an important aspect of any study. In science communication, a field comprised of the mixing of social and physical phenomena, uncertainty is a conventional part of research, though it is met with different levels of acceptance by practitioners. In meteorology, weather forecasts are a product with inherent uncertainty and a wide audience (Compton, 2018). Known as a means of prediction rhetoric (Morss et al., 2008), forecasts have been found to be influenced by linguistic and cultural factors in case studies (Pennesi, 2007). Forecasts are still rarely studied as articles of rhetoric, though influenced by critical paradigms (Compton, 2018). By combining quantitative and post-positivist methods (like linguistics) to evaluate the more critical aspects of forecasts, researchers have a unique opportunity to study forecasts as tools of hazard and risk communication for a mass audience.

1.1 Uncertainty Communication Through the Lens of Rhetoric and Linguistics

Unlike other fields, rhetorical studies acknowledges that in uncertainty communication, the results of studies are based on the temporal and spatial situation of the population, meaning that the answers are heavily influenced by the exact moment the data is gathered. In these moments, arguments take form—visually and textually. In rhetoric, visual uncertainty is defined graphically, displayed through methods such as color gradients, dashed lines on maps to show tentative boundaries, or in the transparency of an image. Linguistic uncertainty is apparent in the verbal expressions individuals use to assert their worldviews (Walsh & Walker, 2016). For example, uncertainty is expressed in hedging, or using qualifying statements when asserting facts or opinions to allow the speaker distance from the piece of information (Hyland, 1996). This distance allows a speaker to be wrong, while making the consequences of the misinformation less tied to the speaker's character or credibility. Using hedges, while giving a speaker the opportunity to save face, can lead to future contradictions if the new findings are drastically different in consequences than the original claim. Scientists feel pressure to not contradict themselves when discussing uncertainty in technical and public forums, as each sphere of argumentation is different in its acceptance of hedges (Walsh & Walker, 2016). The public tends to want to avoid hedging in order to obtain the most certainty on issues that affect their daily life. Despite public pressure, hedging is common in science communication messages tailored for the public where uncertainty is a crucial component (Jensen, 2008)—like forecasts and severe storm warnings.

1.2 Study Goal

Interpretations of forecasts vary based on the format of the forecast information and individual perceptions of hazard and risk that people in different geographical areas develop over time (Morss et al., 2008). With this variance of interpretations, uncertainty becomes a critical component of meteorological communication because messaging often arises from an immediate need to influence behaviors in order to promote safety. Different sectors of society send these messages, with the common goal of relaying the information in a cognitively efficient manner. This study investigates the relationship between the words and phrases that different sectors of the weather community use surrounding uncertainty.

Social media platforms, like Twitter, have been studied in the context of severe weather scenarios, like tornadoes, though the focus has been on the concept of public attention (Ripberger et al., 2014). Public attention was studied through the spread of conversations surrounding an event, which was measured by counting the number of times an event was mentioned or tagged across a wide audience (Ripberger et al., 2014). While attention is important, the accurate interpretation of the hazard information is equally crucial in such weather events. Tornado hazard messaging, due to its short-term threat and overarching potential for damage (Ripberger et al., 2014), provides an opportunity to broaden the analysis of social media use during short-term hazardous scenarios. Tornadoes require quick risk assessment, showcasing the need for easily understandable messages. Social media has been emphasized in the weather community for its ability to distribute risk information (Demuth et al., 2018). Social media messages can be analyzed linguistically, focusing on the contextual information within messages and its potential to affect information processing. The guiding research question for this study is as follows: How is uncertainty represented by different sources in severe weather social media messaging?

CHAPTER 2. LITERATURE REVIEW

Misunderstandings between scientists and the public are all too common and all too unfortunate. Scientists process massive amounts of data and information every day that have varying degrees of certainty. However, the public has difficulty understanding and applying this data easily, especially in a risk scenario. Understanding the role of uncertainty in science communication is important because when uncertainty information is easy to comprehend, the affected audience can better decide its responses to environmental stimuli (National Academy of Sciences, 2006).

While scientists are aware of the role uncertainty plays in their work, as it is a result of their instruments, models, and/or calculations, the public typically interprets uncertainty as a lack of knowledge or as a plot of deceit, sparking distrust (Retzbach & Maier, 2015). In hazard scenarios, public distrust of subject matter experts can work against experts' goal of protecting the public. Understanding the complexities of communicating uncertainty to lay audiences can help scientists communicate effectively during emergencies, when information must be processed accurately and efficiently to keep people safe. If researchers analyze uncertainty using different scientific and social lenses, perhaps a more mutual understanding of uncertainty can be reached between the public and information providers.

2.1 Uncertainty Through an Interdisciplinary Lens

2.1.1 Scientific Uncertainty

Uncertainty, as a concept, is a known aspect of scientific research. However, because of its large presence in scientific fields, uncertainty has a range of definitions. For example, scientific uncertainty is "when results of a study are not yet validated, contradictory, inconsistent, or not reproducible" (Heidmann & Milde, 2013, p. 2), or when there are gaps within the data of a study that hinder decision-making (Benessia & De Marchi, 2017). Scientific uncertainty also comes from the act of science; sources of uncertainty are found in measurement error, instrument imprecision, randomness in a study, and in unobservable phenomena that inherently affect research results (Broomell & Kane, 2017). Model approximations, sample sizes, and systematic biases also play a role in uncertainty, depending on the field (Broomell & Kane, 2017). The overarching connection among definitions of scientific uncertainty is that the limitations to a perfect understanding within a study are due to the tools that scientists use to process and collect information.

Technical uncertainty is the "expression of likelihood and probability that professional groups use to manage their knowledge-making activities" (Walsh & Walker, 2016, p. 75). Technical uncertainty ties mathematical reasoning to communication and social problems (Walsh & Walker, 2016). For example, confidence intervals display technical uncertainty because they show the range of uncertainty in the findings on a numerical scale. These scales are often representations of systematic limits, such as the limits of representative statistics and time (Walsh & Walker, 2016). Technical uncertainty is used to evaluate the validity of a scientific work, which places more emphasis on the reported confidence intervals in studies. While some scientists are wary of the public misinterpreting technical information, effective science communication that contains technical information about uncertainty is completely possible with crafted messages (Fischhoff, 2013).

The perception of scientific and technical uncertainty is what makes the term problematic; scientists' perspectives on uncertainty suggest that having uncertainty about a study's results is a sign of a deeper understanding of the field, while laypeople may interpret uncertainty as a signal that the work is untrustworthy (Rabinovich & Morton, 2012). When experts disagree within a field, which scientists understand is a natural part of research, this can signal to laypeople that they should have lower confidence in the results due to this disagreement (Broomell & Kane, 2017). While complete scientific consensus would be ideal, the public often overlooks the years and studies that go into achieving widespread agreement. When the public ignores a scientific consensus because there is not perfect agreement, like with the matter of climate change, the public may critically underestimate an issue. The gap between the acceptance of uncertainty by scientists and by the public displays the complexity in communicating across fields of study.

2.1.2 Uncertainty in Risk Communication

Uncertainty can be defined as the quantification of risk in an uncontrolled environment (Spiegelhalter, 2017). This definition acknowledges the interplay of the different theoretical perspectives that inform risk communication. The quantification of risk comes from statistical and scientific uncertainty within risk communication scholarship, while risk perceptions and responses are studied through behavioral studies and cognitive processing (Spiegelhalter, 2017). Situational uncertainty describes the factors that individuals consider in the moment (e.g., if I evacuate ahead of the hurricane, will I be able to keep my medicine refrigerated and feed my family?), which are typically noticed in the decisions people make during risk events (Benessia & De Marchi, 2017). When managing public safety, information providers often downplay situational uncertainty to lessen panic, but at the cost of downplaying scientific uncertainty as well (Benessia & De Marchi, 2017).

A clear message that addresses scientific uncertainty can provide the public with trustworthy information during a hazardous situation. Different types of people have different expectations for reporting uncertainty. For example, Maier et. al (2016) studied how scientists, journalists, and laypeople perceived uncertainty and the expectations they felt the other groups had about mentioning uncertainty. They found that while scientists and journalists believed that, in general, uncertainty should be pointed out, laypeople were not aware of uncertainty unless it was explicitly revealed to them and pertained to their daily lives (Maier et al., 2016). However, when the uncertainty involved controversial issues, scientists were the most hesitant about communicating uncertainty and the journalists were the most excited to do so. Yet, other studies found that journalists may avoid reporting uncertainty around issues, even though they think it is important, because they fear that the public will distrust their products (Retzbach & Maier, 2015). Scientists also fear that a lack of reporting uncertainty will likewise cause distrust in their work and institutions (Retzbach & Maier, 2015). This threat to scientists' credibility arises mainly with controversial science, where skepticism is more rampant in the discourse surrounding the issue (Retzbach & Maier, 2015). Though conflict is seen as a news value in journalism (Bednarek & Caple, 2012), it is not as valued in scientific discourses. Threats to trust because of conflict are often shied away from in science. Public trust and source credibility remain important dimensions of uncertainty communication, as they often inspire risk-induced behaviors.

2.1.3 Behavioral and Psychosocial Uncertainty

Uncertainty has been studied in the fields of psychology and behavioral studies, especially as it applies to risk determination and decision-making. Uncertainty describes the probability of a random event and its subsequent outcomes, and is sometimes associated with the terms ambiguity, imprecision, and vagueness (Broomell & Kane, 2017). The concepts of ambiguity aversion and conflict ambiguity have been studied as psychological functions of uncertainty. Ambiguity aversion occurs when decision-makers have a strong disinclination towards a choice if there is imprecision or randomness associated with making that choice (Broomell & Kane, 2017). Some of the imprecision in ambiguity aversion can be described as conflict ambiguity, or when stakeholders have different sources providing conflicting or disagreeing information (Broomell & Kane, 2017). For example, a person may feel aversion towards choosing a physician if one potential doctor is saying that the reason the person feels tired is because the person's iron levels are in a lower range of acceptable values, while another potential doctor is saying that the person is just not getting enough sleep. With these conflicting reasons, the person may ultimately never choose a doctor and instead try to self-medicate. This response is the opposite of what a doctor would typically want, at the risk of the patient's health.

Uncertainty reduction theory was introduced in 1975 as a means to describe how individuals respond to uncertainty (Goldsmith, 2001). Initial studies suggested that uncertainty provoked anxiety within individuals, and, through measures that reduced uncertainty, individuals gained a higher level of self-efficacy in their environment and interactions (Brashers, 2001). According to the theory, when people believe they do not have all the knowledge available or required to make a decision, they feel uncertain in an uncertain situation (Brashers, 2001). Feelings of uncertainty, and the anxiety associated with them, lead people to make decisions that reduce the uncertainty they are feeling. Applying this behavioral theory to discourse studies, scholars have found that the different meanings of uncertainty must be examined in socio-cultural contexts in order to understand how the individual responds to such situations (Walsh & Walker, 2016). Socio-cultural contexts are found in speech communities, which are groups of individuals who use speech and discourse to communicate and set rules (Goldsmith, 2001). The idea of introducing a cultural context into the study of uncertainty points towards an epistemological shift away from the positivist and post-positivist roots of scientific uncertainty to a more critical paradigm.

2.1.4 Rhetorical Studies as a Means of Uncertainty Communication

Rhetoricians have used the spheres model as a framework to approach understanding how people assess and analyze risk as a strategy to mitigate uncertainty (Walsh & Walker, 2016). The spheres model, shown in Figure 1, describes the interaction of social contexts in the process of creating community discourse. The technical sphere encompasses the more scientifically based sectors of society, like researchers and science agencies. The public sphere encompasses actors, like government and media, that hold public forums for debate. The personal sphere covers individuals as they interact in society. These groups are different spheres of argumentation, which are the discourses formed from different groups within a community (Goodnight, 1982).

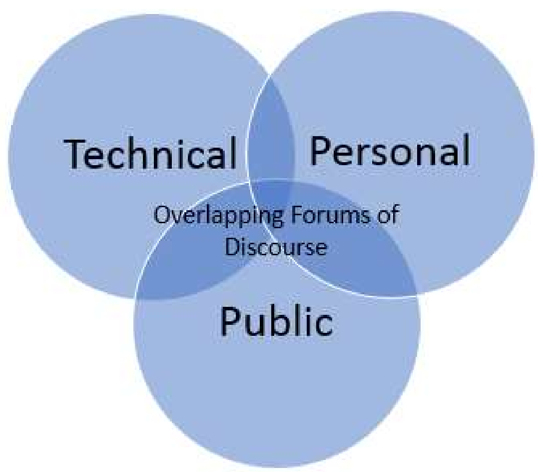


Figure 1. Spheres model, based on Walker and Walsh's (2016) interpretation of Goodnight (1982).

Risk messages are often found in the discourses that overlap these spheres, as multiple groups often need to work together in a hazardous or uncertain scenario. Goodnight (1982) argues that as the number of uncertain issues grows, patterns emerge. While these issue argumentation patterns may be displayed over similar communication channels, the major differences between these spheres lie in the forums in which some discourses are debated. For example, the technical sphere would argue at a conference, whereas the public sphere would argue at a townhall meeting. These spheres can overlap, as arguments tend to move from forum to forum depending on how their actors circulate in society (Walsh & Walker, 2016). The overlapping of these spheres creates hybrid forums that serve the political process of assembling a discourse. Pertaining to risk, the spheres model acts as a heuristic to track how uncertainty changes as it moves through different forums (Walsh & Walker, 2016).

This approach to understanding risk has taken on a more critical epistemology in comparison to a significant portion of the risk communication scholarship. Rhetorical studies acknowledge that in uncertainty communication, findings are more value-laden, because the methodologies required for studying discourse communities align with the perception that a measured reality is shaped around the historical situation of a community (Guba & Lincoln, 1994). While positivist researchers prefer to reduce or eliminate uncertainty, the spheres model's view and the rhetorical approach to this concept show new community discourses that can be centered around risk and uncertainty. Post-positivist researchers would still prefer to eliminate uncertainty, but understand that this may never be able to be accomplished when studying the real world. These discourses can elaborate on the complexity of uncertainty as a concept, in addition to the multiplicity of its definitions (Walsh & Walker, 2016). The personal sphere of argumentation, which houses the individual as an actor of argumentation, however, has a specific rhetorical branch that is interesting to note due to its connection to information processing: linguistic uncertainty.

2.1.4.1. Linguistic Uncertainty

Linguistic uncertainty refers to “verbal expressions of [varying levels] of commitment to beliefs about the world,” and is a fundamental element of how individuals assert their worldviews (Walsh & Walker, 2016, p. 77). Linguistic uncertainty is shown in hedging, which occurs when a speaker uses qualifiers when making assertions. Hedging allows the speaker to create some distance from the information in case it is wrong, so it does not reflect on the speaker personally (Jensen, 2008). However, hedging can lead to misunderstanding (Hyland, 1996). For example, the American judicial system is known for its linguistic uncertainty, as the legal standards of proof use terms such as “beyond a *reasonable* doubt,” “*preponderance* of the evidence,” and “*probable* cause” (Weiss, 2003). These hedges are commonly misunderstood and have disagreements surrounding how they are used in practice. For example, the concept of a reasonable person as a standard for determining liability in criminal law has a different meaning to each actor in the courtroom because of its vagueness, and thus is highly argued.

A more thoughtful way to classify uncertainty was put forth by the Intergovernmental Panel on Climate Change (IPCC) in 2001. The IPCC system uses words and statistics to avoid the widespread misinterpretations that the legal standards of proof have. The IPCC assigned a qualitative label to uncertainty that was associated with its Bayesian statistical probability: >99% was virtually certain, 90–99% was very likely, 67–90% was likely, 33–67% was medium likelihood, 10–33% was unlikely, 1–10% was very unlikely, and <1% was exceptionally unlikely (Weiss, 2003). This combination of subject phrasing and mathematical support helped standardize the way that scientists describe the likelihood of a climatic event (National Academies of Science, 2016). This standardization only works for a probability distribution that is known, and not all aspects of science have a non-subjective probability distribution.

Additionally, however revolutionary this standardization of hedges in climate change communication was, each sphere of argumentation differs in its acceptance of hedges, depending on the subject. Scientists, therefore, may stray from using hedges when discussing uncertainty in scientific and public forums (Walsh & Walker, 2016). By observing the use of hedges and qualifiers in risk communication efforts, researchers can analyze hazard discourses and uncertainty expressions through a linguistic view.

2.1.5 Uncertainty in Meteorology and Forecasting

Climate change has been a popular case study of science communication studies and rhetorical analyses in recent years. Climate change is a deceivingly complex subject; founded in the interaction of social and environmental sciences, climate change is both a political problem and a scientific problem (Walsh, 2015). Climatology, the science upon which climate change is based, is the study of the global climate. Climate can be further defined as weather over time (Broomell & Kane, 2017). In the form of an analogy, climate is akin to one's personality, while weather is like a mood.

By studying the dynamics of the seasonal and shorter-scale hydrometeorological system, scientists can forecast future climatic conditions. Climatology is therefore inherently post-positivist; while all answers cannot be known about the climate of the past or future, research can help scientists narrow towards a truth. However, political biases have influenced the public's perception of uncertainty in climate change (Broomell & Kane, 2017). Climate change, as a subject, has been the center of many forums of public debate, which is atypical of most physical sciences (Rabinovich & Morton, 2012). The communication of uncertainty in climate change has led to public skepticism and a decrease in trust between scientists with competing ideas

(Retzbach & Maier, 2015). The emphasis on climate change in rhetorical and communication studies is arguably due to the politicization of the topic away from its scientific origins.

Meteorology, as a base science for climatology, has not been studied as much in science communication scholarship, compared to climate change. Uncertainty in forecasts has been studied as an element of communication, for both experts and non-experts (Joslyn & Savelli, 2010; Nadav-greenberg & Joslyn, 2008; Savelli & Joslyn, 2012). Meteorology is the study of weather systems and hydrological processes that change in the short term and seasonally (National Academy of Sciences, 2006). This science combines the interactions of atmospheric fluid dynamics, chemistry, hydrology, and computer modeling that must adapt to address the inherent rapid changes within the coupled earth system. While these sciences are physical, weather plays a role in the social and economic sectors as well, affecting decision-making, risk assessment, agricultural yields, and other aspects that request predictions within economic markets. Due to the overarching influence of meteorology on different fields of research and on society, more communication research centered around uncertainty and meteorological prediction would showcase the unique aspects of forecast communication.

The atmosphere is a dynamic system that can be described through a series of partial differential equations. However, the definition of a dynamic system can also be extended to systems where the measured state at one moment can approximately determine a near-future state (Zeng, Pielke, & Eykholt, 1993). With this extended definition, a physical system such as the atmosphere can be measured, even though its behavior has a systematic randomness or uncertainty (Lorenz, 1990). This randomness and erraticism are often characterized as chaos. Chaos can be considered as order without periodicity, sensitivity of prediction based on initial conditions, intermittency and alternations of behavior over time (which is more commonly seen in the literature regarding turbulence), or noise in a power spectrum of turbulence (Zeng et al., 1993). As the atmosphere is chaotic, meteorologists accept the limitations of accurate predictions in the long term. However, the constant order and disorder of the atmosphere can strongly affect even short-term predictions of weather phenomena. This tension between long-term and short-term predictability due to chaos goes hand-in-hand with uncertainty; both concepts depend on the context and temporal situation in which they are initially measured.

Uncertainty is a fundamental characteristic of weather forecasts and seasonal predictions (National Academy of Sciences, 2006). As meteorology relies on observational and modeled data, uncertainty is a common concept to scientists within the field. Additionally, as meteorology is a highly predictive field, meaning that a major aspect of work within it deals with forecasting and predicting future weather phenomenon, uncertainty is an especially common trait (Morss et al., 2008).

Weather and meteorological uncertainty also have an obvious connection to rhetoric and community discourse. Discussing the weather and its impacts is a highly common conversation; it can be traced across cultures and sectors of society. Community planning is habitually centered around using forecasts as a tool for uncertainty reduction. Therefore, because meteorology influences daily life, researchers who study meteorological uncertainty can provide insight into the study of decision-making, hazard preparedness, and emergency messaging. While the act of procuring forecasts in meteorology is inherently post-positivist due to the focus on approaching a truthful prediction with uncertainty, a critical approach to this field can highlight and explore some of the difficulties in communicating weather information.

2.2 Time in Forecasting

Studies show that time influences behavior under uncertainty. For example, in economics, uncertainty has a stronger influence on risk aversion in the short term (Hirshleifer, 1989). For example, with natural disasters, this would mean that people would more likely take a behavior to reduce their risk for a severe storm that was happening in the next few hours, but they may not take the same level of preventative behavior for an earthquake that may or may not happen over the course of a few years. When it comes to the uncertainty surrounding natural hazards, people take risks less often because they cannot control the outside influences (Hirshleifer, 1989).

In weather forecasting, predictions are more accurate closer to the initial conditions. For example, there is more uncertainty for precipitation forecasting further out in time. This is due to a high number of variables influencing storm activity, such as freezing level, modeling method, horizontal transposition, available atmospheric moisture, etc. (Micovic, Schaefer, & Taylor, 2015). With the difficulty in forecasting the further out storm systems are in time, how people assess their personal risk is not as cleanly evident. People's risk aversion behaviors are more evident as the threat moves closer in time. Social media provides a unique chronological record of risk assessment, as posts on Twitter (for example) have a time-stamped record of a source's actions, feelings, and perceptions (Demuth et al., 2018). Thus, time is an interesting factor to study in decision making, risk messaging linguistics, and pre-event behaviors.

2.3 Sources of Severe Weather Information

The perceptions an audience has of a source can influence how the audience interprets and adopts behaviors from a hazard or risk message (Morss, Cuite, Demuth, Hallman, & Shwom, 2018). The higher the levels of trust or reliability in a source, the more likely the audience will be to follow the recommendations in the message (Morss et al., 2018). Trust and reliability are built through the feeling audience members have that their best interests are being consistently considered (Eisenman, Cordasco, Asch, Golden, & Glik, 2007). Additionally, credibility is established when risk communication is done in a timely and understandable manner (Fitzpatrick-Lewis, Yost, Ciliska, & Krishnaratne, 2010). Especially during severe weather events, the public needs to obey evacuation orders and other public safety messages (Drost, Casteel, Libarkin, Thomas, & Meister, 2016). Credible sources garner more attention from an audience than non-credible sources (Fitzpatrick-Lewis et al., 2010). Thus, timeliness and clarity remain important aspects of source credibility in risk messaging.

Studies of the risk communication surrounding hurricane evacuation orders have found that people are more likely to evacuate if they view public officials' advice as important (Burnside, Miller, & Rivera, 2007). Public officials can be more broadly described as authorities in risk communication efforts because they disseminate critical messages that require immediate decision-making. While government leaders and career meteorologists are common authorities in severe weather communication, media workers, such as broadcast meteorologists, are additional authorities amid natural disasters. TV weathercasters are highly trusted, elite sources about severe weather (Bloodhart, Maibach, Myers, & Zhao, 2015; Doherty & Barnhurst, 2009). As broadcasters and weathercasters also cultivate their social media presence, their connection with their audience continues online as well as through the television.

Not only are trust and credibility important for weathercasters, but timeliness is especially crucial in crises and natural disaster reporting (Lachlan, Spence, Lin, Najarian, & Greco, 2014). Media outlets are important information providers due to the speed with which they provide updated information to their audiences (Perez-Lugo, 2004). This updated information can come before or after a severe weather event. For example, in the aftermath of Hurricane Georges in Puerto Rico, the internet was the main source of information about the disaster, becoming a vehicle for locals to cope with the damage from the event, including those who were more isolated (Perez-Lugo, 2004).

In Entman's (2003) cascading activation model, the hierarchy of framing around a public discourse has government administrators, who typically have more power, at the top, moving to other elite members like congressional representatives, to the media who use words and frames to communicate to the public. This model posits that the administration and elite groups influence the media, which shapes public opinions and behaviors (Entman, 2003). Other studies have looked at different groups associated with hurricane forecasting, showing that weather government, weather media, and emergency managers have their own specialties (geographical or subject-matter) when communicating about a severe threat, with overlaps between groups in some cases (Demuth, Morss, Morrow, & Lazo, 2012). A one-way flow of information model would be appropriate for this study, as we are only looking at original tweets from a source. While the cascading activation model is not as accurate in some discourses, in the context of severe weather, the actors within each group may change, but the hierarchy has the potential to hold. With government (consisting of meteorologists from entities like NOAA or NWS) still at the top of the hierarchy, the elites become actors like emergency managers and other weather personnel who work with communities to maintain public safety and may use forecast information from the government sources. Other examples of elites are trained individuals who understand meteorology, even if their direct profession is not in forecasting (e.g., storm spotters or NWS Cooperative Observers). The weather media, such as TV broadcasters, typically utilize the information from the other groups in their own message dissemination. Thus, a modified cascading activation model (shown in Figure 2*)* may be more appropriate for this study.

Figure 2. Severe weather (Wx) cascading activation model, inspired from Entman,2003.

The words and frames these groups use in their messaging surrounding natural disasters and uncertainty may be different at each level, showing a change in uncertainty language as information cascades down to the public.

2.4 Uncertainty Typologies

Uncertainty has been studied across many fields of research, including behavioral studies, risk management, mass communication, rhetoric and composition, and society and technology studies (STS). From these fields, six dyads of uncertainty typologies have been identified that can be applied to weather forecasts. These are:

[1] intrinsic uncertainty vs. extrinsic uncertainty, where uncertainty is displayed through the manipulation of visual elements in a graphic (e.g., colors meaning different things on a forecast map of a storm path), or where uncertainty is displayed through the addition of objects or elements onto an established graphic (e.g., grids or isobars placed on top of an existing map), respectively (Gershon, 1998; Kinkeldey, Maceachren, & Schiewe, 2014).

[2] visually integrable vs. visually separable uncertainty, where a graphic cannot be understood if it is separated from the data and contextual information (e.g., a map of Colorado with glyphs located throughout the state would not make sense without knowing what the glyphs represent), or where a graphic can be understood independently from the data and contextual information (e.g., a graph of rising temperatures with a key to explain what each line represents), respectively (Kinkeldey et al., 2014; Maceachren, Brewer, & Pickle, 1998).

[3] static vs. dynamic visuals, where visuals display uncertainty classically with visualizations that do not move (e.g., a map of the U.S. with an unmoving cone of uncertainty as part of a hurricane forecast), or animatedly with interactive controls (e.g. animated hurricane path maps that show a moving cone of uncertainty), respectively (Kinkeldey et al., 2014).

[4] confidence statements vs. likelihood statements; the former are expressions that qualify or quantify one's assessment of epistemic (knowable) uncertainty (e.g., "I am 70% sure it will rain today"), while the latter are expressions that qualify or quantify one's assessment of aleatory (random) uncertainty (e.g., "There is a high probability of rain today"), respectively (Ülkümen, Fox, & Malle, 2016).

[5] precision vs. vagueness, where a precise statement is one that tends to be highly specific, exact, or narrow in scope and is often associated with a high level of confidence

and expertise (e.g., 2.5 inches of rain are expected to fall in the next hour), and a vague statement is absent of specifics and is large in scope (Løhre & Teigen, 2017) (e.g., a few inches of rain are expected to fall).

[6] probabilistic vs. deterministic information, where probabilistic information is presented as a probability rather than as a frequency (e.g., bar charts of typical temperature ranges for an area by season), and deterministic, or point, information is presented in the forecast format of a single value or categorical forecast (Juanchich & Sirota, 2014; Marimo, Kaplan, Mylne, & Sharpe, 2015) (e.g., a list of forecasted high and low temperatures for the upcoming week).

From these dyads, it was decided for this study to focus more on the verbal and numerical expressions of uncertainty in forecasts, which relates to the dyads of [5] precision vs vagueness, as well as [4] confidence vs likelihood expression. Verbal and numerical expressions are displayed in writing, making a connection to linguistics and rhetoric. Additionally, while visuals and graphics contain much interesting material to study uncertainty and information processing, they are outside the scope of this study. This study looks to the written-based dyads as a way to characterize uncertainty expression.

2.5 Explication of Uncertainty and Confidence Expression in a Severe Weather Context

As uncertainty is an interdisciplinary concept, one to which different fields have attached their own theories and terminologies, to use the word "uncertainty" merely as the label is not sufficient to explain the nuances of uncertainty in severe weather. Since this term cannot mean the same thing to different disciplines, uncertainty needs to explicated with theory from linguistics, rhetoric, and severe weather.

2.5.1 Uncertainty Expression

Verbal uncertainty expressions use phrases like "certain" or "likely," also known as qualifiers or hedges, and imprecise evaluative labels like "high," "low," "strong," and "weak," to indicate probability (Arvai & Rivers III, 2013). Numerical uncertainty expressions use numerals, frequencies, odds, or ranges, and can also be demonstrated in the use of statistical figures to express mathematical likelihood, such as graphs with errors bars to show the range of average annual precipitation with outliers (Arvai & Rivers III, 2013).

2.5.2 Confidence Expression

Confidence expressions, though seemingly opposite to uncertainty expressions, are different, nuanced expressions that convey information with more surety. Linguistic markers of confidence are defined as expressions with more assurance due to the weight of the evidence (Arvai & Rivers III, 2013). Signs of confidence include the use of personal pronouns like "I," "we," and "our," linguistic markers such as "sure," "certain," and "will," and simplified or smoothed curves or boundaries in a visual, with highly precise or specific claims in text.

2.5.3 Conflict Expressions

When claims about the certainty of a forecast conflict, it can be confusing to the public. Conflict within the language of a message can occur when there are multiple ways uncertainty is discussed around one topic. For instance, if a group of people are told that their meteorologist is sure it is going to snow, and later told that there is a 90% chance of snow, the difference in the degree of certainty regarding the impending hazard could confuse the audience, even though these two statements agree. Additionally, the phrase "will be possible" is equally confusing;

though the word “will” is used to signal the future tense of the verb “to be,” there is also confidence within “will” that can make it difficult to assess the uncertainty when connected to the uncertain word “possible”. This is an instance of conflict within three words. Noting instances of conflict can show where sectors of the weather community differ linguistically, as well as showcase possible instances where a risk message and warning may not be heeded in pre-event preparations.

2.6 Hypotheses

The literature about sources of information and perceived credibility suggests that there is a positive relationship between credibility and the acceptance of hedging (Maier et al., 2016; Walsh & Walker, 2016). While weather media are one of the lowest sources for perceived information credibility because they may not create their own forecasts, as seen in Figure 2, media workers also have some of the lowest tolerances for hedging in reporting information (Jensen, 2008). Likewise, subject-matter experts and government authorities are some of the more highly credibly sources when they generate information (Entman, 2003), and yet scientists use a high number of hedges in their messages (Hyland, 1996). Noting these differences in language use amongst sources, the predicted effect will be:

> **H1:** Fewer expressions of uncertainty for a tornadic event will occur in tweets from media sources than from government sources.

Additionally, there is an opportunity within the data to see if there exists a relationship between targets that weather sources include with their forecasts and the uncertainty they express. For this study, timing, location, intensity, social impact, and hazard were targets that were deemed important dimensions to what meteorologists discuss within their forecasts. Timing and location detail the logistics ("when" and "where") of a threat, while intensity, social impact, and hazard detail the type, strength, and the resulting community effects due to a weather threat. Understanding uncertainty expressions by topic can provide a closer view into where different sources are more uncertain and shed more light into how the field is discussing different aspects of their forecasts to a general audience. This idea leads to an exploratory research question:

RQ1: Do sources vary in their use of uncertainty expression for different targets?

While confidence and uncertainty expressions can occur in a single message, which is considered conflict, these expressions often appear on their own. This pattern is especially likely because tweets are short. Therefore, the second hypothesis is as follows:

H2: Confidence and uncertainty expression will have an inverse relationship across all tweets.

Conflict within messages is also a part of the determination of source credibility. Like controversial issues (Retzbach & Maier, 2015), risk messages that contain conflicting information on a hazard can confuse readers, as well as dissuade them from taking action. With forecasts, taking action in the face of a hazard is crucial, especially in severe weather contexts (Lachlan et al., 2014; Mileti & Sorensen, 1990). Conflict can be described as when two or more sources disagree about a fact, or when one source contradicts themselves in their own message. Conflicting claims within a message is an interesting aspect of uncertainty communication, leading to the next hypothesis:

H3: Across tweets, there will be more tweets with conflict than those without.

Additionally, it will be interesting to investigate how time plays a role in uncertainty expression. Time is an important dimension of risk messaging, as the desire for the quick processing of messages points to a desire for immediate action (Lachlan et al., 2014). Thus, there may be a difference in the communication of uncertainty in the forecasted days before the event as compared to the actual event. This difference makes sense because of the scientific limitations of models, as outlooks get more accurate in the shorter term. Tornadoes, while short-term events, have one of the largest lead times in forecasting for watches and warnings. Tweets, however, often communicate more than just the NWS product. This study examines the uncertainty expressions from a source for a four-day outlook leading to the first touchdown of a series of tornadoes, leading to the fourth hypothesis:

H4: Tweets will display less uncertainty about the tornado as the tornado event gets closer in time.

Finally, locality may play a role in risk communication, and it can be looked at in the context of severe weather. It has been found that the public often believes localized information from social media is more credible than national information from social media, like Twitter (Lachlan et al., 2014). While Lachlan et al. (2014) found this belief in Twitter discourse about a winter storm, which progresses less rapidly than a tornado (Drost et al., 2016), the idea of localized information and source credibility having a relationship, especially as uncertainty expression is often connected to credibility, leads to the fifth hypothesis:

H5: In tweets, non-local sources will express more uncertainty than will local sources.

CHAPTER 3. METHODS

3.1 Theoretical Framework of the Method

A quantitative content analysis was chosen as the research method for this study because it allows for the examination of textual material about an event, while using statistical analysis to investigate the relationships between elements of uncertainty (Neuendorf, 2002).

3.2 Sample

The sample of tweets was collected as part of a NOAA-funded VORTEX-SE research grant (Grant Number NA16OAR4590217) under the Weather Risks and Decisions in Society (WRaDS) group at the National Center for Atmospheric Research (NCAR). The data from the Risk, Information, and Vulnerability for Evolving Tornado Threats (RIVETT) project was made available as part of the NCAR Advanced Studies Program (ASP) for visiting graduate students. Tweets were collected through a former academic data sharing partnership between the University of Colorado Boulder and Twitter/GNIP. Tweets were collected in a contextual-plus method from a list of authoritative sources. This method was used by this group in other studies, and collects every tweet, reply, and retweet for a user in the determined time period as a contextual tweet stream (Bica, Demuth, Dykes, & Palen, 2019).

Regarding this individual event, this collection of tornadoes was interesting because there were no fatalities, though there were six tornadoes in the Birmingham, Alabama, county warning area, including two EF0, two EF1, one EF2, and one EF3[1] magnitude tornadoes (Figure 3). Additionally, there were only five injuries as a result of this cluster, which is incredibly low. The EF3 tornado affected the entire campus of Jacksonville State University, but many students were

[1] EF# = Enhanced Fujita scale (EFScale); rates the intensity of tornadoes from 0-5

gone as it was spring break. An EF2 was confirmed in Tennessee, an EF0 in Mississippi, and an EF1 that started in Alabama was confirmed to continue through Georgia; however, the majority of tornado reports came from Alabama for this cluster (*20180319's Storm Reports (20180319 1200 UTC - 20180320 1159 UTC)*, 2018).

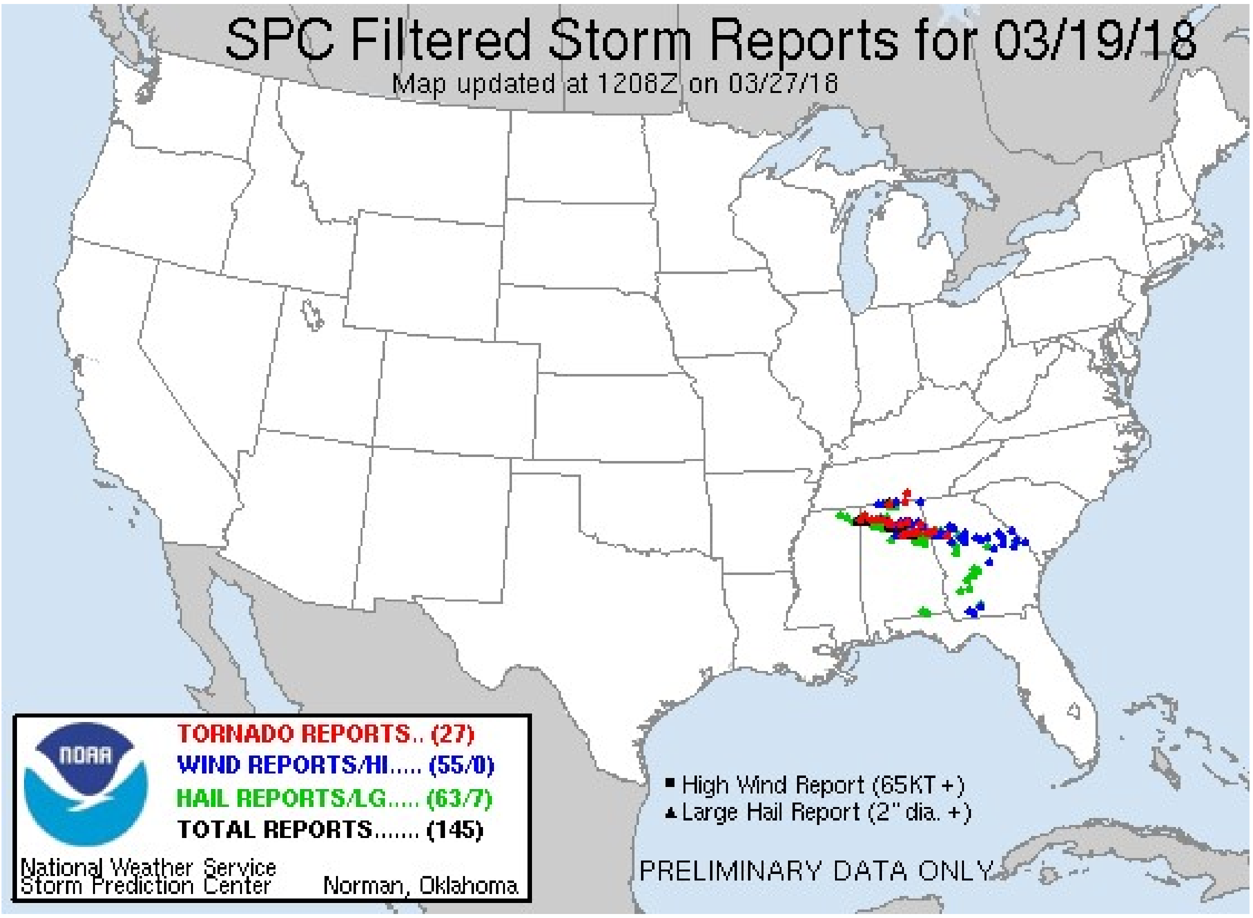


*Figure 3. Map of tornadoes from study cluster (*20180319's Storm Reports (20180319 1200 UTC - 20180320 1159 UTC)*, 2018).*

3.3 Selection of Twitter Sources

Twitter users were chosen based on their proximity to the threat area and having established careers associated with the weather sector (i.e., from weather forecasting offices, broadcasters, and other related officials). National figures who consistently report on national weather phenomena were also selected. This selection criteria resulted in a sample of 401 users.

Of those, 17 did not tweet or retweet (RT) during the time frame that data was collected. Therefore, the sample of Twitter users for this study was 384.

3.4 Selection of Dates for Study

Six tornadoes occurred between approximately 7:00 and 9:00 p.m., CDT on March 19 (0:00-2:00 UTC[2] March 20), with most of the tornadoes occurring in the Birmingham, Alabama, county warning area (CWA). Outlooks started four days prior to the first touchdown. Thus, Contextual-plus Twitter collection, where chronological streams of tweets were collected of every tweet for each determined user (Bica et al., 2019), began on March 16 (either at 0:00 UTC or 9:00 UTC / 4:00 a.m. CDT) and went through the end of March 20. For the purposes of the study, the data was truncated at the last warning as a hard boundary for sampling and analysis so that the uncertainty measured is based on the threat of the event, not the aftermath of the storm. The latest warning for this event was issued by the Atlanta/Peachtree NWS forecasting office, and it expired at 3:30 UTC on March 20. Thus, 3:30 UTC on March 20 is the end boundary for data collection from Twitter. Time is written in UTC from this point in this study, as the tornadoes crossed between Central and Eastern time zones.

3.4.1 Background of Tornado Region and Season

As tornado season in the United States is typically between March and June, an outbreak in March is earlier in the expected tornado season. While spring typically sees the maximum amount of tornadoes in this region, tornadoes can happen at any point of the year, even in the "cold season" (Childs & Schumacher, 2018). However, while this cluster of tornadoes on March 20, 2018 (UTC), was one of the largest for that month in Alabama, it was not the first outbreak of the season (National Centers for Environmental Information, 2011). There was some activity

[2] ## UTC = Time in Universal Time (UTC)/Greenwich Mean Time (GMT)/Zulu

in late February as well, which may have influenced communities' hazard preparation in the target area. Tornadoes have happened in every state in the continental United States, though some areas are more prone than others. Commonly referred to as "tornado alley" in the U.S., there is a high likelihood yearly for tornadoes to appear from Texas to South Dakota. Shown in the Figure 4 below, this region has been expanded throughout the years to include other southeastern and midwestern states. Alabama is within the "new" region due to the synoptic makeup of the area near the Gulf of Mexico, which predisposes the state to have some of the highest numbers of EF5 tornadoes in the country.

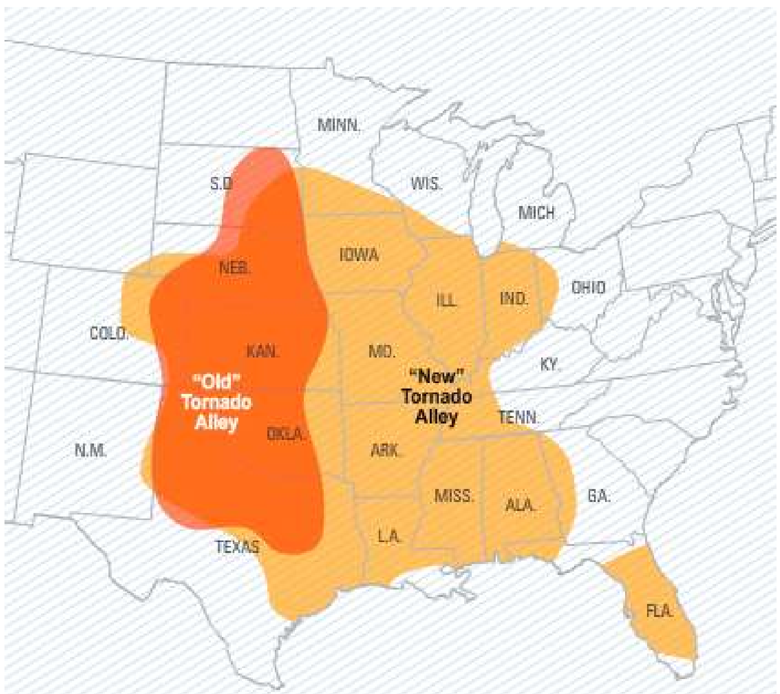


Figure 4. Map of tornado alley in the US, credit to Doyle Rice, Jerry Mosemak, and Julie Snider, USA Today.

An important piece of information to keep in mind is the possible influence of the 2011 historic outbreak of tornadoes. While seven years prior to this study's outbreak, the "Super Outbreak of 2011" was so devasting, especially in Alabama, that the impact and memories of local community residents still are affected (National Centers for Environmental Information, 2011). In a matter of three days, 305 tornadoes landed across the plains and southeastern United

States. Of the 305 tornadoes, there were three EF5s, 12 EF4s, and 21 EF3s, which inflicted major damage across the United States. Post-storm analysis confirmed 350 deaths from this outbreak, most of which occurred in Alabama. The most destructive tornado of the outbreak, which caused more than a thousand injuries and 65 fatalities, laid its path across central Alabama, hitting the major cities of Tuscaloosa and Birmingham (National Centers for Environmental Information, 2017). On the ground for about 80.3 miles, the wind speeds of this EF4 tornado reached 190 mph across a 1.5-mile maximum path width (National Centers for Environmental Information, 2017). Tuscaloosa and Birmingham were almost destroyed, amongst other cities like Chattanooga, Tennessee, and Smithville, Mississippi, costing about $11 billion in damages (National Centers for Environmental Information, 2017). The debris cleanup in Tuscaloosa cost $100 million alone (National Centers for Environmental Information, 2017). The cities that experienced the 2011 disaster overlap with the 2018 cluster, so the risk messaging and forecasting language may have been altered into what we read today due to the public memory and responses since 2011.

3.5 Data Set Cleaning

The data set originally contained a total of 121,078 tweets from the 384 users during the designated time period. All of the tweets from these users were collected through a former academic data sharing partnership between the University of Colorado Boulder and Twitter/GNIP. All tweets were chosen for analysis instead of only analyzing those with related hashtags; this decision was made in order to see the development of uncertainty language over time, rather than highlight those that were tagged by the user.

Retweets (RTs), which are the shares of original posts, were excluded from study. This choice was made because this study focuses on the uncertainty phrases from users, not the spread of their digital impact, which RTs can show. When RTs were removed, the sample was reduced to 33,662 tweets.

Replies were also excluded from this study. This decision was made so that uncertainty was the focus of the original posts, rather than the discourses that arose in a conversational context. Once replies were removed[3], the data set was reduced to 22,338 posts.

3.6 Variables

3.6.1 Variables Related to Data Set Cleaning

Several variables were coded for in the data set as a means of ensuring that only relevant tweets were included. The first variable was severe_tor_info, which considered the relevance of the tweets regarding severe weather or tornadoes. The relevant severe weather for this study included severe storms, storms in any capacity (i.e., spotter classes, services, donations), thunder, funnel clouds, tornadoes, flooding, hail, and rain. It did not include winter weather (i.e., snow, freezing temperatures, etc.).

The next variable is forecast_info. This variable was used to check if the tweet conveys forecast/threat information. Examples of forecast/threat information include remarks on the impending storm system and prediction of the physical hazards. If the tweets *only* had information about post event/impacts (e.g., clean-up of the community after the storm had passed through, monetary losses due to storm damage, etc.), personalization of the threat/event (e.g., personal experiences within the event, such as expressions of fear in current weather, pictures of children in a tornado shelter, etc.), or observational data without forecasting (e.g., radar, satellite images, pictures of clouds), they are not considered forecasts.

[3] Excluding replies, which have the potential to be coded at a later date as part of a dialogue study, was done by finding if user_screen_name = contextualPlus on the spread sheet, as well as if the tweet did not begin with "@username", which is a syntactical marker of a reply.

Tweet characterization (tweet_char) was coded for, classifying which type of tweet was being looked at. The categories were [a] a tweet with text only, [b] a tweet with a visual only (where a visual is an attached photograph, GIF, or video), and [c] a tweet with text and a visual. Text within the visual was still classified as a visual.

A flag to check for original posts (i.e. not replies or RTs) was included as a confirmation for sample-level intercoder reliability (ICR).

3.6.2 Variables Related to Message Content

An NWS classified threat (haz_man) was coded from each tweet as a check on whether the tweet explicitly mentioned an issued watch or warning for a weather hazard. There were seven codes for this variable: tornado watch, tornado warning, severe thunderstorm watch, severe thunderstorm warning, another severe threat generally (including outlooks, straight line winds, etc.), flooding, or if there were multiple hazards mentioned.

3.6.2.1. Coding for Source

To test H5, it was important to differentiate the types of sources that interact with and produce hazard communication. The location of the sources of the tweets was coded (Loc_geog), asking "where is the originator/source of the tweet from?" The first location was used as the primary location of the sources[4]. If missing in the first tweet, the information was gathered from the profile bio on the person's twitter account. "Local" was the spatial qualifier used to describe a relatively small geographic area that shared a unique experience as a result of its location or social hierarchy. A source was local if the tweeter was within state boundaries of the touchdown of the tornado cluster (i.e., Alabama, Mississippi, Tennessee, Georgia). Non-

[4] To find this information in the tweets, coders looked at the the cell "user_location" in the CSV file of the ContextualPlus data. IF "user_screen_name" was the same as "contextualPlus" in the file, then the location was that of the original poster.

local was classified as every other state or region not included within the boundaries of the tornado cluster, including regional and national bounds. This classification was needed, as a large volume of tweets from non-local sources concerned winter storm warnings (Washington, D.C.) and mudslides (California), which were not applicable to the study. An unclear location was coded when the given location was a vague statement that does not actually convey a physical location (e.g., “Up to mother nature,” “in the world,” etc.).

Source type (source_type) was a variable that identified what sector the originator/source of the tweet belongs to. There were two broad classifications of sources: weather-related and non-weather related. This refers to whether the person’s job is centered around weather. Beyond these classifications, the sources within this study included people working in the media field and people working in government. Other classifications of source type were included in the code book (Appendix A), but were not found within this study’s sample. Examples of people within these classifications are given below.

3.6.2.1.1. Government

Weather government sources were considered to be agencies and groups that work as a federal agency to produce, research, and disseminate information about meteorological and atmospheric sciences. Within the U.S., the National Oceanic and Atmospheric Administration (NOAA) under the Department of Commerce oversees the National Weather Service (NWS), the National Centers for Environmental Prediction (NCEP), Environmental Modeling Center, Weather Prediction Center (WPC), Ocean Prediction Center, Climate Prediction Center (CPC), Aviation Weather Center, Storm Prediction Center (SPC), National Hurricane Center (NHC), Space Weather Prediction Center, local weather forecasting offices (WFOs), and River Forecasting Centers (RFCs) (NWS, 2018). The National Aeronautics and Space Administration

(NASA) was also considered a weather government agency due to its involvement with atmospheric sciences.

Classified as "other" government sources in this study, in the United States, government was defined as agencies, bureaus, boards, commissions, and committees that fall under the executive, legislative, or judicial branches of the federal structure (USA.gov, n.d.). Each works in a system of checks and balances to create policy and enforce laws, while seeking to provide a service for the people of the country. The 15 main agencies under the executive branch are shown in Table 1. Within the bounds of this study, other public officials (mayors, sheriffs, senators), emergency managers (state-level and FEMA), and military were considered to be government figures.

Table 1. U.S. government departments.

Department of Agriculture	Department of Commerce	Department of Defense	Department of Education	Department of Energy
Department of Health and Human Services	Department of Homeland Security	Department of Housing and Urban Development	Department of Justice	Department of Labor
Department of State	Department of the Interior	Department of the Treasury	Department of Transportation	Department of Veterans Affairs

3.6.2.1.2. Media

According to the American Meteorological Society, a broadcast meteorologist should give weather forecasts and communicate forecast information in a technically sound and responsibly delivered way, be competent, have a background in meteorological science from an accredited university, and be the primary media representative of the meteorological profession to the public (AMS, 2018).

Apart from this purely classified weather media source, other media workers, such as anchors and reporters, deliver information on current events and newspeech. Newspeech is when an on-air (broadcast) speaker formulates meanings of current events to aid the audience's understanding and to encourage the audience's acceptance of his or her word as truth (Doherty & Barnhurst, 2009). Thus, other media workers can provide information on weather. Framed as a public service, the media aim to seek the truth and report it, providing information to all sectors of society (SPJ, 2014). Non-weather media sources included news and media agencies, television or website, not specifically related to weather (e.g., photographers, bloggers, or general broadcasters).

3.6.2.1.3. Other Weather Sources

Credible sources that do not work for media or government, but that have validity in being included in the study (e.g., the weather elites classification from Figure 2) were classified as "other." These included private industry meteorologists, storm spotters, NWS Cooperative Observer volunteers, and more. Students not yet affiliated with meteorology as a career, but who were studying meteorology in college, fell in this category as well. The strict "other" code was reserved for stakeholder groups that did not fall in the other categories (e.g., utilities companies, nonprofits, tourism-related, hospitals).

3.6.2.2. Coding for Linguistics

Examples of linguistic codes with their associated tweets are located in Appendix B. Verbal uncertainty expression (unc_verb) included hedges, which were classified as qualifying phrases, likelihood statements, or imprecise evaluative levels for assessing probability. Qualifiers included words like "uncertain" or "unlikely." Other hedges in the text included "could," "may," "might," etc. Likelihood statements included words like "chance," "likelihood," "possible," etc. Examples of imprecise evaluative labels are "high," "low," "strong," "weak."

Numerical uncertainty expressions (unc_num) used numerals, frequencies, odds, or ranges to convey uncertainty. These expressions were also demonstrated in the use of statistical figures to express mathematical likelihood (e.g., box plots, cumulative distribution function).

Conflict (unc_con), regarding uncertainty information, was classified through inter-message content. If there were conflicting elements within the tweet, i.e., within the tweet text, within the visual, or between the tweet text and visual, then conflict was noted. Additionally, if there were contradictory forecast uncertainty claims or phrases about the same target (e.g., different hedges around the timing of a storm), conflict was apparent. Likewise, the combination of a confident phrase and an uncertain phrase in one message was a sign of conflict.

Confidence expressions had more defined and assured verbiage (e.g., "will," "does," simplified or smoothed curves or boundaries in a visual, and highly precise claims). Confidence also was often found alongside specific claims due to the weight of the evidence. Confidence was recorded for instances within messages under "conf_1."

3.6.2.3. Coding for Uncertainty Expression

Starting with the variables that relate specifically to the words within the messages, unc_det noted the presence of any forecast uncertainty present in the tweet. Uncertainty was defined as an expression of a lack of sureness surrounding a message due to a possible knowledge gap on the issue, or randomness, characterized with vagueness, qualifiers, or impersonal pronouns.

3.6.2.4. Coding for Targets of Uncertainty

Targets of uncertainty information were also included as variables for the exploration of what topic of information sources discussed with uncertainty in their forecasts. The included targets were timing, location, intensity/severity, social impact, and hazard, which are further described below:

[1] Timing measured uncertainty regarding the onset of the forecasted severe weather. This included timing of when storms would reach a certain area, how long the storm would last (duration), when it would end, etc.

[2] Location measured uncertainty regarding the "where" of the forecasted severe weather. This included possible affected counties, forecasted/projected storm tracks, etc. Just a mention of an area was not necessarily a discussion of location; the mention needed to be in a reference to a forecast (i.e., projected movements in areas, not observational mentions of counties). The word "along," for example, constituted uncertainty as it had ambiguity regarding location.

[3] The Intensity/Severity variable coded for uncertainty regarding the strength and magnitude of the forecasted severe weather. This included predicted strengths (e.g., EF3), forecasted wind speeds, predicted heaviness of precipitation, etc.

[4] The Social Impact variable coded for uncertainty regarding possible impacts resulting from the forecasted severe weather that were not physical in nature. For example, social impacts included the closing of schools and roads, destruction of personal property or infrastructure, the calling off of outdoor events due to the weather, etc. The word "damaging,", like in regard to wind, was considered a social impact, as damaging refers to infrastructure.

[5] Hazard coded for uncertainty regarding the physical weather phenomena as part of the forecasted severe weather event (e.g., tornado, hail, wind, lightning, flooding, storms).

3.7 Inter-Coder Reliability (ICR) of the Coding Scheme

3.7.1 Training Data, Coder Training, and Pilot Testing

ContextualPlus data, the type of data within the data set, was gathered for two clusters of tornadoes from Spring 2018. The April 13-14, 2018 tornadic event, gathered using the same process as the March data, was used as training for coding and for codebook development. While the event in April was not exactly the same as the event in March, the information gained from examining this event helped construct this study's concepts. For example, Twitter sources from April were looked at, as were the types of information that these sources typically discussed in their forecasts.

Coder training took place through separate coding of the April data. The coders convened to discuss where agreements and disagreements were within the codes, and the codebook was adjusted. This iterative process led to the final refinement of the codebook before moving to pilot testing.

For pilot testing the coding scheme, five sources were randomly chosen from the April data set using a random number generator. The coders independently coded 182 tweets from 5 Twitter sources. To calculate ICR for this quantitative content analysis, Krippendorff's alpha (α) was used. Krippendorff's alpha was run using IBM's SPSS software to measure the levels of chance-adjusted agreement between coders for the training data. This measure can be used for any number of coders, sample size, measurement level (nominal, ordinal, interval, or ratio), or amount of missing data values, which makes it applicable for this study (Hayes & Krippendorff, 2007). Ideally, an alpha of 0.80 or higher for each variable is sought, as this level is the standard within the social sciences. Two coders were used to establish ICR.

For this last iteration of coder training, the alpha values are shown in Table 2 for the 5 sources (182 tweets) in this pilot test.

Table 2. Measures of agreement on 182 tweets of training data.

Variables Related to Data Set Cleaning	
Variable Description	**Alpha**
Severe Weather Confirmation	0.70
Forecast Confirmation	0.69
Tweet Characterization	0.75
Flag of Original Message	N/A
Variables Related to Message Content	
Variable Description	**Alpha**
Mention Labeled Hazard Threat	0.71
Marker for Total Confidence	-0.38
Source Location	-0.14
Source Sector	1.00
Timing Identifier	-0.45
Timing Verbal Uncertainty	0.00
Timing Numeric Uncertainty	0.00
Timing Confidence	0.00
Timing Conflict	0.00
Location Identifier	0.42
Location Verbal Uncertainty	0.00
Location Numeric Uncertainty	0.00
Location Confidence	-0.50
Location Conflict	0.00
Intensity Identifier	0.81
Intensity Verbal Uncertainty	0.00
Intensity Numeric Uncertainty	-0.50
Intensity Confidence	-0.41
Intensity Conflict	-0.67
Social Impact Identifier	-0.24
Social Impact Verbal Uncertainty	N/A
Social Impact Numeric Uncertainty	N/A
Social Impact Confidence	N/A
Social Impact Conflict	N/A
Hazard Identifier	-0.53
Hazard Verbal Uncertainty	0.00
Hazard Numeric Uncertainty	-0.25
Hazard Confidence	-0.53
Hazard Conflict	0.00

The two coders discussed negative values, and the coding scheme was adjusted. As this was a small subset of five sources, the 0.70 agreement beyond chance for most variables showed promise that, in a larger intercoder reliability test, reliability would be achieved. As some variables did achieve 0.80 agreement, future reliability was promising on a larger sample of the data. “N/A” meant that reliability could not be determined within the pilot, as the tweets either did not contain content that could be coded, or there were too few instances to determine a relationship. However, we knew these codes would appear more often in a larger sampling. The codes were determined important to keep in the study

3.7.2 Study Data Cleaning and Testing

To test ICR for the study sample, approximately 10% of the tweet sources were coded, which equates to 39 sources out of the original 384. The 39 users were obtained through a simple random sample. During the process of coding the 39 users, the coders noted that many of the non-local sources were diluting the data set, as there were simultaneous severe storms in Texas and Florida that did not yield tornadoes. As the coding scheme captured severe thunderstorms, events in Texas and Florida were being captured, even though they were not about the Alabama-centered cluster.

The coders decided that the non-local Twitter users were to be removed from the study to narrow down the set by filtering by location instead of adding an additional code. While this local-only set more correctly represented the type of information we wanted to code, it did make us unable to test H5 in its original form. This will be discussed in the Results section.

When the non-local users were removed from the data set, the total number of Twitter users for the study was reduced to 146. The non-local users were also removed from the ICR random sample, which reduced the ICR to 16 Twitter users. These 16 users represented 10% of the 146 total users (10.96% to be exact), so ICR could be calculated. Krippendorf’s alpha was then run on each variable to test agreement between coders. As Table 3 shows, the variables related to cleaning the data set were reliable, but many of the variable related to message content did not achieve reliability.

Table 3. ICR measures of agreement on March data with non-local sources removed.

Variables Related to Data Set Cleaning	
Variable Description	**Alpha**
Severe Weather Confirmation	**0.93**
Forecast Confirmation	**0.86**
Tweet Characterization	**0.93**
Variables Related to Message Content	
Variable Description	**Alpha**
Mention of NWS Classified Threat	**0.87**
Marker for Total Confidence	**0.86**
Source Sector	**1.00**
Timing Identifier	**0.75**
Timing Verbal Uncertainty	**0.72**
Timing Numeric Uncertainty	**0.93**
Timing Confidence	-0.04
Timing Conflict	-0.00
Location Identifier	0.30
Location Verbal Uncertainty	N/A
Location Numeric Uncertainty	N/A
Location Confidence	N/A
Location Conflict	N/A
Intensity Identifier	0.47
Intensity Verbal Uncertainty	0.25
Intensity Numeric Uncertainty	0.67
Intensity Confidence	-0.02
Intensity Conflict	0.31
Social Impact Identifier	**0.92**
Social Impact Verbal Uncertainty	0.00
Social Impact Numeric Uncertainty	**0.78**
Social Impact Confidence	N/A
Social Impact Conflict	N/A
Hazard Identifier	0.07
Hazard Verbal Uncertainty	0.05
Hazard Numeric Uncertainty	0.67
Hazard Confidence	0.22
Hazard Conflict	0.21

Boldness denotes acceptable alpha value.

The alpha values that were not bolded were lower than desired. To address the problem with codes that did not achieve reliability, the targets were then collapsed together, combining [1] timing and location variables, and [2] intensity, hazard, and social impact variables. These groupings were due to the similarity in nature between topics. For example, timing and location were often discussed at the same time, as people often want to know where and when a threat appear. Intensity and hazard often are described together, as the strength and type of weather threat are used often in an adjective-noun format. These were combined with social impact as well, as magnitude of a threat can be easily connected to an audience both for the phenomenon and for its impact onto a community. As Table 4 shows, by collapsing the targets into these two larger categories, we can more reliably identify instances of uncertainty expression (both verbal and numerical). Generally, the collapsed categories indicate higher agreeance between coders, though uncollapsed, verbal is better for time, but not location. Thus, timing/location verbal uncertainty code was not used in the analysis of the data.

Additionally, while alpha values of around 0.70 are lower than what is generally wanted, due to the context of this study, these values were acceptable. Few researchers have looked into uncertainty language in severe-weather forecasts. As this is a newer study into the relationships between sources and linguistics, a more exploratory approach with a lower ICR standard level is rational. From this point, one coder coded the rest of the data.

Table 4. ICR measures of agreement on local-only March data, collapsed by target.

Collapsed Variables Related to Message Content	
Variable Description	**Alpha**
Timing and Location Identifier	**0.73**
Timing and Location Verbal Uncertainty	0.46
Timing and Location Numeric Uncertainty	**0.85**
Timing and Location Confidence	-0.01
Timing and Location Conflict	-0.01
Intensity/Social Impact/Hazard Identifier	**0.82**
Intensity/Social Impact/Hazard Verbal Uncertainty	**0.80**
Intensity/Social Impact/Hazard Numeric Uncertainty	**0.72**
Intensity/Social Impact/Hazard Confidence	0.10
Intensity/Social Impact/Hazard Conflict	0.31

Boldness denotes acceptable alpha value.

After these attempts to get ICR between the two coders, confidence and conflict could not be determined to have reliability. Thus, these variables were set aside. In the Discussion section, the problems will be talked about further.

CHAPTER 4. RESULTS

4.1 Description of Data Set

After limiting the data set to include only local Twitter users, the total number of tweets during the time period was 5,409 tweets. Of this number, 3,395 (62.77%) tweets were related to severe weather. Only 2,549 tweets that were related to severe weather were also forecasts. Thus, the sample for this study is 2,549 tweets. Of the total sample, 2,042 (80.14%) were tweets with text and images, 6 (0.24%) were tweets with just an image, and 501 (19.66%) were text-only tweets.

Across the five-day period, there were more tweets the day before the tornadoes touched down (March 19) and the day of the tornadic event (March 20) than in the forecast tweets leading to the event from March 16, 17, and 18 (see Figure 5). The increasing frequency of tweets makes sense, as the number of messages should increase the closer one is in time to the impending hazard. March 20 still having more tweets than March 16, 17, and 18 also makes sense, as the tornadoes were spread across the area throughout the entire day.

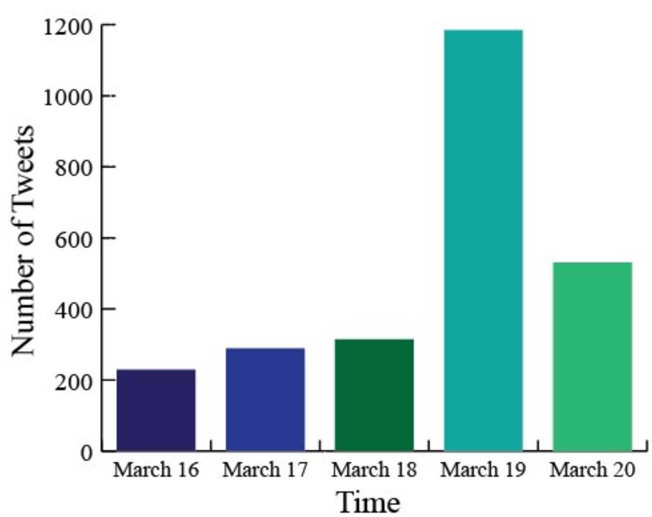


Figure 5. Histogram of tweet frequency, by time.

With the limiting of the data set to only local users, the "other" category for source no longer appeared in the set. As a result of this decision, there were only three types of sources within the data: weather media, weather government, and non-weather government. As shown in Figure 6, media sources were the dominant group in the data set, with the largest number of tweets for any source group. Media was also by far the largest group in the data set (Figure 7).

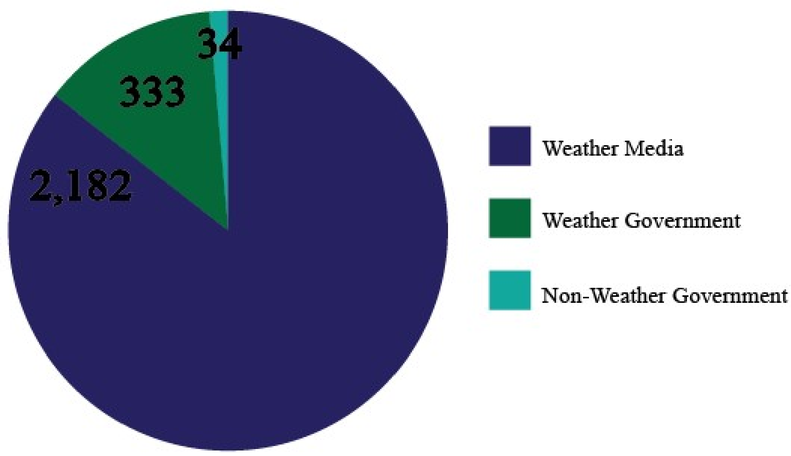


Figure 6. Total number of tweets in sample, broken down by source.

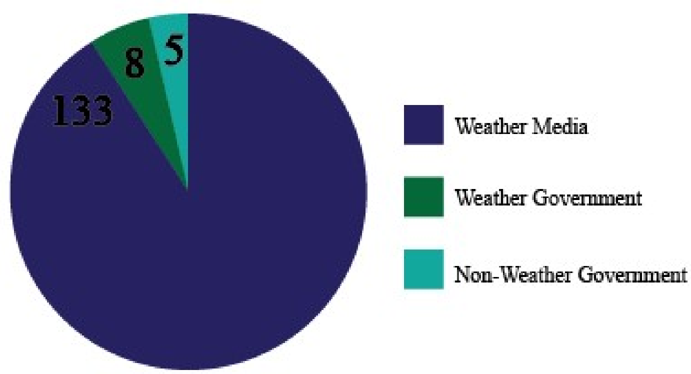


Figure 7. Distribution of total Twitter sources across all states.

Of the 146 local Twitter users, the dispersion of users by state was varied (Figure 8). The largest number of sources came from Alabama, with Mississippi having the least. More users from Alabama makes sense as there were more tornadic events in that state (see Figure 3 for a reminder of where tornadoes were reported). Likewise, less users in the other states aligns with the fewer events in this cluster. The breakdown of the number of tornadoes per state are described in Chapter 3.

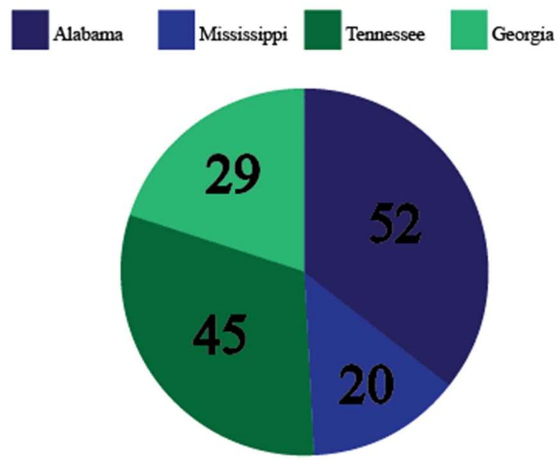


Figure 8. Distribution of Twitter users in the data set, by state.

The distribution of sources varied by state. Non-weather government had no users from Mississippi, as shown in Figure 9. Thinking about where the tornadoes were most geographically, the greater numbers in Alabama, and then Tennessee respectively, are reflected in the source variances.

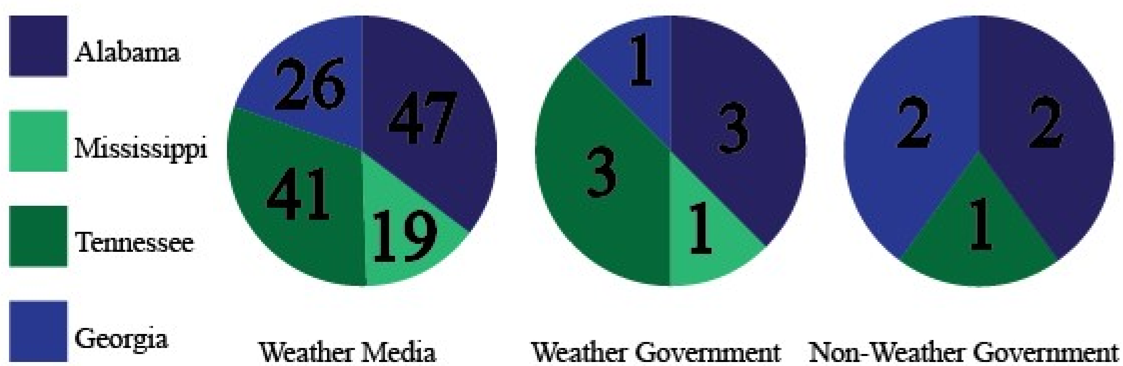


Figure 9. State distribution of Twitter users, by source.

Of the relevant tweets in the data set, the average number of tweets per user (across all sources) was 18.46 (*SD* = 16.66, range: 1–82 tweets). As seen in Figure 10, weather media sources tweeted an average of 17.30 times (*SD* = 15.37, range: 1–82 tweets). Weather government sources tweeted an average of 41.63 times (*SD* = 21.31, range: 17–69 tweets). Non-weather government sources tweeted an average of 6.80 times (*SD* = 10.40, range: 1–25 tweets).

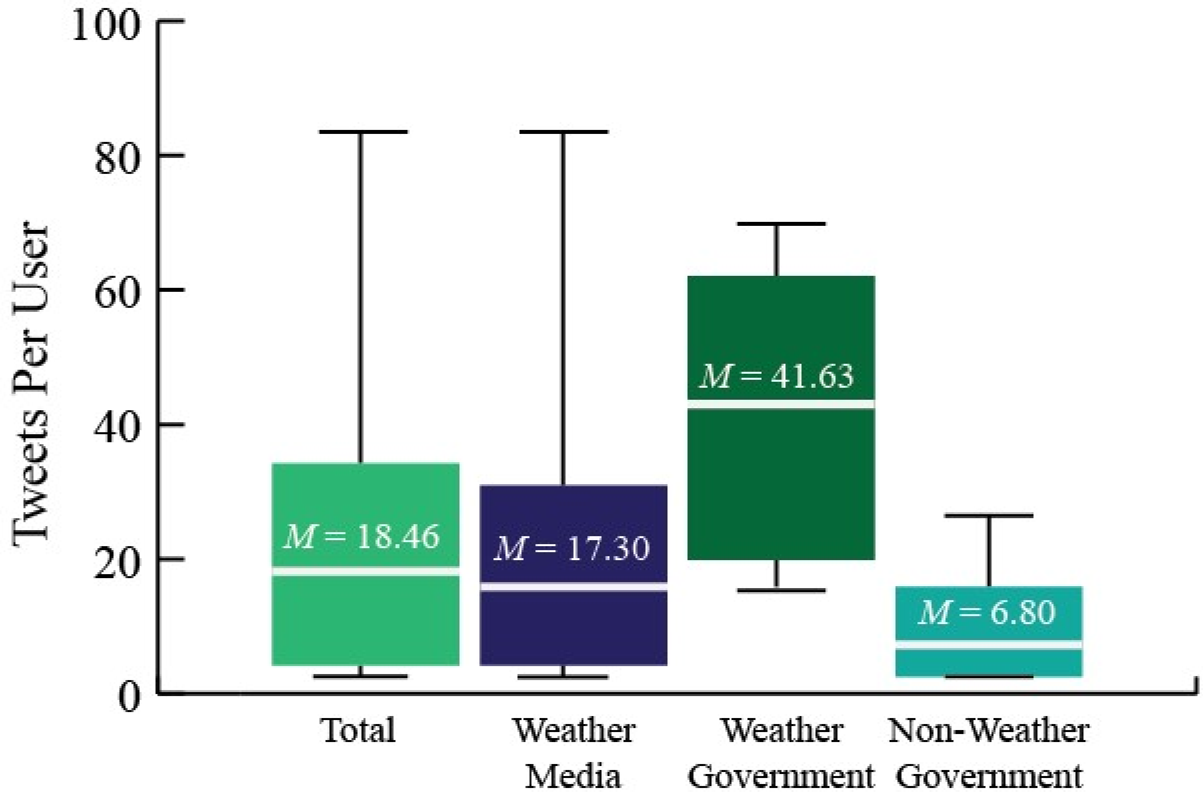


Figure 10. Boxplot of the number of tweets per user.

4.2 Statistical Testing of Hypotheses

Chi-square tests were carried out to test the hypotheses in this study. These tests are appropriate for analysis due to the nominal level of the variables and the nature of the relationships to be tested (Neuendorf, 2002).

4.2.1 H1: Fewer expressions of uncertainty for a tornadic event will occur in tweets from media sources than from government sources.

With the decision to include only local users within the data set, non-weather media and “other” weather and non-weather sources were removed from the study. Thus, H1 was revised to compare weather media sources to government sources (both weather and non-weather government sources).

A 2 x 3 contingency table analysis was conducted to evaluate if fewer expressions of uncertainty were in tweets from weather media sources compared to government sources (weather and non-weather government). The two variables were uncertainty expression (the presence or absence of it within a tweet) and source (weather media or government). Source and uncertainty expression were found to be significantly related, Pearson $\chi 2(2, N = 2{,}549) = 141.63$, $p < 0.001$. This has a medium effect size (Cramer's $V = 0.24$). The percentage of uncertainty expressions from weather media sources was 40%, from weather government sources was 71%, and 91% from non-weather government sources.

Follow-up pairwise comparisons were conducted to evaluate the difference among these proportions. The Bonferroni method, also known as the Bonferroni correction, was used to control for familywise Type I error at the 0.05 level across both comparisons (Hayes, 2005). As a result, the alpha for these chi-square tests was set at 0.01. Both comparisons were significant (Table 5).

Table 5. Results for the pairwise comparisons of source and present uncertainty expression.

Comparison		Degrees of Freedom	Pearson Chi-Square	p-value	Cramer's V
Weather Media (n = 2,182)	vs Weather Government (n = 333)	1	112.42	0.00*	0.21
	vs Non-Weather Government (n = 34)	1	35.71	0.00*	0.13

Asterisk (*) denotes significance.

Weather government sources were 177.5% more likely to use uncertainty expressions in a forecast tweet than weather media sources (71/40). Non- weather government were 227.5% more likely to use uncertainty expressions than weather media sources (91/40). This pattern makes sense, as typically media sources are more confident with their audiences and are less likely to use hedges.

4.2.2 RQ1: Do sources vary in their use of uncertainty expression for different targets?

As weather media sources were less likely to use uncertainty expressions than government sources (H1), the question of whether the relationship between source and uncertainty expression differed by target was raised. The six targets, as previously defined in the methods section, were timing, location, intensity, social impact, and hazard. While coders did not achieve intercoder reliability in identifying uncertainty expression within these targets individually, they could reliably identify uncertainty expression within larger categories: timing/location and intensity/social impact/hazard. The logic behind these collapsed groupings is in the Methods section. The collapsed category of timing/location had a total of 342 uncertainty expressions out of the 2,549 tweets (13.42%). The collapsed category of intensity/social impact/hazard had 1,022 uncertainty expressions out of the 2,549 tweets (40.12%). RQ1 can be broken into two parts for testing, divided by collapsed target.

4.2.2.1. RQ 1a. Do sources vary in their use of uncertainty expression for timing/location?

A two-way contingency table analysis was conducted to investigate this research question. The two variables were the Twitter user source (weather media, weather government, and non-weather government) and uncertainty expression (presence or absence) for timing/location.

Mention of uncertainty for timing/location varied significantly by source type, Pearson $\chi 2(2, N = 2{,}549 = 78.88, p < 0.001$. This relationship has a small effect size (Cramer's V = 0.18). The percentage of uncertainty expressions for timing or location from the weather media sector was 14%, from the weather government sector was 13%, and 65% from the non-weather government sector.

Follow-up pairwise comparisons were conducted to evaluate the differences among these proportions. The Bonferroni method was used to control for Type I error at the 0.05 level across both comparisons. As a result, the alpha for these chi-square tests was set at 0.01. Non-weather government sources were significantly more likely to mention uncertainty in tweets than were weather media sources and weather government sources (Table 6).

Table 6. Results for the pairwise comparisons of source and timing/location uncertainty expression.

Comparison		**Degrees of Freedom**	**Pearson Chi-Square**	**p-value**	**Cramer's V**
Weather Media (n = 272)	vs Weather Government (n = 48)	1	0.98	0.32	0.02
	vs Non-Weather Government (n = 22)	1	79.30	0.00*	0.19
Weather Government vs Non-Weather Government		1	50.55	0.00*	0.37

Asterisk (*) denotes significance.

Non-weather government sources were 464.29% more likely to use uncertainty expressions in tweets about timing/location than weather media sources (65/14). Non-weather government sources were 500% more likely to use uncertainty expressions in tweets about timing/location than weather government sources (65/13).

4.2.2.2. RQ 1b. Do sources vary in their use of uncertainty expression for intensity/social impact/hazard?

Type of Twitter source and the mention of uncertainty in reference to the intensity/social impact/hazard category were significantly related, Pearson $\chi2(2, N = 2{,}549) = 150.96$, $p < 0.001$. This relationship has a medium effect size (Cramer's $V = 0.24$). The percentage of uncertainty expressions for intensity, social impact, and hazard from the weather media sector was 35%, from the weather government sector was 11%, and 82% from the non-weather government sector.

Follow-up pairwise comparisons were conducted to evaluate the differences among these proportions. The Bonferroni method was used to control for Type I error at the 0.05 level across comparisons. As a result, the alpha for these chi-square tests was set at 0.01. As shown in Table 7, the comparisons of weather media vs non-weather government and weather media vs weather government were significant, whereas there was no significance when comparing weather government vs non-weather government.

Table 7. Results for the pairwise comparisons of source and intensity/social impact/hazard uncertainty expression.

Comparison		Degrees of Freedom	Pearson Chi-Square	p-value	Cramer's V
Weather Media (n = 769)	vs Weather Government (n = 225)	1	136.00	0.00*	0.22
	vs Non-Weather Government (n = 28)	1	32.20	0.00*	0.12
Weather Government vs Non-Weather Government		1	3.15	0.08	0.09

Asterisk (*) denotes significance.

Weather media sources were 318% more likely to use uncertainty expressions in their tweets about intensity/social impact/hazard when compared to weather government sources (35/11). Non-weather government sources (0.82) were 234.29% more likely to use uncertainty expressions in their tweets about intensity/social impact/hazard than weather media sources (82/35).

4.2.3 H2: Confidence and uncertainty expression will have an inverse relationship across all tweets.

As confidence did not achieve intercoder reliability, this hypothesis cannot be tested.

4.2.4 H3: Across tweets, there will be more tweets with conflict than those without.

As conflict did not achieve intercoder reliability, this hypothesis cannot be tested.

4.2.5 H4: Tweets will display less uncertainty about the tornado as the tornado event gets closer in time.

A two-way contingency table analysis was conducted to evaluate the relationship between uncertainty expression and time. The first variable was the calendar day leading to the tornado, essentially sorting by time. The tweets were broken up by day (in UTC), beginning four days before the event and ending with the day of the touchdowns. This approach broke the variable into five levels. The second variable was the presence or absence of uncertainty expression.

Calendar day and uncertainty expression were significantly related, Pearson $\chi 2(4, N = 2{,}549) = 128.09$, $p < 0.001$. This relationship has a medium effect size (Cramer's $V = 0.22$). The percentage of uncertainty expressions for March 16 was 59%, for March 17 was 54%, for March 18 was 60%, for March 19 was 43%. and for March 20 was 27% (see Figure 11).

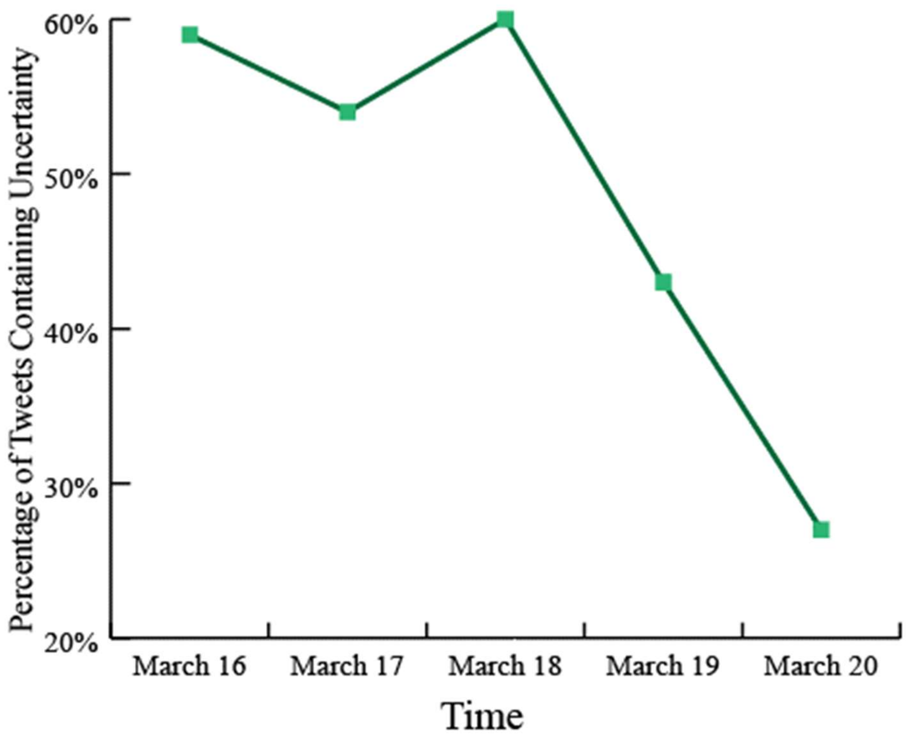


Figure 11. Use of uncertainty expressions in tweets over time.

Looking at the pattern in the graph, uncertainty expressions generally decrease in time. Decreasing proportions of uncertainty expression make sense, as there should be relatively little uncertainty the day of the event, whereas there should be more uncertainty the farther out in time the forecast is to the event.

Follow-up pairwise comparisons were conducted to evaluate the differences among these proportions. The Bonferroni method was used to control for Type I error at the 0.05 level across all comparisons. As a result, the alpha for these chi-square tests was set at 0.005. As shown in Table 8, all comparisons were significant, except for the cross tabulations between March 16, 17, 18. Additionally, the nonsignificant differences between the first three days can also be seen in the similarity of values among the uncertainty expression proportions. In other words, there was more uncertainty expressed the farther away the forecast tweet was from the event.

Table 8. Results for the pairwise comparisons of time and present uncertainty expression.

Comparison		Degrees of Freedom	Pearson Chi-Square	p-value	Cramer's V
March 16 (n = 222)	March 17	4	1.14	0.29	0.05
	March 18	4	0.11	0.74	0.01
	March 19	4	19.07	0.00*	0.12
	March 20 (n= 529)	4	70.18	0.00*	0.30
March 17 (n = 280)	March 18	4	2.29	0.13	0.06
	March 19	4	11.32	0.00*	0.09
	March 20	4	59.56	0.00*	0.27
March 18 (n = 306)	March 19	4	29.08	0.00*	0.14
	March 20	4	91.38	0.00*	0.33
March 19 (n = 1,176)	March 20	4	40.63	0.00*	0.15

Asterisk (*) denotes significance.

4.2.6 H5: In tweets, non-local sources will express more uncertainty than will local sources.

As the data set only included states with tornado touchdowns (i.e., the data set only included local Twitter sources), the hypothesis as originally written could not be tested. However, in the spirit of this hypothesis, a new question arose about whether there was a relationship between the number of tornadoes within a state and the proportion of uncertainty expressed in the tweets from that state. Does a larger number of tornadoes, i.e., higher threats, affect what words people use because more people are potentially in danger? As Alabama had most of the tornadoes and severe weather threats out of the four states, it would be interesting to see if the proportion of uncertainty expressions in tweets from Alabama was different than in the other three states.

A two-way contingency table analysis was conducted to evaluate the relationship between uncertainty expression (present or absent) and Twitter source location (Alabama or

Mississippi/Tennessee/Georgia). Source location and uncertainty expression were found to be significantly related, Pearson $\chi2(1, N = 2{,}549) = 20.78$, $p < 0.001$. This relationship has a small effect size (Cramer's $V = 0.09$). The percentage of uncertainty expressions in Alabama (39%) was significantly less than in the Mississippi, Tennessee, and Georgia area (48%) (Figure 12).

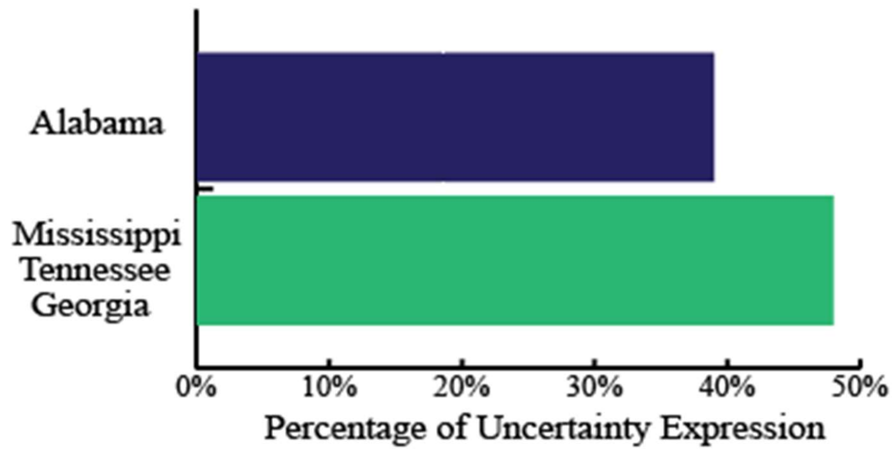


Figure 12. Percentage of uncertainty expression, by state.

4.3 Emergent Research Questions

As the coding scheme provided additional reliable information about the data set, an opportunity arose to see if there were significant relationships surrounding verbal and numerical uncertainty, as well as significance around uncertainty and NWS classified threats. Examining whether different sources are more prone to use verbal or numerical uncertainty expressions in their tweets can shed light on how audiences may respond to forecasts. Also, investigating patterns between uncertainty expression and an NWS classified threat (e.g., watches or warnings) allows for the opportunity to see where uncertainty expressions are more likely to occur. These questions will be analyzed like the previous hypotheses—using chi-square tests and their appropriate post-hoc analyses.

4.3.1 RQ2: Is there a difference in the extent to which sources express verbal or numerical uncertainty in their tweets?

Excluding verbal uncertainty for location, there were 951 tweets with verbal uncertainty expressions across targets. Of these, 226 (23.76%) were from weather government sources, 696 (73.19%) were from weather media sources, and 29 (3.05%) were from non-weather government sources. There were 586 tweets with numerical uncertainty. Of these, 171 (29.18%) were from the weather government sources, 398 (67.92) were from weather media sources, and 17 (2.90%) were from non-weather government sources. These totals are shown graphically in Figure 12.

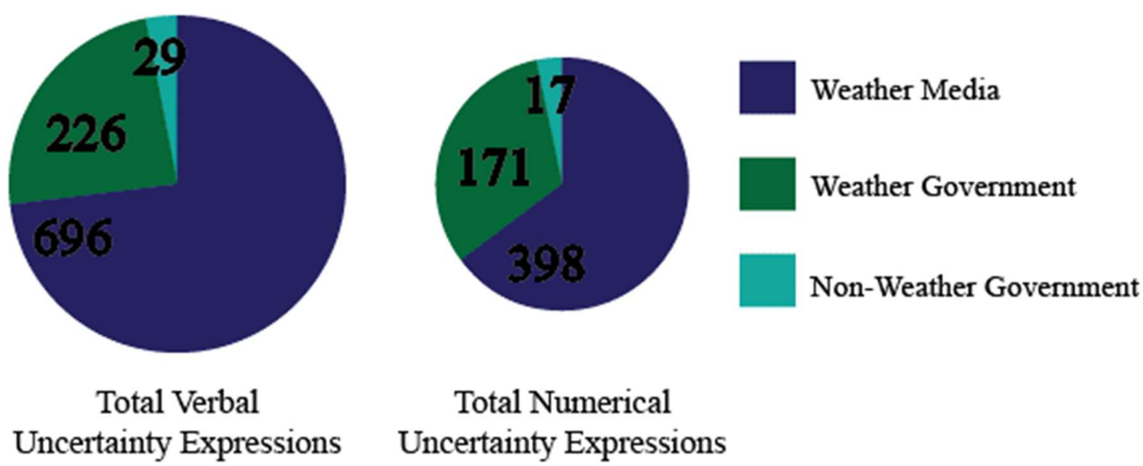


Figure 13. Scaled pie charts of verbal and numerical uncertainty expression, by source.

Chi-square tests were conducted to see whether sources used numerical or verbal expressions of uncertainty to differing extents. The two variables were the Twitter source and the presence or absence of verbal uncertainty [RQ2a] or of numerical uncertainty [RQ2b]. There were three levels to the source variable (weather media, weather government, and non-weather government).

4.3.1.1. RQ2a. Is there a difference in the extent to which sources express verbal uncertainty in their tweets?

As a reminder, verbal uncertainty for location was excluded from this analysis because it did not achieve intercoder reliability. A two-way contingency table analysis was conducted to evaluate the relationship between verbal uncertainty expression (present or absent) and the Twitter source (weather media, weather government, and non-weather government).

Source and verbal uncertainty expression were found to be significantly related, Pearson $\chi 2(2, N = 951) = 193.37$, $p < 0.001$. This relationship has a medium effect size (Cramer's V = 0.28). The percentage for verbal uncertainty expression was 81% for weather media sources 97% for weather government sources, and 97% for non-weather government sources (see Figure 14).

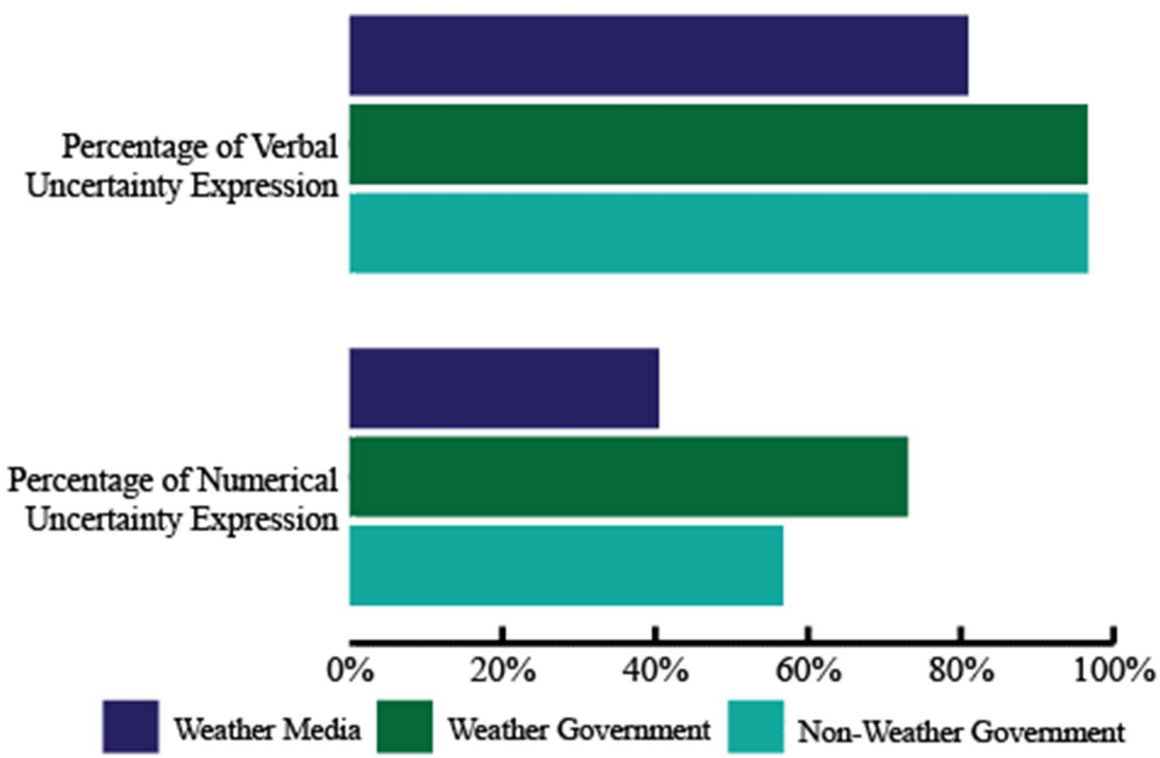


Figure 14. Percentage of verbal and numerical uncertainty expression, by source.

Follow-up pairwise comparisons were conducted to evaluate the difference among these proportions. The Bonferroni method was used to control for Type I error at the 0.05 level across comparisons. As a result, the alpha for these chi-square tests was set at 0.01. As shown in Table 9, weather media sources were significantly less likely to use verbal uncertainty in tweets than were weather government and non-weather government sources. Weather government and non-weather government verbal uncertainty expressions had a nonsignificant relationship for verbal uncertainty expression.

Table 9. Results for the pairwise comparisons of source and verbal uncertainty expression.

Comparison		Degrees of Freedom	Pearson Chi-Square	p-value	Cramer's V
Weather Media (n = 696)	vs Weather Government (n = 226)	1	160.65	0.00*	0.25
	vs Non-Weather Government (n = 29)	1	43.30	0.00*	0.14
Weather Government vs Non-Weather Government		1	4.42	0.04	0.11

Asterisk (*) denotes significance.

4.3.1.2. RQ2b. Is there a difference in the extent to which sources express numerical uncertainty in their tweets?

A two-way contingency table analysis was conducted to evaluate the relationship between numerical uncertainty expression (present or absent) and the Twitter source (weather media, weather government, and non-weather government).

Source and numerical uncertainty expression were found to be significantly related, Pearson $\chi 2(2, N = 586) = 192.78$, $p < 0.001$. This relationship has a medium effect size (Cramer's $V = 0.28$). The percentage of numerical uncertainty expression was 41% for weather media sources, 73% for weather government sources, and 57% for non-weather government sources. These percentages are also located in Figure 14.

Follow-up pairwise comparisons were conducted to evaluate the differences among these proportions. The Bonferroni method was used to control for Type I error at the 0.05 level across comparisons. As a result, the alpha for these chi-square tests was set at 0.01. As shown in Table 10, weather media sources were significantly less likely to use numerical uncertainty in tweets than were weather government and non-weather government sources. Weather government and non-weather government were not significantly related for numerical uncertainty expression.

Table 10. Results for the pairwise comparisons of source and numerical uncertainty expression.

Comparison		**Degrees of Freedom**	**Pearson Chi-Square**	**p-value**	**Cramer's V**
Weather Media (n = 398)	vs Weather Government (n = 171)	1	180.63	0.00*	0.27
	vs Non-Weather Government (n = 17)	1	22.15	0.00*	0.10
Weather Government vs Non-Weather Government		1	0.23	0.88	0.01

Asterisk (*) denotes significance.

4.3.2 RQ3: Do NWS classified watches use more uncertainty expression than warnings?

A two-way contingency table analysis was conducted to evaluate the relationship between uncertainty expression and an NWS classified threat. The two variables were the type of NWS classified threat (watch or warning) and the presence/absence of uncertainty expressions in the text of the users' tweet forecasts. For this analysis, severe thunderstorms and tornadoes were combined. Tweets that contained both a watch and a warning were excluded from this analysis.

NWS threat classification and the presence of uncertainty expression were found to be significantly related, Pearson $\chi2(1, N = 1{,}157) = 5.32$, $p = 0.02$ (Table 11). This has a small effect size (Cramer's $V = 0.07$). The percentage of uncertainty expression for watches was 31% and 24% for warnings (Figure 15).

Table 11. Results for the pairwise comparisons of NWS classified threats and present uncertainty expression.

Comparison	Degrees of Freedom	Pearson Chi-Square	p-value	Cramer's V
Watch (n = 208) vs Warning (n = 949)	1	5.32	0.02*	0.07

Asterisk (*) denotes significance.

A watch was 129.17% more likely to have an uncertainty expression than a warning. This makes sense as well, as watches are disseminated before warnings, so there is usually more uncertainty surrounding a hazard at that point in time.

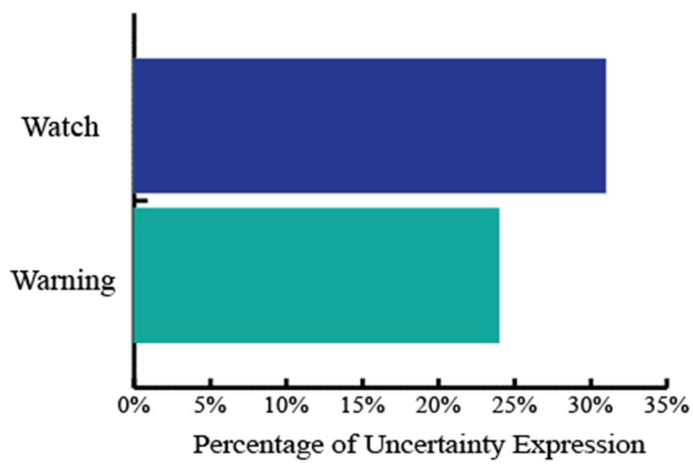


Figure 15. Bar chart of uncertainty expression for watches and warnings.

There should be a greater difference between the percentage of uncertainty expressions between these two groups because watches are uncertain by NWS definition and warnings are deterministic by NWS definition. Thus, it would make sense to separate each classified product by tornado or severe thunderstorm for analysis.

Separating by hazard and analyzing the watch/warning presence to the overall presence of uncertainty expression, the relationship was still found to be significantly related, Pearson

$\chi2(3, N = 1{,}157) = 46.21$, $p < 0.001$, Cramer's $V = 0.20$. This has a medium effect size. The percentage of uncertainty expressions for a tornado watch was 30%, tornado warning was 13%, severe thunderstorm watch was 43%, and severe thunderstorm warning was 31%.

As shown in Table 12, a tornado watch had significantly more uncertainty expressions than a tornado warning. A source was 230.77% more likely to use uncertainty expression in their forecasted tweets in a tornado watch (0.30) than a tornado warning (0.13), see Figure 16.

There should have been a significant relationship with a severe thunderstorm watch compared to a severe thunderstorm warning, but was nonsignificant. This could be due to a smaller n for severe thunderstorm watches in the set. Future research could look at this pattern more explicitly.

Table 12. Results for the pairwise comparisons of NWS classified threats (tornado and severe thunderstorm separated) and present uncertainty expression.

Comparison	Degrees of Freedom	Pearson Chi-Square	p-value	Cramer's V
Tornado Watch (n=187) vs Tornado Warning (n=381)	1	24.30	0.00*	0.21
Severe Thunderstorm Watch (n=21) vs Severe Thunderstorm Warning (n=568)	1	1.37	0.24	0.48

Asterisk (*) denotes significance.

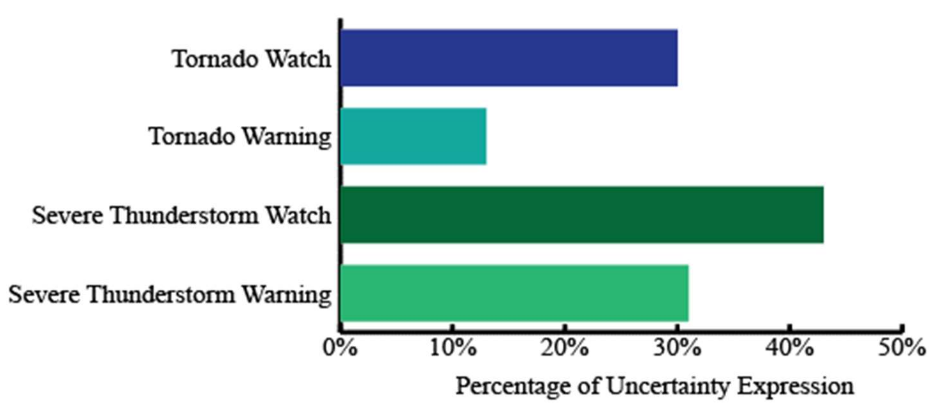


Figure 16. Bar chart of uncertainty expression for watches and warnings, by hazard.

CHAPTER 5. DISCUSSION, LIMITATIONS, AND CONCLUSIONS

Severe weather events, especially tornadoes, are multifaceted threats to public safety that warrant almost immediate responses from the public and local authorities. Twitter, as a forecast dissemination channel, has been studied in the context of the public's attention to severe weather scenarios (Ripberger et al., 2014), but not through the lens of risk message linguistics and rhetoric. Weather forecasts are influenced by linguistic factors, and can be studied as artifacts of prediction rhetoric (Compton, 2018; Morss et al., 2008). Thus, this content analysis investigated if there were patterns in linguistic representations of uncertainty in Twitter forecasts during a cluster of tornadoes in March 2018. Interesting patterns emerged amongst sources, time leading into the tornadic event, proximity to the threat, and uncertainty expression.

5.1 Interplay of Source and Uncertainty Expression

Information sources are critical figures of risk communication. Public authorities, such as government officials and media figures, must make decisions quickly and disseminate critical information (Burnside et al., 2007). With the pressure to release information as fast as possible to protect the most people (Jensen, 2008), it makes sense that weather authorities would release a message, even if not completely certain of every aspect of the threat. Releasing a message that contains uncertainty is an accepted aspect of meteorological messaging, as the atmosphere is chaotic in nature and constantly changing (Zeng et al., 1993; National Academy of Sciences, 2006). With an acceptedly uncertain atmosphere, different sources have different ways of communicating forecast information. As shown in literature and in the results of H1, media sources tend to avoid uncertainty expression when reporting to the public (Retzbach & Maier, 2015). The spheres model (Figure 1) describes how different areas of a community interact and form discourses. The technical and public spheres are represented in this study, between the government and media sources, respectively. The model posits that the public sphere of argumentation desires less uncertainty expression, though the more technical sphere prefers more (Walsh & Walker, 2016). Scientists, operating under the technical sphere of communication, have a desire to use more uncertainty expressions as a way to justify their findings within the correct error bounds (Rabinovich & Morton, 2012), whereas the public often interprets scientists' uncertainty expressions as a lack of knowledge (Retzbach & Maier, 2015). These contrasting interpretations of uncertainty expression provide a tension on information sources to appropriately convey uncertainty. This tension, amongst other reasons, is a major factor in why media sources stray from using uncertainty expressions in their public reports (Jensen, 2008). Aligning with the literature on media sources' preferences for uncertainty expression, the results from H1 show that weather media sources were about half as likely to use uncertainty expressions within their tweets than were non-weather government and weather government sources.

If we break down the uncertainty expression by target, as shown in RQ1a and RQ1b, weather media were more likely to express uncertainty around timing/location than weather government sources. Entman's (2003) cascading activation model posits that administrative groups, like government officials, influence the media, which subsequently influences the public's opinions and actions. Modifying this hierarchy to encompass the weather field (Figure 2), the cascade of information from scientists to the media to the public makes sense with the context of the weather field. This study did not show the second tier (Wx elites), but the relationship between the first (Wx government) and third (Wx media) tiers can be seen in the uncertainty expression proportions per target (RQ1a/b). The difference surrounding the timing/location uncertainty expression could also be due to the fact that weather media sources can often hyperlocalize their forecast information for their audience, while NWS forecasters have to address a more general area.

While the initial production of the forecast information was not directly investigated in this study, as detailed in the limitations sections, weather media sources expressing more uncertainty around timing/location agrees with the statistical results as well as the model. RQ1b, centering around intensity/social impact/hazard, also supports a modified cascading activation model for uncertainty dissemination (Entman, 2003). While government sources may express more uncertainty overall, when media sources were uncertain, they were more uncertain about the specifics of the threat (e.g., the windspeed or size of hail, etc.) for the severe threats. The results from this research question follow the cascading activation model, though the "why" is not as clear. Weather media sources can also make or can borrow forecast information, which may explain more uncertainty on this timing/location target. Future study could look at training level for this source and uncertainty expression.

Another contribution this study provides to the literature is that it divides linguistic uncertainty into numerical and verbal uncertainty and then compares them by source. Verbal and numerical uncertainty have been studied as dimensions of technical uncertainty, where mathematical reasoning connects to social issues through communication (Walsh & Walker, 2016).

Verbal and numerical expressions of uncertainty are interesting to view by the information source. Media and government sectors have different ways of expressing uncertainty, even while having the same Twitter audience when tweeting forecasts (Twitter is open to anyone to read and interact with, not just identified stakeholders). This study looked at the patterns within source for verbal and numerical uncertainty expression. There was a large number of verbal uncertainty expressions across tweets. This could be because the media sources were more dominant in tweet frequency and in number of sources (i.e. heavy media representation in the data set). Also, the verbal uncertainty expression use could be due to the fact that a media source could think that his/her audience would not be as understanding of numerical information, opting to use more verbal expression. This idea is not largely unfounded, as the public often has difficulty understanding and applying data, unless it is put into a format that is easier to comprehend (National Academy of Sciences, 2006). As Twitter and social media in general relies mainly on words, more instances of verbal uncertainty can be expected than numerical uncertainty expressions, which is reflected in the results for RQ2a. RQ2b shows that weather media sources were significantly less likely to use numerical uncertainty in tweets than were weather government and non-weather government sources in their Twitter forecasts. As weather government sources translate numerical information into forecasts, numerical uncertainty expressions are logical from this source. For example, a government source would have to interpret mathematical values and probabilities in order to convey the estimate of what size hail may fall from a cell of the storm into their messages.

Overall, the desire to communicate uncertainty effectively to a general audience, verbally or numerically, is an agreed-upon goal of science communication (National Academy of Sciences, 2006). The consequences of uncertain language can affect public action, despite the magnitude of the threat. Sources often downplay situational uncertainty during hazards, opting to mitigate panic at the cost of explicitly reporting scientific uncertainty (Benessia & De Marchi, 2017). Future analysis of verbal and numerical uncertainty expressions will provide a deeper understanding into how sources craft their messages to the public and could provide insight into public responses to uncertainty. Additionally, as public understanding of risk could be shown through the replies and discourses between the public and authoritative sources in social media messages (Bica et al., 2019), uncertainty expression should be studied across the entire message threads.

5.2 Interplay of Spatial and Temporal Proximity with Uncertainty Expression

Rhetorical studies, as a field, acknowledges that the "when" and "where" of a population at a specific moment influences the community's response to an event (Walsh & Walker, 2016). Time becomes an important dimension of uncertainty and a necessary factor to look at in risk messaging. Time can be viewed as a measure of distance from a threat. As a timely and understandable message bolsters credibility, information sources work to provide the best messages they can for their constituents (Fitzpatrick-Lewis et al., 2010). Time is a major aspect of uncertainty in meteorology, and the reception of scientific uncertainty depends on the field (Broomell & Kane, 2017). In weather prediction, uncertainty decreases as models become more accurate the closer they are to an event (Micovic et al., 2015). As shown in the results of H4, uncertainty expressions decreased over time. Across the five days in the data set, uncertainty expressions were less likely on the last days. This result also makes sense in the context of watches and warnings. As watches are disseminated before warnings, there is usually more uncertainty surrounding a hazard at that point in time, which is reflected in the results for RQ3.

Time is also an important aspect of human behavior. Shorter term threats have a strong influence on peoples' risk aversions, compared to long term threats (Hirshleifer, 1989), and people tend to make fast decisions when they feel uncertain (Brashers, 2001; Lachlan et al., 2014). Tornadoes are fast and can catch a group off guard. As the time leading to a severe weather threat does have a significant relationship with uncertainty expression, and studies have shown that behavior under uncertainty becomes critical in short time frames, a future study that looks into a connection between public behavior and uncertainty expression in severe risk scenarios could provide an interesting study of messaging.

Individuals' perceptions of hazard and risk have been shown to vary based on geographical situation, and affect forecast interpretations (Morss et al., 2008). The way an audience interprets risk is different in different areas due their experience and community history with different threats. States with more tornadoes, for example, should have a different response to this hazard than states with fewer tornadoes because these two areas have two different lived experiences. Information sources will try to adapt to this idea in their messaging in order to get their desired responses. For example, communities from the super outbreak of 2011 may respond more to the forecasters in 2018 that have been around since that time. Public figures, especially from the media, tend to cultivate relationships with their specific audience (Bloodhart et al., 2015). These relationships are localized, as communities tend to trust their local sources, like TV weathercasters, as elite sources of severe weather information since they themselves are members of the community (Doherty & Barnhurst, 2009). Not only do the communities have different frequencies of weather hazards, but they also have different information sources that commonly talk to them about meteorological threats. A meteorologist from the Northwest, for example, may not garner the same respect from a community in the Southeast, even if they are equally as capable of producing accurate tornado forecasts. It is logical that the way risk is conveyed would differ geographically in order to cater to the audience.

H5 was revised in the results to analyze this idea, and it found that the probability of a source using uncertainty expressions in tweets was 82% more likely for Mississippi, Tennessee, and Georgia than for Alabama. As Georgia, Mississippi, and Tennessee had the fewest number of tornadoes, more instances of uncertainty expressions make sense when compared to a state with a large number of confirmed tornadoes. Accuracy and relevancy become important dimensions of uncertainty expression in forecasts, as sources want to make sure that people respond appropriately to a threat, even over a large warning area. Tweets may become a way to essentially hyper-localize warnings, as there is an opportunity for location specifics in this medium.

5.3 Difficulty in Coding Confidence Expressions

Part of the goal of this study was to capture confidence expressions in Twitter forecasts. Confidence, from a broad view, is often misconstrued as the direct opposite of uncertainty—if one is unsure about an idea, then the opposite feeling would be surety. However, confidence expressions are operationally more difficult to capture than this simple view. Confidence expressions are defined conceptually as a qualification or quantification of an assessment of knowable uncertainty that is highly precise and based on evidence (Ülkümen, Fox, & Malle, 2016; Juanchich & Sirota, 2014; Arvai & Rivers III, 2013). For example, a confidence expression would be "I do not know the threat, but I will know tomorrow." Confidence expressions are nuanced, especially in the context of forecasting. For example, from a linguistic standpoint, the statement "it is obvious that there will be severe weather in the next 48 hours," is an expression of confidence (i.e., "obvious"), even though it has a dimension of uncertainty (the time span). Linguistically, confidence expressions use adjectives, pronouns, and adverbs, so they are perceived to have more assurance (Arvai & Rivers III, 2013). However, it is important to note that this linguistic way of defining confidence (e.g., use of "will") may not translate to a forecasting context directly. Operationalizing confidence this was does not work across disciplines, as the future tense of verbs could get misinterpreted for confidence unintentionally.

Future work with forecasting linguistics needs to have different markers of confidence in order to more accurately catch these expressions.

The coding scheme was designed so that coders would capture uncertainty expressions first as a necessary condition, and then confidence expressions, which may be the major reason why it was difficult to capture confidence expressions reliably. Also, the difficulty with capturing confidence expressions could be also because tweets are short and may not give enough context for the coders to identify confidence; in a longer text artifact, it could be easier to identify confidence expressions. As confidence did not achieve intercoder reliability, H2 could not be tested. Placing a more defined code for confidence expressions higher in the coding hierarchy could have helped us reliably find this construct. Additionally, tweets may be too short of an artifact to capture confidence expressions linguistically.

In a differently defined codebook with more nuanced markers for confidence expression, insight into where scientists and public officials are the most sure for severe weather hazards could unearth an interesting pattern for risk messaging. If we knew where different groups were less uncertain, hazard messages could be tailored to address this for the public audience. It is worthwhile to figure out how to capture confidence expressions in a linguistic study, as these expressions increase source credibility by building trust with an audience (Fitzpatrick-Lewis et al., 2010; Retzbach & Maier, 2015). If audience members trust a source, they are more likely to heed the advice of the source, like evacuating during a hazardous event (Burnside et al., 2007).

5.4 Difficulty in Coding Conflict Expressions

Another aspect of linguistic uncertainty that this study tried to capture was conflict expression. In written messages that express uncertainty, an audience will read the information provided more critically (Flemming, Feinkohl, Cress, & Kimmerle, 2015). This critical lens can be detrimental in hazardous situations when decisions need to be made quickly and accurately. Skepticism, as a result of critically analyzing the content of a message or information source, can result from people processing conflicting claims (Retzbach & Maier, 2015).

A conflicting claim, or conflict expression, can be conceptually defined as when two or more sources disagree on a message, or when one person disagrees with themselves in a message. Disagreeing information between sources or within a message can confuse an audience and dissuade them from taking action (Broomell & Kane, 2017; Retzbach & Maier, 2015). This disagreeing information can be content-based, meaning that different sources are providing two different answers about one question, or expression-based, meaning that uncertainty and confidence expressions are being used about the same subject. An example of a content-based disagreement would be if one scientist stated that it was going to rain today and a different scientist stated that it was not going to rain today. A conflicting claim that centers around expression would be, “I am not sure when the storm will start, but it will be in the afternoon.” This statement is both unsure and sure of the start time for the storm, contradicting themselves and providing a potential audience with conflicting information. Source credibility can come into question when there is conflict (Retzbach & Maier, 2015), and confusing an audience and keeping them from acting during a severe weather hazard is dangerous. As a result, conflict is important to study in hazard messages.

As with confidence expressions, the coding scheme was designed so that coders would capture uncertainty expressions first as a necessary condition, and then conflict expressions, which may be the major reason why it was difficult for coders to identify conflict expressions reliably. With the realization afterwards that conflict could exist with or without uncertainty expressions, it was thought that additional study in the future would help showcase this concept.

By moving the codes for conflict expressions to not depend on the presence of uncertainty expressions, or by centering the study more around capturing conflict and confidence expressions, this idea has the potential to be studied in the future. However, as conflict did not achieve intercoder reliability, H3 was not tested.

Conflicting claims have been operationalized in other contexts, like news, for general reporting (Bednarek & Caple, 2012). An opportunity arises for future research to refine this operationalization of conflict for weather reporting. A study looking into broadcasted forecasts could see if the value of conflict is apparent between topics and build a tie between conflict, reporting, and weather. Conflict is an important concept that should be studied in a severe weather messaging context; with the changing climate, severe weather is only increasing in frequency and magnitude, putting more people at risk.

5.5 Limitations and Future Research

Limitations to this study include focusing on the nominal presence of uncertainty in the tweets, rather than classifying the text more deeply. More variable levels, i.e. ordinal, interval, or ratio, would aid in the complexity of analysis. For example, an ordinal scale measure of uncertainty expression, such as the IPCC's probability index (Weiss, 2003), would add a deeper level of understanding to the linguistic characteristics of uncertainty. Additionally, ordinal levels to the uncertainty variable on degrees of uncertainty not based on Bayesian probabilities (i.e., mostly uncertain, slightly uncertain, not uncertain at all) could provide rich insight to the analysis. Also, the coders were incapable of reliably identifying these conflict and confidence expressions using the current codebook in this study. In the future, either a more specific codebook with the more accurate conceptualizations of the variables or more coder training would be recommended, in addition to the recommendations in the previous section.

As this study was looking at a one-way flow of information from the original tweet to the public, the cascading activation model fit this particular study. However, Twitter is not a one-way flow media channel. Some of the richest information from Twitter comes from the dialogues and conversations between original posters and their audience. Other models, like a model from a more constructionist viewpoint for message creation, would be useful a future study was looking at replies and the retweets. Conversations on Twitter might influence both the forecaster and the audience, so keeping this in mind would be important in future work.

Additionally, focusing on the original messages may not convey all instances of uncertainty, as uncertainty has been shown to be expressed in Twitter dialogues and replies. If included, replies could have shown how people discuss threats, as well as made a digital sphere of argumentation that could have added a dimension to the rhetorical lens of this study. Social media, as a channel for forecasts and a product of prediction rhetoric (Compton, 2018), is complex, and could arguably be studied as its own sphere of argumentation.

While most degreed and certified broadcast meteorologists prepare their own forecast products, not everyone does. This study did not check whether each media figure was certified to create forecast values and graphics. Future research could look into the difference between uncertainty expression use among degreed broadcast meteorologists and non-degreed weathercasters.

An individual's expression of qualities like humor or anxiety has been shown to be present when discussing uncertainty (Lachlan et al., 2014). Emotional responses, like humor, have been shown to act as a coping behavior in a risk scenario (Demuth et al., 2018). While social media can help us understand the role of emotional response from an audience during hazardous weather (Demuth et al., 2018), in-depth interviews of the sources would have provided this context for how they wanted their messages to be read, including tone and inflection, which are often misinterpreted online.

This study was also limited from exploring the relationship of uncertainty expression with theories like diffusion, as retweets were excluded. While diffusion is important for delving into the effect of a risk message, this study was more focused on the content of the message. Future work could analyze whether, in a severe weather forecasting scenario, highly uncertain messages are more often spread (i.e., obtaining virality), or if more confident messages are diffused over a large scale. The combination of diffusion and message content could provide a unique niche for studying risk messaging linguistics.

Additionally, this study focuses on verbal and numerical uncertainty, classifying the words within visuals as verbal uncertainty. The study did not look at the more visual elements of uncertainty, such as intrinsic or extrinsic manipulation of colors, integrable or separable graphical elements, or the static or dynamic nature of the images in the tweets (Gershon, 1998; Kinkeldey et al., 2014; Maceachren, Brewer, & Pickle, 1998). Future work could study the visual and graphic elements of tweets, as there are many dimensions of uncertainty present within those. Forecast graphics typically rely on color gradation and lines to demonstrate uncertainty, and coding for dynamic imagery could reveal a lot about uncertainty expression, especially with the rise in the popularity of sharing weather radar GIFs.

Most notably, this study focuses on one cluster of tornadoes, which are only one type of severe weather, in one location, at one point in time. The study did not capture that states have different experiences and histories with events, which affects how residents respond. While the historic 2011 tornadoes were acknowledged as a possible influence on hazard response for this study, this idea was not specifically searched for. Checking if the Twitter sources were in these job positions in 2011 could show a possible connection. Another way could be to see if the Twitter sources mentioned 2011 for context in their 2018 forecasts.

Different severe weather events have their own heuristics and behaviors, which may have different uncertainties associated with them. For example, a tornado warning may warrant more action in a community than a severe thunderstorm warning because the population could perceive thunderstorms as less damaging than tornadoes. Studies in one area about how different sources use uncertainty by storm type could show a relationship in future research.

5.6 Conclusion

Results indicate there were significant relationships between the source of a forecast (i.e., weather media, weather government, and non-weather government) and uncertainty expression. Weather media sources were significantly less likely than government sources (weather and non-weather) to use uncertainty expressions within their tweets forecasting a severe weather event. The location of the source and the uncertainty expressed within a forecast also had a significant relationship, showing that areas with a greater number of threats will typically express less uncertainty than areas with fewer threats. Also, time was shown to have a significant relationship with uncertainty expression, as the amount of uncertainty expressed decreased the closer in time the messages were to the tornadic event.

While conflicting claims and linguistic confidence could not be reliably analyzed, the literature shows a promising avenue for future research on these topics, as outlined in the previous section. Additionally, future research could look more into the interplay of uncertainty expression and NWS issued watches and warnings for different threats, by including threats other than tornadoes and severe thunderstorms.

Expanding studies on uncertainty beyond Twitter to include other forecast products would shape a broader understanding of linguistics as they relate to meteorological uncertainty. While Twitter is a unique medium to study such messages, it should be studied in a way that highlights the discourse opportunities the forum provides. Moving forward, research should be undertaken for different severe weather events and clusters, and it should include deeper analysis of information sources and their personal intentions behind the textual products they disseminate. As Niehls Bohr once said, prediction is difficult, especially about the future. Due to the large amount of uncertainty in weather prediction, meteorological forecasts during severe events provide a unique, fascinating area to study risk communication and public safety messaging.

REFERENCES

20180319's Storm Reports (20180319 1200 UTC - 20180320 1159 UTC). (2018). Retrieved from https://www.spc.noaa.gov/exper/archive/event.php?date=20180319

AMS. (2018). Certified Broadcast Meteorologist Program (CBM). Retrieved from https://www.ametsoc.org/index.cfm/ams/education-careers/ams-professional-certification-programs/certified-broadcast-meteorologist-program-cbm/

Arvai, J., & Rivers III, L. (Eds.). (2013). *Effective Risk Communication* (1st ed.). London: Routledge.

Bednarek, M., & Caple, H. (2012). "Value added": Language, image and news values. *Discourse, Context and Media*, *1*(2–3), 103–113. https://doi.org/10.1016/j.dcm.2012.05.006

Benessia, A., & De Marchi, B. (2017). When the earth shakes … and science with it. The management and communication of uncertainty in the L'Aquila earthquake. *Futures*, *91*, 35–45. https://doi.org/10.1016/j.futures.2016.11.011

Bica, M., Demuth, J. L., Dykes, J. E., & Palen, L. (2019). Communicating Hurricane Risks: Multi-Method Examination of Risk Imagery Diffusion. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. https://doi.org/https://doi.org/10.1145/3290605.3300545

Bloodhart, B., Maibach, E., Myers, T., & Zhao, X. (2015). Local climate experts: The influence of local TV weather information on climate change perceptions. *PLoS ONE*, *10*(11), 1–14. https://doi.org/10.1371/journal.pone.0141526

Brashers, D. E. (2001). Communication and uncertainty management. *Journal of Communication*, *51*(3), 477–497. https://doi.org/10.1093/joc/51.3.477

Broomell, S. B., & Kane, P. B. (2017). Public perception and communication of scientific uncertainty. *Journal of Experimental Psychology: General*, *146*(2), 286–304. https://doi.org/10.1037/xge0000260

Burnside, R., Miller, D. M. S., & Rivera, J. D. (2007). The impact of information and risk perception on the Hurricane evacuation decision-making of greater New Orleans residents. *Sociological Spectrum*, *27*, 727–740. https://doi.org/10.1080/02732170701534226

Childs, S. J., & Schumacher, R. S. (2018). Cold-season Tornado Risk Communication: Case Studies from November 2016 to February 2017. *Weather, Climate, and Society*. https://doi.org/10.1175/wcas-d-17-0073.1

Compton, J. (2018). When Weather Forecasters Are Wrong: Image Repair and Public Rhetoric After Severe Weather. *Science Communication*, 1–11. https://doi.org/10.1177/1075547018799101

Demuth, J. L., Morss, R. E., Morrow, B. H., & Lazo, J. K. (2012). Creation and communication of hurricane risk information. *Bulletin of the American Meteorological Society*. https://doi.org/10.1175/BAMS-D-11-00150.1

Demuth, J. L., Morss, R. E., Palen, L., Anderson, K. M., Anderson, J., Kogan, M., … Henderson, J. (2018). "Sometimes da #beachlife ain't always da wave": Understanding People's Evolving Hurricane Risk Communication, Risk Assessments, and Responses Using Twitter Narratives. *Weather, Climate, and Society*. https://doi.org/10.1175/WCAS-D-17-0126.1

Doherty, R., & Barnhurst, K. G. (2009). Controlling nature: Weathercasts on local television news. *Journal of Broadcasting and Electronic Media*, *53*(2), 211–226. https://doi.org/10.1080/08838150902907710

Drost, R., Casteel, M., Libarkin, J., Thomas, S., & Meister, M. (2016). Severe Weather Warning

Communication: Factors Impacting Audience Attention and Retention of Information during Tornado Warnings. *Weather, Climate, and Society*, *8*, 361–372. https://doi.org/10.1175/WCAS-D-15-0035.1

Eisenman, D. P., Cordasco, K. M., Asch, S., Golden, J. F., & Glik, D. (2007). Disaster planning and risk communication with vulnerable communities: lessons from Hurricane Katrina. *American Journal of Public Health*, *97*, S109–S115. https://doi.org/10.2105/AJPH.2005.084335

Entman, R. M. (2003). Cascading Activation: Contesting the White House's Frame after 9/11. *Political Communication*. https://doi.org/10.1080/10584600390244176

Fischhoff, B. (2013). The sciences of science communication. *Proceedings of the National Academy of Sciences*, *110*(Supplement_3), 14033–14039. https://doi.org/10.1073/pnas.1213273110

Fitzpatrick-Lewis, D., Yost, J., Ciliska, D., & Krishnaratne, S. (2010). Communication about environmental health risks : A systematic review. *Environmental Health*, *9*(67), 1–15.

Flemming, D., Feinkohl, I., Cress, U., & Kimmerle, J. (2015). Individual Uncertainty and the Uncertainty of Science : The Impact of Perceived Conflict and General Self-Efficacy on the Perception of Tentativeness and Credibility of Scientific Information. *Frontiers in Psychology*, *6*(1859), 1–8. https://doi.org/10.3389/fpsyg.2015.01859

Gershon, N. (1998). Visualization of an Imperfect World. *IEEE Computer Graphics and Applications*, (July/August), 43–45. https://doi.org/0272-1716/98/

Goldsmith, D. J. (2001). A normative approach to the study of uncertainty and communication. *Journal of Communication*, *51*(3), 514–533. https://doi.org/10.1093/joc/51.3.514

Goodnight, G. T. (1982). The Personal, Technical, and Public Spheres of Argument: A

Speculative Inquiry Into the Art of Public Deliberation. *Journal of the American Forensic Association*, *18*(Spring), 214–227. https://doi.org/10.1017/CBO9781107415324.004

Guba, E. G. E., & Lincoln, Y. S. Y. (1994). Competing Paradigms in Qualitative Research. *Handbook of Qualitative Research*, pp. 105–117. https://doi.org/http://www.uncg.edu/hdf/facultystaff/Tudge/Guba%20&%20Lincoln%201994.pdf

Hayes, A. F. (2005). Statistical methods for communication science. In *Statistical Methods for Communication Science*. https://doi.org/10.4324/9781410613707

Heidmann, I., & Milde, J. (2013). Communication about scientific uncertainty: How scientists and science journalists deal with uncertainties in nanoparticle research. *Environmental Sciences Europe*, *25*(1). https://doi.org/10.1186/2190-4715-25-25

Hirshleifer, J. (1989). *Time, Uncertainty, and Information*. Oxford: Basil Blackwell Ltd.

Hyland, K. (1996). Writing without conviction? Hedging in science research articles. *Applied Linguistics*, *17*(4), 433–454. https://doi.org/10.1093/applin/17.4.433

Jensen, J. D. (2008). Scientific Uncertainty in News Coverage of Cancer Research: Effects of Hedging on Scientists' and Journalists ' Credibility. *Human Communication Research*, *34*, 347–369. https://doi.org/10.1111/j.1468-2958.2008.00324.x

Joslyn, S., & Savelli, S. (2010). Communicating forecast uncertainty: Public perception of weather forecast uncertainty. *Meteorological Applications*. https://doi.org/10.1002/met.190

Juanchich, M., & Sirota, M. (2014). How to improve people ' s interpretation of probabilities of precipitation. *Journal of Risk Research*, *19*(3), 388–404. https://doi.org/10.1080/13669877.2014.983945

Kinkeldey, C., Maceachren, A. M., & Schiewe, J. (2014). How to Assess Visual Communication of Uncertainty? A Systematic Review of Geospatial Uncertainty Visualisation User Studies. *The Cartographic Journal*, *51*(4), 372–386. https://doi.org/10.1179/1743277414Y.0000000099

Lachlan, K. A., Spence, P. R., Lin, X., Najarian, K. M., & Greco, M. Del. (2014). Twitter Use During a Weather Event: Comparing Content Associated with Localized and Nonlocalized Hashtags. *Communication Studies*, *65*(5), 519–534. https://doi.org/10.1080/10510974.2014.956940

Løhre, E., & Teigen, K. H. (2017). Probabilities Associated with Precise and Vague Forecasts. *Journal of Behavioral Decision Making*, *30*(May), 1014–1026. https://doi.org/10.1002/bdm.2021

Maceachren, A. M., Brewer, C. A., & Pickle, L. W. (1998). Visualizing georeferenced data: representing reliability of health statistics. *Environmnet and Planning*, *30*, 1547–1561.

Maier, M., Milde, J., Post, S., Gï¿½nther, L., Ruhrmann, G., & Barkela, B. (2016). Communicating scientific evidence: Scientists', journalists' and audiences' expectations and evaluations regarding the representation of scientific uncertainty. *Communications*, *41*(3), 239–264. https://doi.org/10.1515/commun-2016-0010

Marimo, P., Kaplan, T. R., Mylne, K., & Sharpe, M. (2015). Communication of Uncertainty in Temperature Forecasts. *Weather and Forecasting*, *30*. https://doi.org/10.1175/WAF-D-14-00016.1

Micovic, Z., Schaefer, M. G., & Taylor, G. H. (2015). Uncertainty analysis for Probable Maximum Precipitation estimates. *Journal of Hydrology*, *521*, 360–373. https://doi.org/10.1016/j.jhydrol.2014.12.033

Mileti, D. S., & Sorensen, J. H. (1990). *Communication of emergency public warnings: A social* *science perspective and state-of-the-art assessment*. https://doi.org/10.2172/6137387

Morss, R. E., Cuite, C. L., Demuth, J. L., Hallman, W. K., & Shwom, R. L. (2018). Is storm surge scary? The influence of hazard, impact, and fear-based messages and individual differences on responses to hurricane risks in the USA. *International Journal of Disaster Risk Reduction*, *30*(January), 44–58. https://doi.org/10.1016/j.ijdrr.2018.01.023

Morss, R. E., Demuth, J. L., & Lazo, J. K. (2008). Communicating Uncertainty in Weather Forecasts : A Survey of the U . S . Public. *Weather and Forecasting*, *23*, 974–991. https://doi.org/10.1175/2008WAF2007088.1

Nadav-greenberg, L., & Joslyn, S. L. (2008). The Effect of Uncertainty Visualizations on Decision Making in Weather Forecasting. *Journal of Cognitive Engineering and Decision Making*, *2*(1), 24–47. https://doi.org/10.1518/155534308X284354.

National Academies of Science. (2016). Communicating Science Effectively: A Research Agenda. In *The National Academies Press*. https://doi.org/10.17226/23674

National Academy of Sciences. (2006). Completing the Forecast: Characterizing and Communicating Uncertainty for Better Decisions Using Weather and Climate Forecasts. In *National Research Council Committee on Estimating and Communicating Uncertainty in Weather and Climate Forecasts* (Vol. 129). https://doi.org/10.1017/CBO9781107415324.004

National Centers for Environmental Information, N. (2011). *State of the Climate: Tornadoes for April 2011*. Retrieved from https://www.ncdc.noaa.gov/sotc/tornadoes/201104

National Centers for Environmental Information, N. (2017). On This Day: 2011 Tornado Super Outbreak. Retrieved from https://www.ncei.noaa.gov/news/2011-tornado-super-outbreak

Neuendorf, K. A. (2002). *The Content Analysis Guidebook*. Thousand Oaks: Sage Publications.

NWS. (2018). National Weather Service Organization. Retrieved from https://www.weather.gov/organization/

Pennesi, K. (2007). IMPROVING FORECAST COMMUNICATION: Linguistic and Cultural Considerations. *Bulletin of the American Meteorological Society*, *88*(7), 1033–1044. https://doi.org/10.1175/BAMS-88-7-I033

Perez-Lugo, M. (2004). Media uses in disaster situations: A new focus on the impact phase. *Sociological Inquiry*, *74*, 210–225. https://doi.org/10.1111/j.1475-682X.2004.00087.x

Rabinovich, A., & Morton, T. A. (2012). Unquestioned Answers or Unanswered Questions: Beliefs About Science Guide Responses to Uncertainty in Climate Change Risk Communication. *Risk Analysis*, *32*(6), 992–1002. https://doi.org/10.1111/j.1539-6924.2012.01771.x

Retzbach, A., & Maier, M. (2015). Communicating Scientific Uncertainty: Media Effects on Public Engagement With Science. *Communication Research*, *42*(3), 429–456. https://doi.org/10.1177/0093650214534967

Ripberger, J. T., Jenkins-Smith, H. C., Silva, C. L., Carlson, D. E., & Henderson, M. (2014). Social Media and Severe Weather : Do Tweets Provide a Valid Indicator of Public Attention to Severe Weather Risk Communication ? *Weather, Climate, and Society*, *6*(4), 520–530. https://doi.org/10.1175/WCAS-D-13-00028.1

Savelli, S., & Joslyn, S. (2012). Boater Safety: Communicating Weather Forecast Information to High-Stakes End Users. *Weather, Climate, and Society*. https://doi.org/10.1175/wcas-d-11-00025.1

Spiegelhalter, D. (2017). Risk and Uncertainty Communication. *Annual Review of Statistics and Its Application*, *4*, 61–30. https://doi.org/10.1146/annurev-statistics-010814-020148

SPJ. (2014). *Code of Ethics*. Retrieved from https://www.spj.org/ethicscode.asp

Ülkümen, G., Fox, C. R., & Malle, B. F. (2016). Two Dimensions of Subjective Uncertainty : Clues From Natural Language. *Journal of Experimental Psychology: General*, *145*(7). https://doi.org/http://dx.doi.org/10.1037/xge0000202

USA.gov. (n.d.). Branches of the U.S. Government. Retrieved from 2018 website: https://www.usa.gov/branches-of-government

Walsh, L. (2015). The visual rhetoric of climate change. *Wiley Interdisciplinary Reviews: Climate Change*, Vol. 6, pp. 361–368. https://doi.org/10.1002/wcc.342

Walsh, L., & Walker, K. C. (2016). Perspectives on uncertainty for technical communication scholars. *Technical Communication Quarterly*, Vol. 25, pp. 71–86. https://doi.org/10.1080/10572252.2016.1150517

Weiss, C. (2003). Expressing scientific uncertainty. *Law, Probability, and Risk*, *2*, 25–46. https://doi.org/10.1093/lpr/2.1.25

Zeng, X., Pielke, R. A., & Eykholt, R. (1993). Chaos Theory and Its Applications to the Atmosphere. *Bulletin of the American Meteorological Society*, *74*(4), 631–644.

APPENDIX A: CODE BOOK

Tornadic ContextualPlus Tweet Uncertainty Coding Scheme

The data to be coded with this codebook include tweets sources from 384 local and non-local weather personnel surrounding the March 19, 2018 tornadoes that touched down in the southern United States. Below are instructions for coding, following a script format, where you will be tracking the occurrences of each variable. Variables are defined below, with examples, so as to aid in the identification process.

Coding Instructions:

Follow the path of the questions below. If you come up with a "no" response, stop coding for that thread of questions. Only code for the variables outlined below.

Coding Unit: Tweet

Coding Strategy: For each target of uncertainty, code presence of a variable in each tweet.

Codes and Definitions As Scripted:

1. severe_tor_info

- Is the tweet relevant? I.e. Is the tweet regarding severe weather or tornadoes?
  - NOTE: The relevant severe weather for this study DOES include severe storms, storms in any capacity (i.e. spotter classes, services, donations), thunder, funnel clouds, tornadoes, flooding, hail, and rain. It DOES NOT include winter weather (i.e. snow, freezing temperatures, etc.).
  - **[Code 0 for no, 1 for yes]**

[if severe_tor_info = 1 = yes, then Continue coding, else go to next tweet]

2. forecast_info

- Does the tweet convey forecast/threat information?
    - Examples of forecast/threat information include remarks on impending storm system and prediction of the physical hazards.
  - If ONLY information about post event/impacts, do NOT code
    - Examples include information regarding clean up of the community after the storm has passed through, monetary losses due to storm damage, etc.
  - If ONLY info about personalization of the threat/event, do NOT code
    - Examples include personal experiences within the event, like expressions of fear in current weather, pictures of children in a tornado shelter, etc.
  - If ONLY observational data (e.g., radar, satellite) [without forecasting], do NOT code

        - Examples include radar images of current conditions, pictures of clouds, or text describing satellite images that do not have a futuristic forecasting element.
    - **[Code 0 for no, 1 for yes]**

[if forecast_info = 1 = yes, then Continue coding, else go to next tweet]

3. Tweet characterization

- What type of tweet are you looking at?
    - Tweet with text only **[Code 0]**
        - NOTE that a tweet with an embedded thumbnail image, like <u>this</u>, should be coded as text only (specifically, the text that can be seen without traversing the link) because we <u>will</u> code the text in the thumbnail but NOT the image
    - Tweet with Visual only **[Code 1]**
        - A visual is an attached photograph, GIF, or video.
        - Text within the visual is still classified as a visual.
    - Tweet with text and visual **[Code 2]**
        - NOTE that a tweet with <u>this</u> kind of embedded image should be coded as text + visual
            - Multiple embedded images that are attached to the image are considered visuals to be coded. If the image is a thumbnail that links to an outside source, it is *not* a visual, and should <u>not</u> be traversed or coded.

4. Sources location/geography

- Where is the originator/source of the tweet from? I.e. Where is their residence?
- To find this information in the tweets, look at the the cell "user_location" in the CSV file of the ContextualPlus data. IF "user_screen_name" is the same as "contextualPlus" in the file, then the location is that of the original poster.
    - NOTE: IF "user_screen_name" = "contextualPlus", but text starts with "@username", DO NOT CODE. This is a reply and not an original post.
        - **Mark coding flag in code sheet [Original_Flag] as YES (1) or NO (0) for original post. If YES, continue coding. Else, stop and go to next tweet in set.**
- The first location will be used as the primary location of the sources. If missing in first tweet, gather this information from the profile bio on the person's twitter account.
    - Local **[Code 0]**
        - Within state boundaries of the touchdown of the tornado (Alabama, Mississippi, Tennessee, Georgia).
    - Non-local **[Code 1]**
        - Every other state or region not included within the boundaries of the tornado within the continental United States.
    - Unclear **[Code 2]**
        - Example: "Up to mother nature", "in the world", vague statements that do not actually convey a physical location, etc.

5. Source type

- What sector can we classify the originator/source of the tweet?
  - Wx-govt **[Code 0]**
    - Weather government is considered to be agencies and groups that work as a federal agency to produce, research, and disseminate information about meteorological and atmospheric sciences.
      - Examples include: NWS, NOAA, NASA, SPC, CPC, SSL
  - Wx-media/news **[Code 1]**
    - Broadcast meteorologist or media conglomerate that gives weather forecasts and is the primary representative of the meteorological profession to the public in an official/professional capacity. Can be associated with a news station, they are the designated weather contact or are an entirely dedicated weather station.
      - Examples include, Accuweather, Capital Weather Gang, Wunderground, TWC, or a highlighted broadcast meteorologist.
  - Wx-other **[Code 2]**
    - Examples include: Independent weather experts, researchers, storm chasers, personal weather bloggers, students of meteorology or a related field that are not yet professionally associated with weather as a career.
  - Non-wx media/news **[Code 3]**
    - News and media agencies, television or website, not specifically related to weather. These are typically found on Twitter with usernames that appear as acronyms with 'K' in the beginning and a channel number at the end, i.e. KABC7.
      - Examples include photographers, bloggers, or general broadcasters
  - Non-wx govt **[Code 4]**
    - Agencies, bureaus, Boards, Commissions, and Committees that fall under the executive, legislative, or judicial branches of the federal structure.
      - Examples include: FEMA, Emergency Managers, Military, etc.
  - Other **[Code 5]**
    - Examples include: Utilities companies, nonprofits, tourism-related, hospitals, etc.

6. Mark down manifest mention of hazard (Haz_Man)

- Does the tweet explicitly mention an issued watch or warning for a weather hazard?
  - **Code 0** tornado watch
  - **Code 1** tornado warning
  - **Code 2** severe thunderstorm watch
  - **Code 3** severe thunderstorm warning
  - **Code 4** other severe threat generally, including outlooks, straight line winds etc.
  - **Code 5** flooding
  - **Code 6** for multiple hazards, that is, > 1 of the other categories
    - NOTE that if there are multiple general severe threats, which would be coded as #4, then do NOT code this

6. Forecast Uncertainty present at all vs. not (all determinism)

- Is uncertainty present within the tweet (regarding the forecast)?
    - Uncertainty can be defined as an expression of a lack of sureness surrounding a message due to a possible knowledge gap on the issue, or randomness.
        - "Uncertainty is an overarching term that refers to the condition whereby the state of a system cannot be known unambiguously. Probability is one way of expressing uncertainty" (NRC, 2006).
        - Characterized with vagueness, qualifiers, impersonal pronouns, etc.
    - Determinism provides only *one* prediction of the future state of a system within a forecast, with no information regarding forecast uncertainty (NRC, 2006).
        - Has more defined and assured verbiage; i.e. "will", "does", etc., simplified or smoothed curves or boundaries in a visual, and highly precise or specific claims.
  - Uncertainty shown at all **[Code 0]**
  - Determinism shown only **[Code 1]**

[if uncertainty [0] = yes, then Continue coding, else go to next tweet]

Targets of uncertainty/determinism

- Timing
  - Uncertainty regarding the 'when' of the forecast severe weather.
    - This can include timing of when storms will reach a certain area, how long the storm will last (duration), when it will end, etc.
    - A range of timing information IS considered uncertainty, regardless of whether it's conveyed verbally (e.g., morning to afternoon) or numerical (e.g., 10 am - 2 pm)
    - Imprecision/ambiguity in timing does not necessarily equal uncertainty; for example, a threat that simply says "this afternoon" -- i.e., without any range in timing -- is not uncertainty
    - *NOTE:* 'brief' in regards to a tornado or other system is NOT a marker of timing, nor any other target. However, 'rapidly' IS a marker, as it constitutes uncertain movement.
  - **[Code 0 for no uncertainty, 1 for yes uncertainty]**
    - **IF timing = 1 = yes, continue coding. ELSE move to next target.**
  - unc_verb -- Is there Verbal uncertainty expression?
        - Phrases like 'uncertain' or 'unlikely', also known as qualifiers or hedges.
        - Present hedges in the linguistics of the text; i.e 'could,' 'may,' 'might,' etc.
        - Likelihood statements like 'chance,' 'likelihood,' 'possible,' etc.
        - Imprecise evaluative labels like 'high,' 'low,' 'strong,' 'weak,' in regards to an assessment of probability.
    - **[Code 0 for no, 1 for yes]**
  - unc_num -- Is there Numerical uncertainty expression?

            - Expression of a proposition of certainty using numerals, frequencies, odds, or ranges.
            - Can also be demonstrated in the use of statistical figures to express mathematical likelihood (e.g., box plots, cumulative distribution function).
        - **[Code 0 for no, 1 for yes]**

    - Confidence_1-- Confidence Markers
        - Is confidence detected in the tweet?
            - Confidence can be defined as expressions with more assurance due to the weight of the evidence.
                - Signs of confidence include the use of personal pronouns like "I', 'we', or 'our', linguistic markers such as 'sure', 'certain', 'certain', 'will', simplified or smoothed curves or boundaries in a visual, and highly precise or specific claims.
        - **[Code 0 for no, 1 for yes]**
    - unc_con -- consistent / conflicting uncertainty info
        - Are there conflicting elements within the tweet, i.e., within the tweet text, within the visual, or between the tweet text and visual?
            - Are there contradictory forecast uncertainty claims or phrases about the same "aspect"/target? I.e. Does the uncertainty claims in the tweet match amongst itself?
                    - Example: Does one tweet say "might" and "probable" in the same line of text?
            - Is there a deterministic marker and an uncertainty marker about the same "aspect"/target, and do they agree?
                    - Example: Does the text say "storms may develop" and the image says "storms will develop"?
                - If no, then there is an apparent conflict.
        - **[Code 0 for no, 1 for yes]**

- Location
    - Uncertainty regarding the "where" of the forecast severe weather.
        - This can include possible affected counties, forecasted/projected storm tracks, etc. NOTE: Just a mention of an area is not necessarily a discussion of location, it needs to be in a reference to a forecast (i.e. projected movements in areas, not observational mentions of counties).
        - The word 'along', for example, DOES constitute uncertainty as it has ambiguity regarding location.
            - **NOTE A CHANGE TO THIS:** in Dec 2018, we made a decision to change this so that the imprecision/ambiguity does not necessarily equal uncertainty -- this is to be consistent with our prior decision that imprecision .ne. uncertainty for other uncertainty targets, like time
    - **[Code 0 for no uncertainty, 1 for yes uncertainty]**
        - **IF location = 1 = yes, continue coding. ELSE move to next target.**
    - unc_verb -- Is there Verbal uncertainty expression?

            - Phrases like ‘uncertain’ or ‘unlikely’, also known as qualifiers or hedges.
            - Present hedges in the linguistics of the text; i.e ‘could,’ ‘may,’ ‘might,’ etc.
            - Likelihood statements like ‘chance,’ ‘likelihood,’ ‘possible,’ etc.
            - Imprecise evaluative labels like ‘high,’ ‘low,’ ‘strong,’ ‘weak,’ in regards to an assessment of probability.
        - **[Code 0 for no, 1 for yes]**
    - unc_num -- Is there Numerical uncertainty expression?
            - Expression of a proposition of certainty using numerals, frequencies, odds, or ranges.
            - Can also be demonstrated in the use of statistical figures to express mathematical likelihood (e.g., box plots, cumulative distribution function).
        - **[Code 0 for no, 1 for yes]**

    - Confidence_1-- Confidence Markers
        - Is confidence detected in the tweet?
            - Confidence can be defined as expressions with more assurance due to the weight of the evidence.
                - Signs of confidence include the use of personal pronouns like “I’, ‘we’, or ‘our’, linguistic markers such as ‘sure’, ‘certain’, ‘certain’, ‘will’, simplified or smoothed curves or boundaries in a visual, and highly precise or specific claims.
        - **[Code 0 for no, 1 for yes]**
    - unc_con -- consistent / conflicting uncertainty info
        - Are there conflicting elements within the tweet, i.e., within the tweet text, within the visual, or between the tweet text and visual?
            - Are there contradictory forecast uncertainty claims or phrases about the same “aspect”/target? I.e. Does the uncertainty claims in the tweet match amongst itself?
                    - Example: Does one tweet say “might” and “probable” in the same line of text?
            - Is there a deterministic marker and an uncertainty marker about the same “aspect”/target, and do they agree?
                    - Example: Does the text say “storms may develop” and the image says “storms will develop”?
                - If no, then there is an apparent conflict.
        - **[Code 0 for no, 1 for yes]**

- Intensity/Severity
    - Uncertainty regarding the strength and magnitude of the forecast severe weather.
        - This can include predicted strengths (i.e. EF3), forecasted wind speeds, predicted heaviness of precipitation, etc. NOTE: Forecasted hail size (i.e. “up to 1 inch”) is a marker of intensity, rather than of hazard.
    - **[Code 0 for no uncertainty, 1 for yes uncertainty]**

- **IF intensity = 1 = yes, continue coding. ELSE move to next target.**
- unc_verb -- Is there Verbal uncertainty expression?
  - Phrases like 'uncertain' or 'unlikely', also known as qualifiers or hedges.
  - Present hedges in the linguistics of the text; i.e 'could,' 'may,' 'might,' etc.
  - Likelihood statements like 'chance,' 'likelihood,' 'possible,' etc.
  - Imprecise evaluative labels like 'high,' 'low,' 'strong,' 'weak,' in regards to an assessment of probability.
  - **[Code 0 for no, 1 for yes]**
- unc_num -- Is there Numerical uncertainty expression?
  - Expression of a proposition of certainty using numerals, frequencies, odds, or ranges.
  - Can also be demonstrated in the use of statistical figures to express mathematical likelihood (e.g., box plots, cumulative distribution function).
  - **[Code 0 for no, 1 for yes]**

- Confidence_1-- Confidence Markers
  - Is confidence detected in the tweet?
    - Confidence can be defined as expressions with more assurance due to the weight of the evidence.
      - Signs of confidence include the use of personal pronouns like "I', 'we', or 'our', linguistic markers such as 'sure', 'certain', 'certain', 'will', simplified or smoothed curves or boundaries in a visual, and highly precise or specific claims.
  - **[Code 0 for no, 1 for yes]**
- unc_con -- consistent / conflicting uncertainty info
  - Are there conflicting elements within the tweet, i.e., within the tweet text, within the visual, or between the tweet text and visual?
    - Are there contradictory forecast uncertainty claims or phrases about the same "aspect"/target? I.e. Does the uncertainty claims in the tweet match amongst itself?
      - Example: Does one tweet say "might" and "probable" in the same line of text?
    - Is there a deterministic marker and an uncertainty marker about the same "aspect"/target, and do they agree?
      - Example: Does the text say "storms may develop" and the image says "storms will develop"?
      - If no, then there is an apparent conflict.
  - **[Code 0 for no, 1 for yes]**

- Human / social community and individual effects/impacts
  - Uncertainty regarding possible impacts resulting from the forecast severe weather that are *not* physical in nature.
    - I.e. the closing of schools and roads, destruction of personal property or infrastructure, the calling off of outdoors events due to the weather, etc.

- NOTE: The word ‘damaging’, like in regards to wind, is coded as Social Impact and NOT intensity, as damaging refers to infrastructure.
- **[Code 0 for no uncertainty, 1 for yes uncertainty]**
    - **IF social_imp = 1 = yes, continue coding. ELSE move to next target.**
- unc_verb -- Is there Verbal uncertainty expression?
    - Phrases like ‘uncertain’ or ‘unlikely’, also known as qualifiers or hedges.
    - Present hedges in the linguistics of the text; i.e ‘could,’ ‘may,’ ‘might,’ etc.
    - Likelihood statements like ‘chance,’ ‘likelihood,’ ‘possible,’ etc.
    - Imprecise evaluative labels like ‘high,’ ‘low,’ ‘strong,’ ‘weak,’ in regards to an assessment of probability.
    - **[Code 0 for no, 1 for yes]**
- unc_num -- Is there Numerical uncertainty expression?
    - Expression of a proposition of certainty using numerals, frequencies, odds, or ranges.
    - Can also be demonstrated in the use of statistical figures to express mathematical likelihood (e.g., box plots, cumulative distribution function).
    - **[Code 0 for no, 1 for yes]**

- Confidence_1-- Confidence Markers
    - Is confidence detected in the tweet?
        - Confidence can be defined as expressions with more assurance due to the weight of the evidence.
            - Signs of confidence include the use of personal pronouns like “I’, ‘we’, or ‘our’, linguistic markers such as ‘sure’, ‘certain’, ‘certain’, ‘will’, simplified or smoothed curves or boundaries in a visual, and highly precise or specific claims.
    - **[Code 0 for no, 1 for yes]**
- unc_con -- consistent / conflicting uncertainty info
    - Are there conflicting elements within the tweet, i.e., within the tweet text, within the visual, or between the tweet text and visual?
        - Are there contradictory forecast uncertainty claims or phrases about the same “aspect”/target? I.e. Does the uncertainty claims in the tweet match amongst itself?
            - Example: Does one tweet say “might” and “probable” in the same line of text?
        - Is there a deterministic marker and an uncertainty marker about the same “aspect”/target, and do they agree?
            - Example: Does the text say “storms may develop” and the image says “storms will develop”?
            - If no, then there is an apparent conflict.
    - **[Code 0 for no, 1 for yes]**

- Hazards

- Uncertainty regarding the physical weather phenomena as part of the forecast severe weather event.
    - e.g., tornado, hail, wind, lightning, flooding, storms
    - NOTE: If mention of one hazard with confidence and another with uncertainty, then apparent conflict.
- **[Code 0 for no uncertainty, 1 for yes uncertainty]**
    - **IF hazard = 1 = yes, continue coding. ELSE move to next target.**
- unc_verb -- Is there Verbal uncertainty expression?
        - Phrases like ‘uncertain’ or ‘unlikely’, also known as qualifiers or hedges.
        - Present hedges in the linguistics of the text; i.e ‘could,’ ‘may,’ ‘might,’ etc.
        - Likelihood statements like ‘chance,’ ‘likelihood,’ ‘possible,’ etc.
        - Imprecise evaluative labels like ‘high,’ ‘low,’ ‘strong,’ ‘weak,’ in regards to an assessment of probability.
    - **[Code 0 for no, 1 for yes]**
- unc_num -- Is there Numerical uncertainty expression?
        - Expression of a proposition of certainty using numerals, frequencies, odds, or ranges.
        - Can also be demonstrated in the use of statistical figures to express mathematical likelihood (e.g., box plots, cumulative distribution function).
    - **[Code 0 for no, 1 for yes]**

- Confidence_1-- Confidence Markers
    - Is confidence detected in the tweet?
        - Confidence can be defined as expressions with more assurance due to the weight of the evidence.
            - Signs of confidence include the use of personal pronouns like “I’, ‘we’, or ‘our’, linguistic markers such as ‘sure’, ‘certain’, ‘certain’, ‘will’, simplified or smoothed curves or boundaries in a visual, and highly precise or specific claims.
    - **[Code 0 for no, 1 for yes]**
- unc_con -- consistent / conflicting uncertainty info
    - Are there conflicting elements within the tweet, i.e., within the tweet text, within the visual, or between the tweet text and visual?
        - Are there contradictory forecast uncertainty claims or phrases about the same “aspect”/target? I.e. Does the uncertainty claims in the tweet match amongst itself?
                - Example: Does one tweet say “might” and “probable” in the same line of text?
        - Is there a deterministic marker and an uncertainty marker about the same “aspect”/target, and do they agree?
                - Example: Does the text say “storms may develop” and the image says “storms will develop”?
            - If no, then there is an apparent conflict.
    - **[Code 0 for no, 1 for yes]**

Helpful Additional Definitions and Notes:

PDS = Particularly Dangerous Situation

Z = Time in Zulu/Universal Time (UTC)/Greenwich Mean Time (GMT)

Wx = Weather

SWP = Severe Weather Potential

SPC = Storm Prediction Center

STP = Significant Tornado Parameter

NAM = North American Model

WRF = Weather Research and Forecasting Model

EF# = Enhanced Fujita scale (EFScale); rates the intensity of tornadoes from 0-5

APPENDIX B: SAMPLE TWEETS

NWS Birmingham @NWSBirmingham Follow

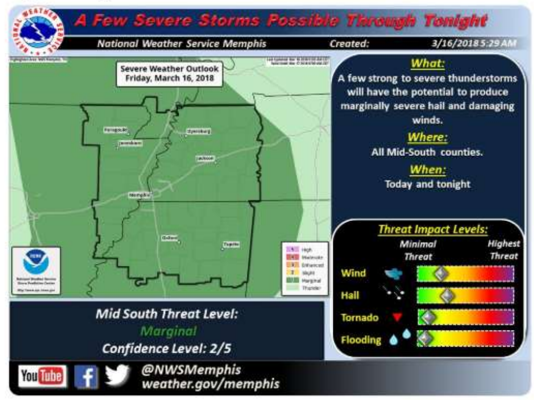
In addition to the main threat this evening, scattered severe storms may develop this afternoon. #ALWX #BMXWX

8:53 AM - 19 Mar 2018

Example of verbal uncertainty and confidence, hazard.

NWS Memphis @NWSMemphis Follow

A few strong to severe storms are possible across the Mid-South through tonight. The main hazards will be hail, gusty winds, and lightning. #tnwx #arwx #mswx #mowx



3:59 AM - 16 Mar 2018

Example of verbal uncertainty, location and hazard/intensity.

WFAA-TV Weather @wfaaweathertoo Follow

Any storms late this afternoon into this evening won't be widespread. May only have a handful of them at all. BUT if they form, they will likely be severe with large hail the main threat. Isolated storms possible anywhere from DFW to the Red River. #wfaaweather

7:15 AM - 18 Mar 2018

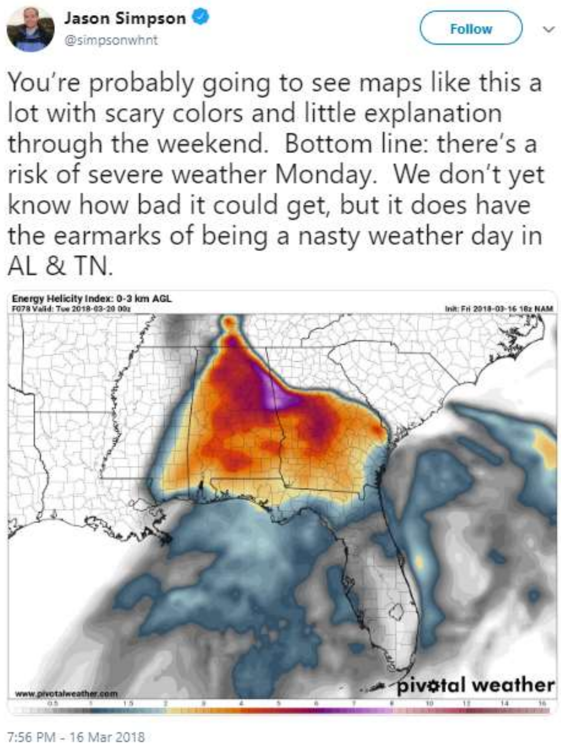
Example of conflict and verbal uncertainty, location.

Katie Walls @KatieWallsWSB Follow

Plan for it now -- Wet roadways could be problematic on your Monday AM commute. The weather overnight into the AM, however, isn't what concerns me. It's the severe risk arriving Monday afternoon. I'm breaking down that timeline at 9:16. #gawx

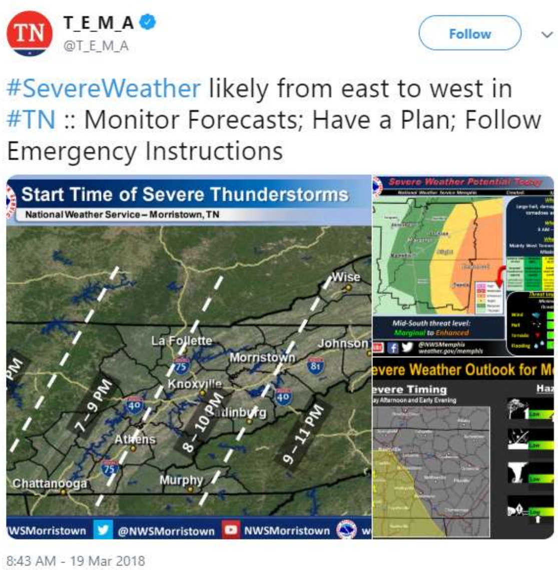
6:04 AM - 18 Mar 2018

Example of verbal uncertainty, social impact.



Example of verbal uncertainty, intensity.

Example of numerical uncertainty, timing. Verbal uncertainty on hazard, intensity, location.



Example of numerical uncertainty, timing; verbal uncertainty location.

Example of uncertainty on timing and hazard.

Justin Chambers @jctvweather Follow

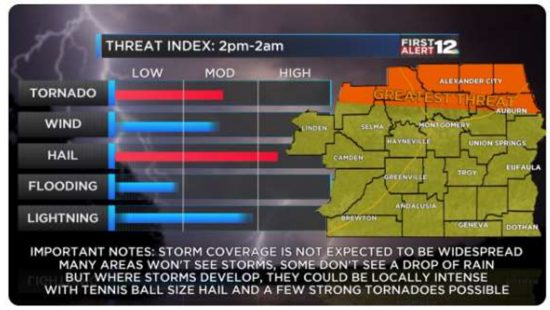
It's the last day of winter! Still some snow for our friends in the Midwest. We will be dealing with spring like storms this afternoon. @foxnashville #TNWX #SkyWatch17

5:00 AM - 19 Mar 2018

Example of confidence, hazard and timing.

Eric Snitil @EricSnitilWx Follow

Our window of severe weather potential runs from roughly 2pm to 2am with isolated (not widespread) storms capable of very large hail, damaging winds and tornadoes.



3:37 AM - 19 Mar 2018

Example of uncertainty, timing.