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Tweets About Tornado Warnings: A Spatiotemporal And Content Analysis

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TWEETS ABOUT TORNADO WARNINGS: A SPATIOTEMPORAL AND CONTENT ANALYSIS

by

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ABSTRACT

Throughout the United States, tornadoes frequently occur throughout the entire year. With each tornado there is a tornado warning that the National Weather Service (NWS) issues with a goal of protecting life and property. By using social media, these messages quickly reach the public. By analyzing Twitter data, this study aims to gain a spatiotemporal understanding of tweets, including when and where they most frequently occur. Most tweets occur within the warning time (temporal) and inside the warning polygon (spatial). To gain a better understanding of the information the tweet contains, a content analysis shows key warning characteristics such as hazard, location, guidance, time and the source of information (Mileti & Peek, 2000; Mileti & Sutton, 2009) that are present or absent. Findings suggest that many warnings disseminated through Twitter contain variations of these characteristics, however most do not contain all five key characteristics. There is also extensive variation in portraying the information, such as varying colors for warning polygons and lack of protective action suggestions. With many discrepancies present in the findings of this research, the meteorological community needs a uniform approach to warning, limiting confusion by the user and milling time. Future work would need to consist of social scientists and meteorologists to better understand the magnitude that these discrepancies occur.

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CHAPTER 1: INTRODUCTION

Each year, the United States averages nearly 1,300 tornadoes nationwide with every state experiencing them (NCEI, n.d. a). With each of these events, the National Weather Service (NWS), whose mission is, "…provid[ing] weather, water, and climate data, forecasts and warnings for the protection of life and property and enhancement of the national economy." (National Weather Service, n.d. a), issues tornado warnings. A tornado warning, as defined by the National Weather Service glossary (a), is "…issued when a tornado is indicated by the WSR-88D radar or sighted by spotters; therefore, people in the affected area should seek shelter immediately" (NOAA National Weather Service (NWS) n.d.).

It is not just the NWS that aims to protect life and property during these events, however. As technologies and dissemination methods improve, various entities, such as local media stations, private weather entities, weather enthusiasts, and the public, have begun using social media to redistribute warnings to inform more people about the impending threat. All warning information posted to social media contains a variety of content including images, graphics, radar data, locations, etc. It is a consensus that improved forecasts, warning methods, and dissemination techniques have all aided in the decrease of fatalities associated with tornadoes (AMS, 1997) and that these scientific advances have been able to transfer into societal benefit (Golden & Adams, 2000).

Current research themes on hazard warnings focus on message content (wording, color, visual cues) (Lindell & Perry, 1992; Brotzge & Donner, 2013; Luchetti, 2013) and new delivery channels such as social media (e.g., Terpstra et al., 2012, de Albuquerque et al., 2015, Cervone et al., 2016; Li et al., 2017). The objective of this research is to bridge the gap between tornado warnings and the use of Twitter for dissemination and integrate these two research themes by conducting a spatiotemporal and content analysis of tweets containing the words 'tornado' and 'warning' in relation to the warning polygon and time. This will provide insight into the information posted on social media about tornadic threats from all users of Twitter.

By gaining an understanding of tornado warning information posted to Twitter, the NWS and meteorologists in other sectors can gain an understanding of the differences that exist. By understanding and seeing the differences that exist in warning messages, there may be a spark of interest to create a uniform approach that everyone follows when issuing warnings to alleviate public confusion the public. All meteorologists have a common goal of protecting life and property, but take different approaches to doing so. This study provides evidence that a uniform approach may be necessary amongst the meteorological community when issuing warnings in order to alleviate confusion amongst the public and to achieve the goal of protecting life and property.

1.1 RESEARCH QUESTIONS

This research aims to identify spatial, temporal, and compositional patterns of tornado warning tweets for January through July of 2017 throughout the contiguous United States. Three questions guide the study.

RQ1: When do the maximum number of tweets occur during tornado warning events and do these occur within or outside of the warning time?

RQ2: What is the spatial variation/extent of tweets that occur in relation to the official National Weather Service tornado warning polygon?

RQ3: Are there similarities/differences in the message content spatially (inside versus outside the official National Weather Service warning polygon) or temporally (inside versus outside the official National Weather Service warning time)? What are these specific similarities and differences?

1.2 THESIS STRUCTURE

Six different chapters provide unique information that aid in understanding this study. Chapter 2 examines the relevant literature and sets the stage for what is known about tornado climatology, tornado warning characteristics, and messaging techniques. Chapter 3 explains the data collection process, including where and when the study focuses, along with the methodology used to complete both the spatial and temporal analysis portion of this study. Chapter 4 expands upon the spatiotemporal analysis portion and presents the results and discussion.

Chapter 5 consists of the content analysis portion of this project. This chapter outlines the various methods used in understanding and analyzing the content of the tweets, along with the extensive results of both the spatial content analysis and the temporal content analysis. This chapter further discusses what these results mean and utilizes unique graphs to aid in the reader's understanding. Chapter 6 presents the limitations of the study, a discussion, and conclusion of what all the findings mean and why they are important to the meteorological community.

CHAPTER 2: BACKGROUND/ RELEVANT LITERATURE

2.1 TORNADO CLIMATOLOGY

Every year the United States averages more tornadoes than any other country (Aguado & Burt, 2015). To more closely examine the spatial and temporal variation in tornado occurrence across the contiguous United States, meteorologists use a tornado climatology, or the frequency of tornadoes for a given location (Simmons & Sutter, 2011). Such a climatology provides the initial context for this research. For example, Simmons & Sutter (2011) analyzed a tornado climatology based on the tornado records obtained from the Storm Prediction Center (SPC) from 1950-2011. They found that the contiguous United States had a total of 50,961 tornadoes, with only 10,291 of them ranked as an (E)F2 or higher. Although each state experiences tornadoes, the risk of experiencing a tornado is not the same across all states. Dixon et al. (2011) further investigate tornado risk by calculating tornado density in ArcGIS and yielded the probability of a tornado occurring per square kilometer across the United States, without regard to the intensity of the tornado. Areas known as “Tornado Alley”, which extends from east Texas to eastern Kansas and Nebraska, and “Dixie Alley”, which extends from east Texas to Georgia, have a higher density and thus a higher probability, or risk, of a tornado occurring compared to west of the Rocky Mountains or in New England. (Boruff et al., 2003; Dixon et al., 2011; Simmons & Sutter, 2011; Aguado & Burt, 2015).

When completing an analysis of all tornado occurrences, there is an increase in spatiotemporal variability since the 1970s (Brooks et al., 2014). One explanation for this variability is in the evolving methods of reporting tornado occurrences throughout time. In recent times, there appears to be more tornadoes occurring, however this is due to more effective reporting and documenting of tornadoes through advanced technologies and the spatial migration of populations that cover more area and observe them more frequently compared to the past (Simmons & Sutter, 2011). Analyzing the tornado data through time also provides insight into when the highest frequency of tornadoes occurs throughout the year (Figure 1). According to Brooks et al. (2014), "The definition of the beginning of a season is somewhat ambiguous and arbitrary" (p. 350). They continue on to say that defining a tornado season is a subjective task, which helps to explain why various studies have used different months for their analysis such as Kelly et al. (1978) who used March thru June, Aguado & Burt (2015) who used March thru July, and Simmons & Sutter (2011) used April thru July. These studies, along with the 2017 tornado frequency, aided in determining the tornado season to study for this project.

Although there are variations in defined tornado seasons, they all occur within the spring and summer months. This is due to the atmospheric set-up providing key ingredients for tornado formation during these months. For a tornado to form we need a source of moisture, atmospheric instability, wind shear, and lift (Di Liberto, 2017). With the United States bordering the Gulf of Mexico, ample moisture advection occurs over the United States, ultimately colliding with cool, drier air. This contrast in air masses is key, as it provides a source of lift for the storm to continue to grow and creates what we know as the jet stream (Aguado & Burt, 2015). Other sources of lift may include drylines and topography. The jet stream is also a critical component in where tornadoes are likely to form as it helps aid in rising motion from aloft. According to Di Liberto (2017), a jet stream is, "…an area of fast moving winds high in the atmosphere that serves as a storms highway and reflects the boundary of cold air to the north and warm air to the south." Due to the positioning of different air masses throughout the year and the other tornadic components, tornadoes tend to occur in the southeast in the winter (Childs & Schumacher, 2018), and as the seasons transition, they shift north and west to be located primarily in the Great Plains area (Figure 2.1) (Di Liberto, 2017). By understanding the tornado climatology of the United States, one can now understand the basic spatiotemporal aspects of tornado warnings and where they are most likely to occur. Tornado warning occurrence parallels the physical tornadoes occurring, as one often accompanies the other, and thus a similar spatiotemporal pattern exists for both features and is important to this study.

2.2 HISTORY OF TORNADO WARNINGS

In recent decades, the world has seen an evolution of severe weather forecasting and the ability to issue tornado warnings. A tornado, according to the NOAA NWS Glossary (n.d. b), is "a violently rotating column of air… with circulation reaching the ground." These atmospheric phenomena are, "…nature's most violent storms… [that] can cause fatalities and devastate a neighborhood in seconds." (Tornadoes, n.d.). When these storms threaten an area, the NWS often issues tornado watches and warnings, however many people do not understand the difference in meaning between these terms. The Storm Prediction Center (SPC) (a branch of NWS) issues a tornado **watch** when conditions are favorable for tornado development in a specific area. These usually last for 4 to 8 hours and the public should treat this as a time to take precautionary measures and prepare in case the threat becomes reality. These often encompass multiple counties

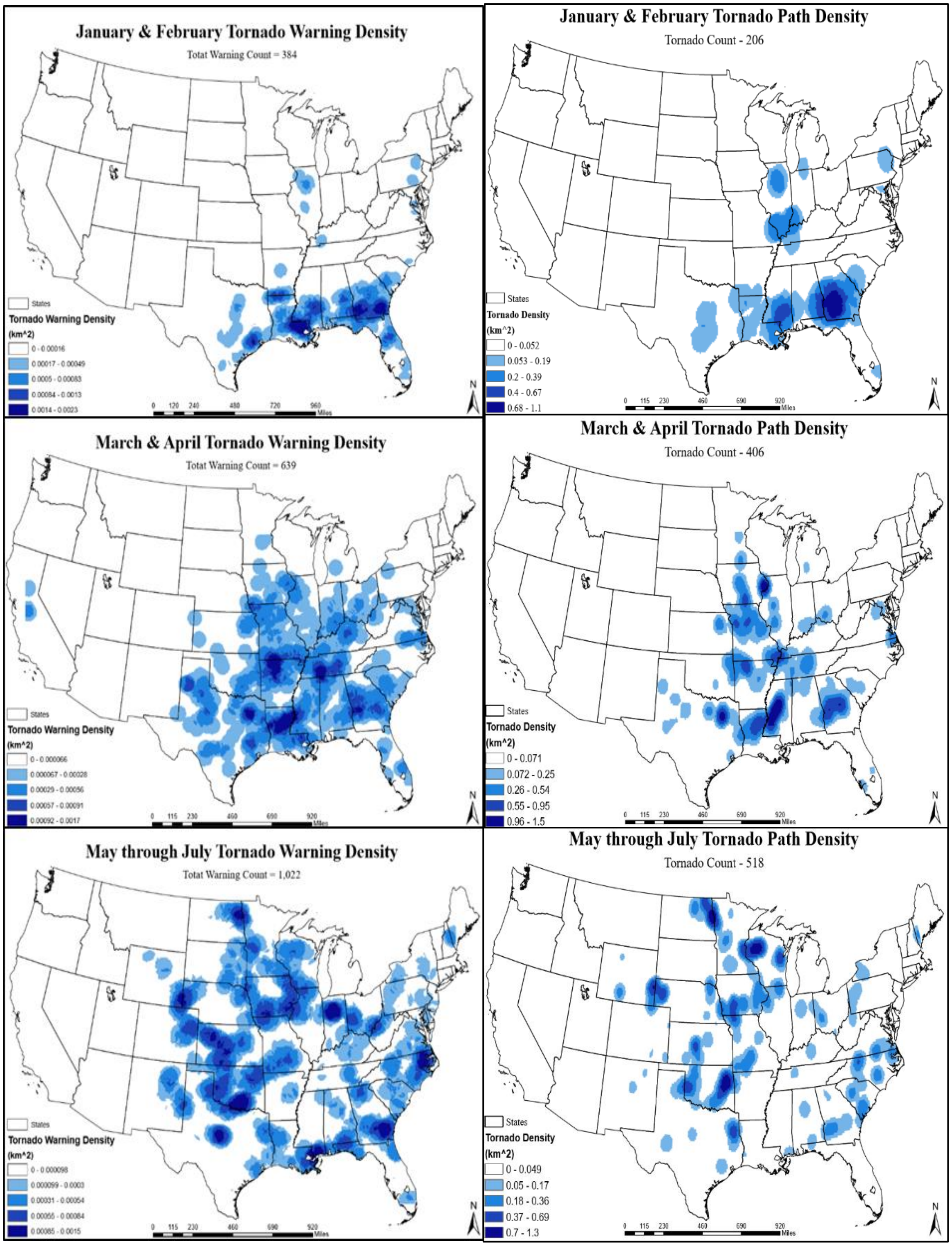

Figure 2.1: Tornado warning & path density.
This figure displays the transition in tornado occurrence from more southerly towards the north based on the density of tornado warning polygons provided by the Iowa State Environmental Mesonet (IEM) (left) and the density of the tornado warning tracks by SPC (right) during the appropriate months in 2017.

and have a larger spatial scale. This precautionary time is not the focus of this study. Once the threat of a tornado has become more imminent based on indication by WSR-88D Weather Radar or by someone on the ground observing the storm, local Weather Forecast Offices (WFOs) issue a tornado **warning** (Doswell et al., 1999; Brotzge & Donner, 2013; NWS Binghamtom, n.d.). These indicate that there is an immediate threat of a tornado in the area and people should take shelter immediately. Unlike watches, these typically last around 30 minutes and often cover a much narrower geographic region (NWS Binghamtom, n.d.). This more specific threat period is the focus of this study because of the critical nature of the information relayed to the public by professional sectors to aid in the decision making process (Figure 2.2). Figure 2.2 summarizes who is responsible for issuing watches and warnings on severe weather days,

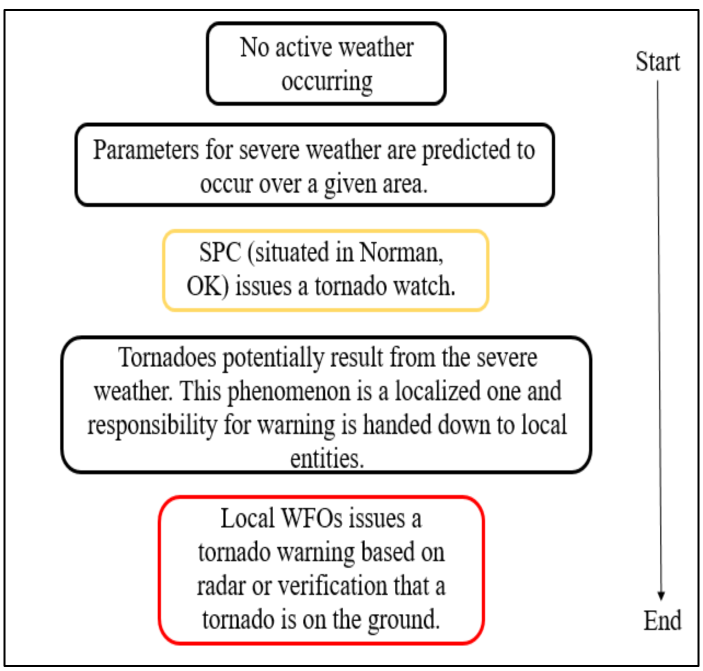

Figure 2.2: National Weather Service responsibilities for severe weather detection and warning.
A basic flowchart portraying the responsibilities of various NWS entities on severe weather days, specifically for tornadoes.

specifically for tornadoes.

Tornado warnings have experienced an interesting evolution throughout history (Figure 2.3) (Bradford, 1999; Vasquez, 2009; Coleman et al., 2011; Brotzge & Donner, 2013; NWS, n.d. c). In tandem with physical and social understanding of tornadoes, the 1950s and 1960s were also a time of rapidly developing technology and changes to public warning media which increased lead times aided in alerting and motivating the public to take protective action (Coleman et al., 2010; Corfidi, 2010). During this time, the public primarily received tornado warnings through commercial television and radio stations. In the 1970s, use of air-raid sirens from the Cold War era became another means to reach the public. After the Super Outbreak of 1974, the use of National Oceanic and Atmospheric Administration (NOAA) Weather Radios expanded, with hopes that these would allow more direct access to warning people in their homes. As time continued on and technology evolved, using the internet became a more frequent method of getting warning messages out to the public. Collaboration among many stakeholders, including emergency managers and broadcasters, has been critical to the evolving dissemination methods of tornado warnings throughout history and the increasing number of people receiving the message (Tan, 1976; Doswell et al., 1999; Coleman et al., 2010).

Although there have been many breakthroughs in the tornado warnings dissemination process, there have always been some challenges to the warning systems, even today, that Brotzge & Donner (2013) discuss. The biggest challenge is the cost of these warning dissemination systems. To implement many of the methods discussed above, ample resources have had to go towards them. There is also the concern with having to maintain old systems along with new sensors, having people consistently use them, providing for access to poor communities, and involving private sector warning methods (Miller, 2018). Aside from the physical maintenance of the systems, there are also many societal concerns that stem from various warning dissemination methods. These include receiving warnings at night (Mason et al., 2018), effective communication of the warning, and if they are multilingual. Improvements to these challenges have occurred using social media and the analysis done in the study.

2.3 CHARACTERISTICS OF TORNADO WARNINGS

Tornado warnings portray certain information, but with so many dissemination entities, this information gains unique characteristics. There are five primary characteristics that are important when assembling the content of a warning intended for public use (Mileti & Peek, 2000; Latimer, 2009). Mileti and Peek (2000) outline these characteristics as hazard, location, guidance, time, and source. In summary, this means that every warning should contain information about the impending hazard, specific location as the degree of risk is a function of the proximity one is to the event, information about what to do to protect themselves, a specific time to allow for proper preparation, and a credible source. Along with these key components, the warning also must be specific, consistent, have a sense of certainty, clear, accurate, sufficient, and portrayed over multiple channels. These key components of every warning provides the basis for the content analysis of tweets referring to tornado warnings.

One characteristic of tornado warnings is the wording used. NOAA requires the NWS to have tornado warnings contain specific language on the area at risk, relevant time frames, specific hazard information, recommended actions to take, and the issuing office. This frame work accounts for both the physical and social science components of

1870

Weather Bureau is established (Bradford, 1999)

1948

The 1st successful verbal tornado warning is issued by Ernest Fawbush & Robert Miller on Tinker Air Force Base (Bradford, 1999)

1950

Ban on the word 'tornado' is completely lifted (Coleman et al., 2011)

1953

Severe Local Storms Warning Center (SELS) was established & began to aid in public safety improvements (Corfidi, 2010)

1965

Weather Bureau officially adopts the phrase 'tornado warning' in response to the 11 April Palm Sunday Tornado Outbreak (NWS, n.d. c)

1974

Super Outbreak sparks NOAA Weather Radio Growth (Coleman et al., 2011)

2007

Warning methods were translated from county based to storm based warnings (Coleman et al., 2011)

Figure 2.3: History of tornado warnings.
A timeline of key events that occurred throughout history and have played a role in establishing the modern tornado warning

a warning (AMS, 1997; Golden & Adams, 2000; Mileti & Peek, 2000; Mileti & Sutton, 2009; Luchetti, 2013; Lindell et al., 2016; NWS, n.d. c). Forecasters, however, can have a difficult time translating what is going on into terms the public can understand. An example of this would be if a forecaster informs the public that a rapidly moving mesocyclone is approaching the area instead of simply saying that the threat of a tornado is imminent. The utilization of technical language in warnings has little impact on the user, other than a potential to scare or confuse them. It is key to keep language used geared toward the audience using it (Sandman, 1994). However, if warnings do not convey enough critical information, the public will begin to search elsewhere for the information and confusion may result (Mileti & Sutton, 2009). Forecast offices can also use more urgent language, which is known as an impact-based warning (IBW). IBWs vary between offices, but some use it as a source of detailed information about the potential impact of the storm and the degree of danger posed in the situation (Ripberger et al., 2015).

The usage of graphics to portray warnings follows very similar ideas as the wording. The way people interpret and react to warnings may be opposite of what the forecaster intended (Ash et al., 2014; Drost et al., 2016). There are several factors that facilitate a person's ability to interpret, comprehend, and respond to warnings given to them. These factors include individual capacity to interpret and analyze the information given and various socio-cultural aspects, such as a person's attitude toward the event. Brotzge & Donner (2013) found that the public is more likely to understand a warning if the information provided includes maps and details pertaining to the local area. Other factors such as color of the warning and an individual's location within the warning polygon also influences the likelihood that they will take the recommended protective actions (Mileti & Sutton, 2009; Ash et al., 2014; Lindell et al., 2016).

With a transition in the content contained in tornado warning message, there has also been a shift in the geographical extent for which tornado warnings span. Original tornado warnings conveyed information to large spatial areas, such as entire counties, that the threat of a tornado was imminent, which resulted in a larger number of people under the warning at any given time (NWS, n.d. b). Current tornado warnings have transitioned to storm-based warnings, which are more geographically specific by not warning for an entire county at one time, but rather a specific section of a county (NWS, n.d. b). According to Golden & Adams (2000), the NWS appears to be moving away from warnings based on detecting already existing tornadoes to an era of warnings based on forecasts of tornado formation. The evolution of better warning technologies drives this transition, along with forecasters confidence in the capability to accurately warn the public for tornadoes (Golden & Adams, 2000; Brotzge & Donner, 2013).

One observed example of this evolution is the shape of the polygon that represents the tornado warning. On 1 October 2007, warning methods translated from county-based warnings to storm-based warnings (Figure 2.4) (Coleman et al., 2011) with a goal of improving the NWS warning accuracy and quality (NWS, n.d. b). Storm-based warnings show the specific area under threat using polygons determined by the forecaster and do not conform to geopolitical boundaries, such as counties. To warn the public, the vertices of the polygon are used to disseminate information to only people residing in that area. This has allowed a reduction in the amount of area warned and subsequently the amount of people under the warning (Sutter & Erickson, 2010; Coleman et al., 2011;

Simmons & Sutter, 2011; Ash et al., 2014, Shupp et al., 2017). From 1996 to 2004, the total time spent under tornado warnings estimated the cost at $2.7 billion, but with storm-based warnings it is estimated that $564 million is saved, showing positive economic impacts associated with this shift in warning type (Sutter & Erickson, 2010).

2.4 DISSEMINATION CHANNELS

As seen in the case of the Palm Sunday Outbreak, amongst others, failure to communicate the danger of approaching storms can result in a high number of fatalities. A goal of fatality reduction in conjunction with technological advances has allowed meteorologists to more readily relay the threat to the public (Coleman et al., 2011). In the 1950s and 1960s, tornado warnings were primarily disseminated to the public using local radio and television stations. After the Super Outbreak of 1974, the United States saw an expansion of the NOAA Weather Radio (NWR) Network to provide fast and direct information from the NWS to the public, which now over 95% if the population has access to (NWS El Paso, n.d.) and which has provided significant benefits to public health and safety (Miller, 2018). A final dissemination tool used to relay the imminent threat of tornadoes to the public are the use of air raid sirens installed as a response to the atomic threat the U.S. faced in the 20th century. The use of these sirens to warn the public about the threat of a tornado occurred as early as 1970 (Mileti & Sutton, 2009; Coleman et al., 2011).

With the advent of the internet and the need for information to be readily accessible (Tan, 1976), today's warnings rely heavily on electronic media due to the increased speed of dissemination of warning information (Golden & Adams, 2000; Ash et al., 2014), which has caused the methods discussed prior to be less beneficial (Miller,

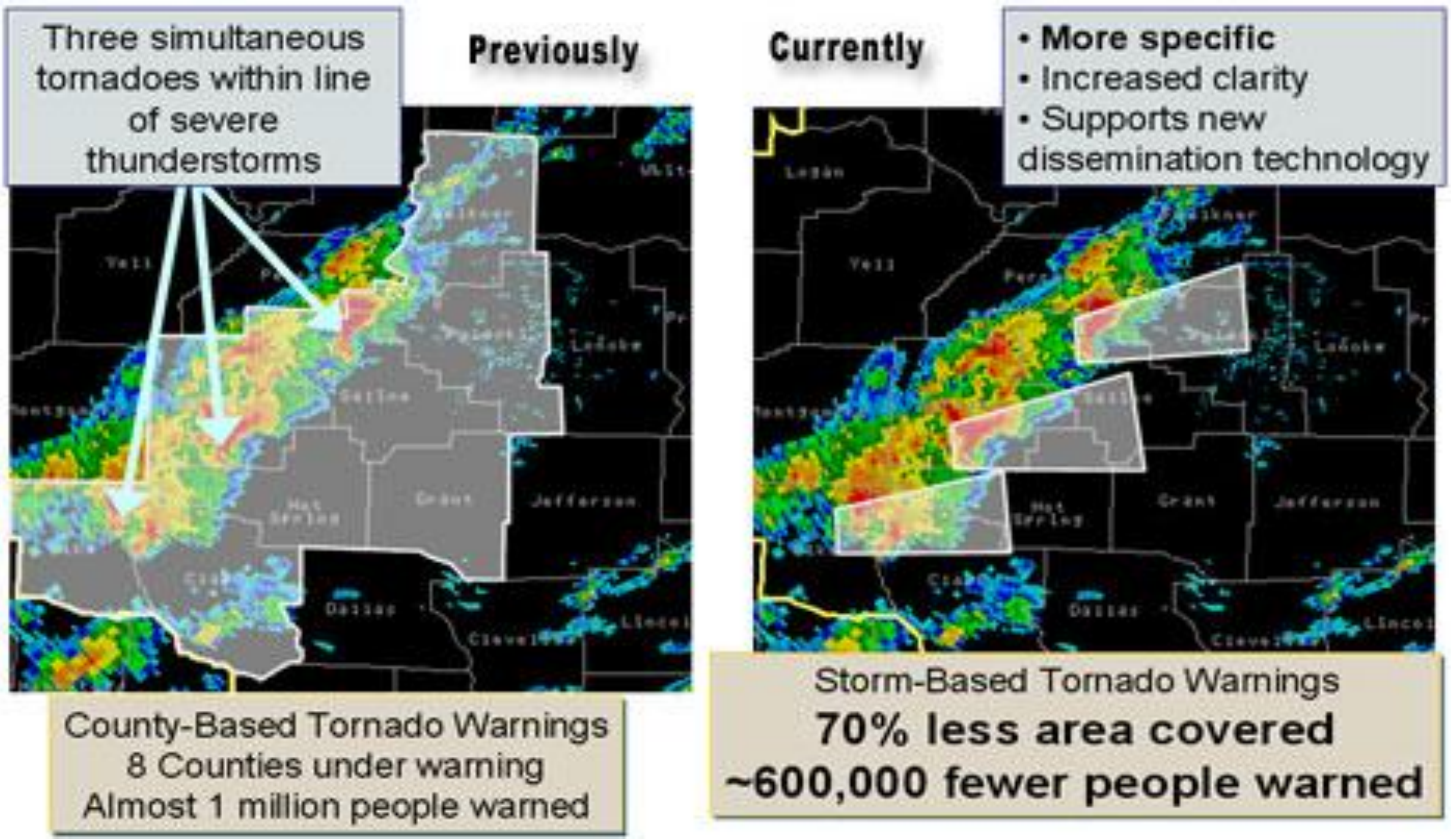

Figure 2.4: County-based vs. storm-based warnings.
The transition from county-based warnings (left) to storm-based warnings (right) occurred in 2007. This allowed for a more focused warning area and has decreased the amount of people and total area that is under the warning (NWS, n.d.b).

2018). The internet has allowed millions of Americans to directly access any NWS product, not limited to warnings (Simmons & Sutter, 2011). In conjunction with that, many local media and other private companies have begun to disseminate tornado warnings through various social media platforms, including Twitter, to make the information readily available to their viewers (Coleman et al., 2011). Although these methods have all acted to reduce tornado related fatalities, they have not helped in reaching people during nocturnal events, which is problematic (Mason et al., 2018).

Founded in 2006, Twitter has become one of the leading microblogging platforms around the world (Weller, 2013), with more than 328 million active users each month and approximately 500 million tweets sent each day (Aslam, 2017). Twitter allows for unidirectional and bidirectional relationships amongst individuals everywhere, along with connections between them, media outlets, businesses, and other organizations (Weller, 2013). Studies using Twitter data have been done for a variety of fields to help gain an understanding of: response to floods (Murthy & Longwell, 2013; Cervone et al., 2016; Li et al., 2017), disaster management and flood mapping (de Albuquerque et al., 2015; Li et al., 2017), perceived threats and physical disaster effects (Kryvasheyeu et al., 2016), evacuation compliance during hurricanes (Martin et al., 2017), communication efforts and sheltering methods during tornado outbreak (Stokes & Senkbeil, 2017), amongst many others. There is also an increase in research analyzing how people portray information on social media (Demuth et al., 2011; Ash et al., 2014; Ripberger et al., 2014; Huang & Xiao, 2015).

Of interest in this study is the use of Twitter during tornado warning time periods. During these events, communication between the NWS, media outlets, and emergency managers is imperative (Doswell et al., 1999; Golden & Adams, 2000; League et al., 2010) due to the need of timely and effective communication to make critical decisions (Mileti & Peek, 2000). By using social media as a method of disseminating tornado warning information, the entire weather enterprise can provide usable information to the public in a variety of formats, creating a dynamic environment for warning messages (Demuth et al., 2011) and a method of reaching sub-populations where other warning methods are not present (Mileti & Sutton, 2009).

It has become clear throughout this chapter that understanding one's risk for tornadoes, the content of a tornado warning message, and the dissemination channels all play vital roles in keeping the public safe and reducing fatalities. Mileti & Sutton (2009) sums up the important aspects of warnings in that the message should be clear, specific, accurate, confident, and consistent about what, when, and where the threat is along with why its important information and who it concerns. By repeating and disseminating these key concepts of warnings over multiple communication channels, there is a reduction in the likelihood of confusion. This study focuses specifically on one channel: Twitter. All the characteristics that fall under each of these categories were the driving influence of this studies content analysis, along with observing key components of warnings that are missing or that are changing between entities on Twitter.

CHAPTER 3: METHDOLOGY

3.1 STUDY AREA & DATA

For this study, the defined tornado season in the U.S. extends from January through July 2017 (Table 1). Data on confirmed tornadoes (date, time, latitude/longitude to create path, etc.) were gathered from the Storm Prediction Center (https://www.spc.noaa.gov/gis/svrgis/). Data on tornado warnings (time, date, location, etc.) were obtained from the Iowa State Environmental Mesonet (https://mesonet.agron.iastate.edu/request/gis/watchwarn.phtml). Typical seasons do not account for winter months; however, this year saw an abnormally high tornado occurrence in both January and February. In January, the total number of confirmed tornadoes was nearly four times greater compared to the average of 35 for the month and in February they were nearly double the average of 29 for the month (NCEI, 2017 a & b). In conjunction with an abnormally high number of confirmed tornadoes within the winter months, there was also a very large number of tornado warnings that occurred. It is important to note that there are typically more tornado warnings within a given month compared to confirmed tornadoes as not all warnings produce tornadoes (Table 3.1). In January and February combined, there were 384 tornado warnings. Because this project focuses on tornado warnings, including January and February could provide additional evidence of spatiotemporal or content patterns within tweets referencing tornado warnings. In total, there were 1,130 confirmed tornadoes according to the SPC for the

Table 3.1: Confirmed tornado count vs. warning count.

Month	**Confirmed Tornado Count**	**Tornado Warning Count**
January	137	276
February	69	108
March	192	284
April	214	355
May	291	567
June	146	310
July	81	144
August	119	993
September	51	437
October	75	311

This table depicts the total number of confirmed tornadoes for January through October 2017 compared to the amount of warnings that occurred in each month. The warning count always exceeded the actual number of tornadoes, with may experiencing the most confirmed tornadoes and August experiencing the most tornado warnings. The tornado counts are courtesy of the Storm Prediction Center and the warning count is courtesy of the Iowa State Environmental Mesonet.

2,044 tornado warnings issued by the NWS that are from the IEM analyzed using social media during this study.

Due to the ample amount of tornadic activity associated with Hurricane Harvey in Texas and Hurricane Irma in the Southeast, this study excludes the month of August to the end of 2017. With those two landfalling hurricanes in the U.S. in the month of August, there were a total of 993 tornado warnings which would have skewed the results of the analysis and potentially given results that were not reflective of the true nature of tornado warnings on social media.

For the established tornado season, using the Twitter Stream API allowed for the collection of geotagged Twitter data, initially querying for the word ‘tornado’. There were 77,086 tweets that contained the word 'tornado' from 1 January 2017 to 31 July 2017. After acquiring these data, narrowing the dataset down to include any tweets with the root word 'warn' is important as it allows for all words containing those letters, such as 'warning' and 'warned', to be in the final dataset which ensures analyzing anything referencing a tornado warning during the study. This query totaled 19,940 tweets. This however, was not the final data set as manual examination of the content of all tweets found additional tweets to be irrelevant based on topic, location, emergency alert system (EAS) tests, etc. As a final dataset for analysis, there are 18,210 tweets.

3.2 METHODS

To answer questions both spatially and temporally, a multi-method approach allows for the comparison of geotagged tweets to the tornado warning time and warning polygon (Figure 3.1), addressing research questions one and two. Research question one asks: 'When do the maximum number of tweets occur during tornado warning events and do these occur within or outside of the warning time?' To answer this question and complete a temporal analysis of this data (left side of Figure 5), tweets 'within' and 'outside' of the warning time were determined using Excel and mapping them in ArcGIS (Figure 3.2). The goal of creating the two subsets of data was to be able to determine when the most tweets occurred and to eventually be able to determine the differences in content (Chapter 5). There are 65% (11,885 tweets) 'within' the warning time, 15% (2,792 tweets) 'outside' of the warning time, and a remaining 20% excluded from the analysis due to lack of knowledge about when the tweet occurred in relation to the appropriate warning (Figure 3.3). Using the 'within' and 'outside' data subsets, a two-proportions Z-test determined if the number of tweets inside the warning time was

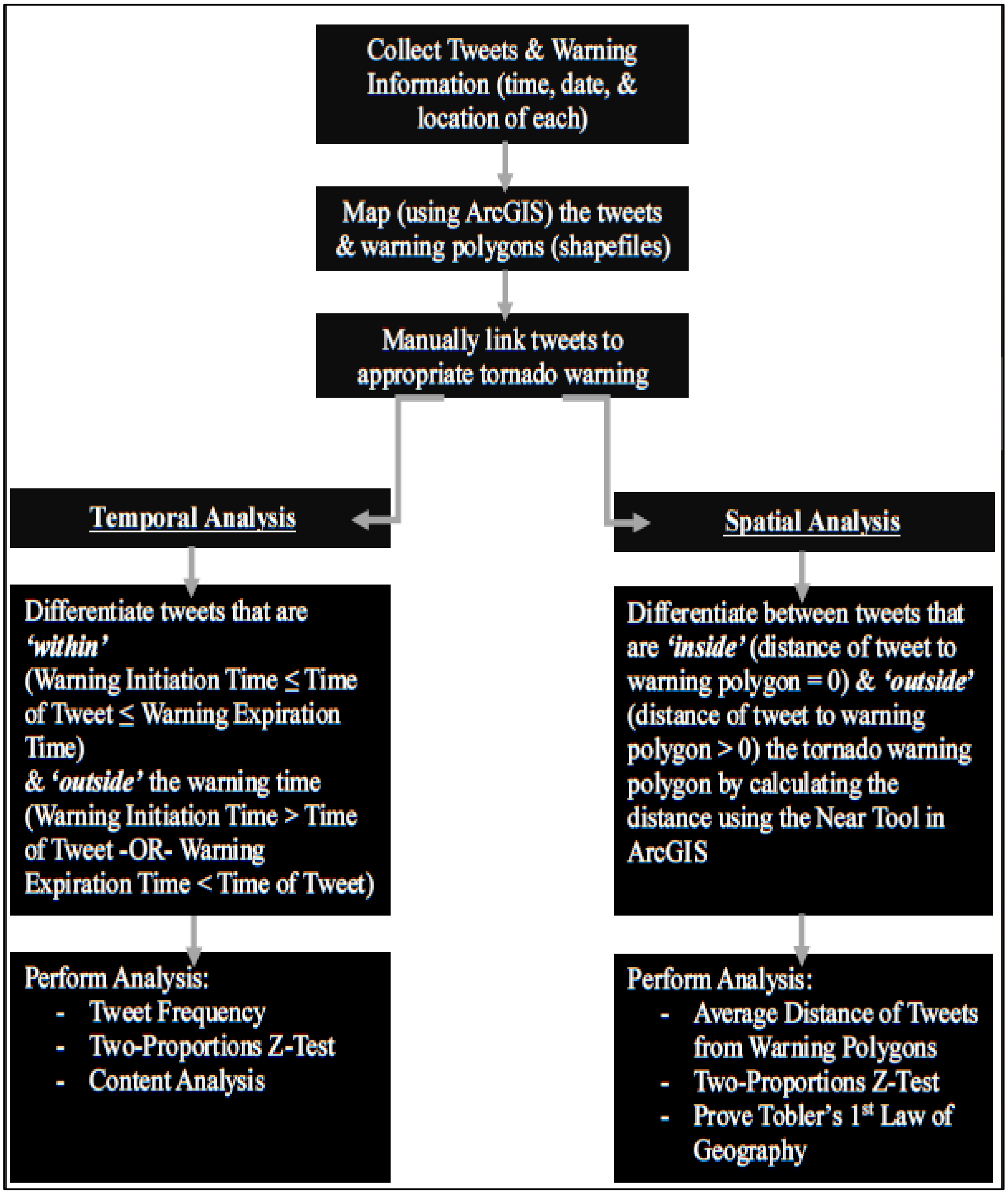

Figure 3.1: Twitter analysis work flow.
This is the basic methodology used to complete the spatiotemporal analysis using primarily Excel and ArcGIS.

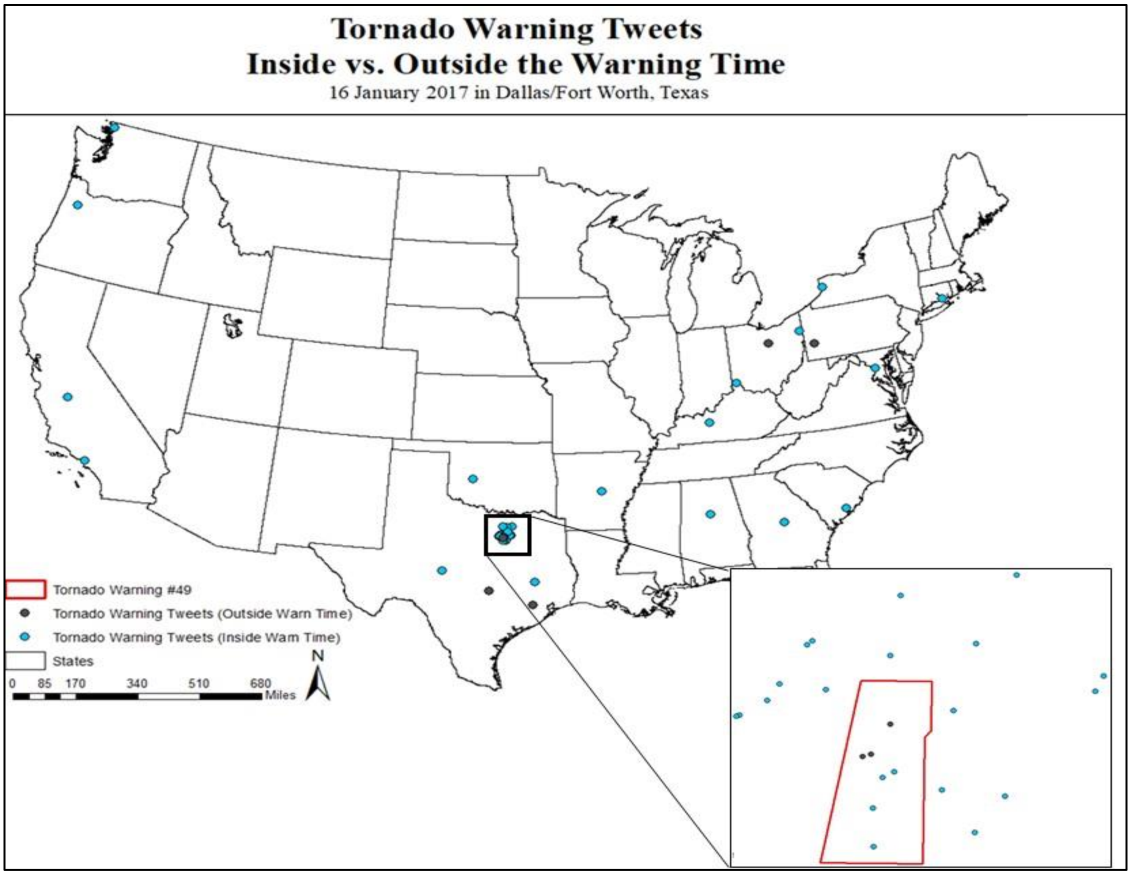

Figure 3.2: Tweets within vs. outside the warning time.
This map portrays the spatial variation of tweets that fall within the warning time (blue) compared to tweets inside the warning time (grey). Both subsets of tweets occur within the warning polygon.

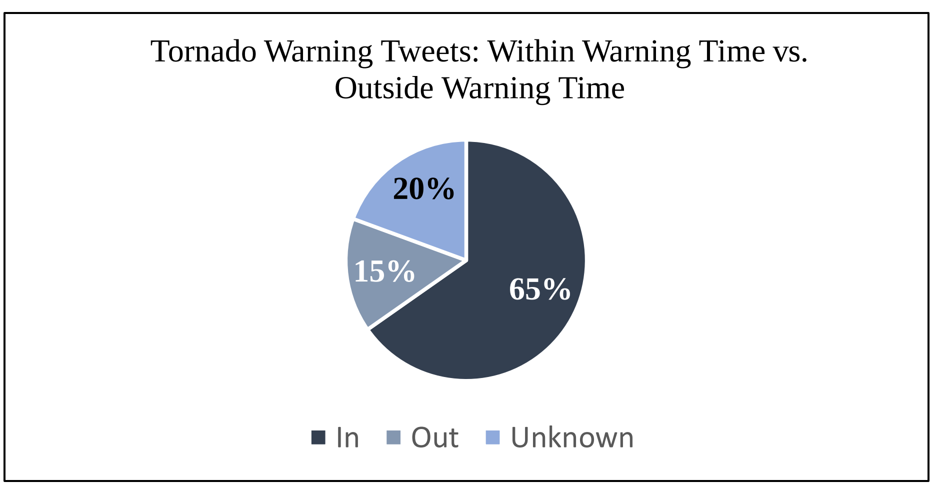

Figure 3.3: Warning time breakdown.
This pie chart shows the percentages of tweets that fell within the warning time, outside the warning time or that could not be determined in the analysis.

significant compared to those that fell outside of the warning time. Determining if it is significant allowed for a better understanding of when most tweets occurred and provided insight into the magnitude of each characteristics seen through the content analysis.

A spatial analysis of tweets in relation to the official tornado warning polygons issued by the NWS answers research question two. This question asks: 'What is the spatial variation/extent of tweets that occur in relation to the official National Weather

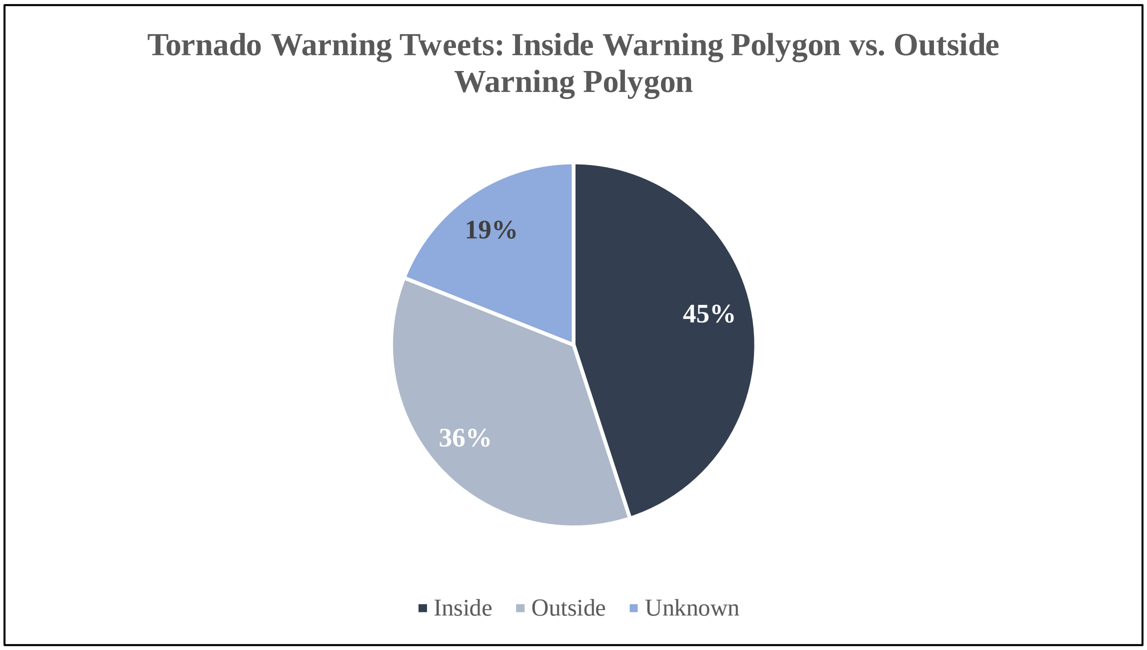

Figure 3.4: Tweet location breakdown.
This pie chart shows the percentages of tweets that fell inside the warning polygon, outside the warning polygon, or that could not be determined in the analysis

Service tornado warning polygon?' To answer this question and complete the spatial analysis portion of this project (right side of Figure 3.1), tweets 'inside' and 'outside' of the warning polygon were determined using ArcGIS (Figure 3.5). Some tweets marked as 'not determined' meant that the associated polygon was unknown or that the tweet itself was referencing two tornado warnings and was unable to link to both. A key assumption in the spatial analysis was that any tweets occurring outside, but directly near a warning polygon, were associated with that warning if they occurred during the warning time frame. In total, 45% of all tweet fell 'inside' the warning polygon, 36% fell 'outside' the warning polygon, and 19% could not be determined (Figure 3.4). One important drawback to this methodology for the spatial analysis was that the tweets geolocated to state or city centers are inside or outside of the polygon based on calculated distance. This ultimately may have taken away or added some tweets to either being inside or outside the polygon, which could have skewed some of the statistical analysis.

After determining where each tweet fell spatially regarding the warning polygon,

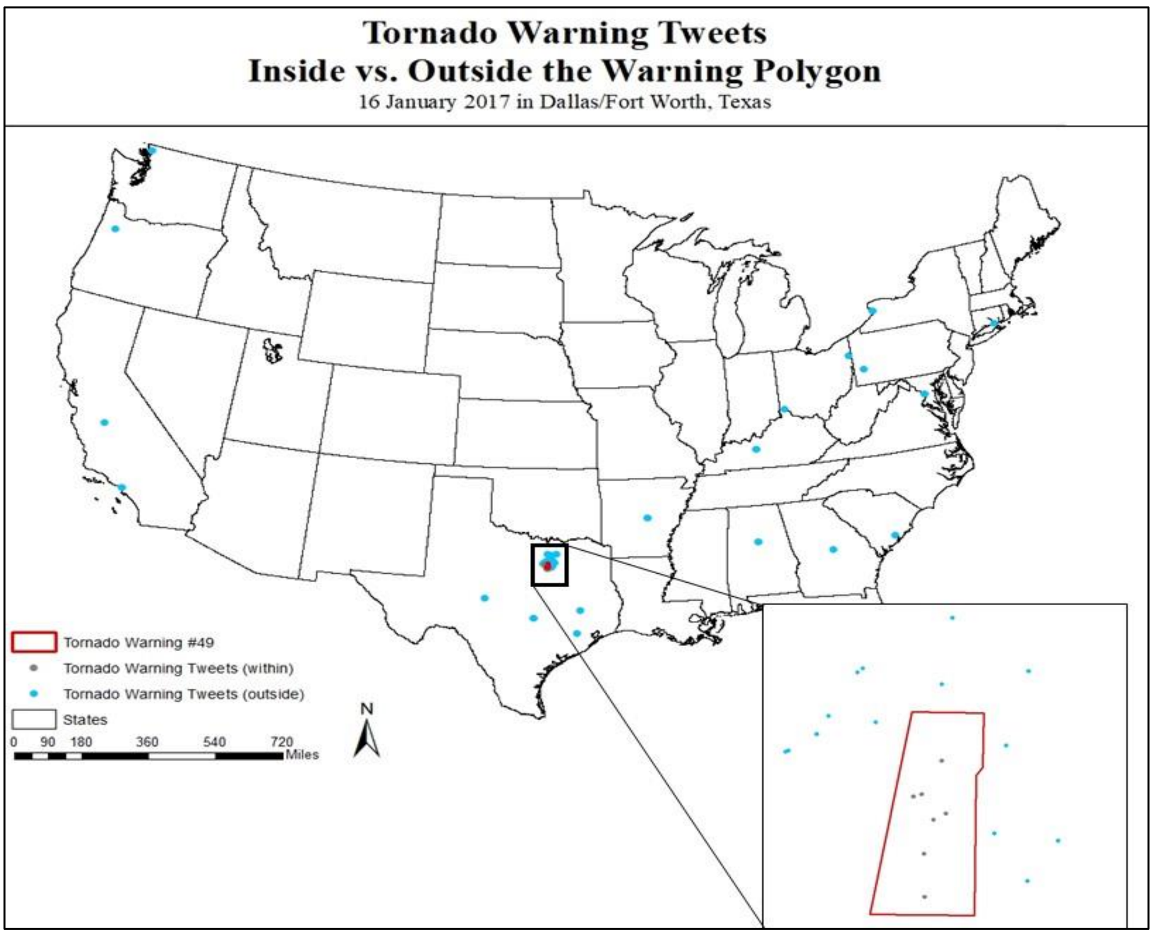

Figure 3.5: Tweets inside vs. outside the warning polygon.
This map portrays the spatial variation of tweets that fall inside the warning polygon (grey) and outside the warning polygon (blue).

a two-proportions Z-test determined if the number of tweets inside the warning polygon was significantly more than outside the warning polygon. This allows for a basic understanding of where most tweets occurred, and which groups of tweets would exhibit more characteristics once the content analysis was complete (Chapter 5). Although this test would provide enlightenment about the spatial distribution of tweets, it did not provide a precise measurement of where the tweets fell in relation to the tornado warning polygon.

In other research, Twitters users within an impacted area were more likely to contribute meaningful information during times of disaster compared to further away (Tobler, 1970; Haung & Xiao, 2015; Martin et al., 2017). The creation of thirteen buffers (1, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, and 60 miles) surrounding each warning polygon attempts to validate if this statement is true in this research. If this statement is true, the graph will be represented of a distance decay function, and if it is false the graph will be representative of a different function. This will aid in determining if tweets are more concentrated near the warning polygon and less concentrated as the distance from the polygon increases.

CHAPTER 4: SPATIOTEMPORAL ANALYSIS

Tweets referencing tornado warnings occur at all times of the day and across the contiguous U.S. These same tweets can occur within or outside a given spatial or temporal boundary. Variation in temporal frequency can occur due to technological delay, time spent reflecting about a storm, attempts made to post information about the threat, amongst others. Spatial variation in tweets may occur due to the geolocation specificity of the individual (i.e. county, city-center, latitude/longitude, etc.), global positioning system (GPS) location, and others. The following section explores both the temporal and spatial variation in tweets about tornado warnings and what it all means.

4.1 TWEET TIMING

In completing a temporal analysis of tweets focusing on tornado warnings, it was apparent that most tweets occurred within the tornado warning issuance and expiration period. Referring to established tornado climatology, the typical time of maximum tornado occurrence across the contiguous United States is from 4 to 9 pm (NSSL, n.d.). By graphing the number of tweets for each hour of the day, the maximum occurs in the evening hours with a minimum in the overnight hours, suggesting that one can use the timing of tweets to establish frequency in specific events (Figure 4.1). In this case, by focusing on tornado warning tweets, the highest frequency of tweets occurs in the same time frame as the highest actual tornado frequency.

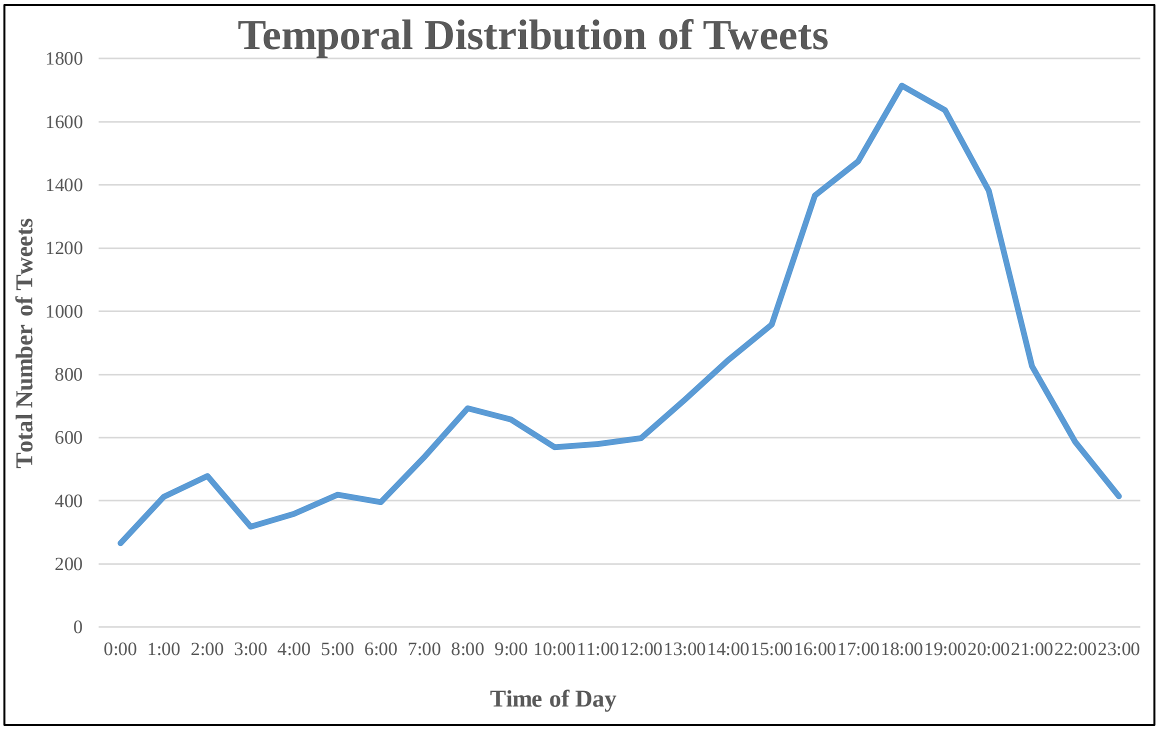

Figure 4.1: This displays the distribution of tweet frequency throughout the day, with the peak frequency in the evening hours.

Establishing that the highest frequency of tweets occurs in the evening hours, further analysis addressed the first research question to determine if the number of tweets that occurred within the warning time (11,885) was significantly more than the number of tweets that occurred outside the warning time (2,792). After completing the two-proportion Z-test, a p-value near 0 (p-value<2.2^{-16}) and a meaningful difference in the number of tweets inside the warning time compared to outside the warning time exists, thus rejecting the null hypothesis. With significantly more tweets occurring in one-time frame compared to the other, the content analysis results reflected similar findings, with higher percentages for each characteristic present within the warning time compared to outside the warning time (Chapter 5.3).

4.2 SPATIAL ANALYSIS

A tornado warning polygon is a very specific location outlined due to the enhanced tornadic threat during a given time. However, these lines do not confine Twitter users to within its boundaries, in fact many tweets came from outside the warning polygon also. By using thirteen buffers starting from within one mile to within 60 miles, it was determined that the number of tweets within the warning polygon is quite large and consistently decreases as the distance from the polygon increases. Originally the number of tweets inside the warning polygon exceeded 3,000 due to the automatic tweets provided from NWS. To gain a better understanding of the tweet location of the public alone, the 1,813 automatic tweets were subtracted and 1,330 tweets were sent by the public from within the warning polygon. Other tweets from the NWS were kept as these tweets were provided from specific offices and were not part of the automated system. When the number of tweets in each buffer was determined using ArcGIS, the graph resembles a distance decay model (Figure 4.2). This finding supports Tobler's Law, the theory that there would be a higher occurrence of tweet frequency near the center of action (warning polygon) and decrease as one moves away.

4.3 DISCUSSION

The goal of completing a spatiotemporal analysis was to answer research questions one and two, along with providing a foundation for the content analysis portion of this study. Research question one asks, "When do the maximum number of tweets occur during the tornado warning events and do these occur within or outside of the

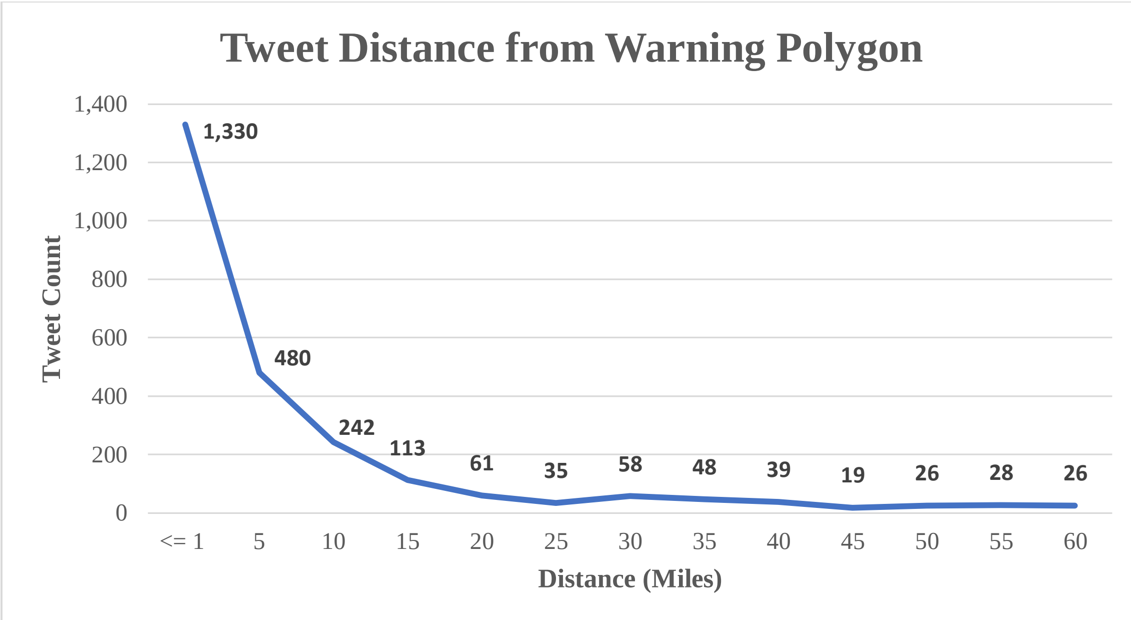

Figure 4.2: This displays the number of tweets that occurred within each buffer, starting within the warning polygon and extending to the number of tweets found between 55 to 60 miles away from the warning. The graph resembles a distance decay model.

warning time?" Through completing the temporal analysis, the maximum number of tweets occurs in the evening hours, similar to the time when the maximum number of tornadoes also occurs. When accounting for all tweets and tornado warnings, however, most tweets, no matter the time, fall within the warning. Based on these findings, people are more likely to tweet during the ensuing event, rather than wait and tweet after. This could suggest more urgency in relaying information about the tornado warning compared to less urgency once the storm has passed. A shift in the content of tweets within and outside the tornado warning time is expected.

Although understanding when the tweets occurred is important, knowing where they occurred is equally important. By completing a spatial analysis, answers to research question two, which asks "What is the spatial variation/extent of tweets that occur in relation to the official National Weather Service tornado warning polygon?" emerge. Even with the ability for people to tweet about anything from anywhere, the majority of tweets about tornado warnings occurred within the warning polygon. This suggests that people closest to the event are more likely to tweet about the event versus people further away. By creating a random data set, amplification of this theory may exist and the original dataset would be statistically closer to the center of action (warning polygon) than the random dataset. This was not the case however, which suggests that although more tweets occurred within the warning polygon, the ones that occurred outside the warning polygon were extremely far away, overshadowing the significance of ones located near. Overall, by knowing where the majority of tweets are located in relation to the warning polygon, the majority of the characteristics in the content analysis is likely to come from these tweets.

In completing the spatiotemporal analysis, there were many key results that give insight into the potential content analysis results. Noting that the majority of tweets occurred within the warning time and inside the warning polygon, this suggests that the majority of characteristics from tornado warnings will also occur in these spatiotemporal boundaries. In conjunction with the support of Tobler's Law, the fact that significantly more tweets occur within the warning boundary compared to outside suggests that the these tweets may contain important information. With answers to research question one and two, a content analysis will provide answers to the last research question.

CHAPTER 5: CONTENT ANALYSIS

5.1 METHODS

After creating various subsets of tweets and establishing spatial and temporal patterns, the content analysis portion of the project became the focus to answer research question 3. Research question 3 asks, "Are there similarities/differences in the message content spatially (inside versus outside the official National Weather Service warning polygon) or temporally (inside versus outside the official National Weather Service warning time)? What are these specific similarities and differences?"

To begin answering this question, a web-based text reading and analysis software, Voyant Tools (Sinclair & Rockwell, 2018), analyzed the text of all the tweets. The result led to an understanding of differences amongst tweets containing 'tornado warning'. This tool is scalable, which allows for comparing much larger documents and is ubiquitous, which allows other platforms to run the software through coding and allows for easy transfer of Voyant Tools results to other documents, such as Microsoft Word or websites. The program uses various visual and analytical tools to aid in understanding the data, along with the ability to analyze the content or compare data subsets. Data analysis considered attributes such as the document length, word density and frequency, words per sentence, and distinctive words. Various visual tools aided in this analysis such as word clouds (Figure 5.1), word linkages, trends, and bubble lines. With all these tools in Voyant Tools, the most frequent exact terms were able to be determined.

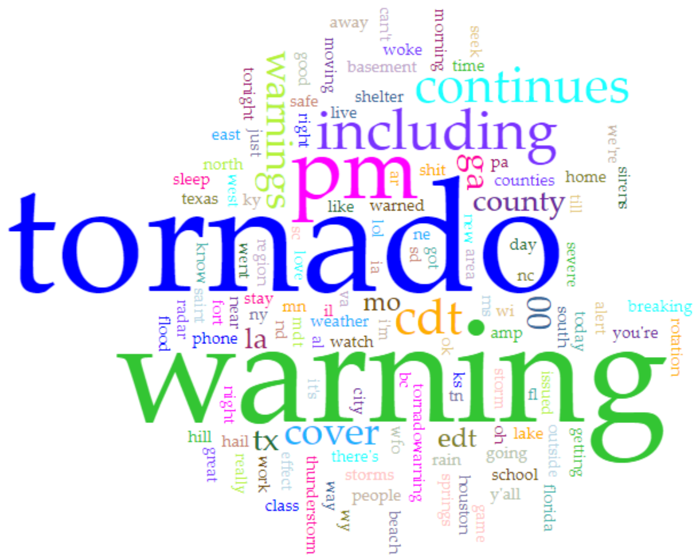

Figure 5.1: Word cloud for all tweets.
This word cloud represents the common words used amongst all tweets. 'Tornado' and 'warning' are the most common, but other words such as 'cover', 'county', and 'PM' are also common.

By gathering a basic understanding of the tweets, further investigation of research question 3 was complete by performing a subjective analysis of all tweets that contain a link by using specific descriptive attributes (Table 5.1) based on common characteristics of tornado warnings (Appendix A). By using nominal scores (present=1; absent=0) and categorical descriptors (Facebook, web page, ect.), differences amongst the content of tweets in various subsets became clear. Performing a subjective analysis was necessary as no known software can summarize various characteristics of other media associated with tweets, but rather only the words.

Table 5.1: Summary of attributes.

General Category	Sub-Category Attributes
Source Information	Link
	Active Link
	Link Source
	User Type
	Media Type
Social Media Content	Storm Related Image
	Radar/Satellite Imagery
	Image Containing a Graphic
	Video
	Website
Graphical Information	Radar Imagery
	Warning Polygon Color & Shape
	Time
	Location
	Primary Threat
	Protective Action
	Geographical Context
Video Information	Time
	Location
	Radar Imagery
	Live Feed of the Storm
	Warning Polygon Color & Shape
	Primary Threat
	Protective Action
Website Information	Geographical Context
	Time
	Location
	Warning Polygon Color & Shape
	Protective Actions
	Primary Threat
	Radar Imagery
	Storm Images

Through other research, it is evident that Twitter users within an impacted area are more likely to contribute meaningful information during times of disaster compared to areas farther away (Huang & Xiao, 2015). By using content analysis, which is a technique that allows us to discover and describe the focus of a group of data (Stemler, 2001), differences both spatially and temporally, can be discovered. Hsieh & Shannon (2005) outlined three specific approaches to the content analysis process: conventional, directed, and summative content analysis. A directed content analysis is one for which the topic in question has some prior research and understanding (Hsieh & Shannon, 2005). In this research, using prior knowledge of characteristics of tornado warnings outlined by Mileti & Peek (2000) and Mileti & Sutton (2009), including the need for a warning to include the hazard, location, guidance, time, and source, allow for completion of the content analysis.

Coding individual characteristics (Stemler, 2001) by using numbers or various symbols allows for easy analysis after compiling all the data (DiStaso & Bortree, 2012), in this case for specific characteristics of each tweet containing a link. In this study, assigning 'dummy' variables to represent characteristics, ranging from 0 to 10, with -9 representing a not-applicable feature, allows for easy analysis. With a dataset created, a summary of all these variables determined the occurrence of each characteristic in each tweet throughout the entire dataset (18,210 tweets), and particularly out of all the tweets that contained active links (10,322 tweets). Based on these numbers there were nearly 20% more tweets that contained links compared to ones without links, and the majority of those were active, meaning the website is still accessible. By using the methodology outlined above, both the spatial and temporal content analysis is complete. It is important to note that the data is the percent of the subset that the characteristic represented; which is a method of normalization, allowing for easy comparison amongst data subsets, both spatially and temporally.

5.2 OVERALL RESULTS

When uploading all the tweets (18,210) to Voyant Tools, the top five most frequent words used, excluding 'tornado' and 'warning', were 'PM', 'including', 'CDT', 'continues', and 'cover' out of a total of 247,715 words in the document (Table 5.2). Of these words, three of them have some type of temporal context, suggesting many of the tweets discuss time in relation to tornado warnings. The other words, without any contextual reference, suggest attributes within the warning and potential actions to take. In Figure 12, a word cloud, which is, "…an image composed of words used in a particular text or subject…" (Oxford Dictionary, n.d.), containing frequently used terms in the tweets can be seen. This suggest other words, such as 'phone', 'county', 'sleep', 'live', and 'school' are also frequently used words throughout all the tweets.

Table5.2: Top 10 words for entire dataset.

	Word	Count	% of Document
1.	Tornado	18,638	7.5%
2.	Warning	17,303	6.2%
3.	PM	4,969	2%
4.	Including	3,410	1.4%
5.	CDT	2,829	1.14%
6.	Continues	2,798	1.13%
7.	Cover	2,033	0.8%
8.	TX	1,689	0.7%
9.	GA	1,682	0.7%
10.	LA	1,498	0.6%

Word clouds are not the only useful tool that Voyant provides in analyzing the data, however. Trends in the word frequency determine when the maximum frequency of the word takes place within the document. This is especially useful in comparing two datasets and understanding the peak time of the word occurring. The tweet frequency trend for all the tweets is in Figure 5.2. In this graph, both the words 'tornado' and 'warning' occur frequently throughout the entire dataset, however the other three words have a peak maximum occurrence near the middle of the dataset along with and upward trend near the end. It is important to note that all these tweets were uploaded in the order in which the tweets occur, which suggest a higher use of the words in the middle and end of the established tornado season.

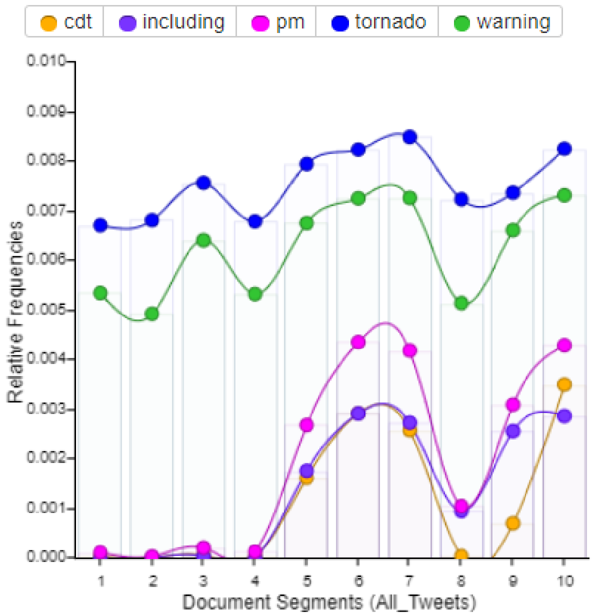

Figure 5.2: Word frequency.

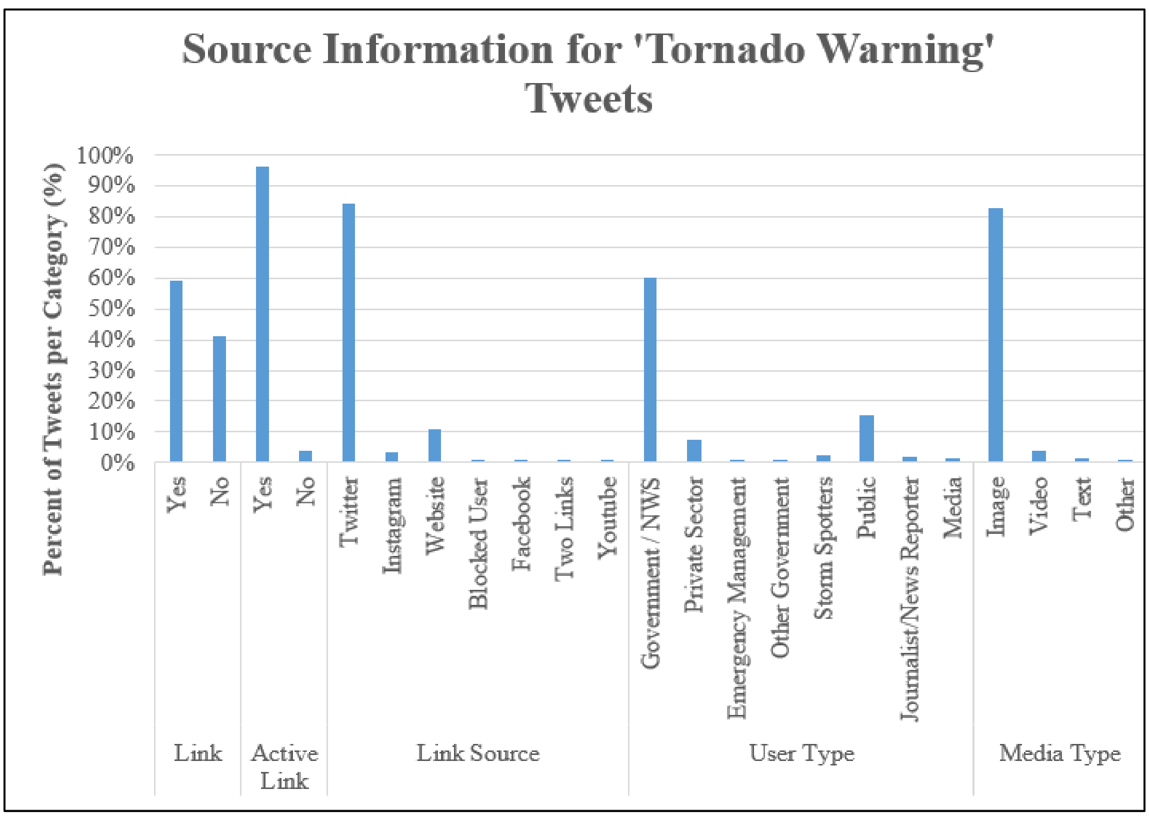

Figure 5.3: This is the basic source information for all tweets that contain a link within the data set.

With so many active links, the subjective part of the content analysis was critical in understanding the entire picture of what data was being portrayed through tweets relating to tornado warnings. Figure 14 shows a breakdown of the primary attributes initially looked at. The most common source of additional information provided by links came from the Twitter platform itself (84%), with websites providing the second largest source of additional information (11%). With further investigation of these platforms, it became clear that the entity posting the most additional information on Twitter was the NWS itself, who produces the actual warning and much of the information remained consistent from this entity. The second highest primary user who posted additional information was the public (15%). This group represented anyone who did not appear to have any meteorological or emergency management background or knowledge but was simply posting or retweeting various aspects about the warning.

Although obtaining some basic knowledge of what the data set was looking like, it became more important to look and analyze the content and variation that occurred with various attributes in the dataset. When looking at what type of additional information entities posted, images were the largest with 83% additional information being an image. These images could consist of photographs of the storm, radar images, and graphics, amongst others. The most common type of image posted on Twitter to convey additional information was a graphic, with 61% of the tweets containing at least one. A graphic is a conglomerate of information put together by an individual or entity, such as one made on a PowerPoint slide and disseminated for all to see. Figure 5.4 shows various examples of graphics examined in this study. Of all of the graphics examined, the most common features that occurred were warning polygons that were red (60.95 %) and storm-based (61.06%), a time reference (61.04%), a location type that included listing both the county and the city (60.67%), a threat type of both hail and a tornado (60.11%), and a geographical context of the warning (60.14%). The graphics most commonly lacked information such as protective action suggestions and radar imagery.

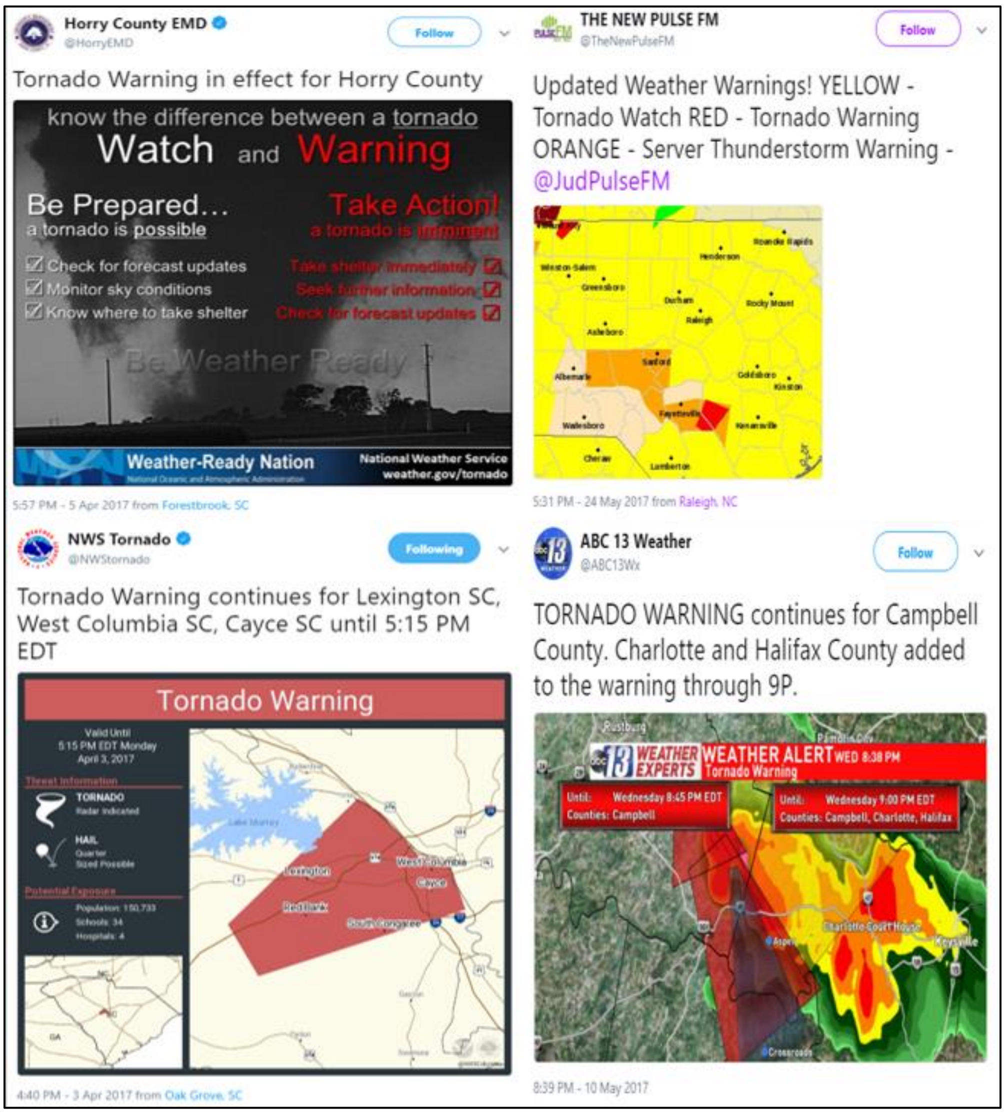

Figure 5.4: Examples of graphic images.
These posts to Twitter all contained an image that was considered to be a graphic during the subjective content analysis portion of this project.

Although graphic images lacked in radar imagery, a total of 11% of the entire data set consisted only of radar images. An image was considered radar if it consisted of primarily data obtained using a radar, such as reflectivity or velocity signatures (Figure 5.5). Throughout all the radar images, there were some common attributes. For example, in nearly all the images, either a city (7.05%) or both a city and county (3.43%) are visible in relation to the radar data and tornado warning polygon. Most of the images also

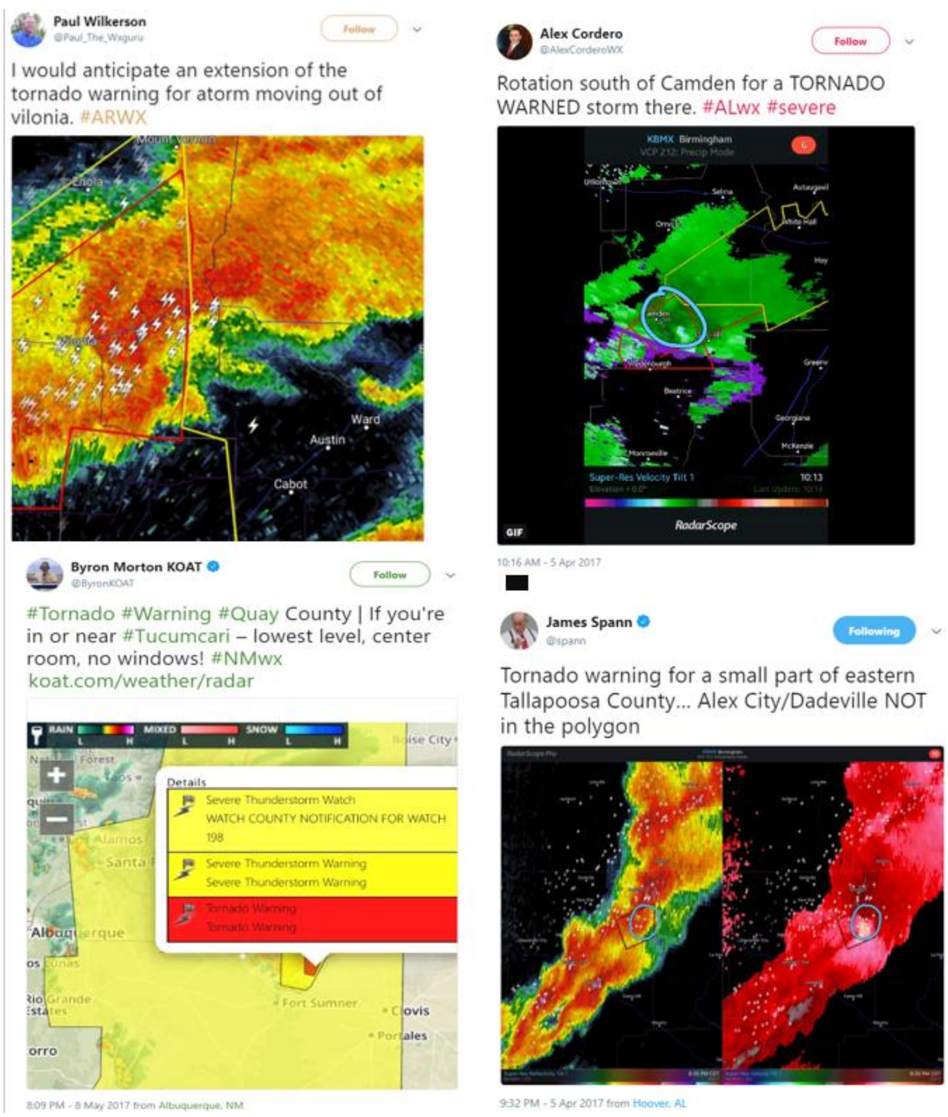

Figure 5.5: Examples of radar imagery.
These posts to Twitter all contained various forms of radar imagery that fall within that category during the subjective content analysis portion of this project.

contained a temporal reference of when the image was collect and/or when the data was from (9.36%). Another key attribute present in many of the images was that of a warning polygon. All the images that contained a polygon were storm-based (9.62%) and most of them were red (9%). There, however, was a variation in color that is worth noting as both purple (0.16%) and pink (0.19%) were also common colors when displaying the warning polygon. Finally, most of the radar data was either reflectivity (6.73%) or an image that consisted of both reflectivity and velocity (2.23%).

The final common image type that existed throughout the dataset was images that were directly related to the storm (7%). An image was determined as directly related to the storm if the image was of the storm, a protective action, or the storm's aftermath (Figure 5.6). These were often raw images from people who were near the boundaries of the warning polygon. Most of these images consisted of photographs of the storm itself (3.05%) or a storm warning notification received via phone or television (1.78%). Some of these images provided additional information about the storm such as the location (1.5%) and the time (0.79%), however the majorities were simply images with no other contextual information (3.77%).

Aside from images which were the most common type of additional media, videos accounted for 4% of links that provided additional information. In some cases, videos provided more information than an image could. 2.1% of all the videos were of the storm itself following the same guidelines for storm images. Nearly the same percent of videos provided no information as they were in the form of GIFs (1.5%) intended for an emotional context by the user. The most shocking result in this category was that news or weather broadcasts only accounted for 0.1% of the videos posted, which also contained the most information in them.

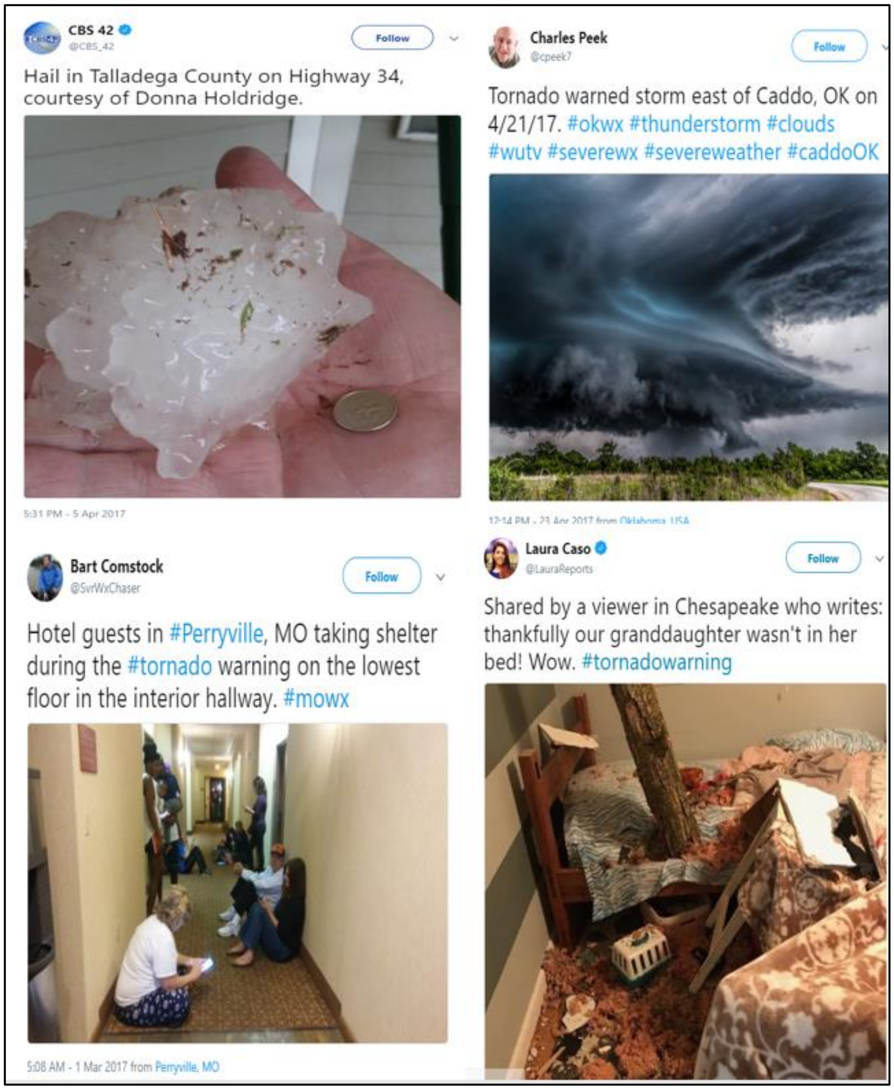

Figure 5.6: Examples of storm related imagery.
These are examples of images posted to Twitter that are storm related for the content analysis portion of this project.

Although the Twitter platform accounted for most of the links that were in the dataset, websites were the second most frequent platform that people linked to Twitter with 11%. Of these websites, the most common producer was other which primarily consisted of warnings posted to the Pacific Disaster Center website (8.4%) with private weather companies contributing additional information in 1.5% of the tweets. On these websites, most of the content consisted of an image with additional information about the event, such as warning time, warning polygons, location, hazards, etc. Updated information was the second highest occurrence on websites, meaning the original information was no longer accessible, occurring in 3.6% of the tweets.

The content analysis portion of this project allowed for the extraction of various words and attributes and the frequency of occurrence. This allowed for an overall understanding of the type of information that people using Twitter are disseminating about tornado warnings and how the information various quite a bit, supporting the hypothesis that no one follows the same guidelines when trying to portray information about a warning.

5.3 TEMPORAL CONTENT ANALYSIS RESULTS

Tweets referencing tornado warnings occur throughout the day, even when there are no active warnings. This variation in tweets can occur for various reasons (Chapter 4), however this section explores the variations in content that these different subsets ('within' the warning time and 'outside' the warning time) contain, with a goal of answering the temporal aspect of research question three. By using the methodology outlined in Section 5.1, the temporal content analysis is complete. It is important to note that the data is the percent of the subset that the characteristic represented; which is a method of normalization, allowing for easy comparison amongst data subsets.

Analysis of the tweets began by using Voyant Tools, before looking at individual attributes. In both data sets, the words 'tornado' and 'warning' were the most common, however the words that followed varied. The list of the top ten words for both subsets of data are in Table 5.3. Within the warning time, the primary focus of the words appears to be in relation to time and specific locations (i.e. PM, Georgia (GA), Texas (TX), etc.), while outside the warning time focusing more on personal experiences with the storm and

Table 5.3: Top 10 words within and outside the warning time.

Tweets Within Warning Time			
	Word	***Count***	***% of Document***
1.	Tornado	12,256	7.7%
2.	Warning	10,975	6.9%
3.	PM	4,904	3.1%
4.	Including	3,371	2.1%
5.	CDT	2,816	1.8%
6.	Continues	2,762	1.8%
7.	Cover	1,936	1.2%
8.	GA	1,644	1%
9.	TX	1,557	1%
10.	LA	1,424	0.9%

Tweets Outside Warning Time			
	Word	***Count***	***% of Document***
1.	Tornado	2,945	7.4%
2.	Warning	2,595	6.5%
3.	Region	268	0.7%
4.	WFO	265	0.7%
5.	Storm	181	0.5%
6.	Amp	164	0.4%
7.	Just	163	0.4%
8.	There's	144	0.4%
9.	I'm	126	0.3%
10.	Weather	121	0.3%

general areas (i.e. region and weather forecast office (WFO)). In both documents, the word 'tornado' makes up approximately 7% of the entire document, and approximately 2% more than the word 'warning' does.

With a basic understanding of the word breakdown of the tweets, content analysis reveals similarities and differences between attributes. It is important to note that the percent of tweets outside the warning time contained far fewer links than the tweets within the warning time, which could account for some of the differences discovered. In Figure 5.7, various graphs to show the differences and similarities within the basic source information for each of the groups of tweets. In both cases, Twitter is the most common link source, however there is also a large portion of tweets that were out of the warning time that contained links to websites. One stark contrast comes to light when looking at who was tweeting during both time periods. During the warning time, most tweets came from the NWS, but tweets coming from outside the warning time were primarily from the public. However, no matter who was tweeting when, the most common type of attached media was images.

As mentioned previously, the most common entity to tweet within the warning time was the NWS and that entity was often tweeting images in the form of graphics (Table 5.4). In total, 52.26% of all tweets within the warning time were graphics compared to only 2.61% of tweets outside the warning time. With such a high percentage occurring inside the warning time, the analysis of these tweets and what they contained took precedence as they provided more information than a simple in/out of the temporal constraint. Very few of these tweets contained any form of radar imagery; however most of them displayed a warning polygon over the impacted area. Out of the polygons displayed, all of them were storm-based warnings. 73.29% of these warning polygons were red with purple being the second most popular color. Also aiding individuals in understanding the location of the warning, the tweets contained a city and/or county, with 72.67% of them containing a geographical context allowing the viewer to see the location of the warning both zoomed in and at a larger spatial extent. In conjunction with where the event was occurring, 72.65% of the tweets contained a threat of both hail and a tornado with very few suggesting any form of protective measures taken to mitigate against these threats.

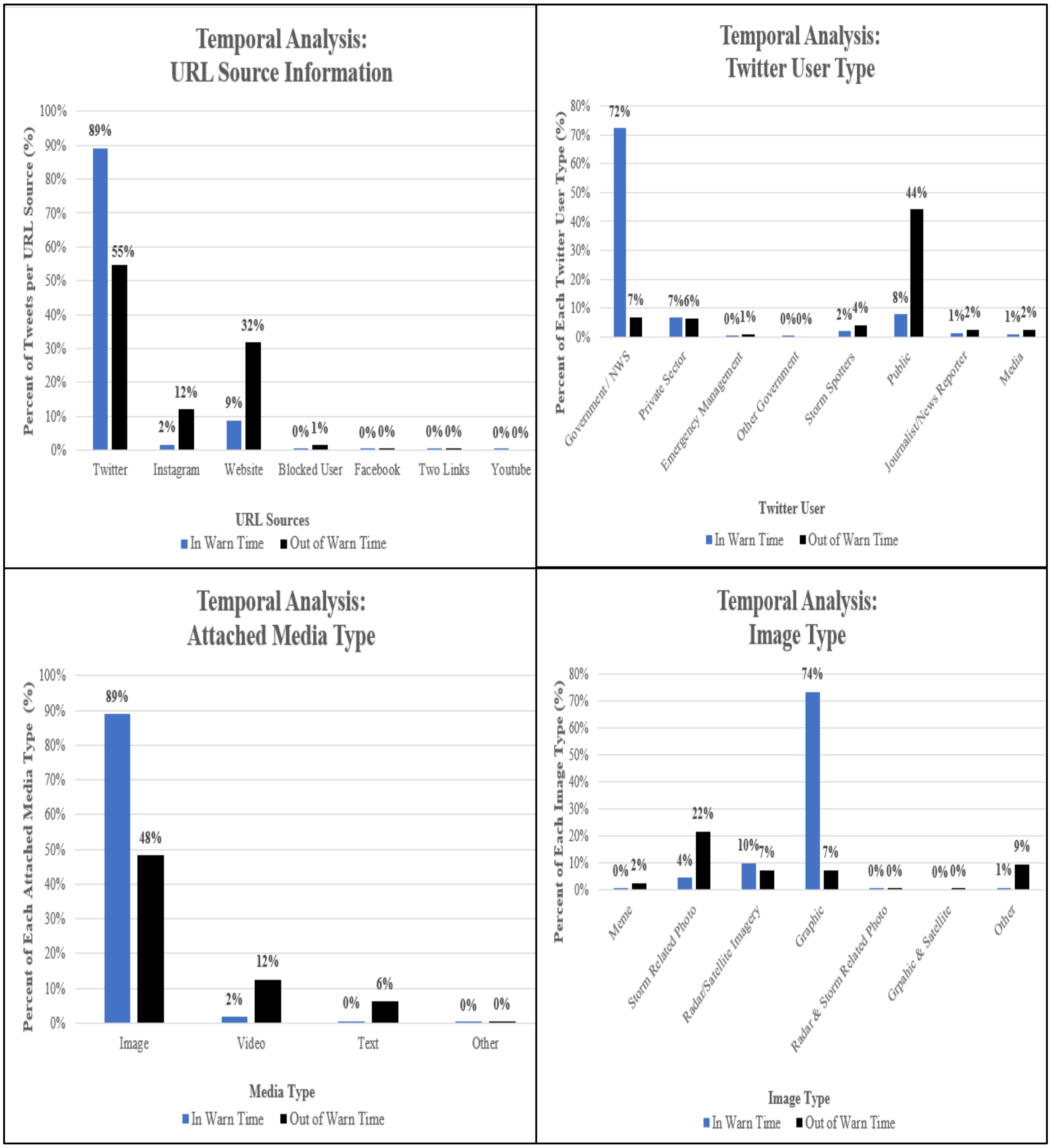

Figure 5.7: Temporal analysis source information.
This portrays various characteristics that fall within the warning time (blue) and outside the warning time (black), allowing for easy comparison. The graphs consist of the URL information (top left), the type of Twitter user (top right), the type of attached media (bottom left), and the type of image attached (bottom right).

Table 5.4: Graphic images in each temporal subset.

		% In Warn Time	% Out of Warn Time
Graphic Image	Yes	52.26	2.61
	No	47.74	97.39
Radar Data Type	Reflectivity	0.44	0.79
	Velocity	0.07	0.00
	Correlation Coefficient	0.07	0.00
Warning Polygon Color	Red	73.29	6.84
	Orange	0.01	0.00
	Yellow	0.02	0.00
	Green	0.00	0.00
	Blue	0.02	0.00
	Purple	0.04	0.00
	Pink	0.02	0.00
	Black	0.00	0.10
Warning Polygon Shape	County Based	0.01	0.00
	Storm Based	73.40	6.94
Time Included	Yes	73.45	6.94
	No	0.15	0.30
Location Type	Street	0.01	0.00
	County	0.05	0.00
	City	0.32	0.69
	Latitude/Longitude	0.00	0.00
	Landmark	0.00	0.00
	County & City	73.20	6.44
Threat Type	Tornado	0.32	0.20
	Wind	0.00	0.00
	Hail	0.00	0.00
	Flooding	0.00	0.00
	Hail & Tornado	72.65	6.05
	Tornado & Wind	0.00	0.10
	Wind, Lightning, Hail, Tornado	0.01	0.00
	Tornado & Heavy rain	0.01	0.00
	Tornado, wind, hail	0.00	0.10
Action Type	Shelter Immediately	0.08	0.20
	Stay Indoors	0.01	0.00
	DUCK (Down to the lowest level, Under something	0.04	0.00

	sturdy, Cover your head, Keep in the shelter until the storm has passed)		
	Shelter & Monitor Conditions	0.01	0.00
	DUCK (Down to the lowest level, Under something sturdy, Cover your head, Keep in the shelter until the storm has passed) & Monitor	0.01	0.00
	Have a method of receiving warnings	0.00	0.10
Geographical Context Included	Yes	72.67	6.05
	No	0.89	1.19

When analyzing the tweets that occurred outside the warning time, the most common type of image that was tweeted was storm related imagery (Table 5.5). Out of all the storm related images outside of the warning time, 11.2% of the tweets were of the storm itself with sheltering/protective action (3.17%) and impacts and storm warning notifications (2.28%) following next. In some cases, tweets provided additional information along with the image that primarily consisted of time and/or location which gave the viewer more context, especially with the storm already passing and no active warning going occurring.

Table 5.5: Storm related images in each temporal subset.

		% In Warn Time	**% Out of Warn Time**
Storm Related Image	Storm Itself	1.39	11.20
	Debris	0.00	0.79
	Shelter/Protective Actions	0.75	3.17
	Impacts	0.17	2.28
	Phone/ Storm warning Notification	1.52	2.28
	Forecasting/Monitoring	0.65	0.69
	After the Storm	0.00	1.29
	Warning text from NWS	0.04	0.30

	Storm & Debris	0.00	0.00
Storm Related Image Information	Time	0.70	1.39
	Location	0.79	5.45
	Time & Location	0.53	1.49
	Time, Location, Threat	0.28	0.10
	Time, Location, Radar	0.26	0.20
	Time, Location, Radar, Polygon, Threat	0.06	0.10
	Time and Radar	0.01	0.00
	Time, Location, Action	0.04	0.10
	Time, Location, Action, & Threat	0.02	0.10
	None	1.78	12.98

Although there was a stark contrast in the most common types of tweets seen within and outside of the tornado warning period, there were also similarities that existed between the two. Within both time frames, radar imagery was commonly tweeted. This imagery often consisted of locations such as city and/or counties mentioned along with a time reference to allow the viewer to know when the radar imagery was relevant. Every tweet that consisted of a warning polygon was in the shape of a storm-based warning with the most common color being red, followed again by purple and pink. Aside from warning information, each of these images also provided additional raw data from the radar itself. This was most commonly in the form of reflectivity (approximately 5%) with velocity (approximately 1.5%) next. Within the warning time frame, however, correlation coefficient was also common, often used to determine if debris balls are present with the ongoing storm.

Although images were far more common in each time frame compared to videos, there are some key characteristics of videos that results from this analysis (Appendix C). The most common video type within the warning time, which provides no additional information about the storm itself, were graphical interchange formats (GIFs). Outside of the warning time, the most frequent videos posted were of storm warning notifications, such as the broadcasted alert on television, followed by GIFs. Very few videos that were tweeted were of news or weather broadcasts, which contained the most additional information in this format.

The last major group of links that tweets contained were to websites. The most common form of information both inside and outside of the warning time posted to a website was an image with additional information about the storm. The main source of these links was the Pacific Disaster Center, which did not appear to also post tornado warning readily as they were present in both time periods. These links primarily consisted of the threat type and location of where the storm was with minimal additional information present. The second most common link to a website was for written news stories which made up 0.72% of the tweets occurring outside the warning time and 0.33% of tweets occurring within the warning time. These appeared to contain the most diverse listing of threat type (tornado, hail, wind, lightning, etc.) and location types (city, county, landmarks, roads, etc.). These also contained links to other websites that could contain more information about the event but fall outside the purpose of this study. Overall, there were many similarities and differences that existed within and outside of the tweets, which were important to note to understand the information disseminated during the warning time that the public may receive.

5.4 SPATIAL CONTENT ANALYSIS RESULTS

In completing the spatial analysis portion of this project, it became clear that tornado warning polygons do not constrain tweets to within their boundaries. By following the content analysis methodology outlined prior, answering research question three regarding tweets 'inside' the warning polygon and tweets 'outside' the warning polygon allow for the comparison of similarities and differences of content variables. The data recorded as the percentage of the subset for that specific attribute represents a way of normalizing the data for easy comparison. One drawback to the methodology applied in this portion of the study is tweets geolocated to state or city centers are located inside or outside of the polygon based on the calculated distance. This basic assumption may not reflect the true location of the tweets and may have ultimately taken away or added some tweets to either subset, skewing the statistical analysis.

A comparison of frequently occurring words from both data subsets along with the content of tweets containing links showed the words 'tornado' and 'warning' were the most common, however 'warning' did occur nearly 1% less than 'tornado' (Table 5.6). Aside from the top two words, many of the words inside the

Table 5.6: Top 10 words inside and outside the warning polygon.

Tweets Inside Warning Polygon			
	Word	***Count***	***% of Document***
1.	Tornado	8,660	8%
2.	Warning	7,846	7.2%
3.	PM	4,691	4.3%
4.	Including	3,317	3.1%
5.	CDT	2,742	2.5%
6.	Continues	2,718	2.5%
7.	Cover	1,802	1.7%
8.	GA	1,583	1.5%
9.	TX	1,489	1.4%
10.	LA	1,416	1.3%

Tweets Outside Warning Polygon			
	Word	***Count***	***% of Document***
1.	Tornado	8,660	8%
2.	Warning	6,629	7.4%
3.	County	812	0.9%
4.	Storm	496	0.6%
5.	Just	456	0.5%
6.	Issued	373	0.4%
7.	Amp	365	0.4%
8.	I'm	299	0.3%
9.	Shelter	294	0.3%
10.	There's	294	0.3%

warning polygon focused on specific time (PM, CDT, etc.) and locations (GA, TX, LA, etc.). The words outside the warning polygon were vague in terms of location (County, etc.) with more descriptive words referring to the storm itself (storm, issued, etc.).

The words that make up the most common words throughout the Twitter data are important in giving insight to what the tweets are focusing on. A comparative content analysis between inside and outside the warning polygon gains insight into the actual content of the tweets and warning related information disseminated through Twitter. It is important to note that this content analysis was only on tweets that contained an additional link to other media forms as these are the ones that provided additional information beyond words. In both data sets, the number of tweets that contained a link were under half of the entire set, however most of the links present were also active, meaning the links are accessible online. In Figure 5.8, key attributes for these tweets with links are compared for inside and outside the warning polygon. In both locations, the more common URL source was Twitter (accounting for 89% inside and 74% outside) followed by websites. Within the warning polygon, the most common user type was the National Weather Service (87%). The NWS was nearly absent outside the warning polygon, with 36% of the users being the public and 24% being private sector weather entities, such as ©WeatherNation. No matter who was tweeting, however, the most common type of attached media was images. Inside the warning polygon, most images (87%) were in the form of graphics, which was consistent with the NWS tweeting the most here. Outside the warning polygon there was a larger variety of image types ranging from radar and/or satellite imagery (35%), storm related photos (18%), and graphics (10%) with other images not being as frequent. With images being the most common media type in both locations, very few tweets contained videos that provided additional information about the storm to the viewer. Videos were more common outside the warning polygon and were in the form of storm videos (4.8%) and GIFs (2.9%).

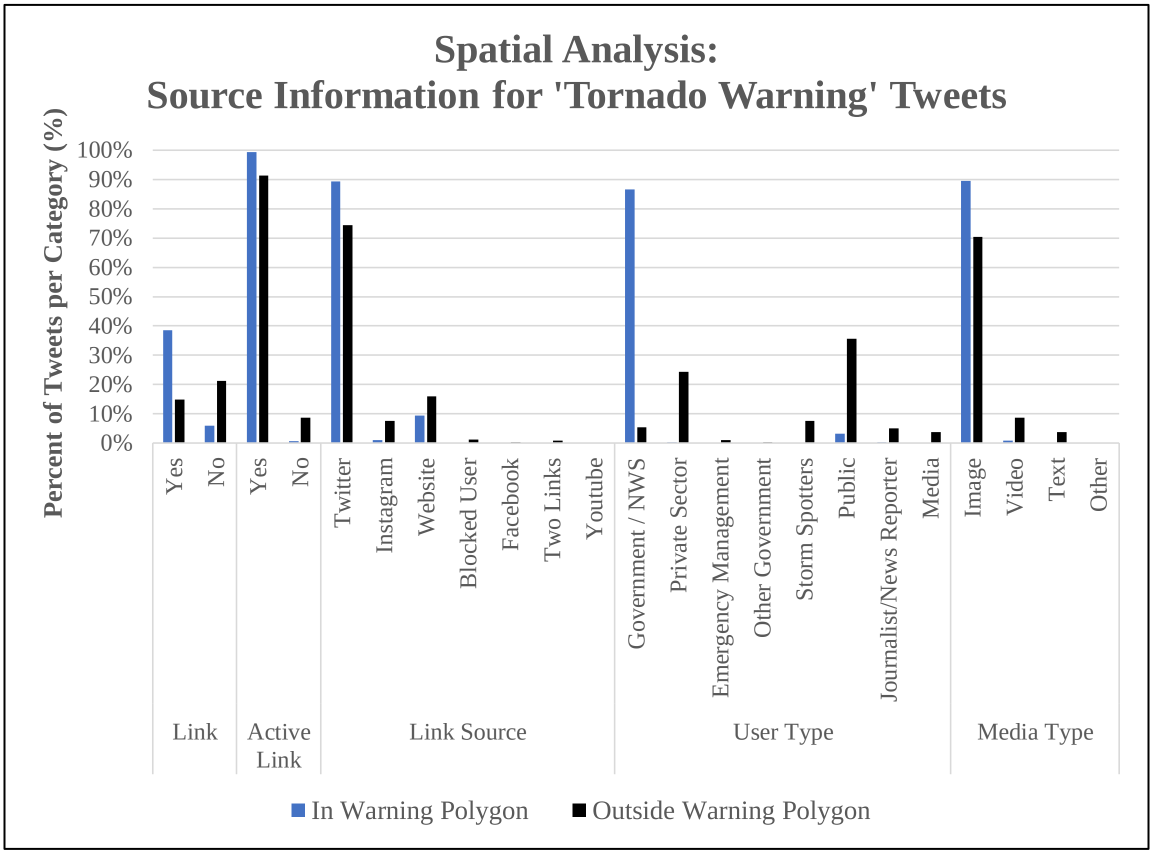

Figure 5.8: Spatial analysis source information.
This depicts the source information for tweets that occurred within the warning polygon (blue) compared to outside the warning polygon (black). The values are the percent of the total data subset that the given characteristic makes up.

As mentioned previously, the second most common URL source for both locations was to websites. Between 5-7% of all tweets in both subsets of data had links that went to various websites outside of Twitter, such as news stations. The most common source inside the warning polygon was other (7.9%) with 8.6% of these tweets containing an image with additional information about the given event. Outside of the warning polygon varied more with 2.8% linked to other websites, 1.8% links to private weather companies, and 1.3% linked to other media outlets such as news stations. The downfall to website links, particularly outside the warning polygon, was that most links went to a webpage with updated information (9.6%). However, images with additional information related to the event (4.8%) and written news stories (2%) were also common media types found in website links.

As already seen, there were stark differences that exists between tweets that occurred outside the warning polygon compared to inside. One difference that exists was the largest image type in both data sets. One common image type primarily seen outside the warning polygon was storm related images. Of all these images 7.9% of these were of the storm itself, 4.25% of these were storm warning notifications, followed by sheltering and forecasting/monitoring the weather. Additional information for these images often included the date and/or time or had nothing added at all, simply the image. Although storm related images were common, for tweets that occurred outside the warning polygon, radar images were the most common image type (Table 5.7), with 13.41% of the tweets containing a radar image. This information was often in the form of a screen shot from either a computer or cellular device of an application called ©RadarScope, amongst various other sources of radar information. These images frequently contained the location of the event by naming the city and/or county along with a temporal reference. All the warning polygons displayed in radar images are storm-based warnings, however there was a variation in the colors used to present the warning polygon. The most common color was red (30.05%) followed by pink (0.73%), purple (0.57%), and yellow (0.32%). The final attribute analyzed was the type of data that the radar imagery portrayed. The most common data type was basic reflectivity (20.17%) and/or velocity (6.44%), sometimes posted in the same Tweet, but most commonly observed separate.

Table 5.7: Radar imagery in each spatial subset.

		% in Warning Polygon	% Out of Warning Polygon
Radar Image	Yes	0.47	13.41
	No	99.53	86.59
Radar Location Type	Street	0.00	0.00
	County	0.00	0.41
	City	0.42	21.02
	Latitude/Longitude	0.00	0.00
	Landmark	0.00	0.04
	City & County	0.11	13.24
	City & Road	0.00	0.32
	City, County, & Road	0.00	0.24
	City & Landmark	0.01	0.00
Radar Time	Yes	0.33	31.47
	No	0.21	4.29
Radar Polygon Color	Red	0.32	30.05
	Orange	0.00	0.08
	Yellow	0.00	0.32
	Green	0.00	0.00
	Blue	0.00	0.08
	Purple	0.00	0.57
	Pink	0.00	0.73
	Black	0.01	0.20
	White	0.00	0.08
Radar Polygon Shape	County Based	0.00	0.00
	Storm Based	0.33	32.12
Radar Data Type	Reflectivity	0.49	20.17
	Velocity	0.00	6.44
	Correlation Coefficient	0.00	0.16
	Reflectivity & Velocity	0.06	8.06
	Velocity & Correlation Coefficient	0.00	0.41
	Velocity & Echo Tops	0.00	0.04
	Hydrometer Classification	0.00	0.12
	Velocity, reflectivity, & Correlation Coefficient	0.00	0.28
	Reflectivity & Correlation Coefficient	0.00	0.08
	Satellite	0.00	0.00

Although radar imagery was the most common image type outside of the warning polygon, the most common type inside was in the form of graphics (Table 5.8). In these graphics, the warning polygon's shape is storm-based, with the most common color being red (86.61%) and location being the city and county. Both features, along with a zoomed in and larger spatial reference gave the viewer a better geographical context of the event in most cases. Although these were tornado warning related tweets, the most common threat that as listed was both hail and tornado (86.55%). Many of these tweets came from the NWS which likely explains the redundant patterns seen within certain characteristics.

Table 5.8: Graphic images for each spatial subset.

		% in Warning Polygon	**% Out of Warning Polygon**
Graphic Image	Yes	74.46	3.65
	No	25.54	96.35
Radar Data Type	Reflectivity	0.01	1.78
	Velocity	0.01	0.20
	Correlation Coefficient	0.03	0.41
Warning Polygon Color	Red	86.61	8.55
	Orange	0.00	0.00
	Yellow	0.00	0.08
	Green	0.00	0.00
	Blue	0.00	0.08
	Purple	0.00	0.12
	Pink	0.00	0.08
	Black	0.00	0.04
Warning Polygon Shape	County Based	0.00	0.00
	Storm Based	86.61	8.95
Time Included	Yes	86.61	9.07
	No	0.01	0.61
Location Type	Street	0.01	0.00
	County	0.00	0.16
	City	0.03	1.30
	Latitude/Longitude	0.00	0.00
	Landmark	0.00	0.00
	County & City	86.59	8.10
Threat Type	Tornado	0.06	1.01

	Wind	0.00	0.00
	Hail	0.00	0.00
	Flooding	0.00	0.00
	Hail & Tornado	86.55	6.20
	Tornado & Wind	0.00	0.04
	Wind, Lightning, Hail, Tornado	0.00	0.04
	Tornado & Heavy rain	0.00	0.04
	Tornado, wind, hail	0.00	0.04
Action Type	Shelter Immediately	0.01	0.28
	Stay Indoors	0.00	0.04
	DUCK (Down to the lowest level, Under something sturdy, Cover your head, Keep in the shelter until the storm has passed)	0.00	0.12
	Shelter & Monitor Conditions	0.00	0.04
	DUCK(Down to the lowest level, Under something sturdy, Cover your head, Keep in the shelter until the storm has passed) & Monitor	0.00	0.04
	Have a method of receiving warnings	0.00	0.00
Geographical Context Included	Yes	86.53	6.28
	No	0.09	3.40

Although expecting to follow similar patterns as the images, videos and websites differed in content. In the case of videos, they were not common in either location. Storm videos are the most common type and often portray the storm itself, storm alert broadcasts, or the impacts that the storm has caused (Appendix D). The links did not contain a temporal reference very often, but the location was which allows the viewer to have some reference to where the event was occurring and potential areas of impact.

Another commonality between inside and outside the warning polygon was that the links that went to websites most often had an image with additional information posted on it. Many of these links were from the Pacific Disaster Center and contained information such as the time with the city and/or county affected. Of all the links categorized under this website content type, none of them contained any additional geographic content that would aid in the viewer gaining more of a spatial reference to the hazard area. There were also very few that contained radar information along with warning polygons, but the ones that did were red and storm-based in nature. The most common threat type listed was simply a tornado with no additional threats mentioned. Overall, these websites contained very basic information for the public to receive with much of it being non-specific to a given event.

CHAPTER 6: LIMITATIONS, DISCUSSION, & CONCLUSION

Throughout this study, it became apparent that the bulk of analysis was determining the content of each tweet based on temporal and spatial subsets. By using Twitter, a large set of data allows for an overall understanding of the information disseminated to the public about tornado warnings, however this study also has a few limitations that could account for statistical differences. This study provides evidence for the lack of uniformity of tornado warning information and suggests a uniform approach may limit confusion amongst the public.

6.1 LIMITATIONS

Gaining an understanding of tornado warning content using Twitter as the source of data through temporal, spatial, and content analyses was the primary objective of this research. Although there were many interesting findings of this paper, it is important to note some drawbacks of using Twitter data for such studies. One drawback is that the data obtained from Twitter is "thin", meaning there is not an overabundant amount of information one can draw from an individual, 140-character tweet or about the person who tweeted it (Goodchild & Li, 2012; Ruths & Pfeffer, 2014; Huang & Wong, 2016). There is also the problem of not obtaining a representative dataset from all the tweets sent out on Twitter (Ruths & Pfeffer, 2014; Huang & Wong, 2016). With only 1% of Twitter data being geolocated, and then only approximately 1% of that being available to the public, this does not allow for a representative sample of Twitter data.

Although there is a small sample of data available to the public, this data also contains population biases that does not allow for representation of the entire population (Ruths & Pfeffer, 2014; Huang & Wong, 2016). For example, elderly people are not as likely to use Twitter to obtain or disseminate tornado warning information, thus any information they have will not be on Twitter. The final drawback of using geotagged Twitter data is that the location of a Tweet is dependent on Global Positioning System (GPS) which provides only an estimate of the position on Earth (Goodchild, 2007). In this analysis, the margin of error could mean that some tweets in fact did occur inside the warning polygon, or vice versa, which may have slightly changed the outcome of the analysis.

6.2 DISCUSSION & CONCLUSION

Throughout history, the concept of a tornado warning has evolved from the government banning its use to issuing them with enough lead time to save many lives. Dissemination of these warning can be through word of mouth, television, radio, etc. and have recently through social media. By using social media, a broad group of people, from professional entities to public users, can post information about the storm in various forms. This study aims to gain an understanding in the spatiotemporal variability of tweets containing ‘tornado warning’ across the United States for 2017 (January through July), along with an understanding of the information and mechanisms used to portray that content within the tweet.

In completing the spatiotemporal analysis, most tweets occurred within the evening hours with the majority occurring within the warning time (research question 1).

With most tweets occurring within the warning polygon, as the distance increased from that polygon, the number of tweets decreased, confirming Tobler's Law (research question 2). The answers to these research questions confirmed my hypotheses and supported the findings of prior research.

When completing the content analysis portion of this project, tornado warning characteristics varied for all subsets of data created during the spatiotemporal analysis. With both the spatial and temporal subsets of data, ample differences existed between the spatiotemporal boundaries, with few similarities. The rest of this section looks further into the exact similarities and differences that exist between the subsets of data and what these mean (research question 3).

One important attribute analyzed before looking at the specific content of links on Twitter, was the word usage and frequency of those words. With the primary focus of this project being tweets that contain 'tornado' and 'warning', both words are very common due to the premise of the project and often occur in conjunction with one another. However, even with both words occurring frequently, they do not occur at the same frequency. 'Warning' likely occurred less due to the varying nature of the word as it can also be 'warn', 'warnings', 'warned', etc. compared to the word 'tornado' which is typically the only word used to describe the event. In the spatial analysis, the top words occurred the most within the warning polygon suggesting that the variation in wording is greater outside the warning polygon and more monotonous inside the warning polygon. In all data subsets, words describing time and location were common, however there are few words that describe any emotional sentiment (scared, nervous, excited, etc.) towards the event and descriptive words (dark, strong, huge, etc.). These types of words would create more of a personal attachment of the user to the storm, but it appears that facts about the storm are more commonly tweeted. One of the most common words was 'PM'. The use of this in many tweets suggests that most tornado warnings occurred in the afternoon/evening hours. With constant research to make improvements to existing warning systems, social media may be another warnings source that can reach the public at night.

By looking specifically at the results of the temporal and spatial content analyses, it becomes apparent that there are many differences that lie between the two subsets of data for each analysis. For the temporal analysis, there are discrepancies that exist between within the warning time and outside the warning time, which may be in part to the two times frames posing a different level of inherent risk to Twitter users. Within the warning time, there is more immediate danger and the information regarding safety, such as location and time, are what people are most concerned with. Outside of the warning time, users potentially have more time to reflect and tweet about their experience, which reflects the fact that tweets in this time frame tend to be more personal. When comparing inside the warning polygon compared to outside the warning polygon, similar trends emerge with the wording inside the warning polygon being more specific on the threat, location, and time compared to outside the warning polygon that typically offers sheltering advice and personal opinions about the storm.

Aside from solely looking at the wording used within tweets to gain a basic understanding of the focus of people within the respective time or location, further analysis looks at the content contained within the links embedded in certain tweets. One key attribute that appeared to vary across all spatiotemporal subsets of data was the warning polygon color. Most tweets containing a warning polygon have it displayed in red, however various sources also used the colors orange, yellow, blue, purple, pink, white and black. There are many potential problems that exist with multiple sources using different colors to represent the same thing. One problem is increasing the potential of confusion amongst the viewers. Using various colors can become confusing for users that are relying on Twitter, and even other sources, for their warning information, primarily because one post may not be directly related conceptually to another post discussing the same event. Various users that posted about tornado warnings took it upon themselves to post images, question, and concerns about what the different colors on the maps mean because they were not sure what threat they should be concerned with. One anonymous Twitter use posted about the confusion surrounding color, asking, "Social scientists: why is a severe t-storm warning poly the same color as a tornado warning poly?" Although the color can confuse people about what exactly they should be aware of, it can also pose problems to those who have color blindness. Further research investigating the color variation and how they impact people who cannot see them, especially for warnings, would be interesting.

When additional information on Twitter contained an outline of a warning polygon, there was often some form of radar or satellite imagery that accompanied it, no matter which subset of data the tweet fell into. This data is often the raw radar data in the form of reflectivity, velocity, correlation coefficients, or other data that tells meteorologists where the highest ongoing tornado threat is occurring, which may not be intuitive to the general user. By adding this additional information that is not required for a warning according to Mileti & Sutton (2009), the public may become more confused, increasing the milling time and decreasing the time actively taking protective action against the hazard. Although radar provides critical information to meteorologists, it may not be providing the right information to the public during the critical warning time.

When looking at all tweets, and not by individual subsets, one common trend is the most frequency threat posted included both hail and tornado. This is interesting as issuing a tornado warning only happens based on the observation of a tornado or a radar indication within the velocity field. There are many other threats that accompany a tornado, such as hail, straight-line winds, lightning, and flooding, however hail was the only common threat co-posted on Twitter with tornado. Various reasons could explain this, including the potential for these characteristics of a storm to cause damage, however additional research can investigate why this trend occurs.

Another interesting point that pertains to all tweets within the warning time period and inside the warning polygon, was in relation to who was tweeting. For both data subsets, the NWS was the primary provider of information on social media. This makes sense as the NWS is the primary provider of tornado warning information, however the content of these tweets is what is in question. The NWS along with various private sector weather entities all strive to protect life and property from the harshest weather that Mother Nature has to offer, however when tweeting about these weather events, they tend to provide little to no additional advice on immediate actions to take for an individual to help protect their life and property. This is a key warning characteristic that Mileti and Sutton (2009) and Mileti and Peek (2000) focus on, however many entities do not include. Throughout the various subsets, recommended protective actions included sheltering immediately, staying indoors, monitoring conditions, amongst others. These most commonly occur outside the warning polygon, which is interesting as this is not the area that is in the immediate risk area.

As already established, the NWS was the primary provider of tweets throughout the entire dataset. The largest discrepancy in the variation of users occurs when looking at tweets inside the warning polygon compared to outside the warning polygon. The NWS tweets more frequently within the warning polygon compared to the public and other weather entities that tweet more outside the polygon. In completing the data set for this project, it became obvious that the NWS geolocated their tweets to be at the center of the warning polygon (Figure 6.1), where other entities are geolocated from their actual location. Due to the automatic geolocation of the NWS tweets to the center of the

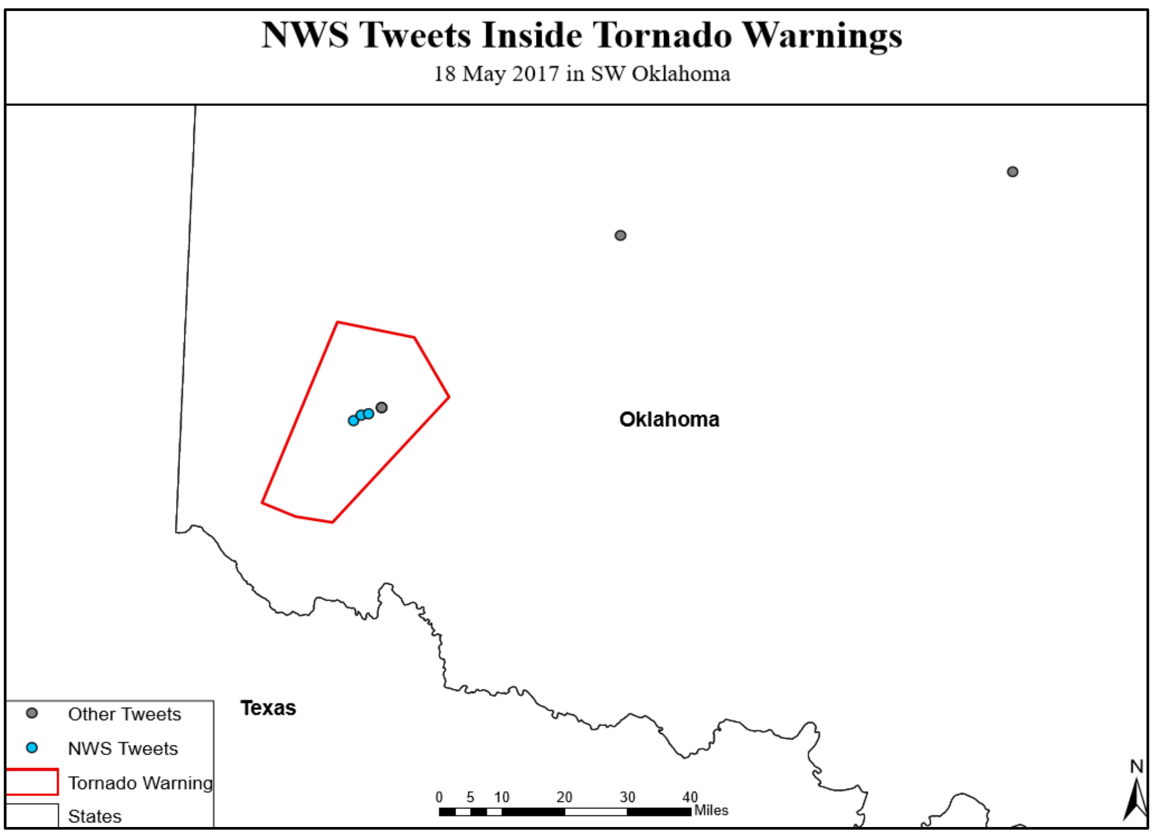

Figure 6.1: This map is on 18 May 2017 and is an excellent example of how the NWS geolocates their tweets in the center of the polygon for warnings.

polygon, this could be a potential drawback to the data set as it does not represent the people truly tweeting from inside the polygon but allows for the gathering of important information about the specific tornado warning.

Although completing an extensive content analysis of all tweets within subsets allows for easy comparison, the discussion above outlines the key findings of this study and potential research opportunities. Variations in other attributes, such as in videos and websites, also existed however they did not represent a very large portion of tweets or contain any significant finding that stuck out. The largest differences existed in the physical attributes of the warning, such as polygon color and protective actions. Within the warning time and inside the warning polygon saw more consistent characteristics compared to outside those spatiotemporal constraints, which saw more variations in everything. Overall, the most common type of additional information posted to social media was in the form of images, followed by videos and websites, and were all analyzed for warning characteristics.

By manually going through every tweet to analyze its content, it became apparent that many people do not take tornado warnings seriously when reading tweets such as, "Sometimes my bed is just to comfy to worry about a tornado warning" and "A tornado "warning" in Mississippi translates to "get your umbrella; it might rain" #Ridiculous #BoyWhoCriedWolf #TheyMissedThatLesson" which are tweets from a few anonymous Twitter users. This study provides evidence that a uniform approach may be necessary amongst the meteorological community when issuing warnings to alleviate confusion amongst the public and to achieve the goal of protecting life and property. Through completing a spatiotemporal and content analysis of tweets containing 'tornado warning' it has become apparent that the information disseminated to people across the United States is inconsistent and can even be confusing. Warnings of any kind should be consistent in the information presented and should not confuse someone who could potentially be immediately in harm's way. Future work will need to consist of social scientists and meteorologists/disaster scientists working together to better understand the magnitude at which these discrepancies are occurring, along with potential ways in which to fix them, this research simply provides the foundation and evidence needed to proceed.

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APPENDIX A: CONTENT ANALYSIS BREAKDOWN

The following table displays the breakdown of how I completed the content analysis of tweets containing links during this study. The process was subjective but followed these parameters.

Content Analysis Breakdown		
Warn_FID	Code assigned to a Tweet based on the associated tornado warning FID	
In/Out_Poly	Don't Know	0
	In	1
	Out	2
Dis_to_Poly (m)	Distance from the tweet to the polygon, measured in meters. If the value is 0, then tweet falls within the polygon. If it is recorded as -9 then the tweet is not linked to a warning.	
In/Out_WarnTime	Don't Know	0 (in time but not certain on warning)
	In	1
	Out	2 (not in warn time at all)
Link	No	0
	Yes	1
Active_Link	No	0
	Yes	1
	N/A	-9
Link Source	Twitter	1
	Instagram	2
	Website	3
	Blocked user/ cannot be determined	4
	Facebook	5
	Two active links	6
	YouTube	7
	N/A	-9
Social Media Analysis Breakdown		
User Type *(user_type)*	Government/NWS	1
	Private Sector/ Other Meteorologists	2
	Emergency Managers/ Emergency Personnel	3
	Other Government	4
	Storm Spotters	5

	Public	6
	Unknown	7
	Journalist/ News Reporter	8
	Media (news, radio, etc.)	9
	N/A	-9
Media Type *(media_type)*	Image	1
	Video	2
	Text	3
	Other	4
	N/A	-9
Image Type *(Img_type)*	Meme	1
	Storm Related Photo	2
	Radar/ Satellite Imagery	3
	Graphic	4
	Other	5
	Radar & Storm Related Image	6
	Graphic & Radar/Satellite Imagery	7
	N/A	-9
Storm Related Image *(SR_Image)*	Storm Itself	1
	Debris	2
	Shelter/ Protective Actions	3
	Impacts	4
	Storm Warning Notification	5
	Forecasting/ Monitoring	6
	After the Storm	7
	Warning text from NWS	8
	Storm & Debris	9
	N/A	-9
Additional Storm Related Image Information *(SR_Img_Info)*	None	0
	Time	1
	Location	2
	Time & Location	3
	Time, Location, & Threat	5
	Time, Location, & Radar	6
	Time, Location, Radar, Polygon, & Threat	7
	Time & Radar	8
	Time, Location, & Action	9
	Time, Location, Action, & Threat	10
	N/A	-9
Radar/ Satellite Imagery *(Rad_Img)*	No	0
	Yes	1
	N/A	-9
Locations *(Rad_Img_Loc)*	No	0
	Yes	1
	N/A	-9
Location Type *(Rad_Img_Loc_Type)*	Street	1
	County	2
	City	3
	Latitude/ Longitude	4
	Landmark	5
	City & County	6

	City & Road	7
	City, County, & Road	8
	City & Landmark	9
	N/A	-9
Time *(Rad_Img_Time)*	No	0
	Yes	1
	N/A	-9
Warning Polygon *(Rad_Img_Poly)*	No	1
	Yes	2
	N/A	-9
Warning Polygon Color *(Rad_Img_Poly_Clr)*	Red	1
	Orange	2
	Yellow	3
	Green	4
	Blue	5
	Purple	6
	Pink	7
	Black	8
	White	9
	N/A	-9
Warning Polygon Shape *(Rad_Img_Poly_Shp)*	County Based	1
	Storm Based	2
	N/A	-9
Radar/ Satellite Data Type *(Rad_Img_Data)*	Reflectivity	1
	Velocity	2
	Correlation Coefficient	3
	Reflectivity & Velocity	4
	Velocity & Correlation Coefficient	5
	Velocity & Echo Tops	6
	Hydrometer Classification	7
	Velocity, Reflectivity, & Correlation Coefficient	8
	Reflectivity & Correlation Coefficient	9
	Satellite Imagery	10
	N/A	-9
Graphic Image *(Grfc_Img)*	No	0
	Yes	1
Radar/Satellite Included *(Grfc_Rad)*	No	0
	Yes	1
	N/A	-9
Radar/ Satellite Data Type *(Grfc_Rad_Data)*	Reflectivity	1
	Velocity	2
	Correlation Coefficient	3
	Reflectivity & Velocity	4
	N/A	-9
Warning Polygon *(Grfc_Poly)*	No	0
	Yes	1
	N/A	-9
Warning Polygon Color *(Grfc_Poly_Clr)*	Red	1
	Orange	2
	Yellow	3
	Green	4

	Blue	5
	Purple	6
	Pink	7
	Black	8
	N/A	-9
Warning Polygon Shape *(Grfc_Poly_Shp)*	County Based	1
	Storm Based	2
	N/A	-9
Time Included *(Grfc_Time)*	No	0
	Yes	1
	N/A	-9
Location Included *(Grfc_Loc)*	No	0
	Yes	1
	N/A	-9
Location Type *(Grfc_Loc_Type)*	Street	1
	County	2
	City	3
	Latitude/ Longitude	4
	Landmark	5
	County & City	6
	N/A	-9
Primary Threat *(Grfc_Threat)*	No	0
	Yes	1
	N/A	-9
Threat Type *(Grfc_Threat_Type)*	Tornado	1
	Wind	2
	Hail	3
	Flooding	4
	Hail & Tornado	5
	Tornado & Wind	6
	Wind, Lightning, Hail, & Tornado	7
	Tornado & Heavy Rain	8
	Tornado, Wind, & Hail	9
	N/A	-9
Protective Actions *(Grfc_Act)*	No	0
	Yes	1
	N/A	-9
Protective Action Type *(Grfc_Act_Type)*	Shelter Immediately	1
	Stay Indoors	2
	DUCK (Downstairs, Under table, Cover Head, Keep away from windows)	3
	Shelter & Monitor Conditions	4
	DUCK (Downstairs, Under table, Cover Head, Keep away from windows) & Monitor	5
	Have a method of receiving warnings	6
	N/A	-9
Geographical Context *(Grfc_Geo)*	No	0
	Yes	1
	N/A	-9

Video Type *(Vid_Type)*	GIF	1
	Storm Video	2
	News and/or Weather Broadcast	3
	Other	4
	Phone/ Storm Warning Notification	5
	Forecasting/ Monitoring	6
Storm Video *(SR_Vid)*	Storm Itself	1
	Debris	2
	Shelter/ Protective Actions	3
	Impacts	4
	Storm Alert Broadcast	5
	Storm Itself & Storm Alert Broadcast	6
	N/A	-9
Storm Video- Additional Information *(SR_Vid_Info)*	None	0
	Time	1
	Location	2
	Time & Location	3
	Radar & Warning Polygon	5
	N/A	-9
News Broadcast *(Vid_Bdct)*	No	0
	Yes	1
	N/A	-9
Time *(Vid_Bdct_Time)*	No	0
	Yes	1
	N/A	-9
Location *(Vid_Bdct_Loc)*	No	0
	Yes	1
	N/A	-9
Location Type *(Vid_Bdct_Loc_Type)*	Street	1
	County	2
	City	3
	Latitude/Longitude	4
	Landmark	5
	City & County	6
	City, County, & Landmark	7
	City, County, & Road	8
	N/A	-9
Radar Imagery *(Vid_Bdct_Rad)*	No	0
	Yes	1
	N/A	-9
Radar Imagery Data *(Vid_Bdct_Rad_Data)*	Reflectivity	1
	Velocity	2
	Correlation Coefficient	3
	Reflectivity & Velocity	4
	N/A	-9
Video of Storm/ Live Feed *(Vid_Bdct_LF)*	No	0
	Yes	1
	N/A	-9
Tornado Warning Polygon *(Vid_Bdct_Poly)*	No	0
	Yes	1
	N/A	-9
Tornado Warning Polygon	Red	1

Color *(Vid_Bdct_Poly_Clr)*	Orange	2
	Yellow	3
	Green	4
	Blue	5
	Purple	6
	Pink	7
	N/A	-9
Tornado Warning Polygon Shape *(Vid_Bdct_Poly_Shp)*	County Based	1
	Storm Based	2
	N/A	-9
Primary Threat *(Vid_Bdct_Threat)*	No	0
	Yes	1
	N/A	-9
Primary Threat Type *(Vid_Bdct_Threat_Type)*	Tornado	1
	Wind	2
	Hail	3
	Flooding	4
	Hail & Tornado	5
	Tornado, Flood, & Wind	6
	N/A	-9
Protective Actions *(Vid_Bdct_Act)*	No	0
	Yes	1
	N/A	-9
Protective Action Type *(Vid_Bdct_Act_Type)*	Shelter Immediately	1
	DUCK (Downstairs, Under table, Cover Head, Keep away from windows)	2
	Keep Shoes On	3
	N/A	-9
Website Analysis Breakdown		
Producer Type *(Prod_Type)*	Government Emergency Management Website	1
	Government Weather Website	2
	Private Weather Company	3
	Other	4
	Media (newspaper, radio, magazine, etc.)	5
	N/A	-9
Media Type *(Web_Med_Type)*	Information is updated on website and the original content cannot be gathered	0
	Written News Story	1
	Image with information posted on website	2
	Video/News Broadcast	3
	Other	4
	Warning Text	5
	N/A	-9
Written News Story *(New_Story)*	No	0
	Yes	1
	N/A	-9
Location *(New_Story_Loc)*	No	0
	Yes	1

	N/A	-9
Location Type *(New_Story_Loc_Type)*	Street	1
	County	2
	City	3
	Latitude/Longitude	4
	Landmark	5
	City & County	6
	Landmark & City	7
	County & Road	8
	City, County, & Road	9
	N/A	-9
Time *(New_Story_Time)*	No	0
	Yes	1
	N/A	-9
Link to another Site *(New_Story_Link)*	No	0
	Yes	1
	N/A	-9
Protective Actions *(New_Story_Act)*	No	0
	Yes	1
	N/A	-9
Protection Action Type *(New_Story_Act_Type)*	Shelter Immediately	1
	Go to lowest floor	2
	Shelter in place	3
	DUCK (Downstairs, Under table, Cover Head, Keep away from windows)	4
	N/A	-9
Primary Threat *(New_Story_Threat)*	No	0
	Yes	1
	N/A	-9
Threat Type *(New_Story_Threat_Type)*	Tornado	1
	Wind	2
	Hail	3
	Flooding	4
	Hail & Tornado	5
	Hail, Tornado, & Wind	6
	Tornado & Flooding	7
	Wind, rain, lightning, hail, & tornado	8
	N/A	-9
Warning Polygon *(New_Story_Poly)*	No	0
	Yes	1
	N/A	-9
Warning Polygon Color *(New_Story_Poly_Clr)*	Red	1
	Orange	2
	Yellow	3
	Green	4
	Blue	5
	Purple	6
	Pink	7
	N/A	-9
Warning Polygon Shape *(New_Story_Poly_Shp)*	County Based	1
	Storm Based	2
	N/A	-9

Image with Information Posted on a Website *(ImgWeb)*	No	1
	Yes	2
	N/A	-9
Geographical Context *(ImgWeb_Geo)*	No	0
	Yes	1
	N/A	-9
Time *(ImgWeb_Time)*	No	0
	Yes	1
	N/A	-9
Meme *(ImgWeb_Meme)*	No	0
	Yes	1
	N/A	-9
Warning Polygon *(ImgWeb_Poly)*	No	0
	Yes	1
	N/A	-9
Warning Polygon Color *(ImgWeb_Poly_Clr)*	Red	1
	Orange	2
	Yellow	3
	Green	4
	Blue	5
	Purple	6
	Pink	7
	N/A	-9
Warning Polygon Shape *(ImgWeb_Poly_Shp)*	County Based	1
	Storm Based	2
	N/A	-9
Protective Actions *(ImgWeb_Act)*	No	0
	Yes	1
	N/A	-9
Protective Action Type *(ImgWeb_Act_Type)*	Seek Shelter Immediately	1
	DUCK (Downstairs, Under table, Cover Head, Keep away from windows)	2
	N/A	-9
Primary Threat *(ImgWeb_Threat)*	No	0
	Yes	1
	N/A	-9
Primary Threat Type *(ImgWeb_Threat_Type)*	Tornado	1
	Wind	2
	Hail	3
	Flooding	4
	Hail & Tornado	5
	N/A	-9
Location *(ImgWeb_Loc)*	No	0
	Yes	1
	N/A	-9
Location Type *(ImgWeb_Loc_Type)*	Street	1
	County	2
	City	3
	Latitude / Longitude	4
	Landmark	5
	County & City	6
	N/A	-9
Radar *(ImgWeb_Rad)*	No	0

	Yes	1
	N/A	-9
Radar Data Type *(ImgWeb_Rad_Data)*	Reflectivity	1
	Velocity	2
	Correlation Coefficient	3
	Reflectivity & Velocity	4
	N/A	-9
Storm Related Image *(ImgWeb_SR)*	No	0
	Yes	1
	N/A	-9
Storm Related Image Type *(ImgWeb_SR_Type)*	Storm Itself	1
	Debris	2
	Shelter/Protective Action	3
	Impacts	4
	N/A	-9
Video/ News Broadcast *(WebVid)*	No	0
	Yes	1
	N/A	-9
Radar *(WebVid_Rad)*	No	0
	Yes	1
	N/A	-9
Radar Data Type *(WebVid_Rad_Type)*	Reflectivity	1
	Velocity	2
	Correlation Coefficient	3
	Reflectivity & Velocity	4
	N/A	-9
Time *(WebVid_Time)*	No	0
	Yes	1
	N/A	-9
Warning Polygon *(WebVid_Poly)*	No	0
	Yes	1
	N/A	-9
Warning Polygon Color *(WebVid_Poly_Clr)*	Red	1
	Orange	2
	Yellow	3
	Green	4
	Blue	5
	Purple	6
	Pink	7
	N/A	-9
Warning Polygon Shape *(WebVid_Poly_Shp)*	County Based	1
	Storm Based	2
	N/A	-9
Location *(WebVid_Loc)*	No	0
	Yes	1
	N/A	-9
Location Type *(WebVid_Loc_Type)*	Street	1
	County	2
	City	3
	Latitude / Longitude	4
	Landmark	5
	N/A	-9
Primary Threat	No	0

(WebVid_Threat)	Yes	1
	N/A	-9
Primary Threat Type *(WebVid_Threat_Type)*	Tornado	1
	Wind	2
	Hail	3
	Flooding	4
	Hail & Tornado	5
	N/A	-9
Protective Actions *(WebVid_Act)*	No	1
	Yes	2
	N/A	-9
Protective Action Type *(WebVid_Act_Type)*	Shelter Immediately	1
	N/A	-9
Video/ Live Stream *(WebVid_LS)*	No	0
	Yes	1
	N/A	-9
Video Content *(WebVid_LS_Content)*	Cannot be determined/ LS Cut	0
	Storm Itself	1
	Debris	2
	Shelter/ Protective Actions	3
	Impacts	4
	N/A	-9

APPENDIX B: ALL CONTENT ANALYSIS RESULTS

The following tables display the raw results from the content analysis I completed of all the tweets in my dataset containing a link.

Storm Related Images		
		% of Tweets with Link Containing Variable
Storm Related Image	Storm Itself	3.05
	Debris	0.12
	Shelter/Protective Actions	1.15
	Impacts	0.44
	Phone/ Storm warning Notification	1.78
	Forecasting/Monitoring	0.78
	After the Storm	0.17
	Warning text from NWS	0.06
	Storm & Debris	0.01
Storm Related Image Information	Time	0.79
	Location	1.50
	Time & Location	0.75
	Time, Location, Threat	0.25
	Time, Location, Radar	0.31
	Time, Location, Radar, Polygon, Threat	0.08
	Time and Radar	0.03
	Time, location, action	0.06
	time, location, action, threat	0.03
	None	3.77

Radar Images		
		% of Tweets with Link Containing Variable
Radar Image	Yes	6.20
	No	93.79
Radar Location Type	Street	0.01

	County	0.10
	City	7.05
	Latitude/Longitude	0.00
	Landmark	0.01
	City & County	3.43
	City & Road	0.11
	City, County, & Road	0.06
	City & Landmark	0.02
Radar Time	Yes	9.36
	No	1.62
Radar Polygon Color	Red	9.00
	Orange	0.04
	Yellow	0.10
	Green	0.00
	Blue	0.05
	Purple	0.16
	Pink	0.19
	Black	0.06
	White	0.02
Radar Polygon Shape	County Based	0.00
	Storm Based	9.62
Radar Data Type	Reflectivity	6.73
	Velocity	1.66
	Correlation Coefficient	0.05
	Reflectivity & Velocity	2.23
	Velocity & Correlation Coefficient	0.11
	Velocity & Echo Tops	0.01
	Hydrometer Classification	0.03
	Velocity, reflectivity, & CC	0.09
	Reflectivity & Correlation Coefficient	0.04
	Satellite	0.01

Graphic Images		
		% of Tweets with Link Containing Variable
Graphic Image	Yes	34.74
	No	65.26
Radar Data Type	Reflectivity	0.49
	Velocity	0.09
	Correlation Coefficient	0.06
	Reflectivity & Velocity	0.12

Warning Polygon Color	Red	60.95
	Orange	0.01
	Yellow	0.02
	Green	0.00
	Blue	0.02
	Purple	0.05
	Pink	0.02
	Black	0.01
Warning Polygon Shape	County Based	0.01
	Storm Based	61.06
Time Included	Yes	61.04
	No	0.25
Location Type	Street	0.01
	County	0.04
	City	0.53
	Latitude/Longitude	0.00
	Landmark	0.00
	County & City	60.67
Threat Type	Tornado	0.31
	Wind	0.00
	Hail	0.00
	Flooding	0.00
	Hail & Tornado	60.11
	Tornado & Wind	0.01
	Wind, Lightning, Hail, Tornado	0.01
	Tornado & Heavy rain	0.01
	Tornado, wind, hail	0.03
Action Type	Shelter Immediately	0.09
	Stay Indoors	0.01
	DUCK	0.05
	Shelter & Monitor Conditions	0.01
	DUCK & Monitor	0.01
	Have a method of receiving warnings	0.01
Geographical Context Included	Yes	60.14
	No	1.11

Storm Videos		
		% of Tweets with Link Containing Variable
Storm Video	Storm Itself	1.75
	Debris	0.03

	Shelter/Protective Actions	0.08
	Impacts	0.08
	Storm Alert Broadcast	0.12
	Storm itself & Alert Broadcast	0.06
Storm Video Information	Time	0.02
	Location	0.58
	Time & Location	0.11
	Radar & Polygon	0.02
	None	1.40

News/Weather Broadcast		
		% of Tweets with Link Containing Variable
News Broadcast	Yes	0.06
	No	99.93
Time Included	Yes	0.08
	No	0.04
Location Type	Street	0.00
	County	0.00
	City	0.02
	Latitude/Longitude	0.00
	Landmark	0.00
	City & County	0.05
	City, County, & Landmark	0.02
	City, County, & Road	0.01
Radar Data Type	Reflectivity	0.06
	Velocity	0.02
	Correlation Coefficient	0.00
	Reflectivity & Velocity	0.03
Video of Storm/Live Feed	Yes	0.00
	No	0.11
Polygon Color	Red	0.10
	Orange	0.00
	Yellow	0.01
	Green	0.00
	Blue	0.00
	Purple	0.00
	Pink	0.00
Polygon Shape	County Based	0.00
	Storm Based	0.11

Threat Type	Tornado	0.04
	Wind	0.00
	Hail	0.00
	Flooding	0.00
	Hail & Tornado	0.01
	Tornado, Flooding, Wind	0.01
Action Type	Shelter Immediately	0.03
	DUCK	0.03
	Keep Shoes on	0.02

Written News Story		
		% of Tweets with Link Containing Variable
Written News Story	Yes	0.34
	No	99.64
Location Type	Street	0.00
	County	0.10
	City	0.08
	Latitude/Longitude	0.00
	Landmark	0.03
	City & County	0.22
	Landmark & City	0.03
	County & Road	0.08
	City, County, Road	0.04
Time Included	Yes	0.47
	No	0.14
Link to another Website Included	Yes	0.08
	No	0.52
Action Type	Shelter Immediately	0.12
	Go to Lowest Floor	0.00
	Shelter In Place	0.01
	DUCK	0.07
Threat Type	Tornado	0.12
	Wind	0.00
	Hail	0.00
	Flooding	0.01
	Hail & Tornado	0.06
	Hail, Tornado, Wind	0.03
	Tornado & Flooding	0.04
	Wind, Rain, Lighting, Hail, Tornado	0.04
Polygon Color	Red	0.10

	Orange	0.00
	Yellow	0.00
	Green	0.00
	Blue	0.00
	Purple	0.00
	Pink	0.00
Polygon Shape	County Shape	0.00
	Storm Based	0.10

Image with Additional Information on Website		
		% of Tweets with Link Containing Variable
Image with Information Posted on Website	Yes	4.01
	No	95.98
Geographical Context Included	Yes	0.00
	No	7.08
Time Included	Yes	7.07
	No	0.01
Meme	Yes	0.00
	No	7.08
Polygon Color	Red	0.07
	Orange	0.00
	Yellow	0.00
	Green	0.00
	Blue	0.00
	Purple	0.00
	Pink	0.00
Polygon Shape	County Based	0.00
	Storm Based	0.07
Action Type	Seek Shelter Immediately	0.01
	DUCK	0.02
Threat Type	Tornado	6.99
	Wind	0.00
	Hail	0.00
	Flooding	0.00
	Hail & Tornado	0.01
Location Type	Street	0.00
	County	0.00
	City	0.00
	Latitude/Longitude	0.00
	Landmark	0.01

	County & City	7.01
Radar Data Type	Reflectivity	0.06
	Velocity	0.00
	Correlation Coefficient	0.00
	Reflectivity & Velocity	0.00
Storm Related Image Type	Storm Itself	0.00
	Debris	0.00
	Shelter/Protective Actions	0.01
	Impacts	0.00

Video/News Broadcast on Website		
		% of Tweets with Link Containing Variable
Video/ News Broadcast	Yes	0.01
	No	99.98
Radar Data Type	Reflectivity	0.00
	Velocity	0.00
	Correlation Coefficient	0.00
	Reflectivity & Velocity	0.00
Time Included	Yes	0.00
	No	0.02
Polygon Color	Red	0.00
	Orange	0.00
	Yellow	0.00
	Green	0.00
	Blue	0.00
	Purple	0.00
	Pink	0.00
Polygon Shape	County Based	0.00
	Storm Based	0.00
Location Type	Street	0.00
	County	0.00
	City	0.00
	Latitude/Longitude	0.00
	Landmark	0.00
Threat Type	Tornado	0.00
	Wind	0.00
	Hail	0.00
	Flooding	0.00
	Hail & Tornado	0.00
Action Type	Shelter Immediately	0.00

Video/Live Stream Included	Yes	0.00
	No	0.02
Video Content	Cannot be Determined	0.00
	Storm Itself	0.00
	Debris	0.00
	Shelter/Protective Actions	0.00
	Impacts	0.00

APPENDIX C: TEMPORAL CONTENT ANLAYSIS RESULTS

The following tables display the additional raw results from the content analysis I completed comparing the tweets that were found within the tornado warning time period and outside the tornado warning time period. This analysis was only done on the tweets that contained a link.

Radar Images			
		% In Warn Time	**% Out of Warn Time**
Radar Image	Yes	7.07	2.76
	No	92.92	97.24
Radar Location Type	Street	0.00	0.00
	County	0.12	0.00
	City	5.88	5.15
	Latitude/Longitude	0.00	0.00
	Landmark	0.01	0.00
	City & County	3.77	1.68
	City & Road	0.07	0.20
	City, County, & Road	0.02	0.40
	City & Landmark	0.00	0.10
Radar Time	Yes	8.83	5.45
	No	1.15	2.38
Radar Polygon Color	Red	8.65	3.37
	Orange	0.02	0.00
	Yellow	0.08	0.10
	Green	0.00	0.00
	Blue	0.01	0.10
	Purple	0.15	0.10
	Pink	0.19	0.20
	Black	0.07	0.00
	White	0.02	0.00
Radar Polygon Shape	County Based	0.00	0.00
	Storm Based	9.21	3.87

Radar Data Type	Reflectivity	5.65	5.05
	Velocity	1.72	1.39
	Correlation Coefficient	0.05	0.00
	Reflectivity & Velocity	2.30	0.89
	Velocity & Correlation Coefficient	0.12	0.00
	Velocity & Echo Tops	0.01	0.00
	Hydrometer Classification	0.04	0.00
	Velocity, reflectivity, & CC	0.06	0.20
	Reflectivity & Correlation Coefficient	0.02	0.00
	Satellite	0.00	0.00

Storm Videos			
		% In Warn Time	**% Out of Warn Time**
Storm Video	Storm Itself	0.72	6.34
	Debris	0.00	0.30
	Shelter/Protective Actions	0.02	0.10
	Impacts	0.04	0.30
	Storm Alert Broadcast	0.07	0.10
	Storm itself & Alert Broadcast	0.05	0.10
Storm Video Information	Time	0.01	0.10
	Location	0.20	2.87
	Time & Location	0.07	0.20
	Radar & Polygon	0.01	0.00
	None	0.60	4.06

News/ Weather Broadcast			
		% In Warn Time	**% Out of Warn Time**
News Broadcast	Yes	0.08	0.00
	No	99.92	100.00
Time Included	Yes	0.08	0.00
	No	0.02	0.00
Location Type	Street	0.00	0.00
	County	0.00	0.00
	City	0.01	0.00
	Latitude/Longitude	0.00	0.00
	Landmark	0.00	0.00
	City & County	0.06	0.00
	City, County, & Landmark	0.02	0.00

	City, County, & Road	0.01	0.00
Radar Data Type	Reflectivity	0.06	0.00
	Velocity	0.01	0.00
	Correlation Coefficient	0.00	0.00
	Reflectivity & Velocity	0.04	0.00
Video of Storm/Live Feed	Yes	0.00	0.00
	No	0.11	0.00
Polygon Color	Red	0.09	0.00
	Orange	0.00	0.00
	Yellow	0.01	0.00
	Green	0.00	0.00
	Blue	0.00	0.00
	Purple	0.00	0.00
	Pink	0.00	0.00
Polygon Shape	County Based	0.00	0.00
	Storm Based	0.11	0.00
Threat Type	Tornado	0.05	0.00
	Wind	0.00	0.00
	Hail	0.00	0.00
	Flooding	0.00	0.00
	Hail & Tornado	0.01	0.00
	Tornado, Flooding, Wind	0.01	0.00
Action Type	Shelter Immediately	0.04	0.00
	DUCK	0.04	0.00
	Keep Shoes on	0.02	0.00

Written News Story			
		% In Warn Time	**% Out of Warn Time**
Written News Story	Yes	0.33	0.72
	No	99.67	99.28
Location Type	Street	0.00	0.00
	County	0.09	0.10
	City	0.05	0.40
	Latitude/Longitude	0.00	0.00
	Landmark	0.02	0.10
	City & County	0.18	0.69
	Landmark & City	0.00	0.30
	County & Road	0.08	0.00
	City, County, Road	0.04	0.10
Time Included	Yes	0.39	1.49
	No	0.07	0.50

Link to other site Included	Yes	0.08	0.10
	No	0.38	1.88
Action Type	Shelter Immediately	0.09	0.40
	Go to Lowest Floor	0.00	0.00
	Shelter In Place	0.01	0.00
	DUCK	0.05	0.30
Threat Type	Tornado	0.13	0.10
	Wind	0.00	0.00
	Hail	0.00	0.00
	Flooding	0.01	0.00
	Hail & Tornado	0.02	0.40
	Hail, Tornado, Wind	0.01	0.20
	Tornado & Flooding	0.01	0.20
	Wind, Rain, Lighting, Hail, Tornado	0.05	0.00
Polygon Color	Red	0.08	0.30
	Orange	0.00	0.00
	Yellow	0.00	0.00
	Green	0.00	0.00
	Blue	0.00	0.00
	Purple	0.00	0.00
	Pink	0.00	0.00
Polygon Shape	County Shape	0.00	0.00
	Storm Based	0.08	0.30

Image with Additional Information on Website			
		% In Warn Time	**% Out of Warn Time**
Image With Information Posted on Website	Yes	3.78	9.53
	No	96.22	90.47
Geographical Context Included	Yes	0.00	0.00
	No	5.32	26.36
Time Included	Yes	5.32	26.26
	No	0.00	0.10
Meme	Yes	0.00	0.00
	No	5.32	26.36
Polygon Color	Red	0.08	0.00
	Orange	0.00	0.00
	Yellow	0.00	0.00
	Green	0.00	0.00
	Blue	0.00	0.00

	Purple	0.00	0.00
	Pink	0.00	0.00
Polygon Shape	County Based	0.00	0.00
	Storm Based	0.08	0.00
Action Type	Seek Shelter Immediately	0.00	0.10
	DUCK	0.02	0.00
Threat Type	Tornado	5.21	26.26
	Wind	0.00	0.00
	Hail	0.00	0.00
	Flooding	0.00	0.00
	Hail & Tornado	0.01	0.00
Location Type	Street	0.00	0.00
	County	0.00	0.00
	City	0.00	0.00
	Latitude/Longitude	0.00	0.00
	Landmark	0.00	0.10
	County & City	5.25	26.26
Radar Data Type	Reflectivity	0.07	0.00
	Velocity	0.00	0.00
	Correlation Coefficient	0.00	0.00
	Reflectivity & Velocity	0.00	0.00
Storm Related Image Type	Storm Itself	0.00	0.00
	Debris	0.00	0.00
	Shelter/Protective Actions	0.00	0.10
	Impacts	0.00	0.00

Video/News Broadcast on Website			
		% In Warn Time	**% Out of Warn Time**
Video/ News Broadcast	Yes	0.01	0.04
	No	99.99	99.96
Radar Data Type	Reflectivity	0.00	0.00
	Velocity	0.00	0.00
	Correlation Coefficient	0.00	0.00
	Reflectivity & Velocity	0.00	0.00
Time Included	Yes	0.00	0.00
	No	0.01	0.10
Polygon Color	Red	0.00	0.00
	Orange	0.00	0.00
	Yellow	0.00	0.00
	Green	0.00	0.00

	Blue	0.00	0.00
	Purple	0.00	0.00
	Pink	0.00	0.00
Polygon Shape	County Based	0.00	0.00
	Storm Based	0.00	0.00
Location Type	Street	0.00	0.00
	County	0.00	0.00
	City	0.00	0.10
	Latitude/Longitude	0.00	0.00
	Landmark	0.00	0.00
Threat Type	Tornado	0.00	0.00
	Wind	0.00	0.00
	Hail	0.00	0.00
	Flooding	0.00	0.00
	Hail & Tornado	0.00	0.00
Action Type	Shelter Immediately	0.00	0.10
Video/Live Stream Included	Yes	0.01	0.00
	No	0.00	0.10
Video Content	Cannot be Determined	0.00	0.00
	Storm Itself	0.01	0.00
	Debris	0.00	0.00
	Shelter/Protective Actions	0.00	0.00
	Impacts	0.00	0.00

APPENDIX D: SPATIAL CONTENT ANALYSIS RESULTS

The following tables display the raw results from the content analysis I completed comparing the tweets that were found within the tornado warning polygon and outside the tornado warning polygon. This analysis was only done on the tweets that contained a link.

Storm Related Images			
		% in Warning Polygon	**% Out of Warning Polygon**
Storm Related Image	Storm Itself	0.50	7.90
	Debris	0.00	0.32
	Shelter/Protective Actions	0.56	2.27
	Impacts	0.17	1.01
	Phone/ Storm warning Notification	0.66	4.25
	Forecasting/Monitoring	0.06	2.35
	After the Storm	0.00	0.53
	Warning text from NWS	0.00	0.24
	Storm & Debris	0.00	0.00
Storm Related Image Information	Time	0.43	1.74
	Location	0.19	4.41
	Time & Location	0.10	2.15
	Time, Location, Threat	0.06	0.85
	Time, Location, Radar	0.04	0.85
	Time, Location, Radar, Polygon, Threat	0.04	0.12
	Time and Radar	0.00	0.04
	Time, location, action	0.01	0.12
	time, location, action, threat	0.00	0.12
	None	1.07	8.46

Storm Videos			
		% in Warning Polygon	% Out of Warning Polygon
Storm Video	Storm Itself	0.34	4.05
	Debris	0.01	0.08
	Shelter/Protective Actions	0.03	0.04
	Impacts	0.01	0.20
	Storm Alert Broadcast	0.00	0.28
	Storm itself & Alert Broadcast	0.01	0.16
Storm Video Information	Time	0.00	0.08
	Location	0.11	1.54
	Time & Location	0.00	0.32
	Radar & Polygon	0.00	0.04
	None	0.30	2.84

News/ Weather Broadcast			
		% in Warning Polygon	% Out of Warning Polygon
News Broadcast	Yes	0.00	0.14
	No	100.00	99.86
Time Included	Yes	0.00	0.28
	No	0.01	0.08
Location Type	Street	0.00	0.00
	County	0.00	0.00
	City	0.00	0.04
	Latitude/Longitude	0.00	0.00
	Landmark	0.00	0.00
	City & County	0.00	0.20
	City, County, & Landmark	0.00	0.08
	City, County, & Road	0.00	0.04
Radar Data Type	Reflectivity	0.00	0.20
	Velocity	0.00	0.04
	Correlation Coefficient	0.00	0.00
	Reflectivity & Velocity	0.00	0.12
Video of Storm/Live Feed	Yes	0.00	0.00
	No	0.01	0.36
Polygon Color	Red	0.00	0.32
	Orange	0.00	0.00
	Yellow	0.00	0.04
	Green	0.00	0.00

	Blue	0.00	0.00
	Purple	0.00	0.00
	Pink	0.00	0.00
Polygon Shape	County Based	0.00	0.00
	Storm Based	0.00	0.36
Threat Type	Tornado	0.00	0.16
	Wind	0.00	0.00
	Hail	0.00	0.00
	Flooding	0.00	0.00
	Hail & Tornado	0.00	0.04
	Tornado, Flooding, Wind	0.00	0.04
Action Type	Shelter Immediately	0.00	0.12
	DUCK	0.00	0.12
	Keep Shoes on	0.00	0.04

Written News Story			
		% in Warning Polygon	**% Out of Warning Polygon**
Written News Story	Yes	0.12	0.76
	No	99.88	99.24
Location Type	Street	0.00	0.00
	County	0.04	0.24
	City	0.01	0.28
	Latitude/Longitude	0.00	0.00
	Landmark	0.00	0.12
	City & County	0.06	0.73
	Landmark & City	0.00	0.12
	County & Road	0.01	0.24
	City, County, Road	0.00	0.16
Time Included	Yes	0.14	1.50
	No	0.00	0.57
Link to another site Include	Yes	0.00	0.32
	No	0.14	1.74
Action Type	Shelter Immediately	0.09	0.24
	Go to Lowest Floor	0.00	0.00
	Shelter in Place	0.00	0.04
	DUCK	0.03	0.20
Threat Type	Tornado	0.10	0.20
	Wind	0.00	0.00
	Hail	0.00	0.00

	Flooding	0.00	0.04
	Hail & Tornado	0.01	0.20
	Hail, Tornado, Wind	0.00	0.12
	Tornado & Flooding	0.00	0.12
	Wind, Rain, Lighting, Hail, Tornado	0.00	0.16
Polygon Color	Red	0.04	0.28
	Orange	0.00	0.00
	Yellow	0.00	0.00
	Green	0.00	0.00
	Blue	0.00	0.00
	Purple	0.00	0.00
	Pink	0.00	0.00
Polygon Shape	County Shape	0.00	0.00
	Storm Based	0.04	0.28

Images Posted with Additional Information			
		% in Warning Polygon	**% Out of Warning Polygon**
Image with Information Posted on Website	Yes	7.35	1.80
	No	92.65	98.20
Geographical Context Included	Yes	0.00	0.00
	No	8.55	4.78
Time Included	Yes	8.55	4.74
	No	0.00	0.04
Meme	Yes	0.00	0.00
	No	8.55	4.78
Polygon Color	Red	0.01	0.24
	Orange	0.00	0.00
	Yellow	0.00	0.00
	Green	0.00	0.00
	Blue	0.00	0.00
	Purple	0.00	0.00
	Pink	0.00	0.00
Polygon Shape	County Based	0.00	0.00
	Storm Based	0.01	0.24
Action Type	Seek Shelter Immediately	0.00	0.04
	DUCK	0.03	0.00
Threat Type	Tornado	8.51	4.50
	Wind	0.00	0.00
	Hail	0.00	0.00

	Flooding	0.00	0.00
	Hail & Tornado	0.01	0.00
Location Type	Street	0.00	0.00
	County	0.00	0.00
	City	0.00	0.00
	Latitude/Longitude	0.00	0.00
	Landmark	0.00	0.04
	County & City	8.55	4.50
Radar Data Type	Reflectivity	0.00	0.24
	Velocity	0.00	0.00
	Correlation Coefficient	0.00	0.00
	Reflectivity & Velocity	0.00	0.00
Storm Related Image Type	Storm Itself	0.00	0.00
	Debris	0.00	0.00
	Shelter/Protective Actions	0.00	0.04
	Impacts	0.00	0.00

Video/ News Broadcast

		% in Warning Polygon	**% Out of Warning Polygon**
Video/ News Broadcast	Yes	0.01	0.02
	No	99.99	99.98
Radar Data Type	Reflectivity	0.00	0.00
	Velocity	0.00	0.00
	Correlation Coefficient	0.00	0.00
	Reflectivity & Velocity	0.00	0.00
Time Included	Yes	0.00	0.00
	No	0.01	0.04
Polygon Color	Red	0.00	0.00
	Orange	0.00	0.00
	Yellow	0.00	0.00
	Green	0.00	0.00
	Blue	0.00	0.00
	Purple	0.00	0.00
	Pink	0.00	0.00
Polygon Shape	County Based	0.00	0.00
	Storm Based	0.00	0.00
Location Type	Street	0.00	0.00
	County	0.00	0.00

	City	0.00	0.00
	Latitude/Longitude	0.00	0.00
	Landmark	0.00	0.00
Threat Type	Tornado	0.00	0.00
	Wind	0.00	0.00
	Hail	0.00	0.00
	Flooding	0.00	0.00
	Hail & Tornado	0.00	0.00
Action Type	Shelter Immediately	0.00	0.00
Video/Live Stream Included	Yes	0.01	0.00
	No	0.00	0.04
Video Content	Cannot be Determined	0.00	0.00
	Storm Itself	0.01	0.00
	Debris	0.00	0.00
	Shelter/Protective Actions	0.00	0.00
	Impacts	0	0