Assessing the Value of Crowdsourced Data in Aiding First Responders: A Case Study of the 2013 Boston Marathon

by

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A Thesis Presented to the
Faculty of the USC Graduate School
University of Southern California
In Partial Fulfillment of the
Requirements for the Degree
Master of Science
(Geographic Information Science and Technology)

August 2018

To my children: Donovan, Fiona, and Malcolm

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Acknowledgements

I am grateful to my advisor, Dr. Darren Ruddell, for his guidance and to my other faculty who gave me assistance when needed. I am also indebted to the first responder interviewees who generously shared their experiences and opinions. Finally, I would like to thank my wife, Susannah Howieson, who pushed me to always do better; without her support I would not have made it this far.

List of Abbreviations

AGI	Ambient Geographic Information
API	Application Program Interface
EMS	Emergency Medical Services
FBI	Federal Bureau of Investigation
GIS	Geographic information system
GISci	Geographic information science
IED	Improvised Explosive Device
IRB	Internal Review Board
JMA	Japan Meteorological Agency
MIT	Massachusetts Institute of Technology
NED	New event detection
OSM	OpenStreetMap
RED	Retrospective event detection
SMI	Social Media Ingestor
SSI	Spatial Sciences Institute
SVM	Support vector machine
US	United States
USC	University of Southern California
USGS	United States Geological Survey
VGI	Volunteered Geographic Information

Abstract

Terrorism continues to be one the most significant security threats of our time. Recent terrorism events include mass shootings and bombings in the U.S. and worldwide. First responders—law enforcement, emergency medical services, and fire services—are responsible for managing the chaos in the immediate aftermath of a terrorism event. Providing first responders with high quality, detailed information as quickly as possible could greatly enhance their ability to respond effectively. Recently, crowdsourced data available through platforms such as Twitter, Facebook, and other social media outlets, have emerged as a potential source to aid first responders following a terrorism event. The focus of this thesis is to determine if Twitter posts are a useful source of intelligence for first responders. Mining this readily available data could also be useful following a natural disaster.

The utility of twitter data for first responders was explored using a case study of the events following the Boston Marathon bombing in 2013. Twitter data was collected via GNIP, a social media API aggregation company. Through text analysis and interviews with first responders, a list of relevant keywords was developed. Kernel density was used to determine density of tweets in relation to events that took place from April 15th through April 19th, 2013. Spatio-temporal analysis was conducted to show when and from where tweets were being sent on April 15th, 2013. Results show that on Monday through Thursday the greatest density of tweets was surrounding the bombsites; when events related to the suspects occurred on Thursday and Friday, the density of tweets around those events increased. The spatio-temporal results show that as the day progressed, the majority of tweets spread throughout the Boston Metropolitan area. The overall finding of this thesis is that crowdsourced data, such as Twitter, can provide potentially useful information to aid first responders following a terrorism event.

Chapter 1 Introduction

According to Global Terrorism Database (GTD) over 150,000 incidents of terrorism occurred between 1970 and 2015. Some recent terrorism events include the May 2017 bombing of an arena in Manchester, England, United Kingdom, Pulse Nightclub shooting Orlando, Florida, November 2015 Paris Attacks Paris, France, and the 2015 San Bernardino attack San Bernardino, California. Since it is difficult to prevent these tragic events, assistance should be provided to those who respond to mitigate the damage. First responders are those who arrive first to an emergency to render assistance in the capacity of their duties. Time is a valuable asset for first responders. The faster first responders can receive information, the better they are prepared to respond to said situation. Geospatial information in the form of locations or places is one of the important bits of data that is needed to respond to an emergency situation.

The communication of pertinent information via social media could be beneficial to first responders. In the current smartphone age, geospatial data can be shared instantaneously on social media. Social media is a new source of news and information. When incidents occur people immediately post about what they have witnessed or are still witnessing. It is this quick release of data that could be taken advantage of by first responders.

There are many areas in which geospatial intelligence can be beneficial, including for military support, cybersecurity, resource mapping, and disaster response and management. This thesis focuses on whether geospatial intelligence can benefit first responders after a terrorism event using crowdsourced data from Twitter.

1.1. Definitions

In 2003, President George W. Bush released Homeland Security Presidential Directive 8 which defined first responder as “individuals who in the early stages of an incident are responsible for the protection and preservation of life, property, evidence, and the environment, including emergency response providers as defined in section 2 of the Homeland Security Act of 2002 (6 U.S.C. 101), as well as emergency management, public health, clinical care, public works, and other skilled support personnel (such as equipment operators) that provide immediate support services during prevention, response, and recovery operations" (HSPD-8). The Homeland Security Act of 2002 defines emergency response providers as "Federal, State, and local governmental and nongovernmental emergency public safety, fire, law enforcement, emergency response, emergency medical (including hospital emergency facilities), and related personnel, agencies, and authorities" (6 U.S.C. § 101(6)).

Social media contains geospatial information in a variety of ways. It can be done through posts on Facebook, Twitter, YouTube, or other platforms. Volunteered geographic information (VGI) describes any geospatial information that is volunteered through any number of sources, from OpenStreetMap (OSM) to social media. Goodchild (2007) refers to VGI as user-generated geographic information that is volunteered by non-professionals, and therefore may not be as accurate as professionally created spatial data. Stefanidis et al. (2013) argues that geospatial information transmitted by reference only should be called ambient geographic information (AGI). This is because people are not directly volunteering geographic data via social media, but are simply referencing it. These references are the key to gathering spatial information that can provide intelligence to first responders. Crowdsourced data falls into the category of VGI. Many of the terms that describe volunteered involvement relating to geographic information science (VGI, crowdsourcing, AGI) are used interchangeably. This paper uses the term crowdsourced data.

1.2. Motivation

This research is beneficial for spatial sciences because it looks at a relatively new area in which spatial data can be collected. In Stefanidis et al. (2013), the authors suggest that humans are transformed into sensors by reporting real time events through the use of Twitter. Having hundreds if not thousands of different sensors reporting real time events in an emergency situation could give first responders more on-the-ground intelligence.

There may be some downfalls to this data, however, which is why it is an important topic to research thoroughly. The main issue that affects the utility of crowdsourced data is its accuracy. Goodchild and Li (2012) note that the quality of the data is variable and highly undocumented. The unknown quality of data does not preclude using crowdsourced data as data source so long as it is verified. According to Comber et al. (2013), VGI can be accurate if it can be cross-referenced with control data. However, identifying control data in an emergency may be complicated.

It has only been a decade since the term VGI was coined by Goodchild. In that span there have been many studies involving VGI and crowdsourcing. However, there appears to be a gap in the research involving gathering intelligence from social media for use by first responders. There is a lot of the research related to the emergency response and management of an environmental hazard, but not relating to terrorism or other homeland security threats. For example, Crooks et al (2013) used Twitter data to determine an epicenter and the reach of an earthquake in Virginia in 2011. Another paper by Mills et al. (2009) discusses how Twitter can be used as an emergency communication system. The authors describe first responders using social media to communicate to the public, rather than the other way around. There is a lack of research conducted on the effectiveness of using crowdsourced data to inform first responders.

1.3. Objectives

It is important for first responders to use any and all sources of potential information. It could be beneficial for first responders to use crowdsourced data that contains either volunteered or referenced geospatial information. The overall goal of this study is to determine if crowdsourced data could aid first responders during a terrorism event. The study investigates the following objectives:

(1) What type of information is found in crowdsourced data during a terrorism event

(2) What type of information within crowdsourced data could be useful to first responders during a terrorism event.

(3) How geospatial information is included in crowdsourced data during a terrorism event.

(4) How timely is the information found in crowdsourced data during a terrorism event.

This study uses on Twitter data from the Boston Metropolitan Area during the events related to the 2013 Boston Marathon bombing. Through text analysis, interviews, spatial analysis, and spatio-temporal analysis this study examines if crowdsourced data can aid first responders during a terrorism event. If this paper shows that crowdsourced data contains valuable geospatial intelligence, first responder agencies could set up systems to automatically harvest relevant information in case of terrorism or other homeland security event.

1.4. Boston Marathon and Bombing Events

The Boston Marathon is an annual race held on the third Monday of April. The Boston Athletic Association sponsors the 26-mile 385-yard race, which started in 1897. In 2013, the race had its 117th running with 26,839 entrants. The event attracts 500,000 spectators making it New England’s most viewed sporting event (Boston Athletic Association).

This thesis is using the Boston Marathon bombing events in Boston, Massachusetts (Figure 1) as a case study. The events surrounding the Boston Marathon bombing lasted 5 days from April 15th, 2013 to April 19th, 2013. On April 15th at 2:49 p.m., during the annual running of the marathon, the first of two bombs was detonated at 671 Boylston Street; the second bomb was detonated thirteen seconds later at 755 Boylston Street (After Action Report 2014). Homemade improvised explosive devices (IEDs) hidden in backpacks caused the explosions. The bombs took the lives of three individuals and injured 264 more (After Action Report 2014). On April 18th, the Federal Bureau of Investigation (FBI) released photos of the two suspects. That evening a Massachusetts Institute of Technology (MIT) Police Officer was fatally shot in his marked police vehicle on the MIT campus in Cambridge, MA (After Action Report 2014). Later that same night, the suspects committed a carjacking in the Allston neighborhood of Boston. Before 1 a.m. on the 19th, Watertown, MA police responded to the location of the carjacked vehicle and engaged in a firefight with the suspects, where one of the suspects was killed and the other suspect escaped. The evening of April 19th, Watertown police received a 911 call from a resident reporting he saw the suspect in a boat parked in his yard at 67 Franklin Street (After Action Report 2014). Police responded and took the suspect into custody at 8:41 p.m.

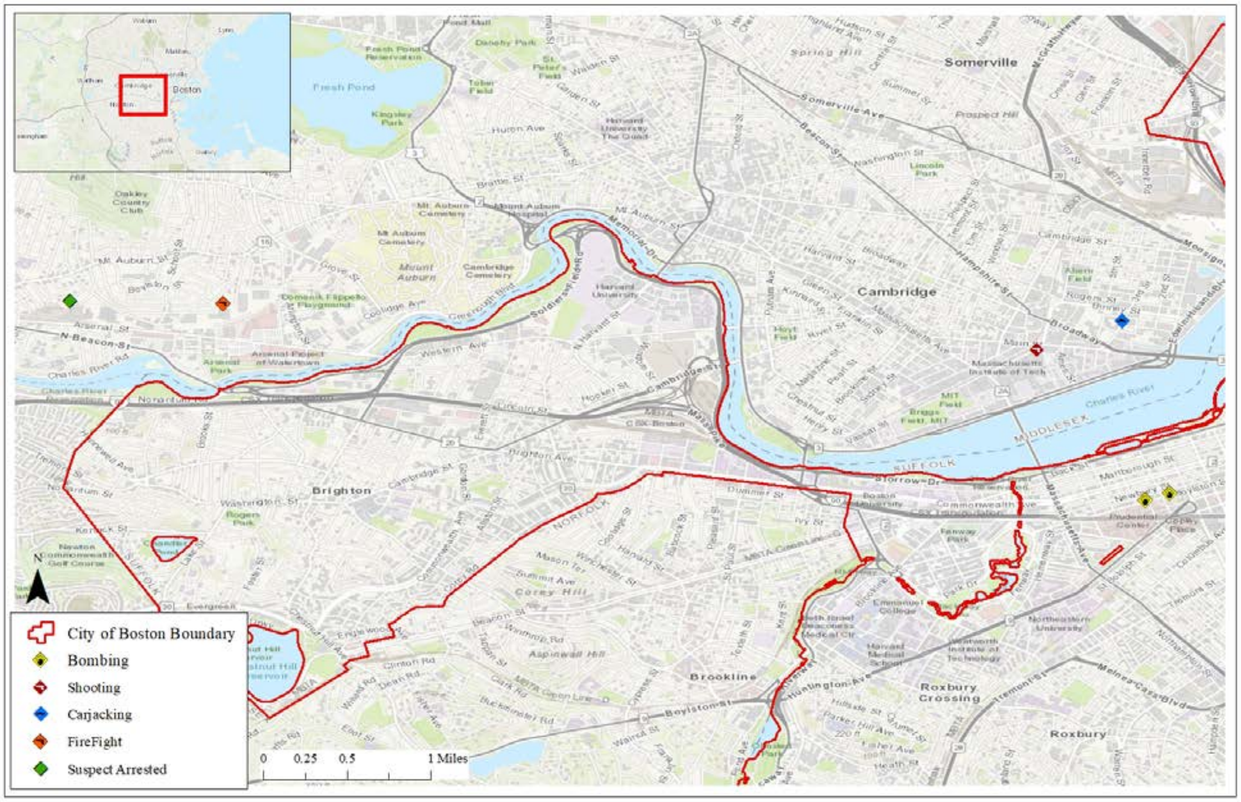

Figure 1 Events Surrounding the 2013 Boston Marathon Bombing

1.5. Study Area

The major events took place in Boston, Cambridge, and Watertown, Massachusetts. These cities are part of the Boston metropolitan area, which has a population over 4 million. The events are all within a 10-mile radius of the bombing event. This thesis studies a 25-mile radius around the Boston Marathon finish line (Figure 2). This area was chosen because the suspects' location was unknown at the time of the bombing and all the events fell within this area.

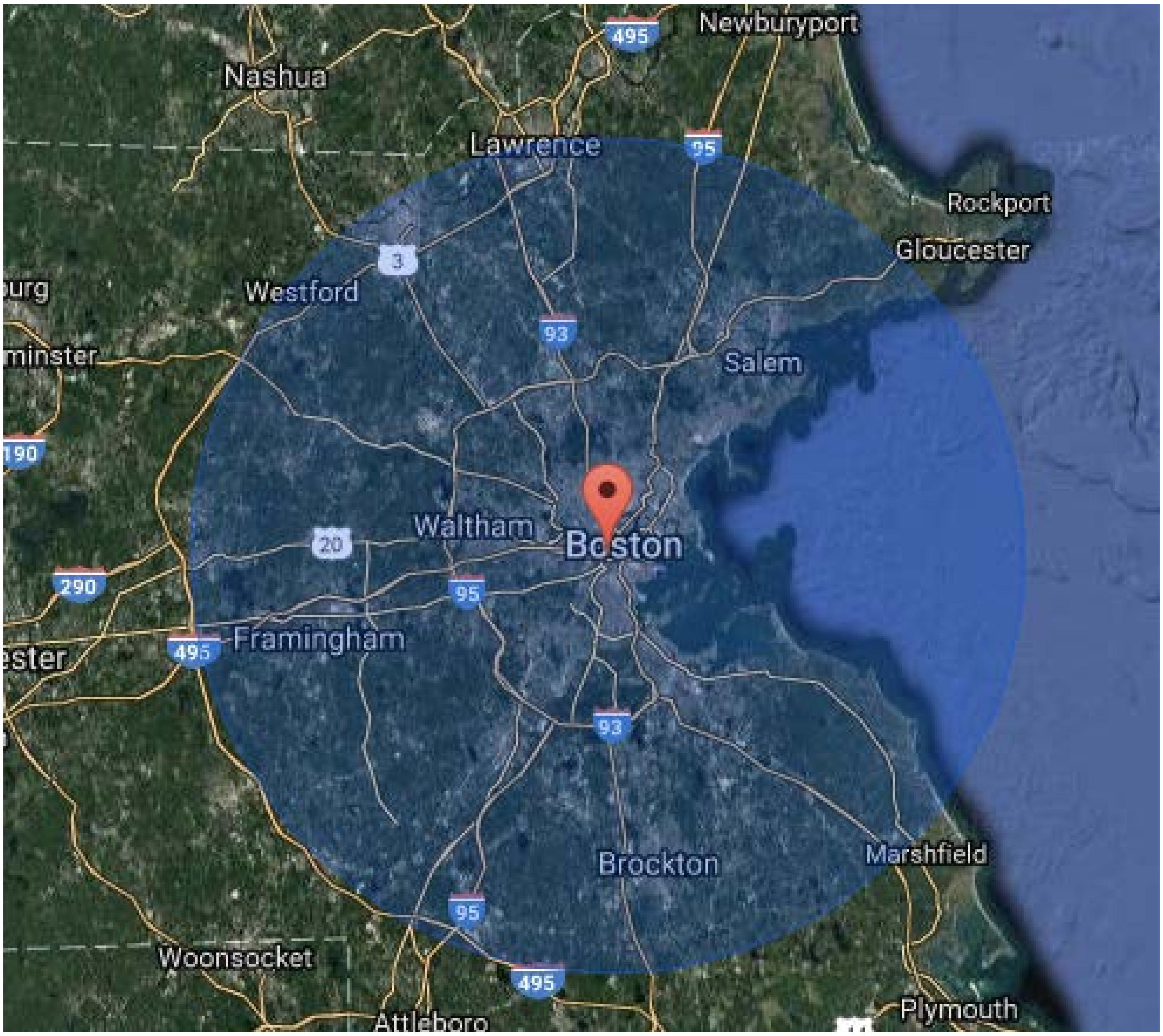

Figure 2 Twenty-Five Mile Radius Around Boston Marathon Finish Line

1.6. Thesis Outline

Following the concepts in the introduction, there is a review of the related literature, methodology for assessing the use of Twitter data by first responders, results of the analyses, and discussion of the findings.

In Chapter 2, related literature is reviewed. To be able to assess the usefulness of Twitter in this study, previous studies in crowdsourcing are discussed. These studies focus on event detection using Twitter and similar platforms. This chapter ends with a section on data quality, which is a key concern working with VGI, such as crowdsourced data.

In Chapter 3, a methodology is presented. First this paper discusses the gathering of Twitter data from a third party. Approval from USC's Internal Review Board (IRB) was needed to conduct interviews. Keyword development was based on text analysis of the Twitter data and responses from interviews. Finally, it describes using kernel density for spatial analysis, and tweet time stamps and coordinates to show spatio-temporal analysis.

Chapter 4 shows the results of text analysis and interviews used to establish keywords for searches of geotagged tweets. The spatial analysis shows density of relevant geotagged tweets to the events. The spatio-temporal analysis presents the relationship between time and space of the relevant tweets.

Chapter 5 discusses conclusions from the results and takeaways from the overall process of the thesis. This chapter also explores the limitations of the methods and suggests improvements for future work. Lastly, it gives recommendations for future study and describes how this project can potentially provide insight to future efforts to use Twitter for intelligence gathering.

Chapter 2 Related Work

Crowdsourced data has been shown to be a useful source of information with event detection. However, there does not seem to be literature on crowdsourcing for intelligence gathering purposes as it relates to first responders. This thesis will follow similar processes of some of the research discussed in this chapter.

2.1. Crowdsourced Data

Crowdsourced data falls into the category of VGI. Goodchild (2007) was the first to coin the term VGI, which describes an information-gathering process that uses people who have no formal qualifications to voluntarily collect geographic information. Examples of VGI include OpenStreetMap (OSM), Twitter, and "Did you Feel it".

Building on Goodchild's concept, Stefanidis et al. (2013) suggest the use of social media produces a new form of VGI that they call ambient geographical information (AGI). People using social media are not directly providing the geospatial information, but still transmit it in a variety of ways. Geospatial information in social media posts can be geotagged (contain coordinates) or can refer to place (e.g. Boston, MA). It is through crowdsourced data that geospatial information can be harvested for the first responders.

There have been multiple studies in which crowdsourcing geographic information is discussed. Crowdsourcing is a process of acquisition and analysis of big data generated by a diverse number of sources (Xu et al. 2015; Xu et al. 2016). With advances in technology such as the smartphone, millions of people globally now have the capability to create and share geospatial data, whether its active (updating OSM) or passive (geotagged tweet) in nature.

Many of the terms that describe volunteer involvement relating to geographic information science (GISci) (VGI, crowdsourcing, AGI) are used interchangeably (See et al. 2016; Spyratos et al. 2014). This paper uses the term crowdsourced data for geotagged tweets.

2.1.1. OpenStreetMap

One example of the power of VGI is OpenStreetMap. OSM began as an open-source street map of the world. It is an open-source application that anyone can contribute to. The contributions come in the form of adding and updating data about roads, trails, cafés, railway stations, and more. OSM is one of the best-known forms of crowdsourcing of geospatial data (Heipke 2010; Goodchild and Li 2012). Over the last decade, OSM's number of users has grown in excess of 4 million (https://www.openstreetmap.org/stats/data_stats.html). This allows for mass amounts of crowdsourced geospatial data to be shared and edited.

OSM has the ability to aid in natural disasters. After the 2010 Haiti earthquake, OSM was used to provide rescue workers with geospatial data. A detailed city map of the Haitian capital, Port-au-Prince, containing bridges, functioning infrastructure, and damaged buildings was completed a few days after the earthquake (Heipke 2010). The ability to have a volunteer service with firsthand knowledge of an area can allow for more comprehensive mapped areas. However, completeness of an area depends on the population density, and more affluent areas are better mapped then more deprived areas (Heipke 2010). In many situations, OSM can produce a detailed, user-generated up-to-date map.

2.1.2. Twitter

Twitter is a micro-blogging application that began in 2006. It is currently the most popular micro-blogging service, and is the eighth most popular site (from 2012) in the world according to the three-month Alexa traffic rankings (Atefeh and Khreich 2015). Twitter allows users to submit posts (tweets) containing 140-characters. These tweets are automatically posted as a stream on the user's profile and shared with the user's network of followers. Posts can be made using Twitter's mobile app or via their website. These posts contain a wide variety of topics, from sports, politics, and natural disasters. According to Twitter's website (https://about.twitter.com/company), there are currently 328 million active users, with 79 percent outside the United States. Like other forms of crowdsourcing social media feeds, Twitter can provide geographic information, whether it is from geotagged tweets or a reference to a location in a tweet. Geotagged tweets are where coordinates are embedded into a tweet. However, this feature's default is off so users have to turn it on.

Unlike OSM, social media feeds are not a source where people purposely contribute geographic information to update or expand a geographic database (Crooks et al. 2013). Twitter users share geographic information actively by mentioning place or passively through geotagged tweets. This is why Stefanidis et al. (2013) coined the term AGI, because people are not directly volunteering geographic data but they are still creating it. Twitter has consequently become a new potentially valuable source of geographic information. Twitter users are the sensors that generate this information (Crooks et al 2013; Sakaki et al. 2013). With hundreds of millions of users, there is potential to collect geographic information about a single event from multiple sensors.

2.2. Event Detection

Being able to detect an emergency or major event is not a simple task. It takes a lot of information to know when, what, and where an event is taking place. One of the areas in which social media data is currently being used is event/emergency detection (Gulnerman and Karaman, 2017). The increased use of social media during crises allows for information to be used by authorities during emergencies (Yin et al. 2012). Spatial and temporal information can be extracted from social media to detect real-time events (Xu et al. 2015). Since this a newer area of study, event detection from Twitter creates new challenges (Atefeh et al. 2015). It is by overcoming these challenges that this emerging field can prove helpful in event detection.

Environmental disasters affect every part of the globe, and come in many different forms. They require geospatial information to prepare for, monitor during, and respond to. Kongthon et al. (2012) mention that Twitter has had a growing role as a collector and distributor of information regarding emergencies and disasters such as wildfires, floods, hurricanes, earthquakes, and tsunamis. Through the use of crowdsourced data like Twitter posts, pertinent information can be gathered about environmental disasters. This data can then be used by agencies to respond to these disasters. The focus of this thesis will be on geospatial information taken from Twitter.

Earthquakes are one of the most unpredictable disasters, which is why it is important to collect information on the extent of an event. One of the earliest forms of crowdsourced geospatial data relates to earthquakes. This is the United States Geological Survey's (USGS) "Did You Feel It?" project (http://earthquake.usgs.gov/earthquakes/dyfi/) that gathers information from people who felt an earthquake (Heipke 2010; Crooks et al. 2013). Through the use of social media data can be gathered real time by those affected by earthquakes.

Twitter can also be a used to gather data on earthquakes according to a number of sources (Sakaki et al. 2010; Crooks et al. 2013; Sakaki et al. 2013; Stefanidis et al. 2013). These sources refer to users as sensors sending out information in regards to the earthquakes they felt.

Sakai et al. (2010) investigate the real-time nature of Twitter, as it pertains to earthquakes. Data was gathered using Twitter's application program interface (API), and then was classified as positive or negative via a support vector machine (SVM) algorithm based on the content of the tweets. They use particle filtering to estimate the locations of earthquakes, between August and October 2009. Particle filtering is an algorithm maintains a probability distribution for the location estimation. They were able to create location estimates for 25 earthquakes from 621 tweets. They then developed an earthquake detection system. In Sakai et al. (2013) an update to their previous research they reported on their system "Toretter". Their system was able to detect 93 percent stronger earthquakes than the Japan Meteorological Agency (JMA) scale. However, the precision is low and the system can produce a lot of false-positives. The authors admit they need to change certain conditions to gain better precision.

Crooks et al. (2013) analyze the spatial and temporal characteristics of Twitter activity responding to an earthquake that occurred on the east coast of the United States in August 2011. Their analysis consists of a three-step process of harvesting. These steps are extract data through a providers API, store data in a local database, and analyze the data for information of interest. They received a 1 percent random sample filtered within the contiguous 48 states over an eight-hour period after the earthquake. From the sample 144,892 tweets referenced earthquakes and 21,362 were geolocated with coordinates. They show that tweets on the event appeared in locations two to three minutes before the seismic wave. Through further analysis of tweets within the first ten minutes they are able to approximate an impact area (Crooks et al. 2013). This study shows that social media can be used to analyze the extent of the earthquake from its epicenter.

Harvesting AGI from social media is the topic of the Stefanidis et al. (2013) paper. They gather data through provider APIs and process it with their prototype system Social Media Ingestor (SMI). The SMI analyzes the data to extract content of interest (tweets on earthquake), and then inserts it into a database. Twitter data was collected on the Sendai earthquake in March of 2011. Their analysis was able to identify two major distributors of information (users: NHK_PR, asahi_tokyo); NHK_PR is a national news organization, and asahi_tokyo tweets about local information. The data analyzed can identify clusters of users who share interests; with these shared interests the main providers of information can distribute that information to large groups of users. It is through the distribution of tweets from popular users that allows for the collection of useful information on natural disasters.

Floods affect populations all over the world every year. As a hazard floods pose a seasonal and extended time period threat (Palen et al. 2010). It is because of this seasonal/ extended threat that social media like Twitter can be a successful tool in preparing for and responding to floods. Kongthon et al. (2012) suggests that Twitter has played an increasing role in distributing information for emergencies such as floods. Floods are another disaster where Twitter can be used to gather and distribute information about.

Starbird et al. (2010) and Palen et al. (2010) use the same data in researching the flooding of the Red River Valley in early 2009. Both articles refer to the micro-blogging of Twitter as computer mediated communication (CMC). The purpose of their research is to analyze CMC in relationship to an emergency event (Red River Valley flood). They collected data from a 51 day period between March and April 2009 via Twitter's API. The keywords *red river and redriver* returned 4,983 unique authors and a second search to collect the entire stream for each user resulted in 4,592,466 tweets. Data was produced in different geographical locations, and relative distance from the event. Local users or those connected another way to the area provided data about the floods. Some regular users posted almost exclusively on flood-related matters during critical times (Palen et al. 2010). This information came from original posts, to sharing information from other posts/users. The authors suggest that official information remains important and is complemented by social media communications.

Analyzing the role Twitter played in 2011 floods in Thailand was the focus of Kongthon et al. (2012) paper. Thailand is a country prone to flooding during the rainy season. During this period Twitter traffic in Thailand grew over 50 percent. For their research they collected 175,551 tweets with a keyword hashtag #thaiflood, this was narrowed down to 64,582 after removing retweets and duplicates. The tweets then were separated into five categories: situational announcements and alerts (39.1 percent), support announcements (10.2 percent), requests for assistance (8.4 percent), requests for information (5 percent), and other (37.3 percent). Government agencies receiving real-time information could use it in combination with requests for assistance to provide help in a timely manner. Most of the top users during this period are flood/disaster related government or private organizations. This allowed for citizens to choose which sources of information they would follow during the flood to obtain the most relevant, up-to-date, and credible information. The authors conclude that Twitter is effective tool for Thai citizens to obtain and distribute real-time information during a disaster. However, like other forms of VGI data quality is a main concern.

Social media has the ability for information to be distributed faster than standard forms of communication. According to Yin et al. (2012), research was to use Twitter data to provide near-real-time-data on an emergency situation. Using the Twitter API to search the Australia, and New Zealand regions they collected 66 million tweets. Their data covered a wide variety of topics such as cyclones, earthquakes, and floods. The data was processed using various methods, including burst detection, text classification, online clustering, and geotagging. Burst-detection method continuously monitors a Twitter feed and alerts when it detects an incident. This method was able to have a detection rate of 72.13 percent with a false alarm rate below 2 percent. Text classification used naive Bayes algorithm (86.2 percent detection rate) and SVM (87.5 percent detection rate) to extract useful data, while also removing a list of stop words. Online clustering uses an algorithm that groups tweets by similar topics. For geotagging they employ a tweet's coordinates or the location information from the user's profile. Through the public's collective intelligence, proper authorities could better understand critical situations, and make the best decisions for deploying aid, rescue, and recovery operations

Atefeh and Khreich (2015) discuss different types of techniques that have been used for event detection with Twitter. The first technique classifies unspecified and specified event detection. An unspecified detection relies on the temporal signal of Twitter to detect an event, while specified detection relies on specific information that is a known event. The authors classify tweets into retrospective event detection (RED) and new event detection techniques. Last they categorized tweets into supervised and unsupervised (or both) techniques. Unspecified events are generally detected by exploiting the temporal patterns in Twitter streams. These streams can have a sudden increase in the use of specific keywords. Specified events include known or planned events, and they could be partially or fully specified with the relation to content, and metadata (location, time, and venue). New event detection involves continuous monitoring of Twitter streams for new events in near real time. This is best suited for detecting unknown events. Twitter's historical data is best suited for RED techniques. The unsupervised technique focuses on clustering, while the supervised technique uses classification algorithms such as SVM. The authors believe that Twitter provides valuable user generated content. However, all the data has to be filtered and classified into the many event techniques.

Xu et al. (2015) focus on emergency event detection via crowdsourcing. Weibo, a Chinese micro-blogging service similar to Twitter was used to conduct the research. The authors propose their 5W model of What, Where, When, Who, and Why. This model is very basic in identifying an emergency event. “What” is to identify what happened during the event. “Where” is for locating the event. “When” is for creating a timeline of the event. “Who” identifies person in different roles during the event. “Why” allows for information to be given for response. In identifying a fire in Guangzhou their search returned 246 messages relating to a fire. Of this 246, 21 messages satisfied the “what” criteria and had location information, check-in information, and an image. The “where” was taken from 12 of the 21 messages that identified Beijing Road as the location. When was taken from the messages timeline, first message appearing at 15:24 and the last message at 16:41. The reason (Why) for the fire was damage to the electric wiring in an old house; an official user posted the information (police of Guangzhou). The authors show spatial data can be taken from social media for event detection and that their 5W method can be accurate and effective.

Xu et al. (2016) conducted a follow up study using a knowledge base approach to be able to detect an emergency event. A knowledge base system uses an algorithm that has the ability to filter the noise and redundant information of social media. The knowledge base design is based on keywords, patterns, sentences, keyword graphs, and temporal features. The authors suggest a three-layer method (social sensor, crowdsourcing, and knowledge base). The method is then separated into three steps, selecting candidate messages, creating semantic, temporal, and spatial information from the messages, and adding temporal feature to knowledge base. There are four principles that guide candidate message selection. Messages are selected from Weibo using keywords; these words are weighted depending on their importance. A fire event occurred

Beijing Road on May 29, 2014 in Guangzhou. Five keywords were used which returned 246 messages with 21 messages complying with the four principles. These messages were used to build a knowledge base. Spatial and temporal data was taken from the 21 messages gibing five spatial locations and six time stamps that coincide with the changing of the event. The author's proposed knowledge base algorithm showed good performance and effectiveness in the detection of emergency events.

Another example on how Twitter can be used for event detection is the attempted coup on July 15th 2016 in the Republic of Turkey. The coup failed because the rogue military members lacked access to mainstream and social media (Esen and Gumuscu, 2017). It was the Turkish people who helped stop the coup. They took to Twitter to mention jet and tank sightings occurring in Ankara and Istanbul (Unver and Alassaad, 2016). It is through the use of social media that the locations of rogue troops were know.

Unver and Alassaad (2016) compared social media data to data on mosques that used loud speakers to broadcast salah prayers to mobilize against the coup. They used algorithms that collected social media and open source data with a high level of spatial and temporal accuracy. Their analysis showed that there was a notable mobilization against the coup an hour before President Erdogan suggested it. The digital resistance of the coup over Twitter started because a military blockade of a bridge in Istanbul, at the same time mosques started to play the salah prayers. Their analysis showed that the social media mobilization had roughly the same geospatial networks as the mosques' 300-meter loudspeaker radii. Their conclusion was that social media played a role in the victory of the over the failed coup.

Monitoring to coup attempt in Turkey by comparing social media data to traditional media data is the focus of Gulnerman and Karaman (2017). The use geotagged tweets from a ten-hour period from within the boundary of Istanbul, comparing it to spatial data that was published in the news. There were thirty-nine events that were identified. They used hot-spot analysis to compare tweet density to traditional media data. They conducted text analysis to create a list of keywords. Some of the of the thirty-nine events had limited number of keywords. The results of their study show that the social media density does not always match up with the events mentioned in traditional media. They conclude that social media can be a source for event detection, but there needs to be further study on accuracy control.

2.3. Terrorism

The reaches of terrorism have no boundaries; it can happen any place and any time. There are a multitude of reasons for an individual to commit an act of terrorism. According to the FBI, terrorism is split into two categories, international and domestic. They define international terrorism being “perpetrated by individuals and/or groups inspired by or associated with designated foreign terrorist organizations or nations (state-sponsored).” While domestic terrorism is “perpetrated by individuals and/or groups inspired by or associated with primarily U.S.-based movements that espouse extremist ideologies of a political, religious, social, racial, or environmental nature.” (FBI, 2016).

With emerging technologies terrorist events can be detected and planned. When dealing with terrorism Twitter can be beneficial in identifying threats, but also can be a facilitator in coordinating terrorist activities (Cheong and Lee, 2011). In a study by Oh, Agrawal, and Rao (2010) they showed that Twitter indirectly contributed to situational awareness of terrorists during the 2008 Mumbai terrorist attacks. This was because operational sensitive information was exposed via Twitter. In another study by Cheong and Lee (2011) simulated terrorist events were used by randomly injecting terrorist related keywords into original tweets surrounding two events. The clustering of tweets around and during their scenarios can chronicle civilian response. Their framework can be used in real-world situations by agencies to immediately record and respond to terror events. This has the ability can give first responders the information they require to respond appropriately.

2.4. Data Quality

The use of VGI as a tool that gather geospatial information from multiple sources can be useful. The question is whether that information is actually useable. Data quality with VGI has been a concern from the beginning. Data quality is a major concern, because volunteered information does not have assurances officially created data has (Goodchild & Glennon, 2010). Volunteered geographic information offers an alternative for the acquisition and gathering of geographic information. Goodchild & Li (2012) believe VGI suffers from a general lack of quality assurance. The reason data quality is an issue is that anyone can delete or modify data, and the data entered may not be accurate. Comber et al. (2013) mention the main issue with VGI is the unknown quality, but in their study of land cover it can be used as long as it is linked to control data.

While the quality of VGI may always be questionable, social media data is full of misinformation. This is one area that may hinder the effectiveness of VGI as an intelligence source. In the aftermath of the 2013 Boston Marathon bombing, there was some misinformation. Starbird et al. (2014) showed that misinformation was circulated via twitter after the bombing. Tapia et al. (2014) showed that a crowdsourced investigation fueled misinformation and was further amplified by the nature of retweeting and social media. The problem that will be faced is that people will continue to post information that is not accurate. This can delay the response to the actual emergency. While relying on the public to give spatial information, the concern is whether it is accurate.

The research that is currently available on VGI covers a range of issues. However, there is little focused on intelligence gathering for first responders. The research on using social media for intelligence highlights the issues with volunteered information. That issue is the accuracy. While VGI can be a source of geospatial information, it needs be evaluated further for authenticity.

2.5. Conclusion

The advancement of technology over recent years VGI has given geographic information system (GIS) a new sensor for collecting spatial information. The wide variety in which VGI is available allows for many types of user driver content, from OSM to Twitter. Volunteered Geographic information has taken a step further into the realm of crowdsourcing. With social media accessible around the world millions of people are able to share geospatial information.

Crowdsourced information is slightly different from basic VGI, as it is not actively shared. One of the leading sources of this data is Twitter, with millions of active users and billions of tweets shared. Through crowdsourcing natural disasters have the ability to be monitored, responded, and even detected in near real-time. It is through the use of Twitter this thesis will attempt to gather pertinent information that can be valuable to first responders.

Chapter 3 Methodology

This chapter details the methods used to determine if crowdsourced Twitter data can be a useful source of intelligence for first responders. The methods that will be used in this thesis will follow a mixed methods approach by using both qualitative and quantitative data. First, Twitter data was collected, filtered for time relevant and geotagged data. Then, a text analysis of the data and interviews with first responders were conducted for keyword development. With this information spatial, and spatio-temporal analysis was conducted.

3.1. Twitter Data Analysis

There are two ways in which Twitter data could be collected for this thesis. The first option was to write your own API to harvest tweets, users, entities, and places directly from Twitter. However, using Twitter's API only allows you to go back seven days. The other option was to get Twitter data through a third party. This study acquired Twitter data through GNIP, which is Twitter's enterprise API platform (gnip.com). Using a third party to collect Twitter data allowed for easier acquisition of data, because it did not require learning programming language for an API request.

GNIP is a social media API aggregation company that collects data from various social networks (GNIP 2017). GNIP allows access to Twitter's full archive via their PowerTrack. PowerTrack provides customers with the ability to filter a data source's full archive, and only receive the data that they are interested in. Using GNIP's PowerTrack filtering language allows matching of tweets based on a range of attributes. These include user information, geolocation, language, and others. This allows for historic and real-time data analysis.

3.1.1. Obtaining IRB Approval and Requesting Twitter Data

Twitter data has possible identifying information (username, location, etc.). To be able to research this data correctly a USC IRB application was submitted. IRB approval was obtained for the twitter data analysis. Data was obtained through a third party, GNIP.

In order to obtain the data needed for this thesis, review of PowerTrack was needed to determine the best filter(s). Careful consideration was made in the selection of the filter(s) used for data collection; the filter that was selected was point radius. Point radius matches against the exact coordinates (x,y) against a "Place" geo-polygon, where the Place is contained within the defined region (GNIP 2017). This was chosen because the events took place within a ten-mile radius of the finish line (site of explosions). The maximum radius of 25 miles was used with the center point being the finish line with the coordinates coming from Google Earth.

Historical data was requested with a start date of April 15, 2013, the day of the marathon, and an end date of April 20, 2013, the day after the suspect's apprehension. This is because GNIP's timestamps are in Greenwich Mean Time (GMT), which was five hours ahead of Eastern Standard Time (EST). For format, Twitter's native format JOSN was selected. The filter(s) that was applied was point_radius:[-71.07861111 42.34972222 25.0mi].

3.1.2. Twitter Data Receipt, Conversion, and Filtering

Assessing if Twitter can be valuable using keywords from geotagged posts began by receiving 864 gzip (.gz) compressed files from GNIP. Combining and uncompressing was the next step in the process, this yielded 154,915 individual tweets in JavaScript Object Notation (JSON) format (Figure 3). With the data in JSON, it was filtered for the timeframe (14:40 4/15/13 to 21:10 4/19/13) surrounding the bombing events. It was then converted to comma separated values (CSV) format using JSON-CSV.com Desktop Edition. The CSV files were separated into separate days Monday through Friday. There were 117,003 total tweets during the researched time period.

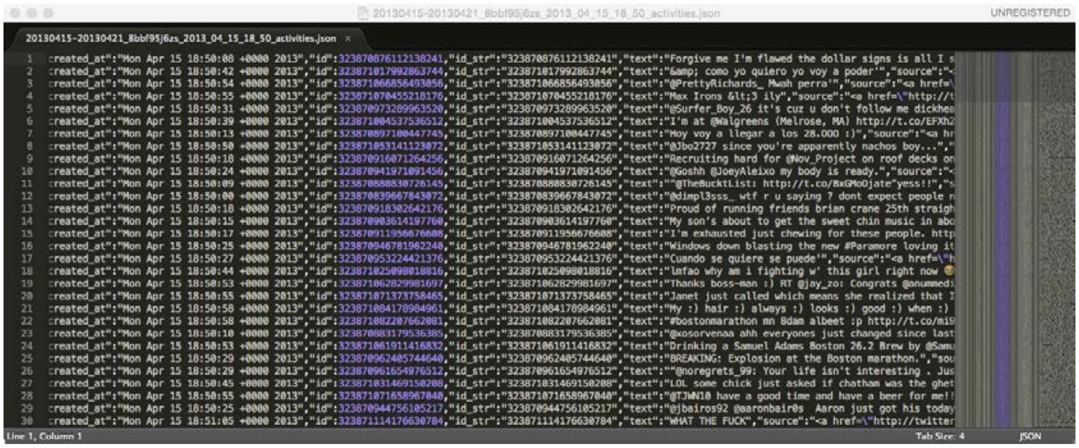

Figure 3 Tweets in JSON Format

Each row representing one tweet potentially contained user name, user screen name, user location, language, tweet, and latitude and longitude. Tweets without latitude and longitude were excluded by filtering in Microsoft Excel. This left a total of 99,756 geotagged tweets during this time period. A breakdown of total tweets and geotagged tweets for each day can be seen in Table 1.

Table 1 Tweets by Day Following Boston Marathon Bombing 2013

	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Total**
	4/15/13 (Begins at 14:40)	4/16/13	4/17/13	4/18/13	4/19/13 (Ends at 21:10)	
Total Tweets	17,653	19,959	21,699	21,876	35,816	117,003
Geotagged Tweets	14,892	17,602	18,899	19,117	29,246	99,756

Geotagged tweets were separated into a new database and visualized in ArcMap 10.5 (Figure 4). The new databases were loaded into NVivo 11 to identify frequency of keywords and Microsoft SQL Server to run queries of keywords. Keywords relevant to Boston Marathon bombing events were determined using the methods described in *Section 3.2*.

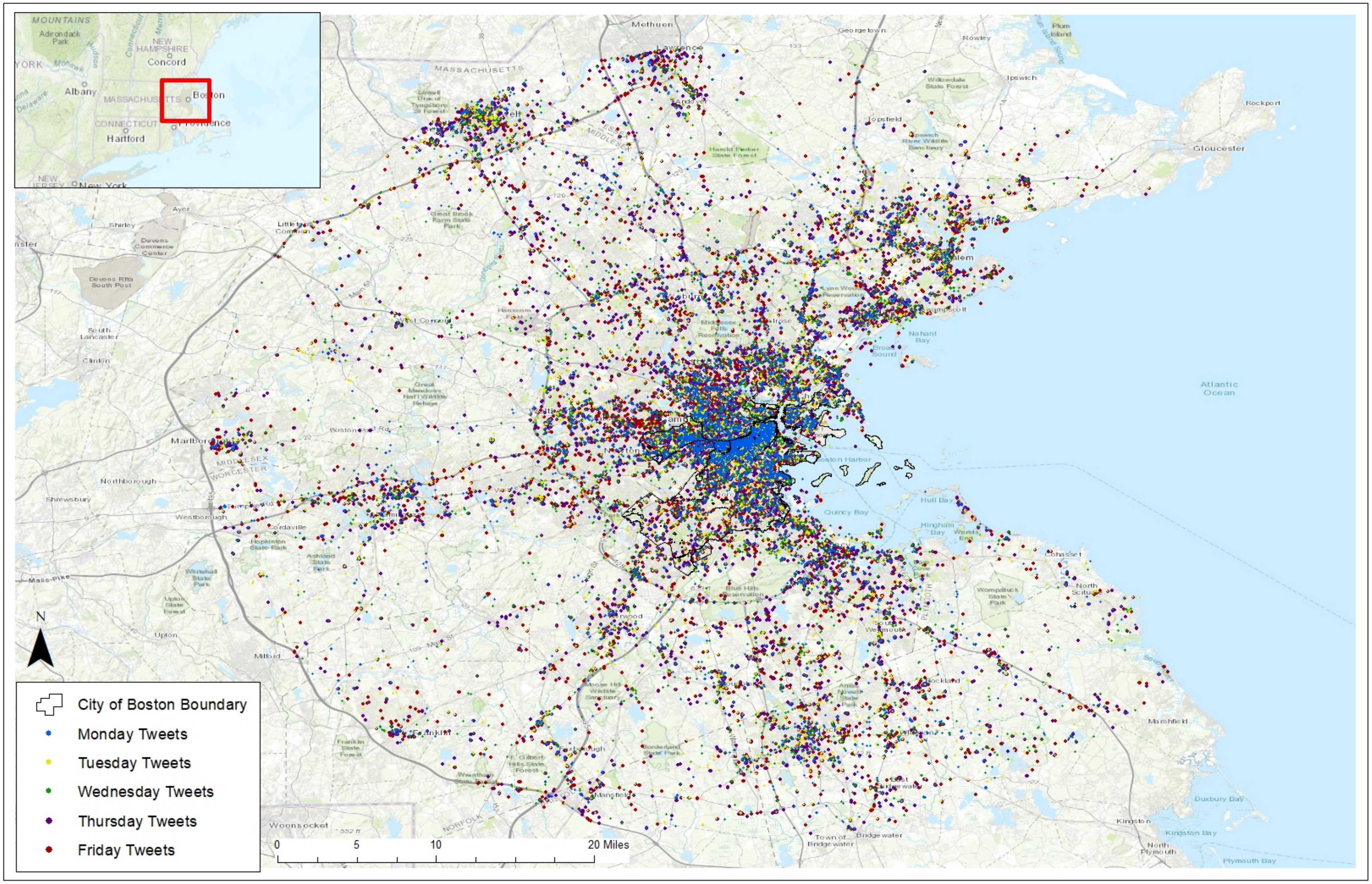

Figure 4 Geotagged Tweets Monday 15 April- Friday 19 April 2013

3.2. Keyword Development

To collect useful Twitter data, keywords need to be determined. The purpose of the interviews is to vet the type and characteristics of the information that would be useful to first responders. Based on the background research and literature review, an initial list was developed. Once the list was revised based on input from interviewees, it was verified using text analysis. A final list of keywords for the twitter data search was then determined.

3.2.1. Text Analysis

In order to validate the interview results, text analysis of the twitter data (see previous section for more information on obtaining and initial processing of twitter data) was performed using NVivo 11. After uploading tweets into NVivo separated by day, searches were run to identify the 500 most frequently used words. Frequency searches were conducted for each day individually and for all five days together. Before using the most frequently used words for the keyword determination. Irrelevant words were removed, including http and lol (text speak for "laugh out loud").

3.2.2. Interviews

Since determining if Twitter data will be useful to first responders is the goal of the project, they were the targeted interviewees. Interviews were conducted with 9 first responders from various agencies across the country (Table 2). Interviewees were from local, state, and Federal agencies that covered law enforcement, EMS, and firefighters. The interviewees possessed different skill sets and experience levels. This diversity allowed for a variety of perspectives, not just the point of view from personnel at a single organization or experience level. Initial candidates were former military law enforcement colleagues. These colleagues are now members of local and Federal agencies, including the Quincy Police Department (Quincy, Massachusetts), St. Louis Fire Department (St. Louis, Missouri), Army Criminal Investigative Division, and FBI. In order to identify additional interviewees, the research relied on the chain-referral approach to sampling interviewees, whereby initial interviewees identify additional ones (Atkinson and Flint 2001).

Table 2 First Responder Interviewees

Date	Position	Organization	Experience
10/12/17	Police Officer	Marine Corps Police Department	5 years
10/15/17	Military Police Sergeant	United States Marine Corps	8 years
10/19/17	Fire Private	St. Louis Fire Department (St. Louis, MO)	1 year 10 months
10/21/17	Special Agent	Federal Bureau of Investigation	1 year
10/27/17	Sheriff's Deputy	Franklin County Sheriff's Office (North Carolina	4 ½ Years
10/29/17	Special Agent	US Army Criminal Investigation Command	2 ½ years 10 years other Law Enforcement
10/30/17	Sheriff's Deputy	Duchess County Sheriff's Office	2 years 3 months 3 years other Law Enforcement
11/2/17	Patrolman	Quincy Police Department	5 years 2 years other Law Enforcement
11/5/17	Patrol Officer	Owatonna Police Department (Owatonna, MN)	4 Years 2 Years other Law Enforcement

3.2.2.1. Creating Protocol, Obtaining IRB Approval, Piloting, and Revisions

An interview protocol for piloting was created based on the background research and literature review. The protocol began with an introduction to the purpose and background of the research project. Interviewees were informed that the interview was completely voluntary and asked for permission to audio record. The topics of the questions were:

- Background, current agency, and position of interviewee
- Experience with emergencies, number and type
- Current use of social media as an information source during an emergency
- Types of information interviewee found/would find useful during an emergency, e.g. location of event, extent of affected area, type of damage (e.g. fire, gas, flooding, active shooter, etc.), severity of damage, location and number of casualties, presence of other first responders (Fire, Police, Medical), etc.
- Characteristics of information interviewee would find useful during an emergency, e.g. more definite location, more detail, more timely, etc.

The protocol was targeted to last between 30 minutes and 1 hour.

Since this research involved interviewing human subjects (first responders) review from USC's IRB was needed. An application for an exemption for human subjects research was submitted to USC's IRB. The research methodology, interview protocol were submitted. After a review from IRB this thesis's research was approved for exemption.

Pilot interviews were conducted with former military law enforcement colleagues. Based on their input, revisions to the questions were made. These revisions included making questions clearer if any are confusing and cutting or adding questions (See Appendix A for final protocol).

3.2.2.2. Conduct Interviews

These interviews were held in October and November 2017. After obtaining permission, each interview was audio recorded. Once the interviews were completed, they were transcribed into word files and then organized each interview file by topic. For each topic, the responses were compiled and summarized from all the interviews.

3.2.3. Finalize Keywords and Search Tweets

In order to be considered a keyword for this study the words had to appear on both the text analysis and from list created through interviews. Based on the compiled interview responses and text analysis, a revised the list of keywords for the twitter data search was created. Tweets were searched using these keywords.

3.3. Spatial and Temporal Analysis

In order to evaluate the use of Twitter to aid first responders, spatial and temporal data needs to be reviewed. An emergency event such as the bombing is not only spatially import but also time sensitive. The distribution of tweets will be compared to event locations. The Twitter data timeline can be compared to event time to determine temporal accuracy.

3.3.1 Kernel Density

Geotagged tweets that contain at least one of the keywords will be used to show the spatial distribution of information. This thesis will use the kernel density tool in ArcMap to analyze the data. The Calculate Distance Band from the Neighbor Count tool in ArcMap will be used to determine the average distance between geotagged tweets. The average distance will be used as the search radius for kernel density tool. This will show how tweets are distributed around event locations. Figures will display the geographic density distribution of keyword tweets.

3.3.2 Spatio-Temporal Analysis

Whenever a tweet is posted it has a time stamp of when it occurred. With these time stamps a timeline can be created from the information relating to the events. This timeline will start with the first and end with the last tweet that contains a keyword. This will help show the spatio-temporal data that is associated with each tweet following the bombings. It is through this data, tweets can be analyzed showing where and when they occurred. This will allow for a timeline showing each individual tweet and where those tweets came from. These tweets will be mapped based of the times they occurred. Tweets will be grouped together based on time sent. This information will be visualized showing where and when tweets were sent for Monday.

Chapter 4 Results

This thesis looks at crowdsourced data as a possible aid to first responders. Over one hundred thousand tweets surrounding the time of the Boston Marathon bombing and subsequent related events were analyzed. This chapter describes the results of a text analysis of the tweets and interviews with nine first responders that were used to establish a list of keywords. After identifying tweets with the keywords, spatio-temporal analysis was conducted.

4.1. Establishing Keywords

The final set of keywords (Table 10) was the result of comparing the text analysis to the interview responses. Words that appeared in both were used for this study. There is also a brief discussion of the presence of fuck as one of the consistently most frequently used words.

4.1.1. Text Analysis

Tables were compiled for each day analyzing the frequency of words found in tweets. NVivo 11 placed similar words into one ranking (Tables 3-8). Tables were compiled for each individual day and one for Monday through Friday combined. For this study, Boston will be disregarded even though it holds the number one spot on all days. This is because Boston is too general of a location. In each table, there are the ten most frequent words followed by the frequency rankings of possible keywords.

Monday's results were compared to interview results focusing on the bombings. Table 3, shows that variants of Boston showed up 2113 times, representing the number one spot, and variants of exploding (498) only showed up 26 times. Bomb and variants is thirteenth with 534 appearances. Other possible keywords include marathon (and variants), which appeared 649 times, and explosives (and variants), which appeared 576 times, and represent the seventh and ninth most frequently cited words, respectfully. There are a total of fourteen possible keywords with variants that were pulled from the top 500.

Table 3 Monday’s Ten Most Frequent and Words of Interest

Rank	Word	Count	Similar Words
1	boston	2113	#boston, @boston, @bostons, boston, bostons
2	thank	1031	#thankful, #thanks, thank, thankful, thankfully, thanking, thanks
3	just	947	@just, just, juste
4	prayforboston	762	#prayforboston, prayforboston
5	people	750	people, peoples
6	safely	665	#safe, safe, safely
7	marathon	649	#marathon, @marathon, marathon, marathoner, marathoners, marathons
8	loving	607	#love, #lovely, @lovely, love, loved, lovee, lovely, loves, loving
9	explosives	576	#explosion, #explosions, explose, explosion, explosions, explosive, explosives
10	fuck	564	#fuck, #fucked, fuck, fucked, fucking, fucks
13	bomb	534	#bomb, #bombing, #bombings, #bombs, bomb, bombe, bombed, bombes, bombing, bombings, bombs
17	bostonmarathon	473	#bostonmarathon, @bostonmarathon, bostonmarathon
68	injured	174	injure, injured, injuring
72	police	162	#police, police
96	dead	133	#dead, dead, deadly
101	dying	128	#die, #dying, die, died, dies, dying
146	attack	93	attack, attacked, attacking, attacks
173	terrorists	82	#terrorist, terrorist, terroristes, terrorists
194	fired	74	fire, fired
207	boylston	70	#boylston, boylston
271	terrorism	51	#terror, terror, terrorism, terrorized
280	cops	49	cop, copped, cops
293	blasts	47	blast, blasting, blasts
498	exploding	26	explode, exploded, explodes, exploding

Tuesday’s results (Table 4) are similar to Monday’s but not identical. Bomb (and variants) drops from thirteenth to forty-fourth. Variants of marathon dropped to the thirty-fourth spot and variants of explosive to the two hundred and twelfth spot. The ten additional possible keywords range from thirty-fourth to four hundred and seventy-third. No words relating to ‘suspect’ were in the top 500, which may not be surprising since no suspects had been identified or apprehended at this point.

Table 4 Tuesday’s Ten Most Frequent and Words of Interest

Rank	Word	Count	Similar Words
1	boston	1748	#boston, @boston, @bostons, boston, boston', bostoner, bostons
2	just	967	just
3	liking	700	like, liked, likely, likes, liking
4	loving	687	#love, #lovely, love, loved, lovee, lovely, lovelys, loves, loving, 'loving
5	getting	682	@get, get, gets, getting
6	today	514	#today, today, todays
7	days	502	#day, day, days
8	thanks	492	#thankful, #thanks, thank, thanked, thankful, thankfully, thanks
9	ones	479	one, 'one, ones
10	now	468	#now, now
34	marathoners	240	#marathon, marathon, marathoner, marathoners, marathons
39	@bostonmarathons	226	#bostonmarathon, @bostonmarathon, @bostonmarathons
44	bombs	209	#bomb, #bombing, bomb, bombe, bombed, bombes, bombing, bombings, bombs
192	police	78	#police, police
195	boylston	76	#boylston, boylston
212	explosive	72	#explosion, #explosions, explosion, explosions, explosive, explosives
425	terrorize	39	terror, terror’, terrorism, terrorize
434	cops	38	#cops, cop, copped, cops
461	attack	36	attack, attacked, attacking, attacks
473	blast	35	blast, blasted, blasts

Continuing onto the results of Wednesday’s text analysis (

Table 5), there is no direct mention of words relating to the bombing events in the top ten. Variants of marathon fell to the sixty-ninth spot and explosives did not even make it in the top 500 most frequent words. There are seven other possible keywords ranging from thirty-third to four hundred and twenty-ninth. Variants of suspect broke into the top 500 for the first time at one hundred-sixtieth with 97 occurrences, even though there were still no suspects publically identified or in custody.

Table 5 Wednesday’s Ten Most Frequent and Words of Interest

Rank	Word	Count	Similar Words
1	boston	1620	#boston, @boston, boston, boston', bostoner, bostons
2	just	1007	just
3	liking	856	like, liked, likee, likely, likes, liking
4	getting	827	get, gets, getting
5	loving	644	#love, @love, @lovely, love, loved, lovee, lovely, loves, loving
6	now	547	now
7	fucks	543	#fuck, fuck, fucked, fucking, fucks
8	days	539	day, days
9	knows	487	know, knowing, knows
10	timing	448	@time, time, time', timee, times, timing
33	bombs	275	#bombings, #bombs, bomb, 'bomb, bombe, bombed, bombing, bombings, bombs
69	marathoners	168	#marathon, @marathon, marathon, marathoners, marathons
121	@bostonmarathon	112	#bostonmarathon, @bostonmarathon
160	suspects	97	#suspect, suspect, 'suspect, suspecte, suspected, suspects
175	police	91	police
264	boylston	64	#boylston, boylston
429	blasts	42	blast, blasted, blasting, blasts

On Thursday two events took place that added to possible additional words – the release of the suspects’ identities and the shooting of the MIT police officer. The results (Table 6) had eleven possible keywords, all of them outside the top ten. Variants on marathon fell to the one hundred and third spot and explosives to the three hundred-fiftieth spot. Variants on the word suspect climbed slightly to the one hundred twenty-seventh spot with 113 occurrences. Words such as MIT (76), Cambridge (93), and shooting (259) saw spikes that were likely related to the shooting.

Table 6 Thursday's Ten Most Frequent and Words of Interest

Rank	Word	Count	Similar Words
1	boston	1431	#boston, #boston#bostonstrong#marathon#backbay#prayforboston, @boston, @bostons, boston, 'boston
2	just	996	@just, just, justing
3	liking	848	like, liked, likee, likely, likes, liking
4	getting	830	#get, @get, get, gets, getting
5	loving	672	#love, #lovely, @love, @lovely, love, loved, lovely, loves, loving
6	days	531	#day, day, days
7	now	517	now, 'now, nows
8	fucks	499	#fuck, fuck, fucked, fucking, fucks
9	ones	491	@one, one, ones
10	goodness	477	#good, @goode, good, goodness, goods
58	bombs	176	#bombing, #bombings, bomb, bombed, bombing, bombings, bombs
76	mit	159	#mit, @mit, mit, mits
93	cambridge	139	#cambridge, cambridge
103	marathoners	129	#marathon, marathon, marathoners
127	suspects	113	#suspect, #suspects, suspect, 'suspect, suspects
163	police	98	#police, police
210	officer	78	office, officer, officers, offices
214	boylston	75	#boylston, boylston
259	shooting	65	#shooting, shoot, shooting, shootings, shoots
262	@bostonmarathon	64	#bostonmarathon, @bostonmarathon, @bostonmarathons
350	explosion	48	explosion, explosions, explosive

Friday was the final day of the events surrounding the Boston Marathon bombing and subsequent identification and capture of the suspects alleged to be responsible. Several events took place, starting in the early hours. There was a carjacking, a firefight during which one of the suspects died, and later the other suspect was apprehended. The full results can be seen in Table 7. Suspects jumped from the one hundred twenty-seventh spot all the way to ninth. Other words in the top ten were Watertown (6) was the location of the firefight and police (7). There were 21 other possible keywords outside of the top ten. Even the living suspect's name appeared in the top 500, with 291 mentions of Tsarnaev and 190 of Dzhokhar.

Table 7 Friday’s Ten Most Frequent and Words of Interest

Rank	Word	Count	Similar Words
1	bostons	2826	#boston, @boston, @bostons, boston, 'boston, bostons
2	just	1801	@just, just
3	getting	1474	get, 'get, gets, getting
4	now	1354	#now, now, 'now, now#realheroes, nows
5	liking	1313	like, liked, liked’, likee, likely, likes, liking
6	watertown	1188	#watertown, watertown
7	police	1114	#police, polic, police
8	fucks	1059	#fuck, fuck, fucked, fucking, fucks
9	suspects’	1027	#suspect, #suspects, suspect, suspect#2, suspect’, suspected, suspects, suspects', suspects’
10	thanks	1018	#thank, #thankful, #thanks, thank, thankful, thankfully, thanking, thanks
40	bombs	483	#bomb, #bombing, bomb, bombed, bombing, bombings, bombs
65	cambridge	325	#cambridge, @cambridge, cambridge
66	manhunts	316	#manhunt, @manhunt, manhunt, manhunting, manhunts
72	mit	309	#mit, @mit, mit
78	cops	297	#cops, cop, cops
95	shots	273	shot, shots, shots', shotting
100	custody	251	#custody, custody
112	marathon	221	#marathon, marathon
146	bombers'	188	#bomber, bomber, bombers, bombers'
148	terrorists	183	#terrorist, #terrorists, terrorist, 'terrorist, terroriste, terroristing, terrorists
159	explosives	177	#explosion, #explosions, explosion, explosion', explosions, explosive, explosives
166	sirens	172	siren, sirens
188	shooting		#shooting, shoot, 'shoot, shooting, shootings, shoots
222	#bostonbombings	140	#bostonbomb, #bostonbomber, #bostonbombers, #bostonbombing, #bostonbombings
228	guns	138	gun, gunned, gunning, guns
277	helicopters	110	#helicopter, helicopter, helicopters
291	tsarnaev	101	#tsarnaev, tsarnaev
300	enforcement	97	enforcement, enforcements, enforcers
309	dzhokhar	94	#dzhokhar, @dzhokhar, dzhokhar
319	#bostonmarathon	91	#bostonmarathon
326	campus	88	campus, campuses
327	captured	88	#captured, capture, captured, captures, capturing
481	arrests	59	#arrest, arrest, arrested, arresting, arrests

The text analysis of all five days combined shows that there are no possible keywords in the top ten most frequent (Table 8). However, words that appeared in the top 500 on only a couple of days made the combined day list because they appeared so often on those days. Suspect only appeared Wednesday through Friday, but was used enough to make the combined day list. Watertown only appeared on Friday's top 500 but was fifty-second in the combined day list. Then there are other examples such as bomb (twenty-eighth), which showed up every day.

Table 8 Combined Days Ten Most Frequent and Words of Interest

Rank	Word	Count	Similar Words
1	bostons	9738	#boston, #boston#bostonstrong#marathon#backbay#prayforboston, @boston, @bostons, boston, boston', 'boston, bostoner, bostons
2	just	5718	@just, just, juste, justing
3	getting	4344	#get, @get, get, 'get, gets, getting
4	liking	4275	like, liked, liked’, likee, likely, likes, liking
5	now	3440	#now, now, 'now, now#realheroes, nows
6	loving	3322	#love, #lovely, @love, @lovely, love, loved, lovee, lovely, lovelys, loves, loving, 'loving
7	thanks	3172	#thank, #thankful, #thanks, thank, thanke, thanked, thankful, thankfully, thanking, thanks
8	fucks	3120	#fuck, #fucked, fuck, fucked, fucking, fucks
9	peoples	2696	peopl, people, peoples, peoples'
10	knows	2652	@know, know, knowing, knows
28	bombs	1677	#bomb, #bombing, #bombings, #bombs, bomb, 'bomb, bombe, bombed, bombes, bombing, bombings, bombs
33	police	1543	#police, polic, police
39	marathons	1407	#marathon, @marathon, marathon, marathoner, marathoners, marathons
46	suspects’	1267	#suspect, #suspects, suspect, 'suspect, suspect#2, suspect’, suspecte, suspected, suspecting, suspects, suspects', suspects’
52	watertown	1199	#watertown, watertown
68	bostonmarathon	966	#bostonmarathon, @bostonmarathon, @bostonmarathons, bostonmarathon
75	explosives	904	#explosion, #explosions, explose, explosion, explosion', explosions, explosive, explosives
113	cambridge	715	#cambridge, @cambridge, cambridge
165	mits	539	#mit, @mit, mit, mits
211	cops	438	#cops, cop, copped, cops
218	shots	423	#shots, shot, shots, shots', shotted, shotting
285	manhunts	323	#manhunt, @manhunt, manhunt, manhunting, manhunts
305	terrorists	310	#terrorist, #terrorists, terrorist, 'terrorist, terroriste, terroristes, terroristing, terrorists
311	boylston	304	#boylston, boylston
338	sirens	275	#sirens, siren, sirene, sirens
387	attack	238	attack, attacked, attackers, attacking, attacks

Only possible keywords that showed up in the top 500 most frequent words each day were considered for the tweet searches. Some of the highest were in the top ten while the lowest was four hundred ninety-eighth. The text analysis allowed us to establish a baseline for suitable keywords.

4.1.2. Interview Responses

Interviews were conducted with nine first responders over a four-and-a-half-week period in October and November 2017. Eight out of nine of the interviewees were law enforcement and the other interviewee was a firefighter; all considered themselves to be first responders. They ranged from over a decade of experience to just a year; and as such their responses varied.

Every interviewee has responded to an emergency, while two have responded to a major emergency (boiler explosion and Blue Angel crash). None of the interviewees have responded to a terrorist event. However, they all train for these types of events.

When responding to an emergency, all interviewees said location is one of the most important pieces of information needed. “Without a location, how are we going to know where to go,” one interviewee said. The next most popular result was what type of emergency they are responding to. Then other responses related to more detailed information on the event (e.g. suspect information, injuries, site security). After reviewing all responses from interviewees, specific words that were provided for each day can be found in Table 9.

Table 9 Words Relating to Events provided by First Responders

Monday	Tuesday	Wednesday	Thursday	Friday
Attack	Attack	Attack	Attack	Attack
Back Bay	Black Hat	Black Hat	Bomb/ Bombing	Bomb/ Bombing
Blast	Bomb/Bombing	Bomb/Bombing	Boston	Boston
Bomb/ Bombing	Boston	Boston	Boylston	Boylston
Boom	Boylston	Boylston	Cambridge	Cambridge
Boston	Cops	Cops	Cops	Cops
Boylston	Explosive/ Explosion	Explosive/ Explosion	Dzhokhar Tsarnaev	Dzhokhar Tsarnaev
Cops	Finish Line	Finish Line	Explosive/ Explosion	Explosive/ Explosion
Explosive	Marathon	Marathon	Finish Line	Finish Line
Explosion	Police	Police	Marathon	Marathon
Finish Line	Suspects	White Hat	MIT	MIT
Fire	Terrorist/ Terrorism		Police	Police
Injured	White Hat		Shooting	Shooting
Marathon			Suspect	Suspects
Police			Tamerlan Tsarnaev	Terrorist/ Terrorism
Suspects				Watertown
Terrorist/ Terrorism				

4.1.3. Keywords for Searches

A list of keywords was developed through text analysis and interviews for each individual day. In order to be a keyword, it had to be on the most 500 frequent words from the text analysis and be mentioned in an interview. Not every possible keyword from the text analysis was used, and the same can be said about words provided by interviewees. Boston was the most frequent word for every day and was brought up by interviewees, but it was omitted from the keyword list for being too broad of a location.

The keywords (Table 10) are separated by day. The number of keywords on Monday and Friday were the highest, these are the two days were major events took place; Monday had the bombing, while Friday had a firefight and arrest. Thursday is the next highest, this coincides with the release of suspect identities and MIT Police Officer shooting. Monday through Wednesday focus around the marathon bombings. Thursday and Friday show need for all of the week's events.

Table 10 Final List of Keywords for Each Day

Monday	Tuesday	Wednesday	Thursday	Friday
Attack	Attack	Bomb/Bombing	Bomb/Bombing	Bomb/Bombing
Blast	Bomb/Bombing	Boylston	Boylston	Cambridge
Bomb/Bombing	Boylston	Marathon	Cambridge	Cops
Boom	Cops	Police	Cops	Dzhokhar Tsarnaev
Boylston	Explosive/ Explosion	Suspect	Explosive/ Explosion	Explosive/ Explosion
Cops	Marathon		Marathon	Marathon
Explosive/ Explosion	Police		MIT	MIT
Fire	Terrorist/ Terrorism		Police	Police
Injured			Shooting	Shooting
Marathon			Suspect	Suspects
Police				Terrorist/ Terrorism
Terrorist/ Terrorism				Watertown

Microsoft SQL Server searches were conducted using the keywords in Table 10. A search of Monday's twelve keyword variants resulted in 2410 geotagged tweets from 2:40 p.m.to 11:59 p.m. Tuesday's results from the eight keyword variants produced 949 geotagged tweets. Wednesday produced the smallest results of 672 geotagged tweets; it also only had five keyword variants. With other events occurring on Thursday, there was an increase of keywords to ten, but still only 979 geotagged tweets. Friday, which had the most events take place, had twelve keyword variants and returned the most geotagged tweets at 4453.

4.1.4. Text Anomaly Analysis

Fuck was in the top ten every day but Tuesday (when it ranked 11th), and was in the top ten for the aggregate results. As an expression of raw emotion, it could also be related to the terrorism event. It may be worth adding fuck to the list of keywords if it can be determined that it was used frequently to reference the terrorism event and the other keywords were not also included in the tweet. For example, on Monday there were 600 tweets containing the word after the bombing occurred; 109 also included keywords and 491 did not.

There were 120 tweets containing the word fuck in the first hour following the bombing. Forty-five of these tweets contained another keyword and the remaining tweets were reviewed for relevance to the terrorism event. For example, the first time it was used after the bombing was 2 minutes. Someone tweeted, “WHAT THE FUCK,” in all capital letters. Though there are no details, it could have been related to the bombing because it was sent from about two blocks away. However, it is hard to know for sure since we cannot be certain of the context. Some tweets are obviously not related to the bombing (@vanillaice. Word to ya mother brother fucka), and a portion are simply hard to tell. Table 11 displays the analysis of the tweets containing the word fuck for the first hour following the bombing.

Table 11 Relevance of Tweets with the Word Fuck One Hour Following the Bombing

	Keyword	Probably Relevant	Unclear	Not Relevant	Total
Tweets	38	26	41	15	120

4.2. Spatial Analysis

The results from the keyword searches were used to produce images to show the distribution of tweets along with their density. In this section, images for each individual day are presented and examined.

4.2.1. Daily Results

Looking at Monday's tweet density (Figure 5), the majority of the study area is blue, meaning it has a low density. However, there are pockets of higher tweet density areas throughout the study area. The largest pocket of high tweet density is made up of neighborhoods such as Fenway, Back Bay, Beacon Hill, and Downtown. This high tweet density area is approximately 3.4 square miles, and includes the marathon finish line and the sites of the two explosions.

There are roughly 800 geotagged tweets occurring from pre-explosion to just before midnight in this area. These tweets make up a third of tweets returned from the keyword search. The largest clusters of tweets surround the explosion sites.

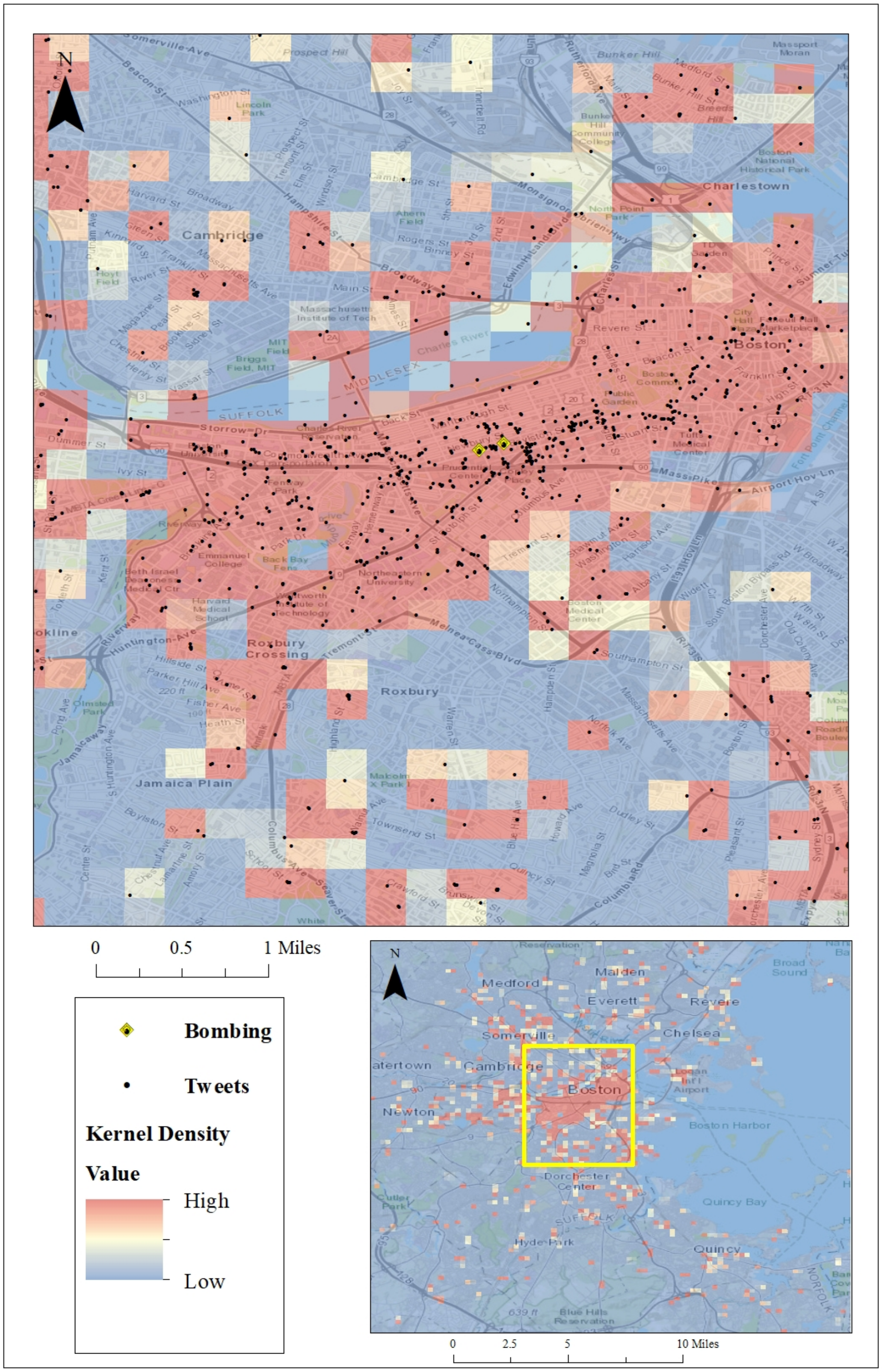

Figure 5 Density of Tweets on Monday 15 April 2013

Moving on to Tuesday (Figure 6), it can be seen that the majority of the study area's tweet density is low. There are fewer pockets of higher density locations, but on average, they are larger than Monday's. The largest pocket occurs in relatively the same location as Monday, but is only approximately 2 square miles. There is another high tweet density pocket that is separate from the others. It is in the Fenway neighborhood and is a little over 0.5 square miles. A high-density of tweets is also at Logan International Airport.

The decrease in density size of the main location can partially be attributed to the smaller number of keywords used and therefore smaller number of tweets returned by the search. The overall number of geotagged tweets between Monday and Tuesday dropped by more than half. The largest density area contained about 440 tweets, or about 46 percent of the entire day. The largest clusters of tweets were still around the bombing locations. The other two large clusters in Fenway neighborhood and Logan International airport had just 50 and 20 tweets, respectfully. In the majority of tweets, the focus is mostly about the events of the previous day.

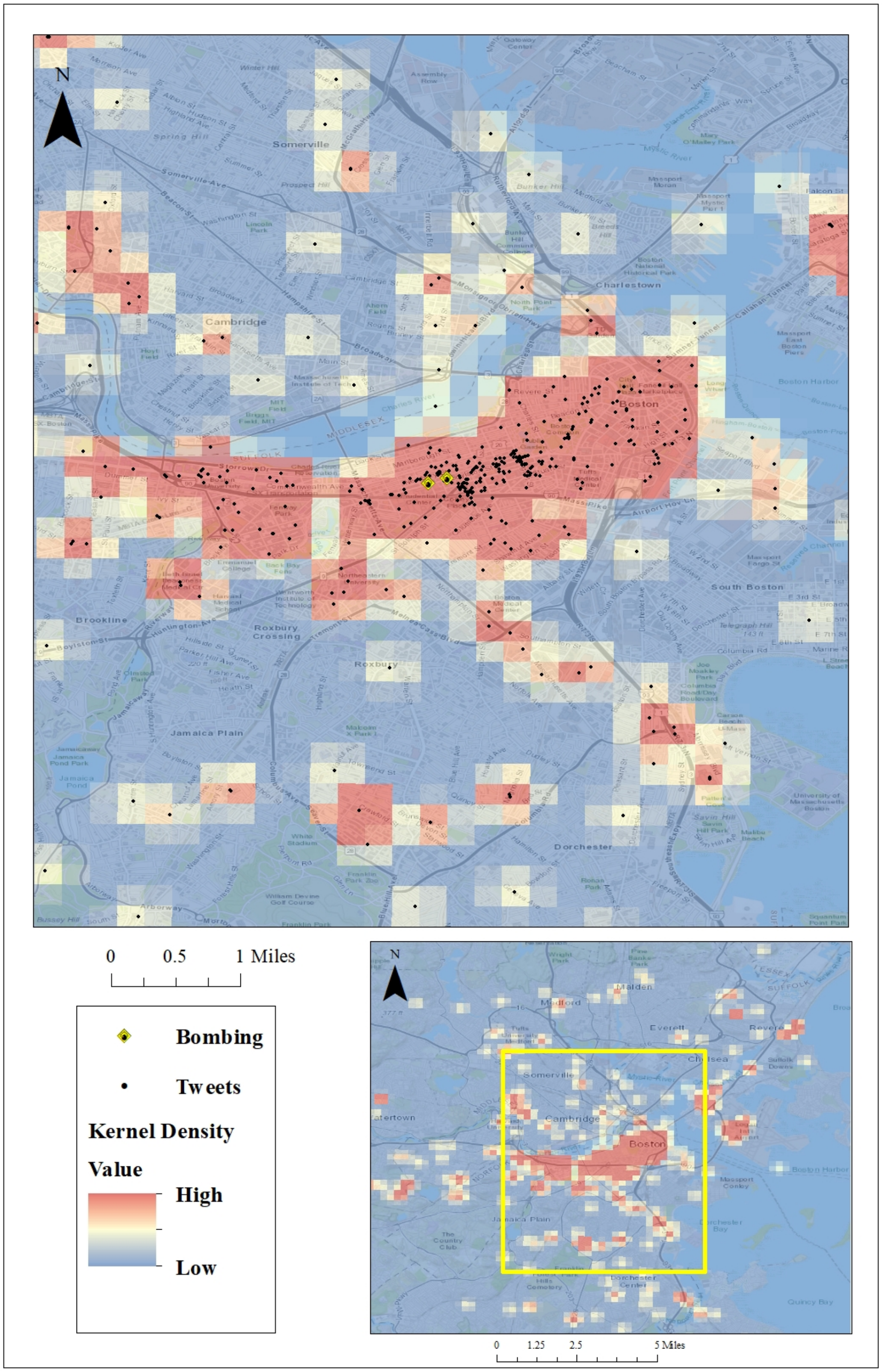

Figure 6 Density of Tweets on Tuesday 16 April 2013

Wednesday's results (Figure 7) show similar trends as seen in Tuesday's results. There is another decline in keywords, which results in fewer geotagged tweets than the previous day. The largest density cluster is still in the same neighborhoods as before, and the Fenway cluster from Tuesday is now reconnected to the main density cluster. The area of the largest density cluster is approximately 2.8 square miles, and is still smaller than Monday's results. There are other noticeable clusters at Logan International Airport, East Boston, and Cambridge, all under 0.25 square miles.

The geotagged tweets continued to drop between Tuesday and Wednesday, with a difference of 277. Over half (53 percent) of the daily geotagged tweets were in the largest density cluster. The largest tweet clusters for the third day were still around the bombing locations. Logan International airport had 9 tweets, East Boston had 6 tweets, and Cambridge had 13 tweets. Most tweets were supportive in nature, and still related to the events that took place on Monday.

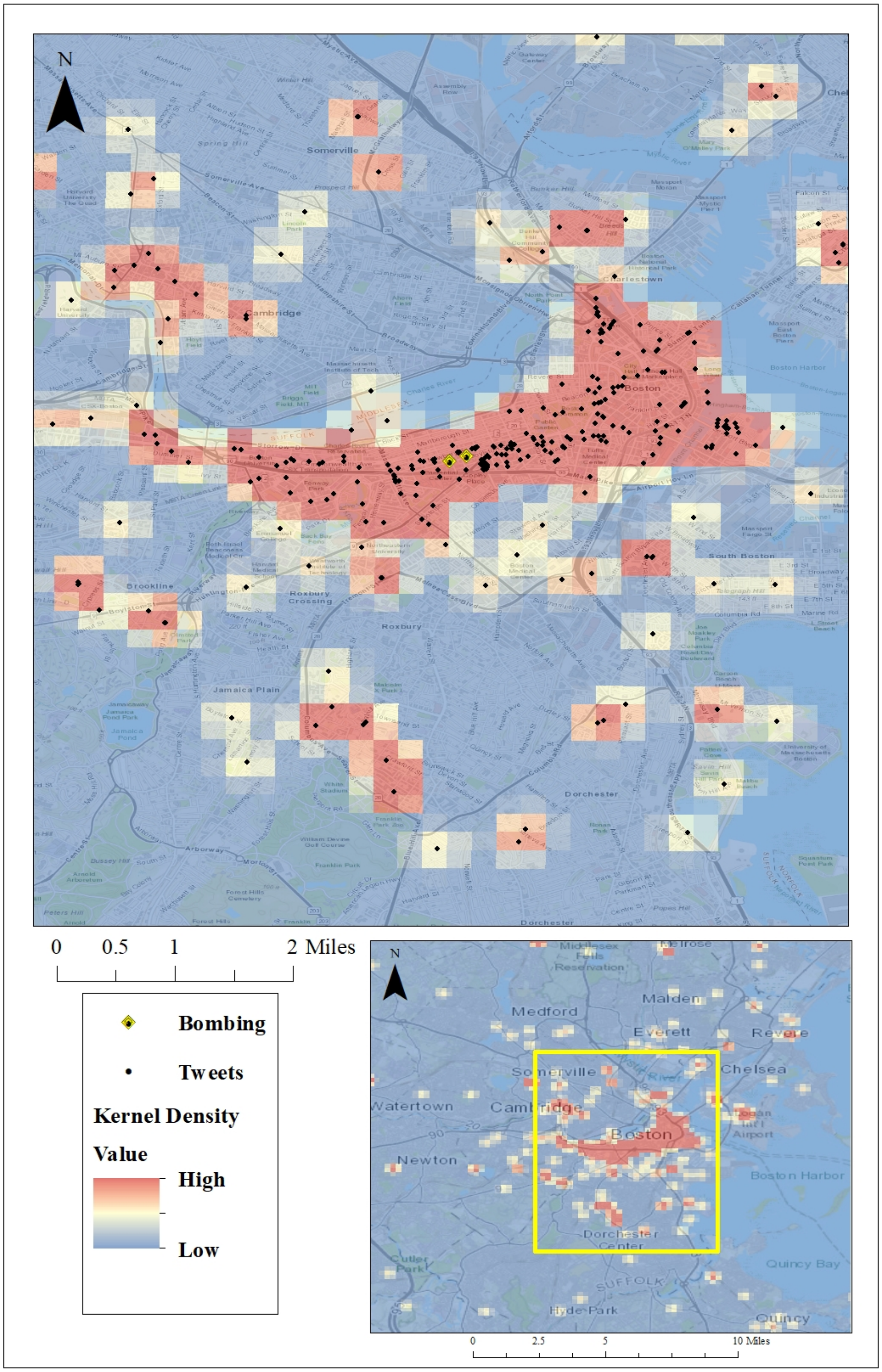

Figure 7 Density of Tweets on Wednesday 17 April 2013

On Thursday, with the occurrence of a new event (MIT Police Shooting), the results shifted to reflect this (Figure 8). With the addition of this event, keywords increased and changed. Correspondingly, the number of geotagged tweets increased. However, it is still fewer than Monday's results. The biggest change from the previous day is that there is a large density cluster in Cambridge where MIT is located. This density cluster is approximately 1.8 square miles. The largest cluster that contains the bombing locations is approximately 3.7 square miles, which is slightly larger than Monday's results. This shows the tweet density increased in both areas with the addition of the shooting.

Between Wednesday and Thursday, the number of geotagged tweets from keywords increased by 307. The main cluster density contained 376 geotagged tweets, about 38 percent of the daily total. The Cambridge cluster around the shooting location contained 141 tweets, about 14 percent of the daily total. Over half of the tweets from Thursday came from these two density clusters, meaning there are groupings of tweets around both the bombing and shooting sites. In addition to the shooting, an increase in tweets came from the release of the identities of the two suspects.

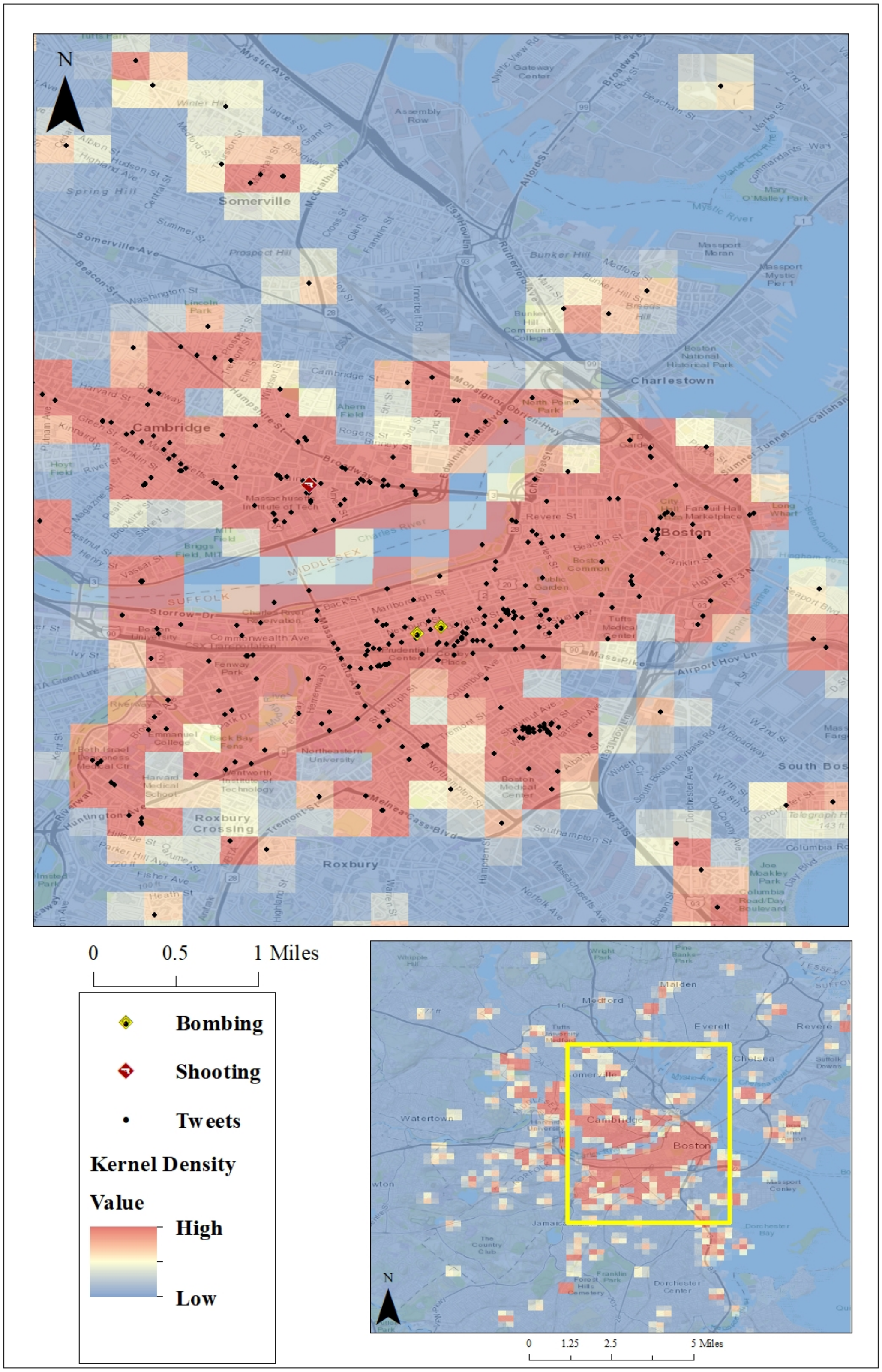

Figure 8 Density of Tweets on Thursday 18 April 2013

The final day of the events surrounding the Boston Marathon bombing took place on Friday, April 19th, 2013. This was the day in which the keywords returned the most geotagged tweets at 4453, and they were spread throughout 21 of the 24 hours in the day. The results show that there is no single massive density cluster like the four previous days (Figure 9). Instead there are multiple smaller clusters throughout the study area. The largest pocket of approximately 0.6 square miles, is near the explosion sites, but no longer includes them. The other event locations fall within or adjacent to high tweet density locations. These events took place within a 5-mile radius of each other within the Boston Metropolitan area. The largest density near the explosion sites represent 226 geotagged tweets, about 5 percent of the daily total. The cluster around the shooting/carjacking sight contained 33 tweets. Near the firefight location, there was 146 geotagged tweets. These occurred from the midnight hour all the way to 8:00 p.m. The final cluster location, where the suspect was apprehended, only had a handful of tweets; these referenced the street that it occurred on.

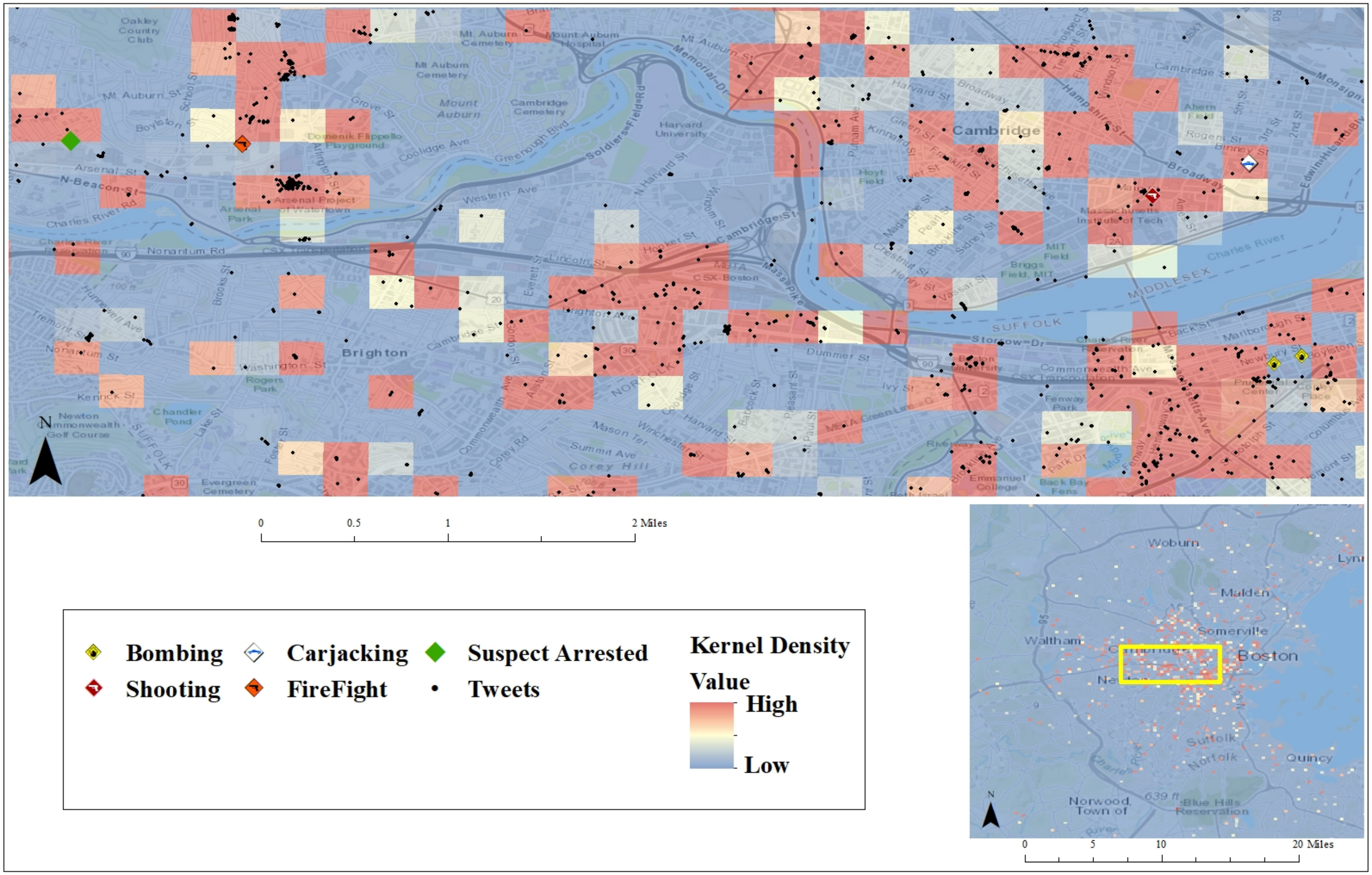

Figure 9 Density of Tweets on Friday 19 April 2013

4.2.2. Spatial Analysis Takeaways

Comparing Figures 4 through 8, you can see the change in spatial distribution of the tweets. Although each day varied in the number of tweets returned from keywords, the densities from which they came stayed relatively the same. When other events occurred the spatial distribution of tweets sent changed with them. The higher density of tweets appeared around each new event that took place. Geotagged tweets are following the course of events, giving locations and information.

Another point to note is that when fewer keywords were used, fewer tweets resulted from the searches. This means useful tweets could have been excluded simply because its particular keyword was not mentioned frequently enough on the day in question.

4.3. Spatio-Temporal Analysis

In this section, the temporal data surrounding the bombing events that occurred on Monday was analyzed. Temporal data is a key piece of information needed to respond to an emergency event.

4.3.1. Analysis of Monday's Tweets

The temporal analysis of tweets resulting from the keyword searches started at the point when the first explosion took place at 2:49 p.m. There were 2387 geotagged tweets from the time the bomb went off until midnight. It can be seen in Figure 10 that the first tweet referencing the explosion did not occur until 3 minutes after the bomb. There were ten non-bombing related tweets before 2:51 p.m. that were removed from the dataset, meaning a total of 2377 tweets were analyzed. The figures that follow show the relevant tweets in the first 15 minutes, 16 minutes to one hour, and more than one hour.

2013-04-15 14:52:00.000	Two explosions just rocked the finish line of the Boston Marathon. Sirens galore. People running in fear. Wonder what happened.	30984340	-71.08332	42.34919
2013-04-15 14:53:00.000	Two bombs just went off on boylston.....	260360663	-71.079603	42.349521
2013-04-15 14:53:00.000	We are just past #kenmore in the #bostonmarathon and they just stopped the race #Boston #2013	19348087	-71.089242	42.348841
2013-04-15 14:54:00.000	Two explosions at Copley square. Not sure what's going on but people are running.	6596692	-71.078454	42.354554
2013-04-15 14:54:00.000	Cheers runners! #bostonmarathon CC @TerryOReillys http://t.co/H6kNi0sHwn	15743181	-71.191806	42.330128
2013-04-15 14:54:00.000	Wtf just happened at the #bostonmarathon !?	382113265	-71.071895	42.351628
2013-04-15 14:55:00.000	2 explosions just happened here on boylston st. #boston #bostonmarathon	35643935	-71.088446	42.347066

Figure 10 First Tweets Mentioning Events, 15 April 2013

The spatio-temporal results of the first 15 minutes show where the tweets immediately after the bombing came from (Figure 11). The first tweet was 0.12 miles away from the explosion site or approximately two city blocks. Within the first 15 minutes, 56 tweets were sent, the most (7) occurring 6 minutes after. The distances from the bomb locations ranged from 252 feet to 22 miles. There are 33 tweets within a one-mile radius of the bombing sites, making up 59 percent of the tweets from the first 15 minutes. Looking at the content along with the location shows that they are informative tweets, and occurred around the event bombing locations. While the tweets from farther out are helpful with relaying information, they would not be useful in communicating information to first responders.

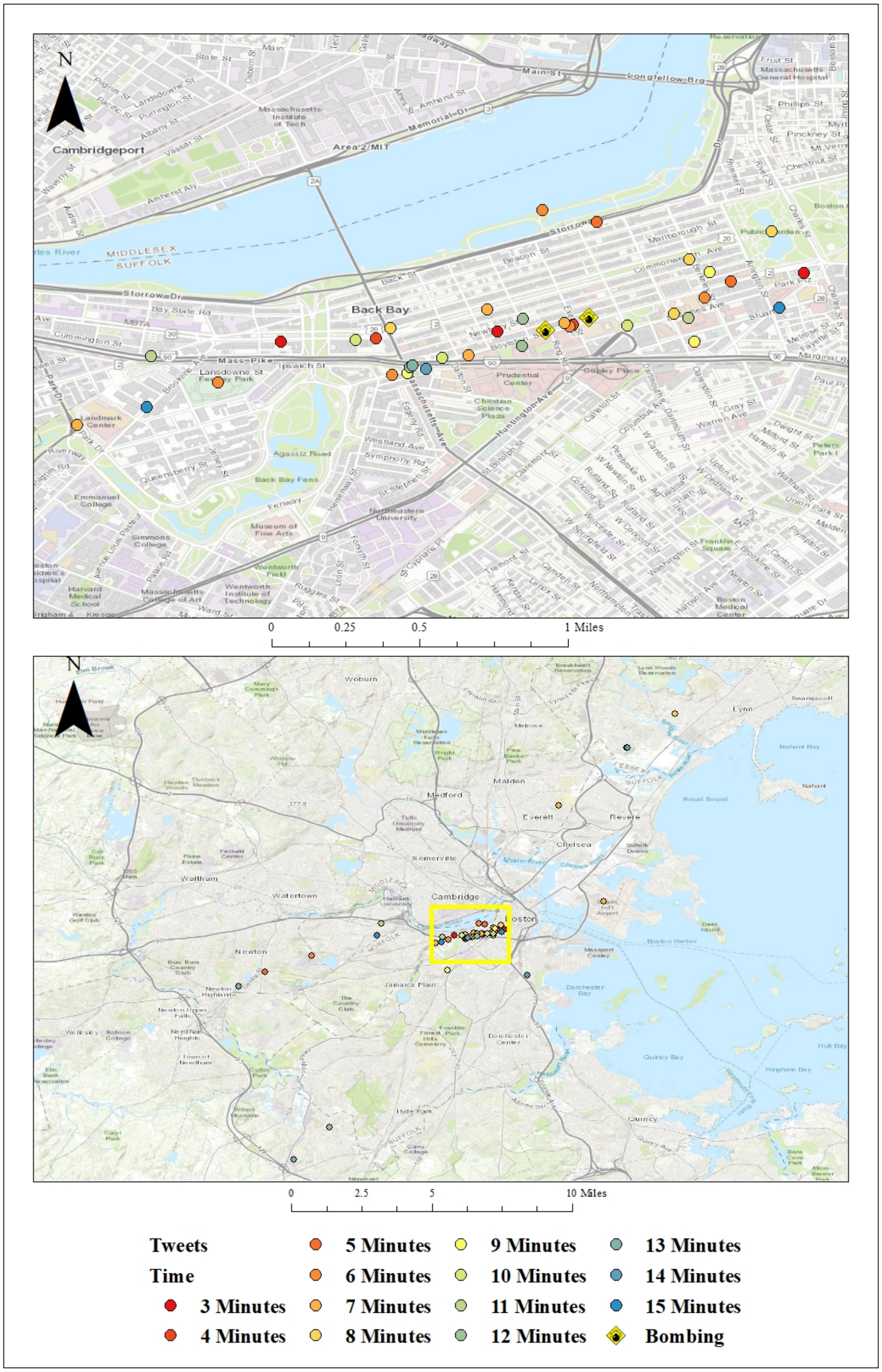

Figure 11 Monday Tweets From First 15 Minutes After Bombing

The results from the second time period – 16 minutes to 1-hour (Figure 12) show a large increase of tweets. There were 588 keyword tweets in this 45-minute period, for a 950 percent increase over the first 15 minutes. There were five-time ranges for this period. The first was 16-20 minutes, which had 43 tweets. In the next 5-minute period, 59 tweets were sent. The third period, which ended at 30 minutes, had 76 tweets. There were 235 tweets sent between 31 and 45 minutes. The hour ended with an additional 175 tweets. Within the first hour of the bombing a total of 644 tweets were sent. This accounts for 27 percent of the relevant tweets found through the Monday keyword search.

Like the first 15 minutes, tweets sent in the next 45 minutes were sent from a variety of locations. The tweets display a similar density pattern to the tweets over the entire day, as seen earlier in Figure 4. The two closest tweets to each individual bombsite were 26 feet and 152 feet, respectfully. The farthest tweet during this time period was 24 miles away. There were 155 keyword tweets that fell within a one-mile radius of the bombing sites. This accounted for 26 percent of the tweets within this time period.

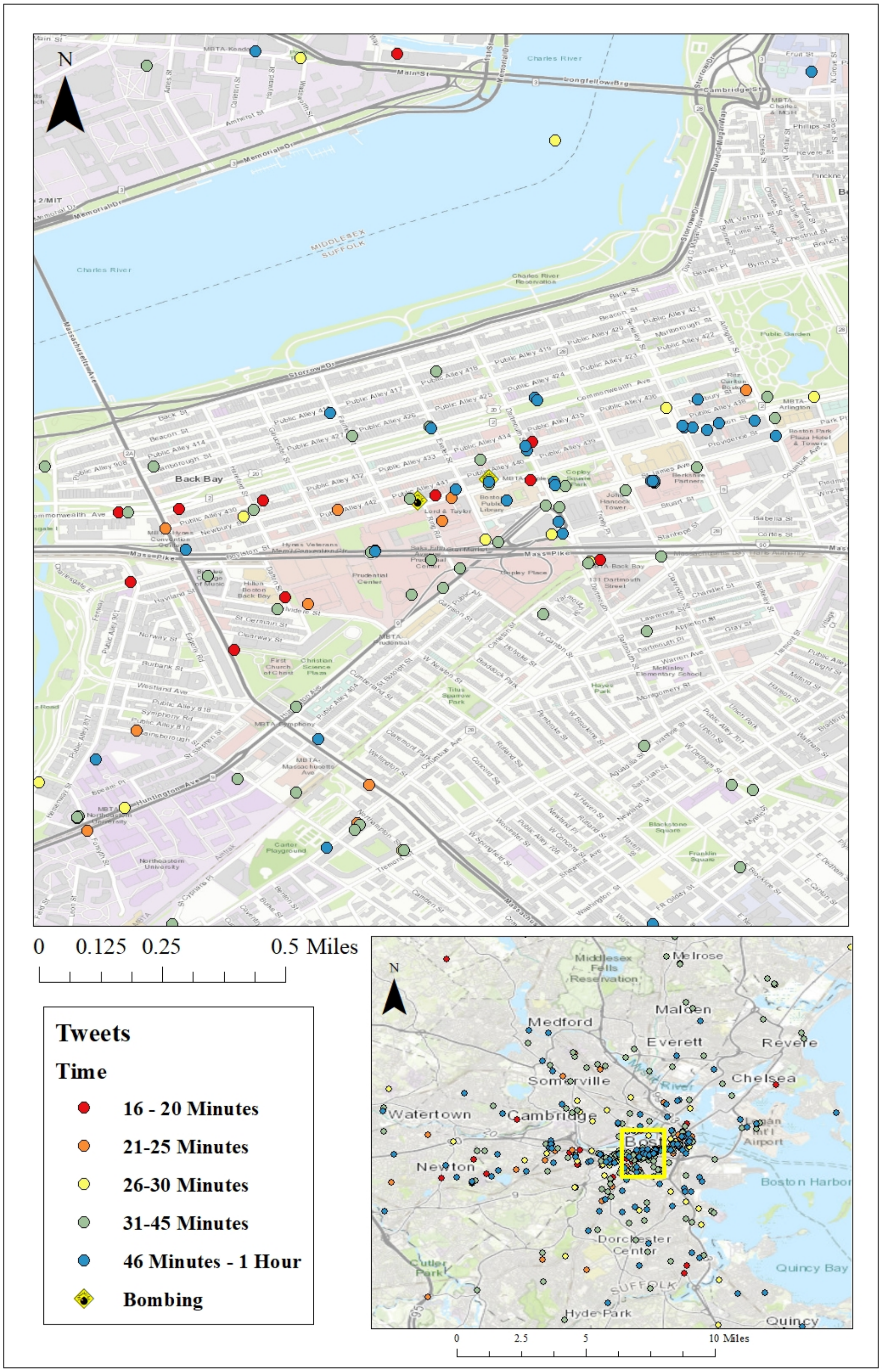

Figure 12 Monday Tweets Between 16 Minutes and 1 Hour After Bombing

The remaining temporal information that this thesis analyzed were the tweets from more than an hour after the explosions occurred (Figure 13). The results show six time ranges: five in one-hour intervals up to 5 hours, then one more than 5 hours. In the remaining eight hours and ten minutes of the day, 1735 keyword tweets were returned. This meant an average of over 200 tweets an hour. The individual breakdown of tweets per range were 596 for 1-2 hours, 375 for 2-3 hours, 222 for 3-4 hours, 178 for 4-5 hours, and 364 for over 5 hours. The largest number of tweets was sent the first hour after the explosions.

As with the previous two temporal analyses, the keyword tweets all fall within the 25-mile original search radius. The tweets display a similar density pattern to the tweets over the entire day, as seen earlier in Figure 4. There were tweets sent from the bombing sites, they just referred to what had happened earlier that day. Around 20 percent of the tweets sent after an hour came within a one-mile radius of the bombing sites. It can be seen that the informative tweets regarding the bombing events spread throughout the Boston Metropolitan area after the first hour.

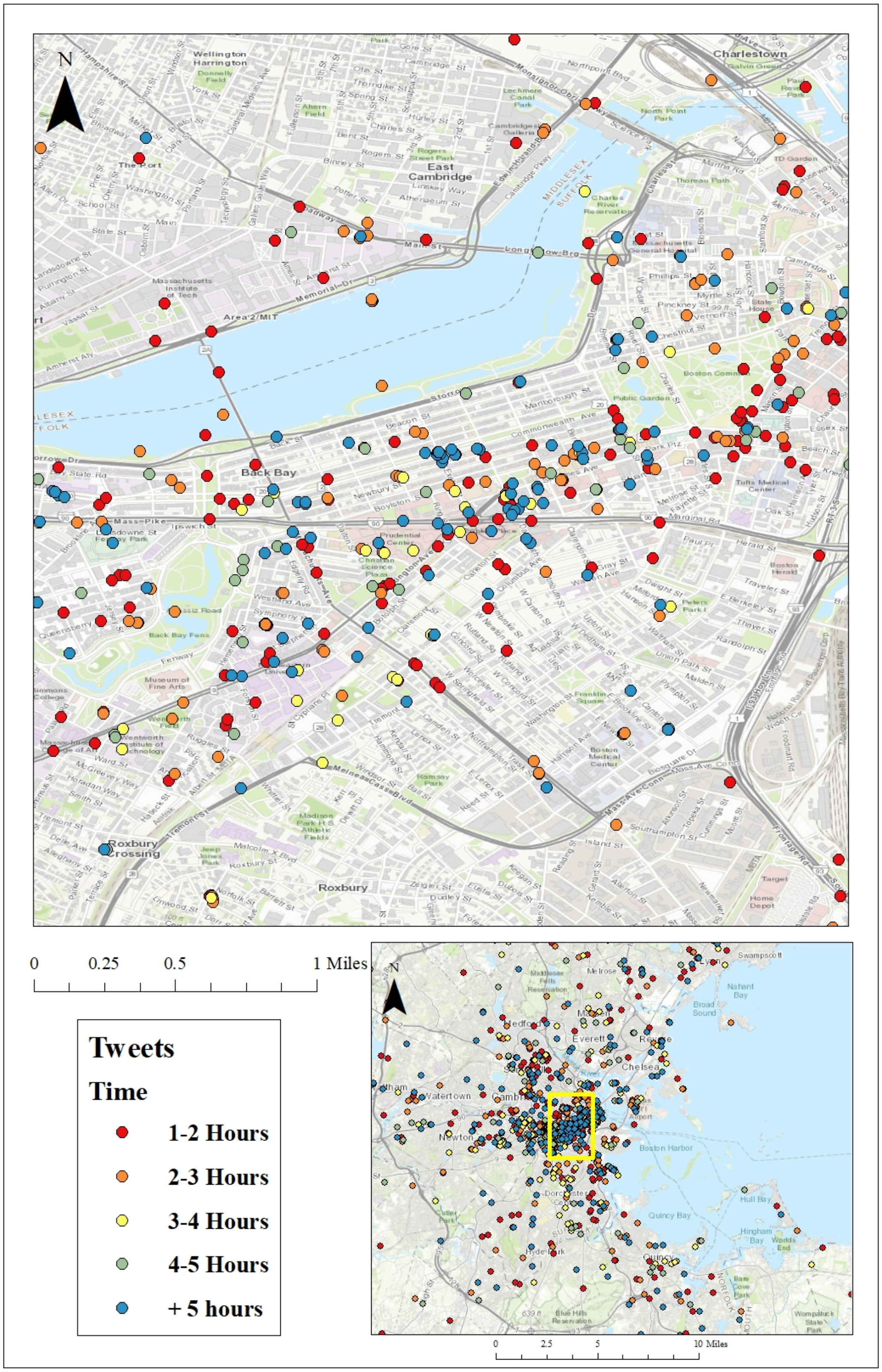

Figure 13 Monday Tweets Over an Hour After Bombing

4.3.2. Text Anomaly Spatio-Temporal Analysis

There were 120 tweets containing the word fuck in the first hour following the bombing (Figure 14). Thirty-eight of these tweets contained another *keyword* (red) and so were already captured by the previous spatio-temporal analysis. There are three other classifications of tweets containing this word. There is *probable* (orange), which probably reference the bombings as determined through context or other words pertaining to the events that are not keywords. Then there is *unclear* (yellow), which are tweets that contain fuck and may or may not relate to the bombing. Finally, there is *not related* (blue); these contain the word fuck, but definitely in another context. Twenty-one of the tweets (or 17.5%) with the word fuck within the first hour were located within a one-mile radius of the events. None of these tweets was *not related*; they were either *keyword*, *probable*, or *unclear*. The first tweet (WHAT THE FUCK) came two minutes after the explosion and was classified unclear.

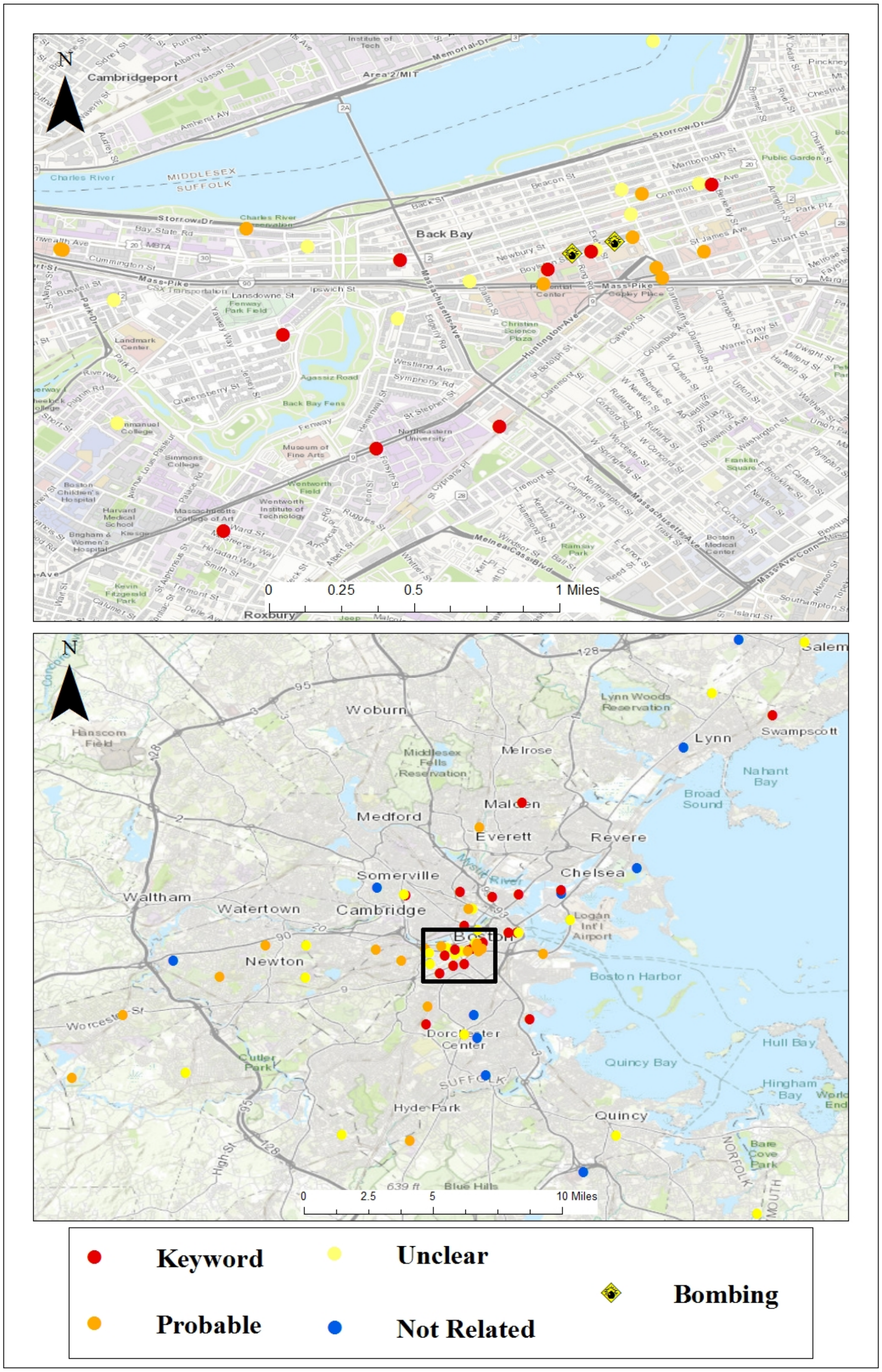

Figure 14 Tweets Within First Hour Containing Fuck

4.3.3. Spatio-Temporal Analysis Takeaways

Comparing the three spatio-temporal figures show that, over time, keyword tweets spread farther out from the bombing sites. Within the first 15 minutes the majority of tweets were focused around the bombing sites. In the remaining 45 minutes of the first hour two things are noticed. The first is that there is more Twitter activity surrounding the bombing sites and the second is that a larger number of tweets have spread throughout the 25-mile radius study area. With just the spatial and temporal data it is certain that an event took place, where it occurred, and that information spread over time throughout the Boston Metropolitan Area.

Looking at the content along with the location shows that there were informative tweets in an extremely timely manner (just 3 minutes after the first bomb). These geotagged tweets came from users that were around the event bombing locations. If first responders had access to these tweets, they could have learned valuable information about the explosions and known approximately where they took place.

Chapter 5 Conclusion

Crowdsourced data can be a useful tool in aiding first responders in an emergency event. This work shows various ways in which spatially referenced Twitter data offers unique insight into a terrorism event using the 2013 Boston Marathon bombing as a case study. People become sensors by following their natural tendency to share information during an emergency. Instead of a single source of intelligence for an emergency, crowdsourced data has the potential to have hundreds, if not thousands, of sources.

The results of this thesis show: 1) what type of information was found in tweets during the Boston Marathon bombing terrorism event, 2) what type of information would be useful for first responders during the event, 3) how geospatial information was included in the tweets, and 4) the timeliness of the information. While there are some limitations to this study and the data used, Twitter has the potential to be a great source of intelligence, though it will likely require an automated process to sift through all the crowdsourced data in real time.

5.1. Findings

The overall finding of this thesis is that crowdsourced data, such as Twitter, can provide potentially useful information to aid first responders following a terrorism event.

This study determined what type of information is found in crowdsourced data during a terrorism event through text analysis of Twitter data. Many of the top 500 words resulting from the text analysis were irrelevant. The text analysis did lead to keywords useful for the case study, but only because targeted searches were possible since the events were known. Text analysis of the most frequent words would not necessarily lead to useful information in a real time situation. All the keywords used for Twitter data searches were located in the top 500 words. In addition, due to the different events that occurred through the week (a bombing, a shooting, a carjacking, and a firefight), useful keywords were different each day.

Fuck also appeared in the top ten most frequent words every day but Tuesday, and in the aggregate results. Human interpretation allowed for the determination that it is likely that some of the tweets with the word fuck, but without other keywords, were related to the terrorism event. However, without context, it will be very difficult for a machine to determine whether a simple statement like “what the fuck” is related to some event or part of regular speech. The only way relevance was determined was by reviewing both the location and timing of the tweet, and this was only possible because we already knew an event took place.

Interviews with first responders provided data on what type of information would be useful for first responders during a terrorism event. The results of the interviews confirmed that there are multiple pieces of information needed to respond to an emergency. The most popular answer was location; this is because first responders need to know where to go during an emergency. In regards to the case study, the interviewees referred to the marathon finish line, Boylston Street, and other location identifiers. Interviewees also said what kind incident and all information pertaining to the incident was also important. In reference to the Boston Marathon bombing, interviewees mentioned, bomb, explosion, firefight, suspect names, etc. These findings were combined with the findings of the text analysis to establish keywords for the Twitter data search.

This study showed that geospatial information was present in Twitter data around the Boston Marathon in two ways. All geotagged tweets had absolute location by including a set of coordinates in their metadata. A subset of tweets also included relative location by referencing locations of the events, such as Boylston Street or Watertown. Tweets showed the particular street where the bomb went off and that it was the finish line of the Boston Marathon. The spatial analysis shows that location matters and proximity matters in crowdsourced data. The largest density of tweets was centered on the bombing location. As other events occurred, the density of tweets around those events increased in turn. First responders could track spikes in tweet density, which could serve as a type of alarm that something was happening in the area. If this were coupled with a broad array of keywords relevant to emergencies, then first responders would know where and what was happening.

Not only was the information found in crowdsourced data during the Boston Marathon useful, but also it was also timely. The spatio-temporal analysis was performed for Twitter data from Monday. Within three minutes, the data showed that an explosion occurred in the Back Bay neighborhood of Boston. As time passed, more and more tweets were produced; there was a 950 percent increase between the first 15 minutes and the next 45 minutes. This shows that first responders could access information using crowdsourced data following a terrorism event within just a few minutes.

5.2. Recommendations for First Responders

Based on the results of this study, social media data appears to be a valuable resource for first responders to examine during a terrorism event. As such, this thesis leads to several recommendations for how first responders can use crowdsourced data as a source of intelligence:

- Agencies need to develop or acquire the ability to collect crowdsourced data in real time.
- Agencies need to develop a list of keywords that are specific to their area of operations (events, locations, possible targets).

- Agencies need to develop a list of keywords that pertain to events they may be responding to (bomb, shooting, etc.).
- Agencies should create a buffer around their area of operations to focus on things that are occurring in their response area.
- Agencies should also develop or acquire machine-learning programs to identify spikes in keywords or anomaly words.
- Agencies should use social media as a tool to disseminate information to the public during an emergency situation.

5.3. Study Limitations

While this study successfully assessed crowdsourced data during an emergency, there are areas for improvement. The limitations include: only 1 percent of the tweets in this time period were studied, the accuracy of the contents of the tweets, and the keywords used. Learning from the limitations that were confronted in this study will help improve the methodology in future research of this kind.

5.3.1. Data Limitations

One of the biggest limitations that were encountered in this study was the data received. Twitter data received from the third-party source GNIP is technically incomplete; you only receive 1 percent of the tweets from the requested time period up to a maximum of one million. Based on the number of tweets received, there were potentially 15,491,500 tweets during this time period. Accessing the full number of tweets has the possibility of giving even more information to assist first responders.

The next data limitation is data quality. As with any form of crowdsourced data, what someone tweets may not be accurate. Starbird et al. (2014) explained this well with analysis of

Twitter data following the Boston Marathon bombing. They discussed three rumors, a death of a young girl, a false flag attack, and releasing the wrong identities of the suspects. Anyone can say anything on a social media platform, regardless of truth, much like speech in general. There are certain limited situations during which speech is not protected by the First Amendment, e.g. falsely yelling "Fire!" in a crowded theater. However, so far no one has been prosecuted for spreading false information on Twitter. This means that first responders will have to check the accuracy of tweeted information, using up valuable time they could be acting.

5.3.2. Method Limitations

While the methods used to determine keywords provided useful results, they did constrain the search criteria. The text analysis performed using NVivo 11 had certain limitations. NVivo 11 produced the most frequently used words; this study looked at the top 500, but the program can do more. However, it does not recognize open compound words, such as "finish line"; these words would be separated as "finish" and "line" in the search results. This means that some words that should have been important may not have been recognized as such because "finish" and "line" may not be deemed relevant on their own.

The creating of the final keyword list depended on a word appearing as a top word in the text analysis and included as an interview response. This caused for the keywords to vary from day to day depending on the frequency, as well as a whole list of possible keywords provided by the text analysis and interviews to go unused. The fact that only 1 percent of texts were searched for keywords could also impact the results. Lastly, a keyword might show up in a tweet but have no connection to the events taking place; for example, "slurpees are so underrated #bomb" returned from Monday's keyword search.

5.4. Moving Forward

This study shows that crowdsourced data such as Twitter can be used in gathering information in an emergency. Through the analysis, the results show where and when these tweets were issued. After examining the findings of this study, it appears that there is a need for a meta-analysis of terrorist events and the use of social media. The events surrounding the Boston Marathon were uncommon for a terrorist event because it took place over multiple days, while most are single day discrete events. This meta-analysis should look at a number of topics including single and multi-day events; different social media platforms; if first responders were on scene (like Boston Marathon) or not; and events that occurred in other countries. Another area that could be looked into is mass casualties events such as the 2017 Las Vegas Shooting. Examining studies related to these topics has implications on how to best utilize social media data for first responders.

Given the volume of data produced on social media (potentially 15 million tweets over five days within 25-mile radius), an automated process would be needed to review all the Twitter data during real time. There are currently companies such as Dataminr that use machine learning for detecting, classifying, and determining the significance of public information in real time. Machine learning could be the key to being able to use crowdsourced data for intelligence purposes. There is too much social media traffic for an analyst to search. Also, there are many different types of emergency events, so keywords would need to be different for each one. An automated process could provide real time information for any number of events, and filter out unnecessary data. Analysis could also be done to determine if the frequency of the use of the word fuck increased dramatically after the bombing and other events. Even though the exact event would not be immediately obvious from many of the tweets, if there was a sudden uptick of emotive tweets, a machine could potentially detect it.

As the day and then the week went on, more tweets appeared away from the event sites. This shows that Twitter is also a good way to disseminate information to the public. People miles away from the explosions shared information within minutes. In this way, Twitter can also assist first responders by communicating important information to the public rather than only through harvested intelligence from tweets. It could ultimately help intelligence gathering if a member of the public that is informed via Twitter has important intelligence to share later.

While the Boston Marathon bombing was a major emergency event, it may not have been the best choice for assessing the value of crowdsourced data for first responders. The main reason being that there were already first responders on the scene for the marathon. These first responders would be providing on the ground intelligence about the incident. Intelligence gathered from tweets may prove to be even more useful during an unknown event where there are no first responders initially, such as the Pulse Night Club shooting in Orlando, Florida or the Las Vegas mass casualty event in Nevada. In those cases, geotagged tweets could have led first responders to the exact site of the emergency faster than 911 calls or other more conventional methods. Crowdsourced data would also be less useful during the firefights with the Boston Bombing suspects. Law enforcement on the ground would have better intelligence than any bystanders providing information through Twitter.

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Appendix A: Interview Protocol

Introduction

Terrorism continues to be one the most significant security threats of our time. Recent terrorism events include mass shootings and bombings in the U.S. and worldwide. First responders—law enforcement, emergency medical services, and fire services—are responsible for managing the chaos in the immediate aftermath of a terrorism event. Providing first responders with high quality, detailed information as quickly as possible could greatly enhance their ability to respond effectively. The focus of this thesis is to determine if Twitter posts are a useful source of intelligence for first responders.

The utility of twitter data for first responders is being explored using a case study of twitter posts immediately following the Boston Marathon bombing in 2013. Determining if tweets can help first responders determine the location of event, extent of affected area, type of damage, severity of damage, location and number of casualties, and presence of other first responders. Information mined from tweets will be compared to the actually available information to determine if it could have provided a more definite location, more detail, and was timelier. This thesis also discusses related research questions about using crowdsourced data for intelligence purposes including the relative accuracy of the data the potential for automating searches and pushing the information to first responders in case of an emergency, and whether there are ways to encourage or boost social media use to augment available information following an incident.

1. Do you consider yourself a first responder?
2. How would define the term first responder?
3. What organization are you a first responder for?
4. How long have you been with this agency?
5. What is your current position/title?
6. Do you have other experience as a first responder, and in what capacity?
7. Do you have experience as a first responder in a emergency situation?
8. Does your organization classify emergency events? How?
9. How do you receive information for responding to an emergency?
10. What type of information do you receive?

11. Do you know if your organization uses social media during an emergency, either to gather information or disseminate information to the public?
    a. If yes, is there a designated person in your agency responsible for social media?
12. What information would you find useful during an emergency?
    a. Location of event
    b. Extent of affected area
    c. Type of damage (e.g. fire, gas, flooding, active shooter, etc.),
    d. Severity of damage
    e. Number of casualties
    f. Presence of other first responders (Fire, Police, Medical), etc.
13. Have you ever responded to a terrorist event?
14. Do your answers from above change if you are considering a terrorist event?
15. Do your answers from above change if you are considering a multi-day event such as the Boston Marathon bombing events?
16. What characteristics of information would you find useful during an emergency?
    a. More definite location
    b. More detail
    c. Timelier, etc.
17. Do your answers from above change if you are considering a terrorist?
18. Do your answers from above change if you are considering a multi-day event such as the Boston Marathon bombing events?
19. How often do you train to prepare for a major emergency/terrorist event?
20. Is there anyone you would recommend for this interview?