Modeling Cognitive Response to Wireless Emergency Alerts to Inform Emergency Response Interventions

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Executive Summary

Wireless Emergency Alerts (WEAs) are a critical mitigation measure employed during emergencies to inform and keep the public safe. Research on WEAs and disasters conducted by the Pacific Northwest National Laboratory (PNNL) and Advanced Brain Monitoring (ABM) has found that individuals perceive the threat of floods differently than other types of disasters on a physiological level within the frontal lobes of the brain. This difference occurs both when subjects are told they are about to watch a video about floods and when they are watching or reading alerts about floods. The perceived urgency of floods also appears to be more sensitive to the personality characteristics of individuals than during other types of disasters.

Methodology

The PNNL and ABM effort collected 20-channel electroencephalography (EEG) data from 51 subjects as part of an experiment to evaluate the ways in which people perceive different kinds of disasters, and their response to different types of social media content related to disasters. Subjects were presented with a series of 50 WEA and Twitter messages collected from each of five types of disasters (blizzard, flood, gas leak, hurricane and tornado) for a total of 250 messages, and asked after reading each if they would share that message over their own personal social network. These messages were a combination of those shared by actual Twitter users and disaster alerts sent by news stations and other emergency alert services at the time of the disaster. Prior to exposure to a disaster-specific set of messages, subjects were told what type of disaster they were about to view, and then shown a contextual news broadcast related to that type of disaster. All subjects were exposed to the same 50 WEA and Twitter messages for each disaster, but the order in which the disasters were presented was changed randomly each time.

Response to Wireless Emergency Alerts and Social Media Messages

Subjects were more predisposed to share WEA and disaster tweets expressing a dismissive sentiment (i.e., a message that advocates or expresses intent to ignore a disaster alert) about floods than they were other types of disasters. Analysis of EEG data from the subjects during the period of time when they were deciding if they would share a given message with their peers over a social network suggests that this decision making process occurs primarily within the frontal lobe. This is significant because it aligns with other published research postulating the frontal lobes are essential for all aspects of decision-making and play an important role in many higher cognitive functions[1]. Subjects in our study typically had higher levels of brain activity when deciding to share a message as compared to when deciding not to share a message, suggesting a more deliberative thought process. Brain activity changes were especially pronounced when subjects were choosing to share disaster alerts. Older subjects (age 50+) were significantly more likely to share messages of all types with their social network than younger

[1] Pizzagalli, D.A., Sherwood, R.J., Henriques, J.B., Davidson, R.J. (2005). Frontal brain asymmetry and reward responsiveness: A Source localization study. *Psychological Science*, 16, 805-813.

subjects. Overall, all subjects were highly responsive to all types of disaster messages (WEAs and tweets) and shared them a majority of the time.

Video Response

Our findings suggest that subjects have different brain responses towards different types of disasters that are inversely correlated with the volume of danger perceived. During the subject trials, all subjects were shown a context video (news coverage of the specific disaster) immediately prior to responding to WEAs and tweets associated with that disaster. Subject brain activity during these videos was analyzed and compared across disaster types to assess how the subjects perceived the disasters. Previous research by Dennis et al. (2010), exploring the impact of emotional film clips, discovered that subjects with higher levels of electrocortical activity in the frontal lobes were less effected by the stimulus, and the influence of the stimulus was shorter lived[2]. This is consistent with what we observed. Our analysis also found that subjects with the highest levels of activity during the video stimulus were also those who were less likely to share informative WEAs and tweets about the disaster with their peers.

The subjects' brain activity prior to the presentation of the context videos was also examined. Before the beginning of context videos, subjects were presented with a message explaining that they were about to see a video and tweets about a particular type of disaster. We observed that users have an immediate change in physiological disposition. Their response, therefore, was not shaped by the particulars of the video itself, but only their immediate, visceral disposition towards that type of disaster. *This analysis suggests that subjects' response to floods is due to their fundamental perceptions of the dangers of floods, and not the specifics of the scenario*. Conversely, upon being told they were about to view a video about tornados, subjects showed unusually high attention — a stark contrast to the response seen towards floods.

Conclusions

Overall, the WEAs tested proved to be highly effective across all disaster types and when compared to other social messages, the WEAs were among the most shared by the test subjects. Even when subjects chose to share these alerts, however, the EEG responses to flash-flood specific alerts were distinct from other disasters. When shown context videos for each type of disaster, and particularly for floods, subjects with the least levels of attention and engagement during the video stimulus were also those who were less likely to share informative tweets about the disaster with their peers. Additionally, subjects more frequently shared messages expressing a dismissive sentiment (i.e., a message that advocates or expresses intent to ignore a disaster alert) regarding floods than they were other types of disasters. These responses appeared to be the most exaggerated when among subjects with the least depressive personality types.

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[2] Dennis, Tracy, Beylul S. "Frontal EEG and emotion regulation: Electrocortical activity in response to emotional film clips is associated with reduced mood induction and attention interference effects" Biological Psychology, 2010. Vol. 85.

Together, these findings suggest that the subjects perceived the threat or urgency posed by a flash flood quite differently than other disasters on a physiological level. The response also appears to occur almost instantaneously, suggesting that the response is perhaps reflexive or develops over their lifetime. This response appears to manifest itself in the form of subjects both appearing less mentally engaged with the news coverage of floods, as well as an increased willingness to ignore or actively dismiss the associated weather alerts. Limitations with the study conducted are detailed within this report.

Recommendations

The PNNL and ABM team have one primary recommendation and one secondary recommendation for the use of WEAs coming from this research.

Recommendation 1. When compared to tornado, hurricane, gas leak and blizzard WEAs, flood WEAs were systematically perceived differently in our study group. **This leads the PNNL team to suggest that additional attention be directed at communicating the risk of floods to citizens.** For example:

- The WEA could focus on stating specific and direct action for recipients.
- Various formulations of WEA could be disseminated specifically for floods as a special case.
- Although geo-targeting of WEA was not in the scope of the PNNL study, providing citizens with location relevant information may further encourage action.
- Education stressing the seriousness or severity of floods and other similarly dismissed disasters might help reduce the public’s flippant response to the alerts.
- Users act as a megaphone for disaster alerts in other instances, amplifying the exposure of the alert by repeating its information, particularly for tornados. DHS should consider identifying methods to better harness this effect for perpetuating the flood alerts.
- Further understanding of how citizens perceive the risk of disasters in specific regions or of certain cultures is needed. PNNL noted social media users dismissing specific types of disaster alerts (floods) based on Southern California flash floods. Citizens in other types of disasters in other locations (i.e., Southern U.S. as opposed to the Northeastern U.S.) might treat hurricane warnings with similar disregard because they are more common.

Recommendation 2. The results of this study in combination with several recently published reports support the validity of specific neural responses to various types of communications, narratives and messaging that can accurately predict human behavior in response to these communications. We recommend the implementation of platform technology to routinely screen emergency message form and content using neurophysiological, cognitive and other measures to

add to a database acquired for comparisons and data modeling. This approach would include developing a database of responses from a diversity of people representative of the U.S. population demographics and regions. Data would be uploaded via a cloud-based portal that is easily accessible with a PC and Internet access.

1.0 Introduction

1.1 Overview of Project

Decision making under uncertainty is a complex phenomenon that is being researched in this project using neurobiological and psychological concepts. First, information is acquired and processed; however, in times of uncertainty, information may be insufficient (Mileti and Sorensen 1990). Under such conditions, human nature is biased to favor what is established over what remains ambiguous, regardless of the potential that may be extracted from the ambiguity (Ellsberg 1961). The comparative ignorance hypothesis (Fox and Tversky 1995) is founded in the Ellsberg paradox and cites lack of knowledge as the reason behind such ambiguity aversion. Decision making under uncertain and ambiguous circumstances is thus heavily influenced by cognitive biases based in assumption and instinct. This perceived risk is the basis on which public and environmental agencies focus their efforts (Slovic, Fischhoff and Lichtenstein 1979). Thus, understanding perceived risk is necessary to ensure that the efforts of public and environmental agencies are not misdirected and that the receiver is not inundated with irrelevant information.

A goal of active research into hazard risk perception is to explore and analyze the cognitive response guiding an individual's perceptions and to determine why some citizens react to particular hazards with extreme aversion, and with indifference or compliance to others (Slovic, Fischhoff and Lichtenstein 1979). While emergency management personnel have a realistic command of the risks posed by emergencies, citizens have their own perception of the threat posed by a particular type of emergency and, consequently, might evaluate the validity or urgency of alerts in accordance with their perceptions. In extreme cases, individuals might even feel they can dismiss the alert entirely. When the knowledge of the expert is at odds with public perceptions, great difficulties can arise and complicate emergency communications with the public. Understanding how individuals may perceive the threat posed by different categories of disaster can help emergency management professionals adapt their communication methods accordingly and more accurately anticipate the public's response to alerts.

The project's hypothesis is that cognitive responses towards Wireless Emergency Alert (WEA) messages can be used to evaluate how individuals apply their knowledge and emotional response to the process of risk perception of different types of disasters. By assessing the cognitive response to officially documented hazards (specifically, natural disasters) the project seeks to determine the degree to which members of the public respond to WEA messages and the differences in their perceptions of different types of hazards. This was accomplished by collecting wireless electroencephalogram (EEG) data on subject brain activity within an experiment testbed as they were exposed to a variety of news reels depicting emergency situations, social media messages related to those disasters and WEA messages. We then analyzed and modeled this data to determine the factors that motivate a positive response from receivers of an alert. This analysis can then be further used to improve the effectiveness and

efficiency of official alerts and warnings by (1) identifying hazards that the public perceives as marginal or trivial threats, (2) quantifying the level of the public's engagement with alerts pertaining to these threats, (3) building a culture of resilience, (4) reducing risk and uncertainty by increasing propagation of relevant knowledge where necessary, and (5) augmenting preparedness for similar future hazards.

With sponsorship from the U.S. Department of Homeland Security (DHS), Science and Technology Directorate, the Pacific Northwest National Laboratory (PNNL) is addressing these challenges by studying the cognitive models that shape an individual's response to different types of disasters and disaster alerts over social media that allows for better understanding of risk response and thus an improvement in risk communication between the expert and the layperson.

1.2 Background on Risk Communication

At its most basic, risk is the probability that negative consequences arise from a particular event (United Nations 2009). These events can be as common as the choices made in daily life or as complex as the ethics behind drug testing (Tannert, Elvers and Jandrig 2007). Human response to risk has been studied extensively in an attempt to understand the effect of risk perception on decision making.

1.2.1 Understanding Risk Perception and Communication

Trainor (2010) proposes that layperson risk assessment upon initial receipt of a warning or an alert begins with (1) understanding the warning and (2) believing that the warning is credible. Mileti and Sorensen (1990) define understanding as attaching personal meaning to the warning, creating a personalized reality from which further risk judgments will be made. Such differences are why technical terms (e.g., tornado warning versus tornado watch) are not intuitive (Trainor 2010). Furthermore, laypeople must believe that the threat could materialize and become a real and present danger. They must also (3) personalize the threat and believe that the threat will affect them personally. These first three steps are crucial because warnings are more likely to be heeded and responded to with protective action if they are understood, believed and personalized (Mileti and Sorensen 1990). The subsequent processes evaluate the layperson's logistics for initiating protective action. The layperson must determine (4) whether action is needed, (5) whether it is feasible and (6) whether resources are available for execution. Protective action is dependent on the characteristics of independent members of a community who may be better equipped to respond because of sufficient knowledge, previous experience, physical ability or economic resources (Mileti and Sorensen 1990).

1.2.2 Risk Identification

Before risk can be perceived or assessed, a hazard must be identified (Hoppner, Buchecker and Brundl 2010). For instance, an audio alert must be heard by the warning recipient before any

action can be taken (Mileti and Sorensen 1990). Such identification is dependent on information gathering and processing.

The ability of the warning recipient to cognitively process information is dependent on the availability of information. When presented with an impending hazardous event, the warning recipient does not inertly await for more information to be given to him or her; rather, he or she vigorously searches for new information that may allow him or her to decide how to react (Mileti and Sorensen 1990). Furthermore, the layperson must deem this information (e.g., information disseminated through alerts, warnings, news, word-of-mouth) to be convincing and reasonable. Mileti and Sorensen ascribe necessary information as that of (1) location of the risk, (2) guidance and direction provided to the public as a plausible response to the risk, (3) characteristics of the risk, and (4) the amount of time the public has to respond. Thus, it is important for the layperson to fully understand the implications of the risk before making a decisive action plan.

The credibility of the warning is also important. The communicators of the warning must be transparent and trustworthy to inspire belief in their messages (Hoppner, Buchecker and Brundl 2010). For laypeople, credibility is heavily aided by confirmation (Mileti and Sorensen 1990) that may manifest as physical or social cues. Physical cues are reliant on the five senses; for instance, the warning recipient may see the heavy rain that characterizes a flash flood or smell the smoke that accompanies a fire (Federal Emergency Management Agency). These physical cues are processed through various cortices in the brain and form the reality observed by the receiver. It must be noted that such processing is unique to each individual and thus, there is no objective reality (Mileti and Sorensen 1990). Reality is instead confirmed through social cues, such as communication with family and friends to confirm or verify the legitimacy of an alert. This has been shown to be more influential than warnings from officials (Corley et al. 2014), but not as influential as personal experience or perception (Bostrom 1997).

1.2.3 Cognitive Processing of Risk Perception

A prominent theory of perception is embodied cognition, which asserts that the integration of the mind, body and state of the body is essential for cognitive action that will manifest in motor behavior (Borghi and Cimatti 2010). Embodied cognition is closely associated with semantic memory (Binder and Desai 2011) in that the two theories' characterizations of perceptual symbols which, when integrated with a particular context sensed through embodied cognition, motivates action (Barsalou 1999). For instance, language and number representation must be mapped to a perceptual symbol that is processed through embodied cognition to assign it meaning (Andres, Olivier and Badets 2008). The stimulus — in this example, language or number representation — is further tagged with abstract feelings of good or bad (i.e., affect) that associate the input stimulus with the outcome (Schmitt, Brinkley and Newman; Slovic et al. 1999), which is then stored in semantic memory. Semantic memory contains all acquired knowledge, information and perceptual experience that can be recalled to apply to new situations (Binder and Desai 2011). Knowledge retrieval is significant because it integrates individual experience with semantic abstractions in the context of real-world knowledge (Goldberg et al.

2007) to personalize information that can be acted upon from a cognitive and psychological standpoint.

Conceptual abstractness is also supported by the fuzzy-trace theory (Reyna and Rivers 2008), which posits that humans remember in intuitive gist representations of objects or feelings, rather than analytical verbatim-based representations. That is, the semantic features of an event (i.e., the overall idea or concept and the emotions that accompany it) hold much more significance than the specific, factual details of the event. Fuzzy-trace theory has been shown as a derivative of prospect theory (Reyna and Brainerd 2011), which employs heuristics and cognitive biases (i.e., the framing effect) in assessing loss. It posits that loss is more significant than gain, which is significant in risk assessment because it implies that laypeople react more strongly to prevent loss than to take the risk of a probabilistic gain (Kahneman and Tversky 1979).

1.2.4 Linguistic Implications

The frame effect is important in illustrating the importance of language. An experiment conducted by Tversky and Kahneman (1986) poses two treatments of equal value in a positive (i.e., save 200 lives out of 600 total) and negative (i.e., 400 people will die out of 600 total) frame. In conjunction with the prospect theory and fuzzy-trace theory, results revealed that an overwhelmingly greater proportion of people would support a treatment when presented in a positive frame than in a negative frame. Thus, it follows that language that constructs a positive frame encourages risk-aversive behavior, while one that constructs a negative frame will motivate risk-seeking behavior (Tversky and Kahneman 1986).

Though not as striking, positive and negative language can also motivate differences in risk perceptions. Not only is perception dependent on cognitive biases, such as the framing effect, but it is also thoroughly processed by embodied cognition, recalled from semantic memory, and integrated with sensory cues (as discussed above). To unify these concepts, imagine an alert that warns the actor to “flee” as opposed to “run.” The former, placing the actor in a negative frame, elicits a negative effect. Furthermore, when embodied, cognition tells the legs to escape, which recruits the muscles of the legs as if to prepare for the action itself. Simultaneously, a memory of a previous experience in which the actor was similarly fleeing from danger could be recalled. Combined with sensory cues of a large funnel cloud, the sounds of screaming, and retrieved knowledge that the combination of both could only mean a fairly destructive tornado, the risk would be perceived as imminent.

The significance of language is thus undeniable. It has been found that emotions and mood can be abstracted from text such as social media (Aisopos, Papadakis and Varvarigou 2011). Language processing also elicits a neurobiological reaction (Isenberg et al. 1999). Furthermore, with the improving capabilities of artificial intelligence, computers are being trained to process language as well as humans. Linguistic tools, such as Linguistic Inquiry and Word Count (LIWC) and the Penn Treebank Part of Speech (POS) tagger, enable this by parsing complex thoughts and sentences into their fundamental segments (i.e., into dictionaries of word categories

by LIWC and into grammatical parts by Penn Treebank). As posited by the fuzzy-trace theory, the layperson relies on gist representation more than surface verbatim representations in decision making (Reyna and Brainerd 2011). This implies that because the gist of the word is more telling than the word itself; words can be classified in simpler representations of abstract ideas, such as the categories defined by LIWC.

Such division is based on the premise that it is not the content of the sentence itself that matters, but the way in which the content is expressed (Danescu-Niculescu-Mizil, Gamon and Dumais 2011). For instance, Pennebaker (2013) emphasizes that 60 percent of the vocabulary used in daily life is composed of function words (e.g., a, an, the, them, that) that offer no content at all, but are instrumental in communicating ideas. For example, using only pronouns, Pennebaker (2013) was able to determine a writer's personality. Furthermore, as a tense-aspect-mood language, English naturally reflects the speaker's position in time, the continuity of the action in time, and the modality of the action (i.e., degree of obligation, necessity, ability) (Bybee, Perkins and Pagliuca 1994), which reveals much information about the current action or thought process of the speaker.

This thought process is also apparent through sentence construction. The dependency theory and sequential cognition posits that there is a gradual accumulation of meaning through the progression of a body of text (Altmann and Steedman, Schank, Schank and Tesler 1988). Schank and Tesler (1969) represent this in their model of conceptual dependency, which proposes that a word is stored in the mind until a subsequent word is able to give it meaning. It is not that the later words in a sentence are the most important, but that their cumulative meaning is more significant. This is why the full meaning of a sentence can be deduced only at the end of the sentence. The implication of this is that word order is important and must be considered when analyzing the intent and meaning of a text.

1.3 Background on Cognitive Processing of Risk Perception

The ability to clearly communicate between the public and those responsible for assessing, minimizing and regulating risks is critical for successful resolution of a public emergency. Strong personal safety concerns cause the public to develop symptoms of emotional and behavioral distress that adversely affect the perception of risk during a crisis through the evocation of strong emotions such as fear, anxiety, distrust, anger, outrage, helplessness and frustration (Covello 2001). Understanding the dynamics of risk perception during a crisis is crucial for successful emergency response because ultimately people act on the basis of what they believe to be true. Perceived risk is known to have a stronger impact on disaster recovery and preparedness than actual risk as communicated by emergency public information officers. For example, a study on risk communication shows households in America are more strongly motivated to prepare for terrorism and other hazards by observed preparations taken by others than they are by information received from preparedness information providers (Sandman 1989). Although public officials depend on precision and clarity, properly tailoring their communications using derived lexicons is only now being investigated (Temnikova 2014).

The adoption of risk communication strategies that promote trust, credibility, effectiveness, abidance of moral and ethical values, respect, and timeliness can greatly minimize risk perception biases by reducing public emotional and behavioral distress, whether the emergency concerns disease control (Reynolds 2002, Reynolds 2004, CDC 2008), natural/manmade disasters (for example, see Covello 2001), or terrorism (Burns 2007a, Burns 2007b). Because risk perception is also regulated by social identity factors (Douglas 1982, Kasperson 2003, Kahan 2012), adopting effective risk communication strategies that promote trust, credibility, etc., requires due attention to cultural differences that characterize diverse populations including persons with functional and access needs, transients/tourists, elderly/older adults, isolated/rural populations, institutional populations and non-English speaking people.

Moreover, in the past few years, short messages have been used in various forms for disaster-related risk communication. The multistage developmental process for risk communication that is discussed by Fischhoff (1995) is still relevant to short messages and the new generation of communication media. One notable instance was the use of social media to communicate warning messages during the 2008 terror attack in Mumbai, India. The consensus of review articles is that social media is not just a new means to carry out an old risk communication strategy (Hamilton 2009, Burns 2007a and Burns 2007b, Kasperson 1986, Slovic 1982, Slovic 2010). However, language use varies widely, depending on proximity to the disaster, both geographic and experiential (Lin 2014).

Whether for disaster response, advertising campaigns or general entertainment, people leverage social media to spread information to wide and varied audiences. When crafting a message on social media, authors may attempt to consider humor (Evers et al. 2013), trustworthiness (Kietzmann et al. 2011) or timeliness (Lee and Ma 2012), among other factors, to increase the reach of their message. Authors may not consider the personality or mood of target users when anticipating the impact and propagation of their messages. Systematic biases in target populations will confound attempts to understand social contagion (Hodas and Lerman 2014). Because of homophily, personality types will not be randomly distributed in the social network, and users will be exposed to content biased by the personality of their friends (Hodas et al. 2013). It is important to better understand the link between personality, mood and social contagion.

The link between social media posting behavior and personality traits has been well established in literature. For example, Big Five personality scores have been used in predicted models based on participants' recent tweets (Golbeck et al. 2011). Similar calculations were run with social graph and interactions between users taken into consideration (Adali and Golbeck 2012). Big Five personality traits were also modeled on abstract groups of users (such as 'listeners,' 'popular,' 'highly-read' and 'influential') based on user behavior (Quercia et al. 2011). Anti-social traits such as narcissism, psychopathy and Machiavellianism (the "Dark Triad") were predicted and compared with the Big Five personality traits, using language features of tweets (Sumner et al. 2012).

Examination of emotion, personality and brain modeling techniques such as EEG and MRI has been similarly well established, from predicting patterns of regional brain activity related to extraversion and neuroticism (Schmidtke and Heller 2004), to EEG based emotion recognition when listening to music (Yuan-Pin Lin et al. 2010) or stories designed to evoke specific emotions (Correa et al. 2015, Stikic et al. 2014). Broader emotional recognition with EEG has also been examined with high accuracy (Petrantonakis and Hadjileontiadis 2010, Correa, et al. 2015, Stikic et al. 2014), as well as a functional MRI study of the neuroanatomy of grief (Gündel et al. 2003).

A previous effort at fusing EEG, emotion and social media focused on producing tweets reflecting a user's emotions at certain physical locations. These tweets included both an emotion component and geotagged location component ("I am Frustrated at this location (Bus Station)") (Almehmadi et al. 2013). Work has been done to tag content based on neurophysiological signals, a technique described in (Yazdani et al. 2009) to produce implicit tagging of emotional states represented in multimedia via EEG and a brain computer interface.

2.0 Risk Communication and Perception Messages

Upon receipt of a risk communication message (i.e., an alert or warning message) during a crisis, members of the affected population engage in a risk management decision process, which includes steps such as those shown below — adapted from Trainer (2010).

1. *Understand the alert/warning* – Once people receive a warning, they must be able to process the message and understand what it means.
2. *Believe the alert/warning is credible* – People must believe that the source of the warning is reliable and that the threat could materialize.
3. *Confirm the threat* – People must take steps to verify that the threat described in the warning is real.
4. *Personalize the threat* – People must believe that the threat is something that can potentially affect them.
5. *Determine whether protective action is needed* – People must decide whether they need to take action.
6. *Determine whether protective action is feasible* – People must decide whether they are able to take action.
7. *Decide whether you have the resources to take protective action* – Finally, people must have the resources to actually do what is required.

Our work relies on WEA messages that were shared with us by the Federal Emergency Management Agency (FEMA) as a part of this work. We proceeded with extracting a subset of the disasters and associated WEA messages for further study.

2.1 Exemplar Disaster and Alert Selection

We initially chose all alerts from well-known and documented disasters that had a distinct social media signal. The disasters selected for preliminary analysis are Hurricane Sandy, South Dakota blizzard of October 2013, El Reno (Oklahoma) tornado of 2013, Moore (Oklahoma) tornado of 2013, Alamo (California) gas leak of 2013, and Southern California flash floods of 2013. The majority of events selected were natural disasters; however, the Alamo gas leak was included to provide a specific example of a disaster related to industrial/human activity. From the initial set of alerts, we then chose a reduced set of a maximum of four alerts per disaster for Advanced Brain Monitoring (ABM) to present to human subjects based on the value of the alert text field. The WEA selected for this study are provided in Section 9.0.

2.2 Historical Twitter Data Acquisition

Historical social media data were obtained through a social media vendor using their historical data request application programming interface (API). All resulting data were ingested into Elasticsearch, a Lucene-based search engine architecture. Messages matching specific query parameters are marked by the vendor as belonging to that query set, allowing the messages for all disasters to be stored in a single index and simply filtered.

Table 1. Query Definition and Volume of Return – Limited Set

Disaster name	Date range	Tweet volume	Query terms
Alamo, CA Gas Leak	7/23/2013 7/29/2013	120	leak, gas, evacuation, pg&e, pge, pg+e, alamo, danville, shelter
El Reno, OK Tornado	5/25/2013 6/6/2013	1145	tornado, wind, shelter, evacuation, storm, chaser, funnel, EF, hail, moore, noise, warning, samaras, el reno, rotating, debris, disaster, twister, siren
Hurricane Sandy	10/25/2012 11/10/2012	208574	storm, hurricane, sandy, frankenstorm, flood, danger
Moore, OK Tornado	5/10/2013 5/25/2013	5100	tornado, wind, shelter, evacuation, storm, chaser, funnel, EF, hail, moore, noise, warning, rotating, debris, disaster, twister, siren
South Dakota Blizzard	9/28/2013 10/11/2013	761	cattle, blizzard, storm, atlas, south dakota, snow, freeze, frozen, cold, windy, travel restriction, whiteout
Southern California Flash Flood	7/01/2013 12/01/2013	1770	fire, burn, landslide, flood, mud, debris

2.3 Historical Query Design

To generate historical data queries, the project team brainstormed keyword lists for each disaster. To construct this keyword list, we focused specifically on named entities related to the event and on informal language describing the event. A date range for the historical query was selected by taking a range of ±5 days from the event date itself, except for the non-weather related Alamo, California, gas leak, where a date range of +5 days and -1 day around the event date was used.

2.4 Exemplar Tweet Selection

Tweets for each disaster were ranked according to a calculated modified term frequency– inverse document frequency value, providing a rough estimate of semantic content per tweet. This algorithm presents a summary ranking of all tweets in a sample set sorted for uniqueness and semantic content but does not filter for messages specifically related to the disaster. A second pass on the data was made by unsupervised modeling of tweets for each disaster into four Latent Dirichlet Allocation (LDA) topic models. LDA is a topic modeling algorithm that assumes

documents are composed of a mixture of topics. Topic discovery is an iterative process, producing probabilistic models of common words predicted to be members of topic sets. Documents are then scored according to these resultant topics. See Sections 8.0, 9.0 and 10.0 for an enumeration of the data available and selected tweets.

3.0 Disentangling the Lexicons of Disaster Response in Twitter

Over the past few years, short messages have been used in various forms for disaster-related risk communication. The multistage developmental process for risk communication that is discussed by Fischhoff (1995) is still relevant to short messages and the new generation of communication media. One notable instance was the use of social media to communicate warning messages during the 2008 terror attack in Mumbai, India. The consensus of review articles is that social media is not just a new means to carry out an old risk communication strategy. Language use varies widely, however, depending on proximity to the disaster, both geographic and experiential. Here, we present a new strategy for analyzing tweets during an emergency to understand how language is being used and which words help communicate latent factors. By analyzing the mutual information between words within a tweet and the extracted latent variables, we show that each type of disaster has a characteristic lexicon which is often surprisingly different from how the same words are used in typical tweets outside of emergencies.

3.1 Data

Social media is understood as an information propagation tool for reporting on and responding to natural disasters. Emergency management services use social media to issue alerts and warnings, look for reports of emergencies and understand public response to emergencies. Social media is used to share information leading up to, during and after the disasters. For the purposes of this study, tweets around a set of well-known and documented disasters were gathered for examination.

To collect pertinent disaster-related tweets, we used 203 FEMA-declared disasters in the United States from 2012 and 2013 (http://www.fema.gov/disasters). Historical Twitter data was obtained from Gnip, a provider of the Twitter firehose, using their historical data request API. Each query was composed of curated keyword lists, primarily named entities related to a particular disaster and informal language describing the nature of the event. Queries were further filtered both by geo-tagged location and date range. A date range for the historical query was selected by taking a range of ±5 days from the event date itself, except for the (non-weather related) Alamo, California, gas leak, where a date range of +5 days and -1 day around the event date was used. Example keywords used for the Alamo, California, gas leak included the following: leak, gas, evacuation, pg&e, pge, pg+e, alamo, danville and shelter. Geographical filters for the query were established using the area of impact of the emergency declaration, such as a single 25-mile radius around a defined point, or entire regions were selected when more than a single point of impact exists. For example, Southern California flooding and wildfires searched within California, Hurricane Sandy covered multiple states, and the Alamo gas leak was a single point centered on Alamo, California.

Acquired data was ingested into Elasticsearch, a Lucene based search engine architecture. Messages matching specific query parameters were marked by the vendor as belonging to a

specific query set, allowing the messages for all disasters to be stored in a single index and simply filtered for content. A sample of the queries are listed in Table 2, and the complete list is available on request. It is important to note that the nature of collecting only geotagged tweets means that we did not collect the subsequent retweets, but many people retweeted non-geocoded tweets and embedded their own geocode.

To generate a control group, we also randomly selected 50,000 tweets with geo-tags collected from the Twitter sprinkler between April and May 2014. The control group, which may or may not contain any disaster-specific tweets, allowed us to compare how the risk corpus is used outside of emergency scenarios.

3.2 Risk Corpus

To analyze how people communicate during crises, we hand-curated a list of words based on how users actually communicated on Twitter. The relevant geocoded tweets for each disaster were obtained as described in the data section. This collection of tweets was then used to curate a "risk corpus" of 292 words or expressions identified to be (at least partially) relevant to any of the disaster responses. This particular risk corpus was not meant to be definitive, and future work will focus on optimizing the breadth of the corpus and refining feature selection. Although many of the words may not be specific to commonly held notions of risk, we designed the corpus to encompass many of the ways users communicate fear, intent, targets and the issues inducing the risk (i.e., the emergency events themselves).

3.2.1 Clustering

Each item of the corpus was converted into a regular expression to capture common variants and avoid ambiguity. For example, the words smolder and smoldering were represented as smold. Variants of "fire" can be expressed differently to avoid tagging fireworks or firefighters as a variant of fire, which were searched for separately. The complete list is shown in Section 10.0. The resulting crisis related world list alone does not capture how risk is communicated by the public. One would have to identify informative subsets of these words to make sense of the general structure of the risk context conveyed by the public in the tweets. To obtain more relevant semantic clustering, we employed Correlation Explanation (CorEx). CorEx searches for latent variables that explain correlation between the usages of different terms.

A reduced subset of 50,000 tweets was randomly sampled for each disaster type for the final analysis. Some disasters had less than 50,000 tweets, and as many as possible were selected. Each tweet was converted into a vector, X, where X_i is the presence (or absence) of regular expression i in the tweet. For each type of disaster, we used CorEx to generate a tree of latent variables where each variable is constructed to maximally explain the correlations in its children. That is, we simultaneously search over latent variables, Y_j, $j = 1,..., m$, and clusters of words G_j so that $\Sigma_j TC(X_{Gj}; Y_j)$ is maximized. TC represents the amount of correlation in a group of

variables, X_{Gj}, that is explained by Y_j, and is specified by $TC(X_{Gj}; Y_j) = \Sigma_{i\epsilon Gj} MI(X_i; Y_j) - MI(X_{Gj}; Y_j)$ where $MI(X; Y)$ is the mutual information between X and Y. For a group of uncorrelated X_i's, for instance, this expression would give zero, while it would be maximized if all the variables were identical copies. To construct a tree, we take the $Y^{(n-1)}$'s learned on one level and apply CorEx again to learn a representation, $Y^{(n)}$. A detail of a sample tree is shown in Figure 2.

The CorEx algorithm provides a tree of latent variables explaining correlation in the data, but it does not provide explicit labels for the latent variables. To label the latent variable nodes of the tree, we propagated up the tree the corpus entries with the highest weight according to the mutual information between the label and the latent variable to be labeled. Results for the hurricane disaster are shown in Figure 2. To better understand our CorEx results and to test the robustness of our methods, we also applied CorEx to an entirely random sample from our control group, containing no explicitly selected emergency-related tweets.

3.3 Discussion

The CorEx technique succeeds at identifying both disaster specific themes as well as how word usage changes during emergencies. As we see in Figure 1 and Figure 2, the resulting trees are largely dominated by terms commonly used in disaster alerts. For the control tweets, the CorEx analysis produces very different clustering, implying different latent variables underlie the use of risk-related terms outside of emergency situations. For example, during fire events, the words "fire" and "firework" are closely associated, but this is not true outside of fire events. Similarly, outside of disaster events, the CorEx generates labels such as "hot/cold," "hours/minutes," "rain/sunny" and "char/destroy," as in Figure 1(c). During disasters, CorEx tends to identify combinations which are more mutually predictive, such as "power/loss," "evacuation/county" and "issued/until." Thus, we conclude that the resulting lexical analysis is specific to how users respond to disasters and not simply generic relations resulting from artifacts of the hand-curated corpus.

Our results show that tweets tend to focus on announcing the emergency, advising others or describing the damage. Other obvious clusters include expressions of anxiety, frustration and expletives. The CorEx results enable us to show which words in the corpus are most predictive of the latent feature, and thus may communicate the intent of the latent feature most clearly. For each type of disaster, we have produced a list of words that best communicate the latent variables. That is, for each feature X_i, there is a mutual information with each latent variable Y_j. High mutual information implies high explanatory power, and for each type of disasters we present a list of words that have the most explanatory power in each scenario. Because Y_i represent the latent variable which explains the co-occurrence of words below it in the tree, having high $MI(X_i; Y_j)$ means that feature X_i also helps explain why other words are used in combination with it in that disaster scenario. We present a brief list of the most and least informative words for each type of disaster in Table 2.

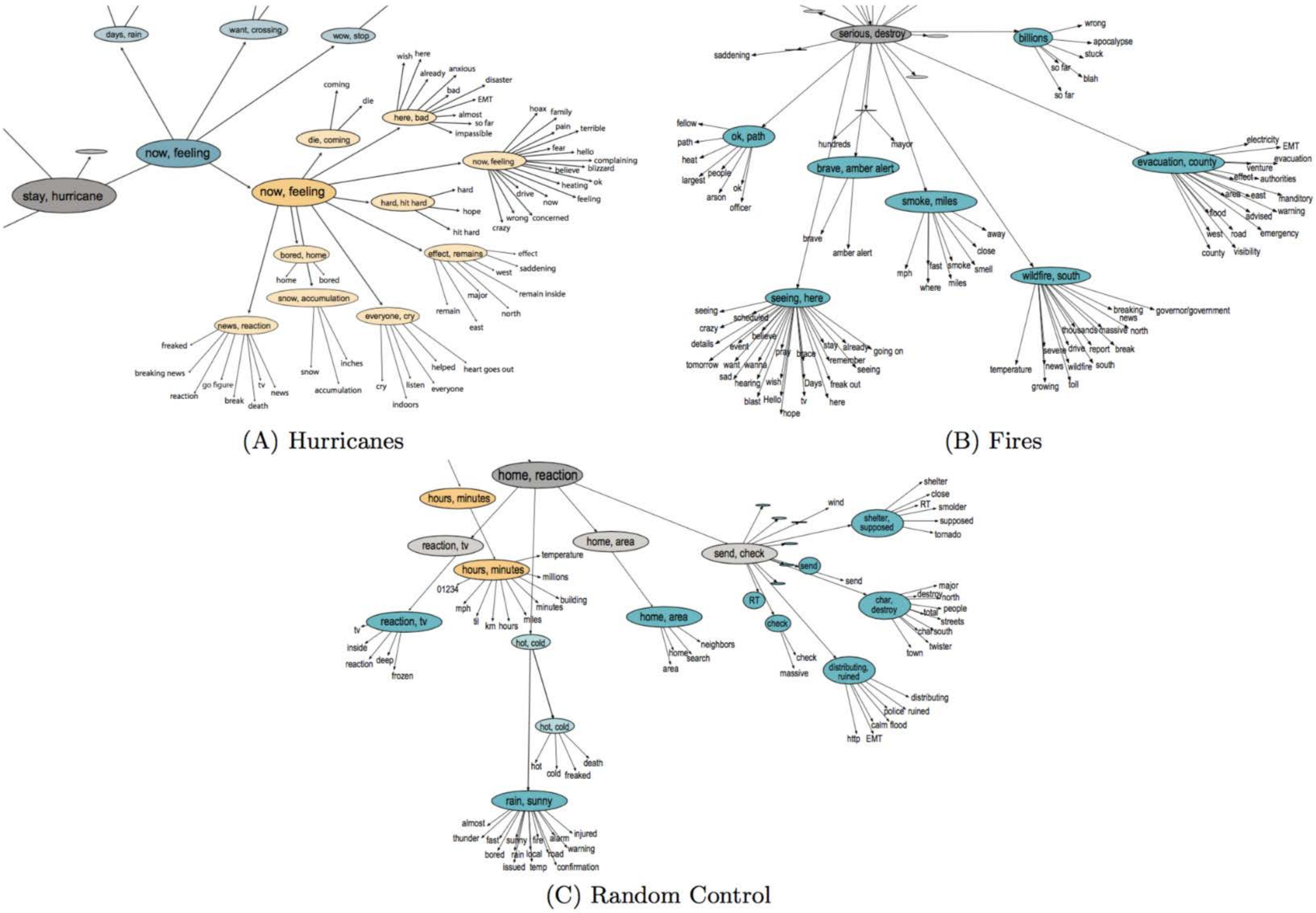


Figure 1. Sample section of CorEx dendrogram for the different disasters and a random sample of tweets from the control group. The inferred latent variable labels are inside the ovals and the terms are on the leaves of the trees. Colors are solely for clarity. For detailed view of a specific dendrogram please see Figure 2.

Table 2. Informative Words and Phrases. We exclude trivial disaster labels, e.g., "hurricane." (01234 indicates numbers)

Disaster Type	**Most Informative**	**Least Informative**
Random	Love, 01234, want, now, day	Mangled, fire dept, funnel, national guard, hoax
Hurricane	01234, house, power, flood, listen	False alarm, mangled, impassible, wind, fire fighters
Fire	01234, burn, smoke, police, firework	Doozy, struggle, ice, blah, arson
Explosion	01234, scared, house, expletive, bomb	Mph, temperature, anxious, remain inside, hoax
Tornado	01234, until, issued, mph, severe	Accumulation, wind, impassible, go figure, remain inside

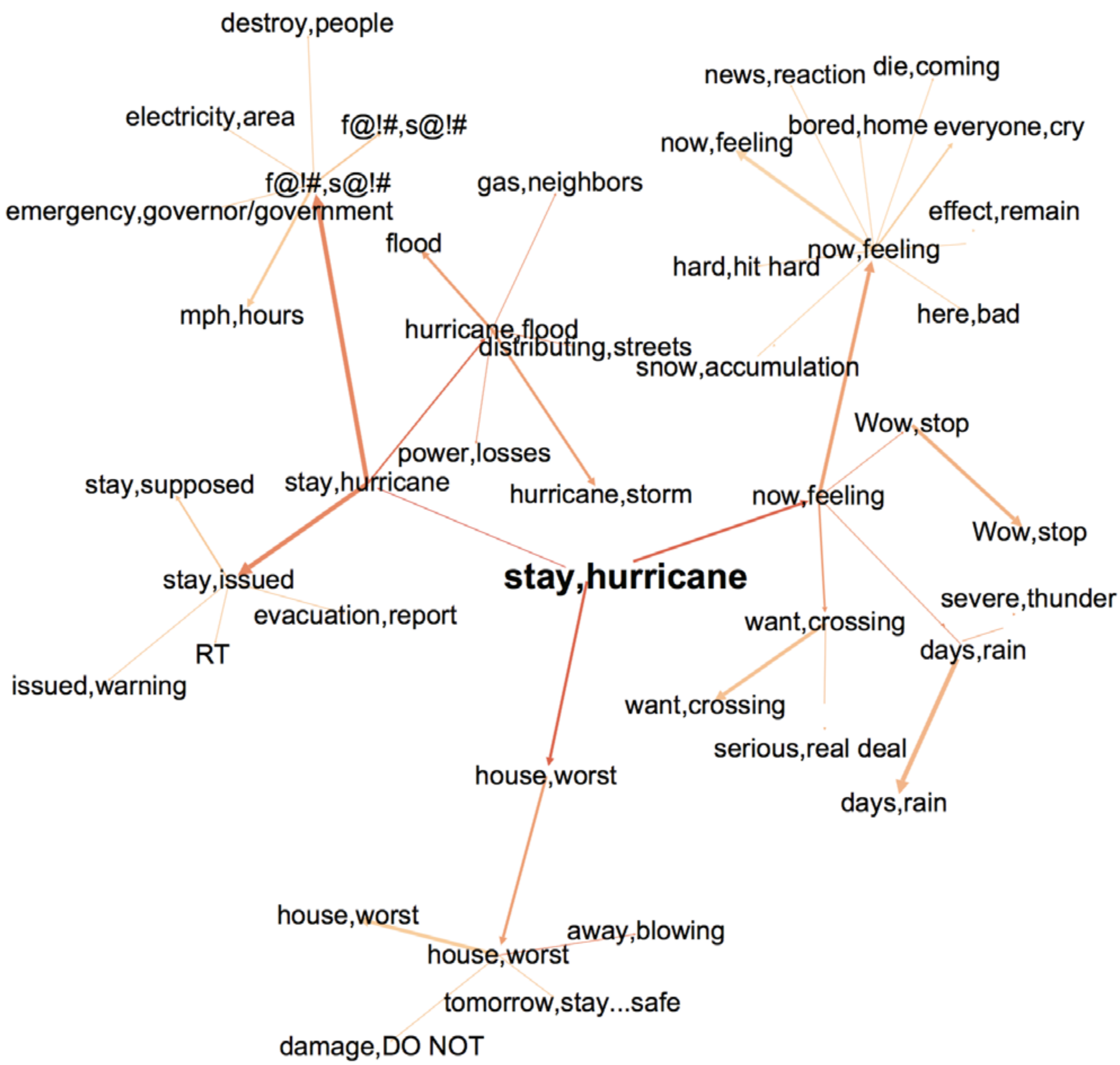


Figure 2. We assign labels to the latent variable tree by propagating highly informative words up the tree. The thickness of an arrow represents the mutual information between a node and its parent. "Stay, Hurricane" is the root node.

3.3.1 Most Informative and Surprising Tweets

The present CorEx technique enables us to analyze each tweet to determine how it is using words from the corpus of risk words. We score each tweet by summing its total correlation with respect to each latent variable for that disaster type. Low-scoring tweets utilize combinations of words in

unexpected ways and often do a poor job at communicating intent. Words that are highly predictive of particular latent variables (and therefore other words), will generally produce "unsurprising" tweets. That is, although the content may refer to a surprising event (tornado, explosion, etc.), the reader should be able to easily interpret how all the terms come together to communicate the inferred latent variable. For example, emergency alerts or discussions of the consequences of disasters tend to be highly informative and unsurprising, while passing comments or references tend to be uninformative and surprising, from our current total-correlation perspective. As a control group, we analyzed random geocoded tweets. We observed the risk corpus flags official National Weather Service (NWS) alerts as highly relevant outside of emergencies, but during emergencies, the most informative tweets tend to be less formal and more emotional than the random sample.

3.3.1.1 Randomly Sampled Tweets

Most Information/Least Surprising

- 50560: severe thunderstorm warning issued may 08 at 2:03pm cdt until may 08 at 2:30pm cdt by nws desmoines http://t.co/. . .
- 56065: severe thunderstorm warning issued may 07 at 9:20pm cdt until may 07 at 10:15pm cdt by nws minneapolis http://t.co/. . .
- 65326: flash flood warning issued april 03 at 4:01pm cdt until april 03 at 10:00pm cdt by nws springfield http://t.co/. . .
- 09:26 bst: temperature: 10.1◦c, wind: ssw, 0 mph (ave), 2 mph (gust), humidity: 89%, rain (hourly) 0.0 mm, pressure: 1015 hpa, rising slowly
- 00:33 bst: temperature: 10.2◦c, wind: s, 0 mph (ave), 0 mph (gust), humidity: 82%, rain (hourly) 0.0 mm, pressure: 1004 hpa, rising slowly

Least Information/Most Surprising

- "@googlefacts: in a tropical climate, oranges are green. in a temperate climate, oranges are orange."that's why our oranges are green!
- cups that change color with temperature are pretty much the reason i still get out of bed most mornings
- @locallink57 exactly! seems everyone selling them tho?!? crazy ! lol
- @name has the same issue, always loved his velocity but his past two starts haven't convinced me to keep him in rotation
- "solidskathniels: kathniel status: exclusively dating Aˆ l' yes magazine, feb issue." omg omg omg

3.3.1.2 Hurricane

Most Information/Least Surprising

- nws bmx has issued a severe thunderstorm warning for pickens county until 1030pm. #alwx "@wsvn: flash flood warning issued for eastern broward county and eastern palm beach county until 4:30 p.m."
- there's a flash flood watch in effect for bay county until 7 p.m. we've had reports of water on several roads. be careful out there!
- just what we (in pb county) need more rain. rt@wptv severe thunderstorm warning for sw palm beach co un til 4:15 p.m. #westpalmbeach
- weather gettin crazy sandy is gonna hit hard..god bless everybody stay safe!!

Least Information/Most Surprising

- finally #sandy. i can finally go play waterworld for real! everyone not on my team is a smoker #gonnagetcha @name so far it's a flood watch where i am no wind advisory
- frankenstorm + canadian earthquake + tsunami advisory for hawaii/alaska/western canada.... aks;fkld apocalypse day after tomorrow
- this wind needs to calm the f**k down! #sandy #wind #noclasses #apocalypse #needfood #thankyousandy
- this storm obviously means a zombie apocalypse is coming. if you don't watch the #walkingdead you're screwed. #rickgrimesforpresident

3.3.1.3 Fires

Most Information/Least Surprising

- bless the 19 fire fighters that have died today protecting us. sending prayers out to all of the families for their loss
- 02:41pm cdt other<-spotr 1 miles ese of lawrence creek, ok-fire storm many homes on fire winds west gust 20-30 mph temp 130 near fire...
- fires and evacuations really freak me out. almost as much as hairless bears, but differently.
- the fire iss like 2 miles aways from where im at & all the smoke is blowing towards palmsprings
- "@nbcbayarea: just in: statewide amber alert issued after deadly house fire in san diego county http://t.co/. . . " shutup

Least Information/Most Surprising

- " my world falls apart when i see the words 'amber alert' thinking it could be one of my family members or friends out there damn..."
- watching tv and an amber alert came on... remember that movie @name @name #sketch
- mayor said today is "a bittersweet day." finally seeing progress with the fire, but hundreds will hear that their homes were destroyed.
- amber alert issued for two children after remains of mother found in suspect's burned home: san diego... http://t.co/. . .
- it's weird/sad to hear the street you grew up on & where your mom still lives is under mandatory evac. #mojavescenic #sharpfire #wrightwood

3.3.1.4 Tornados

Most Information/Least Surprising

- streets are flooded all over, debris all over and sad to hear about the trailer park 7 miles away, totally destroyed. crazy to think...
- watching news of storm damage from the mcdonalds in chandlerok. carney hit hard. thk u 4 prayers 4 @wsbr #okwx http://t.co/. . .
- 37 dead & death toll is rising. same path as 1999 where winds reached 300mph and 44 casualties. news says this is worse #prayersforoklahoma
- 08:08pm cdt tor<-spotr 4 miles w of hesston, ks-large tornado spotted five minutes ago, a few miles to our north...
- please b in prayer 4 those here in st louis who lost homes, injuries & damage 2property in last nites tornado. many r still w/out power.

Least Information/Most Surprising

- #gasland2 tom ridge wasn't lying until he said "no methane in water has ever been connected to fracking." bulls***. much bigger issue now.
- other issues the fire study found was water supply is a primary concern for #adamscounty and #hunterstown is one of several "coverage gaps"
- rt @kfdinews: a significant weather advisory has been issued for butler and sedgwick counties. 50 mph winds are possible. #kswx
- boil water advisory in lyon county. any businesses or homeowners in neosho rapids seeing any issues with this? let me know. #kfn
- severe wether storm in kansas. i am staying in a freaking trailer. 60 mph winds.i'm gonna cry. i am so scared. #tornado #prayforme

3.3.1.5 Freeze

Most Information/Least Surprising

- woman dead after being stranded overnight in snowstorm in local stories, outdoors, staying safe, utah at december 20th, 2012
- ice cycles have taken the place of tornados when it comes to my biggest fear. if one dropped on you, #dead.
- our heater stopped working, and it’s literally freezing, and i don’t want to crawl under the house to fix it. so i’ll just stay in bed #dumb
- #very cold deep freeze cover plants pipes bring in kids and animals. do not leave any outside. be sure to pay attention to weather.
- uh question. were we supposed to pick up our schedules sometime during winter break? or do we get them tomorrow. #clueless #senoritis

Least Information/Most Surprising

- ahhhh. almost 5 hours in a wait list line, 2.5 in the ice and cold and we made it! @sundancefest is intense. @jonathangroff #cog #sendance
- @wx5em: winter weather advisory issued by nws: #skywarn”where??? what state(s)??? please add “??wx” thank you!
- winter weather advisory issued for tempe, az http://t.co1. . .
- winter weather advisory issued for tempe, az http://t.co2. . .
- winter weather advisory issued for tempe, az http://t.co3. . .

3.3.1.6 Explosion

Most Information/Least Surprising

- “rt 70 people confirmed dead, including 5 firefighters & 1 police officer. hundreds of others injured in explosion” donde fue el vergazo?
- 70 people confirmed dead, including 5 firefighters & 1 police officer. hundreds of others injured in explosion http://t.co/. . .
- rt “@breakingnews: texas authorities advise west, texas, residences to leave town immediately following explosion @westisd”
- more sad news. rt @abc: #westtx fertilizer plant explosion update: mayor says 13 confirmed dead. 5 firefighters, 4 emts and 4 civilians.
- a fertilizer plant in west, tx exploded and 60+ people were killed (hundreds injured). sending thoughts and prayers that way. #prayforwest

Least Information/Most Surprising

- boston bombing suspect caught, b1g ten getting rid of legends/leaders to switch to east-west & kim kardashian’s divorce is final. a good day
- my first hard run after the bombings felt perfect and i might finally feel ready for westford in two... http://t.co. . .
- why do i see muslims terrorists & the westboro church being compared on my tl ; the westboro church are assholes but they’re not bombing ppl
- ban the westboro baptist church from entering boston and picketing the funerals of those who died during the bombing http://t.co/. . .
- @espn they talk about they bombing in boston, where is the coverage of the mass explosion in west texas which took many lives?

3.3.2 Discussion on Lexicons

The CorEx analysis provides us a tool to extract useful ways to communicate with the public based on a risk corpus, using language already being used on social networks today. By extracting latent variables, we are revealing how words are used together to communicate coherent messages, and we are able to quantify the latent content of each tweet. That is, each latent variable we identify helps to explain the mutual occurrence of words from the corpus in each tweet. In addition to being a useful clustering tool, the CorEx analysis provides us with a dimensionality reduction by mapping each tweet into a vector of probabilities for representing each of the latent variables. Although we applied the same risk corpus to analyze many types of disasters, words and phrases convey information specific to each type of emergency event. Thus, CorEx and similar analysis can be used to characterize tweet construction, which may help for constructing emergency announcements. Tan et al. (2014) have shown that messages that conform to the community norm have greater propagation through a network. Given this, our work proposes a method for measuring lexical choices against conformity to a norm. In a larger context, one can imagine a scenario where a candidate population is selected; communication in that community is encoded, and then that measurement is used to inform your word selection to increase information propagation.

Future work will quantitatively relate the techniques presented here to observed disaster responses, both in the real world and in controlled experiments. By relating CorEx classification to social media penetration (for example, retweets), we can examine how much fear/doubt exists, compare word-of-mouth advice to official notices, and track if any “bad advice” is spreading.

4.0 Risk Communication and Perception Ontology

4.1 Overview

The purpose of the ontology is to characterize tweets into corresponding categories of risk perception. Though tweets are limited to 140 characters, they enable many possibilities for expression. For instance, mood and emotion are inherent in personal writing (Aisopos, Papadakis and Varvarigou 2011), as are relationships between two tweeters (Adali, Sisend and Magdon-Ismail 2012). The former could reveal the immediate response to a warning or a hazard, while the latter could indicate the social impact and role of the tweeters within their social networks. Twitter was chosen as the textual basis for analysis because its character limit is most representative of the current 90-character allowance for cell phone-based alerts.

Tweets are complex in their contextual form because of content and lack of proper grammatical structure. The challenge lies in accounting for tone, attitude and intention in the absence of a human reader. Because the goal is to devise an automated system that can analyze tweets in terms of risk response and perception, the tweets must be simplified into smaller parts that a machine can process and classify individually or in small clusters, without context attached. By using existing linguistic tools such as LIWC and the Penn Treebank POS tagger, the tweet can be parsed into components for easier classification (i.e., into dictionaries of word categories by LIWC and into grammatical parts by Penn Treebank). The project's approach considers each word using tense, aspect, modality and pre-defined word categories by LIWC in the absence of context.

Tweets posted during five recent disasters — the Moore (Oklahoma) tornado of 2013, the El Reno (Oklahoma) tornado of 2013, the Southern California flash floods of 2013, the Alamo (California) gas leak of 2013 and Hurricane Sandy in 2013 — were harvested to analyze risk communication and risk perception (see Appendix A). The data analysis will be detailed in a future report. Using this data and concepts from cognitive neuroscience and social psychology (as described in the background), an ontology was developed to best categorize perceptions and responses to disaster risk.

4.2 Ontology

The layperson must not be caricatured as exceedingly bright or exceedingly reckless. Trainor (2010) dispels notions that the layperson acts solely to maximize benefits, or irrationally and senselessly to facilitate escape. That is, the layperson should be assumed to act with bounded rationality in wanting to maximize his utility, but within limits of his knowledge, time and ability to cognitively process these factors in the formation of a decision (Gigerenzer and Selten 2001). The ontology reflects bounded rationality by considering the various factors that contribute to making a decision.

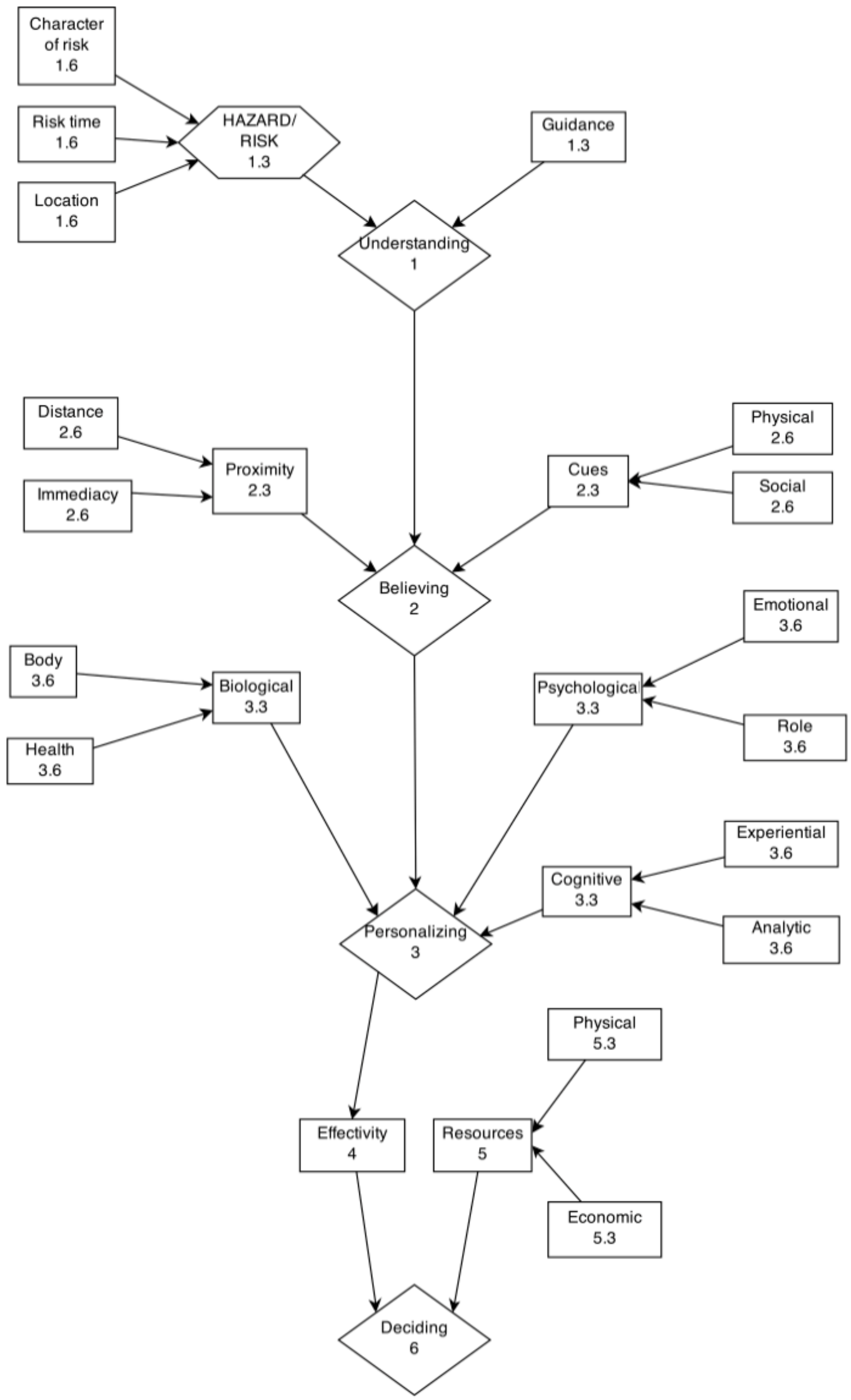


Figure 3. The developed ontology for characterizing risk response. The rhombi represent the key steps in thought processing, and the rectangles represent linguistic categories that are components of each thought process. Hazard/risk is emphasized as the key factor for understanding (the starting point).

4.2.1 Structure

The structure of the ontology is divided into layers that mirror the steps of the thought process. The purpose of this is to reflect the information processing and decision making of the layperson. This decision making is highly contingent upon (1) recognition of the hazard or event, (2) belief that the potential magnitude of the hazard or event will be significant, (3) personalization of the hazard or event and (4) ability to act upon his or her decision (Mileti and Sorensen). Subsequently, the affected layperson must then decide (5) whether protective action is needed, (6) whether those steps are feasible and (7) whether he or she possesses sufficient resources to execute a decision (Trainor).

The ontology is structured from a center-out perspective. There are three levels, with the thought processes (described above) corresponding to the first level, the characteristics of these processes corresponding to the second level and descriptions of these characteristics corresponding to the third level. The progression from the first level to the third level is representative of more detailed analysis and observation (e.g., "hurricane" possesses less detail than "hurricane nearby," which possesses less detail than "destructive hurricane nearby").

The numbers given in each rhombus and box are ordinal and reflect the process of risk response in a quantitative manner. This is important for visualizing the decision-making process of a layperson, as described in Section 4.2.2 'Methodology.' Examples of the process of risk response include the following: understanding; considering location of the risk, hazard and guidance; characteristics of risk and risk timelines; and "believing," which is evaluated by proximity in terms of distance then immediacy.

4.2.2 Methodology

The ontology utilizes the interplay between sentence structure and thought processes not only to classify risk perception, but also to visualize the development of thought process through a tweet. It considers each word individually to eliminate the context that surrounds the word, which allows better coding for automation.

Each word in the tweet is numbered according to position (e.g., for this sentence, "each" = 1, "word" = 2, "in" = 3 … "position" = 10).

The tweet is processed through LIWC and each word is annotated with a category defined by LIWC. This category is matched up with one of the subunits. Words classified as *articles*, *conjunctions*, *fillers* and *impersonal pronouns* are omitted and given a value of zero.

Each subunit (see Section 4.2.3) receives a number that corresponds to the step of processing in decision making, but the number has no cardinal importance. For each classification of a word in the tweet, a coordinate point representing the word number or subunit can be plotted and further processed. Although these points are discrete, they represent the progression of thought process.

Because the subunits are ordinal (see Figure 3) and word order in the tweet is ordinal, a plot of the word number and subunit gives an ordinal representation of the thought process (see Section 4.2.1). For instance, because "deciding" is labeled as 6th in Figure 3, words classified in subunits that are close to 6th (i.e., "resources" or "effectivities") offer a deeper layer of thinking than those that are farther (i.e., "location" or "distance").

Table 3. LIWC2007 Output Variable Information

The following table was adapted from *The Development and Psychometric Properties of LIWC2007* (Pennebaker et al.). The categories shown here are classified in each subunit below. The complete list of words in each category can be obtained from LIWC2007. Because categories are hierarchal, words are classified in the lowest subcategory unless otherwise specified (e.g., "end" would be classified in *time* rather than *relativity*).

Category	Abbrev.	Examples	Words in category
Linguistic Processes			
Word count	wc		
words/sentence	wps		
Dictionary words	dic		
Words>6 letters	sixltr		
Total function words	funct		464
Total pronouns	pronoun	I, them, itself	116
Personal pronouns	ppron	I, them, her	70
1st pers. singular	I	I, me, mine	12
1st pers. plural	we	we, us, our	12
2nd person	you	you, your, thou	20
3rd pers. singular	shehe	she, her, him	17
3rd pers. plural	they	they, their, they'd	10
Impersonal pronouns	ipron	it, it's, those	46
Articles	article	a, an, the	3
[Common verbs][a]	verb	walk, went, see	383
Auxiliary verbs	auxverb	am, will, have	144
Past tense [a]	past	went, ran, had	145
Present tense [a]	present	is, does, hear	169
Future tense [a]	future	will, gonna	48
Adverbs	adverb	very, really, quickly	69
Prepositions	prep	to, with, above	60
Conjunctions	conj	and, but, whereas	28
Negations	negate	no, not, never	57
Quantifiers	quant	few, many, much	89
Numbers	number	second, thousand	34
Swear words	swear	damn, …	53
Psychological Processes			
Social processes[b]	social	mate, talk, they, child	455
Family	family	daughter, husband, aunt	64
Friends	friend	buddy, friend, neighbor	37
Humans	human	adult, baby, boy	61
Affective processes	affect	happy, cried, abandon	915

Category	Abbrev.	Examples	Words in category
Positive emotion	posemo	love, nice, sweet	406
Negative emotion	negemo	hurt, ugly, nasty	499
Anxiety	anx	worried, fearful, nervous	91
Anger	anger	hate, kill, annoyed	184
Sadness	sad	crying, grief, sad	101
Cognitive processes	cogmech	cause, know, ought	730
Insight	insight	think, know, consider	195
Causation	cause	because, effect, hence	108
Discrepancy	discrep	should, would, could	76
Psychological Processes	certain	always, never	83
Inhibition	inhib	block, constrain, stop	111
Inclusive	incl	and, with, include	18
Exclusive	excl	but, without, exclude	17
Perceptual processes[c]	percept	observing, heard, feeling	273
See	see	view, saw, seen	72
Hear	hear	listen, hearing	51
Feel	feel	feels, touch	75
Biological processes	bio	fat, blood, pain	567
Body	body	cheek, hands, spit	180
Health	health	clinic, flu, pill	236
Sexual	sexual	horny, love, incest	96
Ingestion	ingest	dish, eat, pizza	111
Relativity	relativ	area, bend, exit, stop	638
Motion	motion	arrive, car, go	168
Space	space	down, in, thin	220
Time	time	end, until, season	239
Personal Concerns			
Work	work	job, majors, xerox	327
Achievement	achieve	earn, hero, win	186
Leisure	leisure	cook, chat, movie	229
Home	home	apartment, kitchen, family	93
Money	money	audit, cash, owe	173
Religion	relig	altar, church, mosque	159
Death	death	bury, coffin, kill	62
Spoken categories			
Assent	assent	agree, OK, yes	30
Nonfluencies	nonflu	er, hm, umm	8
Fillers	filler	blah, I mean, you know	9

"Words in category" refers to the number of different dictionary words that make up the variable category.

The LIWC dictionary generally arranges categories hierarchically. For example, all pronouns are included in the overarching category of function words. The category of pronouns is the sum of personal and impersonal pronouns. Exceptions to the hierarchy rules include:

[a] Common verbs are not included in the function word category. Similarly, common verbs (as opposed to auxiliary verbs) that are tagged by verb tense are included in the past, present and future tense categories but not in the overall function word categories.

[b] Social processes include a large group of words (originally used in LIWC2001) that denote social processes, including all non-first-person-singular personal pronouns and verbs that suggest human interaction (e.g., talking, sharing).

[c] Perceptual processes include the entire dictionary of the Qualia category (a separate dictionary), which includes multiple sensory and perceptual dimensions associated with the five senses.

4.2.3 Subunits

The subunits in the ontology reflect the factors that comprise each layer. Concepts and terms are based on sensory and cognitive processes, as well as psychometric and sociocultural theories of risk perception. Definitions, unless otherwise indicated, are adapted from Mileti and Sorensen (1990). Italicized words are the word categories that belong in each classification. The categories are taken from the standard LIWC dictionaries (see Table 3) unless otherwise indicated by an asterisk (*).

Understanding – the attachment of meaning to a message, as indicated by verbs in the *present tense* and *future tense* and including:

Guidance – possible measures of protective action, signified by *discrepancy* and *inhibition*

Hazard/Risk – a dangerous event that may cause injury or loss (United Nations), described by:

Characteristics of risk – detailed descriptions of risk, signified by *characteristics of common hazards*

Location – information about which locations are at risk, signified by *place names** and *geographic landmarks**

Believing – the determination of the legitimacy of the message, as indicated by *insight,* through the observation of:

Proximity – the nearness of the hazard, in time and space, as indicated by *prepositions,* via:

Distance – space, as signified by *relativity*

Immediacy – time, as signified by *relativity*

Cues – factors in the environment that serve as signals, as indicated by *perceptual processes,* can be:

Physical, as indicated by *numbers* and *quantifiers*

Social, as indicated by *adverbs*

Personalizing – the implications of risk for oneself, signified by *past tense,* can be evaluated by:

Biological – considerations of impact on a biologic system of the body as indicated by *personal pronouns* and contextualized by:

Body – physical implications on the body, as indicated by *body*

Health – non-physical implications on the body, as indicated by *health*

Psychological – considerations of impact on mental aspects of the body, as indicated by *personal pronouns* and contextualized by:

Emotional – fast, instinctive and intuitive reactions to danger (Slovic et al.), indicated by *affective processes* and *swear words*

Role – the place of the tweeter within his or her social network, which can be defined by *social processes*

Cognitive – considerations of thought processing of the brain, which can be indicated by *personal pronouns* and can be characterized by:

Experiential – founded in memory and intuition (Slovic et al.), signified by *certainty* and *tentative*

Analytic – founded in logic and analysis (Slovic et al.), signified by *causation*

Effectivity – the ability of the tweeter to interact with the environment (Sahin et al.), as signified by *auxiliary verbs*

Resources – possessions of the tweeter, including:

Physical – tangible objects such as a car (e.g., for evacuation), signified by *personal concerns*

Economic – financial prospects that enable action (e.g., money to pay for a hotel after evacuation) and are signified by *personal concerns*

Decision – actions taken by the tweeter, as signified by *absent* or *present progressive* tense

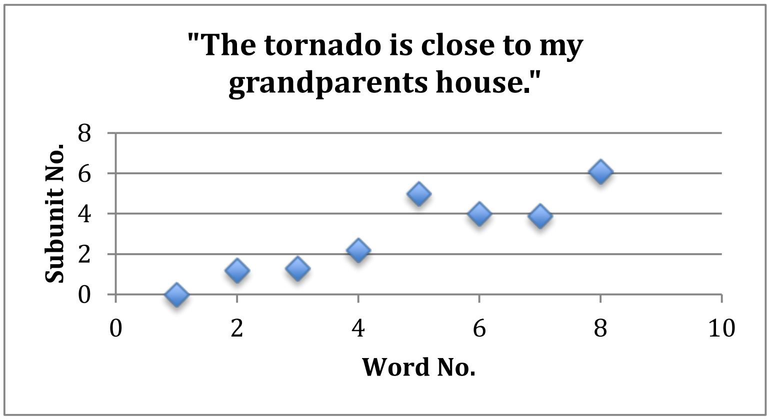
The ontology culminates in the stage of the tweeter's thought process when the tweet was composed.

4.2.4 Sample Ontological Classification

The following tables feature examples of risk responses classified manually by the methodology presented above. The tweets are from two different hazards and demonstrate different progressions in thought; the length of the tweet (i.e., word count) is irrelevant. The trend observed in the scatter is the most important.

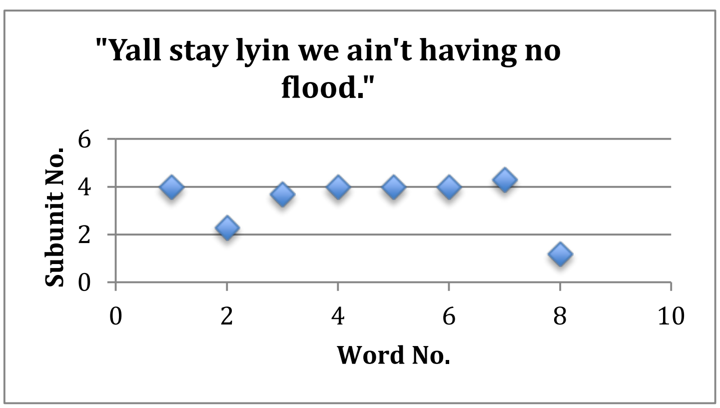
A positive relationship between word number and subunit number indicates that the tweeter is closer to the decision-making part of the thought process, rather than understanding.

Tweet:	The	tornado	is	close	to	my	grandparents'	house
Word No.	1	2	3	4	5	6	7	8
Subunit	N/A	Hazard	Guidance	Distance	Effectivity	Personalization	Family	Physical
Subunit No.	0	1.3	4	2.6	2.3	3	3.6	5.3



In the following example, there is a negative trend between word number and subunit number. This implies that the tweeter is still in the "understanding" part of the thought process.

Tweet:	Yall	stay	lying	we	ain't	having	no	flood
Word No.	1	2	3	4	5	6	7	8
Subunit	Personalization	Immediacy	Deciding	Personalization	Effectivity	Deciding	Analytic	Hazard
Subunit No.	3	2.6	6	3	4	6	3.6	1.3



5.0 Experimental Design and Setup

5.1 Participant Population and Screening

Fifty-one participants, ages 18 to 80 years of age, were recruited. The study aimed to include participants from both genders and all races and ethnic backgrounds since there were no specific race, ethnicity or sex limitations. Participants were recruited through all or some of the following methods: ABM’s website announcements, flyers, newspaper ads and/or from ABM's database of participants from previous studies that indicated they would like to be contacted for future studies. Recruitment was managed by trained research personnel that conducted the pre-screening process over the telephone before scheduling an appointment with interested callers who expressed their willingness to participate.

The telephone pre-screening essentially presented a short list of exclusion criteria. The caller was asked to respond 'yes' or 'no' to the list. If they responded 'no' to all of the questions, the research associate would schedule them for the orientation visit. To establish full eligibility, they were administered a longer, more detailed screener. Please see the attached telephone pre-screener and the paper format of the detailed screener (this screener was computerized). The exclusion criteria listed on the telephone pre-screener were as follows:

- E1: Any known sleep disorder(s), or family history of sleep disorders;
- E2: Any neurological, psychiatric, eating, behavioral or attention disorder(s);
- E3: Any cardio-pulmonary disorders (e.g., high blood pressure, diabetes);
- E4: Recent (past five years) head injury, or older head injury with current symptoms;
- E5: Regular use of pain medications other than over the counter (OTC);
- E6: Current use or a history of use of stimulants (e.g., amphetamine) or illegal drugs;
- E7: Excessive tobacco use (i.e., more than 10 cigarettes a day);
- E8: Excessive alcohol (>5 drinks daily) or caffeine (>4 cups daily);
- E9: Untreated/untreatable vision or hearing problems;
- E10: Pregnant or nursing;
- E11: Inadequate familiarity with the English language;
- E12: Younger than 18 years of age; older than 80; and
- E13: Currently use a form of social media.

Most exclusion criteria pertained to conditions that might alter the electrical activity of the brain or heart (E1–E6, E10), affect the participants’ responsiveness to stress (E1, E2, E5–8) or impair their ability to perform the neurocognitive assessments (E9, E12).

The study screened for those who currently use a form of social media (E13).

In addition, participants were asked to obtain a full night of rest on the days leading up to the study (7.5 to 9 hours).They were informed to refrain from drinking alcoholic beverages beginning at least 24 hours before each visit, caffeinated beverages (e.g., coffee, soda) the day of the study and nicotine beginning one hour before the start of the study visit and until the study was completed.

5.2 Consent and Study Procedures

The study included an introductory/orientation visit and up to two experimental sessions. Each visit lasts approximately two to four hours, depending on the task(s).

5.3 Orientation Session

Participants were scheduled to arrive at the research facility for the orientation visit anywhere between 8:00 a.m. and 4:00 p.m. During this visit, a research technician explained the informed consent document to the participant and obtained his/her consent. All research technicians at ABM were required to pass an online Good Clinical Practice/Protection of Human Subjects course (NIH and CITI) prior to this experiment. They would ensure participants had sufficient time to review the document, and that all of their questions were answered before they signed the informed consent document. Researchers reminded participants that participation was entirely voluntary and they would not face any consequences if they chose not to participate or if they decided to drop out of the study at any time after consent. All researchers at ABM reviewed the informed consent document and were trained to answer any questions the participants might ask. Chris Berka, the Principle Investigator (PI), was also available to answer any questions during the introductory visit. Because of the inclusion/exclusion criteria for the study (healthy, fully-rested participants over the ages of 18), the participants were 18 or older and of normal mental capacity, therefore, were able to provide their own consent. No study procedures were conducted until the consent was fully explained, all of the participants' questions and/or concerns were addressed, and the consent form was signed.

After signing the consent form, the participant was asked to fill out a more detailed computerized general screener (please see attached paper copy). Once submitted, the screener reported whether the participant was fully eligible for the study. If the participant was eligible, the technician administered additional questionnaires pertaining to subjective reports of, for example, mood, stress, sleep and anxiety. Please see Section 5.13, "Surveys, Questionnaires, and Other Data Collection Instruments," for a full list of subjective questionnaires.

Computer based screening materials and questionnaires collected during orientation were all de-identified and saved in a password-protected computer database. Screening material or questionnaires that were not computer based only contained the participant's ID number and were locked in file cabinets in ABM's secure facility.

The orientation session lasted approximately two hours. Upon completion of the consent form, general screener, subjective questionnaires, and, if deemed eligible, the research technician scheduled them for their next two study sessions.

5.4 Benchmark Session - Alertness Memory Profiler (AMP)

During this visit, the participant was asked to arrive at the research facility between 7:30 a.m. and 8:30 a.m. Upon arrival, they were reminded of the study procedures, fitted with an EEG sensor headset and asked to complete any paperwork that was not completed during the orientation visit. The participant then started their baseline, referred to as the Alertness Memory Profiler (AMP). The AMP is a computerized neurocognitive test battery which includes tasks that measure levels of memory, attention, mental workload and learning while simultaneously acquiring EEG and electrocardiographic (ECG; heart rate) signals. Alertness, attention, verbal/visuospatial and memory will be quantified using a combination of EEG and performance metrics. The AMP ranged from 15 minutes to about three hours depending on the tasks to be completed (see Table 4 and Table 5). The set of tasks were determined before the participant was scheduled for their visit; the participant was fully informed of their study schedule before arrival.

It was anticipated that all participants would complete the full 3-hour AMP. Depending on certain time constraints (e.g., participant could not make it for a second experimental visit or if ABM needed to shorten the number of visits for various other reasons), ABM would administer the shorter 15-45 minute AMP, however. If the participant was given the shorter AMP — between 15 and 45 minutes (see Table 5) — the experimental testbed (see Section 5.8, ‘Description of Testbeds’) were administered following the completion of the AMP with an optional break in between.

If, however, this was a returning participant, and ABM already acquired the participants' AMP, and it wasn't more than one year since the participant took the AMP, then their first session would start directly with the experimental testbed. Again, the study coordinator or staff would have already determined and informed the participant about the order and time in which they would complete the study.

5.5 Experimental Session

The participant was scheduled to arrive at the research facility between 7:30 a.m. and 8:30 a.m. The participant was reminded of the study procedures, fitted with an EEG sensor headset, and the experimental testbed would be administered. Please refer to Section 5.8, ‘Description of Testbeds,’ for a detailed summary of the testbed.

During the course of the study, except during the orientation session, the participant wore a wireless device on their head that monitors EEG and ECG signals. An armband might also be used to measure skin conductance (i.e., galvanic skin response (GSR), electrodermal response (EDR)), body temperature and energy expenditure.

5.6 End of Experimental Sessions

Once the participant completed the experiment, any questions that they asked were answered. The participant was informed that their compensation would arrive in the mail within the next few weeks.

5.7 Data Analysis

Each EEG channel was processed with proprietary ABM algorithms to eliminate noise/artifacts, and spectral features (Fourier and wavelet coefficients) were derived for eachtwo2 second data segment with one second (50 percent) overlap. In addition to the time-frequency analyses available in our software, topographic EEG analyses was performed using the free MATLAB toolbox called EEGLAB (Delorme 2004). ECG signals were de-noised, QRS complexes detected, and calculated beat-to-beat heart rate (HR) were converted into second-by-second values. Several time- and frequency-domain measures of heart-rate variability (HRV) were derived from the HR data in accord with the literature (Camm 1996). EEG and electrooculography (EOG; eye movement) signals were processed with our proprietary algorithms for detection for eye blinks and eye fixations, and electromyography (EMG; muscle movement) levels were quantified in each second of the data. In addition to these ‘absolute’ or primary variables, a number of secondary or ‘relative’ variables derived by computing ratios and/or differences between different time instances of the same primary variable or between different but functionally or spatially related primary variables (e.g., anterior-posterior gradient of the alpha EEG power). Finally, brain-state variables quantifying fatigue, alertness and distraction also were derived using our validated classifiers (Berka 2005a, Berka 2005b).

All data, after appropriate de-identification, were made available to the members of the PNNL team. Internally, ABM analyzed the EEG measures of event related potentials (ERPs), power spectral densities (PSDs), wavelet coefficients and the B-alert cognitive state metrics and cognitive workload. In terms of ECG, ABM summarized second by second HR and HRV for all benchmark data, stimuli presentations and responses. A thorough statistical analysis was completed on all measures to meet the study's objective.

5.8 Description of Testbeds

5.8.1 AMP

The AMP was developed by ABM to integrate EEG, behavioral and subjective performance measures in an easy-to-administer platform designed for quantitative assessment of neurocognitive functions including alertness, attention, learning and memory. The AMP uses a multivariate approach that allows simultaneous acquisition and analysis of data that could require days or weeks with conventional laboratory methods. Multiple tests are available including the 3-Choice Vigilance Task (3-CVT) and several versions of the Paired Associate Learning and

Memory Tests (PAL). Two brief sessions (five minutes each) of resting with eyes open (EO) and eyes closed (EC) are used for the extraction of individual baseline EEG features for each tested participants. The 3-CVT challenges the ability to sustain attention by increasing the inter-stimulus interval (ISI) across the four, 5-minute time points. During the first five minutes, the ISI ranges from 1.5 to three seconds, increasing up to six seconds during the second five minutes and up to 10 seconds during the final 10 minutes. The 3-CVT performance has proven sensitive to the effects of full and partial sleep deprivation in healthy participants and to excessive daytime sleepiness in patients with Obstructive Sleep Apnea (OSA)**.**

Table 4. 10 minutes of EO and EC is administered at the start of every benchmark

Resting State Measures	Task Acronym	Cognitive Construct	Time (mins)
Eyes Open	EO	Resting state eyes open	5
Eyes Closed	EC	Resting state eyes closed	5

Table 5. Task list for the shorter AMP ranging from approximately 15 to 45 minutes

Benchmark Tasks	Task Acronym	Cognitive Construct	Time (mins)
3-Choice Vigilance	3-CVT	Active vigilance; sustained attention; processing speed	5 or 20
Visual-Psychomotor Vigilance Task	V-PVT	Passive vigilance	5
Audio-Psychomotor Vigilance Task	A-PVT	Passive vigilance	5
Standard Image Recognition	SIR	Memory; cognitive fluctuation	7

The shorter AMPs consist of four main tasks. The shortest of them is the 15 minute AMP which includes five minutes of the 3-CVT, V-PVT and A-PVT — these three baseline tasks are required to compute ABM's EEG B-Alert Classification metrics of workload and engagement. The 45 minute baseline consists of a 20 minute 3-CVT task, five minutes each V-PVT and A-PVT tasks, and a seven minute SIR task. There is also an option for a 30 minute AMP which simply excludes the SIR from the 45 minute AMP.

If the full AMP is administered, all the tasks from Table 6 are used along with some additional tasks (Table 5); some, such as the SIR and A-PVT, are administered more than once. Please see the protocol sheet for the exact order of tasks.

Table 6. The full AMP; approximately three hours with optional breaks in between tasks

Benchmark Task	Task Acronym	Cognitive Construct	Time (mins)
3-Choice Vigilance	3-CVT	Active vigilance; sustained attention; processing speed	20

Benchmark Task	Task Acronym	Cognitive Construct	Time (mins)
Visual-Psychomotor Vigilance Task	V-PVT	Passive vigilance	5
Audio-Psychomotor Vigilance Task	A-PVT	Passive vigilance	5
Verbal Memory Scan	VMS	Memory; cognitive fluctuation; executive functions	9
Standard Image Recognition	SIR	Memory; cognitive fluctuation	7
Interference Image Recognition	IIR	Memory; inhibition	5
Verbal Paired Association	VPA	Memory; cognitive fluctuation; executive functions	8
Numbers Image PAL	NIR	Memory	8
Forward Digit Span	FDS	Working Memory	12+
Backward Digit Span	BDS	Working Memory	12+

5.8.2 Emergency Response Testbed

Emergency response stimuli (Table 7) sent from PNNL was presented using either E-Prime® or ABM's proprietary test administration software. The participants each watched five, 5-minute video segments. Following each video, a series of approximately 40 tweets and two to four official alerts was presented. The tweets and official alerts were displayed for approximately 3 seconds with a 1.5 second inter-interval time frame. The participant will be asked to respond to randomized prompts in between tweets and alerts. The prompts asked the user whether or not they would re-tweet the message or relay their own message.

Table 7. Sample emergency types and tweets

Type of Emergency	Video File	Sample Tweets
Alamo Gas Leak	Plenty of Finger Pointing After Alamo Gas Leak Forced Evacuations.mp4	Of course I am in Alamo and my phone starts making sounds like a bomb was about to go off I check my phone and there is a evacuation alert!
		woke up to an empty house and a bunch of alerts to evacuate Danville...uh...where's my family ðŸ˜³
		Omg gas leak in Alamo! Omg quick flee to Danville omg tweet about it at the same time ahhhhh
		Powers out, there's a gas leak, and worst of all my dog just pooped in the house. I think it's the apocalypse
Hurricane Sandy	SandyClip.mov	Superstorm Sandy will hit east coast USA - 140 km/hour winds Monday _ Connecticut, New York, New Jersey

Type of Emergency	Video File	Sample Tweets
		Its actually pissing me off that people are saying this storm isn't anything. Im gonna be laughing at your ass when youre floating away
		LETS HOPE THAT THIS STORM DON'T HIT US THAT HARD THE WAY THEY ARE TALKING.
		a mother was trying to drive her 2 young sons to Brooklyn because she was scared about the storm& a huge wave hit them&two baby boys goneðŸ˜¢
Oklahoma Tornado	ElRenoTornadoClip.m4v	11 days after widespread devastation in Moore, OK., people are urged to once again take IMMEDIATE tornado precautions.
		One of the first men I ever looked up to died in the storm tonight. Bill O'neal I always loved you. Rest easy old man.
		I'm sitting in my house listening to hail hit the roof and watching my wife sleep on the couch. Phone is going nuts from good people!
		So sad to hear about the 3 storm chasers that lost their lives during Friday's tornado in Oklahoma. What a tragedy

***Note:** For additional videos and stimuli, please make a request to the primary ABM Institutional Review Board administrator(s) for this project.

5.9 Description of Protocol Devices

5.9.1 B-ALERT® EEG Wireless Sensor Headset

The wireless B-Alert EEG sensor headset developed by ABM combines battery-powered hardware with a sensor placement system to provide a lightweight, easy-to-apply method to acquire and analyze high-quality EEG in three available configurations: (1) B-Alert X10 with 9 channels + 1 additional channel for an optional signal (typically ECG but alternatively can include GCR, respiration or integrated eyetracking); (2) B-Alert X24 with 20 channels of high-quality EEG + 4 additional physiological signals including ECG, EOG, EMG, GCR, respiration or integrated eyetracking; and (3) B-Alert Medical system also with 20 channels of high-quality EEG + 4 additional physiological signals. The ECG leads are attached to the upper right clavicle and lower left rib and plug directly into the wireless amplifier enclosure. All three headsets reference the mastoid using similar leads. The soft EEG foam-sensors require no scalp preparation and provide a comfortable and secure scalp interface for eight to 12 hours of continuous use. The device contains rechargeable lithium batteries. The headset was designed with fixed sensor locations according to the International 10–20 system coordinates. Example sensor site locations on the current B-Alert X10 system include Fz, F3, F4, Cz, C3, C4, P3, P4,

POz, as well as ECG, EMG or EOG. The B-Alert X24 (Figure 4) include sites Fz, F1, F3, F2, F4, Cz, C1, C3, C2, C4, CPz, Pz, P1, P3, P2, P4, POz, Oz, O1, O2 as well as ECG, EMG, or EOG. The B-Alert Medical includes Fz, F3, F4, Cz,C3, C4, P3, P4, Pz, O1, O2, T5, T3, F7, Fp1, Fp2, F8, T4, T6 and POz according to the 10-10 international system as well as ECG, EMG, or EOG. Amplification, digitization and radio frequency transmission of the signals are accomplished with miniaturized electronics in a portable unit worn on the head. The combination of amplification and digitization of the EEG close to the sensors and secure wireless transmission of the data facilitates the acquisition of high quality signals even in high electromagnetic interference environments.

Figure 4. B-Alert X24 sensor headset

The sensor headset is only used for recording physiological signals and does not introduce energy into the body except for minor electromagnetic radiation typically emitted by small electronic devices. The only risk posed by this device is minimal discomfort due to the pressure exerted by the cap and sensors on the user’s head. To minimize this risk, caps are adjustable and sensor strips are available in two sizes. The sensor headset is integrated with the AMP neurocognitive test battery to allow simultaneous acquisition of EEG, performance and heart-rate data during tests of vigilance, attention and memory.

5.9.2 GSR Armbands

The SenseWear armband (Figure 5) is wireless and battery powered. It is used to gather continuous physiological data such as GSR (i.e., electrodermal signals produced through moisture on the skin's surface), body movement (with a 2-axis accelerometer), heat flux, skin temperature, near body temperature and energy expenditure. The armband is placed on the back of the arm, over the tricep, and has adjustable straps made of nylon, polyester and polyisoprene. There is no latex content. Additionally, the monitoring material that rests against the skin consists of acrylonitriel butadiene styrene (ABS), a Food and Drug Administration (FDA)-approved co-polyester and hypoallergenic grade stainless steel.

Figure 5. SenseWear Armband

5.10 Risk/Benefit Assessment

5.10.1 Foreseeable Risks

The recording of physiological data with the EEG/ECG systems poses no known health risk. There was a chance the participant could have experienced mild discomfort due to the pressure exerted by the sensor headset. In previous studies, with a total of over 2,700+ participants, less than 0.05 percent of participants reported discomfort from the headset. The adhesive material that helps attach the ECG electrodes to the chest could have caused minimal discomforts during the attachment and removal of the electrodes, while the jelly-like gel of the ECG electrodes may have felt cold and/or sticky, and may have caused a slight pinching sensation when the electrodes were removed from the skin. Discomfort may also have arisen from a mild allergic response to extended exposure to the conductive gel used in the EEG and ECG sensors. This occurs very rarely: in over 2,700+ participants only seven reported an allergic reaction to the gel, and in all cases, the gel was used for more than four hours. For the purpose of this protocol, the risk was minimal given the participant was exposed to the gel for no more than four hours on each day of data collection. To mitigate this risk, however, alcohol wipes were available to remove the gel immediately, and Benadryl cream was available to reduce any allergic reactions.

Exposure to videos and sound may have been stress inducing but carried minimal risks, as the material that was shown is not substantially different from realistic movies or some television programs and video games to which the participants are, or may be, exposed in their everyday life. The participants were, however, reminded immediately before the beginning of the presentation of the stressful content that they had the right to withdraw from the study at any point in time, including the midst of the presentation.

There may have been other risks that were unknown at the time. If the participant had any injury, bad effect or another unusual health experience during the study, they were told to notify the study coordinator or staff immediately. The participant may have called at any time, day or night, to inform staff of their health experiences.

5.10.2 Risk Management and Emergency Response

No additional compensation or coverage was offered for health care costs due to injury resulting from participation in this study. If emergency response was required, however, the study site had access to 911. Participants were asked to report any discomfort experienced throughout the study, and any adverse events were to be duly reported.

Any adverse events would have been immediately reported to the ALPHA Institution Review Board (ALPHA) for the protection of human participants. An "Adverse Event/Subject Injury" report would have been completed and faxed to the ALPHA, as well as a copy remitted to our funding agency, Defense Advanced Research Projects Agency (DARPA), and any representative they named. Any subsequent correspondence with ALPHA would also have been copied to the funding agency and any designee(s) they required.

5.10.3 Potential Benefits

The benefit of this study was the advancement of science; there were no specific benefits for participants.

5.10.4 Compensation

Participants were compensated $20/hour for every hour spent at ABM research facilities as part of their participation in the study.

5.10.5 Withdrawal from the Protocol

Participants were informed that participation in the study was entirely voluntary, and they had the right to withdraw from the protocol at any time. If they decided to withdraw from the study early, the participant was compensated for what they had completed until the moment they dropped from the study at the rate of $10/hour.

Participation was prematurely terminated by the investigator at the beginning of the visit if non-compliance with the protocol was determined. Non-compliance is defined as any of the following:

- The participant reported drinking alcohol 24 hours before the start of the study visit or caffeinated beverages in the morning before the study visit.
- The participant did not show up for the study visit.
- The participant reported being sleep deprived for the study visit.
- The participant was inappropriate towards research staff (conduct was considered appropriate if in accordance with the workplace environment).
- The participant appeared inebriated or impaired to the research staff.

In all aforementioned cases, the participant was compensated $10/hour for their time.

If, however, the participant was told by the study staff that they had to prematurely withdraw because of instances that were not at the fault of the participant themselves (e.g., equipment malfunction, head size too small), then the participant was compensated the full $20/hour.

5.11 Confidentiality

Federal regulations give the participant certain rights related to their health information. These include the right to know who has access to their information. If the participant chose to be in this study, the study staff obtained information about them, including information that could identify them. ABM collected their name on the consent form and some general health information during the screening process; this is kept in a locked file cabinet and password protected computer database in the locked offices of ABM, located in Carlsbad, California. Only the research staff involved in the study had access to this information. However, the IRB, the Office for Human Research Protections (OHRP), the funding agencies, and/or the FDA could have access to this information to ensure ABM maintains the participants' records in a manner compliant with all human protection regulations. In the case where ABM will need to release information to these parties, absolute confidentiality cannot be guaranteed. The participants' permission for review of confidential information and their acknowledgement that their medical information may be held and processed on a computer was granted by signing the consent forms.

The results of this study may be published in technical reports and scientific journals, or presented at scientific meetings. No publication or presentation will reveal the participants' identities.

5.12 Roles and Responsibilities of Medical Monitor

The medical monitor for this study was Chief Medical Officer Philip Westbrook, MD, ABM. Dr. Westbrook would have reviewed any unanticipated problems involving risk to participants or others, serious adverse events and any participant deaths associated with the protocol, and then have provided an unbiased written report of the event. At minimum, Dr. Westbrook would have commented on the outcomes of the event or problem, and in case of a serious adverse event or death, commented on the relationship to participation in the study. Dr. Westbrook would also have indicated whether he concurred with the details of the report provided by the principal investigator. Reports for events determined by either the investigator or by Dr. Westbrook to be possibly or definitely related to participation and reports of events resulting in death would have been promptly forwarded to the ALPHA reviewing this protocol, the funding agency and any designee they required. Please note that the study protocols involved procedures that have been administered previously in more than 2,000 human participant sessions with no serious adverse events.

5.13 Surveys, Questionnaires and Other Data Collection Instruments

The following data collection instruments will be used during the study:

- Computerized General Screener;
- Telephone Pre-Screener;
- Holmes-Rahe Life Stress Inventory (also referred to as Major Life Stress (MLS));
- The Beck Depression Inventory (BDI);
- Profile of Mood States (POMS);
- State-Trait Anxiety Inventory (STAI);
- Center for Epidemiologic Studies Depression Scale (CESD);
- Pittsburgh Sleep Quality Inventory (PSQI);
- Interpersonal Reactivity Index (IRI);
- NEO Personality Inventory;
- Military Experience Questionnaire; and
- Social Media Questionnaire.

5.14 Experimental Setup

ABM completed testing on 51 subjects in the emergency messaging testbed. The following provides both psychometric and neurophysiological assessment of the testbed.

Initially, we presented five disasters in randomized order (n=5). Following this data collection, we added a random "benchmark" assessment of six neutral tweets presented either immediately before or after the set of disaster blocks (i.e., first or last), see Figure 6. We have five disaster scenarios: tornadoes, hurricanes, gas line explosions, floods and blizzards. Each disaster is presented with a five minute newsreel video followed by a set of 45-50 messages regarding the events portrayed in the video reel, including one to three official notification messages and up to 50 tweets. Each message is presented one by one, for a minimum of one second, and the participants were asked if they would share the message on social media. Each subject receives the disasters and associated messages in random order. Table 8 provides the total number of messages seen for each disaster, and the order the disasters were presented for each of the five participants. Figure 7 presents reaction time by order, with benchmarks being first, last or not included as the lines of data. Figure 8 presents overall reaction times by order (benchmarks combined), based on if they endorsed re-tweeting the message or not.

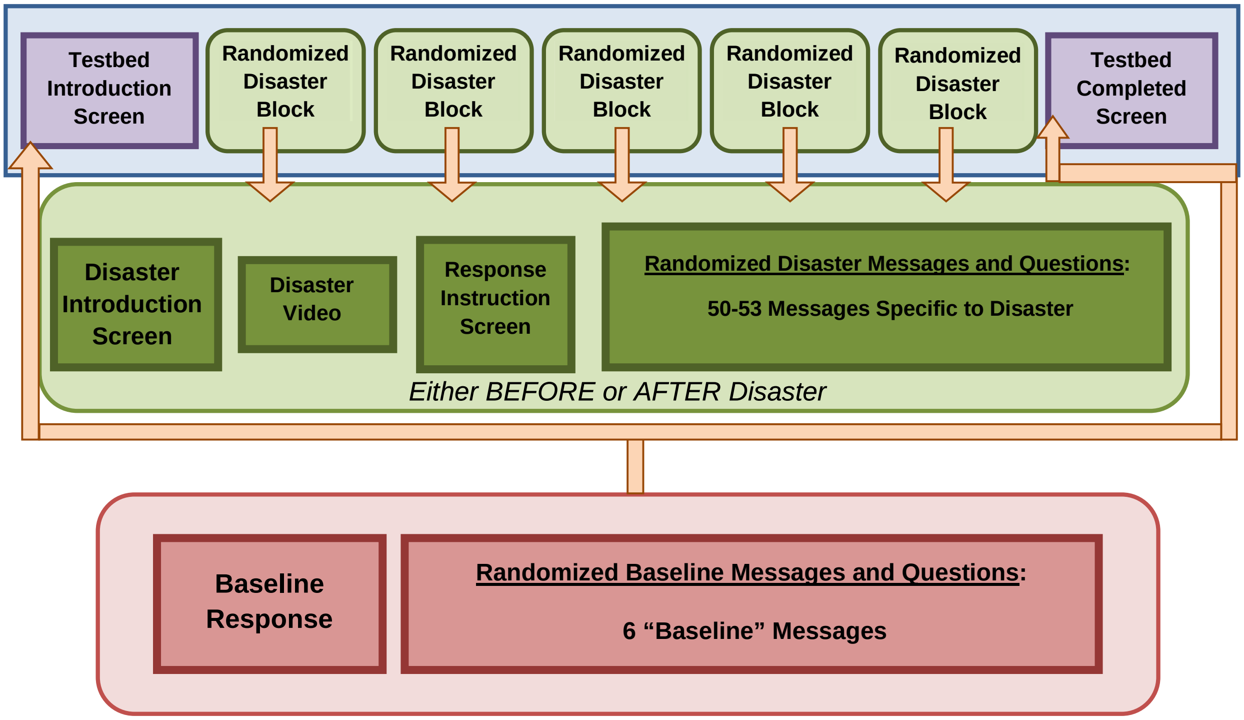


Figure 6. Testbed block design diagram

Table 8. Count of 1) number of messages per disaster, and 2) count of order in which disaster appeared across subjects

		Order					
	Count	1	2	3	4	5	6
Benchmarks	6	24	0	0	0	0	23
Blizzard	53	4	12	9	10	11	6
Flood	51	5	10	11	14	4	8
Gas Leak	51	7	10	7	11	15	2
Hurricane	52	7	10	8	12	13	2
Tornado	51	4	10	17	5	9	7

5.14.1 Performance Data

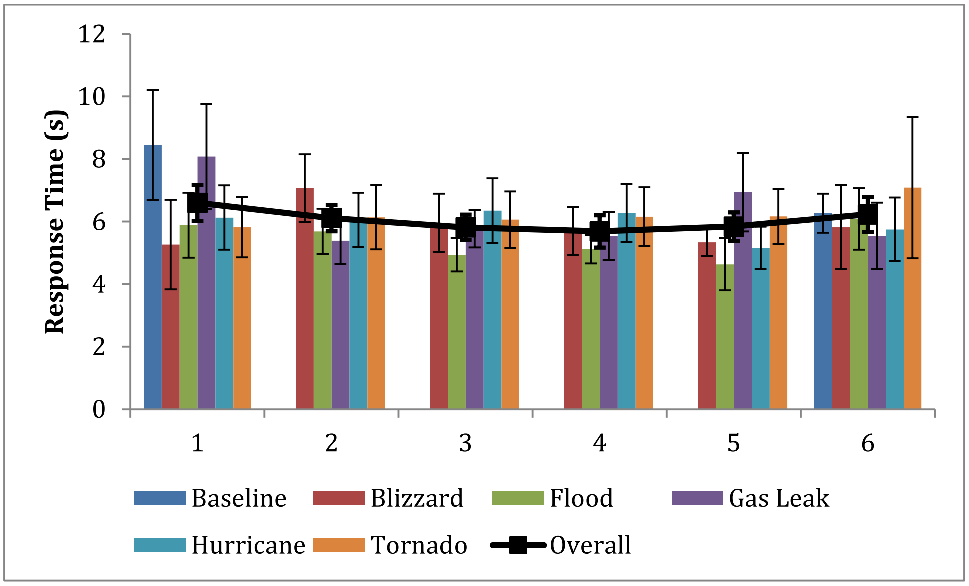


Figure 7. Response time by subject/order

Tornado response times were significantly more variable when presented in the sixth position. This is due primarily to subject 5621, who also had several longer than average response times during baseline. The range of response time was 1–72 seconds, however, response times over 35 seconds were rare (n=15 out of 13464), and participant 5621 was responsible for nine of these, primarily during tornado, but also for baseline, blizzard, hurricane and gas leak messages. No single tweet had a "long" response time for more than one subject.

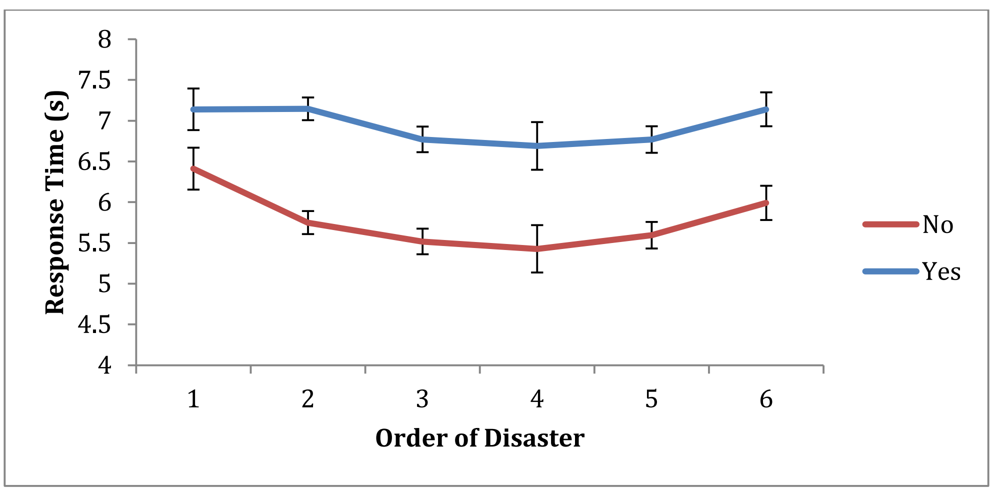


Figure 8. Response time by sharing choice/order

Response times to messages that were retweeted were slower than for those not endorsed for retweeting, regardless of the order, with a mean response time of 5.97 seconds. The retweet rate is fairly consistent across disasters with the exception of flood, at only 15 percent compared to 23-29 percent for other disasters (Figure 9). Retweet rates were also consistent with message

order — although earlier ordered presentations have a slightly higher rate of retweeting, overall (Figure 10). Figure 11 presents order versus disaster retweet rates.

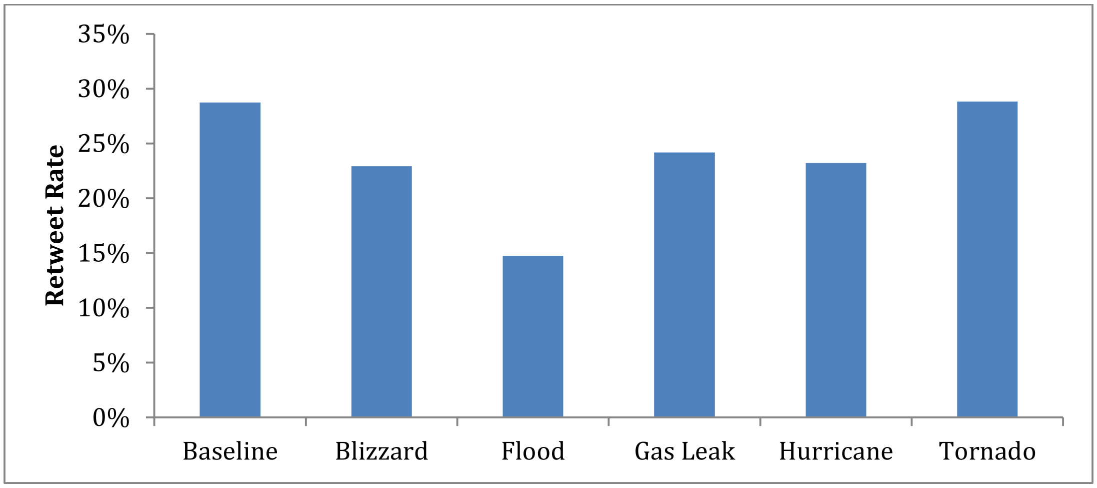


Figure 9. Share rate by disaster

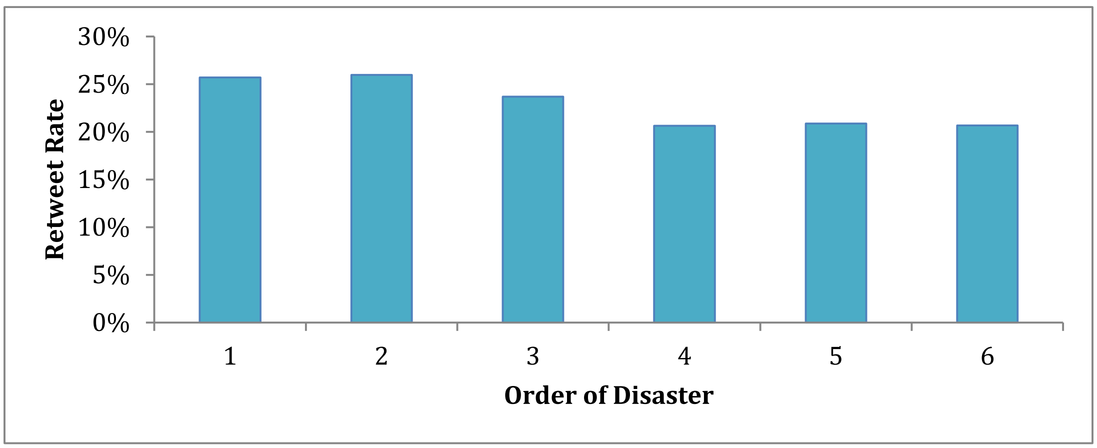


Figure 10. Share rate by order

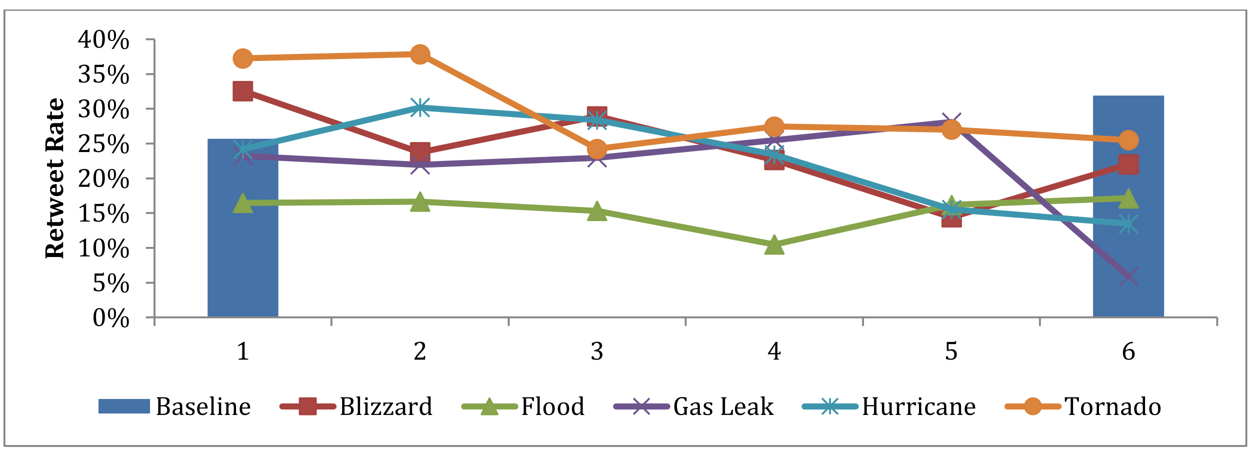


Figure 11. Order by disaster retweet rate

We also examined the rate of sharing overall, commonly shared and rarely shared (tweet was never retweeted, and none were always retweeted), Table 2 presented these data. We see there is a relationship between the overlap across the overall percentage of being shared, regardless of the number of participants that shared, and the number of tweets that were rarely shared (i.e., 15 percent retweet rate overall for flood related tweets, and 49 percent of the tweets were rarely retweeted). In contrast, tornado messages were shared at an overall rate of 29 percent, but 12 percent of those messages were often retweeted and only 16 percent were rarely retweeted, indicating a larger spread of retweeting across messages for the tornado related messages.

Table 9. Shared/never shared rates by disaster

	% Shared	% Shared by More than 25	% Shared by Less than 5
Baseline	29%	0%	0%
Blizzard	23%	8%	19%
Flood	15%	4%	49%
Gas Leak	24%	8%	16%
Hurricane	23%	4%	21%
Tornado	29%	12%	16%

We also examined the response times based on disaster and choosing to share or not share, and found only slight, non-significant differences across disasters, but a trend toward choosing to share taking slightly longer. Figure 12 presents these data.

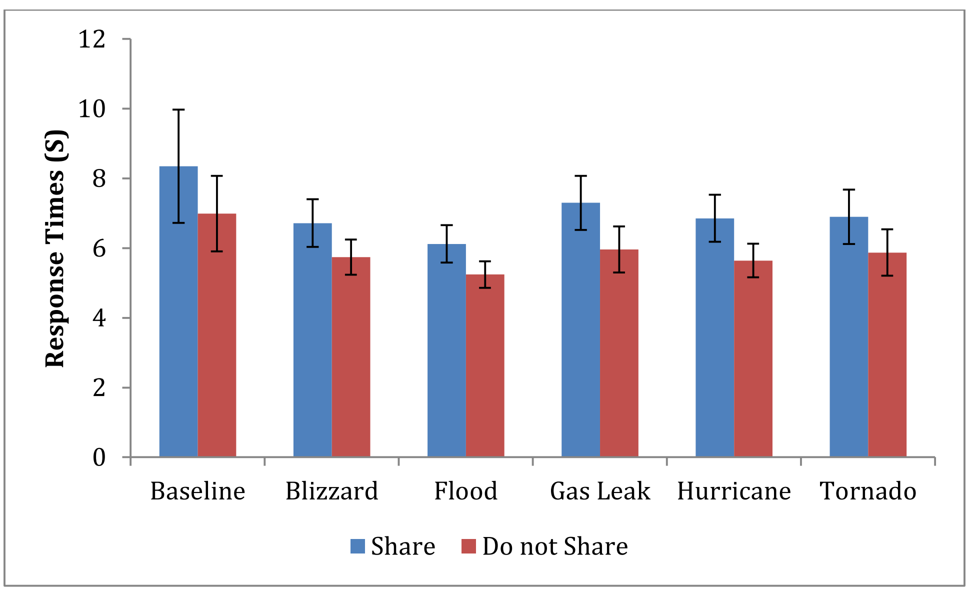


Figure 12. Response times for disaster by retweet endorsement

Next we examined what messages were rarely shared (less than five-six times, or 10 percent), or often shared (more than 25 times, or ~ 50 percent). Table 10 presents messages rarely shared (one-two shares), and Table 11 presents messages often shared. As we found in the initial pilot

data, one of the official emergency messages is always one of the most shared messages, with the exception of gas leak. These messages are retweeted by 49-62 percent of the 51 participants. It should be noted that the official tweet for gas leaks was retweeted by 41 percent of the participants.

Table 10. Rarely shared messages

Disaster	Count	Message
Blizzard	Shared	
1	3	@name Lucky you were under a blizzard warning 7 to 15 inches already.
3	5	@name we had the worst blizzard in the history of souf dadoka
6	6	Am I the only one that saw lightning and heard thunder I this blizzard? That's f$$ rad.
10	4	Blizzard.. Normal.
12	4	Chillin at the Mall in a Blizzard. #snow #blizzard #rapidcity #rushmoremall @ Rushmore Mall
15	6	Digging ourselves out of Blizzard 2013. Going on 31 years without power. Pushing 30 inches of snowfall…
26	6	Like for real listen to the wind in the #blizzard !!! #snowstorm of the century in #southdakota thank…
27	5	Love blizzard but hate snow lol
40	6	Severe blizzard warning tho
45	4	This whole lightning during a blizzard thing is tripping me the f## out. Stop it. I'm going to bed. Night.
Flood		
1	3	Another flash flood warning? Uh ohh I hope there isn't any more thunder storms
2	4	As hot and sunny as it is outside im gettin more flash flood warnings TF
5	3	Flash flood on my tv guys!!!!
12	1	flash flood warning please get off my TV screen.
15	2	Flash flood warnings during this weather pisses me off
19	3	Flash flood? Ain't it gotta rain for that?
20	1	F this flash flood warning s$!! It's so annoying!
21	2	F YOU NATIONAL FLOOD WARNING
22	4	Hmmm should I still clean outside? Flash Flood Warning!! #Yuma @ Fry's #107 Fuel Center
24	3	I hate flash flood warning! S$$ I'm trying to watch my show!!
26	4	I want to punch the person who keeps sending the flash flood warning !!!
28	4	On s$ we are under flood alert!! An I the only one who got this message?!!!
33	1	Soooo tired of these flash flood warnings on my phone
34	2	Stupid flash flood warning ruined my tv show -.- t
35	4	The flash flood warning kept popping up on my phone & scared me every time
38	2	These flash flood warning are Fing annoying & creepy lol
39	1	THIS COMBINATION OF SONGS. FLOOD WARNINGS RIGHT NOW.

Disaster	Count	Message
40	3	THIS FLASH FLOOD IS STRAIGHT NUTTY
41	1	This flash flood warning scared the f out of me.
42	1	THIS STUPID A$$ FLOOD WARNING JUST RUINED MY WHOLE SHOW GO AWAY OMFG
43	3	Those flash flood warnings are always bulls$
46	4	whats up with these flash flood warnings
47	2	When these s$$ go off like Wtf ain't nobody got time foe your flood s
49	1	Wish I'd was here to see the flash flood here. @ Santa Rosa Mountains
50	1	Yall stay lyin we ain't having no flood
Gas Leak		
1	4	emergency evacuation everyone leave yoir hones and travel south me: no
3	4	@name I'm going to your house your safe from the gas leak I don't wanna die
4	1	a gas leak will probably kill everyone in the US! #lynetteispanicing?
11	4	Omg gas leak in Alamo! Omg quick flee to Danville omg tweet about it at the same time ahhhhh
18	1	@name it's cause of the gas leak in Alamo ???? pic.twitter.com/mzGZHi71t7
22	4	Whoa, Contra Costa folks there's an evacuation being ordered. Gas leak along Alamo blvd sounds like.
28	1	The Danville Bubble is keeping me safe from the Alamo gas leak.
30	4	Alamo evacuation for a gas leak on Danville blvd and my family and I are the only ones left on our street- go erickson family ??
Hurricane		
11	4	#poweroff like 4 hours ago so bored stpid#HurricaneSandy
12	5	I'm at Frankenstorm Apocalypse 2012 - Hurricane Sandy (Boston, MA) w/ 442 others
14	4	#sandy go the f## home already ! Jersey is tired of you’re a$$!
18	3	Cruising out into this "storm".. Maybe this is the only way to blow my car up #destiny
19	4	Crushed car...tree just missed that house ... hurricane Sandy u b u ..lol @ NEW YORK
20	3	Damn this storm is gonna be the real deal?
27	5	Devestation of #Frankenstorm #Sandy is the new norm w/ no power/heat still 2 teenaged girls doorbelled us for GOP
38	4	Hurricane sandy is not doing not anything big cause we still got school tomorrow -,-
39	4	Hurricane Sandy is not even going to be that bad!!...right?
46	4	WOW #Sandy you really hit us fing hard...
49	4	Wow after the sandy hits were suppose to get a blizzard FOH
Tornado		
1	4	The tornado is close to my grandparents house.
10	4	this weather man said he wanna see the tornado tighten up . tf ?
23	1	I have to much swag 4 dis tornado.

Disaster	Count	Message
24	4	Wow looks like the storm missed me so I can't watch it
34	4	#everyOklahoman thinks there should be a tornado emoji.
37	4	Damage at the start of the tornado path is like the tree version of a paper cut #okwalk http://t.co/G00DtKbUxt
39	2	When I see a tornado then ill be scared until then everyone just stop
47	3	Y'all act like May ain't tornado season

Table 11. Often/usually shared messages

Disaster	Count	Message
Blizzard	Shared	
5	27	12" of snow so far just NW of Rapid City, SD. Sustained winds over 40 mph. Blizzard warning until tomorrow morning.
29	30	My heart goes out to all of the cattlemen & their families in western South Dakota, I can't even imagine the pain they have to be feeling.
51	25	Severe weather - shelter-in-place. Stay indoors, do not venture out.
53	30	Blizzard Warning this area til 6:00 PM MDT Sat. Prepare. Avoid Travel. Check media. -NWS
Flood		
29	28	San Bernardino And Riverside County Valleys - The Inland Empire Flash Flood Watch in effect until 8PM PDT MON
51	25	Flash Flood Warning this area til 6:00 PM PDT. Avoid flood areas. Check local media. -NWS
Gas Leak		
8	26	Kudos to @Safeway for distributing Free water during the #Alamo gas leak
16	27	Gas leak in Alamo, CoCo County, traffic control in effect at Stone Valley Rd at Danville Blvd and Jackson at Danville Blvd, avoid area
20	30	SIGALERT: Alamo: Danville Blvd closed between Stone Valley & Jackson due to gas leak. Stone Valley ramps from 680 also closed.
36	28	ALERT: Contra Costa County Sheriff's have issued evacuation for parts of Alamo due to gas leak in area along Danville Blvd.
Hurricane		
31	25	Heart goes out to those rocked by #Sandy...
52	30	MANDATORY EVACUATION Zone A, Rockaways, Hamilton Bch, City Is. NYC.gov or 311 for details
Tornado		
2	30	Tornado emergency for Moore #OK from @koconews Take shelter now
9	29	Stunning progress in #Moore. I've always said if Americans could work together everyday like we do in tragedies, we'd be MUCH better off.
13	33	TORNADO ON THE GROUND. Huge wedge tornado crossing I44 near SW 149th. TAKE SHELTER @NEWS9 http://t.co/9rviqj3GwD
25	29	IF YOU ARE IN NORMAN/MOORE TAKE COVER NOW. TORNADO ON THE GROUND IN NEWCASTLE

Disaster	Count	Message
38	34	@4WarnStormTeam: Emergency crews asking you to stay out of Moore area. They are having trouble getting in to help. Please listen.
51	32	Tornado Warning in this area til 9:30 PM CDT. Take shelter now. Check local media. -NWS

5.14.2 Physiological Data

To explore how the overall testbed might relate to time on task fatigue, we utilized ABM's B-Alert classifications for drowsiness, engagement and workload. Figure 13 depicts distraction versus engagement across all subjects for all sessions, with a cut off at 4,000 seconds, while Figure 14 depicts engagement versus workload. Participants completed the session in 2,000-4,200 seconds (30-70 minutes). The longer the subject took to complete the task, the more fatigued they became. Subject 5621, as noted earlier, had some very long response times and took the longest to complete the session: nearly seven minutes longer than the next longest subject. To examine this further, we stratified participants into slow (taking longer than 3,000 seconds), average and fast (taking less than 2,500 seconds). Figure 15 depicts these for drowsiness, engagement and workload. Note that we cut the time off for these graphs at 2,500 seconds, so all data is aligned in time on task.

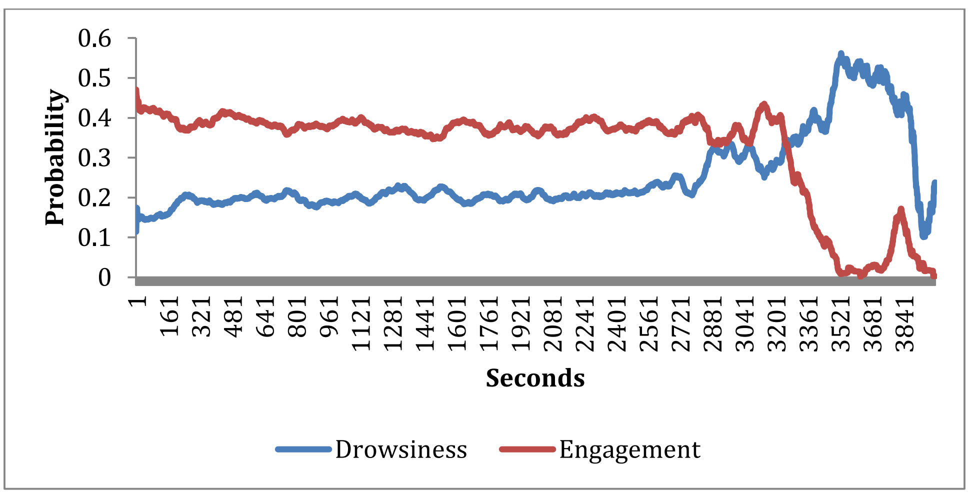


Figure 13. Drowsiness vs. Engagement across all subjects (note that by 3,000 seconds there are 13 participants left, as others completed the task faster)

Note that as a group, drowsiness increases slightly over time, while engagement drifts lower. Those subjects taking longer than 3,000 seconds demonstrate a significant increase in drowsiness and decrease in engagement. We see a similar effect in workload, whereby workload seems to compensate for a drop in engagement.

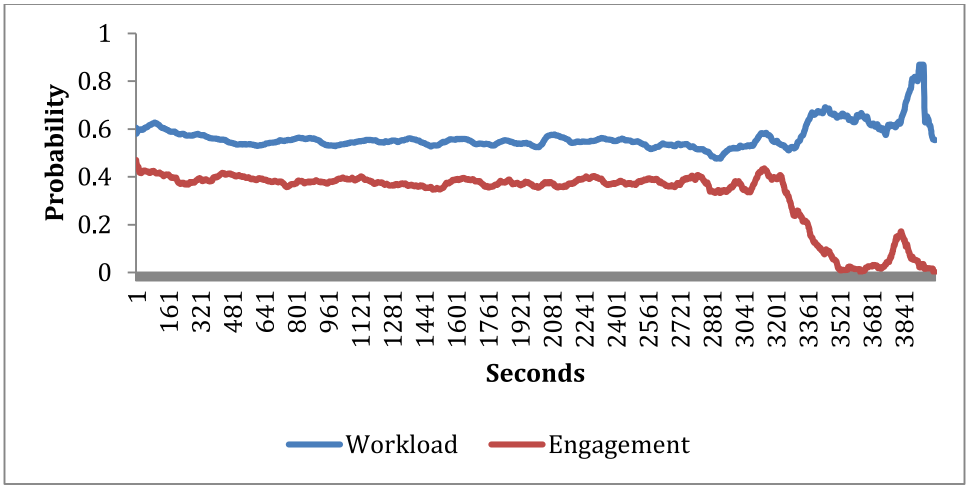


Figure 14. Workload vs. Engagement across all subjects (note that by 3,000 seconds there are 13 participants left, as others completed the task faster)

The changes in these metrics are confined to the extra time they took in completing the task, as we see no such similar pattern emerge if we stratify the metrics by slow, fast and average responders. Rather, slow responders appear to have a higher level of drowsiness overall compared to the other groups. This led us to check what time of day these participants were tested; however, we found no time of day that might explain this finding, and it may simply be that these participants were more fatigued, despite instructions to get adequate sleep the seven nights prior to the study (7.5 hours or more and asleep by 11:30 p.m.).

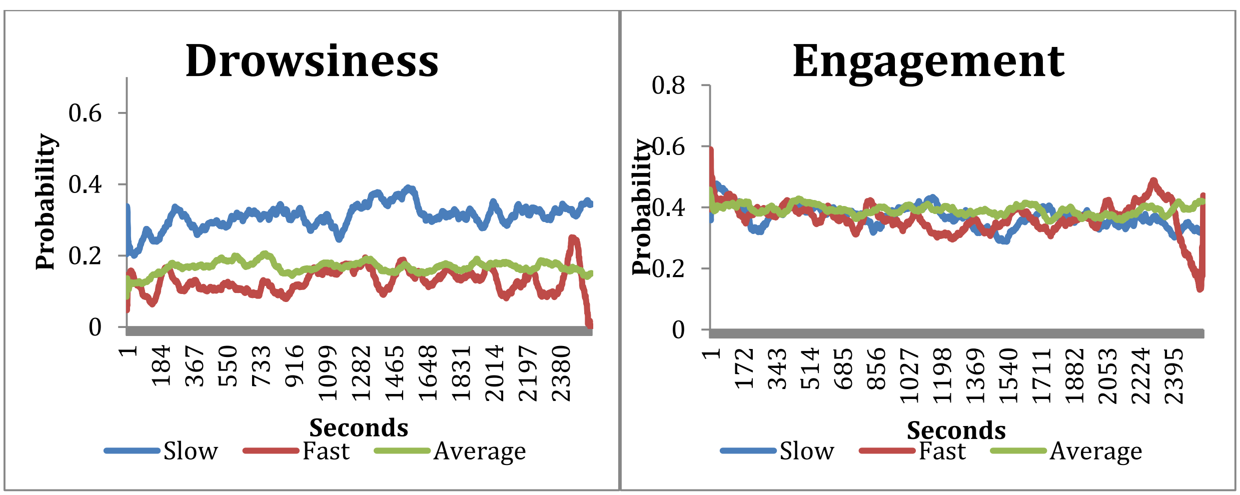


Figure 15. Drowsiness and Engagement stratified by completion times: fast (less than 2,500 seconds), slow (greater than 3,000 seconds) and average (Workload is similar to Engagement and thus not shown)

We also examined stimuli-locked Event Related Potentials (ERPs) for each disaster, with shared versus not shared. There were no ERP differences for the shared versus not shared baseline/Benchmark tweets. For Blizzards, in initial analysis, it appears P300 over frontal right was increased when sharing, but that did not hold up, and in fact the only differences appear at Fp2 and F7, in a higher amplitude P300 peak for shared messages versus not shared. The red

circle highlights the areas noted. The headmap shown in Figure 16 displays the location of each channel. Figures 17-22 are arranged showing the signals from the headmap.

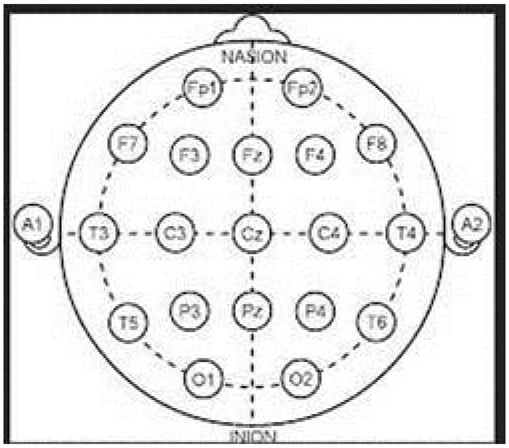


Figure 16. Headmap showing the placement of electrodes on the scalp

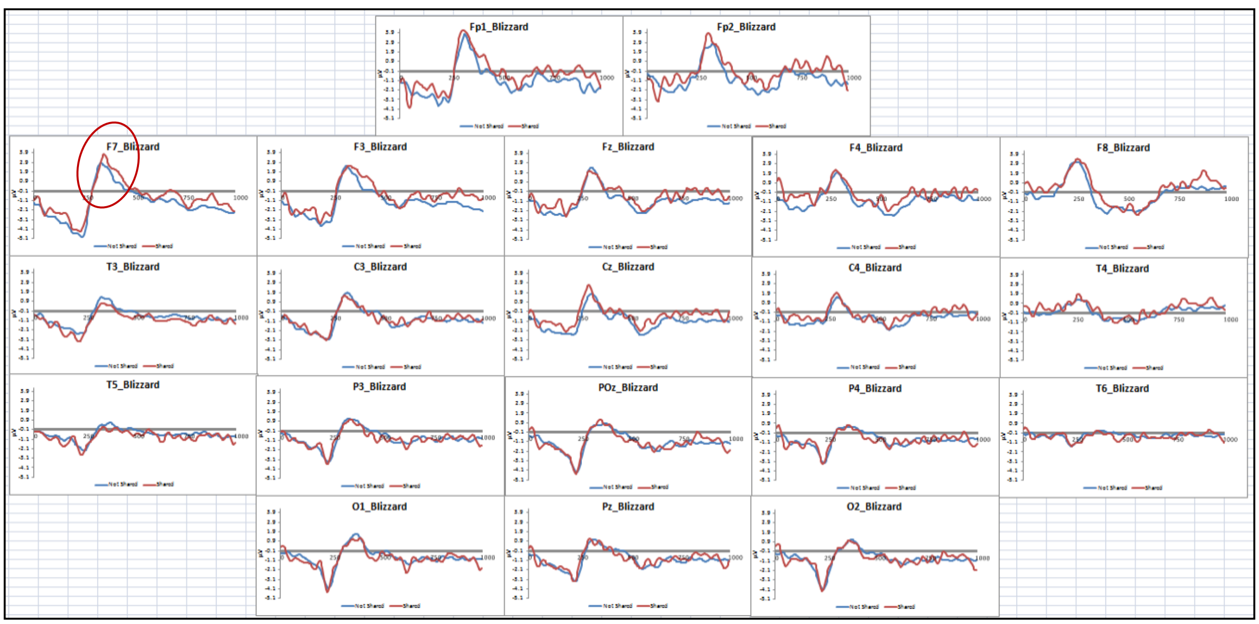


Figure 17. Blizzard ERPs

Hurricanes had an inverse pattern in the initial data and maintained the inversion here, but again, only on frontal right amplitudes; Fp2, F3, F7 and F8 were elevated for those messages that were shared. Figure 18 presents these data and the red circle highlights the areas noted.

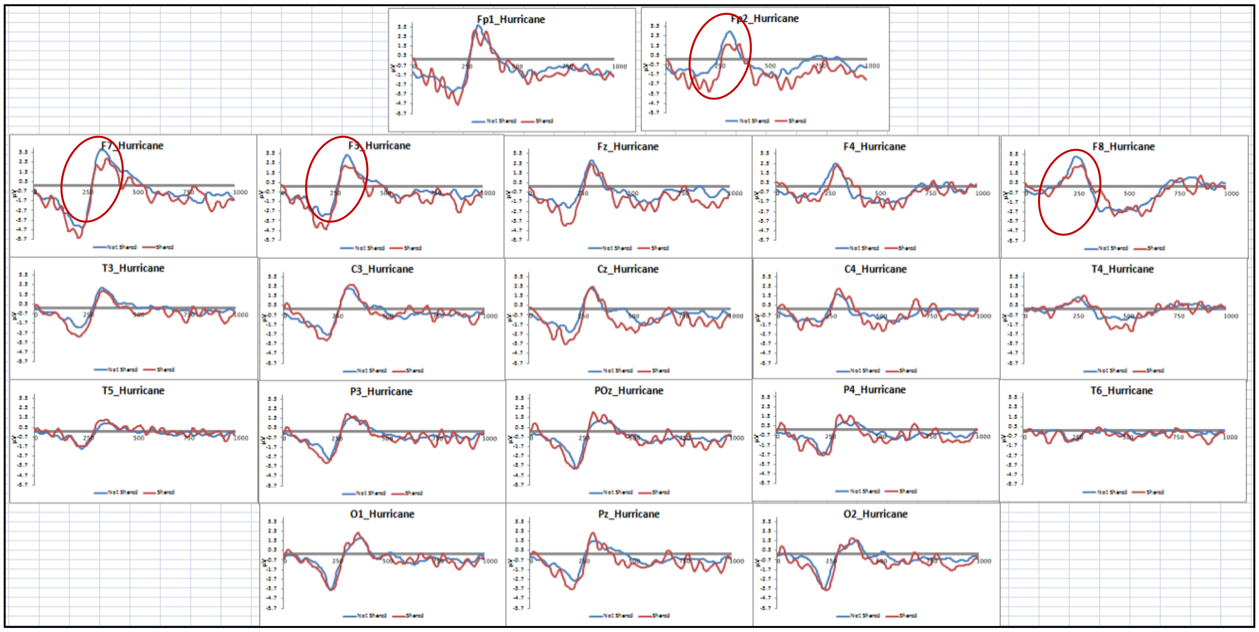


Figure 18. Hurricane related ERPs

Gas leaks have a clear frontal left pattern of both N200 amplitude and P300 amplitude increases for shared messages.

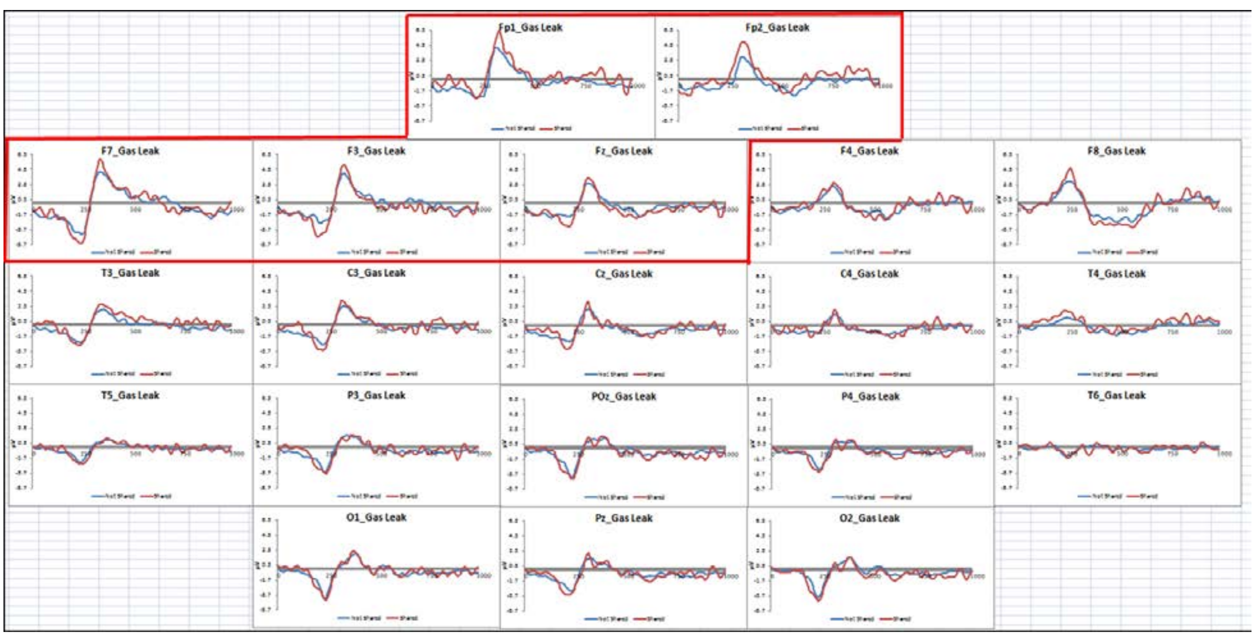


Figure 19. Gas leak related ERPs. The red highlighted plots are regions of the brain that show the most distinctive differences between the decision to share the WEAs or not. These graphs are all organized based on the headmap (see Figure 16).

For tornadoes, the frontal left P300 amplitude peak also occurred, consistent with blizzards and gas leaks.

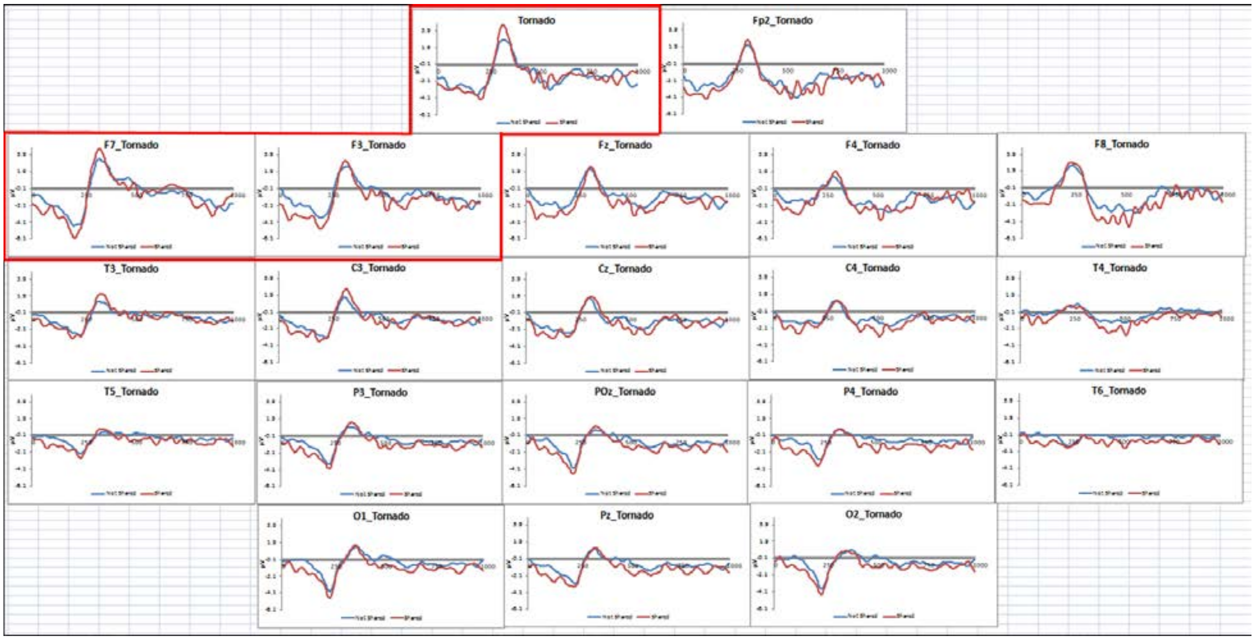


Figure 20. Tornado related ERPs. The red highlighted plots are regions of the brain that show the most distinctive differences between the decision to share the WEAs or not. These graphs are all organized based on the headmap (see Figure 16).

Unlike in the initial analysis, where no ERP differences were found, with the full dataset, floods, too have a frontal left P300 peak for shared messages.

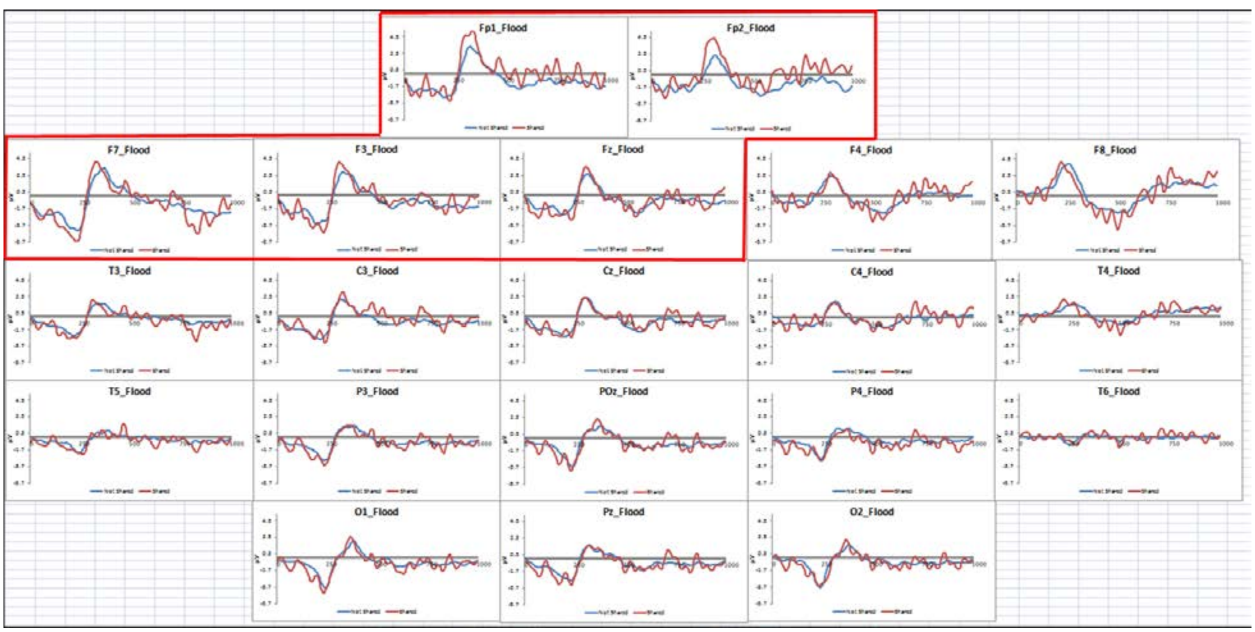


Figure 21. Flood related ERPs. The red highlighted plots are regions of the brain that show the most distinctive differences between the decision to share the WEAs or not. These graphs are all organized based on the headmap (see Figure 16).

We also reorganized these data to compare the shared messages across all disasters (Figure 22), and all of the non-shared messages across disasters (Figure 23). By looking only at the shared data, we see some interesting patterns that indicate that the P300 develops most strongly over the frontal-left and to a somewhat lesser degree, the N200 feature, over the parietal/occipital area for the shared messages. We also see a great deal of variability in the ERP wave form across disasters. While the P300 frontal left and N200 parietal/occipital features also develop in the non-shared messages (Figure 23), the amplitudes are smaller, and there is very little difference across disaster. This may be due in part to the rarity of sharing in general, leading to more variability in the ERP wave form for shared messages, and that across messages we have from two to six messages that are commonly shared, depending on the disaster.

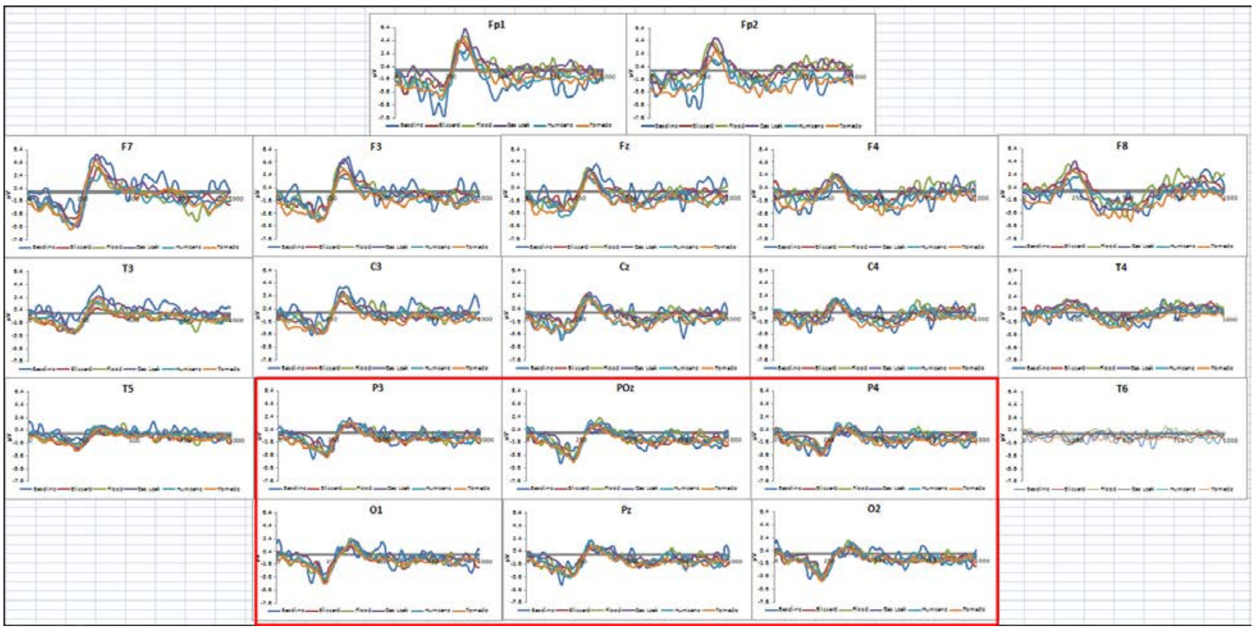


Figure 22. Shared ERPs. The red highlighted plots are regions of the brain that show the most distinctive differences between the decision to share the WEAs or not. These graphs are all organized based on the headmap (see Figure 16).

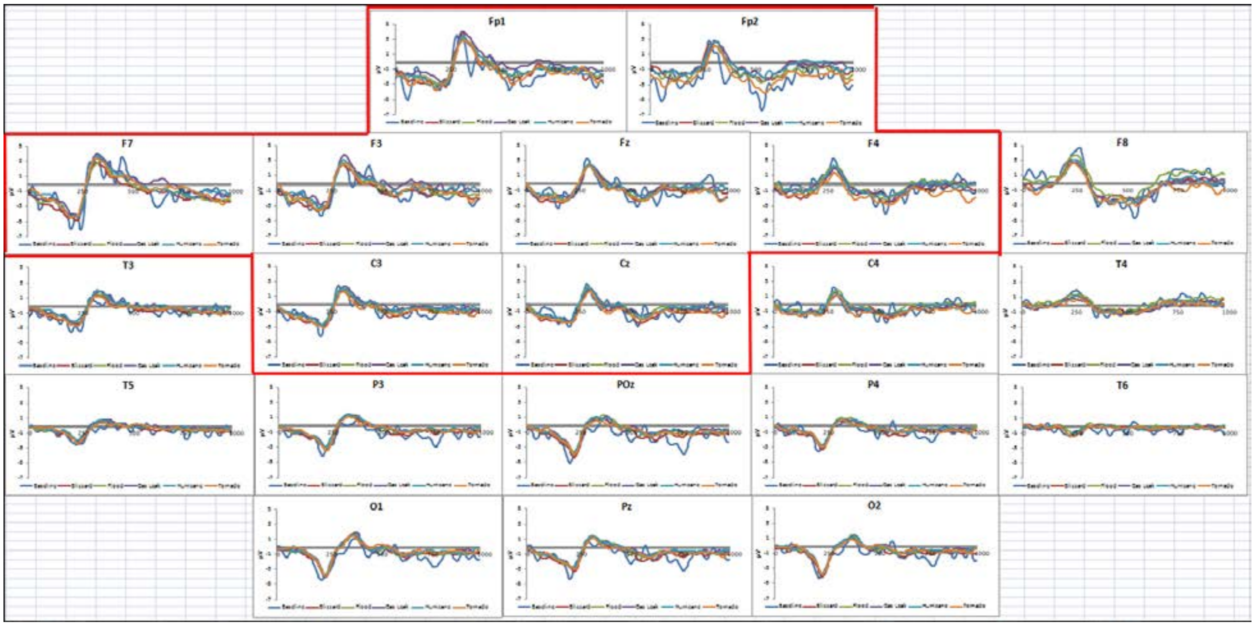


Figure 23. Unshared related ERPs. The red highlighted plots are regions of the brain that show the most distinctive differences between the decision to share the WEAs or not. These graphs are all organized based on the headmap (see Figure 16).

Taken together, these data indicate that the "processing" feature of ERPs, the P300, is likely influential in whether a message is shared or not. N200 may also be a factor, and clearly is for gas leak related messages, but other disasters are less clear and additional data would be needed to determine if the N200 feature is truly informative in identifying messages that are likely to be shared.

6.0 Primary Study Methodology and Experiment Design

6.1 Overview

The purpose of this project, using an EEG data-driven approach, was to evaluate the physiological response of individuals to WEAs and social media content within the context of emergency situations in general. This approach allowed an analysis of how subjects perceive disaster alerts, observation of the level of attention that elicited in subjects, and observation of subjects' response to the question of whether to share such alerts with their peers over a social media platform. Twitter was chosen as the basis for analysis because its character limit is most representative of the current 90 character allowance for cell phone-based alerts about weather-related emergencies and because it is a conventional social media network.

The project evaluated test subjects' willingness to share WEAs and tweets associated with a series of five different types of disasters with their own personal social network. Among these tweets were emergency alerts, messages conveying sympathy for the victims of disasters and other various forms of sociable communication over the social network. Thus, subjects were being asked, within the context of an emergency situation, to evaluate how important they perceived various forms of communication about disasters. By evaluating their responses alongside their physiological response to the messages, the project was able to not only measure their willingness to disseminate information about disasters but also analyze the underlying cognitive models that drive their perceptions and reactions about different types of disasters.

6.2 Methodology

ABM was contracted by PNNL to collect 20-channel EEG data from 51 subjects as part of an experiment to evaluate the ways in which people perceive different kinds of disasters. During the course of the experiment, each subject was presented five disasters in randomized order (n=5). A random benchmark assessment of six neutral tweets (i.e., tweets that were not specific to any type of disaster) were presented either immediately before or after the set of disaster blocks (i.e., first or last). Immediately before each disaster block, subjects were first shown a 5-minute newsreel video depicting news coverage for the disaster type they were about to evaluate.

After the newsreel ended, subjects were presented with a series of 50 WEA and Twitter messages for each of the five types of disasters (blizzard, flood, gas leak, hurricane and tornado) for a total of 250 messages. Each message was presented one by one, for a minimum of one second, and participants were asked if they would share the message on social media. Each subject received the disasters and associated messages in random order.

6.2.1 Description of the Social Media Data

Social media is understood as an information propagation tool for reporting on and responding to natural disasters. Emergency management services use social media to issue alerts and warnings,

look for reports of emergencies and understand public response to emergencies. Social media is used to share information leading up to, during and after the disasters (Bagrow 2011). For the purposes of this study, tweets around a set of well-known and documented disasters were gathered for examination. We sampled the public 1 percent streaming Twitter API for control tweets.

Collection of data was limited to geotagged tweets (tweets containing latitude and longitude coordinates) within the specified timeframe to verify user proximity in both temporal and physical space to the disaster event. A primary goal of the study was characterizing the language around disaster events, as used by people likely to be impacted or otherwise directly involved. While the volume of geotagged tweets was low, we were still able to acquire workable sample volumes for each disaster.

To collect pertinent disaster-related tweets, we used 203 FEMA-declared disasters in the United States from 2012 and 2013 (http://www.fema.gov/disasters). Historical Twitter data was purchased from a social media vendor using their historical data request API. Each query was composed of curated keyword lists, primarily named entities related to a particular disaster and informal language describing the nature of the event. Queries were further filtered both by geo-tagged location and date range. A date range for the historical query was selected by taking a range of less than five days from the event date itself, except for the (non-weather-related) Alamo, California, gas leak, where a date range of one day before to five days after the event date was used.

Geographical filters for the query were established using the area of impact of the emergency declaration, such as a single 25-mile radius around a defined point, or entire regions were selected when more than a single point of impact exists. For example, the Southern California flooding and wildfires searched within California, Hurricane Sandy covered multiple states, and the Alamo gas leak was a single point centered on Alamo, California. Each tweet was also labeled by the type of disaster from which it was queried (e.g., tornado, hurricane, fire, flood). For example, select keywords used for the Alamo, California, gas leak include the following: leak, gas, evacuation, pg\&e, pge, pg+e, Alamo, Danville and shelter. Full query details are available on request. Upon acquisition of this data, it was ingested into Elasticsearch, a Lucene based search engine architecture. The queries are available on request. It is important to note that the nature of collecting only geo-tagged tweets means that we did not collect the subsequent retweets, but many people manually retweeted non-geocoded tweets and embedded their own geocode.

The Twitter messages used in this study were a combination of those shared by actual Twitter users and disaster alerts sent by news stations and other emergency alert services within a defined geographic region surrounding the site of a declared emergency for each respective type of disaster. For disasters that were declared at a definite point (such as tornados), tweets were collected from within the surrounding 25-mile radius. For disasters that affected broader swathes of land (such as hurricanes or blizzards), tweets were selected from within the entire region being

alerted for a weather emergency. Tweets associated with the blizzard class of disaster were collected from a winter storm that struck South Dakota in October 2013. Flash flood tweets were collected from an episode of flooding that occurred in southern California in the summer of 2013. Twitter messages collected for the gas leak disaster type were collected from an incident that occurred in Alamo, California, on July 24, 2013. Tweets for the hurricane disaster type were collected from across the northeastern United States, where the hurricane made landfall in late October 2012. Messages associated with the tornado disaster were collected from the tornado that struck Moore, Oklahoma, on May 20, 2013.

6.2.2 Description of the EEG Data

Data collected by ABM was time-locked to the events occurring within the experiment testbed, meaning that every observation can be associated with the activity being conducted by the subject at the time it was recorded (i.e., if the subject was watching a context video versus responding to a tweet). Furthermore, ABM collected this data at a sampling rate of 256 Hz. (i.e., there are 256 measurements of brain activity taken every second) to provide a high level of fidelity in the analysis. The analysis of this data focused on measuring Event-Related EEG, the brain's electrical response resulting from a direct exposure to a particular cognitive or sensory event. For EEG data acquisition, ABM's B-Alert® X24 wireless EEG system was used. The B-Alert X24 combines battery-powered hardware with a pre-configured sensor strip to provide a lightweight and easy-to-apply system for recording high-quality EEG and ECG. In accordance with International 10-20 system, the B-Alert X24 provides the following 19 EEG channels: Fz, F3, F4, Cz,C3, C4, P3, P4, Pz, O1, O2, T5, T3, F7, Fp1, Fp2, F8, T4 and T6 – plus POz.

6.3 Understanding Action from Subject Response to Disaster Videos

Analysis of subject EEG responses to the context videos in the study suggests that the subjects perceive the five disaster types quite differently, particularly floods. When subjects were told in advance what disaster they were about to evaluate, the subjects had a distinctly different response towards floods as compared to any other type of disaster in the study. Furthermore, once they were watching the context videos, subjects appeared to be less emotionally engaged in the flood context video than the others. Together, these findings indicate that the subjects in the study had a built-in bias to how they perceived the various disaster types before viewing the video itself. While subjects view the video, this discrepancy in their brains' response appears to persist in a fashion that the literature suggests indicates the subjects perceive that particular disaster type as being less immediate or urgent.

Before subjects were exposed to any social media messages, they were presented with a video of news coverage for the type of disaster that they were about to evaluate to provide context for the messages (i.e., a news report on a tornado precedes social media messages related to tornados). Immediately before the subjects were shown the video, they were presented with a disaster introduction screen informing them of the disaster type they were about to evaluate. This

introduction was shown to subjects for an average of three seconds before it transitioned to the video. EEG activity during this time period was evaluated to assess subjects' natural reactions to the concepts of certain types of disasters, independent of effects that may be inherent to the context videos themselves. This analysis showed that subjects typically had considerably more variance in EEG activity recorded over the frontal regions of the brain (channels F7, F8, Fp1 and Fp2) when being informed that they were about to be shown a video and messages about floods than any other disaster type. Conversely, subjects had the lowest variance in brain activity when told they were about to view tornado-related materials. This disparity suggests that the subjects were predisposed to physiologically perceive the disasters differently almost instantaneously.

EEG responses were also evaluated while the subject watched the context videos preceding the social media messages. This analysis also revealed consistently more variance in frontal brain activity while watching the flood context video than for other types of disasters. As before, subjects had the least variance while watching the tornado context video. This effect was most pronounced over the right and left frontal lobes of the brain associated with channels F7, F8, Fp1 and Fp2. Beyond the differences between disaster types, subjects consistently exhibited no distinctive EEG responses to the videos. Several possible explanations exist for these differences. Increased levels of brain activity (variance) when subjects are presented with a negative emotional stimulus has been reported to correspond to a decreased impact of that negative emotional stimulus with the result being the effect of that stimulus is shorter lived. Alternatively, flood alerts are commonly issued for very broad regions while only truly affecting small subsets of regions increasing the perception of false alarms. Thus, the discrepancy in subject brain activity when viewing the flood context video may be indicative of subjects perceiving less threat or urgency posed by that type of disaster compared to other types of disasters.

6.4 Gamma Wave Analysis

Subsequent spectral density estimation allowed the energy associated with particular brainwave types to be calculated for all subjects from their EEG data collected during presentation of the disaster context videos. By decomposing the EEG data into a spectrum of frequencies, the level of activity associated with specific brainwave types for each subject could be quantitatively measured and compared across disaster types. Of particular interest were the gamma waves, which are commonly associated with cognitive functions and attention in healthy human brains (Pulvermüller 1997, Gruber 1999). Once isolated, the power density for the frequencies associated with gamma waves (which are found in the spectrum between approximately 30 Hz to 40 Hz) were averaged across all users by disaster type for all frontal EEG channels.

This analysis yielded findings which were in line with previous observations; specifically that subjects exhibited physiological phenomena within their brains that indicates they were the least engaged with the flood disaster context video, and the most engaged with the context video for tornados, with gas leaks, hurricanes and blizzards falling somewhere in between the two. The discrepancy in gamma wave power density was present in all of the frontal channels examined

(Fp1, Fp2, F7 and F8), though the absolute power density was greatest in the Fp1 and Fp2 channels, again consistent with previous observations. The difference in gamma wave power density was determined to be statistically significant for floods in all channels. Taken together with the previous noted observations of subject reactions to being informed they were about to evaluate flood-related messages as well as other physiological clues suggesting that they were disengaged with this particular type of disaster, provides evidence to believe that the subjects were heavily biased against regarding floods as seriously as other types of disasters.

6.5 Subject Responses to Twitter Messages

Subjects exhibited several characteristic behaviors that differentiated positive responses about sharing content versus when they did not endorse sharing a message over social media. First, subjects universally took slightly longer to make the decision to share content than when they chose not to share content. Second, as compared to other types of disasters, tweets associated with flash floods had the lowest overall sharing rate among the subjects. Third, when subjects chose to share content, their EEG evidenced a significantly greater spike in activity than when they chose not to share content. This "decision-related" peak was found across disaster types; however, it was noted that subjects had a delayed peak in this activity when choosing to share messages associated with floods in particular, indicating that subjects perceived the message somehow differently than other disaster types. Finally, the peaks associated with subjects choosing to share the most popular content (weather alerts from news stations) was significantly greater than those observed for any other set of messages, indicating that such alerts were particularly effective at attracting user attention and eliciting re-tweeting behavior.

ABM performed its own cursory analysis on the subjects' performance when responding to the presented social media messages. This analysis was performed primarily with the intention of identifying any systematic bias that may have been introduced in subject responses arising from message or disaster presentation order, as well as identifying prominent features in the EEG responses. In their analysis, ABM found that subjects took on average one second longer to respond to a tweet that they wished to share (6.9 seconds) than they did for tweets that they did not wish to share (5.3 seconds);, a difference that was observed in their overall responses as well as for all five types of disasters. Overall, test subjects showed no significant difference for either response in their reaction times between disaster types, regardless of the order in which they were presented. Analysis also indicated that no particular individual message had a particularly longer response time for more than one subject.

Subjects' responses to endorse sharing social media tweets over their network were relatively unaffected by the order in which the disaster types were presented. While subjects generally expressed a slight preference for sharing tweets from the first few sets of disaster-related tweets that they were exposed to, the difference was only about 3 percent in the retweeting rate from the first disaster to the last. Across all disaster categories, subjects typically shared tweets about 23

percent to 29 percent of the time. Subjects only chose to share tweets associated with flash floods 15 percent of the time, however, making it appreciably less favored by the test subjects.

Both PNNL and ABM examined the subjects' EEG data before subjects decided whether to share a message. ABM's analysis of the EEG data was time-locked to the stimulus of the subjects two seconds before making their decision. This stimuli-locked analysis found that the most significant changes in EEG were observed over the right and left frontal cortical regions of the brain, specifically for the F7, F8, Fp1 and Fp2 channels. For all disaster types except blizzards, the magnitude of the stimulus-locked EEG was greatest in these channels when choosing to share messages compared to when they elected not to share. The scale and timing of the event-related EEG was similar when choosing not to share a message, although it was of smaller amplitude.

PNNL's analysis of subject EEG data examined brainwave activity during the full duration of the subjects' exposure to the messages. In other words, this analysis captures the physiological response during the full course of their decision-making process, rather than just the window of time immediately preceding their decision. Because subjects took vastly different lengths of time to render their decision for every individual message, however, the EEG data for each individual response was temporally compressed into an equal number of time steps by averaging the appropriate number of event-related EEG readings into each time step. Once the data was compressed, it was possible to compare all subject responses along the same temporal continuum with an equal number of time steps, such that initial exposure to a message occurred at time step zero, and each subject's response occurred at the last time step. This approach enabled all subject ERPs to be compared in such a way that all meaningful features were temporally aligned. Evaluating subject responses revealed similar patterns to those observed by ABM wherein a more exaggerated peak of brain activity over the right and left frontal cortical regions preceded the decision to share a message, while subjects choosing not to share messages had a similar wave shape and timing with a smaller peak in brain activity.

The decision not to share content resulted in an event-related peak in EEG over the left-frontal region (channel F7) occurring shortly after being presented with the message content. The immediacy of this response indicates that subjects were able to quickly identify messages that they did not find worth endorsing or sharing among their peers. Interestingly, during a disaster-specific analysis of subject responses, this same peak only appeared in association with instances in which subjects chose to share content for their social network for flood-related content. For all other disasters, this signal was only observed preceding a negative response from the subject.

PNNL further analyzed subject response to messages specific to each disaster type. Again, for each disaster type (with the exception of gas leaks), the decision-related peak in EEG was more exaggerated for those choosing to share messages than it was for those choosing not to share messages. It was noted that this peak in activity for subjects choosing to share messages was considerably prolonged when responding to flash floods than it was for any other disaster type, however. The response pattern observed for subjects choosing not to share messages about flash

floods was roughly equivalent to other types of disasters in shape, intensity and the time when it occurred. The protracted response being unique to subjects choosing to share messages about flash floods suggests that the process was either more deliberative or more prolonged than for other disasters.

Finally, the fifteen individual messages that were shared most frequently across all subjects (regardless of disaster type) were examined as a subset relative to the overall responses. These messages were, predominantly, emergency weather alerts from local news stations and weather agencies, although three were sent by individuals who expressed empathy for the victims following the blizzard and tornado disaster. The average EEG response from subjects when choosing to share these messages resembled those observed for other types of disasters with regards to the timing and wave shape. The EEG response peaked at significantly higher levels than those observed for any other messages, however. This suggests that the content of these messages was particularly effective at eliciting a physiological response from the subjects.

6.6 Personality Influences on Perception of Disasters

During the subject screening and selection process, ABM had all candidate test subjects fill out a series of questionnaires that evaluates their dispositions and personalities based on a number of characteristics. ABM made this information available to PNNL for the subjects who participated in the study, and subject responses were examined in addition to these personality dimensions to identify response behaviors that might be associated with certain personality types. While these questionnaires examined a number of personality dimensions, the most meaningful differences in subject responses were noted for the depressive and extroversion personality characteristics. PNNL conducted this analysis by dividing the subjects into quartiles for both their depressive and extroversion scores. The response rates and EEG data for the top quartile of subjects (those who scored the highest on the depression and extroversion tests) were then compared against the bottom quartile of subjects (those which scored the lowest on the depression and extroversion tests).

The subjects with the most depressive personalities (as measured by the Profile of Mood States questionnaire administered by ABM) were almost twice as likely to share disaster alerts as the least depressive subjects in the study. This analysis reveals that subjects with the most depressive personalities exhibited considerably less variance in their brainwave activity while watching the context videos, particularly for floods. The difference in activity during the videos indicates that the most depressive subjects perceived all disaster types included in the study, and floods in particular, with a greater sense of urgency than their least depressive peers. This effect appeared to manifest itself in the form of the most depressive subjects being nearly twice as likely as the least depressive subjects to share information about disasters over social media. While a subject’s personality score for extroversion appears to influence their willingness to share certain forms of predominantly social content, neither group was more likely to share disaster alerts than the other for any particular disaster.

Examining the differences between cohorts during presentation of the context videos shows that the most depressive subjects had less brain activity than the least-depressed cohort for all disaster types except gas leaks and tornados (where the two cohorts were indistinguishable from each other). This difference was most pronounced for the flood disaster, where the least depressive subjects had considerably more variance in their EEG recorded over the right and left frontal regions (F7, F8, Fp1 and Fp2) during the context video. When subjects were sorted in a similar fashion on the basis of extroversion scores, a similar pattern was again observed; this time, the least extroverted subjects had considerably less variance in their EEG activity during presentation of the context videos compared to the most extroverted subjects. This difference was also again most exaggerated for the flood disaster type, with the two groups appearing largely indistinguishable from each other during the gas leak and tornado context video.

Similar differences in subject behavior were also noted during analysis of their responses towards social media messages. Overall, the most depressive cohort of subjects was 50 percent more likely to endorse sharing messages than the least depressive cohort. The most extroverted subjects also displayed a propensity to share social media content approximately 50 percent more often than their least extroverted peers in the study. In both cases, the effect was consistent across disaster types, with neither group of subjects appearing to prefer any particular type of disaster over another.

6.7 Understanding Types of Disaster Related Messages

When we categorized the messages the study participants viewed into three categories (informative, sympathetic and social) on the basis of their content, further distinctions between these groups were observed. Messages that were deemed to be “informative” (i.e., messages that communicate a direct alert about a disaster with specific times, places and conditions) were heavily favored by the most depressive cohort as measured by the personality survey instrument, which would choose to share such messages nearly twice as often as their least depressive peers (242 shares versus 119 shares, respectively). Conversely, messages conveying a sympathetic message (i.e., sympathy for disaster victims) were shared at an almost identical rate between the two cohorts (94 shares versus 91 shares, respectively).

Extroverted subjects exhibited a similar bias for endorsing different types of messages, the effect of which was once again even across disaster types. While the two cohorts generally chose to share content of an informative or sympathetic nature at a roughly consistent rate (209 versus 189, and 143 versus 106, respectively), the most extroverted subjects demonstrated a clear bias for messages of a social nature (i.e., those that neither convey information about the disaster nor explicitly show sympathy for victims), endorsing these messages more than twice as often as their least-extroverted peers (440 shares versus 206 shares, respectively). The response rate to these three message types for both cohorts across all disaster types is shown in the table below.

Subject behavior also varied with age, although this effect was less pronounced and not specific to any type of disaster. It was noted that the oldest subjects (those 50 years or older) had the highest rate of content sharing as a group (approximately 85 shares per person), higher than the youngest subjects (approximately 60 shares per person). Subjects who were 40 to 49 years of age, however, were notably less inclined to share content of any sort over social media in the study, sharing only about 30 messages per person on average.

These results, together with the literature on this subject, suggest that the most depressive subjects were more emotionally affected by the context videos than their less depressive peers, particularly for the flood disaster. These subjects were also twice as likely to share informative updates about these disasters as their less depressed peers, although this effect was consistent across all of the disaster types in the study. While the most extroverted subjects were twice as likely to share sociable content with their networks, their predisposition to share did not appear to make them any more likely to share emergency information than their less extroverted peers. These findings lead us to conclude that individuals' propensity to depressive personality traits can prime them to perceive certain disasters, notably floods and blizzards, as being more urgent than their peers with fewer depressive personality traits. While the degree to which an individual is extroverted does appear to have some influence an individual's perception of a disaster during the context videos, this did not translate into a difference in their willingness to share information about disasters.

6.8 Flood-Specific Analysis

Throughout this report, numerous examples have been presented that show differences in how the subjects responded to or perceived different types of disasters. In each instance, it was noted that floods appeared as an outlier compared to the other disaster types, with subjects appearing to be less engaged or responsive. First, subjects appear to have had a nearly instantaneous reaction to being told that they would be evaluating flood-related content that was distinct from the other disaster types. Subjects also evidenced significantly greater event-related EEG activity while watching the flood context video than any of the other context videos. This effect was also magnified when personality dimensions of the subjects were taken into account, suggesting subject perception of disaster urgency was the most affected by personal dispositions. Finally, subjects were consistently less responsive about messages related to floods, both sharing them less often than all others and having a distinctly different decision-related EEG signature associated with their decision to share flood-related content. Taken as a whole, this analysis indicates that the subjects were predisposed to react to floods differently on both a conscious and unconscious level, with this difference being heavily shaped by depressive personality traits. By extension, the difference in how subjects perceived the threat posed by floods further appears to have influenced their willingness to share social media content related to that type of disaster.

As noted in the previous sections presenting analysis of subject EEG activity during the context video, subjects typically had the greatest EEG responsivity over the right and left frontal regions — F7, F8, Fp1 and Fp2 in particular — both upon being told what type of disaster they were about to evaluate and during the context video itself. As Dennis et al. (2010) notes, increased frontal activity during presentation of an emotional stimulus (such as the context video) may indicate a weaker emotional impact on a subject. This finding resonates with our test subjects as well, as they were the least responsive to the flood-related messages (with only a 15 percent share rate versus 23 to 29 percent for all other disasters). The response to floods stands in stark contrast to the responses observed for tornados, where subject EEG activity levels were lowest and subjects were most responsive to the messages being presented (with a 29 percent share rate). The comparison of these two disasters strongly suggests that subjects are acting on internalized perceptions about the urgency or threat posed by categories of disasters.

Anecdotally, it was also noted during the experiment design and analysis that many of the messages associated with floods collected from Twitter were highly dismissive in nature. Specifically, it was much more common to find messages indicating that Twitter users were exasperated or frustrated by the intrusion of the flood alerts, while others might suggest that the users were willing to disregard or dismiss the severity of the alert as being exaggerated. Although similar messages were noted in the samples for other disaster types, they appeared to be much less common than they were for floods. While such sentiments are difficult to classify on large data sets, this finding may suggest that the experiment subjects and Twitter users alike have become predisposed to perceive the urgency of various disasters differently. It is worth noting that all of the subjects selected by ABM for this study live in southern California, where flash flood warnings are common and can be highly localized events despite the alerts being transmitted to a broader region, leading to a perception that the majority of such alerts are false alarms. It is possible that a subject pool selected from another geographic region where flash floods are a less frequent occurrence may be inclined to take such alerts more seriously, and instead be biased against other types of disasters (for example, tornado warnings in the Midwest may be similarly less distressing because they are more common).

While previous analysis identified differences in the way cohorts of subjects sorted on the basis of scores for depressive or extroverted personality traits perceive the disasters, in both cases the difference between them was most exaggerated for floods. This finding suggests that floods may be especially prone to the whims of personal dispositions with regards to how much urgency the alerts are given and how willing individuals are to act upon them. The opposing example of this is once again tornados, where there was a non-significant difference between personality trait cohorts, and subjects appeared to regard the urgency of the alerts in a more homogenous fashion. This disparity presents a challenge for emergency management professionals as the public does not appear to treat all disasters alerts as equally urgent.

7.0 Conclusions and Recommendations

7.1 Conclusions

Overall, current WEAs proved to be highly effective across all disaster types and were among the most shared by the test subjects. Even when subjects chose to share these alerts, however, the EEG responses to flood-specific alerts were distinct from other disasters. When shown context videos for each type of disaster, and particularly for floods, subjects with the highest levels of activity during the video stimulus were also those who were less likely to share informative tweets about the disaster with their peers. Additionally, subjects more frequently shared messages expressing a dismissive sentiment (i.e., a message that advocates or expresses intent to ignore a disaster alert) about flood alerts than they were about other types of disasters. These responses appeared to be the most exaggerated among subjects with the least depressive personality types.

As a whole, these findings suggest that the subjects physiologically perceived the threat or urgency posed by a flash flood quite differently than other disasters. The response also appears to occur almost instantaneously, suggesting that the response is perhaps reflexive or develops over their lifetime. This response appears to manifest itself in the form of subjects both appearing less mentally engaged with the news coverage of floods and having an increased willingness to ignore or actively dismiss the associated weather alerts. Consequently, emergency management professionals are at a built-in disadvantage when attempting to communicate the risks of flash floods with the public.

7.2 Limitations

It is important to note the limitations of the study conducted by PNNL and ABM. The 51 subject participants all currently live in Southern California. While many in this region are transient, we do not have available information on where else they might have lived. This may create a geographic bias in the results. We believe the bias is limited as the findings related to floods were consistent across age and demographics groups, however. During the study, we asked the subjects if they would re-share the WEA or social message to their social network. Although this is a valuable surrogate for action, future work should ask participants what actions they would take based upon the WEA received.

7.3 Recommendations

The PNNL and ABM team have one primary recommendation and one secondary recommendation for the use of WEA coming from this research.

Recommendation 1. When compared to tornado, hurricane, gas leak and blizzard WEAs, flood WEAs are systematically perceived differently in our study group. **This leads the PNNL team**

to suggest that additional attention be directed at communicating the risk of floods to citizens. For example:

- The WEA could focus on stating specific and direct action for recipients.
- Various formulations of WEA could be disseminated specifically for floods as a special case.
- Although geo-targeting of WEA was not in the scope of the PNNL study, providing citizens with location relevant information may further encourage action.
- Education stressing the seriousness or severity of floods and other similarly dismissed disasters might help reduce the public's flippant response to the alerts.
- Users act as a megaphone for disaster alerts in other instances, amplifying the exposure of the alert by repeating its information, particularly for tornados. DHS should consider identifying methods to better harness this effect for perpetuating the flood alerts.
- Further understanding of how citizens perceive the risk of disasters in specific regions or of certain cultures could be beneficial. PNNL noted social media users dismiss specific types of disaster alerts (floods) based on Southern California flash floods. Citizens in other types of disasters in other locations (i.e., the Southern U.S. as opposed to the Northeastern U.S.) might treat hurricane warnings with similar disregard because they are more common.

Recommendation 2. The results of this study, in combination with several recently published reports, support the validity of specific neural responses to various types of communications, narratives and messaging that can accurately predict human behavior in response to these communications. We recommend the implementation of platform technology to routinely screen emergency message form and content using neurophysiological, cognitive and other measures to add to a database acquired for comparisons and data modeling. This approach would include developing a database of responses from a diversity of people representative of the U.S. population demographics and regions. Data would be uploaded via a cloud-based portal easily accessible with a PC and Internet access.

8.0 Wireless Emergency Alerts Used in Study

Disaster	WEA Message
Moore, OK tornado of 2013	Tornado Warning in this area til 3:45 PM CDT. Take shelter now. Check local media. – NWS Tornado Warning in this area til 3:15 PM CDT. Take shelter now. Check local media. – NWS Tornado Warning in this area til 6:00 PM CDT. Take shelter now. Check local media. – NWS Tornado Warning in this area til 9:30 PM CDT. Take shelter now. Check local media. – NWS
El Reno, OK tornado of 2013	Tornado Warning in this area til 8:45 PM CDT. Take shelter now. Check local media. – NWS Tornado Warning in this area til 12:00 AM CDT. Take shelter now. Check local media. – NWS Tornado Warning in this area til 6:15 PM CDT. Take shelter now. Check local media. – NWS Tornado Warning in this area til 9:30 PM CDT. Take shelter now. Check local media. – NWS
Alamo, CA gas leak of 2013	Due to a gas leak on Danville Blvd. an immediate evacuation has been ordered for portions of Alamo.
Hurricane Sandy of 2012	Go indoors immediately and remain inside. DO NOT DRIVE. Call 9-1-1 for emergencies only. Blizzard Warning this area til 4:00 AM EDT Wed. Prepare. Avoid Travel. Check media. – NWS MANDATORY EVACUATION Zone A, Rockaways, Hamilton Bch, City Is. NYC.gov or 311 for details Go indoors immediately and remain inside. DO NOT DRIVE. Call 9-1-1 for emergencies only.
SD blizzard of 2013	Severe weather - shelter-in-place. Stay indoors, do not venture out. Travel restriction in Rapid City / Pennington County. No travel allowed. Blizzard Warning this area til 6:00 PM MDT Sat. Prepare. Avoid Travel. Check media. –NWS

Disaster	WEA Message
	Blizzard Warning this area til 7:00 PM CDT Sat. Prepare. Avoid Travel. Check media. – NWS
Southern CA flash floods of 2013	Flash Flood Warning this area til 6:00 PM PDT. Avoid flood areas. Check local media. – NWS Flash Flood Warning this area til 4:15 PM PDT. Avoid flood areas. Check local media. – NWS Flash Flood Warning this area til 4:30 PM PDT. Avoid flood areas. Check local media. – NWS Flash Flood Warning this area til 5:00 PM PDT. Avoid flood areas. Check local media. – NWS

9.0 Twitter Messages Used in Study

9.1 Moore, Oklahoma Tornado

Moore, Oklahoma Tornado
S/O to a great sports figure for coming to Moore, ok to help us out! Thank you @name we appreciate it very much!
The tornado is close to my grandparents house.
Tornado emergency for Moore #OK from @koconews Take shelter now
Monster tornado on the ground near New Castle OKC. My crew safe. Take cover now! Pray for folks in the path.
I lived in this same neighborhood on may 3 1999 and this was all to reminding of that please hold your loved one close and pray for Moore
Living my life long dream of tornado chasing rn man #fwm
Still a tornado warning for Paul's Valley area.. Continue to be taking cover.
They now say the tornado was 2 miles wide. Thank god for Gary England from @NEWS9. Gary you are a life saver!!!
@name I'm been donating supplies and tomorrow me and some friends are going to go move debris at crossroads but doesn't like enough
Please pray for all those in Moore Oklahoma #tornados have devastated the area. http://t.co/b2WhCnNYiR
Stunning progress in #Moore. I've always said if Americans could work together everyday like we do in tragedies, we'd be MUCH better off.
this weather man said he wanna see the tornado tighten up . tf ?
I cannot even imagine being a parent in Moore and told that my kid isn't coming home from school... #prayformoore
Really thinking the worst storms today will be western/NW Oklahoma into SW and central Kansas. Long track tornadoes, damaging hail likely.
TORNADO ON THE GROUND. Huge wedge tornado crossing I44 near SW 149th. TAKE SHELTER @NEWS9 http://t.co/9rviqj3GwD
Taking shelter in our house! Massive tornado just west of us
Just another day in OK- live streaming tornado footage at work while the sirens blare. http://t.co/00nmOklPCN
Tornado shrouded in debris is May 3rd all over again. West Moore High and Warren Theater. South OKC take cover.

Moore, Oklahoma Tornado
RT @NWSNorman: There were approximately 13,500 people in the path of the Newcastle-Moore-OKC tornado on May 20th. #okwx
Death toll in Moore, OK is 5. 3 at a 7-11 near tornado path. #PrayForMoore
HUGE TORNADO in NORTH NORMAN AND SOUTH MOORE. TAKE PRECAUTIONS NOW. WATCHING IT FROM MY UPSTAIRS WINDOW. Deadly, take shelter RIGHT NOW.
Just a regular day at work taking shelter from tornadoes.
That tornado is huge
National guard is in moore now. Thank good.
I have to much swag 4 dis tornado.
Wow looks like the storm missed me so I can't watch it
IF YOU ARE IN NORMAN/MOORE TAKE COVER NOW. TORNADO ON THE GROUND IN NEWCASTLE
Saw two looks like more tornados forming. Taking shelter now. Wish I could reach my family :(
Anyone who steals someone's property after a tornado is sick, absolutely!!!
So that tornado in Newcastle is right where I was about 30 minutes ago.
Pray for our friend that got picked up by the tornado and it throw her and broke her back.
My dog says.... I survived the may 20th tornado! http://t.co/4hC0aTn4dw
this tornado is moving fast
That tornado will knock us all down, but it won't stop us from getting back up.
This is what the tornado looked like from our house. #okwx This is I-40 at Choctaw Road. http://t.co/yEKm22Jt2c
Hopefully this tornado takes me out
#everyOklahoman thinks there should be a tornado emoji.
@name mayor of Moore is going to propose a requirement for shelters in all new construction...but OK isn't a state big on regulation.
NWS confirmation of twister size. I can officially say I've been on the heels of an EF5 tornado. #NotSurprised #CrazyExperience
Pray for Moore!
Like what is he gaining by calling tornados "funnel clouds"? http://t.co/lNOBYETeJV
Damage at the start of the tornado path is like the tree version of a paper cut #okwalk http://t.co/G00DtKbUxt
"@4WarnStormTeam: Emergency crews asking you to stay out of Moore area. They are having trouble getting in to help." Please listen.

Moore, Oklahoma Tornado
When I see a tornado then ill be scared until then everyone just stop
Tornado just touched down three miles from my house...so..
i still havent heard from my grandma and dad that lives in moore.. starting to really worry
Still trying to realize that the tornado that hit Moore was only 0.5 miles away from my house. #moore #tornado
Tornado isn't a verb Mike.
Tornado on the ground. Lake thunderbird
Pray for the people in Moore, OK. A very bad tornado hit there earlier today http://t.co/Zef2SOBpk0
This was the Moore Medical Center. Cars stacked 3 high in the parking lot. @keyetv saw rescue crews searching area. http://t.co/gT9AjUZA55
Crazy tornado has been on the ground for two hours!
Y'all act like May ain't tornado season
Days been bit stressful. Glad I got to help out the town of Moore made quite a few people's day and it felt great.
I thought maybe I'd wake up and this would all have been a dream. But it's real, and now the shock is gone. Tears just keep flowing. #Moore
Just a heads-up, friends, that I may be storm chasing tomorrow. Stay tuned for updates. Initial guess at a target is Kiowa, KS. #chasing

9.2 El Reno, Oklahoma Tornado

El Reno, Oklahoma Tornado
Sooo WINDY! No wonder this is tornado alley.
we in a tornado watch .
“@tornadopayne: Another rotating storm.. Incredible... West of Wynnewood in southern Okla.. http://t.co/nVAJ5Kyl0b”
Landed in OKC just before tornadoes hit. Had to immediately take shelter underneath terminal as a big one passed. Was under there for 3hrs
goin to do work out in the disaster area
@f###tyler I'm about to die. I live in Oklahoma & its about to tornado again.. Please before I die follow me back. That will make my life.

El Reno, Oklahoma Tornado
“@name: Take a shot every time they say tornado”
@name @bbauder3 the wind inside tbe tornados go that fast. They dont move that fast though.
“@name: @name tornado watch for the western part until 10 pm ” in case the tornado finds me, it's been nice knowing all of you.
@name @name @name heavy rain and wind in Calumet. Power flashed a few times.
Hopefully this is the backside of the storm... Lots of rain a little hail. #oklahoma @ Westbury… http://t.co/BmcmsulsYs
It's literally only the sounds of tornado sirens, ambulances, barking dogs, and hail hitting s$$$ right now.
Our shelter is packed!and everyone's not even in it yet!
Probably the question I am asking is. Why was channel 4 telling people to go south or north and drive out the storm. That seems stupid.
tornado chasing cars are not the most comforting thing to see when driving through an area that was… http://t.co/8Sb1RWRkxh
Driving by OKC West heading towards Yukon. Debris everywhere. All this damage is terrible. Breaks my heart.
I can hear the tornado
Here we again with this s$$$, my view from storm shelter http://t.co/OVvKw6Io9h
TORNADO EMERGENCY OKC
Batton down the hatches, here comes the storm. #OklahomaWeather
When I hear the word " tornado " I get scared & have breakdowns.
Go home tornado you're drunk
When there are possible tornados my mom treats everything like a tornado. It's raining, we better get in the cellar.
Physically and mentally exhausted from helping with the disaster relief but at peace knowing I helped make a diff #PrayForOklahoma
Here's my poor trampoline after wind lifted over the fence into the street. Been without electricity for over 3 hrs http://t.co/jod5tql2ZM
Everyone please pray for my kelvy! He lost his house in the tornado but he is fine! I love you so much!! @name

El Reno, Oklahoma Tornado
It's crazy that the guy from storm chasers on discovery channel died chasing the tornado in El Reno :/
F### you wind how dare you blow my chairs off my porch. Hoe
Taking shelter w/ everyone & their dogs! @ All Souls' Episcopal Church http://t.co/ZaUVgdl5wm
Why is that random dude driving through a tornado?
You never realize how much you rely on electricity until a storm turns your power off for a day and a half! I can finally charge my phone!
Tornado is south of us... family in the cellar....
I actually don't understand why people freak out so bad when there's a tornado
Another day of #tornado coverage from #Oklahoma. Gov #Fallin touring damage this morning and will hold presser 9CST. http://t.co/VGrhRZI0Cc
I hope everyone takes shelter and stays as safe as possible.
I pray for Moore its going straight for it
bestfriends in moore, please do not hit moore
I'm never scared about a tornado coming
Hiding out at the Chilis restroom. Storm is right over us! Praying for Gods protection!
Man, had a long night at work just got off almost go hit by tornado
F### storm chasing; this motherf###er is chasing me
Praying this tornado doesn't hit Falls Creek.
Yall see the ratings for last weeks tornado that started in El Reno they just keep getting bigger. http://t.co/hEie1O2Ml9
They just issued a tornado emergency. Higher than a tornado warning. Heading for the OKC metro now. Sirens just started.
After that tornado today I just can't sleep
I hope it doesn't storm like this on us next week..
Well Oklahoma city is under tornado warning like other cities really hope everyone is ok.....
if i die in this tornado .. just know ima miss y'all.
Pray for Oklahoma... I'm safe and I'm headed back into Moore to help. Anybody who wants to join shoot me a text

El Reno, Oklahoma Tornado
Damn.... Another tornado. #prayforoklahoma
Aww hail. Here comes the hail.
I hate tornado season.
My heart breaks hearing that a mother and child have already been killed from this storm. #PrayForOklahoma
the storm chaser is swerving through the highway right now
Here comes the disaster
Damn its getting hit in Moore again
Everybody I'm texting asked me why I'm scarred of the tornado.

9.3 Southern California Flash Flood

Southern California Flash Flood
#MentalHealth Commission to examine flood toll. http://t.co/p63XNw5pcO @abcnews
87F at 00:46 and 109-115F during the day and we've got issued with a flood warning. Go figure.
a flash flood warning in the middle of the desert between LA and Vegas and traffic is at a… http://t.co/z0GzzKanUc
Exactly where is the flood
Flash flood #liverweet #evacuateMovieTheater http://t.co/16327EHHNQ
flash flood amber alerts :(
Flash flood on my tv guys!!!! http://t.co/zau8u6A3vN
Flash flood warning #palmsprings #coachellavalley @name
Flash flood warning
Flash flood warning in PS..we about to get downpoured and I have a showing. Doh. #palmsprings http://t.co/3E9AW8w0jA
Flash flood warning in Southern California #ok
Flash flood warning issued in county: The National Weather Service has issued a flash flood warning for the... http://t.co/kIQKgISe6b
flash flood warning please get off my TV screen.
Flash flood warning? K.
Flash flood warning. What desert? #vscocam @ Ace Hotel & Swim Club http://t.co/Eq2Guj0gLZ
Flash flood warning

Southern California Flash Flood
Flash flood warnings all day. I'm going to board that flood like a boss.
Flash flood warnings during this weather pisses me off
Flash flood watch for valley, mountain and desert areas: A flash flood watch was scheduled for most of San Diego... http://t.co/YwN5ZZkKeh
Flash flood watch scheduled for SD Co.: A flash flood watch was scheduled for most of San Diego County Monday, a... http://t.co/U23NAnGz6W
Flash flood?
F### this flash flood warning s$$$!! It's so annoying!
I hate flash flood warning! S$$$tt I'm trying to watch my show!!
I keep getting these flash flood warnings, but no flash flood
I want to punch the person who keeps sending the flash flood warning !!!
I was stuck here in Laughlin, Nevada for 3 hrs in a stupid a## flood -.- cool experience tho :b
No flood here. Ayeeee http://t.co/lKtihPe0bG
Not cool #brawley #storm #flood @ City of Brawley http://t.co/cXOddVt67U
Oh crap its flooding bad out here. Just saw a 2 fire engines, a battalion chief, a medic unit and a repair unit rush down the road.
San Diego braces for another round of wild weather: A flash flood watch was scheduled for most of San Diego... http://t.co/4akpXhPAer
Seen a flash flood warning lil while ago
Soooo tired of these flash flood warnings on my phone
Stupid flash flood warning ruined my tv show -.- t
the flash flood warning scared me
The flood in Indio hella crazy
These flash flood warning are fcking annoying & creepy lol
These flood warning alerts
This flash flood warning scared the f### out of me. http://t.co/kTsD5AU67W
Those flash flood warnings are always bulls$$$
We've had like seven flash flood warnings these past two weeks & NO FREAKIN RAIN
Wish I'd was here to see the flash flood here. @ Santa Rosa Mountains http://t.co/2z1GWIf2pS
Flash Flood say what?
Hmmm should I still clean outside? Flash Flood Warning!! #Yuma @ Fry's #107 Fuel Center http://t.co/6ZEGodmXAh

Southern California Flash Flood
San Bernardino And Riverside County Valleys - The Inland Empire Flash Flood Watch in effect until 8PM PDT MON http://t.co/h9S9TG5fh7
FLASH FLOOD WARNING.
F### YOU NATIONAL FLOOD WARNING
THIS FLASH FLOOD IS STRAIGHT NUTTY
The flash flood warning kept popping up on my phone & scared me every time
On s$$$ we are under flood alert!! An I the only one who got this message?!!!
Another flash flood warning? Uh ohh I hope there isn't any more thunder storms
Hopefully we have a thunder storm so the school could flood hahahahaha
Flash flood warnings in the desert are no joke!!! We're driving through a river and about to run out… http://t.co/ZIHZJlt3YQ
Saved a bird and helped push a stalled car out of a flood. Two good deeds in one day and my car is the one that overheats and leaks
Flash flood? Ain't it gotta rain for that?
When these s$$$ go off like Wtf ain't nobody got time foe your flood s$$$ http://t.co/cNrnkHPuwj
whats up with these flash flood warnings
As hot and sunny as it is outside im gettin more flash flood warnings TF
Yall stay lyin we ain't having no flood
Flash flood warning on my tv isn't letting me keep up with the kardashians
Why am I getting a Flash Flood Warning? In this place with this kind of heat? I'm praying there'll be a flood.
THIS COMBINATION OF SONGS. FLOOD WARNINGS RIGHT NOW.
THIS STUPID A$$ FLOOD WARNING JUST RUINED MY WHOLE SHOW GO AWAY OMFG

9.4 Alamo, California Gas Leak

Alamo, California Gas Leak
"emergency evacuation everyone leave yoir hones and travel south" me: no
@name it's in Alamo. There's a gas leak on Danville blvd which is the Main Street used for commuting
@name I'm going to your house your safe from the gas leak I don't wanna die
a gas leak will probably kill everyone in the US! #lynetteispanicing☺

Alamo, California Gas Leak
All these Danville people running around looking like chickens with their heads cut off
Breaking news: the people of Danville and Alamo have paid to have the gas leak explode somewhere else
Gas leak in Danville and my sisters stranded home alone my prayers have been answered #jk #kinda
Kudos to @Safeway for distributing Free water during the #Alamo gas leak
Never have I ever been so scared to get out of the car at a gas station than I am in Oakland.
Of course I am in Alamo and my phone starts making sounds like a bomb was about to go off I check my phone and there is a evacuation alert!
Omg gas leak in Alamo! Omg quick flee to Danville omg tweet about it at the same time ahhhhh
Powers out, there's a gas leak, and worst of all my dog just pooped in the house. I think it's the apocalypse
woke up to an empty house and a bunch of alerts to evacuate Danville...uh...where's my family
You people in the bubble wouldn't last a minute in the ghetto, given the reaction to this gas leak.
####Alamo Pintado Rd , Solvang * Gas Leak Outside * 34623910 - 120117898 * FSBC130007408 * E30
Gas leak in Alamo, CoCo County, traffic control in effect at Stone Valley Rd at Danville Blvd and Jackson at Danville Blvd, avoid area
Alamo: Danville Blvd at Stone Valley Rd closed due to possible gas leak
@name it's cause of the gas leak in Alamo pic.twitter.com/mzGZHi71t7
The alert is because there's a gas leak in Alamo.
SIGALERT: Alamo: Danville Blvd closed between Stone Valley & Jackson due to gas leak. Stone Valley ramps from 680 also closed.
Possible gas leak...RT @name: Evacuation for portions of Alamo(31) (http://www.cococws.us)
Whoa, Contra Costa folks there's an evacuation being ordered. Gas leak along Alamo blvd sounds like.
Apparently there is a huge gas leak in #Alamo and the entire area is being evacuated.... http://instagram.com/p/cKNfp2KAWn/
Fat gas leak Danville blvd evacuate Alamo hide your kids
Contra Costa County Sheriff's have issued evacuation for parts of Alamo due to gas leak in area along Danville Blvd. http://bit.ly/kcbslive
@name Apparently, there's a gas leak in Alamo and they're evacuating a pretty wide area
Evacuation Immediate due to gas leak near Alamo. http://1.usa.gov/18Dfjpv #cawx #contracosta
The Danville Bubble is keeping me safe from the Alamo gas leak.

Alamo, California Gas Leak
Gas leak in Alamo, CoCo County, traffic control at Stone Valley Rd at Danville Blvd and Jackson at Danville Blvd. RT @chp_goldengate Alamo evacuation for a gas leak on Danville blvd and my family and I are the only ones left on our street- go erickson family Residents on Alamo Square Drive in Alama ordered to evacuate. @srvfpd_fires confirms gas leak. Story developing Great I'm being forced to evacuate my house from a gas leak in Alamo.... #UPDATE: @PG&E says 3rd party contractor's crew hit #Alamo gas main with backhoe; nearby businesses evacuated http://bit.ly/18DfYai EMERGENCY, evacuation in Contra Costa county, CA Alamo to leave immediately , Gas leak, turn off gas b4 leaving, Animals,leashed or caged.RT Y 4 the whole county? RT @KCBSNews: Contra Costa County Sheriff's issued evacuation Alamo gas leak Danville Blvd http://bit.ly/kcbslive ALERT: Contra Costa County Sheriff's have issued evacuation for parts of Alamo due to gas leak in area along Danville Blvd. Gas leak on Danville Blvd. An immediate evacuation has been ordered for portions of Alamo, Contra Costa County http://www.google.org/publicalerts/alert?aid=7339194caf2078fb&hl=en&gl=US&source=web … Damn, Alamo had a gas leak and they had to evacuate the whole city! #Alamo #Gas Leak: A 3rd-party (non-PG&E) crew struck a gas main; PG&E crews are on scene working 2 repair/make scene safe. Wanted to let everyone know about the gas leak in Alamo. Stay safe! http://fb.me/1RdneP6jG Gas leak in #Alamo forces businesses, homes to evacuate-people asked to avoid area, stay off phones http://bit.ly/1bO2FnL @CCTimes @3rdERH Woah! Reports that Alamo & Danville, CA were evacuated for a GAS LEAK & now ALL of Contra Costa County is supposed to stay indoors!! Gas leak forces evacuations of Alamo shopping center This is what I know up to the moment regarding the gas leak in Alamo. BTW, repairs will take time. http://bit.ly/145gJjN @CCTimes #Alamo Gas Leak Update: @PGE4Me crews are working as quickly as possible to safely stop the flow of gas, and will remain 2 complete repairs Suspicious gas leak in Alamo... pic.twitter.com/npslSX3D7h Alamo Gas Leak Update: The leak was caused by a backhoe! Still no word on when roads will reopen. http://fb.me/2H50ZpCTk VIDEO: Resident carries her pet cat Sabi one mile home in blazing heat during Alamo gas leak.

Alamo, California Gas Leak
PG&E crews worked for 4.5 hours to stop a gas leak which caused evacuations of businesses and residents in Alamo: http://abc7ne.ws/592aj
SHERIFF’S OFFICE: Technical Glitch Caused Countywide Evacuation Orders for Alamo Gas Leak http://tinyurl.com/kdf4wry

9.5 Hurricane Sandy

Hurricane Sandy
Mailbox just blew off house #sandy
Three houses burned to the ground during the storm.
sandy violated nyc 16 people dead...train flooded and tunnel ...sheesh
Congratulations #sandy, my car is now flooded too :(
Death toll now up to 96 from #Sandy. #RIP to the beautiful souls.
Hurricane Sandy Killed the Jersey Shore Boardwalk... :(
#poweroff like 4 hours ago so bored stpid#HurricaneSandy
I'm at Frankenstorm Apocalypse 2012 - Hurricane Sandy (Boston, MA) w/ 442 others
#Sandy go home pls that is it !!!
#Sandy go home! This is supposed to be a time for me and hubby to enjoy surroundings not struggle with hurricane... :(
#sandy go the f### home already ! Jersey is tired of your a$!
Crossing Into powerless part of manhattan. No 3G! May not be able to tweet #Sandy #firstworldproblems
Crossing my fingers that this massive storm doesn't cause another blackout like the one this summer
Cruise is cancelled due to Hurricane Sandy.
Cruising around jersey...doesn't look too good #HurricaneSandy
Cruising out into this "storm".. Maybe this is the only way to blow my car up #destiny
Crushed car...tree just missed that house ... hurricane Sandy u bitch u ..lol @ NEW YORK
Damn this storm is gonna be the real deal…
Damn this storm is no joke, people stop complaining about how cold or how wet you are because these people are losing everything
Hurricanes are expensive. #justsayin

Hurricane Sandy
Deutschland bank in front of us has extra power supply and some rooms have light, but it is sadly empty #Sandy
Devastated about #Sandy. This motherf-er went through my brother and sister-in-laws bedroom window
devastated. the only place i ever felt at home is no more. i feel like the rug was pulled out from beneath me. #njsandy #sandy #seasidepark
Devastating hurricane last week and now a nor'easter snow storm this week??? IT REALLY IS THE END OF DAYS!!!
Devastation on Staten Island. Just helped a church member clean out his entire family owned store. Nothing was salvageable. #Sandy
Devestation of #Frankenstorm #Sandy is the new norm w/ no power/heat still 2 teenaged girls doorbelled us for GOP
heart breaking to watch what's going on in new jersey #sandy.. I think its way bigger than people think #jerseyshore4life
Heart goes out to all the people trying to put their lives back together #sandy
heart goes out to all without power on East Coast tonight. its cold out there, stay warm. weather man says another storm is coming #Sandy
Heart goes out to those rocked by #Sandy...
Heart goes out to those whose life has been changed by Sandy.Our support will be ongoing! OUR CHINS ARE UP FOR YOU.
Heart goes out too NY still suffering frm tht hurricane : (
Hope everybody listen to the warnings and stays safe and we all rise this storm out
Hope everybody made it safe thru Sandy we are all good on my end.God Bless
Hope everybody made it through the storm OK. See you next week!
Hope everybody stays safe with this hurricane that's about to hit!
Hurricane Sandy is not a joke. Wonder whats going to be left?? Heard the OC music pier is gone.
Hurricane sandy is not doing not anything big cause we still got school tomorrow -,-
Hurricane Sandy is not even going to be that bad!!...right?
Hurricane Sandy is not f###ing around. This is serious people. @ New York City
Wow #hurricanesandy truly did destroy my house...
Wow #sandy do you really need to be 800 miles wide?
Wow #Sandy is beating the side of my window really hard. It sounds like the glass is gonna break
wow #sandy is intense...prob the worst thing I have been through. Not gunna lie kinda scared
Wow #sandy whhat did u do to us

Hurricane Sandy
WOW #Sandy you really hit us f###ing hard...
Wow 5.3 million people has no power except me! Hurricane may hit 3 billion dollars damage! Its first billion dollars hurricane!
Wow after hitting Jersey this hurricane has scattered hair gel and tank tops all the way up to Brooklyn #Sandy #Douchey
Wow after the sandy hits were suppose to get a blizzard FOH
Wow all subways and buses are going to be suspended starting 7pm tonight bc of the storm. That's some crazy stuff.

10.0 Query Definition and Tweet Volume – All Weather Emergency Alerts in 2012-2013

Disaster Name	Date Range	Tweet Volume	Query Terms
1st Canyon Fire (FM-5012) Washington	09/08/2012 09/20/2012	1664	fire, burn, "1st Canyon," "First Canyon"
Arapahoe Fire (FM-2992) Wyoming	06/28/2012 07/10/2012	188	fire, burn, Arapahoe
Ask Creek Fire (FM-2989) Montana	06/24/2012 07/07/2012	210	fire, burn, "Ask Creek"
Barker Canyon Fire (FM-5013) Washington	09/08/2012 09/17/2012	1289	fire, burn, "Barker Canyon"
Beaver Creek Fire (FM-5045) Idaho	08/14/2013 08/31/2013	488	fire, burn, "Beaver Creek"
Black Forest Fire (Multiple) Colorado	06/10/2013 06/22/2013	4761	fire, burn, "Black Forest"
Blanco (CR 4901) Fire (FM-2981) New Mexico	06/17/2012 06/27/2012	281	fire, burn, Blanco, "CR 4901"
Brimstone Fire (FM-5039) Oregon	07/27/2013 08/05/2013	4884	fire, burn, "Brimstone"
Byrd Canyon Fire (FM-5015) Washington	09/09/2012 09/20/2012	1514	fire, burn, "Byrd Canyon"
Carpenter 1 Fire (FM-5034) Nevada	07/03/2013 07/18/2013	4250	fire, burn, "Carpenter 1"
Clay Springs Fire (FM-2990) Utah	06/26/2012 07/01/2012	505	fire, burn, "Clay Springs"
Clover Fire (FM-5050) California	09/08/2013 09/15/2013	10106	fire, burn, "Clover"
Colockum Tarps Fire (FM-5038) Washington	07/26/2013 08/15/2013	4542	fire, burn, "Colockum Tarps"
Corral Fire (FM-2987) Montana	06/24/2012 06/30/2012	104	fire, burn, Corral
Dahl Fire (FM-2988) Montana	06/25/2012 07/03/2012	132	fire, burn, Dahl
Dean Peak Fire (FM-5033) Arizona	06/30/2013 07/09/2013	5052	fire, burn, "Dean Peak"
Doce Fire (FM-5029) Arizona	06/17/2013 07/01/2013	4517	fire, burn, "Doce"
Douglas Fire Complex (FM-5037) Oregon	07/26/2013 08/20/2013	12815	fire, burn, "Douglas"
Drumright Fire (FM-5003) Oklahoma	08/03/2012 08/11/2012	861	fire, burn, Drumright

Disaster Name	Date Range	Tweet Volume	Query Terms
Dump Fire (FM-2983) Utah	06/21/2012 06/26/2012	368	fire, burn, Dump
Eagle Fire (FM-5048) Washington	08/19/2013 08/29/2013	2369	fire, burn, "Eagle"
East Peak Fire (FM-5030) Colorado	06/19/2013 06/14/2013	0	fire, burn, "East Peak"
Elk Fire (FM-5043) Idaho	08/11/2013 08/30/2013	580	fire, burn, "Elk"
Explosion (DR-4136/ EM-3363) Texas	04/16/2013 04/21/2013	2154	West, Texas, explosion, fertilizer
Explosions (EM-3362) Massachusetts	04/14/2013 04/23/2013	8078	bomb, terrorist, terrorism, explosion, Boston, explod
Fair Grounds Fire Complex (FM-2997) Oklahoma	07/29/2012 08/04/2012	591	fire, burn, "Fair Grounds"
Falls Fire (FM-5040) California	08/04/2013 08/11/2013	11220	fire, burn, "Falls"
Flooding (DR-4079) New Mexico	06/21/2012 07/13/2012	256	flood, water
Flooding (DR-4118) North Dakota	04/21/2013 05/17/2013	337	flood, water
Flooding (DR-4121) Michigan	04/15/2013 05/15/2013	1452	flood, water
Flooding (DR-4122) Alaska	05/16/2013 06/12/2013	326	flood, water
Flooding (DR-4127) Montana	05/18/2013 06/04/2013	0	flood, water
Flooding (EM-3364) North Dakota	04/21/2013 05/08/2013	0	flood, water
Freedom and Noble Wildfires (DR-4078) Oklahoma	08/02/2012 08/15/2012	1204	fire, burn, Freedom, Noble
Freedom Fire (FM-5000) Oklahoma	08/02/2012 08/13/2012	1065	fire, burn, Freedom
Geary Fire (FM-2998) Oklahoma	08/02/2012 08/08/2012	756	fire, burn, Geary
Glencoe Fire (FM-5002) Oklahoma	08/03/2012 08/11/2012	859	fire, burn, Glencoe
Government Flats Fire Complex (FM-5046) Oregon	08/16/2013 08/27/2013	5867	fire, burn, "High Park," "Government Flats"
High Park And Waldo Canyon Wildfires (DR-4067) Colorado	06/08/2012 07/13/2012	7863	fire, burn, "High Park", "Waldo Canyon"

Disaster Name	Date Range	Tweet Volume	Query Terms
High Park Wildfire (FM-2980) Colorado	06/08/2012 07/02/2012	6443	fire, burn, "High Park"
Highway 141 Fire Complex (FM-5011) Washington	09/04/2012 09/12/2012	1131	fire, burn, "Highway 141"
Hurricane Isaac (Various)	08/25/2012 09/12/2012	31875	storm, hurricane, Isaac, flood, danger, disaster
Hurricane Sandy (Various)	10/25/2012 11/09/2012	208574	storm, hurricane, sandy, frankenstorm, flood, danger, disaster
Karney Fire (FM-5019) Idaho	09/17/2012 09/22/2012	77	fire, burn, Karney
Little Bear Fire (FM-2979) New Mexico	06/03/2012 07/31/2012	1453	fire, burn, "Little Bear"
Livermore Ranch Fire Complex (FM-2976) Texas	04/29/2012 05/04/2012	1865	fire, burn, "Livermore Ranch"
Lolo Creek Fire Complex (FM-5047) Montana	08/18/2013 08/23/2013	139	fire, burn, "Lolo creek"
Lower North Fork Fire (FM-2975) Colorado	03/25/2012 04/03/2012	816	fire, burn, "Lower North Fork"
Luther Fire (FM-5001) Oklahoma	08/02/2012 08/11/2012	929	fire, burn, Luther
Mile Post 10 Fire (FM-5042) Washington	08/09/2013 08/15/2013	1525	fire, burn, "Mile Post 10", "Mile Post Ten"
Myrtle Fire (FM-2996) South Dakota	07/19/2012 07/24/2012	87	fire, burn, Myrtle
Nineteen Mile Fire (FM-5008) Montana	08/27/2012 09/05/2012	178	fire, burn, "Nineteen Mile"
Noble Fire (FM-2999) Oklahoma	08/02/2012 08/13/2012	1056	fire, burn, Noble
Oil Creek Fire (FM-2995) Wyoming	06/30/2012 07/08/2012	136	fire, burn, "Oil Creek"
Pacifica Fire (FM-5036) Oregon	07/18/2013 07/22/2013	1809	fire, burn, "Pacifica"
Peavine Fire (FM-5018) Washington	09/11/2012 09/16/2012	794	fire, burn, Peavine
Poison Fire (FM-5017) Washington	09/11/2012 11/01/2012	6705	fire, burn, Poison
Ponderosa Fire (FM-5007) California	08/17/2012 09/05/2012	13449	fire, burn, Ponderosa
Power House Fire (FM-5025) California	05/30/2013 06/09/2013	13265	fire, burn, "Power House"

Disaster Name	Date Range	Tweet Volume	Query Terms
Region 23 Fire Complex (FM-5009) Nebraska	08/29/2012 09/04/2012	313	fire, burn, "Region 23"
Rim Fire (FM-5049) California	08/19/2013 09/09/2013	27761	fire, burn, "Rim"
Rockport Five Fire (FM-5044) Utah	08/12/2013 08/17/2013	522	fire, burn, "Rockport Five", "Rockport 5"
Romero Fire (FM-2982) New Mexico	06/19/2012 07/07/2012	648	fire, burn, Romero
Royal Gorge Fire (FM-5028) Colorado Royal Gorge Wildfire (DR-4133) Colorado	06/10/2013 06/16/2013	204	fire, burn, "Royal Gorge"
Sawtooth Fire (FM-5016) Montana	09/09/2012 09/17/2012	101	fire, burn, Sawtooth
Severe Freeze (DR-4104) Navajo Nation	12/14/2012 01/22/2013	16204	storm, winter, freez, ice
Severe Storm (DR-4053) Utah	11/29/2011 12/02/2011	51	flood, water, storm
Severe Storm (DR-4054) Alaska	11/14/2011 11/18/2011	19	flood, water, storm
Severe Storm and Flooding (DR-4065) New Hampshire	05/28/2012 06/01/2012	87	flood, water, storm
Severe Storm and Flooding (DR-4088) Utah	09/10/2012 09/13/2012	109	flood, water, storm
Severe Storm And Snowstorm (DR-4051) Massachusetts	10/28/2011 10/31/2011	2542	snow, blizzard, water, storm
Severe Storm, Straight-line Winds and Flooding (DR-4083) Washington	07/19/2012 07/22/2012	606	flood, water, wind, storm
Severe Storm, Straight-line Winds, Flooding and Landslides (DR-4094) Alaska	09/14/2012 10/01/2012	282	flood, water, wind, slide
Severe Storm, Tornado, And Flooding (DR-4066) Vermont	05/28/2012 06/03/2012	109	flood, water, wind, storm, twister, tornado
Severe Storms (DR-4073) District of Columbia	06/28/2012 07/02/2012	5440	flood, water, storm
Severe Storms (EM-3345) West Virginia	06/28/2012 07/11/2012	502	flood, water, storm

Disaster Name	Date Range	Tweet Volume	Query Terms
Severe Storms (EM-3346) Ohio	06/28/2012 07/03/2012	0	flood, water, storm
Severe Storms and Flooding (DR-4069) Minnesota	06/13/2012 06/22/2012	1520	flood, water, storm
Severe Storms and Flooding (DR-4076) Wisconsin	06/18/2012 06/21/2012	0	flood, water, storm
Severe Storms and Flooding (DR-4102) Louisiana	01/07/2013 01/18/2013	2309	flood, water, storm
Severe Storms and Flooding (DR-4120) Vermont	05/21/2013 05/27/2013	1155	flood, water, storm
Severe Storms and Flooding (DR-4123) Standing Rock Sioux Tribe	05/24/2013 06/02/2013	151	flood, water, storm
Severe Storms and Flooding (DR-4128) North Dakota	05/16/2013 06/17/2013	455	flood, water, storm
Severe Storms and Flooding (DR-4138) Florida	07/01/2013 07/08/2013	0	flood, water, storm
Severe Storms and Flooding (DR-4140) Vermont	06/24/2013 07/12/2013	40	flood, water, storm
Severe Storms and Flooding (DR-4143) Arkansas	08/07/2013 08/15/2013	701	flood, water, storm
Severe Storms and Flooding (DR-4147) Santa Clara Pueblo	07/18/2013 07/22/2013	239	flood, water, storm
Severe Storms and Flooding (DR-4148) New Mexico	07/22/2013 07/29/2013	761	flood, water, storm
Severe Storms and Flooding (DR-4151) Santa Clara Pueblo	09/12/2013 09/17/2013	779	flood, water, storm
Severe Storms and Straight-line Winds (DR-4070) New Jersey	06/29/2012 07/04/2012	2172	flood, water, wind, storm

Disaster Name	Date Range	Tweet Volume	Query Terms
Severe Storms and Straight-line Winds (DR-4071) West Virginia	06/28/2012 07/09/2012	431	flood, water, wind, storm
Severe Storms and Straight-line Winds (DR-4072) Virginia	06/28/2012 07/02/2012	0	flood, water, wind, storm
Severe Storms and Straight-line Winds (DR-4075) Maryland	06/28/2012 07/09/2012	0	flood, water, wind, storm
Severe Storms and Straight-line Winds (DR-4077) Ohio	06/28/2012 07/03/2012	0	flood, water, wind, storm
Severe Storms and Tornadoes (DR-4117) Oklahoma	05/17/2013 06/03/2013	8848	flood, water, wind, storm
Severe Storms, Flooding and Landslides (DR-4062) Hawaii	03/02/2012 03/12/2012	526	flood, water, storm, slide
Severe Storms, Flooding and Landslides (DR-4139) New Hampshire	06/25/2013 07/04/2013	1170	flood, water, storm, slide
Severe Storms, Flooding and Mudslides (DR-4141) Wisconsin	06/19/2013 06/29/2013	1370	flood, water, storm, slide
Severe Storms, Flooding and Mudslides (DR-4152) New Mexico	09/08/2013 09/23/2013	39	flood, water, storm, slide
Severe Storms, Flooding, Landslides and Mudslides (DR-4103) Eastern Band of Cherokee Indians	01/13/2013 01/18/2013	1028	flood, water, storm, slide
Severe Storms, Flooding, Landslides and Mudslides (DR-4145) Colorado	09/10/2013 10/01/2013	8721	flood, water, storm, slide
Severe Storms, Flooding, Landslides and Mudslides (DR-4146) North Carolina	07/02/2013 07/14/2013	8327	flood, water, storm, slide
Severe Storms, Flooding, Landslides and Mudslides (DR-4153) North Carolina	07/26/2013 07/28/2013	1059	flood, water, storm, slide
Severe Storms, Flooding, Landslides and Mudslides (EM-3365) Colorado	09/10/2013 10/01/2013	0	flood, water, storm, slide

Disaster Name	Date Range	Tweet Volume	Query Terms
Severe Storms, Flooding, Mudslides and Landslides (DR-4061) West Virginia	03/14/2012 04/01/2012	503	flood, water, storm, slide
Severe Storms, Straight-line Winds and Flooding (DR-4116) Illinois	04/15/2013 05/06/2013	29792	flood, water, storm, wind
Severe Storms, Straight-line Winds and Flooding (DR-4119) Iowa	04/16/2013 05/01/2013	0	flood, water, storm, wind
Severe Storms, Straight-line Winds and Flooding (DR-4131) Minnesota	06/19/2013 06/27/2013	5176	flood, water, storm, wind
Severe Storms, Straight-line Winds and Flooding (DR-4144) Missouri	08/01/2013 08/15/2013	2699	flood, water, storm, wind
Severe Storms, Straight-line Winds and Tornadoes (DR-4058) Indiana	02/28/2012 03/04/2012	1044	flood, water, storm, twister, tornado
Severe Storms, Straight-line Winds, Tornadoes and Flooding (DR-4130) Missouri	05/28/2013 06/11/2013	6189	flood, water, storm, twister, tornado, wind
Severe Storms, Straight-line Winds, Tornadoes and Flooding (DR-4150) Kansas	07/21/2013 08/17/2013	4924	flood, water, storm, twister, tornado, wind
Severe Storms, Tornadoes and Flooding (DR-4125) South Dakota	05/23/2013 06/01/2013	656	flood, water, storm, twister, tornado
Severe Storms, Tornadoes and Flooding (DR-4101) Mississippi	02/09/2013 02/23/2013	1356	flood, water, storm, twister, tornado
Severe Storms, Tornadoes and Flooding (DR-4124) Arkansas	05/29/2013 06/04/2013	178	flood, water, storm, twister, tornado
Severe Storms, Tornadoes and Flooding (DR-4126) Iowa	05/18/2013 06/15/2013	4278	flood, water, storm, twister, tornado
Severe Storms, Tornadoes and Flooding (DR-4135) Iowa	06/20/2013 06/29/2013	928	flood, water, storm, twister, tornado

Disaster Name	Date Range	Tweet Volume	Query Terms
Severe Storms, Tornadoes and Flooding (DR-4137) South Dakota	06/18/2013 06/30/2013	50	flood, water, storm, twister, tornado
Severe Storms, Tornadoes and Flooding (DR-4149) Pennsylvania	06/25/2013 07/12/2013	22960	flood, water, storm, twister, tornado
Severe Storms, Tornadoes, Flooding, Mudslides and Landslides (DR-4059) West Virginia	02/28/2012 03/06/2012	376	flood, water, storm, slide, twister, tornado
Severe Storms, Tornadoes, Straight-line Winds and Flooding (DR-4052) Alabama	01/21/2012 01/24/2012	1172	flood, water, storm, wind, twister, tornado
Severe Storms, Tornadoes, Straight-line Winds and Flooding (DR-4057) Kentucky	02/28/2012 03/04/2012	2715	flood, water, storm, wind, twister, tornado
Severe Storms, Tornadoes, Straight-line Winds and Flooding (DR-4060) Tennessee	02/28/2012 03/03/2012	0	flood, water, storm, wind, twister, tornado
Severe Storms, Tornadoes, Straight-line Winds and Flooding (DR-4063) Kansas	04/13/2012 04/17/2012	1257	flood, water, storm, wind, twister, tornado
Severe Storms, Tornadoes, Straight-line Winds and Flooding (DR-4064) Oklahoma	04/27/2012 05/02/2012	636	flood, water, storm, wind, twister, tornado
Severe Winter Storm (DR-4100) Arkansas	12/24/2012 12/27/2012	3311	storm, winter, snow, ice
Severe Winter Storm (DR-4113) Minnesota	04/08/2013 04/12/2013	5401	storm, winter, snow, ice
Severe Winter Storm (DR-4114) Iowa	04/08/2013 04/12/2013	0	storm, winter, snow, ice
Severe Winter Storm (DR-4154) North Dakota	10/03/2013 10/06/2013	178	storm, winter, snow, ice
Severe Winter Storm (EM-3361) Connecticut	02/07/2013 02/12/2013	6358	storm, winter, snow, ice
Severe Winter Storm and Snowstorm (DR-4105) New Hampshire	02/07/2013 02/11/2013	0	storm, winter, snow, ice

Disaster Name	Date Range	Tweet Volume	Query Terms
Severe Winter Storm and Snowstorm (DR-4106) Connecticut	02/07/2013 02/12/2013	0	storm, winter, snow, ice
Severe Winter Storm and Snowstorm (DR-4107) North Dakota	02/07/2013 02/11/2013	0	storm, winter, snow, ice
Severe Winter Storm and Snowstorm (DR-4109) Oklahoma	02/23/2013 02/27/2013	2203	storm, winter, snow, ice
Severe Winter Storm and Snowstorm (DR-4111) New York	02/07/2013 02/10/2013	0	storm, winter, snow, ice
Severe Winter Storm and Snowstorm (DR-4115) South Dakota	04/07/2013 04/11/2013	159	storm, winter, snow, ice
Severe Winter Storm, Flooding, Landslides and Mudslides (DR-4055) Oregon	01/16/2012 01/22/2012	1722	storm, winter, snow, ice, slide
Severe Winter Storm, Flooding, Landslides and Mudslides (DR-4056) Washington	01/13/2012 01/24/2012	2194	storm, winter, snow, ice, slide
Severe Winter Storm, Snowstorm and Flooding (DR-4110) Massachusetts	02/07/2013 02/10/2013	12199	storm, winter, snow, ice, flood
Severe Winter Storm, Snowstorm and Flooding (DR-4155) South Dakota	10/02/2013 10/17/2013	828	storm, winter, snow, ice, flood
Sheep Herder Hill Fire (FM-5014) Wyoming	09/08/2012 09/17/2012	100	fire, burn, "Sheep Herder Hill"
Shingle Fire (FM-2994) Utah	07/01/2012 07/06/2012	1041	fire, burn, Shingle
Shockey Fire (FM-5021) California	09/22/2012 09/28/2012	4498	fire, burn, Shockey
Silver Fire (FM-5041) California	08/06/2013 08/14/2013	12154	fire, burn, "Silver"
Snowstorm (DR-4112) Kansas	02/19/2013 02/24/2013	5315	storm, winter, snow, ice
Springs Fire (FM-5024) California	05/01/2013 05/12/2013	15216	fire, burn, "Springs"
Squirrel Creek Fire (FM-2993) Wyoming	06/30/2012 07/08/2012	136	fire, burn, "Squirrel Creek"

Disaster Name	Date Range	Tweet Volume	Query Terms
Summit Fire (FM-5023) California	04/30/2013 05/06/2013	9549	fire, burn, "Summit"
Table Mountain Fire (FM-5020) Washington	09/18/2012 09/23/2012	824	fire, burn, "Table Mountain"
Taylor Bridge Fire (FM-5005) Washington	08/12/2012 08/29/2012	2356	fire, burn, "Taylor Bridge"
TRE Fire (FM-2977) Nevada	05/21/2012 05/26/2012	361	fire, burn, TRE
Tres Lagunas Fire (FM-5026) New Mexico	05/29/2013 06/04/2013	504	fire, burn, "Tres Lagunas"
Trinity Ridge Fire (FM-5006) Idaho	08/02/2012 08/07/2012	98	fire, burn, "Trinity Ridge"
Tropical Storm Debby (DR-4068) Florida	06/22/2012 07/27/2012	11166	storm, tropical, Debby, flood, danger, gulf
Tropical Storm Isaac (EM-3347) Louisiana	08/25/2012 09/11/2012	7721	storm, tropical, Isaac, flood, danger, gulf
Tropical Storm Isaac (EM-3348) Mississippi	08/25/2012 09/12/2012	18	storm, tropical, Isaac, flood, danger, gulf
Waldo Canyon Fire (FM-2984) Colorado	06/22/2012 07/09/2012	5967	fire, burn, "Waldo Canyon"
Washoe Fire (FM-2974) Nevada	01/18/2012 01/22/2012	269	fire, burn, Washoe
Weber Fire (FM-2985) Colorado	06/22/2012 07/07/2012	5827	fire, burn, Weber
Wellnitz Fire (FM-5010) South Dakota	08/30/2012 09/03/2012	75	fire, burn, Wellnitz
West Fork Fire Complex (FM-5031) Colorado	06/20/2013 06/25/2013	1571	fire, burn, "West Fork"
West Mullan Fire (FM-5035) Montana	07/17/2013 07/22/2013	101	fire, burn, "West Mullan"
Wetmore Fire (FM-5022) Colorado	10/22/2012 10/27/2012	461	fire, burn, Wetmore
Whitewater-Baldy Fire Complex (FM-2978) New Mexico	05/22/2012 08/01/2012	1733	fire, burn, Whitewater-Baldy
Wildfire (DR-4142) Karuk Tribe	07/28/2013 08/02/2013	7263	fire, burn, Karuk
Wildfires (DR-4074) Montana	06/24/2012 07/11/2012	254	fire, burn
Winter Storm, Snow Storm and Flooding (DR-4108) Maine	02/07/2013 02/10/2013	0	storm, winter, snow, ice, flood

Disaster Name	Date Range	Tweet Volume	Query Terms
Wood Hollow Fire (FM-2986) Utah	06/23/2012 06/28/2012	361	fire, burn, "Wood Hollow"
Wye Fire (FM-5004) California	08/11/2012 08/19/2012	6339	fire, burn, Wye
Yarnell Hill Fire (FM-5032) Arizona	06/29/2013 07/08/2013	5225	fire, burn, Yarnell, hotshot

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