**Supplemental Materials:** **Exploring Social Media Network Connections to Assist During Public Health Emergency Response: A Retrospective Case-Study of Hurricane Matthew and Twitter Users in Georgia, USA**

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**METHODS**

**OUTLIERS IN THE TWITTER DATASET FOR FOLLOWERS OF SCHOOLS AND SCHOOL DISTRICTS IN GEORGIA**

The data used in this project was from tweets posted by Twitter followers of schools and school districts in Georgia. The original complete dataset comprised a total of 458,715 followers of 629 schools and school district Twitter accounts.1 The median number of tweets posted by the followers was 43 (Table S1). When taking a closer look at the followers’ profiles, the top five accounts with the highest number of follower accounts or outliers were identified. The top five accounts were President Barack Obama, National Public Radio, American Red Cross, Whole Foods Market, and an account that belongs to a social media managing company, HootSuite (Table S2). The analysis also included the study of the profiles with the highest number of posted tweets since they could be bot accounts. Bot accounts are profiles that post a high number of posts and tend to be anonymous.2 One of the accounts, Shinobi Ninja, belongs to a Brooklyn band believed to use bots to increase their following.3

**SELECTION OF HURRICANE-RELATED TWEETS**

A ratio index for hurricane-related tweets was calculated following the method proposed by Zou et al.4 to account for tweets related to the event of interest and not all hurricanes mentioned in the dataset posted by those individuals with an imputed location.

Hurricane-Related Ratio Index = Number of hurricane-related tweets by imputed followers / Number of hurricane-related tweets by all followers

In the present study, the ratio value served as a proxy for the level of awareness of the event in the study sample, Hurricane Matthew, among those whose location was identified by the developed imputation method.

**CONTENT ANALYSIS**

To describe the topics mentioned by Twitter users who followed schools’ and school districts’ accounts in Georgia before and during Hurricane Matthew, content analysis was completed. The steps were repeated for original content tweets, retweets, and replies to assess the differences in content per type of Twitter post.We implemented a probabilistic topic model known as the latent Dirichlet allocation (LDA) model, which is a Bayesian mixture model, 5 to categorize tweets by the underlying topics.6 LDA models analyze documents represented by a random mixture of topics and words based on a posterior probability distribution.5-8 LDA models assume that there are a (user-specified) *k* number of underlying topics unknown to the researchers (latent). LDA models assign each word a probability that it belongs to each topic and give each document a probability that it belongs to a topic based on the words in the document.The mathematical equation describing the LDA model relation is as follows:6

, where: = distribution of topics over the vocabulary; = proportion for topic *k* in document *d*; *k* = topics in document that are assumed to be known and fixed; *d* = document; *z* = assignment of topics; *w* = observed words in documents *d*.6

Each dataset was converted into a document-term-matrix, where each row corresponded to a tweet in our data and each column a term. Each document (tweet) was tokenized by separating each word, removing symbols, numbers and stop-words, and transforming the text to lower-case letters.9,10 The LDA model was trained using 90% of the dataset in this project, and the model was tested using the remaining 10% percent of data.7,11

LDA models maximize the log-likelihood of data with respect to the a and b parameters.5 To fit the model, a variational expectation-maximization (VEM) algorithm was used.5,6 The VEM algorithm estimated the maximum likelihood (ML) in an iterative process of two steps, expectation and maximization. The algorithm repeats the expectation and maximization steps until convergence of the lower bound of the log-likelihood. VEM assumes that the variational posterior probability is an adequate approximation of the true posterior probability.5 Prior to model fitting, the number of topics (*k*) had to be determined. The value of *k* was determined by running model simulations with *k*=5 to *k*=100 in the increment of 5 units,9 with 30 iterations, using the training datasets to assess the value of *k*. A perplexity plot was constructed, and the lowest mean perplexity value was selected as the optimal number of topics (*k*) to fit the LDA model with the VEM algorithm. The optimal number of topics for dataset #1 (original tweets) and dataset #2 (retweets) were 30 topics, respectively. The LDA model assigns each document a vector of probabilities belonging to each of the k topics.

Once the optimal number of topics was determined and the LDA model was run, two independent raters (KMR and BOSB) manually reviewed the words of each topic to group the topics into a smaller number of categories that are meaningful to human users and determined the appropriate ones. If the two raters did not agree on a category, they discussed their reasons, reached a consensus, and assigned a definitive category (Table S6). If the two raters reached no agreement, a third rater made the final decision.

**MANUAL CODING FOR CONTENT ANALYSIS CATEGORIES**

Coders were asked to determine the category (N=10) to which each topic belonged. Each category might include one or more topics. If a topic contained two or more words related to one of the categories below, it would be categorized by the appropriate name in the Excel spreadsheet.

Categories:

* *Health-* topics related to health conditions or medications
* *Preparedness­*- topics related to preparation before the event, such as food, planning, school closures, etc.
* *Damage-* topics related to any structural damage to houses, buildings, streets, etc.
* *Awareness* (information related to hurricanes or news)- topics related to hurricanes updates, weather, news, etc.
* *Warnings*- topics related to emergency warnings like move, immediate, threat, flash flooding, among others.
* *Evacuations/Migration*- topics with words related to moving from the area or evacuations.
* *Call for help/action*- topics related to the word help, relief, needs, asking for supplies, among others
* *Shelter*- topics related to moving to a shelter, moving from the area, need to open shelters
* *Emotions/Religions*- topics related to any type of emotion or religion
* *Miscellaneous*- topics that do not fit in any other designated category

If the topic contained words related to multiple categories, the coders would:

1. Count the number of words related to each category and assign the category with the greatest number of words.
2. If the words related to the category appear the same number of times, then use the criteria mentioned above to see the relation with the other words in the topic.

**SENTIMENT ANALYSIS**

Tweets were analyzed to describe the sentiment of Twitter users who followed schools’ and school districts’ accounts in Georgia before and during Hurricane Matthew. A lexicon-approach method was implemented to calculate the average sentiment of words in the tweets.12 Two different lexicon libraries, *Afinn* and *Bing*,12 were used to compare their evaluations in a preliminary analysis. The *Afinn* lexicon categorizes sentiment between -5 to 5, while *Bing* conducts a binary classification of positive and negative sentiment.12 The corpus of tweets was pre-processed to remove numbers, symbols, stop words, and URLs. The text of interest was divided into unigrams (one-unit words) to complete the analysis. General descriptive frequencies were studied for original tweets and retweets. The *Afinn* lexicon was used to analyze the overall changes in sentiment scores over time in a time-series analysis.

**RESULTS**

**DESCRIPTIVE STATISTICS**

Observing tweet frequency and time of posting, the conducted analysis compared it to tropical storms, hurricanes, and major hurricanes in the Atlantic region and those that directly affected the state of Georgia (Figure S1). A hurricane-related ratio index was calculated for each MSA for the original tweets (Figure S2) and retweets (Figure S3). For original tweets and retweets, it was observed that MSAs Savannah, Hinesville, Warner Robins, and Atlanta had the highest index of hurricane-related tweets. The index for the preparedness phase and that for the response phase were also analyzed respectively. During the response phase, a higher number of hurricane-related tweets with a higher index for MSAs were observed out of the hurricane path (0.6734) than those in the hurricane path (0.3266). During the preparedness phase, the index for hurricane-related tweets for MSAs in the hurricane path was 0.2078, and for those outside the hurricane path, 0.7922.

**DESCRIPTION OF THE TOPICS AND SENTIMENT OF TWEETS FROM USERS WHO FOLLOWED SCHOOLS AND SCHOOL DISTRICT ACCOUNTS IN GEORGIA BEFORE AND DURING HURRICANE MATTHEW**

The topics identified for each dataset by the LDA model were manually categorized into ten different categories (Table S6). The top three categories of tweets were awareness, preparedness, and call for help or action for all three datasets. Users in the Hinesville MSA, one of the MSAs in the hurricane path, posted the highest number of original tweets related to preparing for the weather event. There were more retweets than original tweets that were in the ‘damage’ content category. (Figure S4).

Overall sentiment in tweets posted during Hurricane Matthew was analyzed using the *Bing* lexicon library. Negative sentiment values were predominant in the sampled tweets and retweets (Table S4; Table S5). Figure 8 compared the top ten terms that contributed the most to the sentiment scores for original tweets and retweets. The terms ‘breaking,’ ‘emergency,’ ‘damage,’ ‘threat,’ and ‘warning’ were the top negative terms, followed by terms related to death. For the positive category, words such as ‘heaven,’ ‘safe,’ ‘free,’ and ‘relief’ occupied the top categories for both types of tweets (Figure S5).

When focused on the sentiment by week, week 40 (October 2 to 8, 2016), the week of landfall, presented the highest number of times a positive or negative word showed on a tweet. Retweets had higher numbers of positive and negative words than what original tweets had. During week 41, the sentiment was mostly positive in both original tweets and retweets (Figure S6). During week 42, despite the large decrease in the number of posted tweets, a low but negative sentiment in word usage was detected (Figure S7). Throughout all phases of the emergency response cycle, the sentiment changes presented a decrease in total sentiment value, accompanied by a decline in the number of tweets related to Hurricane Matthew.

**Table S1.** Descriptive statistics by unique ID for Twitter followers of schools’ and school districts’ Twitter accounts.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Mean | 1st Quartile | Median | 3rd Quartile |
| Tweets Count | 1,862 | 2 | 43 | 593 |
| Number of Followers | 1,519 | 6 | 35 | 188 |
| Number of Friends | 950 | 43 | 123 | 378 |
| Number of Favorites | 1,047 | 1 | 20 | 348 |

**Table S2.** Twitter followers of schools and school districts in Georgia identified as outliers based on their number of followers.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Twitter user screen name | Tweets count | Followers count | Favorite count | Friends count |
| Barack Obama | 15,469 | 95,958,887 | 10 | 627,350 |
| Hootsuite | 55,078 | 8,163,494 | 19,591 | 1,540,071 |
| National Public Radio | 132,843 | 7,271,436 | 2,270 | 72,538 |
| American Red Cross | 5,452 | 5,063,072 | 4,705 | 39,716 |
| Whole Foods Market | 222,925 | 4,860,107 | 26,811 | 527,777 |

**Table S3.** Twitter followers of schools and school districts in Georgia identified as outliers based on the number of tweets posted.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Twitter user screen name | Type of account | Tweets count | Followers count | Favorite count | Friends count |
| Material Items | Selling bot | 1,476,946 | 9,293 | 0 | 10,444 |
| Producer 9-0 | Individual account | 1,466,969 | 1,080,469 | 100 | 1,000,032 |
| Stock Trade Alerts | Selling bot | 1,237,295 | 131,940 | 3,206 | 128,690 |
| Shinobi Ninja | Band profile which used bots to acquire followers | 1,169,097 | 896,213 | 46,236 | 849,797 |
| FindSalesRep.com | Marketing bot, switch to Trump support page, no longer active | 1,048,056 | 4,795 | 0 | 3,814 |

**Table S4.** Original tweets content analysis and sentiment analysis by lexicon scores examples posted during Hurricane Matthew by Twitter followers of schools and school districts in Georgia.

| Original tweets | MSA | Content analysis categories | Lexicon 1 | Sentiment score | Lexicon 2 | Sentiment score | Lexicon 3 | Sentiment score |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Why yes the climate is changing However it is season | Atlanta | Awareness | AFINN | -2 | Bing et al. | -1 | NRC | 3 |
| Please pray for my family and others who have and will be affected by #HurricaneMatthew | Brunswick | Awareness | NRC | -2 | Bing et al. | 0 | NRC | -2 |
| FIRST ALERT UPDATE Cat 1 #HurricaneMatthew remains on westward track through the Caribbean #track #walbweatherapp | Atlanta | Awareness | AFINN | -1 | Bing et al. | 1 | NRC | -1 |
| Hurricane Matthew to impact the Florida Space Coast as a Powerful Category 4 Hurricane Tropical Storm conditions e | Savannah | Awareness | AFINN | 2 |  |  |  |  |
| IMPORTANT NOTICE PBUSA office will be closed on Thursday October 6 and Friday October 7 due to Matthew | Dalton | Awareness | AFINN | 1 | Bing et al. | 0 | NRC | 2 |
| Good morning Heres the latest news on how #HurricaneMatthew is affecting our area Schools will be closed | Augusta | Call for help or action | AFINN | -2 |  |  |  |  |
| This is what living United looks like 250 volunteers ready to get to work #HurricaneRelief #UnitedWayATL | Atlanta | Call for help or action | AFINN | 3 | Bing et al. | 1 | NRC | 1 |
| Prayers out to everyone that has been in Hurricane Matthews path or will be Hard to really care about when a fball gm is gonna be played | Augusta | Call for help or action | AFINN | 1 |  |  |  |  |
| Help our ministry partner as they seek to bring relief to those affected by Hurricane Matthew | Hinesville | Call for help or action | NRC | -1 |  |  |  |  |
| Now that the storm has passed give utility crews amp first responders time amp space to make sure it is safe #matthew #GA | Atlanta | Call for help or action | AFINN | -1 | NRC | -1 |  |  |
| Were helping affected schools that need student datebooks We hope other companies are able to help in w | Dalton | Damage | AFINN | -3 | Bing et al. | -1 | NRC | -2 |
| #GA could see 200k power outages reminder Stay #FoodSafe during #HurricaneMatthew | Atlanta | Damage | AFINN | -3 | Bing et al. | -1 | NRC | -3 |
| FYI dps is closing EB ramps to I16 as #HurricaneMatthew moves North all traffic on interstate to be Westbound beginning at 930am | Hinesville | Damage | Bing et al. | -1 | Bing et al. | 1 | NRC | -1 |
| Cleanup and relief efforts from the aftermath of Hurricane Matthew are continuing | Albany | Damage | AFINN | -1 |  |  |  |  |
| Multiple deadly s fires everywhere tweets about deadly windmills and global warming hoax #losthismind | Rome | Damage | Bing et al. | 1 | NRC | 1 |  |  |
| #Charleston dogs transferred to #Aiken SPCA before #HurricaneMatthew are still looking for their FURever homes | Augusta | Emotions | AFINN | -1 | NRC | -1 |  |  |
| Monitoring approach of Hurricane Matthew Facilities assessment after storm will determine any operational changes | Hinesville | Emotions | NRC | 0 |  |  |  |  |
| Practice generator safety to keep your family and our linemen safe during storms #season | Valdosta | Emotions | AFINN | 1 | NRC | 0 |  |  |
| Rally Challenge Consolation Match NAVC East 171 National Chris lost to Hurricane VBC 17 Cyclones in 2 2325 1825 | Savannah | Emotions | AFINN | 3 | Bing et al. | 1 | NRC | 1 |
| No is going to stop us from getting the news to you | Hinesville | Emotions | Bing et al. | 1 | NRC | 2 |  |  |
| Glynn County issues voluntary evacuation order for island communities #HurricaneMatthew #GaWx | Brunswick | Evacuation or Migration | NRC | -1 |  |  |  |  |
| This storm will kill you Time is running out We dont have that much time left #HurricaneMatthew | Hinesville | Evacuation or Migration | Bing et al. | 1 | NRC | 2 |  |  |
| Gov Deal puts Chatham Bryan Effingham under states of emergency as Hurricane Matthew nears | Augusta | Evacuation or Migration | AFINN | 5 | Bing et al. | 2 | NRC | 1 |
| As #HurricaneMatthew moves up East Coast #AikenCounty prepares for evacuees headed their way | Augusta | Evacuation or Migration | AFINN | 1 | Bing et al. | 1 |  |  |
| Widow shares story of her husbands death during Hurricane Matthew stressing importance of evacuating | Albany | Evacuation or Migration | NRC | 0 |  |  |  |  |
| Peach County and Georgia Hurricane Updates | Athens | Miscellaneous | AFINN | -2 | Bing et al. | -1 | NRC | -1 |
| Are you prepared #HurricanePrep | Warner Robins | Miscellaneous | AFINN | 1 | Bing et al. | 1 | NRC | 1 |
| Thats the thing about a shes all lightning and wind and rain | Warner Robins | Miscellaneous | AFINN | 1 | Bing et al. | 1 | NRC | 2 |
| Why I became a fan of the Miami Hurricanes | Hinesville | Miscellaneous | Bing et al. | 1 | NRC | 0 |  |  |
| Clemson Engineers Studying Ways To Make Structures More Resilient Against Hurricanes | Warner Robins | Miscellaneous | AFINN | -3 | NRC | 1 |  |  |
| Help prepare your home before a storm w these # prep tips #ThinkSafe | Augusta | Preparedness | NRC | -1 |  |  |  |  |
| 77 shelters still open 6500 people currently in them #HurricaneMatthew | Valdosta | Preparedness | AFINN | -2 | NRC | -1 |  |  |
| As Hurricane Matthew approaches the area with sustained winds at 110 miles per hour several area events are | Savannah | Preparedness | AFINN | -2 | NRC | -1 |  |  |
| Macon businesses step up to help evacuees #HurricaneMatthew #Hurricane | Savannah | Preparedness | Bing et al. | -1 | NRC | -2 |  |  |
| Get the latest on all #GA Dept of #Ags response amp recovery efforts for #HurricaneMatthew here | Atlanta | Preparedness | AFINN | -2 | Bing et al. | -1 | NRC | -1 |
| #TrafficALERTupdate I75 N open now at Hardeman Ave Traffic very slow PLEASE avoid highways due to tr | Warner Robins | Shelter | Bing et al. | -1 | NRC | -1 |  |  |
| SC pricegouging laws are now in affect ahead of #HurricaneMatthew If you suspect it heres how to report it | Savannah | Shelter | AFINN | -3 | Bing et al. | -1 | NRC | -1 |
| Huge #matthew donation response check out the pole Fire Station #7 | Hinesville | Shelter | AFINN | -1 | Bing et al. | -2 | NRC | 0 |
| A Chattanooga nonprofit has 2 employees here and 70 in Haiti right now How theyre dealing with #HurricaneMatthew | Augusta | Shelter | AFINN | 1 | Bing et al. | 1 | NRC | 0 |
| Due to public health response needs with Hurricane Matthew both drive thru flu clinics scheduled for tomorrow in | Warner Robins | Shelter | AFINN | 2 | Bing et al. | 1 | NRC | 1 |
| Hurricane Season Not Over | Albany | Warnings | AFINN | -3 | NRC | -1 |  |  |
| Channel 18 Wx Alert Hurricane Warning for Miller Seminole and Decatur County in GA #GAWX | Gainesville | Warnings | AFINN | 1 | Bing et al. | 0 | NRC | 1 |
| Models showing Hurricane #Matthew uncomfortably close to the Southeast Coast midtolate week Rip currents a big threat | Warner Robins | Warnings | NRC | -1 |  |  |  |  |
| We began monitoring the activity of Tropical Storm 16 today Pay close attention to NOAA NWS National Hurricane | Warner Robins | Warnings | AFINN | 2 | AFINN | -1 |  |  |
| Arriving to set up for todays #HurricaneRelief project Volunteers are you ready #UnitedWayATL | Valdosta | Warnings | AFINN | 2 | Bing et al. | 1 | NRC | 1 |

**Table S5.** Retweets content analysis and sentiment analysis by lexicon scores examples posted during Hurricane Matthew by Twitter followers of schools and school districts in Georgia.

| Retweet | MSA | Content analysis categories | Lexicon 1 | Sentiment score | Lexicon 2 | Sentiment score | Lexicon 3 | Sentiment score |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| RT Hurricane Matthew is supposed to hit on 107 Matthew 107 says Go and announce to them that the Kingdom of Heaven is n | Warner Robins | Awareness | AFINN | 3 | Bing et al. | -1 | NRC | 1 |
| RT Join us October 4 for the Hands On Atlanta Day KickOff Party to help relief efforts #handsonatl | Warner Robins | Awareness | AFINN | 2 | NRC | 1 |  |  |
| RT Here are a few more pictures of damage from around Bryan County in the aftermath of Hurricane Matthew The one on h | Savannah | Awareness | NRC | -2 |  |  |  |  |
| RT 11PM ADVISORY Hurricane Warning Storm Surge Warning now issued for SFL For more info or | Atlanta | Awareness | Bing et al. | 1 | NRC | 0 |  |  |
| RT Learn how to strengthen your home against s #HurricanePrep #HurricaneStrong | Atlanta | Awareness | AFINN | 1 | Bing et al. | -1 |  |  |
| RT Call 2014500 to report damage and use 6448811 for automated reentry information #HurricaneMatthew | Warner Robins | Call for help action | AFINN | -2 | Bing et al. | -1 | NRC | -2 |
| RT Chatham County says 13 million cubic yards of debris have already been cleared after #HurricaneMatthew | Atlanta | Call for help action | AFINN | -5 | Bing et al. | -2 | NRC | -2 |
| RT Make sure your home is in good condition to withstand # damage #HurricanePrep | Atlanta | Call for help action | AFINN | 1 | Bing et al. | 2 |  |  |
| RT The Georgia Dome is under a Hurricane warning we repeat the Georgia Dome is under a Hurricane warning | Columbus | Call for help action | AFINN | -1 | NRC | 0 |  |  |
| RT Hebert Proud of Georgia first responders in dps and proud that could support them #HurricaneMatthew https | Dalton | Damage | AFINN | 2 | Bing et al. | 0 | NRC | 0 |
| RT To all non believersa cross withstanding a doesnt just happen | Gainesville | Damage | AFINN | 2 | Bing et al. | 1 | NRC | -2 |
| RT WE WERE OUT HERE PRAYING FOR FLORIDA TO SAY SAFE FROM HURRICANE MATTHEW LITTLE DID WE KNOW HURRICANE MATTHEW WAS TRYNA | Gainesville | Damage | AFINN | 2 | Bing et al. | 1 | NRC | -2 |
| RT All EMS and SSFD services are now suspended due to winds reaching sustained speeds of 39MPH #HurricaneMatthew | Warner Robins | Damage | AFINN | 1 | Bing et al. | 1 | NRC | -2 |
| RT RIP to all 841 people killed in Haiti by Matthew | Atlanta | Damage | NRC | -1 |  |  |  |  |
| RT Hurricane Matthew is supposed to hit on 107 Matthew 107 says Go and announce to them that the Kingdom of Heaven is n | Atlanta | Emotions | NRC | -2 |  |  |  |  |
| RT As #Matthew approaches here is difference between a watch and a warning #scwx #gawx #caewx | Albany | Emotions | AFINN | -1 | Bing et al. | 0 |  |  |
| RT To my #tvnews friends remember PEOPLE are not evacuated PLACES are #evacuated #HurricaneMatthew | Augusta | Emotions | AFINN | 1 | NRC | 0 |  |  |
| RT Walt Disney World is closing for the 4th time EVER This storm is legit Stay safe everyone #HurricaneMatthew | Hinesville | Emotions | AFINN | 1 | Bing et al. | 1 |  |  |
| RT Swazy Yall pray for Houston County aint nothing wrong were all just hyped up about the fact we have a on the way | Athens | Emotions | AFINN | 1 | NRC | 1 |  |  |
| RT #FBI worked alongside law enforcement partners to provide support amp resources during aftermath of the s | Rome | Evacuation or Migration | AFINN | -2 | Bing et al. | -1 | NRC | 0 |
| RT Thankful that the Hurricane Matthew damages were few here in Statesboro#StatesboroSkies #GeorgiaSouthern #Statesboro | Atlanta | Evacuation or Migration | AFINN | 1 | Bing et al. | 0 | NRC | -2 |
| RT Hurricane Matthew Update Liberty County Schools closed remainder of the week LCSS Schools will reopen October htt | Warner Robins | Evacuation or Migration | AFINN | 0 | Bing et al. | 0 | NRC | 1 |
| RT Hurricane Matthew Update Liberty County Schools will be closed on Tuesday October 11 2016 for all staff https | Atlanta | Evacuation or Migration | AFINN | 1 | Bing et al. | 1 | NRC | 1 |
| RT Impacts on west side of s are always exaggerated If eyewall manages to stay off coast then it will be a | Augusta | Evacuation or Migration | Bing et al. | 0 | NRC | 2 |  |  |
| RT Joel Osteen wont open his church that holds 16000 to victims because it only provides shelter from taxes # | Augusta | Miscellaneous | NRC | 1 |  |  |  |  |
| RT The most notorious portion of the Atlantic # season has arrived | Savannah | Miscellaneous | NRC | 1 |  |  |  |  |
| RT Headline in Savannahs newspaper this morning as residents return to survey damage left behind after Hurricane Marthew htt | Augusta | Miscellaneous | NRC | -1 |  |  |  |  |
| RT Hot meals will be provided at the Poseidon on Hilton Head at 38 Shelter Cove Ln #120 from 124 pm today #HurricaneMatthew #HHI | Augusta | Miscellaneous | AFINN | -2 | Bing et al. | -1 | NRC | -1 |
| RT Hurricane Matthew How you can protect your home before deadly storm | Valdosta | Miscellaneous | AFINN | -1 | NRC | 2 |  |  |
| RT #season started just about a week ago and here is NHCs prediction Expecting a more active season this year | Warner Robins | Preparedness | AFINN | -7 | Bing et al. | -2 | NRC | -1 |
| RT #HurricaneMatthew is headed up the East Coast See more about how you can prepare here | Hinesville | Preparedness | AFINN | -1 | Bing et al. | 0 | NRC | -1 |
| RT Most places are closing ahead of #HurricaneMatthew but not this Steakhouse in Stark | Hinesville | Preparedness | AFINN | -2 | Bing et al. | -1 | NRC | -2 |
| RT Police APD Recruit McCarley is helping victims of Hurricane Matthew He is with the National Guard amp is evacuating victims fro | Atlanta | Preparedness | AFINN | -2 | Bing et al. | 0 | NRC | -2 |
| RT Thank you for your cooperation and be safe #ssu #savannah #HurricaneMatthew | Warner Robins | Preparedness | AFINN | 2 | Bing et al. | 1 |  |  |
| RT the only party i want to attend #HurricaneMatthew #PrayForFlorida #FloridaNow | Augusta | Shelter | AFINN | 2 | Bing et al. | 2 | NRC | -1 |
| RT my moms coworker decided to park her car in her living room for the #HurricaneMatthew | Atlanta | Shelter | AFINN | 1 | Bing et al. | 1 | NRC | 2 |
| RT We will restore power to more than 90 percent of customers affected by Hurricane Matthew by Wednesday night Thank you f | Albany | Shelter | AFINN | 2 | NRC | 1 |  |  |
| RT If youre returning home after #HurricaneMatthew here are some helpful tips to keep in mind | Brunswick | Shelter | AFINN | 1 | Bing et al. | 1 |  |  |
| RT Were tracking Hurricane Irmas pathWatch Updates Radar | Gainesville | Shelter | AFINN | -1 | Bing et al. | 0 | NRC | 1 |
| RT President Obama declares emergency in South Carolina orders federal aid for #HurricaneMatthew response | Warner Robins | Warnings | AFINN | 2 | Bing et al. | 1 | NRC | -2 |
| RT President Obama on Hurricane #Matthew This is still a really dangerous | Warner Robins | Warnings | AFINN | 2 | NRC | -1 |  |  |
| RT Prayers for everyone affected by Hurricane Matthew Especially all of my friendsfamily back at home stay safe #Hurr | Warner Robins | Warnings | AFINN | 3 | Bing et al. | 1 | NRC | -1 |
| RT Hurricane Matthew is supposed to hit on 107 Matthew 107 says Go and announce to them that the Kingdom of Heaven is n | Atlanta | Warnings | NRC | -1 |  |  |  |  |
| RT This map contains shelters that are being constantly updated #HurricaneMatthew | Augusta | Warnings | AFINN | 1 | NRC | -1 |  |  |

**Table S6.** Content analysis categories for hurricane-related tweets posted by followers of schools and school districts in Georgia, USA, during Hurricane Matthew and the number (%) of tweets per category for each dataset.

|  |  |  |  |
| --- | --- | --- | --- |
| **Categories** | **Definition** | **Hurricane Matthew** | |
| Original Tweets (%) | Retweet Tweets (%) |
| Preparedness | Topics related to preparation before the event | 244 (14.53%) | 285 (14.02%) |
| Damage | Topics related to any structural damage | 96 (5.72%) | 135 (6.64%) |
| Warnings | Topics related to emergency warnings | 47 (2.80%) | 53 (2.61%) |
| Evacuations/Migration | Topics with words related to moving from the area or evacuations | 154 (9.17%) | 223 (10.97%) |
| Awareness | Topics related to hurricanes information | 632 (37.64%) | 754 (37.09%) |
| Call for help/action | Topics related to asking for help or action from individuals or government | 365 (37.64%) | 388 (19.09%) |
| Shelter | Topics related to shelter needs | 47 (2.80%) | 75 (3.69%) |
| Emotions or Religious | Topics related to any type of emotion or religion | 53 (3.16%) | 66 (3.25%) |
| Miscellaneous | Topics that do not fit in any other designated category | 41 (2.44%) | 54 (2.66%) |

**Chart, line chart

Description automatically generated**

**Figure S1.** Seasonal plot of hurricane-related tweets posted from 2015 to 2017 by week and tropical storms (TS), hurricanes (H), and major hurricanes (MH) identified by the National Hurricane Center.13,14 The red, green and blue lines represent data from 2015, 2016 and 2017 respectively.

**Map

Description automatically generated**

**Figure S2.** Ratio index for hurricane-related original tweets from followers of schools and school districts in Georgia, USA, during Hurricane Matthew, analyzed by MSA.

**Map

Description automatically generated**

**Figure S3.** Ratio index for hurricane-related retweets from followers of schools and school districts in Georgia, USA, during Hurricane Matthew, analyzed by MSA.

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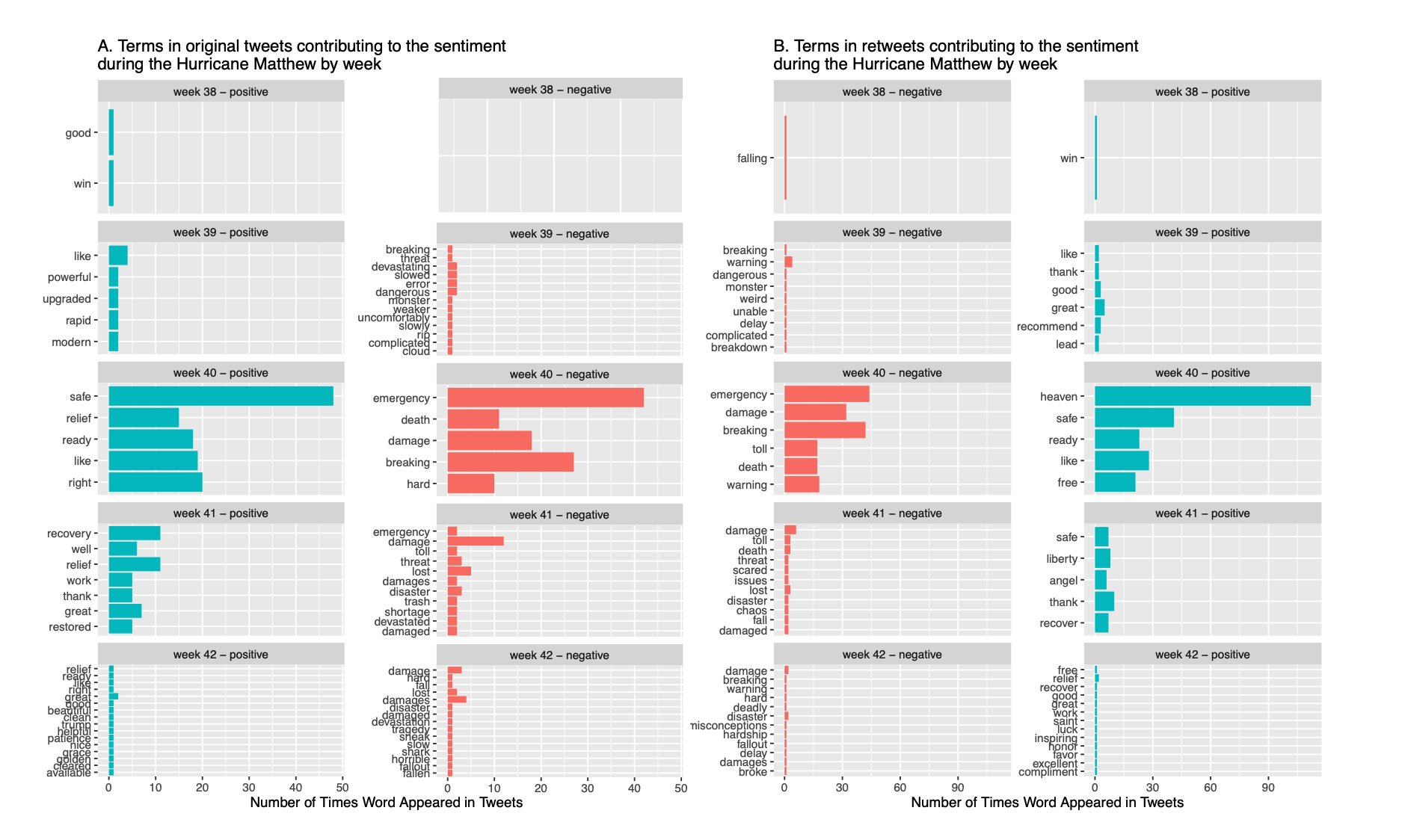
**Figure S4.** Case study for Hurricane Matthew: Distribution of original tweets and retweets by category for each MSA included in the study.



**Figure S5**. Sentiment scores of Twitter posts during Hurricane Matthew for unique tweets by date of post creation posted by followers of schools and school districts in Georgia. Total sentiment score changed across the emergency response cycle. Negative sentiment was predominant during the preparedness phase for original tweets and retweets posted during Hurricane Matthew. During the response phase, original tweets (Panel A) presented higher number messages with positive sentiment than those retweeted (Panel B) in the same phase. The timeframe for each response phase was determined based on the reviewed literature, the emergency cycle phases, and the official FEMA incident period for Hurricane Matthew in Georgia (October 4, 2016 to October 15, 2016).15-17



**Figure S6.** Top terms contributing to the sentiment score for Twitter posts during Hurricane Matthew posted by followers of schools and school districts in Georgia.



**Figure S7.** Top terms contributing to the sentiment score for Twitter posts during Hurricane Matthew by week posted by Twitter followers of schools and school districts in Georgia. No negative sentiment terms were identified during week 38 for the analyzed data.

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