Nat. Hazards Earth Syst. Sci. Discuss., 1, 4155–4179, 2013
www.nat-hazards-earth-syst-sci-discuss.net/1/4155/2013/
doi:10.5194/nhessd-1-4155-2013

Natural Hazards and Earth System Sciences
Discussions
Open Access

Road assessment after flood events using non-authoritative data

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Received: 19 July 2013 – Accepted: 30 July 2013 – Published: 22 August 2013

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Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

This research proposes a methodology that leverages non-authoritative data to augment flood extent mapping and the evaluation of transportation infrastructure. The novelty of this approach is the application of freely available, non-authoritative data and its integration with established data and methods. Crowdsourced photos and volunteered geographic data are fused together using a geostatistical interpolation to create an estimation of flood damage in New York City following Hurricane Sandy. This damage assessment is utilized to augment an authoritative storm surge map as well as to create a road damage map for the affected region.

1 Introduction

Accurate and timely flood assessments are critical during all phases of a flood disaster. In addition, knowledge of road conditions and accessibility is especially important for emergency managers, first responders, and residents. Over the past two decades, the use of satellite remote sensing has become a standard technique for the identification of flood extent. Satellite remote sensing data provide high spatial resolution and the capacity to provide information for areas of poor accessibility or lacking in ground measurements (Smith, 1997). However, in the case of hurricanes, high resolution remote sensing data from satellites might be unavailable for days because of cloud cover or orbital limitations of revisit time.

Satellite data are often supplemented with additional data, such as digital elevation models (DEM) and river gauge data, to provide a more comprehensive flood assessment (Wang et al., 2002; Brivio et al., 2002). RADAR data, in particular, are often a good resource for flood identification because of the capability to distinguish water bodies from other land cover while penetrating through vegetative canopy and cloud cover (Laura et al., 1990; Townsend and Walsh, 1998). Because the application of RADAR data can be difficult due to limited swaths and long revisit times, there are many

NHESSD
1, 4155–4179, 2013

recent efforts for increasing RADAR's availability and accessibility. For example, (Hoelzl et al., 2003) illustrate how a RADAR instrument on an unmanned aerial vehicle (UAV) can be used for flood assessment of targeted areas. Sohn et al. (2008) propose a multi-sensor approach by combining satellite, aerial, and ground data for a more accurate flood assessment. They test how a RADAR sensor onboard a UAV can provide useful data. Aerial platforms, both manned and unmanned, are particularly suited for coastal monitoring after major catastrophic events because they can fly below the clouds, and thus acquire data in a targeted and timely fashion.

In addition to capturing the location and progression of a flood event, remote sensing data are also used to catalog damages to the built environment. In particular, information regarding the accessibility, obstruction, or damage to roadways and bridges is imperative for emergency responders. While a functioning transportation network is essential in day-to-day life, it is particularly critical during and after disasters. For the evaluation of transportation infrastructure following Hurricane Katrina, a variety of assessment techniques were utilized including visual, non-destructive, and remote sensing. However, the assessment of transportation infrastructure over such a large area could have been accelerated through the use of high resolution imagery and geospatial analysis (Uddin, 2011).

Recent studies have focused on the application of remote sensing data after earthquakes or flooding specifically to assess transportation networks. Butenuth et al. (2011) used multi-sensor, multi-temporal imagery to identify flooded roads. Ehrlich et al. (2009) identified, using pre- and post-disaster very high resolution (VHR) optical imagery (1 m or better), infrastructure and road damages after the 2008 Wenchuan earthquake. The combination of optical satellite imagery with a DEM to assess roads for accessibility after flooding was used to create a model for application in near-real time for emergency managers (Frey and Butenuth, 2011).

The integration of new data sources and methods with traditional approaches offers opportunities to provide additional information regarding on-the-ground conditions. For example, non-authoritative data describes any data which are not collected and distributed by traditional, authoritative emergency management methods and agencies. Specifically, these data are generated, and often distributed, by public citizens and offer opportunities to gain additional insight during and after hazard events. For example, volunteered geographic information (VGI) is an emerging and quickly growing data source (Goodchild, 2007). These data are voluntarily contributed, made available, and contain temporal and spatial information. The sources of VGI vary greatly and include pictures, videos, sounds, text messages, etc. An unprecedented and massive amount of ground data have become available through VGI, often in real-time.

Although by definition, non-authoritative data usually carry little scientific merit, it is still possible for them to yield useful information. For example, VGI have been evaluated during disaster and crisis events as a source of situational awareness or as documentation of an event's progression over time (De Longueville et al., 2009; Vieweg et al., 2010). Volunteered data have also been utilized specifically during flood events. For rapid flood damage estimation, Poser and Dransch (2010) interpolated flood inundation depth from VGI and found estimates to be comparable to interpolated in situ measurements as well as model predictions. McDougall (2011) estimated flood extent by using VGI and river gauge data to create a DEM which was then compared to the natural topographic surface.

Another source of non-authoritative, volunteered information harnesses the power of group contribution, or the "wisdom of crowds" (Surowiecki, 2005). Crowdsourcing, a process where a task is undertaken by a large group of people rather than by a single individual or expert, often can result in successful problem solving (Howe, 2006). Examples of successful crowdsourcing include Wikipedia and Open Street Map, where information is voluntarily contributed and the public manages content and errors.[1] Goodchild and Glennon (2010) found the use of crowdsouring during disasters to provide valuable information, although, like any volunteered, non-authoritative data source, there still can be issues related to data quality.

[1] http://www.openstreetmap.org; http://www.wikipedia.org

Because of issues related to uncertainty in non-authoritative data, such as reliability and quality, they have yet to be regularly and systematically applied during large scale disasters (Flanagin and Metzger, 2008; Schlieder and Yanenko, 2010; Tapia et al., 2011). But despite their non-scientific nature, their integration with traditional data sources offers opportunities to include new and additional information which harnesses the power of "citizens as sensors" and "wisdom of crowds" to fill in the gaps (Surowiecki, 2005; Goodchild, 2007; Sui and Goodchild, 2011).

This paper utilizes crowdsourced aerial remote sensing data along with volunteered geographic data for flood damage assessment and the identification of road damages in the New York City area following Hurricane Sandy. Hurricane Sandy was a major storm which impacted a large portion of the US East coast in October 2012 with damages and recovery costs estimated to be between 50 and 60 billion dollars.[2]

2 Data

2.1 Non-authoritative data

2.1.1 Volunteered geographic data

Geolocated videos which documented flooding and damages from Hurricane Sandy were collected from a Hurricane Sandy Google Earth site where posted geolocated YouTube videos from Storyful could be accessed.[3] YouTube, a video-sharing website, is utilized by millions of people for the sharing of videos covering a wide range of topics and experiences. Through this site the public voluntarily shares information, often documenting damages resulting from natural hazards.

Twitter, a social networking site, is often utilized by the public to share information about their daily lives through micro-blogging. Arizona State University's TweetTracker

[2]http://www.washingtonpost.com

[3]https://storyful.com

NHESSD

1, 4155–4179, 2013

provided Twitter data for this project.[4] Tweets generated in the New York City area extending from 40.92° N to 40.54° N latitude and 73.75° W to 74.13° W longitude from 26 October–3 November 2012 containing the word "flood" were used to provide a temporal framework.

2.1.2 Crowdsourced data

The Civil Air Patrol, the civilian branch of the US Air Force, was tasked with collecting aerial photos of the US East Coast following the impact of Hurricane Sandy. Within days of the storm making landfall, hundreds of missions were flown by volunteers from Cape Cod, MA to Cap May, NJ. From these missions, thousands of aerial photos of the coastline were generated, including those documenting heavily flooded areas.

The photos were placed on a Hurricane Sandy Google Crisis Map website (Fig. 1) for the public to assess visible damages through a crowdsourcing portal supported by MapMill.[5,6] This yielded a large damage assessment data set generated from crowdsourced, non-authoritative, non-traditional sources. The photos were also made available online through a Federal Emergency Management Agency (FEMA) website for residents to search by street address to see what, if any, damage their homes may have sustained.[7]

2.2 Authoritative data

The FEMA Modeling Task Force (MOTF) created storm surge maps for the US East Coast following Hurricane Sandy. Surge extent was determined from field-verified high

[4]http://tweettracker.fulton.asu.edu
[5]http://google.org/crisismap/sandy-2012
[6]http://mapmill.org
[7]http://fema.apps.esri.com/checkyourhome

NHESSD
1, 4155–4179, 2013

water marks and storm surge sensor data. FEMA employed these data along with a digital elevation model (DEM) to create a surge boundary for each state.

A FEMA MOTF shapefile was downloaded from FEMA's GeoPlatform website and imported into ArcGIS 10 for analysis.[8] The GeoPlatform site supplies data and analytics for emergency management. The shapefile utilized for this research was the finalized version (dated 14 February 2013) for New York City with a 1 m horizontal resolution and a New York State Plane coordinate system (Fig. 2a).

2.3 Road layer

A 2012 TIGER/line® shapefile of road networks for the New York City area was downloaded from the US Census Bureau.[9] The layer was georeferenced to New York State Plane coordinates in ArcGIS 10. Figure 2b displays the road network for the New York City area as well as the surge extent created by FEMA.

3 Methodology

3.1 Overview

This work is based on the fusion of non-authoritative data and its integration with traditional authoritative sources. Figure 3 illustrates the proposed methodology where non-authoritative data are combined to create an assessment of flooding and damage which is compared to information from authoritative sources to produce spatial and temporal assessments of the disaster.

The novelty of this approach is the utilization of non-authoritative data to produce flood and road damage assessments. Although in this work specific crowdsourced data (Civil Air Patrol photos) and volunteered data (YouTube videos, Tweets) are utilized, this

[8] http://fema.maps.arcgis.com

[9] http://www.census.gov

methodology can be extended to other sources. The goal of this paper is to illustrate how non-authoritative data can augment existing data and methods as well as optimize response initiatives by identifying areas of severe damage.

3.2 Non-authoritative damage assessment

The fusion of data from different sources can be accomplished using a variety of mathematical, statistical, or machine learning approaches. In this paper the integration of non-authoritative data is achieved by interpolating the data sources to create a damage assessment surface. Kriging, a geostatistical technique for interpolation, utilizes the spatial arrangement and variance of the nearby measured values to create interpolated surfaces. The kriging process first creates a variogram to estimate spatial autocorrelation between points which is then used as a weight to predict values (Stein, 1999). The general formula for a kriging interpolator is

$$\widehat{Z}_{(x_0)} = \sum_{i=1}^{n} w_i Z_{(x_i)} \tag{1}$$

where $\widehat{Z}_{(x_0)}$ is an estimator for unknown value (x_0), n is the number of observed values, w_i is the weight assigned by the variogram, and $Z_{(x_i)}$ are the observed values.

3.3 Integration with authoritative data

After a damage assessment surface is created from non-authoritative data, it is integrated with available authoritative information. This integration can be in the form of validation, if ground information are available, or fusion if there are gaps in the spatial or temporal data infrastructure.

For this research, authoritative data in form of a storm surge map created by FEMA MOTF is utilized as a comparison of flood extent as well as to illustrate how non-authoritative data can provide a range of damage estimations enhancing traditional storm surge products.

3.4 Generation of road damage map

Road damage is determined using the damage assessment surface created from the fusion of non-authoritative sources. Utilizing ArcGIS 10 software, a road network is layered over the damage assessment layer. Roads are classified based on the underlying damage assessment.

4 Results

4.1 Damage assessment and authoritative data

4.1.1 Spatial assessment

Civil Air Patrol damage assessments for the area from 33° N to 26° N latitude and 90° W to 84° W longitude were downloaded directly from MapMill. The photographs were collected by the Civil Air Patrol between 31 October and 11 November 2013 (within days of Hurricane Sandy impacting the New York City area). The Civil Air Patrol photos were aggregated into a 500 m grid structure, and the value for each grid point is a function of the number of images present in each grid, and their average crowdsourced damage assessment. As a result, each grid has a value from 1 to 10, with 1 representing no damage and 10 severe damage/flooding.

The videos were provided with geolocated information, and were visually assessed by the author. The small number of videos ($n = 15$) did not require any crowdsourcing or automated assessment. Furthermore, it is shown in (Schnebele and Cervone, 2013) that even a small number of properly located VGI data can help improve flood assessment.

These data were fused together using a kriging interpolation in ArcGIS 10 as described in Sect. 3.2. This resulted in a predicted damage assessment generated solely from non-authoritative data. Figure 2c illustrates the damage assessment within the boundaries of the FEMA surge extent. A histogram (Fig. 4) shows the ranges in these damage assessment values. The peak in medium/severe damage values (7–8) shows how these non-authoritative data may provide information regarding damage not conveyed by the FEMA map.

Ground information in the form of geolocated videos enhances the non-authoritative data set by providing flood information not conveyed in the Civil Air Patrol photos (Fig. 5). As illustrated in (Fig. 6), the locations of the videos (green triangles) did not coincide with locations of photos rated as medium/severe damage (larger orange circles, values 7–10). Reasons for this disparity may include flood waters that were captured on video had receded before the Civil Air Patrol flights, some areas may not have been in a flight path, some documentation of flooding occurred at night, as well as certain areas were unable to be photographed from aerial platforms (i.e. flooding in tunnels, under overpasses).

Overall, there is a very good agreement between the flood extent from FEMA and the assessment generated with the proposed methodology. Figure 9 are examples of agreement between photos identifying flooding/damages and the FEMA generated flood extent while Fig. 10 include examples where the locations of flooding or damages did not agree between the Civil Air Patrol and the FEMA data. These areas were located along coastal edges and therefore precision is most likely the cause of the discrepancies.

A comparison of flood surface area between the two maps was also conducted. The storm surge area on the FEMA map is approximately 121 km^2. Using the higher rated areas of damage (regions with values from 7–10) from the non-authoritative assessment yielded an approximate surface area of flooding and damages of 157 km^2 (Fig. 7). Using only the areas classified as medium-severely damaged, the surface area generated from non-authoritative sources is within 23 % of FEMA's surge extent for New York City.

NHESSD
1, 4155–4179, 2013

4.1.2 Temporal assessment

For this study, Twitter data from TweetTracker[10] were used to provide a temporal rather than spatial assessment. Although Tweets were geolocated using TweetTracker (Kumar et al., 2011, 2012), uncertainty in their location did not allow for a study at a street resolution. However, they provide precise temporal information that can be used to understand the progression of the surge extent over time. To understand the temporal progression is crucial during and after flood events, and is very hard to understand using remote sensing instruments, due to their inherent carrier limitations. Twitter data can effectively be used to overcome this limitation. For example, Fig. 8 illustrates how the peak in the number of tweets containing the word "flood" occurs the day of 30 October 2012 immediately following Hurricane Sandy making landfall the night of 29 October. The approximately 12 h lag between the hurricane's landfall and Twitter activity may be due to the timing of the landfall (night, when the majority of citizens were asleep).

4.2 Road damage map

The non-authoritative damage assessment was also utilized to identify areas of potential road damage. Although in (Fig. 2c) the damage assessment was limited to within the authoritative FEMA surge extent area for the sake of comparison, for the classification of road damages, the area was not limited to the authoritative extent. The fusion of the non-authoritative data predicted flooding and damages outside the FEMA flood extent boundaries, so the full damage assessment was utilized for the road classification. The road network from the TIGER/line® shapefile was layered over the damage assessment map. The road damages were then classified based on the underlying damage assessment layer (Fig. 2d).

[10]http://tweettracker.fulton.asu.edu/

By using the damage assessment layer along with a high resolution road network layer, roads which may have severe damage can be identified at the street level. This allows authorities to prioritize site inspections, task additional aerial data collection, or identify routes which may compromised.

5 Conclusions

The application and integration of non-authoritative data offers opportunities to augment traditional data and methods for flood extent mapping and damage assessment. Although questions of reliability and validity are of concern when utilizing non-authoritative data, especially during natural disasters, these data can be employed along with traditional authoritative data and methods to enhance our knowledge of ground conditions. The fusion of multiple non-authoritative data sources helps to fill in gaps in the spatial and temporal coverage. In addition, the ability to identify potential areas of road damage or inaccessibility from flooding can optimize response initiatives.

Acknowledgements. Work performed under this project has been partially supported by US DOT's Research and Innovative Technology Administration (RITA) award # RITARS-12-H-GMU (GMU #202717). DISCLAIMER: The views, opinions, findings and conclusions reflected in this presentation are the responsibility of the authors only and do not represent the official policy or position of the USDOT/RITA, or any State or other entity.

The authors would also like to thank Huan Liu and Shamanth Kumar of the Data Mining and Machine Learning Lab at Arizona State University for providing the Twitter data.

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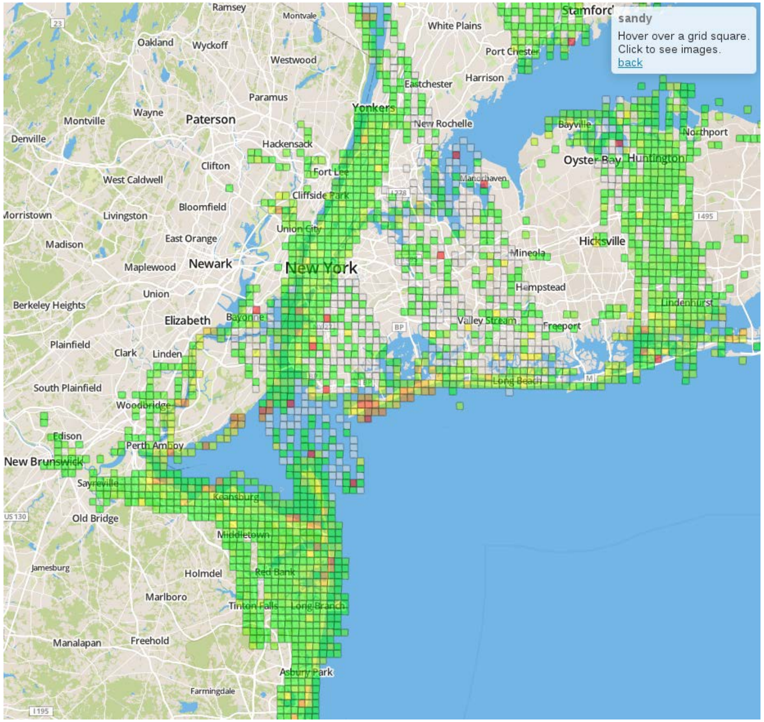
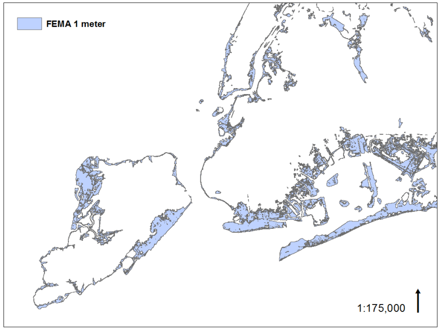
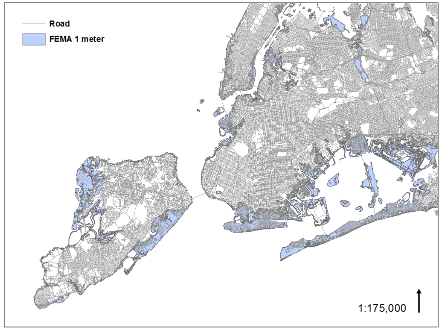


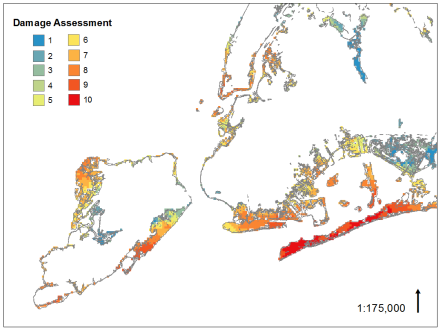
Fig. 1. Crowsourced assessments for the Civil Air Patrol data. Damage assessment: red = high, yellow = medium, green = none.



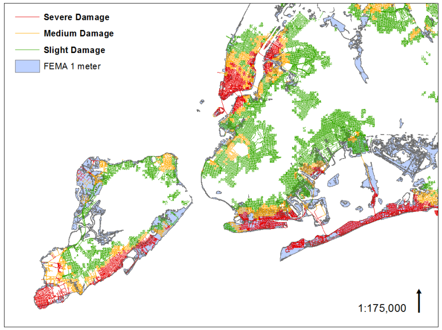
(a) Storm surge created by FEMA MOTF for New York City.



(b) Road network for NYC area and FEMA flood extent



(c) Damage assessment generated from non-authoritative data within FEMA surge boundary.



(d) Road damage assessment based on analysis of non-authoritative data.

Fig. 2. Storm surge extent generated by FEMA and the road layer for New York City area (**a** and **b**). Flood damage assessment generated from non-authoritative data and the subsequent classification of potential road damages (**c** and **d**).

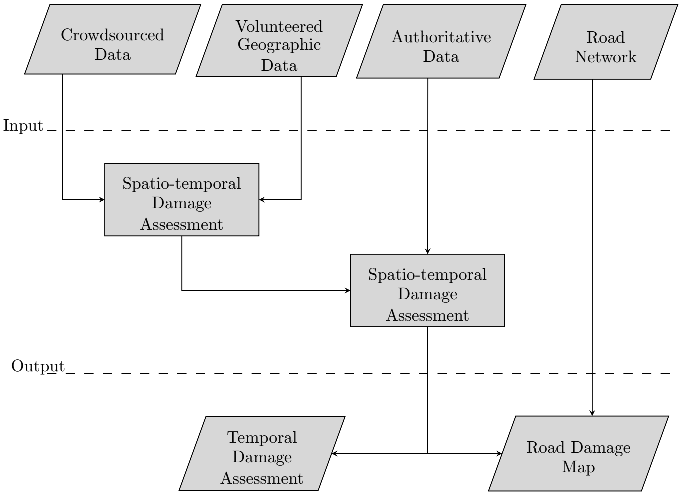


Fig. 3. Flowchart illustrating the methodology for determining road damage from non-authoritative data.

NHESSD
1, 4155–4179, 2013

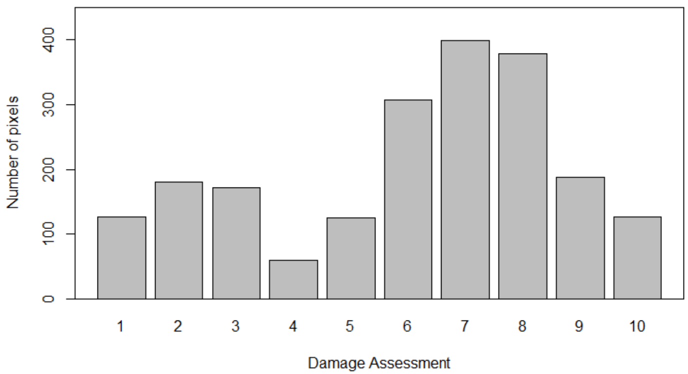


Fig. 4. Classification of damage within FEMA surge extent using non-authoritative sources.

NHESSD
1, 4155–4179, 2013

Non-authoritative data for flood events

E. Schnebele et al.

Fig. 5. Example of YouTube video documenting flooding.

NHESSD
1, 4155–4179, 2013

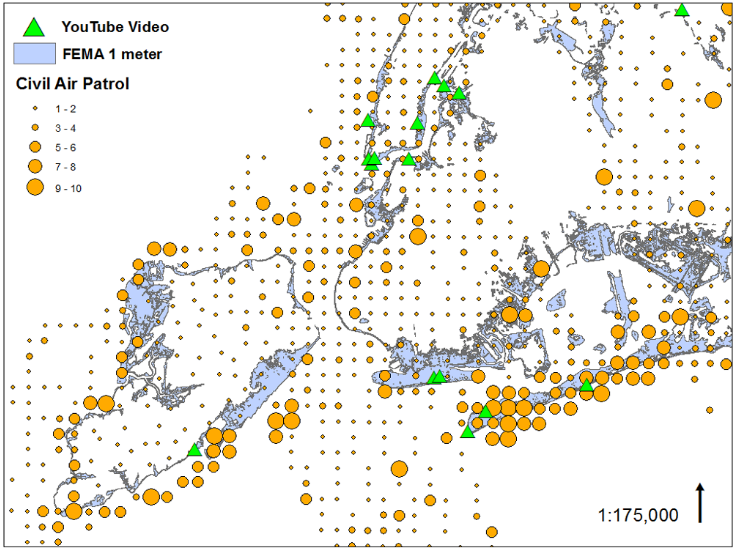


Fig. 6. Locations of Civil Air Patrol photos and geolocated videos documenting flooding.

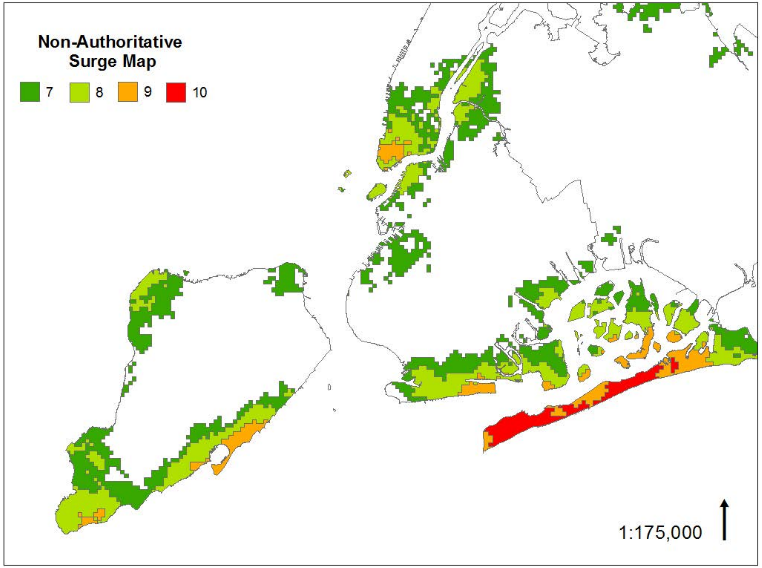


Fig. 7. Designated areas ranging from medium to severely damaged (medium = 7, 8; severe = 9, 10) based on non-authorittave data.

NHESSD
1, 4155–4179, 2013

Non-authoritative data for flood events

E. Schnebele et al.

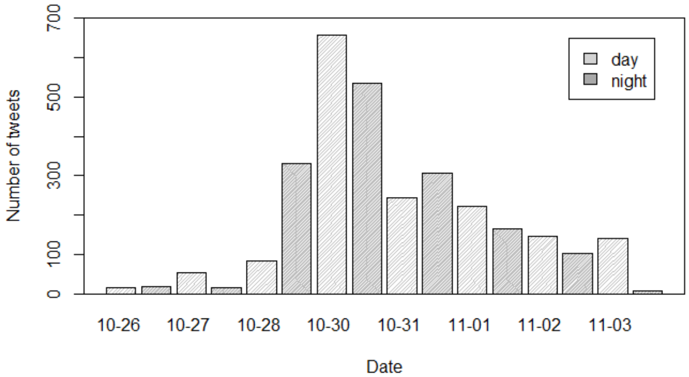


Fig. 8. Progression of tweets mentioning the word “flood” in the New York City area.

NHESSD
1, 4155–4179, 2013

(a) Flooding documented by the Civil Air Patrol and FEMA.

(b) Flooding documented by the Civil Air Patrol and FEMA.

(c) No flood damages documented by the Civil Air Patrol and FEMA.

(d) No flood damages documented by the Civil Air Patrol and FEMA.

Fig. 9. Agreement between Civil Air Patrol photos and FEMA evaluation for flooded (**a** and **b**) not flooded (**c** and **d**).

NHESSD
1, 4155–4179, 2013

(a) Flooding documented by the Civil Air Patrol but not estimated by FEMA.

(b) Flooding documented by the Civil Air Patrol but not estimated by FEMA.

(c) Flooding estimated by FEMA but not confirmed by the Civil Air Patrol.

(d) Flooding estimated by FEMA but not confimed by the Civil Air Patrol.

Fig. 10. Disagreement between Civil Air Patrol photos and FEMA evaluation for flooded (**a** and **b**) not flooded (**c** and **d**).