AsonMaps: A Platform for Aggregation Visualization and Analysis of Disaster Related Human Sensor Network Observations

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ABSTRACT

In this paper, we describe AsonMaps, a platform for collection, aggregation, visualization and analysis of near real-time, geolocated quantifiable information from a variety of heterogeneous social media outlets in order to provide emergency responders and other coordinating federal agencies not only with the means of listening to the affected population, but also to be able to incorporate this data into geophysical and probabilistic disaster forecast models that guide their response actions. Hurricane Sandy disaster is examined as a use-case scenario discussing the different types of quantifiable information that can be extracted from Instagram and Twitter.

Keywords

Visualization of Social Media Data, Human Sensor Network, Mining Crowd-Generated Data, Disaster Management, Near Real-Time Situational Awareness, Citizen Science, Crowdsourcing

INTRODUCTION

Emergency responders have long-established protocols for response management and mitigation. For disaster modeling and risk assessment, they rely on data collected by other government agencies, and on conventional media outlets for communication of risk and evacuation orders to the public. Recently emergency responders have begun utilizing Social Media (SM) outlets such as Facebook and Twitter for the purpose of communicating urgent information to populations affected by disasters. The flow of information from SM users to the Emergency Responders is currently in its infancy and in the early stages of research. For instance, (Goolsby, 2010) lays down the concept of Crisis Community Maps. The paper covers in depth a variety of quickly forming SM communities that emerged as a result of crises such as the terrorist attacks in Mumbai in 2008, the Haiti Earthquake of 2010 etc., and states that emergency responders become more receptive to non-authoritative sources of crisis data in exchange for robust situational updates.

In our work we present an approach that would equip Emergency Responders with tools and methods to "listen" to the affected public by monitoring heterogeneous SM outlets for posts related to the disaster at hand. This approach would be invaluable in providing Emergency Responders with timely understanding of how the disaster has affected different areas and segments of the population and allowing for more accurate assessments of the needs of different neighborhoods. It would also be useful in validating the forecasts of risk assessment and geophysical models.

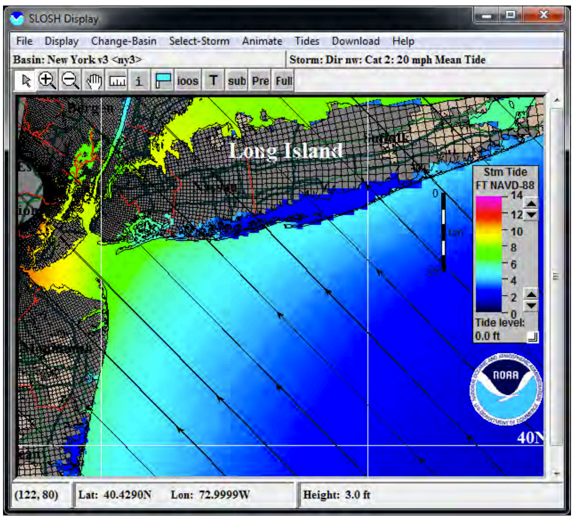
Prior work (Vieweg, Hughes, Starbird and Palen 2010) has already demonstrated the potential use of Twitter microblogs for river flooding and fire situation awareness use cases. A Human Sensor Network (HSN) approach (Aulov and Halem, 2010) - in which SM users are viewed as sensors deployed in the field, and their posts are viewed as data observations – was shown to successfully improve modeling of the Deepwater Horizon oil spill plume movement forecasts. Emergency responders rely on General NOAA Operational Modeling Environment (GNOME) for oil plume movement and shoring forecast. Geolocated photos of oil spill sightings were collected from Flickr – an SM photo sharing outlet - and were used as observations. As a result of the HSN observations, forecast improvement by an order of magnitude was achieved.

In this paper, we utilize the NOAA Operational surge model called SLOSH (Sea, Lake and Overland Surges from Hurricanes) for the prediction of flooding and surge levels to compare with HSN observational data for Hurricane Sandy.

COLLECTION STORAGE AND INDEXING OF HSN OBSERVATIONS

As a use-case scenario, we focus on Hurricane Sandy that devastated the East Coast of the United States in fall of 2012. For this research we collected HSN data from Twitter and Instagram. Twitter is a microblogging social networking service that allows users to post messages of up to 140 characters in length and supports community forming via a "follow" feature. Instagram is a very similar social networking service that is focused on sharing photos - most often taken with smartphones or tablets – applying filters to them and sharing them with followers.

We have collected over 8 million tweets and around 370 thousand Instagram images referencing hurricane Sandy. We started the data collection around 4 am on Monday, October 29th, hours before Sandy made landfall, and stopped the collection around 4 am on Thursday, November 1st, 2012. After several hurricane related search attempts we composed our stream query to filter tweets that mention the terms "Hurricane", "Sandy", "frankenstorm", "frankensandy", "hurricanesandy", "superstorm", "naturaldisaster". Instagram data was collected retroactively since there is no limitation on accessing historical Instagram posts. Most photos have a short description with hashtags. We were able to retrieve the photos related to the hurricane by querying for the "hurricanesandy" hashtag. Many of the users share their geolocation and as a result we can observe a stream of near real-time geolocated human sensor observations. Therefore by subsetting the data based on available geolocations, we were able to reduce the twitter data to ~18,000 tweets and the Instagram photos were reduced to ~ 14,000 photos for the North East area of the United States.



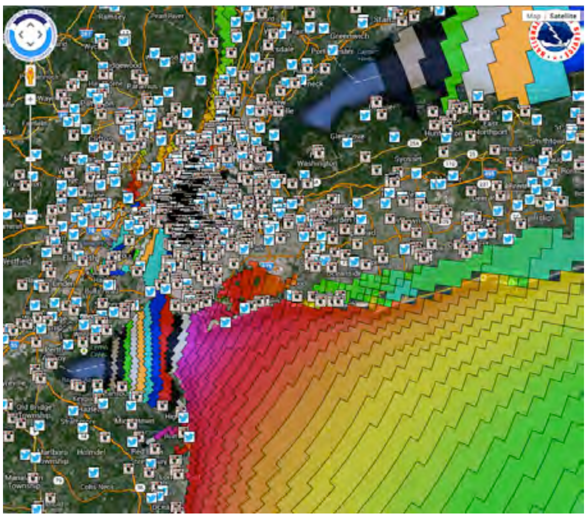


Figure 1a. Screenshot of SLOSH model forecast configured for the New York City basin. Diagonal lines indicate different parallel landfall paths for which the maximum envelope of water is computed.

Figure 1b. Screenshot of AsonMaps platform centered on the greater New York City area. The overlay indicates different surge heights in different colors. Geolocated tweets are marked with a blue bird icon and Instagram images with a camera icon.

CONVENTIONAL STORM SURGE MODELING

Disaster management operatives rely on operational models for prediction and mitigation of disasters. The two main goals of these models are to forecast as accurately as possible the magnitude and location of disasters before they strike, and to determine as accurately as possible the impact of the disaster after it strikes. These forecast models rely on inputs from conventional sensor observations and assimilate them into a mathematical, geophysical model to produce a forecast.

"The SLOSH model is a computerized numerical model developed by the National Weather Service (NWS) to estimate storm surge heights resulting from historical, hypothetical, or predicted hurricanes by taking into account the atmospheric pressure, size, forward speed, radius of maximum winds and track data combined with topography and bathymetry of a given basin. These parameters are used to create a model of the wind field which drives the storm surge."(SLOSH Manual) The main purpose of SLOSH model is to determine the potential surge for a given basin and use it as a basis for risk analysis and evacuation planning. We chose the SLOSH because it is the operational model used by National Hurricane Center (NHC). Figure 1a demonstrates the SLOSH model forecast of a hurricane in the New York City area.

SLOSH model setup requires selection of a basin from a predetermined list of basins for which the model has the terrain and bathymetry data. Surge modeling is deterministic in nature and can generate accurate forecasts given accurate input data from hurricane forecast models of precise landfall location. Since the NHC cannot predict exactly where the hurricane will make a landfall, or at what exact time, the SLOSH model provides a probabilistic forecast of Maximum Envelope of Water (MEOW). For a storm of a given category, wind speed and direction this forecast indicates the highest possible level of surge at any given grid cell. Such an approach is meant to cope with the weather forecast uncertainties. The other forecast that SLOSH provides is Maximum of the Maximums (MOM). This forecast displays the highest level of water for a given tide and hurricane category and is intended for assessing the worst-case scenario of a potential hurricane, since no real hurricane will produce such a surge. The accuracy of the SLOSH model forecast is in the range of +/- 20% based on validation against historic hurricane data. This accuracy is based on assumption that the exact path of the hurricane is known (Glahn 2009; Lee 2011; Liu 2008). Moreover, SLOSH model does not take into account rainfall, wind driven waves, rivers etc.

ASONMAPS PLATFORM

For visualization and analysis purposes, we developed a Google Maps based web application that allows us to combine the geolocated HSN data in the same framework with the storm forecasts from a variety of geophysical and probabilistic models. In this use-case scenario, we use NOAA's SLOSH model and P-Surge (probabilistic surge model) to provide a forecast for Hurricane Sandy. We demonstrate how the model forecasts can be improved using SM data, if combined in a single framework, and can be used for near-real time forecast validation, damage assessment and disaster management. Geolocated and time stamped Instagram photos allow us to not only validate the model forecasts, but also provide the actual levels of surge. Photos of flooded streets, cars and basements allow us to have a rough estimate of the surge level at that given location and time, while photos of rainy, yet not flooded scenes allow us to determine an upper bound beyond which the surge did not spread. Such continuous "sensor observations" of surge heights demonstrate substantial improvement over "trigger alarm" type measurements that were observed in the case of the oil spill (Aulov and Halem, 2010) where the observation only indicated presence of tarballs, but no method was presented to report lack of tarballs, much less to quantify the amount of tarballs observed. A byproduct of geolocated tweets not only monitors the emotional response of different geographic areas affected by the disaster, but also provides insight into the problems that different communities are experiencing, such as power outages, elevated crime (looting etc.), and refusal to evacuate.

Figure 1b demonstrates the AsonMaps platform with the SLOSH model forecast and the HSN observations on the same interactive map. The map is of the greater New York City area. The overlay in the ocean area is the SLOSH model surge forecast. In this example the surge is for a hurricane of category 1 with speeds of 20mph making a landfall at mean tide. The colors correspond to different heights of water. HSN data is marked with icons of a camera for Instagram photos and a blue bird for tweets. All these data are for points that were geolocated using the Latitude and Longitude from the metadata of the post. Even though all the posts are related to Hurricane Sandy, we can subset them by different topics such as "poweroutage" or "flood". The data points on the map are a subset of the available data for only a 12-hour period, yet the Manhattan area is so densely covered with data points that they are indiscernible until the map is zoomed to the street and block level. If a particular data point is clicked, a pop up window appears which displays the content of the tweet or the Instagram photo with caption and date.

OVERVIEW OF THE VARIETY OF HSN MEASUREMENTS

In this section, we demonstrate several heterogeneous HSN measurements that can be collected using our AsonMaps platform. We also discuss some of the methods that can be utilized for faster and more accurate measurements.

One of the most significant measurements that we are able to extract in near real-time are flood levels. On figure 2a we observe Radcliffe Road flooded in Island Park, NY. The building in the photo is the public library adjacent to Francis X Hegarty Elementary School. The level of the water completely covers the wheels of the Toyota Camry parked by the library. We can conclude that the water level is around two feet. From the topography data, we know that the elevation at Lat/Long (40.600498199,-73.657997131) is around 9 feet and therefore the surge level is around 11 feet above sea level. Figure 2b shows a screenshot of a Google Street View of the same location, which in cases when it is difficult to estimate the depth of water, can be used for comparison to see the area without the floodwaters. Additionally, there is an abundance of photos of streets in the rain that are not flooded. Such photos are of high importance as well because they can be used to determine the upper bound of the storm surge beyond which the surge did not spread.

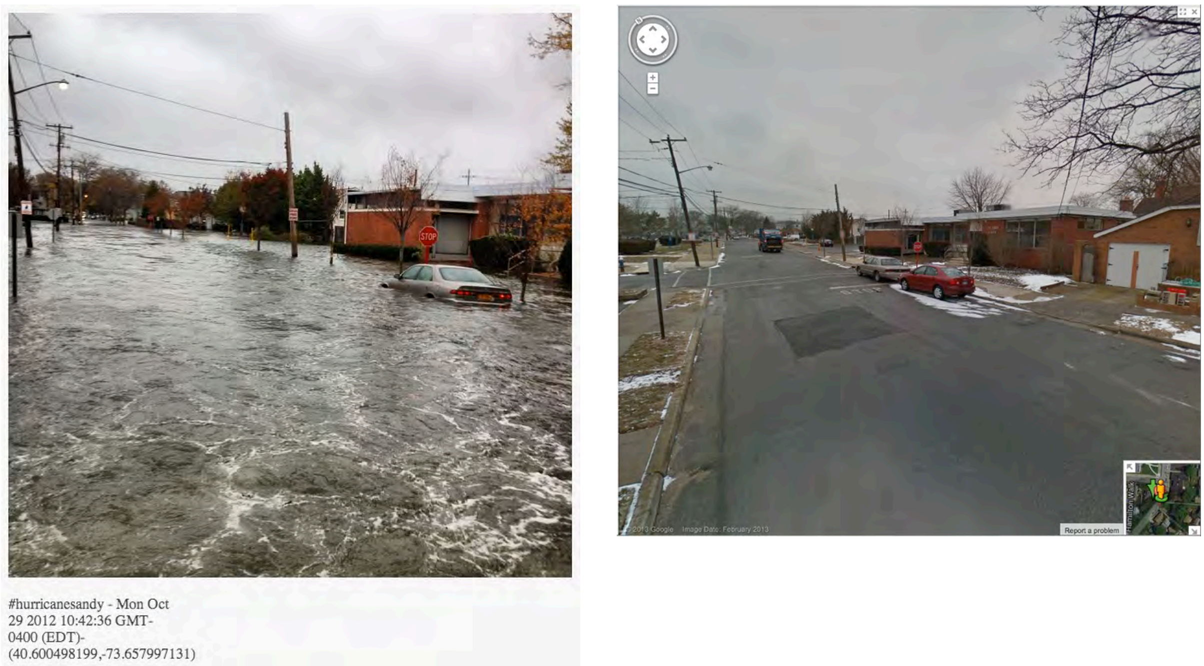


Figure 2 (a) Island Park Public Library on the eve of Hurricane Sandy making landfall, (b) Google Street View of Island Park Public Library for comparison

Another type of sensor data is the detection of power outages. Figure 3 demonstrates two tweets, one mentioning that the user lost power (a); the other one mentions that despite strong winds the user still has power (b). Many Instagram photos show candle lit rooms and have captions mentioning the power outages as well. Users also often tend to report when the power is restored.

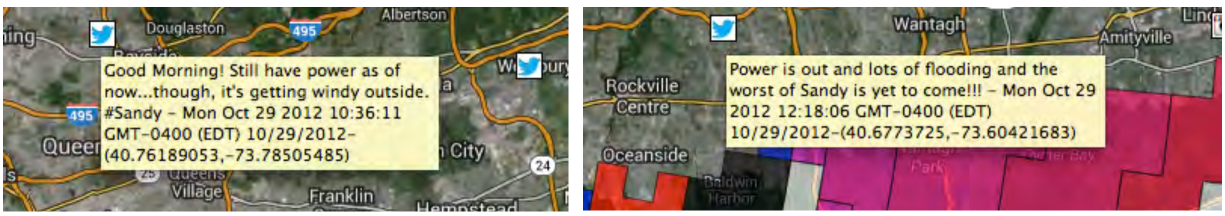


Figure 3. AsonMaps showing the tweet that indicates: (a) power outage and flooding, (b) presence of strong winds and explicitly indicates no power outage

In our use case, we demonstrate near real time HSN data gathering from Instagram and Twitter, assimilation of this data into SLOSH model, and visualization of the different aspects of disaster combined with the model forecasts.

CONCLUSIONS

Our research demonstrates the feasibility of the HSN approach for early validation of the surge model forecasts. Using AsonMaps platform, in the case of Hurricane Sandy, we were able to identify the geographic regions that were flooded and provide a rough estimate of the surge levels as well as determine the flood free regions from the photos of streets that are wet from rain, but not flooded. Given the topography data of the observed location, we determined the elevation at which the given flood occurred and extrapolated it to the neighboring vicinity of other areas of the same elevation. Using the animation mode of the AsonMaps platform we were able to simulate the timeline of a disaster and learn how SM posts trace the disaster impact and correlate with the model forecasts. We demonstrated an actual use case of HSN observations in operational disaster forecast models and presented time sensitive data that can be invaluable for disaster response.

AsonMaps is a beneficial platform that has applications in multiple aspects of disaster management. Before the disaster hits, AsonMaps can be used to monitor the public response to the evacuation requests and other preparation actions. During hurricanes, AsonMaps provides near real-time impact assessment, and following the event can provide a micro-scale geographic evidence of the hurricane impact.

Hurricane Sandy moved in somewhat unlikely path far away from the coast through the Atlantic, and making a somewhat sharp landfall in the North-North-West direction. A much more likely scenario for a future hurricane is to move along the Atlantic coast devastating much wider coastal areas. In those cases, it is necessary to set up the models with accurate initial conditions to better manage and mitigate the communities that are being struck next. After the disaster strikes, AsonMaps Platform can be used as a simulator for disaster response training by replaying the SM observations as if they were happening in real time.

What was critical in the use of SM data in this use case scenario was the fact that the data possessed geolocated information both visual in terms of photos and in natural language content. Although SM sources are rapidly evolving, more and more quantitative information is becoming available from handheld and wearable devices and other SM platforms for physical modeling. The challenge will be in the validation of the quality and reliability of these observations.

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