APPROVAL SHEET

Title of Dissertation: RETRIEVING QUANTIFIABLE SOCIAL MEDIA DATA FROM HUMAN SENSOR NETWORKS FOR DISASTER MODELING AND CRISIS MAPPING

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Doctor of Philosophy,
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Education

Ph.D. in Computer Science - University of Maryland Baltimore County
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M.Sc. in Computer Science - George Washington University December – 2006

B. Sc. in Mathematics and Computer Science - University of Central Missouri
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Associate Degree in Electronics - ORT - College for Advanced Technologies And Sciences (Israel) - May 2001

Technical Skills

Software:	ElasticSearch, CouchDB, MySQL, Gephi, Hadoop, Apache AXIS, Weka, SPSS Modeler (machine learning), AGI Satellite Toolkit (3D visualization and automation), STK Scheduler,
Programming Languages and Frameworks:	Python, NumPy, SciPy, MATLAB, PHP, Java, JavaScript, Android Development, C, Prolog, ARM Assembly, KornShell, XML, SOAP, REST
Natural Languages:	Fluent in Russian and Hebrew

Work Experience

Baltimore, MD	**Graduate Research Assistant at the Center for Hybrid Multicore Productivity Research (UMBC)**
Sep 2010-Present	Developing the concept of a human sensor network, researching ways of extracting quantifiable data from heterogeneous social media sources and assimilating it into a variety of geophysical models in order to improve analysis, forecast and situational awareness during catastrophic events such as the Deepwater Horizon oil spill or Hurricane Sandy. Collected a dataset of over 8 million tweets and 370k Instagram photos referencing the hurricane, including the metadata. Developed a method of assimilating social media data into a geophysical model for improved oil plume movement prediction.

Greenbelt, MD Sep 2005-Aug 2010	**Research Assistant at Joint Center for Earth Systems Technology – (NASA Goddard)** Implemented the Sensor Web simulator and the Target Scheduler components of the Autonomous Objectively Optimized Observation Direction System for future constellation of earth observing satellites. The observation targets were selected using uncertainty matrix and scheduling priorities using information content matrix. Automated the use of AGI Satellite Toolkit for 3D visualization of chemical constituents in the atmosphere and satellites that can observe them. Automated use of STK Scheduler for smart autonomous scheduling of observations. Got familiarized with a variety of data assimilation systems.
Gaithersburg, MD June 2012 – October 2012	**Guest Researcher at NIST** Investigated methods of describing bio-microscopy image quality metrics and cell segmentation accuracy for different types of cells. Developed methods of stem cell colony type classification from automatically segmented images.
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August 2011-Present	**Independent Consultant for DblFuzzr** Developed Android Apps, implementing an encrypted authentication scheme using Java. Implemented several small native functions in ARM assembly and C, integrating them into the App using Java and JNI interface.
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Journal Publications:

O. Aulov, M. Halem "Human Sensor Networks for Improved Modeling of Natural Disasters", Special Centennial Issue of the Proceedings of the IEEE Remote Sensing of Natural Disasters, October 2012

D. J. Lary and O. Aulov, "Space-based measurements of HCL: Intercomparison and historical context," JOURNAL OF GEOPHYSICAL RESEARCH-ATMOSPHERES, vol. 113, no. D15, APR 18 2008.

Conference Publications:

O. Aulov, A. Price, M. Halem “Human Sensor Networks: AsonMaps: A Platform for Aggregation Visualization and Analysis of Disaster Related Human Sensor Network Observations” International Conference on Information Systems for Crisis Response and Management, Penn State Univ. May 2014

O. Aulov, A. Price, M. Halem “Human Sensor Network: A Social Media Observational Tool for Improved Modeling and Mitigation of Extreme Weather Events” American Meteorological Society, 94th Annual Meeting, 2 February, 2014

“Extracting Quantifiable Information From Social Media in the Wake of Hurricane Sandy” Podium Presentation, Northeast Regional Operational Workshop XIV (sponsored by the National Weather Service), Dec. 10, 2013

O. Aulov, A. Price, J. Smith, M. Halem “A Human Sensor Network Framework in Support of Near Real Time Situational Geophysical Modeling” Podium Presentation, AGU Fall meeting, San Francisco, CA Dec. 8, 2013

O. Aulov, A. Price, M. Halem “Human Sensor Networks for Disaster Management” Mid-Atlantic Student Colloquium on Speech, Language and Learning, October 11, 2013

O. Aulov, M. Halem, "Human Sensor Networks For Improved Oil Spill Predictions", AGU Conference on Ocean Sciences, 2012, Salt Lake City, Utah, February 20, 2012

O. Aulov, M. Halem, N. Malakar, D. Lary “Human Sensor Networks: Use of Social Media and Self Organizing Maps for Automated Detection of Oil Spill Plumes in Satellite Observations" Earth Science Informatics Partnership Winter Meeting, January 2012, Washington, DC

O. Aulov, M. Halem, D. Lary, “Assimilation of Real-Time Satellite And Human Sensor Networks for Modeling Natural Disasters” AGU Conference, Fall meeting San Francisco, CA Dec. 17, 2011.

Gregory G. Leptoukh, et al. “Challenges in characterizing, assessing, and capturing quality of remote sensing data.” AGU Conference Fall meeting, San Francisco, CA Dec. 17, 2011.

O. Aulov, Y. Yesha "Human Sensor Networks: Extracting Geophysical Observations from Social Media for Situational Awareness in Natural Disasters", IBM CASCON Conference Toronto, Can. 2011, November 7-10, 2011

O. Aulov, M. Halem "Human Sensor Networks: Improving Oil Spill Model Predictions Using Social Media Data" Earth Science Informatics Partnership Summer Conference 2011, Santa Fe, NM, July 12-15, 2011

O. Aulov, M. Halem "Human Sensor Networks: Improving Oil Spill Model Predictions Using Social Media Data with Geolocation", Gulf Oil Spill SETAC Focused Topic Meeting, April 27th, 2011

M. Halem, Y. Yesha, O. Aulov, J. Martineau, S. Brown, T. Conte "Collaborative Science: Human Sensor Networks for Real-time Natural Disaster Prediction" AGU Conference Fall meeting, San Francisco, CA Dec. 17, 2010.

O. Aulov, D. J. Lary "Objectively Optimized Observation Direction System Providing Situational Awareness for a Sensor Web" AGU Conference Fall meeting San Francisco , CA Dec. 16, 2010.

D. Lary, O. Aulov, A. Rickert "An Objectively Optimized Earth Observing System" Podium Presentation, June 26, 2008, Earth Science Technology Conference (ESTC2008)

Invited Talks:

O. Aulov, M. Halem, "Human Sensor Networks: Information Retrieval of Sensor Data from Heterogeneous Social Media Sources", Colloquium Talk, CSEE UMBC, April 2013

O. Aulov, Human Sensor Networks for Improved Modeling of Natural and Human-Caused Disasters, Colloquium Talk, CSEE UMBC, September 2012

Professional Development Highlights

Lexis-Nexis HPCC Systems Certificate of Completion – Introduction to THOR	March 2012
Lexis-Nexis HPCC Systems Certificate of Completion – Introduction to ECL	March 2012
Intro to Scientific Computing with Python (Enthought)	June 2009
AGI Satellite Toolkit Certification – Recognizing expert knowledge of STK Professional, STK Integration, Terrain, Imagery & Maps, Coverage	January 2007
Computer Security and Information Assurance Graduate Certificate - George Washington University	December 2006

Awards and Honors

Earth Science Informatics Partnership Mini Grant (6 months) - $3,000	2012
IBM Centre For Advanced Studies Research Fellowship (1 year) - $28,000	2011
Earth Science Informatics Partnership Fellow (1 year) - $2,000	2011
ACM Merit Scholarship	2003
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Memberships

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ABSTRACT

Title of Dissertation: RETRIEVING QUANTIFIABLE SOCIAL MEDIA DATA FROM HUMAN SENSOR NETWORKS FOR DISASTER MODELING AND CRISIS MAPPING

Oleg Aulov, Ph.D., 2014

Dissertation directed By: Milton Halem
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This dissertation presents a novel approach that utilizes quantifiable social media data as a human aware, near real-time observing system, coupled with geophysical predictive models for improved response to disasters and extreme events. It shows that social media data has the potential to significantly improve disaster management beyond informing the public, and emphasizes the importance of different roles that social media can play in management, monitoring, modeling and mitigation of natural and human-caused extreme disasters.

In the proposed approach Social Media users are viewed as “human sensors” that are “deployed” in the field, and their posts are considered to be “sensor observations”, thus different social media outlets all together form a Human Sensor Network. We utilized the “human sensor” observations, as boundary value forcings, to show improved geophysical model forecasts of extreme disaster events when

combined with other scientific data such as satellite observations and sensor measurements. Several recent extreme disasters are presented as use case scenarios.

In the case of the Deepwater Horizon oil spill disaster of 2010 that devastated the Gulf of Mexico, the research demonstrates how social media data from Flickr can be used as a boundary forcing condition of GNOME oil spill plume forecast model, and results in an order of magnitude forecast improvement.

In the case of Hurricane Sandy NY/NJ landfall impact of 2012, we demonstrate how the model forecasts, when combined with social media data in a single framework, can be used for near real-time forecast validation, damage assessment and disaster management. Owing to inherent uncertainties in the weather forecasts, the NOAA operational surge model only forecasts the worst-case scenario for flooding from any given hurricane. Geolocated and time-stamped Instagram photos and tweets allow near real-time assessment of the surge levels at different locations, which can validate model forecasts, give timely views of the actual levels of surge, as well as provide an upper bound beyond which the surge did not spread.

Additionally, we developed AsonMaps—a crisis-mapping tool that combines dynamic model forecast outputs with social media observations and physical measurements to define the regions of event impacts.

RETRIEVING QUANTIFIABLE SOCIAL MEDIA DATA FROM HUMAN SENSOR NETWORKS FOR DISASTER MODELING AND CRISIS MAPPING

By

Oleg Aulov

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, Baltimore County, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2014

DEDICATION

To my wife, Erin Aulov

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I thank Rita Rodriguez for awarding us two RAPID NSF grants titled: "An Interactive Human Sensor Web for Improved Model Predictions of the Dispersion of the Deepwater Horizon Gulf Oil Spill", and "Rapid Response for a Human Sensor Aware Fukushima Debris Monitor and Prediction System" without which this dissertation would not have been possible.

I would like to thank my peers Dr. Justin Martineau and Dr. David Chapman for helping me navigate through the various stages of the PhD path.

I would like to thank Dr. CJ Beegle-Krause for the support she provided in understanding the intricate details of the Deepwater Horizon oil spill and for her collaboration with us on proposals on using social media data for oil spill disasters. I would like to thank Dr. Samuel Lomonaco for his help with the Advanced Algorithms class. I thank Dr. John Dorband for providing access to Bluegrit and Bluewave systems, allocating data storage, and helping to resolve compute cluster related problems.

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I would like to thank Ben Kyger for his letters of support, engagement with CHMPR and help with getting in touch with the right people at OR&R.

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I thank Dr. Matthew K. Howard from the Department of Oceanography at Texas A&M University for helping me acquire the winds and currents forecasts in a format suitable for the GNOME oil spill model. I would like to thank Jack Suess, the CIO of UMBC for kindly providing me bridge gap funding for my last semester when all my other grants completely depleted.

I thank my parents for instilling the appreciation for higher education.

I would like to thank my wife, Erin Aulov, for her endless patience and support, her appreciation of my scientific contributions, for proofreading and correcting my papers, making them more readable and less boring, and most of all, for giving me excellent ideas, such as, among others, using Instagram photos for my research.

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INTRODUCTION

Social media has been developing at a very fast pace and is at a stage where there is a live stream of real-time data being shared on social networks. This dissertation presents an approach of collecting quantifiable data from social networks to form a Human Sensor Network (HSN), where the user inputs and devices are viewed as "global sensors" on the planet and their posts as real time geolocated "observations".

Emergency responders have long-established protocols for response management and mitigation. For disaster modeling and risk assessment, they rely on data and geophysical model forecasts collected by other government agencies, and on conventional media outlets for communication of risk and evacuation orders to the public. Only recently have emergency responders begun to utilize Social Media outlets such as Facebook and Twitter for the purpose of communicating urgent information to populations affected by disasters. Physically based ground and satellite sensor observations deployed for potential disasters such as earthquakes, tsunamis, volcanoes, floods, fires, oil spills and even nuclear meltdown events are available to geophysical models in near real time. Currently, the process of harvesting, analyzing and providing spatial and temporal maps from a variety of online social media products available with geolocated features in near real-time to first responders during and after extreme weather events for mitigating the economic and human is non-existent operationally. The flow of information from social media users to the emergency responders is presently in its infancy and in the early stages of research. This dissertation presents methods and frameworks that would allow Emergency Responders to "listen" to the affected public by monitoring Social Media outlets for posts related to the disaster at hand. This approach is invaluable in providing Emergency Responders with timely situational awareness, 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 is also useful in validating the forecasts of risk assessment and geophysical models.

As use-case scenarios, we focus on natural and human-caused disasters such as The Deepwater Horizon oil spill that caused tremendous environmental damage, the Tohoku earthquake and tsunami that resulted in the Fukushima nuclear disaster, the Hurricane Sandy that has devastated the Atlantic coast of the United States and Typhoon Haiyan that has devastated the Philippines.

For the Hurricane Sandy use case scenario over 8 million tweets and around 370 thousand Instagram images referencing hurricane Sandy were collected. For the use-case of Typhoon Haiyan around 900 thousand tweets and over 150 thousand Instagram images were collected. For the Deepwater Horizon oil spill, over 900 photos were collected from Flickr photo sharing social media platform.

Viewing Social Media data as a Human Sensor Network allows us to extract images and named entities as quantifiable geolocated, time stamped sensor observations. We use these observational data to validate geophysical model forecasts during extreme events such as hurricanes, tsunamis and aerosol distributions from fires and volcanic eruptions.

As a result of this research, we developed a heterogeneous, near real-time human sensor web engine called AsonMaps that uses streaming APIs of different social media outlets to harvest posts related to disasters.

1.1 FORMAL THESIS STATEMENT

Quantifiable information from streams of social media data can serve as a real-time, situation aware human sensor network during and after natural and human caused extreme disasters for the purpose of assimilation of social media observations into geophysical models to improve forecasts and to generate locally resolved event driven real-time model output products to address improvements in mitigating the economic and human life toll. .

1.2 CONTRIBUTIONS

This section lists the computational scientific contributions of this dissertation from both a theoretical and applied perspective. Our contributions are:

- Implementing a prototype concept of a Human Sensor Network in which social media posts are viewed as sensor observations and a variety of different social media data sets are acquired and analyzed in near real time following and during real case extreme disasters.
- Studied the use-case scenario of the Deepwater Horizon oil spill disaster of 2010 and presented methods of extracting quantifiable geolocated and time-stamped beached oil observations to be used with the General NOAA Operational Modeling Environment (GNOME) to improve the oil spill plume

movement forecast based on the quantifiable information obtained from the social media data to better determine the uncertainties in model parameters.

- Demonstrated the potential of using social media data for near real-time validation of geophysical model forecasts of storm surges and resulting flooding by studying the use case of the Hurricane Sandy of 2012 that devastated the Atlantic coast.
- Developed and deployed the AsonMaps platform for visualization of social media data and geophysical model forecasts in a single framework that allows coupling geophysical model forecasts with Human Sensor Network observations from social media data and street level mapping information from Google Maps anywhere in the world.
- Generated scripts for semiautomatic near real-time collection and aggregation into BigCouch database of the live stream of social media data from Instagram and Twitter that is ready to be tested in real time during the next disaster.
- Developed the search and sub-setting capability of AsonMaps by implementing ElasticSearch on the CHMPR IBM iDataPlex 'Bluewave' cluster for indexing and filtering of the social media data and have also deployed AsonMaps platform across a 6 node iDataPlex cluster with InfiniBand network for scalability and operational testing of the platform during future live disaster events.
- Showed that AsonMaps capability of invoking geophysical disaster models can be used to validate forecasts using USGS sensor data as well as quantifiable social media data.

1.3 MOTIVATION

In this section, we explain the motivation behind the proposed work as well as potential and real scenarios where the contribution of our research could be invaluable. We use the same definition of "disaster" that is used by FEMA and the community at large. Disaster is "[a]n event that requires resources beyond the capability of a community and requires a multiple agency response". In general, disaster goes through stages of mitigation, preparedness, response, and recovery [1], [2].

In the past decade, the world consistently experienced about 400 disasters a year. According to Peduzzi [3], since the 1900s, there was an exponential increase in the number of disasters, as can be seen on Figure 1 below.

This increase can be attributed to population growth, improvements in information recording and access, or changes in the occurrences of extreme weather events or climate change (such as global warming). Regardless of the exact reasons, people and ecosystems all over the world face dangers to their life, health, property and sustenance. To list just the recent few extreme events in the past three years, consider: Hurricane Sandy in October 2012, which devastated Northeastern United States, portions of the Caribbean, and the Mid-Atlantic, with a cost estimated at 71.3 billion dollars [4]; and the Tōhoku earthquake in 2011 off the coast of Japan and resulting tsunami, which caused 15,870 deaths, with an estimated economic cost of 235 billion US dollars. According to the World Bank report, this was the most expensive natural disaster in world history. The Earthquake and Tsunami caused the Fukushima Daiichi nuclear meltdown disaster—the biggest since Chernobyl—which

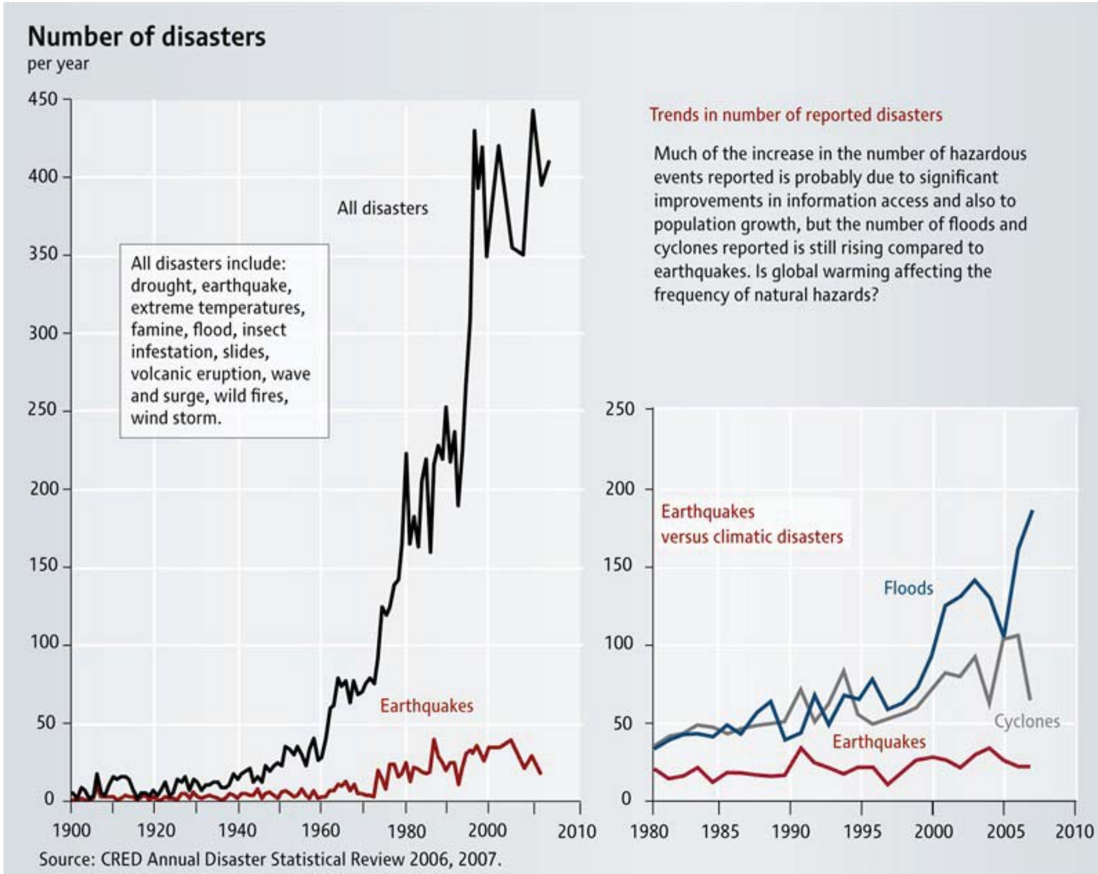


Figure 1 - Trends in number of reported disasters. Peduzzi [3]

resulted in three reactor meltdowns and enormous quantities of radioactive material being leaked into the environment. The list of recent disasters continues with the 2010 Deepwater Horizon oil spill, the 2010 Haiti earthquake, the 2010 eruptions of Eyjafjallajökull volcano, and others.

Red Cross/Red Crescent Emergency Response and Disaster Management Resource Center breaks down the disasters by categories into biological—such as epidemic outbreaks; geophysical–such as earthquakes and landslides; climatological—such as heat waves and droughts; hydrological—such as avalanches and floods; technological—such as blackouts; complex/manmade—such as terrorist attacks; and meteorological—such as tropical cyclones. These designations are

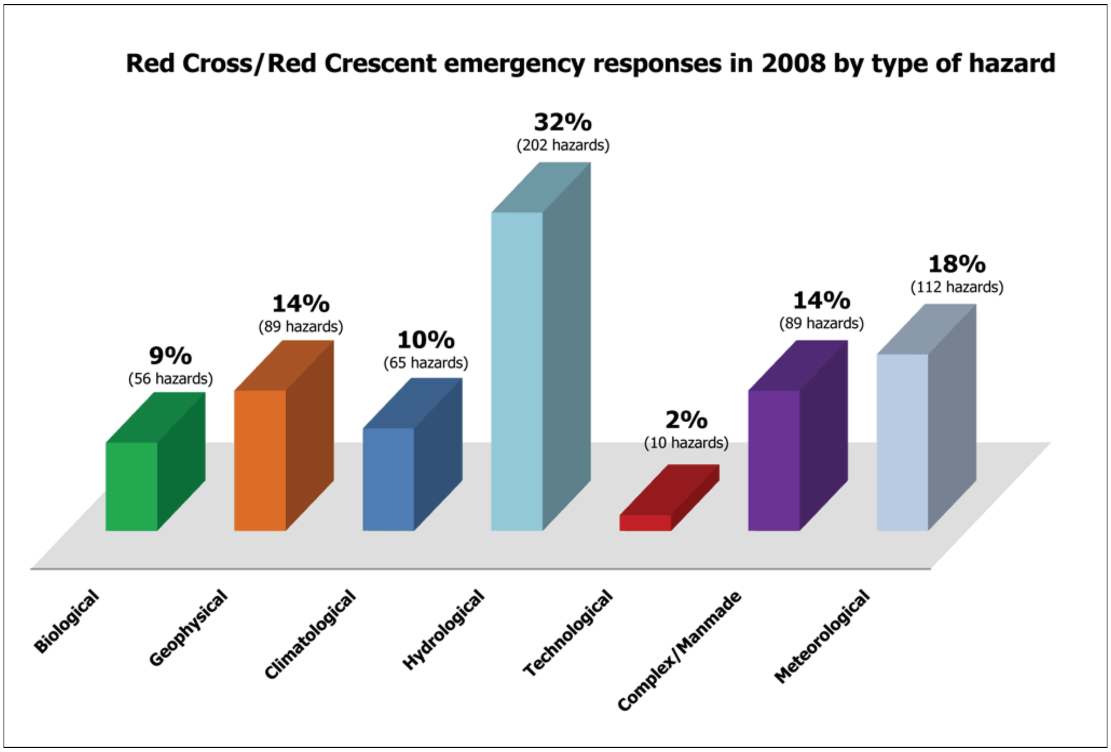


Figure 2 - Disaster related statistics from Red Cross and Red Crescent Societies. Total number of disasters between 2004 and 2008: 1574

shown in Figure 2 above. Hydro-meteorological disasters account for half of all these disasters.

In the past decade we have witnessed the development of disruptive communication technology at a revolutionary rate. In the late nineties websites started deploying technology beyond static pages, and the term "Web 2.0" was coined. Since then, we experienced rapid social media development and now have dozens of sites hosting petabytes of user generated data. The evolution of social media is so rapid that the scientific community is struggling to keep up with mining its data anywhere beyond the mere surface.

During the September 11 terrorist attacks, many people relied on SMS text messaging and pagers for communication. Now – just over ten years later – social media users Tweet and post photos on Instagram in real time from their smartphones

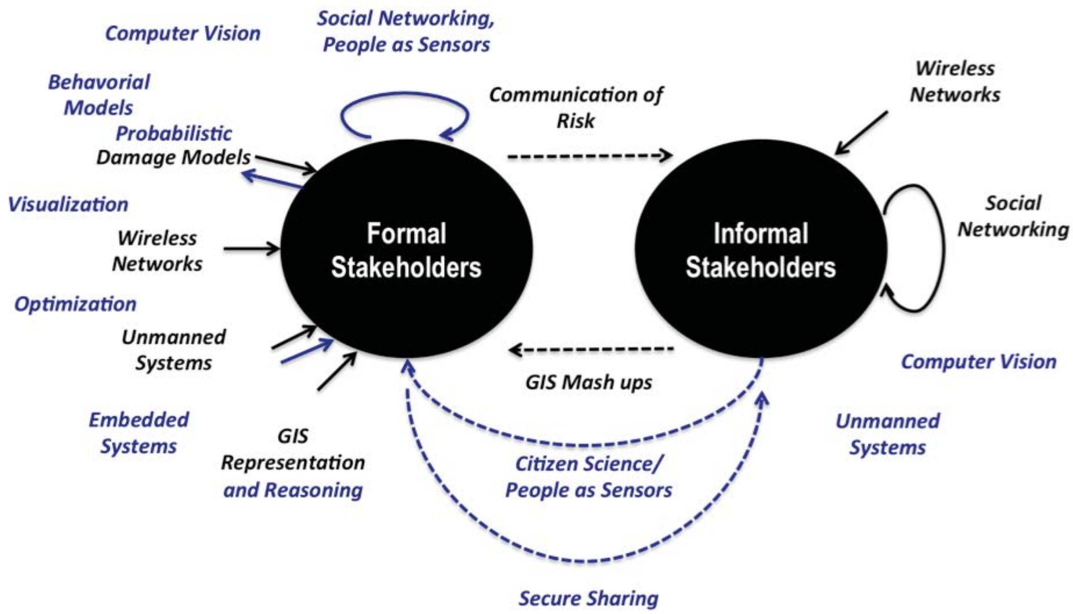


Figure 3 - Illustration from the "Computing for Disasters" report that shows possible data processing improvements that can result from advances in computing [1].

and tablets. Although the primary purpose of such online activity is social interaction between friends, traditional media outlets now look to social media to improve their reporting and get hints about newsworthy events, and corporations use social media to promote their products and increasingly mine it to get insights on public perception and satisfaction with their products. Unfortunately, the use of social media for disaster management is in its infancy.

In April of 2012, the Computing Community Consortium (CCC) held the Visioning Workshop on behalf of NSF and submitted an executive summary report on “Computing for Disaster Management” to the CISE Director. The report recommendations call for fundamental new research in socio-technical systems “to harness the opportunities offered by the spread of new classes of devices, sensors, networks and social media. The needed research investigation will encompass multiple diverse disciplines and will have to address significant challenges of scale complexity and uncertainty" [1], [5]. The report also stipulates that a holistic approach to disaster modeling is needed where there are strong ties of communication between the formal and informal stakeholders (government agencies vs. citizens), as can be seen in the Figure 3 borrowed from the report.

In the past few years, the United States government has expressed increased interest in exploring the use of social media in disaster management not just passively, as a means to disseminate information, but also actively, by using the unique tools of social media to allow emergency responders to communicate directly with disaster victims, and to increase situational awareness by observing user activities during disaster situations.

On September 6, 2011, the Congressional Research Service prepared a resource document for members of Congress entitled "Social Media and Disasters: Current Uses, Future Options, and Policy Considerations." In this document, the researchers express that while currently social media is considered merely an additional tool for emergency management, as the use of social media becomes more and more mainstream, citizens will increasingly expect FEMA and other agencies to communicate in this way. Additionally, the report recognizes that social media has the potential to open up lines of communication that other forms of media do not allow, and can be accessed even when other forms of media are unavailable due to power outages, etc. [5].

On June 4, 2013, the House Homeland Security subcommittee on emergency preparedness, response, and communications held a hearing surrounding the use of social media as a tool during natural and man-made disasters. In this hearing, committee members recognized that social media is no longer just one means of communicating, but is quickly becoming a primary means of communicating and receiving information. Noting the importance of these media during situations like the Hurricane Sandy, the Boston Marathon bombings of 2013 and the 2013 tornadoes in the Midwest, members of the committee expressed interest in utilizing these media more efficiently in order to reduce damages, prevent loss of life, effectively manage the immediate aftermath of the event, and plan for the rebuilding [6].

In both instances, officials acknowledged that many of the potential applications of social media to disaster management were merely speculative, while others have little substantiated evidence because they are only recently being explored [7]. Because of this, many emergency management organizations have continued with passive use of the media to disseminate information, and not explored its full potential as an efficient disaster management tool.

1.4 HARVESTING SOCIAL MEDIA AND GEOPHYSICAL DATASETS

To conduct the experiments in support of the thesis statement, we collected social media data and geophysical data related to a number of distinct types of extreme disaster events.

The first dataset was in support of studying the use of social media data during the Deepwater Horizon oil spill. We obtained the wind fields from NCDC that were generated by the NCEP eta regional forecast model and the ocean current data from the ROM ocean model. The surface winds and ocean surface currents data were retrieved from the repository of the Department of Oceanography at Texas A&M University. We retrieved the USGS shoreline data of the Gulf of Mexico area from the Coastline Database hosted at NOAA's National Geophysical Data Center. We used NOAA/NOS medium resolution coastline data designed for 1:70,000 scales. Chapter 5 provides more details about the collection of this dataset.

In anticipation of landfall from Hurricane Sandy, we have collected over 8 million tweets and around 370 thousand Instagram images referencing Hurricane Sandy including all the metadata related to the user, including the "likes" and the "comments"; and over 900 thousand tweets and over 150 thousand Instagram images referencing Typhoon Haiyan. Twitter is very restrictive with access to historic data and only goes back a few days; as a result we used their real-time streaming API to collect the tweets. 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". For Typhoon Haiyan, we started collecting tweets mentioning the words "typhoon", "haiyan", "yolanda", "yolandaph" on November 6th, 2013 at 9pm and stopped on November 11th.

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, and related to typhoon querying the words "typhoon", "typhoonhaiyan", "typhoonyolanda".

Additionally, we collected other minor Twitter and Instagram datasets that could be useful in future studies. A few noteworthy datasets include tweets mentioning Hurricane Sandy during the 1-year anniversary (#sandyyearlater), and tweets and photos of several snowstorms that affected the greater Washington, DC area.

It is important to note that with such an abundant amount of data available for mining from social media, inadvertently there will be data points that provide false information. For example, during Hurricane Sandy a popular photoshopped image of a baby shark swimming next to someone's front porch was circulating in the social media outlets and was even covered by several TV news channels. Although such cases fall beyond the scope of this dissertation, other researchers are already developing algorithms for detection of such false information [8].

Chapter 2

RELATED WORK

This section provides a summary of related work that includes a variety of projects that successfully used social media to observe and study different geophysical phenomena as well as some traditional sources of sensor observations.

2.1 TWITTER EARTHQUAKE DETECTOR

Many examples have been noted of individuals tweeting about experiencing an earthquake even before media outlets received official reports of the event. Tweets about an earthquake experienced, appear within seconds of the event, as opposed to official scientific reports that can take up to 20 minutes, depending on the location of

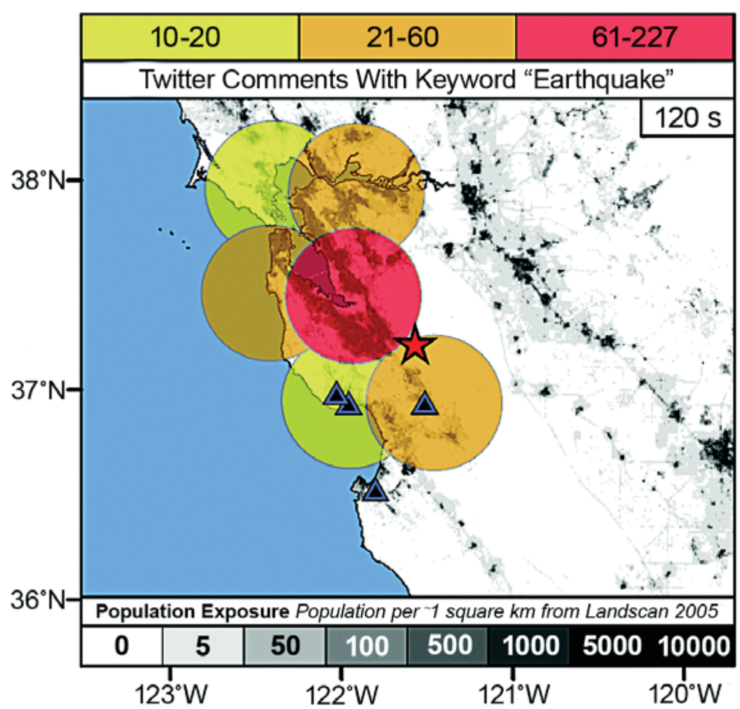


Figure 4 - Screenshot of Twitter Earthquake Detector (TED). Red star indicates the epicenter while circles of different color indicate the frequency of tweets. Note that the red circle is in the area of the highest population rather then around the epicenter.

the earthquake. In response to this trend, U.S. Geological Survey (USGS) developed a Twitter Earthquake Detector (TED) [9]. TED is a system that gathers in real time tweets related to earthquakes, and processes them to provide geolocated areas where people felt shaking. It can potentially improve the earthquake response products as well as hazard information gathering and delivery and could therefore improve the effectiveness of emergency response efforts. Figure 4 shows a snapshot of TED in action displaying a map of the San Francisco, CA area. Different colors of circles indicate frequency of tweets in that area that include the word Earthquake.

2.2 AIRTWITTER

In the past decade, there has been a trend online to create mashups. Mashups are web-based applications that combine together or heavily rely on multiple other

Figure 5 - Screenshot of Air Twitter Mashup displaying air quality related twitter feed.

web-based applications to create a new type of application. AirTwitter is one such mashup application that monitors social media data, identifies air-quality and pollution-related events, and records and monitors this information. AirTwitter aggregates RSS feeds from different social media sites such as Twitter, YouTube, Flickr, Delicious, and others. It processes the data to weed out all the feeds unrelated to air quality. Then, it establishes a baseline of normal frequency of air-quality data. As a result, AirTwitter provides an aggregated, preprocessed, single feed of data with the ability to detect the air-quality-related events, such as volcano eruptions and forest fires as shown on Figure 5 [10].

2.3 #UKSNOW MAP

This Google Maps/Twitter mashup online application, called #uksnow Map,

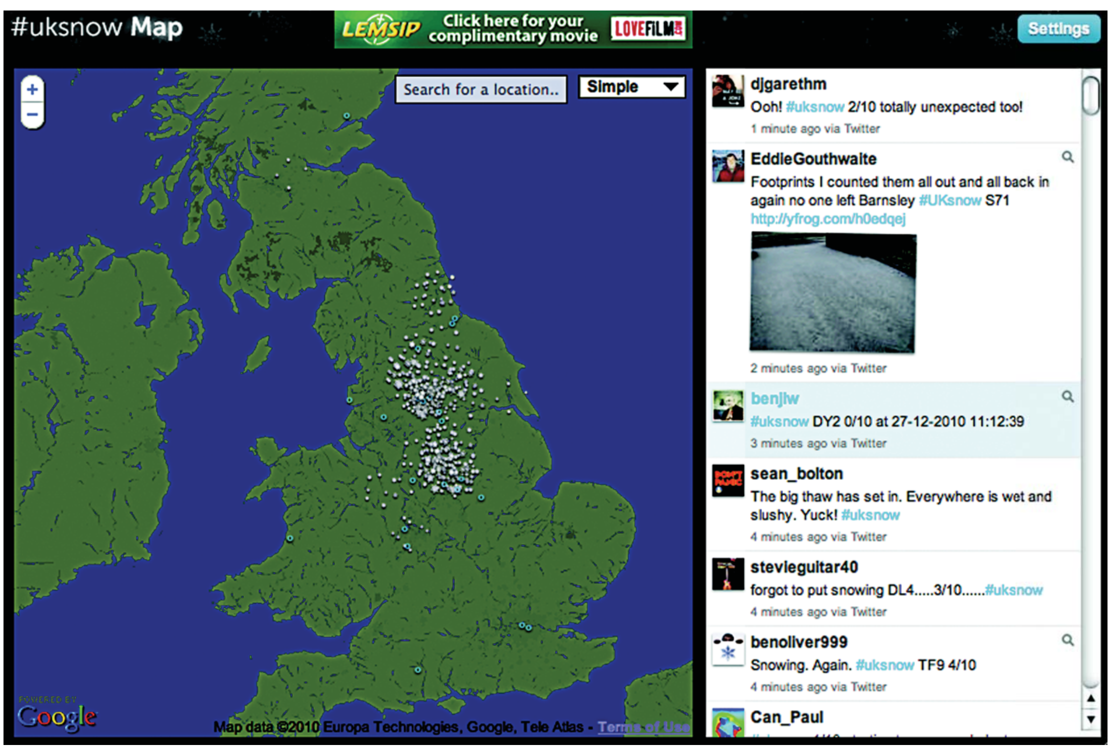


Figure 6 - #uksnow Map. Google Map on the left with white circles of varying size indicating snow conditions. Tweet feed on the right listing tweets that were used to generate the map.

tracks in real time snow reports and displays them on the map. The pound sign in the beginning of the name is a pun on the twitter hash tag used for this application. #uksnow Map is based on crowdsourcing. In this mashup, Twitter users are asked to report about the snow conditions in their area. Tweets should include the #uksnow hashtag, location, and snow rating on a scale from 0 to 10. The location is represented as a postal code, a town name, or a Twitter geotag (latitude and longitude). The snow scale is very loose—the snow is rated as 0 for no snow at all, 1–2 for a few flakes, 5 for a steady snow, and 10 for a blizzard. Attaching photos and including the depth of the snow is also encouraged. The application keeps track of tweets tagged with the #uksnow tag and displays them on a Google Maps map in real time. Figure 6 demonstrates a screenshot of #uksnow Map. On the left portion of the screen is a Google Maps window zoomed into the United Kingdom. Superimposed white circles of varying diameter indicate the intensity of the snow. On the right section of the screen is a live tweet feed that is used to generate the map in real time [11].

2.4 INTERACTION WITH THE AFFECTED POPULATION

In [12] Yefeng et al. presented the MobiQ platform that they developed. This platform allows users to pose questions of geo-temporal importance, such as whether the line is very long at a certain business establishment at the moment, or whether there are any seats left at a social event. MobiQ forwards the question to several Weibo users that, based on their recent posts, are likely to be in the area and know the answer. The replies are then aggregated and presented to the inquiring user. Such a system can also be used in disasters to determine whether neighborhoods lost power, or certain intersections got flooded.

Neubig, et al., in the wake of the 2011 Tohoku earthquake and tsunami in Japan, developed a system based on Named Entity Recognizers and NLP algorithms to mine Twitter for names of people affected by the disaster and assess the status of their safety. The information was aggregated in a central repository for the purpose of helping the relatives find their loved ones and for disaster mitigation tasks [13].

In [14], [15] Goolsby et al. lay down the concept of Crisis Community Maps. The paper covers in depth a variety of quickly forming social media communities that emerged as a result of crises such as the terrorist attacks in Mumbai in 2008 and 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. Information flow and information isolation between different layers of organizations and public are described.

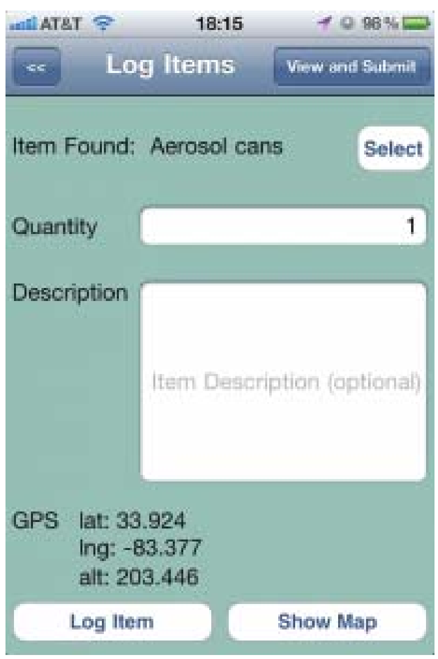


Figure 7 - Screenshot of the Debris Tracker iPhone App. On the bottom of the screen the automatically included GPS position can be seen.

2.5 MARINE DEBRIS TRACKER MOBILE APP

Marine Debris Tracker Mobile App is an app for both iOS and Android devices that was developed by University of Georgia's Southeast Atlantic Marine Debris Initiative in collaboration with NOAA Marine Debris Division. This citizen science app allows users to easily track and upload sightings of debris on the coastlines. The app provides a list of common debris classifiers and automatically geotags the submitted information using the Phone's GPS. Figure 7 shows the screenshot of the Debris Tracker iPhone app. All the submissions are aggregated on the Marine Debris Tracker Website - www.marinedebris.engr.uga.edu/data [16]. Figure 8 shows the screenshot of the Debris Tracker web application that overlays the aggregated debris reports on a Google Maps map.

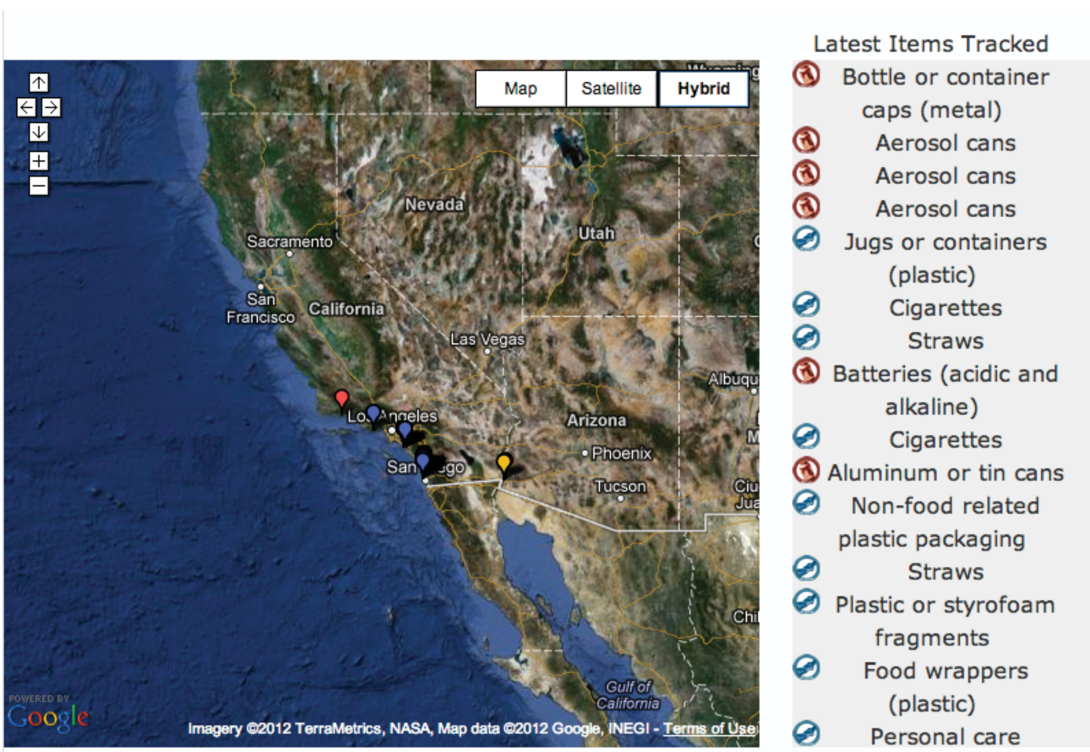


Figure 8 - Screenshot of the Web App of the aggregator part of the debris tracker. Google map is shown with some user uploaded sightings locations.

2.6 LITMUS: LANDSLIDE DETECTION BY INTEGRATING MULTIPLE SOURCES

Musaev et al. from Georgia Institute of Technology developed a landslide detection system that relies on heterogeneous sources of data such as USGS seismic network data, NASA rainfall data and various social media sources. The data from social media sources is processed in a series of steps including keyword filtering, named entity recognition and geolocation and is combined with the USGS and NASA data to produce a list of detected landslides [17]. Figure 9 demonstrates the screenshot of the LITMUS produced map.

2.7 GOOGLE CRISIS RESPONSE

Google has been committed to providing support to emergency responders and the public since Hurricane Katrina of 2005 by providing a variety of tools that allow them to utilize Google frameworks to improve disaster response and mitigation.

Figure 9 - LITMUS Landslide Information System

A non-exhaustive list includes Google Person Finder that during disasters helps emergency responders and the affected population to locate missing people and to reconnect those that got separated. Google Public Alerts is a platform for dissemination of emergency related alerts based on the threat location relative to the user location. Google Crisis Map is a mapping platform based on Google Maps that presents important crisis related information from a variety of sources on a single interactive map. Figure 10 shows a screenshot of the Google Crisis Map showing the path of Hurricane Sandy in a light blue overlay. Orange markers indicate power outage areas as reported by the power companies [18].

2.8 SATELLITE OBSERVATIONS DURING DISASTERS

One of NASA's Earth Science Data Systems Program's products is the Land

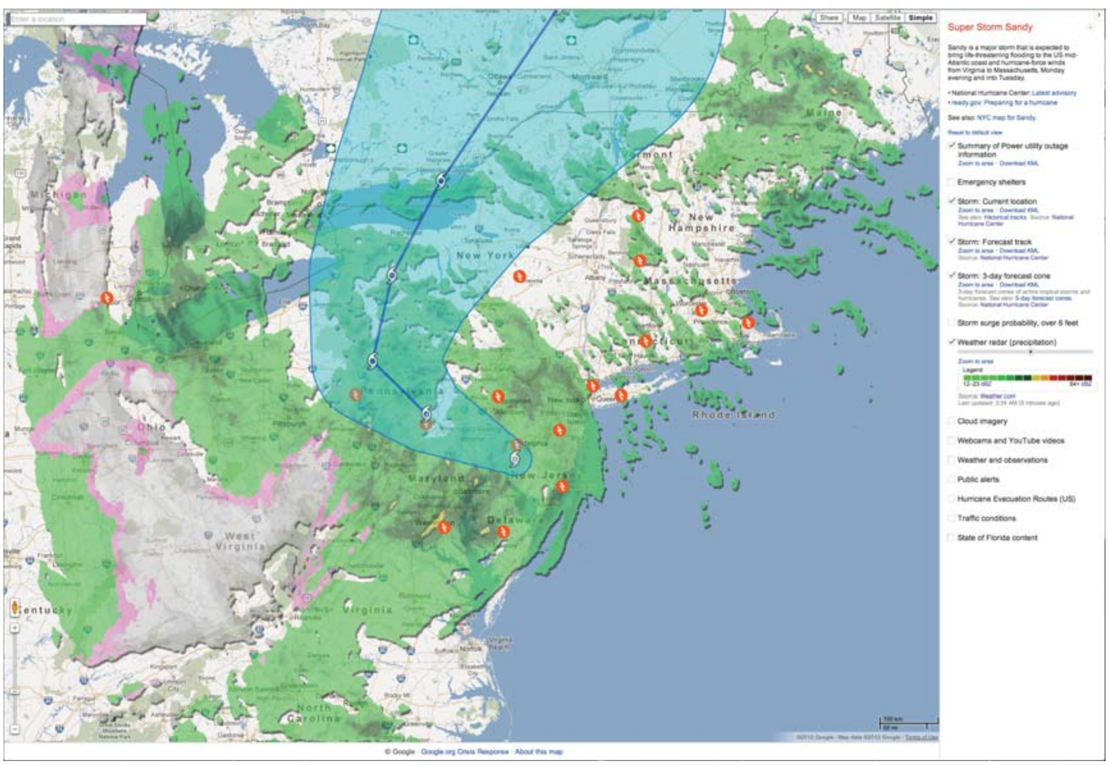


Figure 10 - Google Crisis Map screenshot showing the path of Hurricane Sandy and the locations of the power outages reported by the power companies.

Atmosphere Near real-time Capability for EOS (LANCE). LANCE consists of data products from MODIS, OMI, AIRS, and MLS that are available within 3 hours from observation and is useful for forecasters and emergency responders in cases of disasters [19].

Chapter 3

STATE OF THE ART IN DISASTER MODELING AND FORECASTING

The following chapter describes geophysical models that are operationally deployed for specific extreme events. We describe these models and show how we either have or are currently conducting studies to assimilate social media data to improve their forecast skills.

3.1 GNOME MODEL

For the purposes of oil spill plume movement prediction on the surface of the ocean, NOAA's Emergency Response Division (ERD) of the Office of Response and Restoration (OR&R) employs a geophysical model called GNOME, which stands for General NOAA Operational Modeling Environment. GNOME was extensively used for issuing daily operational oil spill forecasts during the devastating disaster of the Deepwater Horizon oil spill. The model uses surface winds, surface ocean currents, and other processes as input to predict the movement and spread of oil on the ocean surface as well as how the predicted oil trajectories might reach coastal beaches and islands. The model is affected by uncertainty in currents and winds observations and forecasts as well as by the rate of oil spill and the thickness of oil reaching the surface of the ocean. GNOME also has the capability of predicting the weathering behavior of pollutants. The model is initialized by setting up a spill scenario that takes as an input the shoreline, surface winds, surface ocean currents/tides, and the observed location of oil plumes on the surface of the ocean. As an output, GNOME produces an animation of how the plume moves, mixes, and weathers over time as well as a batch file with a series of data points representing time series of predicted locations of oil particles. In its core, GNOME software uses basic Lagrangian-Eulerian particle tracking algorithms [20], [21], [22]. The area of interest is divided into a grid and a certain user-defined amount of oil in each cell is viewed as a single granule [Lagrangian element (LE)] that is influenced by the velocities of the universal movers such as winds and currents. The output of the GNOME model represents the LE of the spilled oil trajectory as splots (spill dots). Black splots represent the best guess trajectory estimate and red splots represent the minimum regret. Best guess trajectories are calculated under the assumption that the winds and currents data accurately represent the actual winds and currents over the period of the scenario, and that the initial input of splots representing the observed location of the sheen of oil from satellite updates are accurate as well. The best guess forecast trajectory takes into account the turbulence that is inherent in the surface winds and ocean surface currents. Red splots, on the other hand, represent the minimum regret trajectory. Minimum regret trajectory takes into account the inherent uncertainty of the winds and ocean currents models and specifies the boundary beyond which there is a high probability that the oil will not propagate (probability in the order of 90%). Minimum regret trajectories are useful for purposes of indicating trajectory uncertainties that are less probable than the best guess trajectory, but that may be potentially more destructive [23], [24], [25]. Figure 11 demonstrates the GNOME model initialized with the coastline of the Gulf of Mexico. Purple arrows visualize the surface currents. The red and black areas are splots of minimum regret and best guess forecasts.

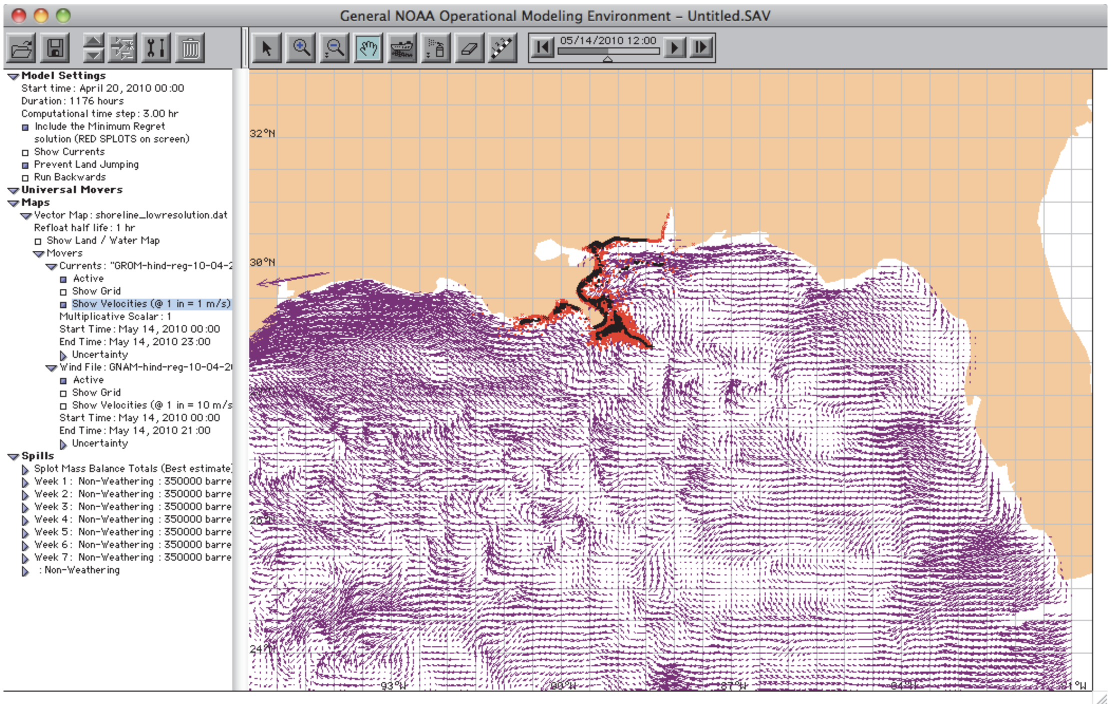


Figure 11 - Screenshot of GNOME initialized with surface winds, ocean currents and coastline data for Deepwater Horizon oil spill scenario.

GNOME has a few parameters that are adjustable by the user and are generally set experimentally. Those parameters include number of splots per spill, windage percentage range for each spill, pollutant release rate, along- and cross-current uncertainty percentage, wind speed scale, and total wind angle scale.

In its core GNOME uses basic Lagrangian-Eulerian equations. We assume that the thickness of the oil slick on the surface of the ocean is negligible in comparison to the thickness of the water [23], [24], [25]. The governing equations for the movement of the oil slick in the 3-D space x, y, z over time t are:

$$\frac{\partial C_s}{\partial t}+\frac{\partial}{\partial x}(u_s C_s)+\frac{\partial}{\partial y}(v_s C_s)=\frac{\partial}{\partial z}\left(K_x\frac{\partial C_s}{\partial x}\right)+\frac{\partial}{\partial y}\left(K_y\frac{\partial C_s}{\partial y}\right)+\left(\alpha_1 v_b C_v+K_z\frac{\partial C_s}{\partial z}\right)-\gamma C_s-S_e-S_d+M_s(x,y)-D_s(x,y)$$

C_s is the concentration of oil on the surface of water;

C_v is the volume of oil concentration in the suspended layer per volume of water

u, v, w are components of surface current velocity;

α_l is the coefficient of the probability of an oil droplet reaching the surface

γ is the surface oil dispersion coefficient

u_s, v_s are the components of the drift velocity

K is the diffusion coefficient in the respective direction

v_b is the buoyant velocity of the suspended oil parcels

S_e is the rate of evaporation

S_d is the rate of dissolution

M_s is the effect on the distribution of the surface oil due to the mechanical spreading;

D_s is the effect on the distribution of surface oil due to the shoreline deposition [25]. According to Reddy, advection is the main mechanism that governs the drifting of the suspended oil and the surface oil slick. The drift velocities u_s, v_s are considered a weighed combination of the velocity of the surface currents with the velocity of the surface winds. The weighting parameters that are generally used to combine the air surface winds and the ocean currents are:

$$0.03v_a + 1.1v_c = v_s \quad [23]$$

3.2 SLOSH MODEL

For the purposes of storm surge forecasting, analysis and evacuation planning, the National Hurricane Center (NHC), National Weather Service (NWS) and Federal Emergency Management Administration (FEMA) employ a computerized numerical model called SLOSH which stands for Sea, Lake and Overland Surges from Hurricanes.

As an input, SLOSH uses storm track, radius of maximum winds and the pressure difference between the storm and the rest of the environment, as well as the topographic and bathymetric data for the basin of interest, and as an output predicts the level of surge at each grid cell of the area of interest. Since it is a lot more important to have a higher resolution forecast around the coastal area than in the open ocean, SLOSH uses a polar or an elliptic/hyperbolic grid as seen on the example image on Figure 12 below.

Surge modeling is deterministic in nature and can generate very accurate forecasts, given an accurate hurricane forecast and precise landfall location. Since the NHC cannot predict where exactly 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.

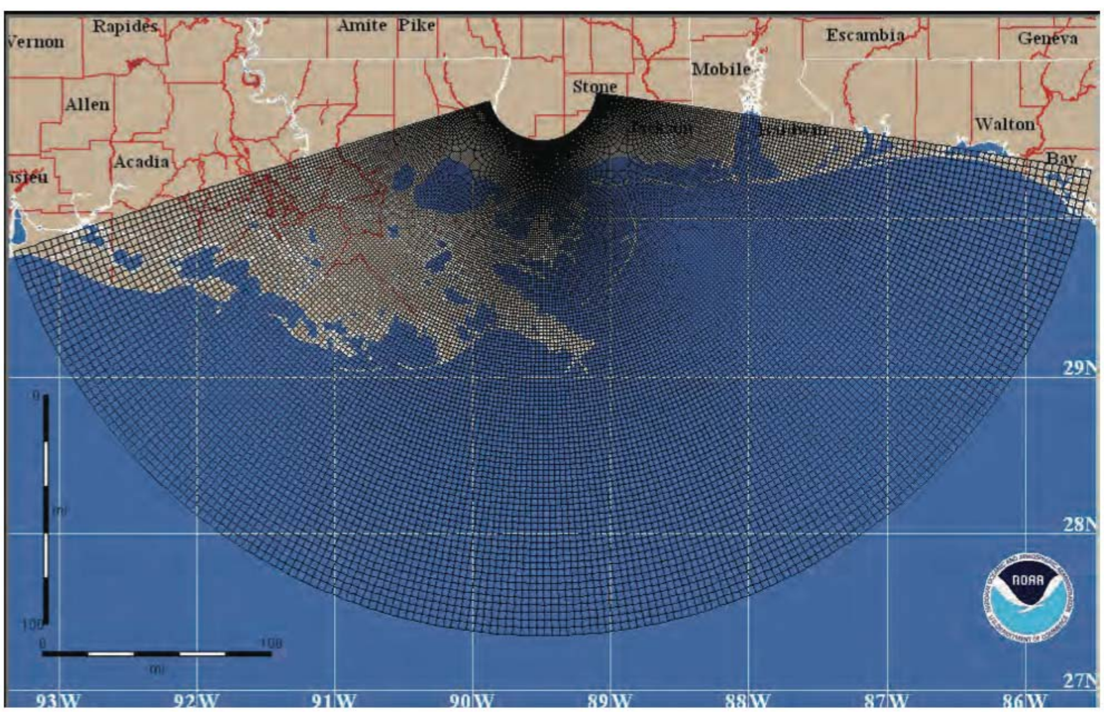


Figure 12 - Screenshot of SLOSH model scenario initialized for the New Orleans area. The grid cells noticeably get smaller and smaller closer to the shoreline, thus providing finer forecast resolution.

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 model does not take into account rainfall or river overflows, and is strongly affected by the uncertainty of its input data, which is often very sparse and inaccurate. Water levels are affected by tides and waves, and the size of grid cells are in the order of kilometers. In order to overcome the shortcomings of a single deterministic surge forecast run, thousands of SLOSH model runs are executed with different input parameters and different hurricane categories to produce, as a result, two composite products – MEOW (Maximum Envelope of Water), MOM (Maximum of MOEWs) as shown in the example in Figure 13.

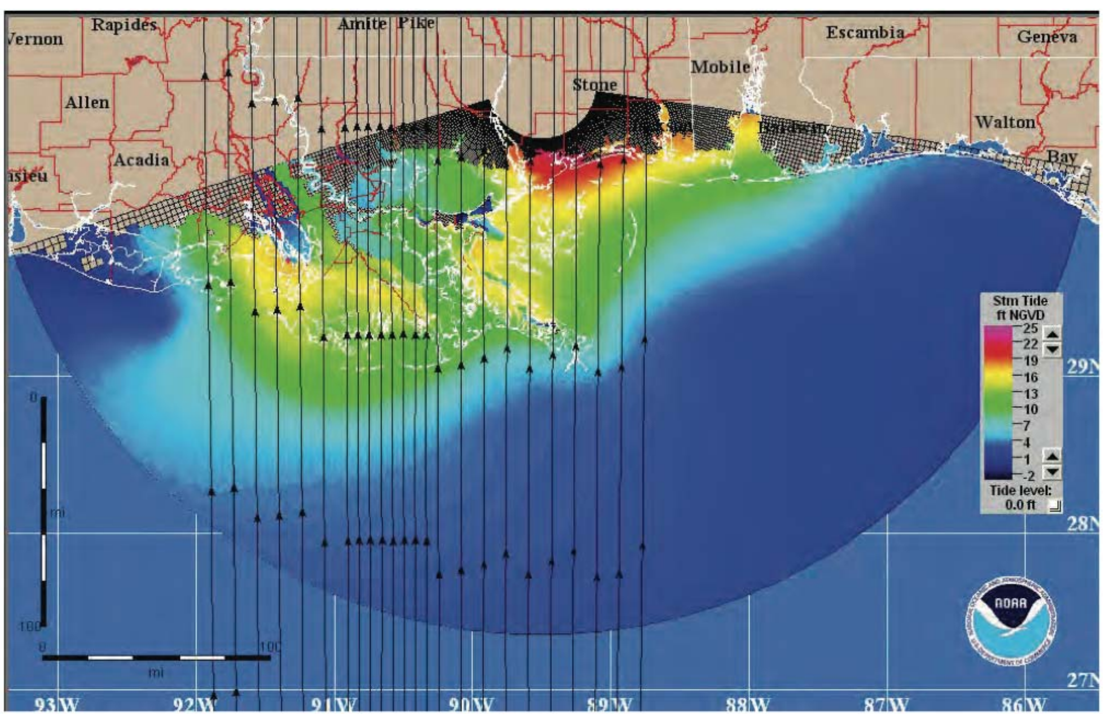


Figure 13 - Screenshot of SLOSH model scenario initialized for the New Orleans area. Displaying the MEOW analysis. The lines indicate possible hurricane path and the color code different level of surge.

Since it is uncertain where exactly a hurricane will make landfall, SLOSH is run multiple times for each hurricane category and forward speed with parallel hurricane tracks, and as a result produces an output of a single MEOW that displays for each grid cell the highest water level the model produced from all the runs. Thus, a single MEOW is generated for a hurricane of a given category and forward speed, tide level and direction. MOM is a composite of all the MEOWs with different forward speeds, tide levels and directions, but same hurricane category; thus each hurricane category will have its own MOM composite product. The purpose of these two composite products is to provide a manageable amount of information for evacuation planning [26].

SLOSH was developed in 1992 by Jelesnianski et al. [26], [27] and is essentially based on the transport equations developed by Platzman in 1963 [28]. The governing equations are as follows:

$$\frac{\partial U}{\partial t} = -g(D+h)\left[B_r \frac{\partial (h-h_0)}{\partial x} - B_i \frac{\partial (h-h_0)}{\partial y}\right] + f(A_r V + A_i U) + C_r^{x_\tau} - C_i^{y_\tau}$$

$$\frac{\partial V}{\partial t} = -g(D+h)\left[B_r \frac{\partial (h-h_0)}{\partial y} - B_i \frac{\partial (h-h_0)}{\partial x}\right] + f(A_r U + A_i V) + C_r^{y_\tau} - C_i^{x_\tau}$$

$$\frac{\partial h}{\partial t} = -\frac{\partial U}{\partial x} - \frac{\partial V}{\partial y}$$

where:

U,V = components of transport

g = gravitational constant

D = relative depth of quiescent water

h = relative height of water

h_0 = hydrostatic water height

f = Coriolis parameter

x_τ, y_τ = components of surface stress

$A_r, \ldots C_i$ = bottom stress terms

3.3 ADVANCED 3-D CIRCULATION MODEL (ADCIRC)

ADCIRC is a finite-element-based 3-D numerical circulation model initially developed by U.S. Army Corps of Engineers and the US Navy to predict sea surface elevation and circulation in coastal areas, and is used, among other things, for flooding and pollutant transport forecasts and studies. Unlike SLOSH, ADCIRC works at a significantly higher resolution and at the same time is capable of generating forecasts over large computational domains [29].

The model is driven by the inputs of surface winds, ocean currents, tides and

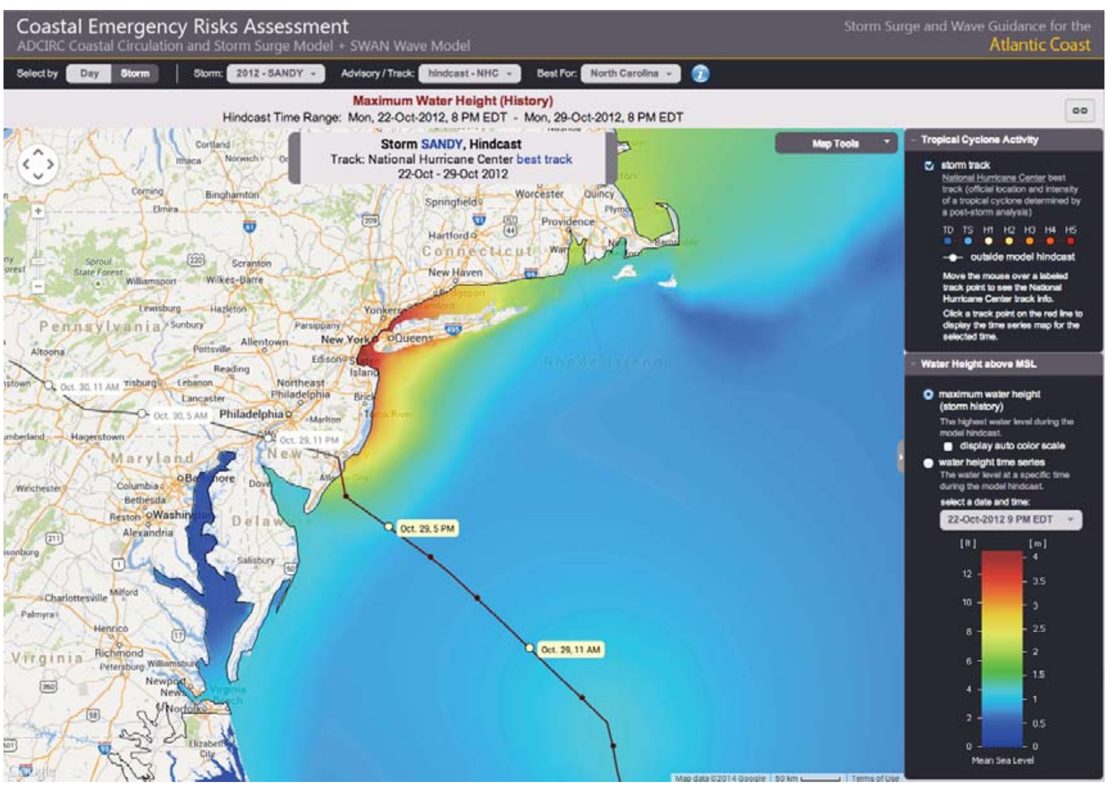


Figure 14 - Screenshot of the CERA webpage showing the ADCIRC forecast for Hurricane Sandy on an interactive map

atmospheric pressure.

The governing equations of ADCIRC model are based on 3-D near-horizontal Cartesian coordinate equations as follows:

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} = 0$$

$$\frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} + w\frac{\partial u}{\partial z} - fv = -\frac{\partial}{\partial x}\left[\frac{p}{\rho_0} - \Gamma\right] + \frac{1}{\rho_0}\left[\frac{\partial \tau_{xx}}{\partial x} + \frac{\partial \tau_{yx}}{\partial y} + \frac{\partial \tau_{zx}}{\partial z}\right]$$

$$\frac{\partial v}{\partial t} + u\frac{\partial v}{\partial x} + v\frac{\partial v}{\partial y} + w\frac{\partial v}{\partial z} - fu = -\frac{\partial}{\partial y}\left[\frac{p}{\rho_0} - \Gamma\right] + \frac{1}{\rho_0}\left[\frac{\partial \tau_{xy}}{\partial x} + \frac{\partial \tau_{yy}}{\partial y} + \frac{\partial \tau_{zy}}{\partial z}\right]$$

where:

f - Coriolis parameter

g - acceleration due to gravity

Γ - tide generating potential

ν - molecular viscosity

p(x,y,z,t) - time-averaged pressure

ρ(x,y,z,t) - density of water

ρ_0 - reference density of water

t – time

Figure 14 shows a screenshot of a Coastal Emergency Risks Assessment (CERA) group’s website overlaying the ADCIRC model forecast for Hurricane Sandy on an interactive map. The purpose of the mapping tool is to provide emergency responders a tool for situational awareness in times of hurricanes.

3.4 ATMOSPHERIC DISPERSION MODEL

Atmospheric dispersion model is a geophysical model that is used to forecast the fate of air pollutants (i.e. movement and dispersion) in the atmosphere. One popular model that is used by NOAA is HYSPLIT. The HYSPLIT (Hybrid Single-Particle Lagrangian Integrated Trajectory) model is a complete system for computing simple air parcel trajectories to complex dispersion and deposition simulations. It computes the trajectory of a single pollutant particle using the winds data and taking into account turbulence and dispersion of a pollutant. Figure 15 below demonstrates the output of the HYSPLIT model overlaid on top of the Google Earth image [30], [31]. The governing equations of the HYSPLIT model are too involved and are omitted from this dissertation in the interest of space, but can be found in the NOAA Technical Memorandum ERL ARL-224 [31].

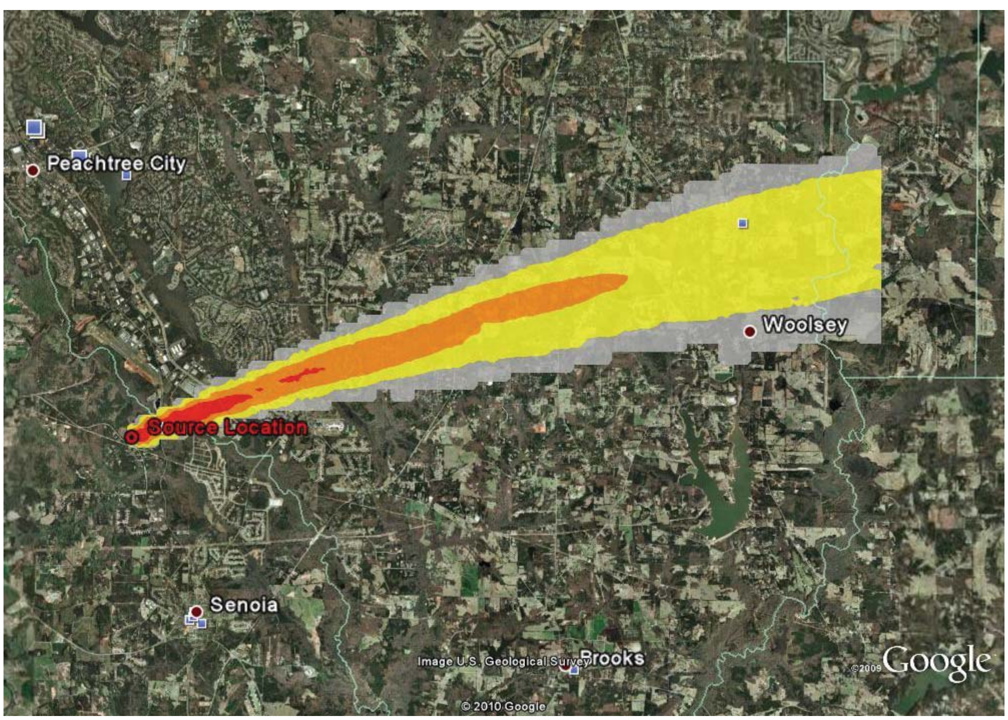


Figure 15 - Example of the HYSPLIT model overlaid on Google Earth depicting the smoke from the fires in Peachtree City, GA

Chapter 4

CONCEPTS OF HUMAN SENSOR NETWORK AND QUANTIFIABLE SOCIAL MEDIA DATA

This chapter describes the concept of Human Sensor Network and presents several different types of quantifiable information that can be retrieved from social media posts.

4.1 A THEORETICAL CONCEPT OF THE HUMAN SENSOR NETWORK

The concept of wireless sensor networks, sensor networks, and sensor web in

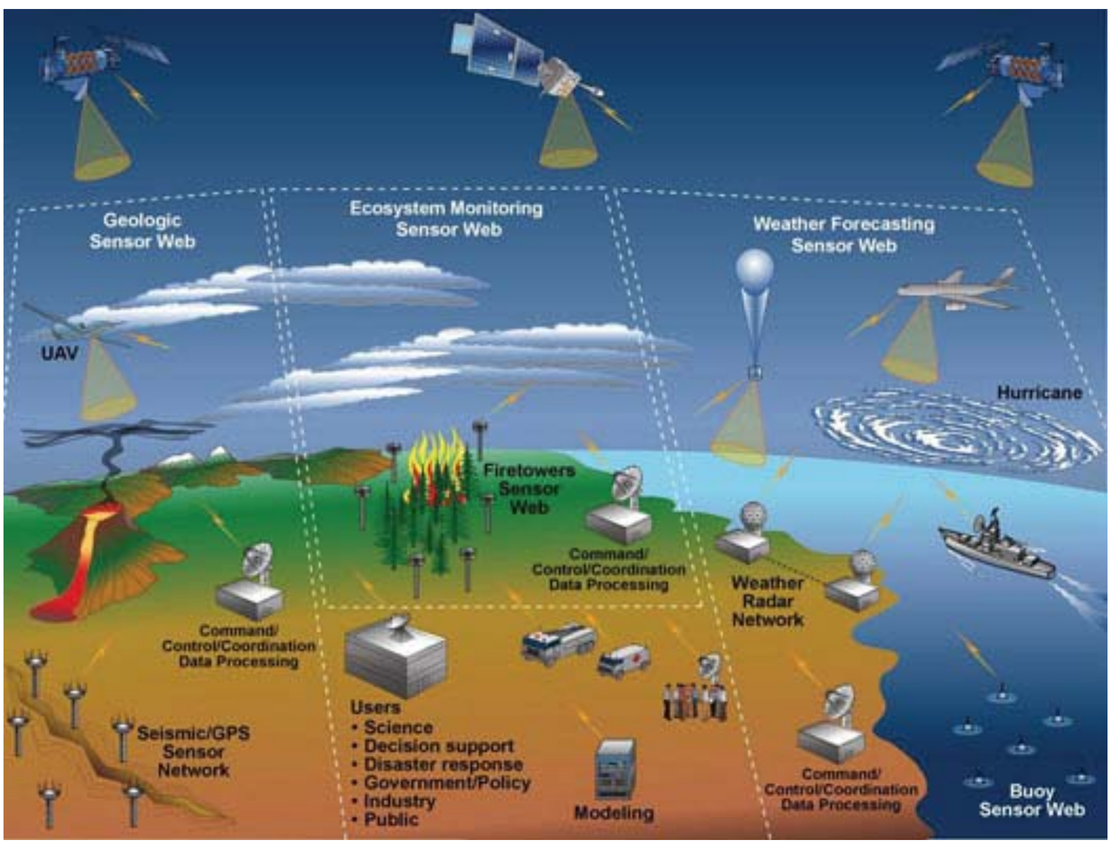


Figure 16 – Visualization of a sensor web. (Courtesy of Matt Heavner, University of Alaska Southeast)

general is well established, with a rich body of research covering plethora of topics such as power harvesting, efficient networking, node security and battling rogue nodes etc., and even has its own standardization body called Open Geospatial Consortium [32]. In this dissertation a novel concept of a Human Sensor Network is presented. Figure 16 shows a visualization of a sensor web.

In this approach the users of different social media platforms are viewed as "sensors" deployed in the field, ands their posts and comments are viewed as "observations". All the different social media platforms combined form a Human Sensor Network. As a result, we get a massive near real-time geo-locatable and time-stamped stream of sensor observations.

These observational data is used to validate geophysical model forecasts during extreme events such as hurricanes, tsunamis and aerosol distributions from fires and volcanic eruptions. Using data assimilation techniques such HSN observations can be directly incorporated into geophysical models to achieve better forecasts as demonstrated in the results section in two different disaster scenarios.

It is important to point out and explain the distinct difference between HSN concept and the complimentary field of Citizen Science. Citizen Science is primarily based on crowdsourcing the tasks to a large group of volunteers that require minimal training to correctly perform these desired tasks to achieve scientific value. In the HSN approach the social media users engage in their day-to-day activities and social interactions and are neither trained to perform any of the observational tasks nor are aware that their posts are being analyzed in such matter.

The term “Human Sensor Network” occasionally appeared in the literature for several years now, those references carried the meaning of humans performing observations in a citizen science paradigm such as in the case of water availability [33], or carried the meaning of a sensor that is carried by a human, such that the average travel speed is determined by interrogating a smartphone without the person’s knowledge [34]. Poser et al. describe the concept of humans as sensors in which quantitative estimates of flood damage were made based on phone interviews with the affected population [35]. In the 2010 American Geophysical Union meeting we presented the concept of Human Sensor Network as a near real-time observational system that is based on querying live streams of social media posts [36].

4.2 QUANTIFIABLE SOCIAL MEDIA DATA

Social media is evolving very rapidly and is useful in many different social aspects of our lives; however, in order to be able to view the social media posts as sensor observations, incorporate them into geophysical and mathematical models, and establish scientifically sound reproducible results, we need to be able to extract quantifiable data from social media.

By quantifiable social media data we mean something that can be measured, identified, located or counted, based on the information provided in the social media post and assigned a numeric value for the data at hand. E.g., a photo indicates presence of oil on the shore – true, false (1 or 0), or a photo indicating 2.5 feet of surge, etc. Identification and extraction of entities from the textual content can also be represented numerically. Once the contents of social media posts are quantified numerically, we are able to integrate it into mathematical and geophysical models in a much similar way to any other sensor network measurements.

There are several conceptual types of quantifiable sensor observations that can be collected from the HSN. One type of sensor is a trigger alarm—the equivalent of a smoke alarm. If a smoke alarm goes off in an apartment building, then the people in the vicinity are alerted to the potential hazard and would check the area and/or evacuate. However, if no smoke alarm is going off, there is no way to know whether everything is safe or there is hazard and the smoke alarm did not detect it, or smoke alarm is malfunctioning or even non-existent. A comparable example from HSN is the oil sensor in the case of the Deepwater Horizon oil spill disaster. Photos from Flickr were collected where beachgoers would take photos of tarballs washing up on the beach. The HSN sensors were acting like trigger alarms. If the photo of tarballs exists then it is clear that in that particular location there is beaching oil, but if there are no photos of tarballs available for a particular location then no information can be perceived about the beaching of oil for that area.

In the case of a categorical sensor a discrete observational value is available such as, for instance, the amount of snow on a scale from 0 to 10 in the #uksnow project mentioned in the related work chapter.

A more sophisticated HSN sensor type provides measurements on a continuous scale such as, for instance, an inundation level in feet during flooding.

Orthogonal to the measurements mentioned above is the named entity recognition (NER) from the textual content of the post. NER algorithms can detect things like names of organizations, locations, quantities etc. from unstructured text and can provide additional source of quantifiable data. Those named entities that have a location associated with them can be geo-referenced using a gazetteer service. A gazetteer service is in essence a directory of names of places and their geographic coordinates. Using such an approach allows us to know the locations of places that are mentioned in social media posts during disasters.

4.3 HANDHELD AND WEARABLE DEVICES FOR HUMAN SENSOR NETWORKS

It is important to point out that although in this work a large portion of social media posts was generated using smartphones equipped with a camera and a GPS, those smartphones constitute just one type of a handheld, networked device. At present, there are many new types of networked handheld and wearable devices that are actively being developed and marketed. Some examples include smartphones with biometric sensors, barometric pressure sensors, Geiger counters [37] etc. Networked wearable devices with personal metrics trackers such as sleep quality, heart rate, blood pressure, steps walked etc. are also gaining popularity [38]. Social media posts that include records from those devices can be an important source of quantifiable data as well. Thus, a Human Sensor Network paradigm in a broader generalized sense pertains to any social media platform and operates with posts submitted from any type of source, whether it is a conventional personal computer, a handheld device or a wearable device.

Chapter 5

EXPERIMENTAL RESULTS USE-CASE 1: HUMAN SENSOR NETWORKS FOR OIL SPILL MODELING

This chapter presents the results of the research that was conducted at the Center for Hybrid Multicore Productivity Research, UMBC that was funded by the National Science Foundation under the RAPID MRI award titled: "An Interactive Human Sensor Web for Improved Model Predictions of the Dispersion of the Deepwater Horizon Gulf Oil Spill". The contents of this chapter are predominantly based on the paper that was published in the Special Centennial Issue of the IEEE on Remote Sensing of Natural Disasters [39]. The research presented and tested a novel approach of incorporating social media data into geophysical models. A new paradigm was proposed in which social media (SM) users are viewed as "sensors" that are deployed in the field, and their posts as "sensor observations". All the users together form a human sensor network (HSN). These observations can serve as a low-cost augmentation to an observing system, which can be incorporated into geophysical models together with other scientific data such as satellite observations and sensor measurements.

This research focused on the Deepwater Horizon oil spill disaster of 2010 as a use case scenario. In the aftermath of the disaster, the public was very active in discussing its impact and implications across a range of social media outlets. Many people who witnessed firsthand the damage caused by the oil—such as birds soaked in oil or tar balls washing up on the shore—reported their accounts in different social media outlets. People posted photos and videos of oiled beaches, tweeted from their smart phones if they were prohibited from swimming because of oil pollution, and so on. The National Incident Command under Admiral Thad Allen saw the potential of this data and utilized social media mining to gauge and monitor the mood of the public affected by the BP disaster [40]. Though the primary purpose of such online activity is social interaction between friends, increasingly traditional media outlets look to social media to improve their reporting and get hints about newsworthy events. In this chapter, we describe how social media data can be used as physical observations to provide boundary forcing corrections to oil spill model predictions that employ generic parameterizations such as the coupling between the surface air and ocean drift velocities. These social media data can help adjust other parameters in the oil spill model as well. We examined various social media outlets and collected the data that were related to the Deepwater Horizon oil spill disaster. We converted these data for scientific use in geophysical models. For many of these data reports, we can extract observation location and temporal information. In addition, by comparing multiple reports from different observers (i.e. sensors), we can apply quality controls on the usefulness of the SM data.

5.1 SHORELINE DATA

In order to make the oil spill movement forecasts, the GNOME model needs to be properly set up with the shoreline data that defines the map separating land from water, as well as the surface winds and ocean currents forecast data. We generated a custom shoreline map data file for the purpose of the boundary condition that specifies where the separation of ocean surface and land is so that the model knows where the oil plume is floating and where it makes landfall. The GNOME model expects a map file that contains a list of latitude/longitude points that represent a polygon of land. We extracted the USGS shoreline data of the Gulf of Mexico area from the Coastline Database hosted at NOAA's National Geophysical Data Center [41]. We used NOAA/NOS medium resolution coastline data designed for 1:70,000 scales. This coastline data consists of many lists of latitude/longitude tuples. Each list contains various numbers of those tuples and represents a small portion of the shoreline in the cylindrical-equidistant projection. Then we linked all these lists together in the right order to create a single list that represented the entire shoreline of the Gulf coast. Since the model expects a polygon representing the land, and assumes that everything else is water, it was necessary for us to add arbitrary latitude/longitude points in the area of the state of New Mexico as well as the South Pacific area of Mexico. As a result, we got a polygon shape that represented the shape of the land around the Gulf of Mexico and that can be ingested into the GNOME model. Although in our model scenario the Pacific Ocean was abruptly starting after New Mexico, it did not matter since the forecasts and computations were strictly limited to a narrow region of the Gulf Coast and the area around the Macondo well. We also did not take into account in our model the unlikely possibility of oil being moved to Europe with the Gulf Stream and therefore we did not incorporate any shoreline data for European countries.

5.2 OCEAN CURRENTS AND SURFACE WINDS DATA

We obtained the wind fields from NCDC that were generated by the NCEP Eta Regional Forecast Model and the ocean current data from the ROM ocean model. The surface winds and ocean surface currents data were retrieved from the repository of the Department of Oceanography at Texas A&M University.

The atmospheric surface wind data are produced by NOAA's NCEP ETA-12 model and provide 24-hour forecasts with output every three hours on a regular grid with a grid spacing of 12 km. The Eta model, developed by Zaviša Janjić and Fedor Mesinger, derives its name from the name of the model's vertical step mountain coordinate. The basis of the model is to minimize errors due to the gradient force computation, advection and diffusion. The vertical coordinate is defined by

$$\eta = \left[\frac{(p - p_t)}{(p_s - p_t)}\right] \times \left[\frac{(p_{ref}(Z_s) - p_t)}{(p_{ref}(0) - p_t)}\right]$$

where p_t is the pressure at the top of the domain, p_s is the pressure of the model's lower boundary, z_s is the elevation of the model's lower boundary and p_{ref} is the reference pressure state [42]. For the purpose of our research we are only interested in the first layer of the model that correlates to the winds on the ocean surface.

The ocean surface currents data are produced by the Regional Oceanographic Modeling System (ROMS) generated by the Texas General Land Office (TGLO). ROMS provides a 24-hour hourly forecast, 4 times a day, on a regular grid. ROMS is a high-resolution, free-surface, hydrostatic, primitive-equation ocean model that uses terrain-following coordinates in the vertical curvilinear coordinates in the horizontal plane [43]. In its core it is based on the S-coordinate Rutgers University Ocean Model (SCRUM) [44]. The primitive horizontal momentum equations of this model are given as

$$\frac{\partial \mathrm{u}}{\partial t}+v\nabla u-fv=-\frac{\partial \phi}{\partial x}+\frac{\partial}{\partial z}\left(K_M\frac{\partial \mathrm{u}}{\partial z}\right)+\mathrm{D_u}+\mathrm{F_u}$$

and

$$\frac{\partial v}{\partial t}+v\nabla v-fv=-\frac{\partial \phi}{\partial y}+\frac{\partial}{\partial z}\left(K_M\frac{\partial v}{\partial z}\right)+\mathrm{D}_v+\mathrm{F}_v$$

where f is the Coriolis parameter, D is the horizontal viscous and diffusive term, F is the forcing term, K_M is the vertical eddy viscosity, and ϕ is the dynamic pressure.

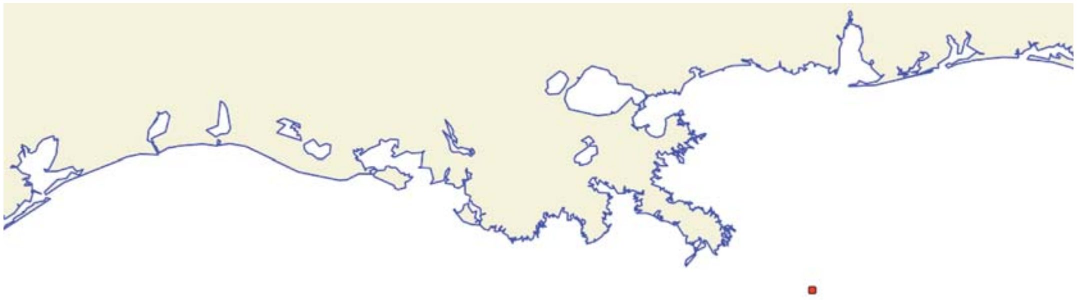
5.3 SOCIAL MEDIA MODEL INPUT DATA

For the purpose of this study, we collected data from Flickr. Flickr is a widely used image and video hosting site as well as a web services framework. It features

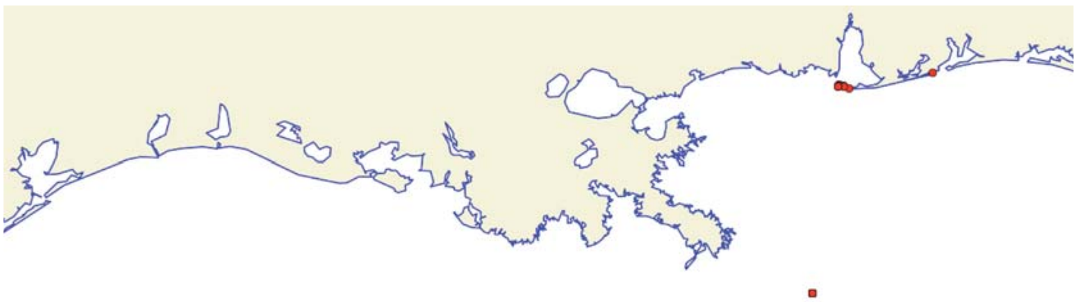

```
http://api.flickr.com/services/rest/?method=flickr.photos.search&api
_key=70920bca63b7452f4ff6a7bdbb7f3f75&tags=tar+balls&min_taken_date=
2010-04-20+00%3A00%3A00 &max_taken_date=2010-10-20+00%3A00%3A00&
bbox=-95.668945%2C+28.07198%2C+-85.825195%2C+31.203405&has_geo=1&
extras=geo%2C+path_alias%2C+date_taken&auth_token=72157626247331502-
22c36f6dd37efa88&api_sig=89078181e2169738d46489f44f070843
```

```
<photo id="5016704044" owner="37281343@N03" secret="9db693ebb5"
server="4144" farm="5" title="DSC_1225" ispublic="1" isfriend="0"
isfamily="0" latitude= "30.371133" longitude="-86.918726"
accuracy="16" place_id="uwvhGpebBZlHgiRz" woeid="2457354"
geo_is_family="0" geo_is_friend="0" geo_is_contact="0"
geo_is_public="1" pathalias="mmmeeks" datetaken="2010-08-04
17:48:24" datetakengranularity="0" />
```

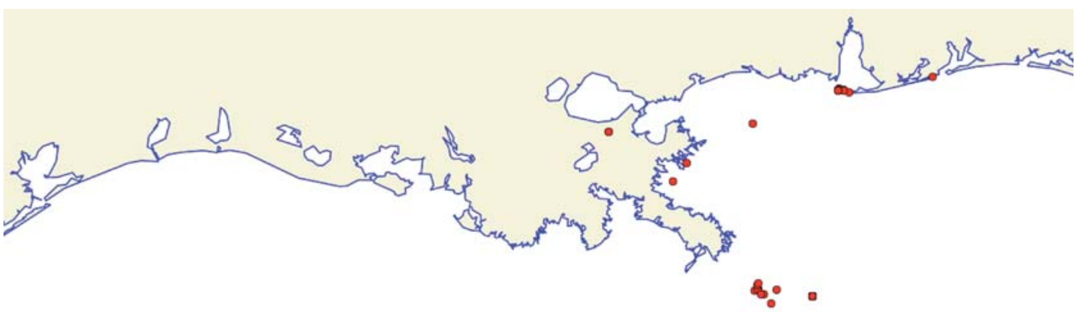

Figure 17 - Example of a Flickr API request query (top) and response (bottom)



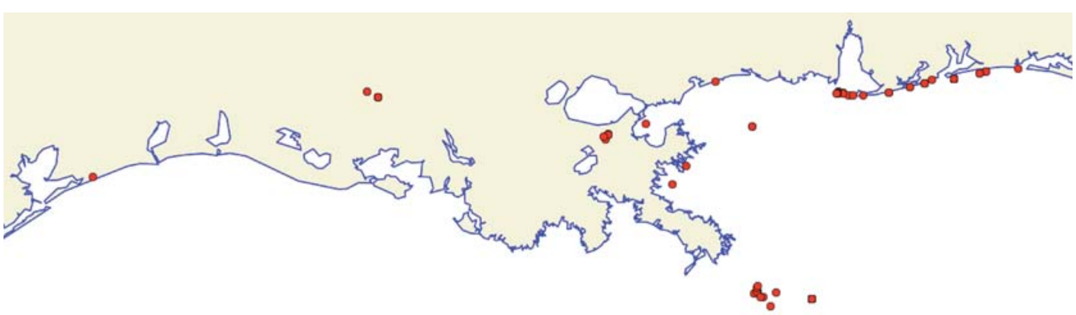
a) April 21st, 2010 – April 27th, 2010



b) April 21st, 2010 – May 11th, 2010



c) April 21st, 2010 – May 30th, 2010



d) April 21st, 2010 – September 9th, 2010

Figure 18 - Accumulative Flicker data superimposed on a regional map. We can observe how as time goes by more and more areas get covered with oil.

many social networking traits such as the ability for users to add people to a list of their contacts, forming communities, tagging people on photos and videos, tagging content with keywords, the ability to comment on photos, etc. As a result Flickr is not only a popular social media portal in its own right, but also widely used by bloggers to host images that are imbedded in their blogs. Unless explicitly disabled by the user, photos and videos posted on Flickr include EXIF metadata such as date and time when the photo was taken, camera make and model, camera settings and geolocation. Although the ratio of geolocated Flickr images is very small, we expect it to grow rapidly due to hi-tech manufacturers objective to embed GPS devices not only in smartphones, but also in regular photo cameras [45]. Currently the vast majority of geolocated photos on Flickr are taken with a GPS enabled smart phone such as iPhone, Blackberry or Android-based device. If the EXIF metadata is not available the user has an option of geotagging the photo by hand by selecting the location on the map where the photo was taken; if the timestamp is not available, Flickr will automatically assume that the upload time is the time the photo was taken. We started our data mining task with a simple search on the Flickr website for the query "BP oil spill", which returned over 20,000 results. Many of those images were related to protests against BP, political events related to the disaster, and other related events that were of no practical use for us, since we were only looking for oil HSN data in the form of images that evidenced oil slicks on the water and oil tar balls washing up on the shores. One such example is shown on Figure 19 showing a photo of oil covered plastic soda bottle lying in the sand. For developers, Flickr provides API access to their service. For our work, Flickr API proved to be much more flexible and

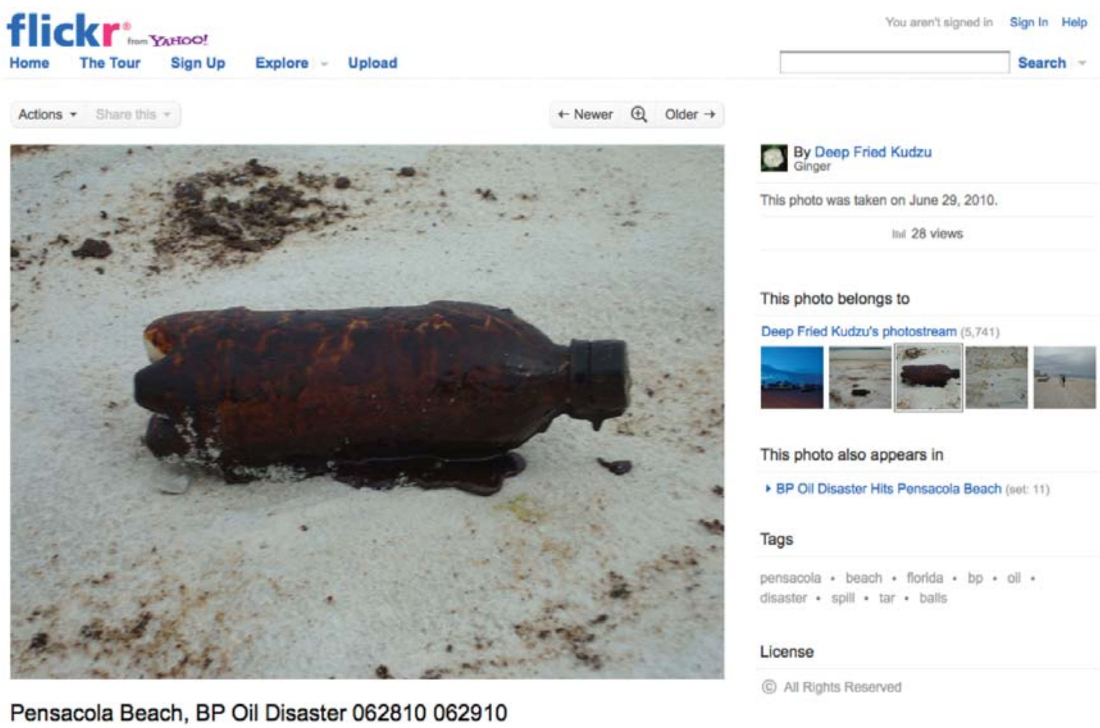


Figure 19 – Screenshot of Flickr website showing an example of the oil spill related photo that was shared showing oil coated plastic bottle on the sand.

powerful then the services accessible via the website. Using Flickr API, we were able to request only the images that were geotagged as well as supply our search query with a bounding box of lower left corner at 28.07198, -95.668945 and upper right corner at 31.203405, -85.825195 to retrieve only the images from the Gulf coast area. We executed two search queries — one for “tar balls”, and the other one for “oil spill” during the period of April 20th, 2010 to October 20th, 2010. They resulted in two disjoint sets of 22 and 168 images respectively for a total of 190 images. Figure 17 shows an example of REST API query, and the corresponding response from the Flickr API. Note attributes “latitude”, “longitude”, “accuracy” and “datetaken”. Accuracy is a value in the range from 1-16 that represents the accuracy of the geo-location with the world level being 1, country level being about 3, region about 6, city -11 and street -16 (Default is 16) [46]. We wrote a script that parses the XML response received from Flickr API and that generates a map with desired markers corresponding to the latitude/longitude tuple of each image. Using this script we generated a series of maps of the Gulf coast of Mexico and incrementally superimposed Flickr data that we collected in the previous step at the corresponding latitude, longitude coordinates. As a result we got a series of maps indicating the sightings of oil or tar balls along the shoreline of the coast at different times. Figure 18 displays the maps that were generated for different periods. Figure 18 (a) shows the points for the period from April 21st through April 27th. Here we only see points around the location of the Deepwater Horizon drilling rig. Figure 18 (b) shows points for the period of April 21st through May 11th, and here we observe additional points for the sightings of oil washing up in the area of Fort Morgan and Fort McRee. Figure 18 (c) is for the period from April 21st through May 30th, and here we see additional points in the regions of Black Bay and Ship Island. Figure 18 (d) is for the period of April 21st through September 9th and we observe that many more areas in-between start to fill in.

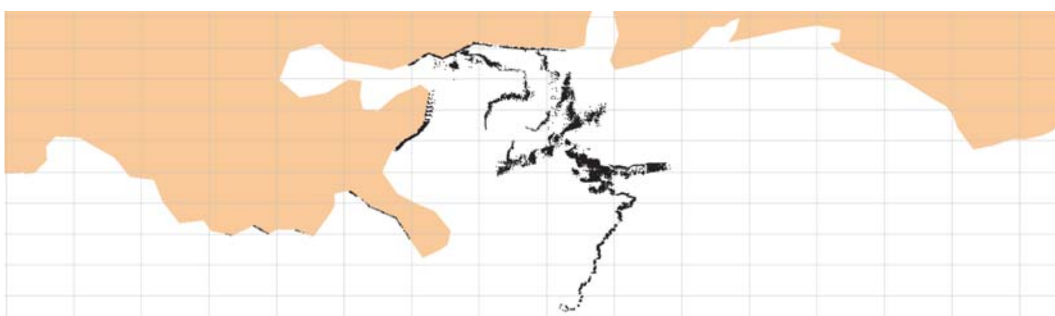
5.4 APPROACH

In this section we describe how we process the social media data and present the results of the integration experiments as series of the GNOME trajectory forecasts with different parameters that explore the parametric sensitivities of the model.

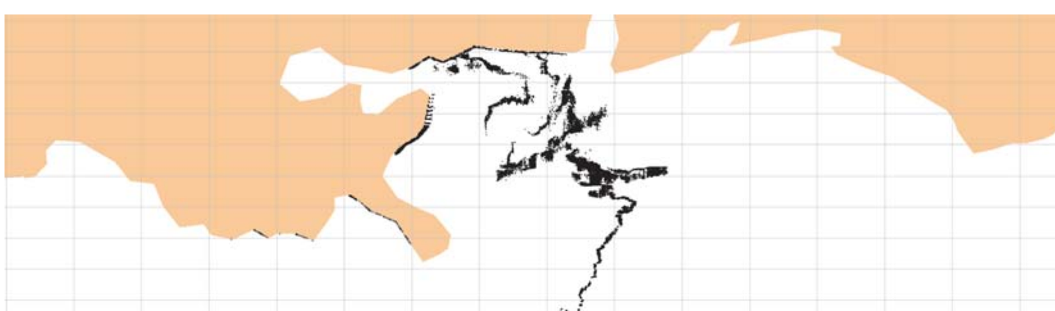
Once the GNOME model was initialized for the area of the Deepwater Horizon oil spill, we introduced the spill itself at the exact location of the rig and for simplicity assumed that all the oil was spilling on the surface. In our first experiment

a)7,000 bbl and 1,000 Lagrangian elements per week, 7 barrels per splot

b) 35,000 bbl and 1,000 Lagrangian elements per week, 35 barrels per splot



c) 35,000 bbl and 5,000 Lagrangian elements per week, 7 barrels per splot



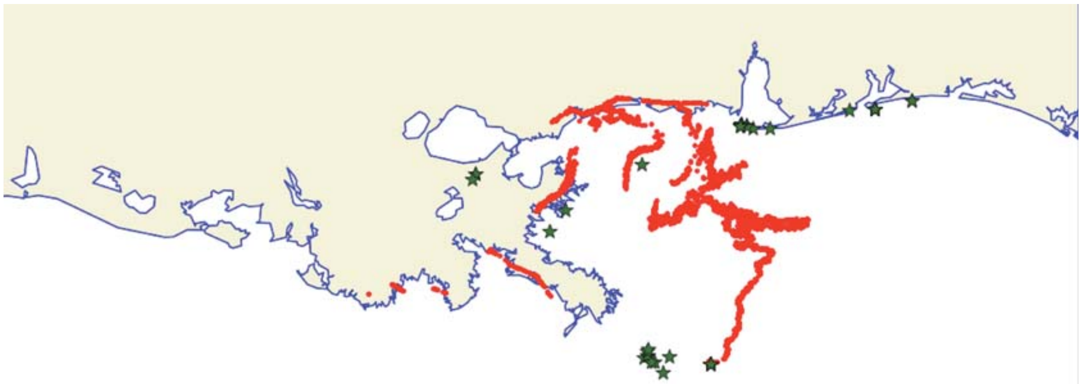
d) 350,000 bbl and 50,000 Lagrangian elements per week, 7 barrels per splot

Figure 20 - The results of different model runs show that the amount of oil released and the number of splots used do not alter the direction of the oil flow and the ultimate location where the model predicts it will make a landfall.

we altered the rate of spill and the number of splots used to represent the oil. We ran the scenario from the moment that the spill started until the 8th of June. Figure 20 summarizes our results. Figure 20 (a) indicates a spill at a rate of 7000 barrels a week with 7 barrels per splot, Figure 20 (b) indicates a spill at a rate of 35,000 barrels a week with 35 barrels per splot, Figure 20 (c) indicates a spill at a rate of 35,000 barrels a week with 7 barrels per splot, and Figure 20 (d) indicates a spill at a rate of 350,000 barrels a week with 7 barrels per splot. Figure 20 (a) and (b) allow us to analyze the influence of the spill rate on the oil propagation given a constant number of splots used in the model. The rate changes from 7000 barrels a week to 35000 barrels a week, but the number of splots is kept at 1000 per week. Figure 20 (b) and (c) allow us to analyze the influence of the number of splots on the oil propagation given a constant spill rate used in the model. The rate of spill is kept at 35,000 per week and the number of splots changes from 1000 per week to 5000 per week. Figure 20 (d) increases both the rate of spill and the number of splots in order to have a bigger picture of the influence of those two variables on the GNOME model. As a result of this experiment, we observed from Figure 20 (a) and (b) that the amount of oil released does not alter the direction of the oil flow or the ultimate location where the model predicts it will make landfall. Likewise, the number of splots does not alter the direction of the oil flow or the ultimate location where the model predicts it will make landfall, as can be seen in Figure 20 (b) and (c). Figure 20 (d) indicates the worst-case scenario (highest rate of spill) with a substantially higher number of splots. The resulting output had exactly the same pattern of oil—however, it had a much better resolution (less grainy). It is important to mention that the model run that generated Figure 20 (d) also took a substantially longer time to run.

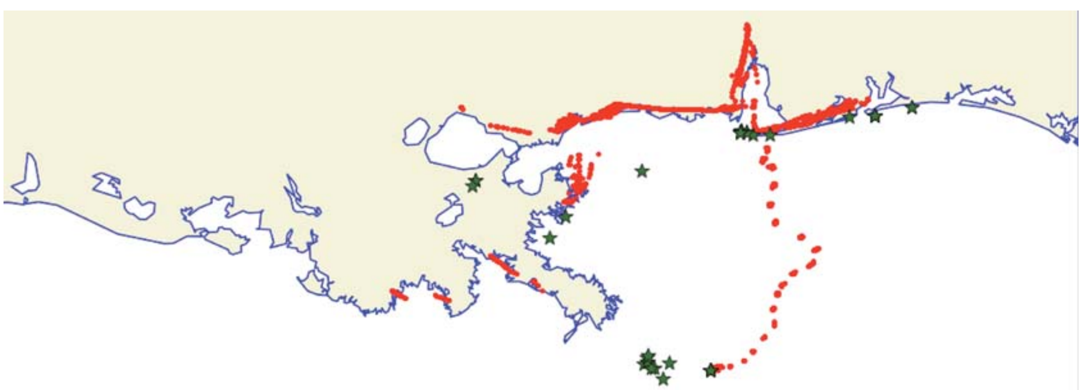
5.5 ASSIMILATION OF SOCIAL MEDIA DATA WITH GNOME MODEL

Now that we developed and presented a method to aggregate social media data, convert it into a format of latitude, longitude, timestamp triplets and plot it on the map, we were able to combine the HSN social media data with different forecasts of the GNOME model that correlate with different variable parameters of the model. We picked June 8th as our comparison date and ran the GNOME model from the day the spill started until June 8th. For the first experiment our spill was set up at a rate of 350k barrels per week with a representation of 1000 Lagrangian elements per week. Then we compared the results of different runs with the HSN data and summarized it in Figure 21 and Figure 22. Green stars indicate the social media data from Flickr, while red dots indicate the GNOME forecast of the oil spill. Figure 21 (a) shows the correlation of the default setting of the GNOME model with wind factor of 1% to 4%. Figure 21 (b) shows the correlation of HSN with the GNOME forecast set to wind factor of 5% to 8%, and Figure 21 (c) is for wind factor of 9% to 12%. For the second experiment, we kept the same date of June the 8th with 350k barrels spilling per week with the representation of 1000 Lagrangian Elements per week and windage of 1% to 4%. This time we introduced diffusion into the model and altered the diffusion variables. Figure 22 displays the results of this experiment on a map. Figure 22 (a) shows no diffusion. Figure 22 (b) shows the forecast with the diffusion coefficient of 100,000 cm2 per second and an uncertainty factor of 2. Figure 22 (c) shows the forecast with a diffusion coefficient of 200,000 cm2 per second and an uncertainty



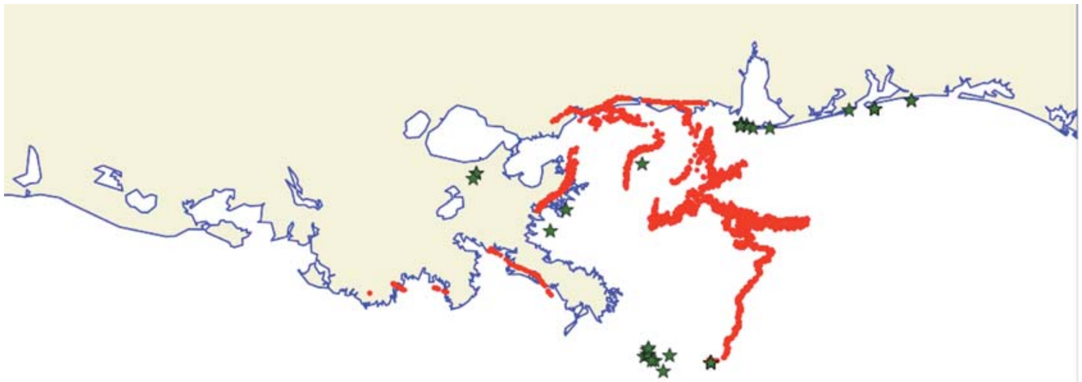
a) April 20 - June 8, 2010 trajectory forecast - 350,000 bbl/week, 1000 Lagrangian elements per week with 1-4% windage and no diffusion

b) April 20 - June 8, 2010 trajectory forecast - 350,000 bbl/week, 1000 Lagrangian elements per week with 5-8% windage and no diffusion

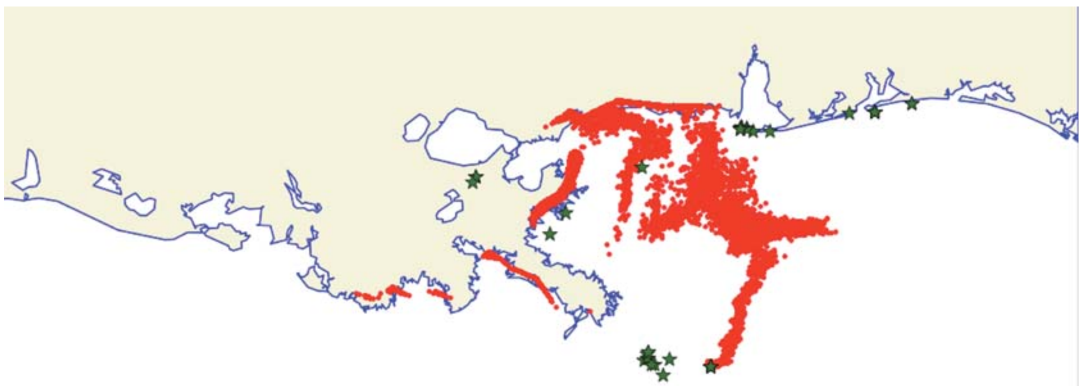


c) April 20 - June 8, 2010 trajectory forecast - 350,000 bbl/week, 1000 Lagrangian elements per week with 9-12% windage and no diffusion

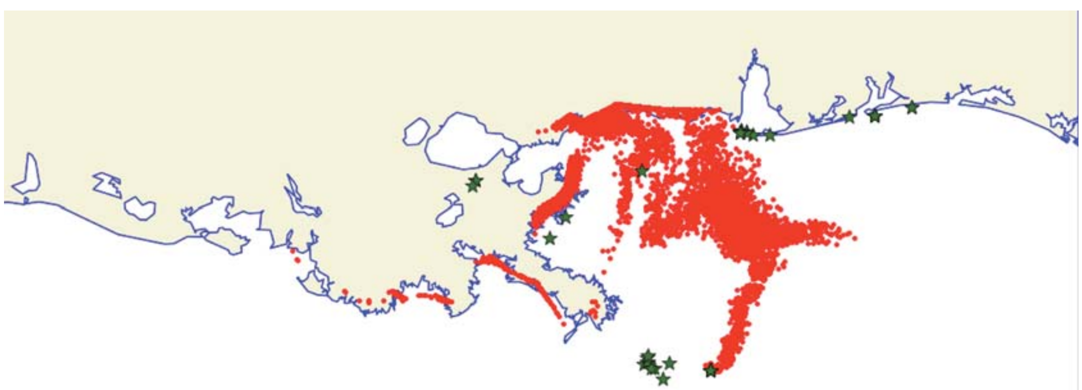
Figure 21 - Comparison of the results of different GNOME model trajectory forecasts and their correlation to social media data. Red dots indicate the Lagrangian elements from GNOME model while green stars represent social media data. We can see that depending on the settings of the model parameters some forecasts correlate better with social media data then others.



a) April 20 - June 8, 2010 trajectory forecast - 350,000 bbl/week, 1000 Lagrangian elements per week with 1-4% windage



b) April 20 - June 8, 2010 trajectory forecast – 350k bbl/week, 1000 Lagrangian elements per week with 1-4% windage, and Diffusion Coeff. of 100k cm2/sec with Uncertainty Factor of 2



c) April 20 - June 8, 2010 trajectory forecast – 350k bbl/week, 1000 Lagrangian elements per week with 1-4% Winds and Diffusion Coeff. of 200k cm2/sec with Uncertainty Factor of 2

Figure 22 - Comparison of the results of different GNOME model trajectory forecasts and their correlation to social media data. Red dots indicate the Lagrangian elements from GNOME model while green stars represent social media data. We can see that depending on the settings of the model parameters some forecasts correlate better with social media data then others.

factor of 2. Now that we have run multiple experiments and have gotten both social media data and GNOME forecast data in the same format, we can analyze the results of our experiments.

5.6 RESULTS

We assumed that the social media data was the ground truth and we compared GNOME model forecasts to that ground truth by calculating the root mean square error (RMS).

The RMS calculation was performed as following: for each point of social media data, we found the closest Lagrangian element point from the forecast and we calculated the geometric distance in kilometers. We squared each such distance, summed all the distances together and extracted the square root of that sum. Our calculations are summarized in Figure 23. The first three entries are for experiments with different winds and currents combinations and no diffusion. The last two entries assume the windage of 1% to 4% and introduce the comparison of two different diffusion coefficients.

Parameters	RMS Error
Windage: 1-4 %	20.443
Windage: 5-8 %	1.365
Windage: 9-12%	11.499
Diffusion: 100,000 cm2/sec	12.096
Diffusion: 200,000 cm2/sec	5.931

Figure 23 – This table summarizes the RMS errors between social media data and different runs of the GNOME model.

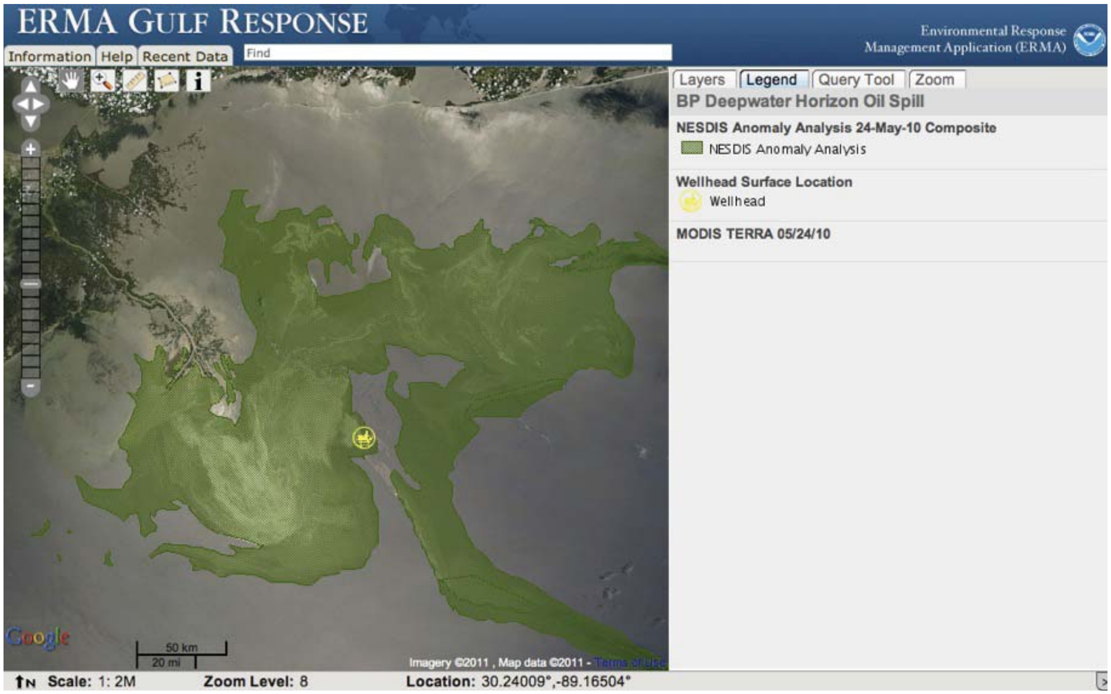


Figure 24 - Screenshot of ERMA Gulf Response mapping site displaying MODIS image of sun-glint reflecting from the oil plume of the Deepwater Horizon disaster on May 24, 2010 as well as NESDIS anomaly analysis composite product derived from COSMO SKYMED-2, MODIS TERRA and RADARSAT-2 for the same date (green superimposed polygon).

It is important to point out that a change of windage of a few percentage points (from 1%-4% to 5%-8%) resulted in the RMS change of an order of magnitude (from 20.4 to 1.3). Similar outcome is observed when diffusion is introduced. We have also conducted additional studies—not presented in this paper—on the size of the initial oil plume, in particular, a simulated hand-drawn map of the oil spill similar to that of the MODIS sun glint reflection on May 24, 2010, shown in Figure 24. This study showed increased beached oil trajectories, indicating the need for realistic quantitative mapping of the thickness of inferred oil spill images [47]. Currently, trained technicians create the NESDIS composite product by hand. Some research has been conducted on automating such processes using Machine-Learning techniques; such as the work of L. Corucci on oil spill classification of multispectral satellite

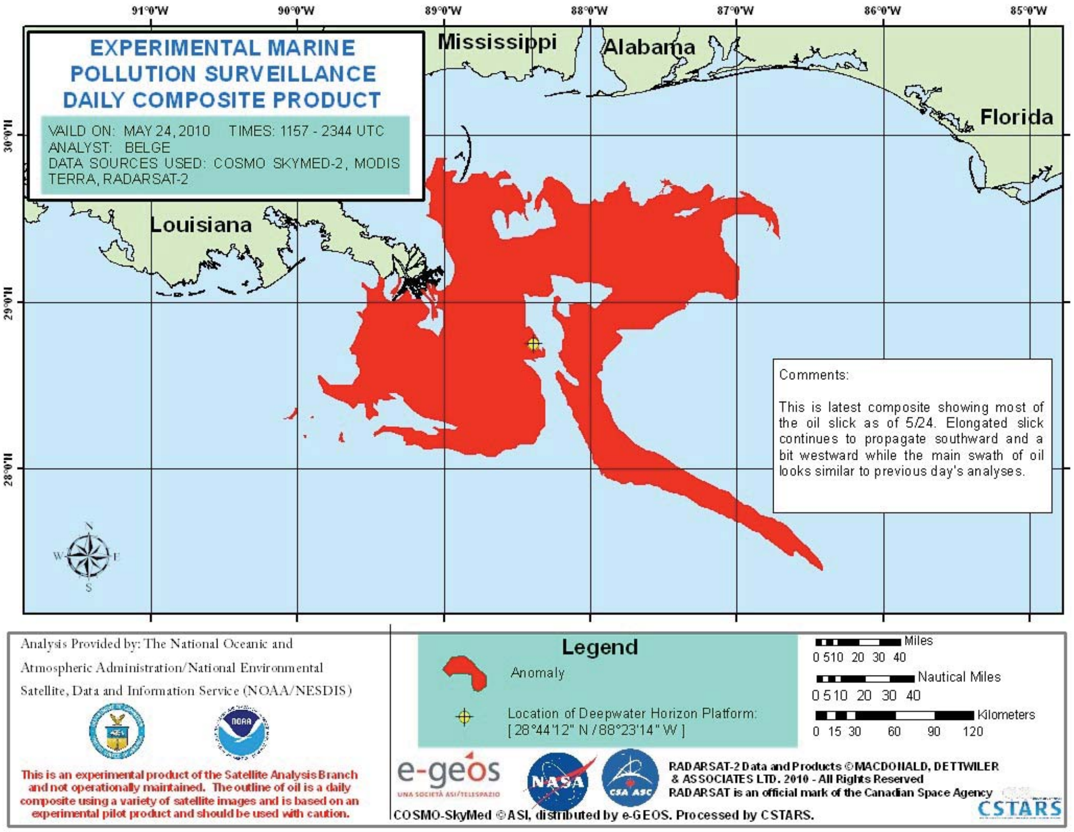


Figure 25 - The NESDIS composite analysis of COSMO SKYMED-2, MODIS TERRA, RADARSAT-2 as of May 24, 2010 displaying the polygon that represents anomaly in red.

images using Neuro-Fuzzy technique [48] and the work of D. Lary on dust source classification from satellite imagery using self-organizing maps [49].

5.7 HUMAN SENSOR NETWORKS FOR OIL SPILL DETECTION FROM SATELLITE IMAGERY

During oil spill disasters, trained analysts at NOAA/NESDIS process satellite observations and manually integrate data from numerous sources to produce a polygonal map that identifies the locations of possible detected oil on the surface of the ocean. These polygon maps are assimilated into GNOME model. Figure 25 shows a NESDIS composite analysis of COSMO SKYMED-2, MODIS TERRA,

Figure 26 - MODIS image for May 24, 2010 that shows sun-glint reflecting from the oil plume of the Deepwater Horizon disaster.

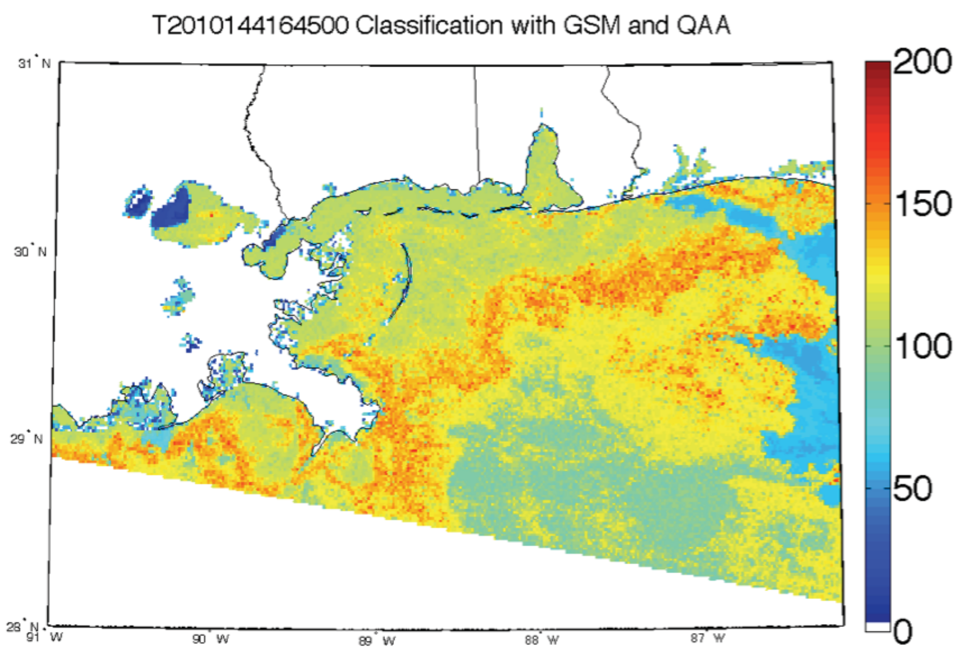


Figure 27 – Self Organizing Map output of the MODIS image for May 24, 2010

RADARSAT-2 as of May 24, 2010 displaying the polygon that represents anomaly in red.

We demonstrated the feasibility of an automated algorithm to detect and map surface oil distributions from satellite observations. We employ a Self Organizing Map (SOM) machine-learning algorithm. A SOM algorithm is a type of an unsupervised neural network that produces a low-dimensional discrete representation of a higher dimensional input space while preserving its topological properties [50]. This low order representation is called a map. It is important to distinguish this lower order discrete representation *map*, which in essence bins the data into groups by similarity, and the geographic *map* on which these data are projected.

Once the map is created we use social media data from Flickr together with other ground observations to make an educated guess of which cluster represents the oil plume.

Shoreline Cleanup Assessment Technique (SCAT) program had multiple teams operating across the coastal zones surveying shorelines, making assessments of the oiling conditions and producing a consistent and standardized data collection.
shows ERMA web tool displaying SCAT data on the map.

Figure 26 is a MODIS image for May 24, 2010 that shows sun-glint reflecting from the oil plume of the Deepwater Horizon disaster. Figure 27 shows the results of processing MODIS data for the same date using SOM algorithm. We can clearly observe that SOM was very successful in picking the regions of oil slick - Figure 27 is in very good agreement with Figure 25 and Figure 26. We also see how social media data, combined with SCAT data on Figure 18 and Figure 28, agrees well with

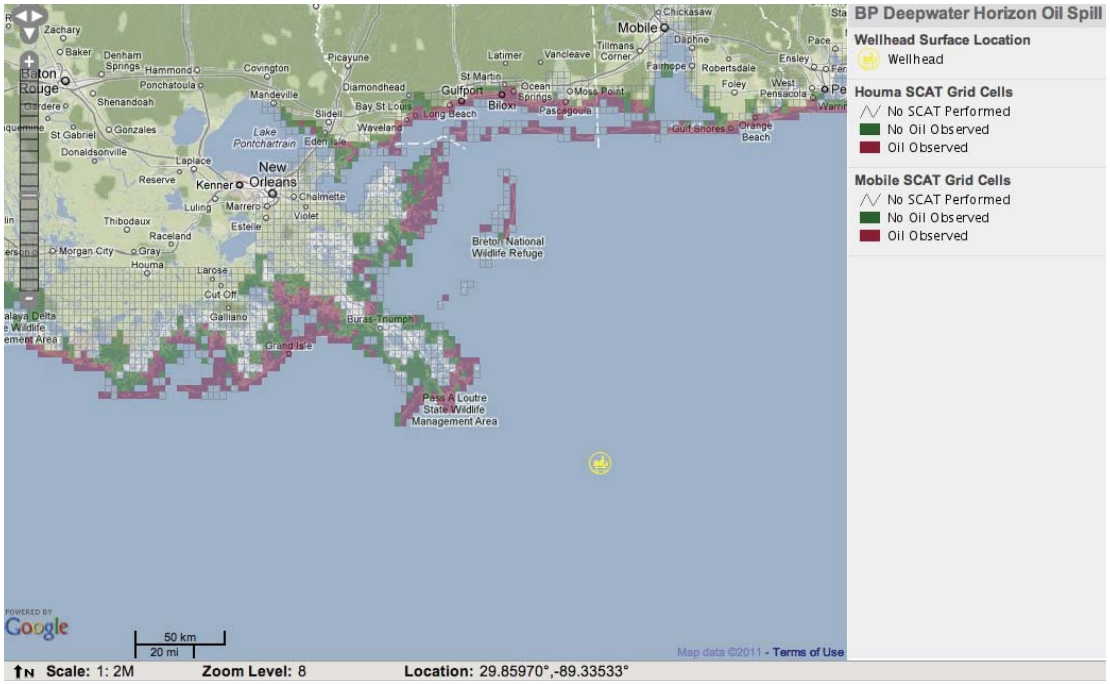


Figure 28 - ERMA web tool displaying SCAT data on the map

the results of SOM in Figure 27. The input space to the SOM was picked by trial and error until satisfactory map was produced. Additional research that falls beyond the scope of this dissertation is required to develop an approach to programmatically pick the group from SOM that is most likely to represent the oil plume.

In the future we plan to develop an approach for selecting the input space automatically. One potential approach that we plan to experiment with is use of genetic algorithms for automated selection of input space.

5.8 SUMMARY

We processed the social media data and converted it to physical observations that list latitude, longitude and timestamp when the oil landfall was observed. The latitude and longitude can be obtained in different ways depending on the source of the post. In the case of a tweet that was posted from a smart phone, this information is available in the metadata of the tweet itself, since Twitter geo-locates tweets that are posted from smart phones. In the case of Flickr images, some cameras, especially those built into smart phones, often automatically geotag the photos, and this information is often preserved in the metadata of the image. In the cases where the tweet was sent from a computer we can still get a more coarse location from the geolocation of the IP address of the Twitter user. Twitter provides such a coarse location as well. In the case where the photograph or the video was not geotagged, as well as in the case of most blog posts we will have to extract such information from the textual content such as image descriptions or reader comments. Such extraction can be automated using text analysis tools and named entity recognizers. In our case we used only the data that was already geotagged. We processed social media data from Flickr to be in the format of the observational geophysical data, and used it as a boundary condition to assess the sensitivity and agreement of time dependent parameters in the GNOME model with social media data. We quantified the differences between the forecast and the social media observations by calculating the RMS error. We observed that minor changes in initial conditions of the forecast model can lead to an order of magnitude increase in consistency with specified Flickr data.

Chapter 6

EXPERIMENTAL RESULTS USE-CASE 2: HUMAN SENSOR NETWORKS FOR DISASTER RESPONSE DURING HURRICANES

This section presents the results of the research that was conducted at the Center for Hybrid Multicore Productivity Research, UMBC, that was funded by the National Science Foundation under the RAPID MRI award titled: "Rapid Response for a Human Sensor Aware Fukushima Debris Monitor and Prediction System". The contents of this section are predominantly based on the short paper that was presented at the 11th International Conference on Information Systems for Crisis Response and Management in May 2014.

As a use-case scenario, we focus on Hurricane Sandy that devastated the East Coast of the United States in fall of 2012. We have collected over 8 million tweets and around 370 thousand Instagram images referencing hurricane Sandy.

In this use-case scenario we use NOAA's SLOSH (Sea, Lake and Overland Surges from Hurricanes) model and P-Surge to provide a forecast for Hurricane Sandy. Due to inherent uncertainties in the weather forecasts, those models only present the worst-case scenario for any given hurricane. We demonstrate how the model forecasts and social media data, if combined in a single framework, can be used for near-real time forecast validation, damage assessment and disaster management. Geolocated and time stamped Instagram photos allow us to assess the surge levels at different locations, thus, not only validating the model forecasts, but

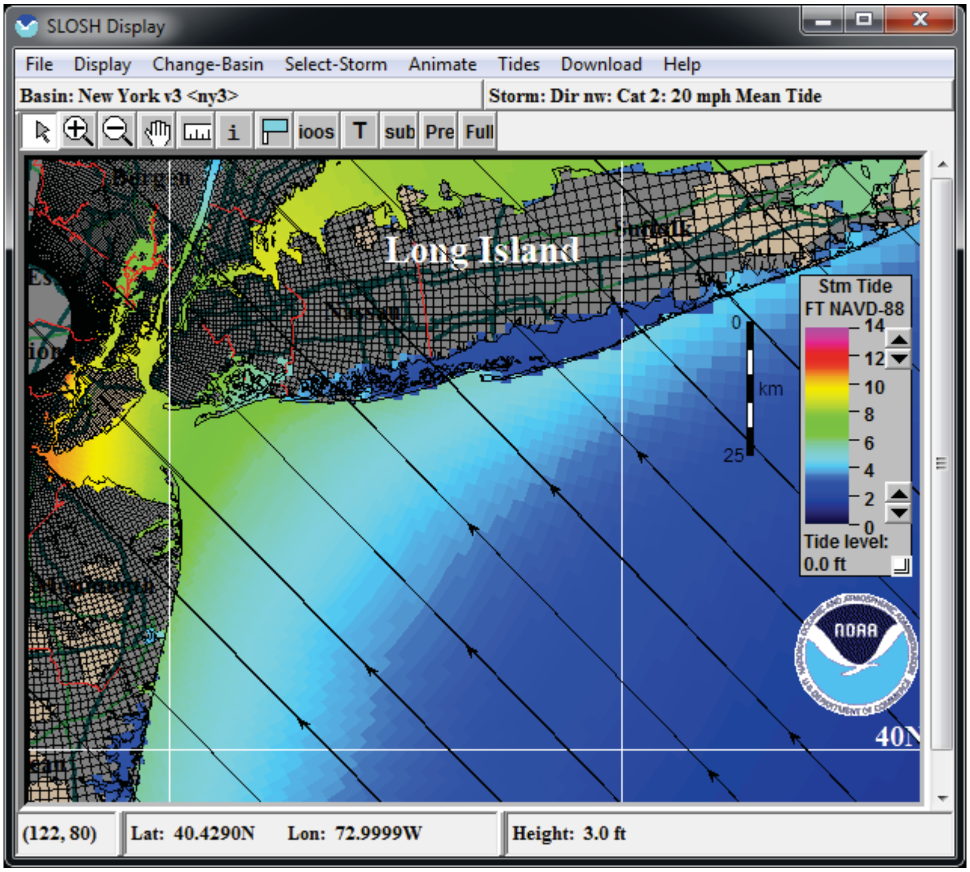


Figure 29 - Screenshot of SLOSH model forecast configured for the New York City basin. Diagonal lines indicate different parallel landfall paths for which the maximum envelope of water is computed.

also giving a timely glimpse into the actual levels of the 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. Geolocated tweets can be used to not only monitor the emotional response of different geographic areas affected by the disaster, but also provide insight into the problems that different communities experience such as power outages, elevated crime (looting etc.), and refusal to evacuate.

6.1 FORECASTING THE IMPACT OF HURRICANE SANDY

"The Sea, Lake and Overland Surges from Hurricanes (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" [51]. 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. Although there are other hurricane models such as ADCIRC, we chose SLOSH because it is the major model used by NHC, FEMA, NWS, NOAA and USACE and is also the basis for Hurricane Evacuation Studies [26], [52].

SLOSH model setup requires selection of a basin from a predetermined list of basins for which the model has the terrain and bathymetry data. Most of the data comes from USGS and NGDC. The model utilizes a polar coordinate system with its center located in the center of the basin. Such a setup has smaller grid cells (higher precision) on land, and larger grid cells (lower precision) out in the ocean where high accuracy is not necessary. As a result, the model is very robust without sacrificing the accuracy on land where it matters most. Figure 29 shows a screenshot of the SLOSH model configured for Hurricane Sandy.

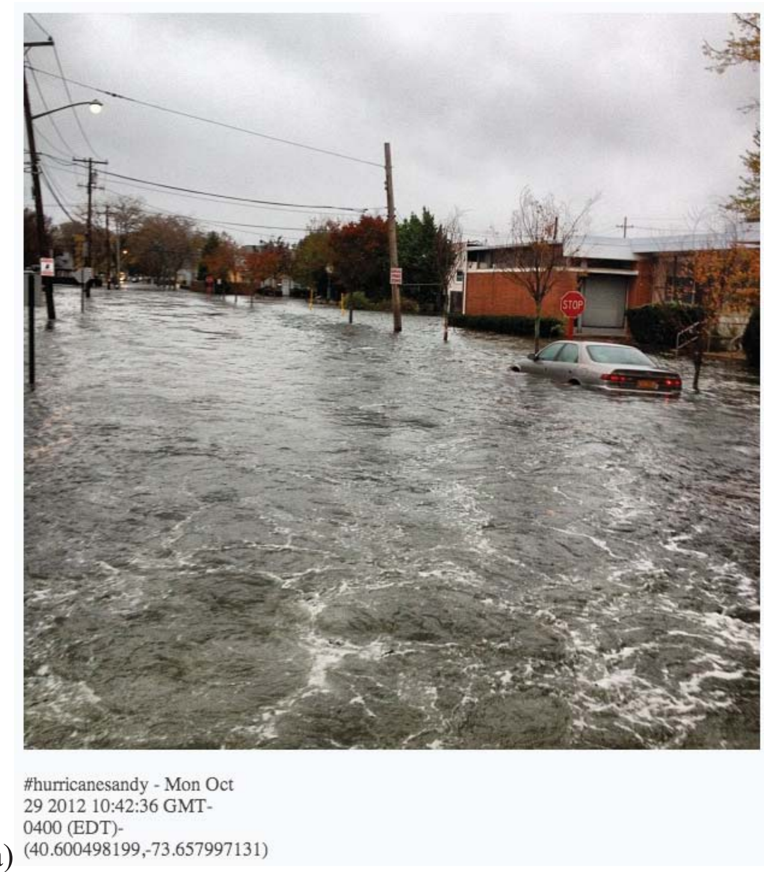
NWS ran thousands of hypothetical surge forecasts for all the basins available in the SLOSH model and provides precomputed MEOW and MOM results for the users.

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 the assumption that the exact path of the hurricane is known [26], [51], [52]. Moreover, SLOSH model does not take into account rainfall, wind driven waves, rivers etc.

6.2 OVERVIEW OF THE VARIETY OF QUANTIFIABLE SOCIAL MEDIA OBSERVATIONS

This subsection demonstrates several types of quantifiable social media observations that can be obtained from the HSN in the case of Hurricane Sandy. The methods that can be utilized for faster and more accurate measurements will also be discussed.

One of the most significant measurements that can be extracted in near real-time is the flood level in different locations and at different times. On Figure 30 (a) 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 30 (b) 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, for instance, the photo on Figure 31 shows Flatbush



(a)

(b)

Figure 30 – (a) Island Park Public Library on the eve of Hurricane Sandy making landfall, (b) Google Street View of Island Park Public Library for comparison.

Figure 31 – Photo of Flatbush avenue in Brooklyn, NY on the morning of October 29th, 2012.

avenue in Brooklyn, NY at location 40.61834, -73.9325 (less then a mile away from Jamaica Bay) that is wet from rain, but is 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.

Another type of sensor data is the detection of power outages. Figure 32 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.

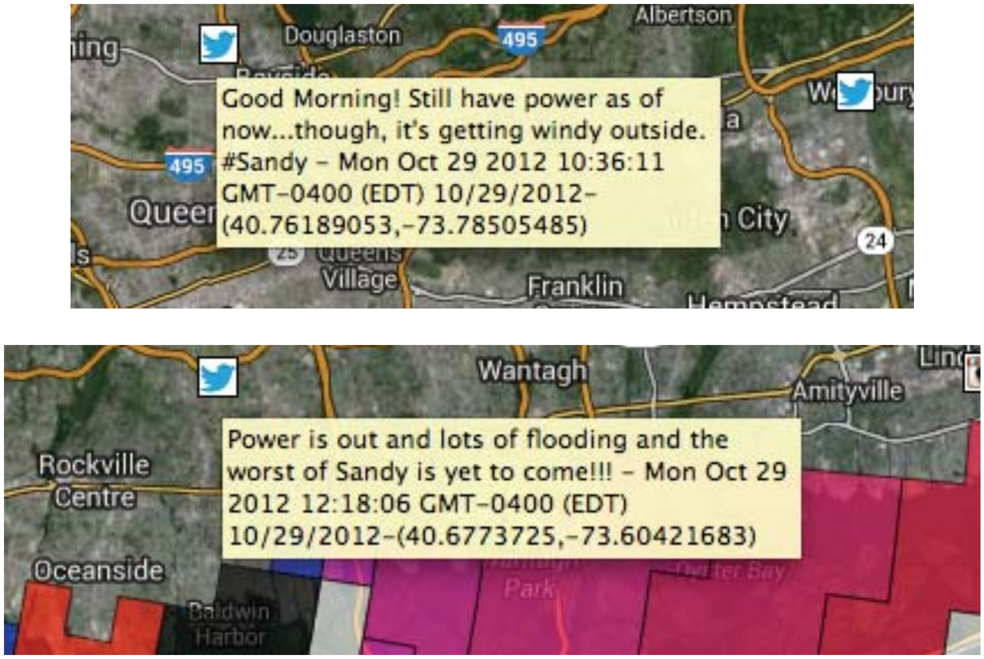


Figure 32 - AsonMaps showing the tweet that indicates: (a) power outage and flooding, (b) presence of strong winds and explicitly indicates no power outage

6.3 THE USGS HIGH WATER MARKS DATASET

In extreme cases such as Hurricane Sandy, at the request of FEMA the USGS deploys teams of expert scientists that survey the flooded areas. As soon as the water retreats and it is safe to conduct the survey, the scientists visit a list of predetermined sites of interest that are known to be in areas prone to flooding, and record the highest level of standing water. The height of water is usually determined by the sludge mark left on the walls of buildings. Figure 33 shows a USGS expert logging the surge level based on a wash line in front of the building. Figure 34 shows a screenshot of the USGS map indicating the locations where High Water Marks (HWM) data is available. The coverage of HWM is very sparse – only around 20 experts were deployed in New York and about the same number in New Jersey [53]. A comparison

Figure 33 – Photo of the USGS expert logging the surge level at location 40.576315, -73.859819 with elevation of 11.2 feet in Queens County, NY based on the wash line in front of building as part of the High Water Marks effort. The height of water above ground was determined to be at 5.4 feet.

of the coverage of HWM on Figure 34 to the AsonMaps coverage of HSN observations on Figure 38 clearly shows the overwhelming abundance of near real-time HSN observations that can be vital for situational awareness in times of disasters and crises.

6.4 VALIDATION OF HSN OBSERVATIONS AGAINST USGS HWM

For the purpose of establishing reproducible scientific basis for validity of HSN measurements, there is a great value in validating the HSN observations against currently established observation methods such as HWM. We identified a multitude of coinciding HSN and HWM observations that would allow us to not only validate the HSN observations, but also determine with much higher resolution the levels of the flooding. It is important to indicate that HSN data was not only abundant along the coast, but also into the mainland.

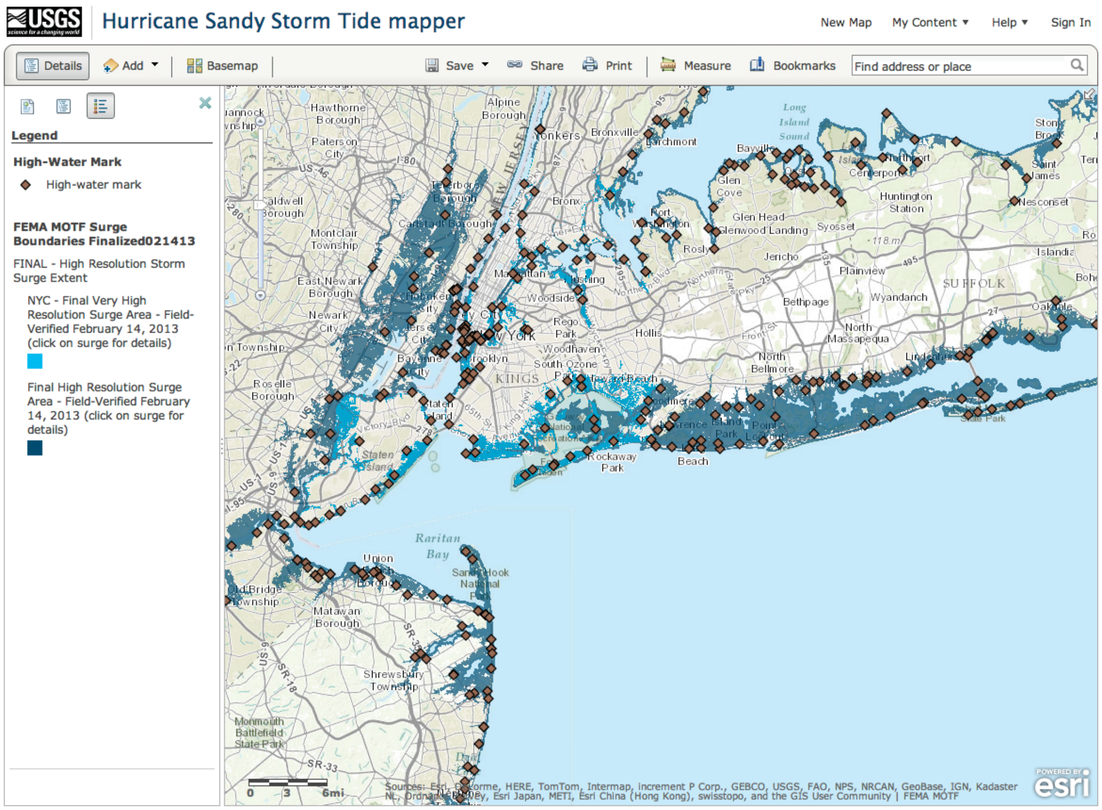


Figure 34 – USGS map of greater New York City area marking the available High Water Marks data points as grey diamonds, and the surge areas in blue.

Figure 35 demonstrates one such validation example where a USGS High Water Marks data point and a Human Sensor observation from Instagram coincide at the same geographic location. Figure 35 (a) shows photos of a flooded house with a wash line clearly seen on the wall, for site “HWM-NY-NAS-708”, which is located at geographic coordinates of 40.59 latitude, -73.64 longitude and elevation of 9.3 feet above sea level. The expert surveyed the location using GPS and marked the peak date of surge of 10/30/2012 with the height of 1.3 feet above ground. For illustrative purposes the field notes are attached in Appendix B. Figure 35 (b) shows an Instagram photo from the same geographic location showing the flooded street.

Figure 35 - Validation example showing USGS HWM data point and HSN observation from Instagram coinciding geospatially.

6.5 RESULTS

In this use-case scenario our research demonstrates the feasibility of the HSN approach in using those observations for early validation of the surge model forecasts. We have applied the proposed principles to the Hurricane Sandy disaster and were able to identify from the HSN observations not only the geographic regions that were flooded with a rough estimate of the water levels, but also the regions that did not get flooded. The photos with flooded streets are used to estimate the flood level, and the photos of streets that are wet from rain but not flooded are used to determine the upper bound beyond which the surge did not spread. Given the topography data of the observed location, we can determine the elevation at which the given flood observation occurred and extrapolate it to the neighboring vicinity of other areas of the same elevation.

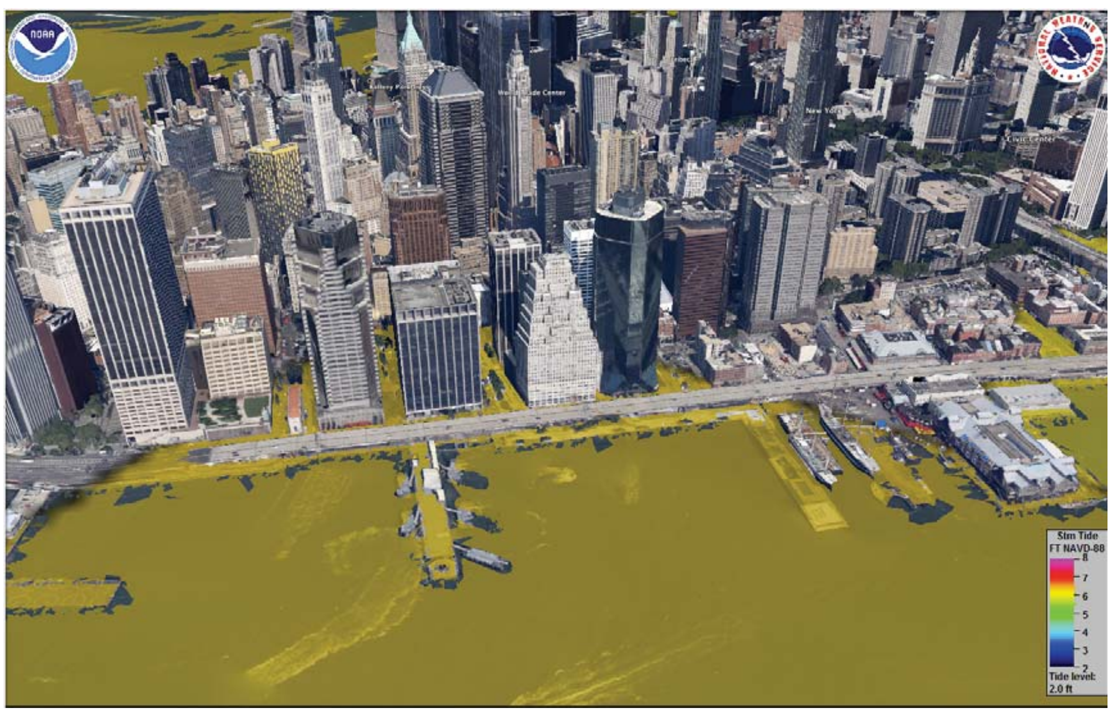


Figure 36 - Google Earth 3D visualization of the SLOSH model forecast for the Lower East Side of Manhattan.

SLOSH forecasts are coarse and inherently imprecise because of the limitation of the grid cell size and because the forecast gives the worst-case scenario for each grid cell. We were able to compare our observations with the SLOSH model forecast, validate the forecast, and attain higher accuracy of flood levels not possible in SLOSH due to the coarse grid level. Figure 36 shows visualization of the SLOSH surge forecast for The Lower East Side of Manhattan in Google Earth. The yellow color corresponds to a surge level of about 6 feet; however, it is clear that several street blocks fall within the same grid point forecast. Figure 37 shows another 3D example of a SLOSH model forecast visualization on Google Earth. Here it is clearly visible that multiple city blocks in Staten Island, NY are covered under a single grid point of the forecast.

Figure 37 - Google Earth 3D visualization of the SLOSH model forecast around Staten Island, NY

Chapter 7

VIRTUAL SOCIAL MEDIA OBSERVATORY FOR DISASTERS

For the purpose of testing the initial formulation of a transformational rapid response to disasters, we developed major components that will eventually lead to a situationally aware Virtual Social Media Observatory for Disasters. The purpose of this observatory is to detect and apply web based information to assist the impacted, as well as to provide responders with more effective information in response to extreme events occurring anywhere in the world. These tools facilitate harvesting of real-time Human Sensor Network observations and generate Disaster Maps that are able to visualize massive amounts of social media data from heterogeneous sources of both text and images. We have also developed the tools to extract quantifiable observations at resolutions down to the street and house level to assess the damage from disasters and locate people in distress.

7.1 ASONMAPS PLATFORM

One of the major components of the Virtual Social Media Observatory for Disasters is AsonMaps. AsonMaps platform consists of a web application front end, and a storage, indexing and geophysical model augmentation back end. The front end provides tools to search, subset, and mark-up social media data and to select the geophysical model forecasts of interest. The results are visualized on a Google Maps map displaying street level satellite imagery, social media observations, and geophysical model forecasts. Figure 38 shows a screenshot of AsonMaps platform set

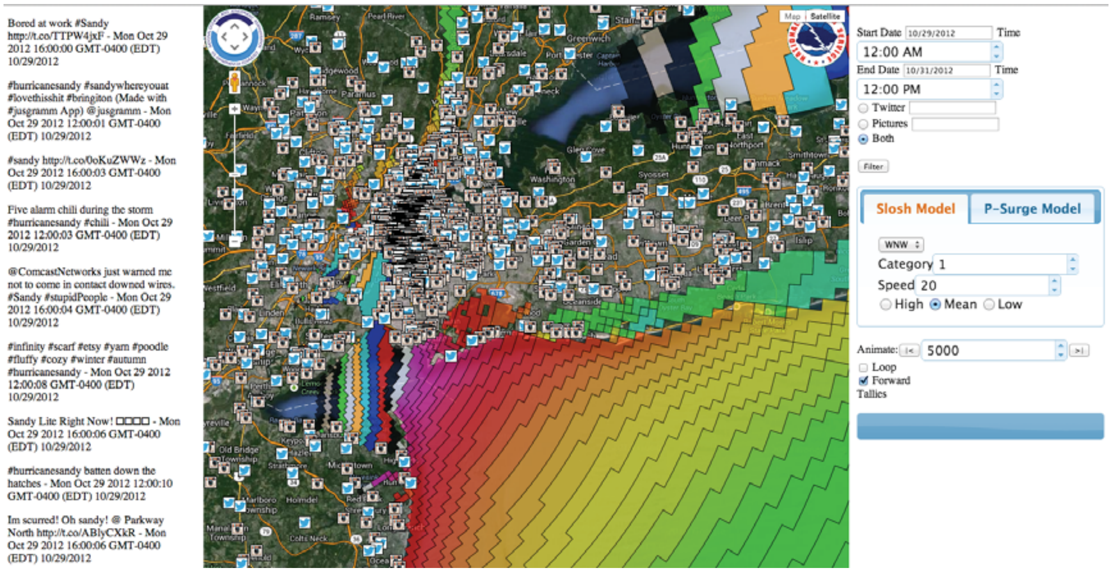


Figure 38 - Screenshot of AsonMaps platform centered on the greater New York City area. The overlay indicates different surge heights in different colors. Geolocated tweets are marked with a blue bird icon and Instagram images with a camera icon.

up for Hurricane Sandy use-case scenario. AsonMaps has the capability to simulate the timeline of a disaster for the purpose of learning in retrospect by animating the social media posts as the disaster progresses.

In order to keep up with the fast stream of live tweets and store them in a flexible format for a variety of future applications we used a 6-node BigCouch cluster. BigCouch is a distributed, scalable implementation of CouchDB. CouchDB is a NoSQL, schema-less key-value database that uses RESTful interface and stores data as JSON objects. There are many reasons why BigCouch was determined to be the best fit for AsonMaps Platform. Some of the major factors are its ability to handle large volume of write operations that is useful in cases of extreme disasters when there is a very high volume of social media activity that needs to be harvested in real time. The very low memory and processor overhead for write operations allows other software, such as ElasticSearch, to run concurrently on the same cluster. BigCouch also implements a feature called "_changes" that makes newly added data instantly available for access.

In order to interpret our data we needed an efficient method of searching and sub-setting it along multiple dimensions. For this task we deployed ElasticSearch on the 6-node cluster. ElasticSearch is a RESTful, distributed search engine based in its core on Apache Lucene text indexing library. The benefit of ElasticSearch in our project is that it is a scalable, standalone engine that can be easily incorporated with other components. Although less popular and less established then Solr, ElasticSearch has some features that make it a much more desirable choice for the AsonMaps platform. ElasticSearch employs the concept of "rivers" which are special plugins that facilitate ElasticSearch to pull data from different sources to be indexed. There is a river for CouchDB that has a capability of following the _changes log of the BigCouch database, thus continuously providing an up-to-date index of the social media data as it arrives without needing to rebuild the index. Such a combination facilitates the AsonMaps platform to provide a near real-time capability of viewing and analyzing the social media data in cases of disasters when timely situational

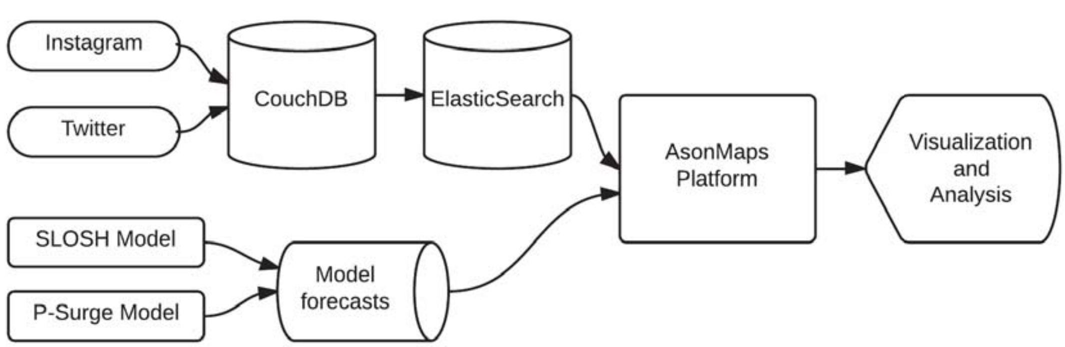


Figure 39 - AsonMaps platform diagram

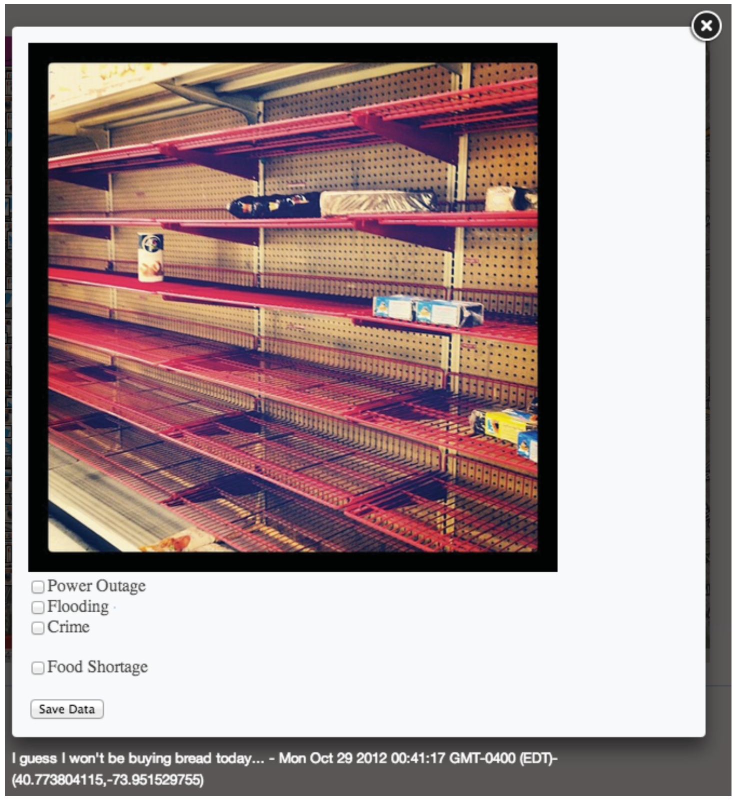
awareness is crucial for emergency response tasks. Figure 39 shows a conceptual diagram of the AsonMaps platform.

The 6-node cluster is part of the IBM iDataPlex system at CHMPR / UMBC that was donated by NASA under the Stevenson-Wydler Congressional Act. Each node is a dual processor, quad core Intel XEON 2.8GHz with 24GB of RAM and 250 GB of local storage interconnected via the InfiniBand switch. Such a setup facilitates robust future expansion of AsonMaps when new sources of social media data and new geophysical models get integrated.

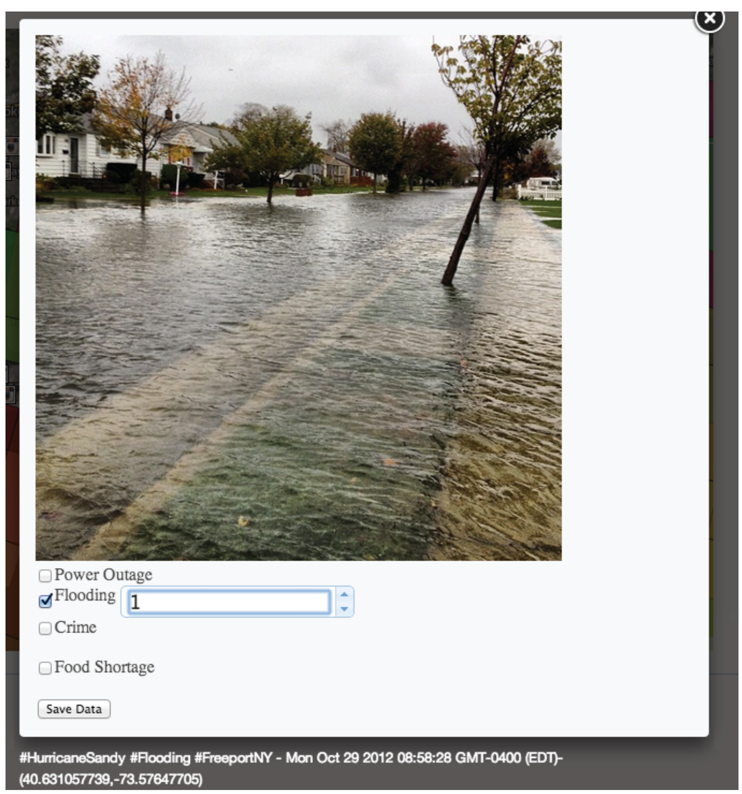
For illustrative purposes of storage needs, in the use-case of Hurricane Sandy, the 8 million-tweet dataset occupies 62 GB of storage, and the 370k Instagram photos occupy around 24 GB of storage with an additional 1.2 GB for the metadata. Some details of data storage, retention, preservation of access, and terms of service of different data providers are discussed in Appendix C, titled Data Management Plan.

7.2 ASONMAPS IN OPERATOR MODE

We developed a special mode of operation of AsonMaps that allows an emergency response operator to browse through a subset of geolocated social media posts and mark-up posts of interest with operator generated metadata that categorizes the post to belong to a criteria of interest and allows for quicker subsequent recall. For example, Figure 40 (a) shows an Instagram photo of empty shelves in the bread aisle at a grocery store with a description stating, “I guess I won’t be buying bread today…” Such a photo is indicative of a food shortage in a given location at a given time and can be marked-up to belong to a “food shortage” category. Multiple such



(a)



(b)

Figure 40 – AsonMaps in Operator Mode. (a) Example of food shortage; (b) Example of flooding with an option of specifying the depth in feet;

posts can be useful for those emergency responders that manage the food supply during disasters.

Figure 40 (b) shows an Instagram photo of a flooded street that in the Operator Mode can be marked-up as such, together with the estimated level of water in feet.

The mark-up categories are flexible and can be easily added or edited based on the disaster at hand. Such a setup potentially makes AsonMaps flexible to be used during disasters that are unprecedented. Appendix D shows additional Instagram photos of interest.

7.3 LIMITATIONS OF ASONMAPS

To give an objective review of AsonMaps, this section will list non-exhaustively some of the limitations of the platform in its present state.

One of the major limitations is that at present no pixel level information is taken into account when indexing and displaying the Instagram observations. Once the photo is placed on the map and the emergency responder views it, the pixel level information is used in the decision to mark up the photo as important or use it as observation. The system also lacks a means of validating the correctness of the photo's geolocation information or distinguishing between the location where the photo was taken from the location where the photo was uploaded and shared.

Although the academic community is actively researching methods of detecting fake, fabricated images posted on social media platforms, our system currently does not employ any such methods.

Chapter 8

CONCLUSIONS

This dissertation reports our findings in researching systematic ways of extracting quantifiable information from social media sources and incorporating it into a variety of geophysical models. The Introduction chapter explained the significance, urgency and societal benefits that would potentially result from our findings.

This doctorate research contributes to the field of Computer Science in the area of data mining of Web 2.0 and beyond by providing scientific knowledge, methodology and algorithms to harvest and represent social media data as sensor observations that allow for the incorporation of these data into a variety of geophysical models.

We have developed the tools to harvest real-time observations from social media and generate Disaster Maps that are able to collect massive amounts of data from heterogeneous social media sources of both text and images. We have also developed the APIs and tools to map these data and extract quantifiable observations that can be used to generate maps at resolutions down to the street and house level to assess the damage from disasters and people in distress.

We coupled these observations with model predictions to correlate observable information with model-based forecasts. Massive quantities of social media data require Big Data solutions for harvesting, storage, and analysis reporting. For this task we used a high performance iDataPlex compute cluster. We used a Map Reduce based BigCouch distributed database to aggregate the data, and ElasticSearch cluster to index the data for rapid querying. As a result we were able to process millions of social media observations.

We developed major components that will eventually lead to a situation aware Virtual Social Media Observatory for Disasters, one of the major components of which is AsonMaps. AsonMaps is a beneficial platform that has applications in multiple aspects of disaster management. Before a disaster hits, AsonMaps can be used to monitor the public response to the evacuation requests and other preparation actions. During hurricanes, AsonMaps provides a near real-time impact assessment, and following the event can provide micro-scale geographic evidence of the disaster impact. The AsonMaps Platform can also be used as a simulator for disaster response training by replaying the social media observations as if they were happening in real time.

Using the 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 were 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.

What was critical in the use of social media 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 social media sources are rapidly evolving, more and more quantitative information is becoming available from handheld and wearable devices and other social media platforms for physical modeling. The challenge will be in the validation of the quality and reliability of these observations.

We demonstrated actual use of Human Sensor Network observations in operational disaster forecast models and presented time sensitive data that can be invaluable for disaster response.

We processed social media data from Flickr to be in the format of the observational geophysical data, and used it as a boundary condition to assess the sensitivity and agreement of time dependent parameters in the GNOME model with social media data. We quantified the differences between the forecast and the social media observations by calculating the RMS error. We observed that minor changes in initial conditions of the forecast model can lead to an order of magnitude increase in consistency with specified Flickr data.

We collected several unique datasets of social media data as well as geophysical and observational data for several disasters, such as Tweets, Instagram photos, USGS High Water Marks, SLOSH forecasts etc. from Hurricane Sandy; Tweets from Typhoon Haiyan; Flickr photos from the Deepwater Horizon oil spill, that can be a valuable resource for future studies in this fast-growing area of research.

Chapter 9

FUTURE WORK

In the future we plan to conduct a comparative study of the datasets from Typhoon Haiyan and Hurricane Sandy and present insights into the similarities and differences of social media reports of similar in nature disasters that affect vastly different types of populations (rural vs. urban etc.).

We plan to expand our framework to be able to integrate it with Amazon Mechanical Turk in order to crowdsource the labeling task. We intend to create a feature that would allow us to rapidly create the labeling guidelines, select the candidate labeling subset of the data, and post the labeling task on Amazon Mechanical Turk.

We also plan to expand our platform to include many other geophysical models that can benefit from augmentation of Human Sensor Network data. Currently we are working on adding the General Operational Modeling Environment and the Hybrid Single Particle Lagrangian Integrated Trajectory Model.

In our current work we assumed that the geolocation information of Instagram photos obtained from the metadata is the actual location of where the photo was taken. However this is not always true. Additionally, only a small percentage of all the photos had geolocation associated with them. We also have not addressed the means of conducting analysis of the photos themselves on a pixel-by-pixel basis. In our future work, we plan on expanding the capabilities of AsonMaps to be able to provide analytical tools capable of using the pixel level data of the photos as well. We will do so by utilizing the capabilities of LIRE library. LIRE (Lucene Image

Retrieval) is an open source Java library for Lucene that has the capability of indexing images and finding images that appear similar visually [54], [55]. Since AsonMaps relies on ElasticSearch, we will add a Content Based Image Retrieval Plugin for ElasticSearch called "ElasticSearch-Image" that in its core is based on the LIRE library. Using such an implementation, we will explore the possibility of aggregating a large reference dataset of geo-referenced street level imagery from Google Street View and using it to geolocate those Instagram photos for which the location was not provided by the API. Those Instagram photos for which the geolocation was available in the metadata will be used to validate our approach.

The situational awareness of our Virtual Social Media Observatory for Disasters can greatly benefit from a crowdsourcing service such as MobiQ because it will provide the means for emergency responders to ask users to upload photos and report on the situation at hand. If such a service appears on Twitter or Instagram it will be a very desirable candidate for incorporation into the AsonMaps platform.

In the future we intend to finalize the experiments of detecting oil plumes from satellite imagery using self-organizing maps and social media observations. Currently, the input space to the SOM is picked by trial and error until a satisfactory map is produced. In the future we plan to develop an approach for selecting the input space automatically, possibly by utilizing genetic algorithms.

In the Deepwater Horizon oil spill study we demonstrated how changes in model parameters result in order of magnitude improvements of the forecast accuracy. However, the parameters were arbitrarily modified from their default settings to demonstrate the proof of concept. In future studies we intend to employ a more systematic approach, such as gradient descent, to figure out which parameters to modify for subsequent model runs. Additionally, we plan on exploring methods of combining HSN observations with conventional sensor observations by using data assimilation. There are several well-known data assimilation techniques that could potentially be applied to HSN. One such technique is discussed in Appendix A.

Appendix A

DATA ASSIMILATION

In earth sciences such as meteorology, oceanography and hydrology we often want to determine as best we can the current state of the underlying geophysical system and predict what the state of the system will be in the near future, a.k.a. forecast. If the system is deterministic, such as a weather system, the better our guess of the current state of the system, the better our forecast of the future state of the system will be [56].

Difficulties arise due to the limitations that we have in our measurements as well as the underlying geophysical model that describes the real-life system. Our measurements have uncertainties due to such factors as the inherent nature of the sensor, the environment in which the sensor is positioned (for instance remote sensing) and the precision of the sensor. In addition to those uncertainties, our underlying physical model also has multiple sources of parameter uncertainties such as the uncertainty due to the grid that we choose to use, the accuracy of our computations, or due to the nature of the model itself. In addition to uncertainty, it is infeasible to gather enough observations to better determine the initial state of our model. A commonly used approach to address such a limitation is to derive initial conditions of the model by using statistical combination of observations and short-range forecasts [56]. "Using all available information to determine as accurately as possible the state of the atmospheric (or oceanic) flow" is known as data assimilation [57]. In a broader sense, data assimilation is the combination of observational data with the underlying dynamical principles governing the system under observation.

Data assimilation carries on by analysis runs or cycles. Each cycle essentially balances the uncertainty in the data and the forecast, and, as a result, produces an analysis that is considered the best estimate of the current state of the system. Each cycle combines the current and the past observations with the underlying numerical model of the system and produces a new state called “analysis”. In the next cycle the model is advanced in time and this newly produced analysis becomes the forecast part of the input into the data assimilation system to produce the next analysis for the next time step.

2-Dimensional Variational Data Assimilation is a particular data assimilation approach that, in its core, is based on the concept of adjusting the initial conditions of the underlying mathematical model instead of the final analysis. In a simplified 2-Dimensional variational data assimilation, a time window of a certain length is chosen from which the observations are ingested. In the simplified 2-DVAR assimilation, the optimal state of the system is found via minimization of a certain cost function J that is defined as:

$$J(x) = \frac{1}{2}(x - x^b)^T B^{-1}(x - x^b) + \frac{1}{2}(y - H(x))^T R^{-1}(y - H(x))$$

where:

x is the predicted model state

x^b is the a-priori (background) model state

B is the background error covariance matrix

y the observed variables

H a non-linear observation operator, which projects the model state in the observation space

R is the observation error covariance matrix.

Generally the observation operator H is non-linear and therefore J has to be found through an iterative process, however in our case of a simplified 2D-VAR we assume that H is linearizable, thus we can calculate the Jacobian through perturbation δx of state x:

$$H = \frac{\delta y}{\delta x}$$

where:

δy is the change in the observation variable y, due to the perturbation of the model state x.

Thus T analyzed state x^a is:

$$x^a = x^b + K\left(y - H(x^b)\right)$$

where K is the gain matrix such that:

$$K = BH^T(HBH^T + R)^{-1}$$

[58], [59].

Appendix B

HIGH WATER MARKS FIELD FORM EXAMPLE

High Water Mark Field Form

(one form per HWM)

Quick Lookup #

DATE: 11/2/12 STORM: Sandy (2012) PARTY: MDC/ WDC

SITE INFORMATION

SITE NAME: HWM-NY-NAS-708 **LATITUDE (DD to 6 places):** 40.590820
(Site Name Format: HWM-SS-COU-###, where SS = state, COU = county, ### = site number)

SITE DESCRIPTION: Boyd Street **LONGITUDE (DD to 6 places):** -73.643354

STATE: NY **COUNTY:** Nassau **Landowner notified (circle one):** Yes No

HWM INFORMATION

HWM identified with: colored flagging, marker, stake, disc, spray paint, other
Type of mark: debris line, mud line, seed line, wash line, other
Mark location (circle one): Inside Outside **Approx. height above ground (ft):** 1.30
Quality of mark (circle one): Excellent (+/- 0.05 ft) Good (+/- 0.10 ft) Fair (+/- 0.25 ft) Poor (>0.25 ft)

ELEVATION INFORMATION

HWM Description: Black mark on wall inside 27 Boyd Street in living room.
* Had to make new mark on outside wall of 24 Boyd ~~Street~~.

HWM Elevation: 9.293

RM Description:

RM #: **RM Elevation:**

Other Notes:

PHOTOGRAPH INFORMATION

Pictures Taken: Yes No **Camera Owner:** MDC

Digital Photo Filenames:

Please complete site sketch on reverse

9.365
9.221
9.293 Avg HWM elev

Poor cell coverage for GPS

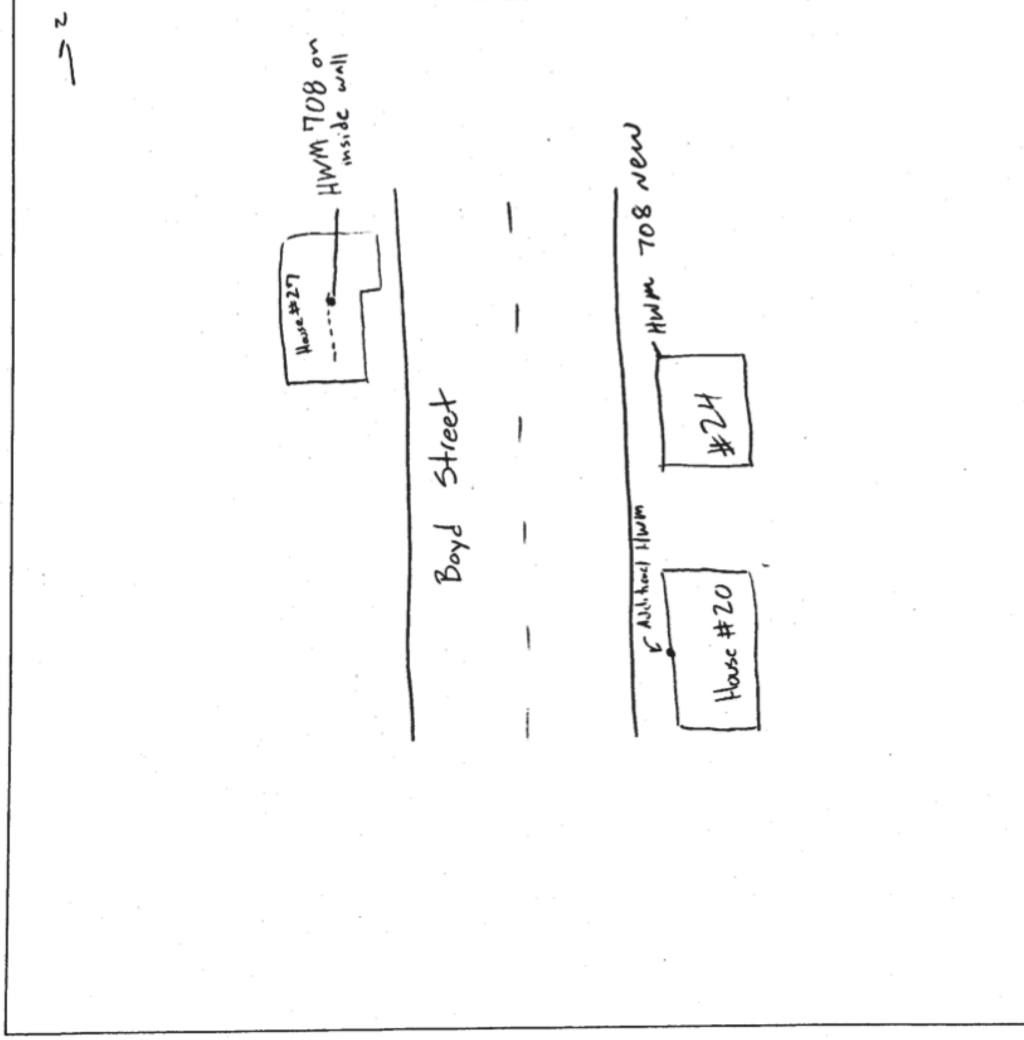
High Water Mark Field Form

(one form per HWM)

Quick Lookup #

DATE: 11/2/12 STORM: Sandy (2012) PARTY: MDC / WDC

SITE MAP



Additional Notes:

Additional HWM → Black mark on good seed line on wall to the right of 20 Boyd Street front door (2.54 ft above deck)

No Access at #27 made mark across street at #24.

Appendix C

DATA MANAGEMENT PLAN

The source code for the front-end of the AsonMaps platform is hosted on Google Project Hosting site and is available to the public as a read-only download at the following address: https://code.google.com/p/asonmaps/

Twitter data and Instagram metadata are stored in a 6-node BigCouch distributed cluster on BlueWave (part of the iDataPlex system at CHMPR / UMBC). The actual photos from Instagram are stored on the NFS drive on Bluegrit.

The data is bound by the Twitter Terms of Service and Instagram Terms of Use agreements respectively, and due to those agreements' strict limitations are currently not allowed to be redistributed, shared or made otherwise publicly available. However, if in the future Instagram or Twitter will change their terms, the data will be made available in compliance with those terms. The current terms of use can be found at the following links:

https://twitter.com/tos

https://dev.twitter.com/terms/api-terms

http://instagram.com/about/legal/terms/api/

The CHMPR center expects the NSF IUCRC phase 2 extension for another 5 years and this data will be available internally for future research for at least the duration of the current NSF extension of the CHMPR center.

Appendix D

INSTAGRAM PHOTOS OF INTEREST

10/29. Flooded & evacuated ER #hospital. Thanks, #HurricaneSandy. □□□□ - Mon Oct 29 2012 22:26:33 GMT-0400 (EDT)- (40.716133117,-74.050109863)

#NYU Hospital being evacuated due to #Sandy #Blackout #HurricaneSandy - Mon Oct 29 2012 23:03:04 GMT-0400 (EDT)- (40.741001129,-73.97566986)

GLOSSARY

ADCIRC –	ADvanced CIRculation Model
AIRS –	Atmospheric Infrared Sounder
API –	Application Programming Interface
CCC –	Computing Community Consortium
CERA –	Coastal Emergency Risks Assessment
CHMPR –	Center for Hybrid Multicore Productivity Research
CISE –	Computer and Information Science Engineering
COSMO -	Constellation of small Satellites for the Mediterranean basin Observation
EOS -	Earth Observing System
ERD -	Emergency Response Division
ERMA -	Environmental Response Management Application
EXIF -	Exchangeable Image File format
FEMA -	Federal Emergency Management Agency
GNOME -	General NOAA Operational Modeling Environment
GPS -	Global Positioning System
HSN -	Human Sensor Networks
HWM -	High Water Marks
HYSPLIT -	Hybrid Single Particle Lagrangian Integrated Trajectory Model
JSON -	JavaScript Object Notation
LANCE -	Land Atmosphere Near real-time Capability for EOS
LIRE -	Lucene Image REtrieval
LITMUS -	Landslide Detection by Integrating Multiple Sources
MEOW -	Maximum Envelope of Water
MLS -	Microwave Limb Sounder
MODIS -	Moderate-resolution Imaging Spectroradiometer
MOM -	Maximum of Maximums
MRI -	Major Research Instrumentation
NASA -	National Aeronautics and Space Administration
NCDC -	National Climatic Data Center
NCEP -	National Centers for Environmental Prediction
NESDIS -	National Environmental Satellite, Data, and Information Service
NGDC -	National Geophysical Data Center
NHC -	National Hurricane Center
NLP -	Natural Language Processing
NOAA -	National Oceanic and Atmospheric Administration
NOS -	National Ocean Service
NSF -	National Science Foundation
NWS -	National Weather Service
OR&R -	Office of Response and Restoration
REST -	Representational State Transfer
ROMS -	Regional Ocean Modeling System

RSS -	Rich Site Summary
SCAT -	Shoreline Cleanup and Assessment Technique
SCRUM -	S-Coordinates Rutgers University Model
SLOSH -	Sea, Lake, and Overland Surges from Hurricanes
SMS -	Short Message Service
SOM -	Self-Organizing Map
TED -	Twitter Earthquake Detector
TGLO -	Texas General Land Office
UMBC -	University of Maryland Baltimore County
USGS -	United States Geological Survey
XML -	Extensible Markup Language

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