3-1-1 Calls Hot Spot Analysis During Hurricane Harvey: Preliminary Results

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ABSTRACT

Hurricane Harvey caused massive damage and necessitated the need for identification of areas under high risk. During Harvey, the city of Houston received more than 77000 3-1-1 calls for assistance. Due to damage caused to the infrastructure, it became difficult to handle and respond to the crisis. Geographic Information Systems (GIS) are a vital technology to assist with real-time disaster monitoring. In this regard, for this work-in-progress paper, we investigated if a correlation could be found between 3-1-1 data calls made during Hurricane Harvey and aerial images captured during the event. Specifically, we were interested to see if 3-1-1 data could be ground-truthed via hot spot analysis. Our preliminary results indicate that visual representation of 3-1-1 call data can aid in analyzing the expected areas of high traffic of calls for assistance and plan an effective way to manage resources. Future work will involve more in-depth analysis of combined 3-1-1 call data with satellite imagery using image classification techniques.

Keywords

Hurricane Harvey, 3-1-1 data calls, hot spot analysis.

INTRODUCTION

Natural disasters affect any geographic area and potentially millions of people residing within it. They are at times difficult to predict or give little to no warning before they turn uncontrollable and fatal. Hurricane Harvey, a natural disaster disguised as a tropical cyclone, caused massive damage mainly due to flooding in the city of Houston, Texas in August 2017. In merely 4 days, the majority of areas within Houston received more than 40 inches of rain, causing alarming levels of flooding which affected thousands of homes, claimed 91 human lives, and over 17,000 people were rescued. During natural disasters, it becomes important to facilitate the identification of risk areas and prioritize the response and mitigation effects involving those areas. 9-1-1 and 3-1-1 services receive massive amount of rescue calls 24/7 in times of mass crisis like Harvey (Harvey's devastating impact by the numbers, n.d.). For example, Houston 9-1-1 received 56,000 calls in first 15 hours and the 3-1-1 department received nearly 77000 calls in those four days of the storm. Loss of power and infrastructure is the most challenging scenario for disaster management as most people are not able to request help using emergency services. Remote sensing can assist in monitoring minute by minute insights of the environmental conditions, providing real-time data estimations which help in disaster response management. During Harvey, this was achieved by government aircrafts capturing aerial images of the flooded and damaged areas, updating every 12 hours. Using the data provided by remote sensors (in this scenario areal images captured by aircrafts), GIS can help in identifying geographic areas which need assistance, thus providing relief to areas most in need. However, it becomes important to ground truth incidents based on these aerial images and the 3-1-1 call service requests. The reason being that it is important to evaluate which regions did call 3-1-1 but did not receive service due to lack of response. Thus, investigating the spatial relationships between aerial image footage and 3-1-1 calls can become crucial to future response evacuation and plans as well as response management.

We present preliminary results of visually analyzing 3-1-1 calls during Houston Harvey to the 3-1-1 ground truth data. By performing spatial analysis to determine statistically significant hot spot areas of 3-1-1 calls, we can identify from which counties we received the highest flooding calls. Ideally, we can potentially find a correlation which would help analyze where can we expect emergency calls from and efficiently plan resources for response management. In our future work section, we discuss how our analysis can be extended by classifying the images using supervised and unsupervised techniques to distinguish the flooded and damaged areas.

The application of our analysis is not limited to floods or hurricanes like Harvey. The visual correlation between 3-1-1 data (or other citizen-generated data) and real time satellite imagery during any disastrous event can lead to better understanding in identifying areas impacted and improve response management.

RELATED WORK

Our literature review is focused on two sections to ground our research in relevant scientific contexts. The first subsection is about the importance of 3-1-1 call analysis, while the second includes techniques and methods used in classification of satellite images.

Data Analysis

Langenberg (2007) represented the case study of Hurricane Wilma, 3-1-1 and Miami-Dade County which implemented implications for effective emergency management and citizen relationship during disasters. As per the case study, (Langenberg & Schellong, 6 Jan. 2007), Miami-Dade's 3-1-1 Answer Center served as a single point of contact and offered the people an access to government services prior as well as post-emergency situations. On an average 3-1-1 was handling 500 calls per day. During the event of an emergency, the call volume surged from average calls of 2000 per day to 12,737 calls per day. Half of the calls made were initiated from mobile phones. In due course of time, as the hurricane accelerated and impacted the infrastructure, power line and cell towers were no more able to function normally. This created a blind spot for the authorities and disaster management teams as help was not reaching places where the damage to infrastructure was substantial and request for rescue was not reaching the helplines. The Wilma 3-1-1 case demonstrates the importance of 3-1-1 request calls, as it is the only means of information for the relief workers to provide relief and perform a rescue. Any natural disaster has the potential to affect infrastructure in a way that it is rendered useless. It leads to victims not being able to request relief thus resulting in loss of life or injury. This inability for citizens to communicate with disaster responders creates an urgent need for an auxiliary source that can provide relief providers with data that can help them perform rescue operations proactively even when the infrastructure is down, and victims are stuck hoping for a miracle.

Yilong Zha et.al (2014) performed extensive analysis and data-based prediction of 3-1-1 calls in New York City (NYC). They provided statistics on complaint types, geolocation, and temporal patterns and displayed the diversity of the big 3-1-1 data along those dimensions (Zha & Veloso, 2014). For temporal distributions, a visual analysis was created to compare the distribution of request volume over days of the week for the different types of complaints. For understanding geo-correlation to population ratio for the different type of events, they calculated geo-correlation coefficient and used it for future predictions to see which areas receive the highest number of calls and for what kind of event. To predict request volume each day they combined data from U.S. calendar and NYC historical weather data. An experiment was performed using random forest trees considering the importance of features. A prediction table was generated by measuring Mean Squared Error (MSE) for the different types of features. Using this value, they predicted which feature was important to predict the types of complains and volume of calls. Using this method to identify which feature is important can help us understand patterns in the subset and detect events. For example, request volumes of storm debris removal can help us identify which areas are damaged and need amenities. In terms of the work presented by Yilong Zha et.al (2014) it can be concluded that, how 3-1-1 call data can be used for understanding urban population characteristics and potential 3-1-1 calls that can come during a disaser event. For example, identifying where socially vulnerable populations live and/or what neighborhoods might be expected to generate high volumes of 3-1-1 calls.

Image Classification Techniques

Supervised Technique

In this method, training areas are selected where the user selects the area of interest. Training sets are created for different classes and these classes are merged into a single signature file (Jog & Dixit, 2016). Classification is performed using maximum likelihood, ISO cluster, class probability and principal components methods using this signature file as the input. The output would create an image with classifications that was created in the input.

Unsupervised Technique

In this method the user specifies the number of classes expected and which bands to use (Prasad, Savithri, & Iyyanki, 2015). The software clusters the pixels with similar characteristics and generate corresponding classes. Generally, the iso data and k means clustering techniques are used.

Object Based Technique

Supervised and unsupervised are pixel-based techniques where each pixel belongs to a class. Object based technique groups pixels into shapes and sizes of homogeneous objects. Multiresolution segmentation process which generates different object representation by grouping pixels represent different features in image like square shaped, elevated, using multiple bands (Prasad, Savithri, & Iyyanki, 2015). Nearest Neighbor classification is one of the method use to perform object-based classification in which after multiresolution segmentation, we classify objects on nearest distance and other statistics.

Need for Correlation

As previously discussed, many past researchers have done 3-1-1 call analysis. But to the best of our knowledge, few studies have specifically combined imagery analysis with 3-1-1 calls. The correlation will help to identify the plan for response activities as well as how decision systems and remote sensing technologies can be coordinated. The correlation of the 3-1-1 helpline services and satellite images captured by national imagery departments will help organizations how to make adaptions during emergency services to enhance cost effectively resilience of services during catastrophic events. Satellite imagery, when transformed into raster environment, covers the entire area analyzed and cause of its spatial ubiquity and multitemporal distribution. It is useful in conjunction with other combined data. Data acquisition and integration of remote sensing can help develop new methods for response and recovery operations. Geospatial cross referencing which combines the 3-1-1 data with image analysis helps in spotting damaged sites such as debris and collapsed houses. It also helps in identification of locations with considerable damages which might suffer from power outages as they lack any request for help over 3-1-1 helpline. Further, image classification can be used to categorize debris for planning purposes. The spectral characteristics in different bands of spectrum of the images helps us in classifying images to distinguish between ground surface materials and debris. Combing the 3-1-1 data and images we can produce maps like thermal images showing hot spots. Cross referencing and correlation can help produce maps for seeing transport status, determine level of elevation of debris, and submerged spots. Thus, combing data sets of calls with image analysis results in streamlined rescue management and proactive recue response.

METHODOLOGY AND PRELIMINARY RESULTS

Dataset

The dataset for 3-1-1 calls analysis is taken from the **City of Houston's 3-1-1 department** (City of Houston Department, n.d.). It contains 77,621 call records, while the imagery data set is taken from the (Hurricane Harvery Imagery, n.d.) Hurricane Harvey Aerial Imagery acquired by NOAA Remote Sensing Division. It has flight images captured from an altitude of 2500 to 5000 feet, using a Trimble Digital Sensor System (DSS) for Houston Harvey.

HotSpot Analysis

We first analyzed 3-1-1 calls made during Hurricane Harvey. To analyze the number of calls reported during flooding, we performed preprocessing of the data that included data cleaning, removing missing values, and extracted the calls with flood service requests. Later, using ArcMap GIS, we mapped the x, y coordinates of the places from where calls have been received using the base of Houston street map as shown in Figure 1.

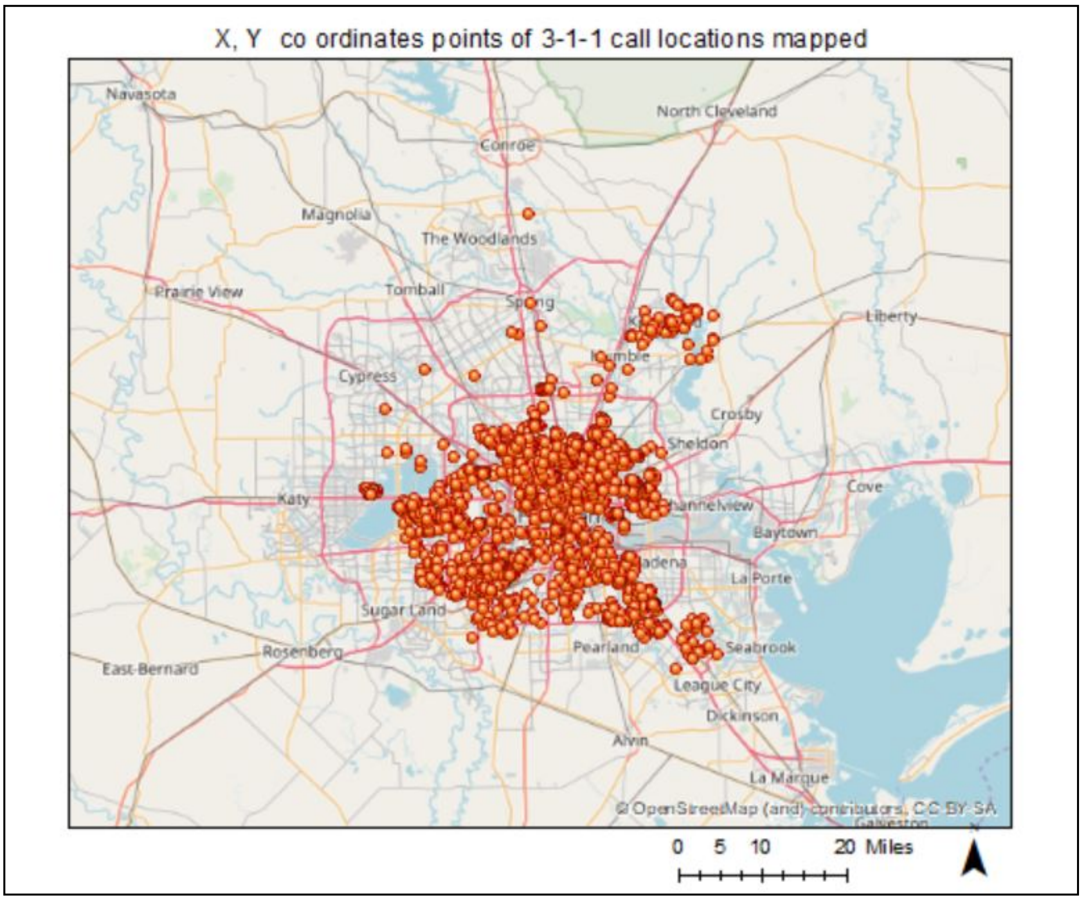

Figure 1. X, Y coordinate points of places with flooding calls

To understand the distribution of calls, their spatial patterns, and to determine resource allocation for emergency response management, we performed hot spot analysis using an industry standard GIS tool. Hot Spot analysis helps understand spatial patterns and determine statistically significant clusters that helps in locating neighborhood optimal locations. For each feature of the input dataset, a Getis-Ord Gi* statistic was calculated that results in z-scores, p-values, and confidence level, i.e the Gi_Bin for respective input feature. Results of this method were used to determine 'cold spots' which are statistically low clustered values and 'hot spots' with statistically high clustered values. Hot Spot analysis uses an input analysis field for determining clustering outputs.

Typically, 3-1-1 calls are highly related to population densities, meaning that populous areas tend to have more calls, which makes the comparison between places with very different population densities unfair. To address this issue, we calculated the density using a count field. A count field is a numerical field that specifies the number of incidents at each location. Using the Esri population census data as the count field and the locations of the received calls as the input, we calculated the density. Using this method, we calculate an appropriate search distance for determining neighborhood size providing output densities in per square miles. In Figure 2, the low to high color scale range represents low to high range densities. Our intent was just to describe the phenomena and not make inferences or predictions or comparisons, in the future work section we discuss ideas for predictions.

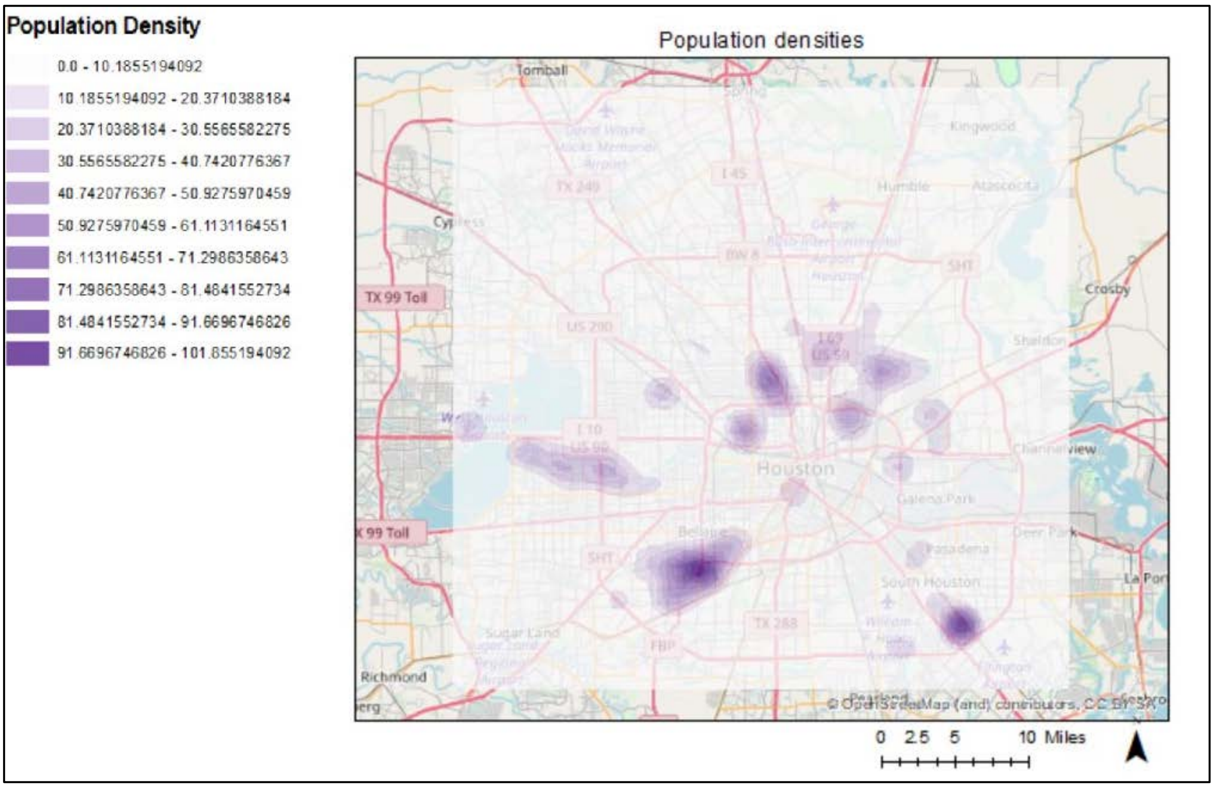

Figure 2. Low to high population density areas

For point data like 3-1-1 call data, which involves spatial clustering associated with incidents, we used several methods to aggregate the data. Since we have x, y coordinate points with short distances between each point, we integrated those points using a neighborhood of 30 feet. The value of neighborhood distance is derived from distance band which is associated to the peak value of incremental spatial correlation which we performed. The output of this spatial aggregation created a new feature called ICOUNT, which represents points with the number of incidents associated at each point. Figure 3 shows the number of incidents at each point where blue points represent locations with more than 4 calls.

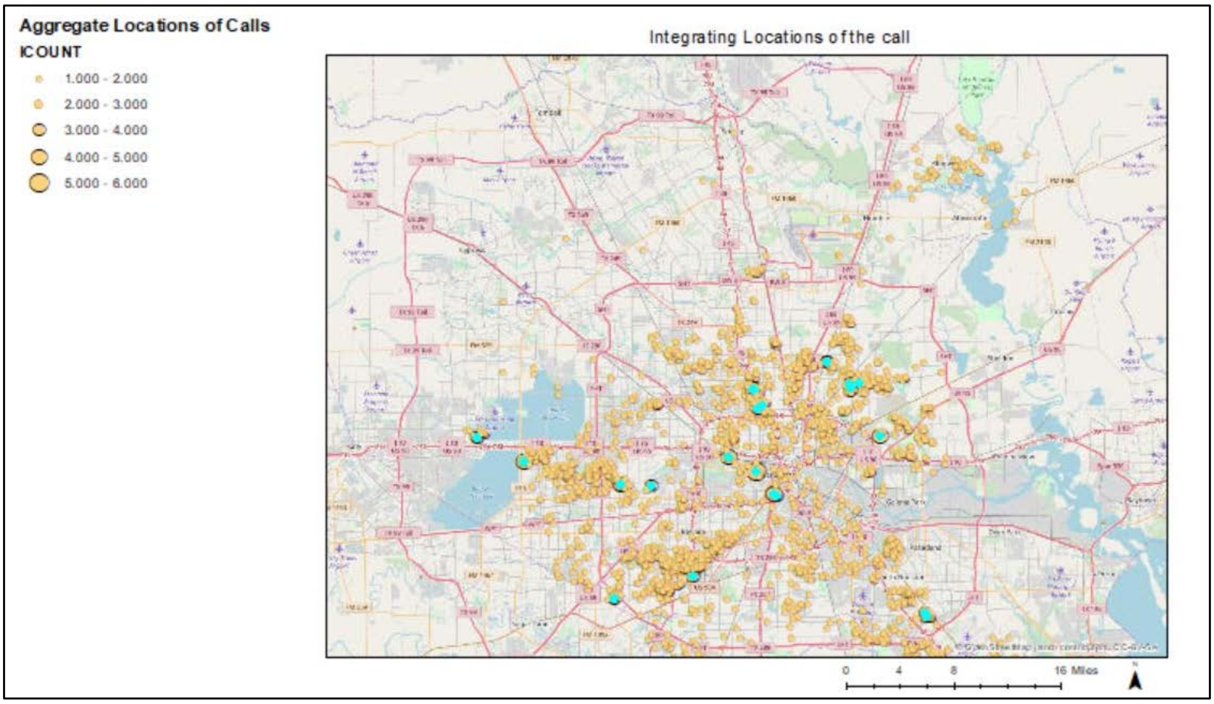

Figure 3. Points in blue represent incidents or number of calls at specific point which have ICOUNT >4

We used the ICOUNT output feature in the hot spot analysis to get the statistics for hot and cold spots. Figure 4 depicts the hot and cold spots with confidence levels. The GI_Bin field depicts the confidence level that helps in identifying low or high clustered points. The confidence level is the proportion of certainty about the true figure (ArcGIS). The proportion can be considered as the confidence coefficient that would be 0.99, 0.95, 0.90. There are different confidence levels for p values and z scores; a p-value represents the probability and z-scores are the standard deviations.

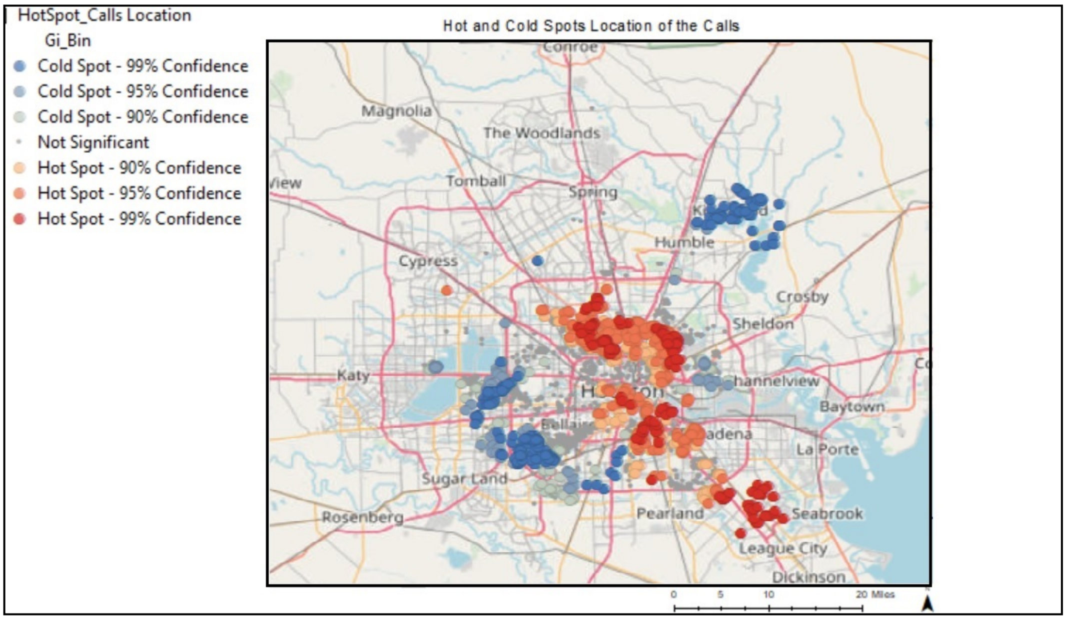

Figure 4. Hot and Cold Spots areas from where flooding calls have been received.

Using the fixed band distance parameter as ICOUNT and Euclidean distance method, we determined the significant spots (as seen in Figure 4) where red areas are the hot spots with high number of calls and blue are cold areas with less number of calls and beige areas are not statistically significant. Hot spots and cold spots are determined by combination of significant z scores and p scores, where a hot spot is an area with the largest number of flood related calls received, while cold spots are less prominent areas from where the calls have received. The z scores above 1.96 value with 95% confidence level is considered significant hot spot and values below 1.96 are less significant. The 1.96 value is defining that 95% of the area of a normal distribution is within the standard deviations and exhibits a normal pattern (Table 1). From the hot spots, we can determine the likely neighborhood spots for receiving the calls.

Table 1

Gi_Bin	Confidence Level
+/-3	99%
+/-2	95%
+/-1	90%
0	Not significant

For better visualization of the clusters, we created a continuous surface using Inverse Weighted Distance (IDW) based on the GiZ score. Where low to high values based on the weighted distance are stretched or interpolated as shown in Figure 5. The higher values are marked as red and stretched from yellow to blue.

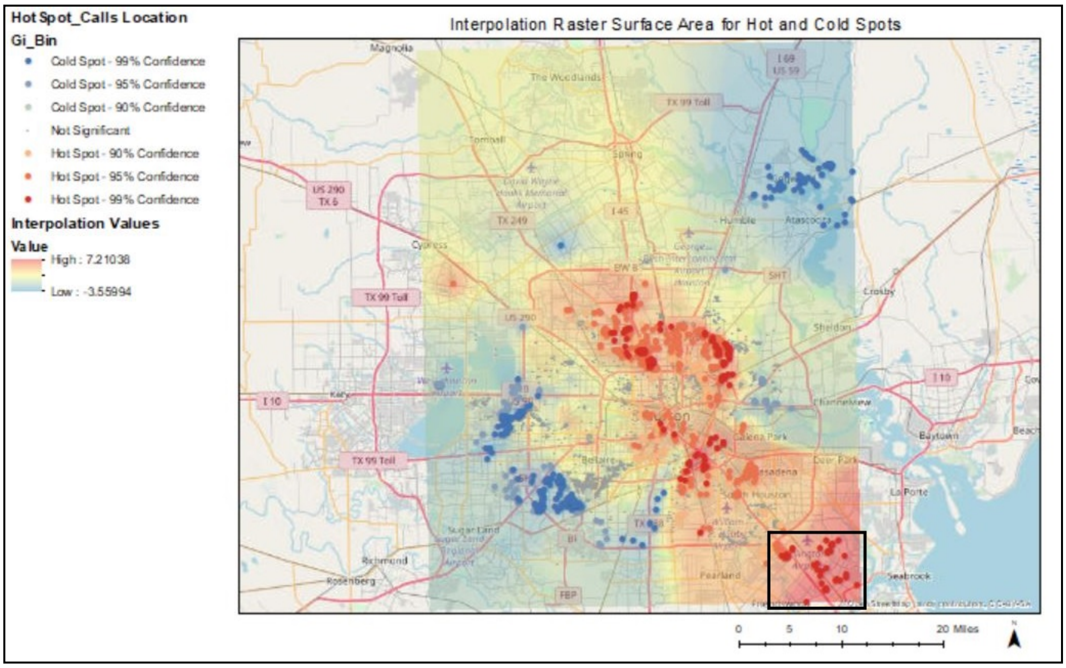

Figure 5. Interpolated raster surface for visualization. The area in the bottom right are the Cities of Dickenson and League City in Galveston County Texas.

Based on the hotspot analysis and IDW surface representation, several interesting patterns in terms of 3-1-1 call volume can be revealed. For example, the bottom right corner of Figure 5 shows a statistically significant area of 3-1-1 calls from the Cities of Dickenson and League City in Galveston County Texas (Burke, 2017). The authors of this paper visited Galveston County Texas in November 2017 and learned from local emergency management officials that Dickenson and League City were particularly inundated by the impacts from Harvey due to low lying elevations. Furthermore, response to this area was hampered by lack of situation awareness in terms of emergency responders having access to real-time data streams to inform response in Galveston County and identify specific areas such as boats for picking up people who were stranded on rooftops. Ideally, methods like the ones we are presenting in this work in-progress paper could be used for real-time analysis of 3-1-1 call data with real time satellite imagery to inform rapid situation awareness and targeted response.

Combined Image Analysis with 3-1-1 Hot Spot Locations

In this section, our aim is to combine satellite images that are geo referenced with the hot and cold spot call locations. Overlaying the significant hot spots and cold spots from where we received the calls over satellite images will enhance the data visualization. The images, associated with the call locations, will give a clear indication of damaged sites. This enables us to determine the ground truth. With the help of overlaying the call locations on imagery, we can pinpoint specific infrastructure locations to locate flooded areas and collapsed structures. With the visualization of damaged sites and correlated calls at that location, we can identify potential areas for evacuation within a ground zero site.

For combined analysis, we need to extract the data from a day flight focusing on specific areas that where depicted as the hot and cold spots. Next, we build a raster dataset of images and convert it the into required band format. These images are then geo referenced and exported in the form tiff to use as a base image.

As shown in Figure 6, we downloaded the image from the NOAA imagery August 30 Flight 1, converted it into a raster dataset, and extracted the University of Houston (UH)downtown area and exported as tiff using image and raster analysis tools in ArcMap. We see significantly hot spot locations near downtown Houston. The UH downtown areas and forest cemetery areas are flooded and damaged. This analysis gives an overview of damaged sites and the neighborhood areas from where calls have received. As per the reports, water-damaged buildings are located primarily in the northern and western areas of downtown. The downtown district was damaged due to increased water levels of Buffalo Bayou.

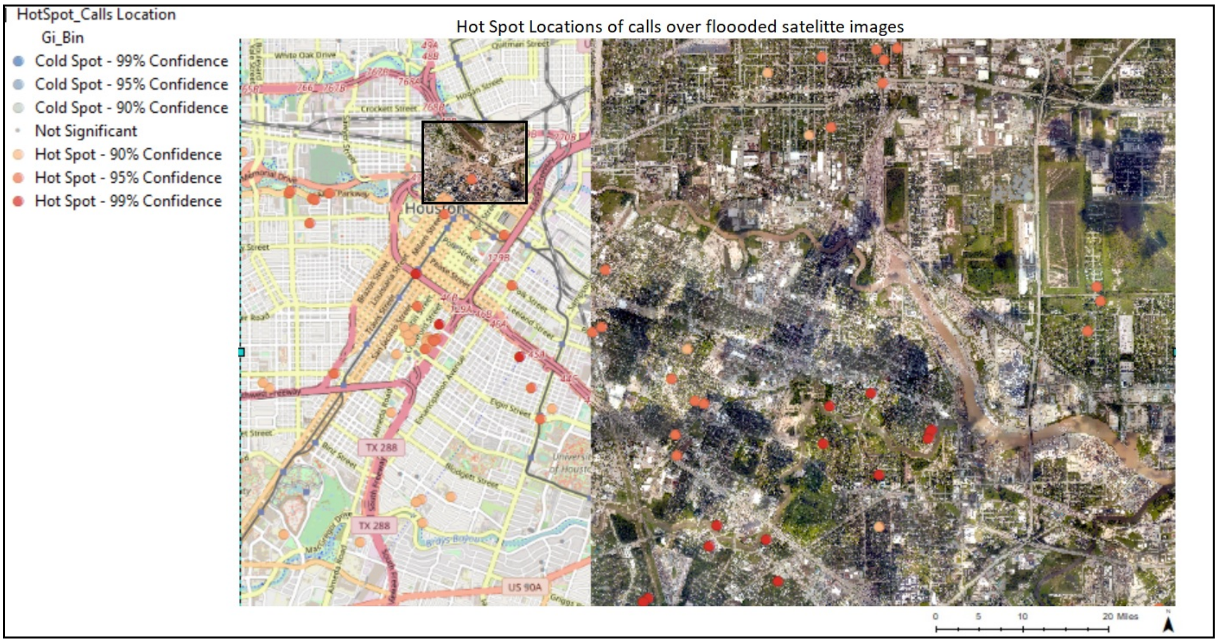

Figure 6. Area in the top left are the hot spots laid over UH downtown imagery and to the right are near Mongolia transit center and Forest cemetery areas

After plotting the referenced images and calls, there were many areas observed as per analysis which were highly damaged, but the locations from where the 3-1-1 had received were significant cold spots. On August 28, the Addicks and Barker reservoirs had filled to the capacity and the infrastructure was shut down (Almukhtar, et al., 2017). A voluntary evacuation was to put to order and the Army Corps of Engineers had to release water from reservoirs to the Gulf (Planas, Satlin, Lohr, & Gordts, 2017).

As reported, the officials did not expect the reservoirs to flood beyond capacity. Before the action was taken, neighborhoods near the dam had already flooded on Sunday night and due to late night help was hardly available. The coast guard rescue boats were sent the next day. The Harris county district emergency services were not available until August 31st. Under such scenarios, the aerial imagery and existing data helps the recovery team to plan evacuation, health and emergency facilities. The Figure 7 below shows the barker reservoir and its neighborhood flooded. But still the number of calls made were less significant due to lack of services available

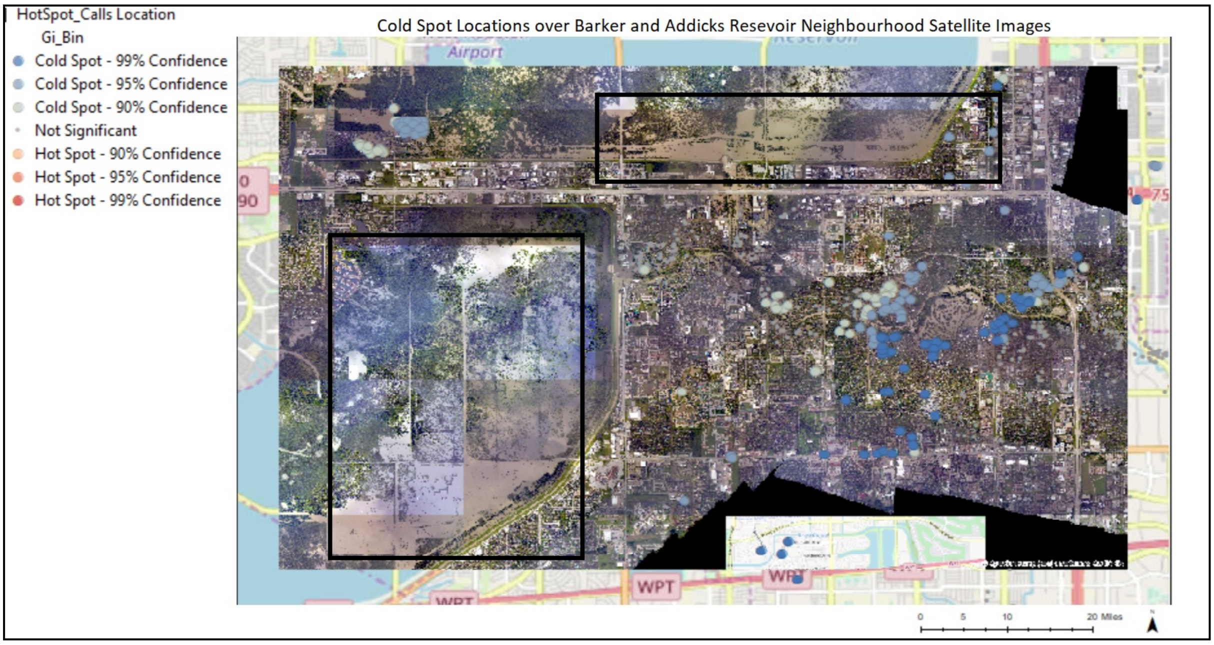

Figure 7. The highlighted areas show the over filled Addick's and Barker reservoir and Cold spots overlaid in their neighborhood areas

Harvey Floods affected Kingwood-Humble areas causing disruption to normal daily life. A lot of houses collapsed and were damaged as the flood gates opened at Lake Conroe, rushing nearly 80,000 cubic feet per second (Kingwood, 2017). A back up was provided for 3-1-1 calls service and a dedicated lime for prompt service was established by the Kingwood Community service and Houston Police. Multiple other online website platforms like nextdoor.com, Kingwood service was used when 3-1-1 dedicated line and other emergency services was not available. In few hours since the storm, the Kingwood areas and communities were stranded without electricity on August 30, 2017 (Kirk, 2017). CenterPoint reported that approximately 100,000 individuals, in its service area across Houston, were without power. The overlaid points of the calls location in the Kingwood areas in the Figure 8. below supports the evidence.

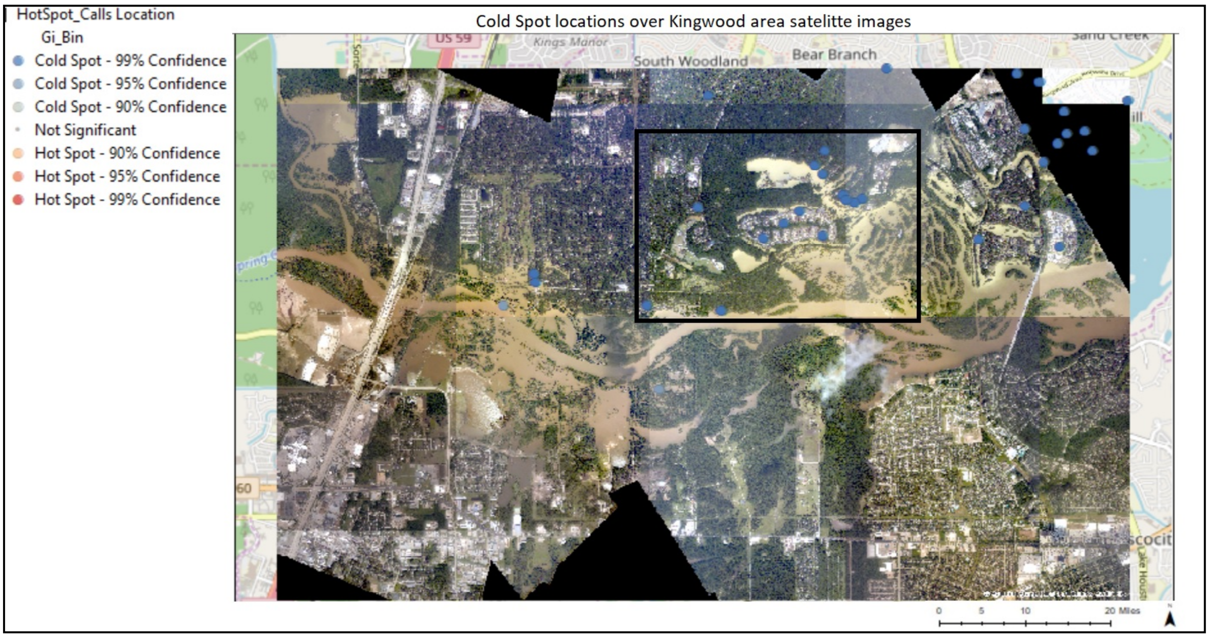

Figure 8. Cold Spots Locations overlaid on satellite images Kingwood areas

FUTURE WORK

Image Analysis

In the work presented here, we have used hot spot analysis to determine clusters of 3-1-1 call data during Hurricane Harvey. We combined statistical hot spots with aerial and remote sensing to have better visual correlation between hot spots and pictorial representation of ground situations. Our future work will involve classification of the images and to use temporal aspect of data to predict hot spot locations from different time slices. In this regard, we present our plan for future work to achieve this research goal.

Classification of images, such as finding patterns and areas of interest is needed for spatial data mining, extracting information for applications, thematic map creation, image interpretation, disaster and emergency response management, effective decision making and field surveys (Prasad, Savithri, & Iyyanki, 2015). In a paper review about the classification methods and techniques, the methods were classified into two categories supervised and unsupervised. The supervised training involves creating training sites based on ground truth samples and prepare images from raw data. Next, create signatures from training samples and apply to the whole image and then transform to create a suitable map (Jog & Dixit, 2016). The most widely used techniques or algorithms for supervised classification are Maximum Likelihood classifier, Minimum distance, and Image Segmentation. The steps involved in unsupervised classification techniques is to create clusters by grouping pixels and later assign labels to meaningful pixels. The most common algorithms used are ISO data and k-means. The methods are reviewed based on classification accuracy and kappa coefficient (Abburu & Babu Golla, June 2015). Based on this measures for multispectral satellite images object-based classification technique is better

ArcMap based texture analysis program for extraction of flooded areas from TerraSAR-X satellite image conducted by Biswajeet Pradhan where they analyzed imagery using pixel-based and object-based classification schemes also concluded that thematic map produced by pixel-based classification did not result in high accuracy results as compared to the object-based approach (Pradhan, Hagemann, Tehrany, & Prechtel, 2013).

This is the second phase where we would analyze the satellite imagery. For Harvey, NOAA collected imagery has from August 27, 2017, to September 3, 2017.We need to extract the data from a day flight focusing on specific areas which where depicted as the hot spots. Later will build raster dataset of images and convert into required band format. To perform classification will use various remote sensing techniques which include supervised, unsupervised and object-based classification.

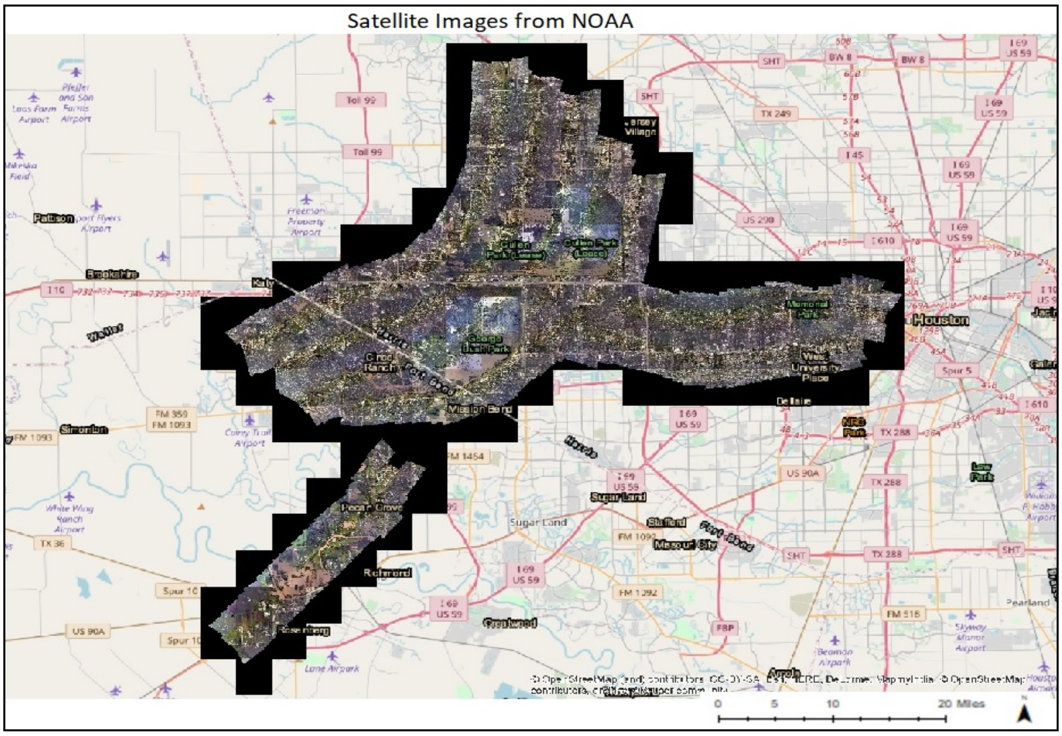

Figure 9. Satellite images from NOAA imported as raster datasets in ArcMap

As shown in Figure 9, we would import satellite images from NOAA Hurricane Imagery as raster datasets. These raster datasets are converted into mosaic dataset for performing different classification technique. To perform supervised classification, we would generate training samples by drawing polygons for different classes (ArcGIS Image Classification, n.d.). The classes would be the flooded water areas, damaged area, roads. After generating training samples, we would run the algorithms to produce classified images. In our case study object- based approach is the best suitable for high spatial resolution images. Multi resolution segmentation uses both spectral and contextual information thus rendering objects with better quality.

Evaluation and Comparison of Analysis.

After analyzing the hot spots, we would investigate the maximum calls where received and then determine the neighborhoods which are at potential risks and need a response. Next, we would do a comparison of these data points with the classified images of damage as per geographical area to find the correlation of the ground truth. We would try plotting and layer this data into an interactive map. To find the ground truth would match the results with Harvey by numbers and FEMA data.

CONCLUSION AND SUMMARY

In this paper we study the 3-1-1 calls Hot Spot analysis during Hurricane Harvey. Thomas Langenberg's case study suggests the need of an axuilarry source of information apart from 3-1-1 calls to effectively manage the rescue operations. Our approach takes into consideration that aspect of diaster management and introduces the correlation of sattlelite imagery with 3-1-1 call data. Our analysis provides detailed information about the situation during the event which can be used by the disaster management to plan effectively. With the combination of spatial and image analysis we can evaluate data closer to ground truth that can facilitate timely and well-informed management decisions. We propose that this analysis can be further applied to any natural disaster with same efficiency.

ACKNOWLEDGEMENTS

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