72nd International Astronautical Congress (IAC) - Dubai, 25-29 October 2021.

IAC-21,B1,5,10,x65420

Supplementing Earth Observation with Twitter data to improve disaster assessments: A case study of 2020 Bobcat fire in Southern California

Swarnajyoti Mukherjee[a,*,#], Krittanon Sirorattanakul [b,*,#], Daniela Vargas-Sanabria[c,*,#], Samridh Patial[d,*,#], Abinash Silwal[e,*,#], Kristine Jane Atienza[f,*,#]

[a] *Space System Engineer & Business Professional, GP Advanced Projects, Srl, Brescia, Italy,* swarnajyoti.mukherjee@gmail.com
[b] *Division of Geological and Planetary Sciences, California Institute of Technology, Pasadena, CA, USA,* krittanon.sirorattankul@spacegeneration.org
[c] *Laboratorio de Investigación e Innovación Tecnológica, Universidad Estatal a Distancia, San José, Costa Rica,* danielavargas1989@gmail.com
[d] *Department of Aerospace Engineering, Indian Institute of Space Science and Technology, Kerala, India,* samridh.sc21m030@pg.iist.ac.in
[e] *Department of Geomatics Engineering, Kathmandu University, Nepal,* afactor.abinash@gmail.com
[f] *World Vision International, Philippines,* kristine.atienza@spacegeneration.org
[#] *Space Technology for Earth Applications (STEA) Project Group, Space Generation Advisory Council (SGAC), Vienna, Austria*
[*] *Corresponding Author*

Abstract

Space-based Earth Observation allows us to simultaneously detect changes on Earth's surfaces over a large area. As a result, it's often used to assist with disaster assessments to understand associated property damages in the affected areas. Geographic Information Systems and Remote Sensing, are very popular for their applications in handling disasters and are being utilized as a key tool to support decision making throughout the disaster management process. And top of it, the use of social media, especially Twitter, has become a popular communication platform which is identified in providing vital information in emergency situations. Twitter users can use the services to work synergistically regardless of physical distance. To demonstrate the benefits of supplementing Earth observations with Twitter data in disaster assessments, we use a recent fire in Southern California, Bobcat fire, that started on September 6, 2020 and burned for over 3 months until it was finally contained on December 18, 2020 as a case study. The plume from the fire spanned more than 1,000 miles with smoke travelling across the entire North American continent. 116,000 acres of land got affected along with unprecedented wildlife loss. Also this fire has turned the high sierra granite gorge into bare and ashen sloped. In this study, we integrated Earth observations with data from Twitter, to assess a more comprehensive view of the overall damages including physical and emotional state as an aftermath of a disaster. Remote sensing data lets us to understand pre post fire conditions of the land as well as temperature variation and soil condition of ground. Geographical locations are analyzed from tweets which are compared with levels of various pollutants measured from ground instrumentations and the amount of smoke coverage from satellite imagery. With the additions of Twitter data, using machine learning and natural language processing, we are able to derive a more holistic impact of the Bobcat fire on California citizens. Thus, augmenting remote sensing data with socially sensed Twitter data will strengthen capabilities of experts and staff working to analyze and manage disaster risk by providing them both spatial and socio-economic information. Moreover, we can also determine how various factors contribute to the superspreading of messages. A better understanding of social media utilization would allow us to determine a better risk reduction tool, whether it would be for the purposes of early warning of disaster events or reducing mental stresses after a disastrous event.

Keywords: Bobcat Fire, Earth Observation, Twitter, Disaster Assessment, California citizen

Acronyms

DOI	Department of the Interior
EO	Earth Observation
EPA	Environmental Protection Agency
FIRMS	Fire In-formation for Resource Management System
FS	Forest Service
GDP	Gross domestic product
GEE	Google Earth Engine
GIS	Geographic Information System
LST	Land Surface Temperature
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NBR	Normalized Burn Ratio index
NFS	National Forest System
NIFC	National Interagency Fire Center
NIR	Near Infrared
NLTK	Natural Language Toolkit
OLI	Operational Land Imager
SWIR	Shortwave Infrared
TIRS	Thermal Infrared Sensor
UN-SPIDER	United Nations Platform for Space-based Information for Disaster Management and Emergency Response
USGS	United States Geological Survey

1 Introduction

Wildfires are unplanned and unwanted fires, including lightning-caused fires, unauthorized human-caused fires, and escaped prescribed fire projects. States are responsible for responding to wildfires that begin on non-federal (state, local, and private) lands, except for lands protected by federal agencies under cooperative agreements. The federal government is responsible for responding to wildfires that begin on federal lands. The Forest Service (FS)—within the U.S. Department of Agriculture—carries out wildfire management and response across the 193 million acres of the National Forest System (NFS). The Department of the Interior (DOI) manages wildfire response for more than 400 million acres of national parks, wildlife refuges and preserves, other public lands, and Indian reservations. Wildfire statistics help to illustrate past U.S. wildfire activity. Nationwide data compiled by the National Interagency Fire Center (NIFC) indicate that the number of annual wildfires is variable but has decreased slightly over the last 30 years and the number of acres affected annually, while also variable, generally has increased. Since 2000, an annual average of 70,600 wildfires has burned an annual average of 7.0 million acres. This figure is more than double the average annual acreage burned in the 1990s (3.3 million acres), although a greater number of fires occurred annually in the 1990s (78,600 average).[1] From 2011 to 2020, there were an average of 62,805 wildfires annually and an average of 7.5 million acres impacted annually. In 2020, 58,950 wildfires burned 10.1 million acres, the second-most acreage impacted in a year since 1960; nearly 40% of these acres were in California. Nearly half of the acres impacted were on NFS lands. These official figures from NIFC reflect downward revisions from earlier reported data for 2020. As of September 8, 2021, nearly 44,000 wildfires have impacted over 5.1 million acres. The nationwide preparedness level has been at the maximum level (5) since July 14, 2021, suggesting a sustained and significant commitment of shared resources [1].

Usually, large wildfires occur often in dry ecosystems of the western United States [2], and around 80% of the world's fires are caused by humans [3]. The study of wildfires dynamics can be supported by Earth Observation (EO) technology. Chuvieco and Congalton (1989) [4] mentioned the advantage of using Geographic Information System (GIS) and satellite images for detecting, monitoring, and assessing the burn scars caused by fires. During a fire event, EO is useful for detecting and locating smoke plumes distribution. For example, multi-spectral satellite data have been used as a tool to aid in the detection of changes to ecosystems for burning biomass [5]. In addition, spectral indexes have been developed to evaluate the frequency, intensity, and localization of a wildfire. One of the frequent indexes used for change detection is based on pre-fire and post-fire images from multi-spectral bands, which can determine biomass loss, smoke production, and carbon release [5]. The thermal infrared band in particular is also very efficient and effective in evaluating environmental changes that are related to wildfires [6]. The brightness in thermal band can be converted to Land Surface Temperature (LST) which has shown to increase significantly during wildfires [7, 8]. We used the Normalized Burn Ratio index (NBR) to highlight burned areas in large fire zones, as in the case of the Bobcat fire, which burned 46,861 ha approximately. Its delta-NBR allows it to estimate the severity of the fire, which means the impact or degree of environmental changes caused by a wildfire [9].

Fine particulate matter (PM2.5) is an air pollutant that when occurs in excessive amounts could pose health concerns such as increased risk of respiratory and cardiovascular diseases [10]. The term refers specifically to particles that are 2.5 microns in diameter or smaller. It is often measured in $\mu g/m^3$. The United States Environmental Protection Agency (EPA) established standards for PM2.5 at 35 $\mu g/m^3$ daily average or 12 $\mu g/m^3$ annual average [1]. Wildfires in California could elevate the concentration of PM2.5 above the standards for a prolonged period of time [11]. As the wildfires become more frequent and intense due to climate change [12], better monitoring of PM2.5 is prudent to avoid health hazards.

The use of social media, especially Twitter, has become a popular communication platform, and is identified in providing vital information in emergency situations has become popular. Twitter users can use the services to work synergistically regardless of physical distance. This paper is concerned with the use of Twitter data to show the effectiveness of society's reaction, awareness, their positive and negative aspects, relief measures, express gratitude, complaints and others. By understanding how various factors contribute to the superspreading of messages, one can better optimize Twitter as an essential communications and risk reduction tool with machine learning algorithms. This study introduces which further define the technological and scientific knowledge base necessary for developing future competency base curriculum and content for Twitter assisted disaster management education and training at the community level.

2 California Wildfires

2.1 Burned Area Statistics

California had more wildfires (See Figure 1) than any other state in 2019, and by California standards, 2019 was a mild year. State and local resources fought 7,860

[1]https://www.epa.gov/pm-pollution/2012-national-ambient-air-quality-standards-naaqs\-particulate-matter-pm#additional-resources

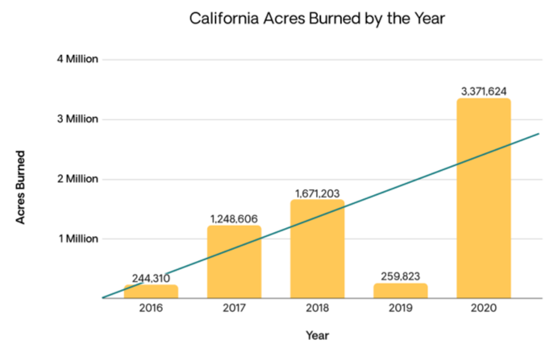

Fig. 1: California Area Burned from 2016 to 2020 [13]

wildfires that burned more than 259,000 acres [13]. In August 2020 alone, nearly 585 wildfires burned nearly one million acres in a week and 700 homes [13]. California has perfect conditions for wildfires. Its risk is directly tied to:

- Dry weather, thanks to the drought.
- Lack of forest management.
- An influx of development in the Wildland Urban Interface.
- High winds.

Native trees and plants are dying off, creating more kindling, and being replaced by invasive grasses that burn easily. The Forest Service tries its best to trim brush and implement prescribed burns to manage the forests and curb the risk of fires, but most of its yearly resources go toward combating massive fires instead.

2.2 Economic Cost

Wildfire destruction is costly. In 2019, more than $12 billion in claims were filed from the 2018 Camp Fire, Woolsey Fire, and Hills Fire. And that's just insured losses – many homeowners most at risk for wildfires may not have coverage. AccuWeather [14]estimates between damage to homes and businesses, belongings and cars, job and wage losses, farm and crop losses, infrastructure damage, school closures, highway closures, and power outage costs puts the 2018 wildfires at $400 billion in

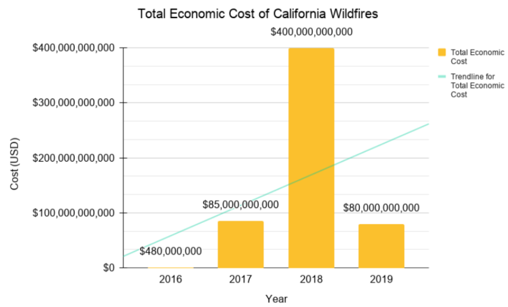

Fig. 2: Economic Cost structure from 2016 to 2019 [14]

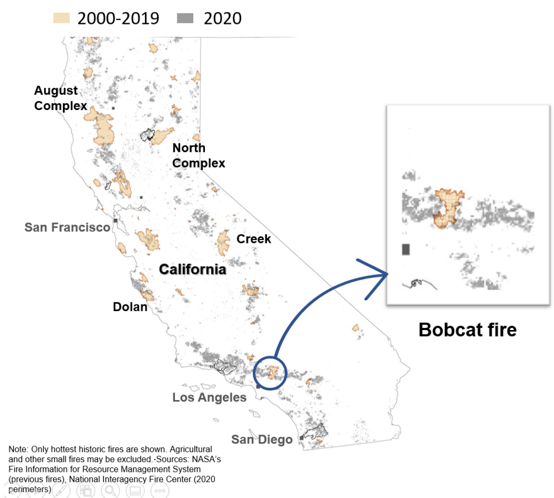

Fig. 3: Where major fires have burned in 2020 in relation to previous ones (2000-2019) Sources: NASA's Fire Information for Resource Management System (previous fires), National Interagency Fire Center (2020 perimeters)

losses (See Figure 2). By 7th December 2020, California's economic cost due to wildfire is \$120bn - \$150bn only in 2020, roughly 0.5% of the United States of America's annual Gross domestic product (GDP).

3 The 2020 Bobcat Fire

Bobcat fire, that started on September 6, 2020 and burned for over 3 months until it was finally contained on December 18, 2020 as a case study. The plume from the fire spanned more than 1,000 miles with smoke traveling across the entire North American continent. This fire has been one of the most devastating fires in the city's history

Fig. 4: Aftermath of fires near the foothill of the San Gabriel Mountains. Picture was taken on September 2021.

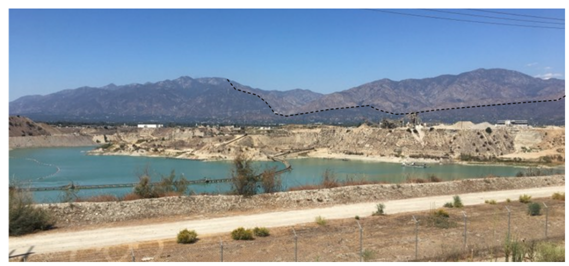

Fig. 5: Fire scar on the San Gabriel Mountains taken near Santa Fe Dam on September 2021. The region above the dotted line was burned during the 2020 Bobcat Fire.

with 26 casualties and over 180 structures damaged due to the fire. Over 116,000 acres of land was affected [2] due to the fire with unprecedented loss of wildlife which is still to be estimated. The fire has turned the high sierra granite gorge into bare and ashen sloped. As per geologists examination and report [2], the land is primed for mudslide condition due to the oncoming winter storm which will setback all the conservation effort done in the past years to the area.

4 Methods

4.1 Fire Mapping

With Google Earth Engine (GEE), we delimit the area affected by fire using an image taken on 2020-11-24

[2] https://www.cityofmonrovia.org/your-government/bobcat-fire

by Landsat 8 OLI/TIRS and atmospherically corrected Surface Reflectance from the collection of the GEE. NASA's Fire In-formation for Resource Management System (FIRMS)[3] is used for validation. We then analyze the severity of the fire within the perimeter of the burned area. This step can be divided into three parts: a general severity map that includes an analysis of the entire period of the wildfire, a weekly severity map, and monthly severity monitoring since the wildfire started in September 2020 until December 2020. We calculate the Normalized Burn Ratio index (NBR), an index highlighting burned areas within the fire perimeters. The formula uses the Near Infrared (NIR) and Shortwave Infrared (SWIR) wavelengths, given as follows:

$$NBR = \frac{NIR - SWIR}{NIR + SWIR} \tag{1}$$

The values of the NBR indicate the healthy vegetation and the low values of the areas that are burned. Then, we follow the UN-SPIDER recommended practices for mapping the severity of the burned areas [4]. Data downloading and processing are done using the GEE platform. To generate the severity map, we use pre-fire and post-fire Landsat 8 images. The pre-fire images were from 2020-01-01 to 2020-08-31, while the post-fire images were from 2020-10-01 to 2020-11-30. We calculate the NBR and the NBR with these inputs, defined as the differences between NBRs from pre-fire to post-fire. We use categories defined by the United States Geological Survey (USGS) to classify delta-NBR into one of the following groups: enhanced regrowth high, enhanced regrowth low, unburned, low severity, moderate-low severity, moderate-high severity, and high severity.

4.2 Land Surface Temperature (LST)

We have used MODIS satellite time series datasets in this study to estimate the LST. The MOD11A2, MODIS LST 6th product provides an average 8-day LST in a 1200 km x 1200 km grid. with 1km spatial resolution. Each pixel value in MOD11A2 is a simple average of all the corresponding MOD11A1 LST pixels collected within that 8-day period [15]. MOD11A2 was selected from

[3] https://firms.modaps.eosdis.nasa.gov/

[4] https://www.un-spider.org/advisory-support/recommended-practices/recommended-practice-burn-severity/in-detail

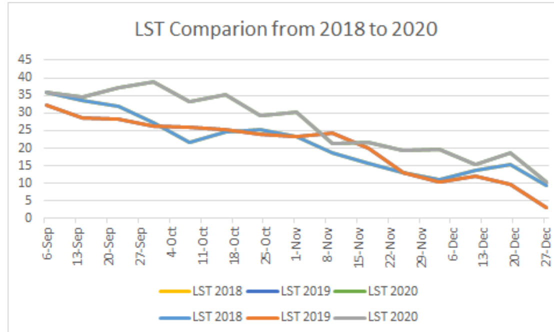

Fig. 6: Land Surface Temperature (LST) comparison between 2018 and 2020

earth engine's MODIS collection and ‘LST_Day_1km' data band was used for retrieval of LST. The graph of LST time series was created from the mean LST data of the study area from September to December for the years 2018, 2019 and 2020. The reason to study the trend of 3 years LST is to compare the variation of LST before and during the bobcat fire. The reason to choose an 8-day compositing period was because the exact ground track repeat period of the Terra and Aqua platforms is twice that period [15]. LST was extracted from the ‘LST_Day_1km' band and converted to degree celsius units and represented in a line graph using google earth engine. It can be observed that there is about 5-10$°C$ increase in the LST of 2020 between September and November than the past trends (year 2018 and 2019) of LST when there was no bobcat fire. This aberration can be due to the fire in bobcat in the year 2020.

4.3 Air Pollutants

Past records of daily PM2.5 data are available through the United States Environmental Protection Agency (EPA) website [5]. Data from recent days are taken from the AirNow portal [6] which is updated regularly. As AirNow data are validated through quality assurance designated by EPA, it will be released to replace data from the AirNow portal. Daily data are calculated from the averaging over a period of one day from midnight to midnight in local time. In the state of California, there are 165 stations that

[5] https://www.epa.gov/outdoor-air-quality-data/download-daily-data

[6] http://www.airnow.gov/

recorded PM2.5 data in 2020. Among them include 30 stations that are located within 100 km from the vicinity of the Bobcat fire. The distance is measured from an assumed reference point within the fire perimeter at latitude 34.2992°N and longitude 117.9617°W. PM2.5 data can be compared with the burned area and land surface temperature measured from Landsat thermal images to assess the effect of the Bobcat fire on the local climate systems.

4.4 Extract & Process Twitter Data

The Bobcat fire started on 9th September, 2020 which effectively engulfed 114,926 acres in which more than 6000 structures were threatened with an unprecedented loss to wildlife [2]. One of the primary purpose of studying the tweet data is to understand the use of twitter by the general public and to introspect their perception around the incident. Primary literature study was done around news covering Bobcat Fire incidents to get an idea which tweet hashtags cover the most information on Twitter. For that reason, we have used snscrape[7] and Tweepy[8] python libraries to extract tweets from August, 2020 to December, 2020. Using these libraries, we have specified to extract only those tweets who has "Bobcatfire" in it as well as tweet data is compiled by considering hashtags like, "#Bobcatfire, #Calfire, #CaliforniaFire", to build the Global database for the Bobcat Fire event. We have analyzed the sentimental analysis of those tweets and by doing that we had to needed to retrieve the date, time, place, number of replies & retweets for each and every tweets.

Later on, we have used Natural Language Toolkit (NLTK), a Python library, to do Natural Language Processing. Firstly, we eliminated the links, mentions to get the core of the tweets and eventually did tokenization to make a list words and punctuations for each sentence. After that, we applied lemmatization to extract the exact verb from different tense forms of the verbs and removed non-alphabetical characters. To understand the usage of word frequency, we have demonstrated the TF-IDF Vectorization algorithm. TF-IDF (term frequency-inverse document frequency) is a statistical measure that evaluates how relevant a word is to a document in a collection of documents. This is done by multiplying two metrics: how many times a word ap-

[7]https://github.com/JustAnotherArchivist/snscrape
[8]https://github.com/tweepy/tweepy

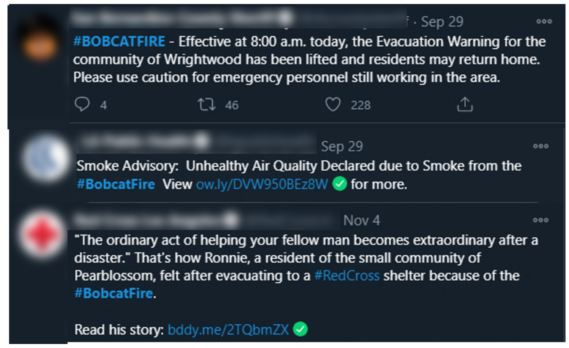

Fig. 7: Examples of Extracted Tweets from Twitter; Due to rules & regulations, account name can't be shared publicly

pears in a document, and the inverse document frequency of the word across a set of documents. Multiplying these two numbers results in the TF-IDF score of a word in a document. The higher the score, the more relevant that word is in that particular document.To put it in more formal mathematical terms, the TF-IDF score for the word t in the document d from the document set D is calculated as follows:

$$tfidf(t,d,D) = tf(t,d) * idf(t,D) \qquad (2)$$

where,

$$tf(t,d) = log(1 + freq(t,d)) \qquad (3)$$

$$idf(t,D) = log\left(\frac{N}{count(d \in D : t \in D)}\right) \qquad (4)$$

For sentimental analysis, we use a python library Textblob [9]. This library contains a trained models that could determine the polarity and subjectivity of a given text. Polarity ranges between -1and 1 with positive values reflecting emotionally positive message and negative values reflecting emotionally negative messages. Those that are neutral would have polarity of 0. Subjectivity ranges between 0 and1 with 1 being subjective and 0 being objective. Using both polarity and subjectivity would allow us to evaluate the sentiments of twitter users toward fire issues.

5 Results and Discussions

5.1 Earth Observation (EO) Data Analysis

Using the methodology (see 4.1) applied for the fire mapping, the delta–NBR index analysis shows a spatial distri-

[9]https://textblob.readthedocs.io/en/dev/

bution of the fire severity (See Figure 9). Overall, there are areas where fires had caused a lot of damage, most of them located toward the south of burned area boundary. Figure 8 shows fire monitoring during the first week, the second week, the first month, and the second month. In the first week, the fire ranged from moderate-low severity to high severity distributed toward the southern boundary of the burned area (See Figure 9). However, in the second week, the first month, and the second month, the severity had increased throughout the entire region. Toward the northern part of the region, there were portions with reduced severity to low and moderate-low. On the other hand, in the southern part, the fire remained severe and was classified as moderate-high and high severity. Figure 9 shows a general severity map indicating the extent of damages to the ecosystems during the most intense fire interval between September and October. Some areas with less intense fire were classified as enhanced regrowth-high and enhanced regrowth-low. Also from MODIS data we can see (Figure 6) the sudden changes in the Land Surface Temperature (LST) in between September to November compare to 2018 & 2019, due to 2020's Bobcat fire.

Stavros and other NASA fire experts[10] have been monitoring the blazes using a suite of satellite sensors. One of them, the Operational Land Imager (OLI) on the Landsat 8 satellite, acquired an image (Figure 10) of the burn scar (above) on September 21, 2020, while the fire was still raging in Angeles National Forest. False color makes it easier to distinguish the burn scar. The image combines shortwave infrared, near-infrared, and green light (OLI bands 7-5-2) to show active fires (bright red), scarred land that has been consumed by the fire (darker red), intact vegetation (green), and cities and infrastructure (gray).

The advantage of using geographic information systems and remote sensing tools made it possible to analyze the effects of fire before, during and after the fire, and generate information related to severity that will be valuable for post studies about recovery and ecosystem restoration. The NBR is a consistent index to map severity, and its results have been demonstrated in previous California wildfires studies [5, 16].

[10]https://earthobservatory.nasa.gov/images/147324/bobcat-fire-scorches-southern-california

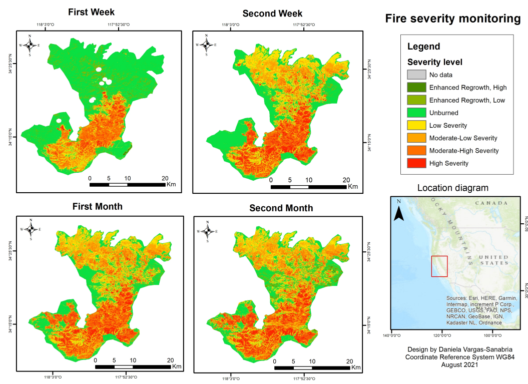

Fig. 8: Fire Severity Monitoring, First week to Second Month of the fire

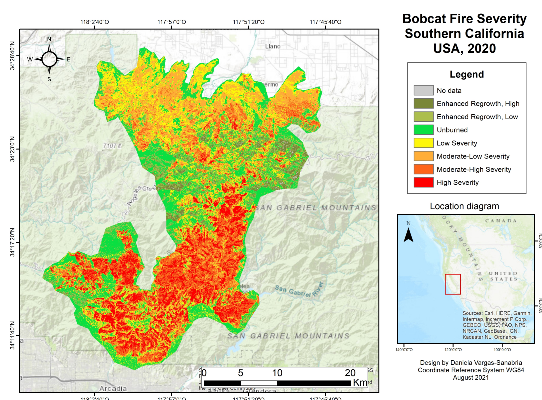

Fig. 9: Overall Bobcat Fire Severity

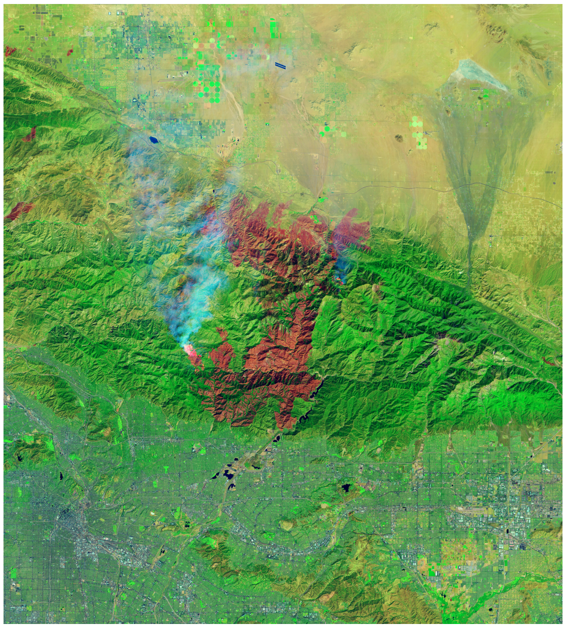

Fig. 10: Landsat 8 satellite image of the burn scar (above) on September 21, 2020

5.2 *Air Pollutants*

Readings of PM2.5 from 7 stations within 40 km from the vicinity of the Bobcat fire is shown in Figure 11. We found that the time evolution of PM2.5 concentration from these 7 stations follows a similar pattern. The level of PM2.5 concentration is clearly elevated during the time of the Bobcat fire and three distinct pulses of high pollutants can be observed. This suggests that the Bobcat fire exhibited complex evolution. We also found that the closest station at Azusa, California generally recorded higher pollutants than further away stations like the one in North Hollywood, CA. Further quantitative analysis could provide insights on the migration of the pollutants.

We also create a spatial map of maximum daily PM2.5 concentrations measured during the Bobcat fire (see Figure 12). We found that this value reaches up to 100 $\mu g/m^3$ at a few nearby stations. The pollutants seem to be spreading out over the entire Los Angeles basin. However, as we move west toward Malibu, CA or south toward San Diego, CA, the coastal ranges seem to be blocking the path of PM2.5 and preventing the majority of pollutants from escaping the Los Angeles basin.

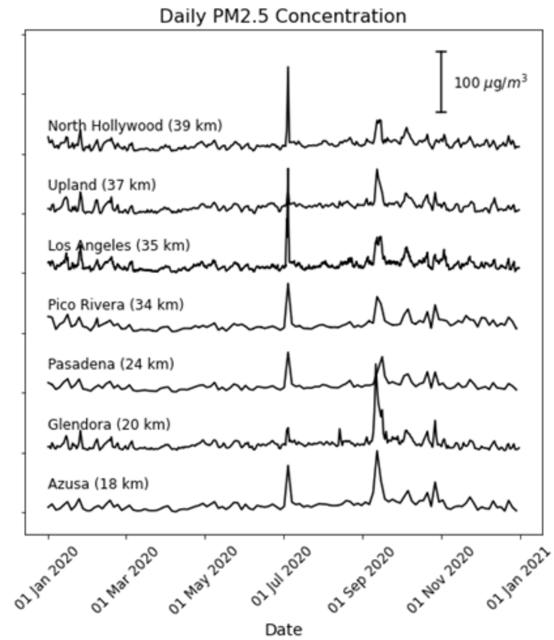

Fig. 11: Time series of daily PM2.5 data recorded from 7 stations within 40 km from the vicinity of the Bobcat fire. Distances are calculated from a reference point (latitude 34.2992°N, longitude 117.9617°W) located within the fire perimeter.

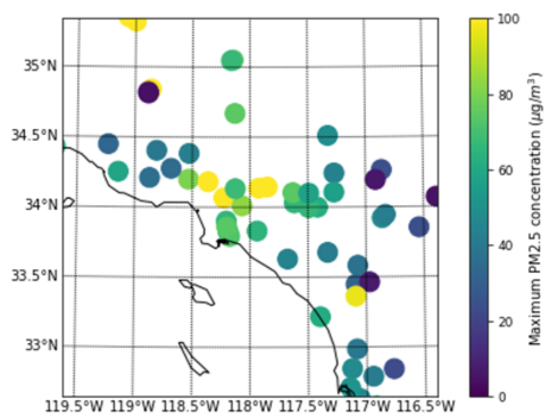

Fig. 12: Spatial distribution of maximum daily PM2.5 concentration over the duration of the Bobcat fire measured at each station

The ground measurements of PM2.5 concentrations used in this study can provide insights into pollutants that are produced as a result of wildfires or other anthropogenic activities. However, their usage can be limited at times. The measurements obtained are very close to the surface and the values could change rapidly as we move up the air column in our atmosphere. Moreover, these measurements are done at discrete points and some areas might not be as well monitored as others. For example, the Central Valley of California has significantly much less number of stations than the Los Angeles basin. Uneven distribution of ground stations can bias the interpretation of the measurements.

5.3 Sentimental Analysis using Twitter Data

As defined earlier (Section 4.4) we have presented histogram (Figure 13) the magnitude of used those hashtags during September, 2020 to December, 2020. As you can see the hike in number tweets in the month of September is quite accurate due to the fire. Also, clearly we can see that people were twitting mostly from late evening to early morning with "#bobcatfire" (Figure 14). With the processed texts, the sentimental analysis reveals that about 55% shows positive polarity and 40% shows negative polarity. In terms of subjectivity of the texts, we found an average subjectivity of 0.2 (see Figure 15). Since this value is closer to 0 than 1, this means that the texts are generally more objective than subjective. Since the content is generally more factual rather than opinions, it is not unexpected that the sentimental of the majority of tweets turns out to be closer to neutral.

6 Conclusions

As such, Twitter is becoming an increasingly important tool to help people prepare for and recover from disasters. In particular, the mechanisms by which information is shared across networks during disaster events can have significant implications for disaster damages and recovery. Our work finds that the time frames in which people communicate on Twitter varies by the time of event. Furthermore, we find that it is people with “average” sized Twitter networks that tweet most frequently during the fire only. Each of these findings provides insight into potential strategies for disaster communication, based on both the disaster context and the importance of general mes-

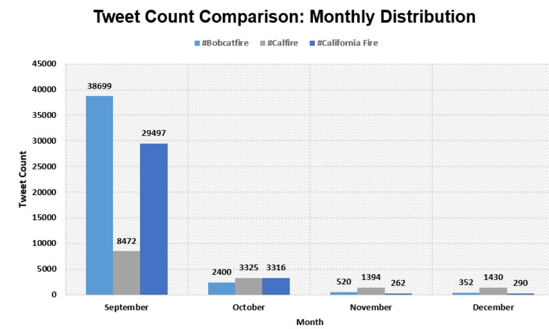

Fig. 13: Tweet Count Comparison between September, 2020 to December, 2020. We have taken three hashtags; #Bobcatfire, #Calfire, #CaliforniaFire

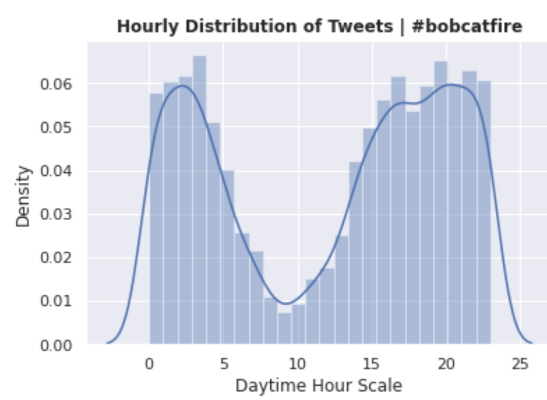

Fig. 14: Hourly Distribution of the Tweets consists #bobcatfire

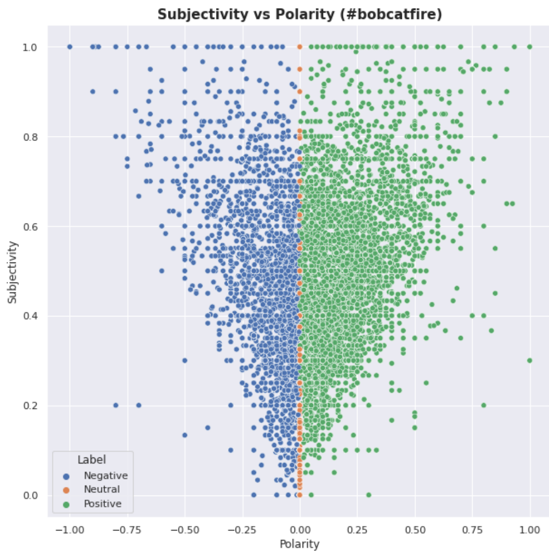

Fig. 15: Sentimental Analysis of tweets consists #Bobcatfire. 55% Positive, 40% Negative, 5% Neutral words used in 41,971 tweets

saging that is applicable to typical Twitter users. Such information can be useful for planning for future disasters and enabling effective recovery following disasters, which will ideally minimize disaster damages and help increase resilience in a changing climate.

The NBR helped us to determine the damage caused by fire in the area, and the risk not only for the ecosystem , but also for people who lived nearby. This data will be useful to examine effects of fire in short-or long-term for decision-making about disaster management. We also found that pollutants are highly elevated to hazardous levels during the Bobcat fire and they are concentrated mostly in the Los Angeles basin where most of the population lives. A better understanding of the effects of fire on pollutants could allow us to be more prepared for the next decades where wildfires are expected to be more frequent and more intense.

Furthermore, analyzing Twitter data along with remote sensing data can be a good source to understand the mental state of the community, estimate the number of injured people, estimate who and what is affected by a natural disaster and model the prevalence of epidemics. Therefore, various groups such as politicians, government, non-governmental organizations, aid workers and the health system can use this information to plan and implement interventions.

References

[1] K. Hoover and Laura A. Hanson. Wildfire statistics. *In Focus*, (39), 2021.

[2] Penelope Morgan, Guillermo E. Defossé, and Norberto F. Rodríguez. Management implications of fire and climate changes in the western americas. In *Fire and Climatic Change in Temperate Ecosystems of the Western Americas*, pages 413–440. Springer-Verlag.

[3] FAO Forestry Paper. *Fire management-global assessment*, 2006.

[4] Emilio Chuvieco and Russell G. Congalton. Application of remote sensing and geographic information systems to forest fire hazard mapping. *Remote Sensing of Environment*, 29(2):147–159, aug 1989.

[5] Jay D. Miller and Andrea E. Thode. Quantifying burn severity in a heterogeneous landscape with a relative version of the delta normalized burn ratio (dNBR). *Remote Sensing of Environment*, 109(1):66–80, jul 2007.

[6] Zhao-Liang Li, Bo-Hui Tang, Hua Wu, Huazhong Ren, Guangjian Yan, Zhengming Wan, Isabel F. Trigo, and José A.Sobrino. Satellite-derived land surface temperature: Current status and perspectives. *Remote Sensing of Environment*, 131:14–37, 2013.

[7] Sander Veraverbeke, Willem W. Verstraeten, Stefaan Lhermitte, Ruben Van De Kerchove, and Rudi Goossens. Assessment of post-fire changes in land surface temperature and surface albedo, and their relation with fire–burn severity using multitemporal modis imagery. *International Journal of Wildland Fire*, 21:243–256, 2012.

[8] E.F. Lambin, K. Goyvaerts, and C. Petit. Remotely-sensed indicators of burning efficiency of savannah and forest fires. *International Journal of Remote Sensing*, 24(15):3105–3118, 2003.

[9] Jon E. Keeley. Fire intensity, fire severity and burn severity: a brief review and suggested usage. *International Journal of Wildland Fire*, 18(1):116, 2009.

[10] Jia C. Liu, Gavin Pereira, Sarah A. Uhl, Mercedes A. Bravo, and Michelle L. Bell. A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke. *Environmental Research*, 136:120–132, jan 2015.

[11] Stephanie E. Cleland, Jason J. West, Yiqin Jia, Stephen Reid, Sean Raffuse, Susan O'Neill, and Marc L. Serre. Estimating wildfire smoke concentrations during the october 2017 california fires through BME space/time data fusion of observed, modeled, and satellite-derived PM2.5. *Environmental Science and Technology*, 54(21):13439–13447, 2020.

[12] Nadin Boegelsack, Jonathan Withey, Gwen O'Sullivan, and Dena McMartin. A critical examination of the relationship between wildfires and climate change with consideration of the human impact. *Journal of Environmental Protection*, 09(05):461–467, 2018.

[13] Thomas W. Porter, Wade Crowfoot, and Gavin Newsom. *2020 Wildfire Activity Statistics*. California Department of Forestry and Fire Protection, 2020.

[14] John Roach. *California wildfires will cost tens of billions, AccuWeather estimates*. AccuWeather, 2019.

[15] Yuanyuan Wang and Guicai Li. Analysis of &#x201cfurnace cities&#x0022 in china using MODIS/LST product (MOD11a2). In *2014 IEEE Geoscience and Remote Sensing Symposium*. IEEE, jul 2014.

[16] Allison E. Cocke, Peter Z. Fulé, and Joseph E. Crouse. Comparison of burn severity assessments using differenced normalized burn ratio and ground data. *International Journal of Wildland Fire*, 14(2):189–198, 2005.