Jennifer Ovist
Dr. Stuhlmacher
GEO 243
4 November 2021

Analyzing the Impact of California's SCU Lightning Complex Fire using Satellite Imagery

Importance

Wildfires have the potential to create long lasting changes to landscapes and to people's lives, therefore it is important that they be studied in order to keep track of the damage and various other effects they cause. One such way is through remote sensing and the use of satellite data. Efforts to use satellite data for wildfire analysis have been increasing, and in particular, there are efforts to use machine learning/deep learning for detection and analysis.

From preliminary research, there is a large amount of research done in Russia, specifically regarding wildfires in Siberia. Another common finding is that satellite imagery was a stepping stone or simply a tool for analysis with other tools, rather than the tool of analysis itself. For example, Subramanian and Crowley use satellite data to look at a wildfire-prone region of Alberta, Canada. They are not geographers but engineers, so they use the satellite data as the source for Deep Learning techniques to detect how wildfires move and interact with the landscape. Another study was done by Domenikiotis, Loukas, and Dalezios, where they also use remote sensing to monitor wildfires and other natural disasters, like flooding. In their study, they used the Normalized Difference Vegetation Index (NDVI) and Surface Temperature (ST) in order to assess various wildfires that occurred in Greece. Essentially, the goal is to analyze the NDVI values to see what state the vegetation is in. Though they recommend more research, this sort of procedure is more akin to what will be carried out in this project.

Given that a majority of academic research has been conducted in different countries, this project will be focusing on the United States, specifically California. According to the state of California's website, 2020 was a record-breaking year with over 42 million acres burned (California Department of Forestry and Fire Protection). There were over 10,000 recorded wildfires in California alone in 2020. Given this large amount of incidents, there are many areas to analyze. This project will focus specifically on the SCU Lightning Complex Fires, which occurred between August 18th and October 1st of 2020 in the San Francisco Bay area. According to the Cal Fire website, this fire destroyed over 220 structures and injured six people in the 44 days it was burning (California Department of Forestry and Fire Protection, 2020). This fire alone covered almost 400,000 acres, which makes it an interesting incident to study.

Methodology

To complete this project, Google Earth Engine as well as imagery from Landsat 8 from 2020 will be utilized. First of all, various images from 2020 leading up to the fire will be used to calculate the Normalized Difference Moisture Index (NDMI). This index looks at the moisture levels specifically in vegetation. It can be used to look at droughts, but it can also be useful in looking at fire-prone areas and assessing the risk of these areas being overtaken by fires (*Band Arithmetic function*). As this is in Google Earth Engine, this will be completed by first filtering the Image Collection to the dates, location, and cloud cover required. A composite will be created, and then a normalizedDifference will be calculated on the composite using Bands 5 and 6, which are the NIR and SWIR bands.

Similar procedure will be followed to calculate the Normalized Burn Ratio (NBR). After filtering the Image Collection and creating a composite, Bands 5 and 7 will be used in the normalizedDifference. These bands are the NIR and SWIR 2 bands. Band 7 is used instead of Band 6 even though they are both SWIR bands because the SWIR band needs to be between 2.08 and 2.35μm (Burn Indices Background). However, instead of simply filtering the Image Collection for dates after the fire, a NBR will also be calculated for before the fire. This will allow for comparisons between both images as well as a better understanding of how the area was truly affected.

The final component is a GIF showcasing the region from before, during, and after the fires. By including images from the entire year, the GIF will be an interesting addition in analyzing how the region changed throughout the year and especially if it was distinctly affected by the fires.

Results

The NDMI for the region was calculated for the beginning of the year, leading up to August. The images were also filtered to have less than 3% cloud cover. The color palette chosen was a diverging palette of red to blue, with red indicating low moisture in the vegetation and blue indicating higher

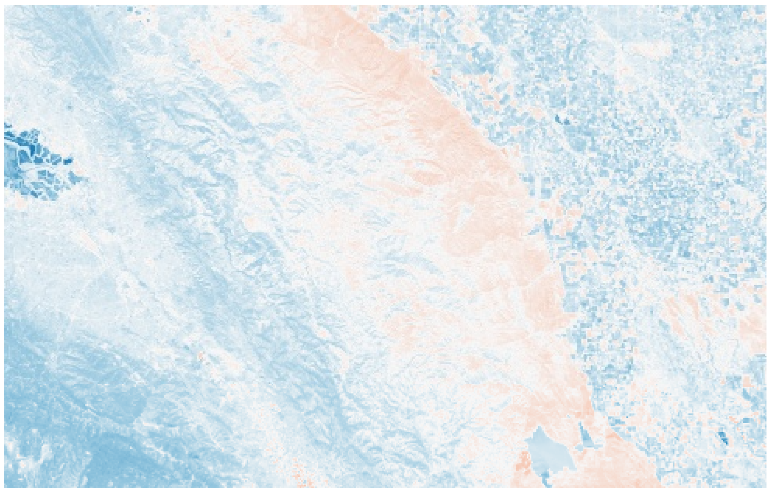
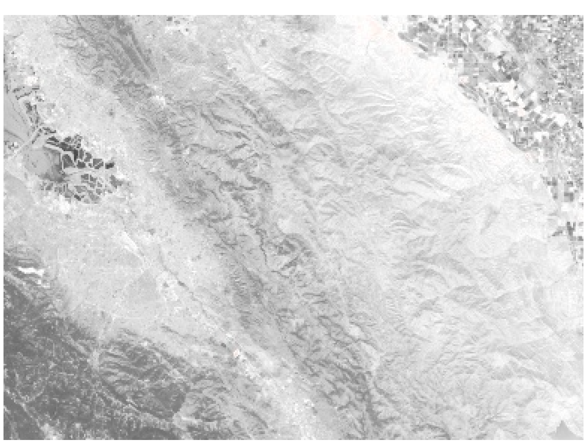
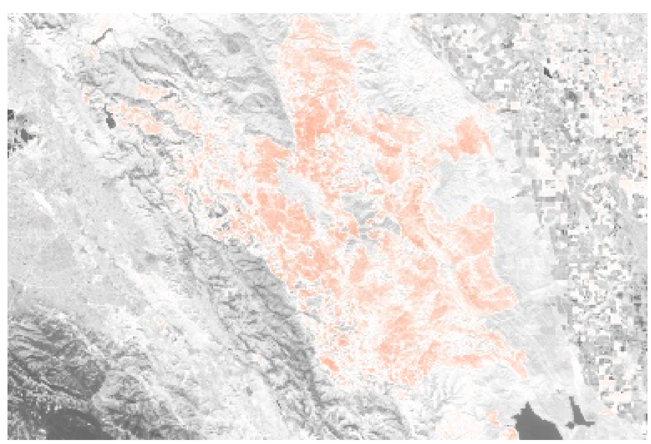


Figure 1 Normalized Difference Moisture Index (NDMI) for the area of the SCU Lightning Complex Fire. Bands 5 and 6 from a Landsat 8 composite from January to August of 2020 were used.

moisture in the vegetation. The NDMI calculated shows that the area in which the fire took place had much lower moisture levels than in surrounding areas. Areas with low moisture levels may be at higher risk of fire, given that drier vegetation could serve as fuel for wildfires. With the map above showing the NDMI levels from before the fire, it showcases that the area was drier than its surroundings and it may have been more prone to a wildfire.

In order to showcase the actual effects of the fire itself, the NBR was used. Images from before and after the fire were filtered to have less than 3% cloud cover. The individual NBR maps also have a diverging color palette, with red at the lower end and a dark gray at the higher end. Lower values





Figures 2 and 3 Normalized Burn Ratio (NBR) for the area of the SCU Lightning Complex Fire. Bands 5 and 7 were used from two Landsat 8 composite images to perform this analysis (left used January-August of 2020 and right used October-December of 2020).

indicate burnt or bare ground while higher values indicate healthy vegetation or unburnt areas. Figure 2 represents pre-fire NBR levels, and figure 3 on the right shows the same region after the fire. The orange parts of the map indicate the areas most affected by the fires. To better visualize this, the ΔNBR was calculated by subtracting the post fire raster from the pre fire raster. This method of analysis

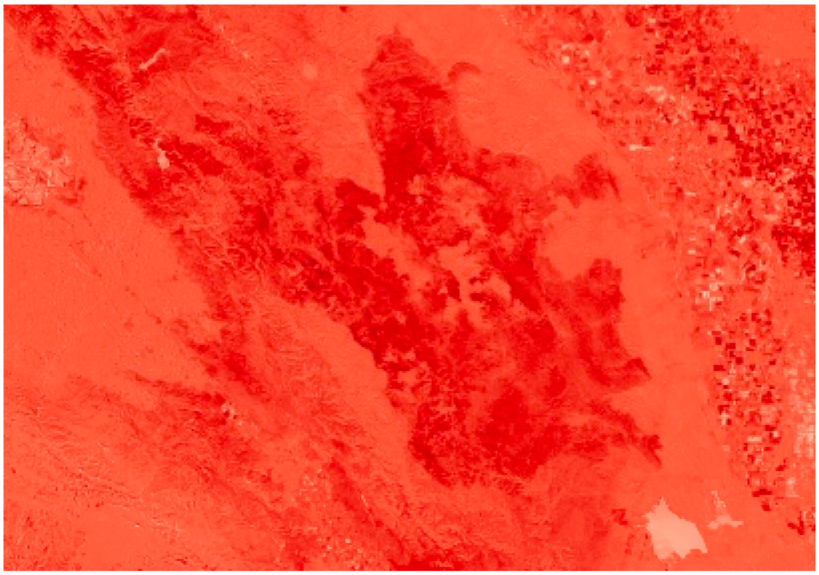


Figure 4 ΔNBR for the area of the SCU Lightning Complex Fire. Figure 3 was subtracted from figure 2 to perform this analysis.

better isolates areas that were severely burned in the fires. A single color palette was used for ΔNBR, with lighter areas indicating vegetation or regrowth and darker areas representing severely burned areas. This visualization emphasizes the same orange area in figure 3, but showcases how truly damaged the terrain was from the fire.

The final component was the GIF. Linked below, it shows frames from all throughout 2020. Throughout the GIF, the terrain can be seen as changing with some areas getting darker as the GIF goes on. It is not particularly clear when the fires occur, but the GIF was filtered for cloud cover. While filtering for cloud cover does help with seeing the landscape clearly, it is possible that this also filtered images with smoke from the fires which affected the final product. The GIF does provide a visual of the changing landscape throughout the year, which does support the intent of seeing how much the landscape evolved.

Significance

This research was successful in showcasing a few ways of analyzing one California wildfire. The visuals generated shows that the NDMI is a useful method of predicting what areas are drier and therefore more susceptible to wildfires. The NBR maps are useful in showing the progression of the burned areas, but the ΔNBR highlights the areas most affected most clearly. This research supports the notion that NDMI can be used in a preventative manner, though more research must be done to support this. NDMI is just one index that is helpful in this case, but there are many more ways remote sensing can be used to determine what areas are most at risk of fires.

Code Links

NDMI Map: https://code.earthengine.google.com/982100abcbd4203d7ea9bd4725ebd16a
NBR Maps: https://code.earthengine.google.com/9da14a6b3a12d7634244330f61fd0462
Time Lapse GIF: https://code.earthengine.google.com/ba657972ad50ab2ccb7642d590900818

Citations

Band Arithmetic function. Band Arithmetic function-ArcGIS Pro | Documentation. (n.d.). Retrieved October 29, 2021, from https://pro.arcgis.com/en/pro-app/latest/help/analysis/raster-functions/band-arithmetic-function.htm.

Burn Indices Background. (n.d.). Retrieved November 10, 2021, from https://www.l3harrisgeospatial.com/docs/backgroundburnindices.html.

California Department of Forestry and Fire Protection (CAL FIRE). (2020, August 18). *SCU Lightning Complex incident*. Cal Fire Department of Forestry and Fire Protection. Retrieved November 15, 2021, from https://www.fire.ca.gov/incidents/2020/8/18/scu-lightning-complex/.

California Department of Forestry and Fire Protection (CAL FIRE). (n.d.). *2020 Incident Archive*. Cal Fire Department of Forestry and Fire Protection. Retrieved November 15, 2021, from https://www.fire.ca.gov/incidents/2020/.

Domenikiotis, C., Loukas, A., and Dalezios, N. R.: The use of NOAA/AVHRR satellite data for monitoring and assessment of forest fires and floods, Nat. Hazards Earth Syst. Sci., 3, 115–128, https://doi.org/10.5194/nhess-3-115-2003, 2003.

Subramanian, S. G., & Crowley, M. (2017). Learning forest wildfire dynamics from satellite images using reinforcement learning. In *Conference on reinforcement learning and decision making*. Ann Arbor MI.