Estimating Carbon Flux from Sonoma County Forest Fires

Source Code (Colab):
https://colab.research.google.com/drive/1tKQuB8Dx_lRE9fjw4sht9lqVnZ2RvD5B?usp=sharing

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ECE-471: Remote Sensing and Earth Observation
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10 May 2021

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Introduction

Forests play a crucial role sequestering carbon[1]; approximately 34% of anthropogenic emissions are absorbed by terrestrial carbon sinks[2]. Wildfires are naturally occurring phenomena, but due to changing climatic conditions their length and frequency have increased.[3] Understanding the flux into and out of terrestrial carbon sinks is important for monitoring their stability. Here, we estimated the carbon emissions from three wildfires in Sonoma County that occurred over the course of October 8, 2017 to November 1, 2017: the Tubbs fire, the Pocket fire and the Nuns fire.

We chose California as our region of interest because of its high rate of wildfires and because the California Department of Forestry and Fire Protection collects substantial data with which we could validate our results.[4] In particular, we chose the Tubbs fire because it was one of the most destructive wildfires in California. We added the Pocket and Nuns fires because they started within days of Tubbs fire and were around the same region.

We estimated the carbon emissions using the following general formula from French *et al.* (2011):[5]

$$C_t = A(Bf_c\beta) \quad (1)$$

where A is the area burned (hectares), B is the biomass density or fuel load ($t\ ha^{-1}$), fc is the fraction of carbon in the biomass (fuel), and β is the fraction of biomass consumed in the burn.

Satellite imagery and remote sensing have been used extensively to study forest cover, deforestation, and tree restoration potential. Such data are typically used in conjunction with empirical observations of allometric relationships to estimate carbon sequestration in woody biomass. We will use pre- and post-fire images of the area of interest to compute the normalized burn ratio with help of a cloud mask algorithm for forest change. The NBR will be useful for estimating the area burned (A) and the extent of biomass combustion (β). The biomass density (B) can be estimated using empirical data on regional biomass density coupled with land cover maps to identify vegetation type. The fraction of carbon in biomass (f_c) is typically between 0.45 and 0.5.

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[1] Lewis, Simon L., et al. "Restoring natural forests is the best way to remove atmospheric carbon." (2019): 25-28.
[2] Keenan, T. F., and C. A. Williams. "The terrestrial carbon sink." *Annual Review of Environment and Resources* 43 (2018): 219-243
[3] Jolly, W., Cochrane, M., Freeborn, P. *et al.* Climate-induced variations in global wildfire danger from 1979 to 2013. *Nat Commun* **6,** 7537 (2015). https://doi.org/10.1038/ncomms8537
[4] CAL FIRE. https://www.fire.ca.gov/
[5] French, N. H. F., et al. (2011), Model comparisons for estimating carbon emissions from North American wildland fire, J. Geophys. Res., 116, G00K05, doi:10.1029/2010JG001469.2

Methods

Introduction

In order to assess the carbon emissions we used Landsat 8 datasets since this satellite has multispectral sensors with a NIR band between 760 - 900 nm and a SWIR band between 2080 - 2350 nm. These ranges are optimal to calculate the NBR index which will allow us to find A in Equation 1. Additionally, Landsat 8 has a great spatial resolution of 30m, making the satellite more viable in calculating area than other satellites such as MODIS, which has a spatial resolution of 500 meters or 250 meters depending on the band being used.

In computing area we used USGS Landsat 8 Surface Reflectance Tier 1[6] data, which can be accessed by the Google Earth Engine API[7]. The Google Earth Engine API in Python was used primarily for the methods in this project. In order to compute the areas of each fire thresholding had to be done on the dNBR (Differential Normalized Burn Ratio) and applied as a mask on the images of each fire. The dNBR is a metric used commonly in remote sensing to detect the change fires had made to the landscape and create burn scars. The metric takes the NBR (Normalized Burn Ratio) of the image obtained before the fire and subtracts that NBR by the NBR of the image obtained after the fire. Overall dNBR can be formulated in the following way:

$$\text{NBR} = (\text{NIR}-\text{SWIR}) / (\text{NIR}+\text{SWIR}) \tag{2}$$

$$\text{dNBR} = \text{NBR}_{\text{BEFORE}} - \text{NBR}_{\text{AFTER}} \tag{3}$$

Preprocessing

In order to compute the area we needed to find the bounding boxes for each fire, the actual area burned, as well as composite or mosaic multiple images from before and after the fire. The reason for the bounding boxes is that, in calculating dNBR over a region, fires may appear to overlap. With this being the case, it is of utmost importance to isolate specific fires to improve the accuracy. Our accuracy is already depleted with the low temporal resolution of our dataset. In calculating a fire, it is always optimal to compute the burn scars as close as possible to before the fire and after the fire but Landsat 8 does not contain as many pictures per month as MODIS does (MODIS has daily images). For this reason we had to mosaic over the images 30 days before the fire, constituting the before image, and 30 days after the fire, constituting the after image, instead of mosaicking for a period of 5 or 7 days before and after the fire. In addition, when loading the data, we applied Landsat 8 Surface Reflectance's cloud mask, filtering out clouds and cloud shadows using its cloud mask band, qa_60, and, in addition, when loading in the data we filtered the region by all of Sonoma County (to make dNBR overall fires more accurate). For our mosaic we used what is known as a quality mosaic, mosaicking over an image based on priority from a certain band. We chose qa_60 as the band to put priority on such that the image would be as

[6] USGS Landsat 8 Surface Reflectance Tier 1 | Earth Engine Data Catalog (google.com)

[7] Google Earth Engine | Google Developers

cloud-free as possible. In addition, the bounding boxes, dates, and true area burned that we found for each fire were derived from the Fire Perimeters[8] geodatabase on CALFIRE.

Thresholding

When thresholding dNBR we first computed a histogram as in Figure 1 of the dNBR values in Sonoma County from October 8, 2017 to November 1st, 2017 since the Tubbs, Nuns, and Pocket fires all occurred during these dates.

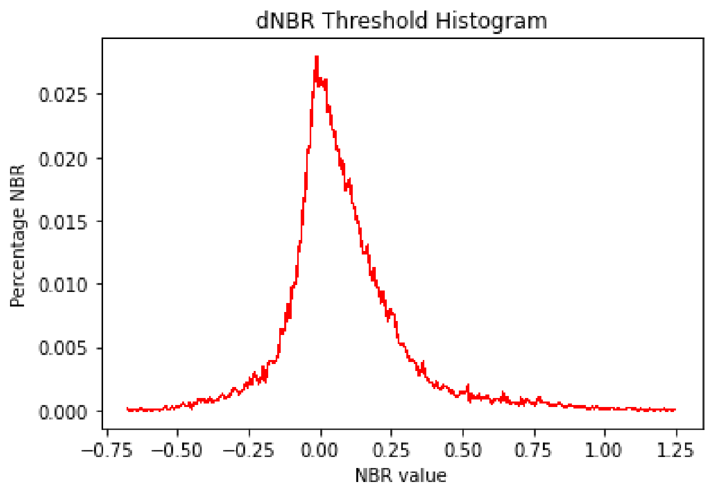

Figure 1. dNBR Histogram over Sonoma County from 10/8/2017 to 11/1/2017

In analyzing the distribution of the histogram and combining those values with what we already know we computed the thresholds as shown in Table 1.

Severity Level	dNBR Range
Enhanced Regrowth	< -0.1
Unburned	-0.1 - 0.1
Low Severity	0.1 - 0.27
Moderate Severity	0.27 - 0.80
High Severity	> 0.80

Table 1. Final dNBR Ranges for Burn Severity Levels

[8] Welcome to GIS Data (ca.gov)

To compute the thresholds for unburned, enhanced regrowth, low severity and moderate severity we consulted with a public data source of thresholds[9]. The specific thresholds that we used, and tested, to mask our images were a threshold for all areas burned (to compute total area burned) and a threshold on high severity. We found the threshold for the area burned by making educated guesses based on Figure 1, validating our results by computing the area of the fire burned when we masked our images, by that specific threshold, and comparing the value against the actual value in the CALFIRE geodatabase. Two major thresholds for overall area stood out and results can be found in Table 2.

Threshold	**Average Percent Error (%)**	**Standard Deviation**
0.05	22.56	25.50
0.1	25.20	7.37

Table 2. Overall Area Burned Threshold Analysis Results

From Table 2 we can see that the threshold at 0.05 was more accurate than the 0.1 threshold by 2.64% but the threshold at 0.05 is much less consistent, with a standard deviation more than 3 times that of when a threshold of 0.1 is used. For the sake of consistency we chose a threshold of 0.1 since we wanted our threshold to be generalizable. Concerning the threshold on high severity we determined the threshold based on what is known as ground validation, applying the threshold masks and visualizing the image. In our case we used false color (swir1, nir, red) and dNBR to visualize the impact. The reason that we chose these visualizations is because they can very easily show the severity. Concerning false color, false color can be used to show vegetation, making the visualization optimal since if any vegetation is burned the color immediately goes from green to black, an obvious contrast. Concerning dNBR, the reason that we are using this visualization is because this is the metric we are thresholding on. Through all of our testing we found that a threshold of 0.8 was best for high severity since, in this threshold, the before and after image for false color have stark contrast. Fig.3 is an illustration of the results.

[9] Work with the Difference Normalized Burn Index - Using Spectral Remote Sensing to Understand the Impacts of Fire on the Landscape | Earth Data Science - Earth Lab

(a) (b) (c)

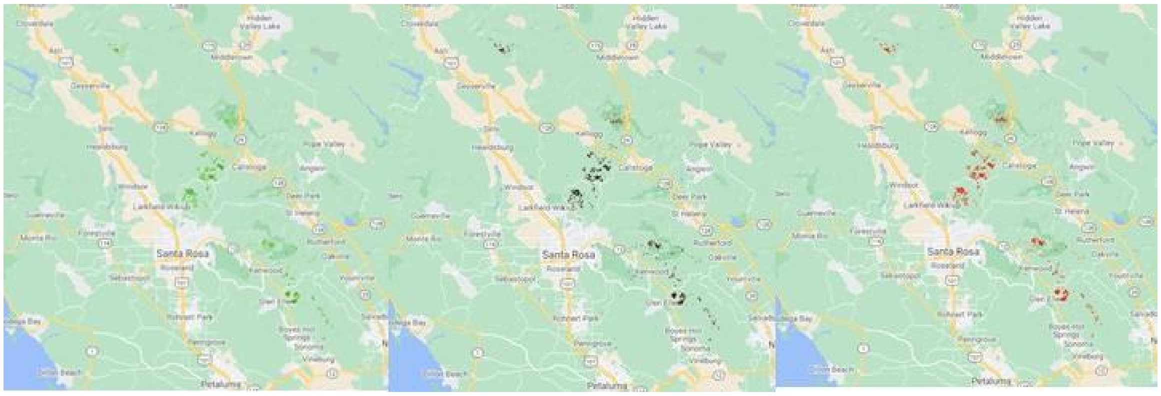

Figure 2. An illustration of Tubbs (middle), Nuns (bottom), and Pocket (top) fires masked by a 0.8 threshold on dNBR, (a) image before the fire in false color (green = vegetation), (b)image after the fire in false color (black = burned vegetation), (c) dNBR (red = high severity)

As shown in Figure 2 under the 0.8 threshold for dNBR, the area is completely burned with no vegetation left from the before false color image in the after false color image. We can also see that the Tubbs fire had the largest severity, agreeing with many external sources[10].

Vegetation

To map vegetation using the NLCD dataset[11], we filtered the year to 2016 and made visualizations of the 'landcover' band. Though all three fires, Pocket, Tubbs, and Nuns, all started in 2017, there was unfortunately no NLCD data from 2017, and so we took data from 2016 instead. There were 20 class values in the 'landcover' band, and we decided to map these class values into 3 custom class mappings: residential plants, ground plants, and forests. We then took our masks for overall area per fire from the thresholding on dNBR in the previous section and added on the forest and ground plant masks to compute the area of forest and ground plant that was burned in each fire. The results can be summarized in Table 6 and visualized in Figure 3.

[10] [Tubbs Fire's Scale of Destruction (arcgis.com)]
[11] [NLCD: USGS National Land Cover Database | Earth Engine Data Catalog (google.com)]

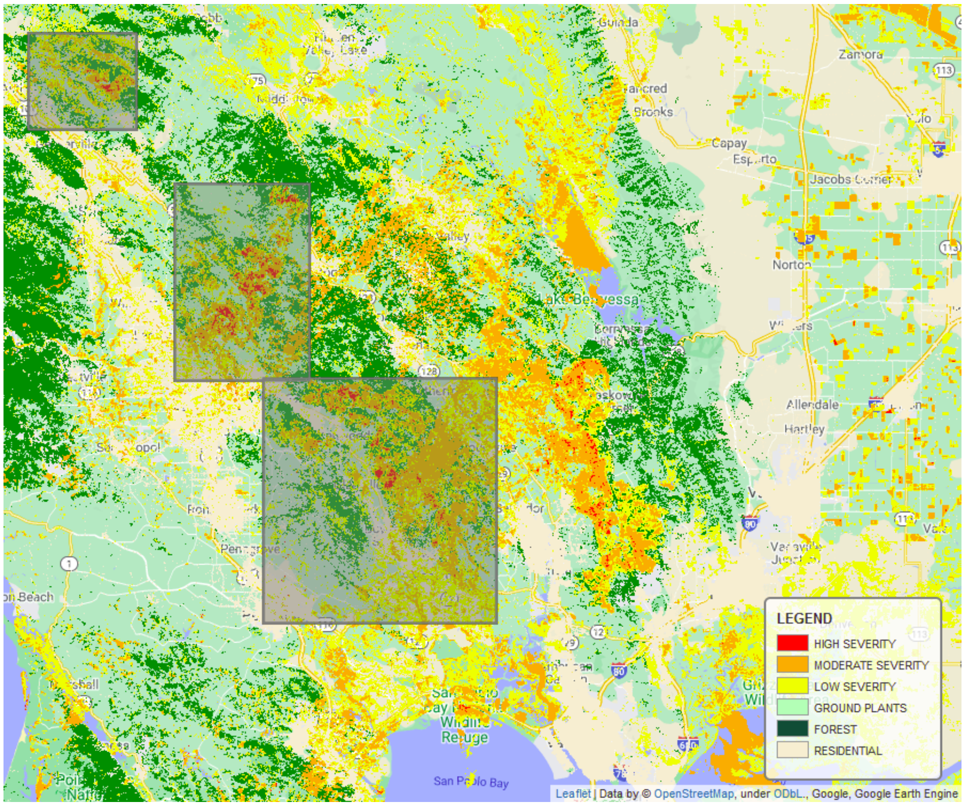

Figure 3. Visualization of Tubbs (middle), Nuns (bottom) and Pocket (top) Fires Against Vegetation and Infrastructure

Biomass Density (B)

We obtained estimates of biomass density from Huang *et al.* 2018, a review article that compares different models for estimating biomass density in Sonoma County, California.[12] We chose to use the data from the United States Forestry Service Forest Inventory and Analysis. Forested areas have a biomass density of 192.4 metric tons carbon per hectare (tC ha^{-1}), and non-forested areas have a biomass density of 20.6 tC ha^{-1}.

Carbon Fraction in Biomass (f_c)

The fraction of carbon in biomass is typically around 0.45-0.5. Because we are considering primarily woody biomass in this study, we assume a carbon fraction of 0.5.

Combustion Efficiency (β)

We assumed a value of 0.8 for the combustion efficiency, a typical value for forest fires.[13]

[12] Huang, Wenli, et al. "County-scale biomass map comparison: a case study for Sonoma, California." *Carbon Management* 8.5-6 (2017): 417-434.

[13] Urbanski, S. P. "Combustion efficiency and emission factors for US wildfires." *Atmospheric Chemistry & Physics Discussions* 13.1 (2013).

Results

Area estimates agree fairly well with area estimates published by CAL FIRE. Overall, the average percent area was 25% across all three fires.

Fire Name	estimated area burned (m^2)	estimated area burned (acres)	true area burned (acres)	percent_error (%)
TUBBS	1.264274e+08	31240.208609	36701.984375	14.881418
NUNS	2.920997e+08	72177.830122	55798.191406	29.355143
POCKET	4.812732e+07	11892.261828	17359.328125	31.493536

Table 5. Estimates of burn scar area.

Using land cover classification data from NCLD 2016, we found the area of forest and non-forest vegetation burned in the fires, and we multiplied the areas by their respective forest and non-forest biomass densities to determine total biomass over the AOI. We then multiplied the biomass by the carbon fraction (0.5) and the combustion efficiency (0.8) to obtain carbon emissions from the fires.

Fire name	estimated forest area burned (m^2)	Estimated forest area burned (ha)	Estimated non forest area burned (m2)	Estimated non forest area burned (ha)
TUBBS	7.250654e+07	7250	3.752563e+07	3750
NUNS	1.251983e+08	12520	1.384179e+08	13840
POCKET	1.885509e+07	1890	2.768088e+07	2770

Table 6. Estimates of forested and non-forested area burned.

We estimated a total flux of 165000 metric tons of carbon (or 605000 metric tons CO_2) as a result of the three fires. For reference, the annual wildfire CO2 emissions in California for 2017 were around 35 million metric tons of CO_2,[14] and global anthropogenic emissions are roughly 40 billion metric tons of CO_2 per year. A breakdown of the carbon emissions from each fire is shown below:

Fire	Pocket	Tubbs	Nuns
Carbon emissions (tC)	53000	97000	15000
(tCO_2)	194000	356000	55000

Table 7. Estimates of carbon emissions from the three fires.

Published estimates of carbon emissions from specific fires are hard to find; however, the accuracy of our calculations depend mainly on our burn scar area estimates, for which there are published values.

[14] California Air Resources Board. *Greenhouse Gas Emissions of Contemporary Wildfire, Prescribed Fire, and Forest Management Activities*. (2020). https://ww3.arb.ca.gov/cc/inventory/pubs/ca_ghg_wildfire_forestmanagement.pdf

Conclusion

If we were to continue working on this project, we would move towards generalizing the model by allowing for region-specific data inputs. We estimated the combustion efficiency factor (β) to be 80%; while this is a reasonable assumption for a first pass, actual fuel consumption depends on factors such as wind speed, temperature, and moisture. Correlations exist (see Ottmar *et al.* 2006) which are based on empirical observations and fuel types.[15] Similarly, we would implement a model to estimate biomass density that uses remote sensing data of the area of interest. If it is sufficiently accurate, such a model could help us achieve more refined estimates of vegetation cover.

[15] Ottmar, Roger D., et al. "Modification and validation of fuel consumption models for shrub and forested lands in the southwest, Pacific Northwest, Rockies, Midwest, southeast and Alaska." *US Bureau of Land Management, Joint Fire Sciences Program, Final Project Report* (2006): 98-1.