ANALYZING, VISUALIZING, AND PREDICTING THE IMPACTS OF VARIOUS NATURAL DISASTERS THROUGH GEOSPATIAL APPLICATIONS

NASA SEES EMERGENCY PREPAREDNESS TEAM 2021

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Scan this QR code to view the presentation slides and code

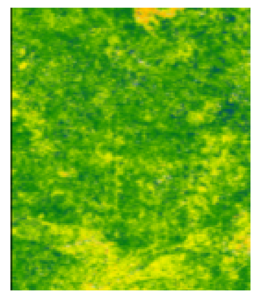
01. INTRODUCTION

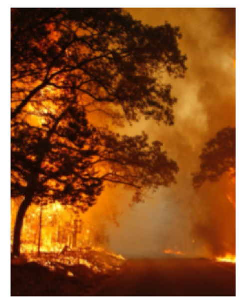
Natural disasters are increasing throughout the world due to increased exposure, vulnerability, and the rise of climate change. Through remote sensing—the process of measuring radiation from Earth using sensors from aircraft and satellites to acquire information about an area—we can analyze the data in order to more effectively predict these disasters and identify ways to reduce their effects.

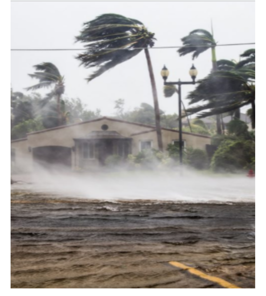

Landsat-8 Satellite
Credit: USGS.gov


IMERG GPM Satellite
Credit: gmp.nasa.gov

For our research, we focused on three areas:


Extreme Heat


Wildfires


Floods/Tropical Storms

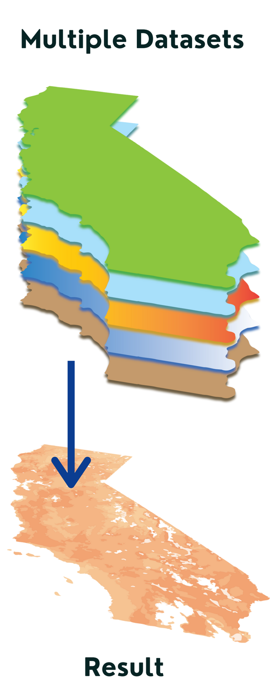
We accessed and analyzed remote sensing data by using tools such as Google Earth Engine, a free remote sensing data analysis tool that provides over 30 years of satellite imagery and geospatial datasets.

02. METHODOLOGY

To access and analyze remote sensing data, we used Google Earth Engine (GEE). Using cloud computing capabilities, GEE offers automated data processing, machine learning algorithms, GUI applications, and other tools to display analysis results. Our team used the Earth Engine JavaScript API through the GEE Code Editor and the Earth Engine Python API through the Google Colaboratory.

The general method for this project includes

- Importing EE (Earth Engine) API and the geemap package,
- Adding and filtering datasets as ImageCollections,
- Selecting regions of interest by masking and clipping,
- Setting visualization parameters,
- And creating and displaying the final layer



We also overlapped and combined multiple datasets by selecting certain bands from datasets and performing calculations using their pixel values.

We referred to NASA's Applied Remote Sensing Training program (ARSET, https://appliedsciences.nasa.gov/what-we-do/capacity-building/arset), a series of training sessions covering a wide variety of datasets and tools relating to specialized environmental applications. We participated in 11 sessions about GEE, Population, Fires, Urban Heat, Blackouts, Tropical Storms, and Flooding. These sessions heightened our proficiency in GEE and allowed us to make deep dives into our topics.

03. EXTREME HEAT

Eashan Hatti, Grady Pennington, Joel Villarino, Sheryl Hsu

Relationship Between Extreme Heat and Urban Heats Islands

Urban Heat Islands — metropolitan areas where human development and geography have contributed to higher surface and air temperatures than surrounding suburban and rural areas — are major contributors to extreme heat. Our goal is to analyze models of surface temperature in and around urban centers to determine whether geographical features and certain human activity impact the extent of the Urban Heat Effect.

Methodology

We utilized the Google Earth Engine code editor to create a Land Surface Temperature map of the San Francisco Bay Area. The depiction allows for us to compare NDVI values with temperature values, visualizing the severity of Urban Heat in specific places.

Function to make NDVI images

```
function ndvi(img) {
  return (
    img.select("B5").subtract(img.select("B4").rename(['B5']))
    .divide(img.select("B5").add(img.select("B4").rename(['B5'])))
    .rename(['NDVI'])
}
```

Results

- San Francisco: LST on the left, NDVI image on the right
- Cooling corresponds to increased vegetation density
- Vegetated areas do not have a cooling effect beyond their immediate vicinity
- Solution: Many smaller areas of vegetation across the entire city as opposed to the current situation of a few large ones spread about

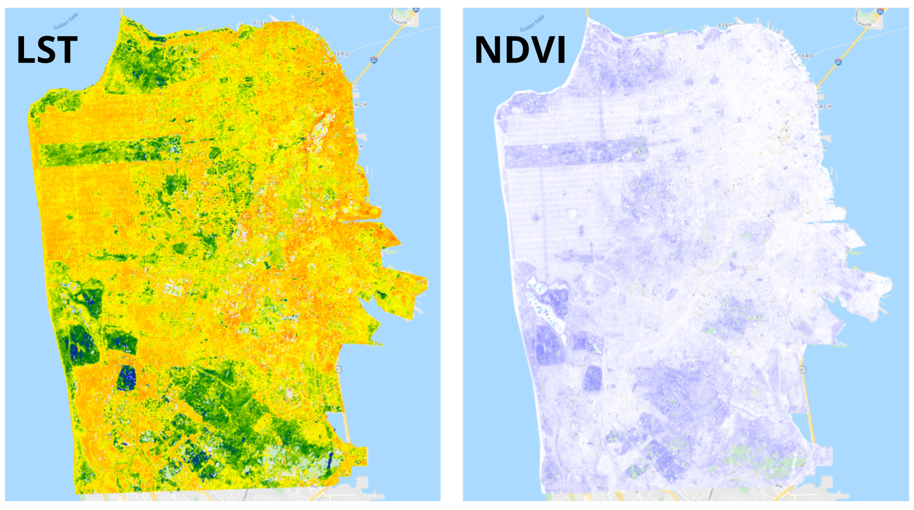
Displaying the LST and NDVI images

```
var ndviImg = ndvi(landsat_image.select(['B5', 'B4']))
print(ndviImg)
var mina = ndviImg.reduceRegion(ee.Reducer.min(), geometry, 30).getInfo().NDVI;
print("NDVI min: " + mina);
var maxa = ndviImg.reduceRegion(ee.Reducer.max(), geometry, 30).getInfo().NDVI;
print("NDVI max: " + maxa);
Map.addLayer(ndviImg, {palette: ['white', 'blue']}, 'NDVI')

var lstImg = makeLstImage(
  landsat_image.select(['B4', 'B5', 'B10']),
  geo2,
  ee.Image(ee.Number(props_img.get("RADIANCE_MULT_BAND_10"))).rename(['B10']),
  ee.Image(ee.Number(props_img.get("RADIANCE_ADD_BAND_10"))).rename(['B10']),
  ee.Image(ee.Number(props_img.get("K1_CONSTANT_BAND_10"))).rename(['B10']),
  ee.Image(ee.Number(props_img.get("K2_CONSTANT_BAND_10"))).rename(['B10']));
Map.addLayer(lstImg, {palette: ['purple', 'blue', 'green', 'yellow', 'orange', 'red'], min: -140.2, max: -140.09}, 'LST');
```

Function to make LST images

```
function makeLstImage(image, geo, M_L, A_L, K_1, K_2) {
  print(image)
  print(M_L)
  var TOA = image.select("B10").multiply(M_L).add(A_L);
  var BT = (K_2.divide((K_1.divide(TOA).log()).add(ee.Number(1)))).subtract(ee.Number(273.15));
  var NDVI = (
    image.select("B5").subtract(image.select("B4").rename(['B5']))
    .divide(image.select("B5").add(image.select("B4").rename(['B5'])))
    .rename(['B10'])
  var NDVI_min = ee.Image(ee.Number(NDVI.reduceRegion(ee.Reducer.min(), geo, 30).getInfo().B10));
  var NDVI_max = ee.Image(ee.Number(NDVI.reduceRegion(ee.Reducer.max(), geo, 30).getInfo().B10));
  var P_v = ((NDVI.subtract(NDVI_min)).divide(NDVI_max.subtract(NDVI_min))).pow(ee.Number(2));
  var ε = P_v.multiply(0.004).add(ee.Number(0.986)).rename('B10');
  var LST = BT.expression(
    "BT / (1 + (0.00115 * BT / 1.4388) * LN)",
    {
      'BT': BT.select("B10"),
      'LN': ε.log()
    });
  var mina = LST.reduceRegion(ee.Reducer.min(), geo, 30).getInfo().B10;
  print("LST min: " + mina);
  var maxa = LST.reduceRegion(ee.Reducer.max(), geo, 30).getInfo().B10;
  print("LST max: " + maxa);
  return LST;
}
```

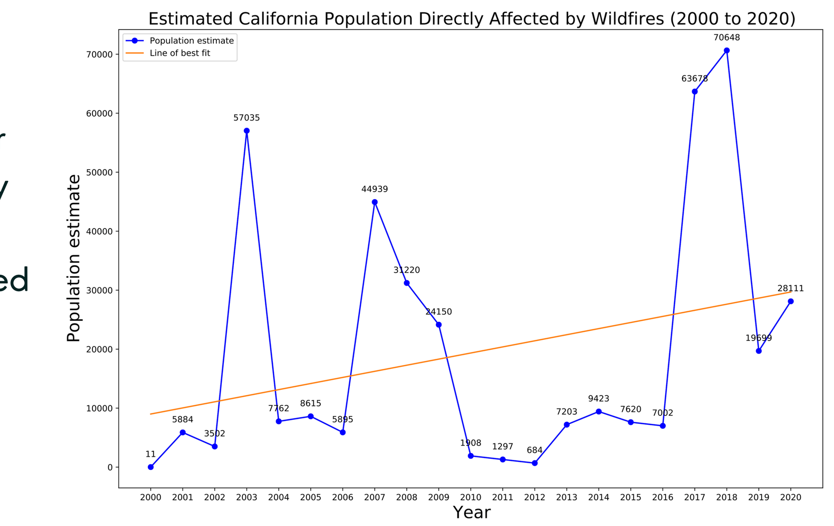


04. WILDFIRES

Alison Soong, Natasha Cordova-Diba

Wildfires Versus Population Analysis:

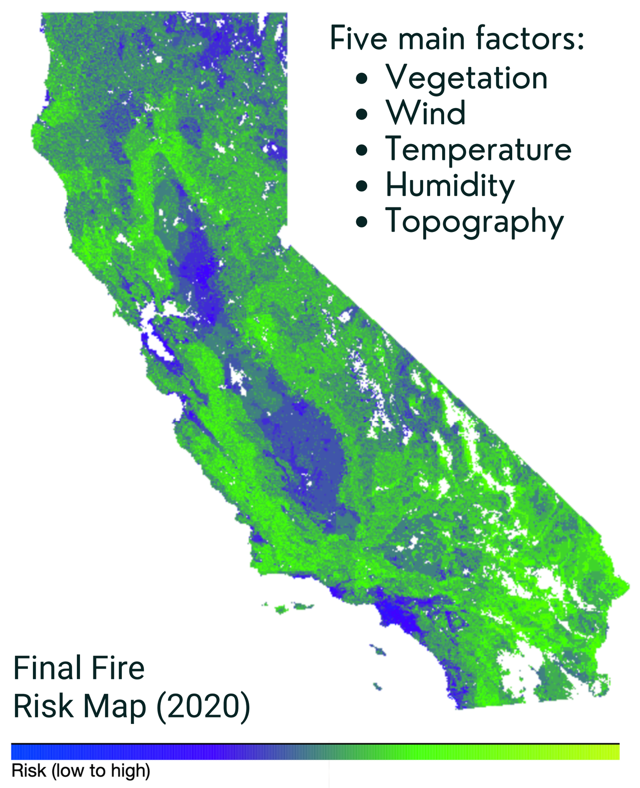
To examine wildfires and their impact on California's population, we overlapped the WorldPop Estimated Residential Population dataset over the MODIS Burned Area dataset to calculate the total population directly affected (residing in burned areas) by wildfires each year from 2000 to 2020. After plotting these values, we created a line of best fit that showed an increase of population affected over time. However, notable outliers featured years with fire conditions such as drought, the dry Santa Ana winds, intense heat, and abnormally high vegetation levels.



Fire Risk Map:

Inspired by our line graph, we decided to focus on five factors that contribute to wildfire vulnerability to create a fire risk map that shows the susceptibility of a given region. We looked at high vegetation values and land cover classification, high wind speeds, high temperatures, low relative humidity, and sloped topography using Landsat 8, GRIDMET, USGS land cover, and NED landforms datasets. For each dataset and factor, individual pixels were assigned a risk score. For example, a pixel with a high vegetation value, hinting at more fuel for wildfires, would be given the highest risk value of 3. This process resulted in 6 simplified maps with pixel values ranging 0-3. We then added all simplified datasets and their risk values to create the final fire risk map.

Our risk map, using only five factors, can only estimate the vulnerability of an area in 2020. However, after comparing our risk map with 2020 burn scars, we saw that many burn scars were located in and around areas marked as high risk according to our map.



Final Fire Risk Map (2020)

Analysis:

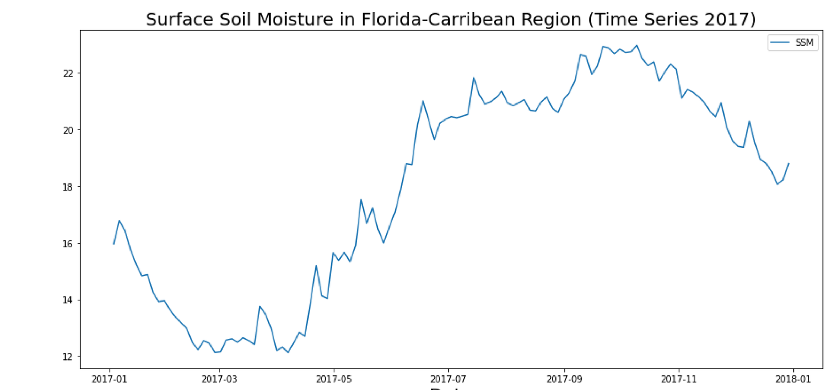
Analyzing past wildfires, evaluating the factors behind them, and scoring and combining multiple datasets led us to create a risk map that addressed our question about the likelihood of wildfires burning in different regions of California.

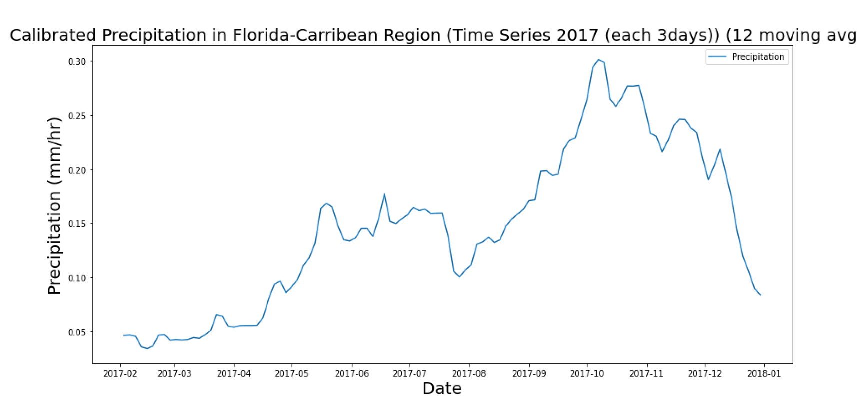
05. FLOODS/TROPICAL STORMS

Adelene Chan, Neha Vardhaman, Sabrina Chang, Sophia Lin

In 2017, Hurricane Irma (August 30th-September 12th) and Hurricane Maria (September 16th-October 2nd) struck Florida and the Caribbean area, causing widespread destruction and thousands of casualties. Our research focused on these areas, and we overlapped maps and graphed time series to identify patterns between the different datasets collected in the area at the time.

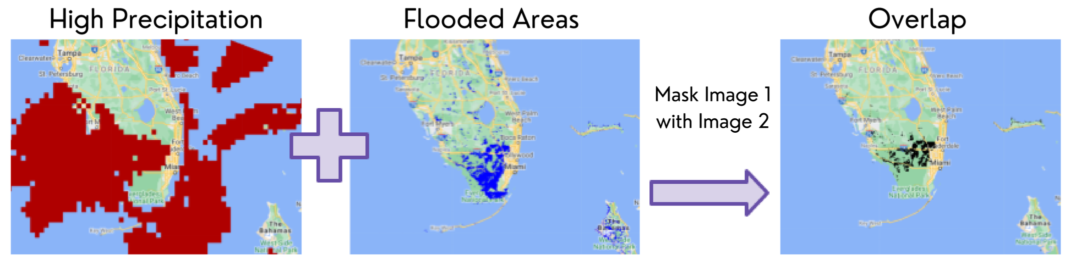
Time Series:



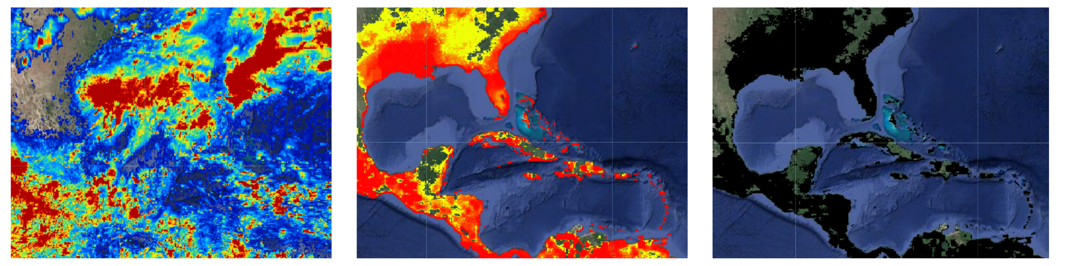


To create a time series chart using Google Colab and the Earth Engine Python API, we needed to reduce our dataset's imageCollection to the specific region and then convert the new FeatureCollection to a Python dictionary. Then, we created a modifiable pandas DataFrame from the dictionary that was used with the matplotlib and seaborn libraries to graph our data table. We graphed a time series of 2017 with intervals of 3 days for Surface Soil Moisture (from SMAP) and Precipitation (from GPM).

Overlapping:



To overlap the maps, we isolated pixels from datasets based on their values. For precipitation, we used the gte() function to retrieve all pixels with values greater than or equal to 0.5. For the Global Active Archive database, we used the subtract function to remove permanent water and isolate flood areas. Finally, we masked the flood area pixels with the high precipitation pixels and displayed the overlap in black.



Precipitation
GPM: Global Precipitation Measurement (GPM) v6

Soil Moisture
NASA-USDA Enhanced SMAP Global Soil Moisture Data

Overlap
Precipitation + Soil Moisture

Overlapping revealed a direct relationship between the maps. Areas of high precipitation values (red) also displayed high soil moisture values (red).

Analysis:

From our research, we found that time series and overlapping are valuable methods for analyzing strong correlations between different datasets, especially because of their adaptability. Using these tools and masking the maps together allows us to identify areas of greatest impact and ultimately helps us recognize patterns for future disasters.

06. CONCLUSION

Our 3 sub-groups each focused on a specific topic area in Extreme Heat, Wildfires, and Floods/Tropical Storms. The final map displays made with Google Earth Engine can be found below and to the left.

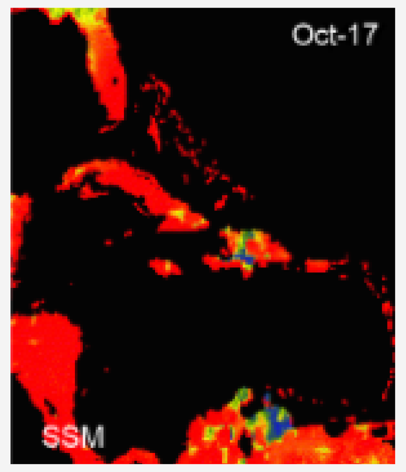
Future Interests

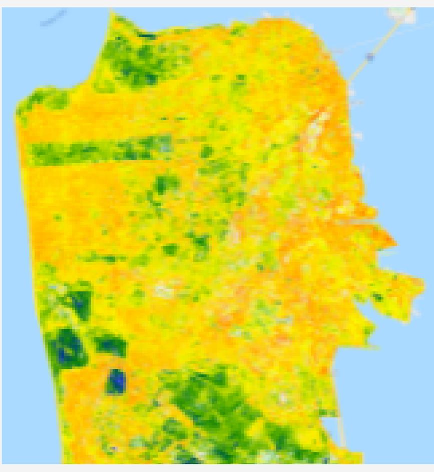
Our future interests include exploring Black Marble Night Lights data, which can be used to further examine how populations have been affected by natural disasters.

Reflections

Throughout our work, our team learned how to research datasets, examine the documentation for these datasets, and evaluate how we could utilize them for data analysis and to reveal a larger significance about natural disasters and their effects on populations. Significant lessons we learned were the importance of collaborating in subgroups while also communicating effectively about our tasks and meeting deadlines as a whole group.

Results





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