Analyzing, Visualizing, and Predicting the Impacts of Various Natural Disasters Through Geospatial Applications

Alison Soong[1], Adelene Chan[1], Grady Pennington[1], Neha Vardhaman[1], Eashan Hatti[1], Sabrina Chang[1], Joel Villarino[1], Sheryl Hsu[1], Natasha Cordova-Diba[1], and Sophia Lin[1]

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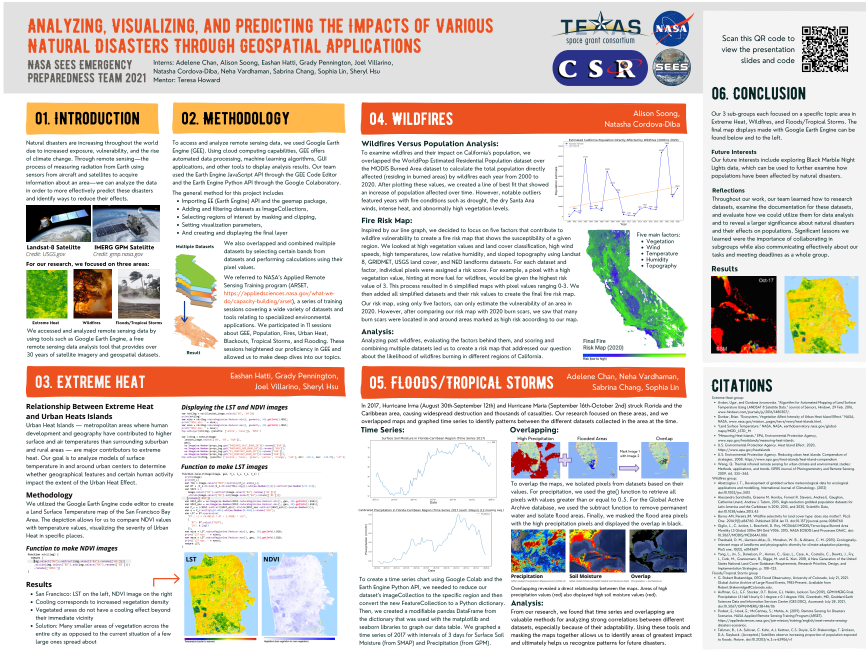
Abstract

Using population grid datasets, satellite imagery, and geospatial data accessed through Google Earth Engine, we identified patterns between natural disasters, their causes, and their impact on communities in order to predict and identify ways to reduce their effects. Techniques used include resampling, grid manipulation, mapping of datasets, and trend examination by creating time-series graphs and visualizations. For wildfires, population data was overlapped by burn scar data to calculate the yearly California population directly affected by wildfires (residing in burn areas) from 2000 to 2020. A line of best fit based on the calculated values showed an increase in population affected over time, and notable outliers revealed years with conditions that contributed to wildfire vulnerability, including high vegetation, high wind speeds, high temperatures, low relative humidity, and sloped topography. Scoring and combining data based on these five factors resulted in a fire risk map that visualizes the susceptibility of California to wildfires. For floods and tropical storms, the hurricane-heavy Florida-Caribbean region was analyzed by processing surface soil moisture (SSM) and precipitation (GPM) datasets to create time series line charts that revealed an upward trend in both SSM and precipitation in the fall of 2017. To examine how susceptible SSM, precipitation, and dense populations were to flooding, we overlapped maps of the various datasets by masking higher values with areas of the map that had flooded. A significant overlap existed with these flood factors, allowing us to generate a map that visualizes areas susceptible to flooding. For extreme heat, San Francisco was chosen as the area of study. We created land surface temperature (LST) and normalized difference vegetation index (NDVI) images of the city to determine the effect of vegetation on extreme heat events in urban areas. Our observations showed that while greenbelts — large vegetated areas dispersed throughout the city — do have a significant cooling effect, this effect does not spread far beyond the limits of the area. A possible solution is to distribute a greater number of smaller green areas evenly throughout the city instead.


ANALYZING, VISUALIZING, AND PREDICTING THE IMPACTS OF VARIOUS NATURAL DISASTERS THROUGH GEOSPATIAL APPLICATIONS
NASA SEES EMERGENCY PREPAREDNESS TEAM 2021
Interns: Adelene Chan, Alison Soong, Eashan Hatti, Grady Pennington, Joel Villarino, Natasha Cordova-Diba, Neha Vardhaman, Sabrina Chang, Sophia Lin, Sheryl Hsu
Mentor: Teresa Howard
TEXAS space grant consortium
NASA
CSR
SEES
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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 Satelitte
Credit: USGS.gov
IMERG GPM Satelitte
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
Multiple Datasets
Result
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.
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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
Displaying the LST and NDVI images
Function to make LST images
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
LST
NDVI
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Wildfires Versus Population Analysis:
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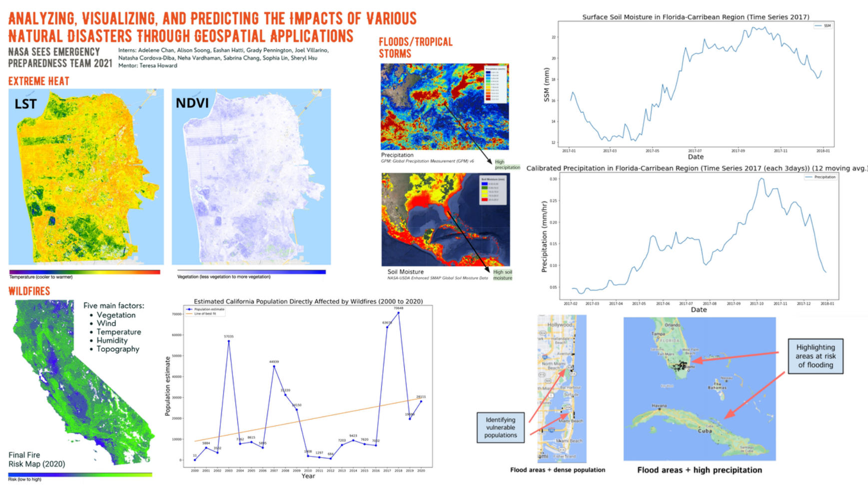
Estimated California Population Directly Affected by Wildfires (2000 to 2020)
Fire Risk Map:
Inspired by our line graph, we decided to focus on five factors that contribute to wildfire vulnerability to create a fire risk map that shows the susceptibility of a given region. We looked at high vegetation 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.
Five main factors:
• Vegetation
• Wind
• Temperature
• Humidity
• Topography
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.
Final Fire Risk Map (2020)
Risk (low to high)
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:
Surface Soil Moisture in Florida-Carribean Region (Time Series 2017)
Calibrated Precipitation in Florida-Carribean Region (Time Series 2017 (each 3days)) (12 moving avg.)
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:
High Precipitation
Flooded Areas
Mask Image 1 with Image 2
Overlap
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
Soil Moisture
Overlap
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
Oct-17
SSM
CITATIONS
Extreme Heat group:
Wildfires group:
Floods/Tropical Storms group: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EXTREME HEAT
LST
NDVI
Temperature (cooler to warmer)
Vegetation (less vegetation to more vegetation)
WILDFIRES
Five main factors:
• Vegetation
• Wind
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Estimated California Population Directly Affected by Wildfires (2000 to 2020)
Population estimate
Year
FLOODS/TROPICAL STORMS
Precipitation
GPM: Global Precipitation Measurement (GPM) v6
High precipitation
Soil Moisture
NASA-USDA Enhanced SMAP Global Soil Moisture Data
High soil moisture
Surface Soil Moisture in Florida-Carribean Region (Time Series 2017)
SSM (mm)
Date
Calibrated Precipitation in Florida-Carribean Region (Time Series 2017 (each 3days)) (12 moving avg.)
Precipitation (mm/hr)
Date
Identifying vulnerable populations
Highlighting areas at risk of flooding
Flood areas + dense population
Flood areas + high precipitation

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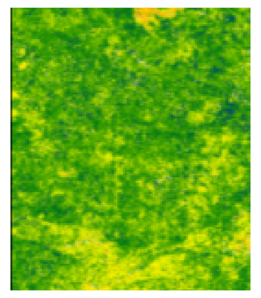
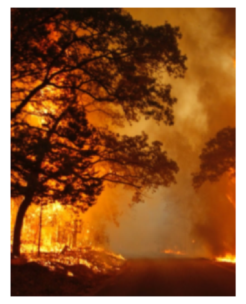
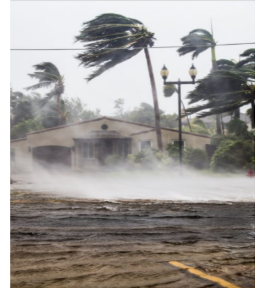


Extreme Heat



Wildfires



Floods/Tropical Storms

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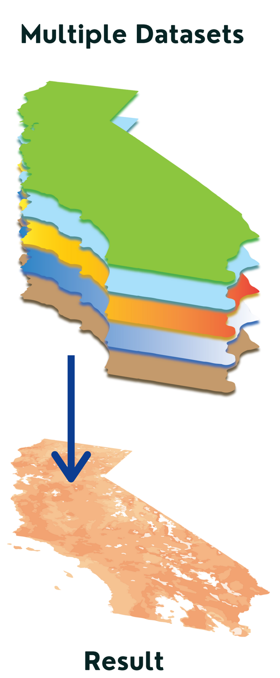

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Methodology

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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);
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  print("LST max: " + maxa);
  return LST;
}
```

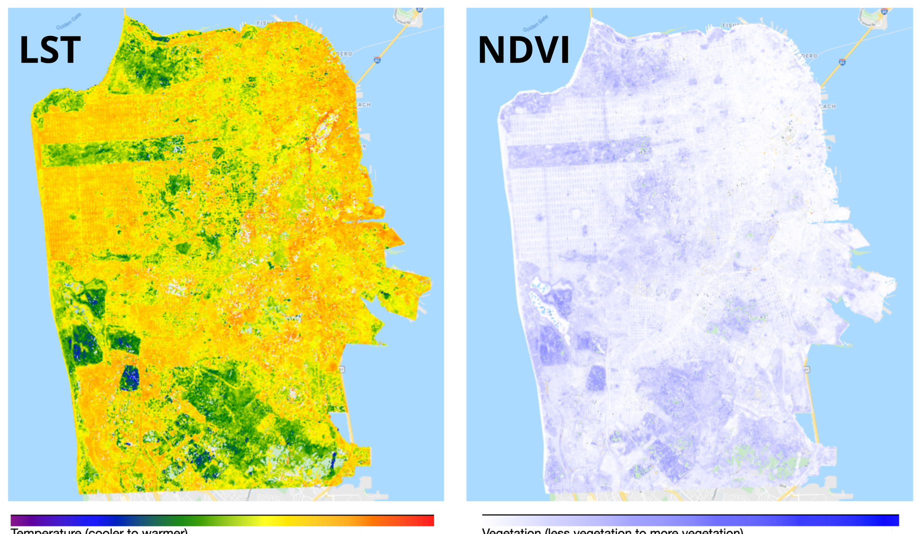

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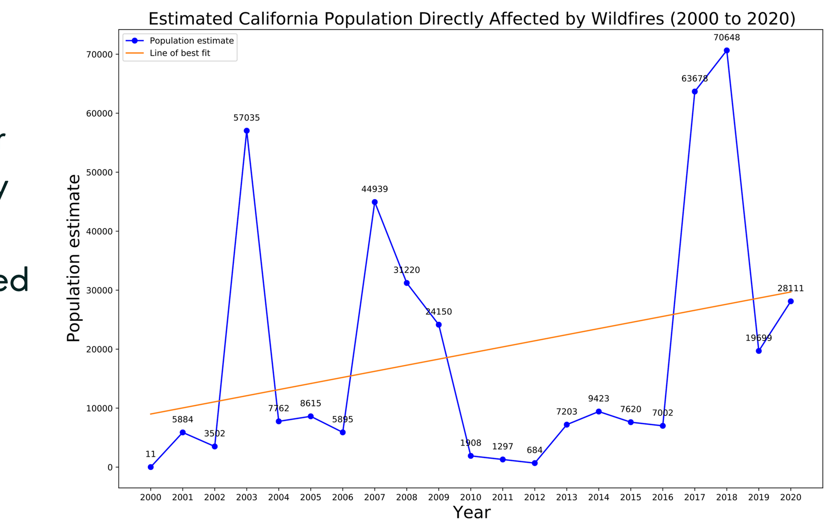

Fire Risk Map:

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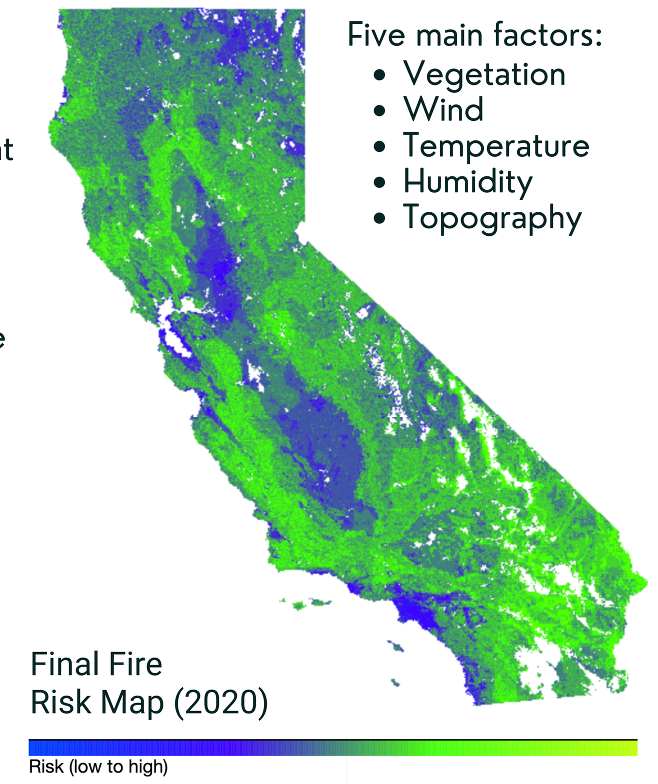

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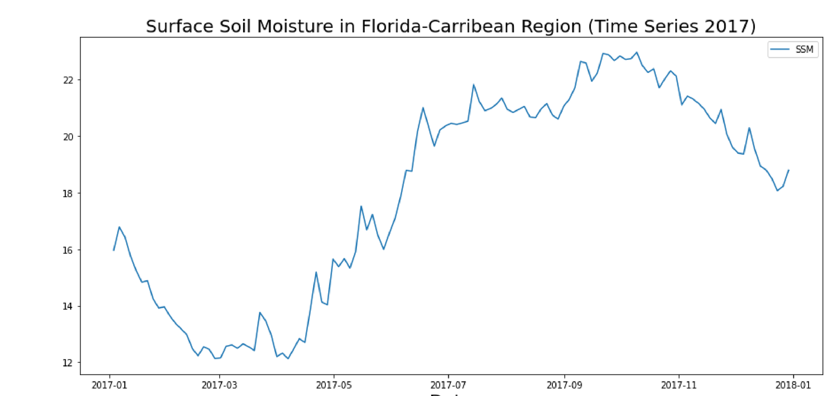
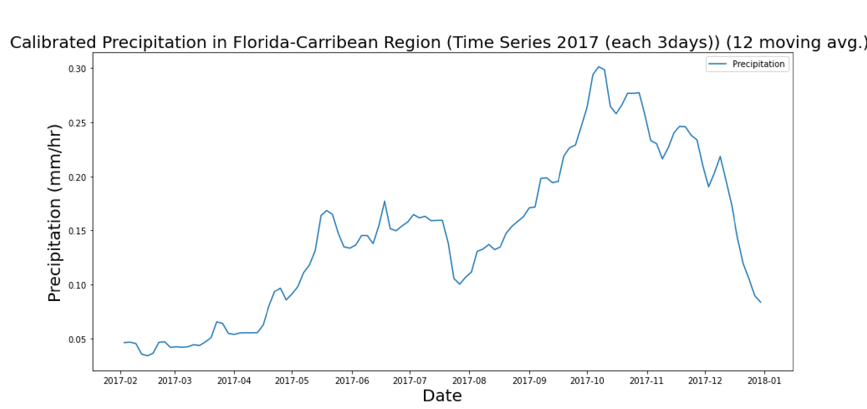
Time Series:





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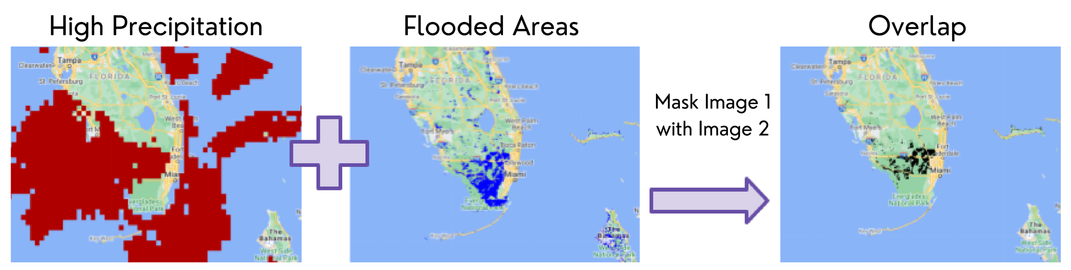
Overlapping:



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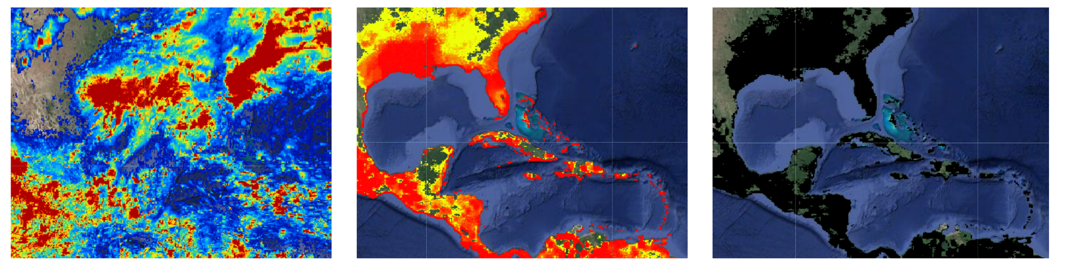

Precipitation *GPM: Global Precipitation Measurement (GPM) v6*

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.

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Future Interests

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Reflections

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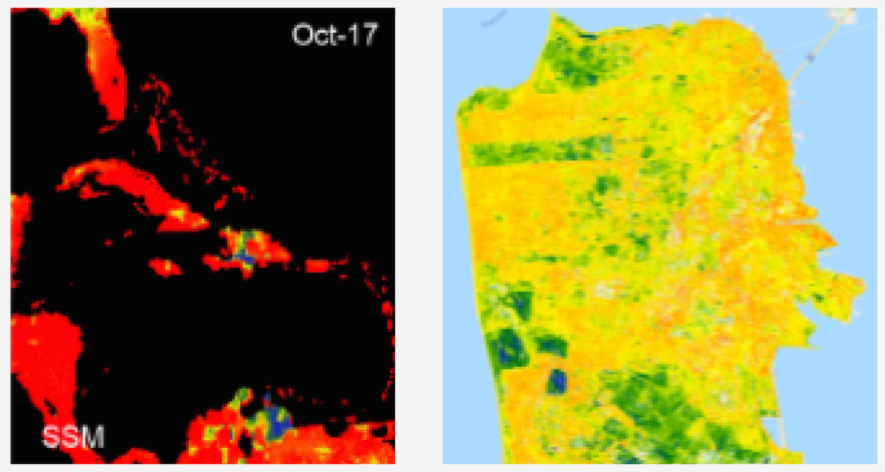
Results



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Extreme Heat group:

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Floods/Tropical Storms group

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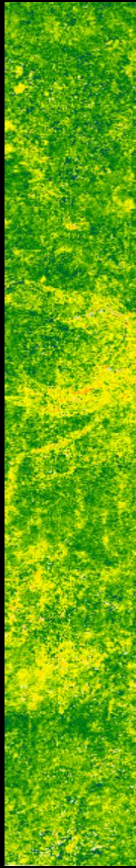
Emergency Preparedness



STEM Enhancement in Earth Science
SEES
SUMMER HIGH SCHOOL INTERN PROGRAM

Science Symposium 2021

OUR TEAM

Adelene Chan

Alison Soong

Eashan Hatti

Grady Pennington

Joel Villarino

Natasha Cordova-Diba

Neha Vardhaman

Sabrina Chang

Sophia Lin

Sheryl Hsu

BACKGROUND

Emergency Preparedness

Remote Sensing

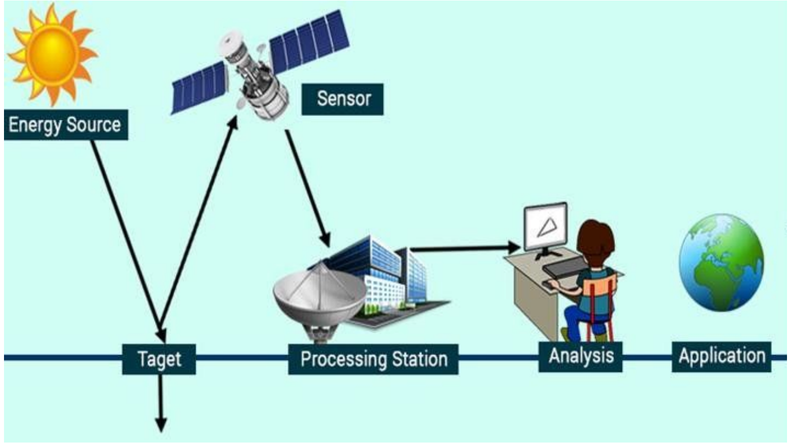
Google Earth Engine

ARSET

What is Emergency Preparedness?

- Natural disasters are worsening (416 natural disasters worldwide in 2020)
- Examine the effects of climate change
- How can we better forecast and prepare for natural disasters?
- Are there changes to infrastructure we can make?
- Can we adjust our response plan - ie FEMA in the United States?

What is Remote Sensing?



Singh, Beependra & Chockalingam, Jeganathan & Rathore, Virendra. (2018). Remote Sensing Technology for Monitoring and Modelling Ecological Processes.

Remote sensing utilizes data collected from specialized sensors on satellites and aircraft

What are its uses?

This data can be used to create models and make predictions for the future

Introduction to Google Earth Engine (GEE) and Relevant Methods

Google Earth Engine

- Free remote sensing data analysis tool open to the public
- More than 30 years of satellite imagery and geospatial datasets
- Automated data processing, machine learning algorithms, GUI applications
- The Earth Engine JavaScript API through GEE Code Editor
- The Earth Engine Python API through Google Colaboratory

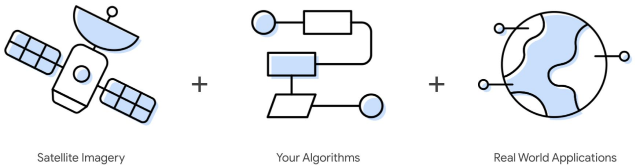


Image credit: Google Earth Engine (https://earthengine.google.com/)

ARSET Trainings

CAPACITY BUILDING
WATER RESOURCES
DISASTERS
ECOLOGICAL FORECASTING
HEALTH & AIR QUALITY
AGRICULTURE

Source: ARSET

ARSET Training Website:
https://appliedsciences.nasa.gov/what-we-do/capacity-building/arset

Data Visualization: Mapping with GEE

1. Import EE API, geemap package
2. Add & filter dataset (ImageCollection)
3. Select region of interest
4. Visualization parameters
5. Add layer & display

EXTREME HEAT

Grady Pennington

Eashan Hatti

Sheryl Hsu

Joel Villarino

Overview of Extreme Heat and Urban Heat Islands (UHI)

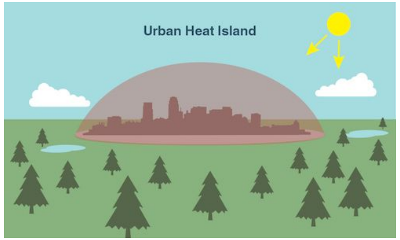
Credit: CDC

Identifying the Issue

Extreme Heat creates dangerous environments in urban areas.

Researching Causes

What geographic and human behavior impacts the severity of extreme heat?



An illustration of an urban heat island.
Image credit: NASA/JPL-Caltech

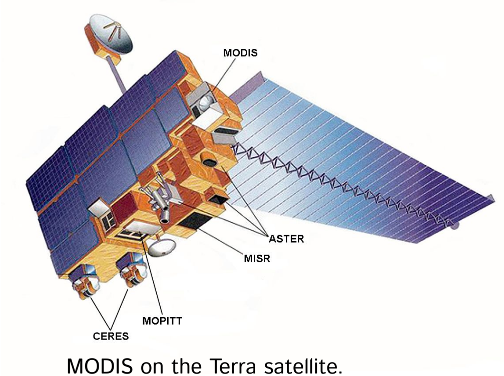
Credit: Unsplash.com

Proposing Solutions

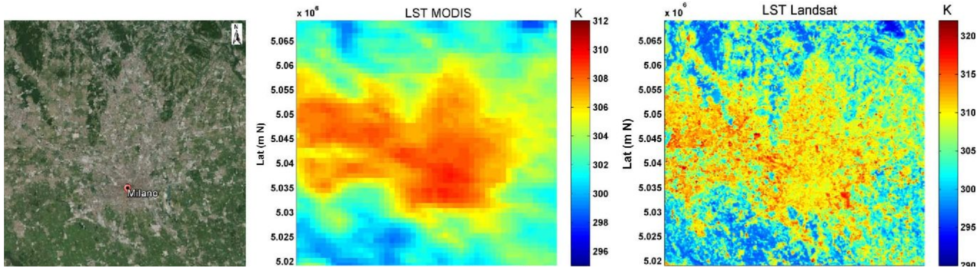
What infrastructure and lifestyle changes can we make to mitigate extreme heat and the UHI effect?

Methodology (Extreme Heat)

An illustration of the Landsat-8 satellite.
Credit: USGS.gov



MODIS on the Terra satellite.
Credit: NASA



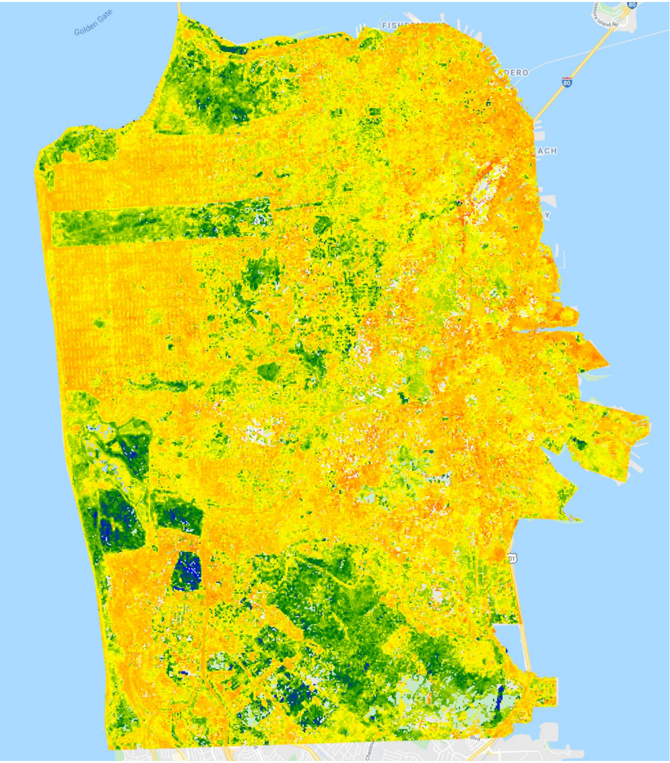
A Comparison of MODIS and Landsat-8 LST measurements.

Bonafoni, S.. “Downscaling of Landsat and MODIS Land Surface Temperature Over the Heterogeneous Urban Area of Milan.” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 9 (2016): 2019-2027.

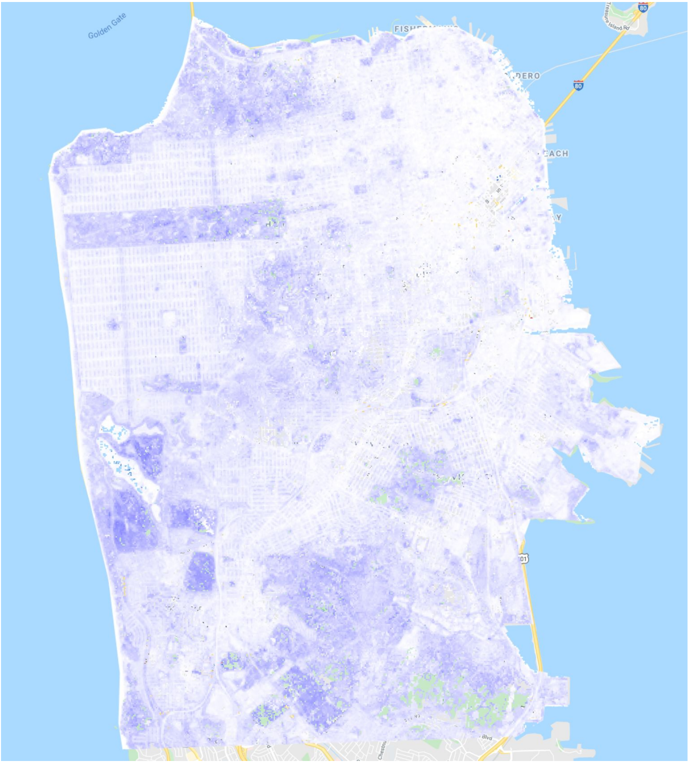
Data

LST (left) and NDVI (right) maps of San Francisco

LST



NDVI



Final Results, Conclusion, and Strategies

Severity is Determined by Several Factors

- Surface Albedo
- Surrounding Terrain
- Energy Usage

If Left Untreated, UHIs can

- Cause Problems for Human Health
- Lead to Increased Energy Costs
- Cause Environmental Damage

Strategies

- Enact Regulation
- Urban Planning
- Energy Conservation

WILDFIRES

Alison Soong

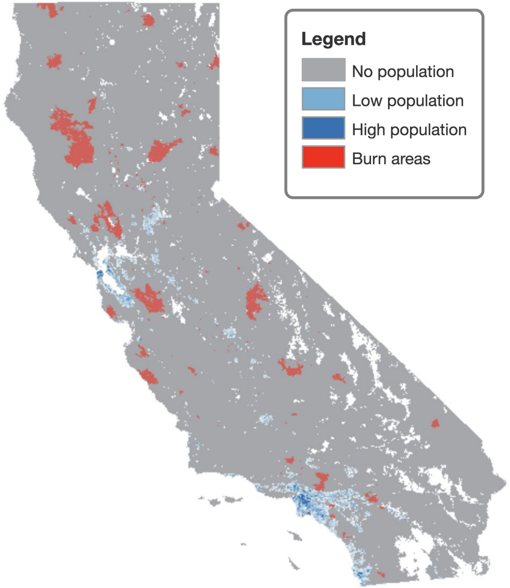
Natasha Cordova-Diba

Wildfires in California

Wildfire season in the Bay Area, September 2020
Image credit: Alison Soong

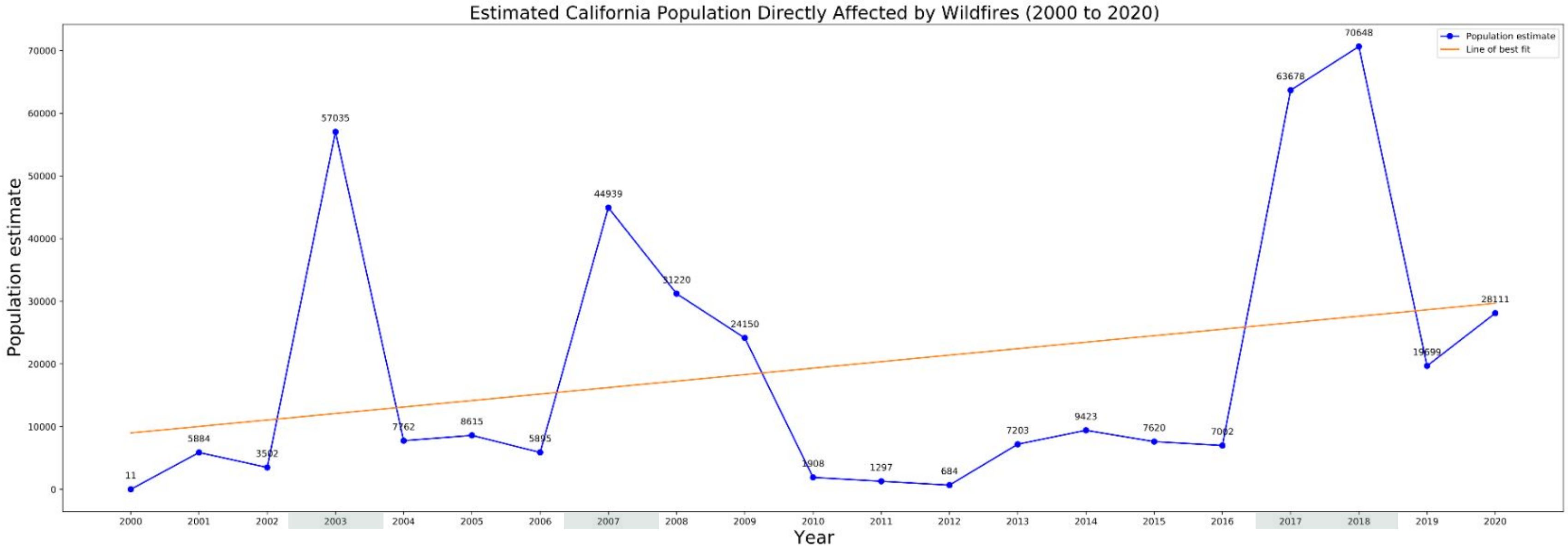
The Dolan Fire in Monterey County in California, 2020
Image credit: Kate Novoa and Connie McCoy for The U.S. Fish and Wildlife Service

2020 Burn Scars and Population



2001 Burn Scars and Population

Datasets used:
WorldPop Global Project Population Data: Estimated Residential Population per 100x100m Grid Square
MCD64A1.006 MODIS Burned Area Monthly Global 500m



2003: Dry Santa Ana winds

2007: Dry conditions due to drought and the Santa Ana winds

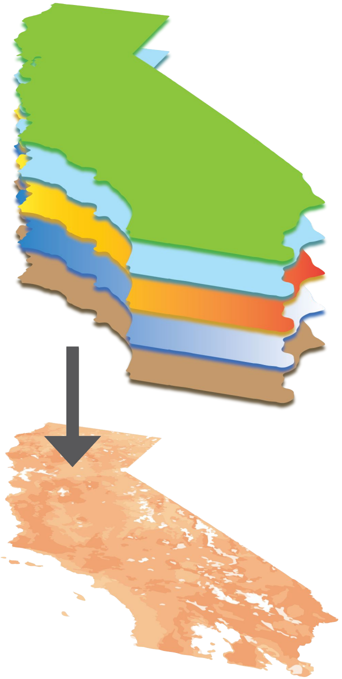
2017: Record precipitation and increased vegetation followed by intense heat

2018: Record warm weather and lower than average precipitation

Methods for a Fire Risk Map

5 main factors:

- Vegetation
- High wind speeds
- High temperatures
- Low humidity
- Topography



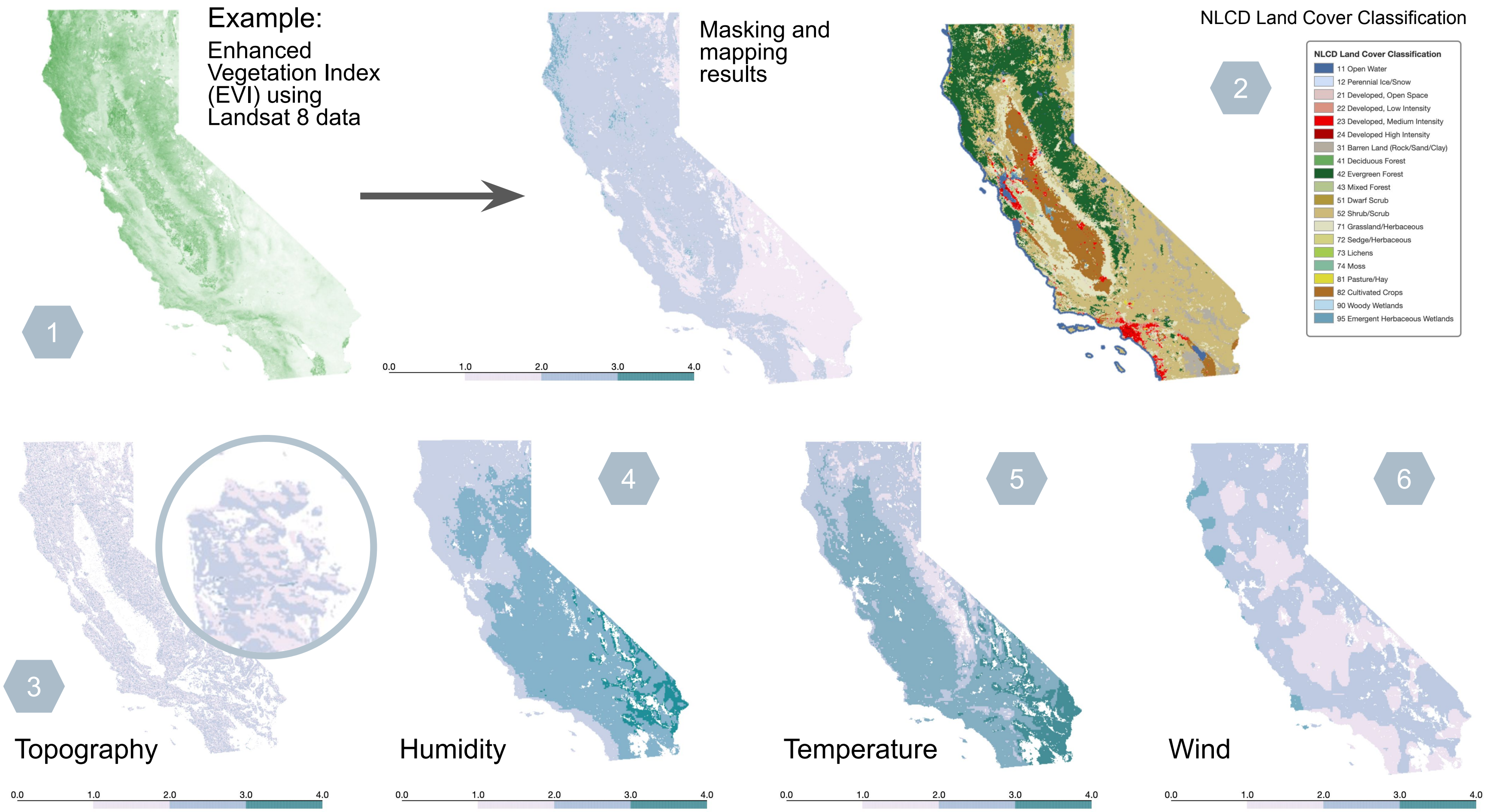
Datasets:

USGS Landsat 8 Level 2, Collection 2, Tier 1 to map Enhanced Vegetation Index (EVI)

GRIDMET: University of Idaho Gridded Surface Meteorological Dataset to map wind velocity at 10 m, maximum temperature, and relative humidity

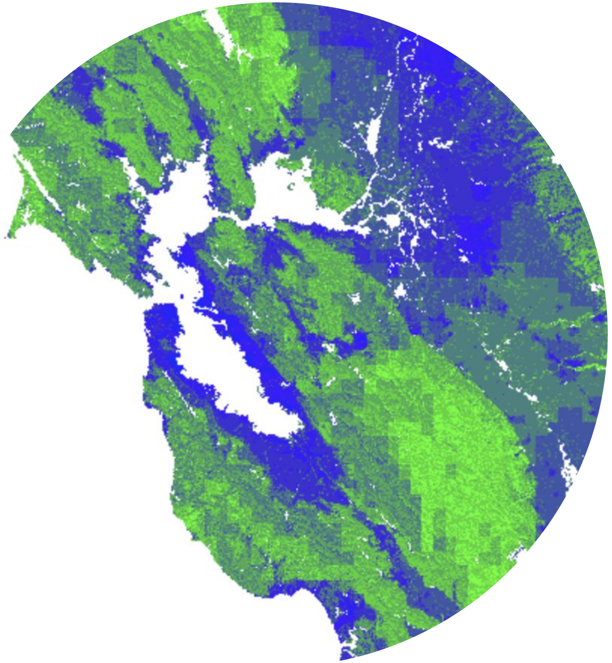
NLCD: USGS National Land Cover Database for land cover classification

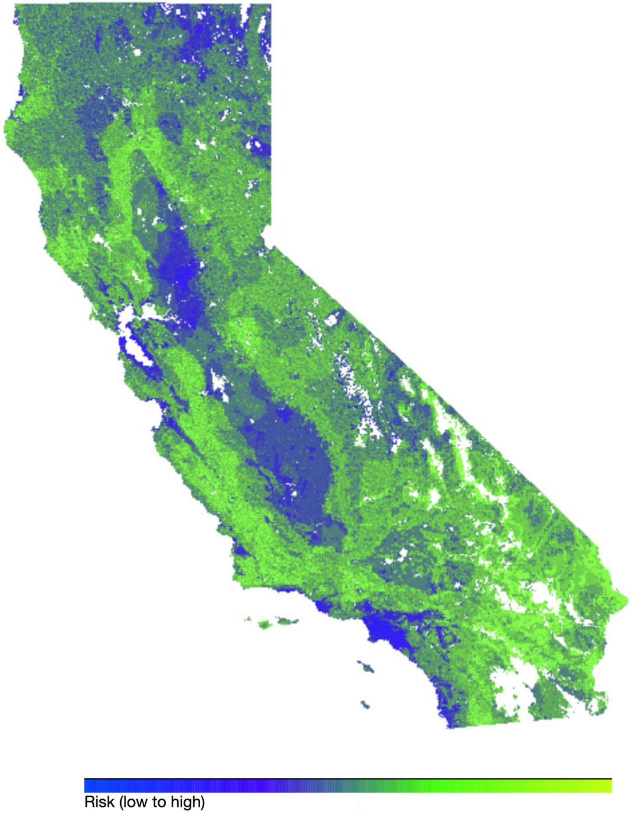
US NED Landforms dataset to map topography



Example:
Enhanced Vegetation Index (EVI) using Landsat 8 data
Masking and mapping results
NLCD Land Cover Classification
NLCD Land Cover Classification
11 Open Water
12 Perennial Ice/Snow
21 Developed, Open Space
22 Developed, Low Intensity
23 Developed, Medium Intensity
24 Developed High Intensity
31 Barren Land (Rock/Sand/Clay)
41 Deciduous Forest
42 Evergreen Forest
43 Mixed Forest
51 Dwarf Scrub
52 Shrub/Scrub
71 Grassland/Herbaceous
72 Sedge/Herbaceous
73 Lichens
74 Moss
81 Pasture/Hay
82 Cultivated Crops
90 Woody Wetlands
95 Emergent Herbaceous Wetlands
1
2
3
4
5
6
0.0
1.0
2.0
3.0
4.0
Topography
Humidity
Temperature
Wind

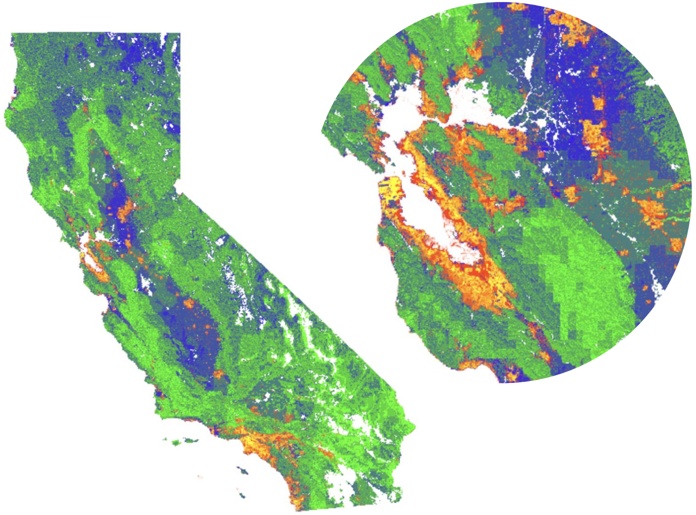
Fire Risk Map





Conclusion and Future Ideas to Pursue

Comparing fire risk map with California population dataset

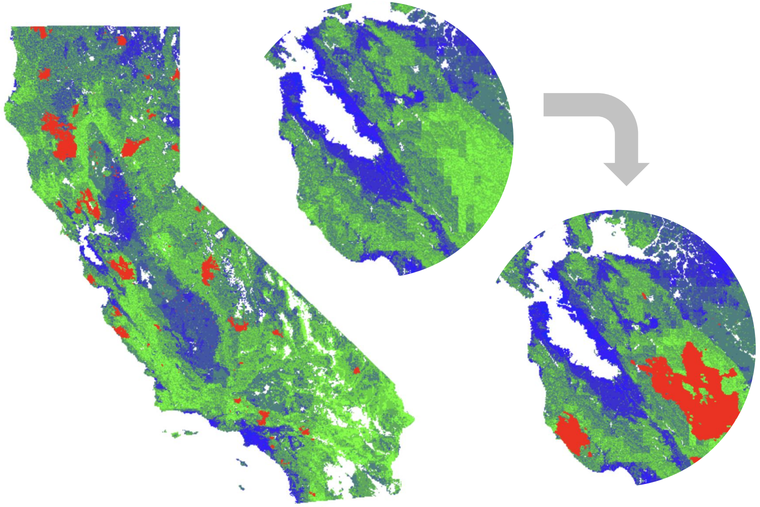


Population (low to high)

Risk (low to high)

Dataset used: WorldPop Global Project Population Data: Estimated Residential Population per 100x100m Grid Square (www.worldpop.org)

Comparing fire risk map with burn scars from 2020 wildfires



Burned area

Dataset used: MCD64A1.006 MODIS Burned Area Monthly Global 500m (DOI: 10.5067/MODIS/MCD64A1.006)

Risk (low to high)

FLOODS & TROPICAL STORMS

Neha Vardhaman

Sabrina Chang

Sophia Lin

Adelene Chan

Background of Floods & Tropical Storms

Area of Interest: Florida, Puerto Rico, the Caribbean

Hurricane Irma

Cost of Damage: $50 billion

Casualties: 134

Wind Speed: 185 mph

Aug 30 - Sep 2017

Hurricane Maria

Cost of Damage: $91.61 billion

Casualties: 3,057

Wind Speed: 174 mph

Sep 16 - Oct 2, 2017

Datasets

Factors that influence risks of flooding from tropical storms

- Soil Moisture
- Impervious Cover
- Flooding
- Population
- Precipitation

Databases:

- NASA-USDA Enhanced SMAP Global Soil Moisture Data
- MCD12Q1.006 MODIS Land Cover Type Yearly Global 500m
- Global Flood Database v1 (2000-2018)
- WorldPop Global Project Population Data: Estimated Residential Population per 100x100m Grid Square
- GPM: Global Precipitation Measurement (GPM) v6

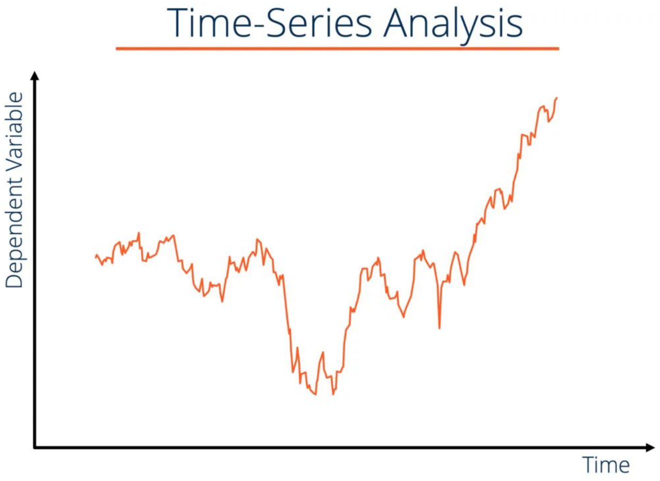
Data Visualization: Time Series

What is a time series (ts)?

A collection of data points with respect to time

How is a ts represented?

Line charts, map animations, etc.



How do we go from EE dataset to chart?

Reduce dataset -> pandas DataFrame -> Graph (ex. matplotlib)

Time Series Data Processing & Chart

Step 1: Reduce data region
(mean of several images)

```
reducer=ee.Reducer.mean()
```

```
def create_reduce_region_function(geometry, reducer=ee.Reducer.mean(),
                                  scale=1000, crs='EPSG:4326',
                                  bestEffort=True, maxPixels=1e13, tileScale=4):
  def reduce_region_function(img):
    stat = img.reduceRegion(
        reducer=reducer,
        geometry=geometry,
        scale=scale,
        crs=crs,
        bestEffort=bestEffort,
        maxPixels=maxPixels,
        tileScale=tileScale)

    return ee.Feature(geometry, stat).set({'millis': img.date().millis()})
  return reduce_region_function
```

```
reduce_ssm = create_reduce_region_function(
    geometry=aoi, reducer=ee.Reducer.mean(), scale=10000)

ssm_stat_fc = ee.FeatureCollection(ssm.map(reduce_ssm)).filter(
    ee.Filter.notNull(ssm.first().bandNames()))
```

Step 2: DataFrame & Rearrangement

```
ssm_df = pd.DataFrame(ssm_dict)
```

	millis	ssm	system:index
0	1483444800000	15.959311	NASA_USDA_SMAP_SM20170103_20170105
1	1483704000000	16.775050	NASA_USDA_SMAP_SM20170106_20170108
2	1483963200000	16.424203	NASA_USDA_SMAP_SM20170109_20170111
3	1484222400000	15.747155	NASA_USDA_SMAP_SM20170112_20170114
4	1484481600000	15.236185	NASA_USDA_SMAP_SM20170115_20170117
...	...	...	...
116	1513512000000	18.795176	NASA_USDA_SMAP_SM20171217_20171219
117	1513771200000	18.500953	NASA_USDA_SMAP_SM20171220_20171222
118	1514030400000	18.064526	NASA_USDA_SMAP_SM20171223_20171225
119	1514289600000	18.213604	NASA_USDA_SMAP_SM20171226_20171228
120	1514548800000	18.788075	NASA_USDA_SMAP_SM20171229_20171231

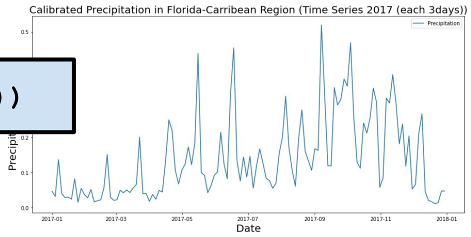
	SSM
date	
2017-01-03 12:00:00	15.959311
2017-01-06 12:00:00	16.775050
2017-01-09 12:00:00	16.424203
2017-01-12 12:00:00	15.747155
2017-01-15 12:00:00	15.236185
...	...
2017-12-17 12:00:00	18.795176
2017-12-20 12:00:00	18.500953
2017-12-23 12:00:00	18.064526

```
ssm_df = ssm_df.set_index('date')
```

Step 3: Graph

```
fig, ax = plt.subplots(figsize=(15,7))
```

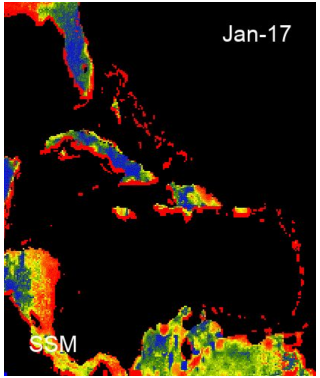
```
sns.lineplot(data=ssm_df, ax=ax)
```

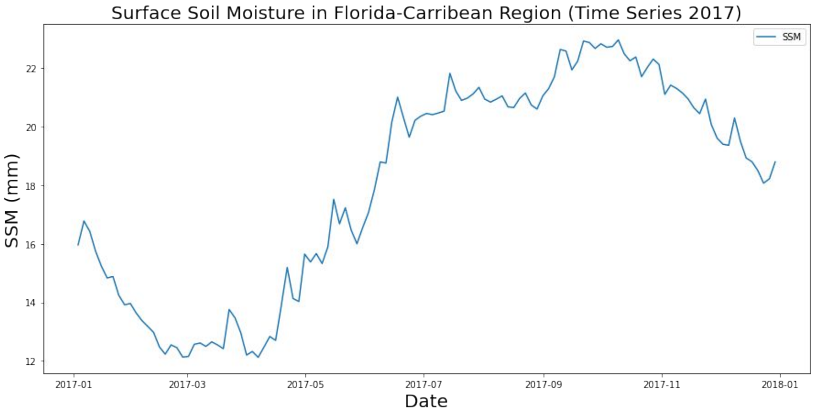


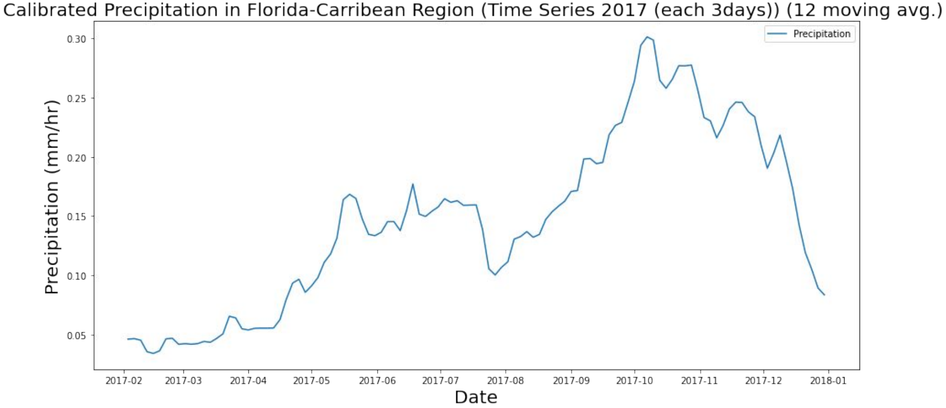
Time Series - Soil Moisture & Precipitation

- Found higher surface soil moisture (upper 10 cm) and precipitation during the 2017 hurricane season (June-Nov).
- Comparison made by 3 day interval time series line charts

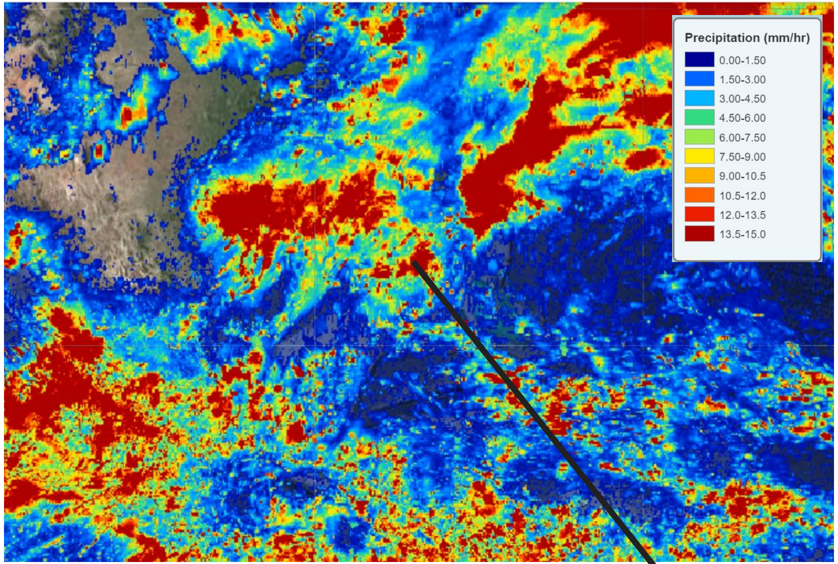
Florida-Carribean Region SSM





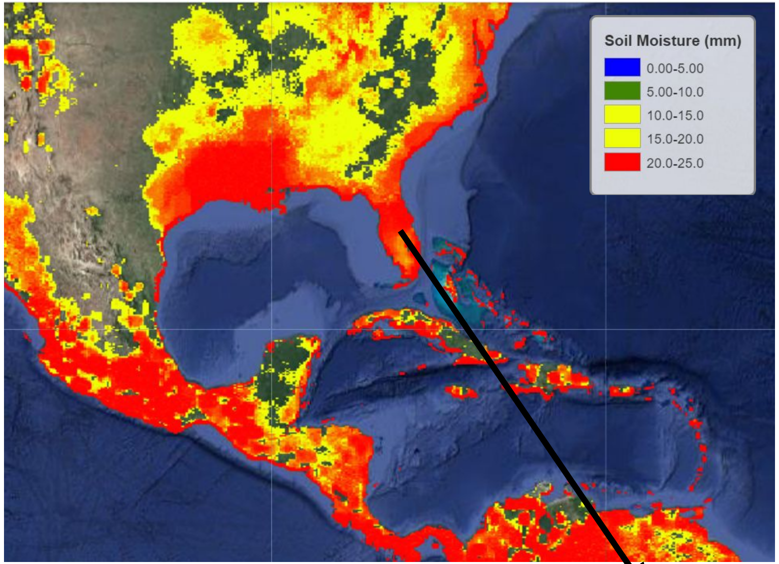


Precipitation & Soil Moisture Mapping



Precipitation
GPM: Global Precipitation Measurement (GPM) v6

High precipitation

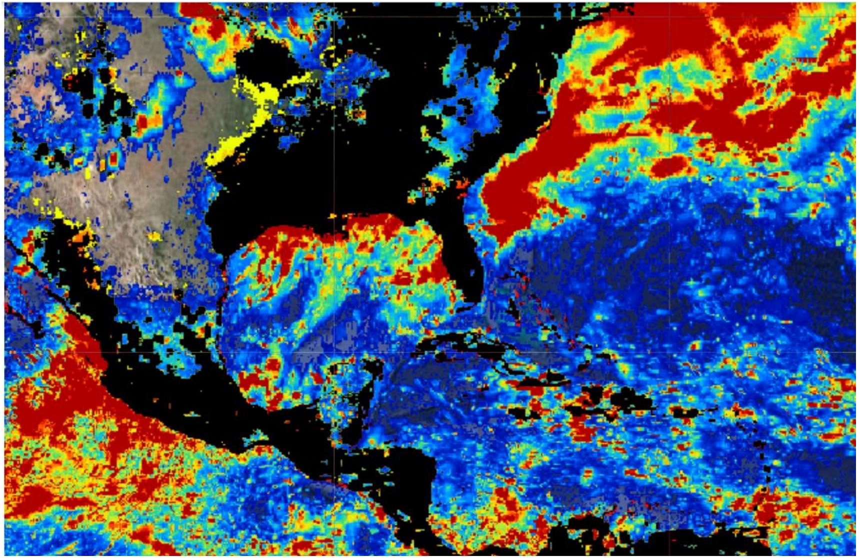


Soil Moisture
NASA-USDA Enhanced SMAP Global Soil Moisture Data

High soil moisture

Overlapping - Precipitation & Soil Moisture

Overlapping Precipitation & Soil Moisture



All Three Layers
(precipitation, soil moisture, overlap)

Overlapping Process

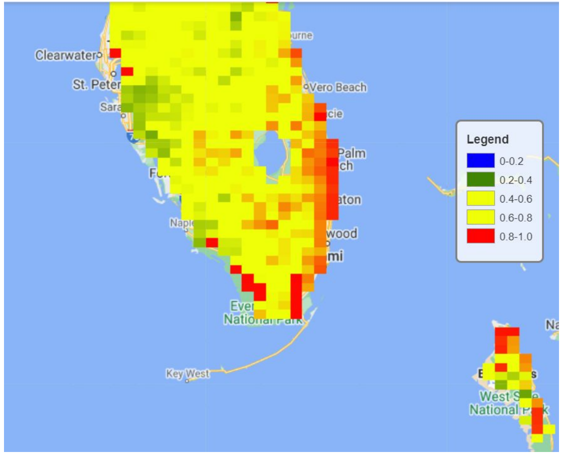
Code:

```
high_smp = smp.updateMask(smp.gte(0.8))
```

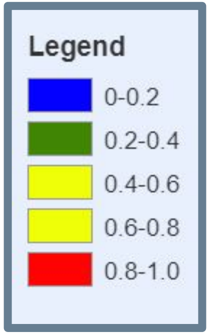
Step 1: Isolate pixels from dataset 1 to be overlapped

ex: Pixels representing high soil moisture profile (smp)

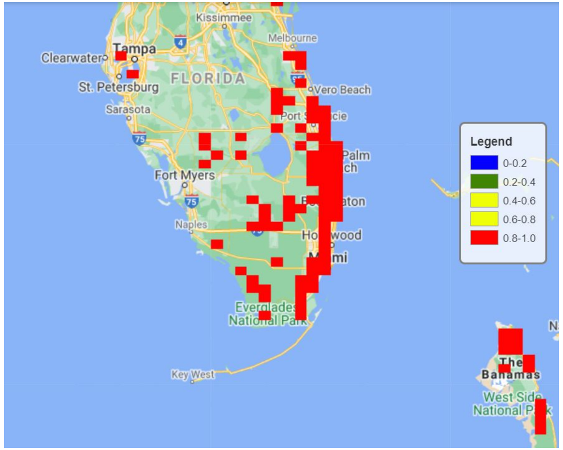
Soil Moisture Layer



Mask out smp values < 0.8



High Soil Moisture Layer



Overlapping Process

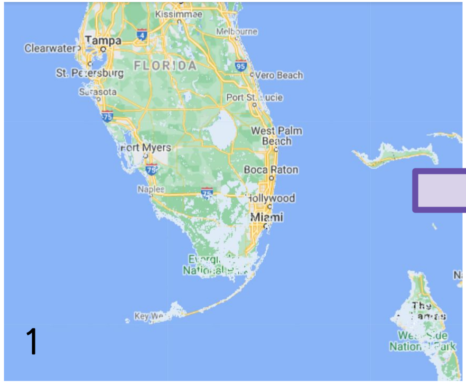
Code:

```
flood_no_perm = gfdFloodedSum.gte(1).subtract(jrc).selfMask()
```

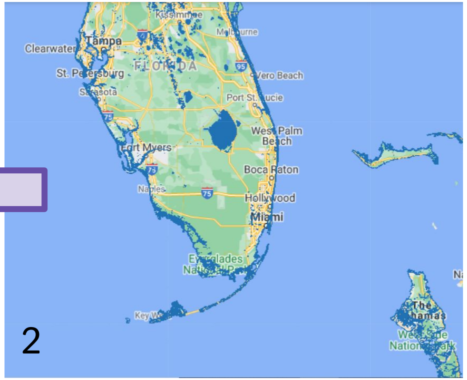
Step 2: Isolate pixels from dataset 2 to be overlapped

ex: Pixels representing flooded areas

All water during flooding

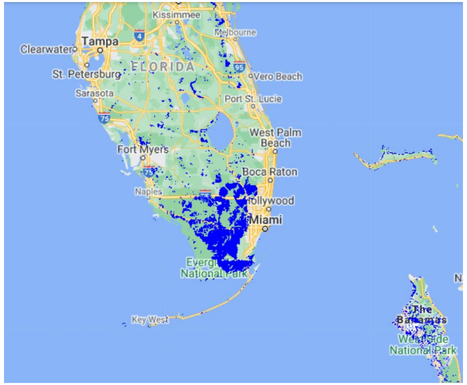


Permanent water



Subtract image 2 from 1

Flooded areas



G. Robert Brakenridge, DFO Flood Observatory, University of Colorado, date received. Global Active Archive of Large Flood Events, 1985-Present. Available from Robert.Brakenridge@Colorado.edu.

Overlapping Process

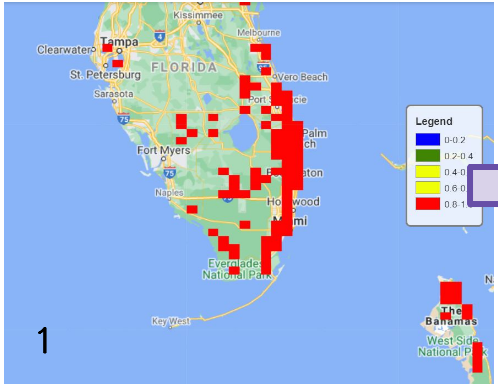
Code:

```
overlap_smp_fld = high_smp.updateMask(flood_no_perm)
```

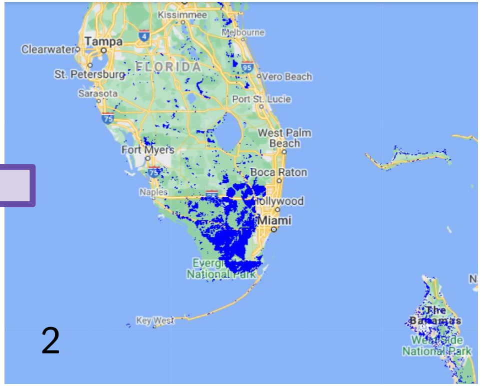
Step 3: Mask Step 2 result over Step 1 result

ex: Mask flooded areas over high soil moisture

High soil moisture profile

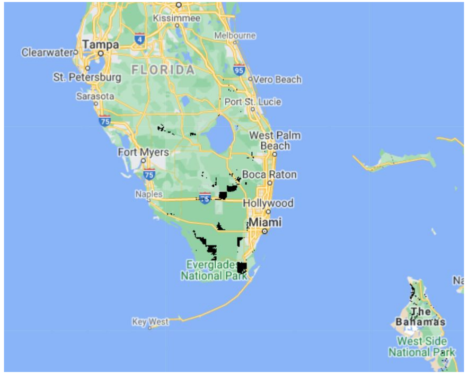


Flooded areas

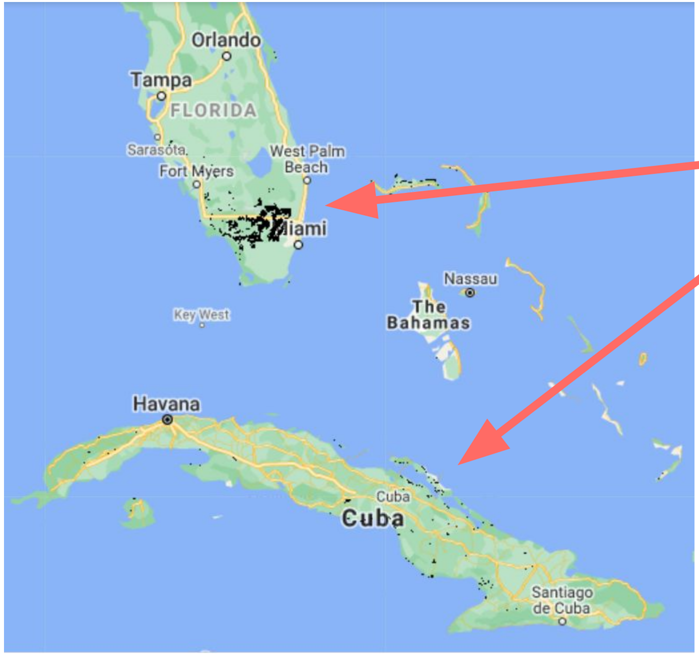


Mask image 1 with image 2

Overlap

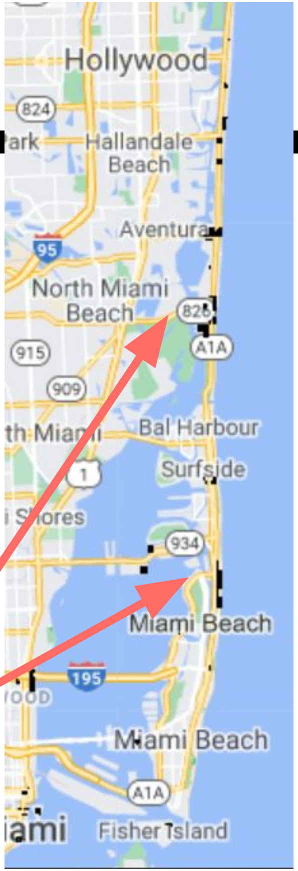


Overlapping Flooding with Precipitation and Population Data



Highlighting areas at risk of flooding

Identifying vulnerable populations



Flood areas + high precipitation

Flood areas + dense population

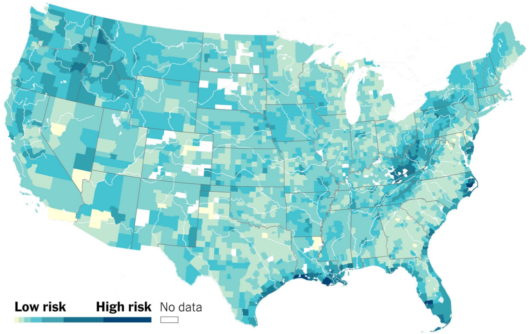
Floods/Tropical Storms Conclusion

Final Thoughts:

- Time Series and Overlapping = valuable methods for analyzing flooding/tropical storms
  - Adaptable to different regions, datasets, time frames
- Found strong relationships between different factors of flooding
  - Precipitation + soil moisture
  - Flooding + precipitation

Future Interest:

- Make a more comprehensive flood risk map combining all factors of flooding



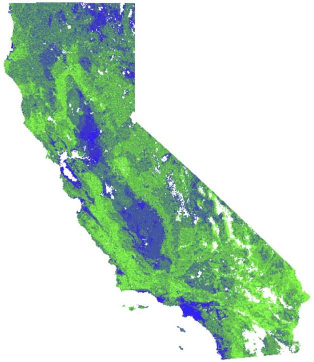
(FEMA Flood Map)

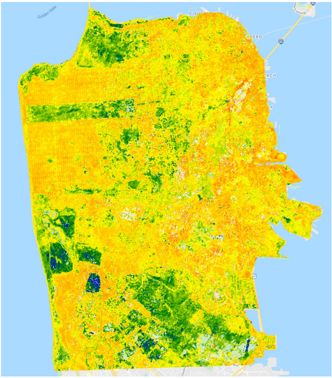
Final Conclusion

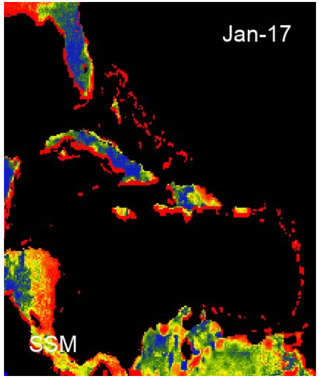
- NASA ARSET Training
  - Use of GEE
  - Relevant datasets
  - Methods to analyze natural disasters
- Converting Javascript to Python in Google Colab
- Future Interest
  - Exploring Black Marble Night Lights Data

Presentation + Code Available at:
https://github.com/alisonsoong/NASA-SEES-2021-Emergency-Preparedness

Maps from the Extreme Heat, Wildfire, Floods/Tropical Storms groups made with **GEE**







Sophia Lin

Rising Senior at Newport High School (WA)

(challenge)

Natasha Cordova-Diba

Rising Senior at Valley Christian High School (CA)

Sabrina Chang

Rising Senior at West Windsor-Plainsboro High School North (NJ)

Joel Villarino

Rising Senior at Sulphur Springs High School (TX)

Alison Soong

Rising Junior at Crystal Springs Uplands High School (CA)

(lesson)

Sheryl Hsu

Rising Senior at Valley Christian High School (CA)

(challenge)

Grady Pennington

Rising Senior at Rockwall High School (TX)

Neha Vardhaman

Rising Senior at Montgomery High School (NJ)

Adelene Chan

Rising Senior at Union County Magnet High School (NJ)

Eashan Hatti

Rising Junior at Washington High School (WV)

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