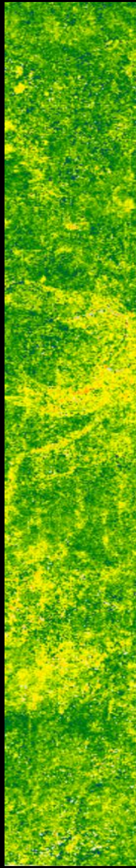
Emergency Preparedness



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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BACKGROUND

Emergency Preparedness

Remote Sensing

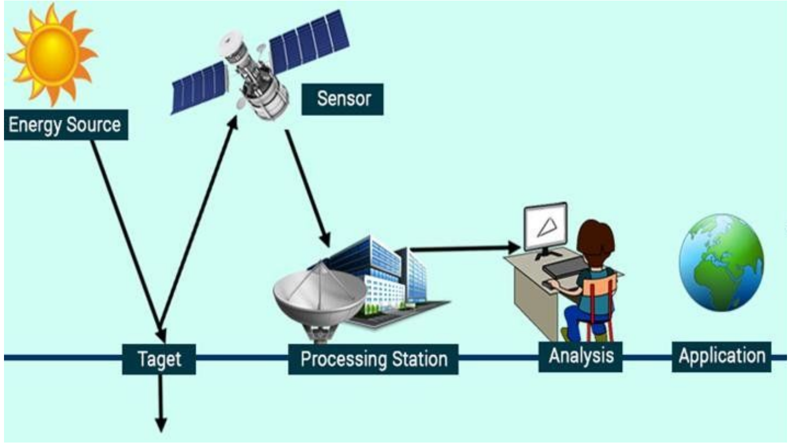
Google Earth Engine

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

Google Earth Engine

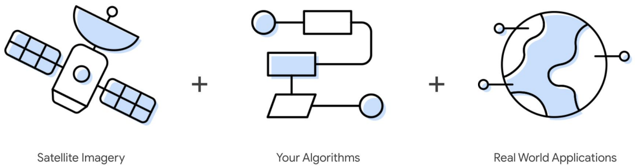


Image credit: Google Earth Engine (https://earthengine.google.com/)

ARSET Trainings

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)

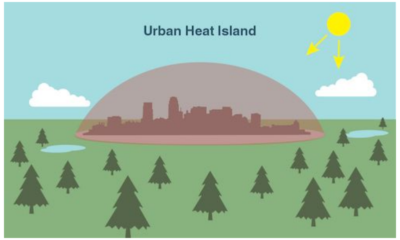

Credit: CDC

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

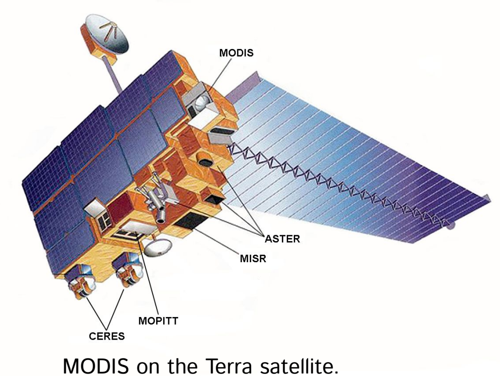

Credit: Unsplash.com

Proposing Solutions

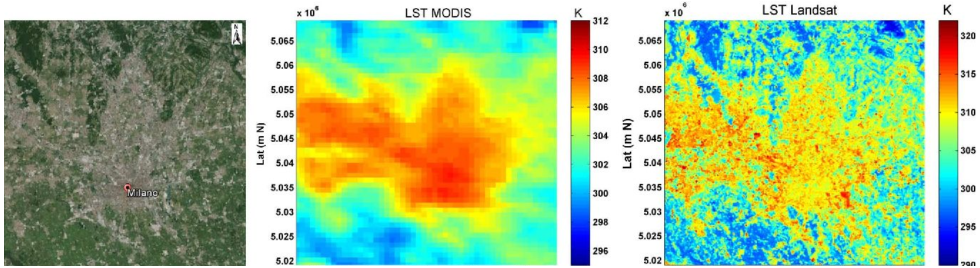
What infrastructure and lifestyle changes can we make to mitigate extreme heat and the UHI effect?

Methodology (Extreme Heat)

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



MODIS on the Terra satellite.
Credit: NASA



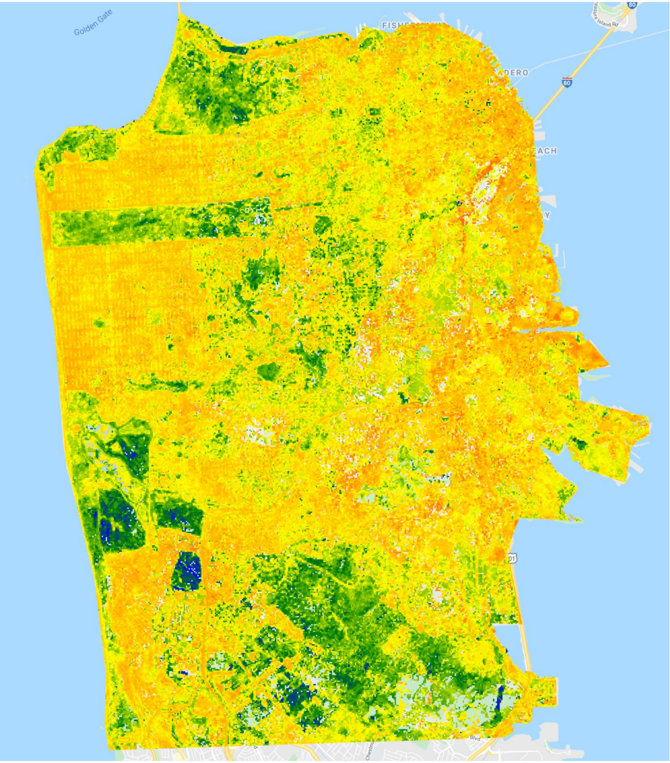
A Comparison of MODIS and Landsat-8 LST measurements.

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.

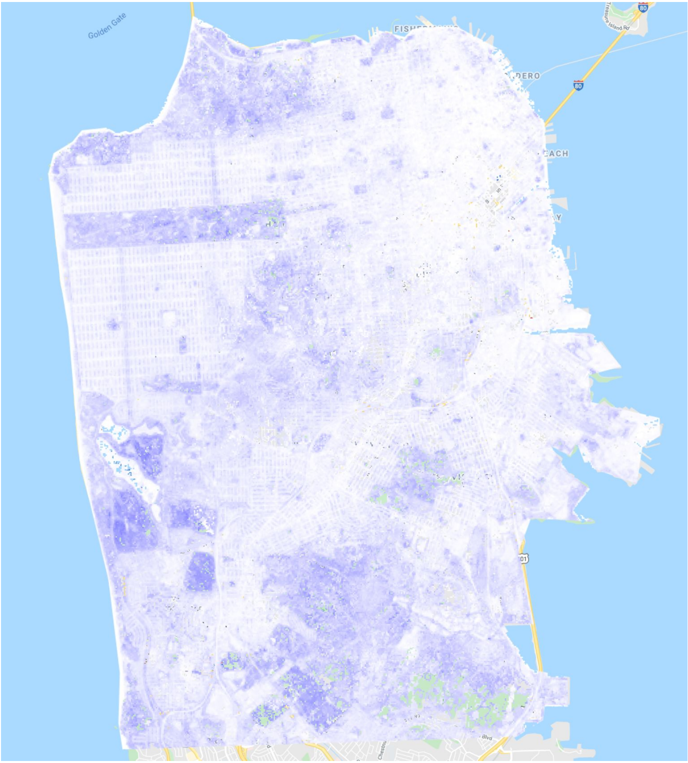
Data

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

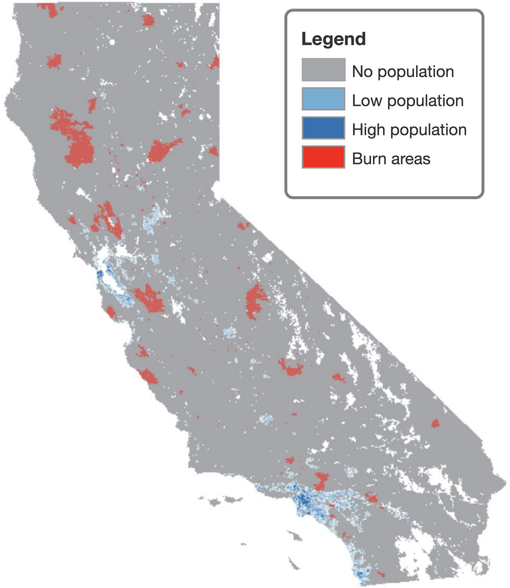
Natasha Cordova-Diba

Wildfires in California

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

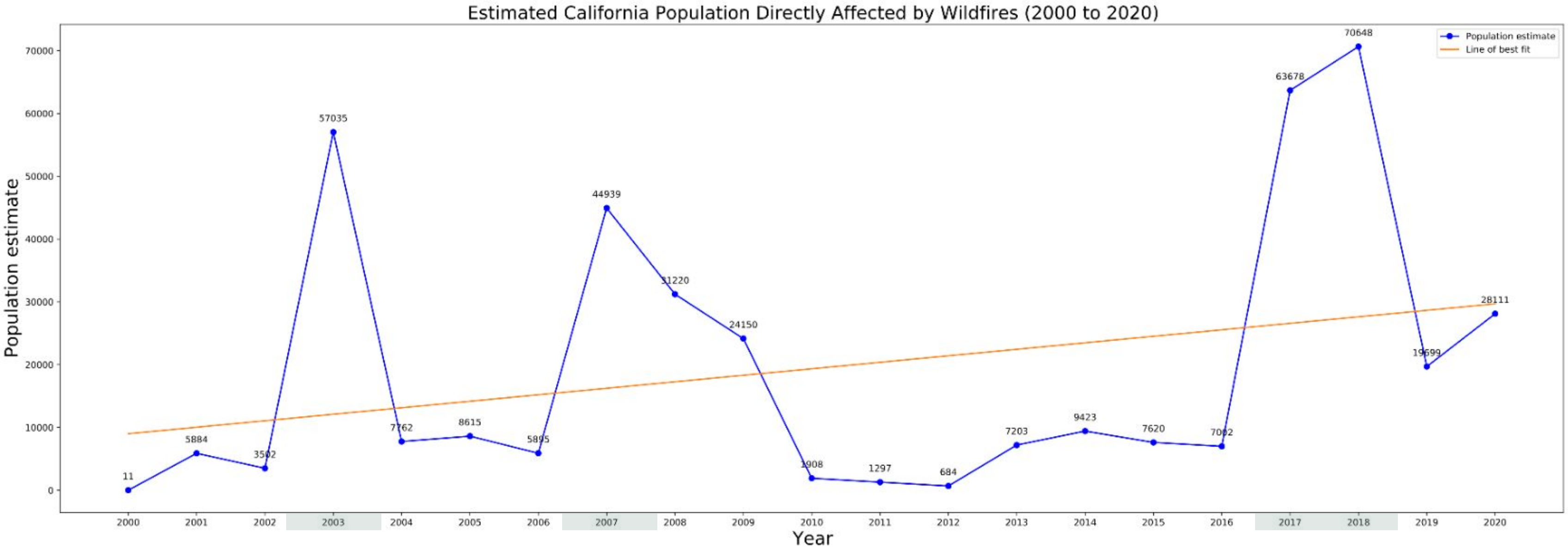
The Dolan Fire in Monterey County in California, 2020
Image credit: Kate Novoa and Connie McCoy for The U.S. Fish and Wildlife Service

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

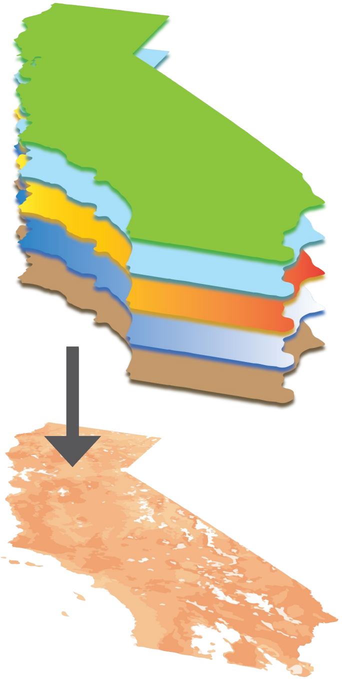
2017: Record precipitation and increased vegetation followed by intense heat

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



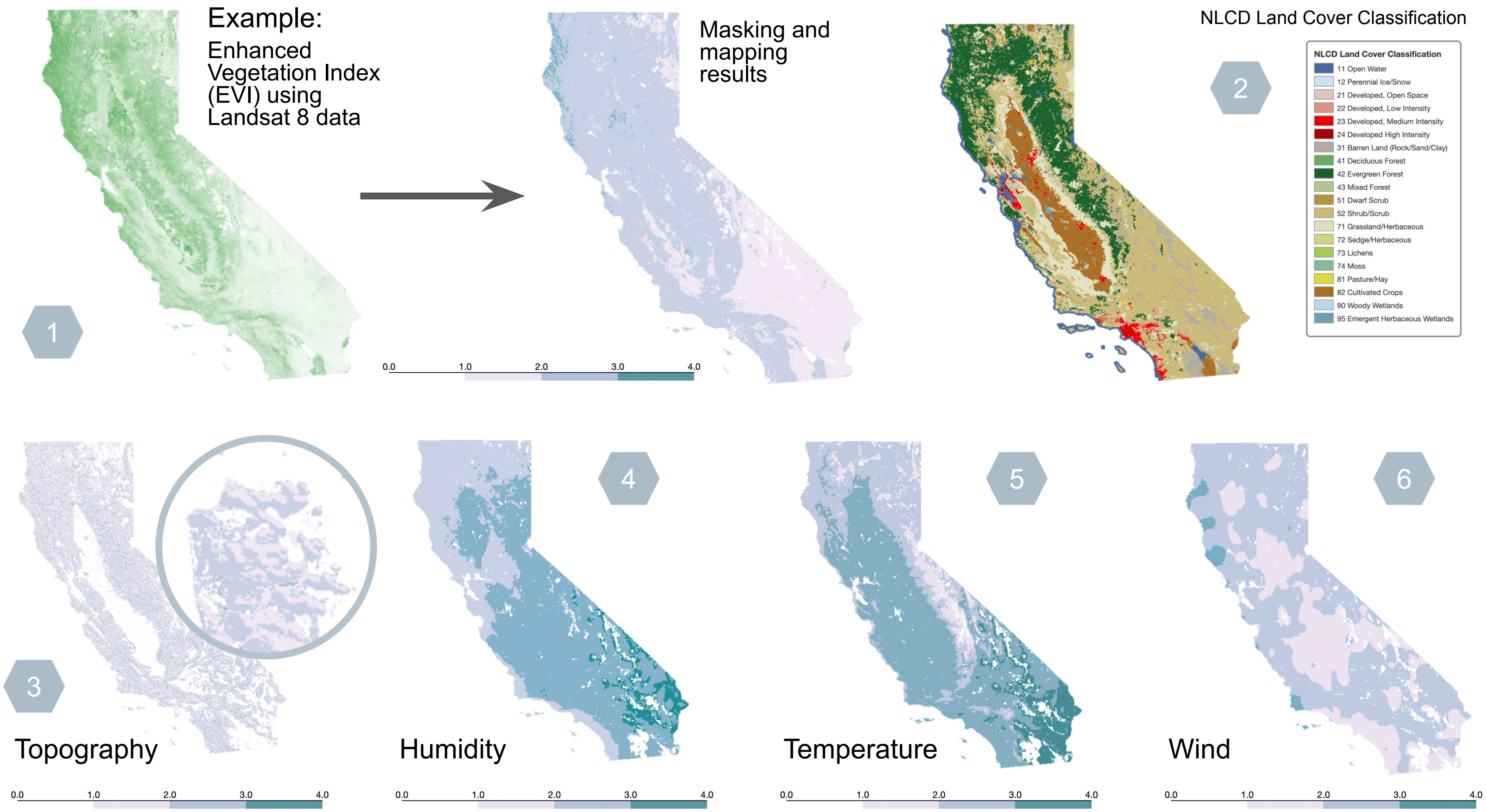
Datasets:

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

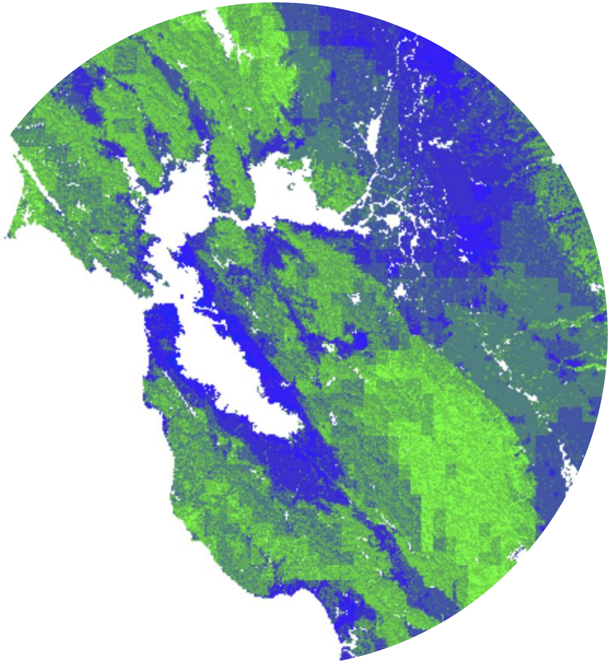
NLCD: USGS National Land Cover Database for land cover classification

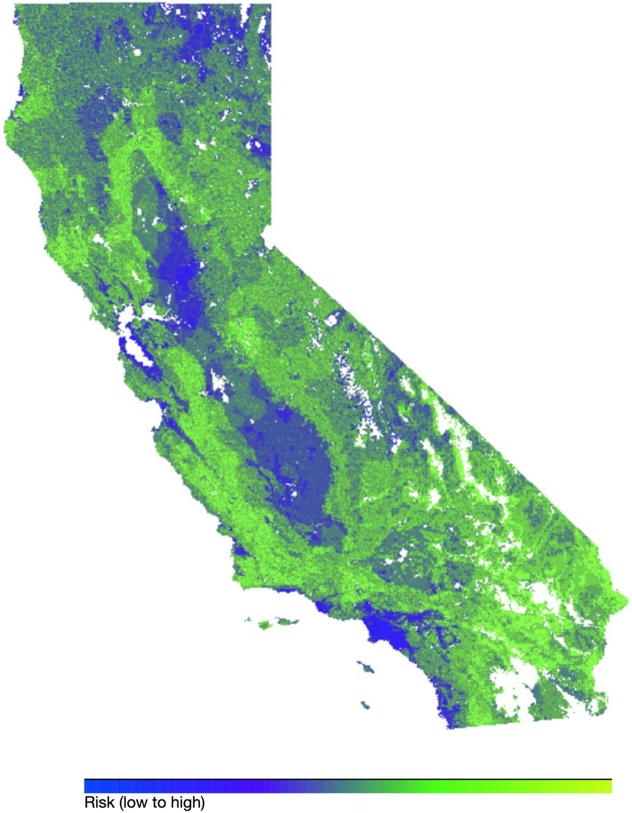
US NED Landforms dataset to map topography



Example:
Enhanced Vegetation Index (EVI) using Landsat 8 data
1
Masking and mapping results
0.0
1.0
2.0
3.0
4.0
NLCD Land Cover Classification
2
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
3
Topography
4
Humidity
5
Temperature
6
Wind

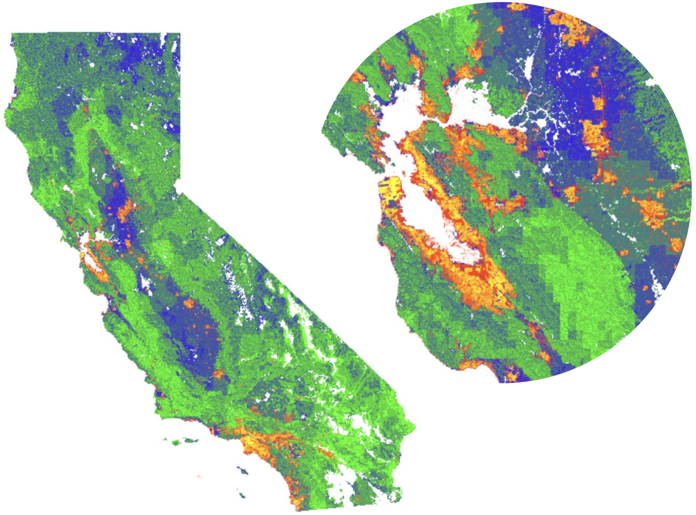
Fire Risk Map





Conclusion and Future Ideas to Pursue

Comparing fire risk map with California population dataset

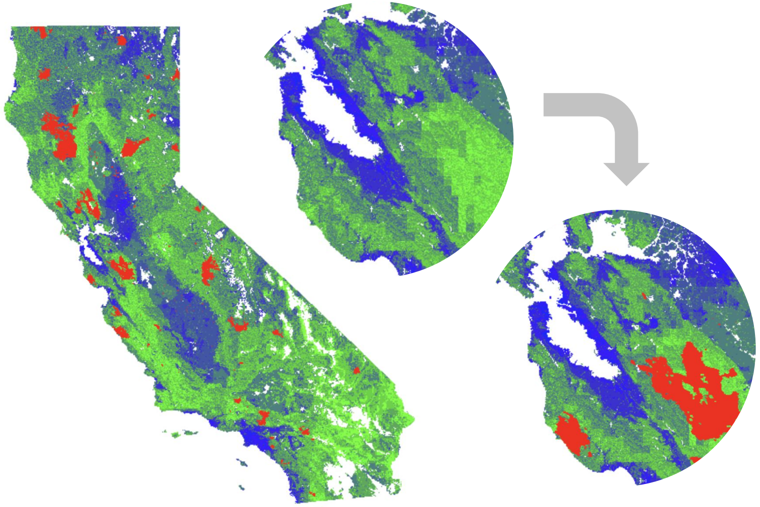


Population (low to high)

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

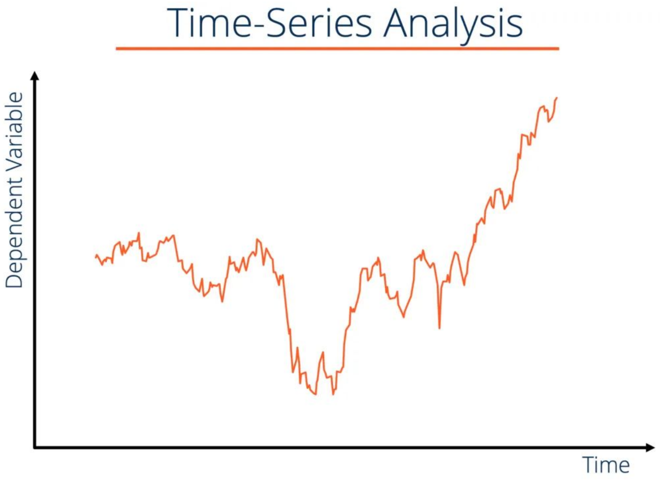
Databases:

- 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

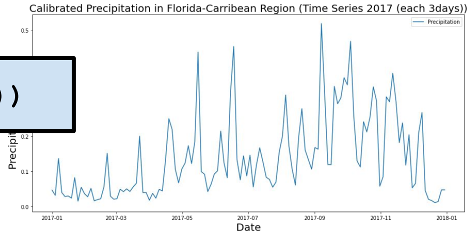
	SSM
date	
2017-01-03 12:00:00	15.959311
2017-01-06 12:00:00	16.775050
2017-01-09 12:00:00	16.424203
2017-01-12 12:00:00	15.747155
2017-01-15 12:00:00	15.236185
...	...
2017-12-17 12:00:00	18.795176
2017-12-20 12:00:00	18.500953
2017-12-23 12:00:00	18.064526

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

Step 3: Graph

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

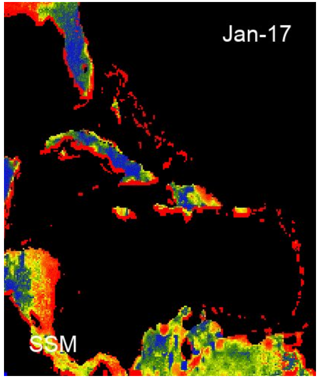
```
sns.lineplot(data=ssm_df, ax=ax)
```

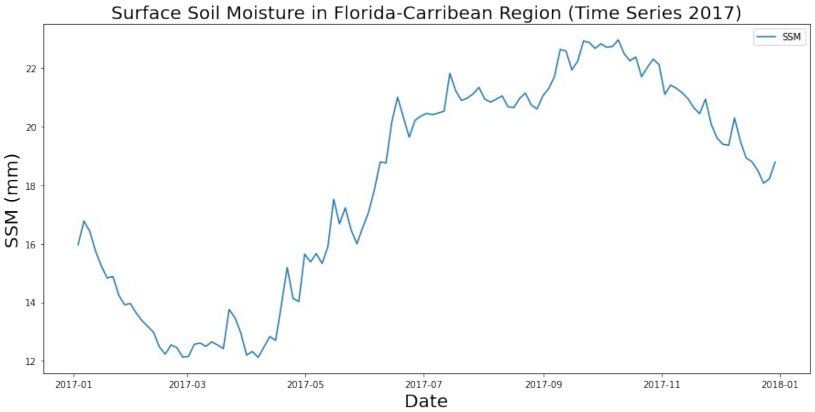


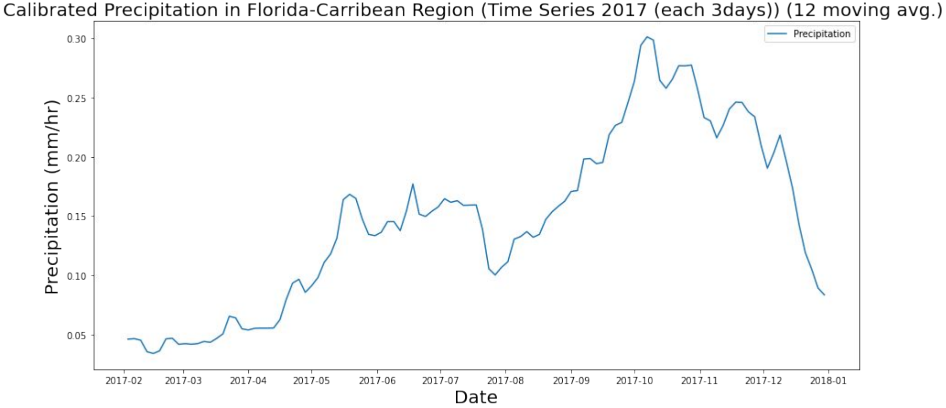
Time Series - Soil Moisture & Precipitation

- 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

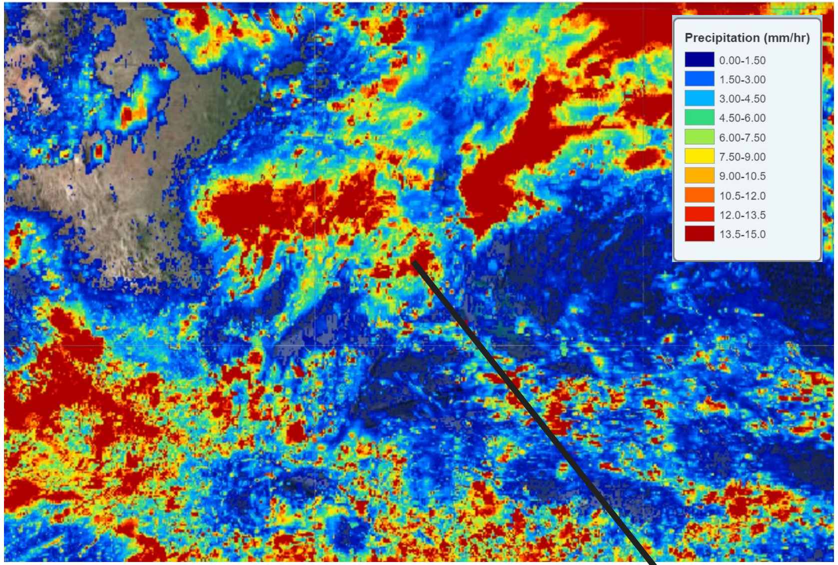
Florida-Carribean Region SSM







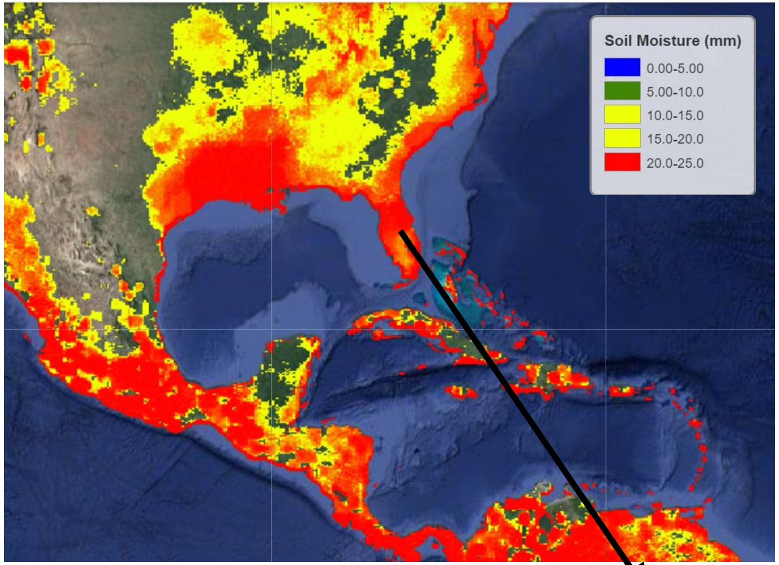
Precipitation & Soil Moisture Mapping



Precipitation

GPM: Global Precipitation Measurement (GPM) v6

High precipitation



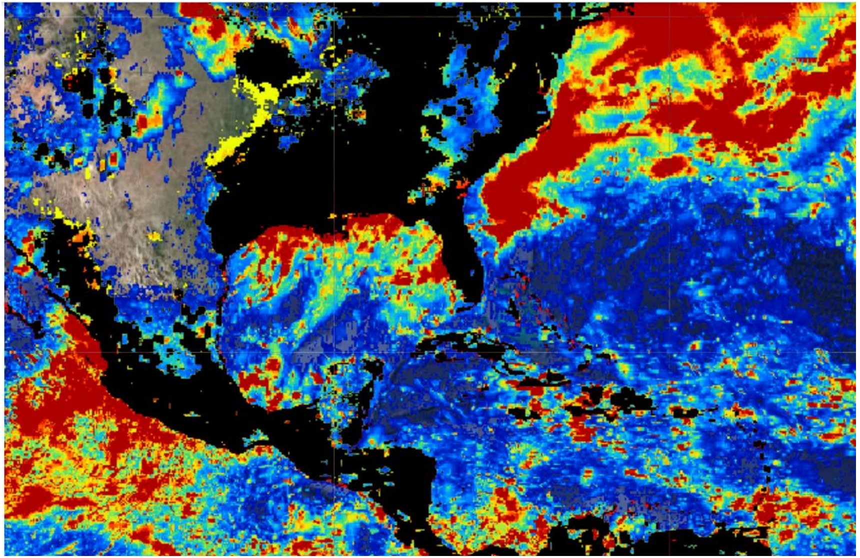
Soil Moisture

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

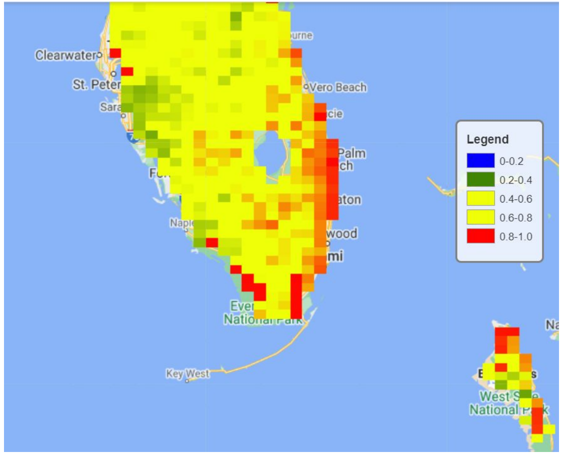
Code:

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

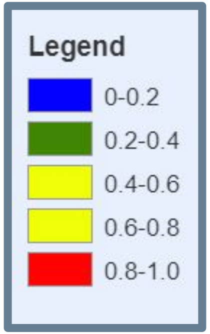
Step 1: Isolate pixels from dataset 1 to be overlapped

ex: Pixels representing high soil moisture profile (smp)

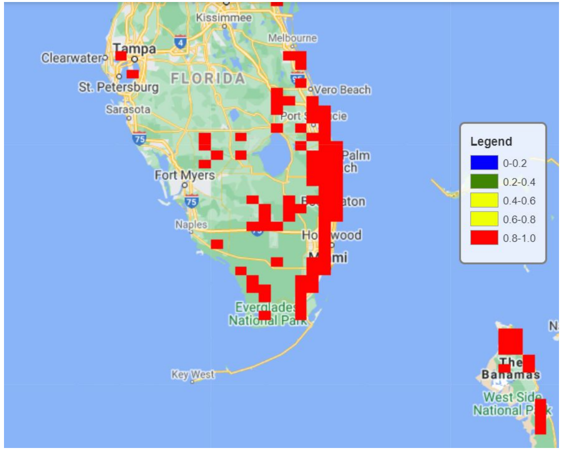
Soil Moisture Layer



Mask out smp values < 0.8



High Soil Moisture Layer



Overlapping Process

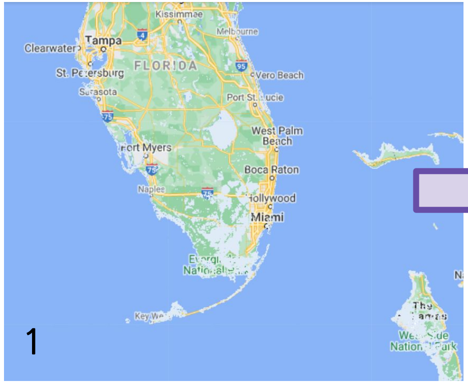
Code:

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

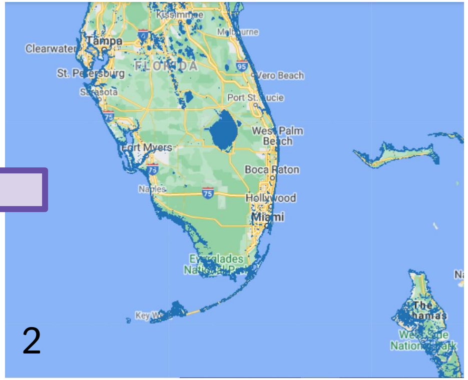
Step 2: Isolate pixels from dataset 2 to be overlapped

ex: Pixels representing flooded areas

All water during flooding

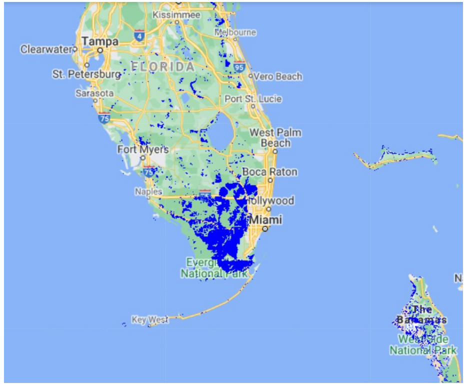


Permanent water



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

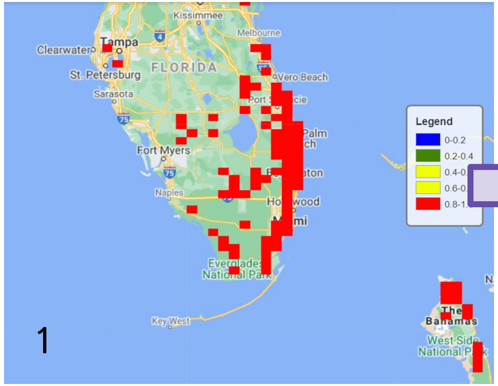
Code:

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

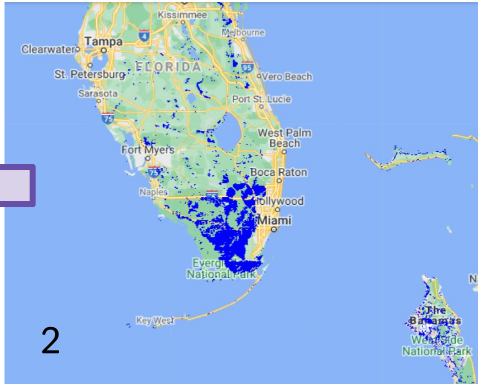
Step 3: Mask Step 2 result over Step 1 result

ex: Mask flooded areas over high soil moisture

High soil moisture profile

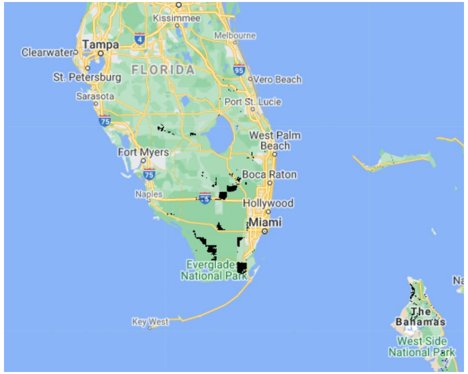


Flooded areas

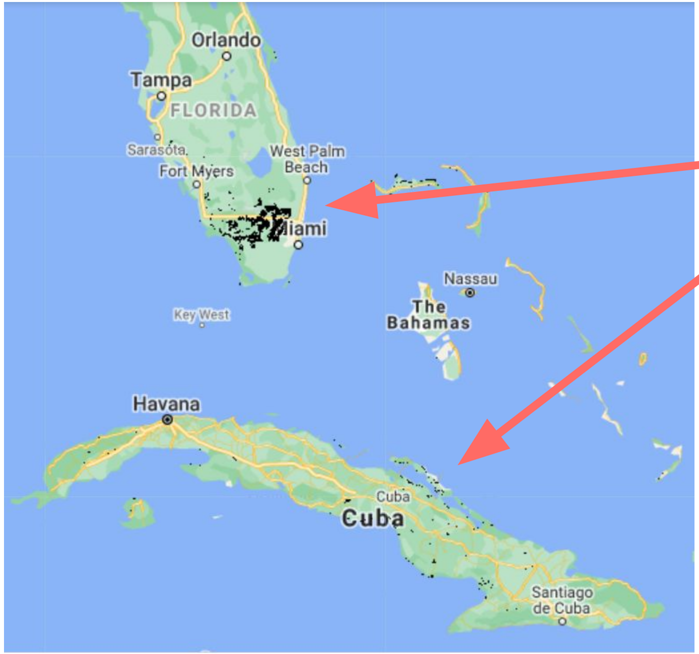


Mask image 1 with image 2

Overlap

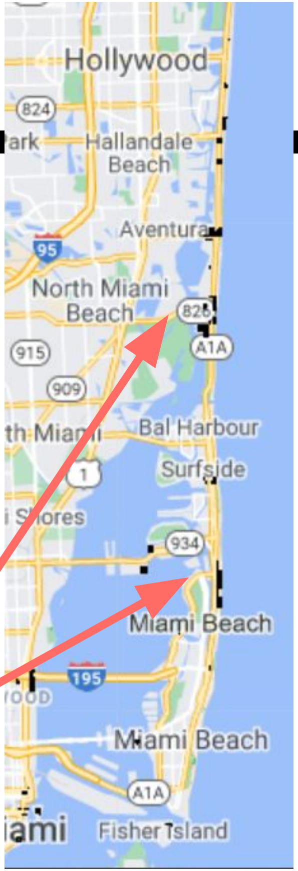


Overlapping Flooding with Precipitation and Population Data



Highlighting areas at risk of flooding

Identifying vulnerable populations



Flood areas + high precipitation

Flood areas + dense population

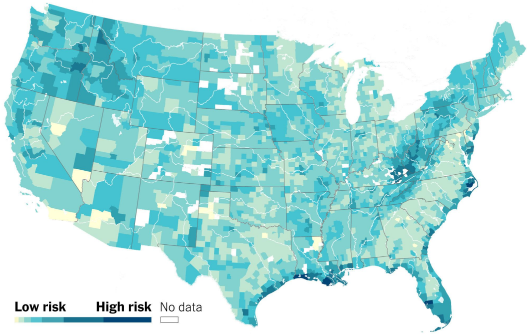
Floods/Tropical Storms Conclusion

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



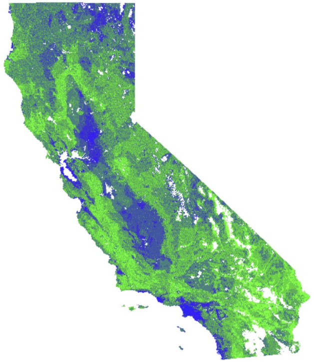
(FEMA Flood Map)

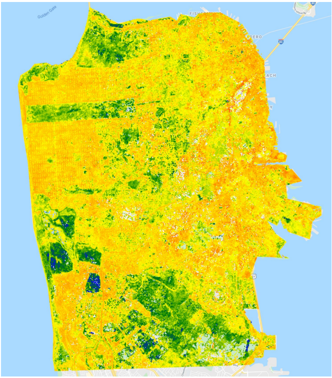
Final Conclusion

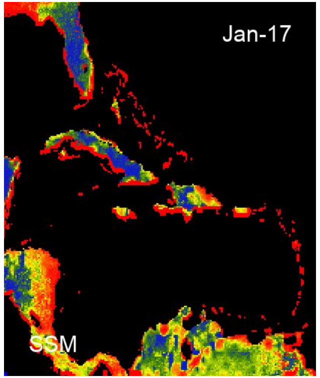
- NASA ARSET Training
  - Use of GEE
  - Relevant datasets
  - Methods to analyze natural disasters
- Converting Javascript to Python in Google Colab
- Future Interest
  - Exploring Black Marble Night Lights Data

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)

Extreme Heat Resources

U.S. Environmental Protection Agency. 2008. Reducing urban heat islands: Compendium of strategies. Draft. https://www.epa.gov/heat-islands/heat-island-compendium

U.S. Environmental Protection Agency. Heat Island Effect. 2020, https://www.epa.gov/heatislands

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