Applying Google Earth Engine to Wildfire Disturbance Detection in the State of Alaska

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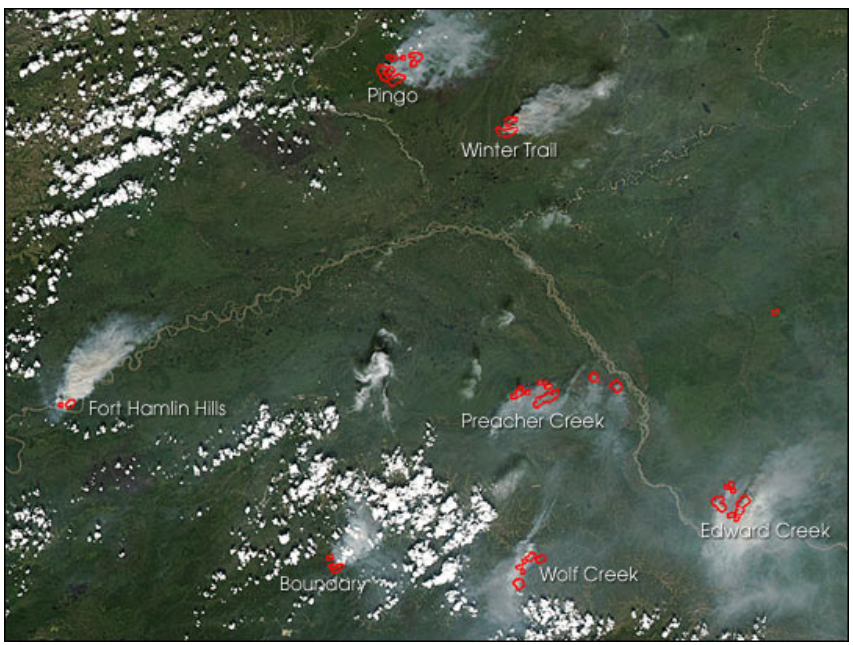
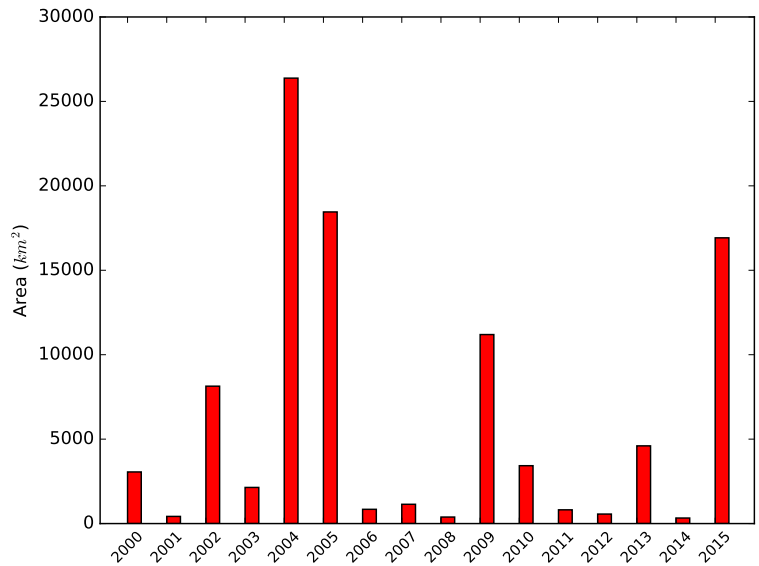
Motivations

- Can we estimate wildfire area extents based on the 2004 wildfire season?
- Can we find the most important attributes from MODIS sensors and daily meteorological variables using Google Earth Engine?
- Can we locate fires located under 1000 acres? (<1000 acres is cutoff from Monitoring Trends in Burn Severity (MTBS) dataset)



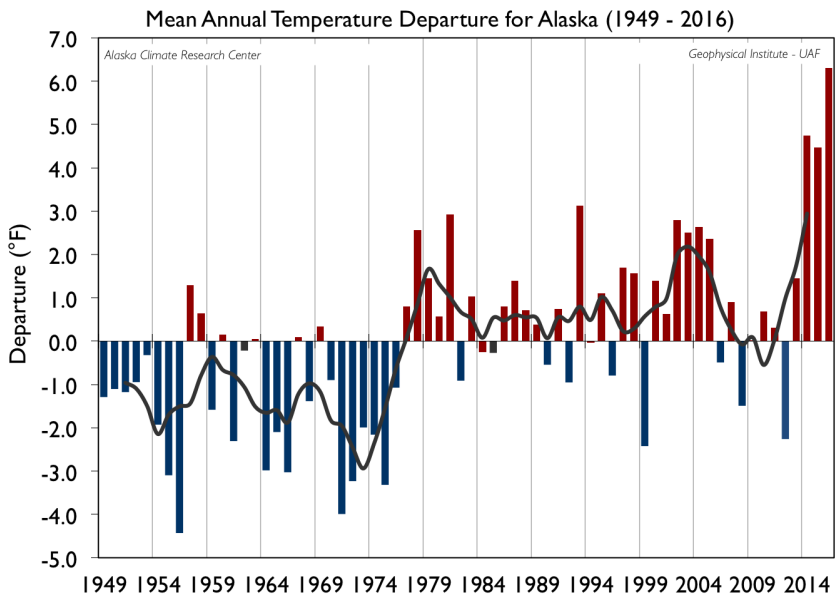
Numerous forest fires (outlined in red) were burning in the Yukon Flats region of east-central Alaska in mid-June 2004 captured by MODIS sensor. (Image Source: NASA)



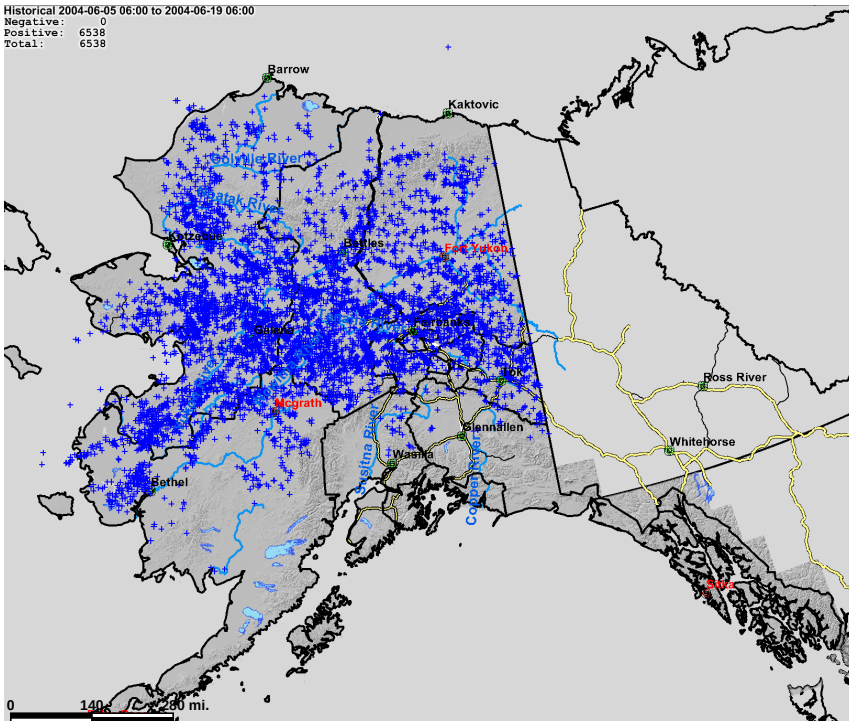
Monitoring Trends in Burn Severity (MTBS) dataset for Alaska from 2000-2015, with 2004 having the most area (km^2) burned.

2004 Wildfire Season

- One of the warmest and driest summer on record.
- Most lightning strikes recorded during summer.
- Wildland fires burned the largest acreage in recorded Alaska history.



Departure from average temperature across Alaska for every year since 1949. (Image Source: Alaska Climate Research Center)

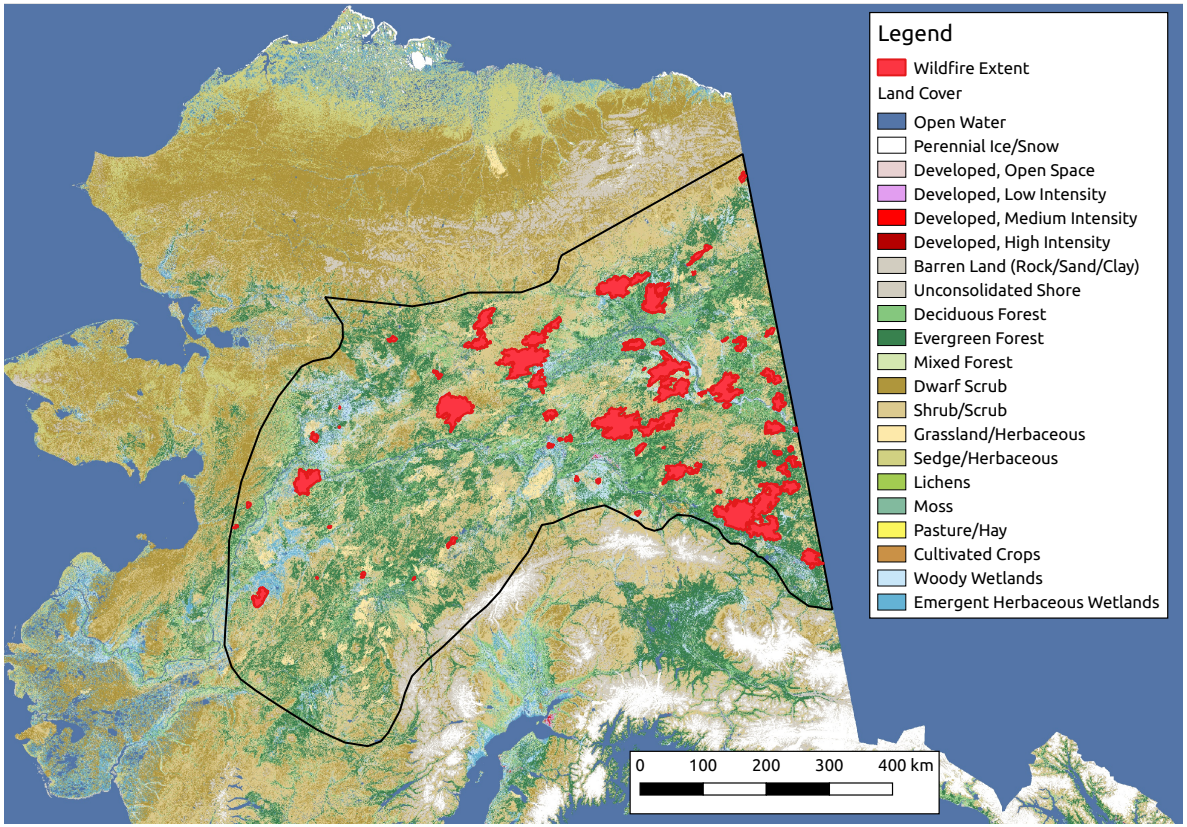


Number of lightnings strikes (6538) in Alaska from June 5 – 19 2004. The grand total was over 147,642 strikes [2].

Study Region

- Study region is based on climate-division boundaries in Interior Alaska [1].
- Wildfires are persistent in this region due to climate patterns, for example, the length of the growing season has increased 45% over the last century [3].

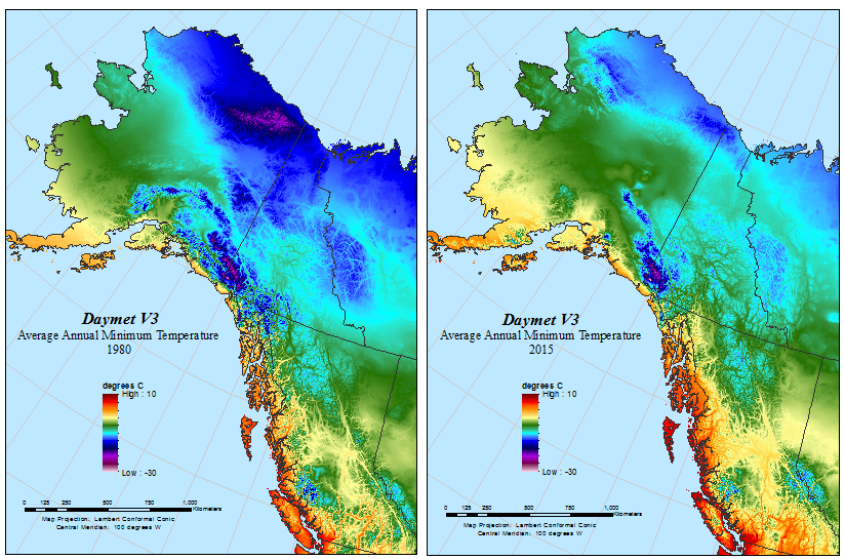
- Monitoring Trends in Burn Severity (MTBS) dataset was used for training MODIS and Daymet variables.
- Binary classification with 0 representing no wildfire and 1 representing a wildfire.



Geospatial Datasets

We used Google Earth Engine (GEE) for processing images and building models. Two types of datasets were looked into:

- MODIS datasets of MOD09A1 (Surface Reflectance 8-Day L3 Global 500m) and MOD11A2 (Land Surface Temperature and Emissivity 8-Day L3 Global 1km) were analyzed [7, 8].
- Daymet, which is a collection of algorithms designed to interpolate and extrapolate from daily meteorological observations to produce gridded estimates of daily weather parameters [6].



Daymet V3 average annual minimum temperature for 1980 and 2015 for a subset of the Daymet domain in Alaska and western Canada.

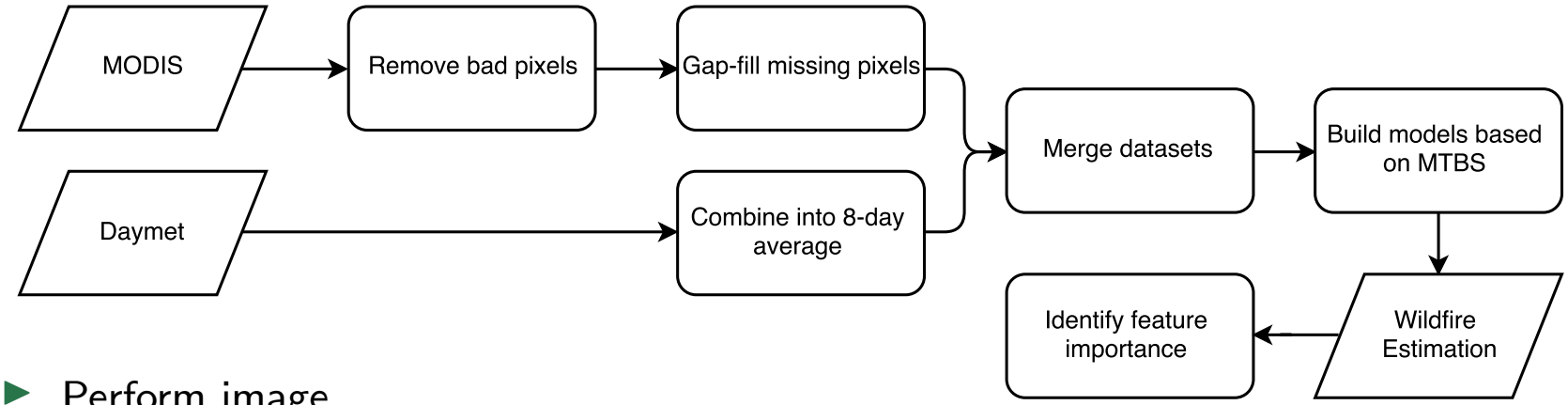
MOD09A1 RGB composite from June 17, 2004.

Geospatial Datasets

Description	Resolution	Variable
GMTED2010	225 m	elevation (m)
	225 m	slope (%)
MOD09A1	500 m at 8 days	NDVI
	500 m at 8 days	EVI
	500 m at 8 days	SAVI
	500 m at 8 days	Bands 1–7 (459–2155 nm)
MOD11A2	1 km at 8 days	Daytime LST (Kelvin)
Daymet	1 km at daily	Daylight period (seconds)
	1 km at daily	Precipitation (mm)
	1 km at daily	Snow water equivalent (kg/m^2)
	1 km at daily	Maximum temperature ($^\circ C$)
	1 km at daily	Minimum temperature ($^\circ C$)
	1 km at daily	Shortwave Radiation (W/m^2)
	1 km at daily	Vapor Pressure (Pa)

Daymet and MODIS products were processed from early-April through late-October in 2004.

Data Workflow



- Perform image processing methods for classification.
- Build models with MODIS (288), MODIS/Daymet (456), and Daymet (168) variables and the MTBS dataset.
- Right Figure: Google Earth Engine interactive development environment [5].

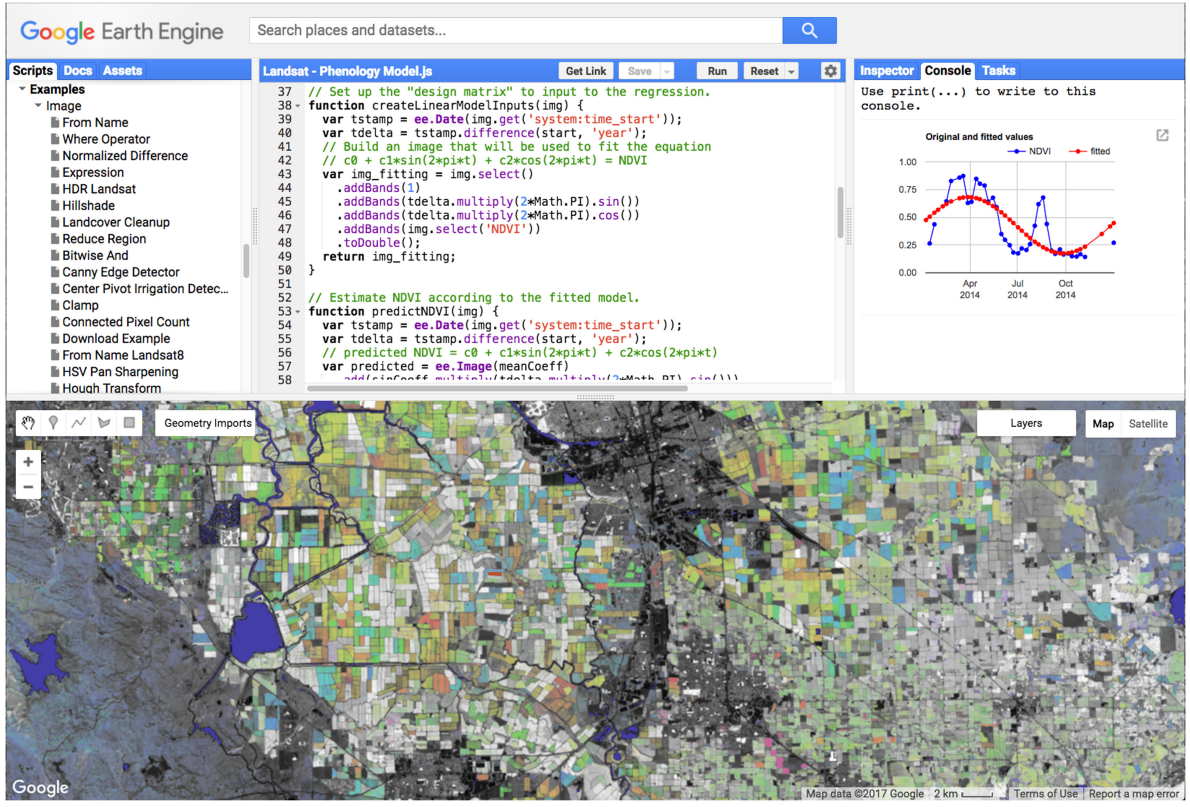
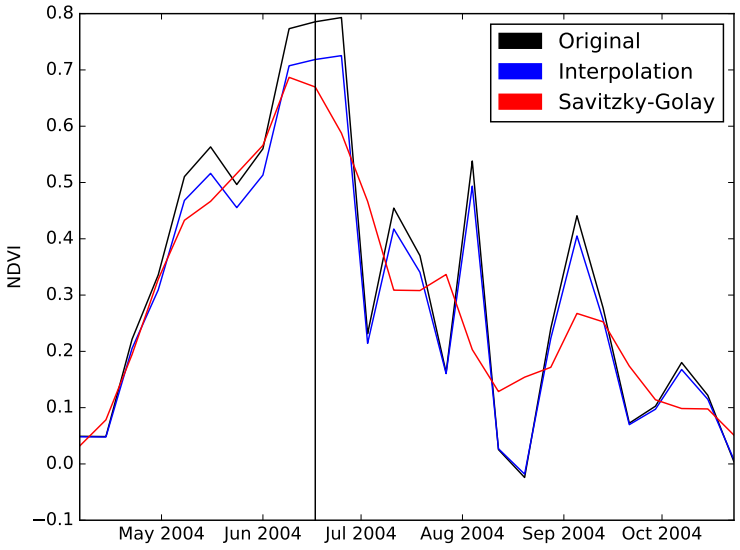
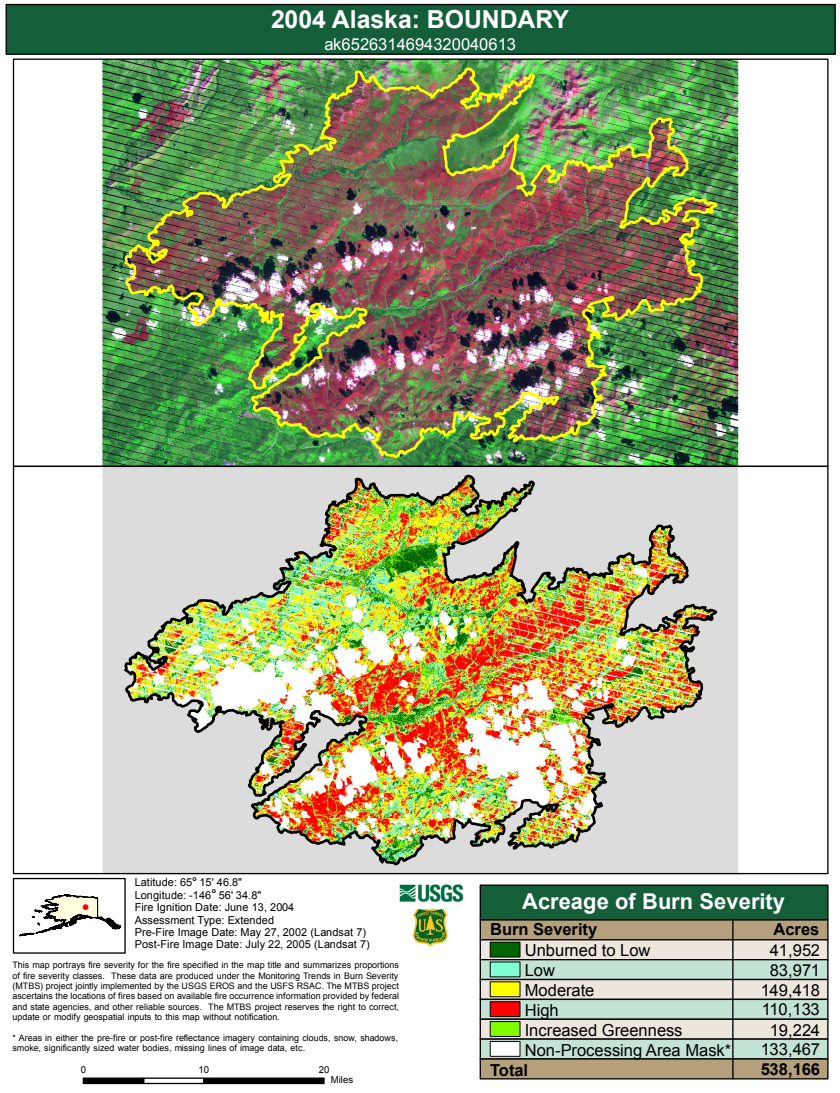


Image Processing

- Increased resolution to 500 m for all datasets, GEE performs nearest neighbor resampling.
- Linear interpolation for missing values.
- Savitzky-Golay filter was applied to smooth out noise [4].
- Daymet variables were merged into 8-day averages.



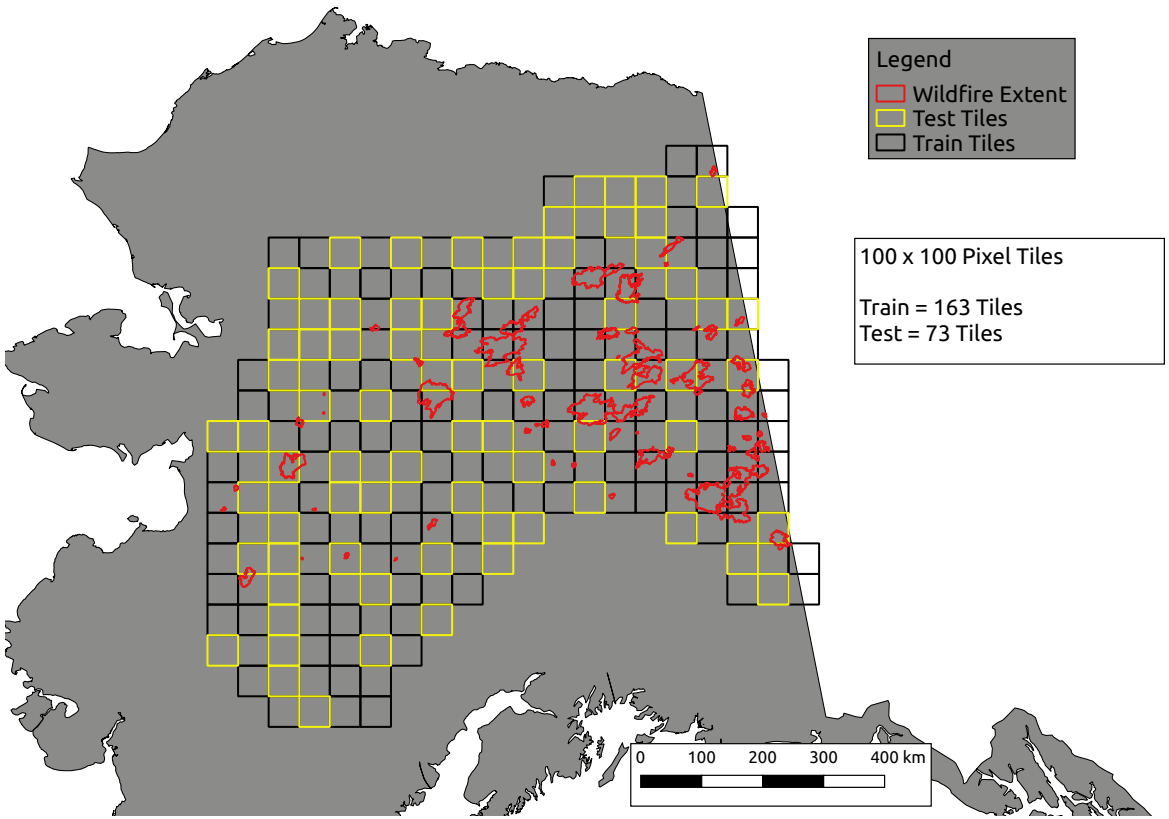
Example image processing workflow applied to a large wildfire, which occurred on June 13, 2004.



Fire severity for the Boundary fire based on Landsat 7. (Source: USGS and US Forest Service)

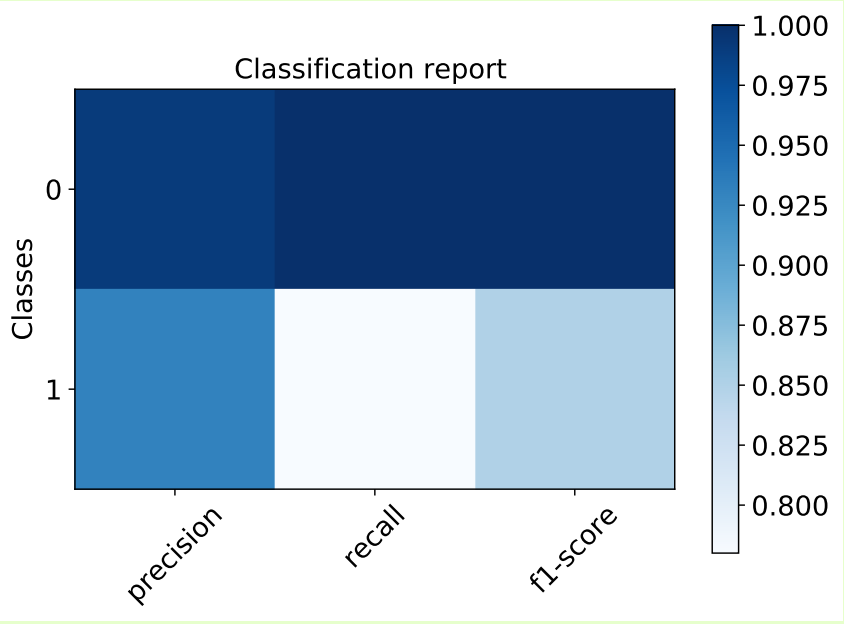
Random Forest

- Random Forest: estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting.
- We split up dataset based on 100 $\times$ 100 pixel tiles, with 163 tiles used for training and 73 tiles used for testing.



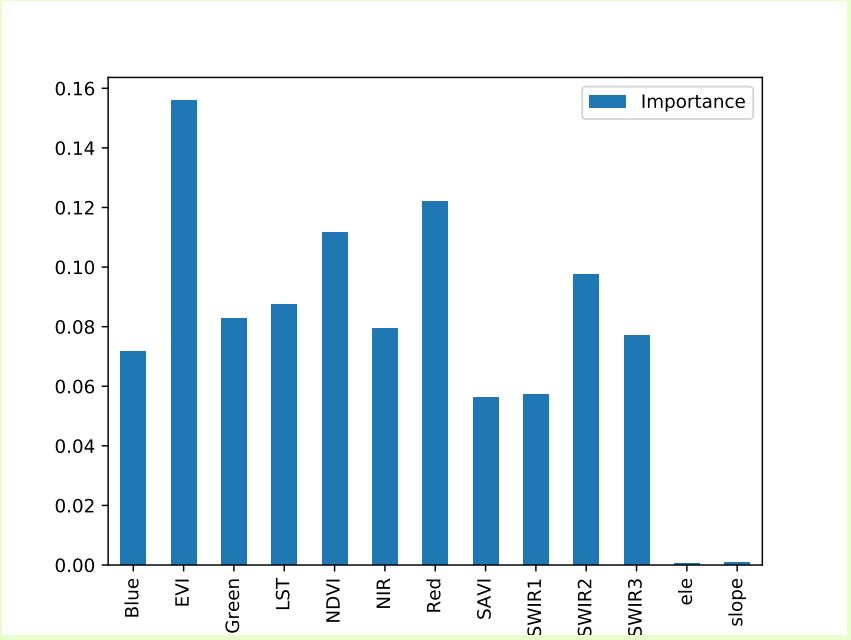
Results: MODIS

Validation Metrics



- Precision, recall, and F1-score for non-wildfire class (n=493710) was 0.99, 1.00, and 1.00, respectively.
- Precision, recall, and F1-score for wildfire class (n=16878) was 0.93, 0.78, and 0.85, respectively.

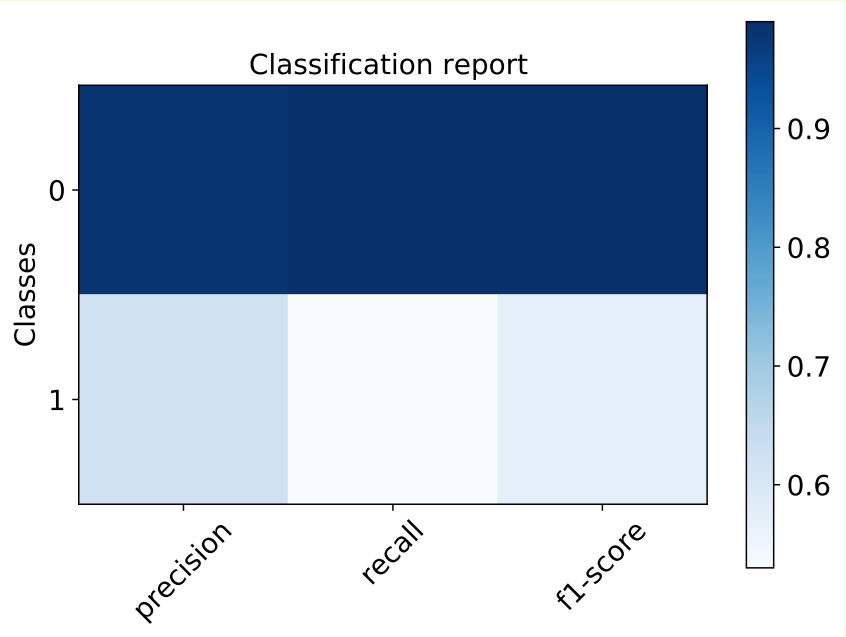
Feature Importance



- EVI, NDVI, and MODIS Red band contributed the most using the Gini feature importance metric.
- Elevation, slope, SAVI, and SWIR1 contributed the least.

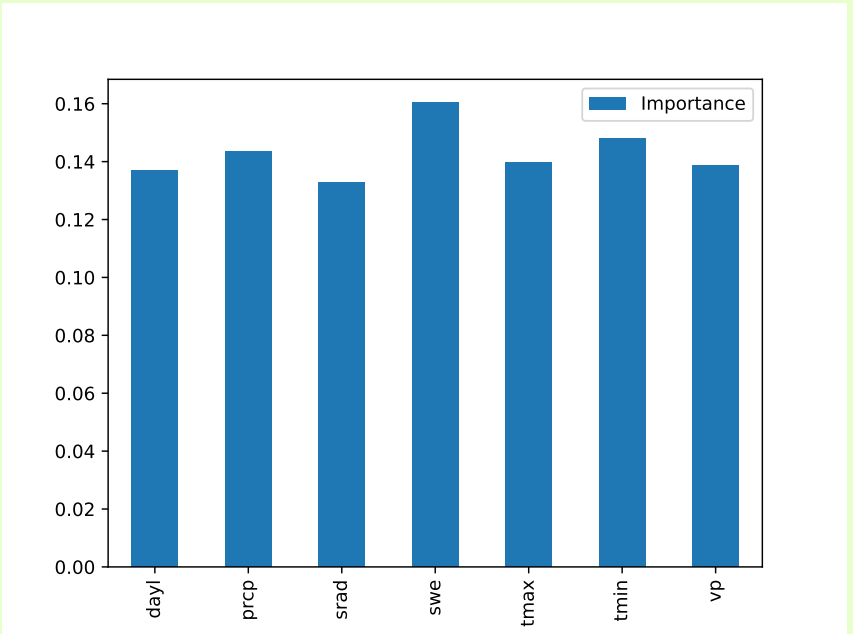
Results: Daymet

Validation Metrics



- Precision, recall, and F1-score for non-wildfire class (n=493710) was 0.99, 1.00, and 0.99, respectively.
- Precision, recall, and F1-score for wildfire class (n=16878) was 0.62, 0.53, and 0.57, respectively.

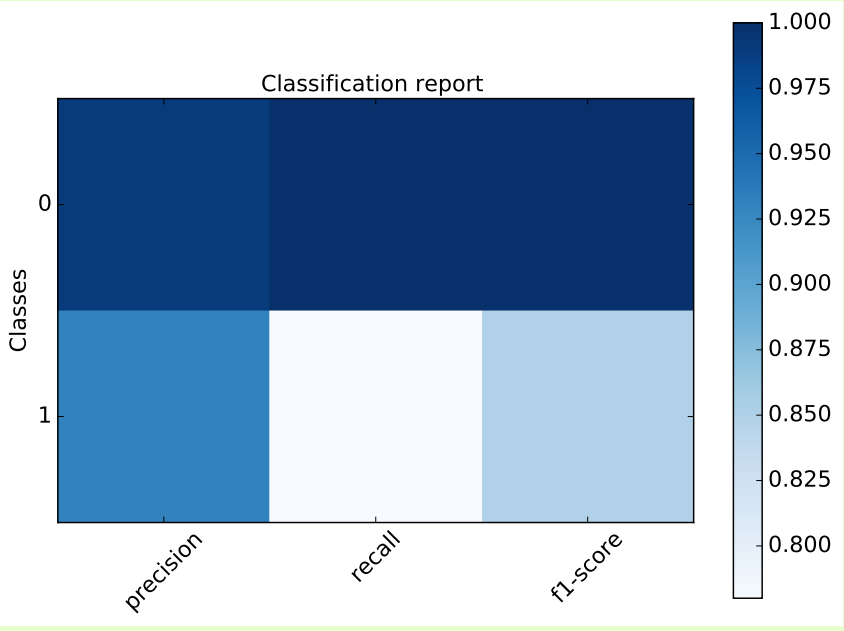
Feature Importance



- Most variables contributed equally for feature importance.
- Snow water equivalent, minimum temperature, and precipitation were the highest scoring features.

Results: MODIS/Daymet

Validation Metrics



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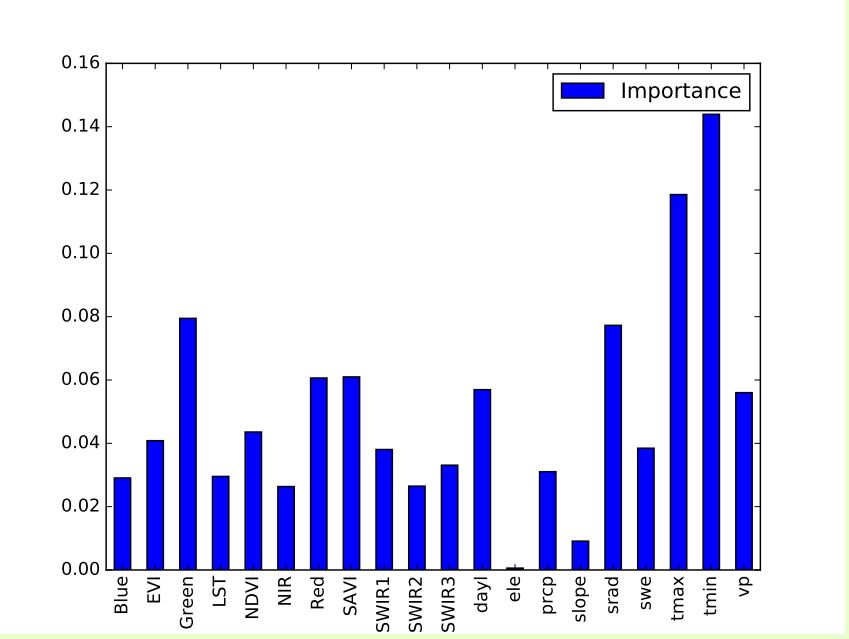
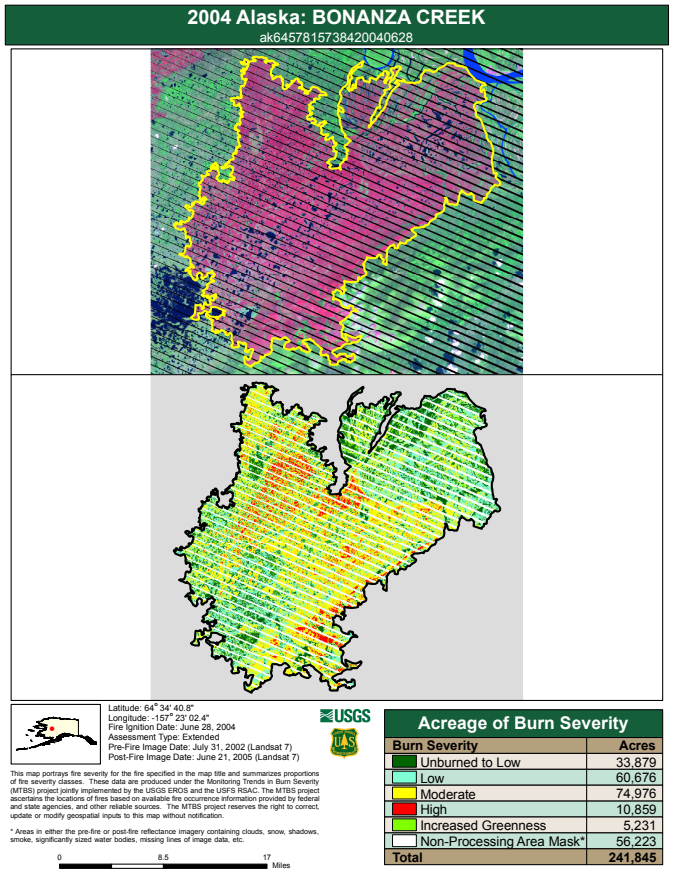
Feature Importance

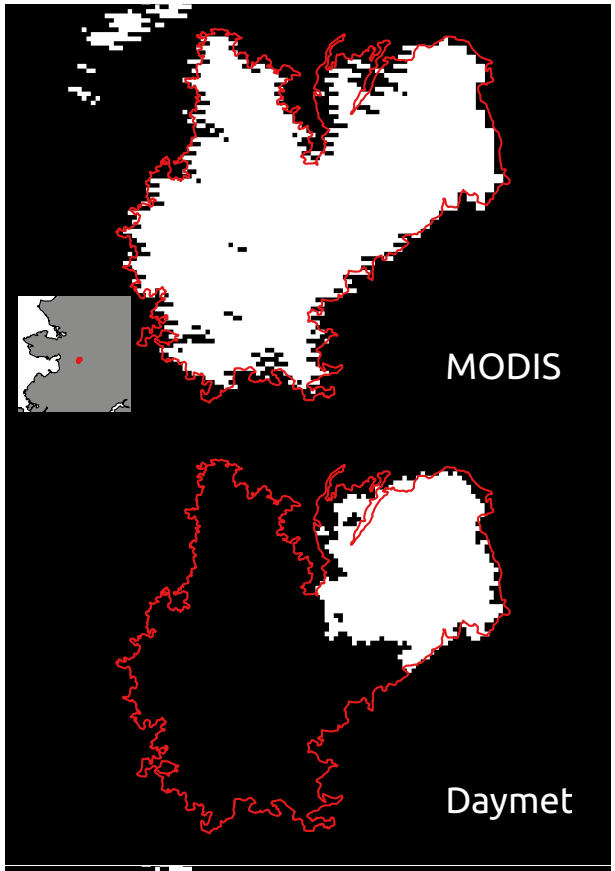


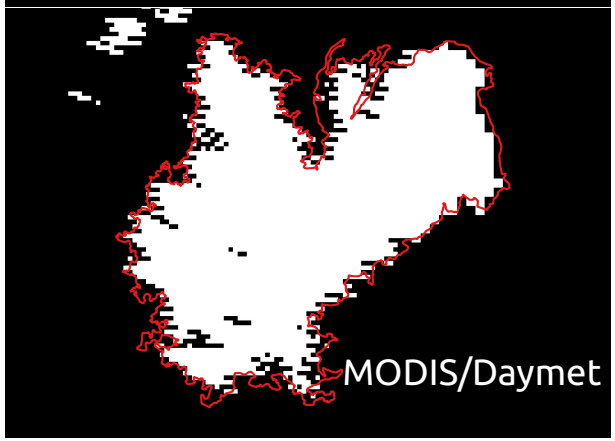
- Daymet variables (minimum temperature, maximum temperature, shortwave radiation) contributed most for Daymet/MODIS classification.
- MODIS Green, Red, and SAVI variables contributed the most.

Results: Test (Bonanza Creek Wildfire)



Fire severity for the Bonanza Creek wildfire based on Landsat 7. (Source: USGS and US Forest Service)

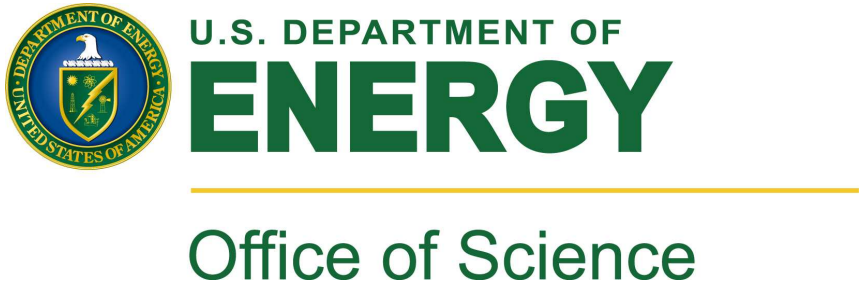




Conclusions

- MODIS (NIR, SWIR), indices (EVI, NDVI, SAVI), and Daymet variables (minimum temperature, maximum temperature, snow water equivalent, shortwave radiation) are the most important drivers for this study.
- Random Forest provides a good approach for understanding feature importance.
- Google Earth Engine provides a great platform for processing and analyzing datasets.
- Future Work:
  - Does varying responses in different years provide a better classification?
  - Investigate class imbalance problem when subsetting data into training and testing.
  - Does including daily meteorological variables for entire year provide better results?

Acknowledgements



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