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

Forrest M. Hoffman[1,2], Zachary L. Langford[2], Jitendra Kumar[1,2], Steve Norman[3], and William W. Hargrove[3]

[1]Oak Ridge National Laboratory, [2]University of Tennessee Knoxville, and [3]USDA Forest Service Eastern Forest Environmental Threat Assessment Center

**2018 US-IALE Annual Meeting**

Chicago, Illinois, USA

April 11, 2018

CLIMATE CHANGE SCIENCE INSTITUTE
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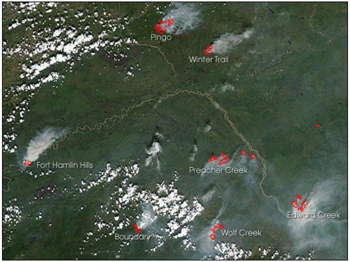
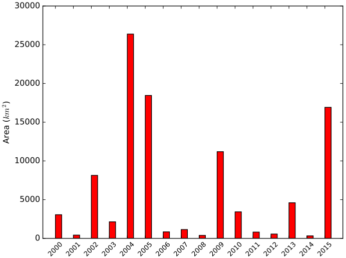
# Rationale

- To use remote sensing and meteorology to estimate wildfire areal extents for the 2004 wildfire season in Alaska
- To test the utility of Google Earth Engine (GEE) to determine the most important attributes from MODIS and Daymet
- Future:
  - **Monitor:** Locate fires under 1,000 acres (below cutoff for Monitoring Trends in Burn Severity (MTBS) dataset)
  - **Predict:** Determine preceding meteorological conditions that result in fire susceptibility




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)

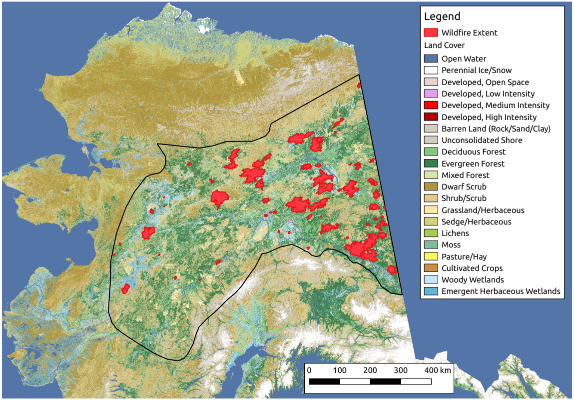



Monitoring Trends in Burn Severity (MTBS) dataset for Alaska from 2000–2015, with 2004 having the most area ($km^2$) burned.

# Study Region: Interior Alaska

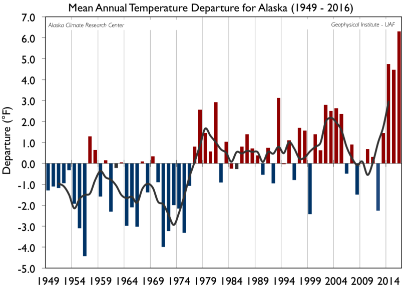
- Study region is Interior Alaska (Bieniek et al., 2012)
- Wildfires are natural and may be increasing in intensity due to climate change (e.g., length of the growing season has increased 45% over the last century (Chapin III et al., 2014)).

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

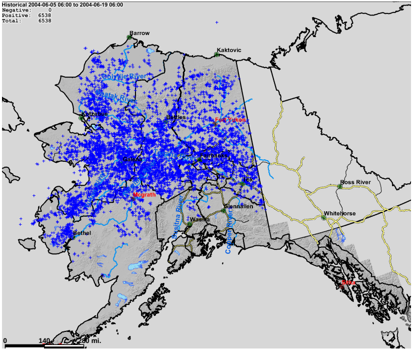


# 2004 Wildfire Season in Alaska

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




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

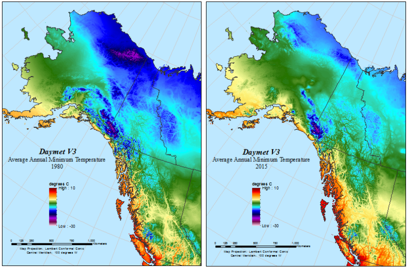



Number of lightnings strikes (6,538) in Alaska from June 5–19, 2004. The grand total was over 147,642 strikes (Chapin et al., 2008).

# Geospatial Datasets

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

- MODIS: MOD09A1 (Surface Reflectance 8-Day L3 Global 500m) and MOD11A2 (Land Surface Temperature and Emissivity 8-Day L3 Global 1km) (Vermote, 2015; Wan et al., 2015).
- Daymet: gridded estimates of daily weather parameters (Thornton et al., 2017).




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

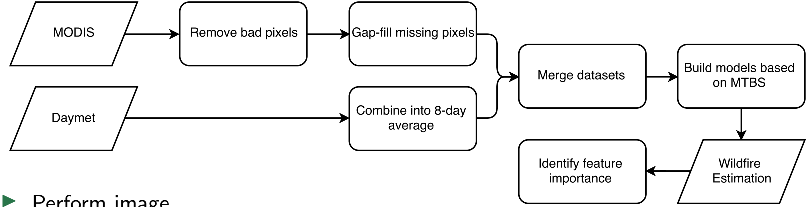

MOD09A1 RGB composite from June 17, 2004.

# Geospatial Datasets

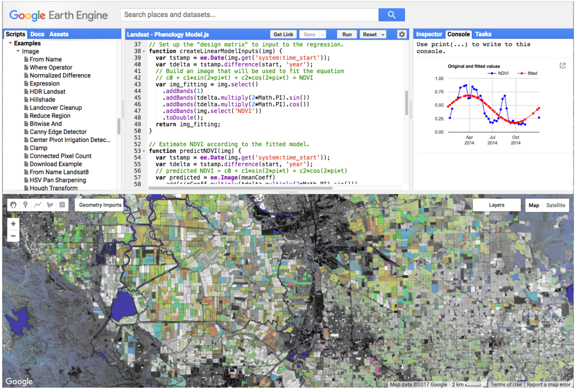
| Description | Resolution | Variable |
|---|---|---|
| GMTED2010 | 225 m | elevation (m) |
| | 225 m | slope (%) |
| MOD09A1 | 500 m at 8 days | NDVI |
| | 500 m at 8 days | EVI |
| | 500 m at 8 days | SAVI |
| | 500 m at 8 days | Bands 1–7 (459–2155 nm) |
| MOD11A2 | 1 km at 8 days | Daytime LST (Kelvin) |
| 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

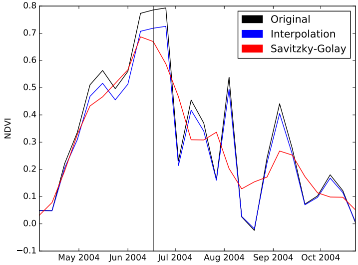



- Perform image processing methods for classification.
- Build models with MODIS (288), MODIS/Daymet (456), and Daymet (168) variables and the MTBS dataset.
- Right Figure: Google Earth Engine interactive development environment (Gorelick et al., 2017).

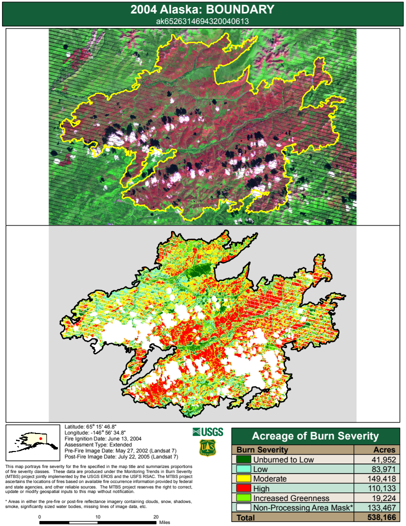


# Image Processing

- 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 (Chen et al., 2004).
- Daymet variables were merged into 8-day averages.



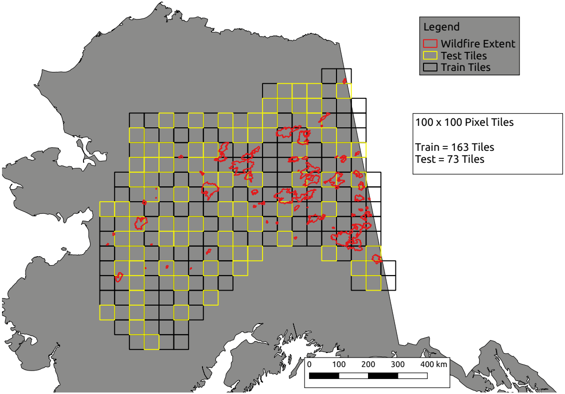

Example image processing workflow applied to a large wildfire, which occurred on June 13, 2004.




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

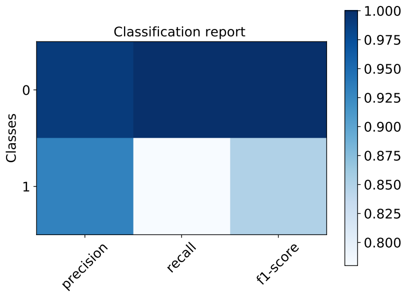
# Random Forest

- 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.



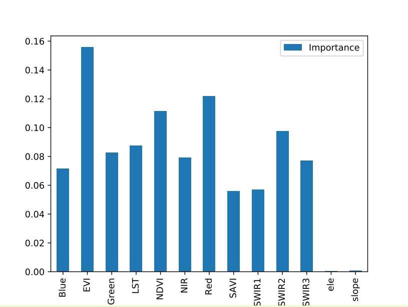
# Results: MODIS

## 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.

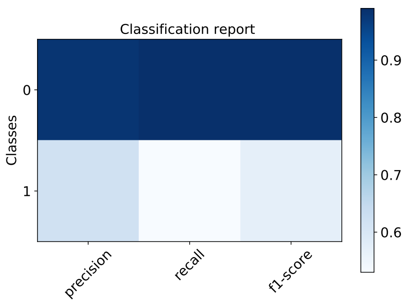
## Feature Importance




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

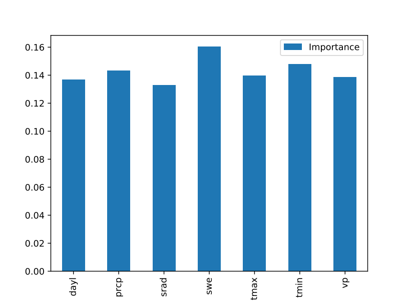
# Results: Daymet

## 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.

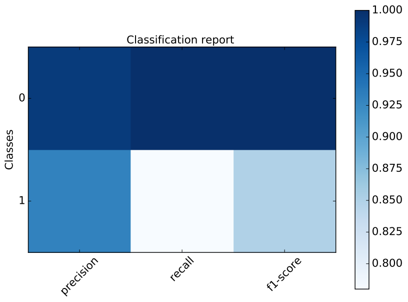
## Feature Importance




- 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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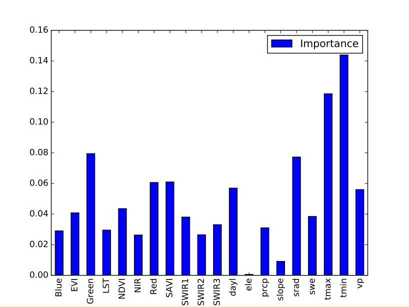
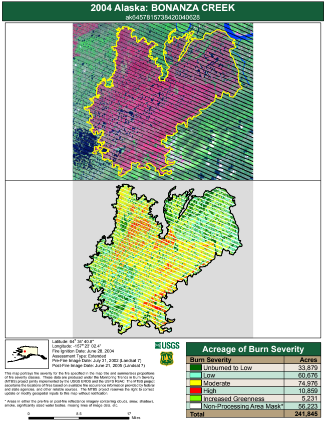
## Feature Importance




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

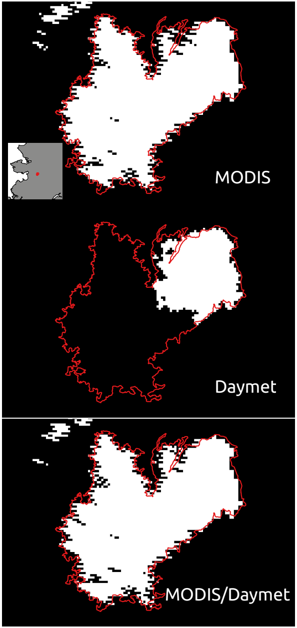
# Results: Test (Bonanza Creek Wildfire)




Acreage of Burn Severity

| Burn Severity | Acres |
|---|---|
| Unburned to Low | 33,879 |
| Low | 60,676 |
| Moderate | 74,976 |
| High | 10,859 |
| Increased Greenness | 5,231 |
| Non-Processing Area Mask* | 56,223 |
| Total | 241,845 |

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



# Conclusions

- MODIS bands and vegetation indices can be used to predict spatial extents of wildfire with good accuracy, and including Daymet does not improve the predictions.
- MODIS (NIR, SWIR), indices (EVI, NDVI, SAVI), and Daymet variables (minimum temperature, maximum temperature, snow water equivalent, shortwave radiation) are the most important factors determining wildfire extent.
- Random Forest provides a good approach for determining feature importance.
- Google Earth Engine provides a powerful platform for processing and analyzing datasets without moving data.
- Future Work:
  - Would even (fire/no fire) sampling for training provide more balanced prediction accuracy?
  - Can the method be used to predict fire extent across multiple years?
  - Can we use antecedent meteorological conditions (for 3 months or 1 year anomalies) to predict fire susceptibility?

# Acknowledgements

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This research was sponsored by the Climate and Environmental Sciences Division (CESD) of the Biological and Environmental Research (BER) Program in the US Department of Energy Office of Science and the US Department of Agriculture Forest Service, and the National Science Foundation (AGS-1048890). This research used resources of the Oak Ridge Leadership Computing Facility (OLCF) at Oak Ridge National Laboratory (ORNL), which is managed by UT-Battelle, LLC, for the US Department of Energy under Contract No. DE-AC05-00OR22725.

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