CE263N / CYPLAN257

Final Project Presentation

Identifying Wildfire Burn Severity Risks in the WUI Landscape Using High Resolution Remote Sensing and GIS Data

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1. Background

Introduction

- Regions in the Wildland Urban Interface (WUI) are at risk of being devastated by wildfires
- Fires are influenced by the landscape's topography, vegetation fuels, and weather
- There is a **disconnect** in our understanding of wildfire-causing factors and wildfire burn severity

Limitations of Related Studies

1. **Wildfire burn area:** Previous works focused mainly on predicting wildfire area instead of wildfire burn severity
2. **Local-scale:** Individual wildfires used to link burn severity and landscape factors
3. **Coarse Spatial Resolution:** Most works used 30 m spatial resolution, but high spatial resolution (<10 m) is required to observe complex landscapes

Graphics: Mark Coolen, PixelXPress

Figure 1: (a) Wildland Urban Interface and (b) Wildland Urban Intermix

Table 1: Description of soil burn severity

Burn Severity	Soil Surface	Vegetation Canopy
Low	Unaltered	Mostly intact
Mod-Low	Moderately charred	Scorched (>50%)
Mod-High	Moderately charred	Lower vegetation scorched
High	Majority charred	Mostly scorched (>90%)

1. Background (Motivation)

Motivation and Our Approach

- **Wildfire burn severity:** Need to understand the relationship between landscape factors and burn severity
- **High Spatial Resolution :** Need to observe landscapes at finer detail and interpret complexity

Research Question

"Which remotely sensed features from the landscape were most correlated with the soil burn severity levels recorded in recent wildfires (2018~2021) in California?"

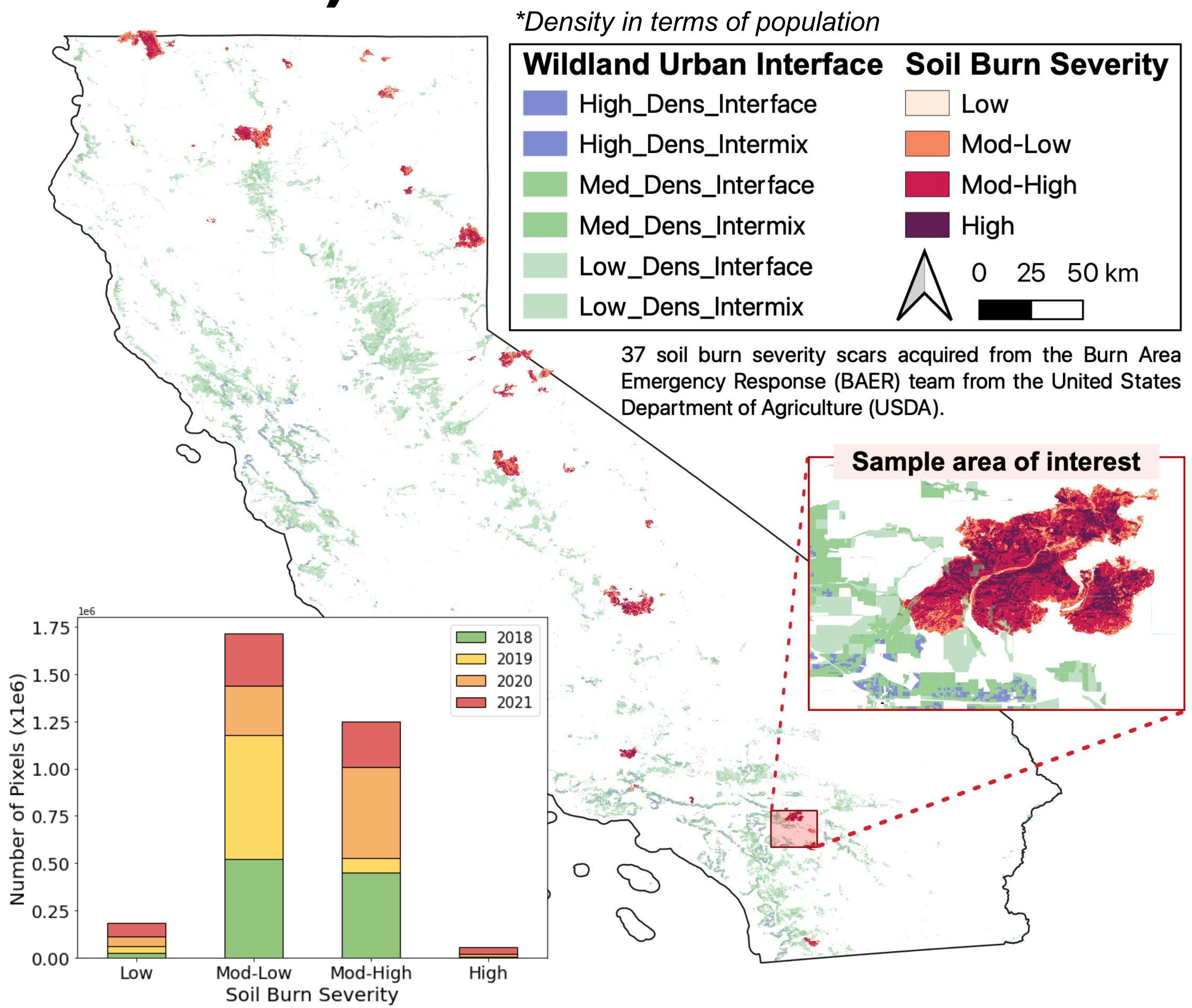

Figure 2: Map of soil burn severity measurements from 37 wildfires

2. Data (Acquisition)

Step 1 : Data Collection and Preparation

Google Earth Engine

python

Training Dataset	Features
Digital Elevation Model (USGS)	Elevation, Slope, Aspect
Satellite Imagery (Sentinel-2)	Blue, Green, Red, NIR, NDVI, SAVI
Land Cover Map (ESA)	Land Cover Classes

Features (10) Labels

Ground Truth	Features
Soil Burn Severity (USDA)	4 categories

Reprojection to same coordinate system & Resampling to 10 m spatial resolution

Input Dataset

Training Dataset (10)	Labels
Blue, Green, Red, NIR, Elevation, Slope, Aspect, Land cover map, NDVI, SAVI	• 1 : Low • 2: Mod-Low • 3: Mod-High • 4 : High

$$NDVI = \frac{NIR-RED}{NIR+RED} \qquad SAVI = \frac{NIR - RED}{NIR + RED + L}(1 + L)$$

Figure 3: Example of input data features and burn severity label

2. Data (Processing)

Step 2 : Data Processing

1. Data Clustering

Features (10) | Labels

K-means Clustering

2. Feature Importance

Features (10) | Labels

Data Preprocessing (Minmax normalization)

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Random Sampling & Train/Test Split

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Machine Learning Model

- Naive Bayes
- Multilayer Perceptron
- Adaboost
- Gradient Boost
- **Random Forest**

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Class prediction and feature importance ranking

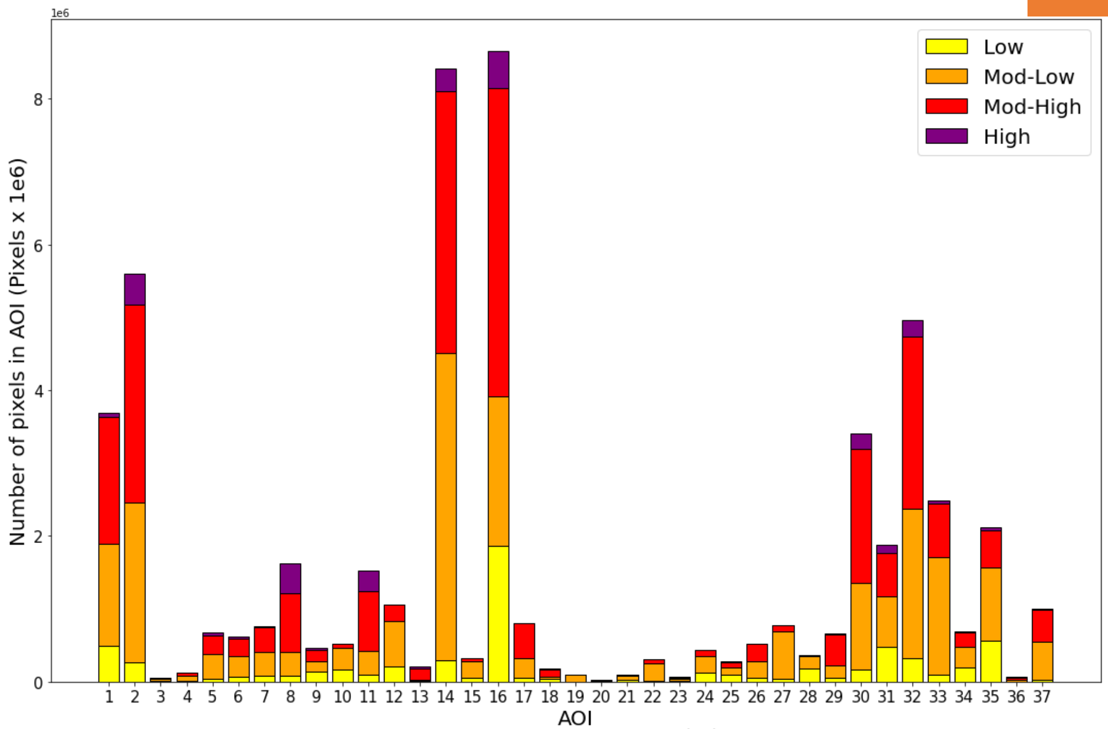


Figure 4: Uneven distribution of fire severity pixels

#	Sampling Method	Dataset (# Samples)
1	**Wildfire Size(Random)** - Pixel count per class by relative size	Train (31948) = 80% Test (7987) = 20%
2	**Fixed sample count** - 300 pixels per class	Train (29760) = 80% Test (7440) = 20%

$$p_{AOI,class} = \frac{n_{AOI,class}}{\sum_{i=0}^{37} n_{AOI,class}}$$

$$n_{AOI,class} = p_{AOI,class} \times n_{sample}$$

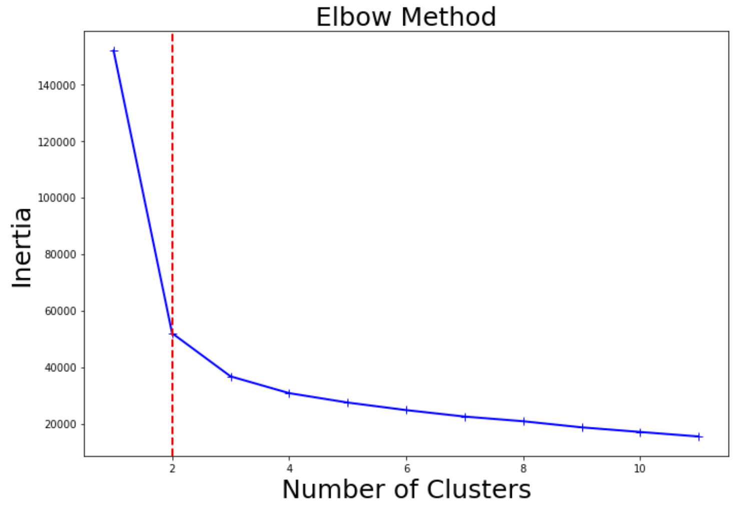
3. Results (K-Means)

Step 1 : Determining K Value

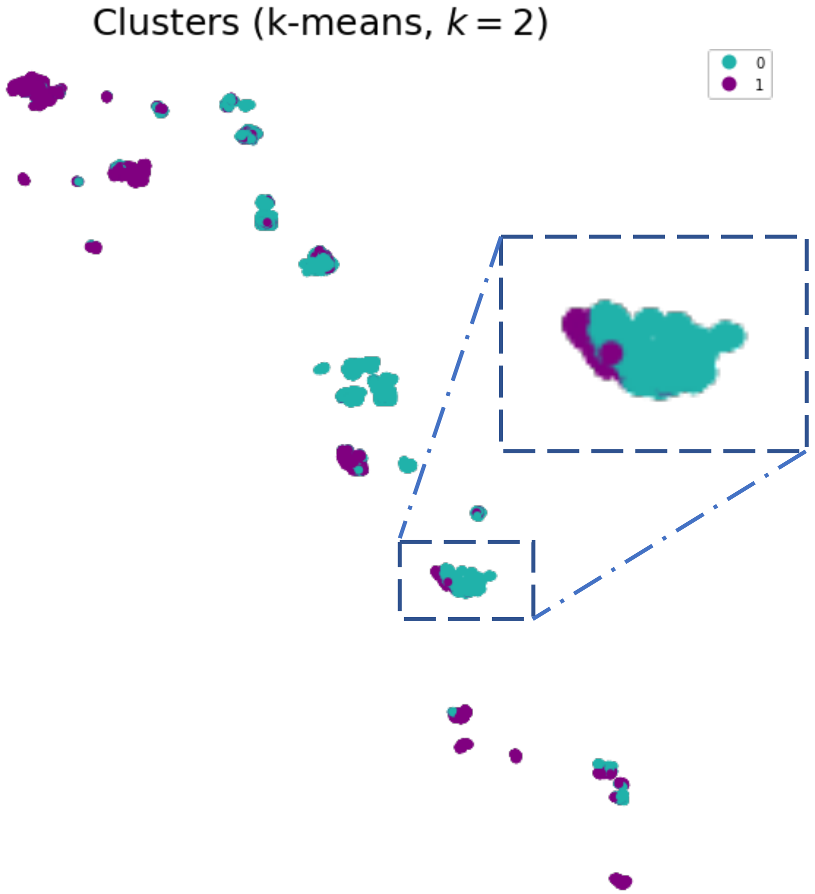
- What is the best number of Clusters?
- Where are Cluster points distributed?

K = 2

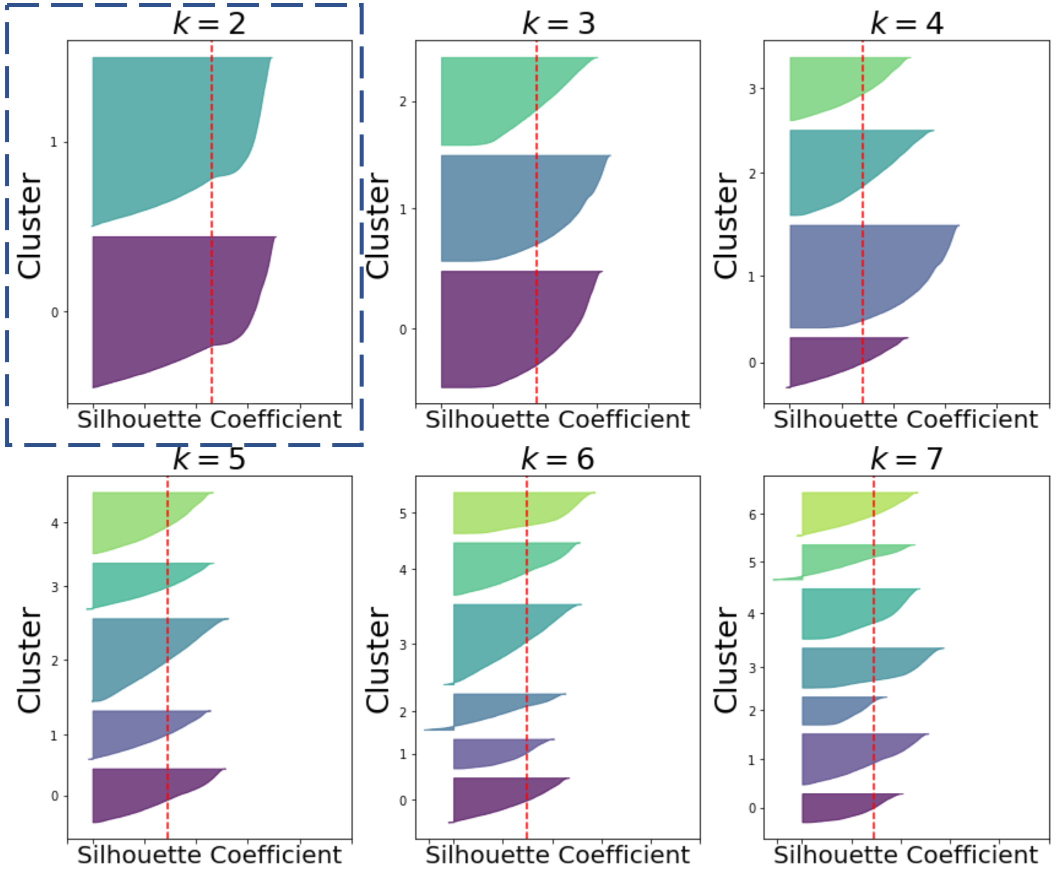
Elbow Method



Silhouette Method



K (Clusters)	Silhouette Score
2	0.534
3	0.395
4	0.305
5	0.273
6	0.280
7	0.294
8	0.295
9	0.317
10	0.332
11	0.342
12	0.351



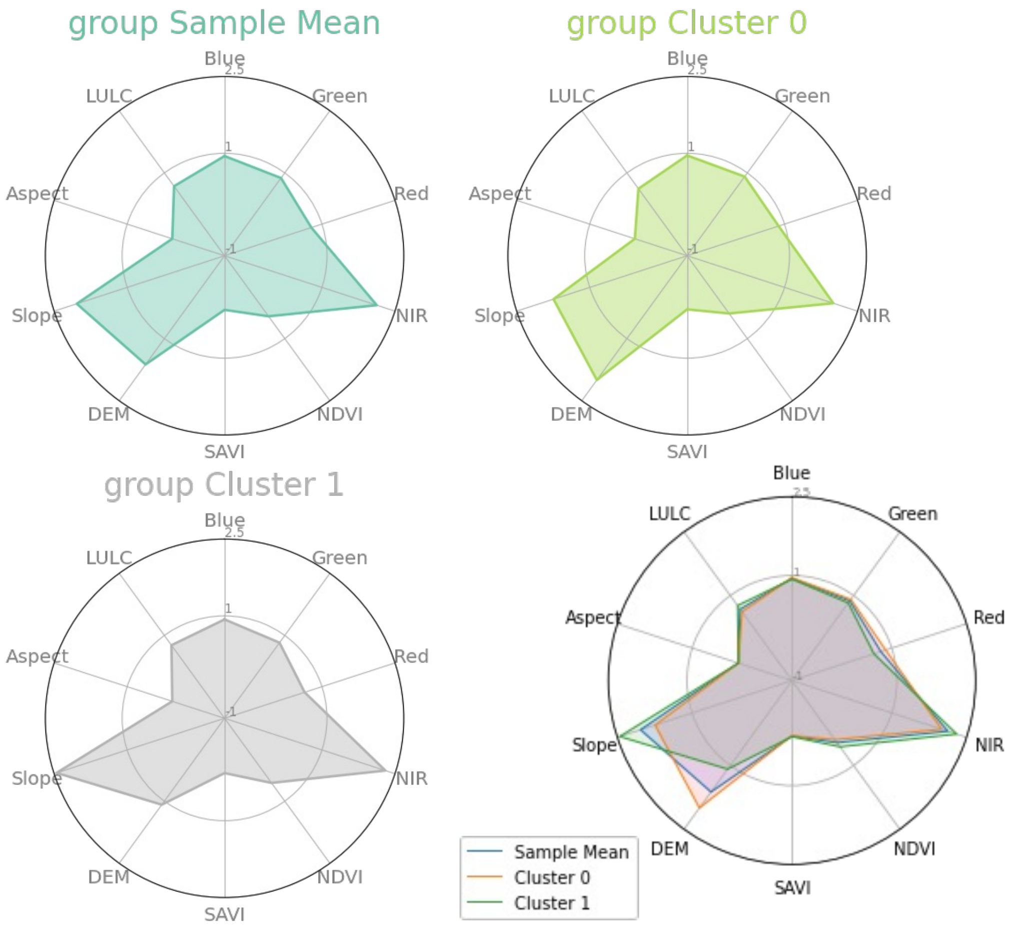
3. Results (K-Means)

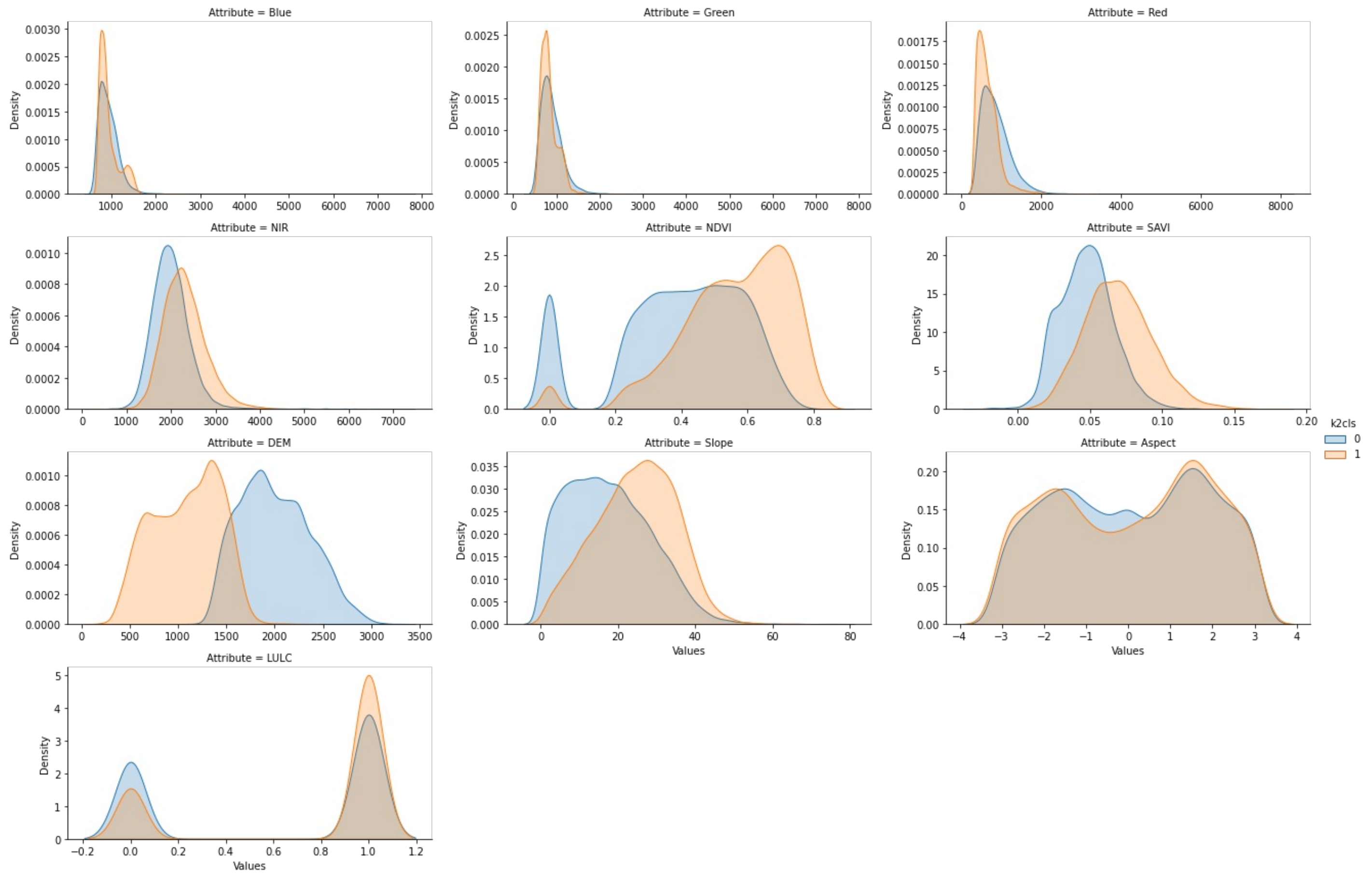
Step 2 : Cluster Interpretation

Cluster Descriptions

Cluster 0: Less Blue, Green, Red | Low NIR | Low NDVI |Low SAVI | High Elevation | Smaller Slope | Less LULC

Cluster 1: More Blue, Green, Red | High NIR | High NDVI |High SAVI | Low Elevation | Larger Slope | More LULC





3. Results (Machine Learning)

Main Experiments

- **Random forest** was found to be the most effective classifier
- Difference between random sampling and fixed random sampling is *minimal* for random forest

Table 2: Accuracy results from random sampling

Models	Random	Fixed
MLP	56.00%	49.23%
Naïve Bayes	40.20%	35.71%
Adaboost	47.49%	42.58%
Gradient Boost	53.59%	49.01%
Random Forest	**59.13%**	**58.00%**

Table 3: F1-scores of RF

Severity	F1-Score
Low	0.64
Mod-Low	0.49
Mod-High	0.47
High	0.75

Results from RF + Random Sampling by Wildfire Size

- **NDVI (vegetation), SAVI (bare soil), DEM (topography)** were most influential
- LULC low for MDI because data is categorical
- DEM products (slope, aspect) lowest

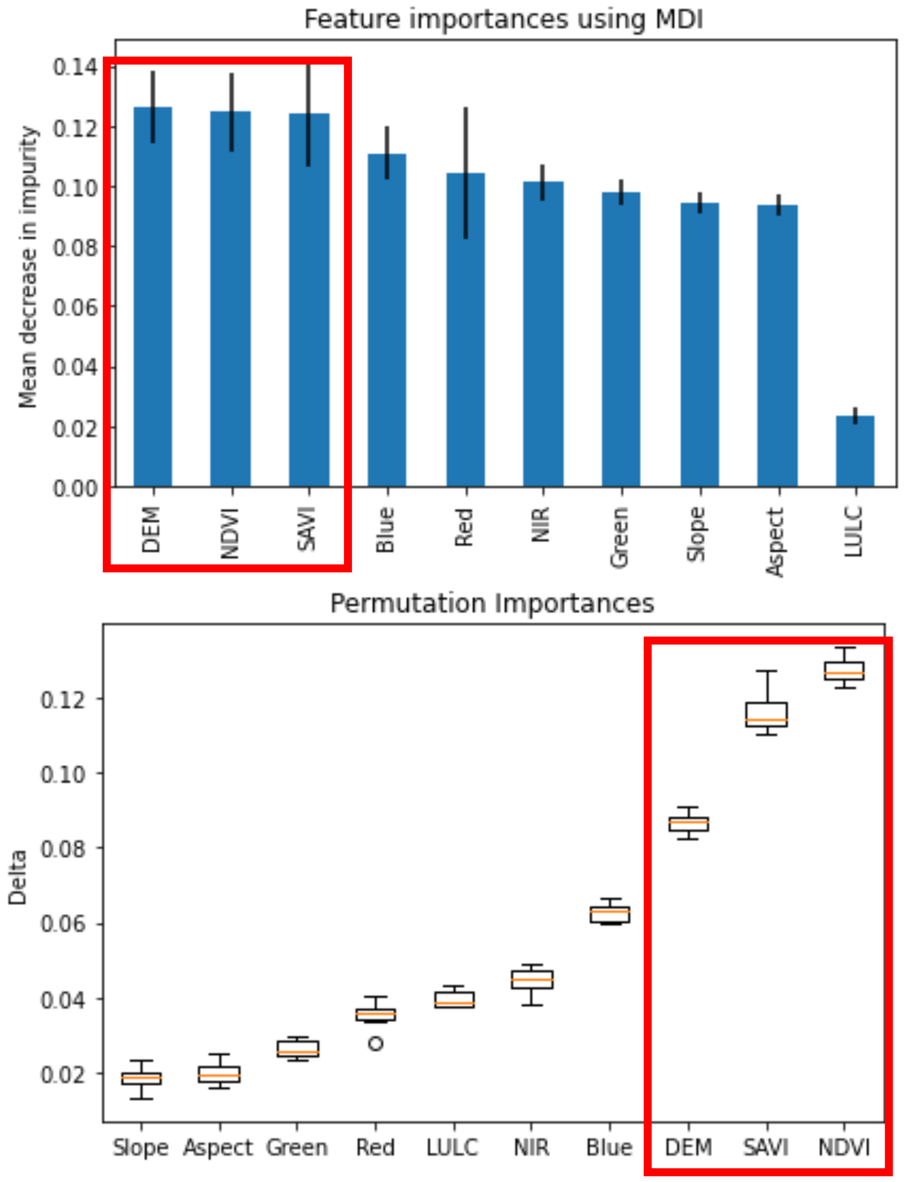
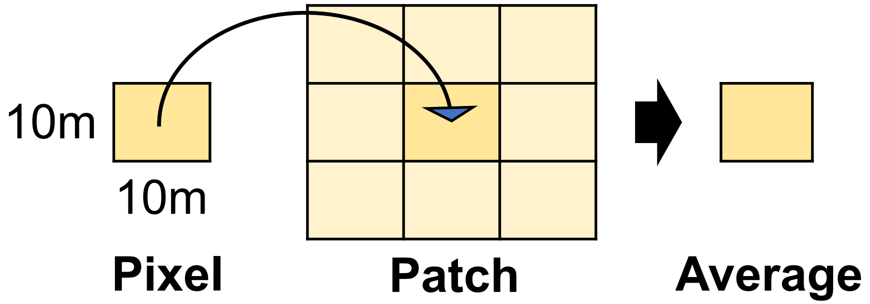


Figure : Feature importance plots

3. Results (Machine Learning)

Additional Experiments

- Multi-scaled patches extracted to compute average values of data features



- NDVI, SAVI, and DEM (both pixel and averages) were most influential again
- All models improve in accuracy
- Random forest continues to improve with larger patches → *Overfitting* (?)

Severity	F1-Score (RF)	F1-Score RF(p=10)
Low	0.64	0.66 (▲0.02)
Mod-Low	0.49	0.52 (▲0.03)
Mod-High	0.47	0.50 (▲0.03)
High	0.75	0.73 (▼0.02)

Table 4: Accuracy results from random sampling with patches (p)

Models	Pixel	p=10	p=20	p=30	p=40	p=50
MLP	56.00%	57.48%	**58.08%**	55.75%	57.60%	57.48%
Naïve Bayes	40.20%	**41.15%**	40.68%	40.11%	40.68%	40.64%
Adaboost	47.49%	**48.82%**	48.13%	47.88%	47.82%	48.01%
Gradient Boost	53.59%	**55.13%**	54.44%	54.03%	54.33%	54.38%
Random Forest	59.13%	60.42%	61.32%	61.83%	62.19%	**62.90%**

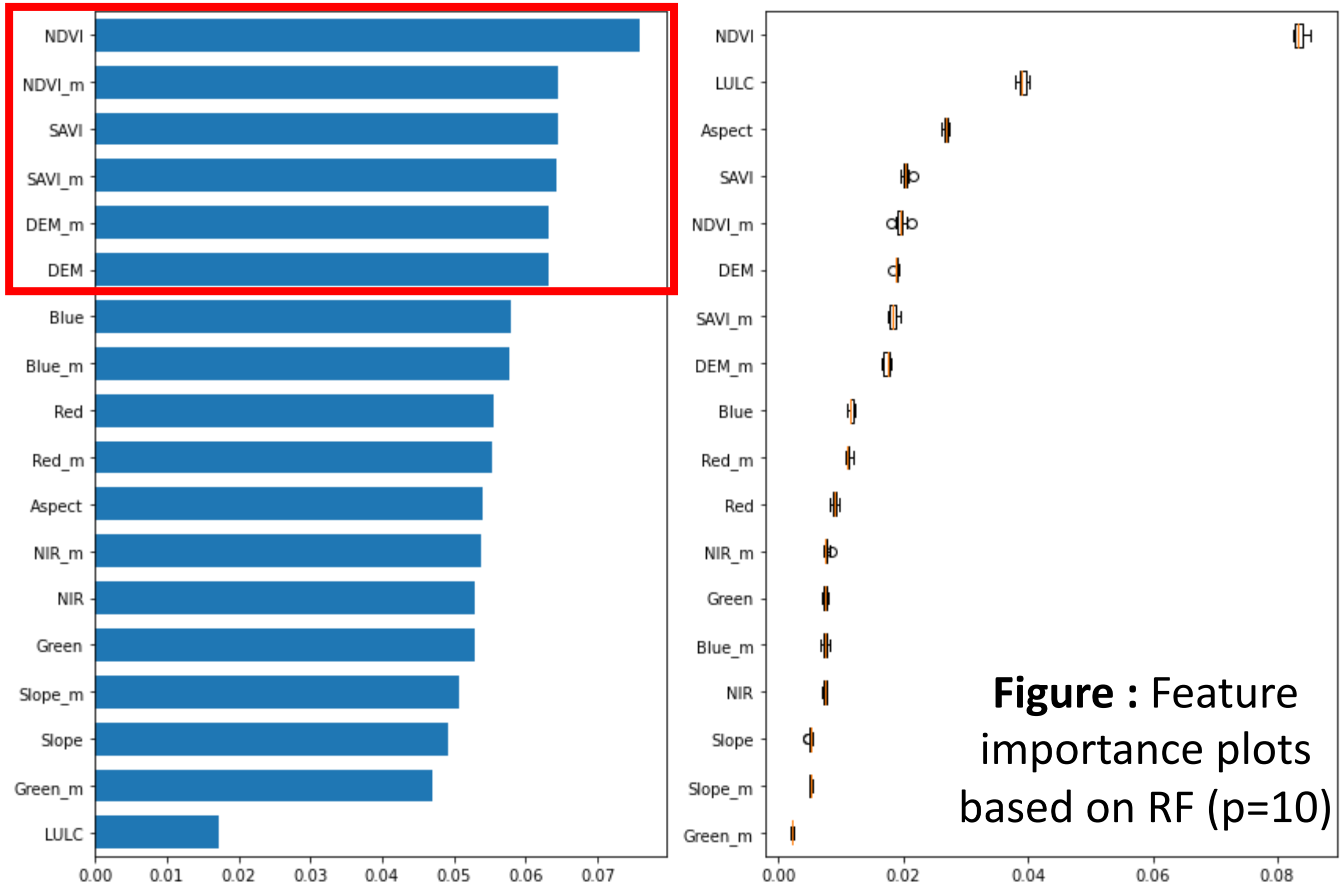


Figure : Feature importance plots based on RF (p=10)

4. Conclusion

Our Contributions

- Linked **high resolution** remote sensing data with a **comprehensive set of soil burn severity**
- Developed open–source data acquisition pipeline (Google Earth Engine)
- Developed **machine learning framework to assess feature importance** using pixels and patch-based features
- Proposed multiple random sampling methods to overcome large data volume

Limitations

- Weather features are needed, but are too coarse to compare with the dataset used here
- Four-year burn severity dataset used due to limited data availability