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NORTHWEST NAZARENE UNIVERSITY

FireMAP/FDL Update

Dale Hamilton PhD, Computer Science Cole McCall, Computer Science 2022 US Frontier Development Lab – Dept of Energy What if we could use ML-enhanced tools to prevent fires from starting or new fires from growing into large mega-fires?

NASA EPSCoR 2022-2023

Evaluation of Spatial Resolution and Spectral Band Selection on Wildland Fire Burn Severity Mapping







WILDFIRE: MULTISPECTRAL ESTIMATION OF FUEL LOADS

FDL 2022 | Technical Presentation Tuesday 20 September 2022





PARTNER

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THE TEAM



Cormac Purcell, Faculty



Ash Hoover, Partner Faculty

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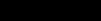




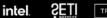


Karol Bot Gonçalves, Researcher

<u>Researchers</u>: Amani Al Abri, Beichen Zhang, Huiqi Wang, Karol Bot Gonçalves <u>Research Support</u>: Carter Katzenberger, Cole McCall <u>Team Leads</u>: Dale Hamilton, Vít Růžička <u>Faculty</u>: Cormac Purcell, Ash Hoover



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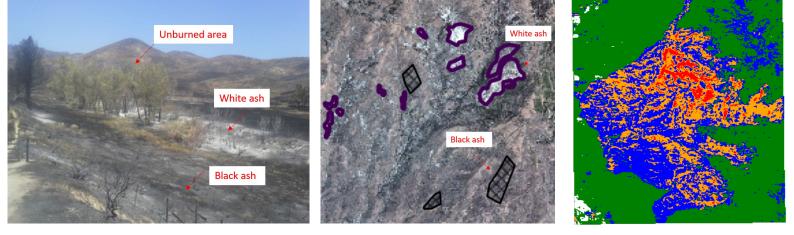
1. Introduction

• Wildfire is a very dynamic process!



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Example of a burn severity map

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High Severity Moderate Severity Low Severity Unburned Enhanced Regrowth

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Example of ground view of fuel consumptions example (US)

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Satellite view of fuel consumptions example (Mesa fire - US)

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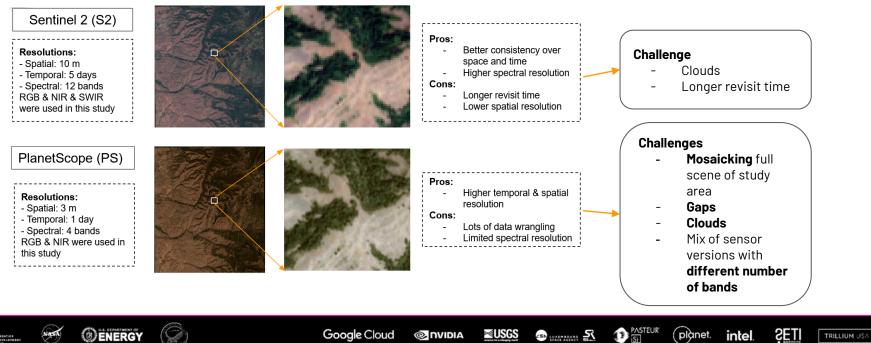


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2. Methodology

• Data acquisition



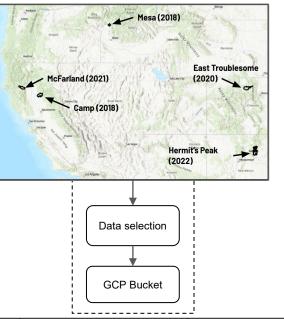


2. Methodology

Data acquisition

- Ο Nearly 10 million square kilometers of PlanetScope imagery was obtained (across 5 different study areas throughout the Western United States).
- Ο As long as the imagery covered enough of the study area (>50%) and did not have significant cloud cover, each PlanetScope and Sentinel-2 image was added to the dataset and could be considered. either pre-fire, active fire, or post-fire imagery.
- Ο Only some locations and time frames were used as datasets for the tested methods.

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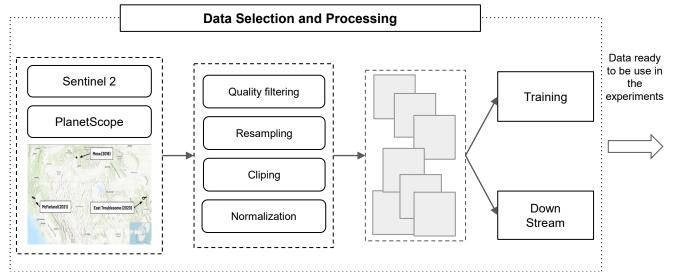
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2. Methodology

- Data pre-processing
 - Once the data has been acquired it is placed in the GCP Wildfire Landing Bucket.
 - This data is not ready for any machine learning or geoprocessing and a few steps need to be followed first:



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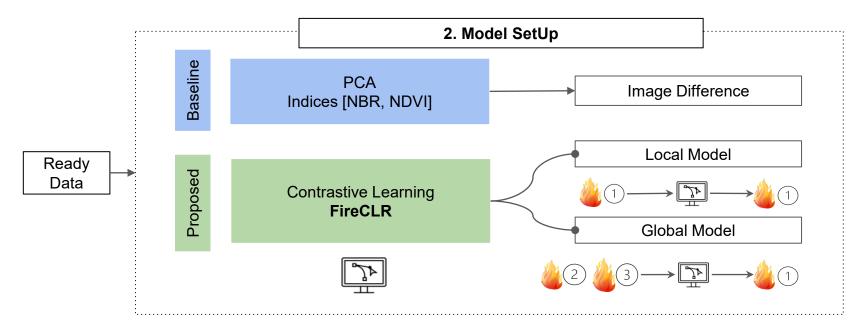


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2. Methodology - Model Setup

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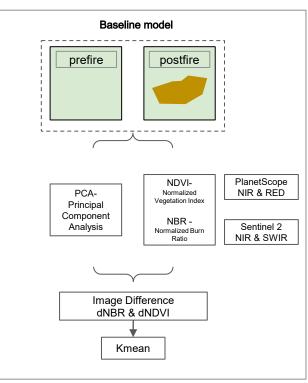
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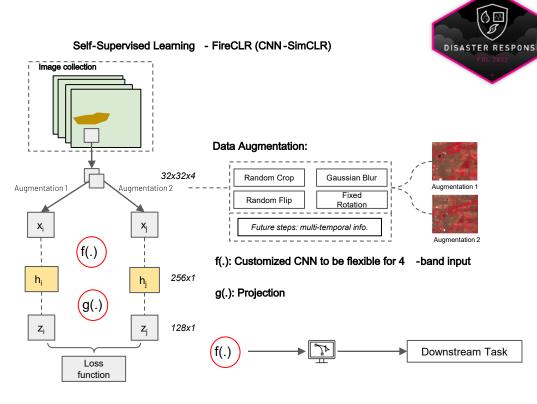
2. Methodology - Model Details



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✓ Pros: Easy to be built and explained

x Cons: Limited learning capability



√ Pros: strong performance on extracting representation, reduce the chance of learning trivia information, SOTA model, best results (so far)

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x Cons: computation and space very expensive, reduced spatial resolution of the output when doing the downstream task

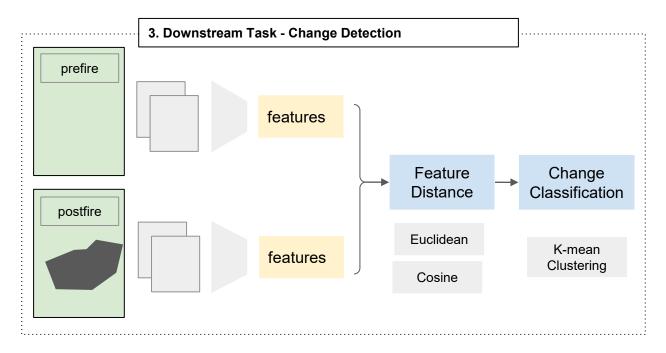
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2. Methodology - Downstream Task



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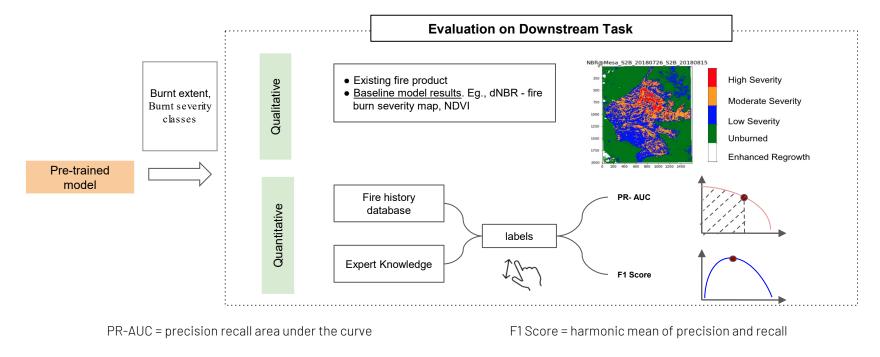






2. Methodology - Model Evaluation

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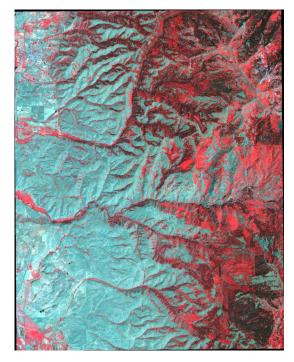
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Downstream task and validation: Mesa Fire in Idaho, US (2018)

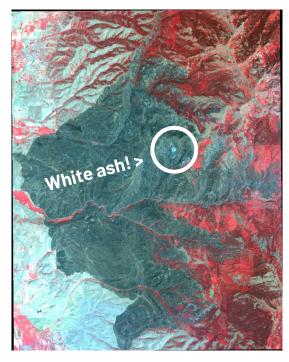
BEFORE PlanetScope - July 26



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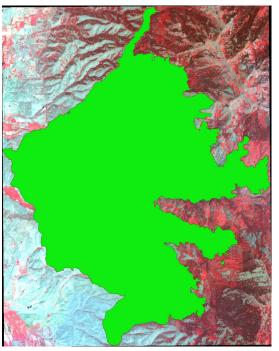
AFTER PlanetScope - August 15



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LABEL of the Burned Area



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3. Results

FireCLR <u>Local</u> model (S2)

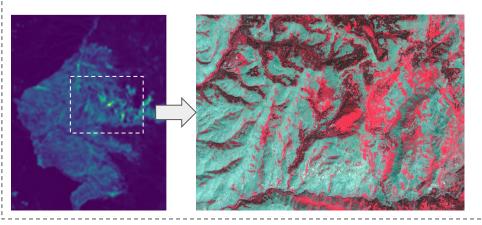
 Trained and evaluated on same geographical location (different days - imagery at Mesa fire on July 26 & August 15)

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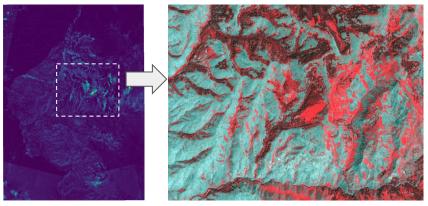
- PR-AUC = 0.99
- Δ (FireCLR baseline) = 0.04

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• FireCLR <u>Global</u> model (PS)

- Trained and evaluated on different geographical location (training using pre- and post-fire imagery at McFarland and East Troublesome fires / downstream using imagery at Mesa fire on July 26 & August 15)
- PR-AUC = 0.80
- $-\Delta$ (FireCLR baseline) = 0.13

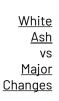


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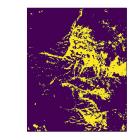
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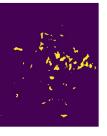
FireCLR Downstream task and validation: Mesa Fire in Idaho, US (2018)

Manual Annotations **PS:** 3-cluster K-means on FireCLR representations **S2:** 3-cluster K-means on FireCLR representations



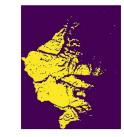






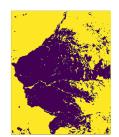








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F1-score based on the Annotated Labels

	White Ash	Black Ash	Unburned
FireCLR + K-means (PS rgb+nir, res: 24m)	0.90	<u>0.86</u>	0.78
FireCLR + K-means (S2 rgb+nir, res: 80m)	0.51	0.82	<u>0.79</u>
PCA + K-means (PS rgb+nir, res: 3m)	0.90	<u>0.86</u>	0.76
PCA + K-means (S2 rgb+nir, res: 10m)	0.59	<u>0.86</u>	0.60
dNBR + K-means (S2 nir+swir, res: 10m)	<u>0.93</u>	0.78	0.76

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6. Conclusions

- Key take away points
 - We developed **an change detection method, assessing the burned severity from a multitemporal perspective**. Our method is **fully unsupervised**.
 - We implemented **baseline methods**(dNBR/dNDVI) and a **contrastive learning ML model called FireCLR** designed to work in two modes, **local** (trained on the same geographical location as evaluated) and **global** (trained on different geographical location than evaluated).
 - For both datasets and both modes, we report increased performance in comparison with the baseline models.
 For the local model, the PRAUC increased from 0.95 (baseline) to 0.99 (ML-model). For the global model, the PRAUC increased from 0.67 to 0.80.

The models were also evaluated using F1-score based on the annotated labels for black and white ashes, against minor and major changes, respectively.











6. Conclusions

- Recommendations for **future works**
 - The proposed future work involves training the SimCLR model to be **invariant to natural changes with longer temporal series of data**.
 - Explore different Planet products (or other vendors) and trade-offs in spatial and spectral resolution relevant to wildfire mapping.
 - **Compare the results produced using contrastive learning against an autoencoder** to see if one algorithm is superior for mapping post fire effects.
 - Use the burn scar mapping from successive days to **produce a fire progression map showing fire growth at a finer temporal scale** than achieved with this experiment which compared pre and post fire imagery.

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• Investigate self-supervised contrastive learning for **identifying tree mortality**, resulting in a reduction in canopy cover.

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NEWS

Climate change: Europe's warm summer shatters records

By Matt McGrath Environment correspondent

I days ago · ₱ Comments



Fires were common in many places including here in Portugal







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2023 NNU FireMAP efforts

Visiting Fellowship with The Australian National University Bushfire Research Centre of Excellence (Spring 2023 Sabbatical)

NASA funded Spatial/Spectral analysis

Reconcile 2022 US FDL Wildfire Challenge, Local vs Global methods

Support DOE funded 2023 US FDL Wildfire Challenge





Questions?