ENEE 408N Team AYA (ECE#10)

Educational Wildfire Simulator Using Machine Learning

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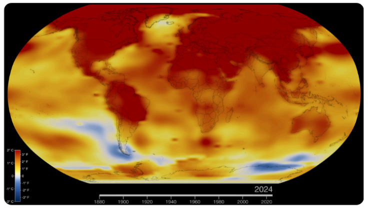
Background

The Earth is heating up faster than ever before.

"Global temperatures in 2024 were **2.30 degrees Fahrenheit** above the agency's 20th-century baseline (1951-1980)... The new record comes after **15 consecutive months** of monthly temperature records."[1]



Rising global temperatures **increase the likelihood and severity of wildfires.** Primarily by drying out vegetation, and lengthening the windows of time when conditions are favorable for burning.[2]

Our goal is to create an educational tool to showcase how wildfires spread under different weather conditions.

Methodology

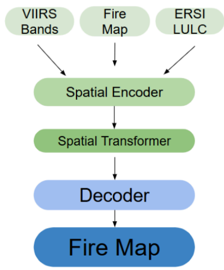
Image Based

Goal

- Produce a fire probability map for the next day of a wildfire

Architecture

- **CNN Encoder:** extracts spatial features at multiple scales
- **Spatial Transformer:** captures long-range dependencies across the scene
- **Decoder:** reconstructs fire probability map



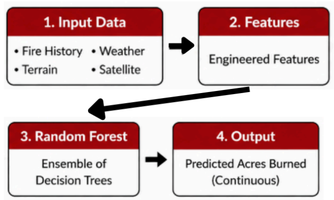
Non-Image Based Architecture

Goal

- Provide a numeric estimate of the total burned acres in a wildfire

Architecture

- **Random Forest Regression:** Captures non-linear relationships between features and fire size



Feature Engineering

- **Several-Day Inputs:**
  - **Weather:** temperature, humidity, soil moisture, precipitation, and wind metrics
  - **Geographic:** NDVI, land cover, elevation, slope, aspect (sin/cos encoding)

API Resources

- **Open-Meteo:** Historical meteorological data for any coordinate in the world
- **Google Earth AI:** Cloud platform for analyzing large satellite datasets with ML and remote sensing tools

Datasets

- Image based dataset based on a curated Satellite Wildfire dataset called TS-Satfire
- Includes VIIRS Satellite bands, Annotated Fire Maps and Land Cover information
- Includes 178 wildfire events with varying days per event
- Ground truth fire percentages range from 2.9% to 81% of the scene per event

MTBS Dataset

Original columns

ignition_date	acres_burned	fire type
2014-01-16	2022	Wildfire
2014-01-30	656	Wildfire
2014-02-02	1652	Wildfire
2014-02-13	1144	Wildfire

+

API-called features (+ more)

temp_max_7d_prior	temp_max_d_minus	temp_ign_1400 (°C)	temp_max_d_plus1
25.6	25.6	25.5	25.6
14	0.9	4.1	4.2
16.2	13.6	-0.1	4.8
17.4	6.1	11.7	16.4

ndvi	land_cover	elevation_m
0.356	10	562
0.40155	4	361
0.50755	4	246
0.39685	8	75

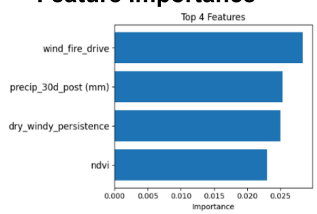
Conclusion

- The image model reliably predicts next day wildfire rarely missing active fire pixels with occasional overprediction
- Results demonstrate the model has learned meaningful relationships between land cover, fire state, and next day spread
- The non-image model accurately predicts total burned acres for smaller and medium-sized fires
- Engineering features rather than using raw data improved the accuracy of the model, as it created larger distinctions between fires of different sizes

1. R. Bardan, "Temperatures Rising: NASA Confirms 2024 Warmest Year on Record," NASA, Jan. 10, 2025.
2. Gutierrez, Aurora A., et al. "Wildfire Response to Changing Daily Temperature Extremes in California's Sierra Nevada." Science Advances, vol. 7, no. 47, 19 Nov. 2021, https://doi.org/10.1126/sciadv.abe641.
3. Zhao, Y., Gerard, S., & Ban, Y. (2024). TS-SatFire: A Multi-Task Satellite Image Time-Series Dataset for Wildfire Detection and Prediction. ArXiv.org. https://arxiv.org/abs/2412.11555

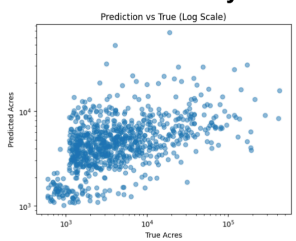
Non-Image Model Results

Feature Importance



Wind_fire_drive: How aggressively fire spreads due to wind and humidity
Dry_windy_persistence: Wind strength weighted by sustained dry conditions
NDVI: Normalized Difference Vegetation Index, measures vegetation health via satellite images
Precip_30d_post: Maximum precipitation during the 30 days after ignition

Prediction Accuracy Plot



The model captures overall fire size trends well, particularly for smaller fires. Prediction variance increases as fire scale increases.

Model Metrics

Metrics (log)	Score
R^2	~0.250
MAE	~0.363

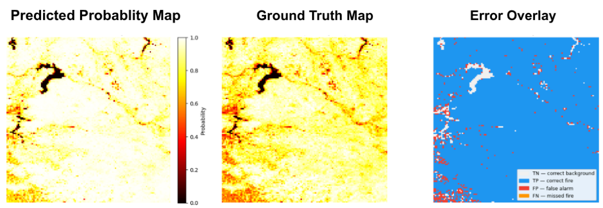
The model demonstrates meaningful predictive capability given the high variability and complexity of wildfire behavior.

Prediction Example

Fire Index	3931
Actual Acres	6758
Pred. Acres	6735.92
Error	22.08

Image Model Results

Example Output



Accuracy	0.86
IOU	0.72
F1	0.83
Precision	0.72
Recall	0.99

The model predicts next day fire spreads well accounting for different geographical features

Confusion Matrix