ML-based fire hazard model trained on thermal infrared satellite data

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Agenda

1. Motivation
2. Research Question
3. Data Sets
4. Methodology
5. Results & Discussion

Motivation

- Vicious cycle of wildfires and climate change
  - Wildfires bootstrap climate change [1]
  - Drier conditions lead to bigger fires [2]
- Why is research needed?
  - Number of wildfires keeps decreasing
  - Tree cover loss is increasing [3]

Wildfire in the Amacro region (Amazonas, Acre and Rondônia states) (Greenpeace, 2022)

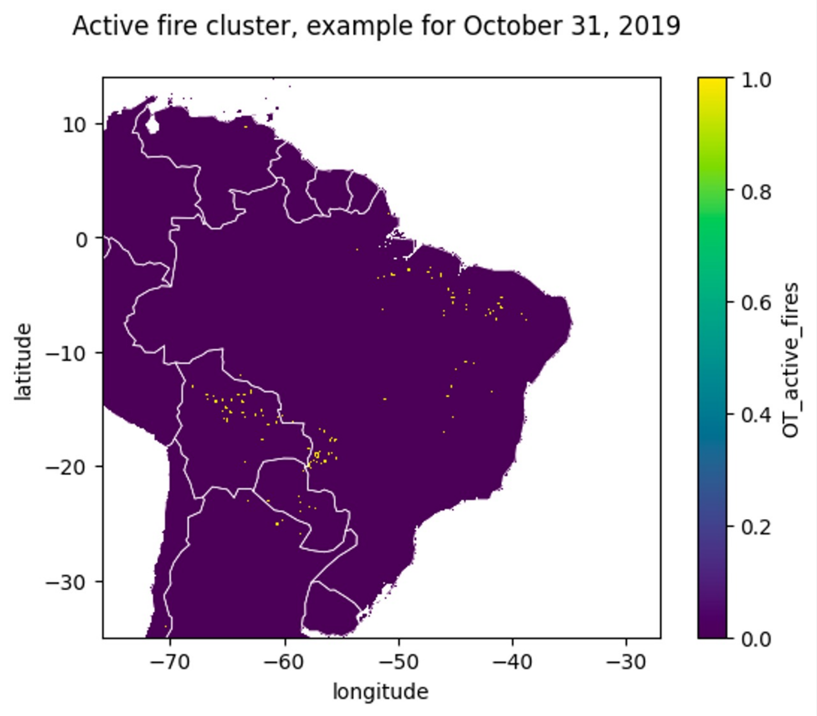
[1] Michael Jerrett, et al. Up in smoke: California's greenhouse gas reductions could be wiped out by 2020 wildfires. Environmental Pollution, 2022.
[2] California Department of Forestry and Fire Protection. Top 20 largest California wildfires. https://www.fire.ca.gov/media/4jandlhh/top20_acres.pdf
[3] Alexandra Tyukavina, et al., Global trends of forest loss due to fire from 2001 to 2019. Frontiers in Remote Sensing, 3, 2022.

Can we model short-term wildfire risk from thermal infrared data?

Ground Truth: Active Fire Clusters

- **Remote sensing data** from > **20 satellites**
  - **MODIS**: Aqua, Terra
  - **VIIRS**: Suomi-NPP, Noaa-20
  - **OLI**: Landsat 8, 9
  - **SLSTR**: Sentinel 3-A, 3-B
  - ...
- Near **real-time information** on **wildfire** occurrence
- Highly **imbalanced**: >99.5% not burned

- Meta data:
  - Spatial and temporal resolution depend on GSD and overpasses of detecting satellites
  - Vector data rasterized to 0.1 deg. resolution (≈ 11km)
  - Aggregated to daily

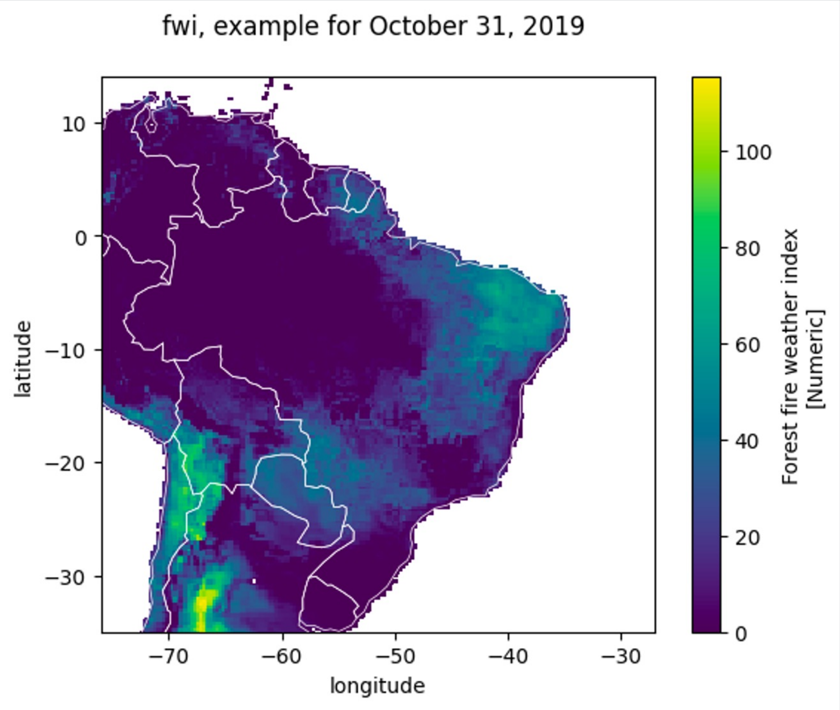


Baseline: Fire Weather Index (FWI)

- Daily **numeric rating** of fire danger:
  - very low: <5.2
  - low: 5.2 - 11.2
  - moderate: 11.2 - 21.3
  - **high: 21.3 - 38.0**
  - **very high: 38.0 - 50**
  - **extreme: >=50.0**
- Based on **weather observations** yesterday at noon
- **Standard fuel** type

- Meta data:
  - Resolution: 0.25 deg. (≈ 30km)
  - Interpolate to 0.1 deg. (≈ 11km)

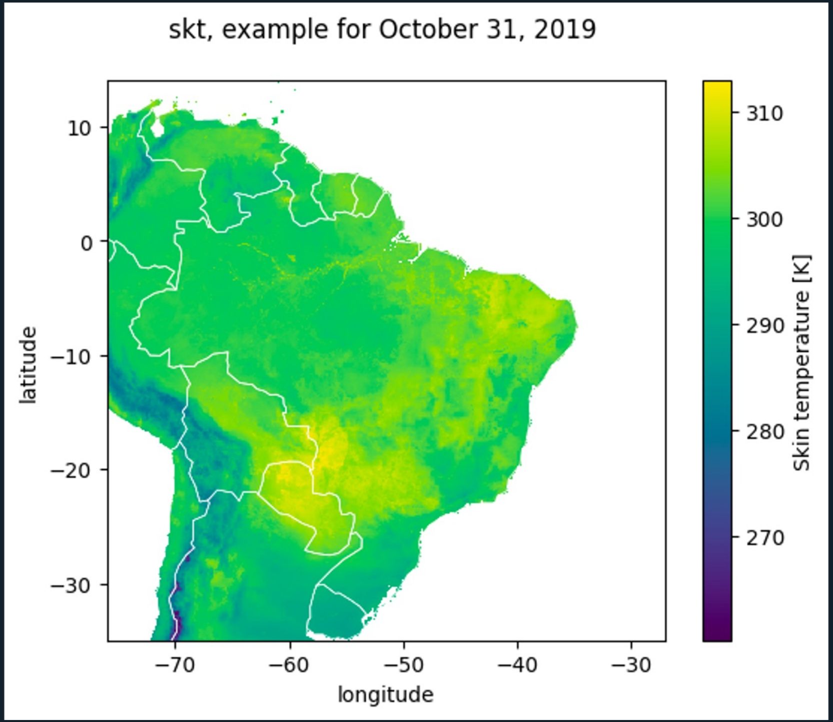
Natural Resources Canada
Canadian Forest Service



Weather: ERA5-Land

- **Wind**
  - eastward component
  - northward component
- **Temperature**
  - skin temperature
  - 2m dew point temperature
  - 2m temperature
- **Additional**
  - total precipitation
  - surface pressure
  - surface net solar radiation

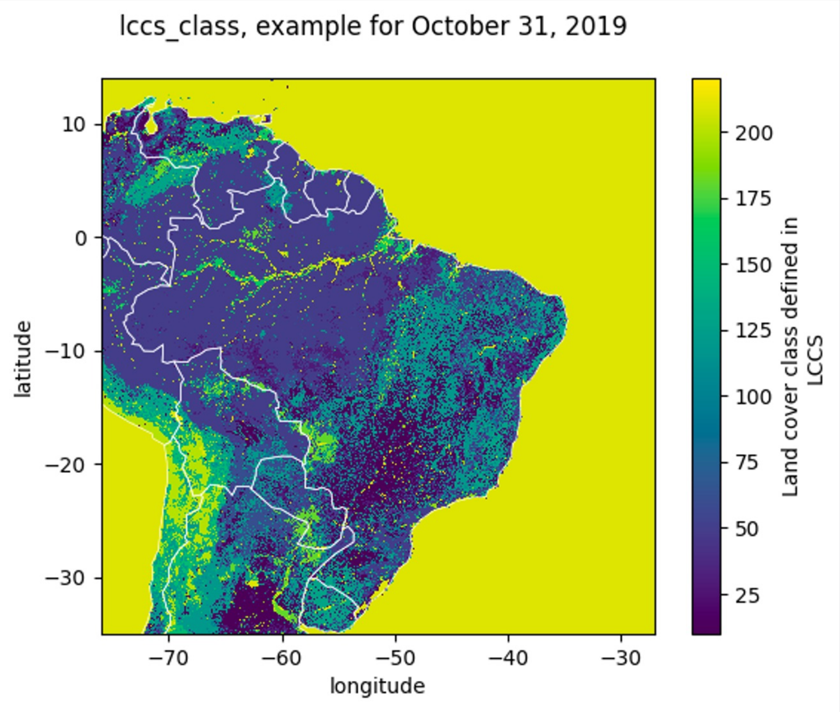
- Meta data:
  - Resolution: 0.1 deg. (≈ 11km)
  - Hourly data aggregated to daily (sum or average)



Fuel: CCI Landcover

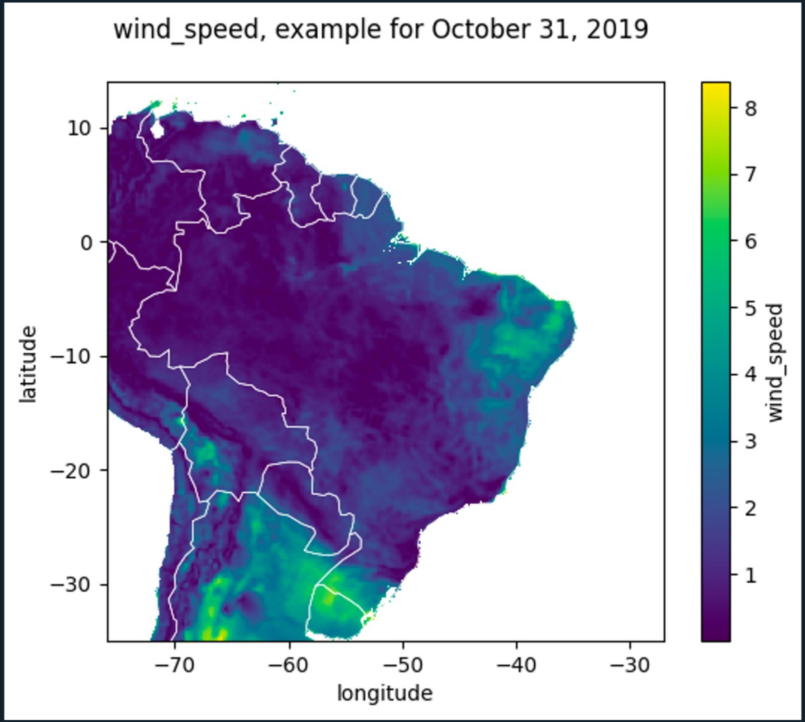
- 22 fine-grained classes of potential fuel for wildfires
- **9 combined** classes
  - Agriculture
  - Forest
  - Grassland
  - Wetland
  - Settlement
  - Shrubland
  - Sparse vegetation
  - Bare areas
  - Water and ice

- Meta data:
  - 2020 version
  - Resolution: 0.0025 deg. (≈ 300m) down sampled to 0.1 deg. (≈ 11km)



Engineered features

- Wind speed
- Latitude
- Longitude
- Circular encoding of day of year
    - Account for seasonal variability



Final data set

Data set

22 features:

8 Climatic variables
9 Fuel variables
5 Engineered features

1 baseline model:

FWI

1 ground truth:

Active fire clusters

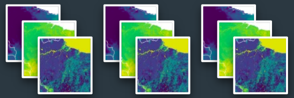
Meta data	
Timeframe	October 2019 - October 2022
Temporal resolution	daily
Spatial resolution	0.1 degree (≈ 11km)

Pipeline

Random crop:
60 x 60 pixels

Lead time:
3 days

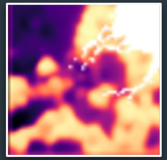
Input tensor:
22 x 3 x 60 x 60



Data loading

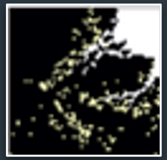
Spatio-temporal
3D U-Net

Prediction:
Sigmoid output



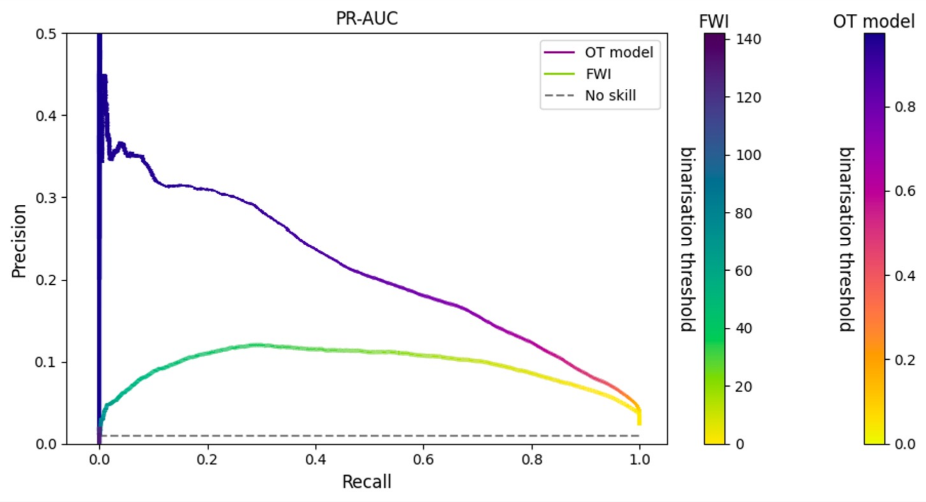
Binarisation:
Threshold = 0.85

Ground truth:
Active fire clusters



Post processing

Results

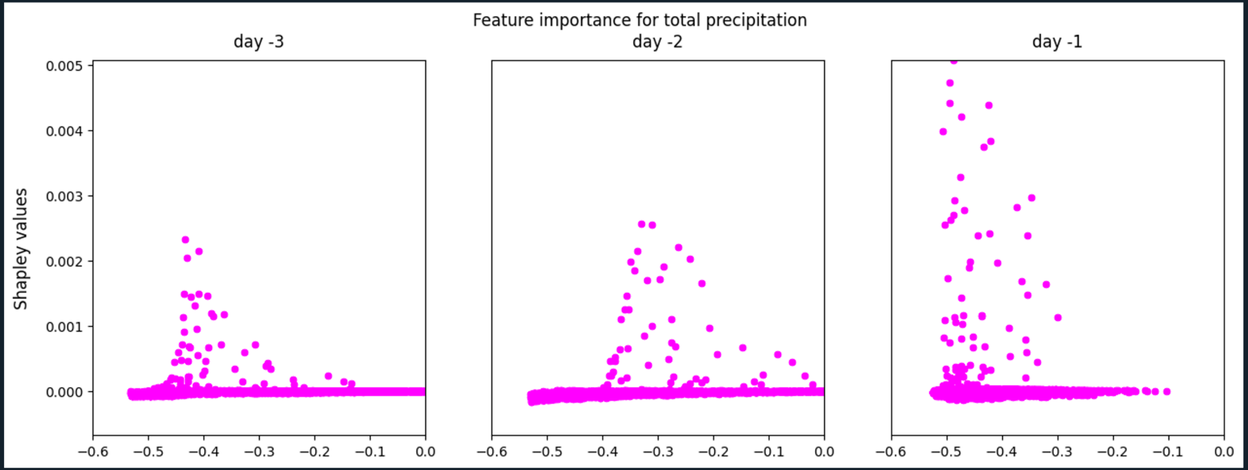


- **OT model:**
  - Best binarisation threshold: **0.85**
  - **F1 = 0.31**

- **FWI:**
  - **Threshold** for high fire danger: **21.3**
  - **F1 = 0.15**

Feature importance: Shapley values

- Originate in **game theory**
- What is the **contribution** of each **input feature** to the model **prediction**?



- **Higher Shapley values** for low total precipitation **closer to predicted fire**
- Drier conditions **increasingly meaningful** in the 3 days leading up to a fire

Discussion / Outlook

- Model outperforms FWI
- Goal: **overcome shortcomings** of FWI
  - Include **fuel information**
  - Account for **daily and seasonal variability** in weather conditions
- Model learns **physical conditions** that influence wildfire behaviour
- Our model can easily be adapted to **other ecosystems**
- Inference on **weather forecast** instead of reanalysis

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