

# Multi-Task Learning for Fire Ignition Maps

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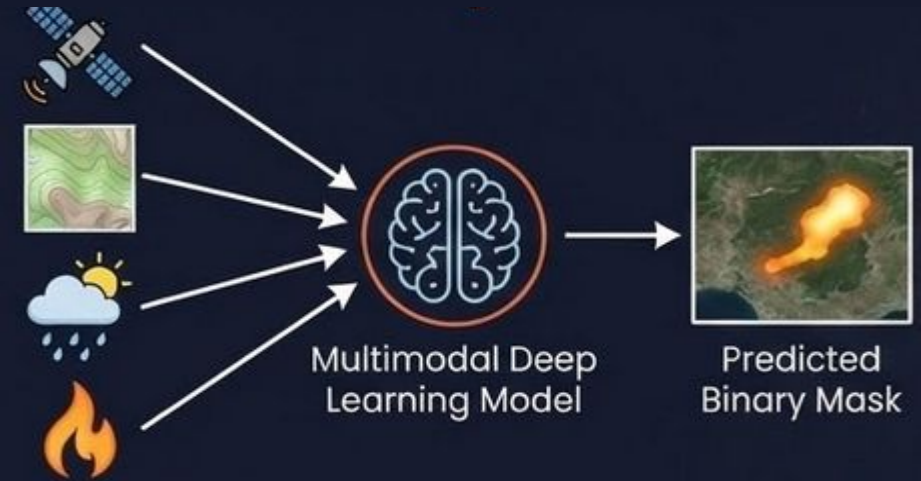
# Project Objective

## Core Objective

To develop a multimodal deep learning model capable of **Predicting the final burned area extent of a wildfire right at the moment of ignition**, using only pre-fire multimodal data that fused into a multimodal model

**Input:** Pre-fire environmental data (Satellite, Topography, Weather) + Ignition Point.

**Output:** Predicted binary mask of the final burned area.



## The Paradigm Shift

**Current State (Reactive):** Remote sensing is primarily used for post-event damage assessment.

**Target State (Proactive):** To estimate the possible spread of fire immediately to allocate resources immediately during the "Golden Hour".



# Value Proposition



## Environmental Impact

Proactive predictions reduce environmental losses by enabling faster response before uncontrolled spread. Fewer hectares burned → lower CO<sub>2</sub> emissions, preserved ecosystems, and reduced long-term regeneration costs.



## Response Efficiency

Early burned-area forecasts help Civil Protection allocate firefighting teams, helicopters, and ground units efficiently. Better situational awareness during the first critical hours improves containment and reduces operational risk.



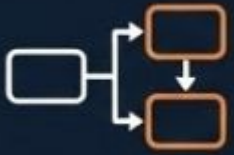
## Innovation & Scalability

The multimodal AI system generalizes across regions where Sentinel-2, Landsat, DEM, ERA5, and infrastructure layers are available. The framework can be replicated globally, providing a reusable template for data-driven wildfire risk management.

# Research Questions



**Can pre-fire multimodal data predict final burned area with sufficient accuracy to support early emergency decisions?**



**Do multi-task auxiliary objectives (e.g., land-cover segmentation) improve burned-area prediction?**



**which input data modalities contribute most to predictive performance?**



# Dataset Exploration



## Piedmont Wildfire Dataset (2012–2024)

**1090** wildfire  
events





# | Pre-Fire Data: Satellite Imagery & Environmental Drivers

## Satellite Imagery (Sentinel-2 & Landsat)

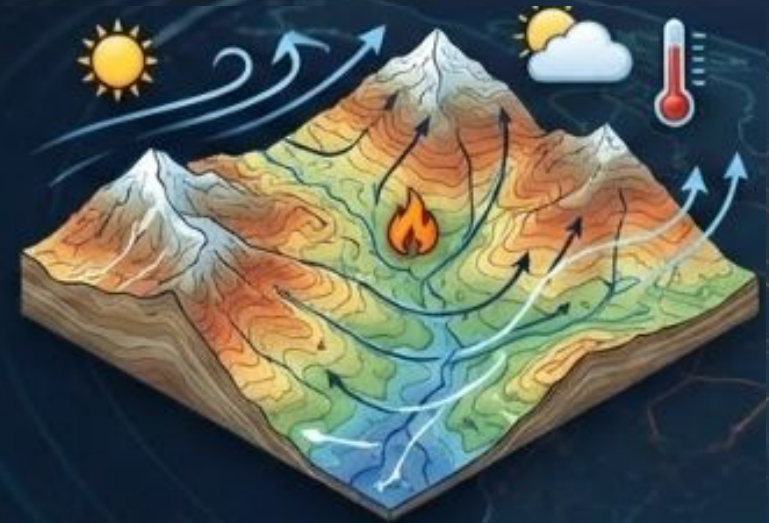


- Sentinel-2 Imagery:** 12-band multispectral, 10-20m res.
- why needed? captures immediate **pre-fire condition** (vegetation & fuel availability)



- Landsat Imagery:** Extra spectral info (SWIR/NIR)
- why needed? Sensitive to vegetation moisture and fuel dryness.
  - Complementary spectral response for fuel characterization.

## Environmental Drivers (DEM & ERA5)



- Topograph (DEM):** Terrain , slopes and valleys (30m res).

- why needed? Fire spreads uphill, **elevation is crucial** for behavior.




- ERA5 weather:** Temperature & wind at ignition time.

- why needed? Meteorological conditions are key drivers of fire expansion.
- wind vectors provide **essential dynamic information** for propagation direction.


## Ground-Truth Fire Labels (BURNED AREA MASK & IGNITION DATA)



 **Burned Area Mask:** Shape of the area that actually burned, Binary Segmentation (1 = burned, 0 = unburned)


**why needed?** Serve as a **target label** for supervised learning segmentation



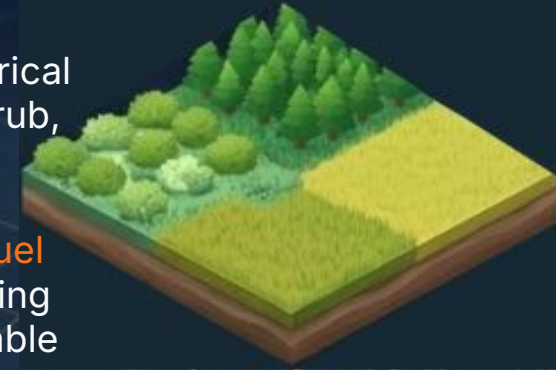
 **Ignition Data:** The exact location where the fire started. (Binary marker), derived from Civil Protection point data.


**why needed?** The model learns how the fire is likely to spread from that specific starting position.

## Land cover , Roads

 **Land cover Classification:** Categorical mask of vegetation types (Forest, Shrub, Grassland, etc.).

**why needed?** Critical for estimating **fuel type**, Assists the model in differentiating propagation potential based on available fuel.



 **Roads:** Binary road mask (10m resolution).

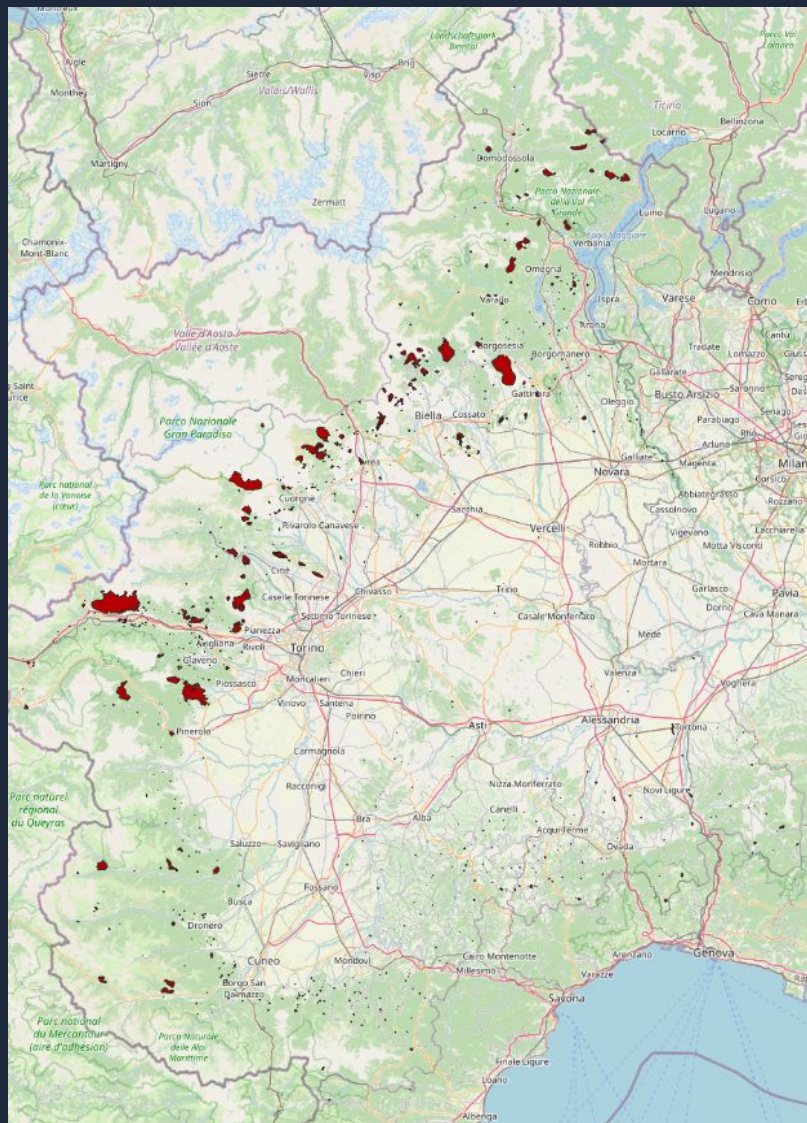
**why needed?** Captures both **human-caused** ignition likelihood and fire break potential.



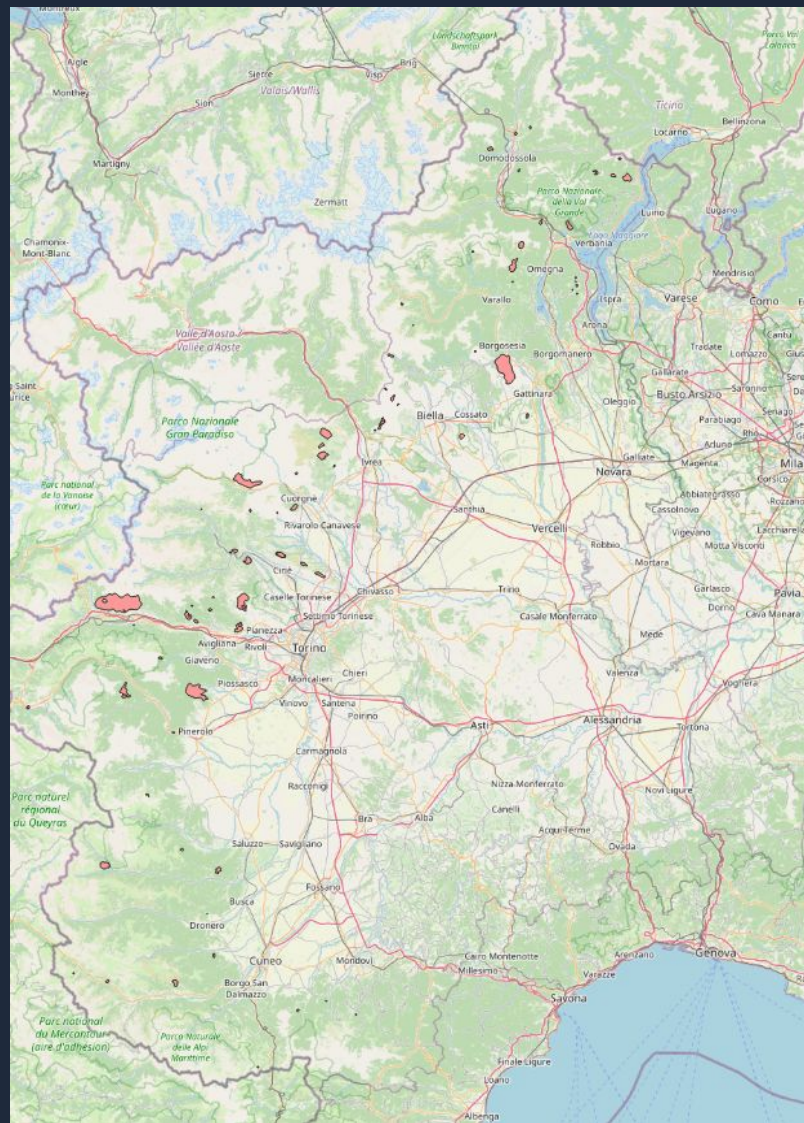


# Full comparison Fires in Piedmont (areas only)

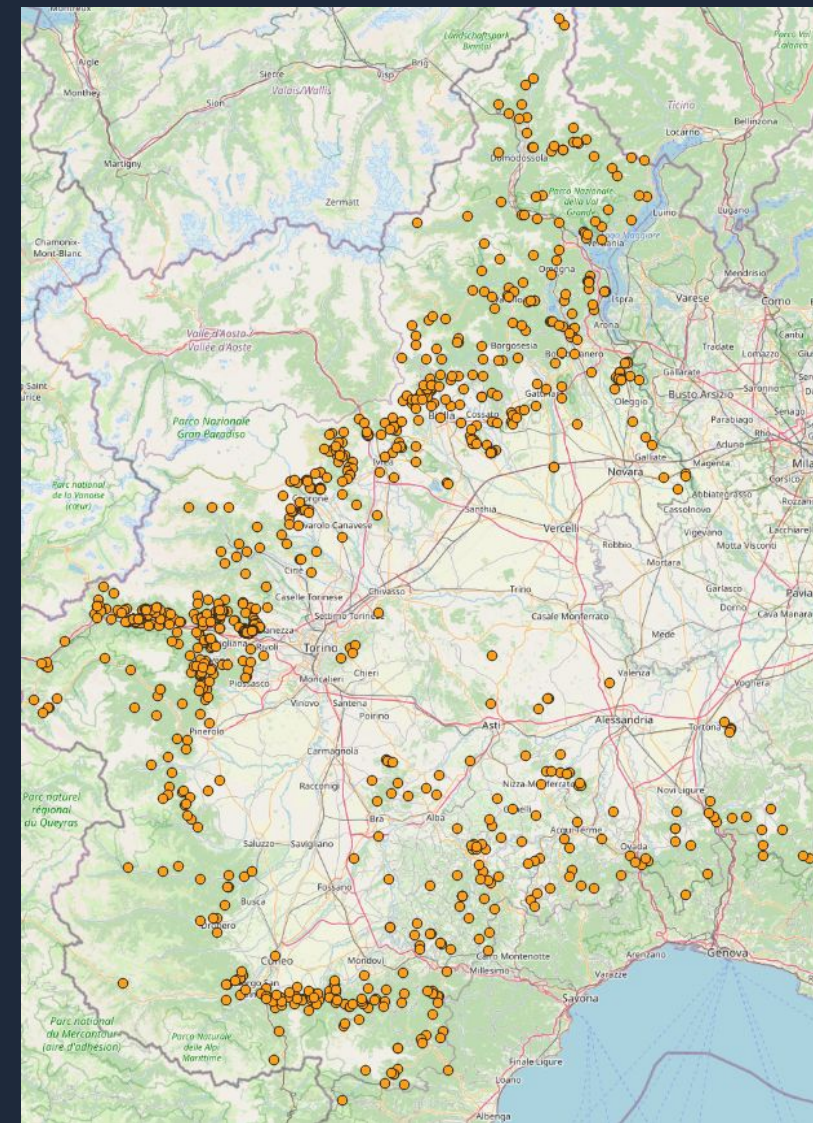
Civil Protection Area



EFFIS Area



Civil Protection Points





# Data Preprocessing: Ground Truth layer





## Data Origin & Projection:

Piedmont wildfires (2012–2024) stored as GeoJSON. Reprojected to UTM 32N (EPSG:32632) to serve as the unified coordinate reference system.



## Rigorous Filtering:

Events retained only if:

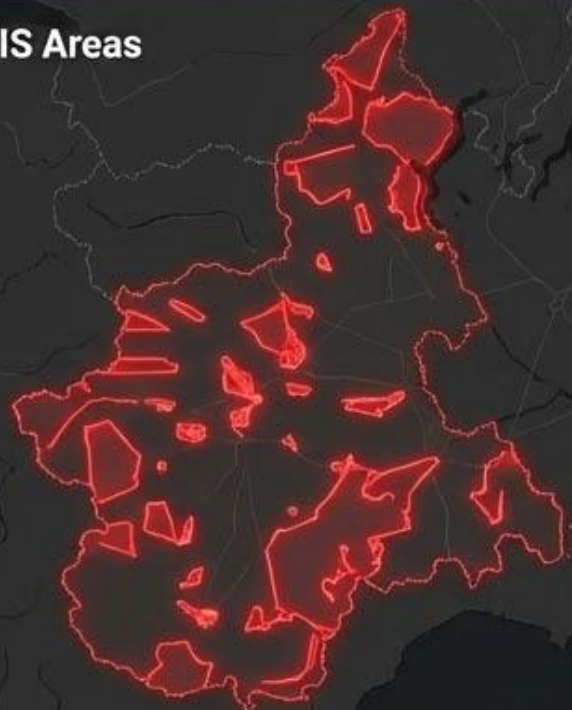
-  **Date  $\geq 2015-06-23$**  (Ensures Sentinel-2 coverage)
-  **Area  $\geq 200 \text{ m}^2$**  (Eliminates sub-pixel noise at 10m)

Civil Protection Areas



(C) OpenStreetMap contributors (C) CARTO

EFFIS Areas



(C) OpenStreetMap contributors (C) CARTO

Civil Protection Fire Points



(C) OpenStreetMap contributors (C) CARTO



# Data Preprocessing: Satellite Imagery

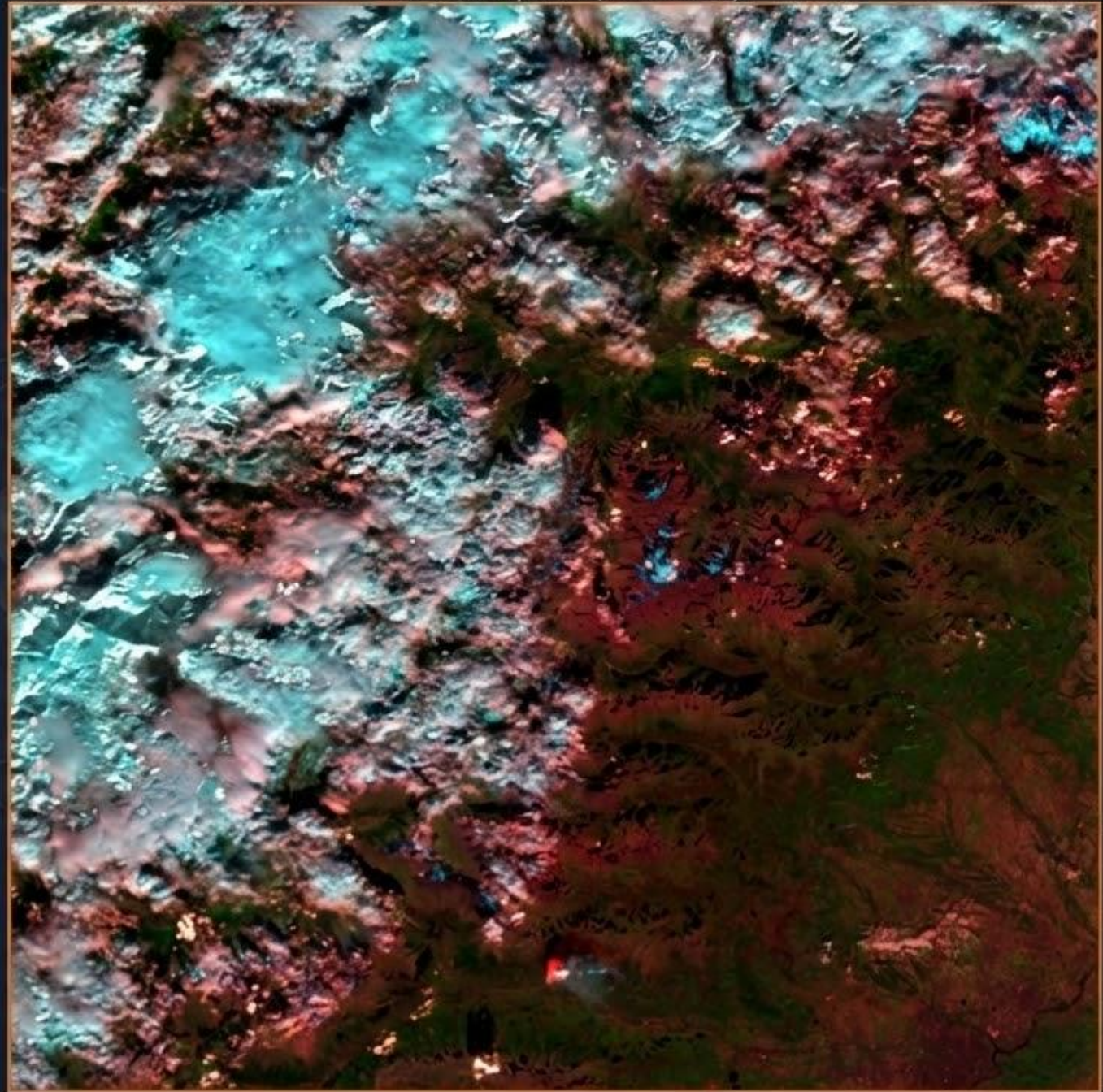
## Sentinel-2 Acquisition

- Queried via Microsoft Planetary Computer with a **7-day pre-fire window**. This captures vegetation conditions immediately preceding the event.
- Multispectral Processing: All bands (10m, 20m, 60m) are reprojected and resampled to the **10m reference grid** using bilinear interpolation.

## Optimization & Landsat

- **The 256×256 Reference Patch:**  
A fixed 2.56 km × 2.56 km square window centred on the fire geometry. This defines the target resolution (10m) and transform for all subsequent layers.
- **Landsat Integration:** Scenes are pre-resampled to **10m** to align perfectly with the Sentinel-2 spatial stack.

False color composition (SWIR/NIR/RED)





# Data Preprocessing: Cloud Exclusion



**Why it matters:** Clouds obscure ground features (occlusion) and alter pixel reflectance values (radiometric noise), creating “blind spots” in the dataset.

**Cloud Masking:** Used CloudSen12 to select the clearest Sentinel-2 acquisition within a 7-day pre-fire window. including cloudy parts forces the model to learn atmospheric artifacts rather than actual terrain features

**After: Clearest Acquisition (Selected)**



Sentinel-2 - Data: 2017-10-22 (Crop)

**Before: Cloudy Acquisition**



Sentinel-2 - Data: 2017-10-27 (Crop)

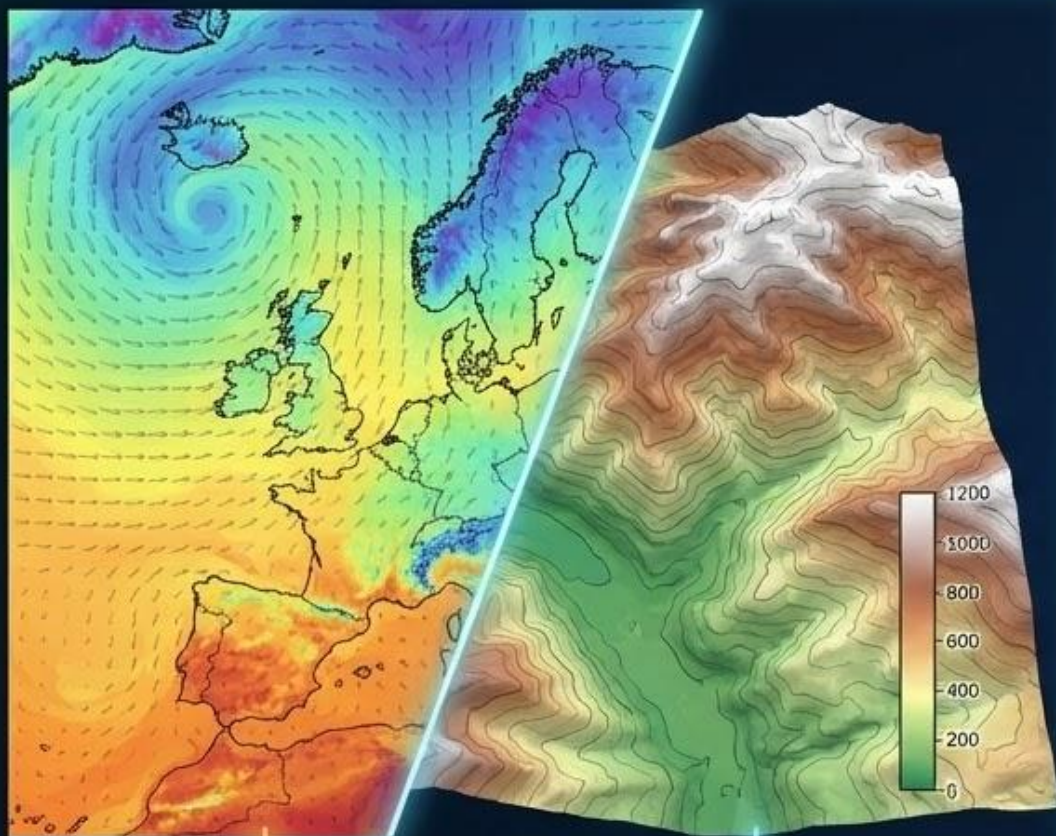
Filtering  
Process







# Data Preprocessing: Climate & Terrain Features



ERA5-Land  
Climate Data

Copernicus  
GLO-30 DEM



## ERA5-Land Climate Fields



**Synoptic Meteorology:** Daily statistics inferred from the pre-fire date.



**Variables:** Air temp (t2m), Dewpoint (d2m), Skin temp (skt), Soil temp profile (stll1–4), and Wind vectors (u10, v10).



**Downscaling:** Raw 0.1° (~10km) data is cropped and resampled to the 10m reference grid.



## Copernicus GLO-30 DEM



**Native Resolution:** 30m resolution is maintained to avoid artificial high-frequency artifacts.



**Process:** Reprojected to EPSG:32632 and resampled to the 256×256 patch (covering approx. 7.68 km × 7.68 km).

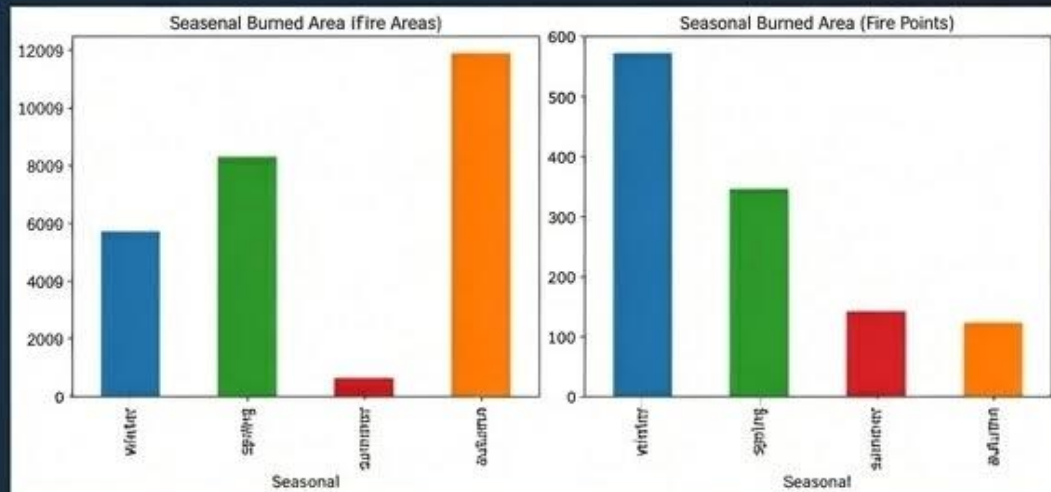


# Dataset Characteristics & Challenges

## Scientific Context: Seasonal Patterns & Imbalance



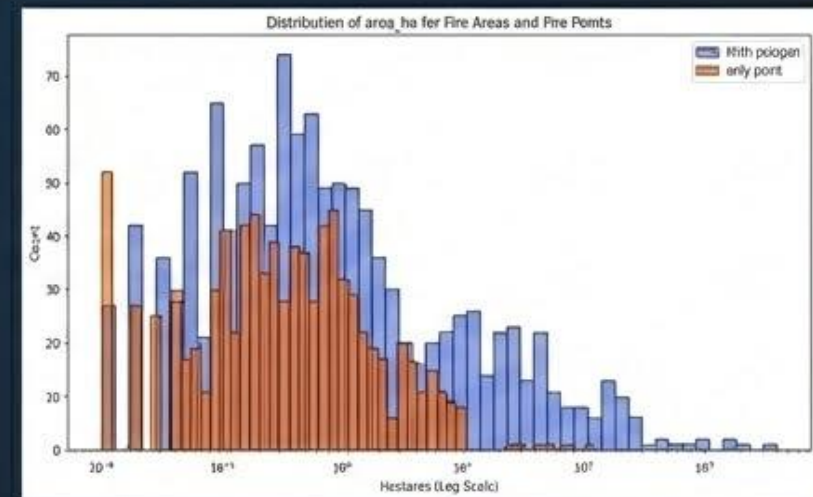
### Seasonal Disparities: Frequency vs. Severity



- The number of fires doesn't match how much land gets burned.
- Winter has the most fire starts, but they usually stay small.
- Autumn has fewer fires, but they grow much bigger and burn more land.
- This means we need to predict how *\*bad\** a fire will be, not just if it will start.



### Size Distribution & Dataset Imbalance



- Our data is very unbalanced, with a 'long tail' of rare events.
- Most fires are tiny (less than 1 hectare, like a small field).
- The "Polygon" data (blue) shows the rare but huge fires (>100 ha) that cause the most damage.
- This imbalance makes it hard to teach a computer model to predict the big, important fires.

# Model Inference Example: Sentinel Input → Fire Mask Output

## Model Output Visualization - Baseline Performance



### Input & Challenge

- Single Sentinel-2 crop (all spectral channels).
- Extremely small ground truth fire footprint creates severe class imbalance.



### Baseline Result

- Model overpredicts and mis-localizes the burned area.
- Visual result matches quantitative score (IoU  $\leq 0.1$ ).

Sentinel Input  
(pseudo-RGB)



Ground Truth  
Burned Area



Predicted  
Burned Area

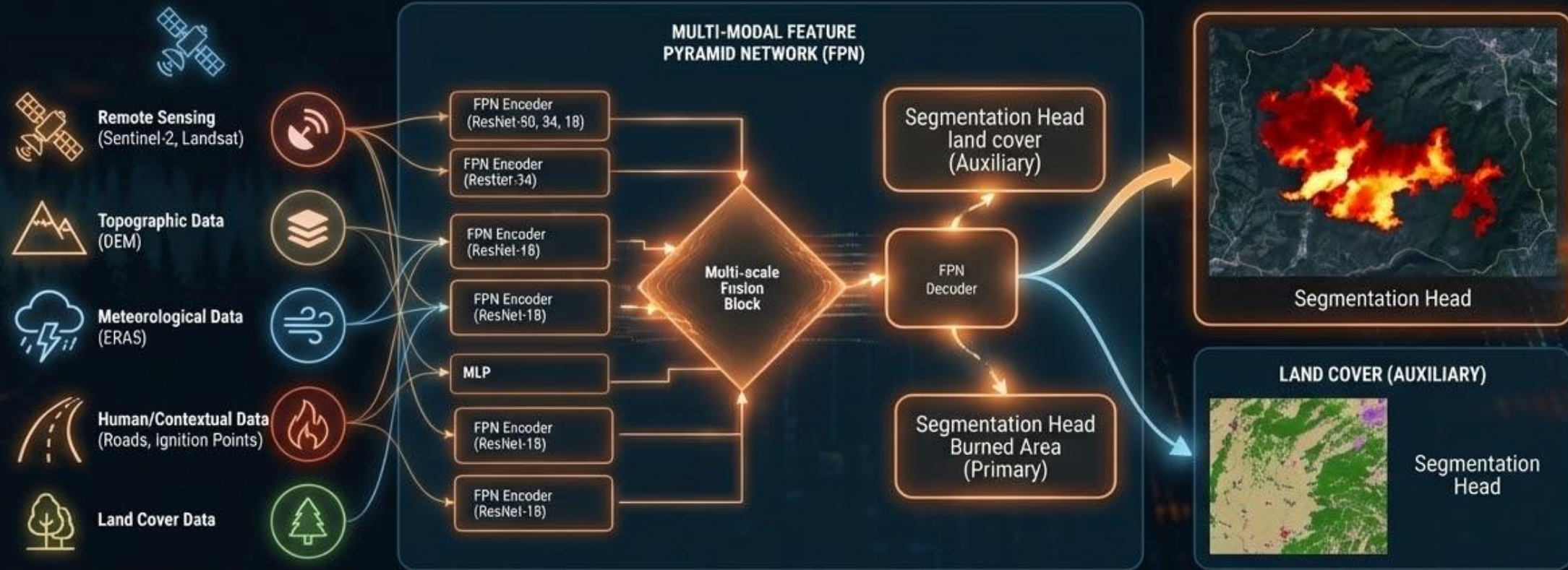


IoU  $\leq 0.1$



# METHODOLOGY: MULTI-MODAL FPN

INPUT DATA:  
MULTI-SOURCE ENVIRONMENTAL & GEOSPATIAL



A custom architecture extending the **Feature Pyramid Network (FPN)** design to handle 7 distinct input streams.

Key Innovation: Specialized encoders for each modality + Lateral Fusion + Multi-Task Heads.



# FUTURE STEPS I: DATA, MODELING & EVALUATION

## 1. EXPAND BEYOND SINGLE-MODALITY INPUT



- Integrate multi-modal data sources: Sentinel optical bands, thermal anomalies, vegetation indices (NDVI), weather forecasts, topography (DEM).
- Objective: reduce reliance on RGB alone and prevent the model from “cheating” by using trivial cues.

## 2. IMPLEMENT SPATIOTEMPORAL MODELING



- Add temporal sequences (pre-fire + fire-progression windows).
- Explore ConvLSTM / Vision Transformer (ViT) temporal stacks.
- Outcome: capture fire evolution dynamics rather than static frames.

## 3. ROBUST EVALUATION FRAMEWORK



- Introduce IoU, precision/recall, F1, Dice Score, and per-class metrics.
- Build a standardized inference pipeline for region-level scoring.
- Add BCS (Burned-Area Consistency Score) to detect implausible segmentations.



Thanks for the attention

Any questions ?