Geospatial foundation models for wildfire detection in the UK

Rémy Vandaele[1], Chunbo Luo[1], Hywel Williams[1], Edward Pope[2]

[1]University of Exeter
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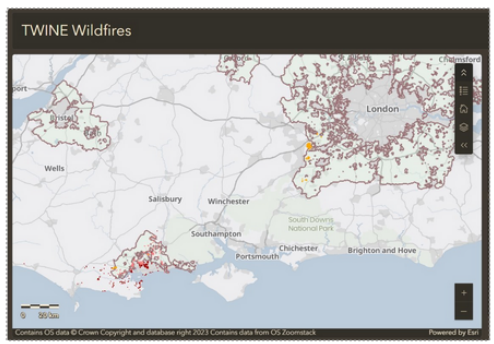
19 June 2025

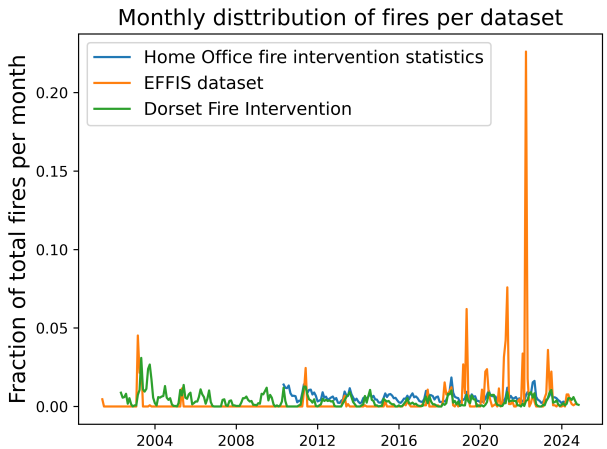
GreenSight project

TWINE Met Office/NERC initiative

- Support the development of **QUEST**
  - Met Office's digital twin demonstrator
  - Assist multi-objective land-use decision
  - Focus on UK green belts
- Inform decisions in two key areas:
  - Carbon dynamics
  - Wildfire occurrence



Current methods and limitations



UK wildfire dataset analysis

- Seasonal patterns/yearly trends

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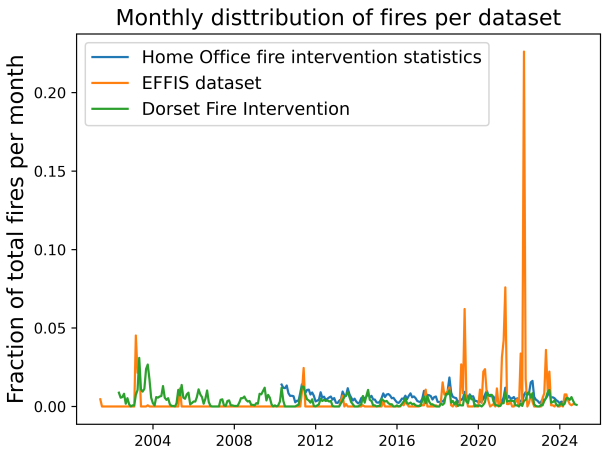

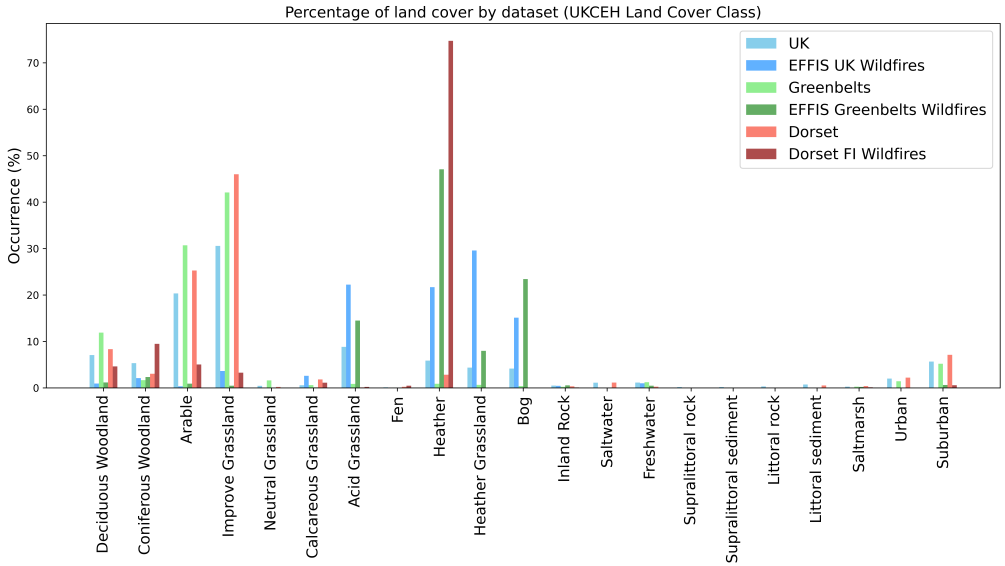

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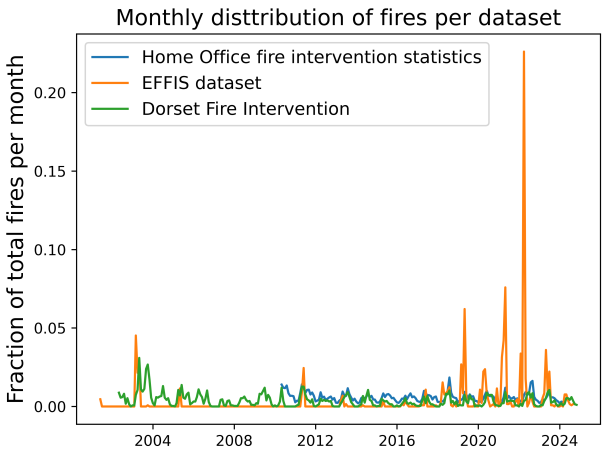
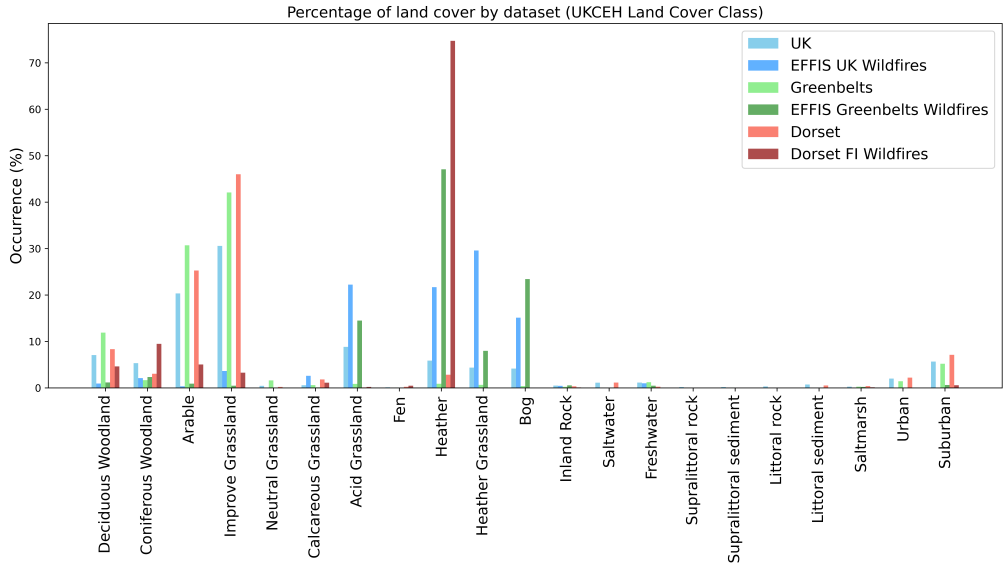


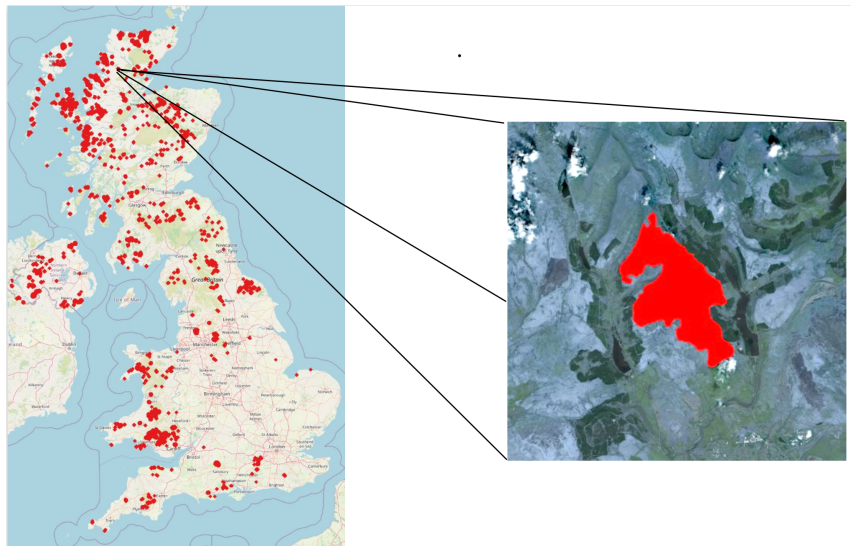


UK wildfire dataset analysis

- Seasonal patterns/yearly trends
- Mapping wildfire polygons with land cover maps (e.g., UKCEH/Natural England)
- Our current 3 wildfire datasets have limitations
  - EFFIS: only large fires are recorded
  - Dorset Fire Intervention: local dataset
  - Home Office statistics: no polygon data / accurate wildfire location

Our objectives

Leverage geospatial foundation models to generate a more consistent and comprehensive record of wildfires in the UK.



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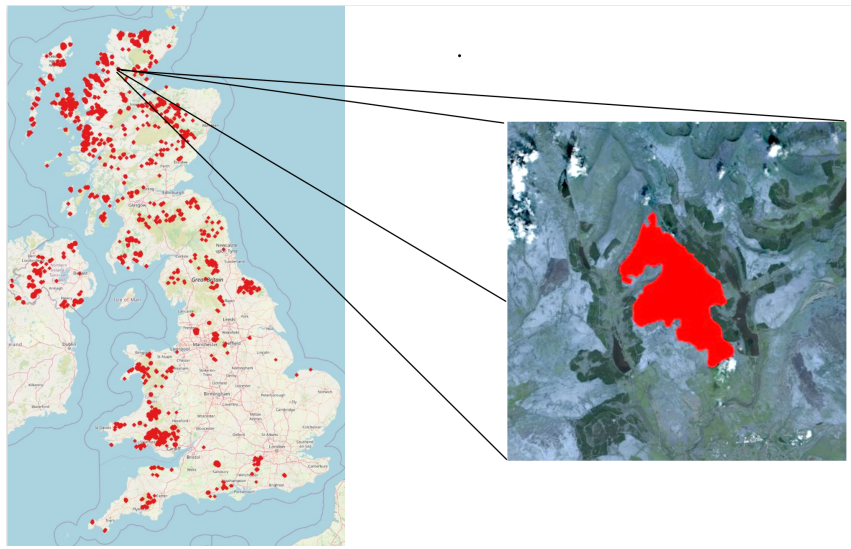

Step 1. Evaluate the performance of the Prithvi geospatial foundation model for wildfire detection

- Fine-tune and validate the model on curated wildfire datasets

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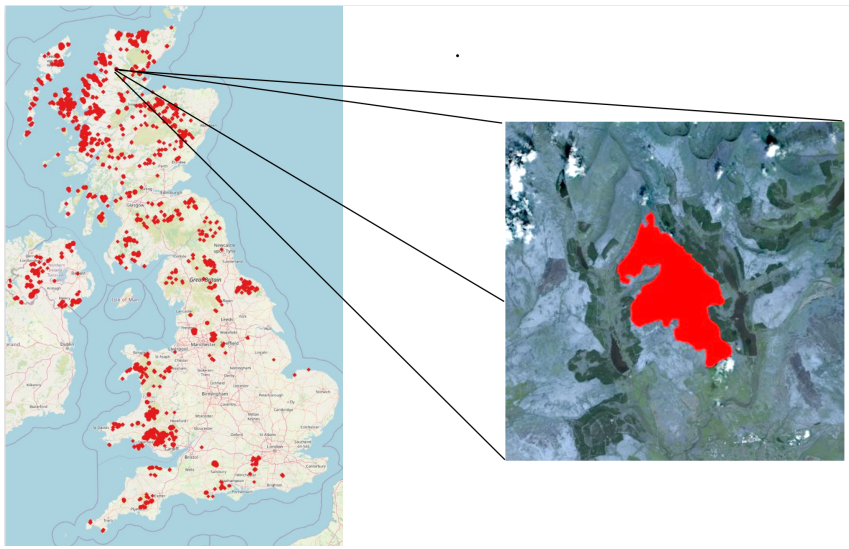

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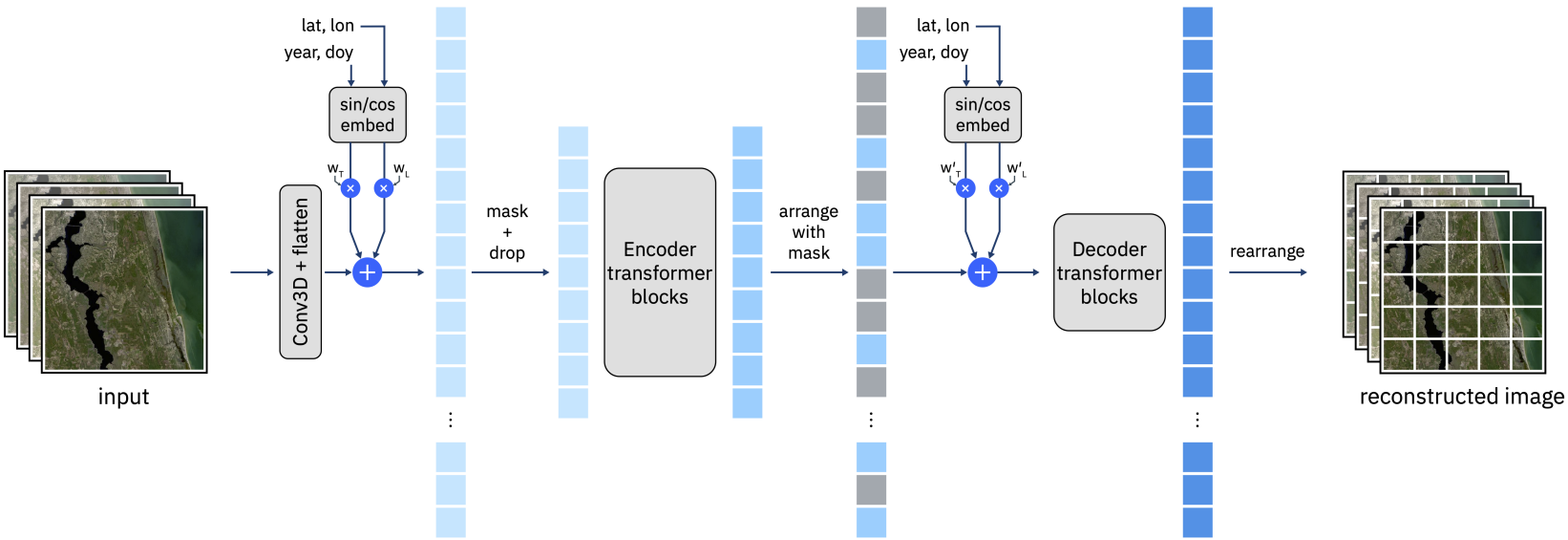
Step 2. Develop a pipeline to create a new database of wildfire records

Prithvi-EO 2.0

Geospatial foundation model developed by IBM Research/NASA

- Vision Transformer architecture
- Pre-trained on a Masked Auto-Encoder task using 4.2M samples



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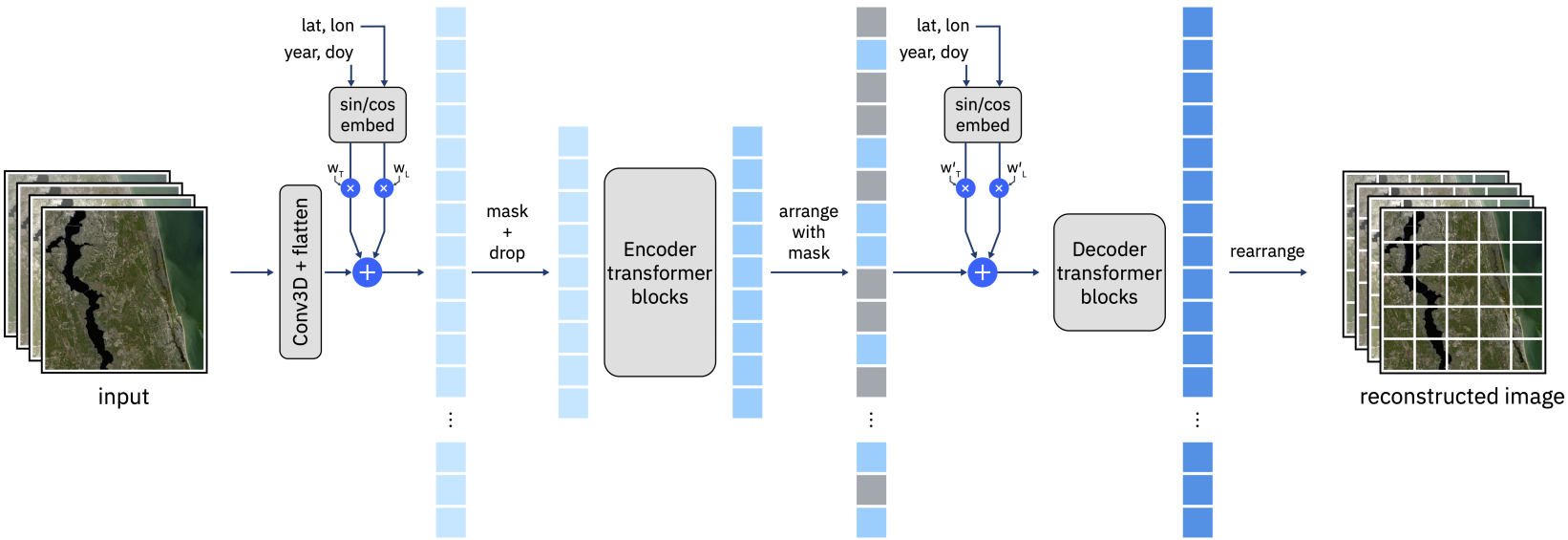

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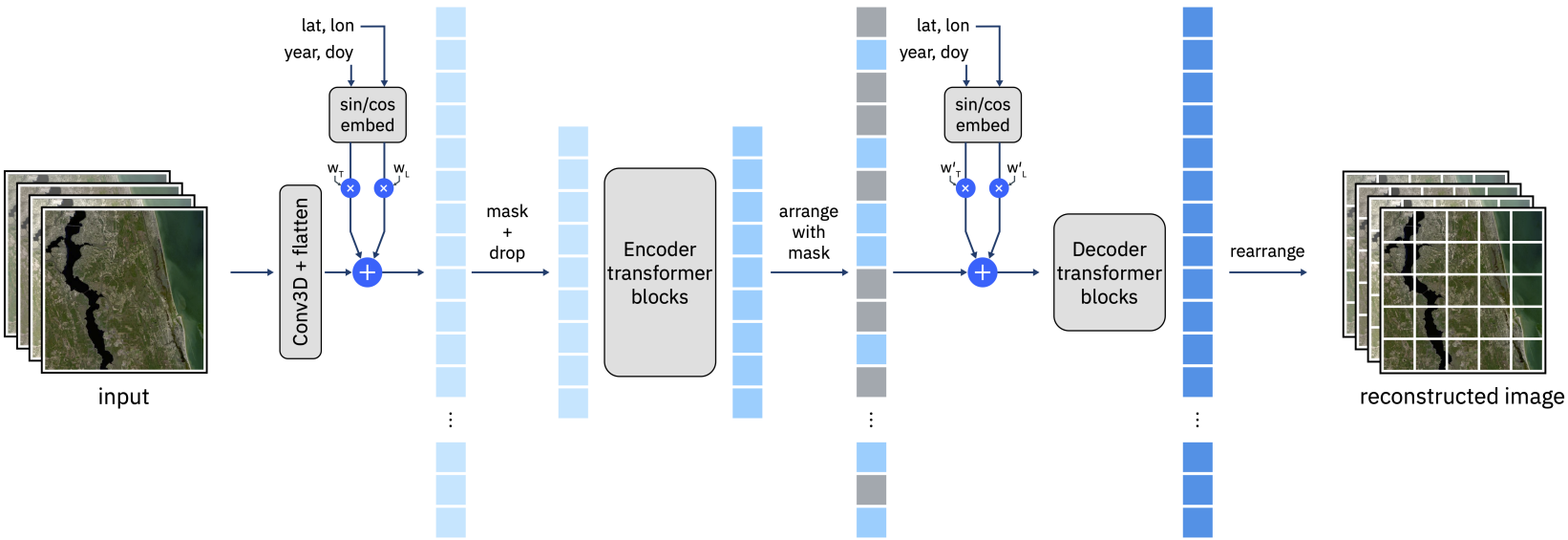
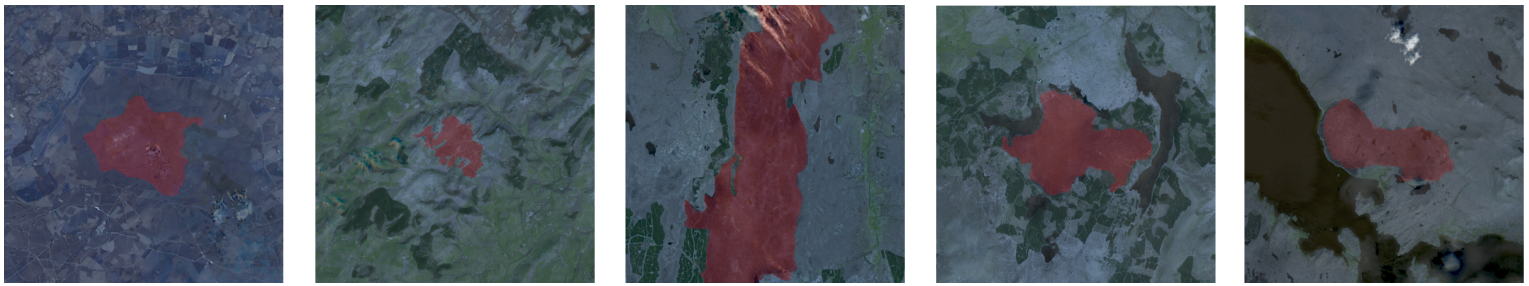


- Fine-tuned and validated on a wide range of applications, including burn scars detection
- Harmonized Landsat and Sentinel (HLS) data
  - 6 bands: blue, green, red, narrow NIR, SWIR1, SWIR2

Building the UK wildfire dataset



Creation of 444×444 HLS patches centered around wildfire polygons

- HLS image must be acquired within 10 days of the wildfire start date
- Patches with more than 50% of no data/cloud are discarded
- Random 224×224 cropping during training

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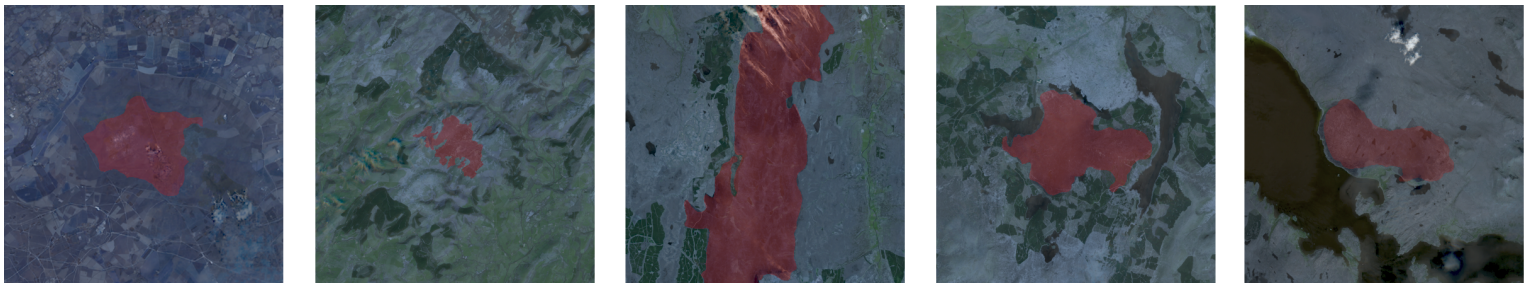

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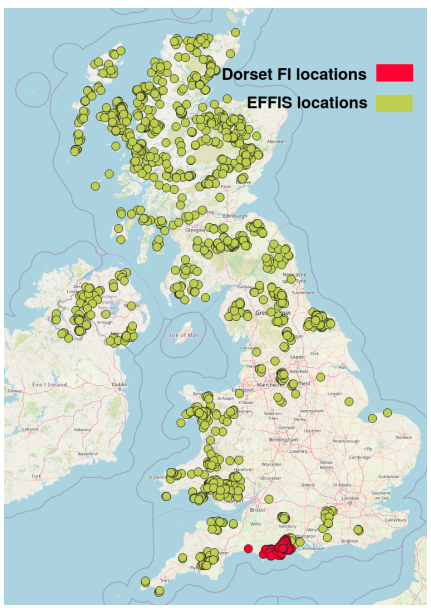

EFFIS dataset (2013 - 2024)

- Captures the large wildfires ($>$ 30ha).
- 940 patches

Dorset Fire Intervention dataset (2013 - 2024)

- Captures smaller wildfires.
- 129 patches
- EFFIS captured 3 wildfires in Dorset

Experimental Protocol

Training and evaluation on EFFIS dataset
5-fold cross-validation for hyperparameter tuning

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Methods compared:

1. Prithvi-EO-2.0
   - With/without pre-training
   - 6 HLS bands
2. Pixel-wise Random Forest classifier
   - 12 HLS bands
   - Random selection of 1000 wildifre and 1000 not wildfire pixels
3. Normalized Burn Ratio (NBR)
   - $NBR = \frac{NIR - SWIR}{NIR + SWIR}$
   - Best threshold chosen at validation for the segmentation

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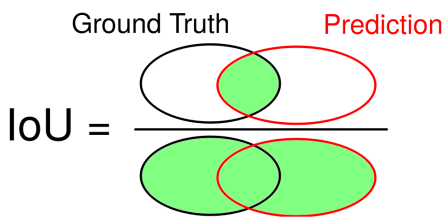
Mean Intersection over Union (MIoU) error criterion:

$$MIoU = \frac{IoU_{wildfire} + IoU_{notwildfire}}{2}$$



Results on the EFFIS dataset

Model	MIoU
Prithvi (pre-trained)	0.94
Prithvi (scratch)	0.89
Random Forest	0.79
NBR	0.61

Prithvi (pre-trained) has the best performance overall

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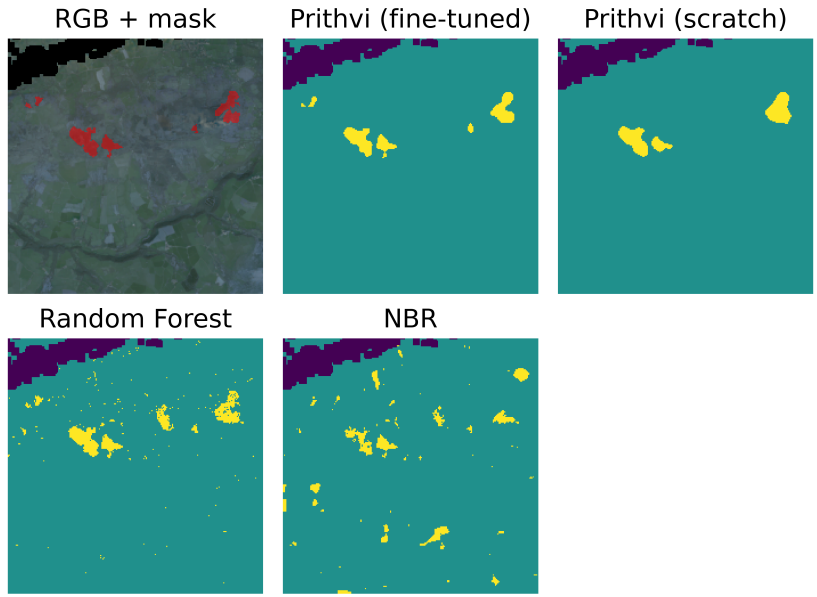

Prithvi (pre-trained) has the best performance overall

- Prithvi (scratch) tends to miss the smaller fires
- Random Forests generate false positives
- NBR generates false positives and false negatives

Results on the Dorset FI dataset

Direct application of the models trained on the EFFIS dataset on the Dorset FI dataset

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$<$ 1ha	0.5	0.5	0.5
$<$ 2ha	0.5	0.5	0.5
$<$ 5ha	0.57	0.5	0.5
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- 50% of Dorset FI dataset fires are $<$ 2ha (22 pixels), hard to detect
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- The results are much better than EFFIS
- No Dorset FI data was used for training

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- Validate the model using additional datasets
- Use the model to generate a new wildfire dataset in the UK (greenbelts)

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