#EUSpace

OVERWATCH

EUSPA AI week 2026

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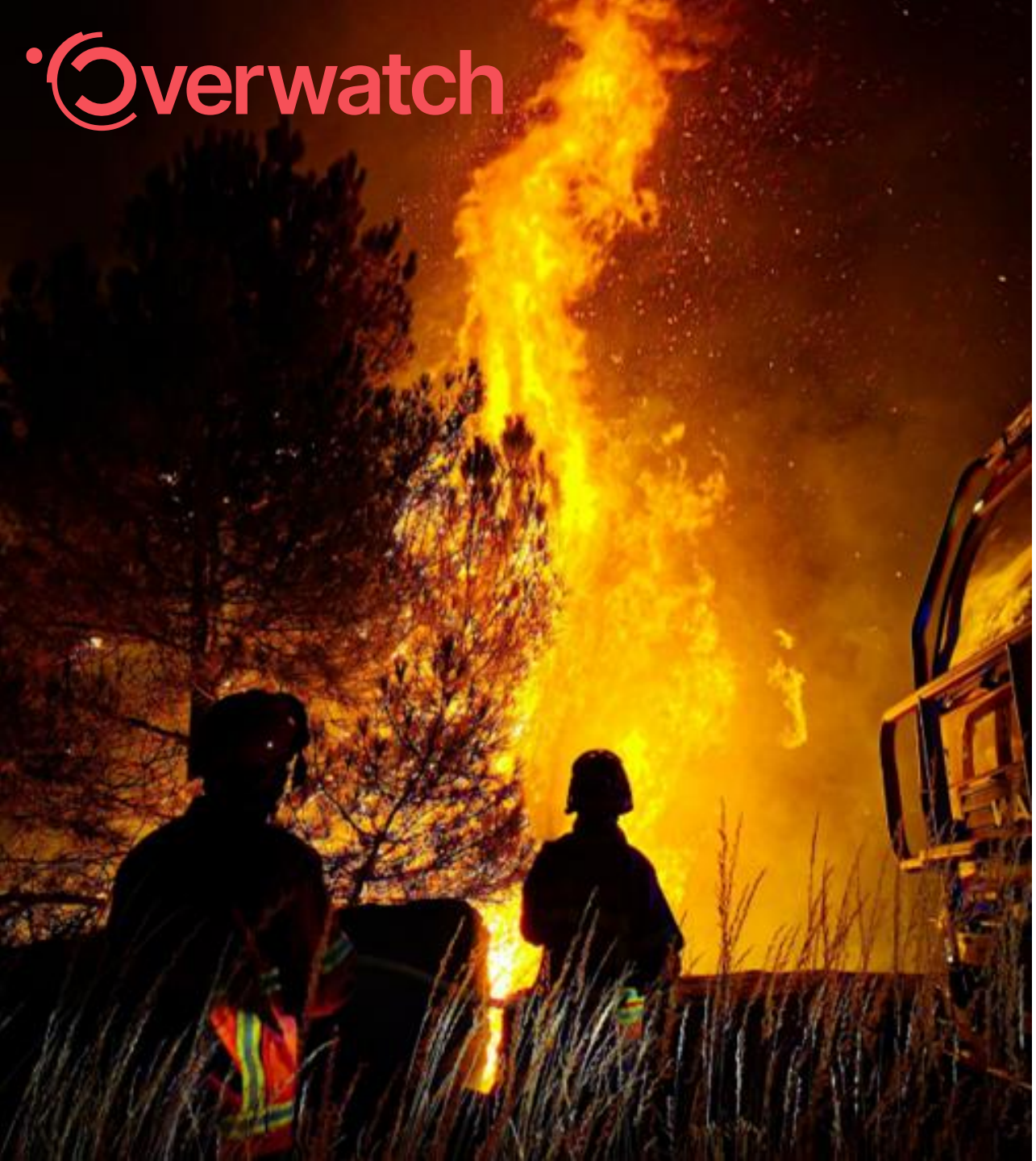
EUSPA
European Union Agency for the Space Programme



Project Overview

https://overwatchproject.eu/en

Project funded from the Horizon Europe call «HORIZON-EUSPA-2021», topic HORIZON-EUSPA-2021-SPACE-02-52 under agreement No. 101082320

#EUSpace

Technologies and aims

The **OVERWATCH** project seeks to develop an integrated **crisis management system** to enhance communication, information gathering and coordination among **disaster response teams** in case of **wildfire and flood events**.

Earth Observation

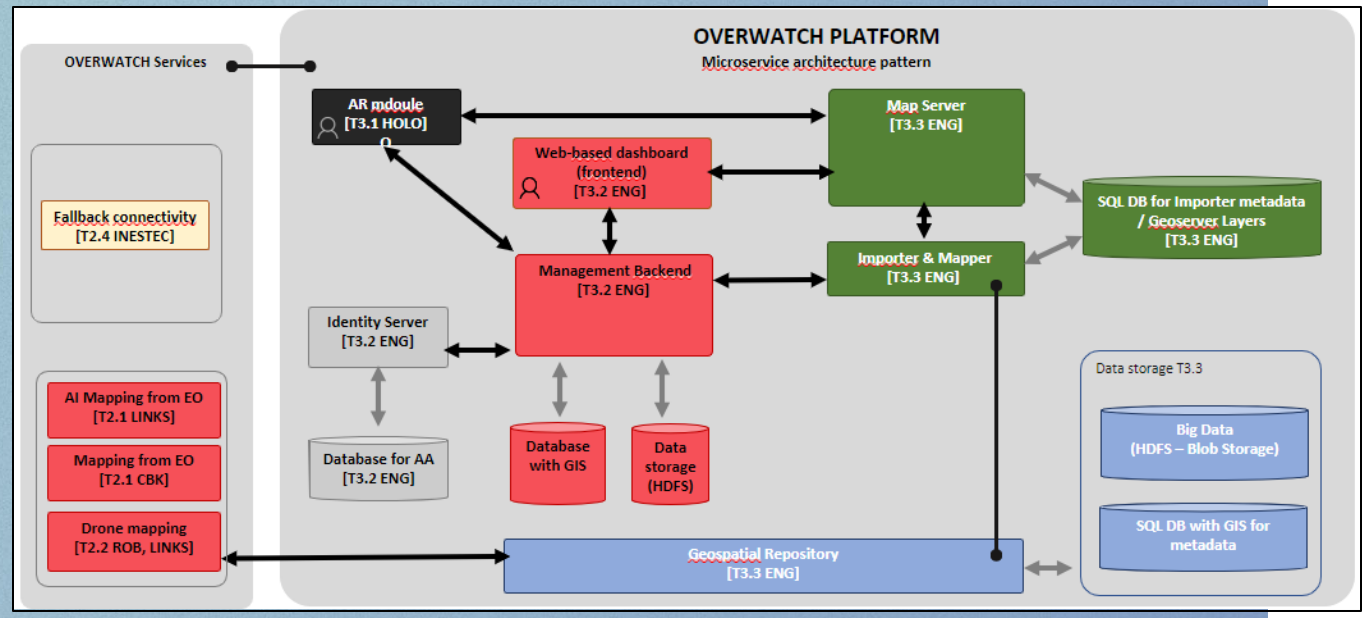
Artificial Intelligence

Drones

Augmented Reality

GNSS – Galileo HAS

System Concept

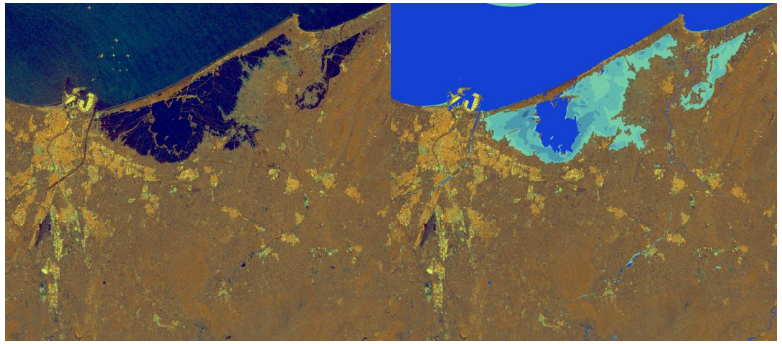


- **OVERWATCH Platform**
  - Management Backend, Map Server, Importer & Mapper, DBs, Data Storage, Geospatial Repository, Identity Server, Web Dashboard
  - AR
- **OVERWATCH Services and Hardware**
  - Fallback Connectivity
  - **AI Mapping from EO**
  - Drone Mapping

Wildfire Pilot Demonstration

Artificial Intelligence & OVERWATCH

Deep learning algorithms streamline the analysis of satellite imagery for **wildfires**, **floods**, and infrastructure **damage assessment**, providing fast, on-demand delineations.



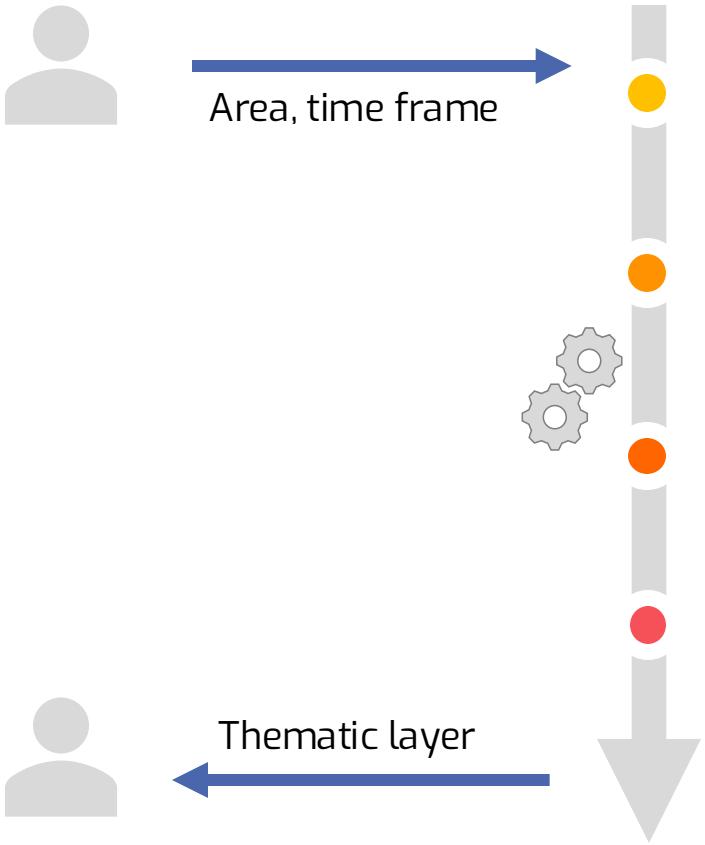
Flood Delineation

Damage Assessment

Burned Area Delineation

AI-Based EO Pipelines

Processing is **orchestrated via Apache Airflow** on a multi-GPU architecture, producing **INSPIRE-compliant GeoTIFF** outputs stored in CKAN databases.



1. Data Acquisition

Sentinel-1 for floods, Sentinel-2 for wildfires, VHR (0.3 to 0.5m) for damage assessment.

2. Pre-Processing

Radiometric Terrain Correction, Image Normalization and Cropping, etc.

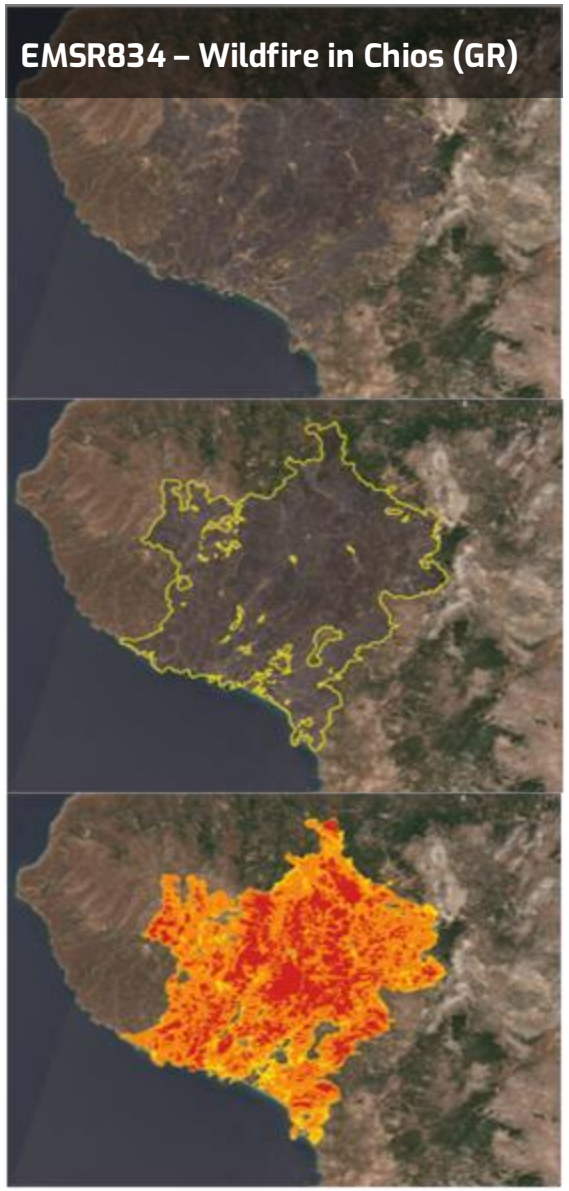
3. AI Inference

Smooth tiling, parallel batching on NVIDIA Triton Inference Server.

4. Storage and Output Delivery

GeoTIFF maps, uploaded to CKAN with INSPIRE Metadata, converted into WMS.

Burned Area Delineation – At a glance

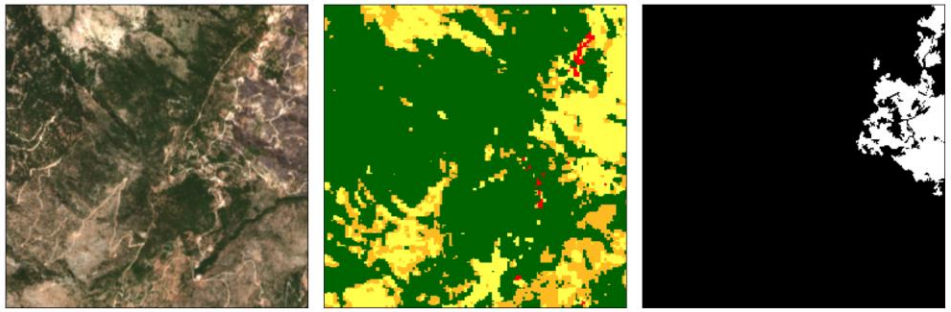


- **OBJECTIVE**
  - Identify burnt areas from Sentinel-2 images.
  - **Task: binary segmentation** → burned areas from post-event images.

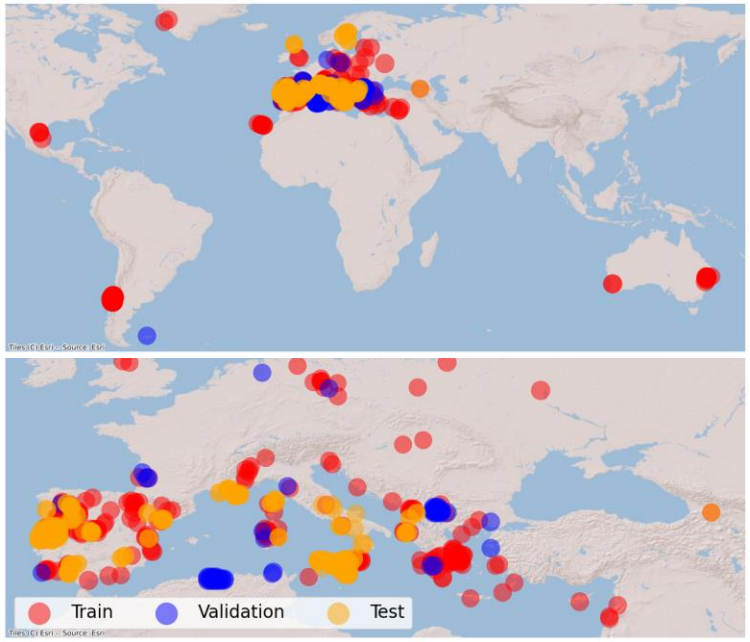
- **INPUTS AND METHODS**
  - Trained on **Sentinel-2 L2A** (10m, all 12 bands)
  - Dataset derived from harmonizing **Copernicus EMS events**, up to late 2023.
  - Method: adapt the model to different geographical conditions and domains **jointly training on land cover and burned area tasks**.

Burned Area Delineation - Dataset

171 wildfire events, for a total of **433 areas of interest**, spanning from **2017 to Q1 2023**. Predominantly concentrated in Europe, with select events in Australia and the Americas.



- **CONTENTS**
  - **Sentinel-2:** satellite imagery with minimum cloud coverage, L2A, 12 bands
  - **Delineation:** binary mask representing the affected area, single band
  - **Grading**: when present, provides a graduated damage scale (0 – 4)
  - **Land Cover:** multi-class segmentation label derived from ESA WorldCover 2020
  - **Cloud Mask:** cloud mask to exclude covered areas, generated through Sencloud12

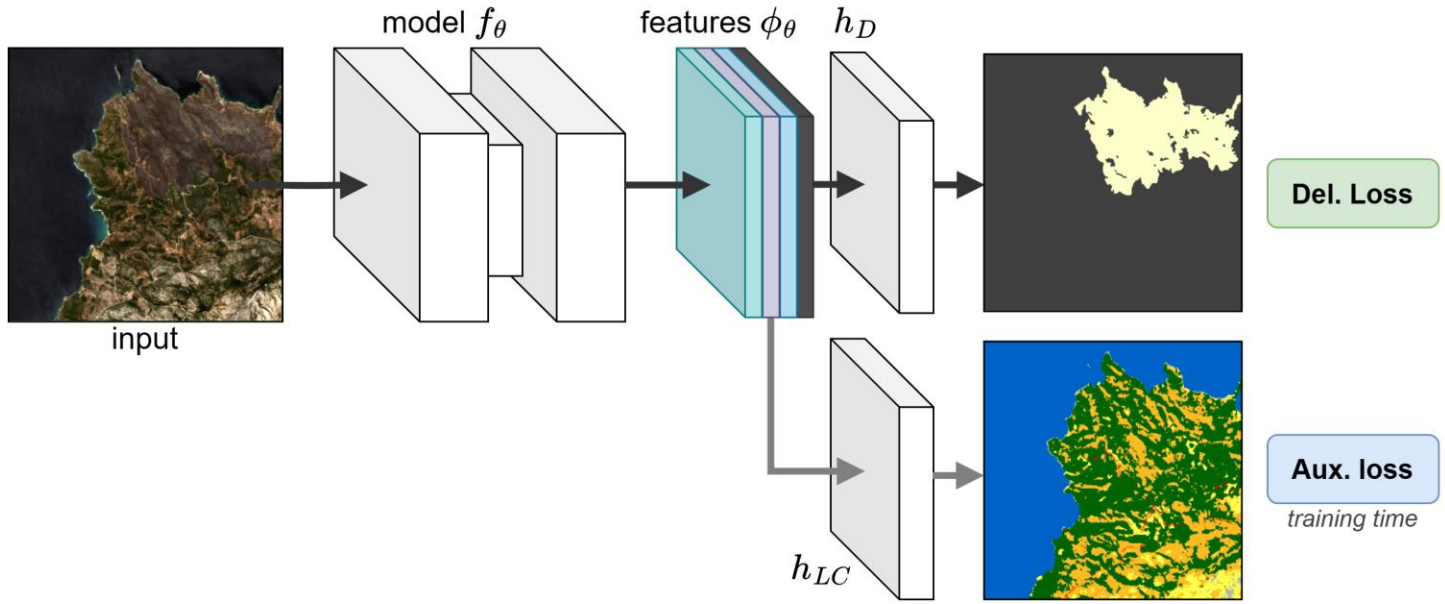


https://huggingface.co/datasets/links-ads/wildfires-cems

Burned Area Delineation - Methodology

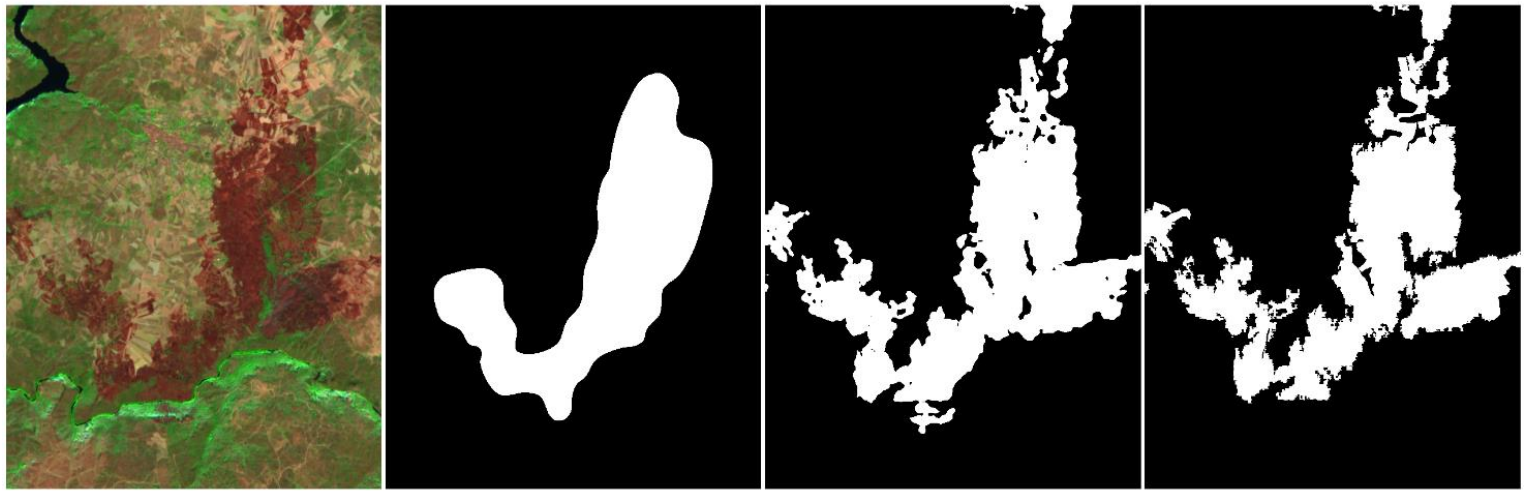
- **Multitask learning framework** for burned area delineation (yD),

  with land cover classification as an **auxiliary target** (yLC).



Burned Area Delineation - Results

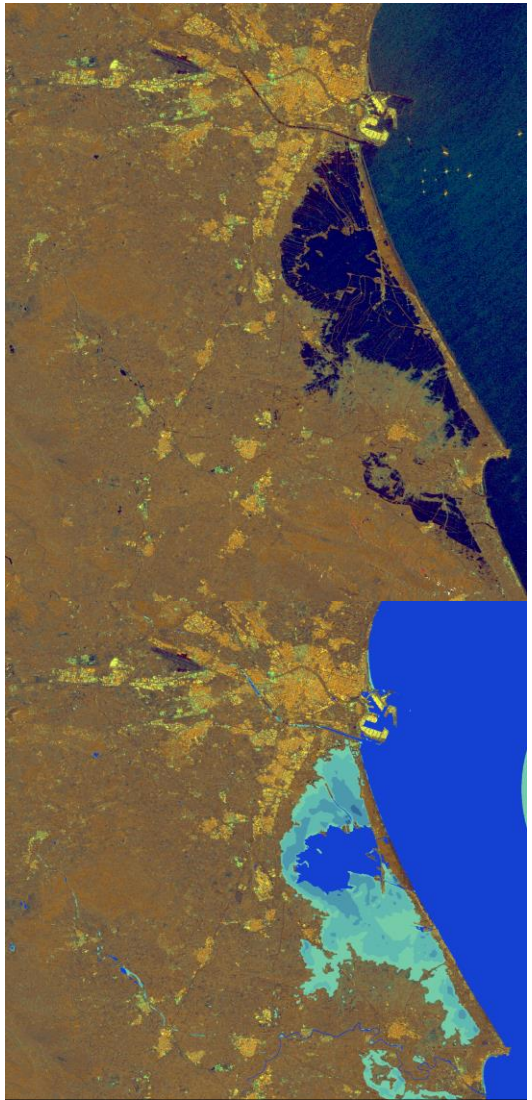
- Burned Area Delineation performance against CEMS-W: **0.92 F1** (ResNet50 - UPerNet decoder)
- Multitask Learning effectively makes **models more robust**, especially when trained from scratch.
- **+13% improvement vs. EFFIS** (200+ events), against manually validated labels.



SENTINEL-2 | EFFIS | Ours | Ground Truth

Metric	EFFIS	Ours
IoU	0.60	**0.73**
Precision	0.73	**0.76**
Recall	0.77	**0.95**
F1-score	0.75	**0.85**

Flood Delineation – At a glance



EMSR773 – Flood in Valencia (ES)

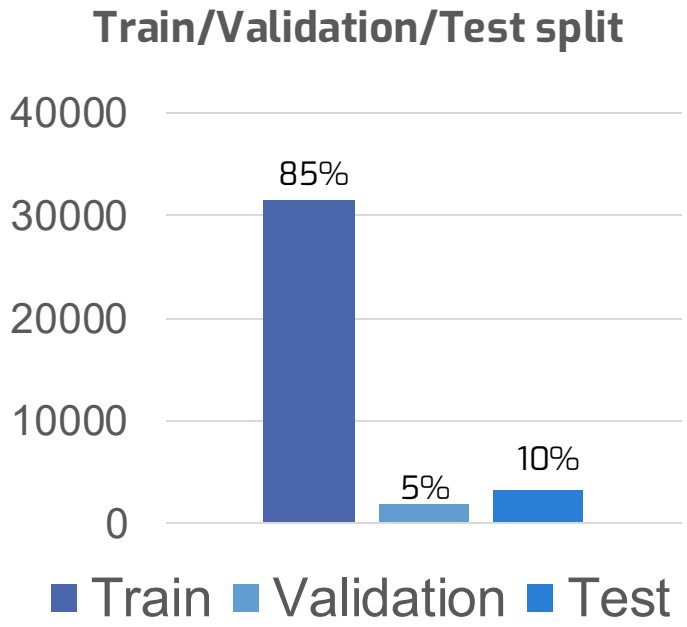
- **OBJECTIVE**
  - Identify flooded areas from Synthetic Aperture Radar (SAR) images.
  - **Task: water body delineation** → flood as difference between pre- and post-event image

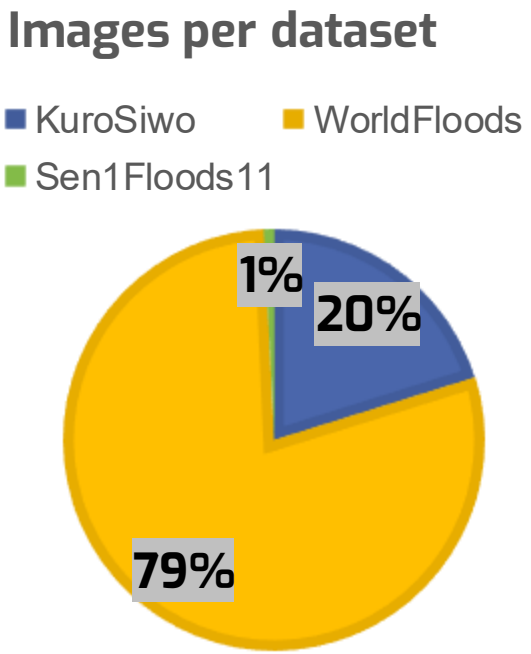
- **INPUTS AND METHODS**
  - Trained on **Sentinel-1 SAR RTC** (10m)
  - Dataset derived from harmonizing **KuroSiwo**, **Sen1Floods11** and **WorldFloods** datasets.
  - Tested several EO Foundation Models as encoder, including **Prithvi**, **DOFA**, and **Terramind.**

Flood Delineation - Dataset

1. **Collect available Flood dataset**
2. **Retrieve missing modalities** (RTC etc.)
3. **Calculate cloud mask**
4. **Apply constraints**
   - Selected only tiles with a **cloud cover lower than 20%**
   - Selected only tiles where both modalities are present and are **not more distant than 7 days**
   - Selected only tiles where **atleast 0.1% of pixels are «water»**

Dataset	No. images before filters	No. images after filters
KuroSiwo	49938	7422
WorldFloods	175514	29080
Sen1Floods11	395	261





Flood Delineation - Methodology

- A set of backbones were trained/evaluated (**ResNet**, **Swin**, **ViT**, **ConvNext,** ...)
- These included models trained *from scratch* and pre-trained Foundation Models

FOUNDATION MODELS

«Fixed» input

SSL4EO (2022)

- Trained ResNet50, ResNet18 and ViT using different **unsupervised techniques** on the **SSL4EO** dataset
- Trained on **Sentinel-2 RGB** and **Sentinel-1 GRD**

SATLAS (2023)

- Pre-trained ResNet50, ResNet152 and Swin on 7 tasks
- Trained on **Sentinel-2 (9 bands)** and **Sentinel-1**

PRITHVI-v2 (2024)

- 6 bands of **Harmonized Landsat-S2** using a masked autoencoder
- Uses **ViT** as a backbone

«Flexible» input

DOFA (2024)

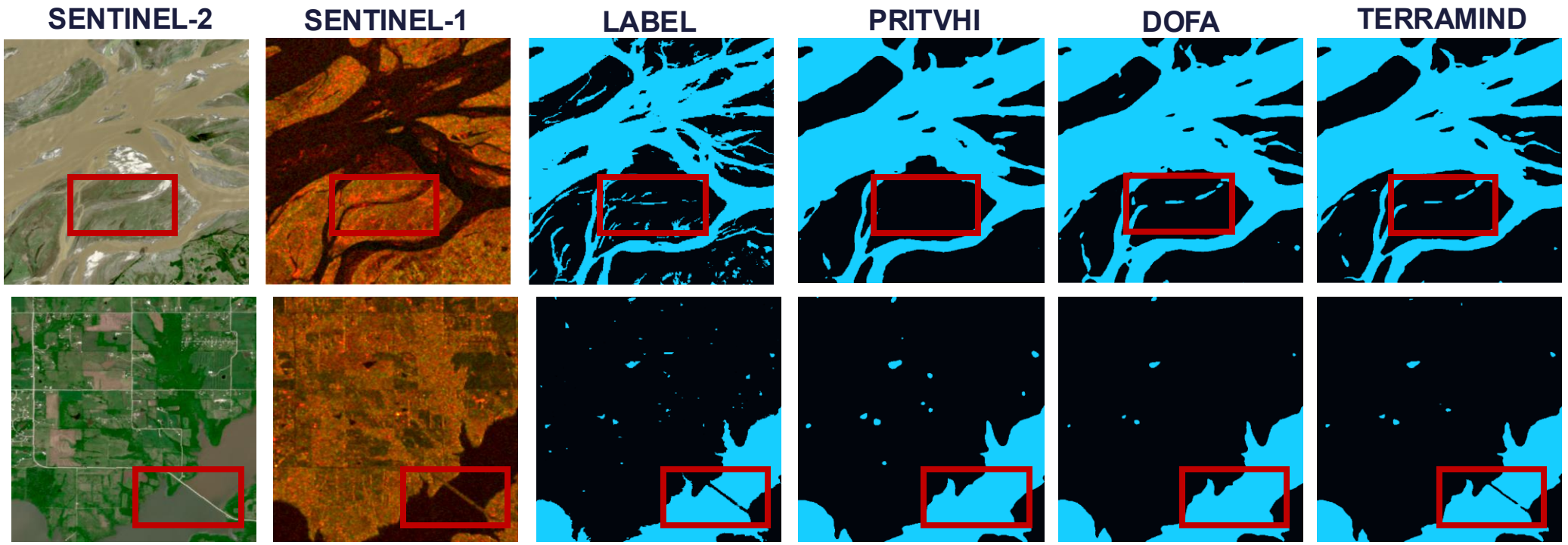
- **wavelength** as a **unifying parameter** across various EO modalities
- **Shared vision Transformer as backbone**
- **Pre-trained** based on optical, SAR and VHR using MAE

TERRAMIND (2025)

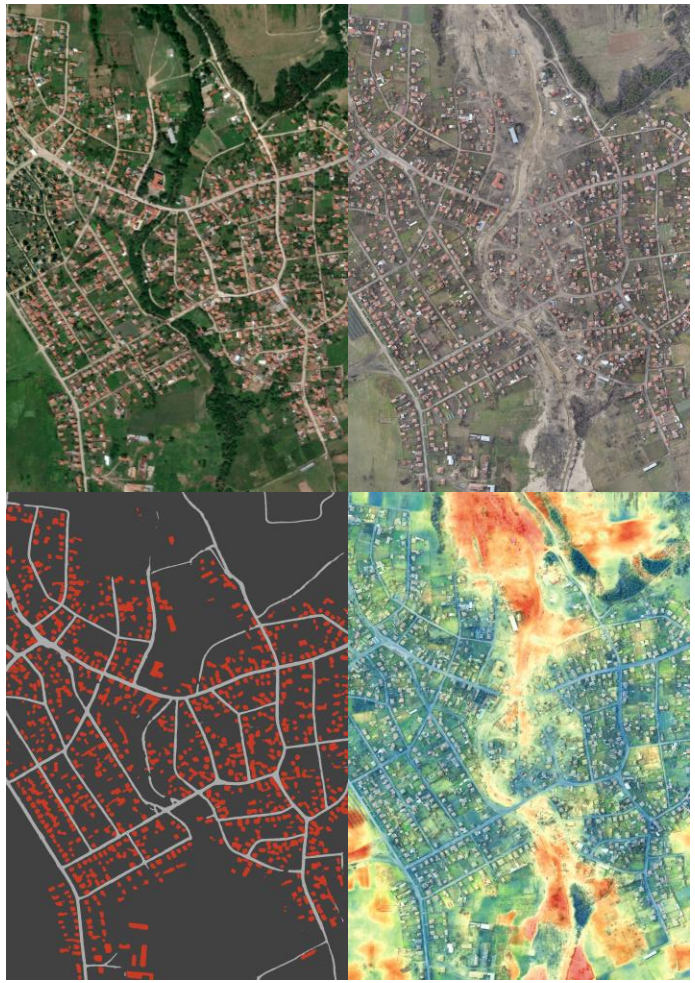
- Pretrained on 9 million samples (optical, SAR)
- Uses **unimodal tokenizer models** to embed the modalities
- Uses **ViT** as a backbone

Flood Delineation - Results

- Delineation performance on **KuroSiwo** (TerraMind): **0.95 F1**
- Delineation performance on **WorldFloodsV2** (Terramind): **0.92 F1**
- **+10% improvement vs. GloFAS** computed against CEMS maps (0.78 vs 0.71 F1 on 2024 floods)

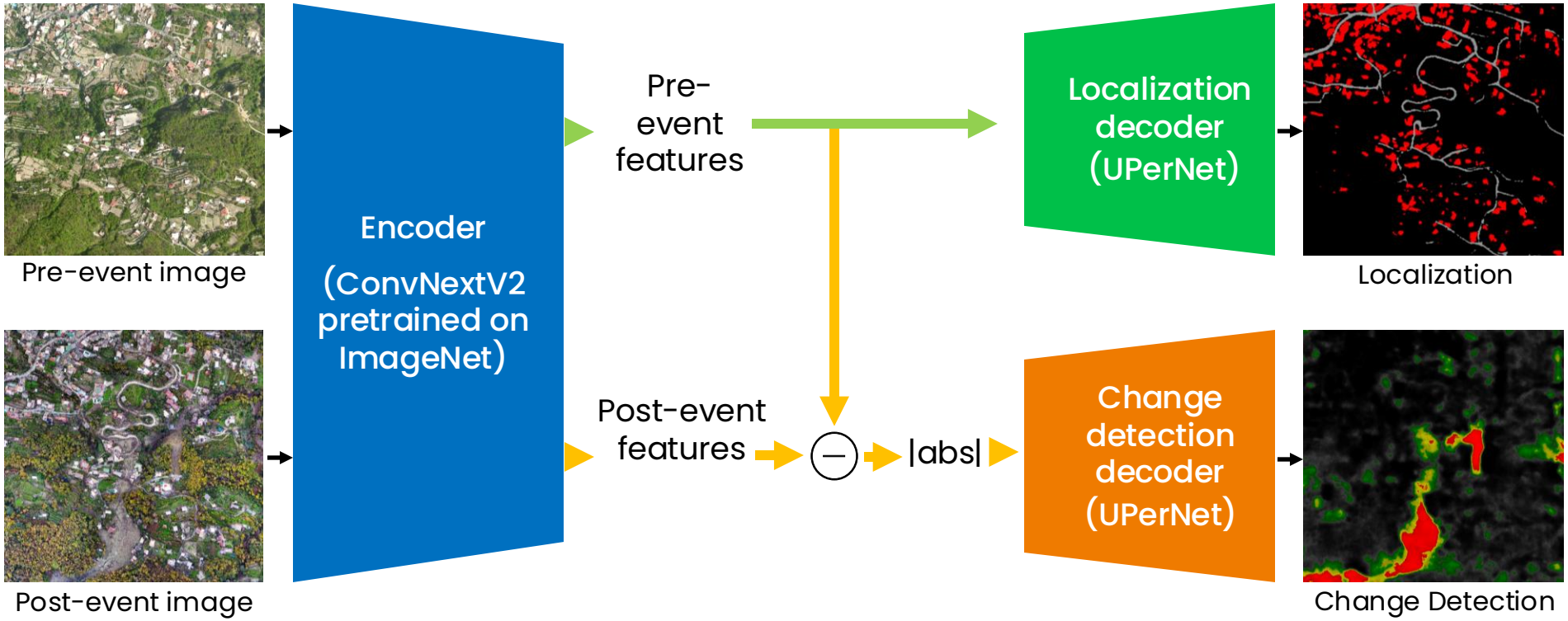


Damage Assessment – At a Glance



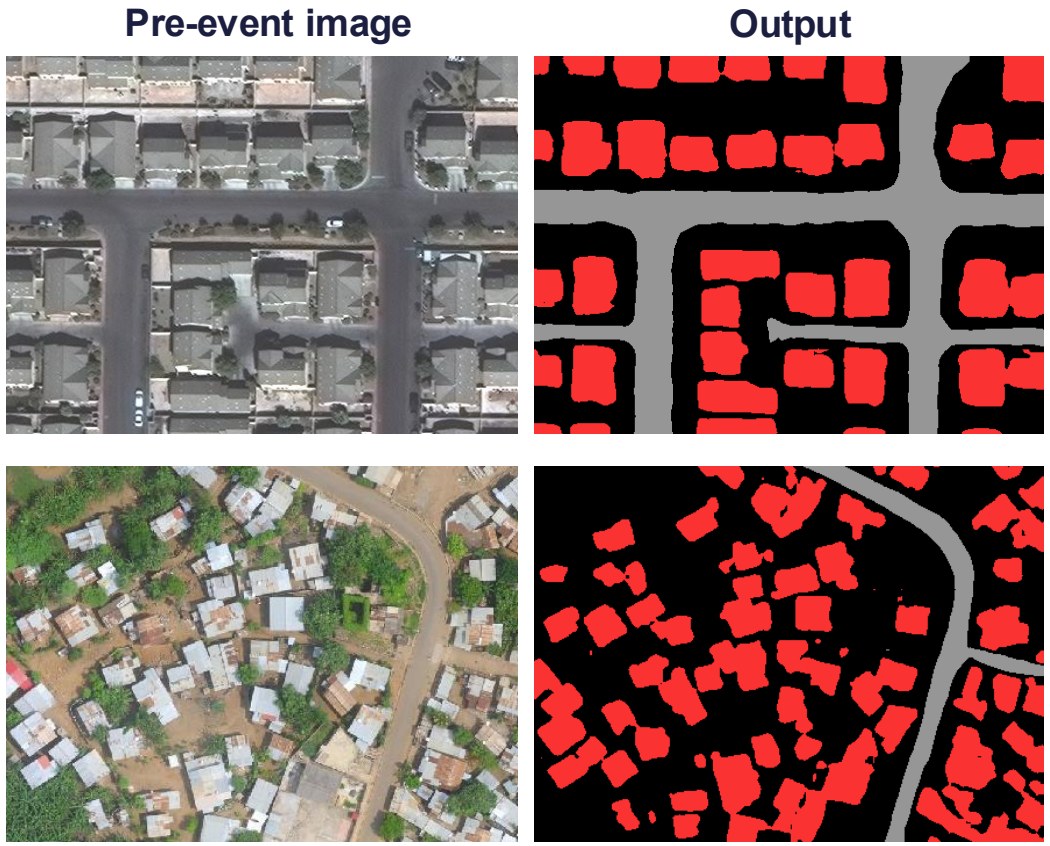
- **OBJECTIVE**
  - **Identify infrastructures** (roads, buildings) and **determine damage**.
  - **Task:**
    - **semantic segmentation** (pre-event image): *delineate structures*
    - **change detection** (pre-post images): *what changed → damaged*
- **INPUTS AND METHODS**
  - Segmentation trained on **OpenEarthMap** (VHR, >0.5m/pixel), **FMARS**
  - Change Det. Trained on **SYSU-CD** (VHR, <= 0.5m/pixel), not only buildings

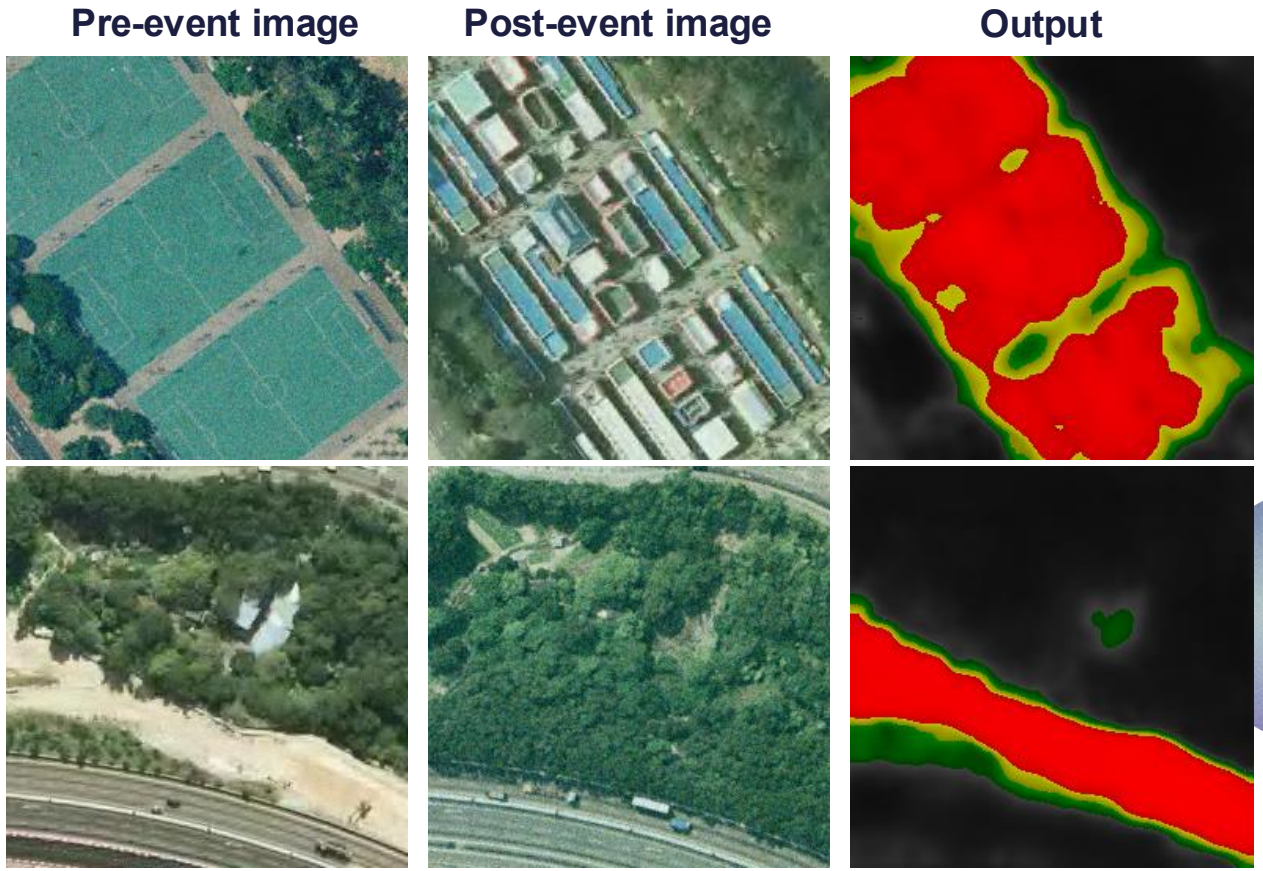
Damage Assessment - Methodology



Damage Assessment - Results

- Segmentation performance on **OpenEarthMap:** **74.25 mIoU**
- Change Detection performance on **SYSU-CD**: **67.80 mIoU**





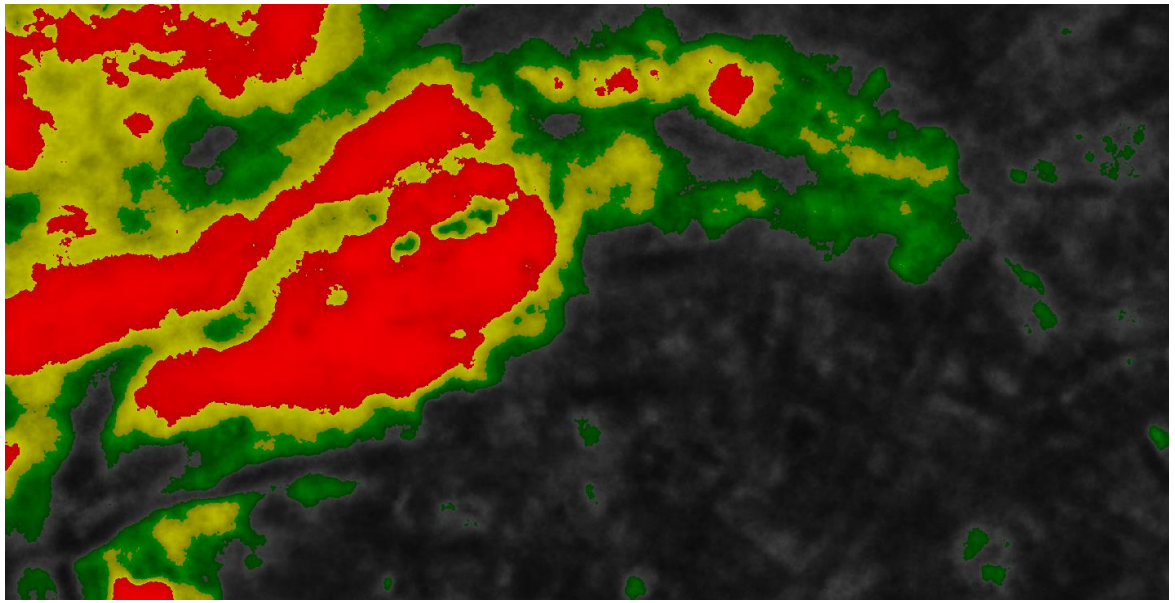
Plovdiv flood (Bulgaria, 2022)

Pre-event

Post-event

Localization

Damage assessment



Images courtesy of JRC/CEMS

What’s Next

METHODOLOGICAL

- **Better Foundation Models** for openly available EO imagery (Sentinels)
- Need for decoder networks **better suited for EO** (less downscaling)

APPLICATIONS

- **Flood Depth** estimation (FLEXTH algorithm, HAND-based, etc.)
- **Active Fire Detection** and **Fire Monitoring** (UNICORN)
- **Fire simulation**, AI-based fire **risk forecasts**

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Linking space to user needs

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