Artificial Intelligence and Earth Observation for Post-Disaster Impact Assessment. Lessons Learned from Multi-Hazard Case Studies.

Silvia L. Ullo, University of Sannio
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Committee on
Earth Observation Satellites

The TEAM

- Dr. Luigi Russo – PhD student
- Dr. Pietro Di Stasio – PhD student
- Dr. Deodato Tapete – ASI
- Prof. Paolo Gamba – University of Pavia
- Prof. Silvia L. Ullo – University of Sannio

UNIVERSITÀ DEGLI STUDI DEL SANNIO Benevento

Agenzia Spaziale Italiana

The Presentation

- A more conceptual description of our contributions (mainly focused on **a new paradigm shift**: **cascade phenomena**)
- Some case studies related to **post-event assessment**

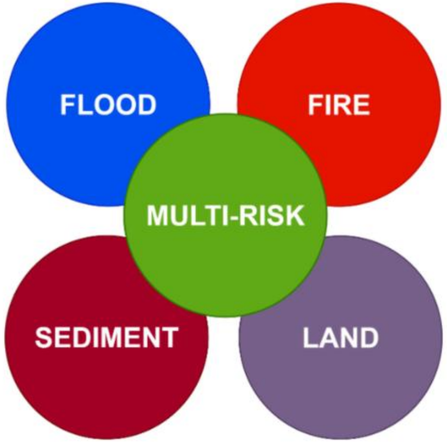
A Paradigm Shift

A new paradigm in risk management

In recent years, the concept of cascading disasters has emerged as an innovative approach in risk management studies.

Cascading processes

Events in which predisposing factors, triggers, and interacting processes combine and amplify each other, leading to complex, multi-hazard situations.



Risk = Hazard x Exposure x Vulnerability

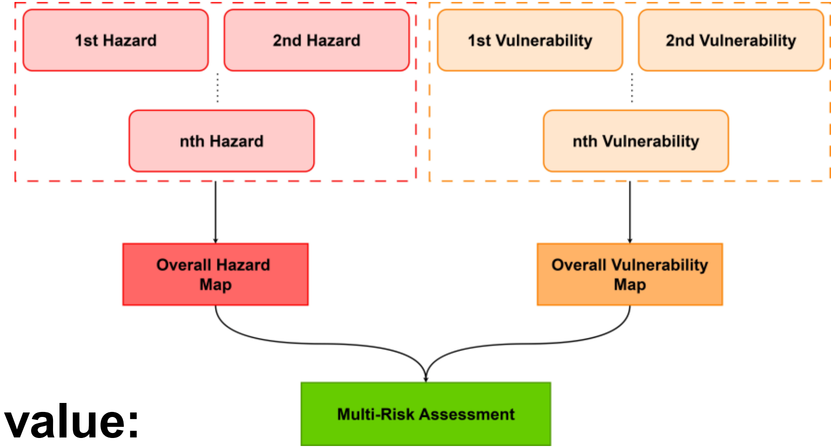
Towards a multi-risk concept

An integrated approach is required to understand the interconnections between hazards and to enhance system resilience against cascading effects.
The overall risk results from the combination of the likelihood of a hazard and the vulnerability of exposed elements.

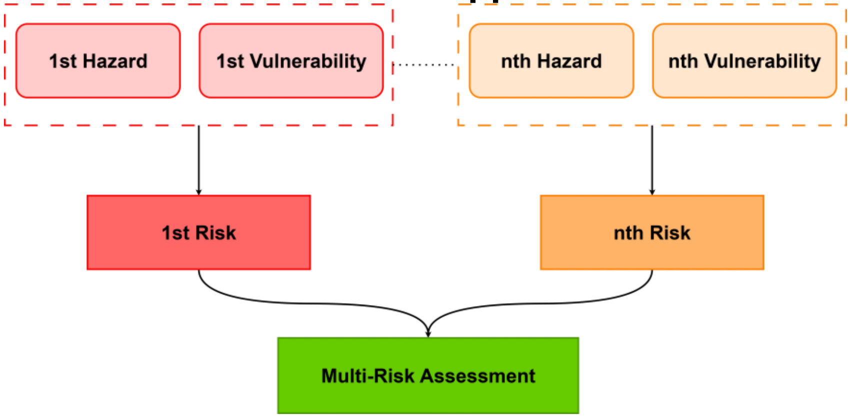
Multi-Risk Assessment

- Each type of hazard generates a specific risk map.
- By combining these maps with the spatial distribution of exposed elements, it is possible to derive composite risk levels.
- These maps are complementary tools, capable of providing integrated and multi-dimensional information.

Component-first approach



Risk-first approach



Added value:

Multi-risk maps are useful to:

- Evaluate the relative weight of different hazards within a local context;
- Support communication among experts, institutions, and stakeholders;
- Provide a common language for risk planning and management.

EO in Risk Management Cycle

Once the multi-risk analysis is established, we can look at the role of EO in the Risk Management Cycle

Mitigation
Hazard and vulnerability analysis to plan targeted actions aimed at reducing susceptibility and increasing system resilience.

Preparedness and Early Warning
Detection of precursor signals for short-term forecasting and activation of early-warning systems.

Response
Support to emergency operations through near real-time synoptic observations of affected areas, essential for damage assessment and humanitarian aid planning.

Recovery
Continuous and cost-effective monitoring of recovery and reconstruction activities, supporting governments and international organizations.

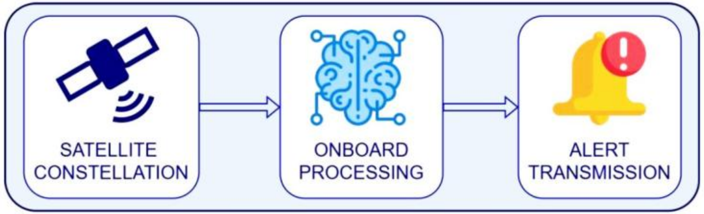
The Challenge in the "Response" phase

Traditional workflows rely on bent-pipe architectures, requiring raw data to be fully downlinked before ground-based processing can begin. This centralized approach introduces severe latency—a structural **Data Bottleneck**—rendering the system incompatible with the strict requirements of true **Near Real-Time (NRT)** cascade monitoring.

AI integration for On-board Data Processing

Advantages

- **Bandwidth Optimization:** Sending compact, decision-ready semantic products
- **Latency Minimization:** Drastically reducing time-to-insight for rapid disaster response
- **Mission Autonomy:** Enabling event-driven prioritization directly in orbit



Challenges (Operational Constraints)

- Strict **limits on power availability**, thermal dissipation, and memory
- **Restricted duty-cycle margins for intensive AI computing**
- **Need for radiation-tolerant hardware** and highly efficient architectures

Team expertise on board AI

Early Detection of Volcanic Eruption - 2022

Early Detection of Volcanic Eruption through Artificial Intelligence on board

1st Pietro Di Stasio, Engineering Department, University of Sannio, Benevento, Italy, pietro.distasio@studenti.unisannio.it
2nd Alessandro Sebastianelli, Engineering Department, University of Sannio, Benevento, Italy, sebastianelli@unisannio.it
3rd Gabriele Meoni, Φ-lab, European Space Agency, Rome, Italy, gabriele.meoni@esa.int
4th Silvia Liberata Ullo, Engineering Department, University of Sannio, Benevento, Italy, ullo@unisannio.it

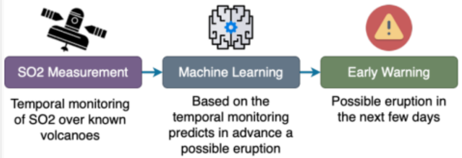
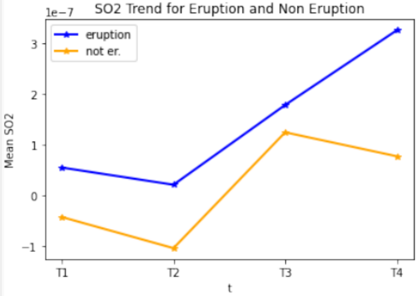


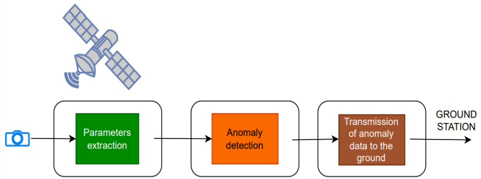
Fig. 1. Proposed Early Warning System

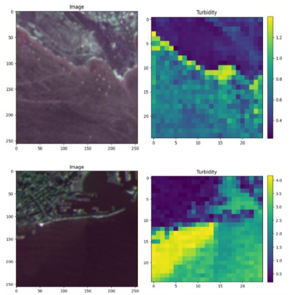


ΦSat-2 Water Quality Monitoring – 2023/2024

AI Techniques for Near Real-Time Monitoring of Contaminants in Coastal Waters on Board Future Φsat-2 Mission

Francesca Razzano, Student Member, IEEE, Pietro Di Stasio, Member, IEEE, Francesco Mauro, Student Member, IEEE, Gabriele Meoni, Member, IEEE, Marco Esposito, Member, IEEE, Gilda Schirinzi, Senior Member, IEEE, and Silvia Liberata Ullo, Senior Member, IEEE

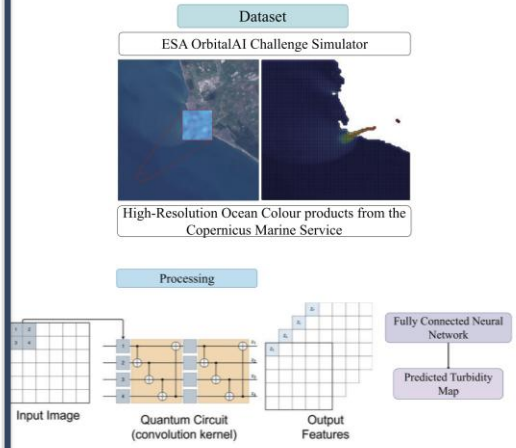




Quantum-Enhanced Water Quality Monitoring - 2025

Quantum-Enhanced Water Quality Monitoring: Exploiting ΦSat-2 Data With Quanvolution

Francesco Mauro, Student Member, IEEE, Francesca Razzano, Student Member, IEEE, Pietro Di Stasio, Student Member, IEEE, Alessandro Sebastianelli, Member, IEEE, Gabriele Meoni, Member, IEEE, Gilda Schirinzi, Senior Member, IEEE, Paolo Gamba, Fellow, IEEE, and Silvia Liberata Ullo, Senior Member, IEEE



Quantum on-board Investigation - ongoing

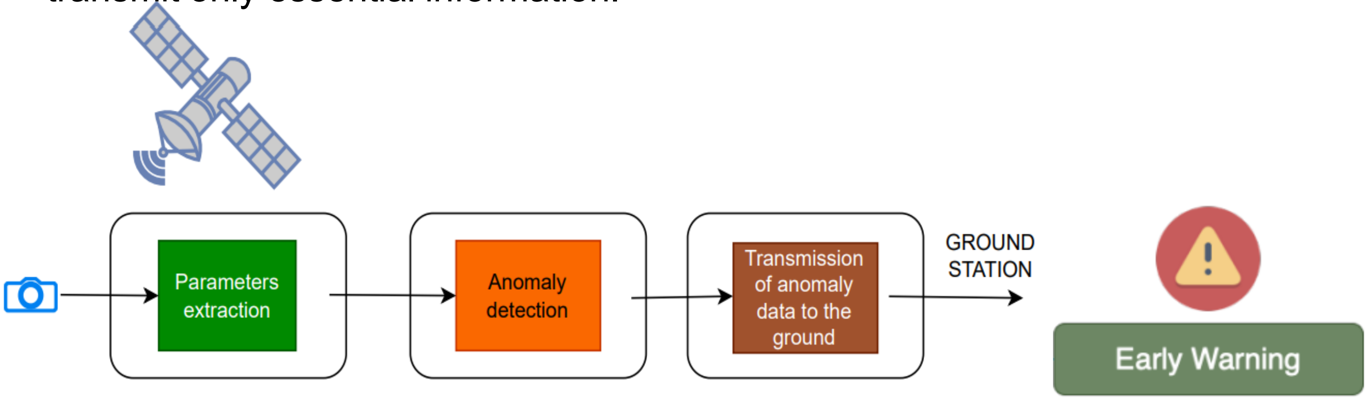
“Water Quality Monitoring (WQM) on-board ΦSat-2 "

Foreign Industrial partners: cosine (Netherlands), WASDI (Luxembourg), and Research Centers partners in Italy: ESA, ASI, University of Naples Parthenope, University of Pavia.

Project Motivation

- A sudden disruption caused by natural hazards or industrial failure (i.e., an earthquake damaging industrial infrastructure and releasing hazardous substances into nearby water systems, or a landslide blocking a dam which suddenly collapses, sending a surge of water mixed with rocks and debris downstream into rivers and coastal areas) belongs to a **special cascade phenomenon category**.

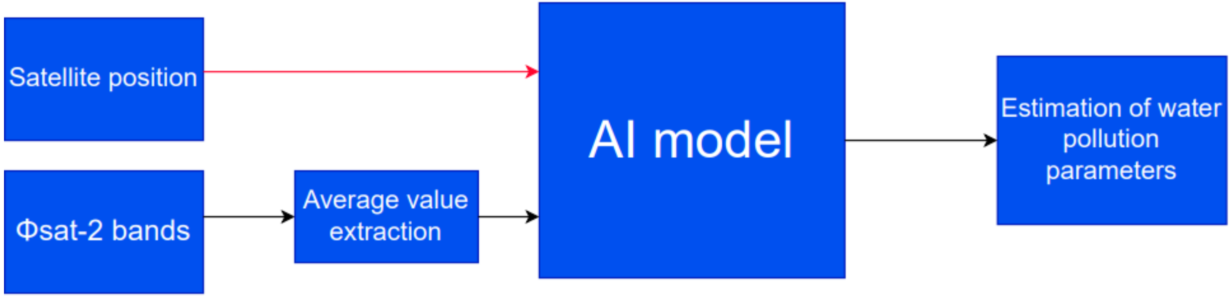
- The proposal suggests implementing a system for **near real-time** detection of water contaminants through monitoring specific parameters and using satellite data and AI techniques to process data **on board** and transmit only essential information.



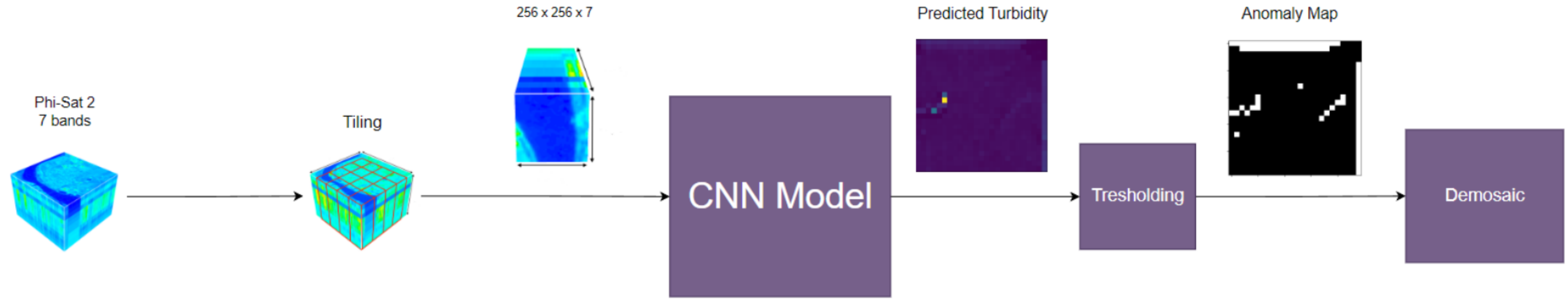
CNN for Environmental Threats Detection

- We assume that it was possible enable the inference only when the satellite is positioned over **marine coastal areas**.
- We built a regression model considering Φsat-2 spectral bands as independent variables and in-situ data measurements as dependent variables.

- We started from a **regression model**. Then we parallelized it by transferring the information to a **Convolutional Neural Network** that makes sure to calculate the regression efficiently.



CNN for Environmental Threats Detection

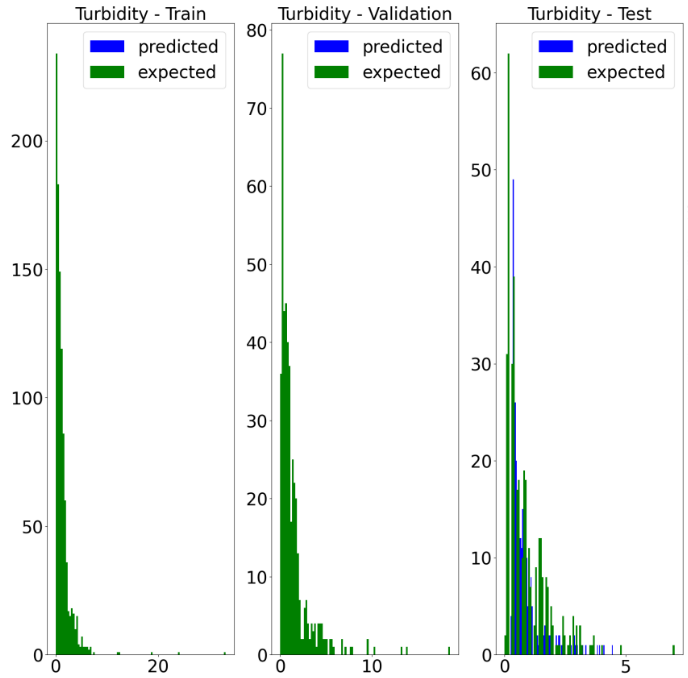


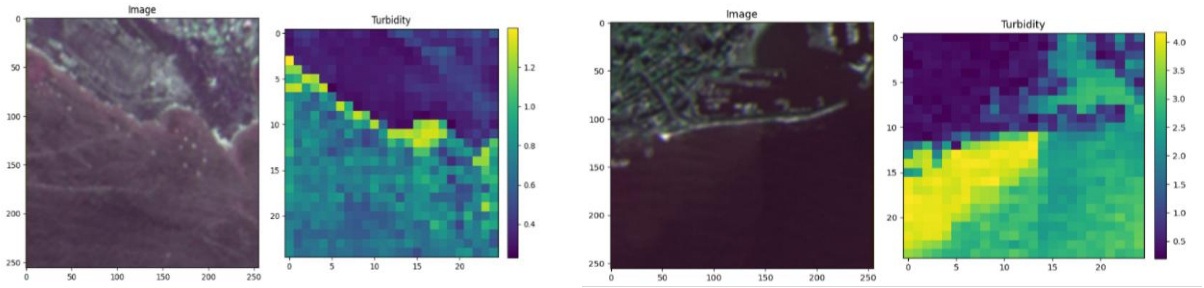
Parameter	Value
Number of hidden layers	5
Number of nodes in hidden layers	[512, 512, 512, 512, 43]
Activation function	Rectified Linear Unit (ReLU)
Batch normalization	Yes
Dropout (p)	0.25
Optimizer	Adam
Loss function	Root Mean Square Error (RMSE)
Number of epochs	2000

Parameter	Value
window size	10
input channels	7
hidden layers	[512, 512, 512, 512, 43]
output channels	1

AI4EDofET: CPU results

- The model AI4EDofET (AI for Early Detection of Environmental Threats) outperformed other AI-based frameworks used for monitoring water contaminants. The distribution of **predicted values** shows a very strong correspondence with the distribution of **expected values**, demonstrating the model's high reliability.





Turbidity (NTU)	Methodology	RMSE	MAE
Proposed study	AI4EDofET	1.0396	0.7311
Kwong et al.	ANN	1.954	1.607
Hafeez et al.	ANN	3.10	2.61

Challenges faced in on-board deployment

Model portability constraints on Myriad 2

- Certain layers and operations (e.g. ensamble-based and non-standard activations) are not fully supported within the OpenVINO-Myriad toolchain.

Trade-off between model performance and deployability

- While CatBoost showed superior regression performance, its ONNX/OpenVINO incompatibility limited on-board execution.

Architecture adaptation is feasible, but not always optimal

- Custom replacements partially solved compatibility issues but introduced new constraints.

Need for flexibility-aware hardware choices

- These limitations highlight the importance of selecting AI accelerators that better support advanced model architectures for on-board AI, if not possible, the Hardware constraints knowledge can help in fine tuning the model.

The Osmanye Case Study (Turkey)

Multi-Temporal Analysis of Urban Dynamics with Sentinel-2 data.

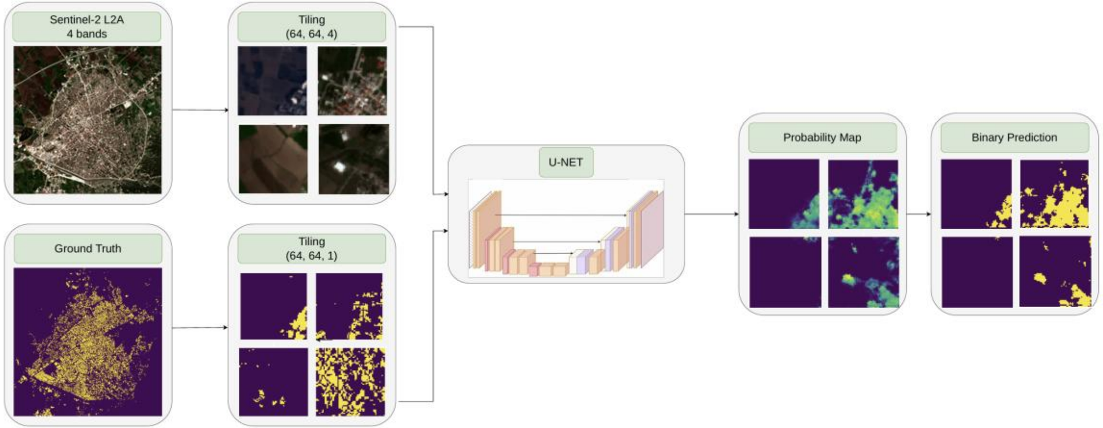
❖ The study aimed to analyze the urban dynamics of the city of Osmaniye in the time frame of 10 years from 2015 to 2025 through the use of Remote Sensing and Deep Learning algorithms.

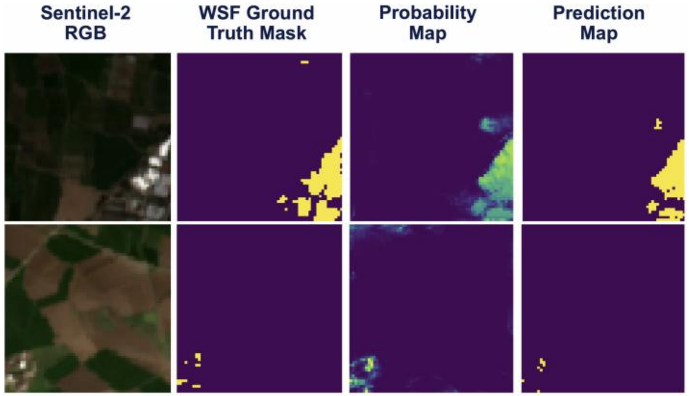
❖ The goal was the development of a model capable of predicting and monitoring the evolution of urbanization.

❖ **Why monitor the urbanization?**

It allows us to understand and manage the changes that occur in the territory, especially in areas subject to rapid demographic transformations, building expansion, and environmental vulnerabilities.

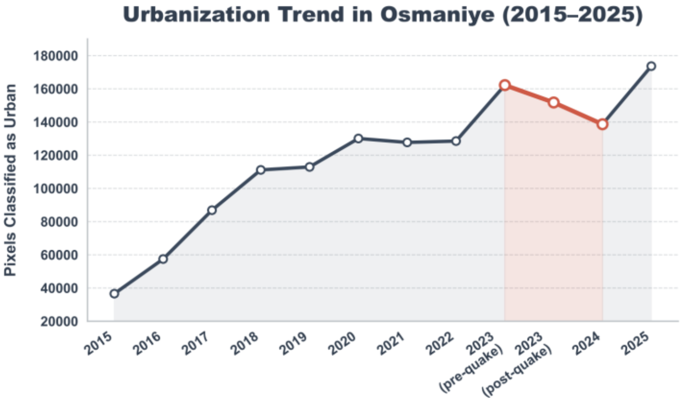
Multi-Temporal Analysis of Urban Dynamics with Sentinel-2 data.





4-band S-2 L2A data
WSF GT data

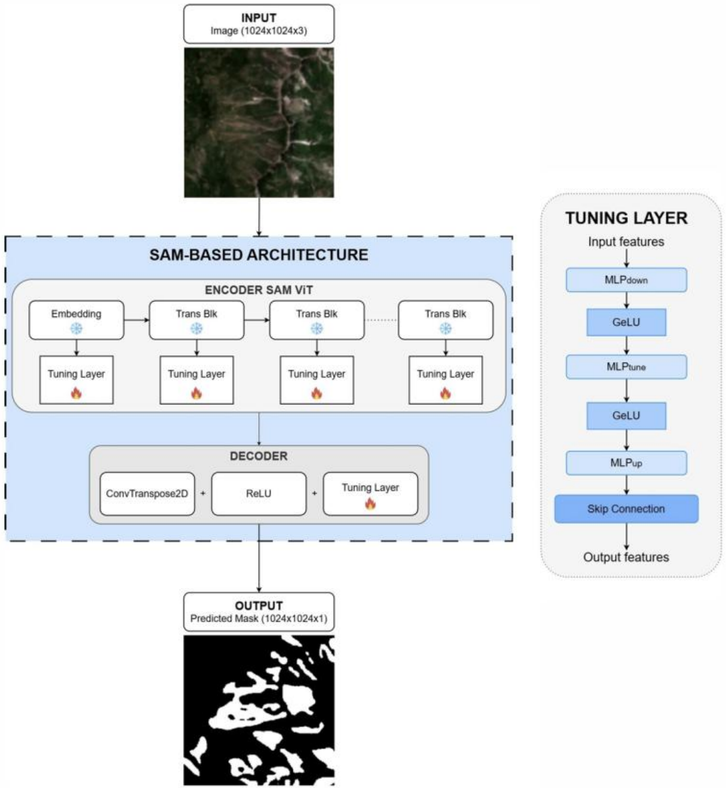
World Settlement Footprint
a DLR product as Ground Truth



Urban sprawl
Over 10 years

The Haiti Case Study (Caribbean)

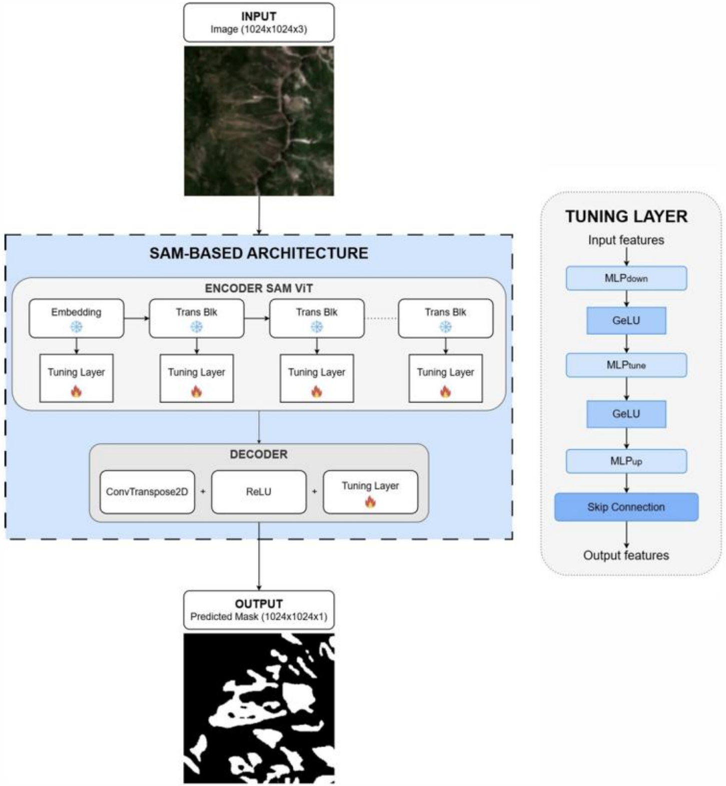
Foundation Models for Landslide Detection in Cascading Hazards Scenario.

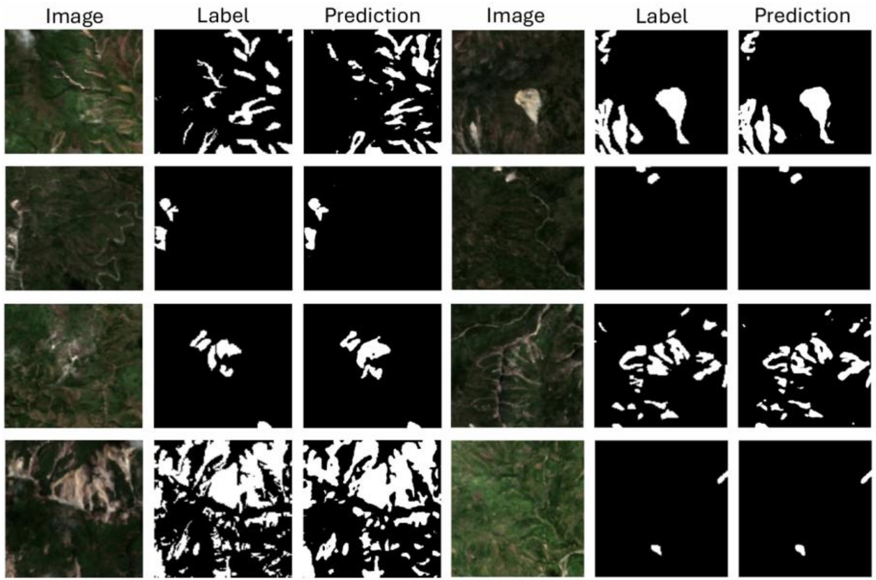


On August 14, 2021, a magnitude 7.2 earthquake struck western Haiti causing widespread damage and loss of lives and triggering landslides throughout the region.

- **The original Segment Anything Model (SAM) we explored relied on prompts and RGB natural images (not suitable for Remote Sensing data complexity).**
- **Fine-tuning approach was the key enabling the model to adapt to landslide segmentation with minimal computational overhead and without full retraining.**
- **The model generated high-resolution, accurate segmentation masks for landslide detection.**

Foundation Models for Landslide Detection in Cascading Hazards Scenario.

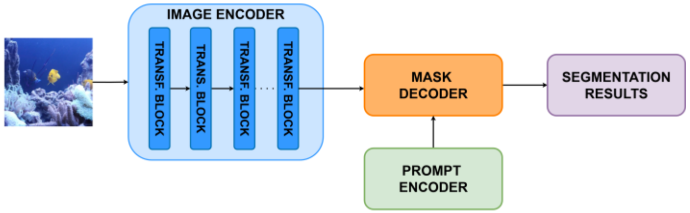




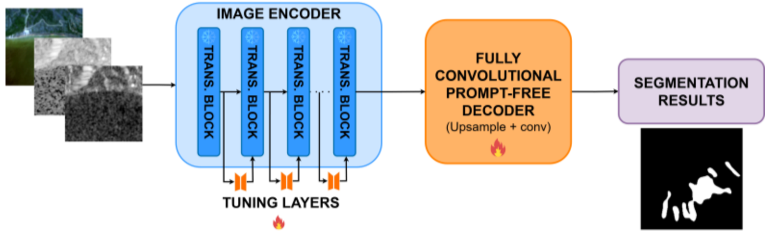
Performance Metrics

	Precision	Recall	F1-score	mIoU	Accuracy
Train	88.06	93.05	90.49	82.63	98.12
Validation	73.29	74.27	73.78	58.45	94.33

Foundation Models for Landslide Detection in Cascading Hazards Scenario with Multi-Modal EO Data.

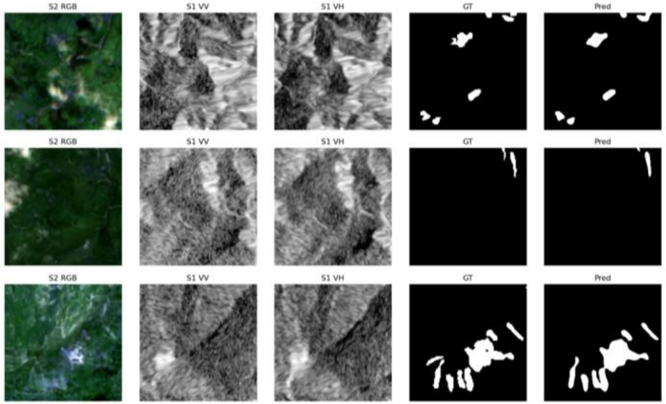


Original SAM Architecture



MM-SAM Architecture

Dataset	Accuracy	Precision	Recall	F1-score	IoU
Training	0.99	0.90	0.89	0.89	0.80
Validation	0.98	0.84	0.72	0.78	0.63
Test	0.98	0.86	0.73	0.79	0.66



- The Hatay Region Case Study (Turkey)

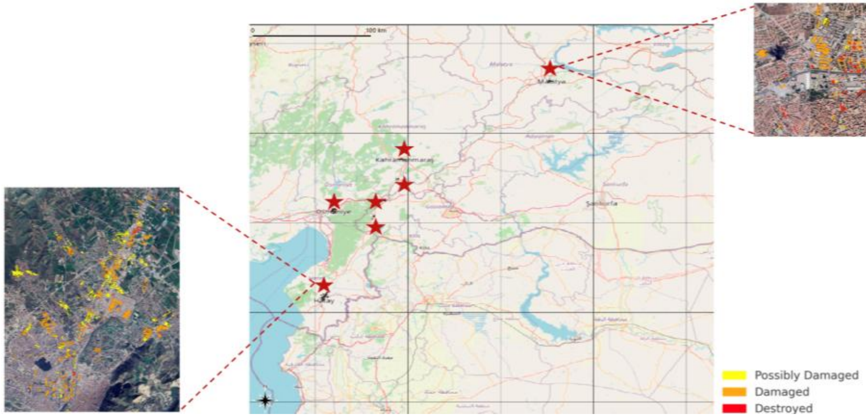
Deep Learning (DL) framework trained on multi-source datasets.

- **Deep Learning (DL)** framework trained on **multi-source datasets**, i.e. **pre- and post-event SAR** imagery & **geospatial information**

- **COSMO-SkyMed (CSK) StripMap images** (2.5 m spatial resolution, HH polarization), acquired shortly before and after the **event** to **detect earthquake-induced changes**

- ASI's **CSK Background Mission archive**

- Additional complementary imagery that ASI collected to support **GSNL Kahramanmaraş Event Supersite**



Study areas considered in this research, highlighting key cities affected by the 2023 **Kahramanmaraş earthquake** in Turkey.
The cities analyzed, listed from north to south, are:

1) Malatya
2) Kahramanmaraş
3) Türkoğlu
4) Nurdağı
5) Islahiye
6) Osmaniye
7) Antakya

- This case study presents an **automatic SAR-based approach**, tested **in the future perspective of providing support to institutions**, **emergency services**, and **international cooperation frameworks** for **disaster mapping** and **response** in the **Hatay Region.**

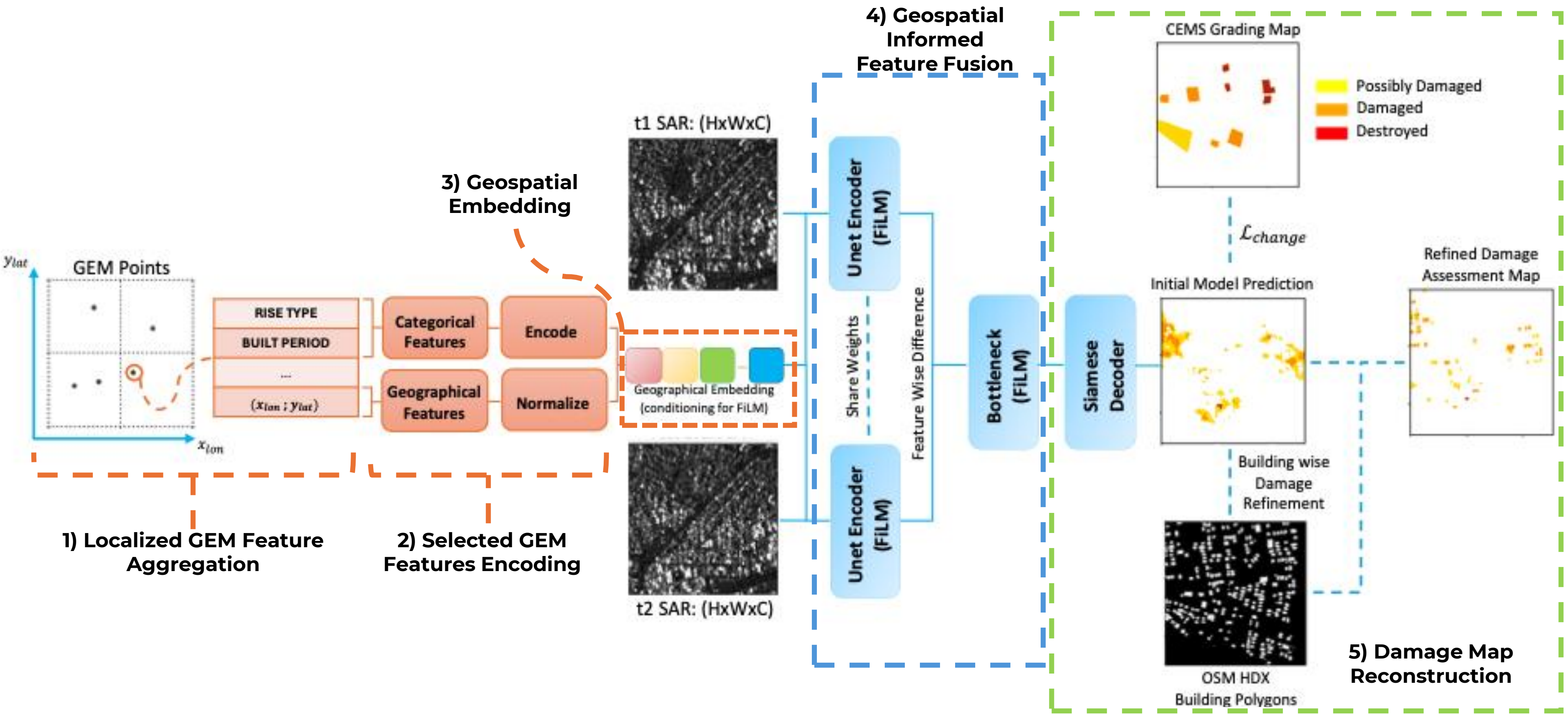
Input Data and Study Areas

Geospatial datasets:

1. **Ground Truth (GT) maps** from the **Copernicus Emergency Management Service (CEMS)**, particularly **grading products** from the **EMSR648 activation [4]**.
2. **Global Earthquake Model (GEM)** data, providing detailed information on **building stock** and **structural attributes** for **exposure assessment [5]**.
3. **OpenStreetMap (OSM)** building footprints, obtained via the **Humanitarian Data Exchange (HDX) [6]**.

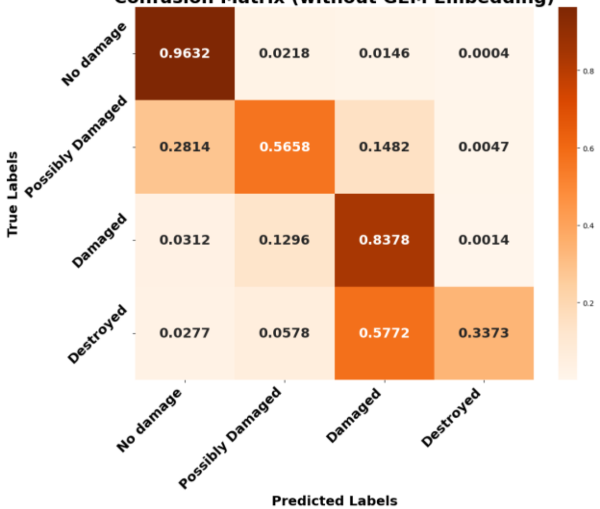
City	Pre-Event	Post-Event	Copernicus EMS	OSM HDX	GEM Exposure
Antakya	CSK1 – 2016-01-20	CSG1 – 2023-03-06	✓	✓	✓
Islahiye	CSK1 – 2016-02-10	CSK4 – 2023-02-25	✓	✓	✓
Kahramanmaraş	CSK4 – 2023-01-20	CSK4 – 2023-03-01	✓	✓	✓
Malatya	CSK2 – 2023-02-03	CSK2 – 2023-02-19	✓	✓	✓
Nurdagi	CSK1 – 2016-02-10	CSK4 – 2023-02-25	✓	✓	✓
Osmaniye	CSK4 – 2023-01-30	CSK4 – 2023-02-15	✓	✓	✓
Turkoglu	CSK1 – 2016-02-10	CSK4 – 2023-02-25	✓	✓	✓

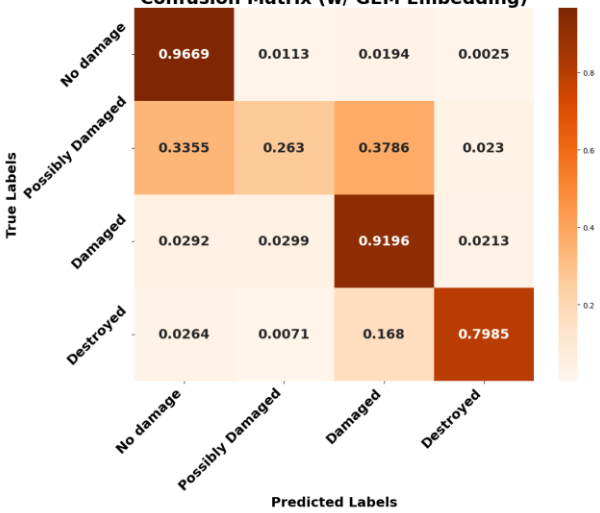
Methodology Workflow



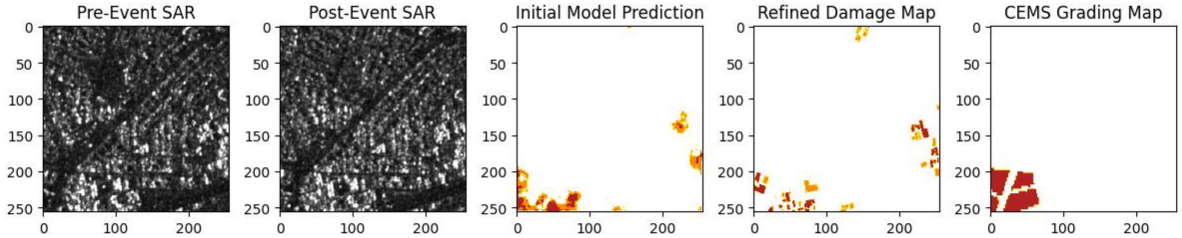
Experimental Results

- Images from different cities were processed into **256×256 pixel patches** and randomly divided into **90% training** and **10% testing**.
- **The model was trained for** 30 epochs, using the Adam optimizer and a learning rate of 0.0001.
- The **GEM-embedded model** improves accuracy for **severely damaged classes**, with **“Damaged”** increasing from **83.78% to 91.96%** and **“Destroyed”** from **33.73% to 79.85%**.
- A slight drop in **“Possibly Damaged”**(56.58% → 26.3%) suggests a shift toward higher severity predictions.





Random Visual Comparison on Validation Set (PR vs GT):



Observations

- The integration of **geospatial and structural attributes** from **GEM** improved the detection of **severely damaged** and **destroyed buildings**, **particularly in urban areas with complex structures**.

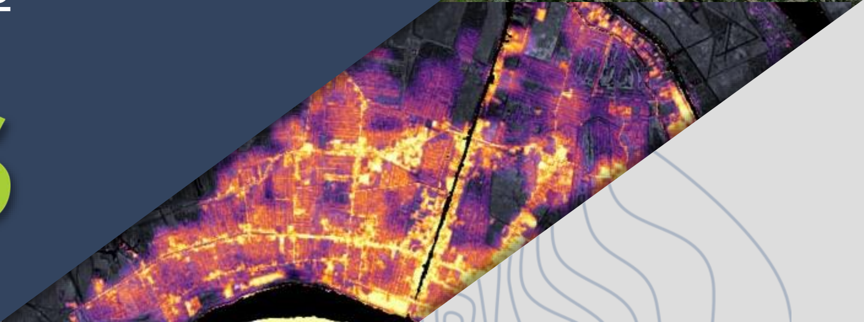
- Refining predictions with **OSM** building polygons enhanced alignment with real-world structures by constraining damage classifications within actual building boundaries, improving the model's focus on true damage zones and localized **backscatter intensity variations**.

- Compared to **CEMS** maps, the model produced **broader** and **denser** **damage predictions**, while EMS maps appeared more **conservative**, often overlooking peripheral or sparsely populated areas.

- Although the model may introduce **more false positives**, **it effectively identifies areas that could be missed during the rapid production of reference maps**.

THANK YOU FOR YOUR ATTENTION





Silvia Liberata Ullo

Contact:

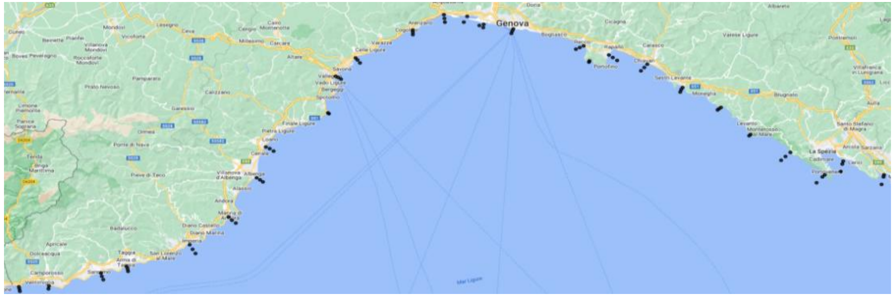
ullo@unisannio.it

LinkedIn:

Silvia Liberata Ullo

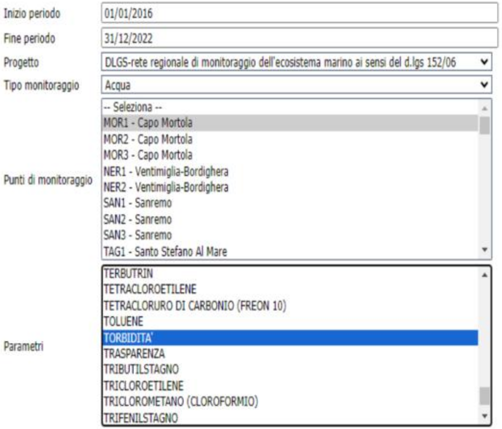
Committee on
Earth Observation Satellites

AOI and Dataset creation



- Since 2007, the **Liguria** coastal water has been divided into 26 macro-areas where the waters, sediments and animal and plant populations are periodically analysed.
- Multiparameter underwater **probes** were used to measure turbidity, along with electrical conductivity, temperature, salinity, and seawater pressure

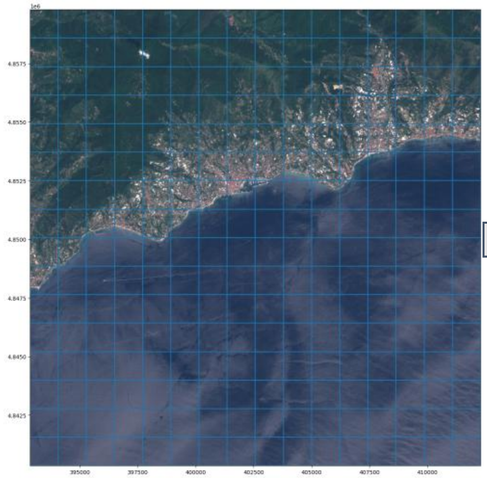
Latitude	Longitude	Water Control Zone	Water Station
43.78038	7.550226787	Capo Mortola	MOR1
43.77521	7.551333426	Capo Mortola	MOR2
43.76945	7.552702608	Capo Mortola	MOR3
43.7823	7.634808842	Ventimiglia - Bordighera	NER1
43.77536	7.633140316	Ventimiglia - Bordighera	NER2
43.81314	7.781480804	Sanremo	SAN1
43.80537	7.785095034	Sanremo	SAN2
43.79731	7.788975109	Sanremo	SAN3



Water Control Zone	Station	Date	Depth	Turbidity
Capo Mortola	MOR1	27/01/2021	-0.5	0.2
Capo Mortola	MOR2	15/06/2021	-0.5	0.7
Capo Mortola	MOR3	14/12/2021	-0.5	0.8
Ventimiglia - Bordighera	NER1	09/03/2017	-0.5	4.8
Sanremo	SAN1	03/08/2017	-0.5	1.5
Sanremo	SAN2	14/12/2021	-0.5	0.4

AOI and Dataset creation

- Bounding box (**bbox**) adjustment from 20140 to 1216 meters, around the **Point of Interest**
- This way, we consider only a restricted area surrounding the Point of Interest, generating a single patch of dimensions 256x256 with a spatial resolution of 4,75 meters.



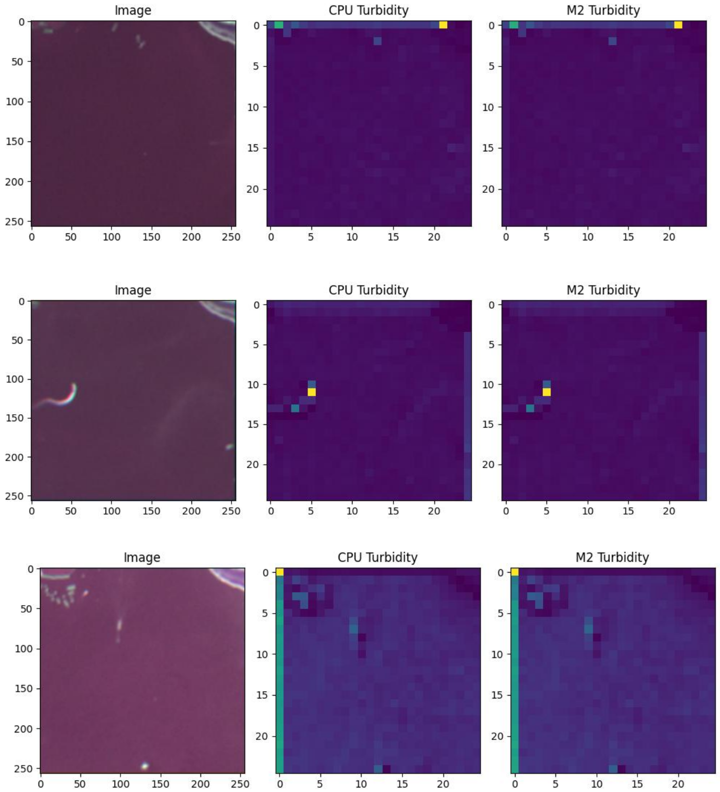
- Data pre-processing operation is performed that calculates a three-day window before and after the original date

- This process enables the download of simulated images using Φsat-2

$$X_{lat,lon} \in R^{W \cdot H \cdot B}$$

- Each sample is represented by latitude, longitude, and a 256x256 pixel image with 8 bands of spectral data

AI4EDofET: Myriad 2 results



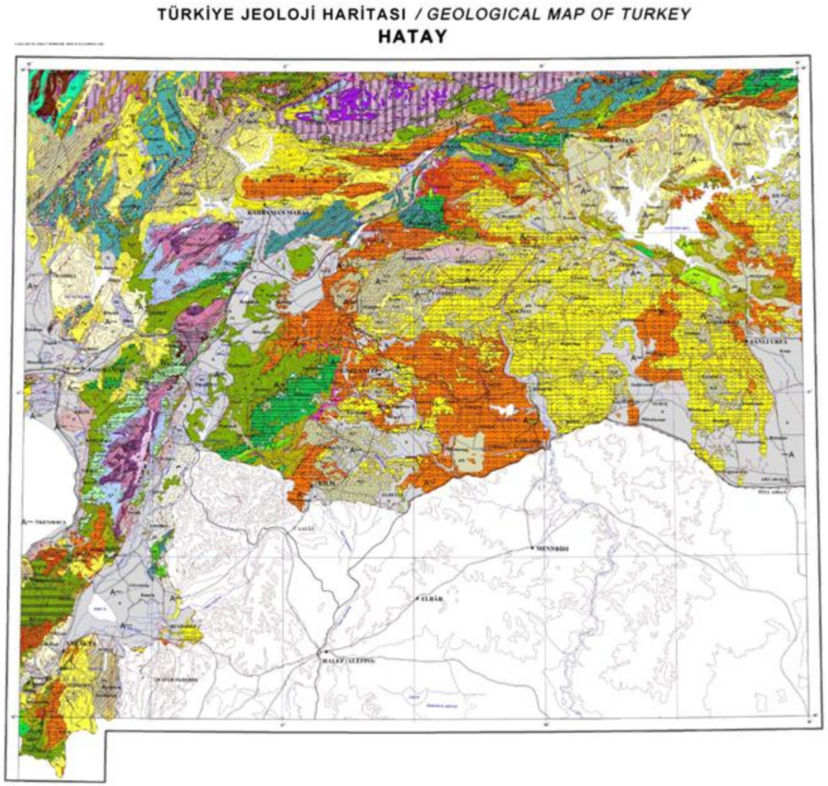
- ➢ Ubotica provided a Python script to handle pre-processing and post-processing for Myriad 2 execution
- ➢ **Model size**: ~4 MB, well within the 250 MB constraint set by ESA
- ➢ **Power consumption**: 1,2 W power envelope for Myriad 2, making further power testing unnecessary
- ➢ Successful integration of the CNN model on Rupia validated the feasibility of the approach, with an **inference time** of 40,5 ms per frame and throughput of 24 FPS

Future Works on this Case Study

- Integrate an **automated 3D building height mapping system** into the existing **damage assessment framework** to enhance accuracy **by incorporating structural vulnerability linked to building height.**

- Investigate **geological factors** contributing to earthquake-induced damages in affected cities.

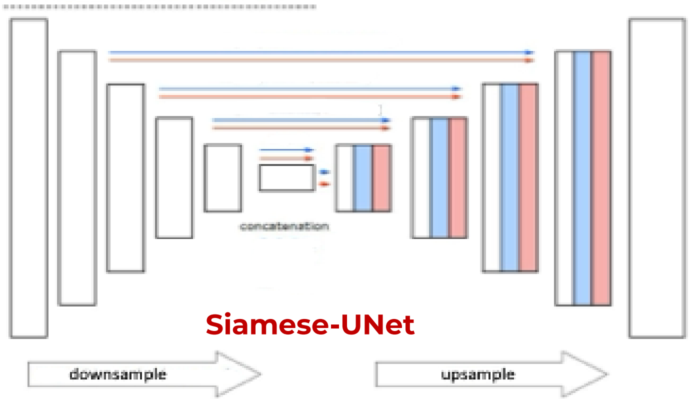
- Correlate **geological insights** with urban damage patterns to refine **risk assessment models** and improve prediction accuracy for future events.



[7] Geological Map of Hatay Region, Turkey.

Damage Map Reconstruction (1)

Model Architecture:



- **Encoders:** identical branches extract features from pre- and post-event data.
- **Feature differences** are computed at multiple levels to capture localized changes.
- **Bottleneck:** captures high-level semantic differences for robust spatial-temporal feature extraction.
- **Decoders:** combines feature differences with skip connections for refined, high-resolution predictions.

Training and Optimization:

Loss Function ($\mathcal{L}_{Change}$):

$$\mathcal{L}_{Change} = \mathcal{L}_{Dice} + \mathcal{L}_{CE}$$

Dice Loss:

$$\mathcal{L}_{Dice} = 1 - \frac{2\sum y_{true} \cdot y_{pred} + \epsilon}{\sum y_{true} + \sum y_{pred} + \epsilon}$$

Ensures better performance on imbalanced datasets by emphasizing overlap between predictions and ground truth.

Cross-Entropy Loss with Class Weights:

$$\mathcal{L}_{CE} = -\sum w_c \cdot y_{true} \cdot \log(y_{pred})$$

Class weights w_c penalize errors in underrepresented classes (e.g., severely damaged structures).

Damage Map Reconstruction (2)

Post-Processing & Refinement

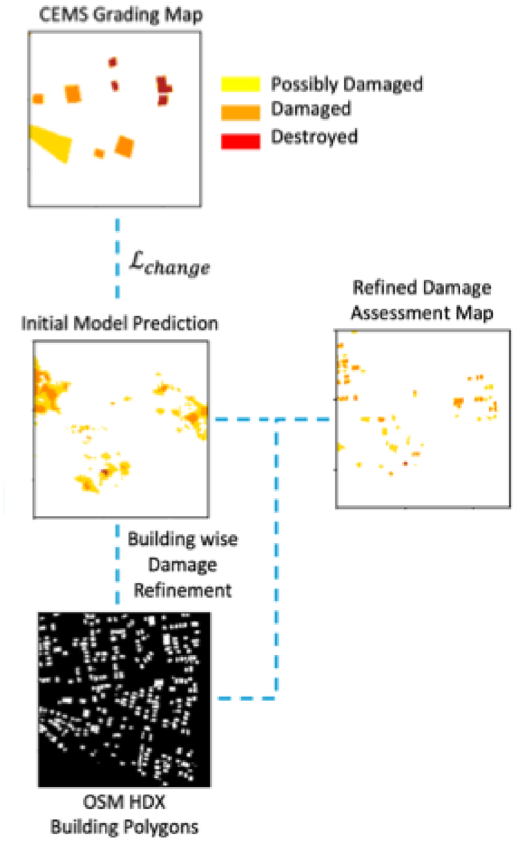
- **Initial Model Prediction:** captures damage zones but may introduce false positives.

OSM Refinement Process:

- Overlays predicted damage regions with **OSM building polygons**.
- Ensures predicted damage aligns with real-world building structures.
- Assigns the **most severe** observed damage class within each OSM polygon.

Final Output

- Produces a Refined Damage Map with improved accuracy, particularly in peripheral and less populated areas.



Real World Validation

Kahramanmaraş (1/3)

10/04/2022

09/02/2023

14/02/2023

Real World Validation

Kahramanmaraş (2/3)

14/02/2023

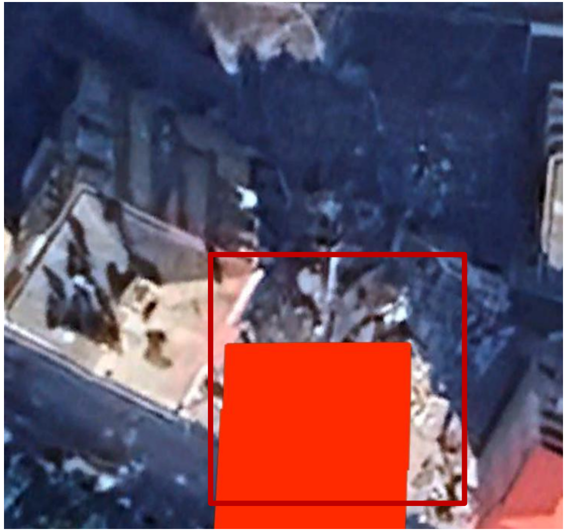
- Model Prediction (**without GEM input**):
0: No Damage
- Model Prediction (**w/ GEM input**):
3: Destroyed Building
- Copernicus EMS:
0: No Damage

Real World Validation

Kahramanmaraş (3/3)

10/04/2022

08/02/2023



- Model Prediction (**without GEM input**):
3: Destroyed Building
- Model Prediction (**w/ GEM input**):
3: Destroyed Building
- Copernicus EMS:
0: No Damage

Real World Validation

Antakya (1/6)

27/09/2021

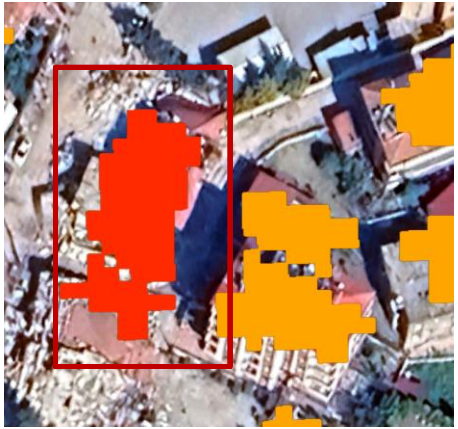
14/02/2023

Real World Validation

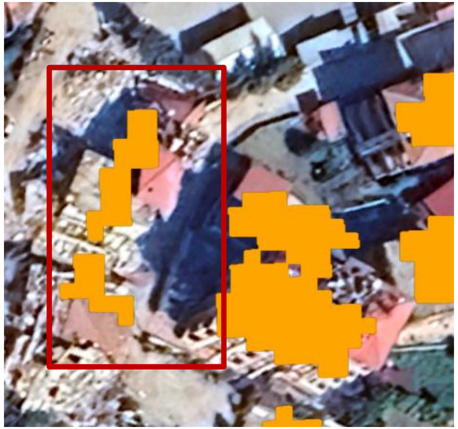
Antakya (2/6)

14/02/2023

Model Prediction
(**without GEM input**):
2: Damaged Buildings



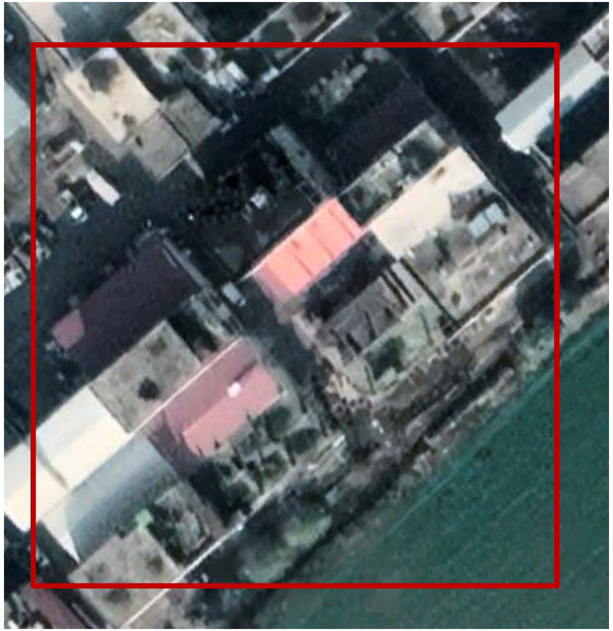
Model Prediction
(**w/ GEM input**):
3: Destroyed Buildings



Copernicus EMS:
2: Damaged Buildings

Real World Validation

Antakya (3/6)



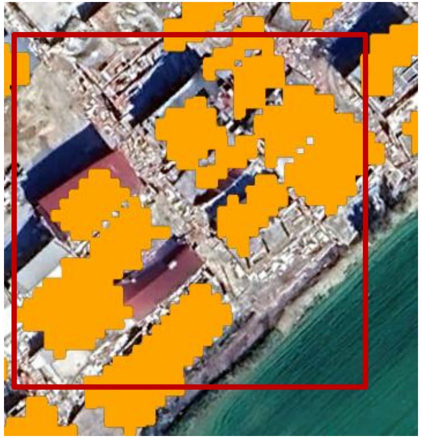
22/12/2022

09/02/2023

Real World Validation

Antakya (4/6)

09/02/2023



Model Prediction
(**without GEM input**):
2: Damaged Buildings

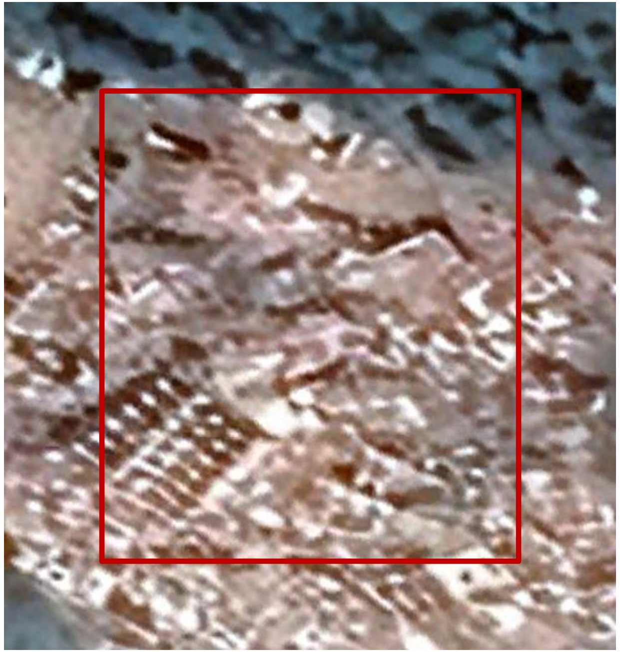
Model Prediction
(**w/ GEM input**):
3: Destroyed Buildings

Copernicus EMS:
2: Damaged Buildings

Real World Validation

Antakya (5/6)

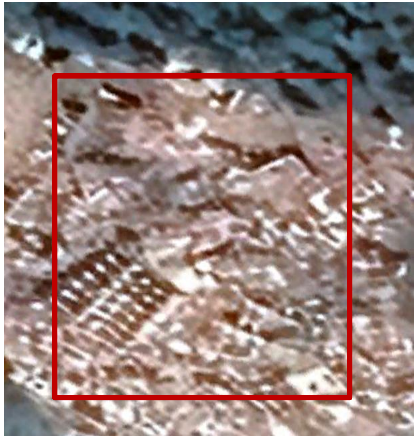
27/09/2021



07/02/2023

Real World Validation

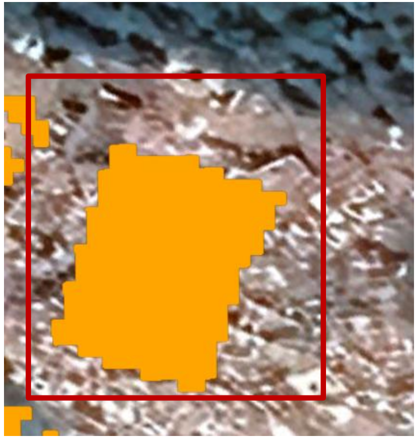
Antakya (6/6)



07/02/2023

Model Prediction
(**without GEM input**):
2: Damaged Building

Model Prediction
(**w/ GEM input**):
3: Destroyed Building



Copernicus EMS:
2: Damaged Building