

WGISS-61 Sentinel-1: A Game Changer for Disaster Response

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LUXEMBOURG
INSTITUTE OF SCIENCE
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- ❖ Over the past few decades, Earth Observation (EO) satellites have emerged as a major data source for providing critical information during disasters.
- ❖ Many satellite constellations, originating from both the private sector and institutional organizations, are increasingly available and feature diverse characteristics.
- ❖ EO satellites have the capability of repetitively acquiring data globally.
- ❖ Optical data can provide detailed information with a high level of granularity.
- ❖ SARs are of special importance because due to their sensitivity to variations in land cover and their near all-weather, day-and-night imaging capability.
- ❖ Combining data from various satellite missions is essential for achieving a high revisit time.

Disaster Managers Needs



- ❖ Regularly updated information at a global scale.
- ❖ Fast access to the information.
- ❖ Higher level of spatial details and large spatial coverage.
- ❖ Avoid downloading large amounts of data.
- ❖ Avoid the need for an IT expert to manage cloud computing infrastructures.

- ❖ Regularly updated Onboard processing capacity.
- ❖ High-performance and cloud computing infrastructures.
- ❖ Advanced deep-learning algorithms to derive value-added information from raw data.
- ❖ AI-based data-driven methods to leverage synergies in the data diversity.

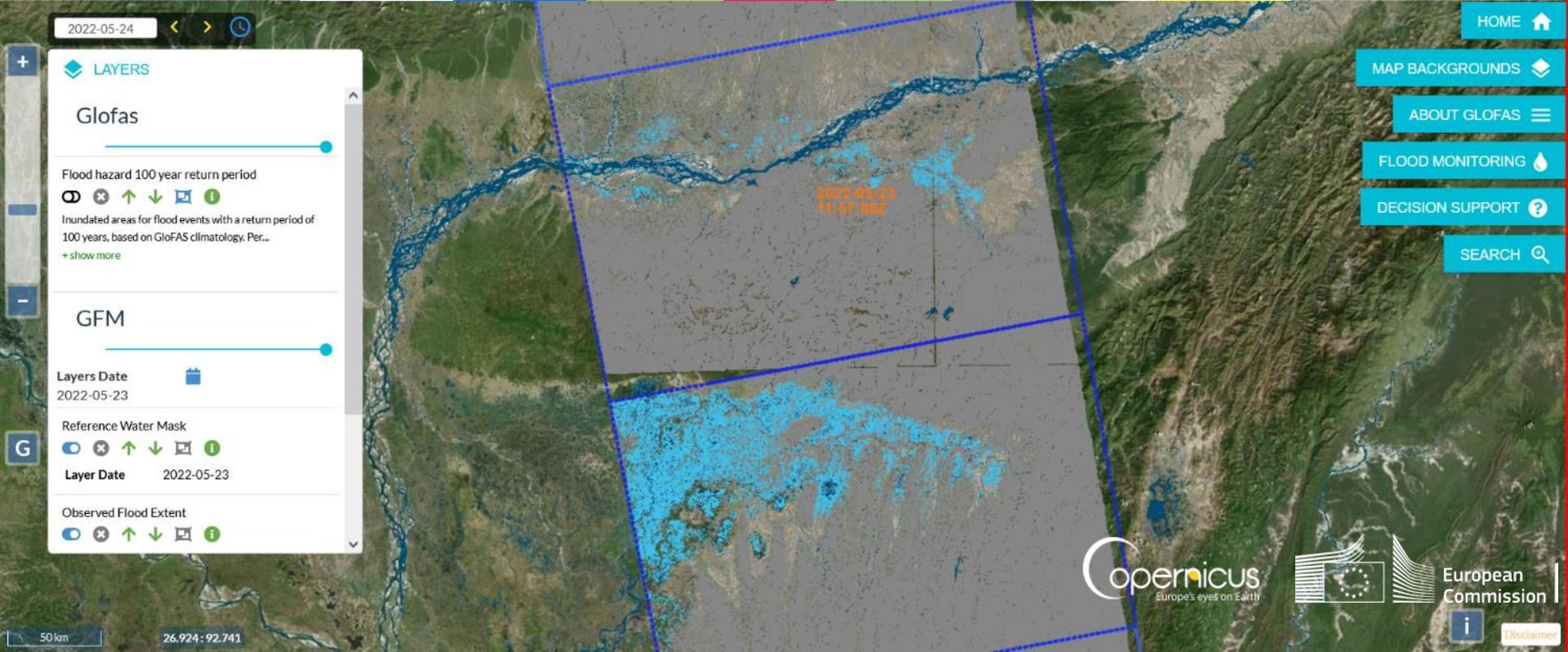
- ❖ Sentinel-1 satellite(s) enabling systematic, high-frequency radar observations at global scale.
- ❖ The InSAR coherence is the normalized cross correlation between images and it is related to the change in the spatial arrangement in time of the scatterers within a SAR image pixel.
- ❖ InSAR coherence is generally affected by spatial decorrelation, so that decreases with the increase of perpendicular baseline
 - ❖ ***Sentinel-1 is a perfect candidate given that the relatively narrow orbit tube (i.e. small perpendicular baseline of interferometric acquisitions)***

Global flood monitoring (GFM)

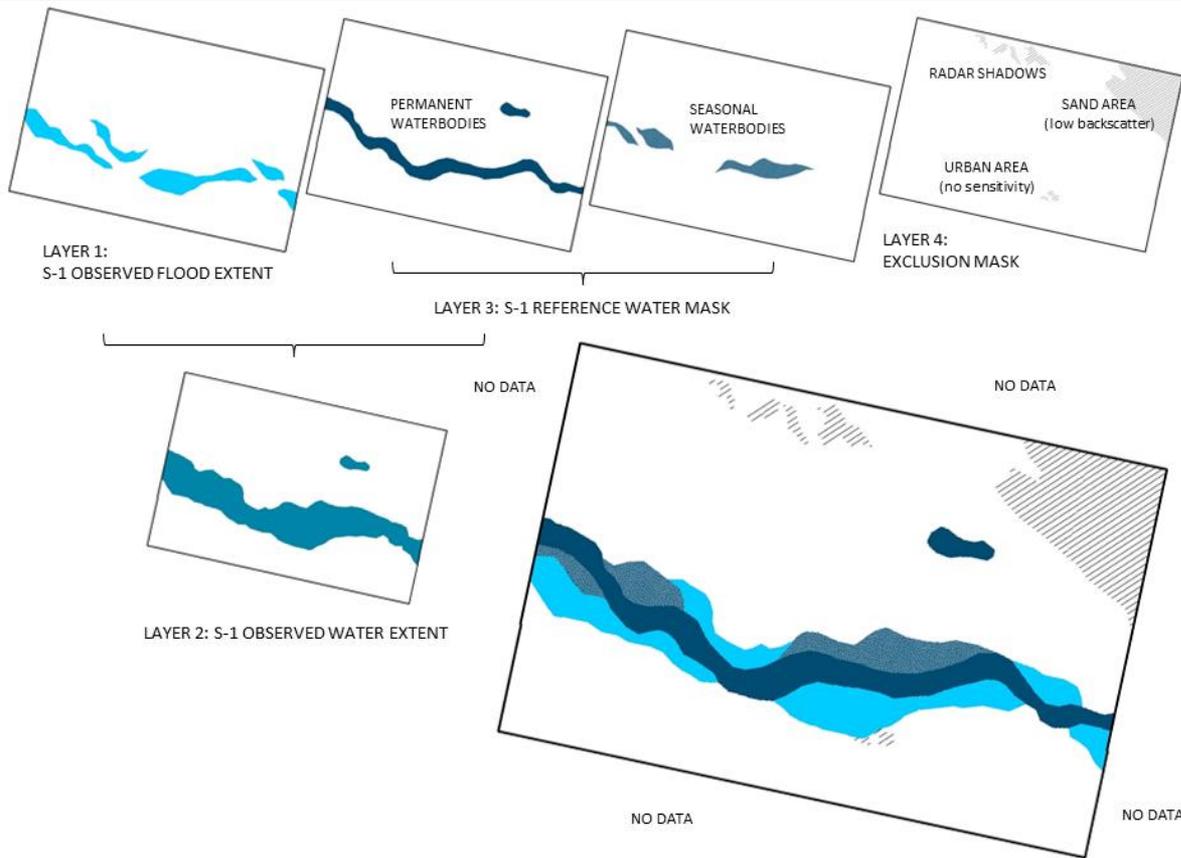


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2022-05-24 | FLOOD RISK | EVALUATION | STATIC | MONITORING | EXTERNAL WMS



Global flood monitoring (GFM)



Floodwater products:

- ❖ Flood extent
- ❖ Permanent water
- ❖ Seasonal water

Floods in urban areas

Sentinel-1 Derived Map of Flood Affected Urban Area - Valencia, Spain

0°36.0'W 0°30.0'W 0°24.0'W 0°18.0'W



The map illustrates the SAR-based inundation extent over bare soil derived from Sentinel-1 GRD data using the HASARD service as well as flood affected infrastructure derived from Sentinel-1 SLC data using the WASDI urban flood mapping service. The built-up area map has been derived from Sentinel-1 and Sentinel-2 data using a WASDI service. All services are based on scientifically validated retrieval algorithms developed by LIST. The processing was done by LIST via the WASDI platform. This map concerns disaster response for Charter Activation 924: Flood in Spain due to the extreme rainfall and flash flooding experienced from 29-31/10

Satellite Data:

Bare Soil Flood Map: Sentinel-1 GRD flood image acquired on 31/10/2024, Sentinel-1 GRD reference image acquired on 19/10/2024.
Affected/flooded infrastructures map: Sentinel-1 SLC flood image acquired on 31/10/2024, Sentinel-1 SLC pre-flood images acquired on 19/10/2024 and 7/10/2024. Basemap: Bing Aerial



Copyright: This map contains modified Copernicus Sentinel data. No liability concerning the content or the use thereof is assumed by LIST. The information has limitations due to the quality and resolution of the original data sources, as well as the uncertainties associated with the retrieval algorithms.



HASARD



Legend

Bare Soil Flooding
Flood Affected Infrastructure
Urban Areas

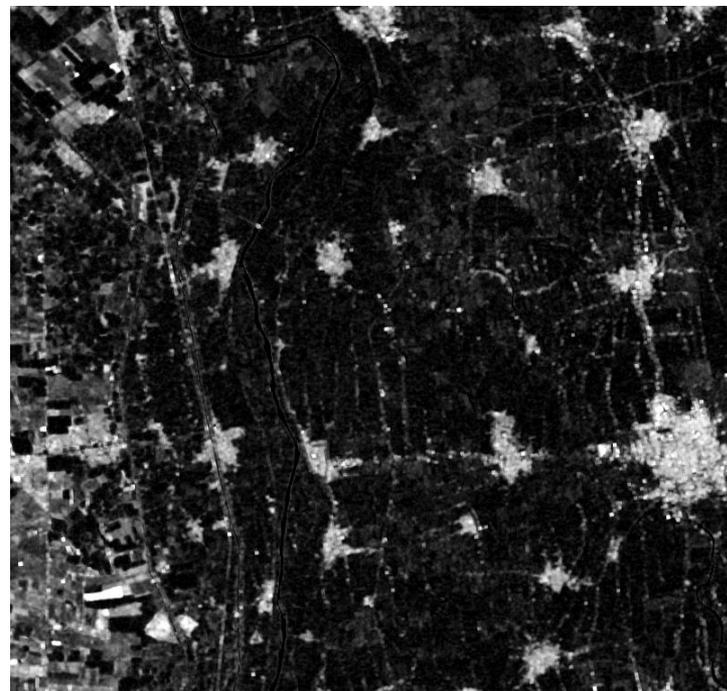


We developed an urban-aware U-Net model that uses Sentinel-1 dual polarization multitemporal intensity and coherence data, along with a building probability map, to identify flooding in bare soil and urbanized areas.

SAR Intensity



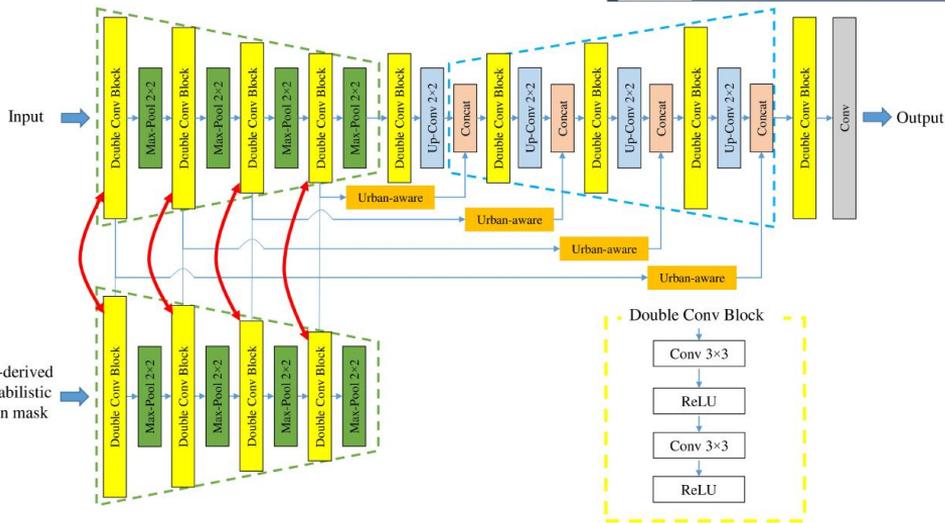
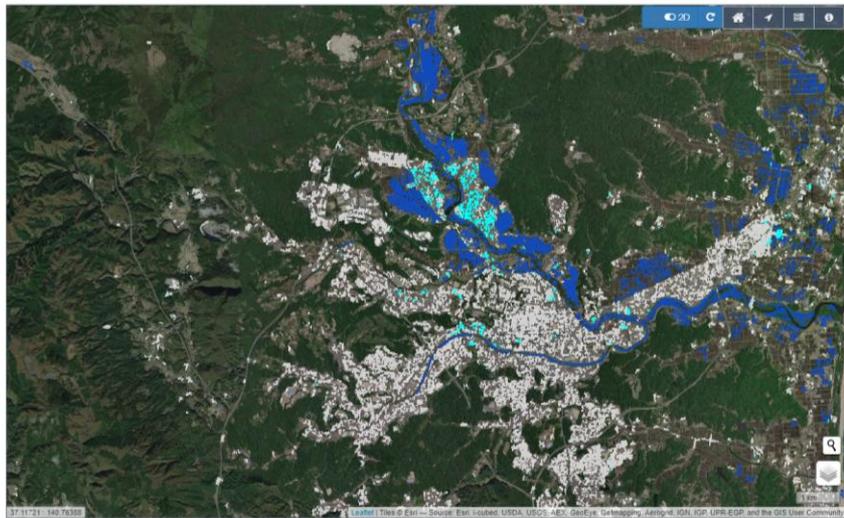
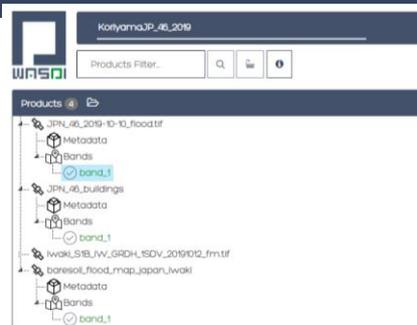
InSAR coherence



- ❖ The urban-aware module is applied to facilitate the learning process of the model by focusing on the more representative and robust features for different targets (i.e., different flood classes).
- ❖ The proposed urban-aware module uses a priori information, i.e., an SAR-derived probabilistic urban mask, and it consists of channel-wise attention and urban-aware normalization submodules to calibrate features and improve the final predictions.
- ❖ The channel attention and urban-aware normalization submodules are applied sequentially.

J. Zhao, Y. Li, P. Matgen R. Pelich, R. Hostache, W. Wagner, M. Chini, "Urban-Aware U-Net for Large-Scale Urban Flood Mapping Using Multitemporal Sentinel-1 Intensity and Interferometric Coherence", IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 60, 2022.

Floods in urban areas



- ❖ Deep Learning (DL) methods are powerful for learning representations from complex and high-dimensional data.
 - ❖ Supervised DL models do not generalize well on test datasets that have a different distribution with respect to training data.
- ❖ Training data is expensive to collect and update.
 - ❖ Only sparse labelled training data are available at a large scale.
- ❖ *We develop an automatic built-up area mapping framework using Sentinel-1 and Sentinel-2 data that:*
 - ❖ Automatically generates labels for training data in a given area of interest.
 - ❖ Trains a cross-fusion neural network using synergies between Sentinel-1 SAR and Sentinel-2 multi-spectral data.

Li, Y., Matgen, P. and Chini, M., "Extraction of built-up areas using Sentinel-1 and Sentinel-2 data with automated training data sampling and label noise robust cross-fusion neural networks," Int. J. Appl. Earth Observ. Geoinf., vol. 139, May 2025, Art. no. 104524 <https://doi.org/10.1016/j.iaq.2025.104524>

Automatic labels generation

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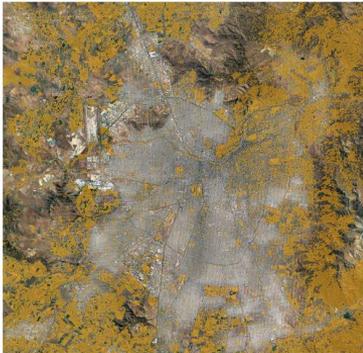
Sentinel-1 backscattering based built-up mask



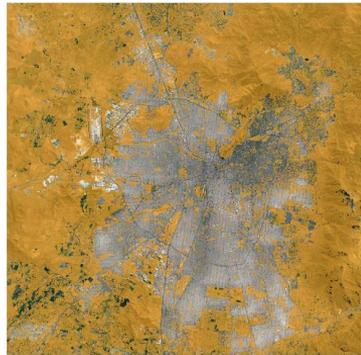
Sentinel-2 NDBI based built-up mask



Sentinel-2 BUI based built-up mask



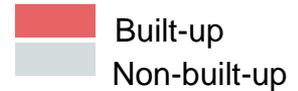
Sentinel-2 NDVI based vegetation mask



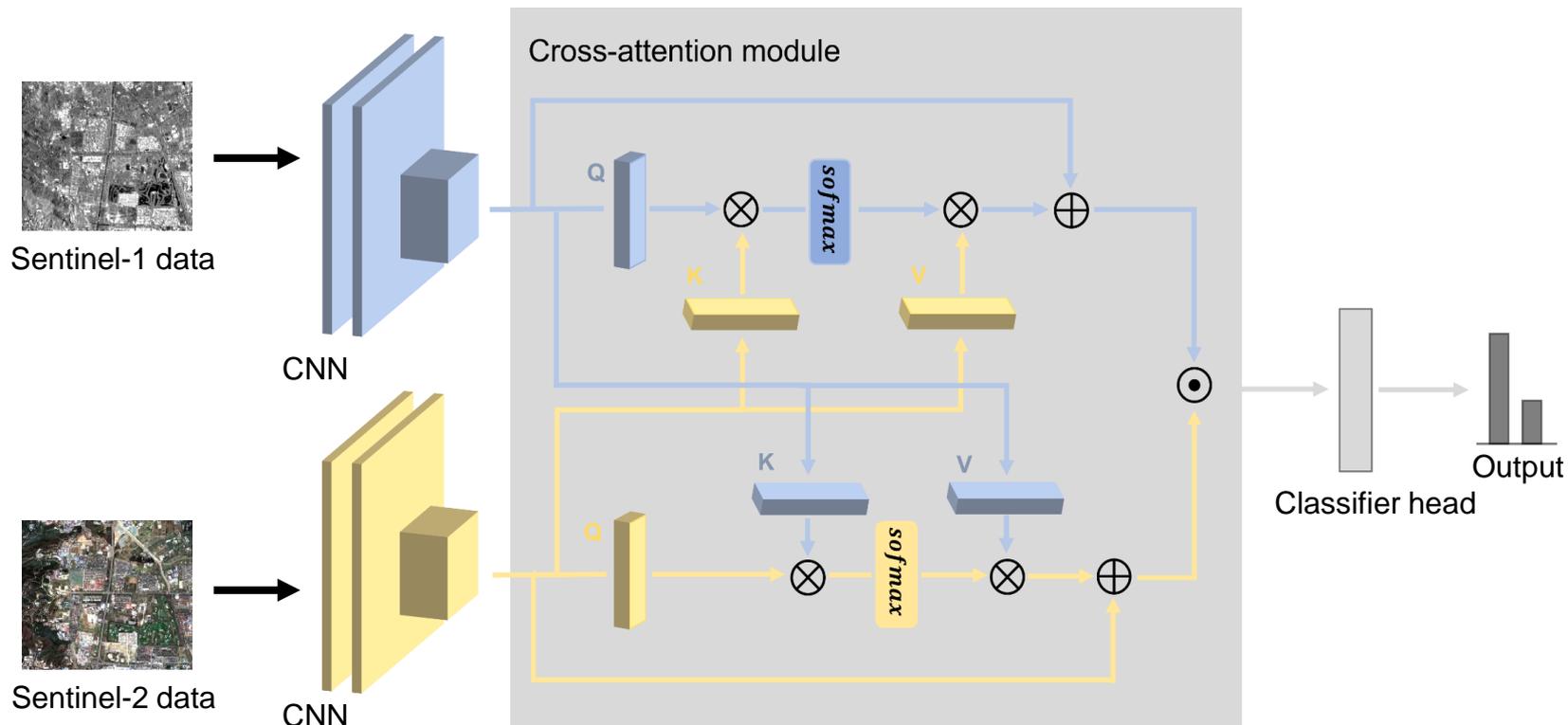
Sentinel-2 NDRB based bareness mask



Labels of training data



Cross-fusion Network



\otimes : Matrix Multiplication

\oplus : Add

\odot : Concatenate

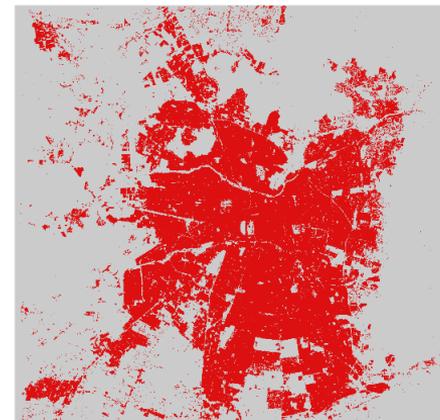
- ❖ The cross-fused features are concatenated for the final prediction.
- ❖ To make the model more resilient to label errors a virtual adversarial training (VAT) regularization is added.
- ❖ The total loss function is composed of a standard cross-entropy term and a VAT regularization term.

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Labels of training data

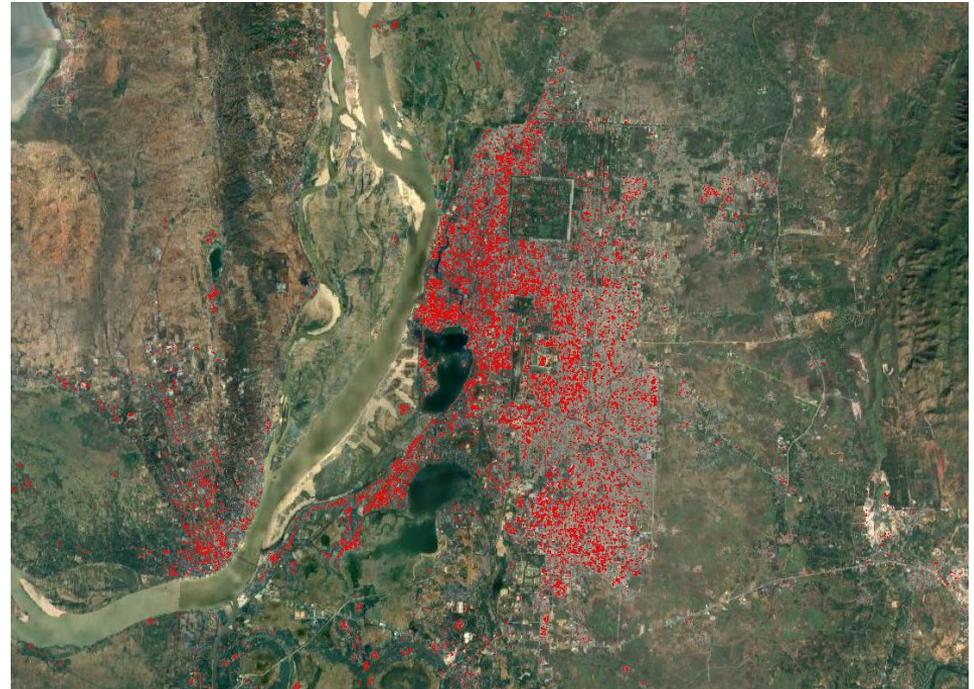
■ Built-up
■ Non-built-up



Final building map

- ❖ All-Weather, Radar-based
Near Real-Time Monitoring
- ❖ Rapid, Large-Scale
Assessment
- ❖ Adaptable & Generalizable AI
- ❖ Efficient Self-Supervised
Learning

2025 Myanmar earthquake



F1 – Score: 0.82

Thanks!!!!



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