

# EO-AI4GlobalChange: Earth Observation Big Data and Deep Learning for Global Environmental Change Monitoring

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## Abstract:

Our planet is facing unprecedented environmental challenges including rapid urbanization, deforestation, pollution, loss of biodiversity, melting glacier, rising sea-level, and climate change. In recent years, the world also witnessed numerous natural disasters, from droughts, heat waves and wildfires to flooding and hurricanes, killing thousands and causing billions in property and infrastructural damages. With its synoptic view, large area coverage at regular revisits, satellite remote sensing has been playing a crucial role in monitoring our changing planet. The overall objective of the EO-AI4GlobalChange project is to develop innovative and robust methods for monitoring global environmental changes using Earth Observation big data and deep learning. In this research, we focus on two of the major global environmental challenges: urbanization and wildfires.

Open and free Earth observation big data such as Sentinel-1 SAR and Sentinel-2 MSI data have been used to demonstrate the novel deep learning-based methods in selected cities around the world, and in various wildfire and flooding sites across the globe. For urban mapping, a novel Domain Adaptation (DA) approach using semi-supervised learning has been developed for extracting built-up areas. The DA approach jointly exploits Sentinel-1 SAR and Sentinel-2 MSI data to improve across-region generalization for mapping built-up areas. Urban mapping experiments conducted over 60 sites across the globe showed that the proposed DA approach achieves strong improvements upon fully supervised learning from Sentinel-1 SAR data, Sentinel-2 MSI data and their input-level fusion (Hafner *et al.*, 2022a).

For urban change detection, several deep learning-based methods have been evaluated and adapted including a dual-stream U-Net and a Siamese Difference Dual-Task network with Multi-Modal Consistency Regularization. Using the Onera Satellite Change Detection (OSCD) dataset, the results showed that the dual-stream U-Net outperformed other U-Net-based approaches together with SAR or optical data and feature level fusion of SAR and optical data (Hafner *et al.*, 2022b). Using bi-temporal SAR and optical image pairs as input, the Siamese Difference Dual-Task network with Multi-Modal Consistency Regularization have been tested in the 60 sites of the SpaceNet7 dataset. The method achieved higher F1 score than that of several supervised models when applied to the sites located outside of the source domain.

For early detection of active fires, we evaluated Gated Recurrent Units (GRU) and Transformer networks using GOES-R (Zhao and Ban, 2022) and VIIRS time series (Zhao *et al.*, 2023). For near real-time wildfire progression monitoring, we investigated two approaches to train the deep residual U-Net model for continuous learning exploiting Sentinel-1 SAR and Sentinel-2 MSI data: 1) Continuous joint training (CJT) with all historical data (including both SAR and optical data); 2) Learning without forgetting (LwF) based on newly incoming data alone (SAR or optical) (Zhang *et al.*, 2022). The results show that the wildfire detection time based on GOES-R data are earlier for most of the study sites than that of the VIIRS active fire products. The Transformer network achieved a significantly higher F1 score than other methods for detecting active fires in California, US and British Columbia, Canada. For wildfire monitoring, the results demonstrated that LwF has the potential to match CJT in terms of the agreement between SAR-based results and optical-based ground truth, achieving a F1 score of 0.8.

These studies demonstrated that integrating multi-resolution multi-sensor EO data and deep learning is promising for urban mapping, urbanization monitoring, early detection and near real-time monitoring of wildfires and rapid damage assessment. Timely and reliable information that the EO-AI4GlobalChange project generates can be used by civil contingency agencies to support effective emergency management and decision making during and after wildfires. Automatic and continuous mapping of urban areas and their changes can be used to support sustainable and resilient city planning and contribute to monitoring the UN 2030 Urban Sustainable Development Goal (SDG 11).

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## References

- Hafner, S., Y. Ban, A. Nascetti and H. Azizpour. 2022a. Unsupervised Domain Adaptation for Global Urban Extraction using Sentinel-1 and Sentinel-2 Data. *Remote Sensing of Environment*. Volume 280, 113192, <https://doi.org/10.1016/j.rse.2022.113192>.
- Hafner, S., A. Nascetti, H. Azizpour and Y. Ban. 2022b. Sentinel-1 and Sentinel-2 Data Fusion for Urban Change Detection using a Dual Stream U-Net. *IEEE Geoscience and Remote Sensing Letters*, Vol. 19, 4019805, DOI: 10.1109/LGRS.2021.3119856.
- Zhao Y, and Y. Ban. 2022. GOES-R Time Series for Early Detection of Wildfires with Deep GRU-Network. *Remote Sensing*. 2022; 14(17):4347. <https://doi.org/10.3390/rs14174347>.
- Zhang, P., Y. Ban, and A. Nascetti. 2021. Learning U-Net without Forgetting for Near Real-Time Wildfire Monitoring by the Fusion of SAR and Optical Time Series. *Remote Sensing of Environment*, 1-12.