AI4EO:

Accelerating Earth Intelligence for All through AI and Earth Observation

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WHAT IS GEO?
GROUP ON EARTH OBSERVATIONS
Our planet is facing **multiple crises that threaten** each and **everyone** of us.

Biodiversity loss and land degradation are weakening our economies and undermining the well-being of billions of people.

GROUP ON EARTH OBSERVATIONS

Hot days and extreme heat events are becoming more intense and more frequent, causing about 500,000 extra deaths a year globally.

Pollution is now claiming nine million lives every year.


WHAT IS GEO?
GEO GROUP ON EARTH OBSERVATIONS
2.4 billion people do not have access to nutritious, safe and sufficient food all year round.
6

And for entire nations, **rising sea levels, droughts and floods** are becoming an existential risk.


Now is the time to use
Earth Intelligence
to make better decisions
for people and planet.

Earth Intelligence for All

Integrate Earth observations, models, and innovative new technologies (including artificial intelligence, machine learning, digital twins, cloud computing) into the design of services that provide Earth intelligence.

Therefore, as it looks to the future, GEO will:

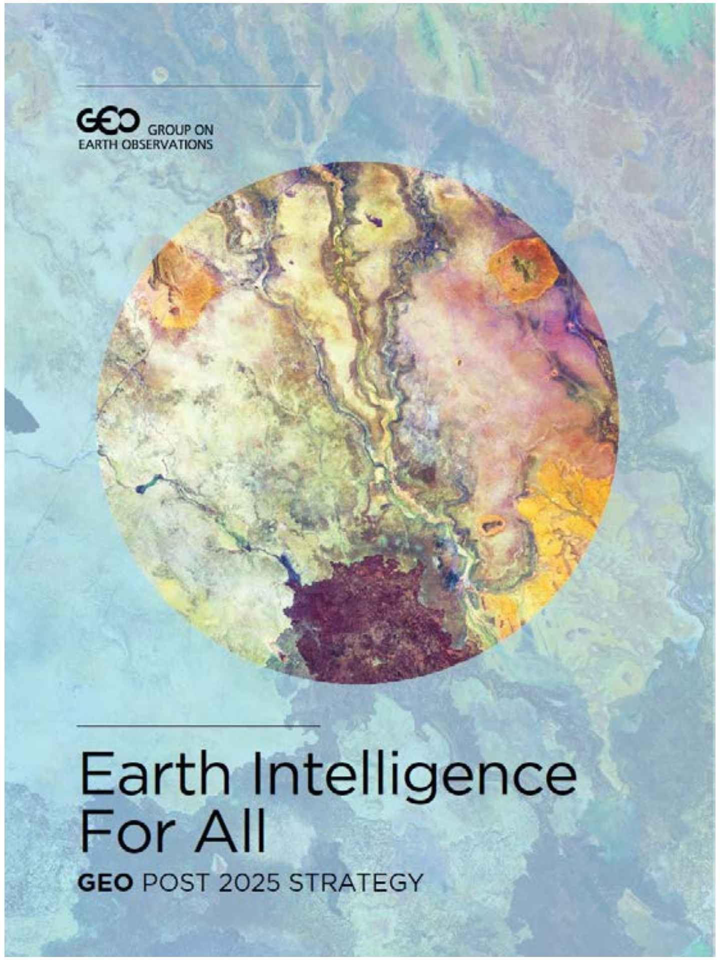
Make Earth intelligence a fundamental pillar of knowledge-based decision-making for sustainable development, building an inclusive, sustainable and resilient future for people and the planet.

Facilitate a shift from a focus on the development of services to a focus on provision of needs-based services to all, in order to bridge global knowledge and information gaps.

Co-design user-orientated services by identifying policy and decision-making needs, designing the services needed to support these needs, creating the products to enable the services, and identifying affordable and trusted Earth observation components — from across the value chain[2] — required to sustain these products.

Integrate Earth observations, models, and innovative new technologies (including artificial intelligence, machine learning, digital twins, cloud computing) into the design of services that provide Earth intelligence.

Enhance inclusivity and adaptability in the GEO community by leveraging expertise and resources from across the scientific community, indigenous peoples and local communities, private sector, civil society and international finance institutions, and by fostering open data and knowledge and building capacities.



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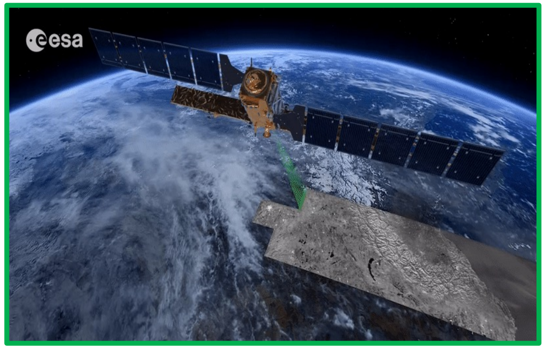
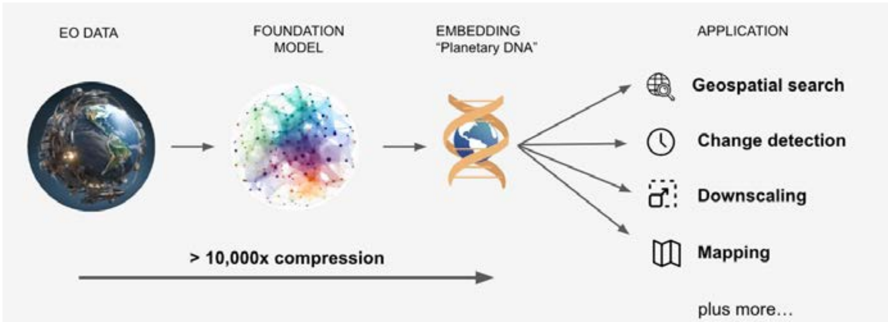
Earth Observation Big Data



AI for EO Big Data: Opportunities

EO Big Data

- EO big data: open access and commercial
- Multi-model EO data: Multispectral, hyperspectral, SAR, LiDAR, etc.
- Multi-resolution/multi-scale
- Long time series



AI for EO

- Advanced deep learning models
- Automated image processing, analysis, classification, change detection, etc.
- Time series processing
- Multi-model data fusion
- Accelerate applications: air pollution, digital agriculture, biodiversity, disaster response & management, urbanization, environmental changes, and SDGs monitoring, etc.

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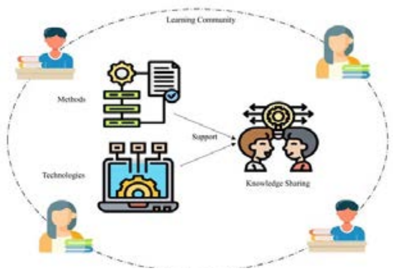
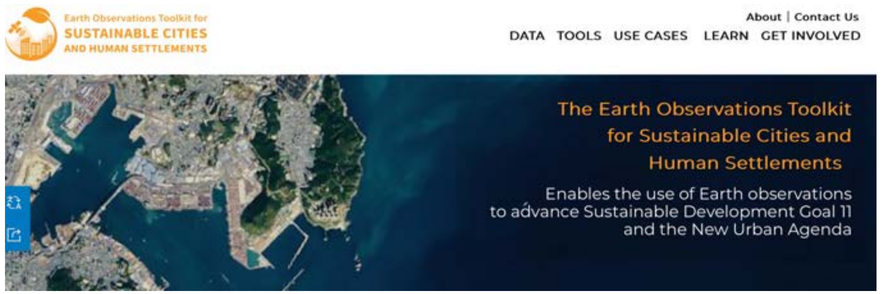
Artificial Intelligence for Earth Observations (AI4EO)

- The **GEO AI4EO Working Group** aims to **integrate AI into Earth Intelligence** by establishing **a network of AI experts** across the GEO community. The Convener's scope includes **advancing AI applications** within the GEO Work Programme, fostering **cross-disciplinary collaboration**, and addressing **ethical considerations** related to AI in Earth observations. It will serve as a central hub to explore, develop, and apply **AI-driven EO solutions** that support **GEO's Post-2025 Strategy**.





GEO GROUP ON EARTH OBSERVATIONS

Earth intelligence for all — GEO Symposium & ODOK Workshop — FROM VISION TO ACTION

AI4EO: Specific Objectives

- Promote Cross-Disciplinary, Cross-Community Collaboration
  - AI4EO aims to connect experts in AI, data science, and EO from various GEO communities, including members of different GWP Focus Areas.
- Support Capacity Building and Knowledge Exchange
  - AI4EO will organize training sessions, webinars, and workshops to share best practices, tools, and techniques for applying AI in EO.
- Develop and Disseminate Cross-cutting AI Tools and Resources
  - AI4EO will curate and advocate for accessible, reproducible AI-driven tools and applications that can be used across various GEO initiatives. These tools - covering areas such as image classification, change detection, predictive modeling, and real-time monitoring—serve as cross-cutting assets that enhance EO capabilities and make Earth Intelligence more actionable and accessible.
- Enhance Data-Driven Decision-Making and Policy Support
  - By integrating AI insights into GEO's data ecosystem, the Convener aims to translate complex data into actionable intelligence.

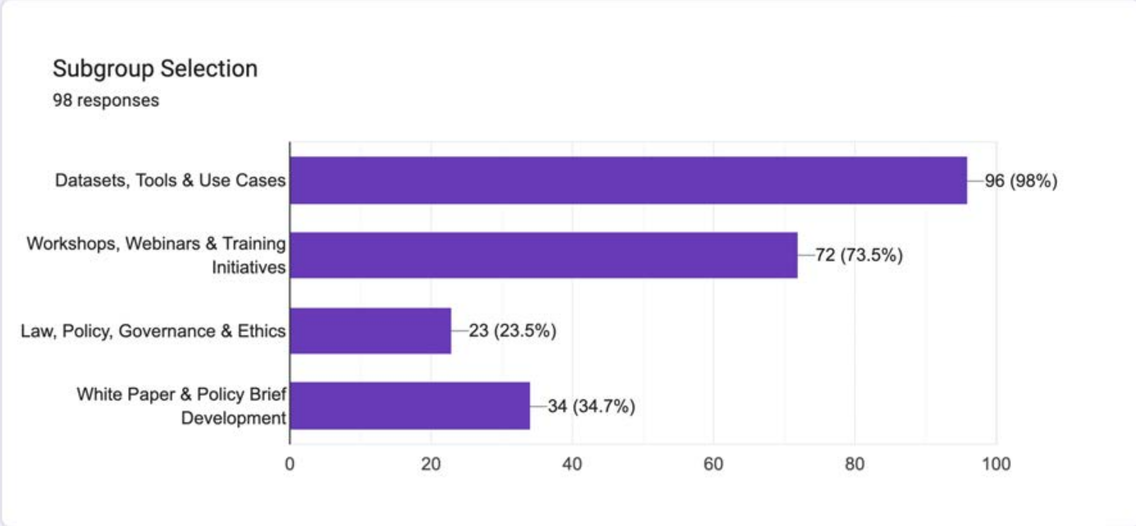
GROUP ON EARTH OBSERVATIONS

Earth intelligence for all
GEO Symposium & ODOK Workshop
FROM VISION TO ACTION

AI4EO Sub-Groups

Subgroup Selection *

- [ ] Datasets, Tools & Use Cases
- [ ] Workshops, Webinars & Training Initiatives
- [ ] Law, Policy, Governance & Ethics
- [ ] White Paper & Policy Brief Development



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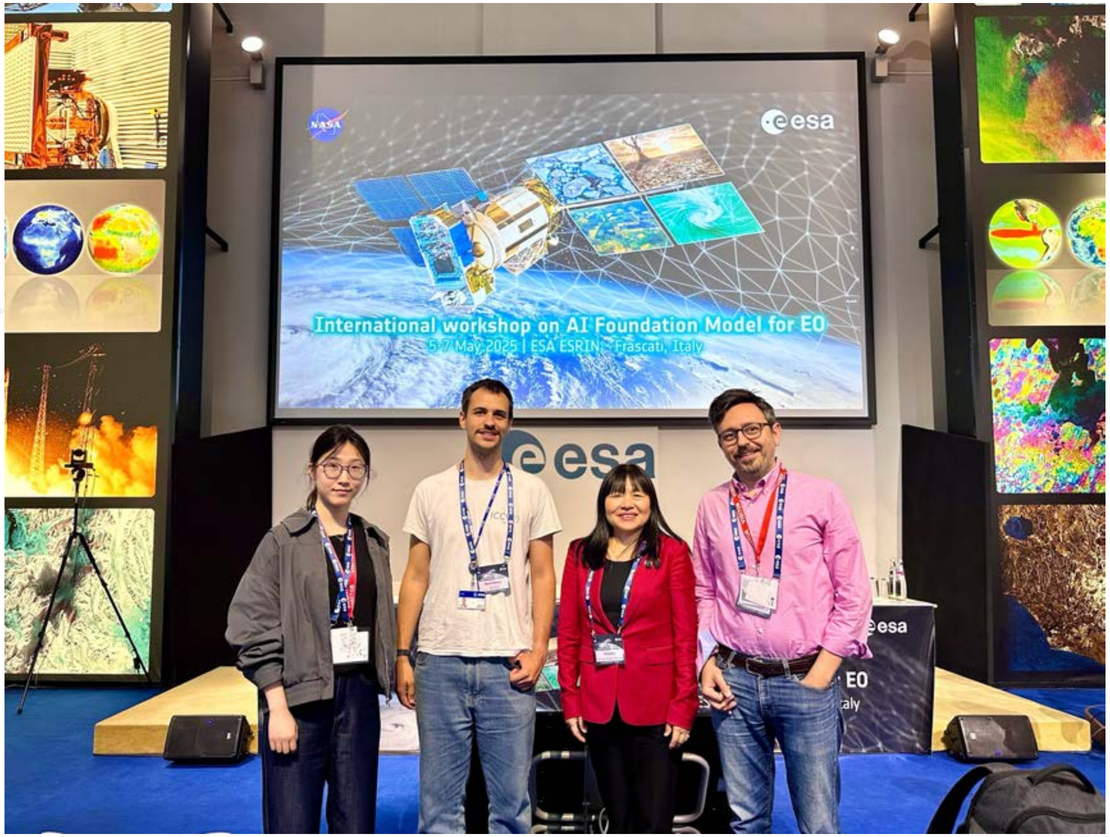
Earth intelligence for all
GEO Symposium & ODOK Workshop
FROM VISION TO ACTION



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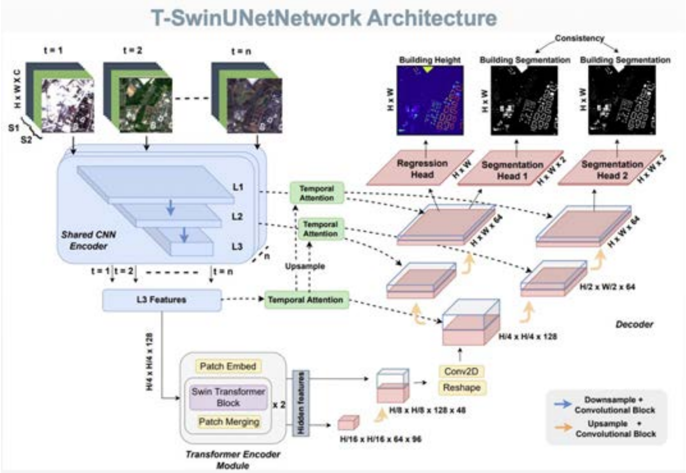
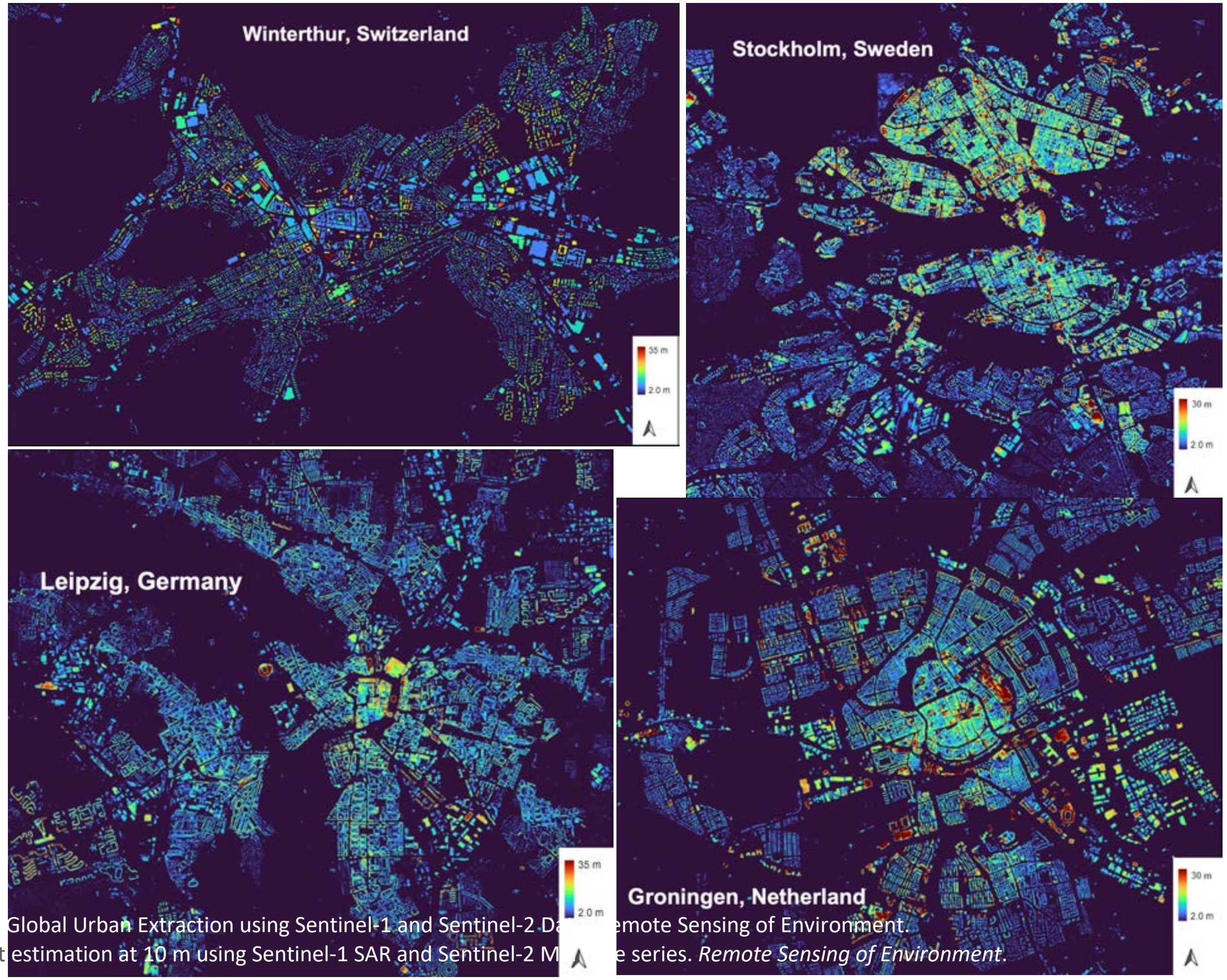
AI-EO for 2D & 3D Urban Mapping



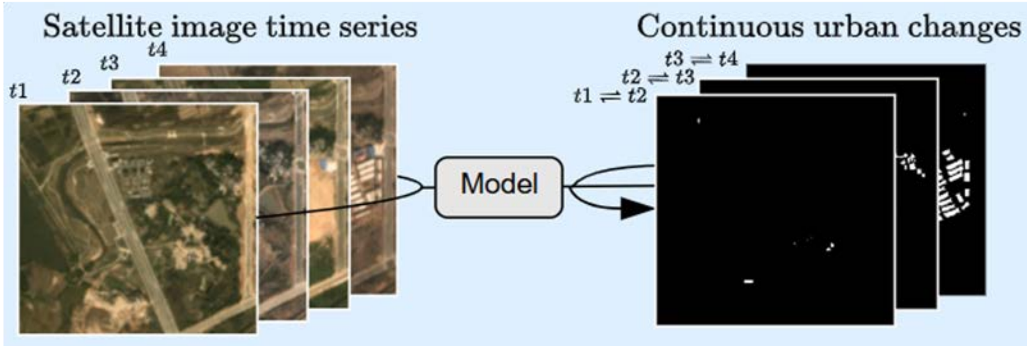


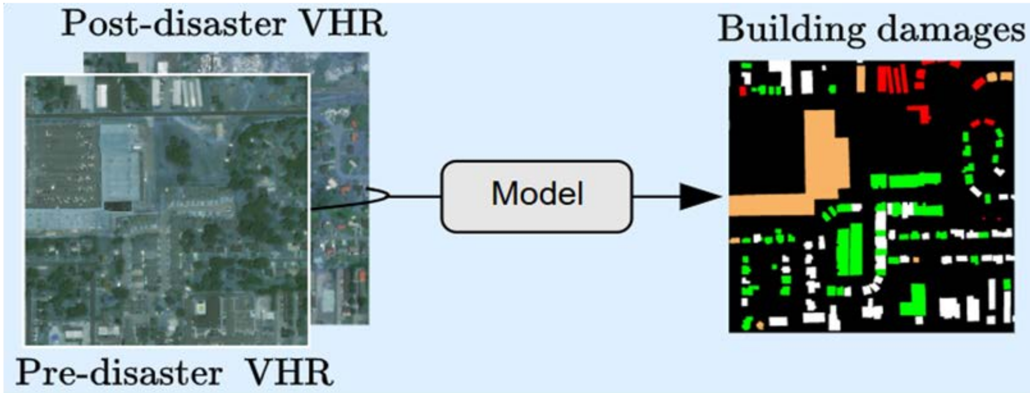
Hafner, S., Y. Ban, and A. Nascetti. 2022. Unsupervised Domain Adaptation for Global Urban Extraction using Sentinel-1 and Sentinel-2 Da emote Sensing of Environment.
Yadav R, Nascetti A, Ban Y. 2025. How high are we? Large-scale building height estimation at 10 m using Sentinel-1 SAR and Sentinel-2 M e series. *Remote Sensing of Environment*.

AI-EO for Urban Change Detection

- Continuous Change Detection

- Building Damage Detection

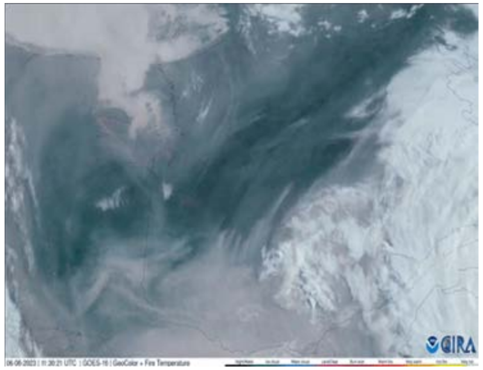


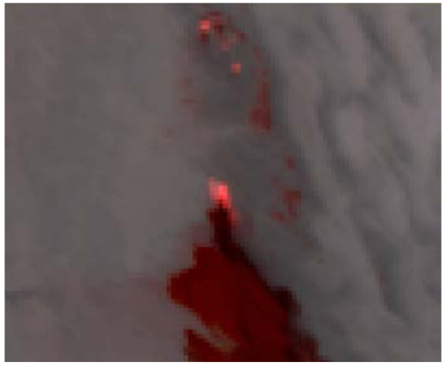


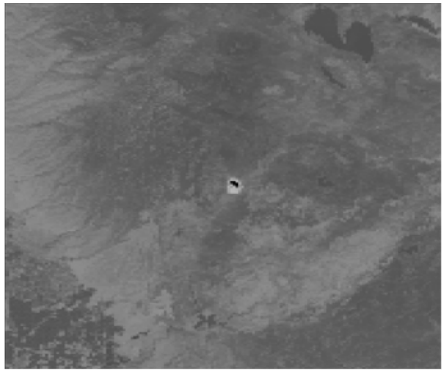
S. Hafner, H. Fang, H. Azizpour, and Y. Ban. 2025. Continuous Urban Change Detection from Satellite Image Time Series with Temporal Feature Refinement and Multi-Task Integration. *IEEE Transaction on Geoscience and Remote Sensing.*

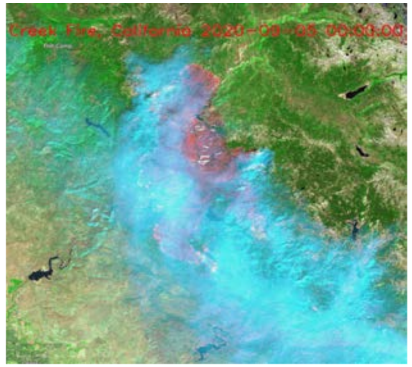
S. Hafner*, S. Gerard*, J. Sullivan, and Y. Ban. DisasterAdaptiveNet: A Robust Network for Multi-Hazard Building Damage Detection from Very-High-Resolution Satellite Imagery. *International Journal of Applied Earth Observation and Geoinformation* (under revision).

AI & EO Time Series for Active Fire Detection

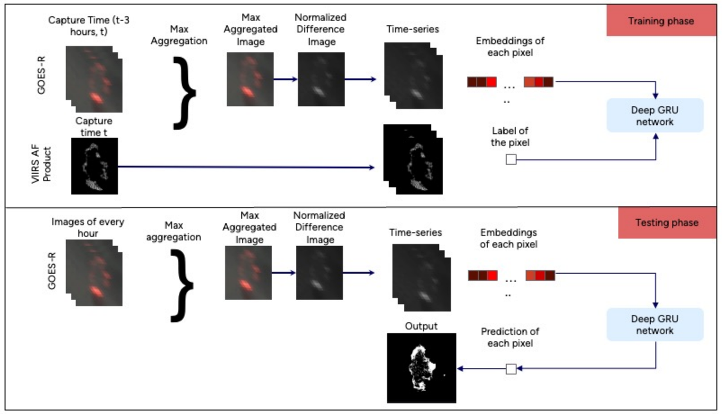




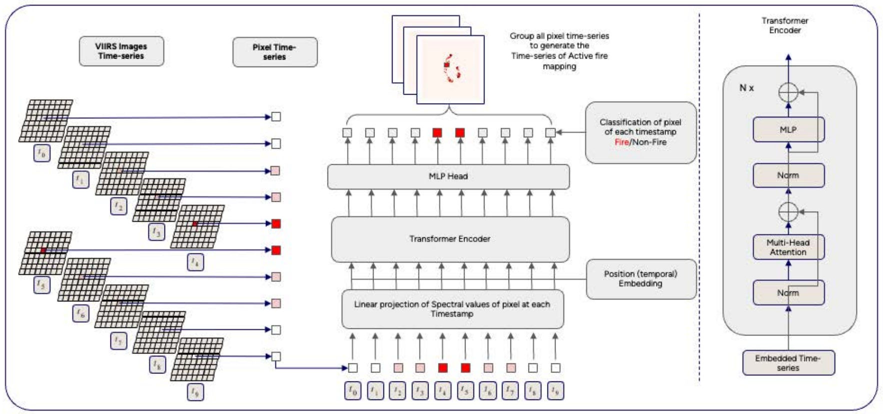




Deep GRU network for Near Real-Time Active Fire Detection with GOES-R series



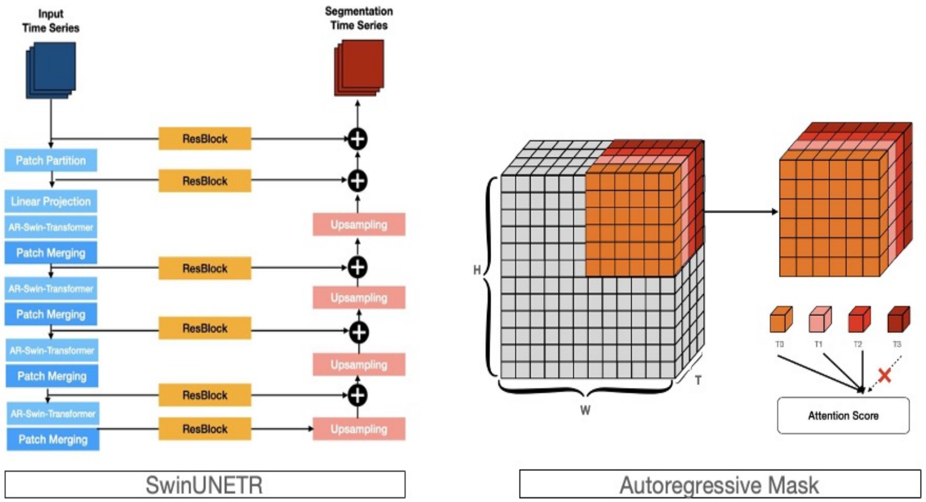
Transformer-based AF detection with VIIRS image Time-series

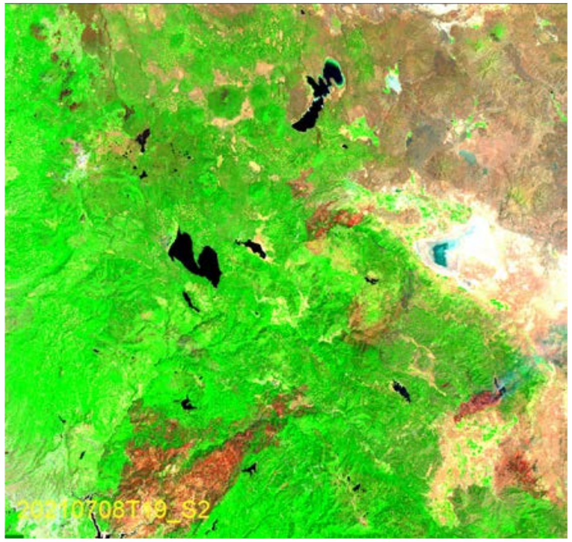


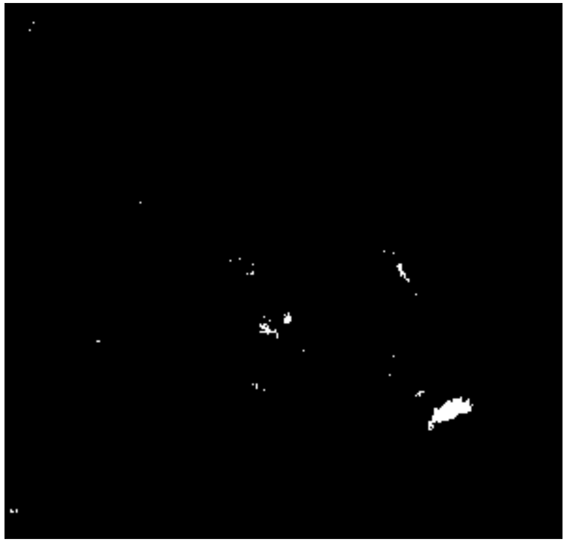
Zhao, Y., Y. Ban, & J. Sullivan. 2023. Tokenized Time-Series Satellite Image Segmentation with Transformer Network for Active Wildfire Detection. *IEEE Transaction on Geoscience and Remote Sensing,* vol. 61, Art no. 4405513.
Zhao, Y. & Y. Ban.. 2022. GOES-R Time Series for Early Detection of Wildfires with Deep GRU-Network. *Remote Sensing*, 14(17), 4347; https://doi.org/10.3390/rs14174347
Hu, X., Y. Ban, and A, Nascetti. 2021. Uni-Temporal Multispectral Imagery for Burned Area Mapping with Deep Learning. *Remote Sensing*, 13, no. 8: 1509.
Hu, X., Y. Ban, and A, Nascetti. 2021. Sentinel-2 MSI data for active fire detection in major fire-prone biomes: A multi-criteria approach. *International Journal of Applied Earth Observation and Geoinformation*, 101.

AI & EO Time Series for NRT Wildfire Monitoring

Daily Burned Area Mapping using SwinUNETR with VIIRS Image Time Series







Ban, Y., Zhang, P., Nascetti, A., Bevington, A. R., Wulder, M. A., 2020. Near Real-Time Wildfire Progression Monitoring with Sentinel-1 SAR Time Series and Deep Learning. *Nature Scientific Reports*, 10(1), 1–15.

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.

Hu, X., P. Zhang and Y. Ban. 2022. Large-scale burn severity mapping in multispectral imagery using deep semantic segmentation models. *ISPRS Journal of Photogrammetry and Remote Sensing*, Vol. 196, pp. 228-240.

Zhang, P., Y. Ban, A. Nascetti. 2023. Total-variation regularized U-Net for wildfire burned area mapping based on Sentinel-1 C-Band SAR backscattering data. *ISPRS Journal of Photogrammetry and Remote Sensing*, Vol. 203, pp 301-313.

Hu, X., P. Zhang, Y. Ban, M. Rahnemoonfar. 2023. GAN-based SAR and optical image translation for wildfire impact assessment using multi-source remote sensing data. *Remote Sensing of Environment*, Volume 289, 113522.

Zhang, P., X. Hu, Y. Ban, A. Nascetti, M. Gong. 2024. Assessing Sentinel-2, Sentinel-1, and ALOS-2 PALSAR-2 Data for Large-Scale Wildfire-Burned Area Mapping: Insights from the 2017–2019 Canada Wildfires. *Remote Sensing*, 16, 556.

Zhao, Y., Ban, Y. 2025. Near Real-Time Wildfire Progression Mapping with VIIRS Time-Series and Autoregressive SwinUNETR. *International Journal of Applied Earth Observation and Geoinformation*, Vol. 136

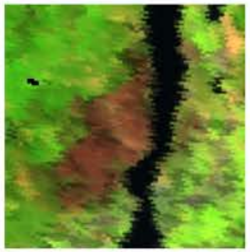
Wildfire Monitoring with Satellite Remote Sensing

Satellite imagery is well-suited for active fire detection and burned area mapping.

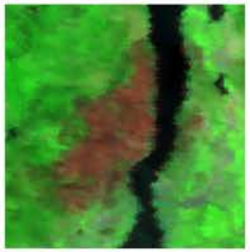
Problem 1: Spatial-temporal resolution trade-off

Low spatial resolution, high temporal frequency
(250-500 m daily coverage)

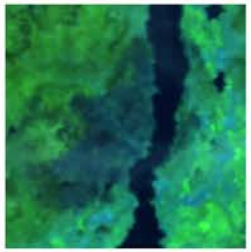
MODIS



VIIRS



Sentinel-3

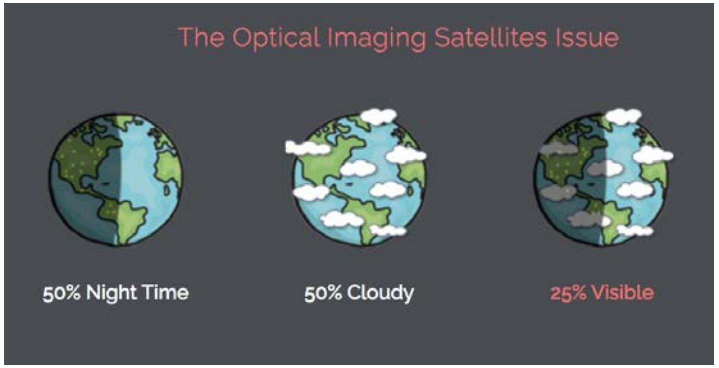


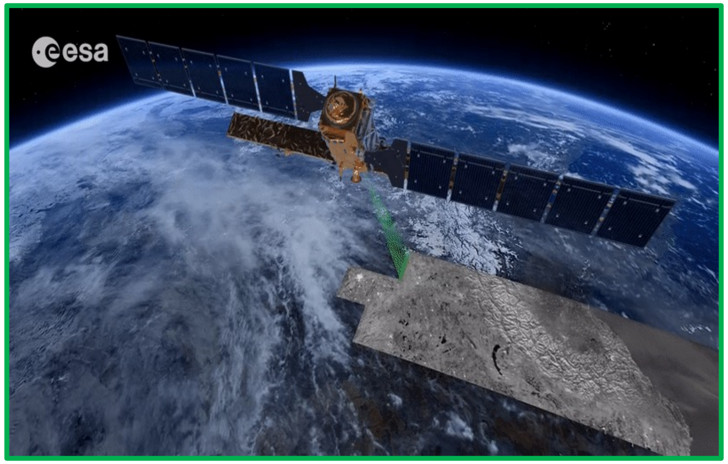
High spatial resolution, low temporal frequency
(10-20 m, 5-day revisit)

Sentinel-2 pre/post-fire

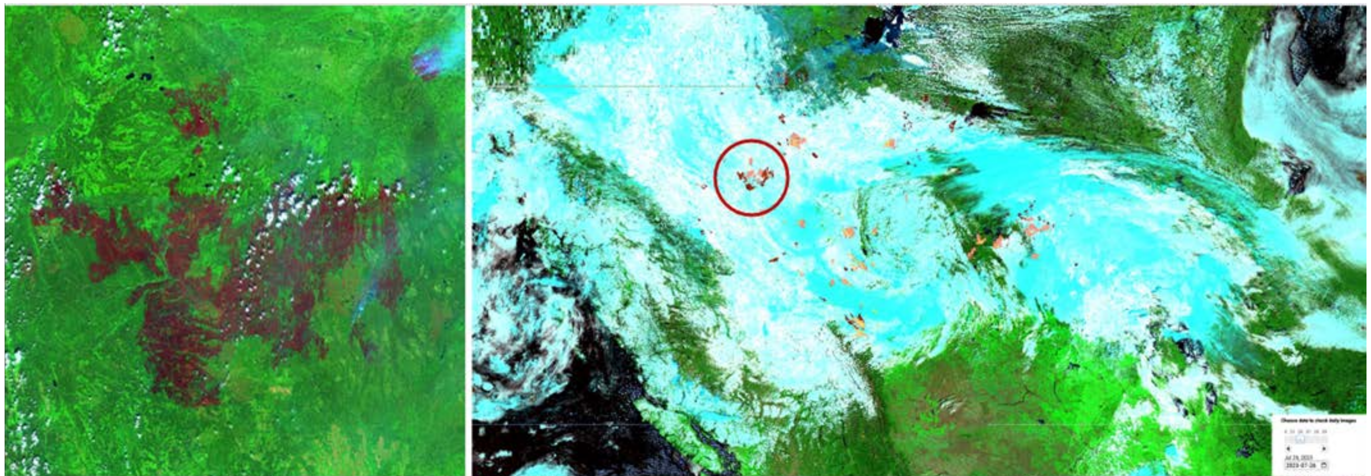
Multisensor Satellite Data for Wildfire Monitoring

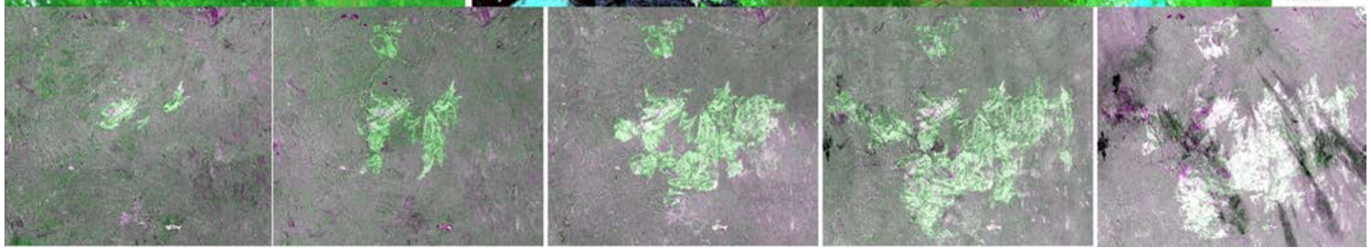
Problem 2: Clouds and smoke obscure optical imagery





Donnie Creek Fire: Sentinel-2 image (Left, 10-20 m resolution) and VIIRS Image (Right, 375 m resolution)

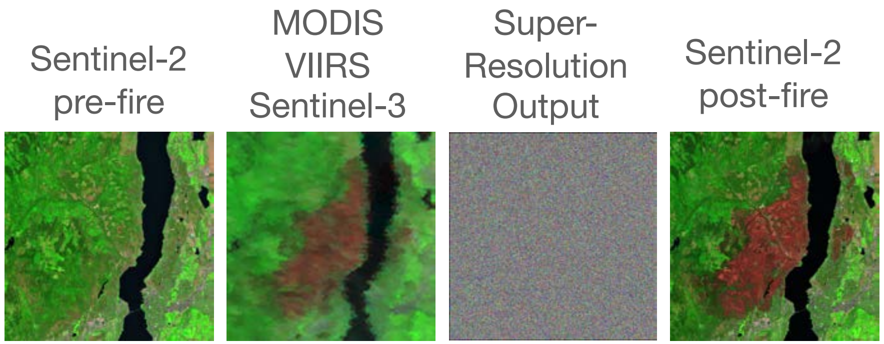


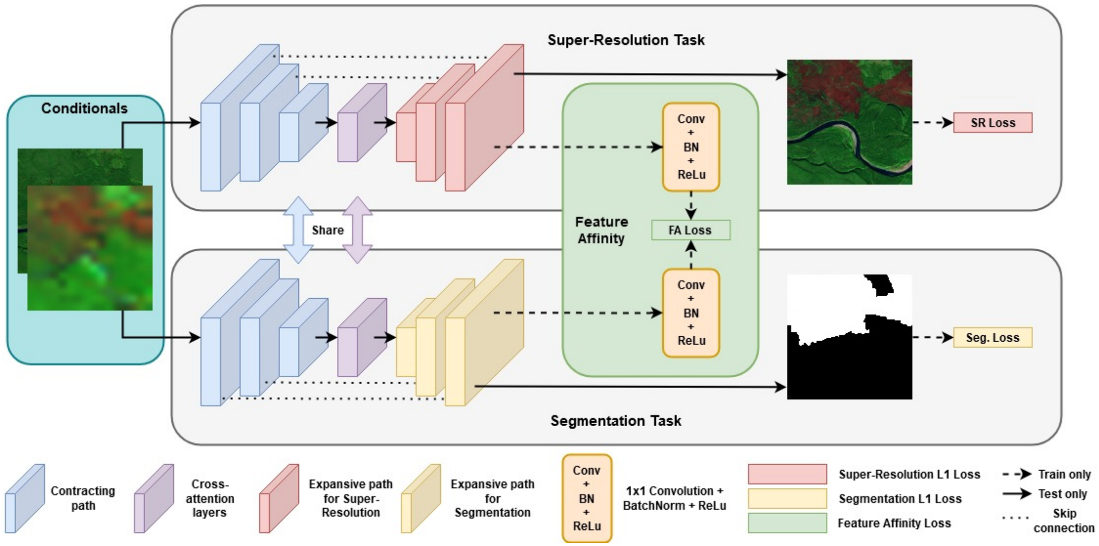


Donnie Creek Fire: Sentinel-1 image time series (20 m resolution)

Image Super Resolution with Denoising Diffusion Probabilistic Model (DDPM)

- Generative deep learning framework in which models learn to predict added noise
- FireSR-DDPM, a multi-task learning DDPM framework
  (only tested on MODIS, need to expand to VIIRS and Sentinel-3)





E. Brune and Y. Ban, 2025. Daily High-Resolution Wildfire Monitoring Using Context-Aware Multi-Task Diffusion Models. Submitted to *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS).*

Preliminary Results: Super Resolution

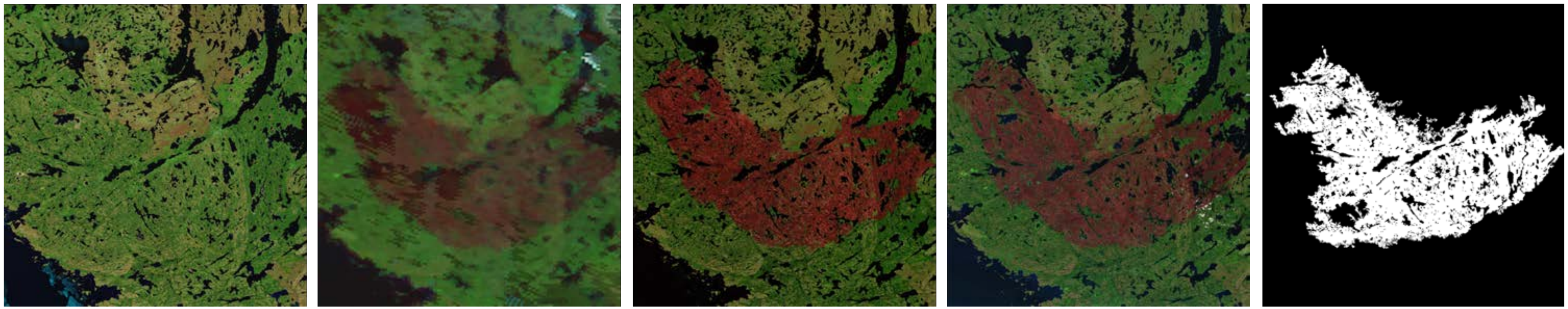
QUANTITATIVE COMPARISON ON THE 2023 FIRES. ARROWS INDICATE WHETHER HIGHER (↑) OR LOWER (↓) VALUES ARE BETTER. LPIPS IS SHOWN IN MEAN ± ONE STANDARD DEVIATION FOR THE TEST PATCHES.

Model	IoU (↑)	F1 (↑)	LPIPS (↓)
MODIS U-Net	0.6795	0.8092	-
SR3	-	-	0.1347±0.0921
U-Net	0.6985	0.8225	-
FireSR-DDPM (ours)	**0.8153**	**0.8983**	**0.1134±0.0677**

RESULTS ON THE 2023 FIRES, SHOWING THE EFFECT OF ADDING LULC, DAYMET DATA, AND THE FEATURE AFFINITY MODULE ($\mathcal{L}_{FA}$) TO THE MODEL.

LULC	Daymet	$\mathcal{L}_{FA}$	IoU (↑)	F1 (↑)	LPIPS (↓)
×	×	×	0.7505	0.8575	0.1178 ± 0.0705
×	×	✓	0.8153	0.8983	0.1134 ± 0.0677
✓	×	✓	0.7868	0.8807	0.1192 ± 0.0757
✓	✓	✓	0.7653	0.8670	0.1450 ± 0.1029

Sentinel-2 Pre-fire | MODIS | FireSR-DDPM | Sentinel-2 Post-fire | NBAC Polygon



Out-of-Distribution Experiments

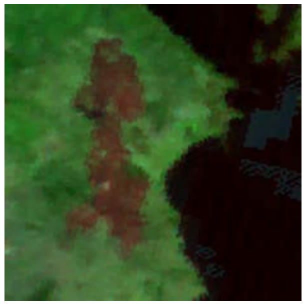
Attica Fire

IoU: 0.7641, F1: 0.8663, LPIPS: 0.1961

S2 Pre

S3

MODIS



FireSR-DDPM

EMS Label

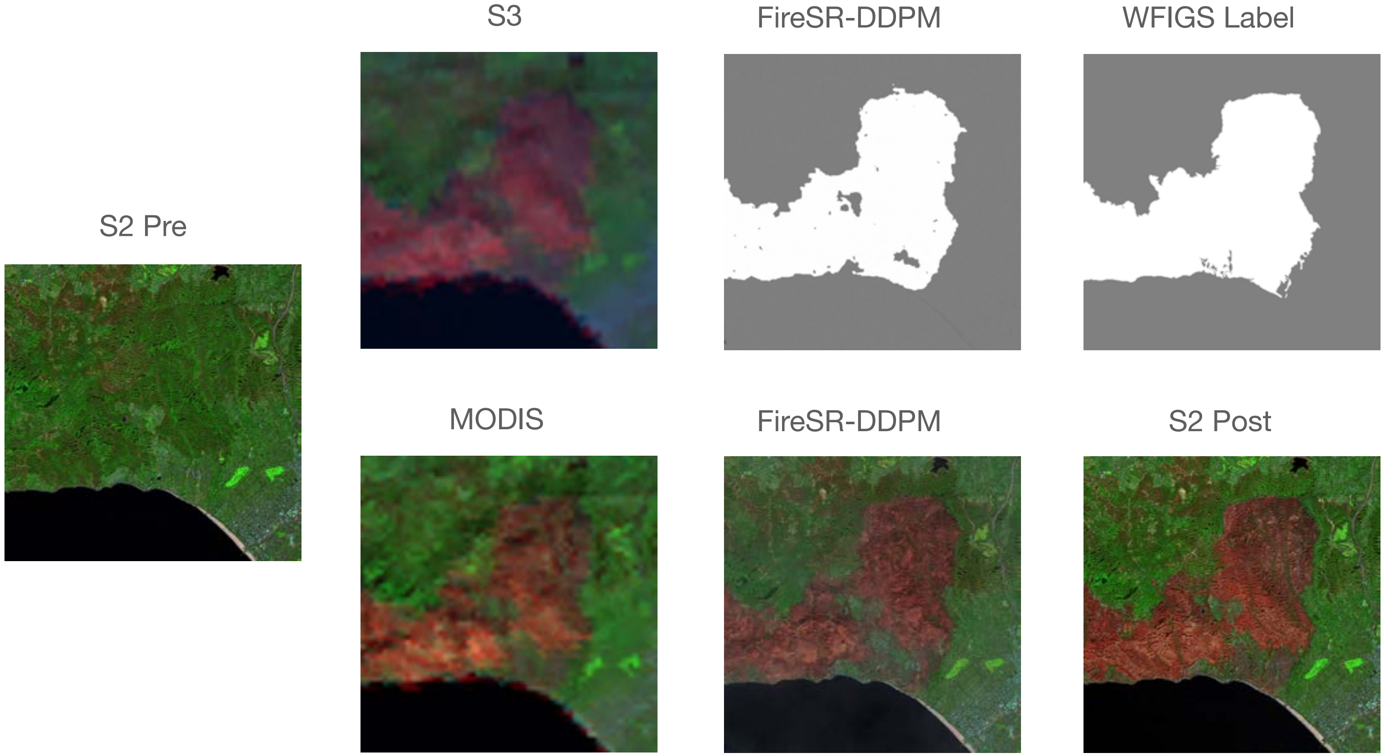
FireSR-DDPM

S2 Post

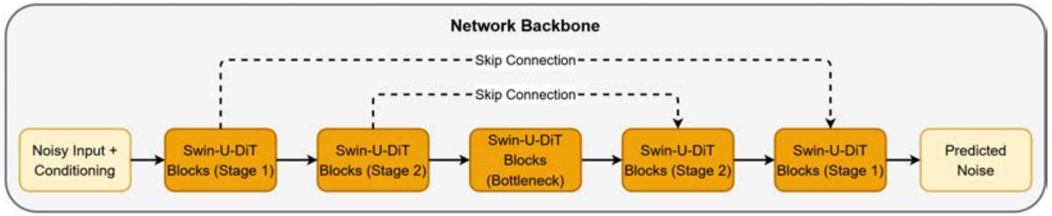
Out-of-Distribution Experiments

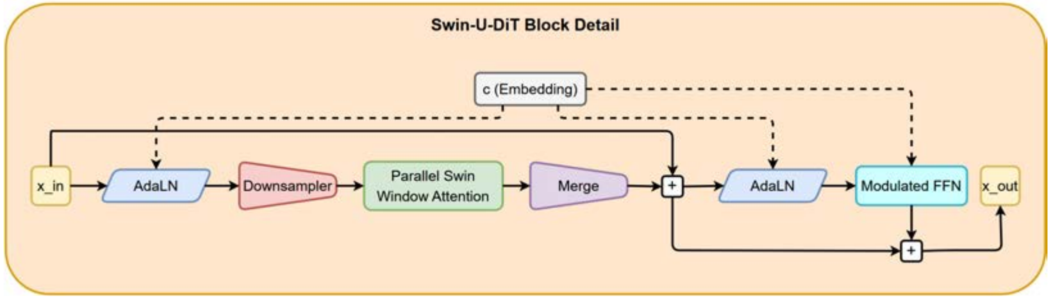
- **Palisades Fire**
  - IoU = 0.7966
  - F1 = 0.8868
  - LPIPS = 0.2171

- Wildland Fire Interagency Geospatial Services (WFIGS) label

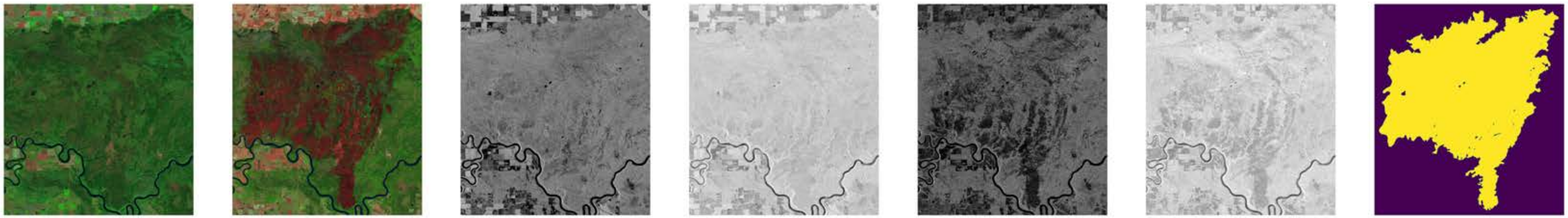


SAR to Optical Image Translation with Denoising Diffusion Implicit Model (DDIM)



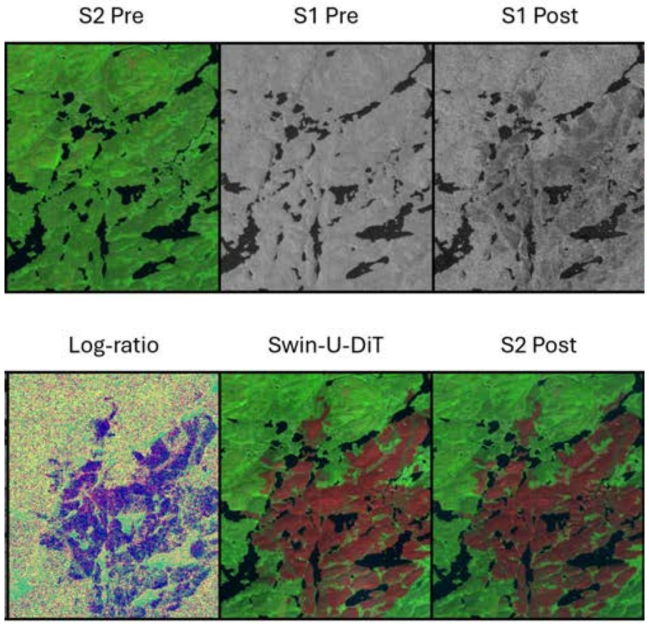


Sentinel-2 Pre-fire | Sentinel-2 Post-fire | Sentinel-1 Pre-fire VV VH | Sentinel-1 Post-fire VV VH | NBAC Polygon



Preliminary Results: SAR to Optical Translation

- Swin-U-DiT (ours) outperforms Pix2Pix on image translation and burned area segmentation



TRANSLATION PERFORMANCE COMPARISON BETWEEN SWIN-U-DIT AND PIX2PIX ON THE CANADA 2022 TEST SET.

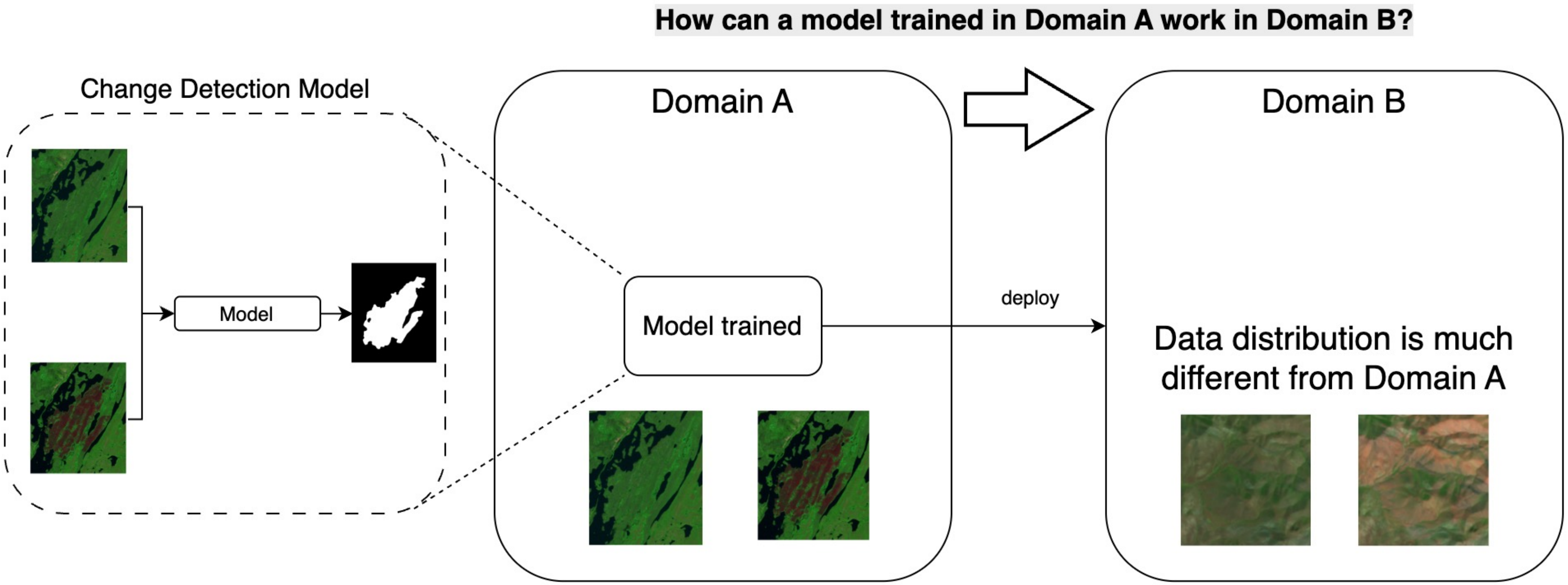
Metric	Pix2Pix	Swin-U-DiT (ours)
FID-335	75.65	**44.31**
LPIPS	0.3718	**0.3037**

QUANTITATIVE SEGMENTATION PERFORMANCE COMPARISON ON THE CANADA 2022 TEST SET USING DIFFERENT INPUTS AND SEGMENTATION MODELS.

Model	None		Pix2Pix		Swin-U-DiT (Ours)	
	IoU	F1	IoU	F1	IoU	F1
UNet	0.5350	0.6970	0.5749	0.7301	**0.6718**	**0.8037**
SegFormer	0.5521	0.7115	0.5612	0.7190	**0.6631**	**0.7974**

E. Brune and Y. Ban, 2025. Enhancing Burned Area Segmentation via Swin-U-DiT for SAR-to-Optical Translation. Submitted to *IEEE Transaction on Geosicence and Remote Sensing.*

Diffusion Foundation Model for Robust Wildfire Monitoring Across Diverse Geographical Regions



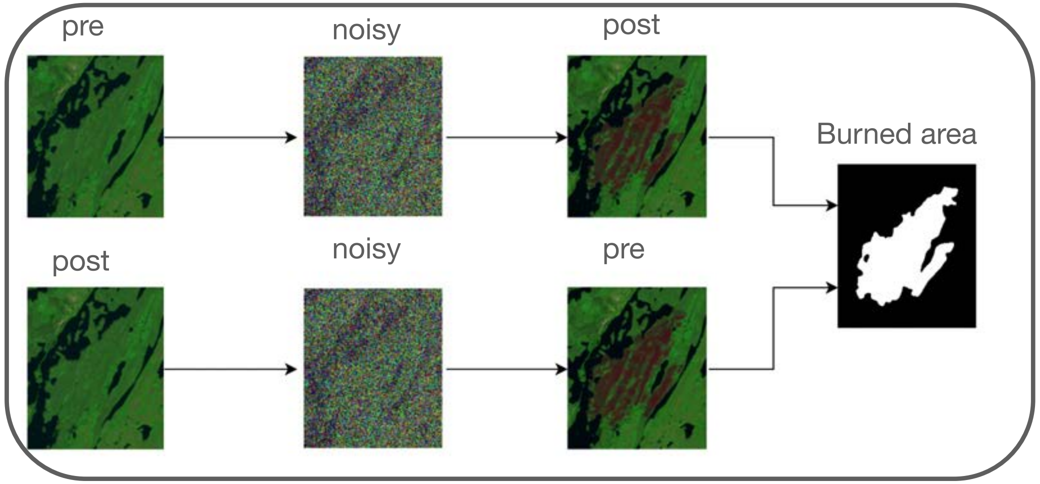
Proposed Solution: Diffusion Model for Domain Adaptation

- **Why Diffusion?**

➢ Leverages noise to learn the change in images.

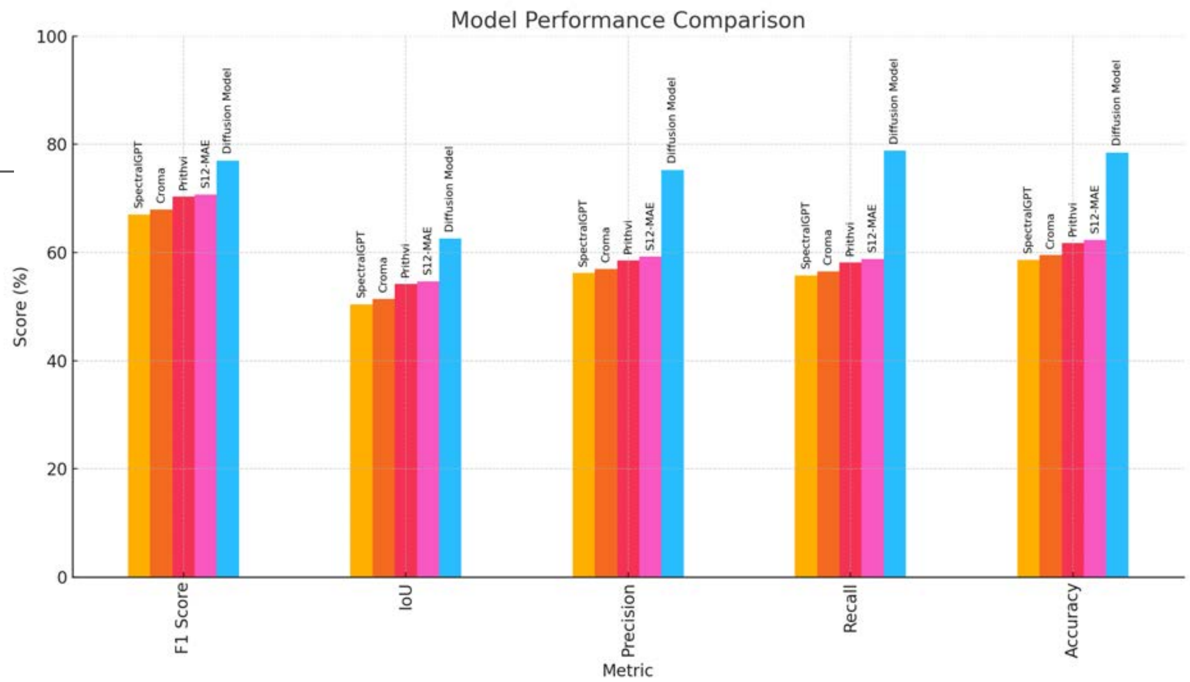
➢ Learns robust features by denoising — enabling better generalization across regions.

➢ Scales with self-supervised pretraining on large unlabeled satellite archives.



Geographic Domain Adaptation: Cross-Region Evaluation Results

Model	F1 Score	IoU	Precision	Recall	Accuracy
Prithvi	70.31	54.22	58.52	58.14	61.73
S12-MAE	70.67	54.65	59.21	58.78	62.27
Croma	67.94	51.45	56.93	56.46	59.49
SpectralGPT	67.03	50.41	56.17	55.74	58.60
Diffusion-CD model (ours)	**76.95**	**62.54**	**75.21**	**78.79**	**78.47**

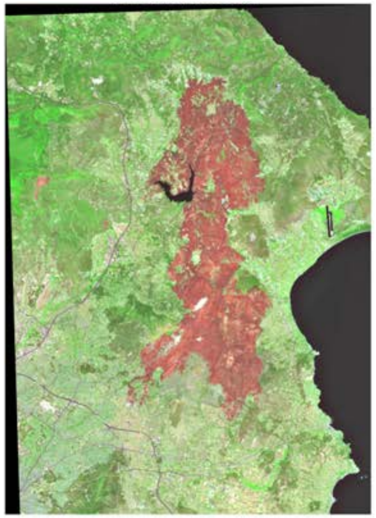


Exploring European Wildfires: Preliminary Generalization Study

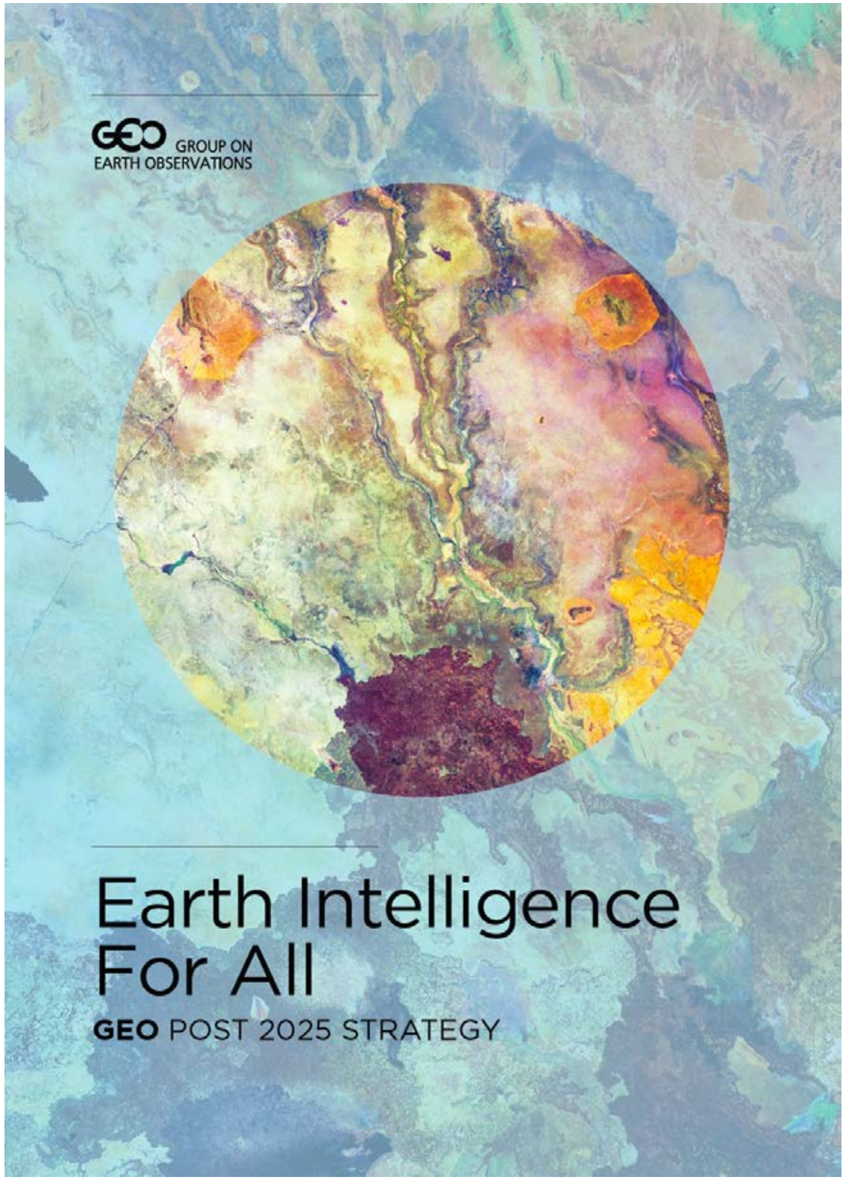
Wildfire in Attica Athens, Greece, 2024

Pre-wildfire image
2024-08-07

Post-wildfire image
2024-08-17



Predicted Burned Area Map



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Questions? Please contact
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