
# 2024 DRAGON SYMPOSIUM

## DRAGON 5 FINAL RESULTS REPORTING

## 24-26 JUNE 2024

# URBAN & DATA ANALYSIS

# ID. 59333 Objectives

| |
|---|
| **O1.** Evaluate Sentinel-1 SAR and Sentinel-2 MSI time series, Chinese EO data and ESA TPM data for improved urban mapping and change detection. |
| **O2.** Develop novel and efficient methods for urban extraction Sentinel-1 SAR and Sentinel-2 MSI time series and deep learning. |
| **O3.** Develop innovative and robust methods for continuous urban change detection using Sentinel-1/-2 SAR MSI time series and Chinese EO data, TPM data using deep learning. |
| **O4. E**valuate the potential of the urban extent and change information derived from the Sentinel big data for monitoring the indicators of the UN 2030 SDG11, Sustainable Cities and Communities. |

# ID. 59333 Achievements

- ID: 59333
  - O1:Data Evaluation
    - ESA Sentinel-1/-2 SAR & MSI Time Series
    - Chinese EO data
    - ESA TPM
  - O2: Urban Mapping
    - Semi-Supervised Learning with Domain Adaptation
    - Multi-Modal Deep Learning
  - O3: Urban Change Detection
    - Several Novel DL Methods for Change Detection
    - SAR & Optical Time Series for Change Detection
  - O4: Environmental Impact & SDG11 Monitoring
    - Environmental Impact Assessment
    - SDG11.3.1 Indicator Monitoring
    - Other SDG Indicators Monitoring

✓ **15 young researchers**

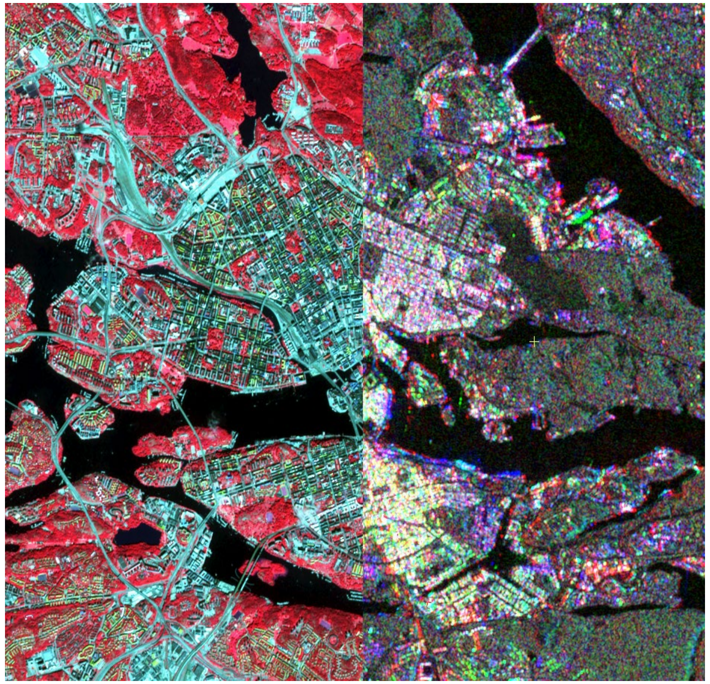
✓ **28 publications**

✓ **10 conf. presentations**

✓ **8 sensors data used**

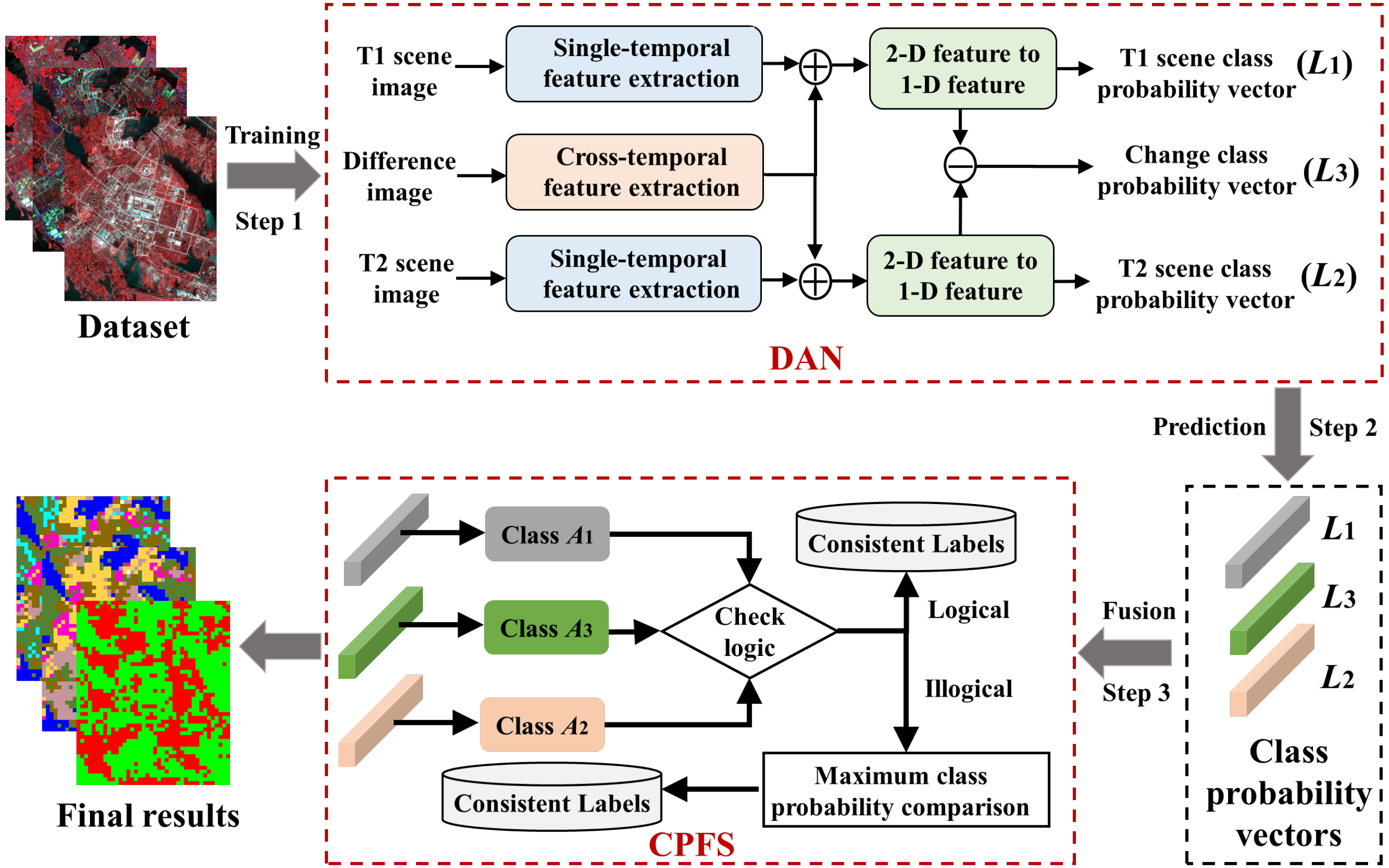
✓ **10 new project proposals**

# EO & AI for Urban Mapping & Change Detection



2017 WorldView

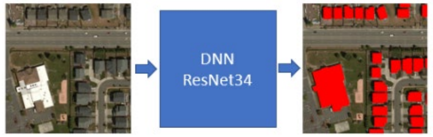
2022 SuperView



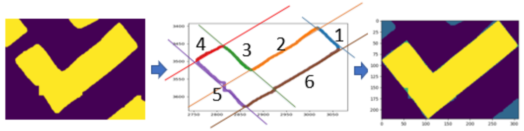
# EO-AI for Global Urban Mapping

- Microsoft Building Footprints as labels

First stage - Semantic Segmentation

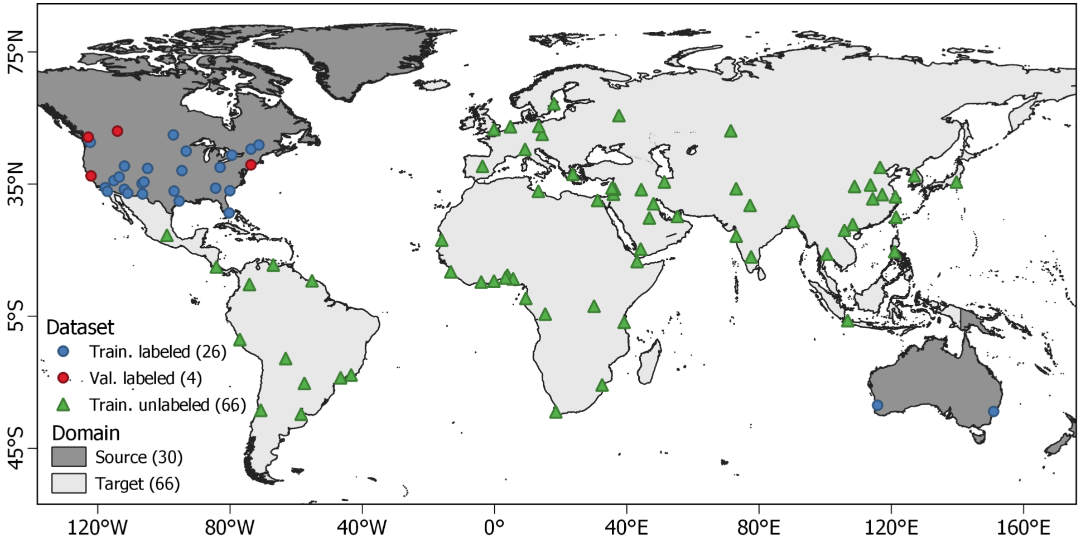



Second stage - Polygonization

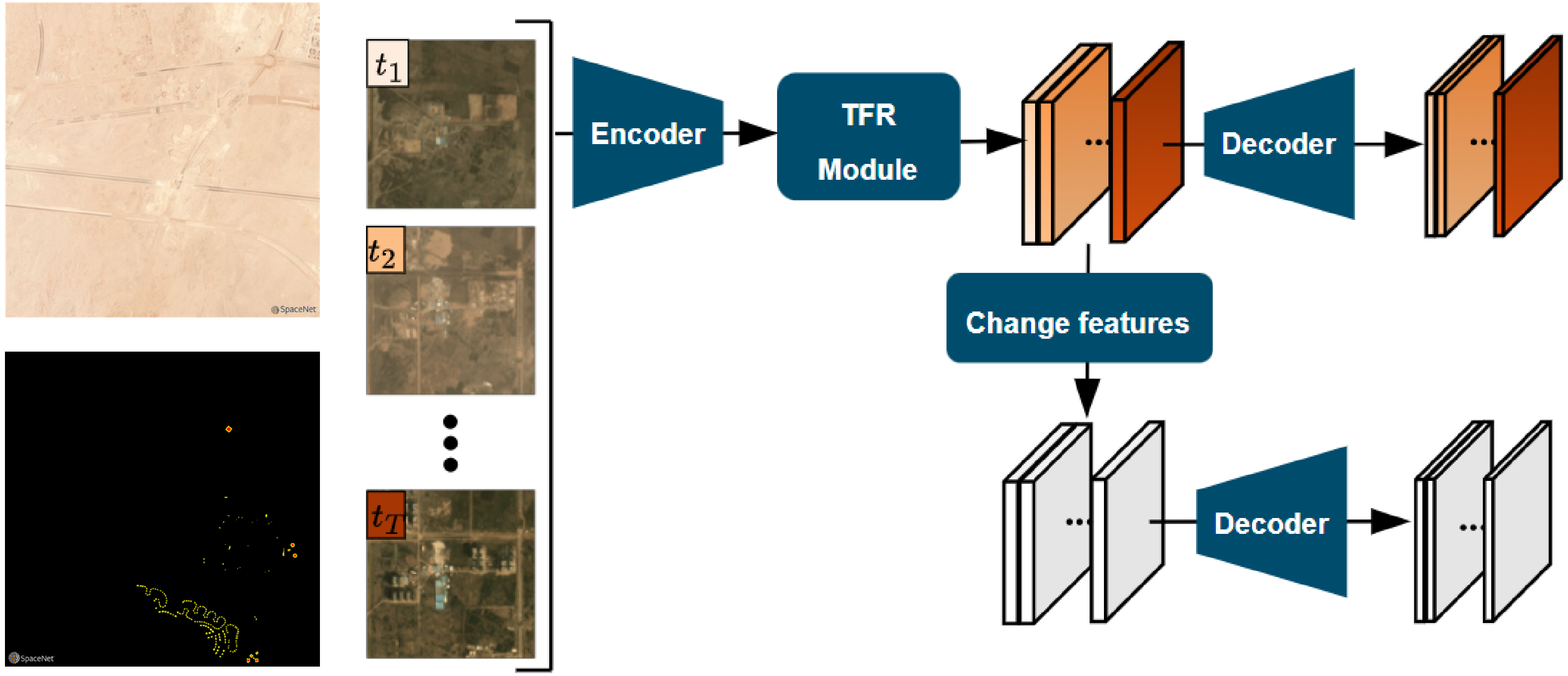



- Introduce a domain gap
- Produced Sentinel-1/2 data and corresponding labels

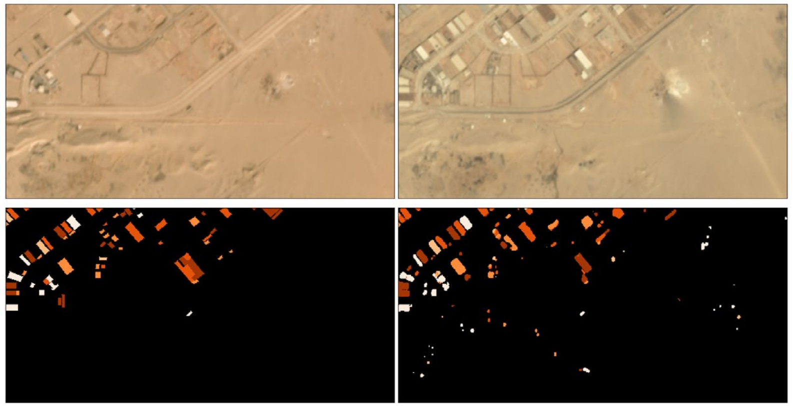
Locations of the training and validation sites



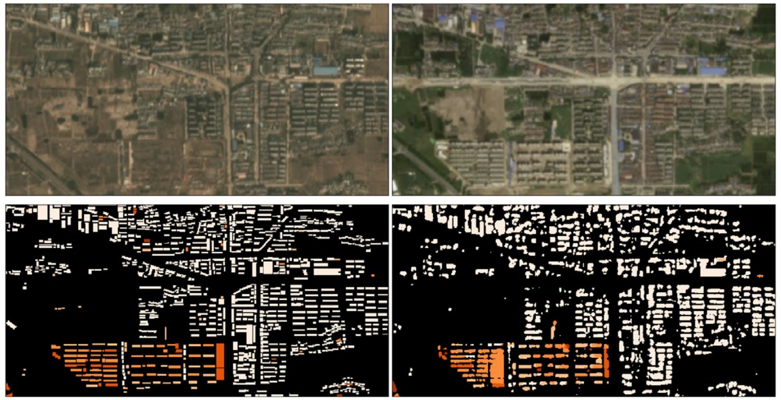

# EO-AI for Urban Change Detection




Egypt



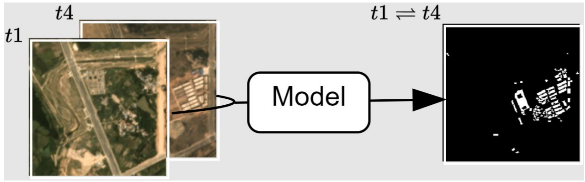
China



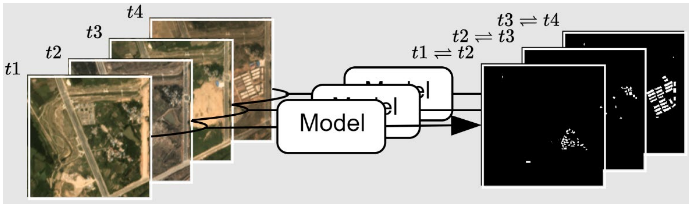
Hafner, S., Heng, F., Hossein, A. and Ban, Y., 2024. Urbanization Monitoring from Optical Satellite Image Time Series Using Transformers and Multi-Task Integration. *IEEE Transactions on Geoscience and Remote Sensing*, (under review).
Hafner S, Ban Y, Nascetti A. 2023. Semi-Supervised Urban Change Detection Using Multi-Modal Sentinel-1 SAR and Sentinel-2 MSI Data. *Remote Sensing.* 15(21):5135. https://doi.org/10.3390/rs15215135.
Yadav, R., A. Nascetti, Y. Ban. 2023. Context-Aware Change Detection With Semi-Supervised Learning. *Proceedings of IGARSS'2023*, Pasadena, California, USA.

# EO-AI for Continuous urban change detection

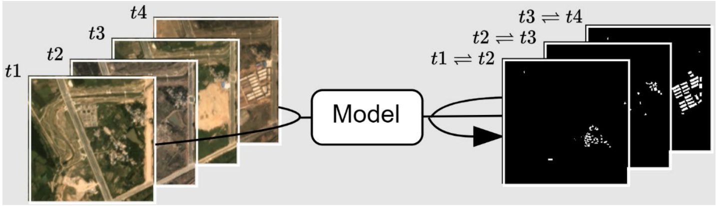
## Motivation




(a) Bi-temporal urban change detection



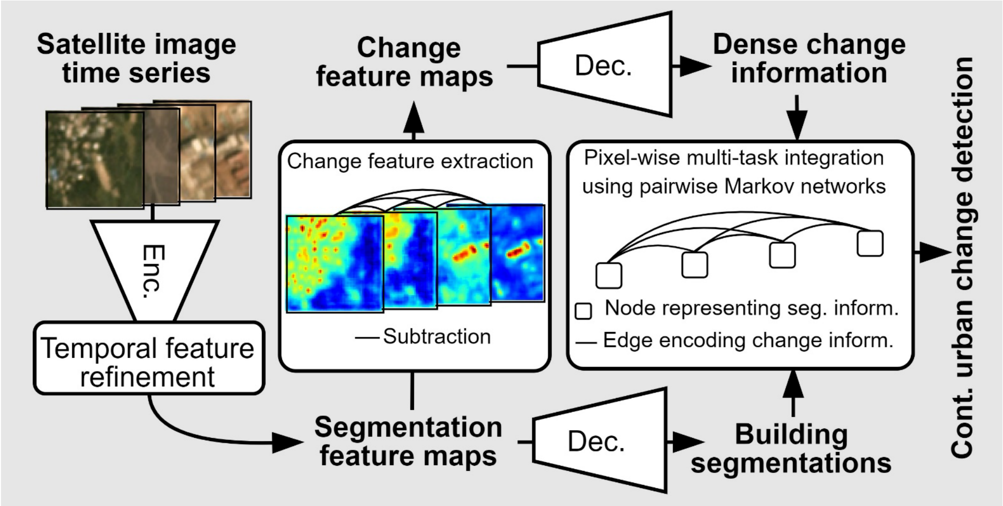

(a) Continuous urban change detection using a bi-temporal model




(a) Continuous urban change detection using a the proposed model

## Methodology

1. Extract feature maps using a shared ConvNet
2. Self-attention to temporally refine feature maps
3. Compute dense change feature maps
4. Multi-task decoding
5. Integration of dense change and segmentation information

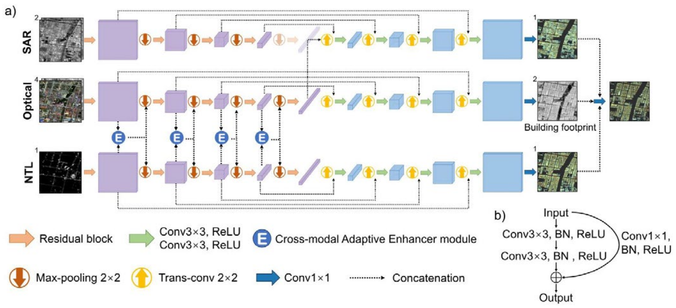


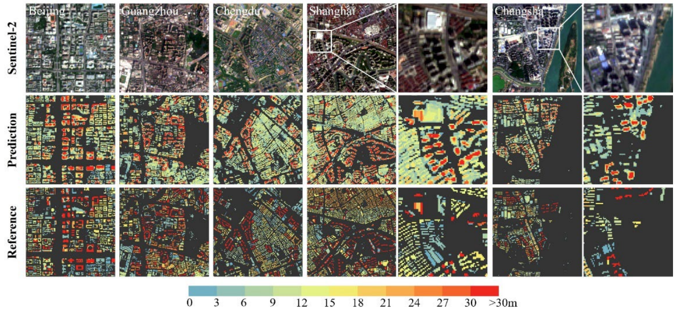

[3] Hafner, S., Fang, H., Azizpour, H. and Ban, Y., 2024. Continuous Urban Change Detection from Satellite Image Time Series with Temporal Feature Refinement and Multi-Task Integration. IEEE Transactions on Geoscience and Remote Sensing, (under review).

# EO for Monitoring SDG11 indicators

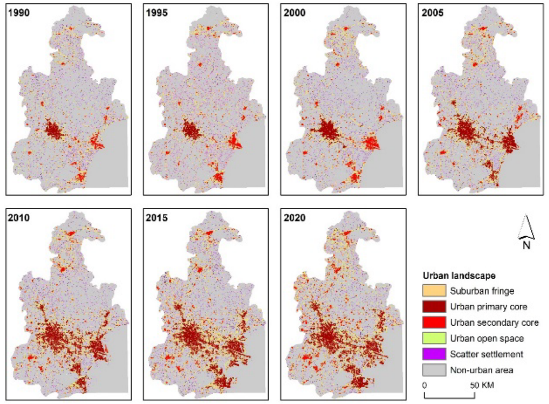
## Sentinel- 1/2

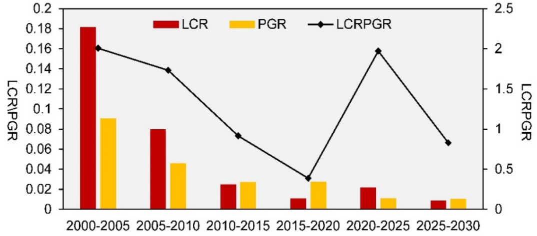
## SDGSAT- 1



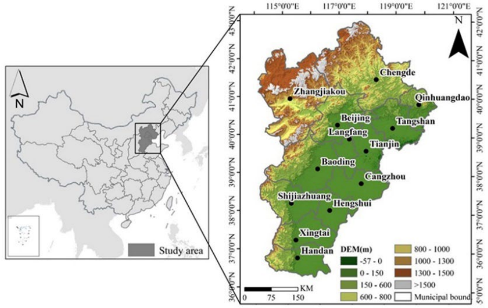



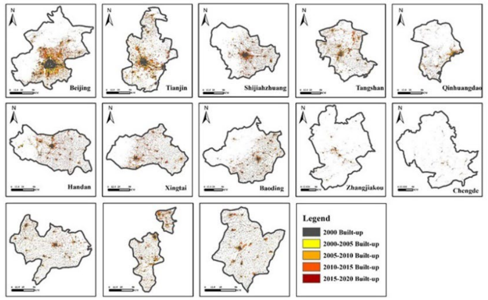

## City



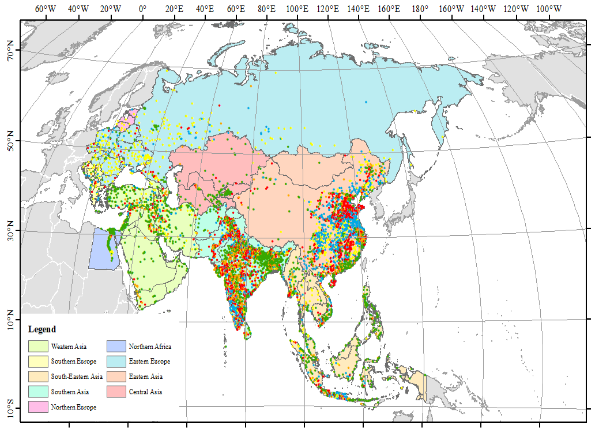



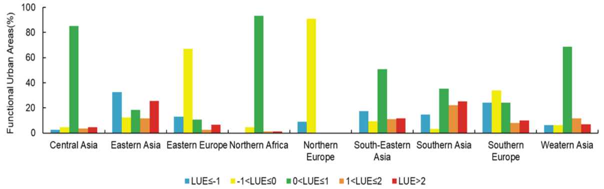

## Urban Agglomeration




## Regional





# ID. 58897 Objectives

| Objectives | Accomplishments |
|---|---|
| **O1.** Monitor and and model urban geological hazards, combining remote sensing, geophysical processes, and hydrogeological theories methods. | • The Monte Carlo algorithm was used to simulate land subsidence rates in the study areas. |
| **O2.** Establish a 3-D monitoring network of land subsidence in urban areas to identify land subsidence, establish dynamic models, and reveal the mechanisms of land subsidence evolution. | • The Extremely Randomized Trees model was utilized to conduct quantitative analysis on the importance of different factors in land subsidence.<br>• Constructed a spatial convolutional long short-term memory neural network (ConvLSTM) based on the spatio-temporal prediction method to predict the land subsidence. |
| **O3.** Develop a comprehensive set of climate indicators for urban areas, aiming to describe the complex interconnections between climate change and urban environment. | • Evaluation of the climate in Beijing, China, and Athens, Greece in terms of droughts and heatwaves, focusing on their compound effects (CDHW). |
| **O4.** Local-scale evaluation of the thermal environment via satellite-derived LST - Statistical downscaling procedure. | • Local climate zones, urban heat risk maps, park cool island intensity. |

# ID. 58897 Achievements

ID: 58897

- **O1:**
  - Monte Carlo algorithm
  - InSAR Time Series Dataset
  - Ground water level change
- **O2:**
  - Extremely Randomized Trees model
  - ConvLSTM convolutional model
- **O3:**
  - Excess heat factor
  - Compound heat and drought events
- **O4:**
  - Local climate zones
  - LST downscaling model
  - Park cool island intensity

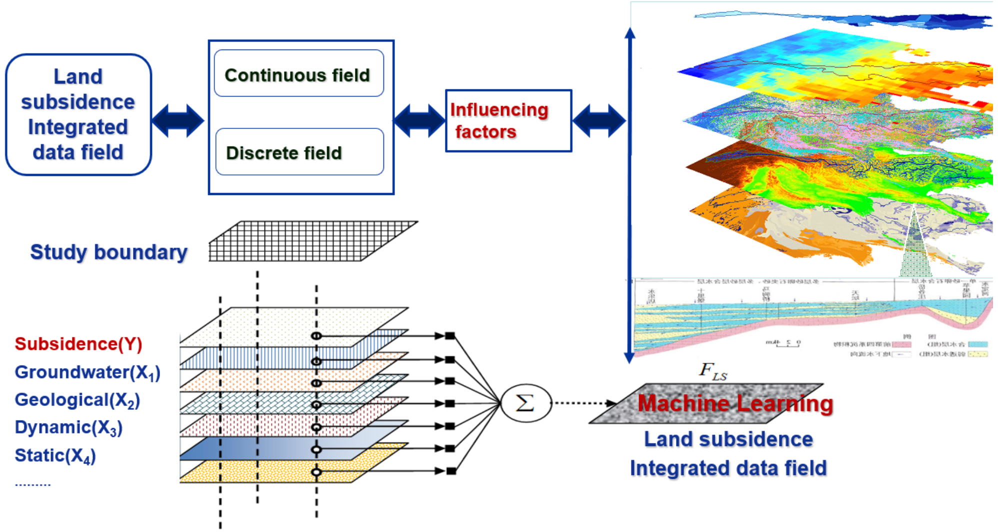
✓ **9 young researchers**

✓ **13 publications**

✓ **9 sensors data used**

# EO Services For Climate Friendly and Smart Cities

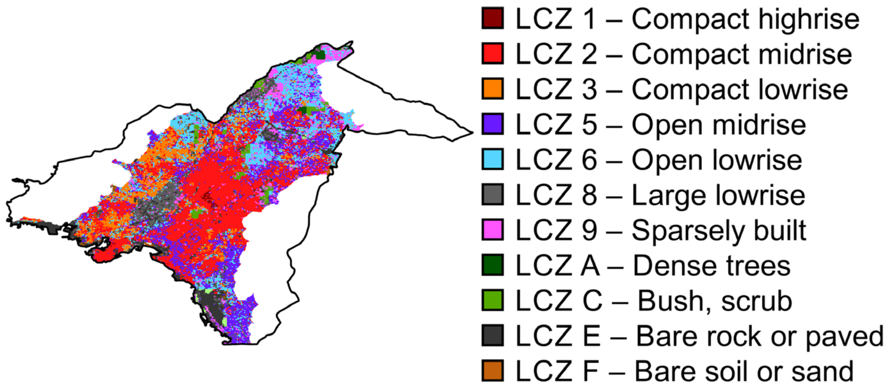
- Monitored and and modeled urban geological hazards, combining remote sensing, geophysical processes, and hydrogeological theories methods.
- Use of InSAR data, ground penetrating radar, and multi-field numerical analysis.
- Identified land subsidence, established dynamic models, and revealed the mechanisms of land subsidence evolution.

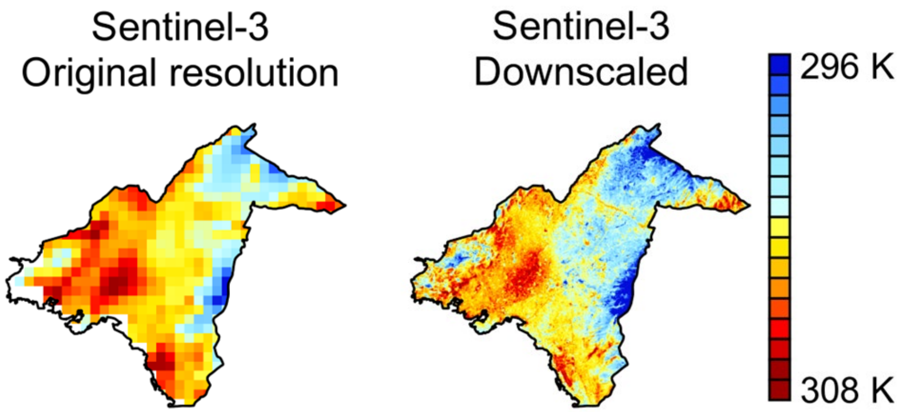



- The Extremely Randomized Trees model used for quantitative analysis on the importance of different factors in land subsidence.
- Spatio-temporal prediction of regional land subsidence via a convolutional neural network model (ConvLSTM).

# EO Services For Climate Friendly and Smart Cities

- Exploited the capabilities of Earth observation techniques to assist in the direction of smart and sustainable urbanization.
- Conducted a multi-faceted investigation of the urban climatic effects at various spatial and temporal scales.
- Identified through remote sensing the most thermally vulnerable areas within cities.
- Evaluated the efficacy of green infrastructure as a heat reduction mechanism.



# ID. 58190 Objectives

| Objectives | Accomplishments |
|---|---|
| **O1.** Develop **weakly supervised** deep learning techniques for object extraction and semantic classification and elaborate **large-scale training** data supporting practical real-world applications | • OpenSARUrban: A Sentinel-1 SAR image dataset<br>• Time-series optical/SAR dataset for LULC<br>• Dimensionality reduction for simple DNN |
| **O2.** Develop deep spatial-temporal networks for large dense SITS analysis to **jointly exploit the temporal, spatial and spectral information** and understand the dynamic processes of the Earth surface | • Multiple Embeddings Contrastive Pretraining for Image Classification<br>• Analyzing the Separability of SAR Classification Dataset in Open Set Conditions |
| **O3.** Exploit **deep change detection** techniques for optical and SAR remote sensing images | • Bag-of-Words (BoW) framework for change detection in remote sensing images<br>• PInSAR estimation of linear deformation rates |
| **O4.** Develop **spatial-temporal fusion of multi-modal**, multi-resolutions and multi-sensor images for SITS analysis and investigate the transferability of trained networks to other imaging modalities | • LRMSNet: A New Lightweight Detection Algorithm for Multi-Scale SAR Objects<br>• Classification of SAR Images With Optical Image Assistance<br>• Estimating NDVI from SAR Images Using DNN<br>• Optical and SAR SITS analysis |

# ID. 58190 Achievements

**ID: 58190**

- **O1: Datasets**
  - OpenSARUrban Dataset
  - Optical/SAR Time Series Dataset
  - Dimensionality Reduction
- **O2: Image Classification**
  - Multiple Embeddings Contrastive Learning
  - Separability Analysis for Open-Set Classification
- **O3: Change Detection**
  - BOW Framework for Change Detection
  - PInSAR Estimation
- **O4: Multi-Modal Fusion**
  - SAR Classification With Optical Assistance
  - Estimating NDVI from SAR Using DNN
  - Optical and SAR SITS Analysis

- ✓ **14 young researchers**
- ✓ **31 publications**
- ✓ **7 lectures**
- ✓ **4 sensors data used**
- ✓ **6 new project proposals**

# Results Highlights: Two Datasets

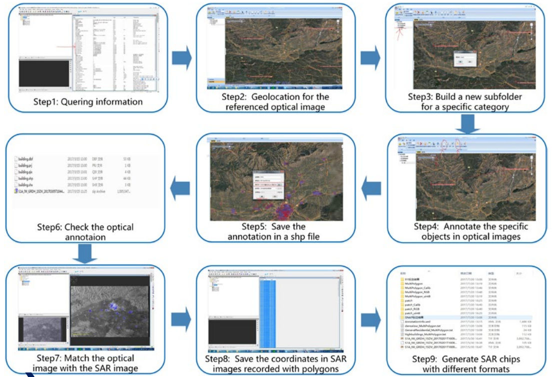
## ■ OpenSARUrban dataset from Sentinel-1 data (open)

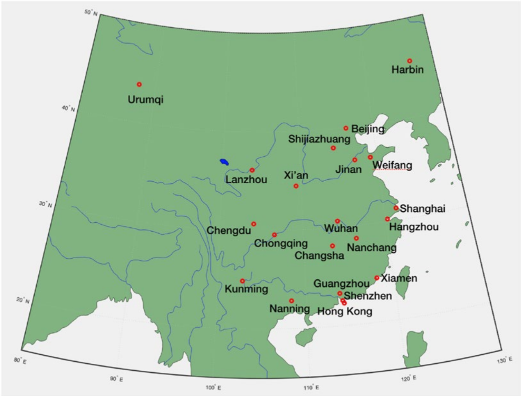
**10** main Chinese Cities

**20m** resolutions

**10** categories

**30000+** tiles




## ■ Time-series optical/SAR dataset for LULC (limited open)

**10+** years

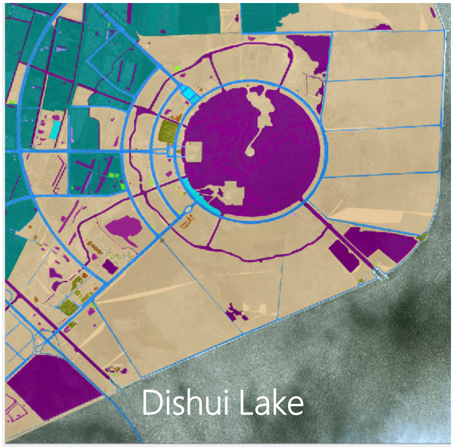
**4** seasons

**2** kinds of sensors

**12** categories

**200+** $km^2$

Dishui Lake, Shanghai




| | |
|---|---|
| farmland | Industrial |
| Bare land | Residential |
| water | woods |
| grassland | park |
| runway | Commerical |
| road | others |

2006 2007 2009 2011 2015 2017 2021 2022


[1]Zhao, J., Zhang, Z., Yao, W., Datcu, M., Xiong, H., & Yu, W. "OpenSARUrban: A Sentinel-1 SAR image dataset for urban interpretation." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 13 (2020): 187-203.

# Results Highlights: Separability Analysis of SAR Classification

## Separability analysis of SAR images with variational-autoencoder (VAE)

- SAR data distributions affected by many factors, separable or not?
- Embedding SAR images into latent space and model the latent features as a mixture of Gaussian distributions
- Training VAE model for each class and assess the separability of different categories

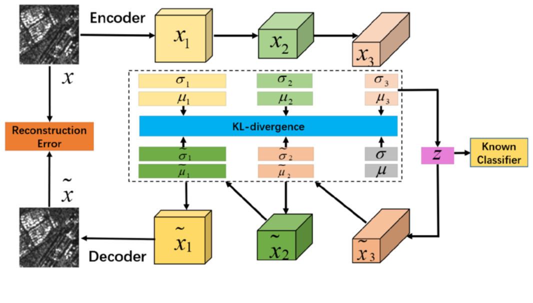


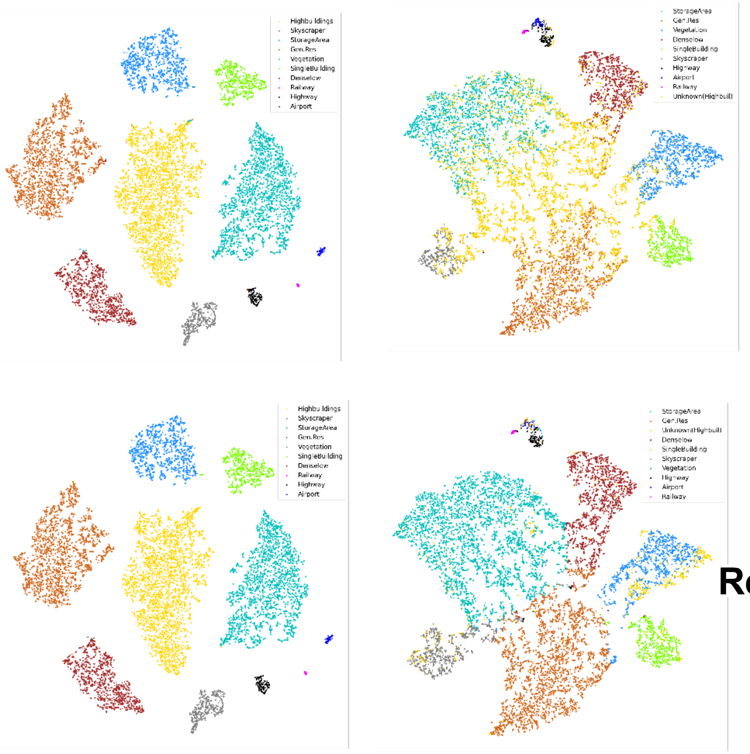

**Fig. 2**. SAR Distinguishability Analysor (SAR-DA)

**Encoder**

$$x_k = \mathrm{Conv}(x_{k-1})$$
$$\mu_k = \mathrm{Linear}(\mathrm{Flatten}(x_k))$$
$$\sigma_k^2 = \mathrm{F}(\mathrm{Linear}(\mathrm{Flatten}(x_k)))$$

**Decoder**

$$d_{k+1} = \mathrm{Unflatten}(\tilde{z}_{k+1})$$
$$x_{k+1} = \mathrm{TConv}(d_{k+1})$$
$$\mu_k = \mathrm{Linear}(\mathrm{Flatten}(x_{k+1}))$$
$$\sigma_k^2 = \mathrm{F}(\mathrm{Linear}(\mathrm{Flatten}(x_{k+1})))$$
$$\tilde{z}_k = \mu_k + \varepsilon \cdot \sigma_k^2, \varepsilon \sim N(0, \mathbf{I})$$



GT

Results

All Known

Highbuildings Unknown

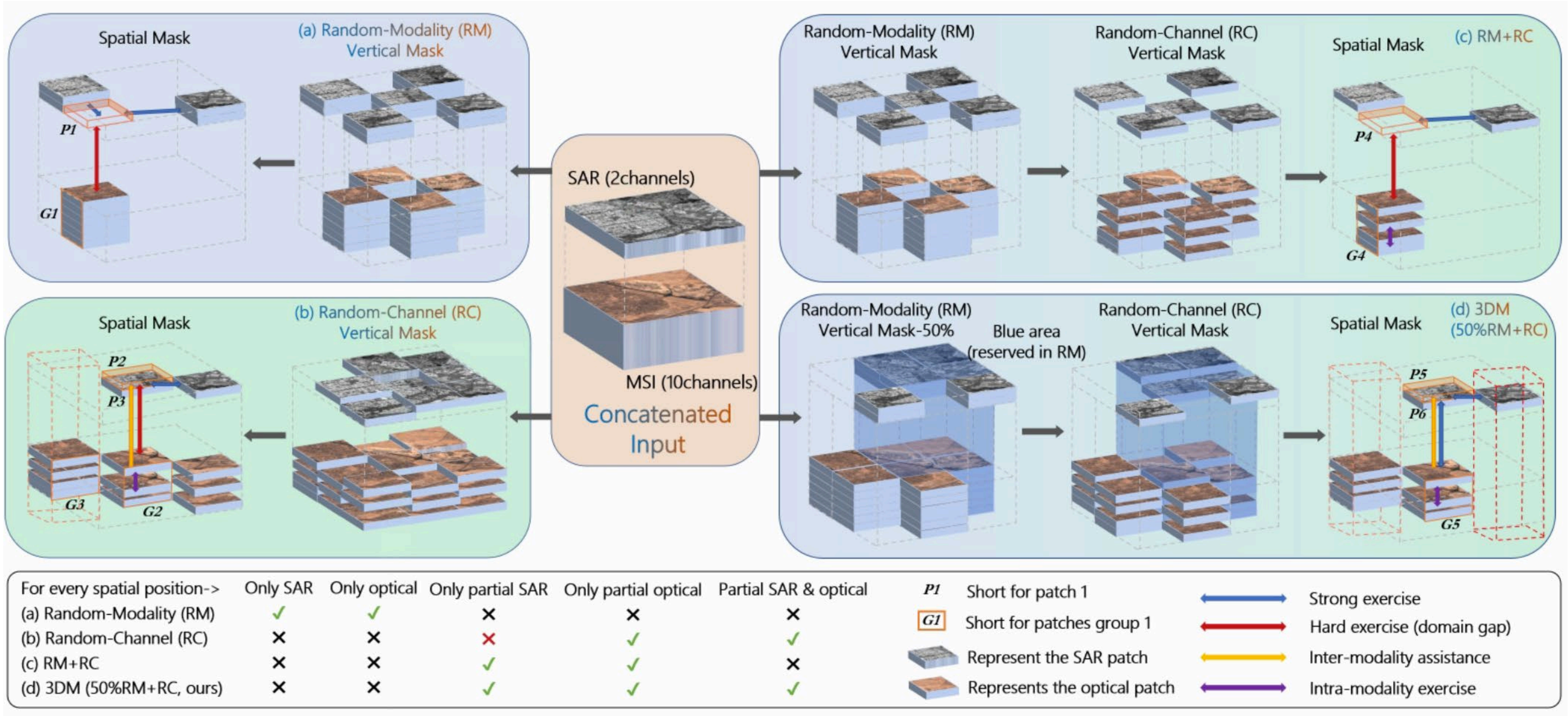

[7] N. Liao, M. Datcu, Z. Zhang, W. Guo, J. Zhao and W. Yu, "Analyzing the Separability of SAR Classification Dataset in Open Set Conditions," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7895-7910, 2021, doi: 10.1109/JSTARS.2021.3100342

[8]L. Dai, W. Guo, Z. Zhang and W. Yu, "Discovering Novel Categories in Sar Images in Open Set Conditions," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, 2022, pp. 1932-1935, doi: 10.1109/IGARSS46834.2022.9883175.

# Results Highlights: Joint SAR/Optical Representative Learning

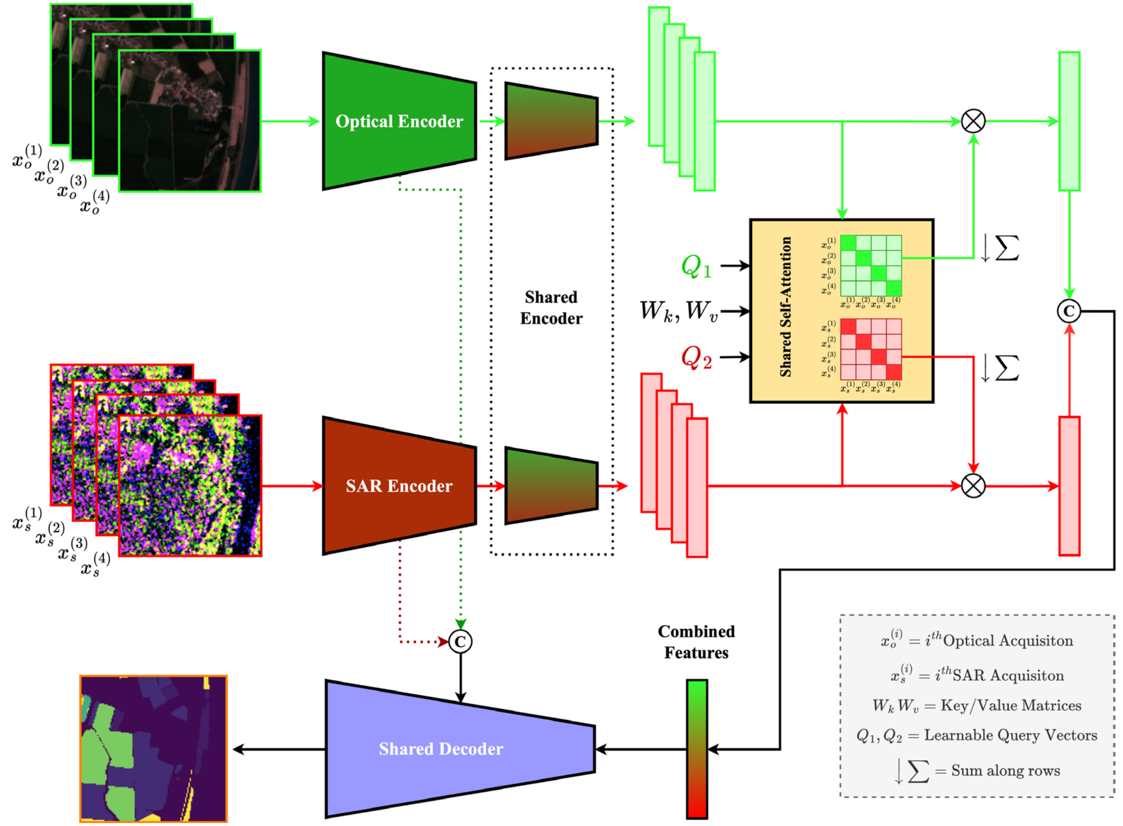
## ■ A 3D-MAE self-supervised learning approach that pre-trains on both SAR and optics

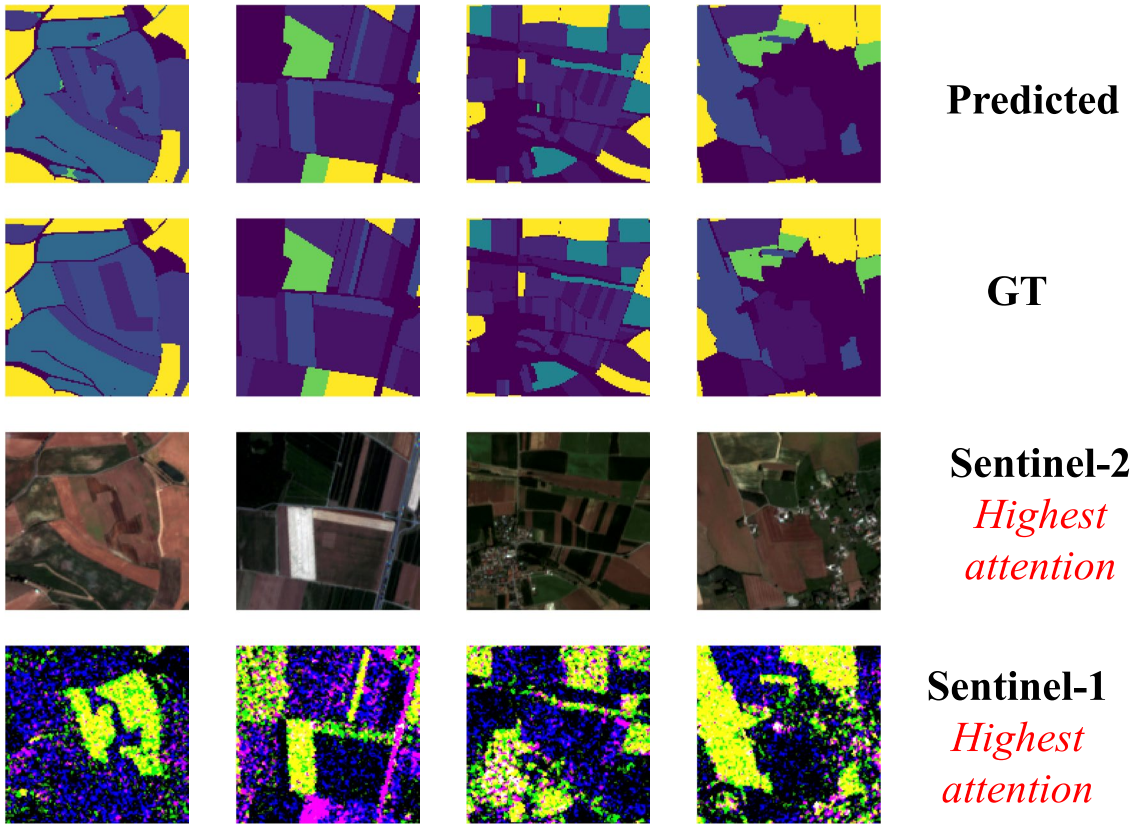
- various mask patterns
- Appliable for various downstream applications
- Good generalization
- Outperform supervised methods




L. Zhang, Weiwei Guo, Z. Zhang, et al., “3DMAE: Joint SAR and optical representation learning with vertical masking,” *IEEE GRSL, 2023.*

# Results Highlights: Semantic Segmentation of Agricultural Fields




- The model has learned not to attend to partially- or fully-clouded images, or to SAR images highly corrupted by noise.


[1] Garnot, Vivien Sainte Fare, and Loic Landrieu. "Panoptic segmentation of satellite image time series with convolutional temporal attention networks." IEEE/CVF 2021.

[2] Garnot, Vivien Sainte Fare, Loic Landrieu, and Nesrine Chehata. "Multi-modal temporal attention models for crop mapping from satellite time series." ISPRS 187 (2022): 294-305.

# Seed questions: Science & Application
## Urban and Data Analysis

What are the remaining issues concerning the exploitation of current mission data?

- A common hub for free and open access of ESA-China EO data (Extension of Copernicus hub)

What are the new science findings in the domain?

- Grow beyond  Computer Vision: Physics Aware and Explainable AI4EO
- Foundations Models vs. Simple or classical methods: Active Learning, Hybrid solutions ”classical&ML”
- Digital Twin Cities/Earth: analytics, visualization, modelling, simulation, prediction and causal analysis
- EO-based Timely and reliable information on urbanization, LST, GeoHazards can support UN SDG and climate adaptation and mitigation.

What is the general performance and what are the limitations of geophysical parameters retrieval?

- Generalization, transfer to new regions or new data
- Not enough essential variables for climate change adaptation, teleconnections, interdisciplinarity
- Not fine-scale thermal data (1 km for Sentinel-3, 100 m for Landsat 8/9)

EO data synergy: is there scope for data synergy and if so which EO missions/sensors are required?

- Synergy + complementarity: dense SITS&global coverage, uniform maps of retrieved parameters, Cal/Val

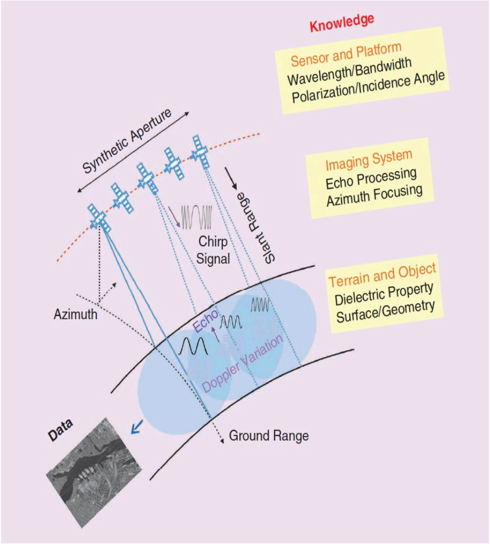
Validation : Have the necessary validation data been collected and shared?

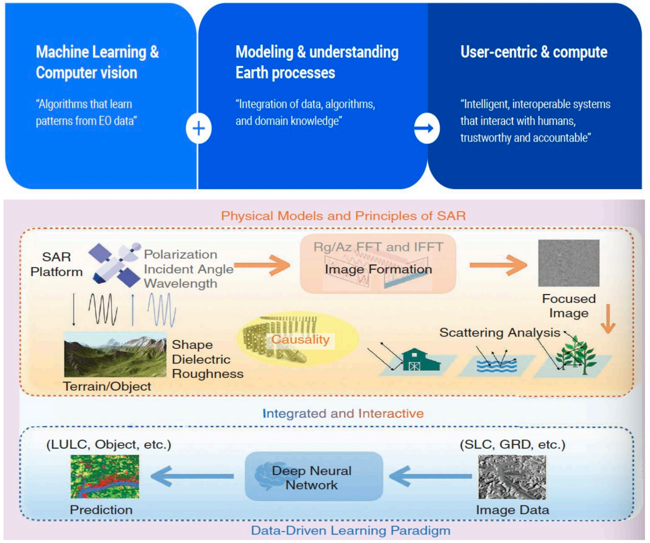
- At limited extent, i.e. benchmarks and training data sets, need for physical parameters data

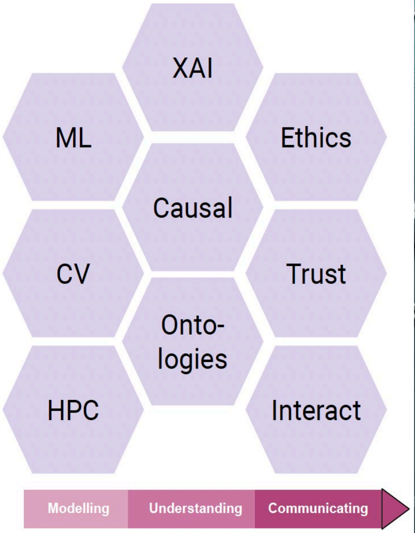
# Seed questions: New EO Mission Exploitation
## Urban and Data Analysis

What are the new domains where further research is needed?

- Multimodal EO foundation models focused on climate-related information extraction for multisource and multitemporal EO data that will enable the quantification of climate change effects, thus supporting adaptation, mitigation and enhancing urban resilience.
- Monitoring urbanisation on the 3rd dimension; Dynamic Digital Twin




# Seed questions: New EO Mission Exploitation

What are the synergy between Europe and China new missions to be exploited?

What complementarity in the operational use of the current / future missions (planning, observations, etc.) could be improved to allow better data exploitation?

What complementarity in the operational use of the current / future missions (planning, observations, etc.) could be improved to allow better data exploitation?

- We started a systematic study of the ESA and China EO missions, from mission parameters, physical/bi0/chemical information potential, data quality…. to identify  the most appropriate synergy for specific domains, with focus on climate change adaptation measures