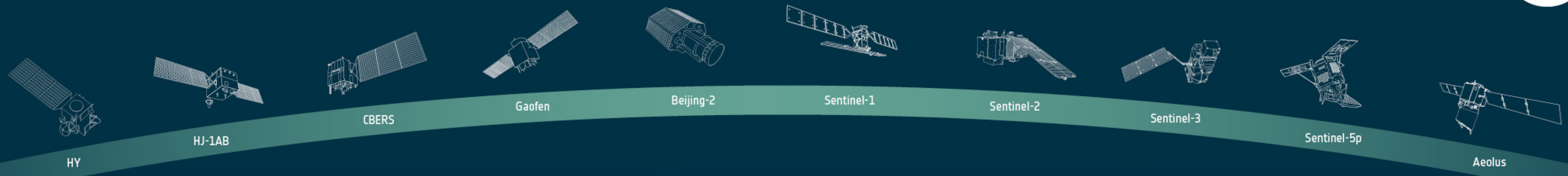


2022 DRAGON 5 SYMPOSIUM

MID-TERM RESULTS REPORTING

17-21 OCTOBER 2022

PROJECT ID. 59333

EARTH OBSERVATION BIG DATA & DEEP LEARNING FOR SUSTAINABLE AND RESILIENT CITIES

TUESDAY, 18/OCT./2022

ID. 59333

PROJECT TITLE: EARTH OBSERVATION BIG DATA AND DEEP LEARNING FOR SUSTAINABLE AND RESILIENT CITIES

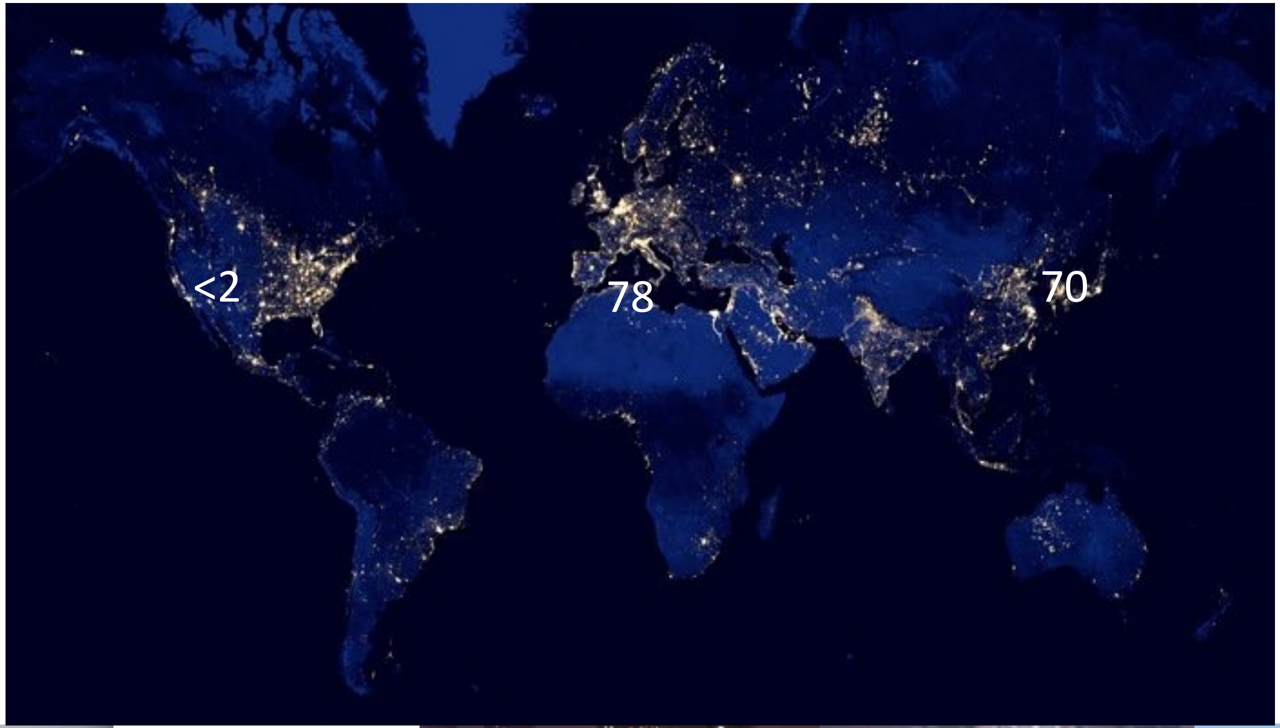
PRINCIPAL INVESTIGATORS: YIFANG BAN & YUNMING YE

CO-AUTHORS: YIFANG BAN, YUNMING YE, PAOLO GAMBA, KUN TAN, LINLIN LU, PEIJUN DU

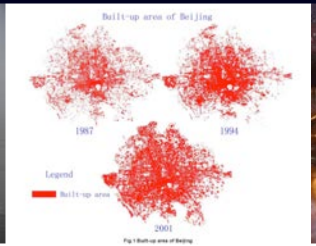
PRESENTED BY: YIFANG BAN

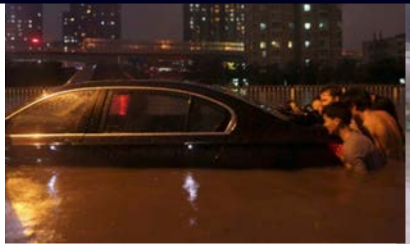
Urbanization

- Today, 56% of the world live in cities.
- By 2050, the world is expected to add an additional 2.5 billion urban dwellers;
- Nearly 90 percent of the increase is concentrated in Asia and Africa (United Nations, 2018).





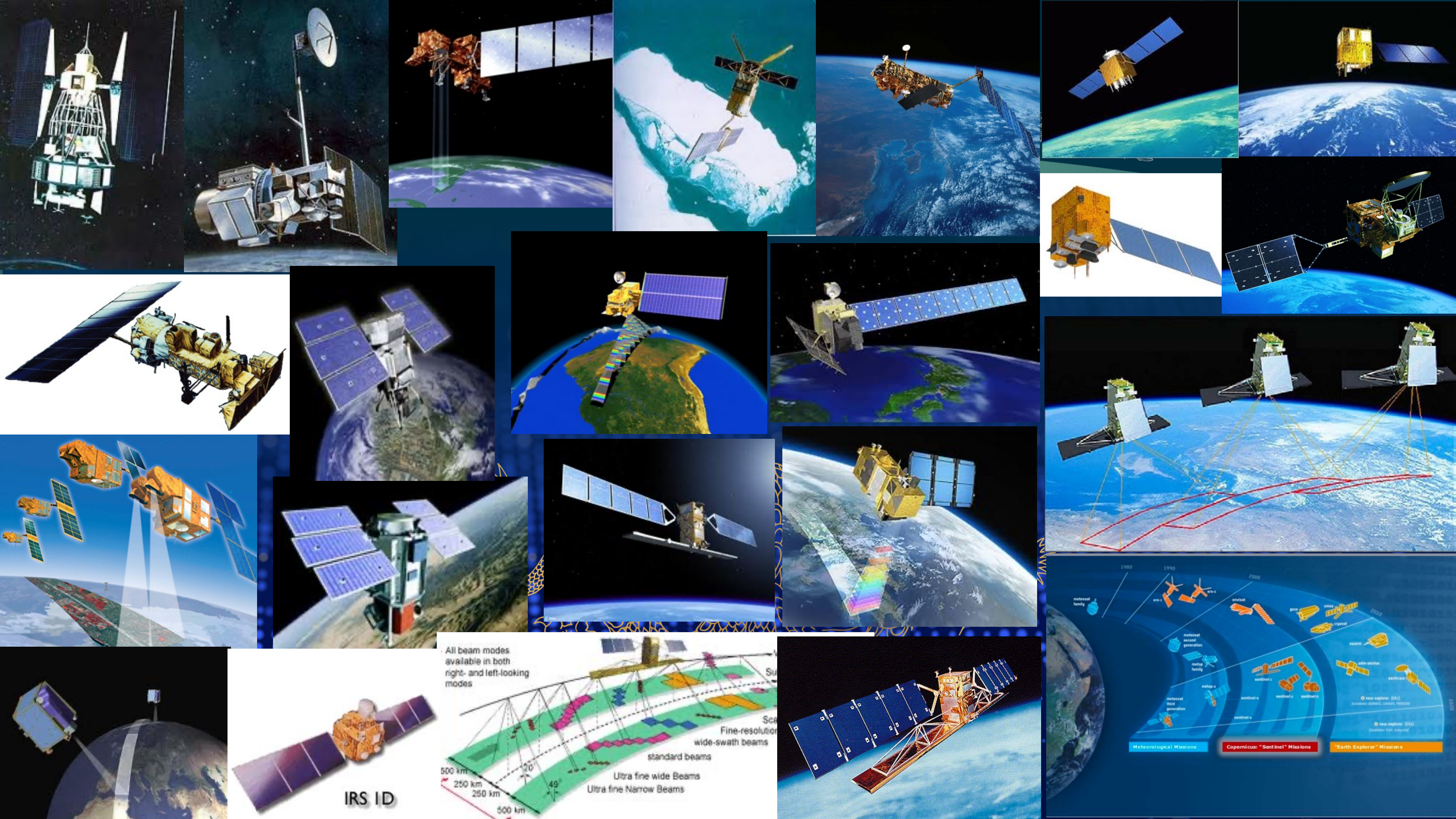




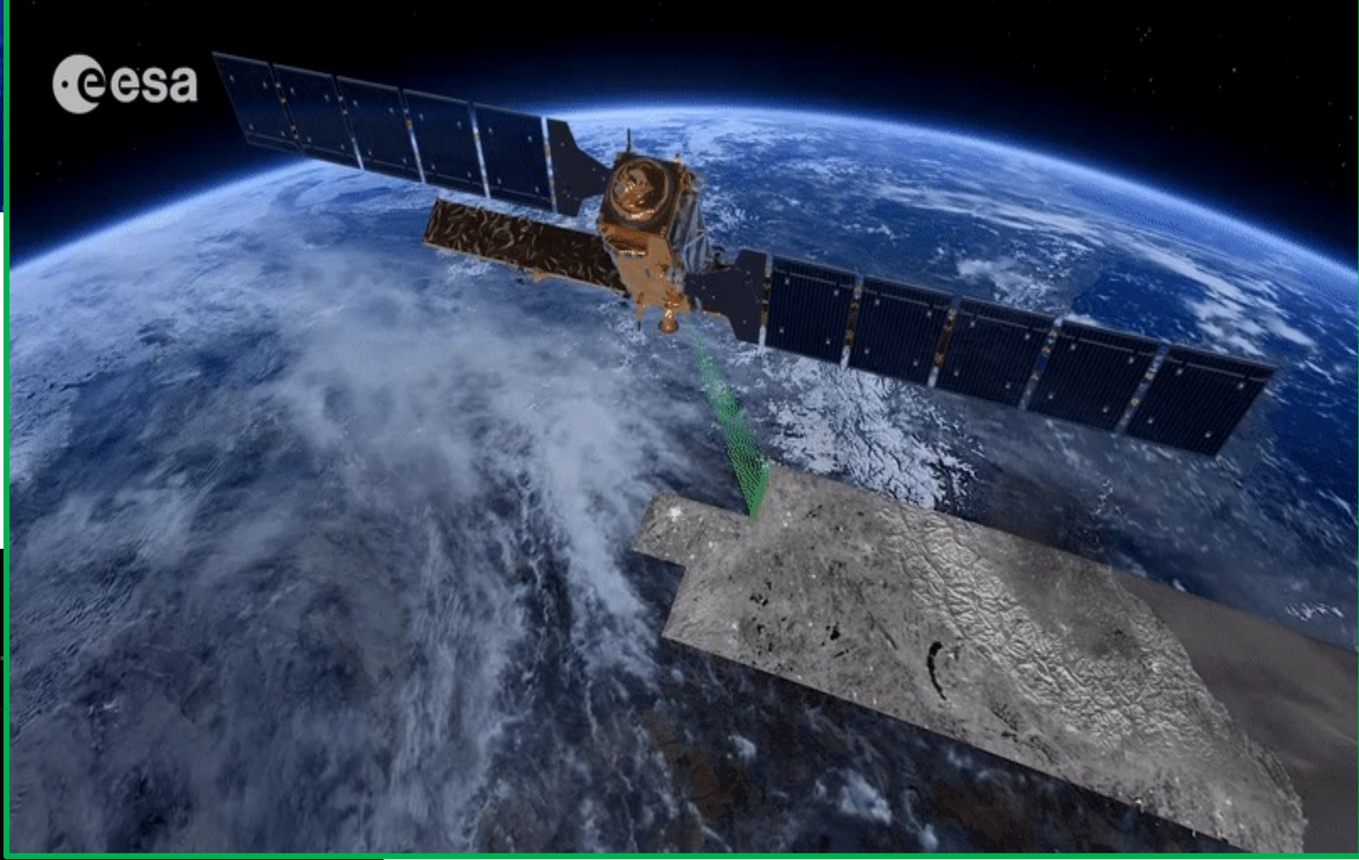

Stockholm: Dynamic Digital Twin


2001


2018


All beam modes available in both right- and left-looking modes
Fine-resolution wide-swath beams
standard beams
Ultra fine wide Beams
Ultra fine Narrow Beams
500 km
250 km
250 km
500 km
IRS ID
Meteorological Missions
Copernicus: "Sentinel" Missions
"Earth Explorer" Missions

Earth Observation Big Data



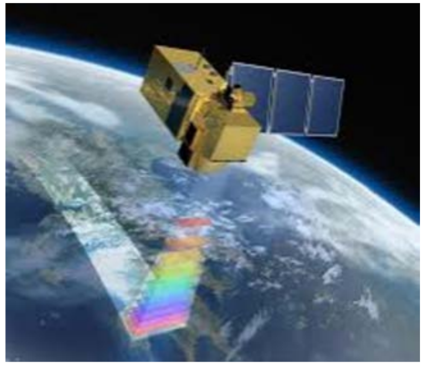
Earth Observation Big Data

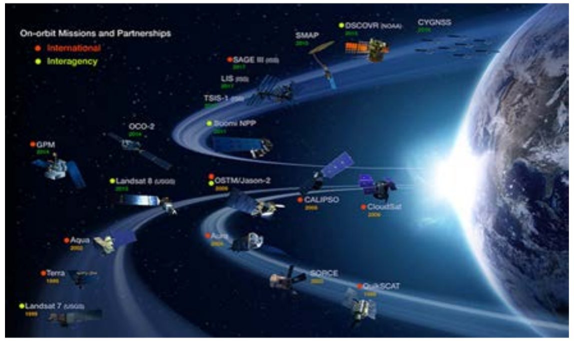
Where do we stand on Earth Observation?

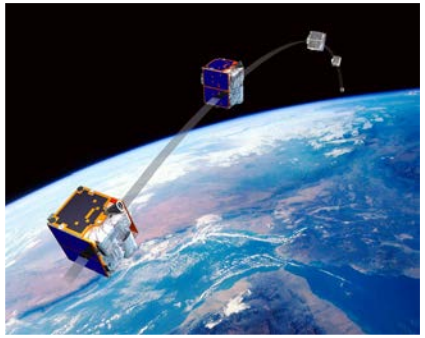
- Thanks to the fast growth of satellite technology we are moving forward into a new era of Earth Observation (EO).

- Both National/International space agencies and innovative companies are supporting various EO programs acquiring huge amounts of data every day

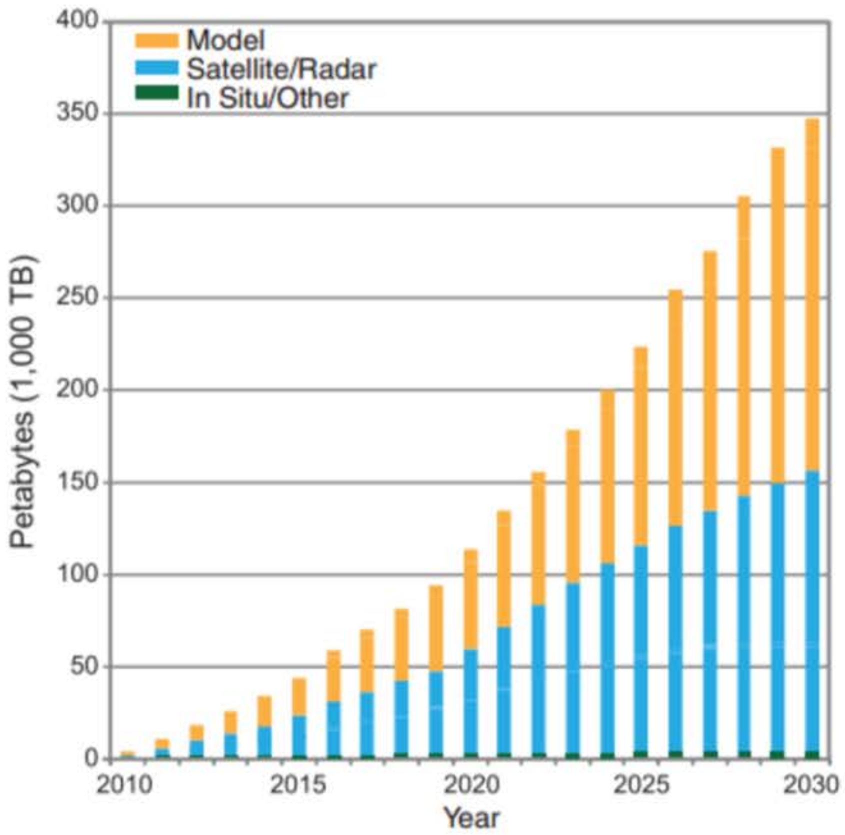




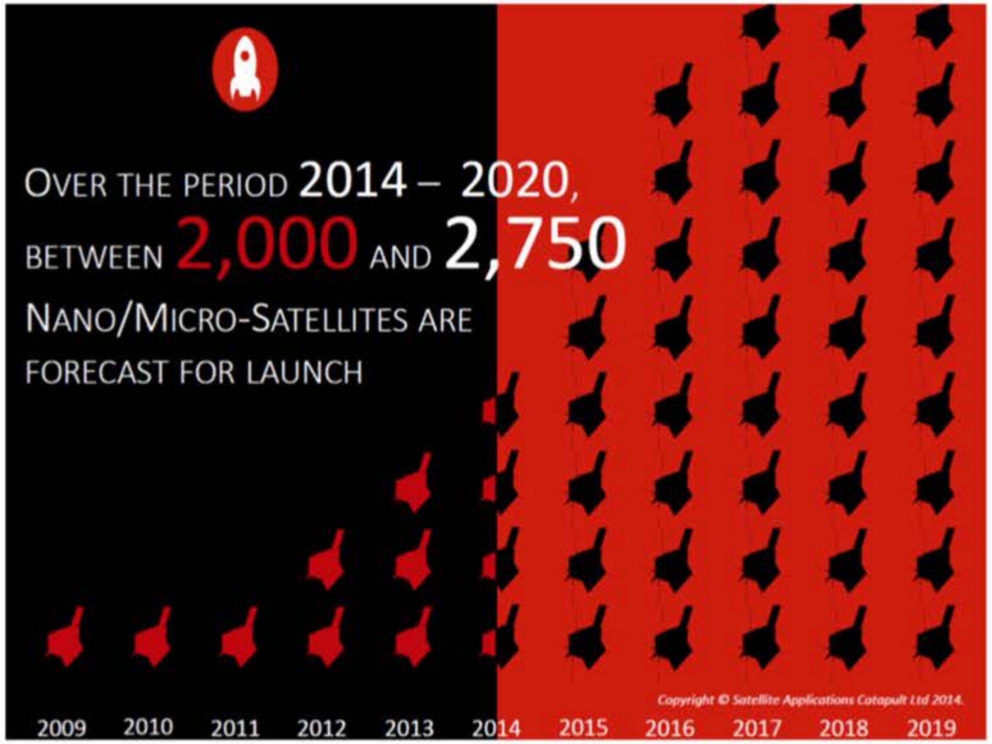




Earth Observation Big Data



Jonathan T. Overpeck et al, Science 2011



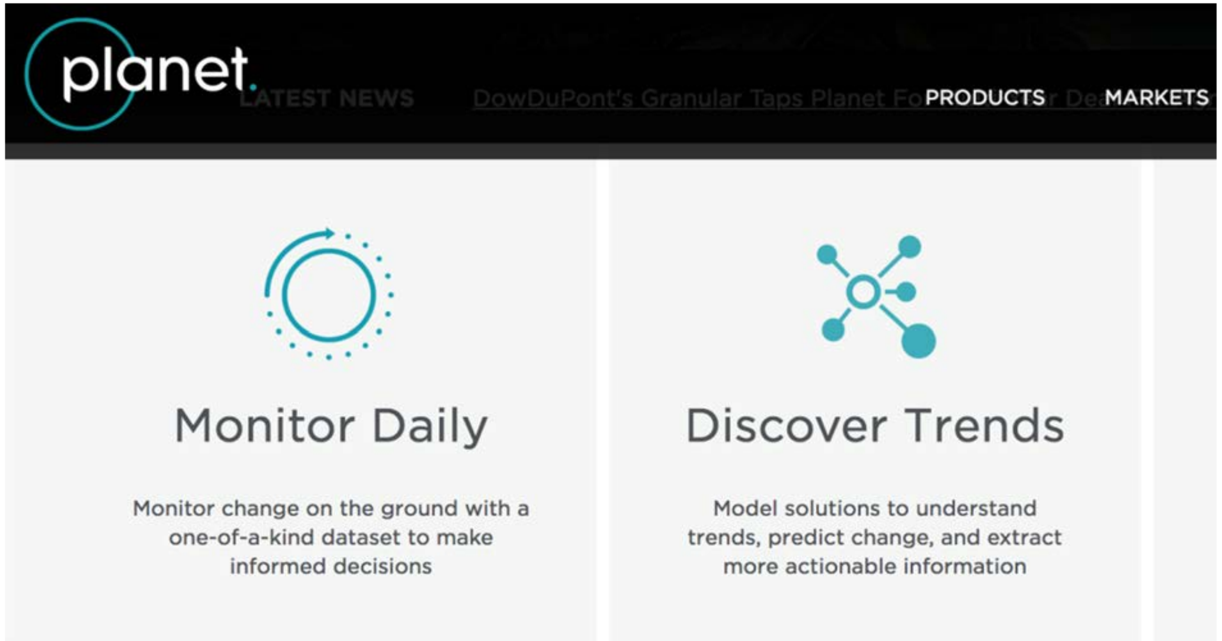
Capella Space planet. Synspective ICEYE

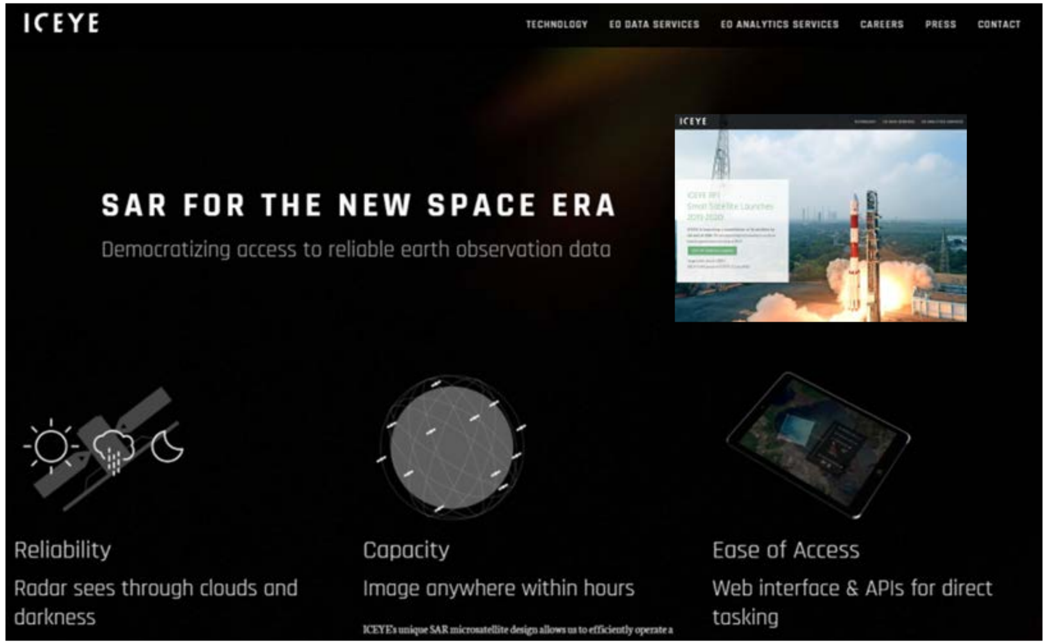
Earth Observation Big Data: New Trends

Planet: more than 175 Doves, 13 SkySats and 5 RapidEye satellites that acquire multispectral imagery of the entire Earth's landmass daily

Capella Space: deploying a SAR CubeSat satellite constellation that will provide hourly imagery with a global coverage

ICEYE: launching a constellation of 18 SAR satellites





Earth Observation Big Data: Opportunities & Challenges

Opportunities

- Near-real time monitoring of phenomena affecting built and natural environment
- Dense time series for analysis of global environmental changes
- New possibility for operational and reliable services

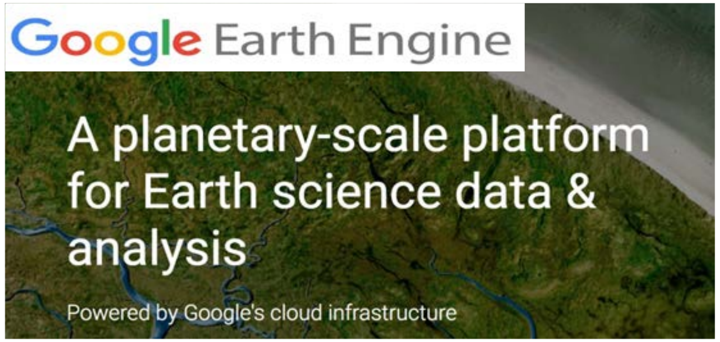
Challenges

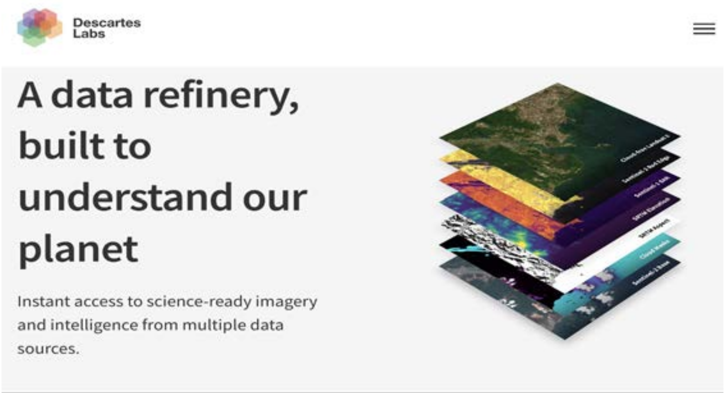
- Need innovative computing infrastructure to handle, store and process the data
- Need new methods and algorithms to extract valuable information
- Integrate the analysis of the EO imagery with other geospatial big data (i.e. social media, ground sensors, crowdsourced data)

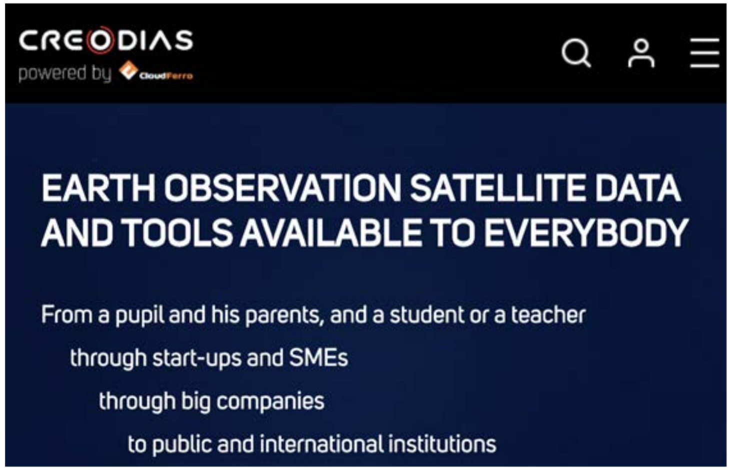
EO Cloud Processing Platform

Several EO CPP are under development with contributions from open source communities (Open Data Cube), space agencies (ESA Thematic Exploitation Platform, DIAS) and private companies (Google Earth Engine, AWS, Sentinel-Hub, Descartes lab)

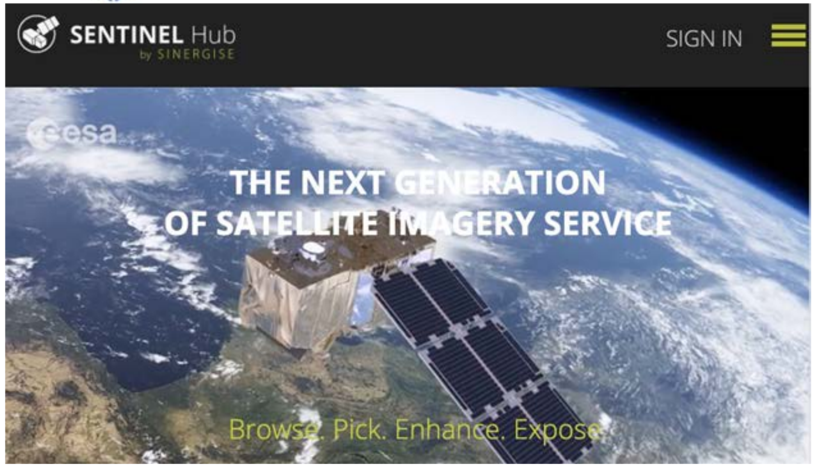
“Often it turns out to be more efficient to move the questions than to move the data.” The Fourth Paradigm – Tony Hey et al.

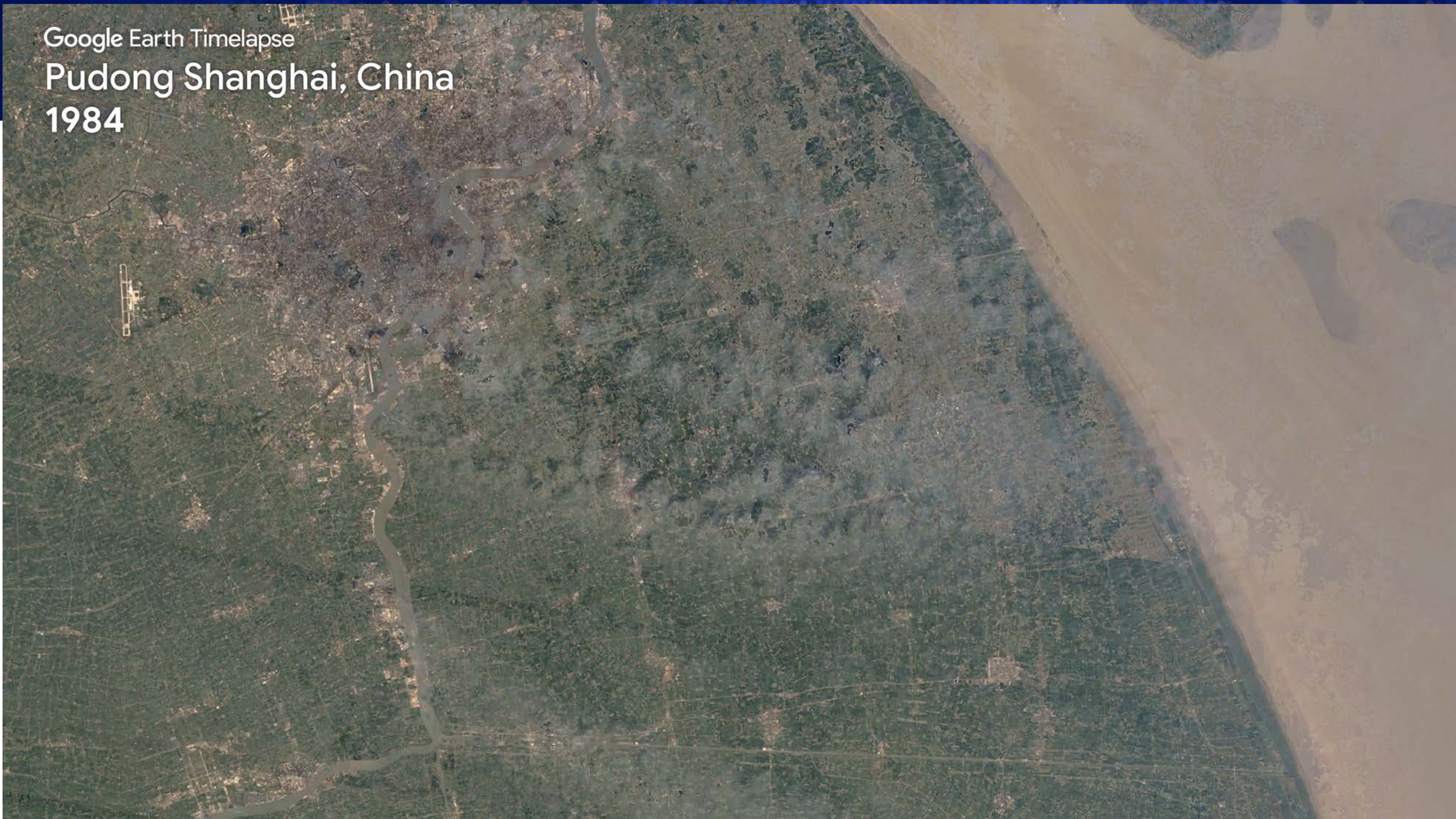






OPEN DATA CUBE




Google Earth Timelapse
Pudong Shanghai, China
1984

Research Objective

- The overall objective is to develop innovative, robust and globally applicable methods, based on EO big data and deep learning, for urban mapping and urbanization monitoring to support sustainable and resilient urban planning.

SUSTAINABLE DEVELOPMENT GOALS

11 SUSTAINABLE CITIES AND COMMUNITIES

13 CLIMATE ACTION

15 LIFE ON LAND

Specific Objectives

- Evaluate Sentinel-1 SAR and Sentinel-2 MSI time series, Chinese EO data and ESA TPM data for improved urban mapping and change detection in both 2D and 3D;
- Develop novel and efficient methods for urban extend extraction and urban land cover mapping with Sentinel-1 SAR and Sentinel-2 MSI time series and deep learning;
- Develop innovative and robust methods for continuous urban change detection using Sentinel-1 SAR and Sentinel-2 MSI time series and deep learning;
- Evaluate SAR-based method for 3D urban change estimation;
- Assess the environmental impact of urbanization at local and landscape scales, and to evaluate 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.

EO Data Delivery

Data access (list all missions and issues if any). NB. in the tables please insert cumulative figures (since July 2020) for no. of scenes of high bit rate data (e.g. S1 100 scenes). If data delivery is low bit rate by ftp, insert "ftp"

ESA Third Party Missions	No. Scenes
1. TerraSAR-X	30
2. Cosmo-SkyMed	50
3. RADARSAT-2, RCM	30
4. Landsat	50
5.	
6.	
Total:	160
Issues:	

ESA Third Party Missions	No. Scenes
1. Sentinel-1	2000
2. Sentinel-2	500
3.	
4.	
5.	
6.	
Total:	2500
Issues:	

Chinese EO data	No. Scenes
1. GF-1	30
2. GF-2	30
3. GF-3	50
4. ZY-3	50
5.	
6.	
Total:	160
Issues:	

Training Data

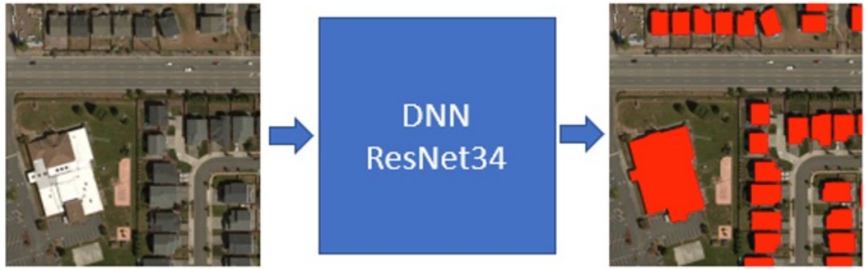
Microsoft building footprints:

- Freely available for US, Canada, Uganda and Tanzania (~150 million footprints)
- Generated using two-stage approach:

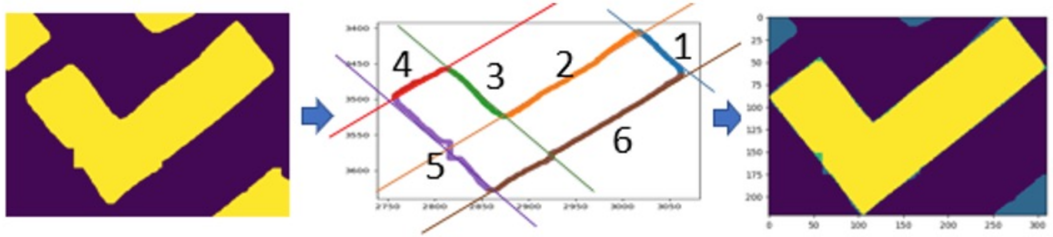
Building Footprints USA, Canada, Uganda and Tanzania

These datasets contain building footprints in the U.S., Canada, Uganda, and Tanzania.

First Stage - Semantic segmentation

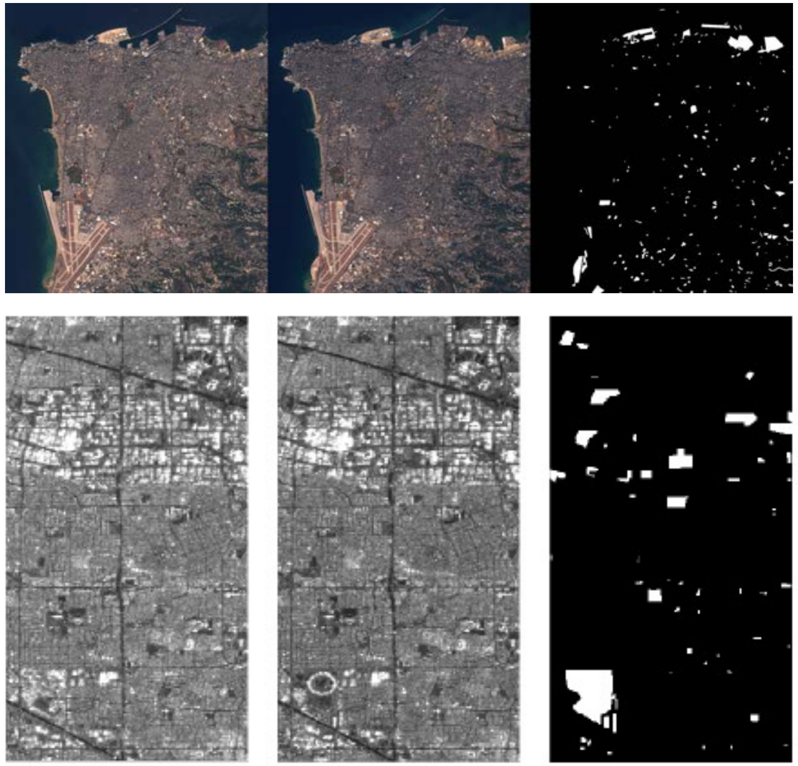


Second Stage - Polygonization



Training & Validation Data

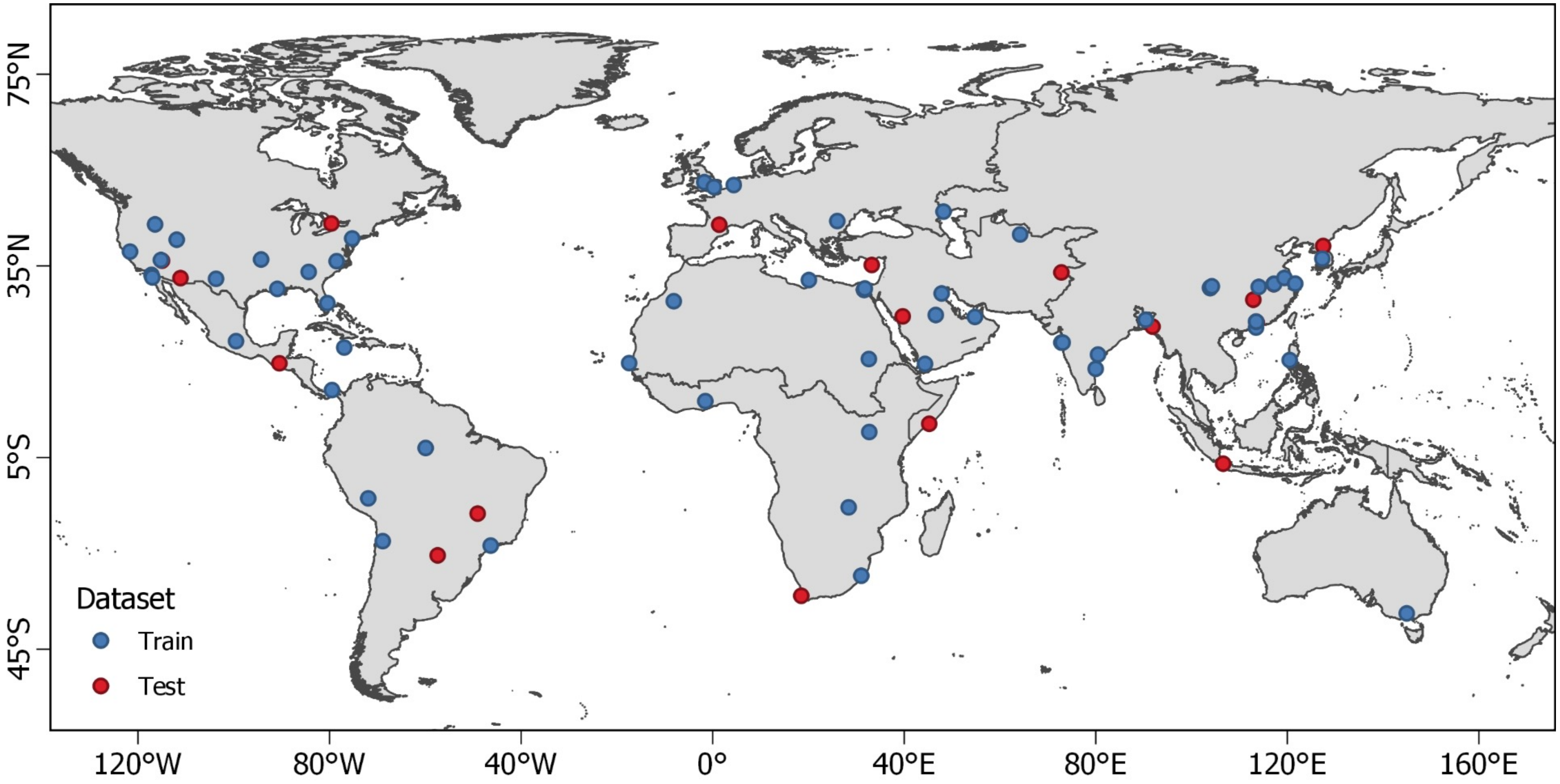
Onera Satellite Change Detection (OSCD)



(a) Image t1 (b) Image t2 (c) label

SpaceNet 7 Challenge:
Multi-Temporal Urban Development

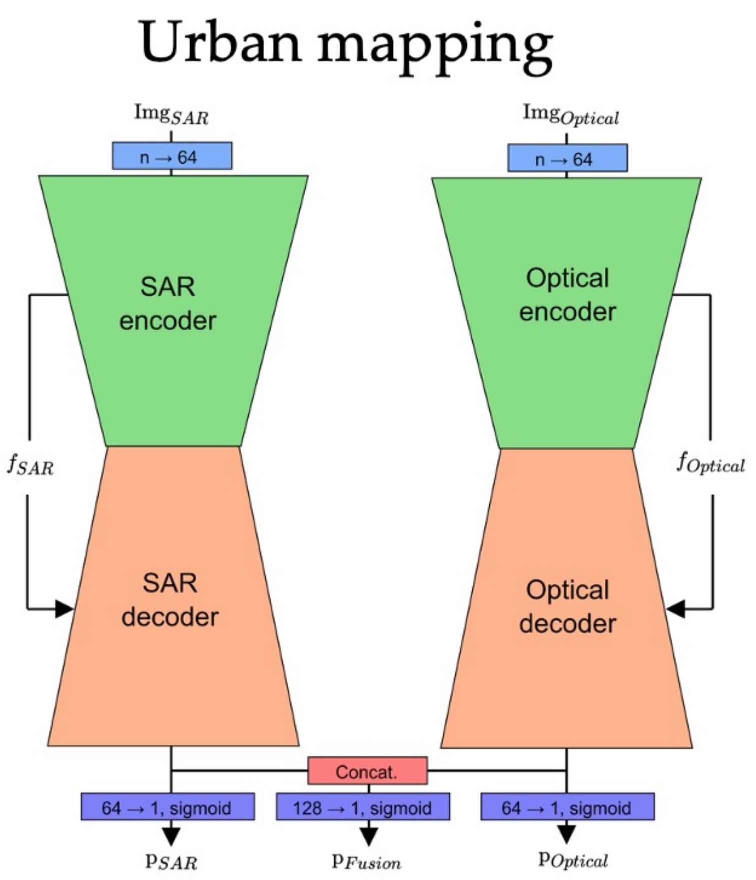
Training & Testing Sites

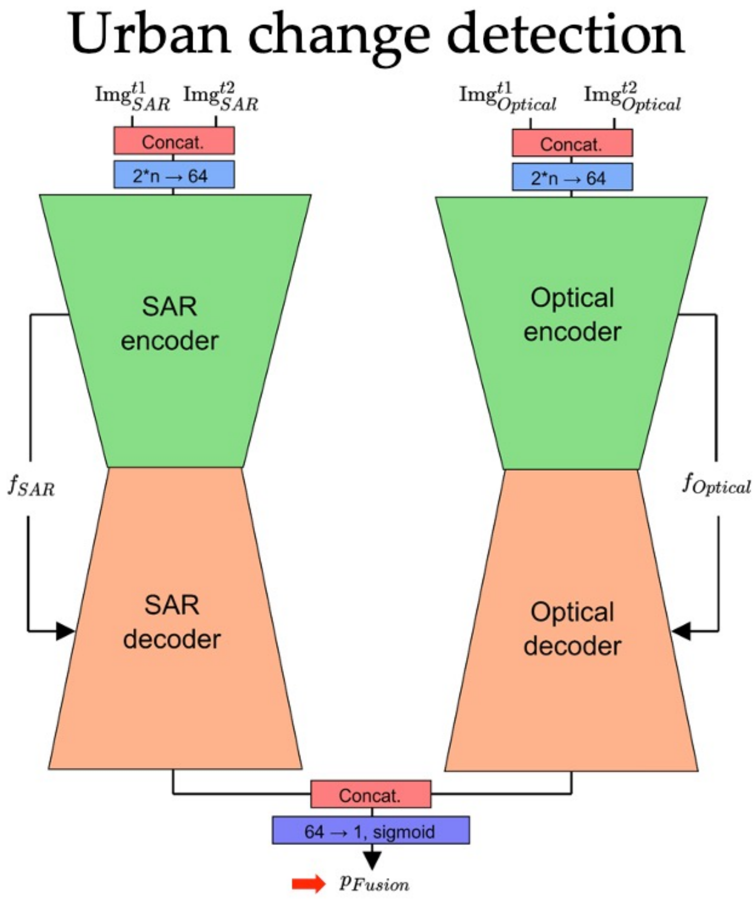


In Situ Measurements

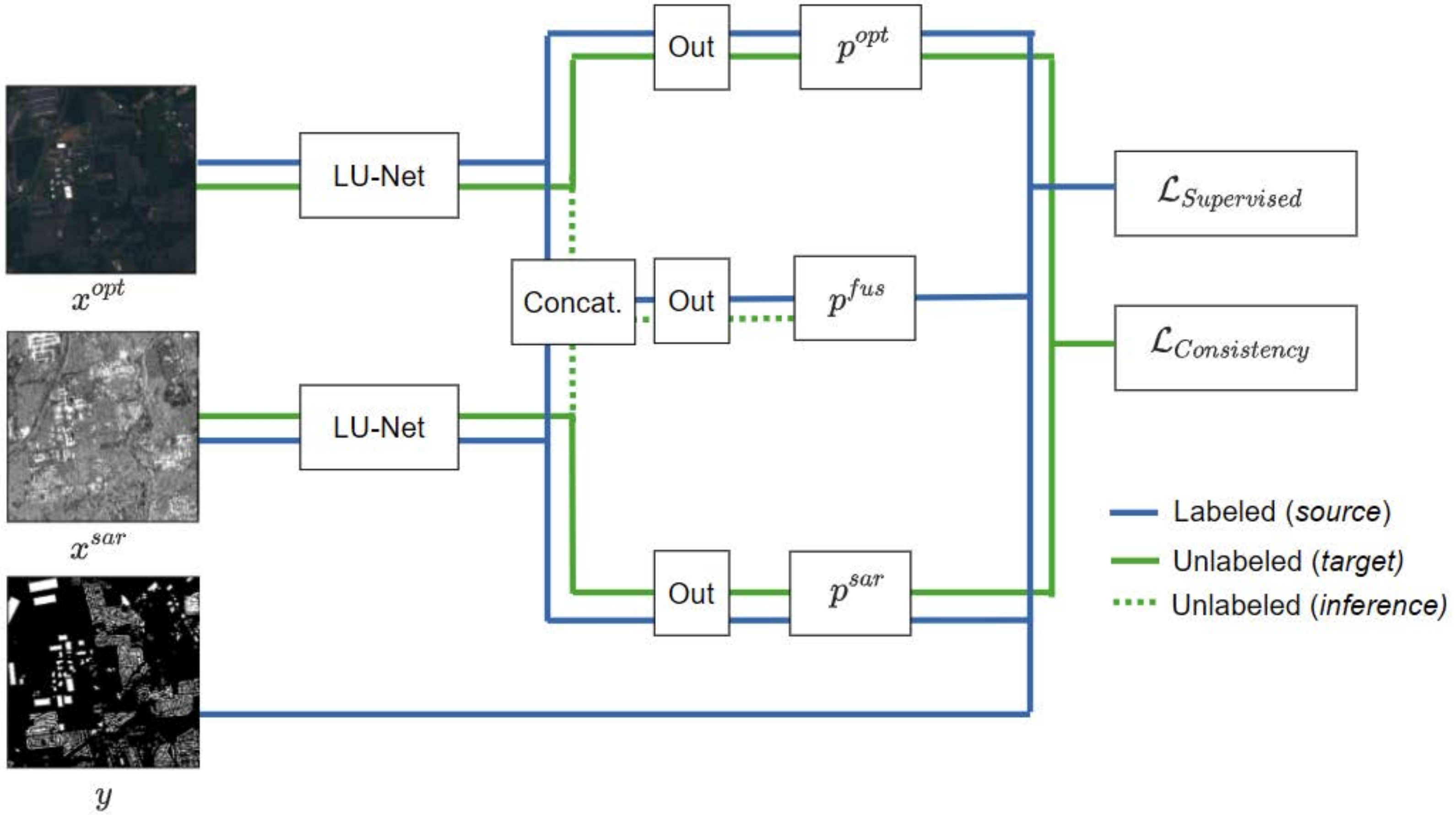
Methodology

Dual Stream Architectures for Multi-Modal Data



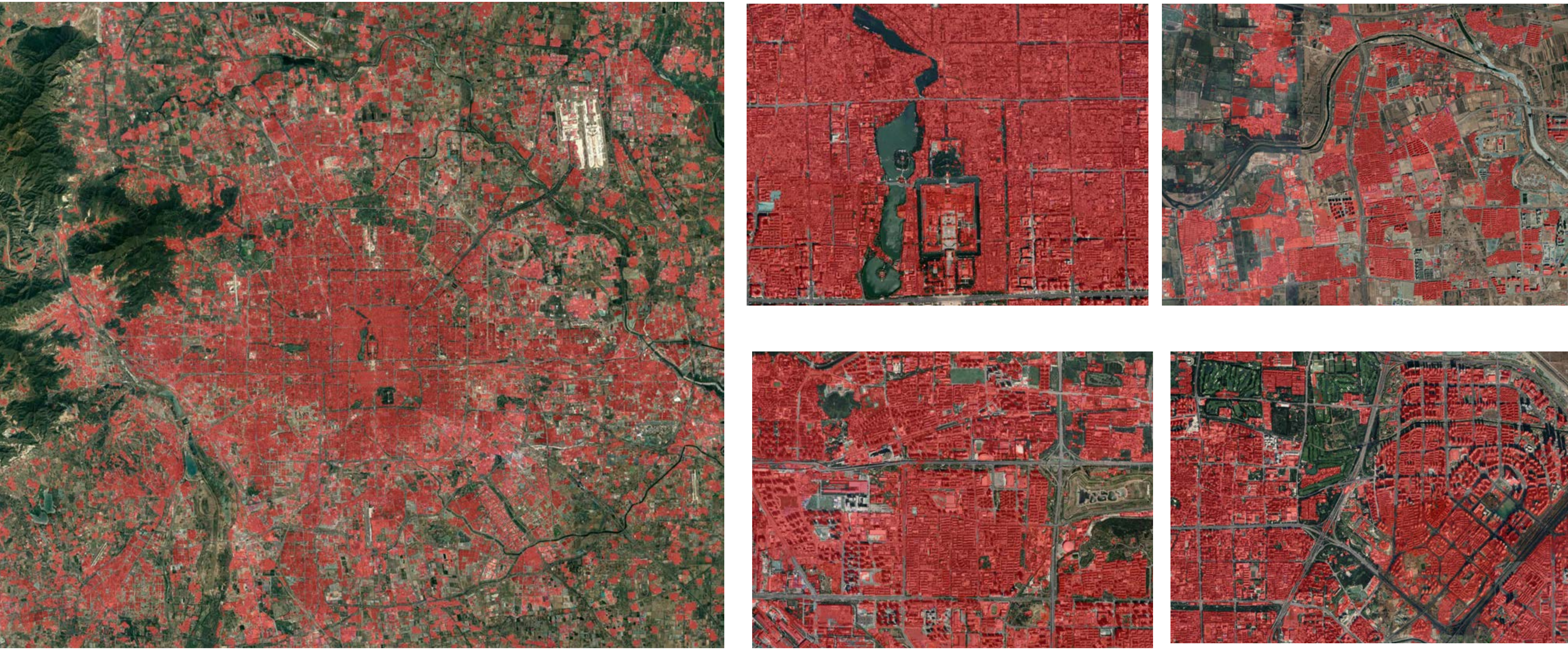


Methodology



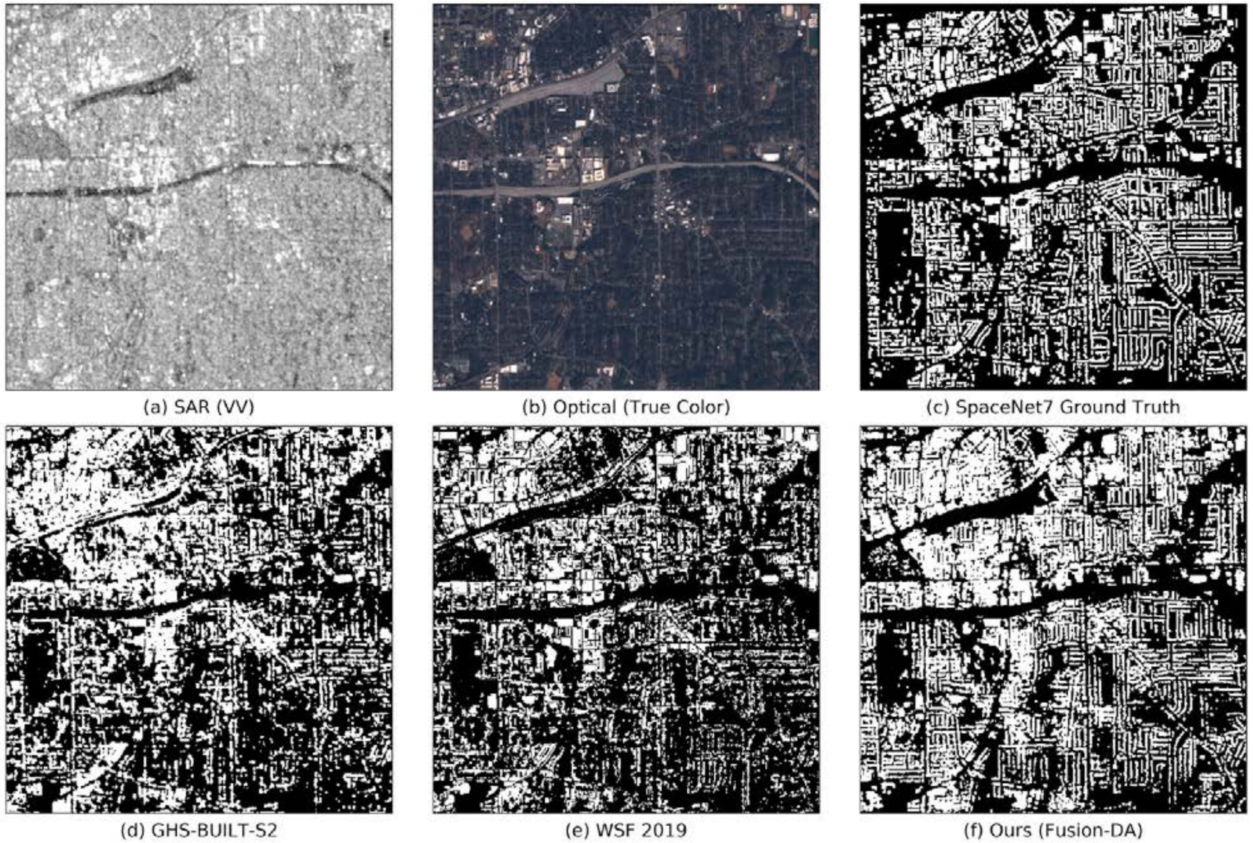
Hafner, S., Y. Ban, A. Nascetti and H. Azizpour. 2022. Unsupervised Domain Adaptation for Global Urban Extraction using Sentinel-1 and Sentinel-2 Data. *Remote Sensing of Environment*. Volume 280, 113192, https://doi.org/10.1016/j.rse.2022.113192.

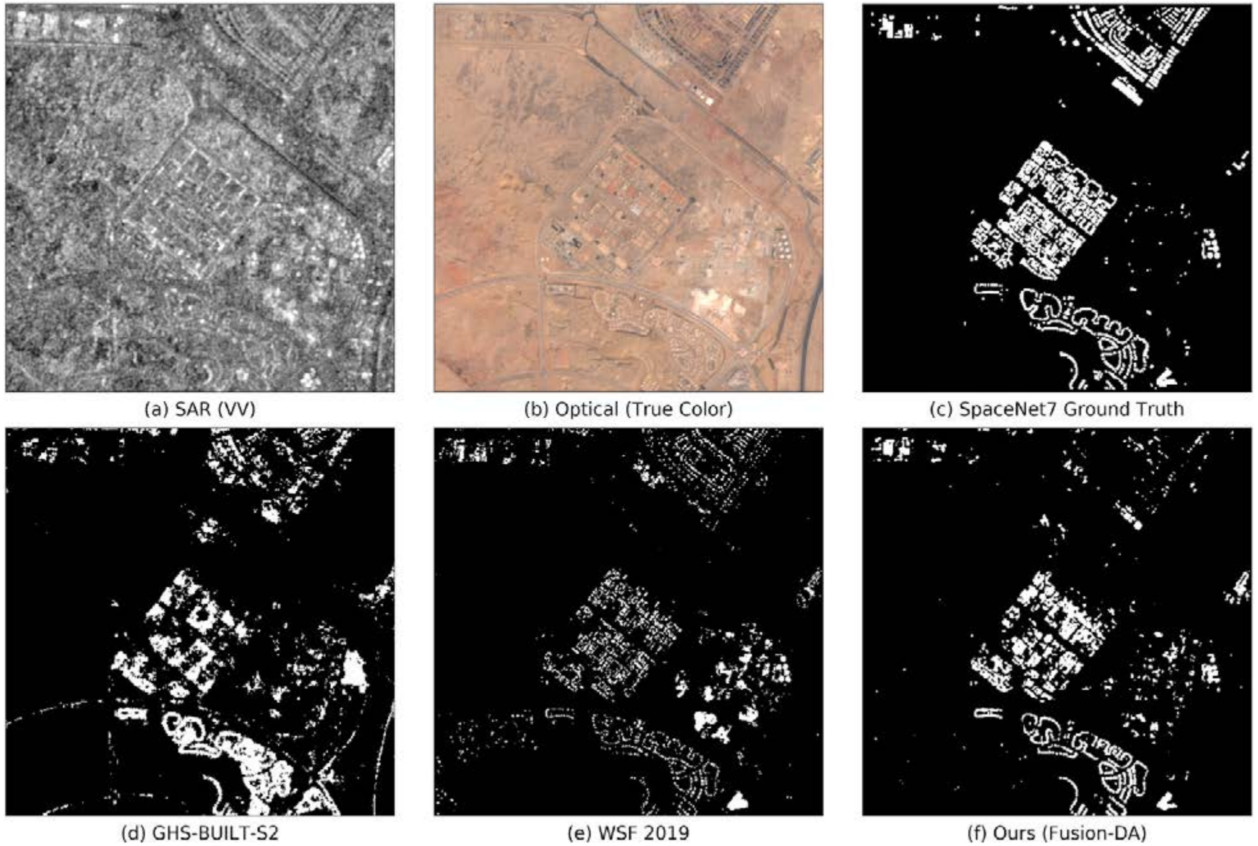
Results: Urban Mapping



Results: Urban Mapping

Results: Urban Mapping

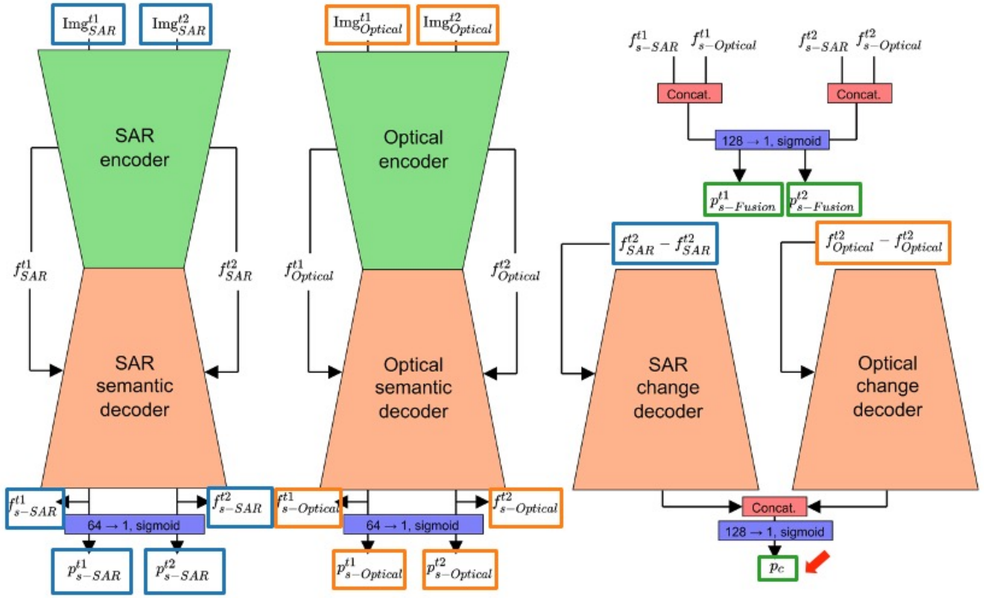




Methodology

Domain Adaptation: Urban Change Detection

Multi-Modal Siam-Diff Dual-Task



Semi-supervised training (again)

$$\mathcal{L}_c = \mathcal{L}_{pJacc}(\boxed{p_c}, y_c)$$

$$\mathcal{L}_s = \mathcal{L}_{pJacc}(p^{t1}_{s-SAR}, y^{t1}_s) + \mathcal{L}_{pJacc}(p^{t2}_{s-SAR}, y^{t2}_s) + \mathcal{L}_{pJacc}(p^{t1}_{s-Optical}, y^{t1}_s) + \mathcal{L}_{pJacc}(p^{t2}_{s-Optical}, y^{t2}_s) + \mathcal{L}_{pJacc}(\boxed{p^{t1}_{s-Fusion}}, y^{t1}_s) + \mathcal{L}_{pJacc}(\boxed{p^{t2}_{s-Fusino}}, y^{t2}_s)$$

$$\mathcal{L}_{cons} = \mathcal{L}_{L2}(p^{t1}_{s-SAR}, p^{t1}_{s-Optical}) + \mathcal{L}_{L2}(p^{t2}_{s-SAR}, p^{t2}_{s-Optical})$$

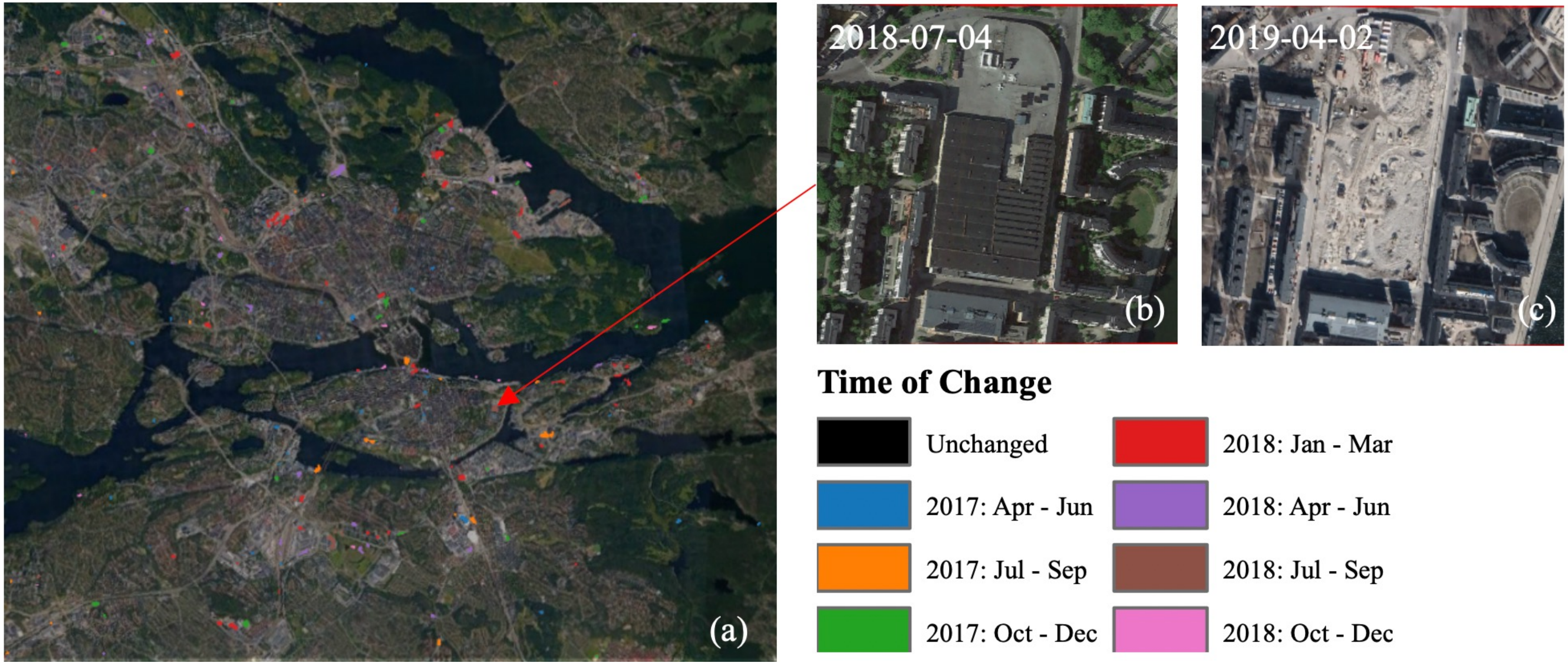
$$\mathcal{L}_{sample} = \begin{cases} \alpha \cdot (\mathcal{L}_c + \mathcal{L}_s), & \text{if } y \text{ exists} \\ (1-\alpha) \cdot L_{cons}, & \text{otherwise} \end{cases}$$

SAR Optical Fusion

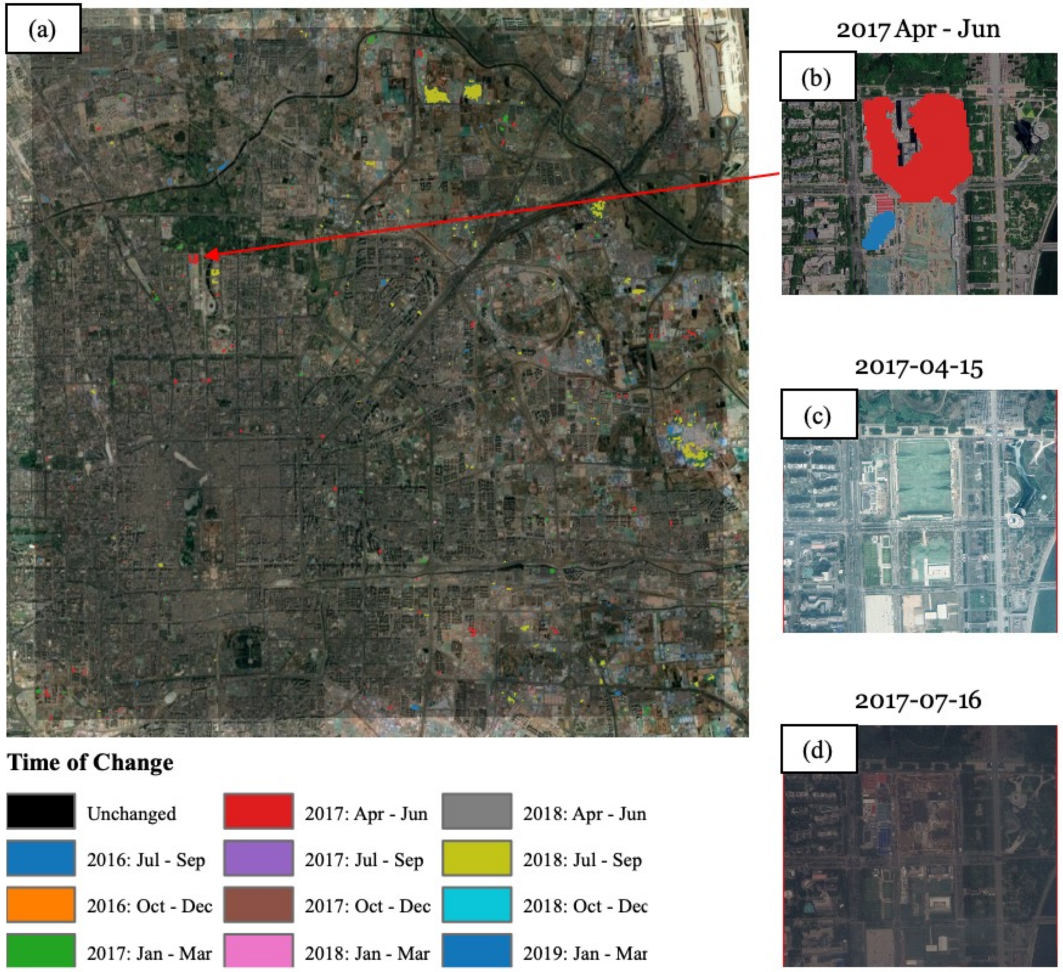
Hafner, S., Y. Ban, & A. Nascetti. 2022. Multi-Modal Consistency Regularization Using Sentinel-1 SAR and Sentinel-2 MSI Data for Urban Change Detection. *ISPRS Journal of Photogrammetry and Remote Sensing* (submitted)

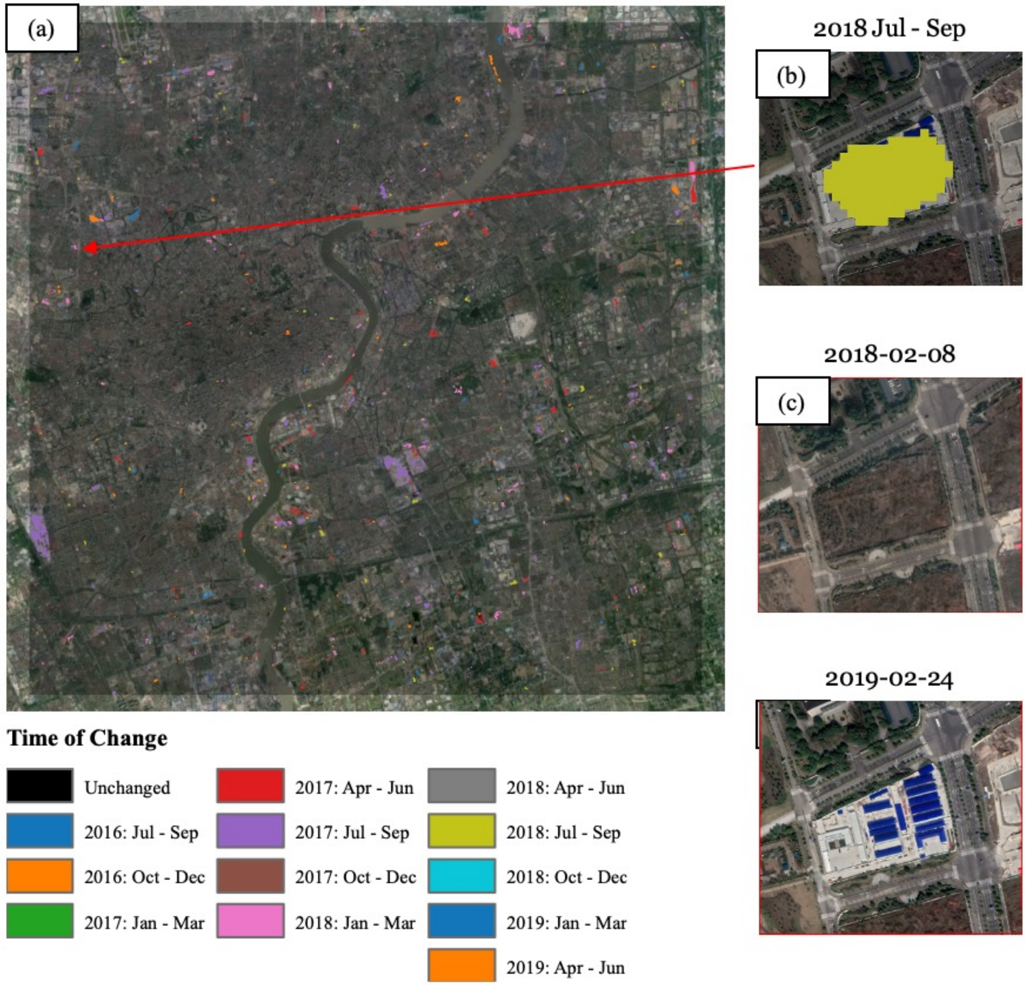
Hafner, S., A. Nascetti, H. Azizpour and Y. Ban. 2022. Sentinel-1 and Sentinel-2 Data Fusion for Urban Change Detection using a Dual Stream U-Net. *IEEE Geoscience and Remote Sensing Letters*, Vol. 19, 4019805, DOI: 10.1109/LGRS.2021.3119856.

Results: Continuous Urban Change Detection

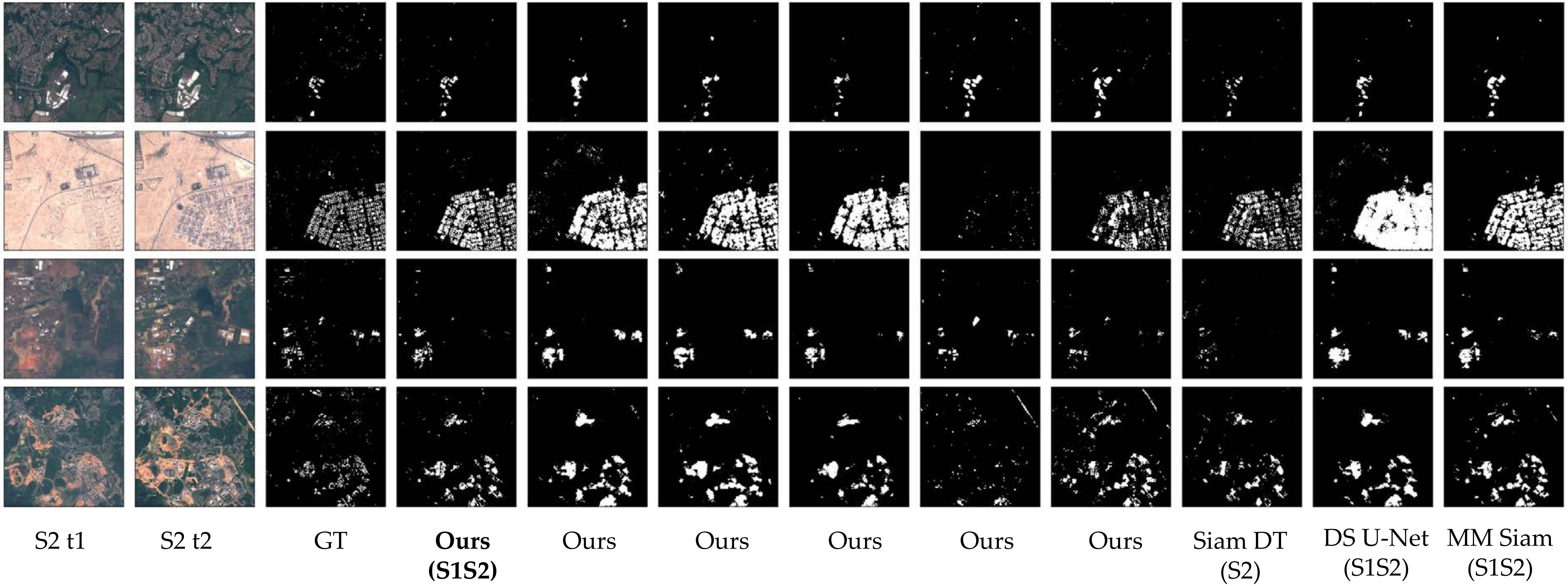


Results: Continuous Urban Change Detection



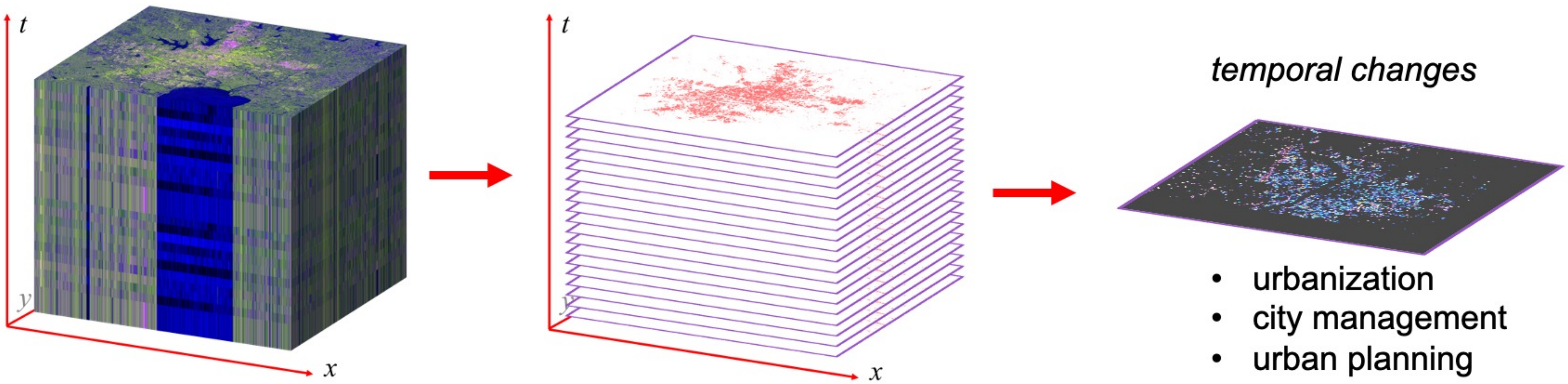


Results: Urban Change Detection



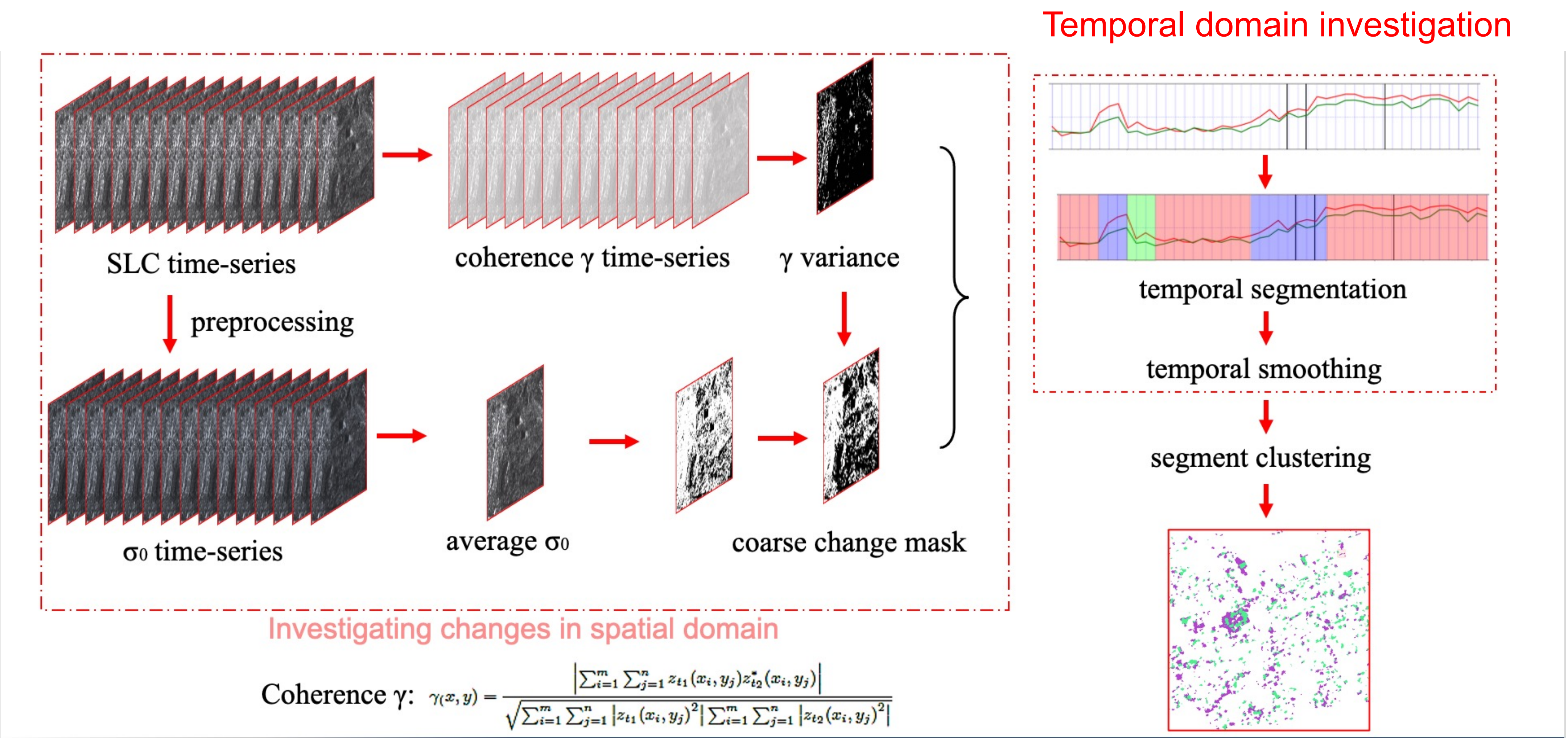
Change Detection in Spatial & Temporal Domain

- The available increasing temporal granularity (temporal resolution) of time-series lead to more detailed investigation of urbanization activities.
- Change detection methods designed for series (thresholding, differencing, segmentation, trajectory classification, regression, and decomposition) are operated separately in time and space domain.
- Traditional changing models are limited to describe the spatio-temporal change patterns

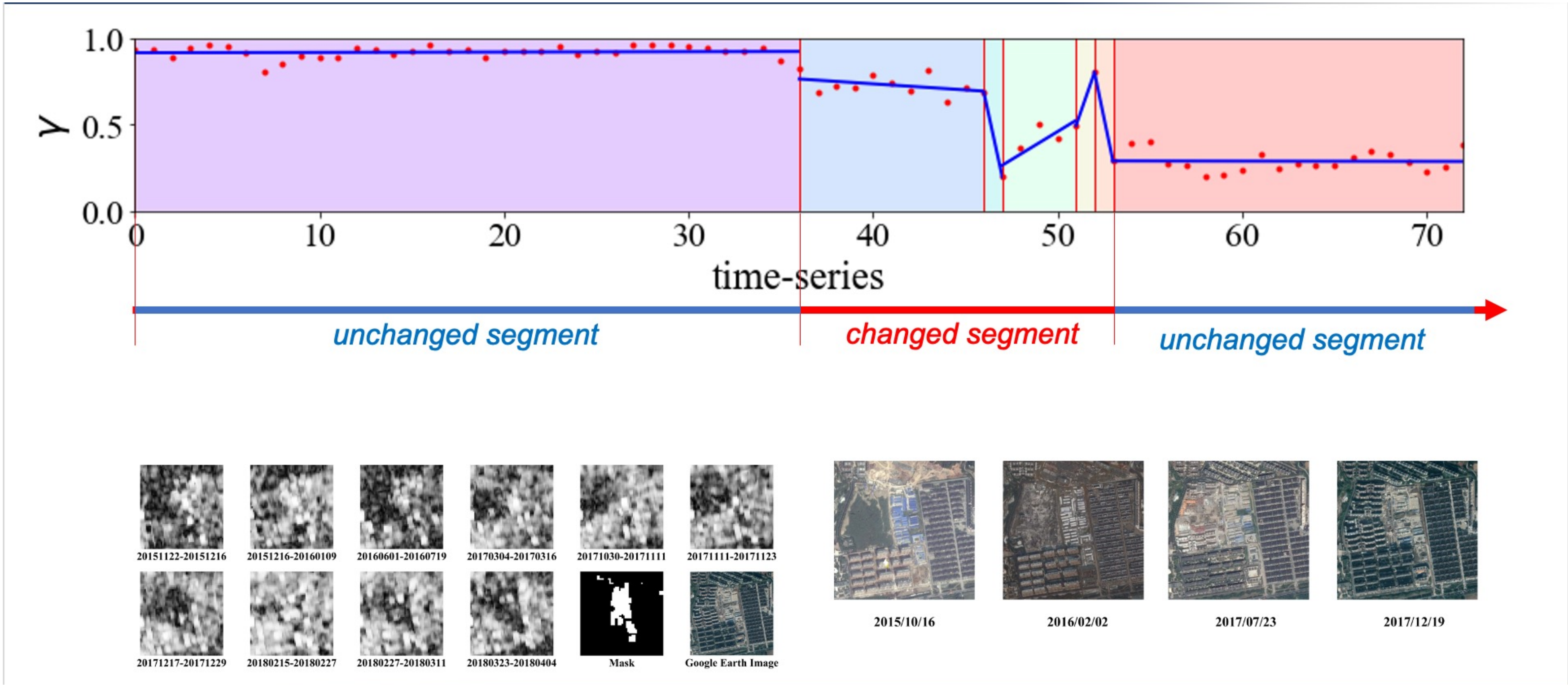


? What kinds of urban change pattern in temporal domain?
? Is it possible to investigate urban change in spatial and temporal domain, rather than separated?
? How to update change with historical temporal information?

Methodology



Results



M. Che and P. Gamba, "Temporal and Spatial Change Pattern Recognition by Means of Sentinel-1 SAR Time-Series," Proc. of IEEE International Geoscience and Remote Sensing Symposium, 2020, pp. 160-163, doi: 10.1109/IGARSS39084.2020.9323365.

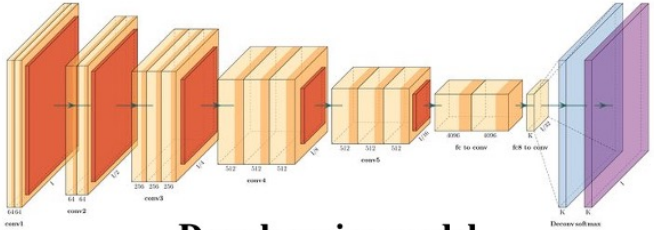
M. Che, A. Vizziello and P. Gamba, "Spatio-temporal Urban Change Mapping with Time-Series SAR data," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2022, doi: 10.1109/JSTARS.2022.3203195.

Urban Change Detection

In the field of **urban change detection**, deep learning techniques have obvious advantages in terms of processing efficiency, accuracy and automation. In practical applications, however, the application effect of deep-learning-based image interpretation model needs to be improved.

In order to solve the bottleneck problem of automatic **extraction of land cover and its change information**, this project establishes an efficient and intelligent land cover remote sensing classification and change detection workflow, which could improve the accuracy of artificial intelligence remote sensing image interpretation. Besides, the effective support of remote sensing technology for **resource condition survey and dynamic monitoring** was been proven in this project.

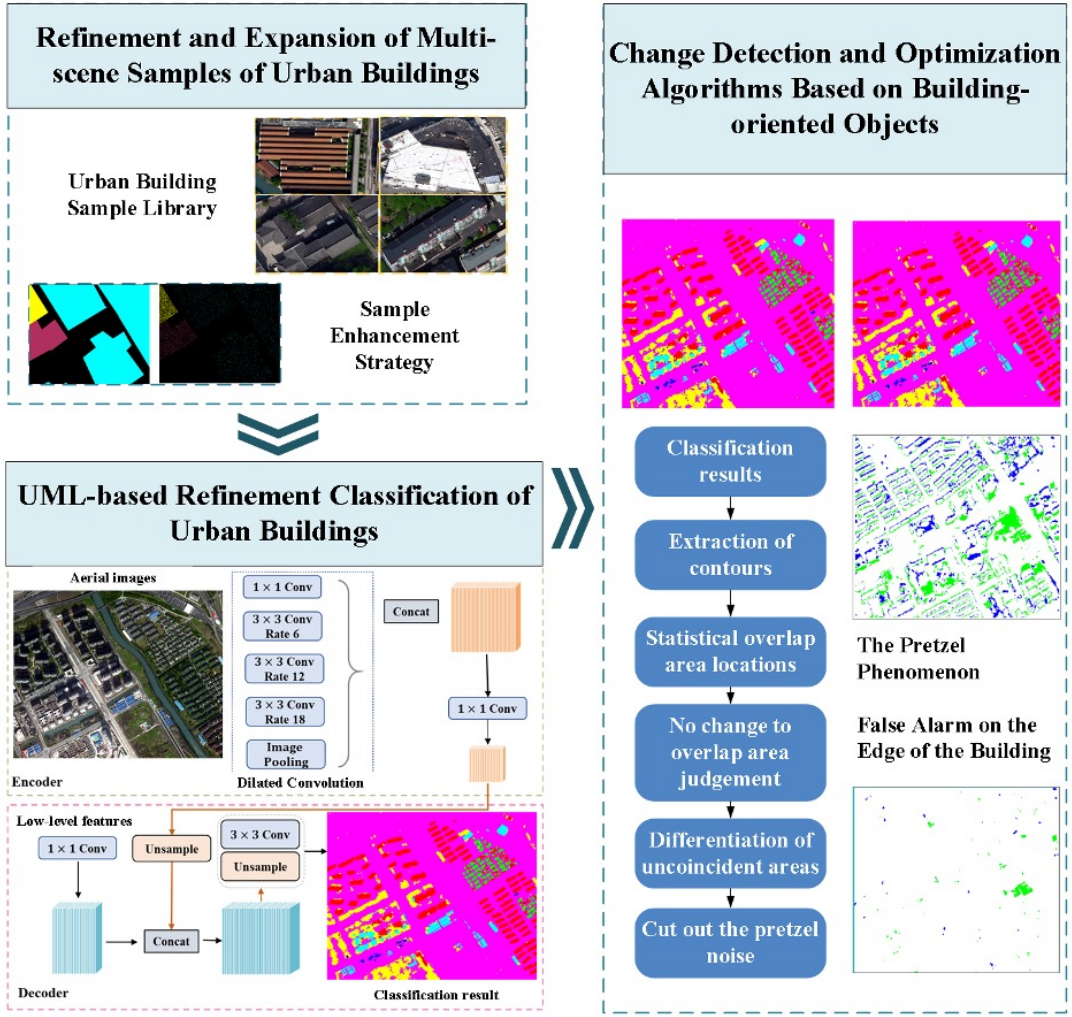
Aerial remote sensing images



Deep learning model

Classification results in different periods

Methodology



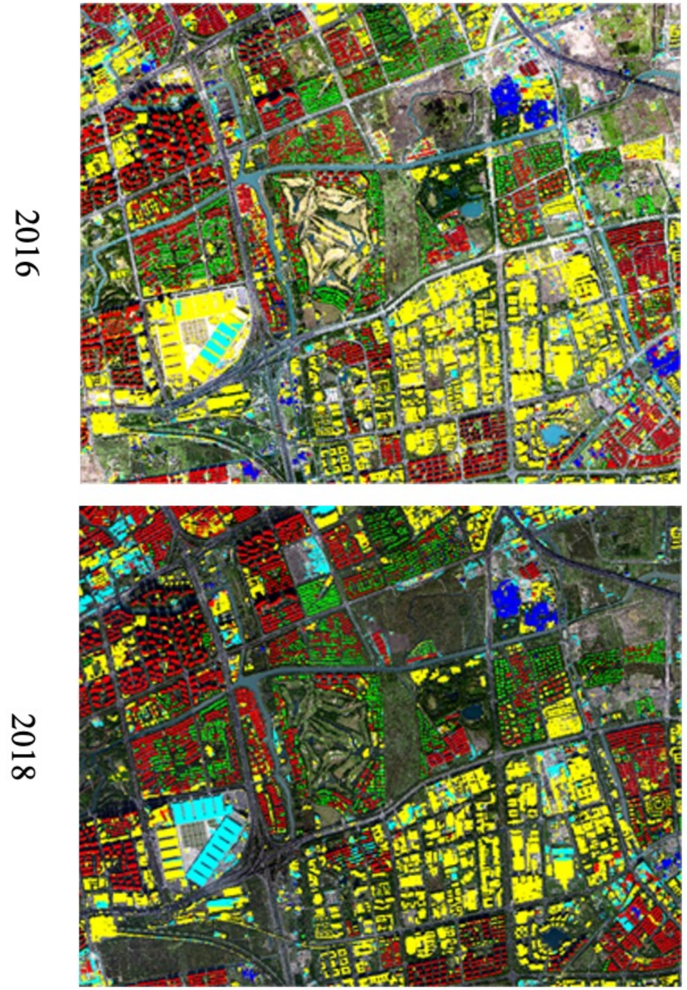
Workflow

This project focuses on the construction of a **multi-scene knowledge base** for different urban building samples. The strategy of random sampling was used for image sample enhancement.

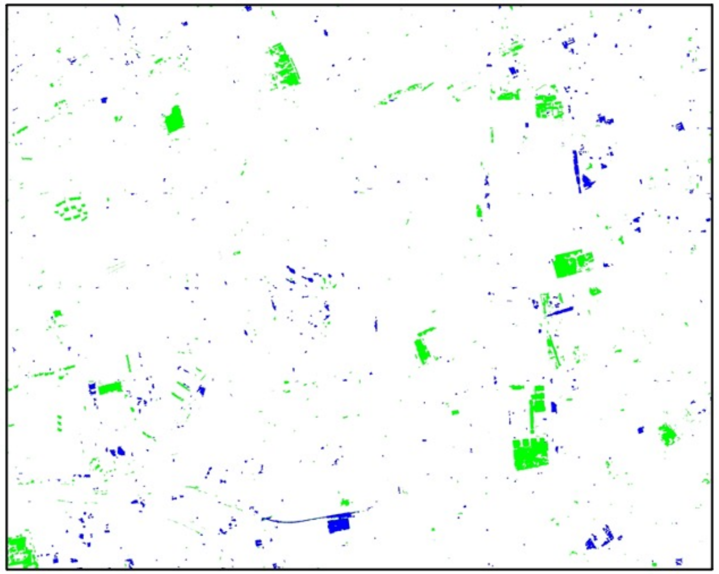
Then, the project designed a **deep learning classification model** (UML) with space-spectrum attention to achieve urban building classification results.

Finally, **a change detection and optimization method for building objects** was applied and obtained high-precision classification and change detection results for urban buildings.

Results



Classification results



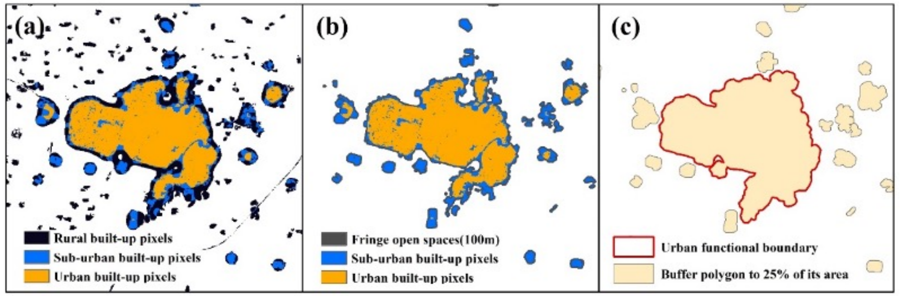
Residential buildings
Villas
Self-built houses
Public buildings
Industrial buildings
Other

Decreased
Increased
Unchanged

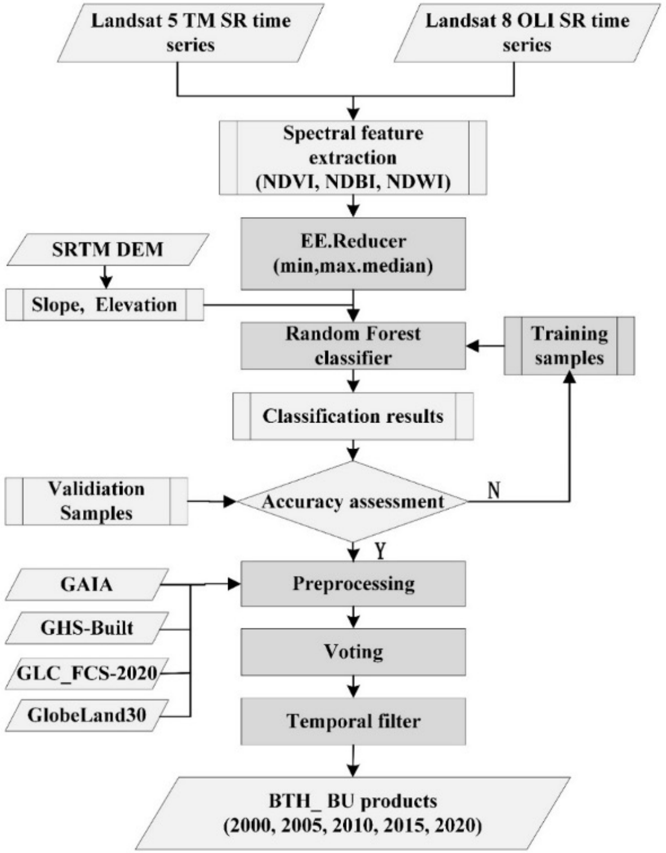
Urban building change detection result in Jiading, Shanghai from 2016 to 2018

Methodology

- Annual composite images were created from the optical, near-infrared, NDVI, NDBI and NDWI bands as input features of a random forest algorithm(RFA). Different strategies for splitting the training and validation samples. The RFA was run iteratively and classification result with the highest OA was taken as the final output.
- The multi-temporal built-up area products were used to calculate SDG11.3.1 indicators in cities of the BTH region.



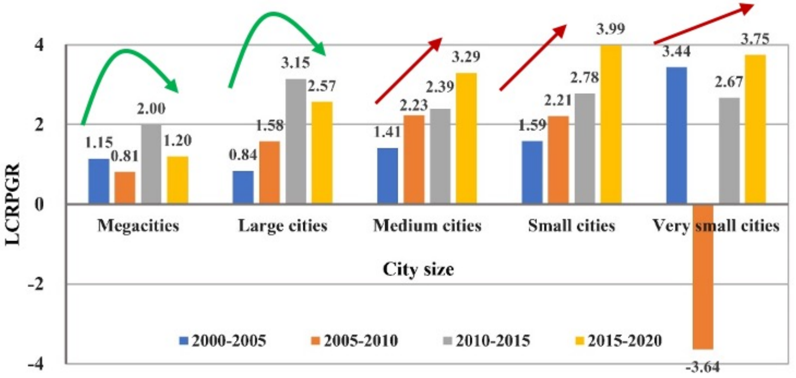
Urban functional boundary extraction

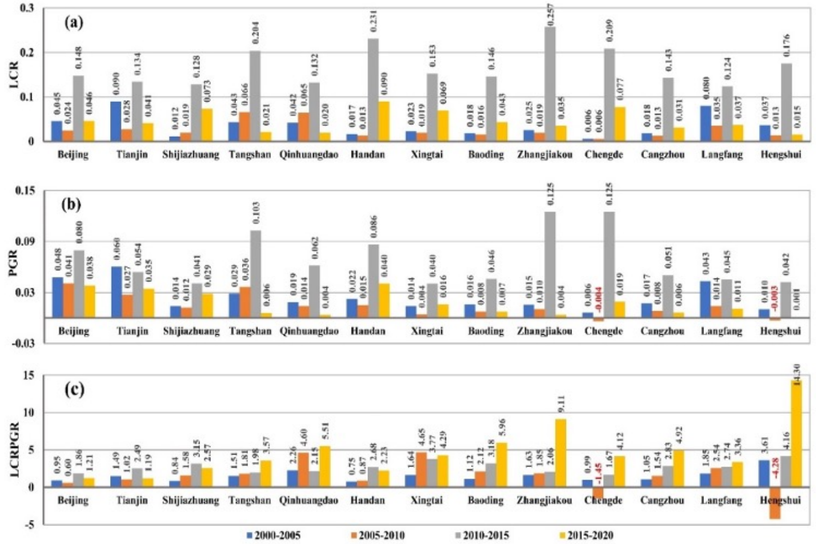


Built-up area extraction workflow

Results

- The overall ratio of the land consumption rate to population growth rate (LCRPGR) in the BTH region fluctuated from 1.142 in 2000–2005 to 0.946 in 2005-2010, 2.232 in 2010-2015 and 1.538 in 2015–2020.
- Diverged changing trends of LCRPGR values in cities with different population sizes in the study area. Apart from the megacities of Beijing and Tianjin, after 2010, the LCRPGR values were greater than 2 in all the cities in the region.
- The cities classed as either small or very small had the highest LCRPGR values. Some of these cities, such as Chengde and Hengshui, experienced population loss in 2005-2010.





Zhou, M.; Lu, L.; Guo, H et al. Urban Sprawl and Changes in Land-Use Efficiency in the Beijing–Tianjin–Hebei Region, China from 2000 to 2020: A Spatiotemporal Analysis Using Earth Observation Data. *Remote Sensing*, **2021**; Vol. 13.

Project Plans

- **Phase 1:** Comprehensive review of existing methodologies, collection of a first set of EO data cubes and the existing urban data.
- **Phase 2:** Development of novel methodologies to characterize urban land cover, urban changes in 2D and 3D in the selected study areas.
- **Phase 3:** Collecting validation data from field campaigns and validation of the first results; improving the proposed approaches and optimization of the techniques by considering emerging methods and additional datasets.
- **Phase 4:** Deploy the developed methods in large number of cities to demonstrate their global applicability.

European Young scientists contributions in Dragon 5

Name	Institution	Poster title	Contribution
Sebastian Hafner	KTH Royal Institute of Technology, Stockholm, Sweden	Balanced Multi-Modal Learning from Sentinel-1 SAR and Sentinel-2 MSI Data for Improved Urban Change Detection	Sentinel-1 SAR and Sentinel-2 Data Fusion for Urban Mapping and Change Detection with Deep Learning
Yuxi Sun	Harbin Institute of Technology, Shenzhen, China	Visual Grounding in Remote Sensing Images	Urban object detection and retrieval from a large-scale remote sensing images