



**UNIVERSITY
OF ICELAND**

Doctoral Defence in Computational Engineering – Surbhi Sharma

Advancing Land-Cover and Land-Use Classification with Semantically Consistent and Data-Efficient Deep Learning on Multi-Source Earth Observation Data

Doctoral Committee:

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Prof. Dr. Gabriele Cavallaro, Associate Professor at the Faculty of Electrical and Computer Engineering, HÍ

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FACULTY OF INDUSTRIAL ENGINEERING, MECHANICAL
ENGINEERING AND COMPUTER SCIENCE

Personal Background



University of Iceland
(PhD in
Computational
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University of Twente
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Indian Institute of Remote Sensing
(M.Sc. in
Geoinformatics &
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Engineering)



Amity University
(B.Tech in
Electronics and
Communication)

Countries

-  Iceland
-  Germany
-  Netherlands
-  India

Image credits

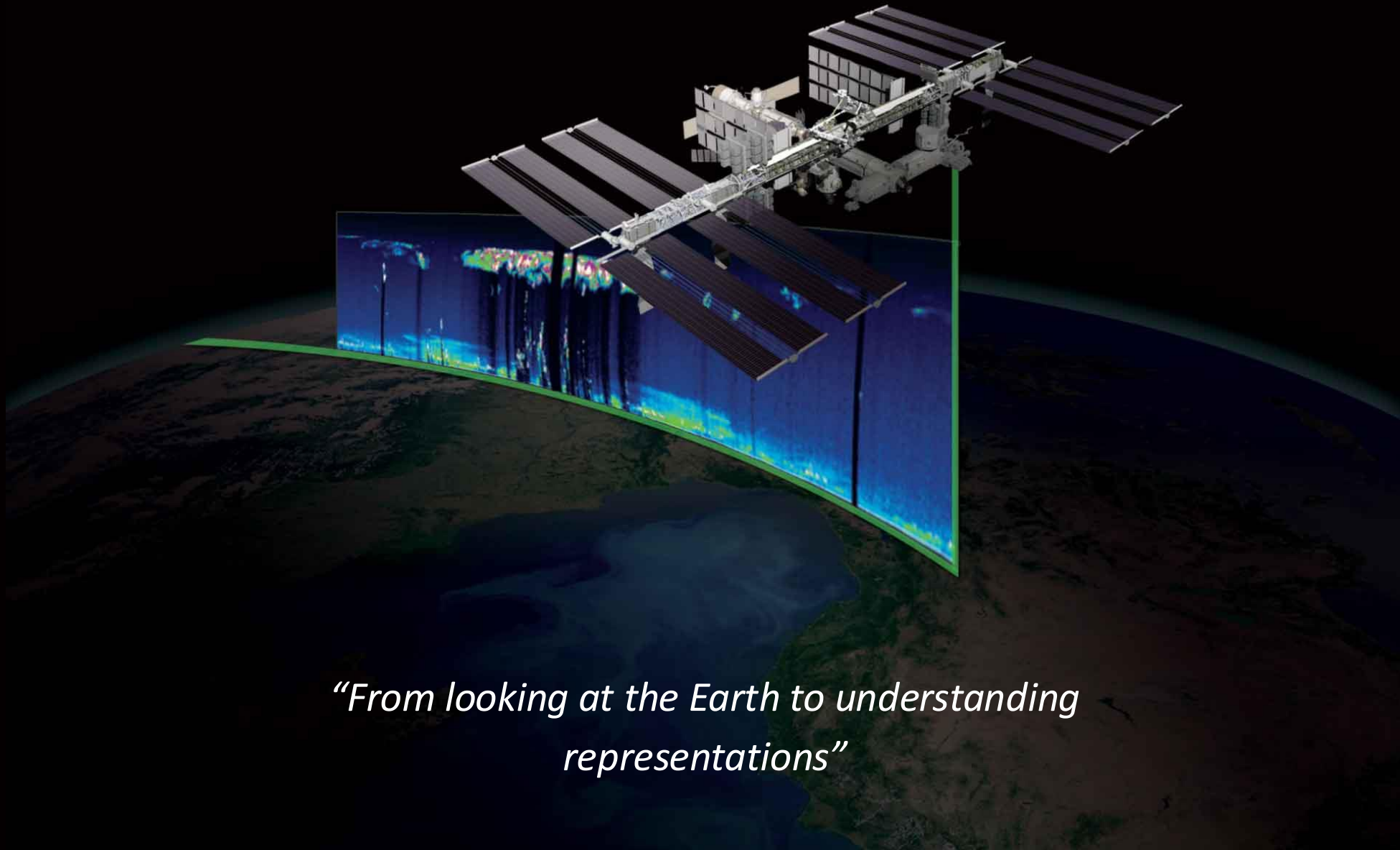
<https://www.iirs.gov.in/construction-and-maintenance-division>

<https://amity.edu/about-university.aspx>

<https://www.facebook.com/ITC.UTwente/posts/today-was-the-time-to-enjoy-a-delightful-snowy-day-with-a-cozy-lunch-walk-around/759069959590208/>

<https://www.aachener-zeitung.de/lokales/region-dueren/juelich/forschungszentrum-droht-millionen-rueckzahlung/159761792.html>

<https://english.hi.is/about-ui/buildings-and-facilities/university-buildings/groska>

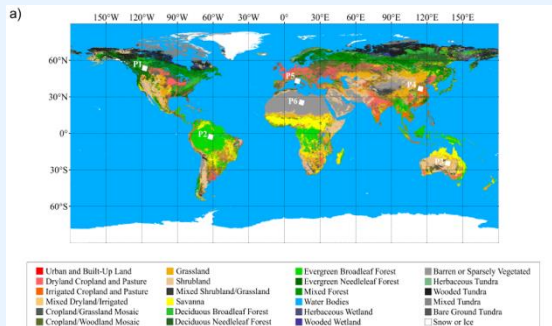


*“From looking at the Earth to understanding
representations”*

From coarse to fine: Advances in LULC Mapping

AVHRR (1990s)

~1 km resolution



[1]



Global LULC mapping



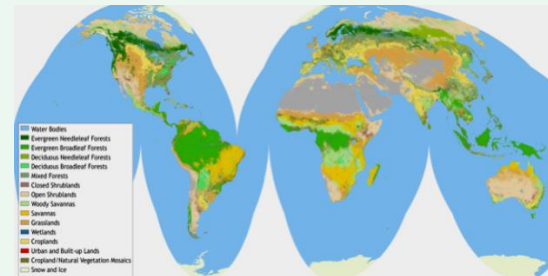
Broad patterns



Mixed pixels

MODIS (2000s-present)

500 m resolution



[2]



Annual global LULC



Improved classes



Better temporal coverage

Sentinel-2 (2015-present)

10 m resolution



[3]



Fine spatial detail



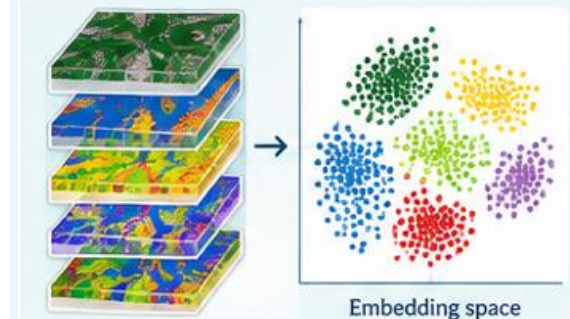
Clearer boundaries



Landscape heterogeneity

Foundation Models/Embeddings (2020s-present)

Learned representations



[4]



Spatial-semantic representations



Transferable across regions



Beyond pixel level

Coarse Spatial Information

Fine spatial detail

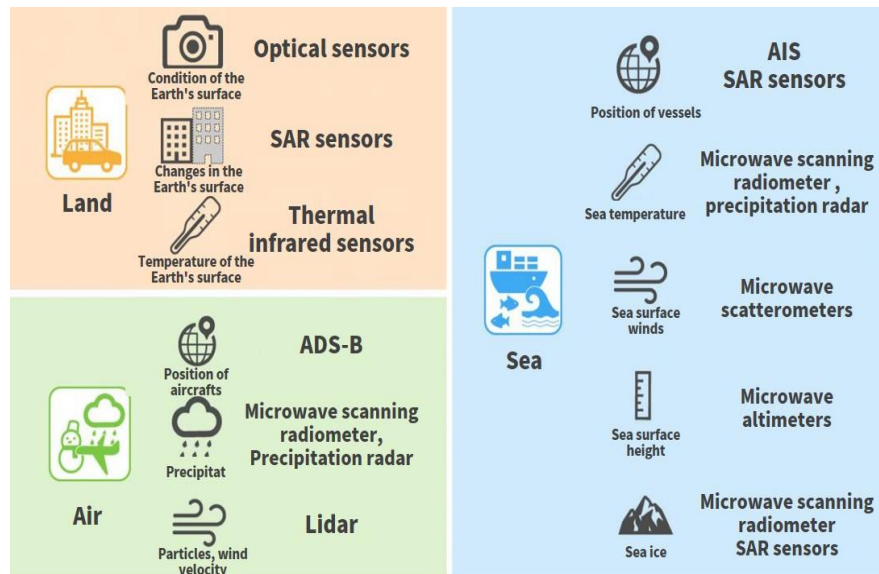
Semantic Richness

Learned representations

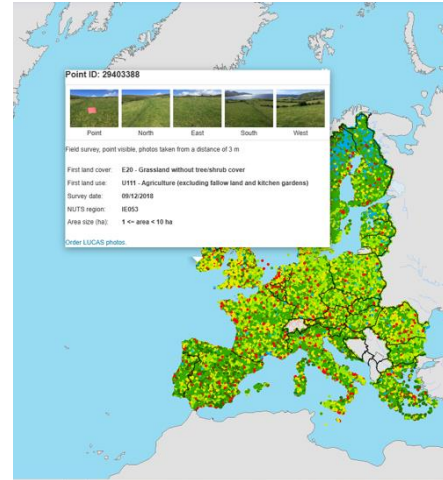
Source:

[1] Ahmed, M. Razu & Ghaderpour, Ebrahim & Gupta, A. & Dewan, Ashraf & Hassan, Quazi. (2023). Opportunities and Challenges of Spaceborne Sensors in Delineating Land Surface Temperature Trends: A Review. IEEE Sensors Journal. 23. 6460-6472. 10.1109/JSEN.2023.3246842. [2] Land Cover Type Yearly L3 Global 500m MCD12Q1 [3] ESA World Cover 2020 [4] Choi, Heejeong & Kang, Pilsung. (2023). Multi-Task Self-Supervised Time-Series Representation Learning. 10.48550/arXiv.2303.01034.

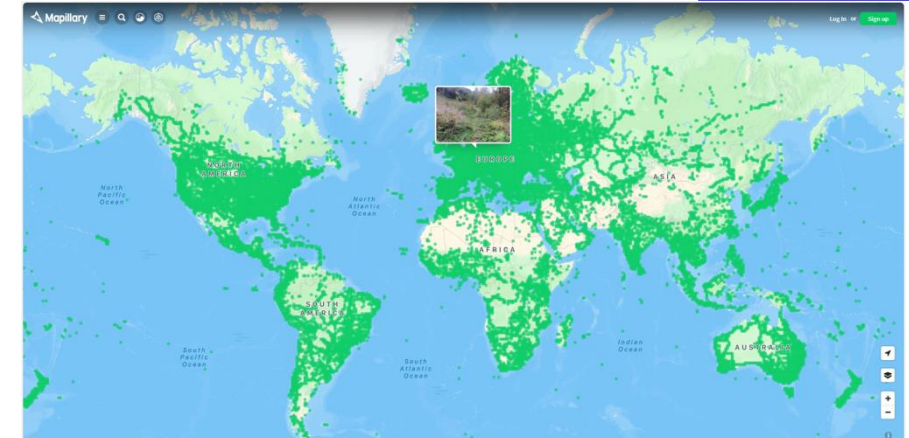
Multi-source Data



Data from different EO sensors [1]



In-situ Data [2]



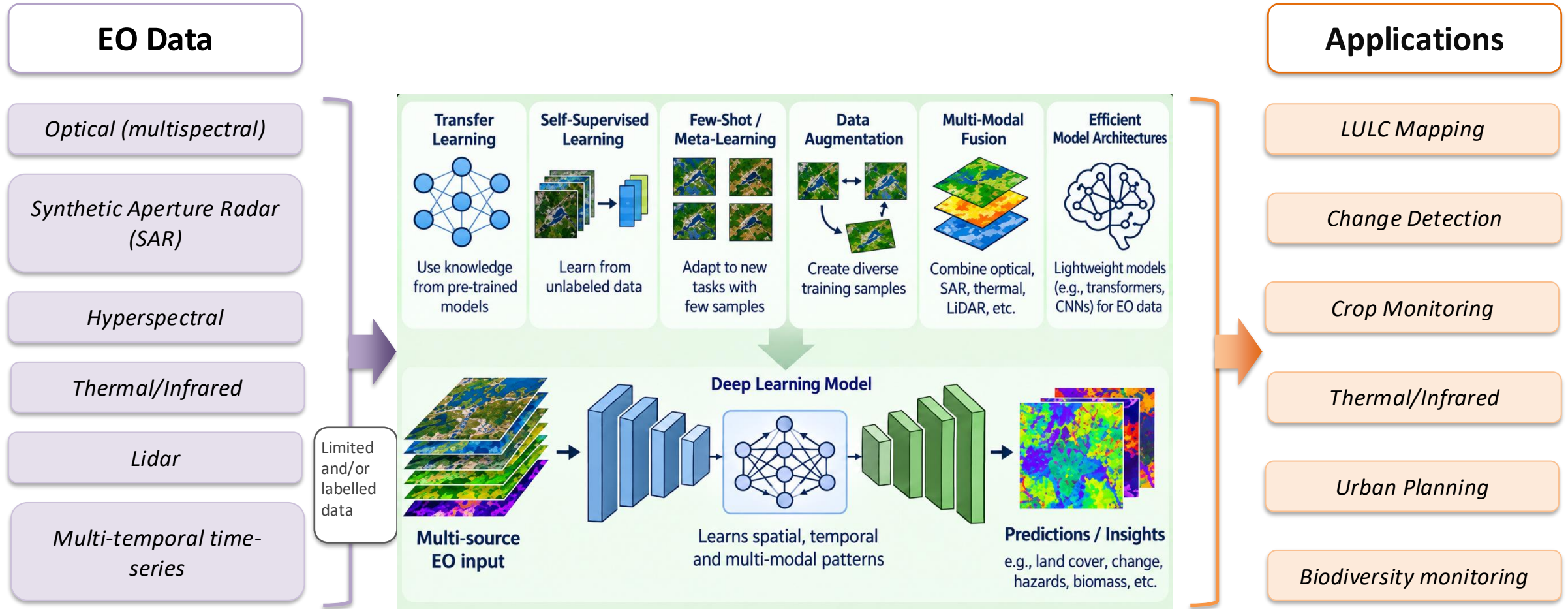
Crowd-sourced Street-level Data [3]

[1] The basics of satellite data — What it tells us, types, observation interval, resolution and use cases . (2020, January 20). Sorabatake. <https://sorabatake.jp/en/9810/>

[2] dAndrimont, R., Yordanov, M., Martinez-Sanchez, L., Eiselt, B., Palmieri, A., Dominici, P., Gallego, J., Reuter, H. I., Joebges, C., Lemoine, G., et al., "Harmonised lucas in-situ land cover and use database for field surveys from 2006 to 2018 in the european union," Scientific data 7(1), 352 (2020).

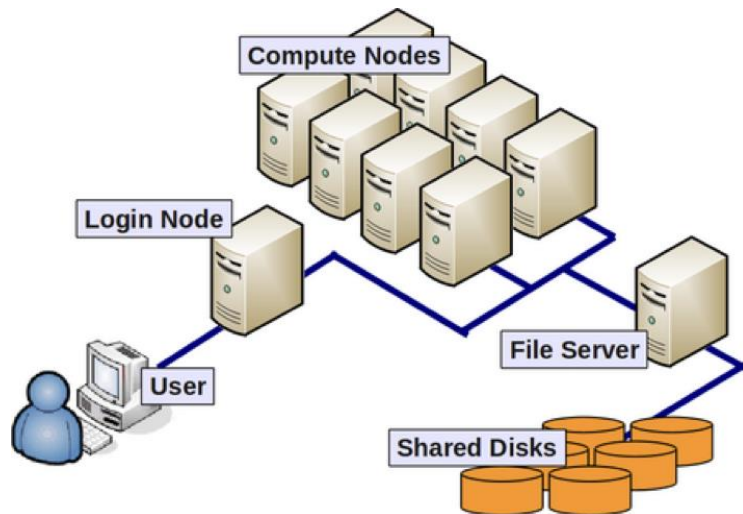
[3] Meta. (2023). Mapillary. <https://www.mapillary.com/>

Data-Efficient Deep Learning Models

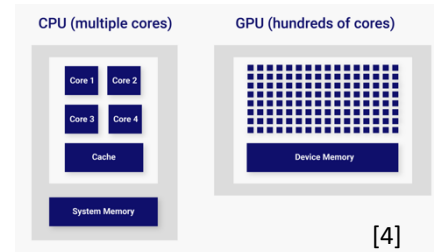


High-Performance Computing Systems

- Uses a cluster of **powerful processors**, working in **parallel** to process big data at high speeds
- Million times faster than a normal desktop
- Has **high-speed, high throughput, low-latency** components such as network, memory, storage and file systems



[1]



[4]

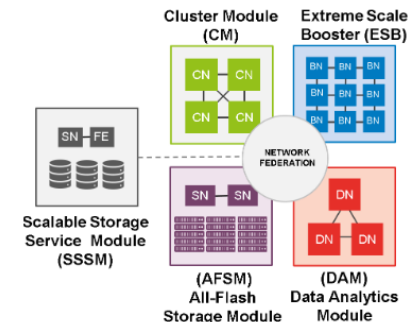


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— Forschungszentrum Jülich

[2]



Modular Supercomputing prototype developed within the DEEP-EST project



System architecture from the DEEP system, implementing the Modular Supercomputing Architecture (MSA)

[3]

[1] https://hbctraining.github.io/Intro-to-shell-flipped/lessons/08_HPC_intro_and_terms.html

[2] <https://www.fz-juelich.de/en/ias/jsc/systems/supercomputers/juwels>

[3] https://www.fz-juelich.de/en/ias/jsc/systems/prototype-systems/deep_system

[4] https://bssw.io/blog_posts/a-gentle-introduction-to-gpu-programming

However,

- "Reliable fine-grained LULC mapping requires not only better models, but **representations** and **reference data** that reconcile semantic, spatial, and annotation limitations across observation scales."

Semantic Limitations

- vocabularies and class definitions
- Ambiguities across sensors and modalities

Spatial Limitations

- Varying spatial resolutions
- Sub-pixel heterogeneity
- Mixed and fragmented landscapes

Annotation Limitations

- Sparse/limited labels
- Class imbalance (e.g., Rare classes)
- Inconsistencies across datasets

- semantic and spatial gap between diverse data modalities,
- the need for more detailed and complex LULC classification legends,
- fine-scale landscape heterogeneity, and
- the scarcity of high-quality reference data.



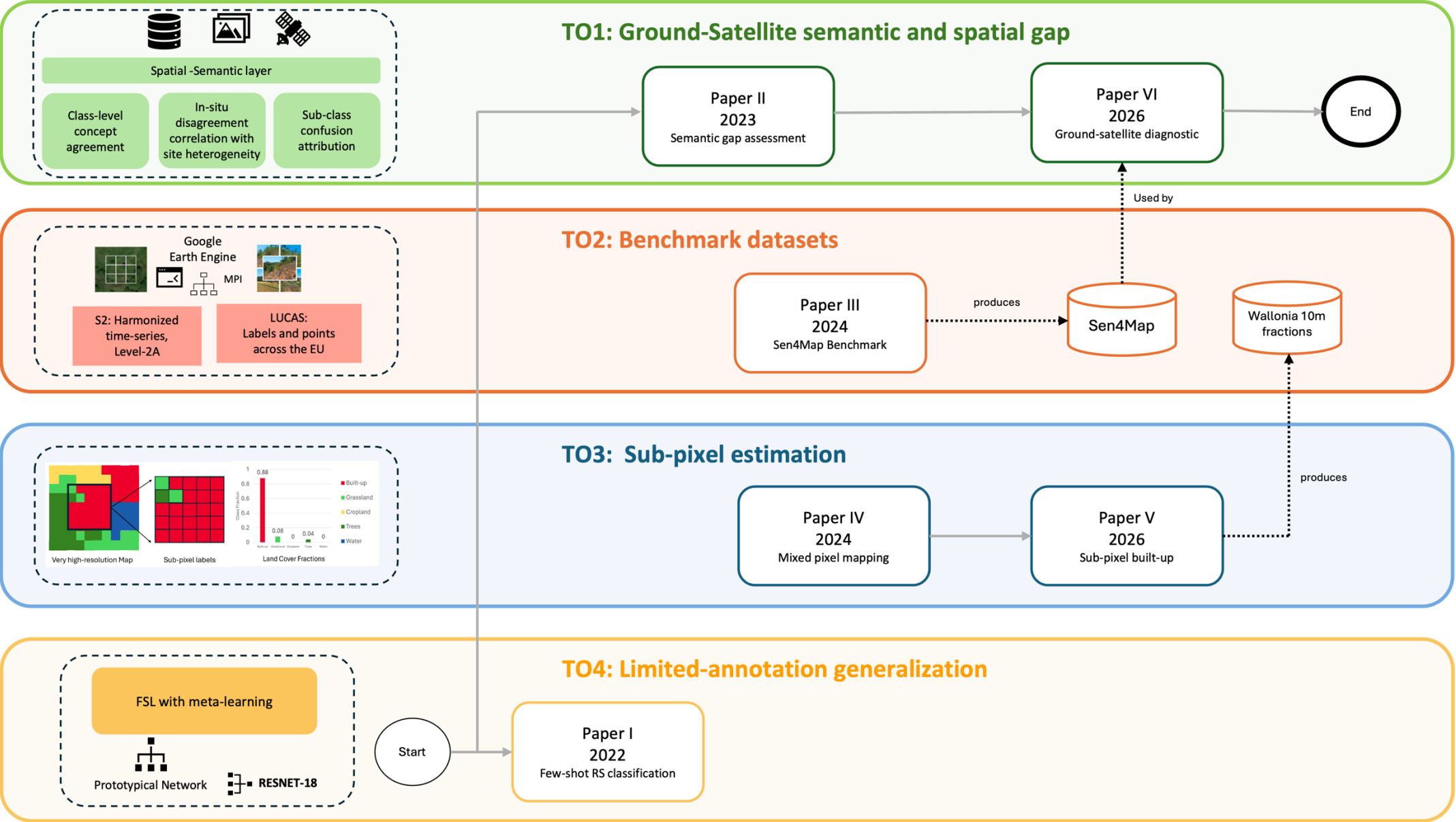
Overall Research Question?

- *How can publicly available, large-scale, multi-source datasets (including multispectral satellite imagery and geo-tagged images) be effectively exploited using advanced DL models to improve satellite-based LULC mapping while addressing the above?*

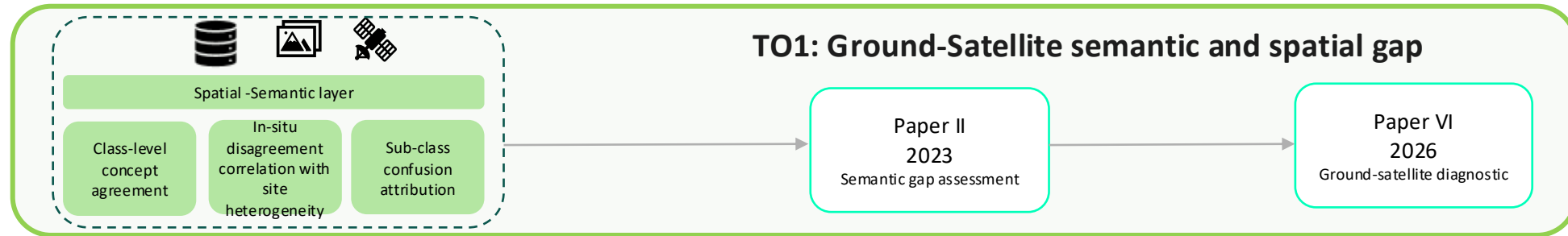
- **TO 1**– Develop advanced DL methodologies that leverage **geo-tagged field data** and state-of-the-art vision **foundation models** to bridge the inherent **spatial and semantic gaps** between in-situ ground-level observations and satellite imagery, enabling the systematic study, characterization, and interpretation of ambiguities and taxonomic inconsistencies to improve the accuracy and reliability of LULC mapping.
- **TO 2** – Establish a **large-scale multi-source benchmark dataset** with **detailed LULC annotations** by integrating multi-temporal satellite imagery with harmonized ground-reference, which advances research in DL-based LULC classification by providing a standardized resource for model training and evaluation for large-scale LULC mapping and monitoring.

- **TO 3** – Build robust **sub-pixel LULC mapping methods** that leverage pretrained EO embeddings together with spectral, spatial, and multi-scale contextual information, to estimate **fractional LC compositions** within mixed pixels in order to better characterize **heterogeneous landscapes** and enhance the precision and reliability of LULC mapping beyond the native spatial resolution of satellite imagery.
- **TO 4** – Investigate and evaluate **annotation-efficient DL models** for LULC classification that maintain high predictive performance with **limited labeled data**, with the objective of reducing annotation requirements and enabling scalable, transferable, and cost-effective RS and EO applications across diverse geographic regions and acquisition conditions.

Thesis Outline

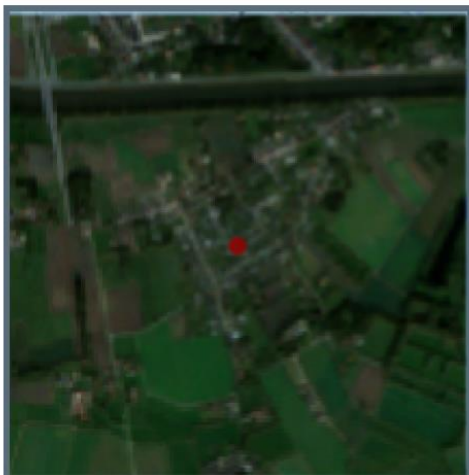


Objective 1: Develop methods that leverage geo-tagged field data to characterize and bridge the spatial and semantic gaps between ground level observations and satellite imagery



- Paper II: C. Paris, L. Martinez-Sanchez, M. van der Velde, **S. Sharma**, R. Sedona, and G. Cavallaro, “Accuracy assessment of land-use-land-cover maps: the semantic gap between in-situ and satellite data”, in Proceedings Volume 12733, Image and Signal Processing for Remote Sensing XXIX, SPIE Remote Sensing, Amsterdam, Netherlands, 2023, <http://doi.org/10.1117/12.2679433>
- Paper VI: **S. Sharma**, R. Sedona, M. Riedel, G. Cavallaro, and C. Paris, “Diagnosing the Ground–Satellite Gap in Land Cover Using Vision Foundation Models and Field Photos”, in Proceedings of the IEEE India Geoscience and Remote Sensing Symposium (InGARSS), 2026 (Accepted)

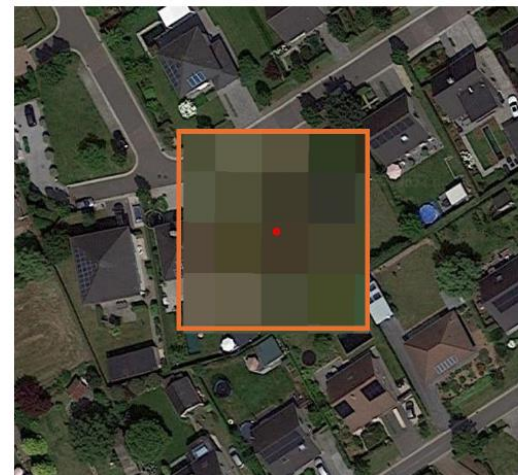
□ Semantic Gap between data modalities



Sentinel-2 yearly
composite [1]



VHR Google Map
Image [2]



3x3 Sentinel-2 patch
(20m radius)



Associated street-level
images [3]

[1] Copernicus. Sentinel-2. <https://sentinels.copernicus.eu/web/sentinel/copernicus/sentinel-2>. Accessed: 2026-06-28. 2026.

[2] Carole Dulong et al. "Google Street View: Capturing the World at Street Level." In: Computer 43 (June 2010), pp. 32–38. DOI: 10.1109/MC.2010.170.

[3] Eurostat. LUCAS: Land Use/Cover Area Frame Survey. European statistical survey for land use and land cover reference data. 2018. URL: <https://ec.europa.eu/eurostat/web/lucas>.

□ Landscape Heterogeneity

[Extracted from Paper II] © 2023 SPIE [1]



Lucas/In-situ [2]:
Street-level image
Label: Woodland

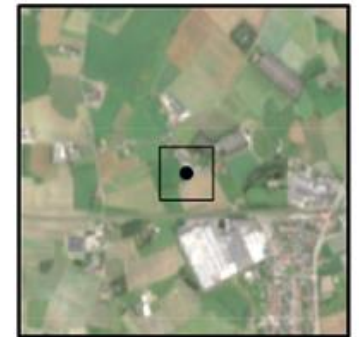


Sentinel-2
[3]

[1]



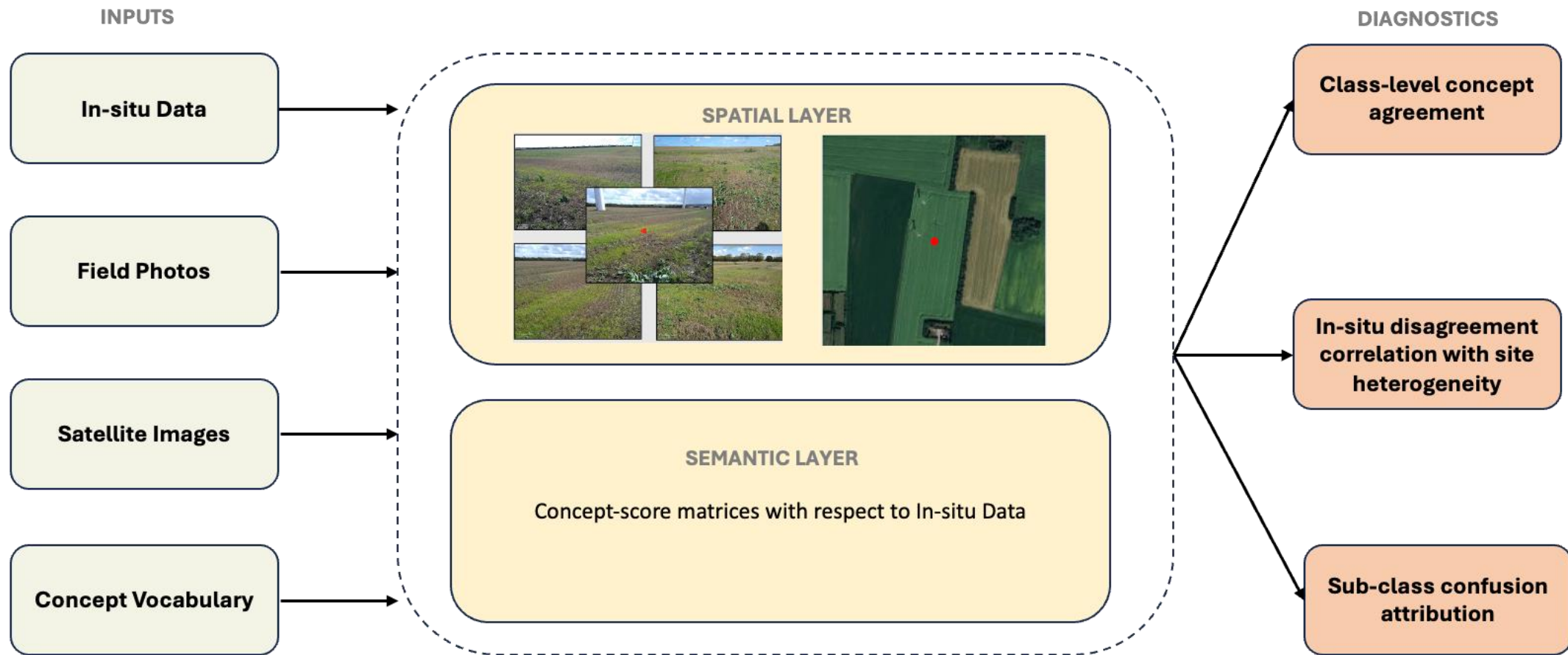
Lucas/In-situ [2]:
Street-level image
Label: Woodland



Sentinel-2
[3]

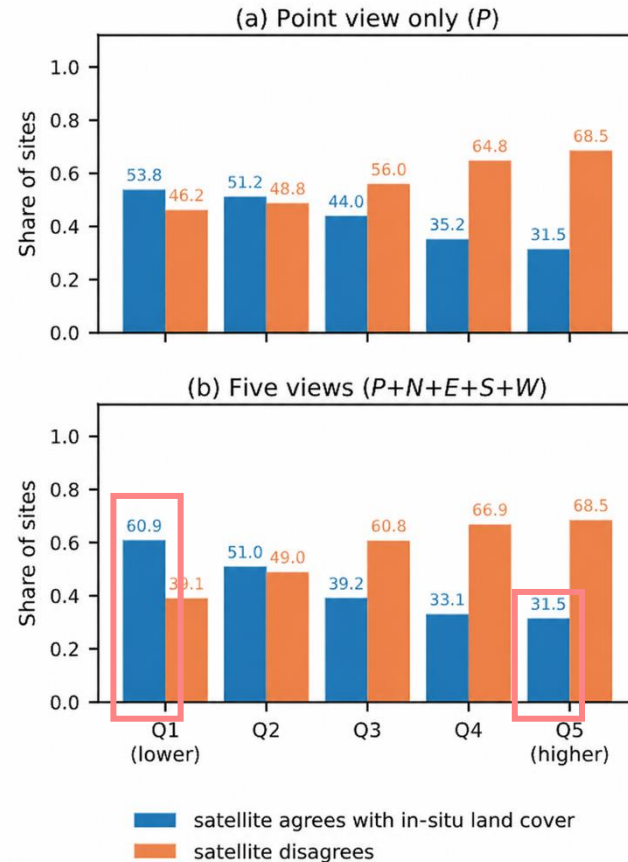
[1] Claudia Paris, Laura Martinez-Sanchez, Marijn van der Velde, **Surbhi Sharma**, Rocco Sedona, Gabriele Cavallaro, "Accuracy assessment of land-use-land-cover maps: the semantic gap between in situ and satellite data," Proc. SPIE 12733, Image and Signal Processing for Remote Sensing XXIX, 127330M (19 October 2023); <https://doi.org/10.1117/12.2679433> , [2] dAndrimont, R., Yordanov, M., Martinez-Sanchez, L., Eiselt, B., Palmieri, A., Dominici, P., Gallego, J., Reuter, H. I., Joebgies, C., Lemoine, G., et al., "Harmonised lucas in-situ land cover and use database for field surveys from 2006 to 2018 in the european union," Scientific data 7(1), 352 (2020). [3] Copernicus Sentinel-2 (processed by ESA), 2021, MSI Level-2A BOA Reflectance Product. Collection 1. European Space Agency. https://doi.org/10.5270/S2_-znk9xsj

TO1: Spatial-Semantic Diagnostic Framework



TO1: Spatial-Semantic Diagnostic Framework

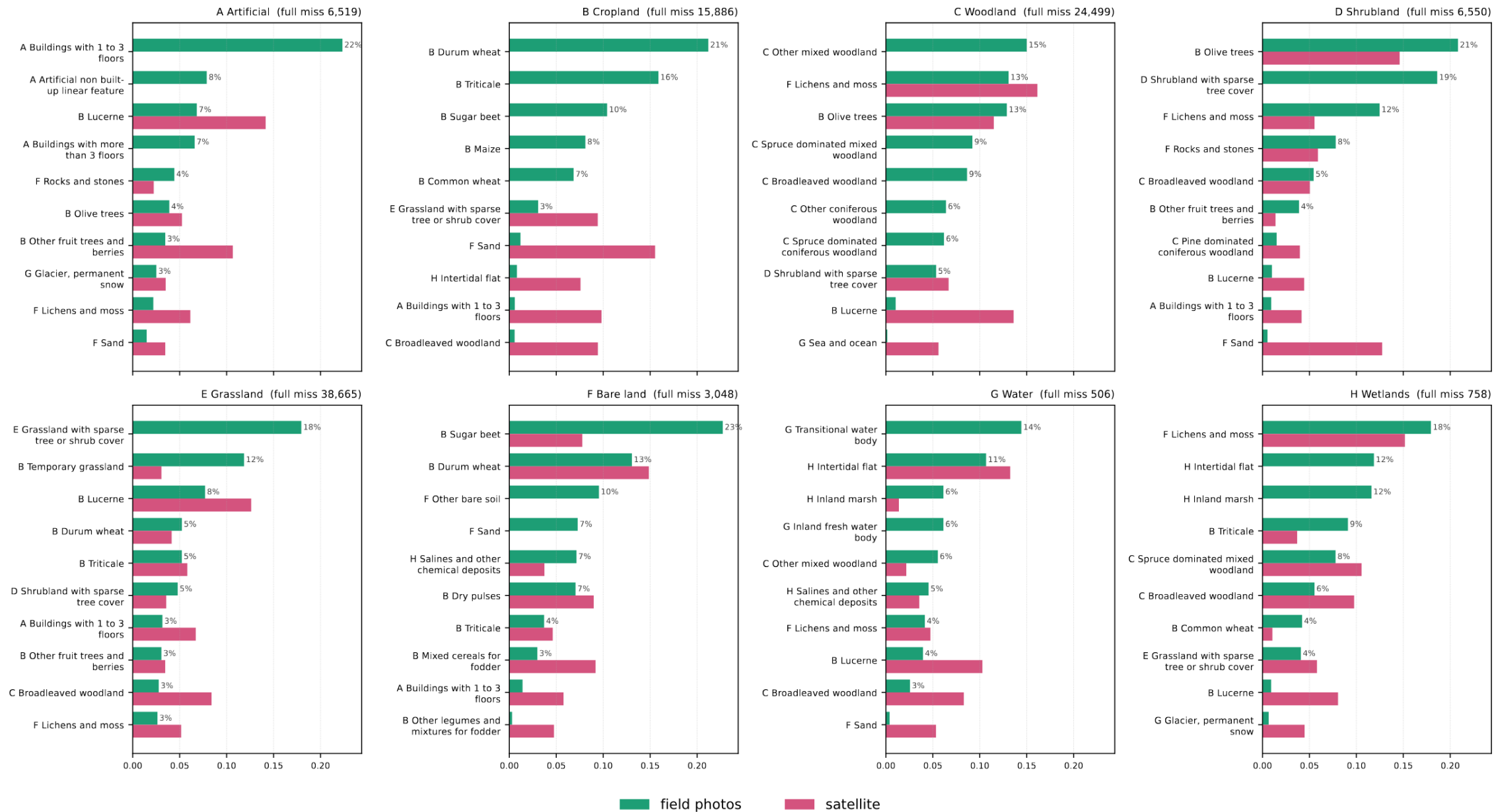
Relationship between field-photo-derived landscape heterogeneity (Hg) and satellite-in situ agreement at LC1 level, grouped into five heterogeneity quantiles (Q1–Q5).



- *Leveraging self-supervised and contrastive representation learning to tailor feature extraction.*
- *DINOv3's self-supervised learning for measuring within-image structural variation*
- *CLIP/SenCLIP's contrastive vision-language pretraining yields embeddings that align naturally with text concepts and support concept-profile comparison.*

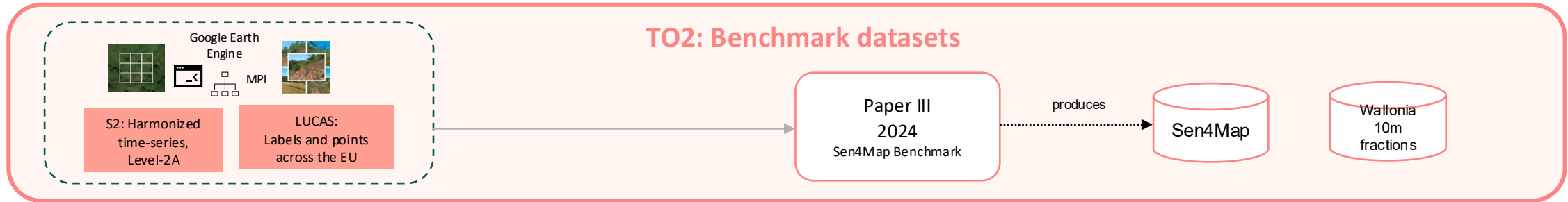
Per-class LUCAS sample support and zero-shot LC1 agreement (top-1 LC3 concept projected to LC1) of the field photos (CLIP) and the satellite (SenCLIP) against the insitu LC1 label.

LC1 class	Samples	Field-photos agr. (%)	Satellite agr. (%)
A Artificial	10,775	53.9	39.5
B Cropland	58,669	90.9	72.9
C Woodland	44,129	62.9	44.5
D Shrubland	7,545	21.9	13.2
E Grassland	43,021	22.0	10.1
F Bare land	3,956	22.9	23.0
G Water	576	31.8	12.2
H Wetlands	911	32.8	16.8
Total	169,582	58.6	43.1



- Using in-situ field observations (**street-level images**) to **bridge** the semantic gap between what is visible from satellite and ground
- Developing **spatial-semantic framework** using **Vision Foundation Models** with field-photos
- Quantifying within-site visual heterogeneity
- Evaluating consistency of LC interpretations across field images, satellite imagery, and in-situ reference annotations

Objective 2: Establish large-scale, multi-source benchmark dataset with detailed LULC information to facilitate the training and evaluation of advanced DL models



- Paper III: **S. Sharma**, R. Sedona, M. Riedel, G. Cavallaro, and C. Paris, “Sen4Map: Advancing Mapping with Sentinel-2 by Providing Detailed Semantic Descriptions and Customizable Land-Use and Land-Cover Data”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS), vol. 17, pp. 13893 - 13907, 2024, <http://doi.org/10.1109/JSTARS.2024.3435081>

□ Popular Benchmark Sentinel-2 based datasets:

Dataset	Scale	Classes	Label Source
Sen4Map (Paper III)	Across EU	Hierarchical	LUCAS + geo-tagged photos
BigEarth Net [1]	590,326 patches	43 (CLC L3)	CORINE Land Cover
EuroSAT [2]	27,000 patches	10	Manual interpretation
ESA World Cover [3]	Global	11	Manual VHR annotation
Dynamic World [4]	Global	9	Manual Sentinel-2 labels
Esri Land Cover [5]	Global	9	Manual Sentinel-2 labels

Paper III: [Surbhi Sharma](#) et al. “Sen4Map: Advancing Mapping With Sentinel-2 by Providing Detailed Semantic Descriptions and Customizable Land-Use and Land-Cover Data.” In: IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 17 (Jan. 2024), pp. 13893–13907. DOI: [10.1109/JSTARS.2024.3435081](#).

[1] Gencer Sumbul et al. “Bigearthnet: A Large-Scale Benchmark Archive for Remote Sensing Image Understanding.” In: July 2019, pp. 5901–5904. DOI:[10.1109/IGARSS.2019.8900532](#).

[2] Patrick Helber et al. “EuroSAT: A Novel Dataset and Deep Learning Benchmark for Land Use and Land Cover Classification.” In: IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (Aug. 2017). DOI:[10.1109/JSTARS.2019.2918242](#).

[3] R. Van De Kerchove et al. “ESA WorldCover: Global land cover mapping at 10 m resolution for 2020 based on Sentinel-1 and 2 data.” In: AGU Fall Meeting Abstracts. Vol. 2021. 2021, GC45I–0915.

[4] Christopher F. Brown et al. “Dynamic World, Near real-time global 10 m land use land cover mapping.” In: Scientific Data 9 (2022), p. 251. DOI: [10.1038/s41597-022-01307-4](#).

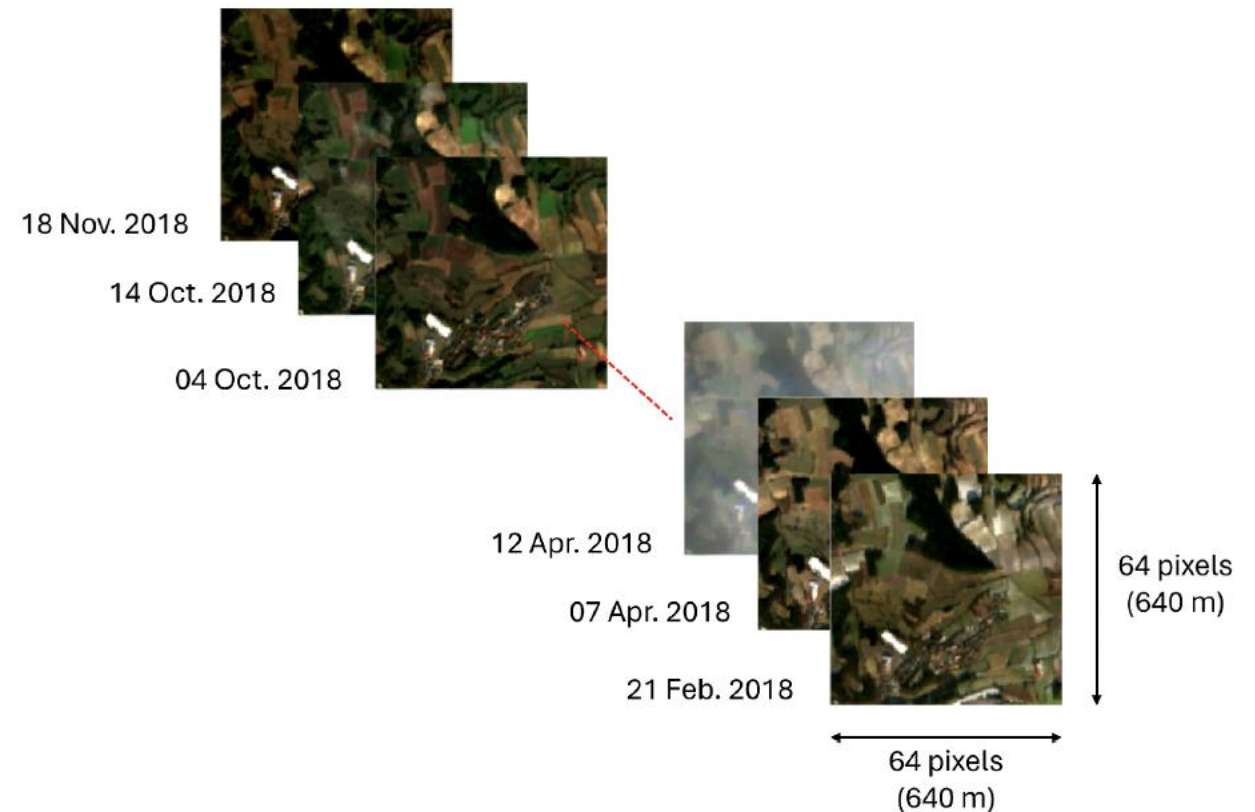
[5] Impact Observatory, Esri, and Microsoft. ESRI 2018 Global Land Use/Land Cover (10m) – Sentinel-2 based. ArcGIS Living Atlas of the World. Global 10m land cover map derived from ESA Sentinel-2 imagery. 2018. URL: <https://www.esri.com/en-us/arcgis/products/arcgis-livingatlas/land-cover>.

TO2: Sen4Map Benchmark Dataset

True color composition of 64 x 64 Sentinel-2 patches belonging to the Sen4Map dataset, which shows the variability of the land-cover classes located in different countries.



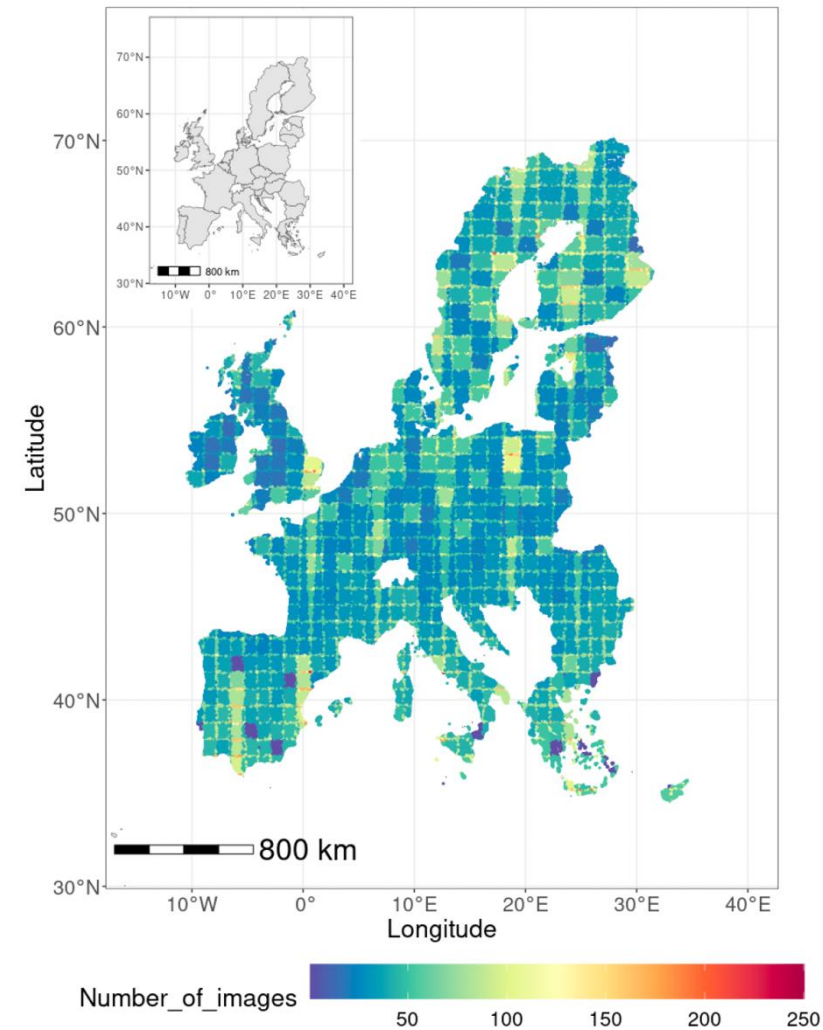
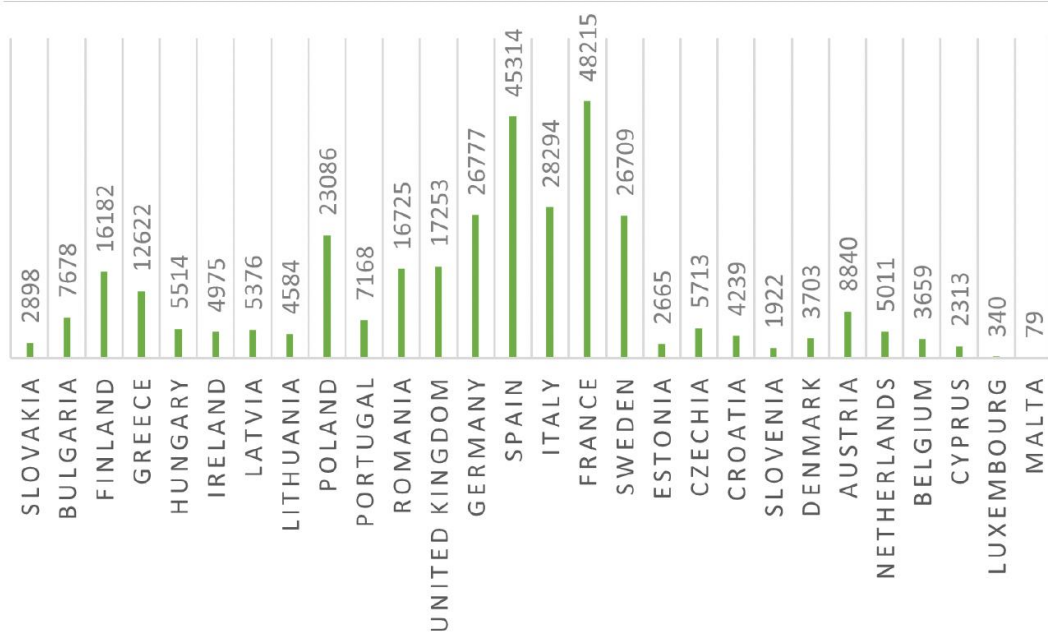
Example of a Sentinel-2 time series from the Sen4Map benchmark dataset



TO2: Sen4Map Benchmark Dataset

Number of Sentinel-2 images having less than 40% of cloud coverage and associated with each LUCAS point.

Country-wise distribution of LUCAS surveyed locations with available in-situ data.



Paper III: **S. Sharma**, R. Sedona, M. Riedel, G. Cavallaro, and C. Paris, “Sen4Map: Advancing Mapping with Sentinel-2 by Providing Detailed Semantic Descriptions and Customizable Land-Use and Land-Cover Data”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS), vol. 17, pp. 13893 - 13907, 2024, <http://doi.org/10.1109/JSTARS.2024.3435081>

Detailed mapping of LUCAS labels for broad land cover and crop classification

Target land-cover	LUCAS land-cover
Artificial Land	A- Artificial Land (Except A22)
Bareland and Lichens/Moss	A22 – Non built-up linear features F – Bareland and Lichens/Moss
Grassland	E - Grassland B50 – Fodder Crops
Cropland	B10 - Cereals B20 - Root Crops B30 - Non-Permanent Industrial Crop B40 – Dry Pulses, Vegetables and Flowers B70 – Permanent Fruits B80 – Other Permanent Crops BX1 BX2
Broadleaves	C10 – Broadleaved Woodland
Conifers	C20 – Coniferous Woodland C30 – Mixed Woodland CXX - LUCAS SU FT
Shrubland	D- Shrubland
Water	G – Water Areas
Wetlands	H - Wetlands

Target land-cover	LUCAS land-cover
Cereals	B11 - Common wheat B12 - Durum wheat B13 - Barley B14 - Rye B15 - Oats B16 - Maize B17 - Rice B18 - Triticale B19 - Other cereals
Root Crops	B12 - Potatoes B22 - Sugar beet B23 - Other roots crops
Non permanent industrial crops	B34 - Cotton B35 - Other fibre and oleaginous crops B36 - Tobacco B37 - Other non-permanent industrial crops
Dry pulses, vegetables and flowers	B31 - Sunflower B32 - Rape and turnip rape B33 - Soya B41 - Dry pulses B42 - Tomatoes B43 - Other fresh vegetables B44 - Floriculture and ornamental plants B45 - Strawberries
Fodder crops	B51 - Clovers B52 - Lucerne B53 - Other leguminous and mixtures for fodder B54 - Mixed cereals for fodder
Bareland	F10 - Rocks and Stone F20 - Sand F30 - Lichens and Moss F40 - Other Bare Soil
Woodland and Shrubland	B71-B77 - Fruit Trees B81- Olive Grooves B82 - Vineyards B83 - Nurseries B84 - Permanent industrial crops C10 - Broadleaved Woodland C20 - Coniferous Woodland C30 - Mixed Woodland D10 - Shrubland with sparse tree cover D20 - Shrubland without tree cover
Grassland	B55 - Temporary Grasslands E10 - Grassland with sparse tree/shrub cover E20 - Grassland without tree/shrub cover E30 - Spontaneously re-vegetated surfaces

TO2: Sen4Map Benchmark Dataset

Classes		Random Forest		Transformer (pixel-based)		ViT		VViT	
		Center pixel	3 x 3 window	Center pixel	3 x 3 window	Center pixel	3 x 3 window	Center pixel	3 x 3 window
	Artificial land	0.49	0.72	0.57	0.78	0.53	0.77	0.59	0.79
	Bareland	0.2	0.38	0.24	0.47	0.2	0.43	0.25	0.5
	Broadleaves	0.69	0.86	0.73	0.9	0.69	0.84	0.75	0.87
	Conifers	0.76	0.88	0.80	0.91	0.78	0.87	0.81	0.9
	Cropland	0.8	0.89	0.83	0.92	0.78	0.87	0.83	0.9
	Grassland	0.69	0.84	0.73	0.89	0.68	0.84	0.73	0.87
	Shrubland	0.29	0.51	0.42	0.73	0.31	0.54	0.43	0.65
	Water	0.61	0.74	0.63	0.79	0.6	0.75	0.65	0.79
	Wetlands	0.6	0.75	0.67	0.87	0.61	0.76	0.7	0.83
W.A. F-score		0.67	0.81	0.72	0.87	0.67	0.81	0.72	0.85
Overall Accuracy		0.68	0.83	0.73	0.88	0.68	0.82	0.73	0.85

Paper III: **S. Sharma**, R. Sedona, M. Riedel, G. Cavallaro, and C. Paris, “Sen4Map: Advancing Mapping with Sentinel-2 by Providing Detailed Semantic Descriptions and Customizable Land-Use and Land-Cover Data”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS), vol. 17, pp. 13893 - 13907, 2024, <http://doi.org/10.1109/JSTARS.2024.3435081>

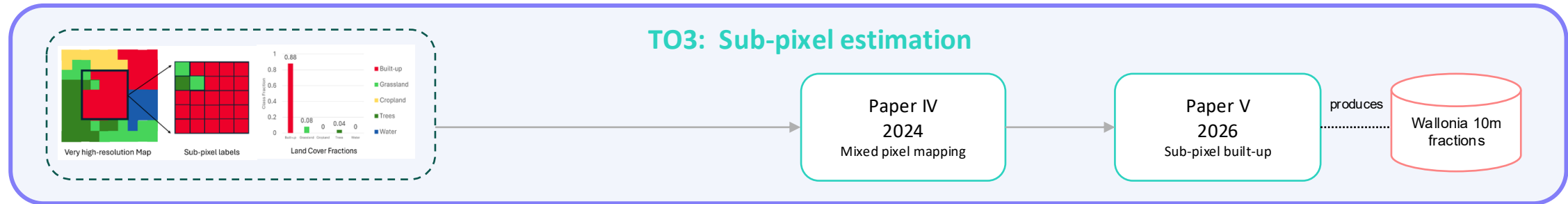
TO2: Sen4Map Benchmark Dataset

Classes		Random Forest		Transformer (pixel-based)		ViT		VViT	
		Center pixel	3 x 3 window	Center pixel	3 x 3 window	Center pixel	3 x 3 window	Center pixel	3 x 3 window
	Cereals	0.78	0.88	0.83	0.93	0.66	0.78	0.79	0.86
	Root crops	0.56	0.69	0.69	0.88	0.24	0.44	0.64	0.75
	Industrial crops	0.64	0.76	0.72	0.88	0.42	0.58	0.67	0.78
	Dry pulses, flowers	0.07	0.1	0.31	0.68	0.04	0.08	0.18	0.35
	Fodder crops	0.01	0.01	0.31	0.64	0.19	0.34	0.37	0.54
	Bareland	0.33	0.47	0.40	0.64	0.21	0.37	0.32	0.47
	Wood/Shrubland	0.88	0.96	0.90	0.97	0.85	0.93	0.88	0.95
	Grassland	0.71	0.88	0.76	0.93	0.66	0.84	0.71	0.87
W.A. F-score		0.77	0.88	0.82	0.93	0.69	0.82	0.76	0.86
Overall Accuracy		0.79	0.89	0.82	0.93	0.70	0.83	0.77	0.87

Paper III: **S. Sharma**, R. Sedona, M. Riedel, G. Cavallaro, and C. Paris, “Sen4Map: Advancing Mapping with Sentinel-2 by Providing Detailed Semantic Descriptions and Customizable Land-Use and Land-Cover Data”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS), vol. 17, pp. 13893 - 13907, 2024, <http://doi.org/10.1109/JSTARS.2024.3435081>

- **Sen4Map**, a large-scale, multi-source benchmark dataset
- Rich spectral, spatial, and semantic representations for **detailed LULC mapping**
- The dataset is publicly available at <https://datapub.fzjuelich.de/sen4map>

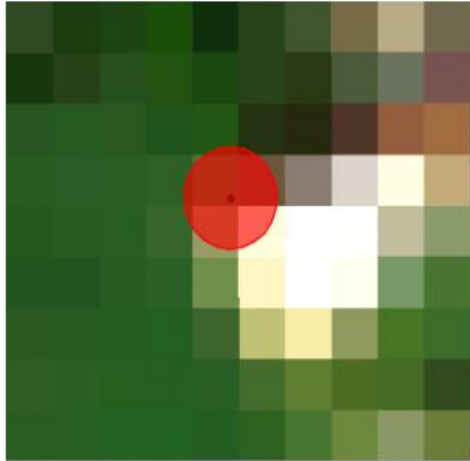
Objective 3: Build methods for sub-pixel LULC estimation to capture fine-scale landscape heterogeneity beyond the native spatial resolution of satellite imagery



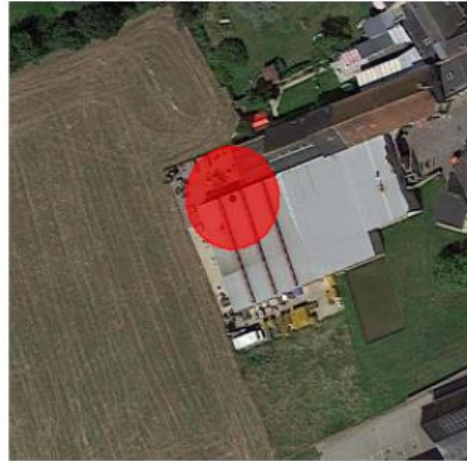
- Paper IV: **S. Sharma**, R. Sedona, M. Riedel, G. Cavallaro, and C. Paris, “Enhancing Land Cover Mapping: A Novel Automatic Approach To Improve Mixed Spectral Pixel Classification”, in Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Athens, Greece, 2024, pp. 1017-1020, <http://doi.org/10.1109/IGARSS53475.2024.10641976>
- Paper V: **S. Sharma**, R. Sedona, M. Riedel, G. Cavallaro, and C. Paris, “Beyond Pixels: Identifying Built-Up Features at Sub-Pixel Level for Enhanced Satellite-Based Land Cover Mapping”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS), 2026, <http://doi.org/10.1109/JSTARS.2026.3712773>

□ Landscape Heterogeneity and Mixed Pixels

[Extracted from Paper IV]



Sentinel-2 Image



High-resolution Google Earth Satellite view



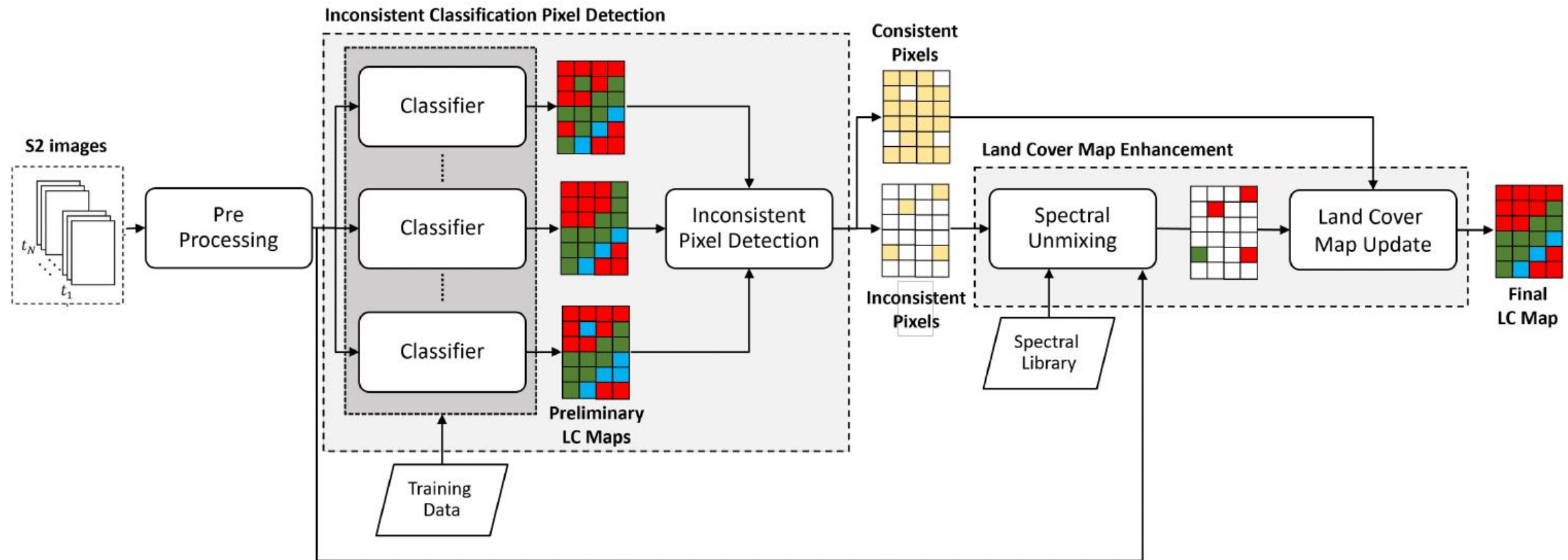
Abundance Map



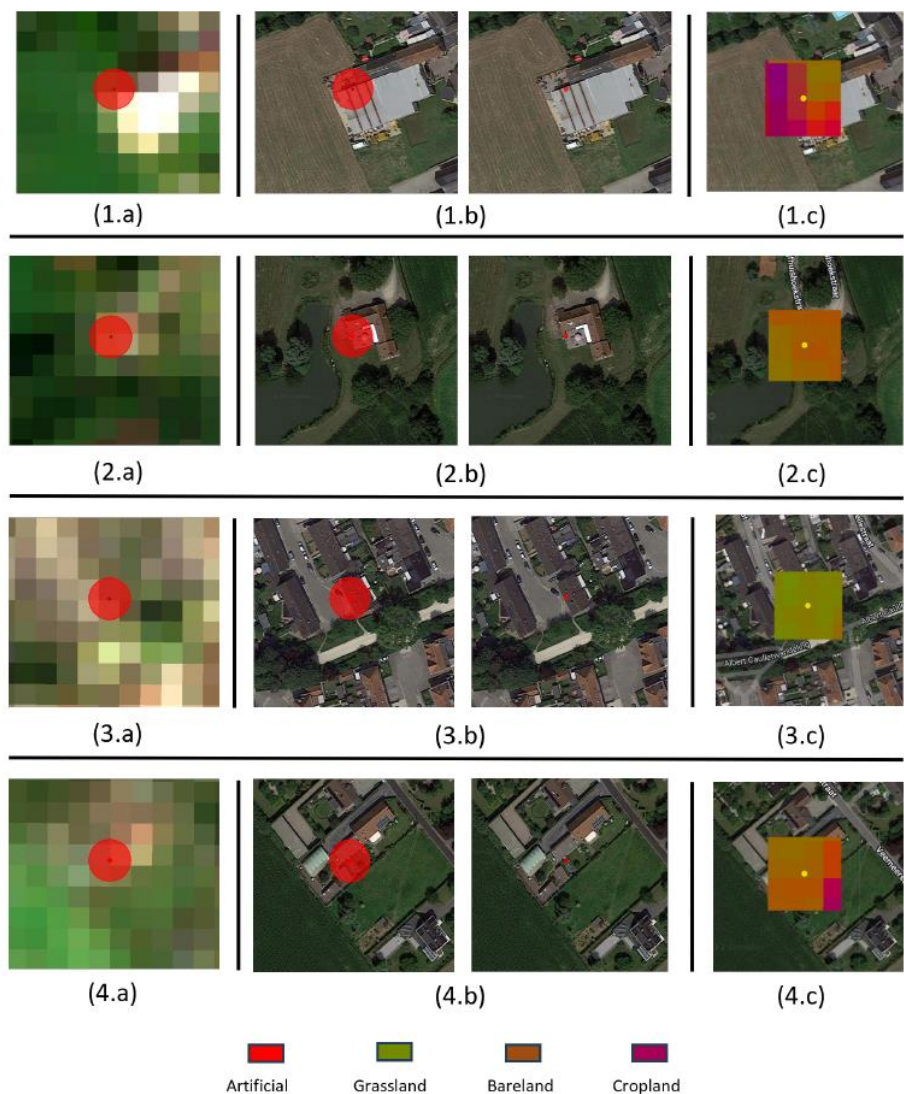
© 2024 IEEE

Surbhi Sharma et al. "Enhancing Land Cover Mapping: A Novel Automatic Approach To Improve Mixed Spectral Pixel Classification." In: IGARSS 2024 -2024 IEEE International Geoscience and Remote Sensing Symposium. 2024, pp. 1017–1020. DOI: 10.1109/IGARSS53475.2024.10641976.

TO 3: Workflow of the proposed data-driven approach to improve LC mapping of the mixed spectral pixels



TO 3: Results (mixed spectral pixels)

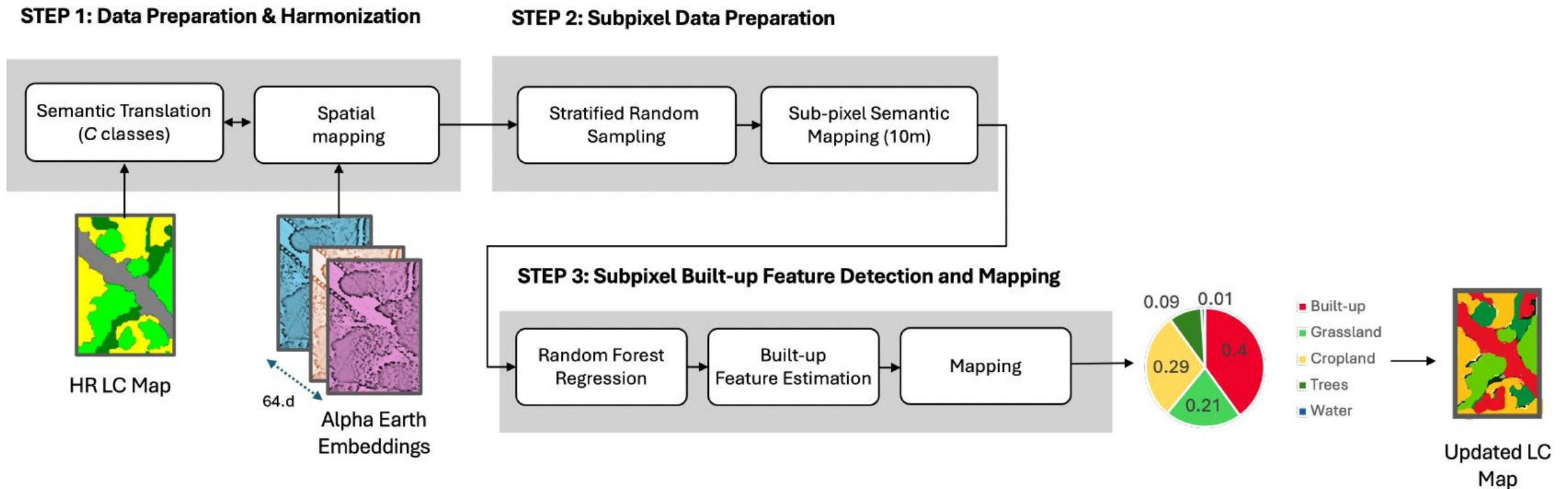


The weighted average F-score and Overall accuracy using the baseline and proposed method.

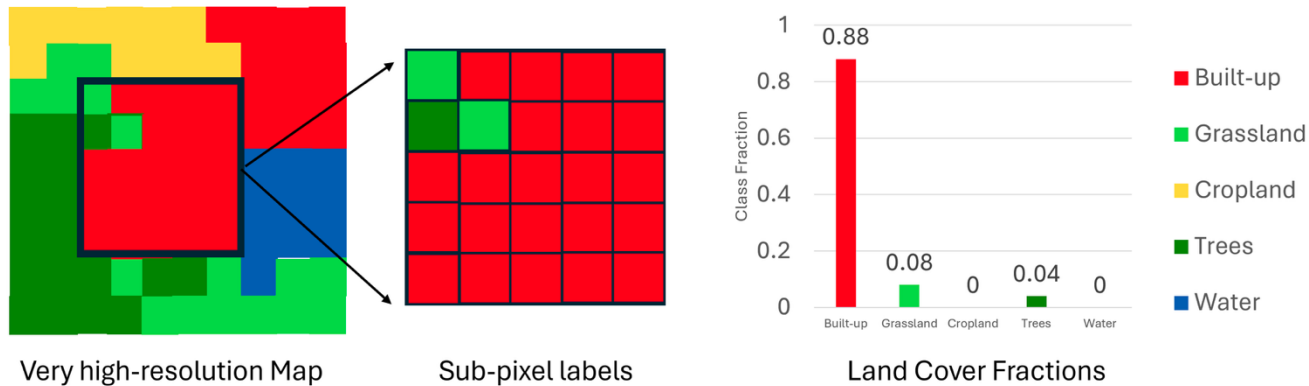
Classes	Belgium		Samples from EU	
	Baseline	Proposed Method	Baseline	Proposed Method
Weighted Average F1-score	0.51	0.63	0.43	0.54
Overall Accuracy	0.54	0.62	0.45	0.54

Abundance Map obtained after Spectral Unmixing for four different LUCAS points, marked as red and yellow, labeled as ‘Artificial Land’. Figures (1.a)-(4.a) and (1.b)-(4.b) show the LUCAS points in Sentinel-2 and High-resolution Google Earth Satellite View. Figures (1.c) - (4.c) represent the Abundance Map obtained from the Sentinel-2 yearly composite of respective LUCAS points.

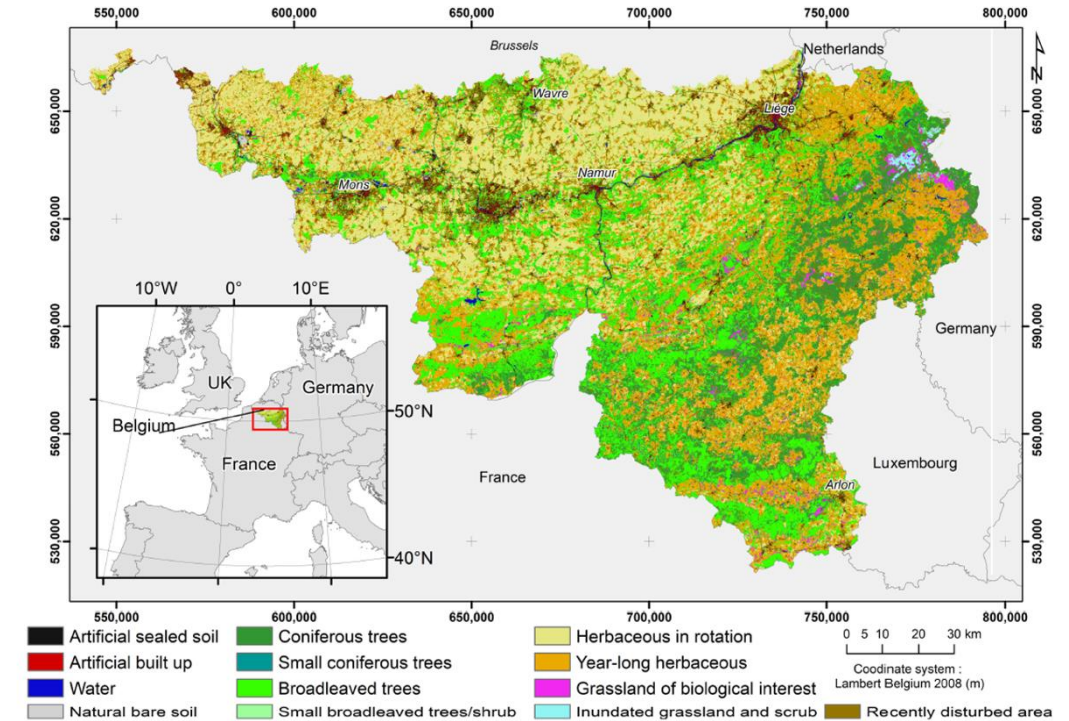
TO 3: Workflow of the proposed method based on three main steps: (1) Data Preparation and Harmonization, (2) Sub-pixel Data Preparation, and (3) Sub-Pixel Built-up Feature Detection and Mapping.



TO 3: Fractional Dataset (Wallonia Region)

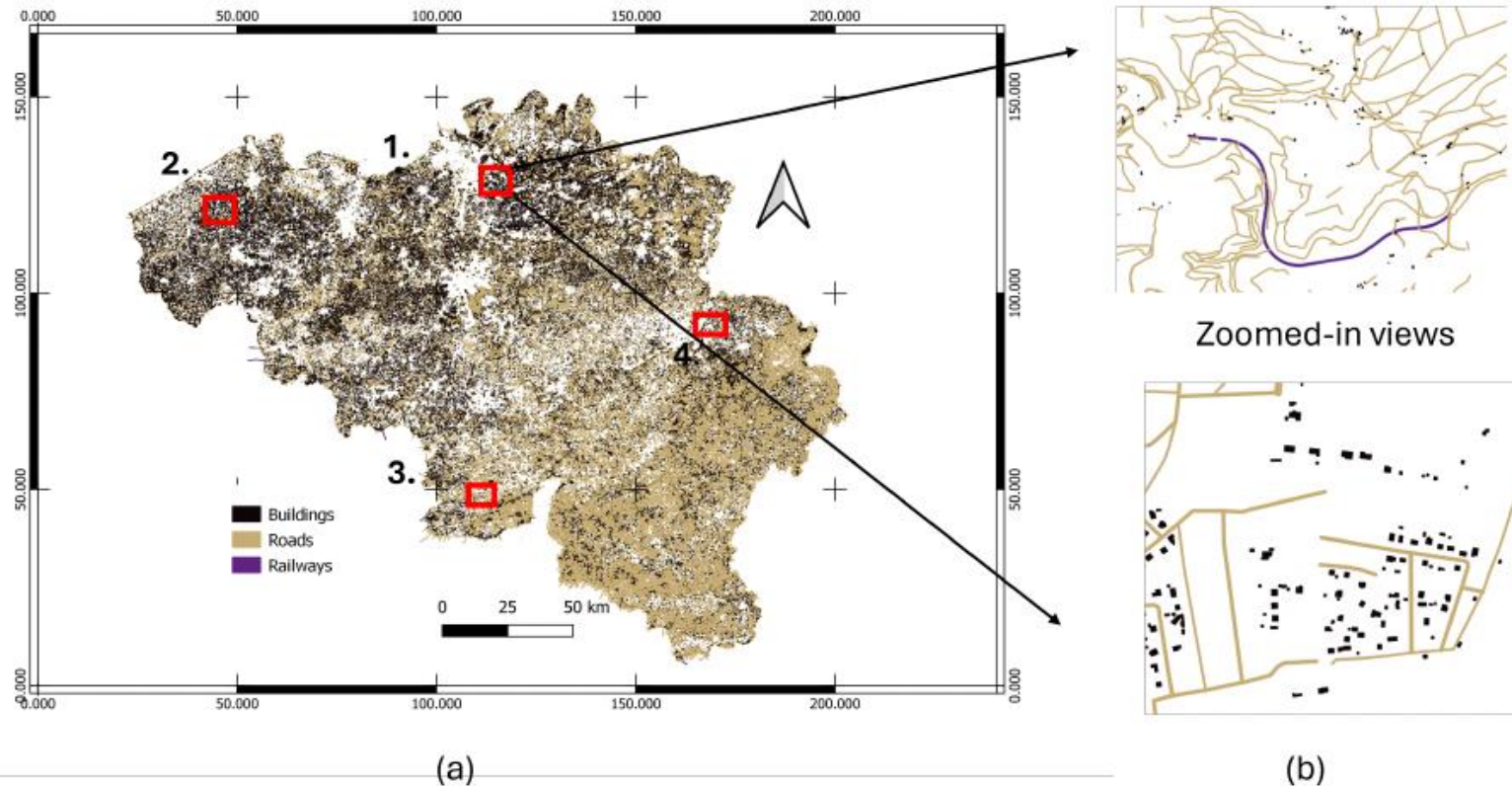


Illustrative example of the computation of land-cover fractions, where all labels within a single satellite pixel are used to calculate the corresponding fractions.



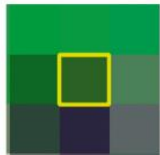
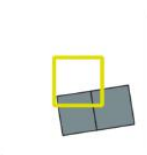
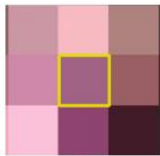
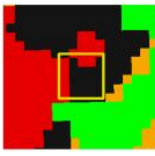
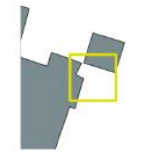
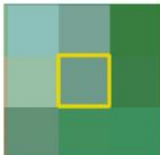
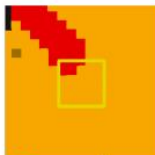
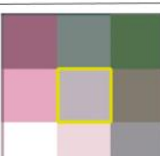
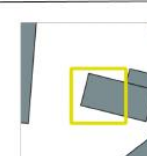
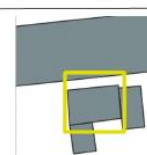
High-resolution land-cover map from Wallonia region.

TO 3: Fractional Dataset (Test patches 'BELGIUM')



(a) Built-up areas undetected by all three global landcover maps. Highlighted in red are the four different test patches.
(b) Zoomed-in views.

TO 3: Sub-pixel Mapping

	VHR base layer (ESRI)	Sentinel-2 pixel (10m)	Wallonia map (2m)	OSM built-up	Reference Fraction (OSM)	Predicted Fraction	Classification Status
10m					0.25	0.07	Misclassified
10m					0.35	0.39	Correct
10m					0.17	0.06	Misclassified
10m					0.47	0.55	Correct
10m					0.67	0.48	Correct

Wallonia map (2m):



Year-long herbaceous



Recently disturbed areas



Artificial sealed soil



Artificial built-up



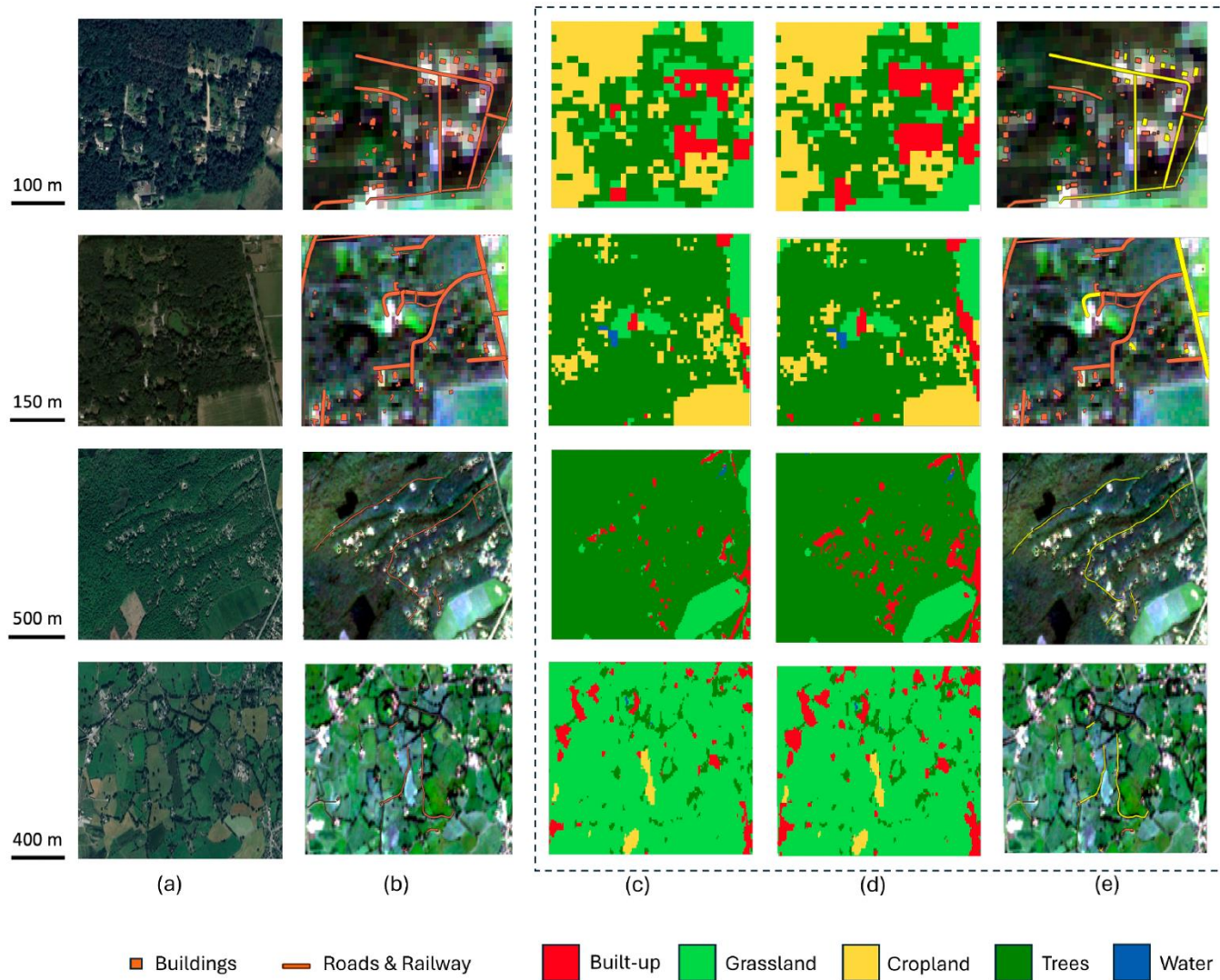
Small broadleaved trees/shrub



Broadleaved trees

Representative examples of different built-up landscape configurations, including centrally concentrated urban cores, edge-dominated urban regions, transition zones, and sparsely built rural settlements. The classification status indicated whether the built-up is the dominant land-cover fraction within the pixel.

TO 3: Sub-pixel Mapping



For each of the four patches: (a) High-resolution Google Earth Image, (b) Sentinel-2 yearly composite for reference. Highlighted in orange are the unidentified overlaid built-up features from OSM in three global land-cover maps, (c) Predicted land-cover Map based on the highest fraction obtained with the proposed model, (d) Updated land-cover map based on a Threshold of 0.20, (e) Highlighted in yellow are the identified built-up features.

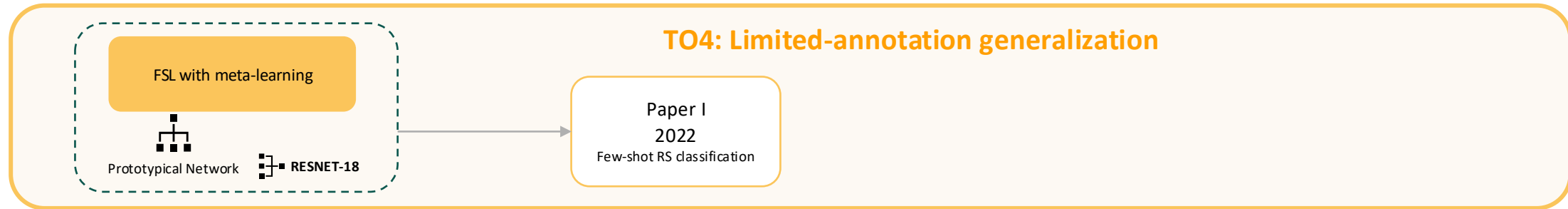
Recovered Built-up:

Buildings: 100 out of 400, 81 buildings of area less than 100m^2 , with 36 buildings having area between $20\text{-}100\text{m}^2$.

Roads and railways: 19 (3-5.5m wide)

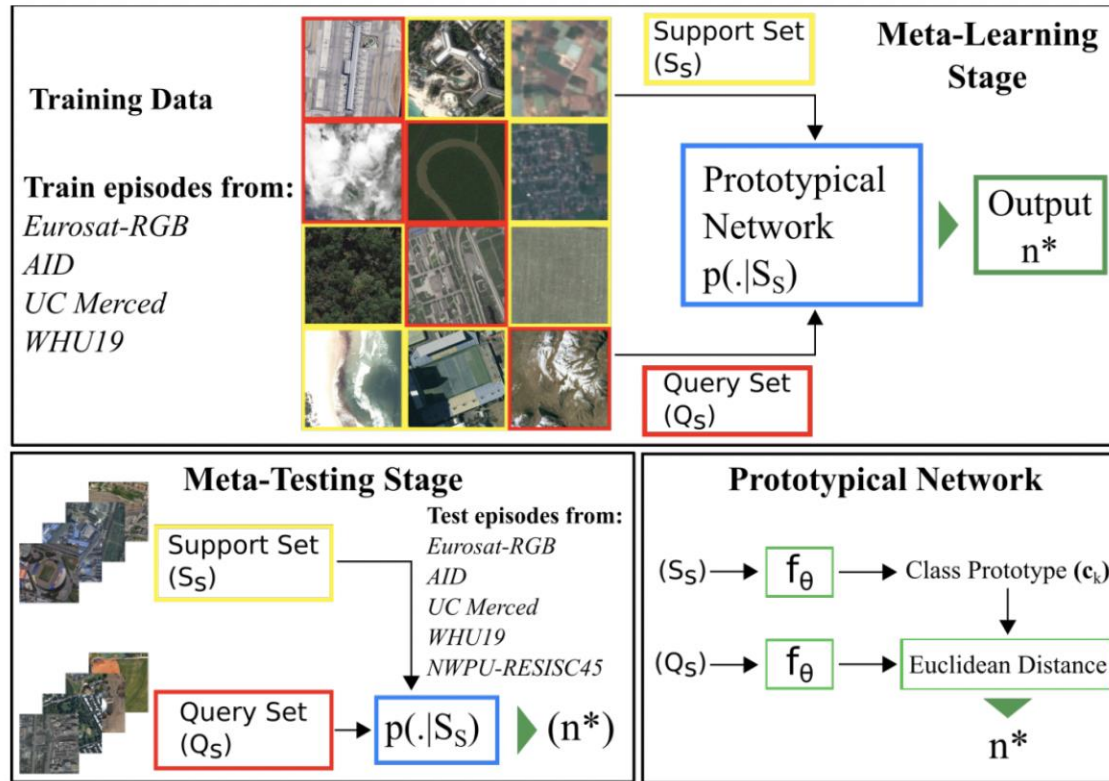
- To identify and map LC classes that are smaller than the sensor's nominal pixel resolution (**<10m**)
- Characterize built-up information within **mixed pixels**
- Capturing fine-scale **landscape heterogeneity** at **sub-pixel level** with **AEDs**.
- **Fractional dataset** for Wallonia region.

Objective 4: Investigate and evaluate the generalization capability of DL models that are resilient to limited annotation availability

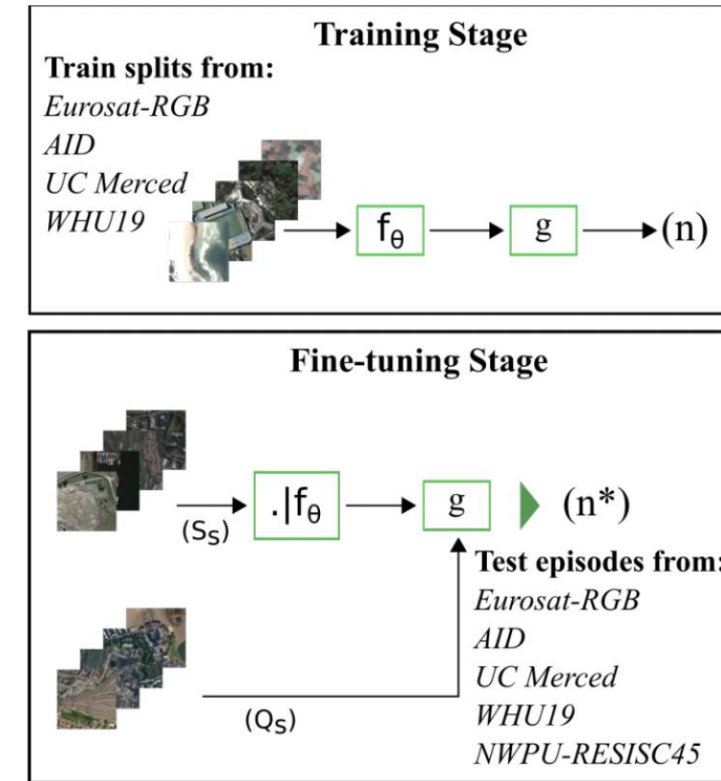


- Paper I: **S. Sharma**, R. Roscher, M. Riedel, S. M. Memon, and G. Cavallaro, “Improving Generalization for Few-Shot Remote Sensing Classification with Meta-Learning”, in Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Kuala Lumpur, Malaysia, 2022, pp. 5061-5064, <http://doi.org/10.1109/IGARSS46834.2022.9884699>

TO 4: Few-shot Learning (FSL) with Meta-learning



(a)



(b)

(a) Meta-learning approach to FSL, and (b) baseline finetuning approach, where f_θ is the feature extraction layer parameterized by θ and g is the embedding function using the ResNet-18 architecture.

TO 4: Few-shot Learning (FSL) with Meta-learning

Table 1. Training Time on a Tesla V100-PCIE-32GB GPU.

Models	Model A	Model B	Model C
Training Time	45 hours	90 hours	30 hours

Table 2. Few-shot RS classification mean Overall Test Accuracies OA in percentage and mean κ computed on 600 episodes. (The percentage in the Dataset column shows the reserved data split for testing purposes)

Test classes for Datasets	Model A		Model B		Model C	
	OA	κ	OA	κ	OA	κ
EuroSAT (15%)	98.4750 +/- 0.2863	0.972333	97.4750, +/- 0.3630	0.946167	99.1833, +/- 0.1833	0.988167
AID (15%)	78.3736 +/- 0.8904	0.668083	82.9958, +/- 0.7779	0.722250	85.8972, +/- 0.7071	0.781139
UC Merced (15%)	88.7305, +/- 0.7843	0.814000	95.1583, +/- 0.4619	0.920333	95.2000, +/- 0.4841	0.929583
WHU19 (15%)	99.2306, +/- 0.2274	0.987167	98.6278, +/- 0.2529	0.982000	99.7694, +/- 0.1032	0.994333
NWPU-RESISC45 (100%)	69.0711, +/- 1.0950	0.596833	81.8329, +/- 0.8740	0.747792	79.9027, +/- 0.8811	0.738003

- **FSL with meta-learning** is resilient to **limited annotation availability**
- The method is able to **generalize** on unseen data

Summary: fulfilling the thesis objectives

Relationship between thesis objectives and papers. Filled circles identify each paper’s principal thesis objective; open circles denote supporting or enabling contributions. Each paper has one principal objective.

	Paper I	Paper II	Paper III	Paper IV	Paper V	Paper VI
TO1		●	○			●
TO2			●		○	
TO3				●	●	
TO4	●					

Summary: answering the research questions

- *How can publicly available, large-scale, multi-source datasets (including multispectral satellite imagery and geo-tagged images) be effectively exploited using advanced DL models to improve satellite-based LULC mapping while addressing:*
 - (i) semantic and spatial gap between diverse data modalities:
 - This thesis uses in-situ field observations (street-level images) to bridge the semantic gap between what is visible from satellite and ground, as in **Paper II**. In addition, this thesis uses VFM along with field photos to diagnose the spatial-semantic gap in LC, in **Paper VI**, using Sen4Map from **Paper III**. The work presented is focused on quantifying within-site visual heterogeneity in field photographs to capture landscape complexity and mixed LC conditions through spatial analysis, while the semantic analysis evaluates the consistency of LC interpretations across field images, satellite imagery, and in-situ reference annotations.

Summary: answering the research questions

- *How can publicly available, large-scale, multi-source datasets (including multispectral satellite imagery and geo-tagged images) be effectively exploited using advanced DL models to improve satellite-based LULC mapping while addressing:*
- (ii) the need for more detailed and complex LULC classification legends:
 - This thesis presents Sen4Map, a large-scale, multi-source benchmark dataset specifically designed to support the development and evaluation of DL models capable of learning rich spectral, spatial, and semantic representations for detailed LULC mapping, in **Paper III**. The dataset is publicly available at <https://datapub.fzjuelich.de/sen4map>. Secondly, a fractional LC dataset from **Paper V** was also introduced to support sub-pixel estimation, providing fine-grained reference annotations for training and evaluating regression-based models using Sentinel-2 imagery.

Summary: answering the research questions

- *How can publicly available, large-scale, multi-source datasets (including multispectral satellite imagery and geo-tagged images) be effectively exploited using advanced DL models to improve satellite-based LULC mapping while addressing:*

- (iii) fine-scale landscape heterogeneity:
 - To identify and map LC classes that are smaller than the sensor's nominal pixel resolution or exhibit complex mixed LC signatures, this thesis uses a Random Forests classification and regression-based sub-pixel mapping approach, **Paper IV, V**. In addition, this thesis leverages pretrained AEDs, which offer rich, multi-temporal feature representations that help separate and characterize built-up information within mixed pixels, enabling the capture of fine-scale landscape heterogeneity.

Summary: answering the research questions

- *How can publicly available, large-scale, multi-source datasets (including multispectral satellite imagery and geo-tagged images) be effectively exploited using advanced DL models to improve satellite-based LULC mapping while addressing:*
- (iv) the scarcity of high-quality reference data:
 - This thesis investigates DL models and methods that are resilient to limited annotation availability, such as FSL with meta-learning, as in **Paper I**. The presented work generalizes well on multiple unseen RS datasets.

Overall Thesis Contribution:

- Semantically rich benchmarks connecting satellite representations with *in-situ* observations
- Spatial-semantic diagnostics to reveal **where learned representations align—or diverge—from reality**
- Embedding-centric workflows and HPC infrastructure for **efficient large-scale analysis**
- Foundations for **multi-modal, zero-/few-shot and language-driven geospatial reasoning**

□ Journal Papers:

- Paper III: **S. Sharma**, R. Sedona, M. Riedel, G. Cavallaro, and C. Paris, “Sen4Map: Advancing Mapping with Sentinel-2 by Providing Detailed Semantic Descriptions and Customizable Land-Use and Land-Cover Data”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS), vol. 17, pp. 13893 - 13907, 2024, <http://doi.org/10.1109/JSTARS.2024.3435081>
- Paper V: **S. Sharma**, R. Sedona, M. Riedel, G. Cavallaro, and C. Paris, “Beyond Pixels: Identifying Built-Up Features at Sub-Pixel Level for Enhanced Satellite-Based Land Cover Mapping”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS), 2026, <http://doi.org/10.1109/JSTARS.2026.3712773>

□ Conference Papers:

- Paper I: **S. Sharma**, R. Roscher, M. Riedel, S. M. Memon, and G. Cavallaro, “Improving Generalization for Few-Shot Remote Sensing Classification with Meta-Learning”, in Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Kuala Lumpur, Malaysia, 2022, pp. 5061-5064, <http://doi.org/10.1109/IGARSS46834.2022.9884699>
- Paper II: C. Paris, L. Martinez-Sanchez, M. van der Velde, **S. Sharma**, R. Sedona, and G. Cavallaro, “Accuracy assessment of land-use-land-cover maps: the semantic gap between in-situ and satellite data”, in Proceedings Volume 12733, Image and Signal Processing for Remote Sensing XXIX, SPIE Remote Sensing, Amsterdam, Netherlands, 2023, <http://doi.org/10.1117/12.2679433>
- Paper IV: **S. Sharma**, R. Sedona, M. Riedel, G. Cavallaro, and C. Paris, “Enhancing Land Cover Mapping: A Novel Automatic Approach To Improve Mixed Spectral Pixel Classification”, in Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Athens, Greece, 2024, pp. 1017-1020, <http://doi.org/10.1109/IGARSS53475.2024.10641976>
- Paper VI: **S. Sharma**, R. Sedona, M. Riedel, G. Cavallaro, and C. Paris, “Diagnosing the Ground–Satellite Gap in Land Cover Using Vision Foundation Models and Field Photos”, in Proceedings of the IEEE India Geoscience and Remote Sensing Symposium (InGARSS), 2026 (Accepted)

Code and Data Repositories:

□ Few-shot Remote Sensing Classification with meta-learning (**Paper I**):

<https://gitlab.jsc.fz-juelich.de/sdlrs/FSL>

□ Sen4Map Data and Code (**Paper III**):

<https://datapub.fz-juelich.de/sen4map>

□ Beyond Pixels: Fractional Data and Code (Paper V):

<https://gitlab.jsc.fz-juelich.de/sdlrs/sub-pixel-mapping>

□ Spatial-Semantic Diagnostic Framework (**Paper VI**):

<https://gitlab.jsc.fz-juelich.de/sdlrs/agrosemanticingarss>, tag v2.1.1.

□ 2021:

- Online Tutorial on Message Passing Interface (MPI) in the course “Artificial Intelligence for Earth Observation powered by High-Performance Computing and Quantum Computing”, UNIVERSIT. DEGLI STUDI DEL SANNIO, Benevento, Italy

□ 2022:

- Webinar for “Remote Sensing” use-case for ADMIRE application, <https://youtu.be/PMYek3VZNB8?si=ZZ1cWHqd6OI6XAsI>
- Lecture at CRS, Iceland: “Few-shot Remote Sensing Classification with Meta-Learning: Challenges and Opportunities”, https://crs.hi.is/?page_id=295

□ 2023:

- Presented at 12th IHPC Workshop, University of Iceland, 2023: “Enhancing LULC classification systems: Harnessing large-scale satellite and street-level geotagged images” <https://www.ihpc.is/events/12th-icelandic-hpc-community-workshop>
- Teaching assistance and lectures in the course “Machine Learning for Earth Observation powered by Supercomputers”, REI506M University of Iceland, 2023

□ 2024:

- Teaching assistance and lectures in the course “Machine Learning for Earth Observation powered by Supercomputers”, REI506M University of Iceland, 2024

Additional Events

- ☐ Attended Living Earth Symposium by ESA in Bonn, 2022
- ☐ Attended ADMIRE Meeting in Paris (in-person) 2022
- ☐ In-person participation as a group leader in Summer School on "Machine Learning and Data Fusion for Earth Observation", University of Pavia, Cremona, Italy, 2023

Visits to Iceland

- ☐ Presentation at yearly PhD retreats
- ☐ Research visits



Images: Morris Riedel, Mengyu Li

Grateful for the People Behind the Journey!



Prof. Dr. – Ing. Morris Riedel
University of Iceland
Jülich Supercomputing Centre



Adj. Associate Prof. Dr. –Ing.
Gabriele Cavallaro
University of Iceland
Jülich Supercomputing Centre



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Assistant Prof. Dr. –Ing.
Claudia Paris
University of Twente



Prof. Dr. –Ing.
Ribana Roscher
Forschungszentrum Jülich
University of Bonn

जिज्ञासया आरभामहे। ज्ञानेन बोधमन्विष्यामः।

Jijñāsayā ārabhāmahe | Jñānena bodham anviṣyāmaḥ |

यथा यथा गहनतरमवगाहामहे, तथा तथा स्वज्ञानस्य सीमाः प्रकाशन्ते।

Yathā yathā gahanataram avagāhāmahe | Tathā tathā svajñānasya sīmāḥ prakāśante

We begin with curiosity. We journey through knowledge.

We arrive not at certainty, but at a deeper understanding of what remains unknown.

Thank you!

Questions?