Remote sensing change detection via weak temporal supervision

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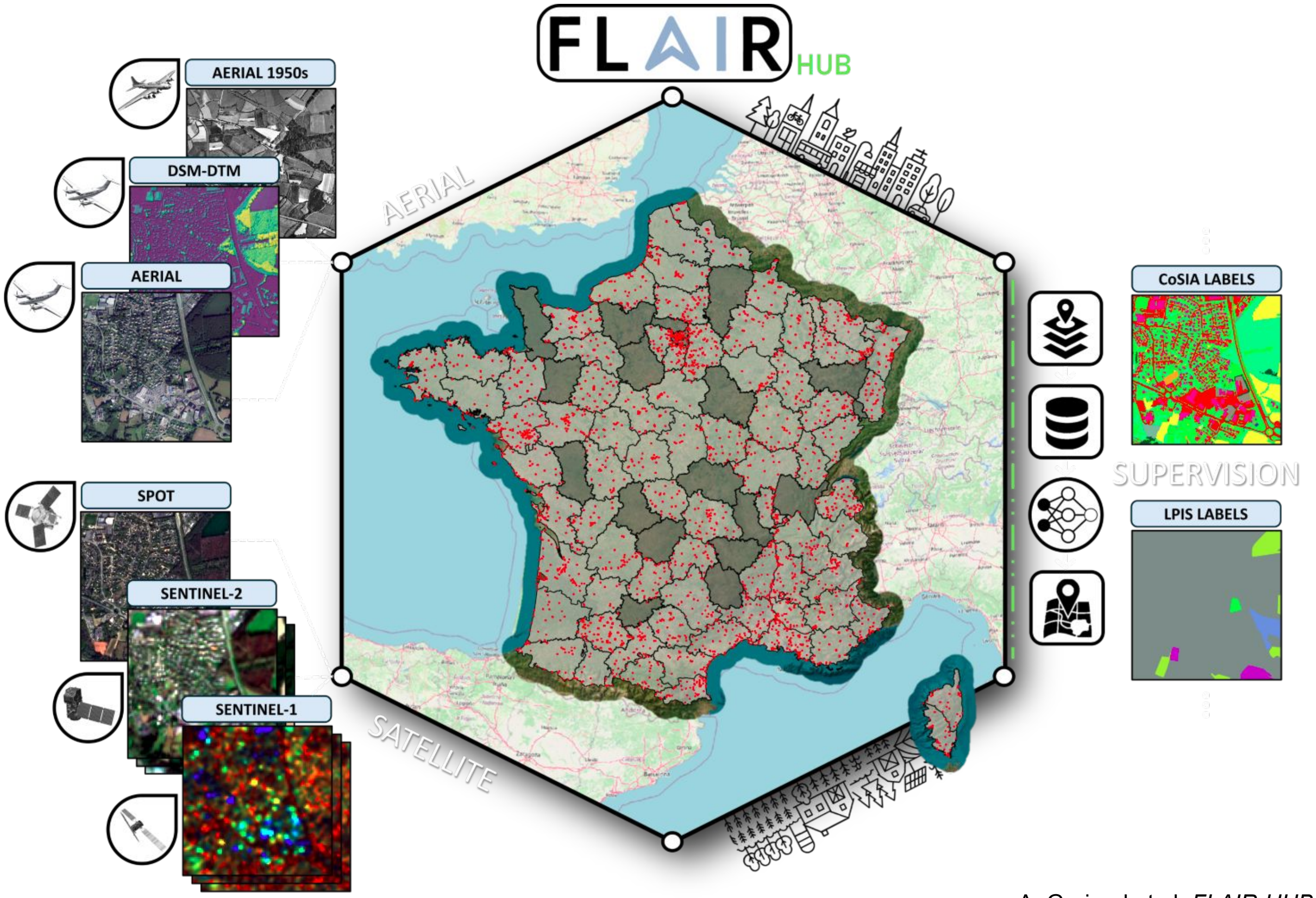
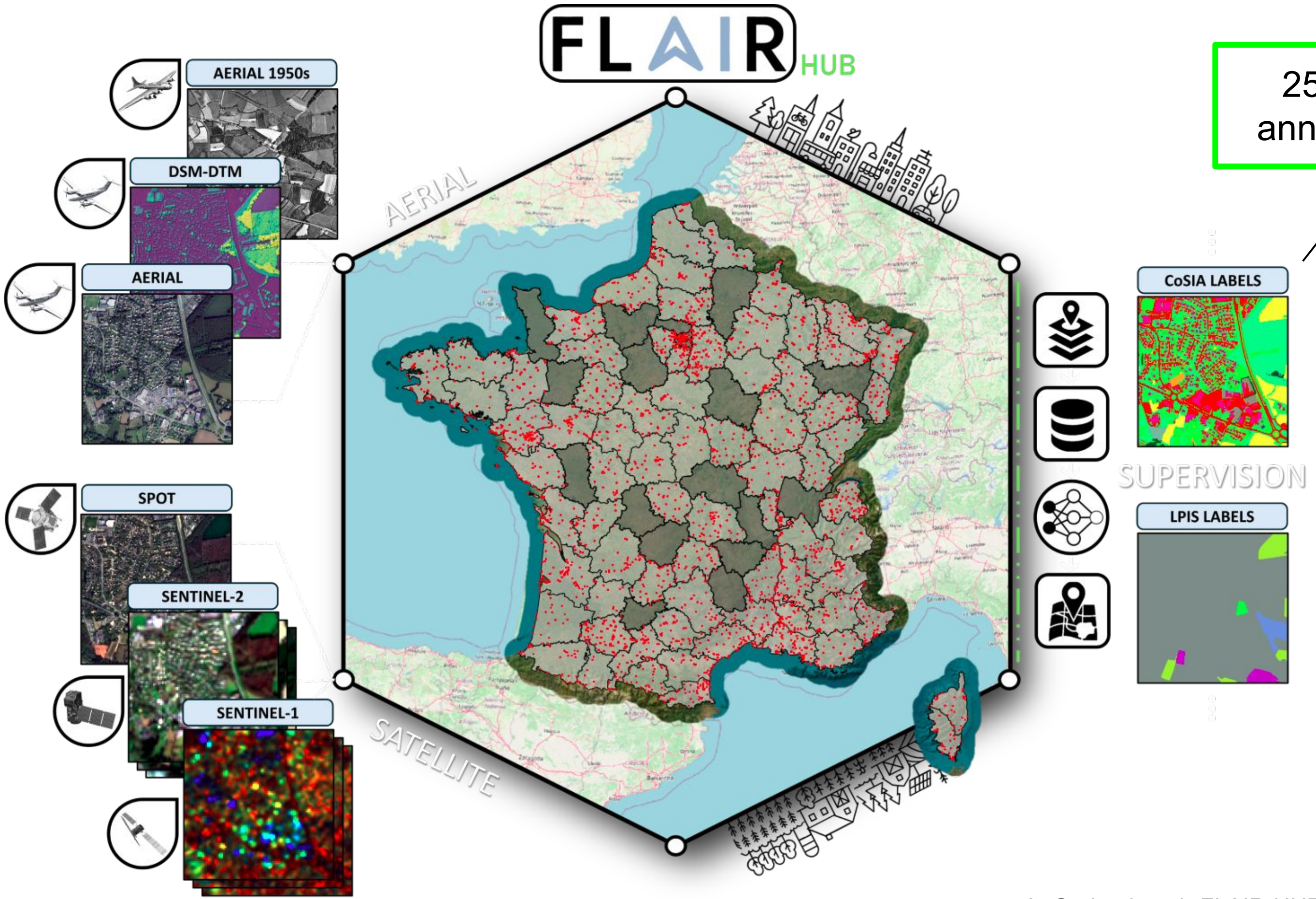
Journée de la recherche 2026

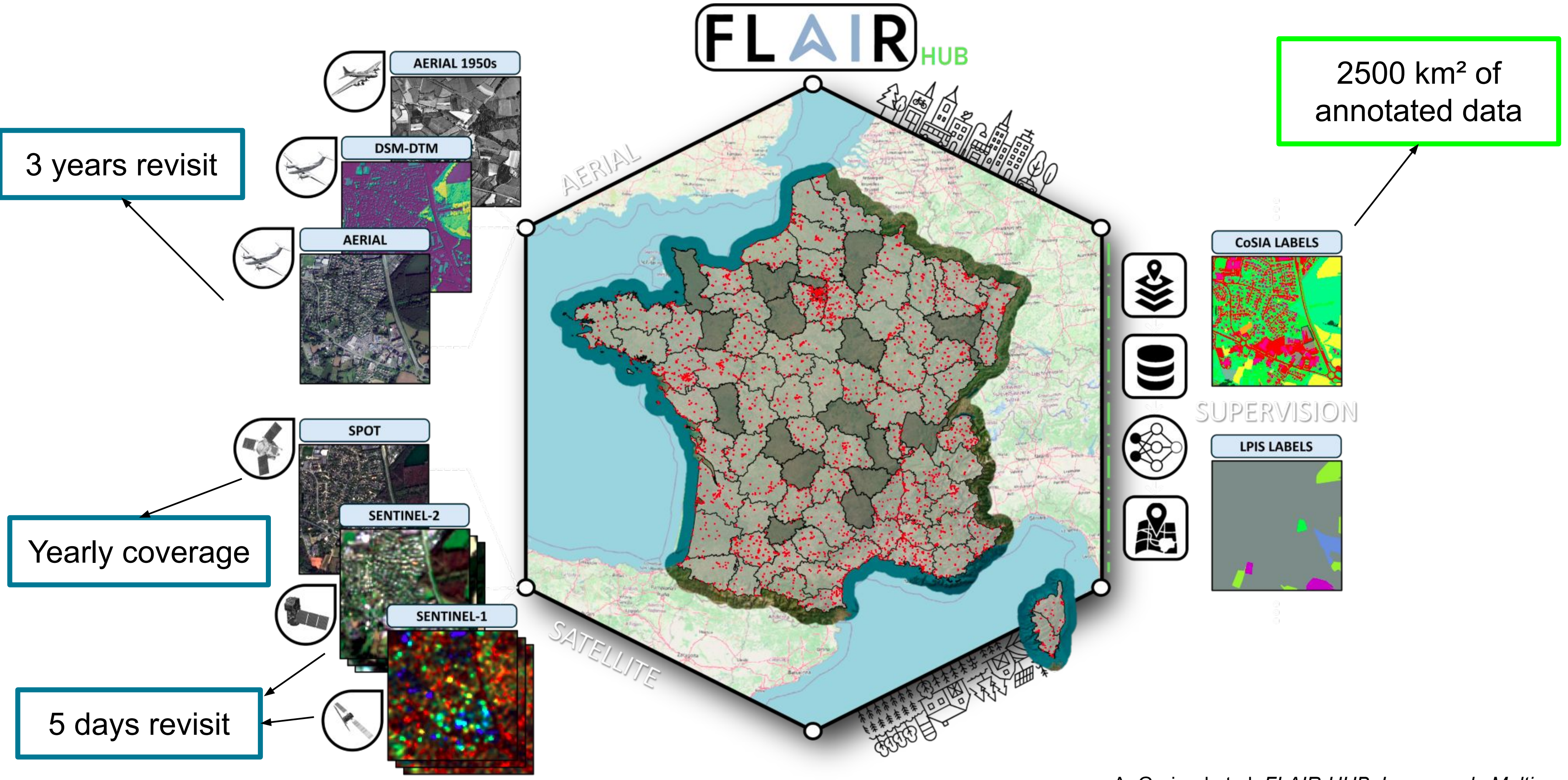


A. Garioud et al. *FLAIR-HUB: Large-scale Multimodal Dataset for Land Cover and Crop Mapping.* (2025).



2500 km² of annotated data

A. Garioud et al. *FLAIR-HUB: Large-scale Multimodal Dataset for Land Cover and Crop Mapping.* (2025).



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Problem

How to benefit from both:

- Extensive single-temporal pixel-wise annotations and
- Regularly acquired unlabeled remote sensing data ?

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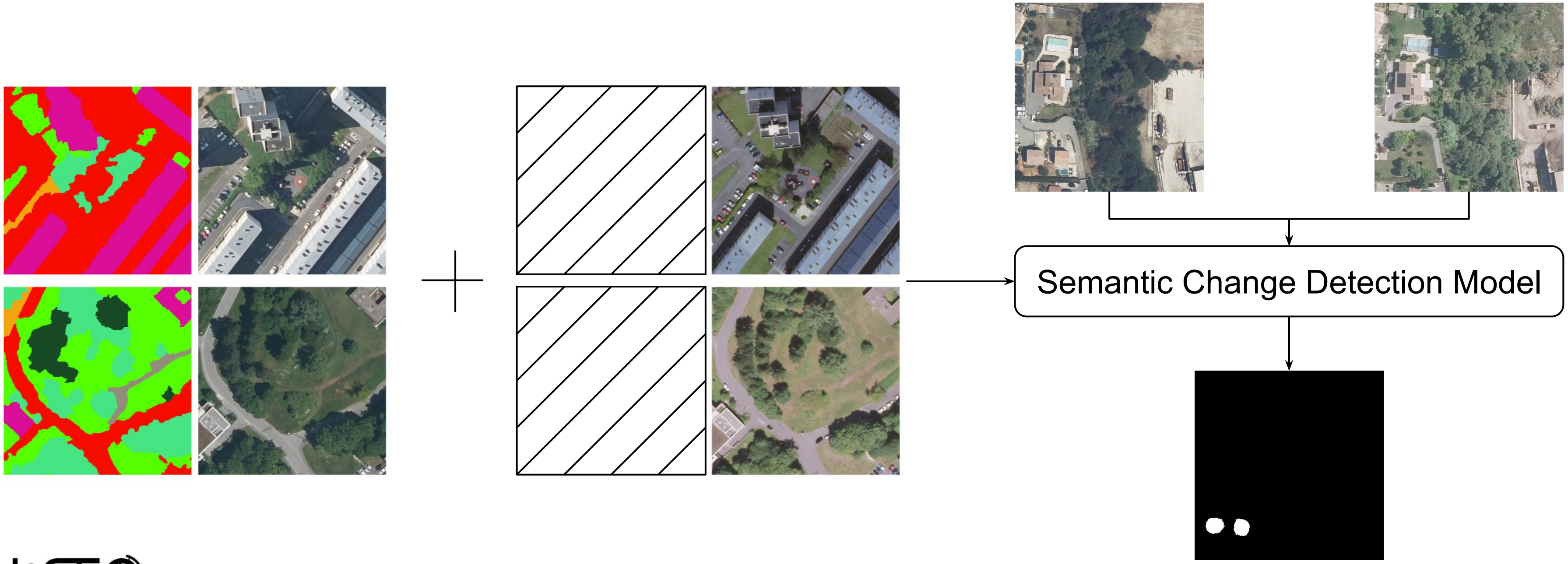
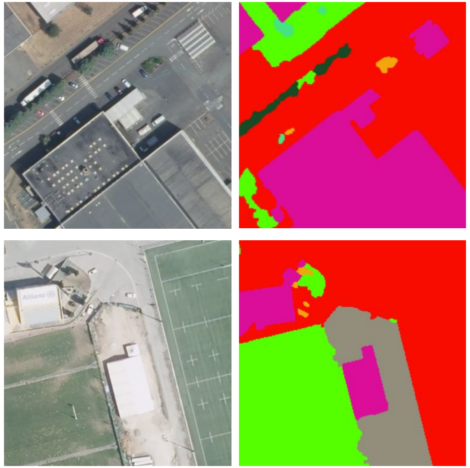
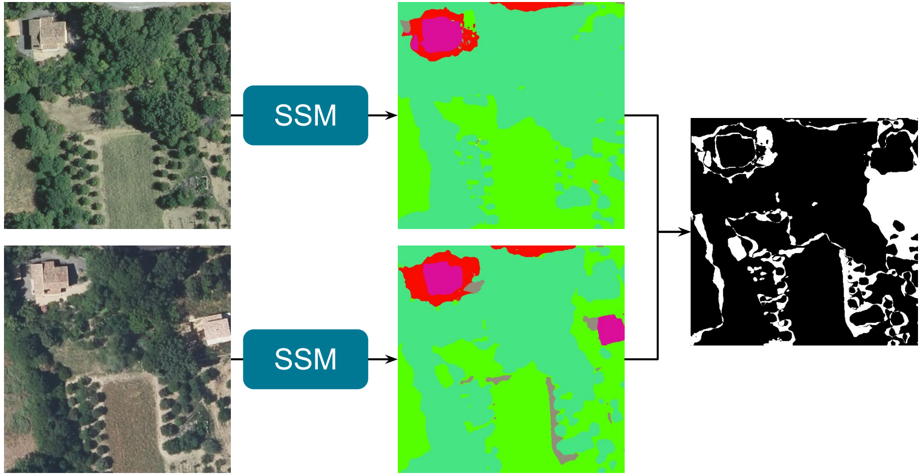


From a semantic segmentation dataset to change detection

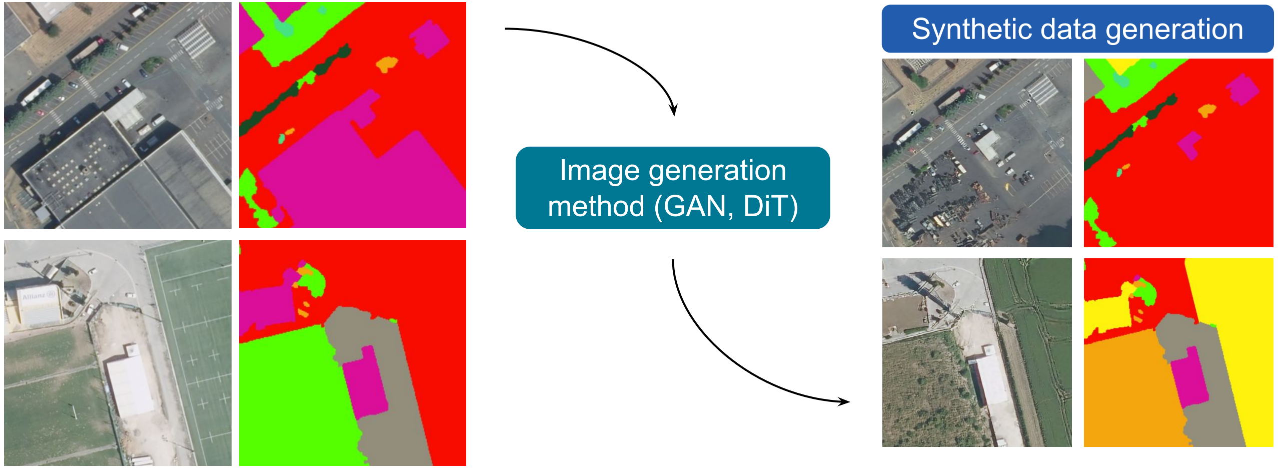


Semantic segmentation model (SSM)

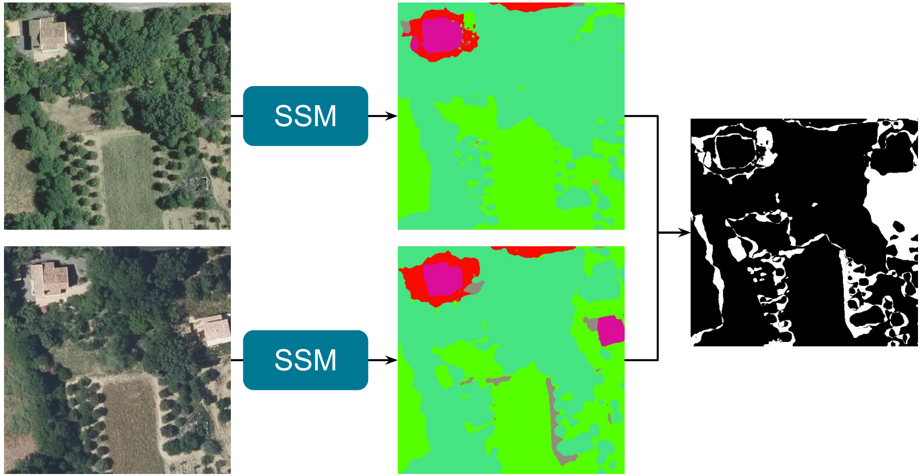
Post-classification change detection



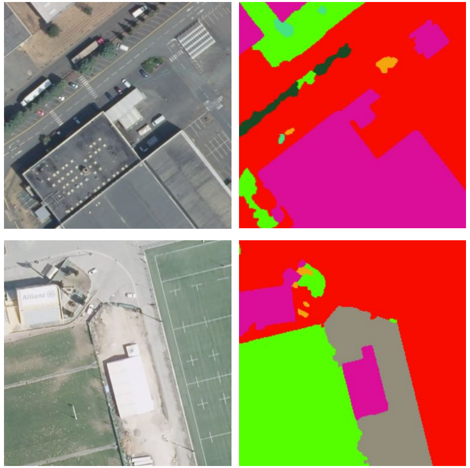
Synthetic data generation



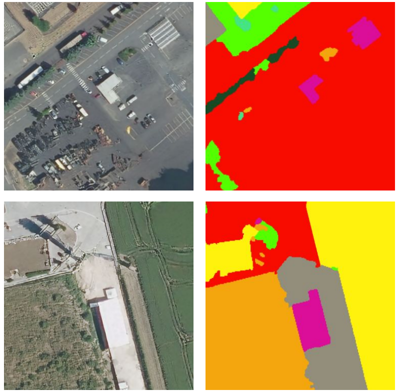
Post-classification change detection



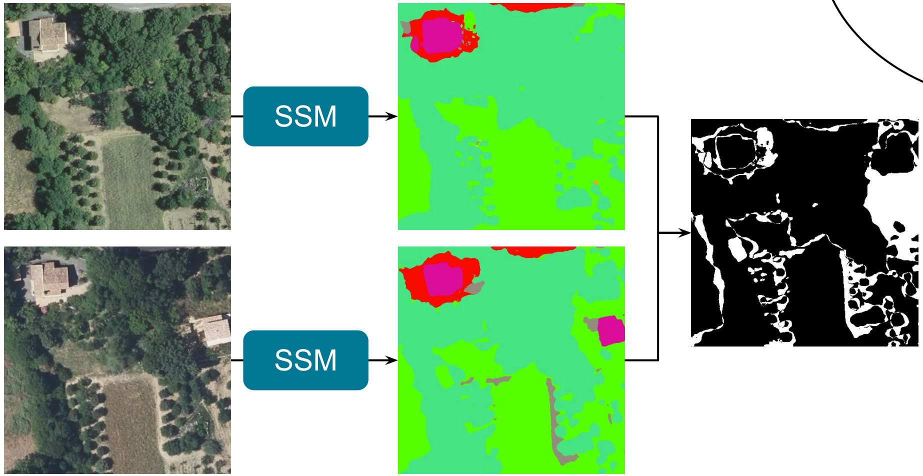
Y. Benidir et al. *The Change You Want To Detect: Semantic Change Detection In Earth Observation With Hybrid Data Generation.* CVPR (2025).



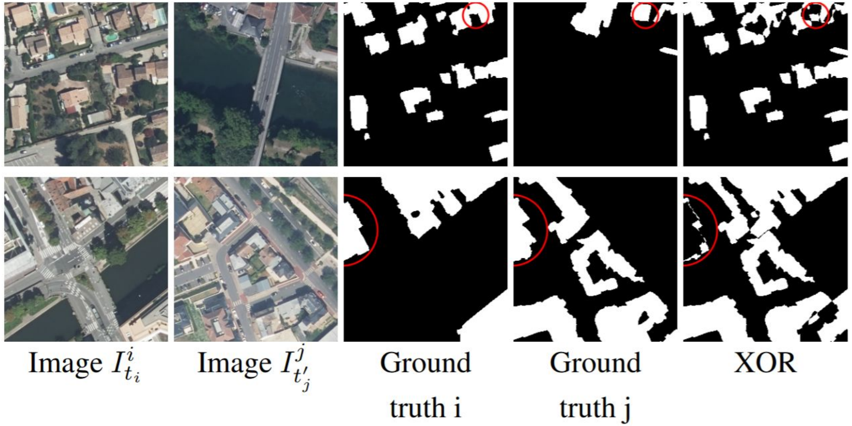
Synthetic data generation



Post-classification change detection



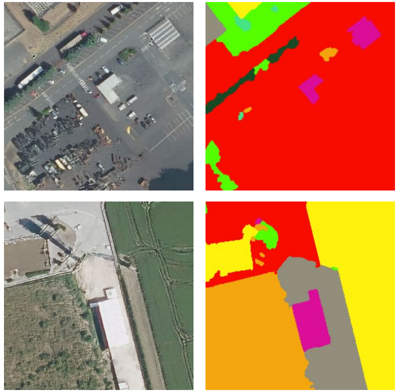
STAR : consider change in unpaired images



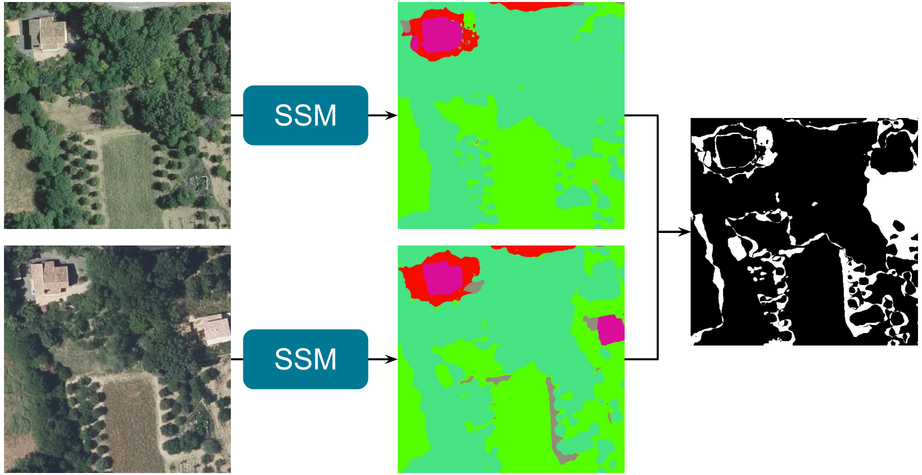
Z. Zheng et al. *Change is Everywhere: Single-Temporal Supervised Object Change Detection in Remote Sensing Imagery.* ICCV (2021).

None of these approaches leverage **new**, **easily accessible**, **unlabeled** data

Synthetic data generation



Post-classification change detection



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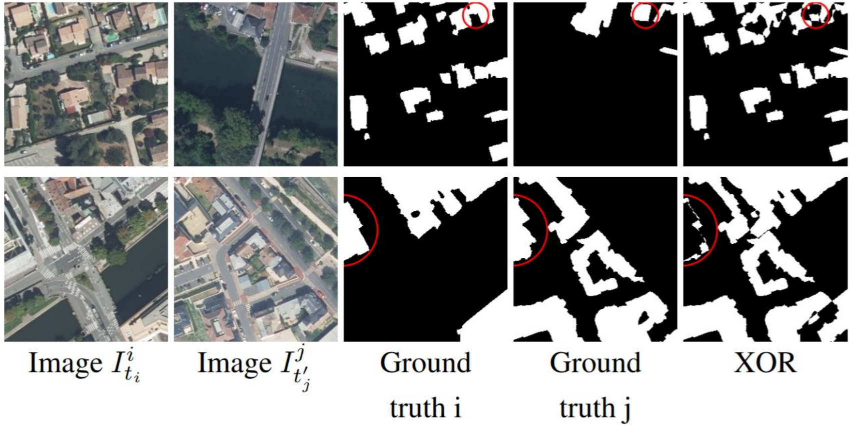


Weak temporal supervision

Mixing *real* bi-temporal pairs

Rough no-change assumption

Weak temporal supervision

Mixing ***real*** bi-temporal pairs and ***fake*** pairs in a batch

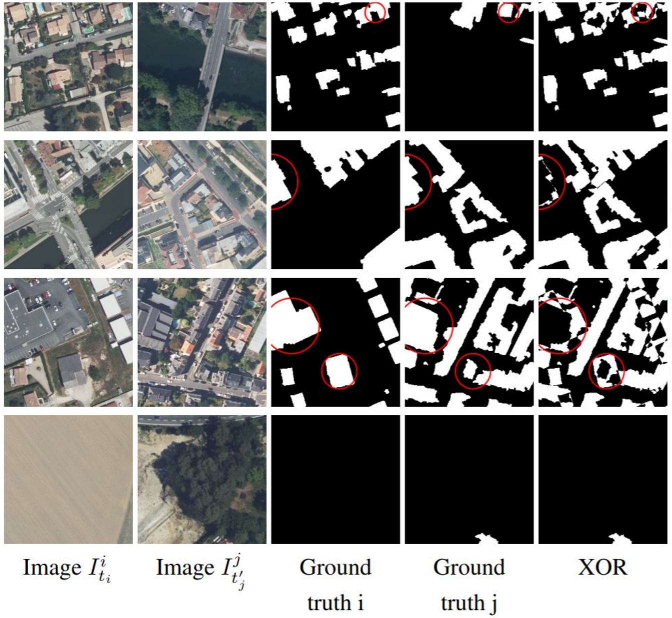
Rough no-change assumption

sIoU-based change maps

Parameter *p*: proportion of real pairs in a batch

Weak temporal supervision

XOR-based change maps



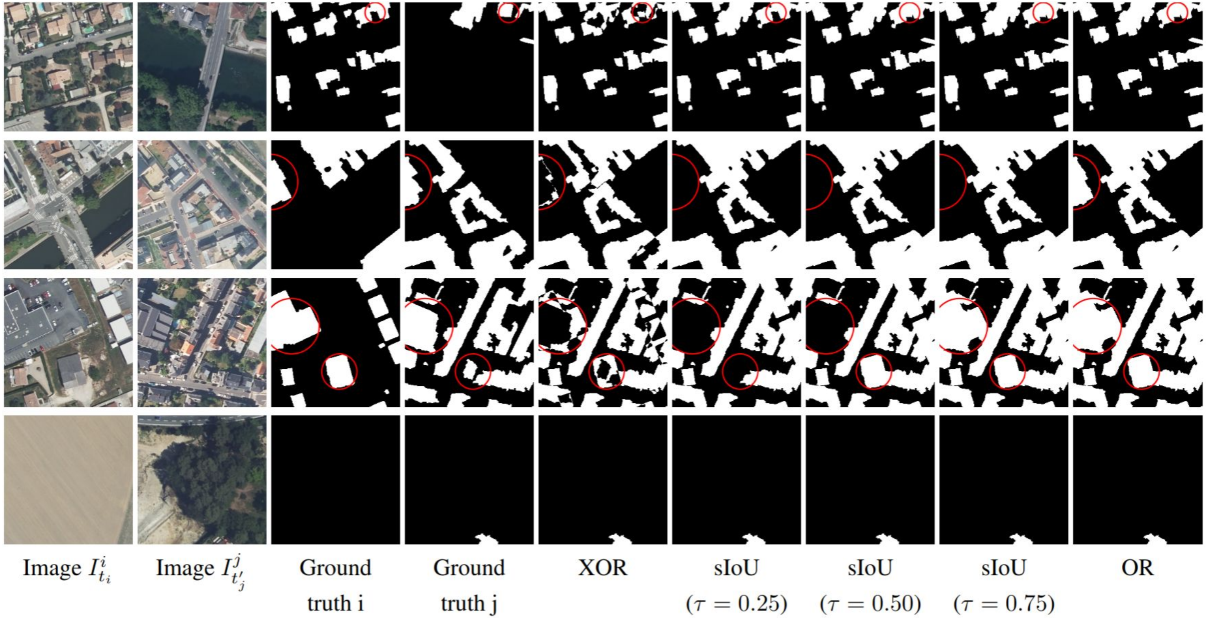
Z. Zheng et al. *Change is Everywhere: Single-Temporal Supervised Object Change Detection in Remote Sensing Imagery.* ICCV (2021).

Weak temporal supervision

sIoU-based change maps

→ A component-level adjusted IoU

→ Thresholded to build change masks (**parameter τ**)



R. Chan et al. *SegmentMeIfYouCan: A Benchmark for Anomaly Segmentation.* NeurIPS (2021).

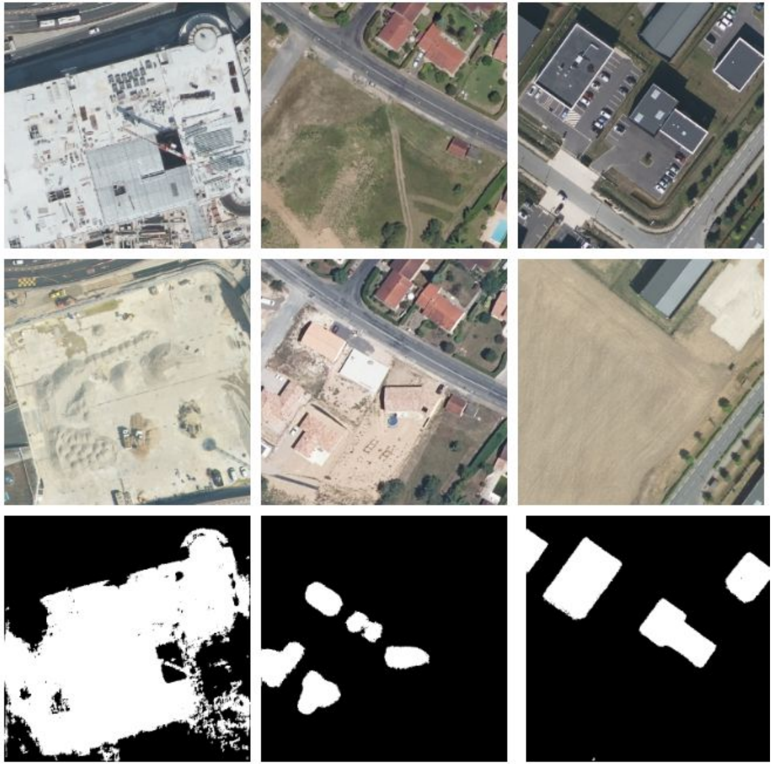
M. Rottmann et al. *Prediction Error Meta Classification in Semantic Segmentation: Detection via Aggregated Dispersion Measures of Softmax Probabilities*. IJCNN (2020).

Weak temporal supervision

Rough “no-change” assumption

- Not true in practice : acquisitions may be years apart
- Such pairs can be detected by the model after training and filtered out
- Iterative refinement (**parameter N_{iter}**)

→ cf. literature on data cleaning



Example of real bi-temporal change pairs identified after the first training iteration

Weak temporal supervision

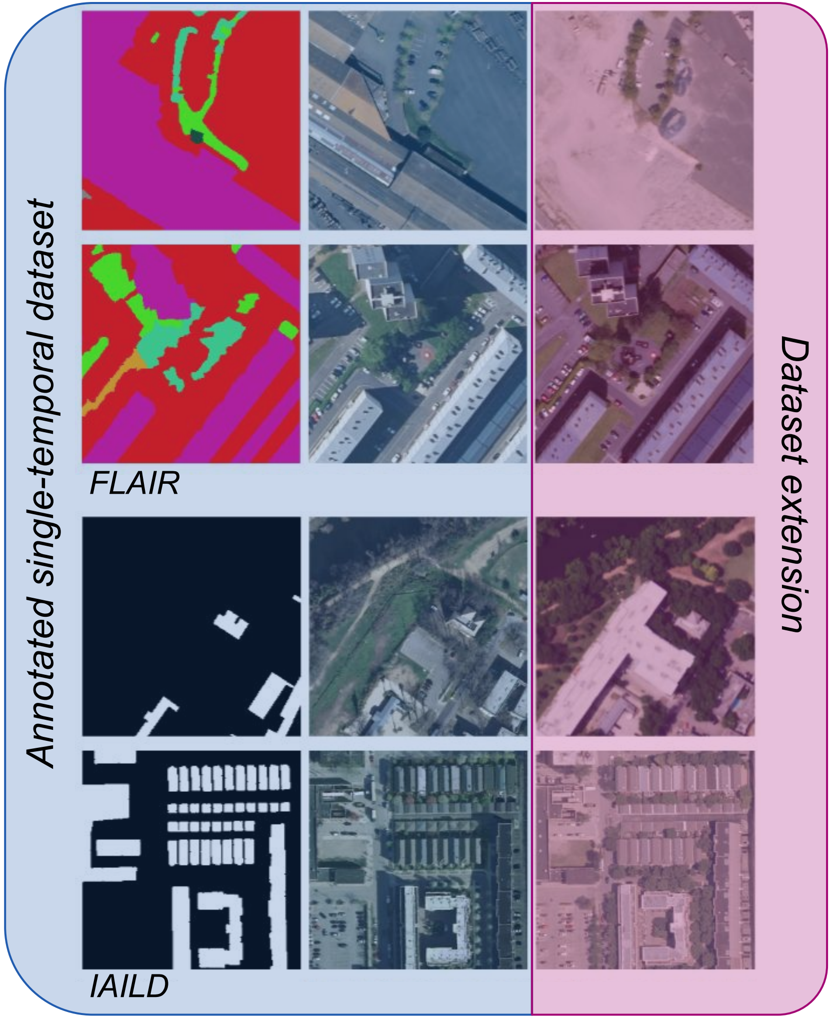
3 main components of our training strategy:

- balanced batch sampling
- sIoU-based change map generation
- iterative refinement

3 main hyper-parameters: $\boldsymbol{p}, \boldsymbol{\tau}, \boldsymbol{N_{iter}}$

+ Extending existing datasets

- FLAIR
- IAILD



Results

In-domain evaluation (curated building change detection test set)

Method	F1 ↑	FPR ↓
Post-classification	64.2	2.87
Post-classification + temporal augmentation	59.0	2.46
Synthetic dataset generation (Changen2)	58.5	3.63
Synthetic dataset generation (HySCDG)	**83.1**	<u>0.73</u>
STAR	75.1	1.58
Ours	<u>79.0</u>	**0.35**

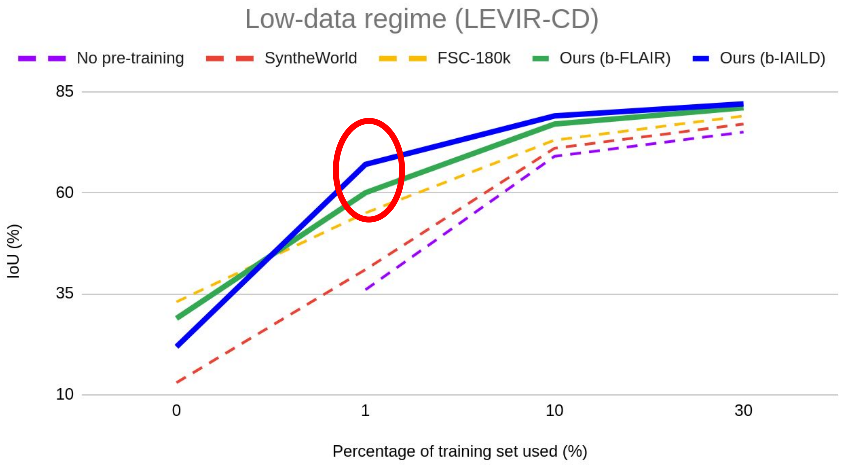
Results

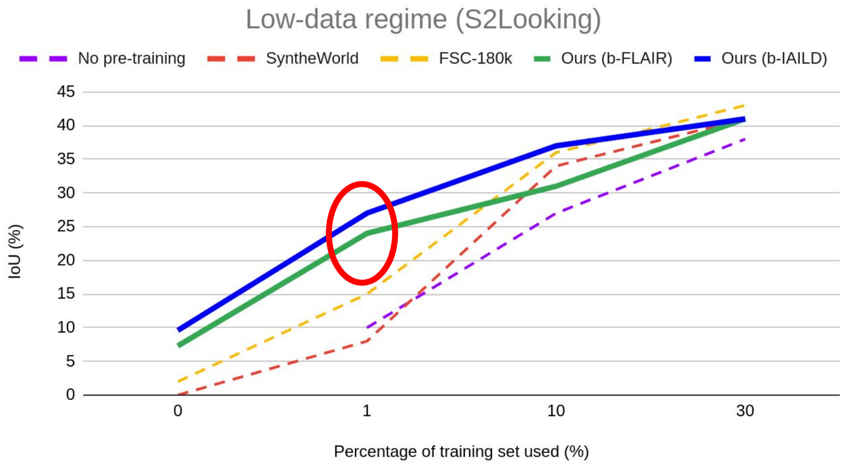
Zero-shot out-of-domain evaluation

	LEVIR-CD		WHU-CD		S2Looking	
Method	F1 ↑	FPR ↓	F1 ↑	FPR ↓	F1 ↑	FPR ↓
Post-classification	51.4	2.40	66.7	4.09	10.6	3.18
Post-classification + temporal augmentation	48.8	2.51	65.6	4.33	8.8	2.06
Synthetic dataset generation (Changen2)	44.8	3.49	63.3	4.46	<u>13.4</u>	2.11
Synthetic dataset generation (HySCDG)	49	—	63.3	3.66	4	—
STAR	**53.3**	<u>1.92</u>	<u>72.4</u>	<u>2.97</u>	11.8	<u>1.36</u>
Ours	44.7	**0.30**	**77.3**	**0.77**	**13.6**	**0.58**

Results

Low-data regime





Results

Large-scale zero-shot evaluation

OCS-GE *Ours* *FSC-180k*

Take-home messages

- A simple approach to leverage
  - annotated single-temporal datasets
  - largely available unlabeled data

- 3 simple components:
  - balanced batch sampling
  - sIoU-based “fake” change maps
  - iterative refinement

- In domain: large-scale deployment with a low false positive rate
- Out of domain: great performance in low-data regime

Thank you for your attention!
Question?

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