

23rd June 2026



Université

de Strasbourg



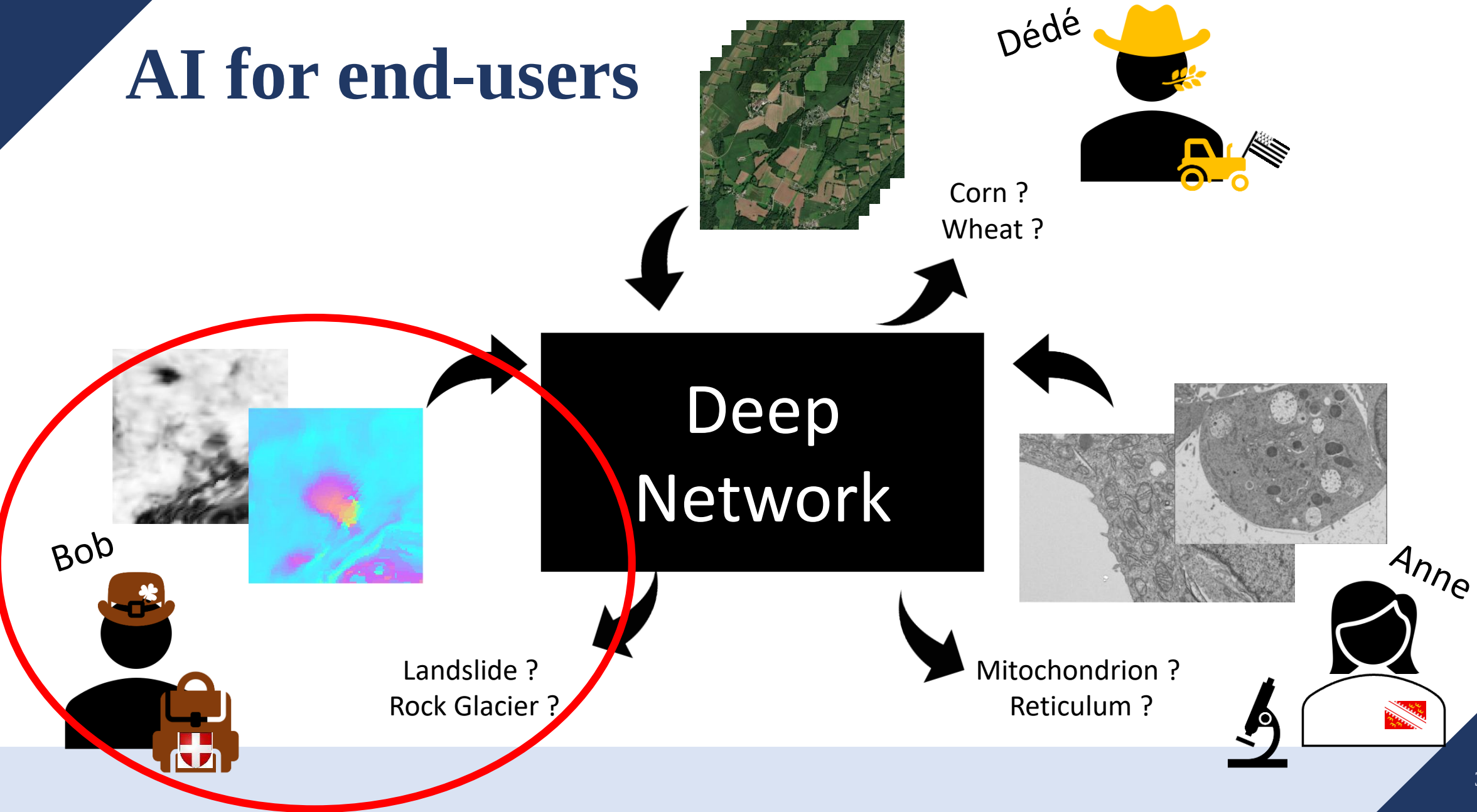
Bridging the Gap Between Deep Learning and End-Users: Application to Instability Segmentation on SAR Interferograms

by Antoine BRALET

Atelier Télédec@USMB 2026

Introduction

AI for end-users





Detecting Slope Instabilities

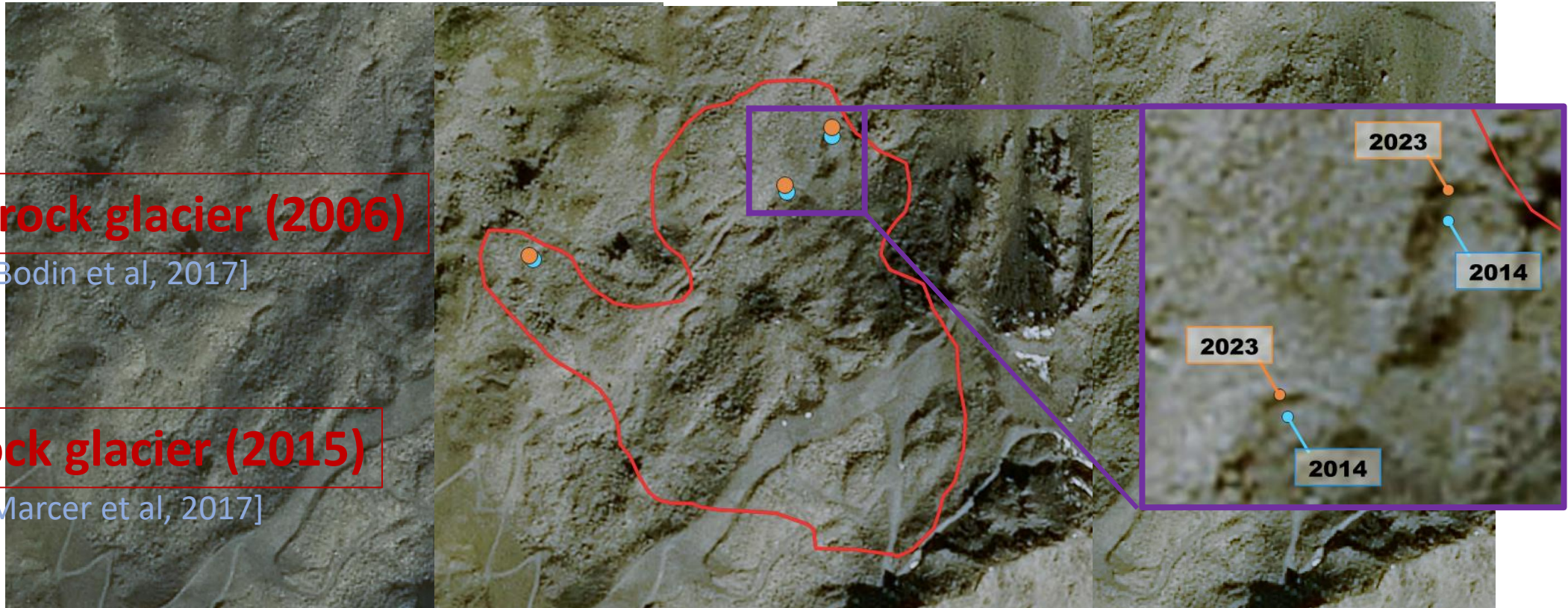
Slow Moving Slope Instabilities

Bérard rock glacier (2006)

[Bodin et al, 2017]

Lou rock glacier (2015)

[Marcer et al, 2017]

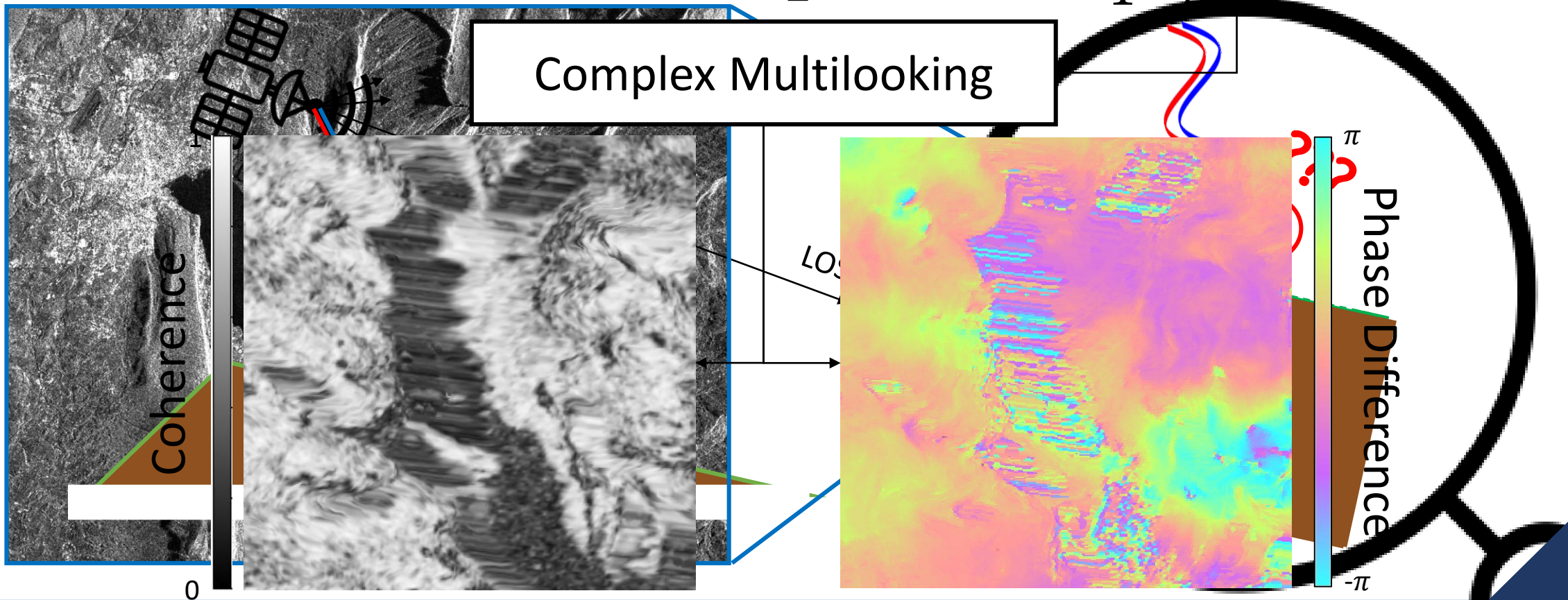


Optical SPOT6/7 - 2014

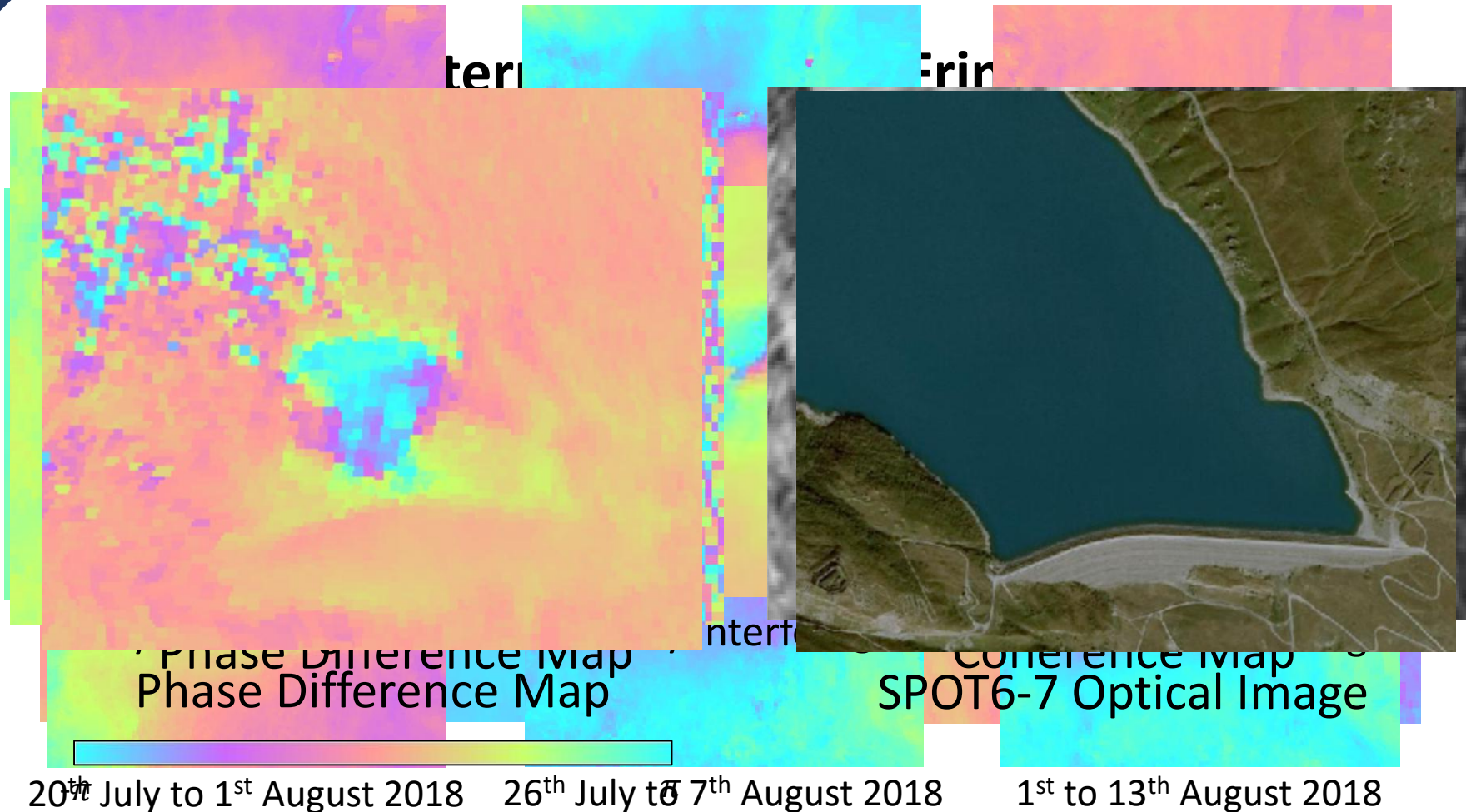
Optical SPOT6/7 - 2023

Interferometric SAR

$$\ast \overline{A_2 e^{i\varphi_2}} = A_1 A_2 e^{i(\varphi_1 - \varphi_2)}$$



Annotation Routine [Bralet et al, 2024]



-
1. Bubbles or Fringes
 2. Temporal Coherence
 3. Baseline Coherence
 4. High Coherence
 5. Optical Clues

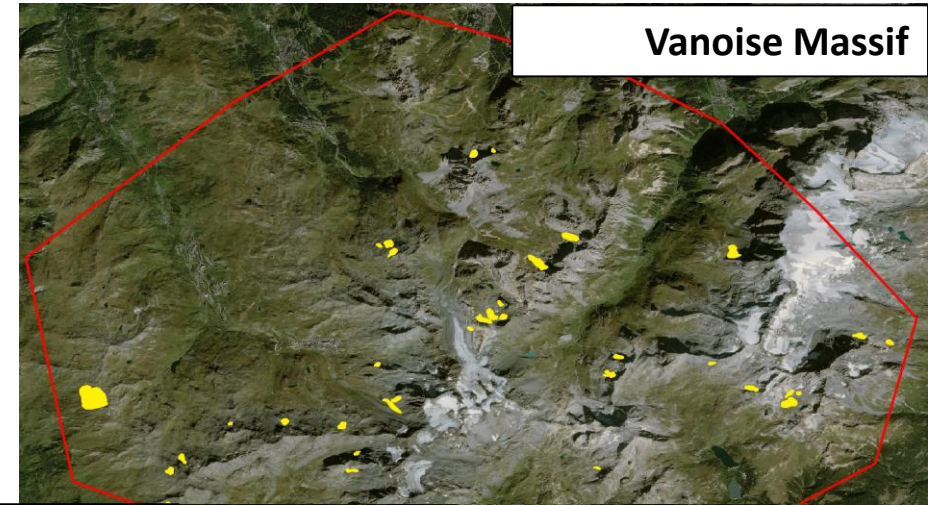
ISSLIDE Dataset

[Bralet et al, 2024]

Region of Interest

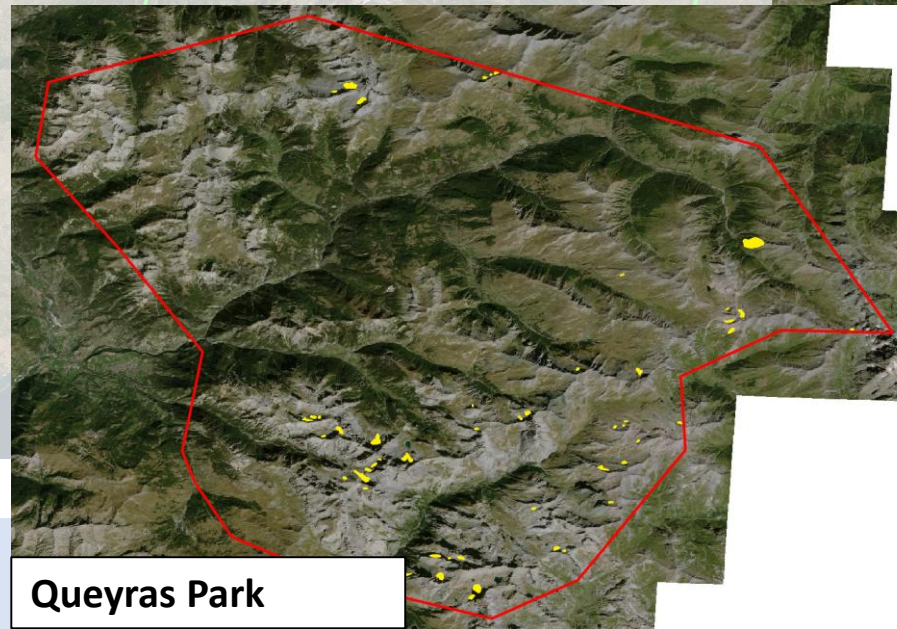


-  Interferogram extent
-  Regions of interest
-  Annotations with a 6-days temporal baseline



Vanoise Massif

Écrin Park



Queyras Park

ISSSLIDE Dataset *[Bralet et al, 2024]*

- 19 Sentinel-1 images from July to October 2018

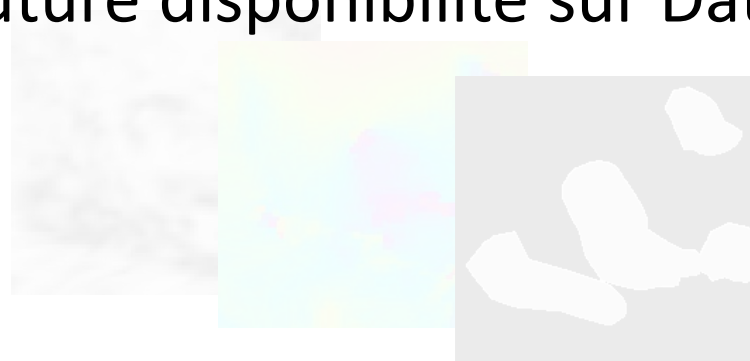
ACTUALISATION EN COURS !

Stage Aurore Benoit

- Données de 2025
- Vérification de la persistance des mouvements
- Future disponibilité sur Data Terra



6-day temporal baseline



12-day temporal baseline

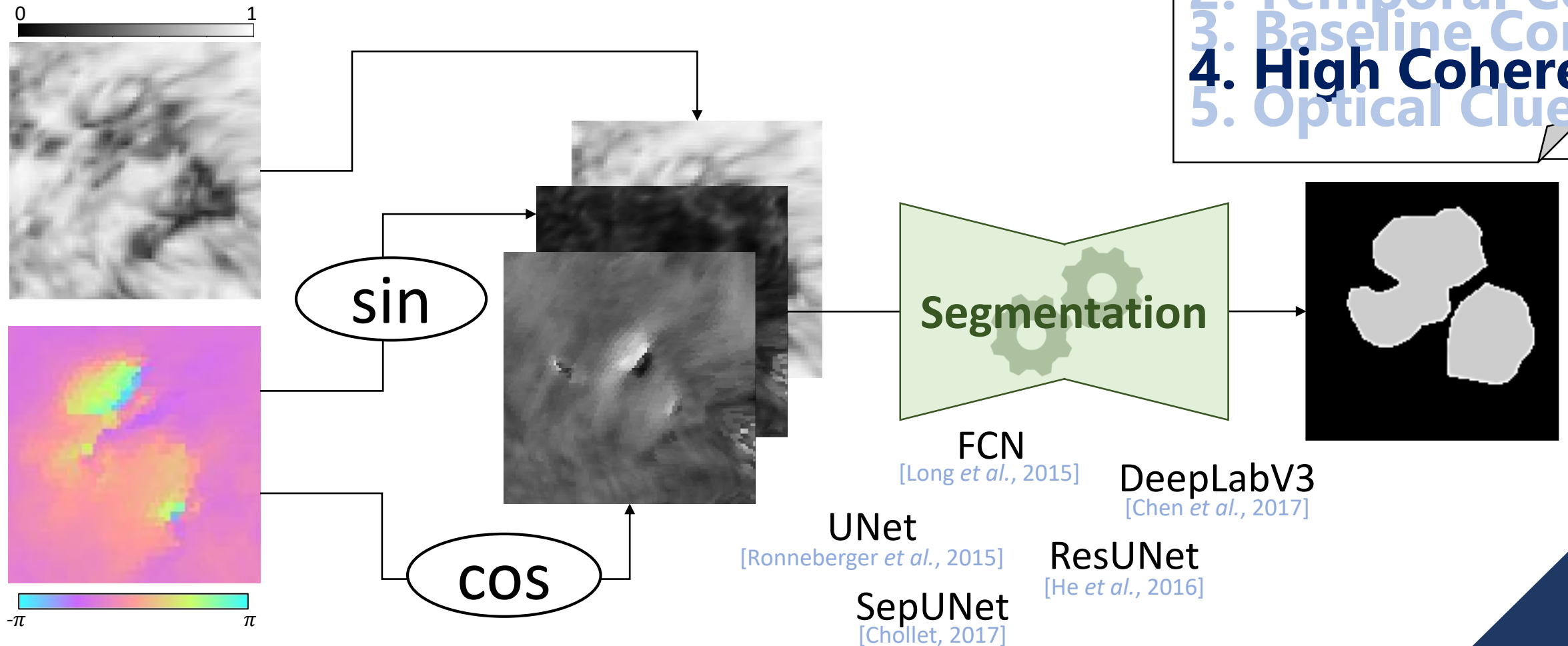


18-day temporal baseline

Interferogram Segmentation

[Bralet et al, 2024]

Training on ISSLIDE



1. Bubbles or Fringe
2. Temporal Cont
3. Baseline Consis
4. High Coherenc
5. Optical Clues

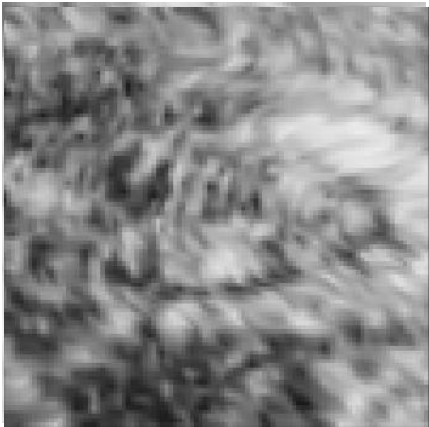
Quantitative Performance

Optimal Threshold

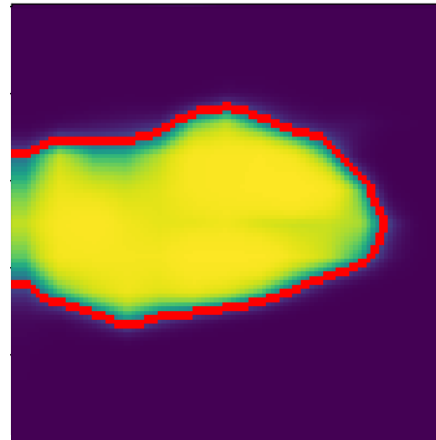
	F1-S $\uparrow$	AUC $\uparrow$	Dice $\uparrow$	IoU $\uparrow$	HD $\downarrow$
FCN _{Scratch} [Long <i>et al.</i> , 2015]	0.690	0.980	0.645	0.503	21.695
FCN _{Pre-trained} [Long <i>et al.</i> , 2015]	0.677	0.976	0.628	0.486	22.951
DeepLabV3 _{Scratch} [Chen <i>et al.</i> , 2017]	0.673	0.978	0.630	0.486	<u>22.352</u>
DeepLabV3 _{Pre-trained} [Chen <i>et al.</i> , 2017]	0.666	0.976	0.620	0.480	22.887
UNet [Ronneberger <i>et al.</i> , 2015]	0.675	0.977	0.636	0.497	25.912
ResUNet [He <i>et al.</i> , 2016]	<u>0.681</u>	<u>0.979</u>	<u>0.639</u>	<u>0.500</u>	25.921
SepUNet [Chollet, 2017]	0.651	0.972	0.606	0.466	28.026

Qualitative Performance

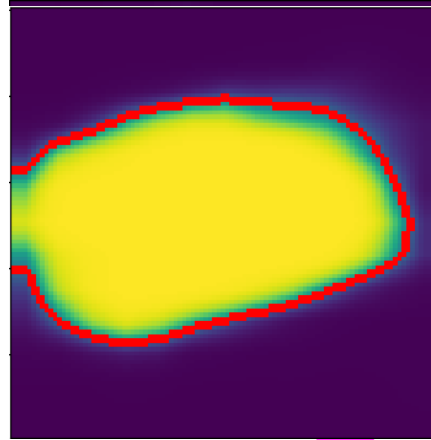
Coherence



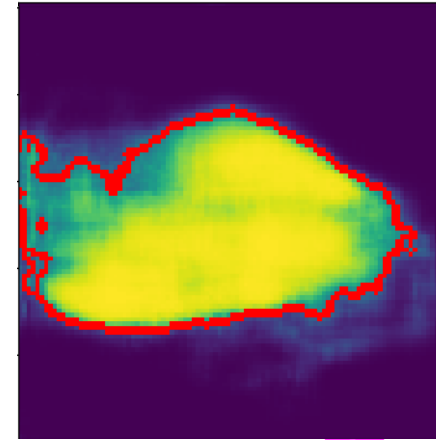
FCN_{Scratch}
[Long *et al.*, 2015]



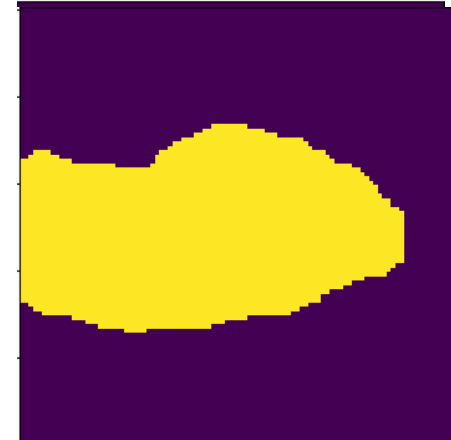
DeepLabV3_{Scratch}
[Chen *et al.*, 2017]



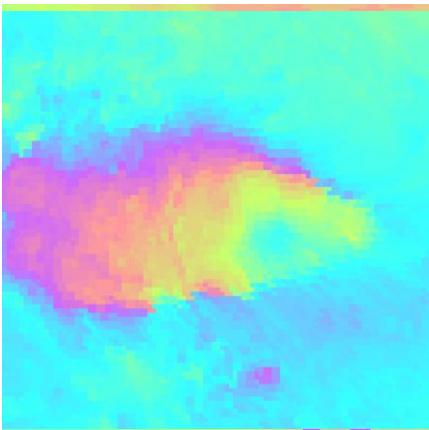
ResUNet
[He *et al.*, 2016]



Ground truth



Phase difference



Key Takeaways

Outcomes:

- Standard networks succeed to process interferograms and identify slow moving instabilities
- Coherence map seems to be correctly interpreted... is it ?

Remaining issues:

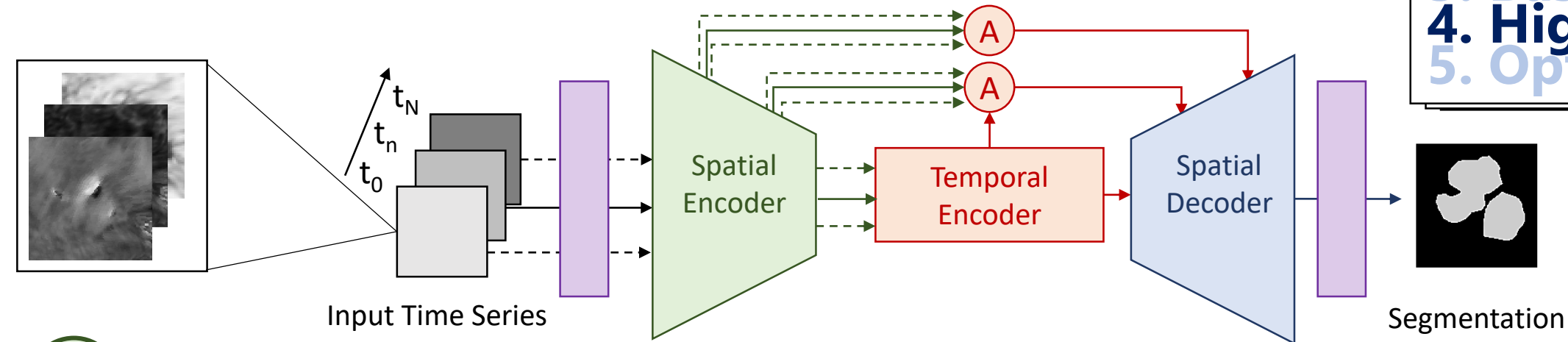
- Great margin for improvements
- Does not follow all geomorphological guidelines

Interferogram Time Series Segmentation

[Bralet et al, 2025]

Standard UTAE *[Garnot et al, 2021]*

1. Bubbles or Fringe
2. Temporal Continuity
3. Baseline Consistency
4. High Coherence
5. Optical Clues



1 Spatial encoding of each time step **independently** with convolutional blocks

2 Temporal encoding with a **L-TAE** *[Garnot et al., 2020]* and use attention maps to fuse intermediate features

3 Decode the latent features to generate a **segmentation** map

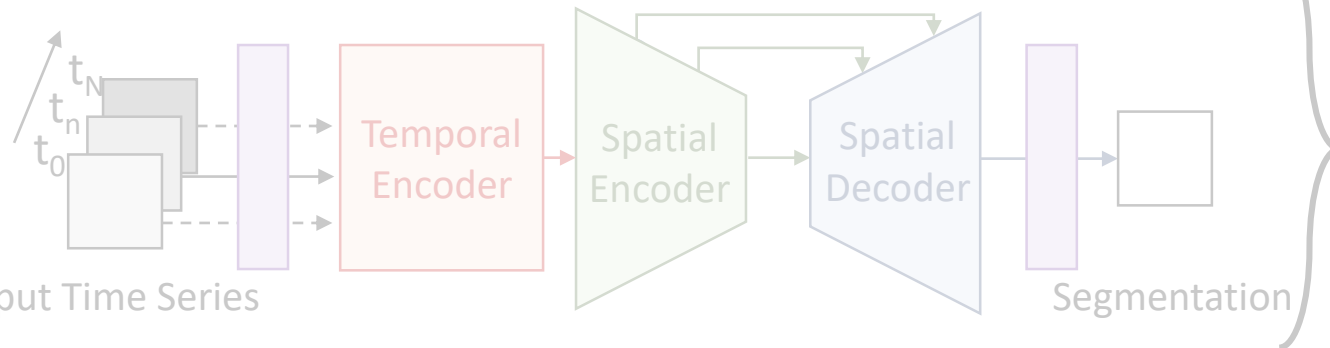
[Garnot et al, 2021] GARNOT, Vivien Sainte Fare and LANDRIEU, Loic. Panoptic segmentation of satellite image time series with convolutional temporal attention networks.

In : *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2021. p. 4872-4881.

[Garnot et al, 2020] GARNOT, Vivien Sainte Fare et LANDRIEU, Loic. Lightweight temporal self-attention for classifying satellite images time series. In : *International Workshop on Advanced Analytics and Learning on Temporal Data*. Cham : Springer International Publishing, 2020. p. 171-181.

Exploiting Temporality

UTAE_{pre}



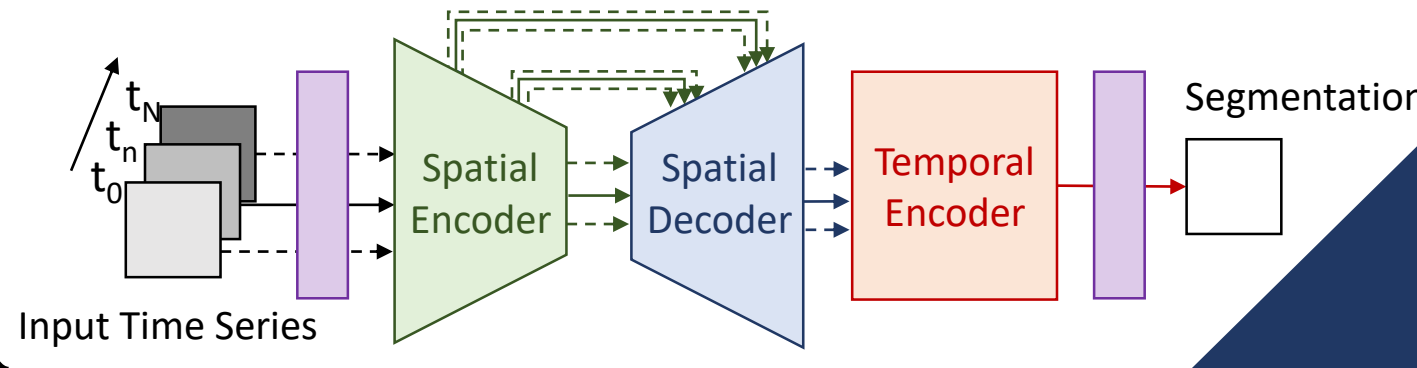
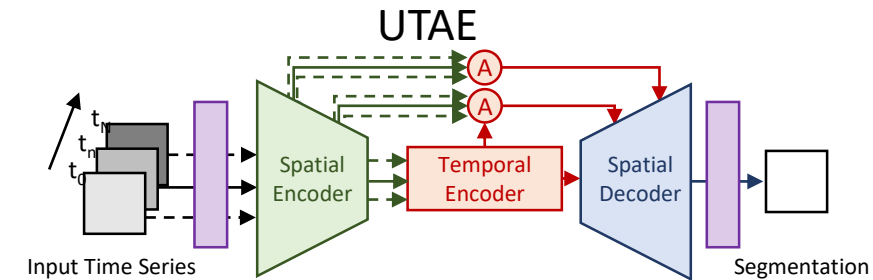
Temporal Encoding prior to Spatial Encoding

- Extract suspicious temporal patterns
- Verify spatial consistency

Spatial Encoding prior to Temporal Encoding

- Extract suspicious spatial patterns (independent)
- Verify temporal consistency

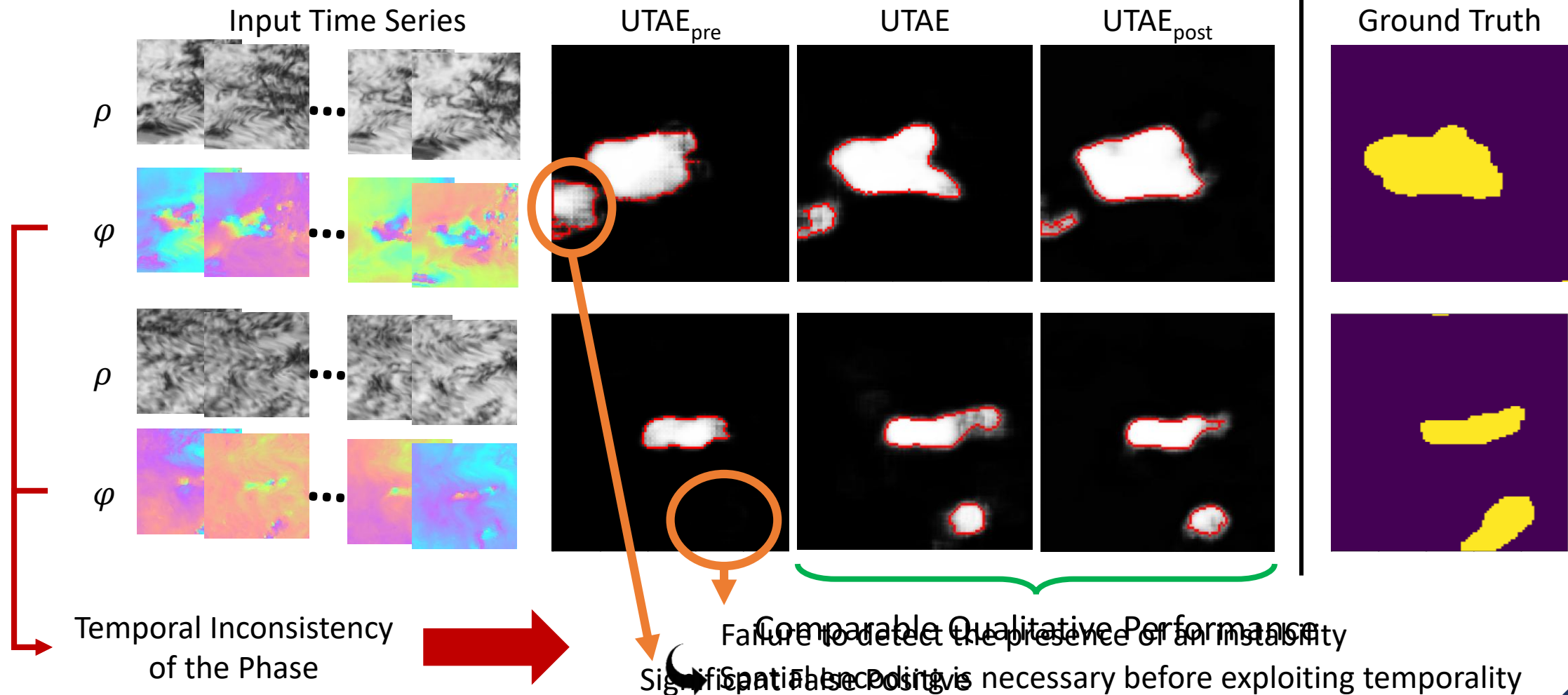
UTAE_{post}



Quantitative Results

	F1-Score	Dice	IoU	HD
<i>Mono-Interferogram Networks</i>				
FCN	0.690	0.645	0.503	<u>21.70</u>
DeepLabv3	0.673	0.630	0.486	22.35
ResUNet	0.681	0.639	0.500	25.92
<i>Interferogram Time Series Networks</i>				
U-TAE	<u>0.738</u>	<u>0.702</u>	<u>0.562</u>	21.94
U-TAE _{pre}	0.693	0.652	0.506	24.58
U-TAE _{post}	0.747	0.713	0.575	20.85

Qualitative Results



Key Takeaways

Outcomes:

- Including the temporality significantly improves performance
- Processing spatial first better follow geomorphological routine

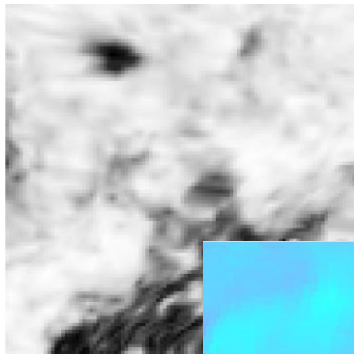
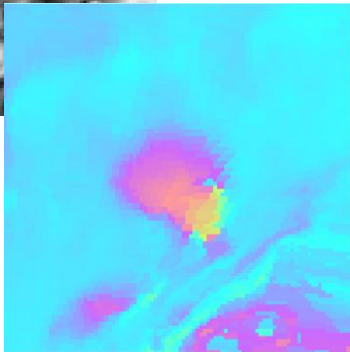
Remaining issues:

- Still a margin of improvement and possibility to reduce false detection
- Closer to geomorphological routine but still missing optical clues
- What helped the network to take the decision? Which time step is the most relevant? Why ?

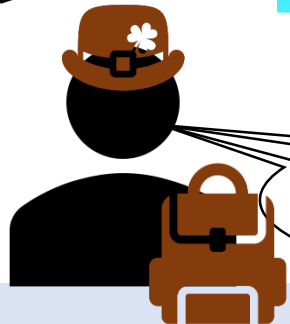
Explainable Detections

[Bralet et al, 2025]

Explainability



Bob



Stop

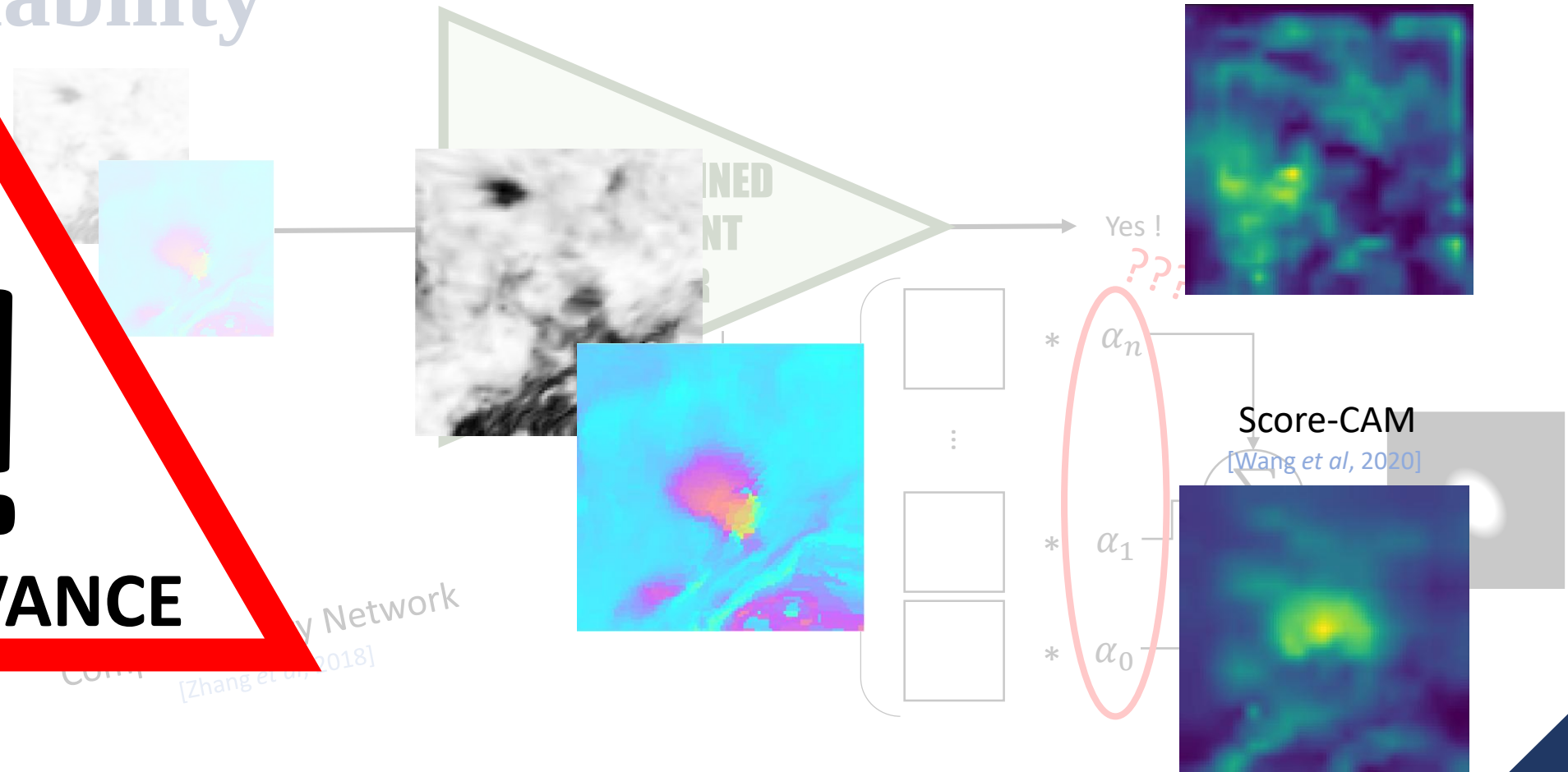
Why ?

```
bob@bobnet:~/BobNet/$
```

```
bob@bobnet:~/BobNet/$ vim BobNetExplain.txt
```

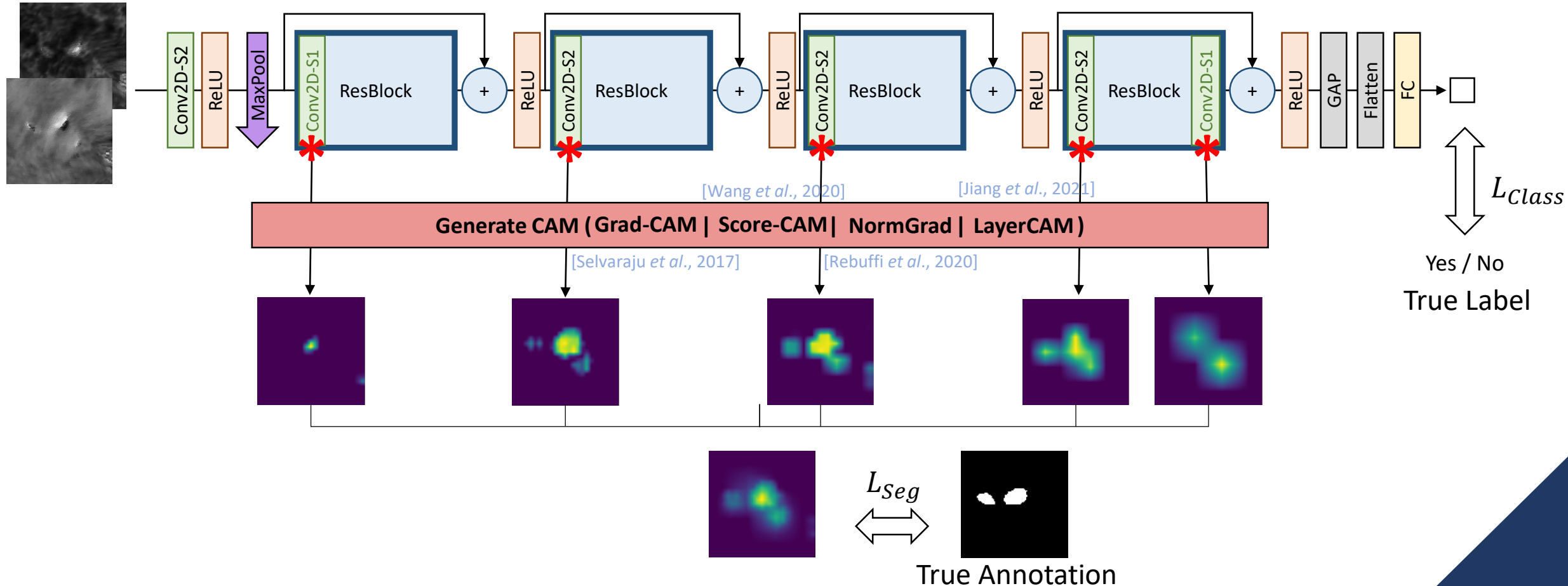
```
The third kernel of the second layer gets an  
activation of 1.705,  
The second kernel of the fifth layer of the second  
branch gets an activation of 2.803,  
Combined with the fact that the first pixel of the  
twentieth row of the image is colored in blue but  
less than the eighth pixel of the fifty-third row,  
...  
...  
...  
It is obvious that there is an instability right  
here !
```

RELEVANCE



Class Activation Maps (CAM)

ECSPLAIN [Bralet et al., 2025]



[Bralet et al., 2025] Bralet, A., Atto, A. M., Chanussot, J., & Trouvé, E. (2025). ECSPLAIN: Explainability Constrained-claSsifier for Pairing the detection and the Localization of moving Areas from SAR INTERferograms. *IEEE Transactions on Geoscience and Remote Sensing*.

[Wang et al., 2020] Wang, B., Gao, M., Yang, D., Zhang, J., & Zhang, J. (2020). Score-CAM: Score Maps as Localization for Deep Neural Networks. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 1303–1313. <https://arxiv.org/abs/2007.02265>.

Quantitative Classification Performance

	Accuracy	Precision	Recall	F1-Score
Trained without the ECSPLAIN framework				
	94,67%	92,43%	92,27%	0,923
Trained with the ECSPLAIN framework				
Grad-CAM <i>[Selvaraju et al., 2017]</i>	95,04%	92,66%	93,15%	0,929
Layer-CAM <i>[Jiang et al., 2021]</i>	94,00%	94,02%	88,40%	0,911
NormGrad <i>[Rebuffi et al., 2020]</i>	95,89%	95,63%	92,44%	0,940
ScoreCAM <i>[Wang et al., 2020]</i>	95,71%	94,47%	93,16%	0,938

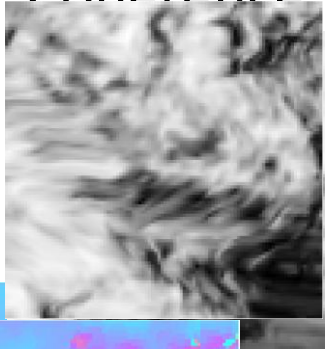
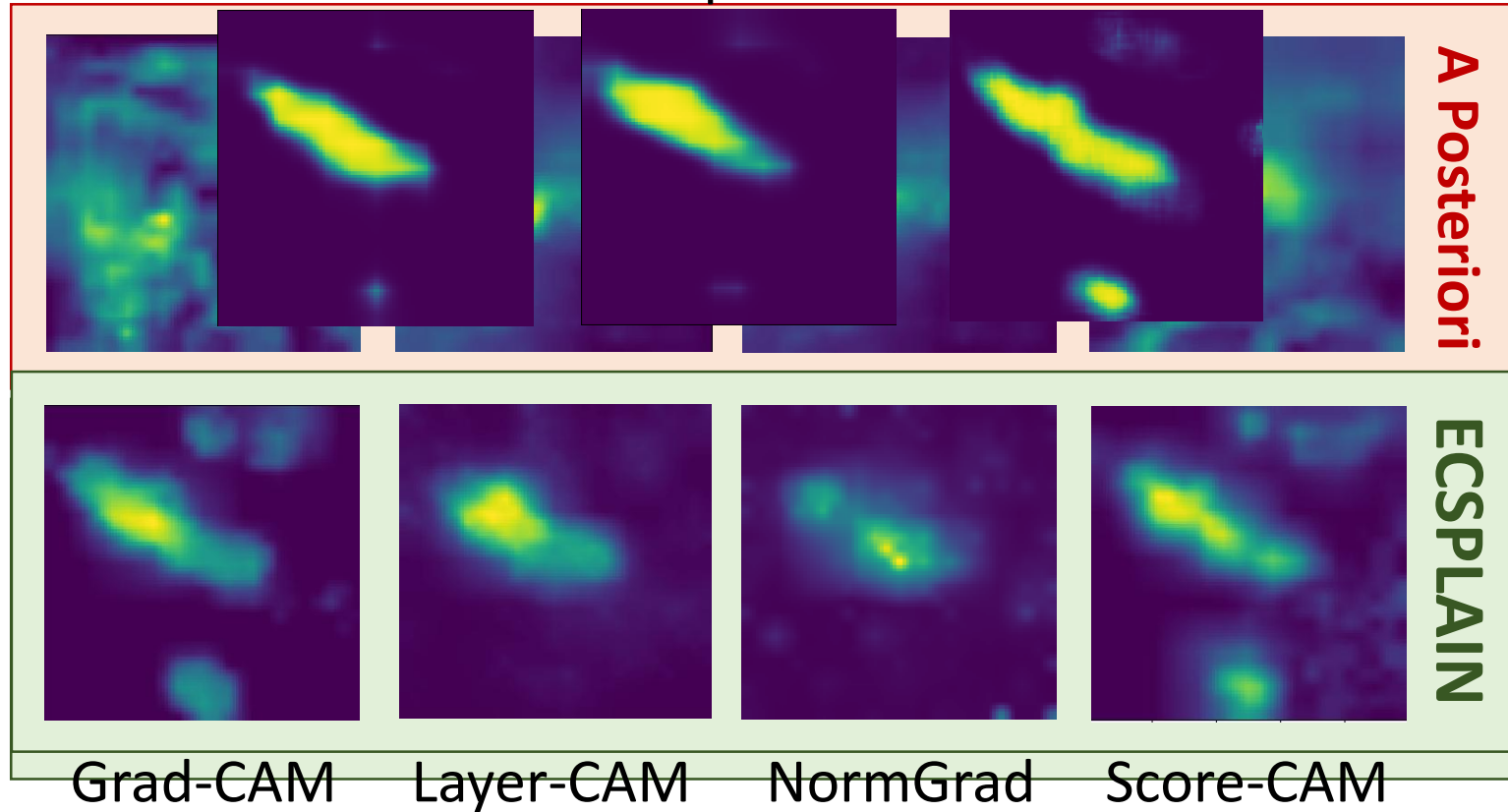
Quantitative Segmentation Performance

	MAE	Dice	mIoU	HD	AUC
	MAE	Dice	mIoU	HD	AUC
Grad-CAM [Selvaraju et al., 2017]	13,74E-02	0,161	0,093	58,01	0,524
Layer-CAM [Long et al., 2015], [2021]	01,36E-02	0,661	0,523	25,52	0,953
DeepGrad [Rebuffi et al., 2020]	01,64E-02	0,622	0,480	36,62	0,955
ScoreCAM [Wang et al., 2020]	01,43E-02	0,684	0,547	25,69	0,964
Trained with the ECSPLAIN framework					
Grad-CAM [Selvaraju et al., 2017]	03,35E-02	0,637	0,504	25,54	0,949
Layer-CAM [Jiang et al., 2021]	04,72E-02	0,570	0,435	26,45	0,920
NormGrad [Rebuffi et al., 2020]	04,73E-02	0,575	0,439	25,98	0,923
ScoreCAM [Wang et al., 2020]	05,92E-02	0,643	0,500	24,08	0,959

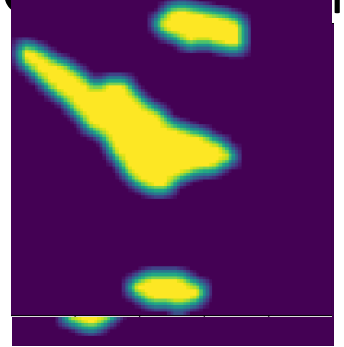
Qualitative Performance

Grad-CAM FCN Layer-CAM DeepLabV3 NormGrad ResUNet Score-CAM

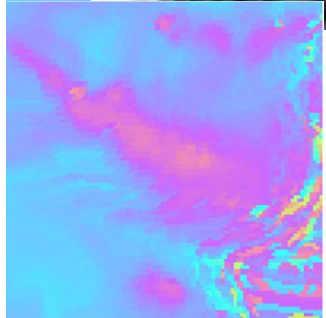
Coherence



Ground truth



Phase Difference
Phase Difference



Key Takeaways

Outcomes:

- Constraining network's explainability improves classification performance
- Segmenting from classification is feasible, lighter, faster and as accurate as standard segmentation networks
- The ECSPLAIN framework detected >800 susceptible instabilities

Remaining issues:

- Are we sure to capture the most accurate features?
- Can we partially guide the network?



What's more?

Future Works

PIPAM

*Knowledge Preserving for SAR-Optical
Modality Alignment*



Baptiste Lafabrègue

APPALOOSA

*Representation Learning Guided
by Statistical A Priori for SAR Image Analysis*



LISTIC



CDR

Groupement
de recherche

IASIS Information Apprentissage
Signal Image viSion

Matthieu Gallet, Yassine Mhri

ANR DECOL

*Domain Adaptation for Crop Type
Classification from Satellite Image Time Series*



UMR

IRISA

Charlotte Pelletier

Thank you for your attention

Antoine BRALET (abralet@unistra.fr)

Atelier Télédec@USMB 2026 – 23/06/2026



References

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Introduction

How to Detect?

ISSSLIDE

Raw Segmentation

Temporal
Segmentation

ECSPLAIN

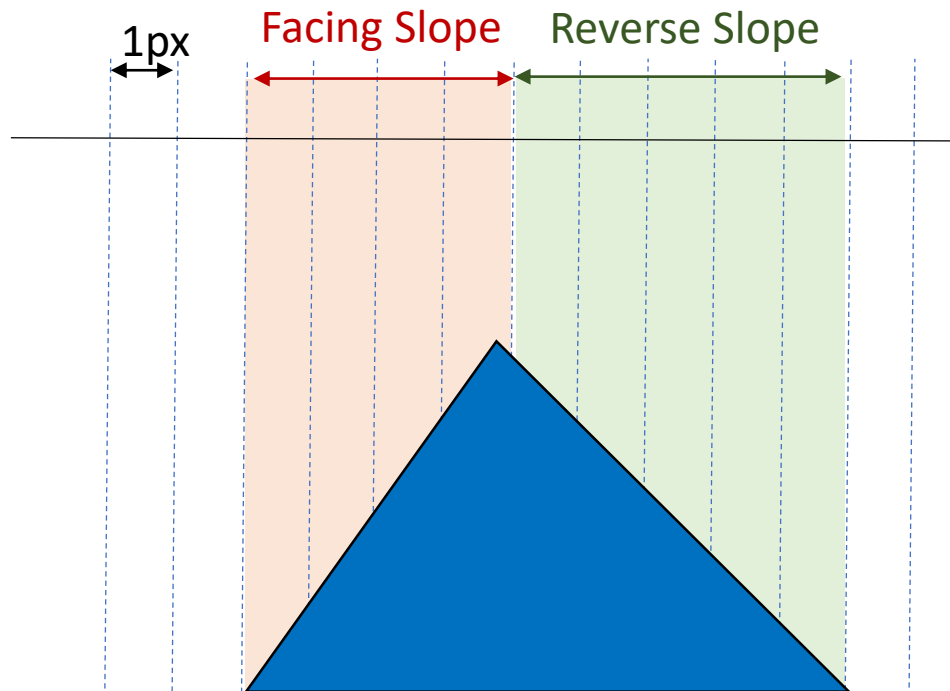
Perspectives



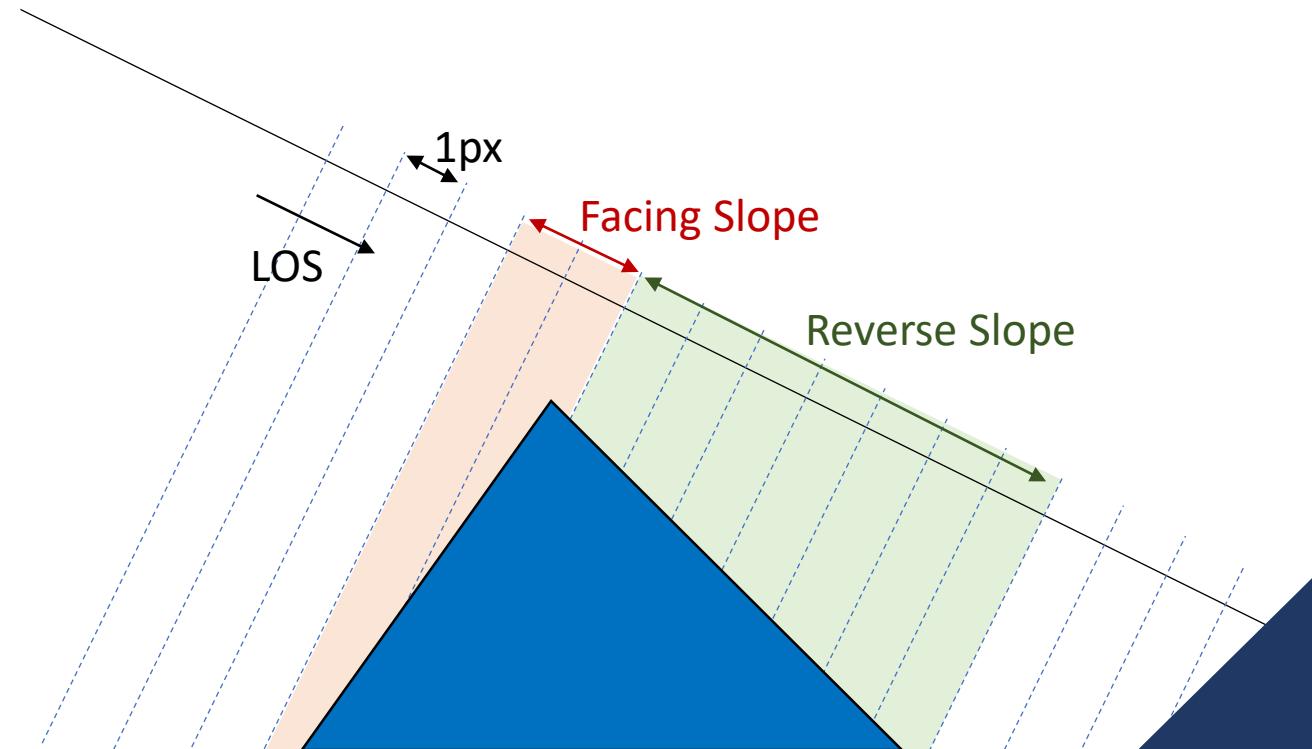
Backslides

Geometrical Distortions

Ground geometry

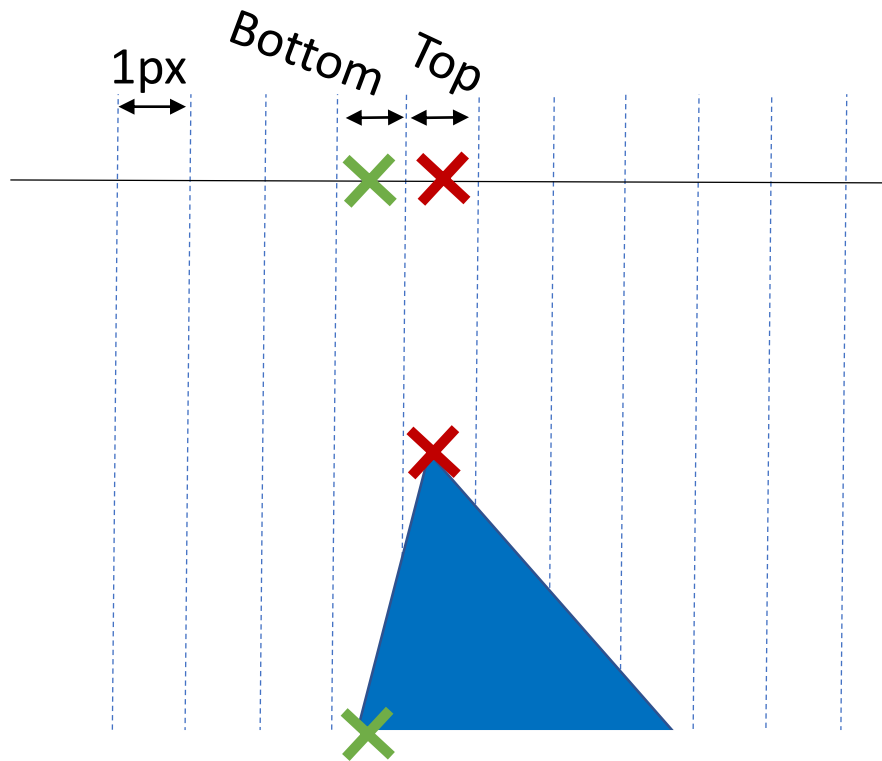


Radar geometry

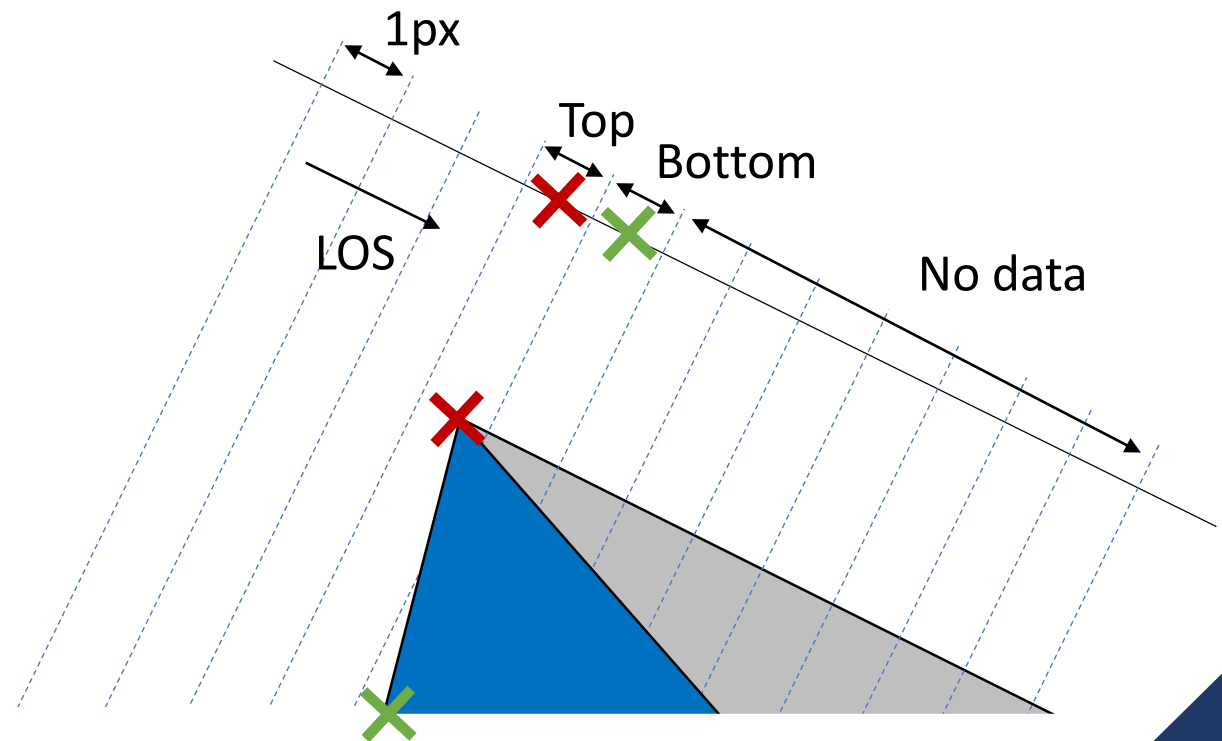


Geometrical Distortions

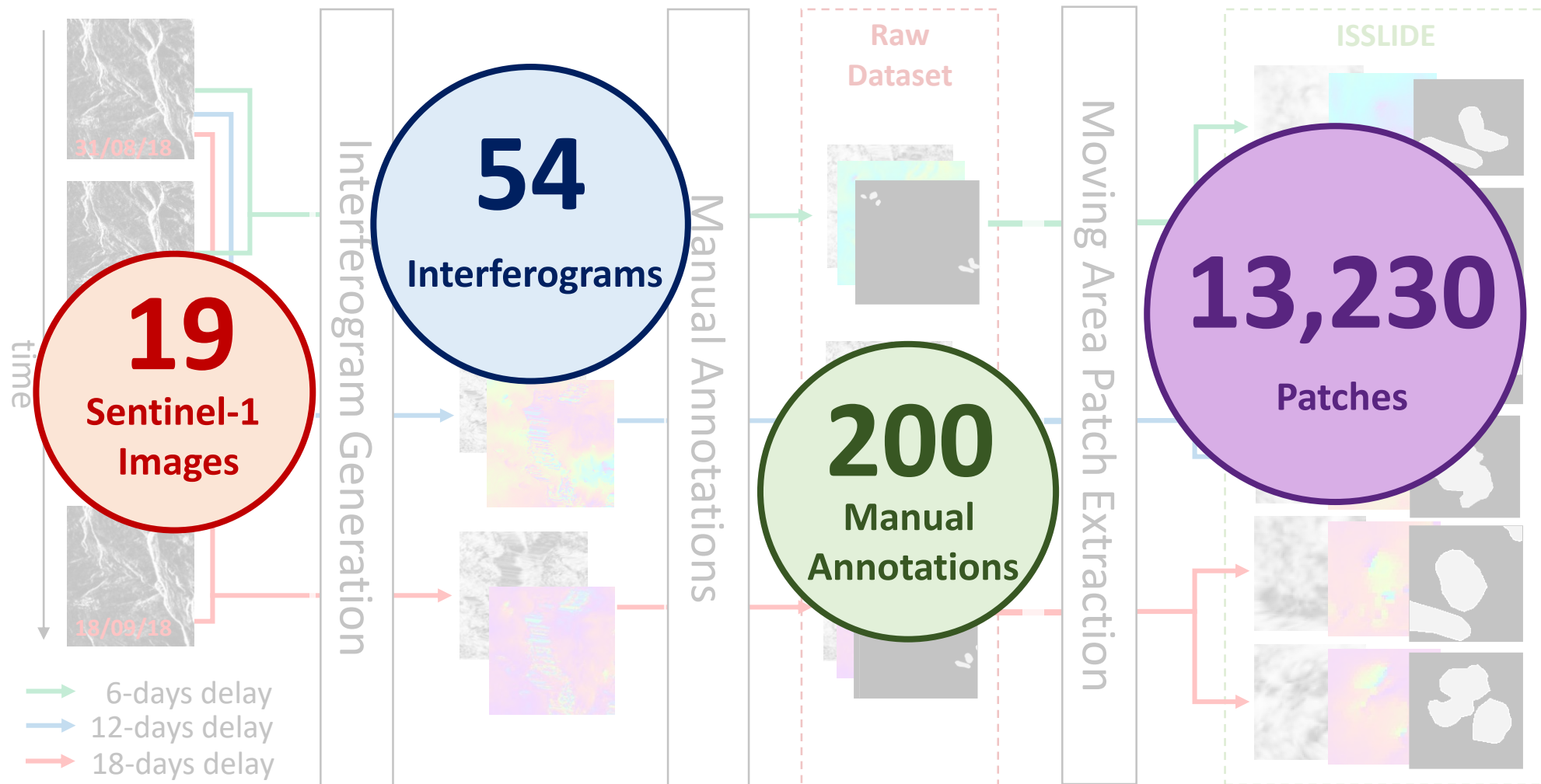
Ground geometry



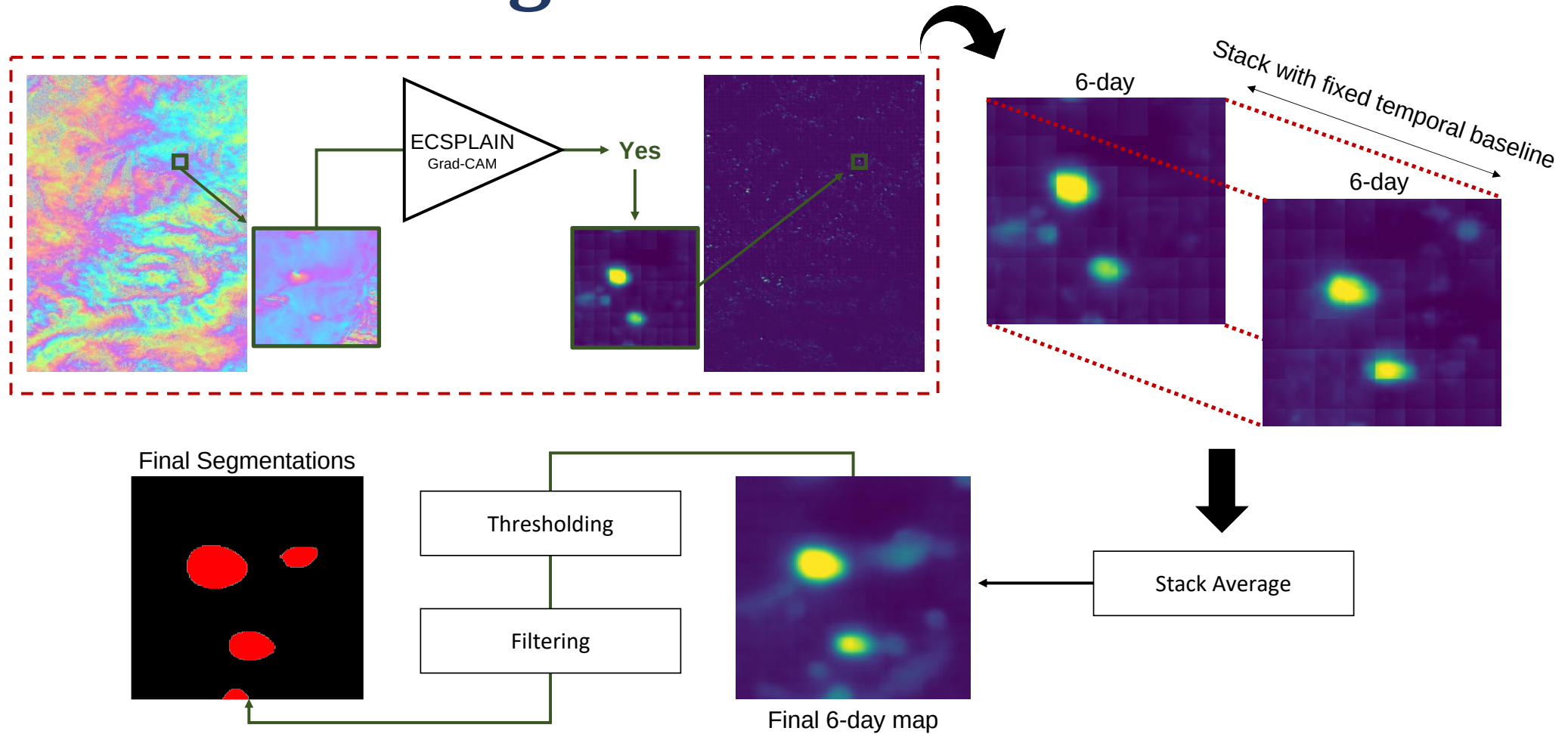
Radar geometry



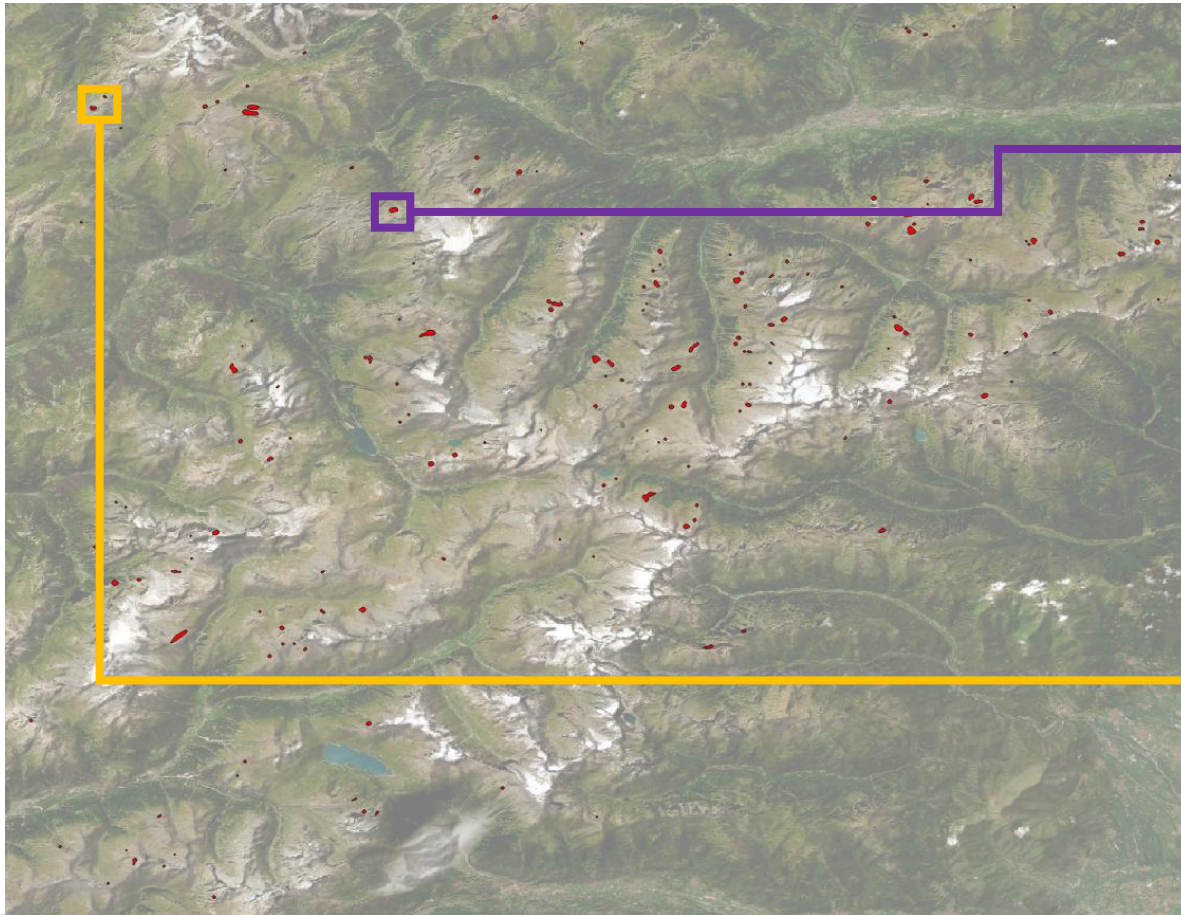
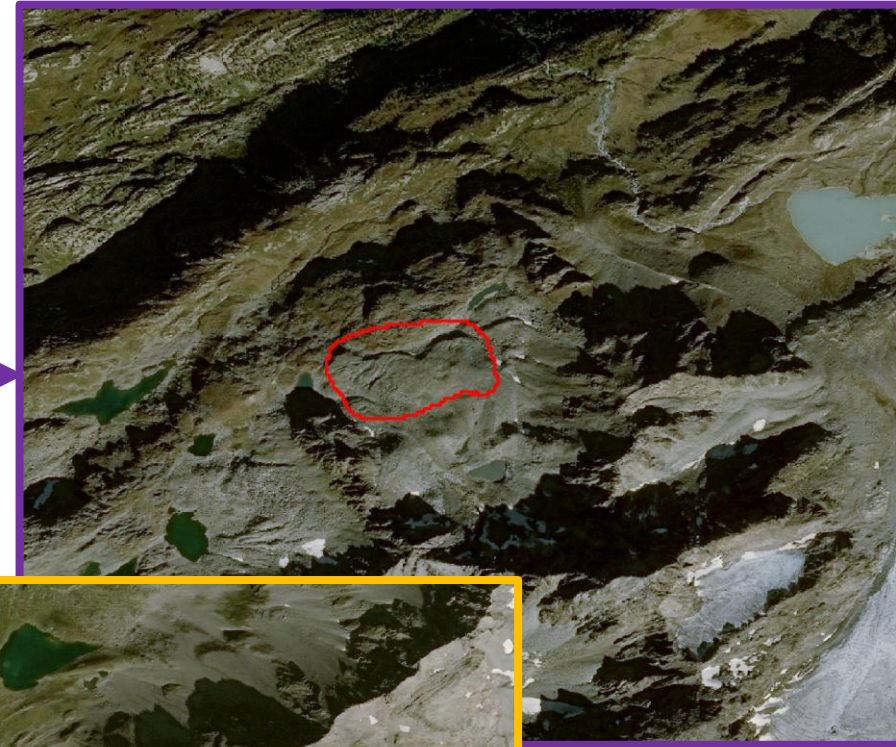
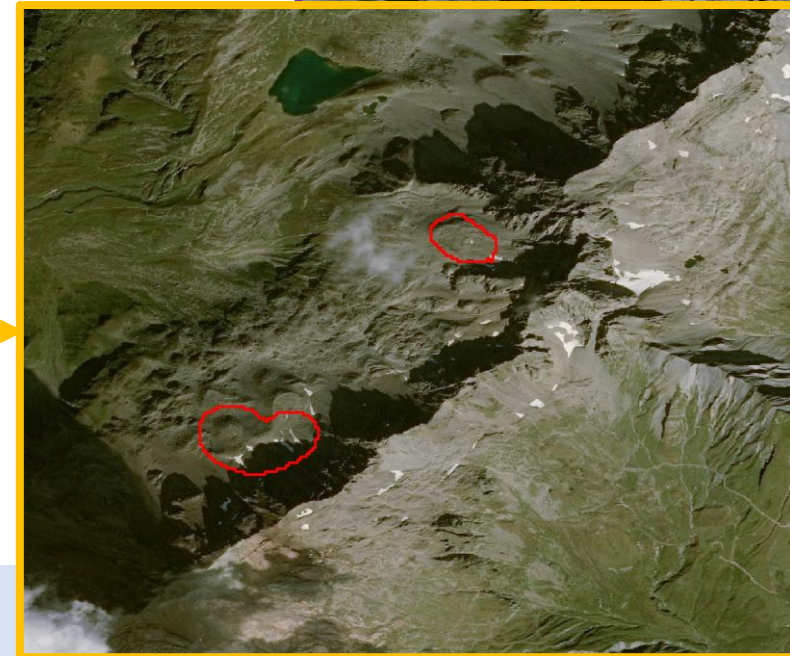
ISSSLIDE Dataset



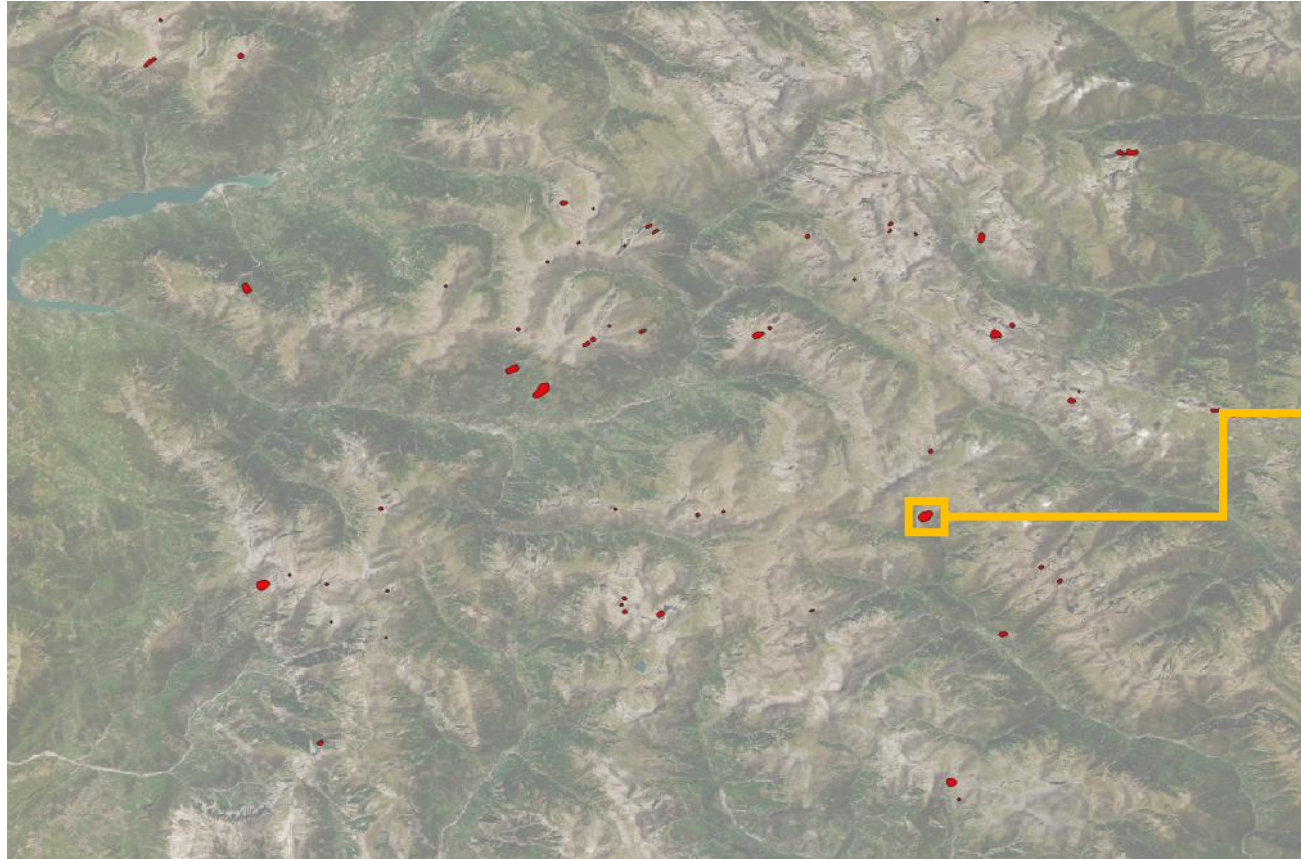
ECSPPLAINing ISSSLIDE



ECSPPLAINing ISSLIDE



ECSPPLAINing ISSLIDE



ECSPPLAINing ISSLIDE Data

	Number of Detections			
Area ($\times 1,000\text{m}^2$)	[10,50]	[50,100]	100 <	Total
6 days	308	118	89	515
12 days	282	121	92	495
18 days	252	96	82	430

178
Common polygons

Hi everyone

● PhD Thesis (oct 2021- oct 2024)

Université Savoie Mont-Blanc, LISTIC

Spécialité STIC, Traitement de l'Information

- ↳ Multimodality
- ↳ Bi-temporality
- ↳ Explainability
- ↳ Remote Sensing



Abdourrahmane Atto, Emmanuel Trouvé
Jocelyn Chanussot

● Post-Doc (dec 2024 - aug 2025)

Université Bretagne Sud, IRISA, Vannes

- ↳ Time Series
- ↳ Domain Adaptation
- ↳ Remote Sensing



Charlotte Pelletier

● Associate Professor CNU 27 (intern) (sept 2025 - now)

Université de Strasbourg, ICube, Strasbourg

- ↳ Representation Learning
- ↳ Domain Adaptation
- ↳ Modality Alignment
- ↳ Biomedical
- ↳ Remote Sensing



Étienne Baudrier, Hassen Drira

