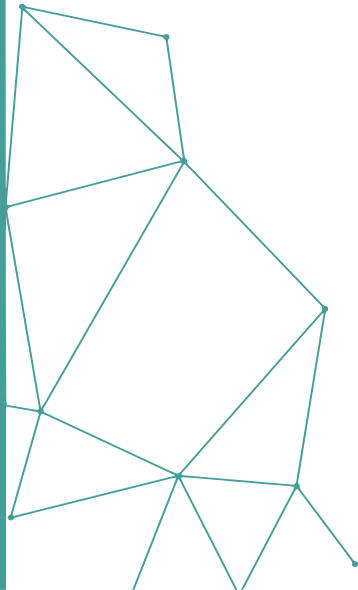




CPAZMaL: Cryosphere Analysis with PAZ Images for Machine Learning

A Comprehensive Benchmark Dataset

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TELEDEC 2026

June 22, 2026



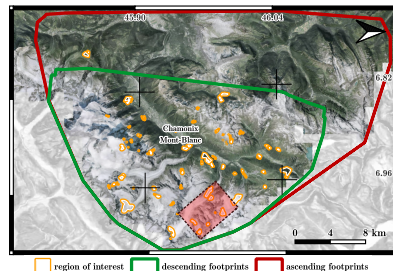
Outline

- ➊ Context & Positioning
- ➋ The CPAZMaL Dataset
- ➌ Statistical & Temporal Analysis
- ➍ ML Benchmarks
- ➎ Conclusion

Mont-Blanc Massif: Why Monitor?

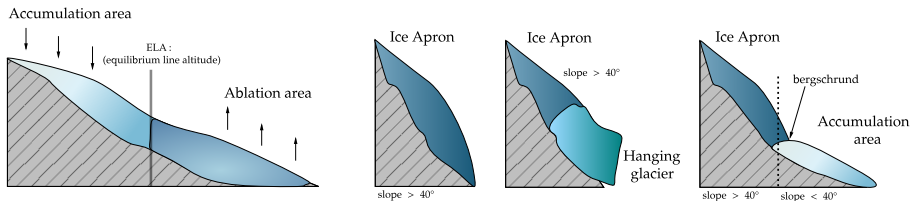
Study area

- 550 km², 28 peaks > 4000 m; 145 km² of glaciers
- Key climate indicator; rapidly retreating
- Steep terrain: field monitoring limited
- High elevation range: strong microclimatic variability
- Diverse glacier surface types: clean ice, debris-covered, ablation and accumulation zones ...



ASC/DSC orbit footprints over MBM.

Focus: Four Glacier Surface Types



ACC/ABL on Argentière glacier; ICA/HAG on SE face of Mont-Blanc.

ABL — Ablation zone

Below ELA: net ice loss, exposed glacier ice.

ICA — Ice apron

<0.009 km², slopes 40–65°, quasi-stagnant.

ACC — Accumulation zone

Above ELA: net mass gain, permanent snow/firn.

HAG — Hanging glacier

Steep faces, serac detachment risk, sparse training data.

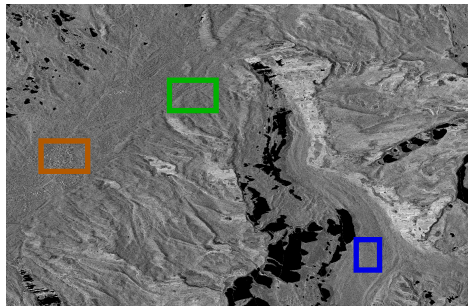
Context: Synthetic Aperture Radar Satellite

Synthetic Aperture RADAR (SAR)

- Active sensor
- All-weather, day and night
- Complex labelling
- Geometric distortions + high clutter
- Multiplicative noise

PAZ satellite (2018)

- X-band 9.65 GHz, ~ 3 m, ~ 11 -day revisit
- Dual-pol HH/HV; ASC & DSC orbits



PAZ X-band (10 Jan 2020); colored boxes mark land cover areas (urban, forest, glacier).

Challenges of mapping with SAR in Alpine Terrain

Geometric distortions

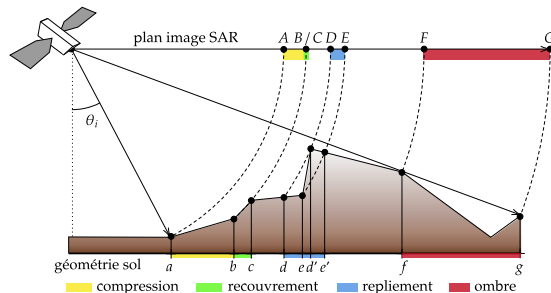
- Layover, shadow, foreshortening on steep slopes
- Sentinel-1 (10–20 m) misses small features

Backscatter ambiguity

- ICA/ACC: similar signatures, spatially adjacent
- Seasonal melt $\Rightarrow$ strong summer signal drop

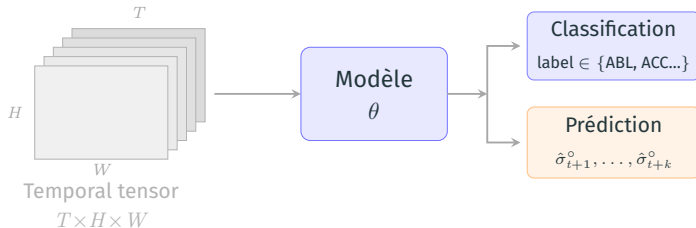
Under-studied types

- ICA: $<0.009 \text{ km}^2$, slopes 40–65°, quasi-stagnant
- HAG: steep faces, serac risk — rarely in datasets



Geometric distortions in SAR imagery.

From Data to Models: The Machine Learning Loop



Pour résoudre un problème spécifique, il faut de **bonnes données adaptées**.

Existing Datasets: A Gap in Alpine SAR Coverage

Dataset	Sensor (Res.)	Acq./yr	Glacier sub-types	Alps
BigEarthNet v2.0	S1+S2 (10 m)	~60	×	~
SEN12MS-CR-TS	S1+S2 (10 m)	~30	×	~
Glacier CCI	S2 (20 m)	static	~	✓
HabitatAlp2.0	Aerial (0.2 m)	3 dates	×	✓
SAR2Height [†]	TSX X-band (1 m)	1–7	×	×
ORION	S2 (20 m)	static	~	✓
CPAZMaL	PAZ X (3 m)	~21	✓	✓

[†] Not open access; designed for height estimation.

Gap: no dataset combines <5 m + dense annual TS + glacier sub-type labels over the Alps.

CPAZMaL: Key Contributions

A dedicated **spatio-temporal** dataset for **machine learning** on various land cover types including **specific glacier surface areas** in the Mont-Blanc Massif.

Dataset

- 182 PAZ images (Jan 2020 – Dec 2022)
- ~11-day revisit; HH/HV + HH single-pol
- Ascending & descending orbits
- 8 classes incl. rare ICA & HAG

ML-ready organisation

- HDF5 hierarchy: Area / Orbit / Pol / Data
- ~9 spatial groups/class for unbiased CV

⇒ **Open access:** HuggingFace + GitHub

4 benchmark scenarios

- **S1:** Spatio-temporal classification
- **S2:** Temporal forecasting
- **S3:** Polarimetric domain adaptation
- **S4:** Orbit/resolution domain adaptation

Outline

1 Context & Positioning

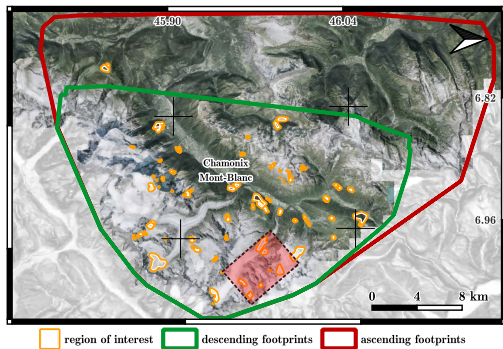
2 The CPAZMaL Dataset

3 Statistical & Temporal Analysis

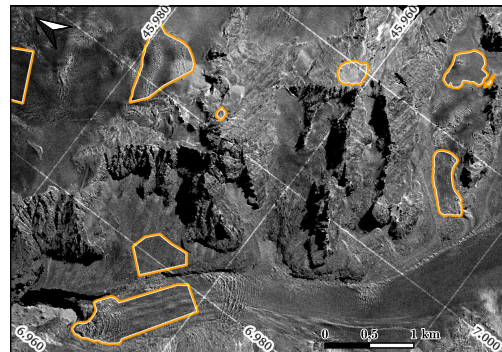
4 ML Benchmarks

5 Conclusion

Study Area: Mont-Blanc Massif



ASC (red) & DSC (green) footprints;
ROI on Mont-Blanc (4810 m a.s.l.).



Zoom: Argentière glacier.
Temporal average of PAZ 2020.

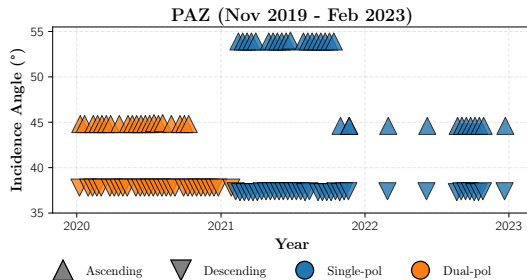
Terrain Classes: 8 Classes in 3 Categories

Category	Class (Acr.)	Groups	Alt. (m)	Slope (°)
<i>Glacial</i>	Ablation (ABL)	7	2577±206	17.1±5.2
	Accumulation (ACC)	9	3077±402	26.1±10.2
	Hanging Glacier (HAG)	7	3203±184	47.2±8.5
	Ice Apron (ICA)	9	3353±295	43.5±12.0
<i>Natural</i>	Forest (FOR)	9	1436±194	24.4±9.3
	Vegetation/Shrubs (PLA)	9	1834±296	18.9±7.5
	Rock / Bare soil (ROC)	9	2333±206	26.6±5.5
	Lake (LAC)	9	1865±616	8.5±6.2

Expert-delineated from Pléiades, BD Ortho & LiDAR (end-of-summer). Valid fraction ~50% post-masking.
2 hold-out polygons per class reserved for final evaluation (not in K-fold CV).

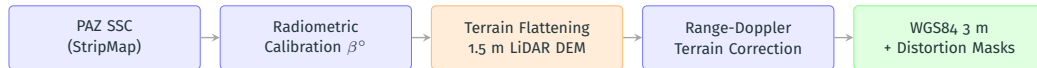
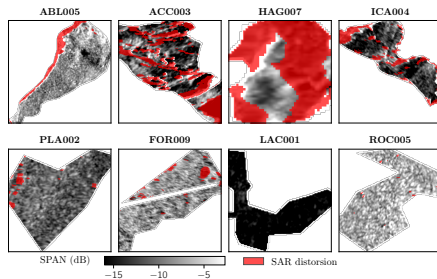
SAR Acquisitions: PAZ X-band 2020–2022

182 images (Jan 2020–Dec 2022), ~11-day revisit, X-band (9.65 GHz), StripMap.



Config.	Orbit	Résolution (R×A)	Superficie
Dual HH/HV	Descending	2.9×6.6 m	~980 km ²
	Ascending	1.7×6.6 m	
Single HH	Descending	2.9×3.3 m	~1600 km ²
	Ascending	2.2×3.3 m	

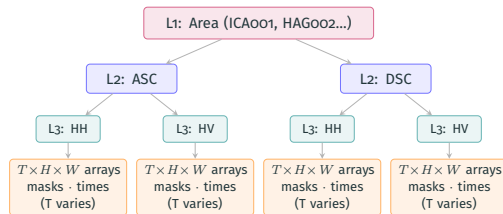
SNAP Processing Chain



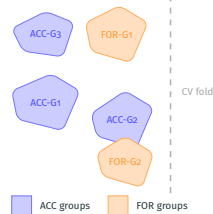
Processed PAZ images, summer 2020 (temporal avg., 4 acq.). Mask: 0=valid, 1=layover, 2=shadow.

Dataset Organisation: HDF5 & Group Sampling

⇒ **HDF5 hierarchy:** Area / Orbit / Pol. / Arrays — **group K-fold** prevents spatial leakage.



Group-based K-fold sampling

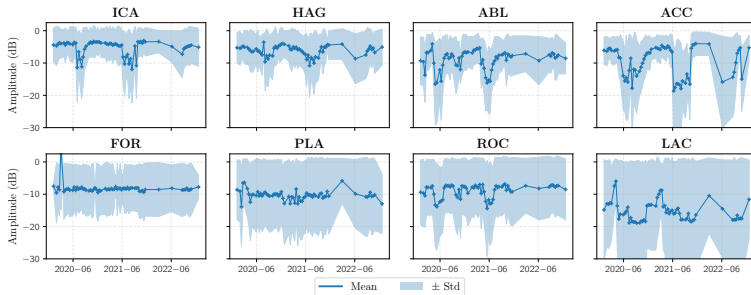


- ~9 polygons/class — geographically separated
- Groups stay in same fold (no leakage)
- Python dataloader per scenario

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Temporal Analysis: Annual Backscatter Trends (DSC HH)

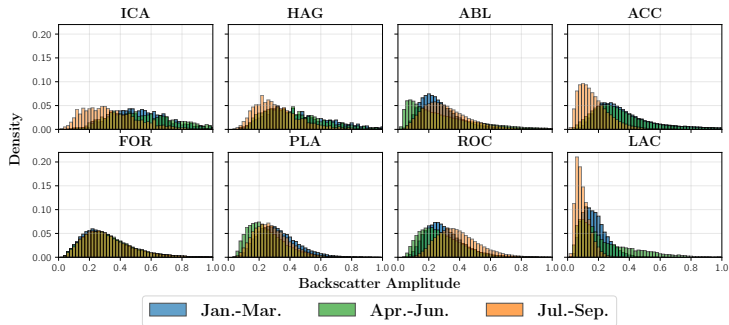


Mean backscatter (dB) $\pm$ std. per class, Jan 2020–Dec 2022.

- **Glacier classes:** summer drop (liquid water absorption)

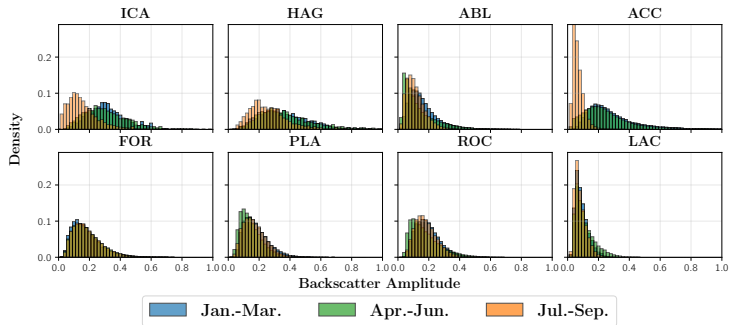
- **Non-glacial:** stable year-round (narrow std on glaciers)

Seasonal Histograms: HH vs HV Polarisation



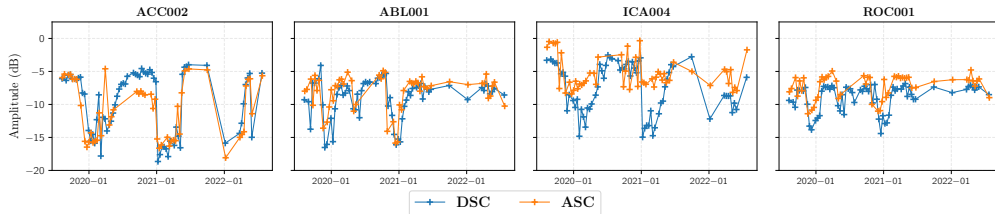
DSC HH — winter/spring/summer, 2020. • ICA/HAG/ACC: shift to lower σ° in summer (melt). ABL melts earlier (lower elevation).

Seasonal Histograms: HH vs HV Polarisation



DSC HV — same seasonal breakdown. • ICA/HAG/ACC: shift to lower σ° in summer (melt). ABL melts earlier (lower elevation). **HV more sensitive** to melt than HH.

Cross-Domain Variability: ASC vs DSC Orbits



HH backscatter: ASC vs DSC, 2020–2022. Differences from incidence angle, slope aspect, resolution.

- Same class, different orbit $\Rightarrow$ significant distributional gap.
- **Motivates Scenario S4:** orbit domain adaptation without full retraining.

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Four ML Scenarios: Overview

S1: Classification

ASC HH+HV, 21 acq. (2020)

MLP & CNN3D — 5-fold

S2: Forecasting

DSC HH, 44 train / 12 test

LSTM & CLSTM — 5-fold

S3: Polarimetric DA

DSC HH → DSC HV (Aug. 2020)

CNN + DeepCoral, DANN — 4-fold

S4: Orbit/Res. DA

DSC 6.6 m → ASC 3.3 m

CNN + DeepCoral, DANN — 4-fold

Evaluation protocol

- Patch: 8×8 pixels
- S1/S2: 5-fold group K-fold
- S3/S4: 4-fold group K-fold
- Geographic train/test split

DA toolbox

Skada (Gnassounou et al., 2024)

Metrics

Accuracy (%) for S1/S3/S4

RMSE (↓) for S2

S3/S4 classes: ACC, PLA, ROC, ABL, FOR

Model Architectures & Acronyms

Supervised models (S1/S2)

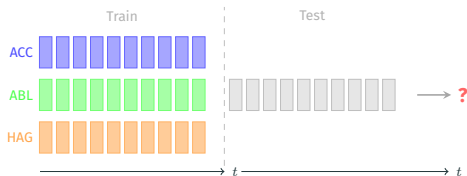
- MLP** Multi-Layer Perceptron — pixel baseline
- CNN3D** 3D Convolution — spatiotemporal patches
- LSTM** Long Short-Term Memory — sequential
- CLSTM** ConvLSTM — spatial + temporal memory

Domain adaptation (S3/S4)

- DeepCoral** 2nd-order covariance alignment.
[\[Sun and Saenko, 2016\]](#)
- DANN** Adversarial domain training.
[\[Ganin et al., 2016\]](#)
- Skada** Python DA toolbox

Evaluation: Patch: 8×8 px • Group K-fold • S1/S2: 5-fold • S3/S4: 4-fold • Metrics: Accuracy (%) / RMSE ($\downarrow$)

S1: Spatio-temporal Classification



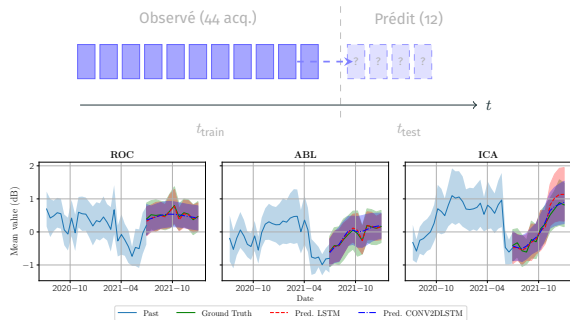
Results — Accuracy (%) ↑

	ACC	HAG	ABL	ICA	FOR	Glob.
MLP	52.2	13.8	51.9	28.5	77.8	62.2
CNN3D	60.7	16.2	57.9	39.2	83.7	69.1

Key findings

- CNN3D: +7% global — spatiotemporal features matter
- HAG/ICA: hardest (few groups, ambiguous signatures)
- FOR: easiest class (stable backscatter year-round)

S2: Temporal Forecasting



LSTM vs CLSTM, 3 classes. Shaded = std. dev.

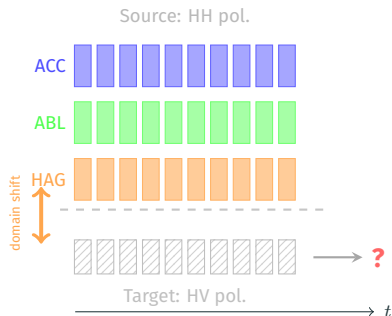
Results — RMSE (↓)

	ACC	HAG	ABL	ICA	FOR	Glob.
LSTM	77.4	89.7	76.7	74.7	63.9	68.6
CLSTM	75.7	82.9	74.9	70.4	58.1	64.5

Key findings

- CLSTM retains spatial context in patches
- Improvement: 1.7–6.9 pts across all classes
- HAG most variable (temporal uncertainty)

S3: Polarimetric Domain Adaptation (HH $\rightarrow$ HV)



Method	ACC	ABL	FOR	PLA	ROC	Global
Baseline	23.6	0.3	25.1	2.9	24.7	11.5
DeepCoral	68.8	12.6	7.7	23.0	7.9	27.7
DANN	73.5	4.1	8.1	5.8	11.3	25.3

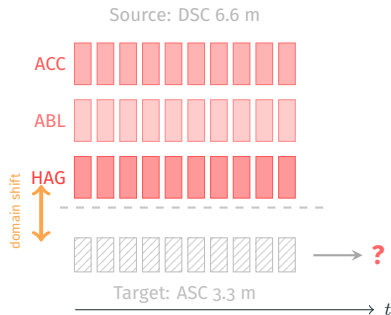
Key findings

- DA strongly improves (11.5 $\rightarrow$ 27.7% global acc.)
- ABL/FOR harder — terrain-dependent backscatter

[Sun and Saenko, 2016]: covariance alignment.

[Ganin et al., 2016]: adversarial training.

S4: Orbit/Resolution Domain Adaptation (DSC → ASC)



Method	ACC	ABL	FOR	PLA	ROC	Global
Baseline	0.0	0.0	0.3	3.7	99.2	12.1
DeepCoral	11.0	6.4	2.4	13.3	84.6	16.7
DANN	8.0	1.9	1.4	8.8	89.2	15.3

Key findings

- Baseline collapses to ROC ($>98\%$ ROC bias)
- DA improves but global acc still low ($\leq 16.7\%$)
- **Harder than S3:** incidence angle + resolution shift combined

Benchmark Summary

Classification & Forecasting

- CNN3D > MLP: **69.1%** vs 62.2%
- CLSTM > LSTM: **RMSE 64.5** vs 68.6
- HAG/ICA: persistently hardest classes

Domain Adaptation

- DeepCoral best overall (covariance alignment)
- S3 (polarimetric) > S4 (orbit/res.)
- Baseline biased toward ROC class

Open challenges

- Few-shot learning for ICA/HAG • Label noise in steep-terrain SAR • Semi-supervised learning
- Multi-temporal domain adaptation

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Conclusion

CPAZMaL contributions

- First open X-band SAR Alpine benchmark
- 182 images, ~3 m, dual-pol + multi-orbit
- 8 classes incl. rare ICA & HAG
- 1.5 m LiDAR DEM $\Rightarrow$ geometric accuracy
- Group-based HDF5 for unbiased ML evaluation

Key findings

- Spatiotemporal features improve classification (CNN3D 69.1%)
- HV more sensitive to summer melt
- Large distributional gap orbit/polarisation
- HAG/ICA: critical, persistently hard

Future directions

- Few-shot & semi-supervised methods
- SAR + optical fusion
- Long-term glacier retreat monitoring

Data Availability

Dataset (HuggingFace) [Gallet et al., 2025]

<https://huggingface.co/datasets/musmb/CPAZMaL>

Pipeline + dataloaders (GitHub)

https://github.com/Matthieu-Gallet/CPAZMaL_dataset/

- HDF5 dataset: all classes, 2020–2022
- SNAP parameters (reproducible)
- Python dataloaders for 4 scenarios
- Pre-extracted 8×8 patches per fold

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