High Resolution Ice Type Retrieval from X-Band SAR and Fused ALS Measurements from the MOSAiC Expedition

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DLR

MOSAiC International Arctic Drift Expedition

AWI

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CICOES

3 Key Questions

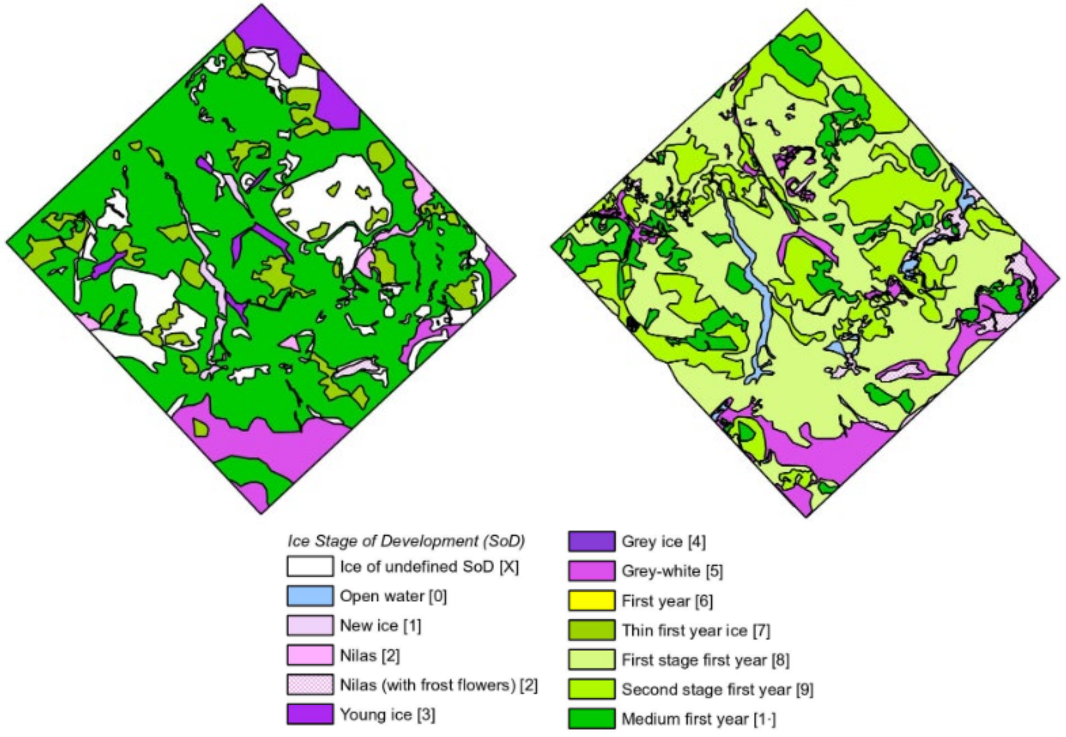
I. Why should we not be satisfied with the current state of SAR sea ice charting?

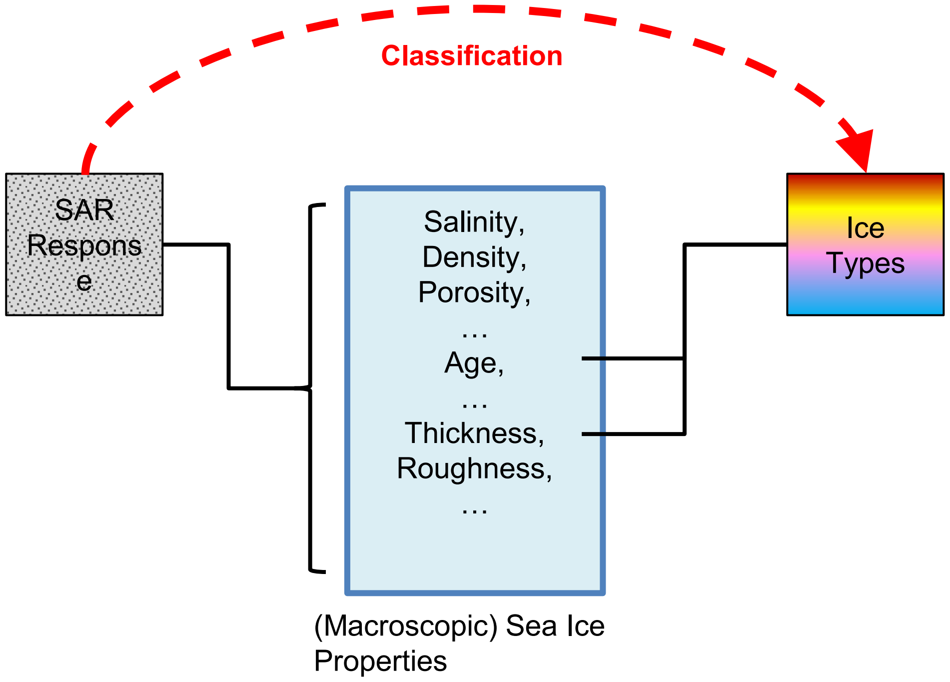
II. How can topographical data from the MOSAiC mission help?

III. How can we extrapolate our retrieval algorithms to unseen regions?

I. Manual Ice Charting – Two analysts compared

Moen et al., 2013, *Comparison of feature based segmentation of full polarimetric SAR satellite sea ice images with manually drawn ice charts,* The Cryosphere, https://tc.copernicus.org/articles/7/1693/2013/



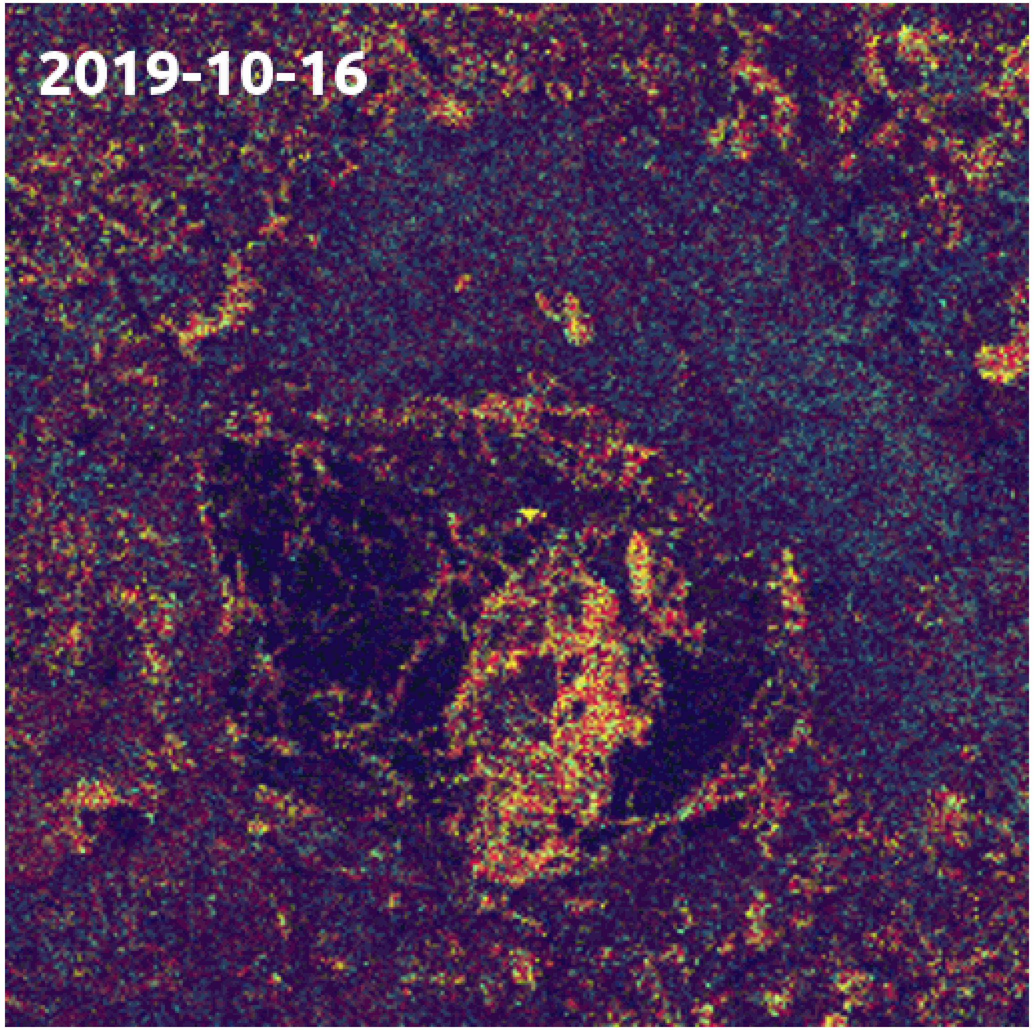


→ Almost impossible to benchmark models.

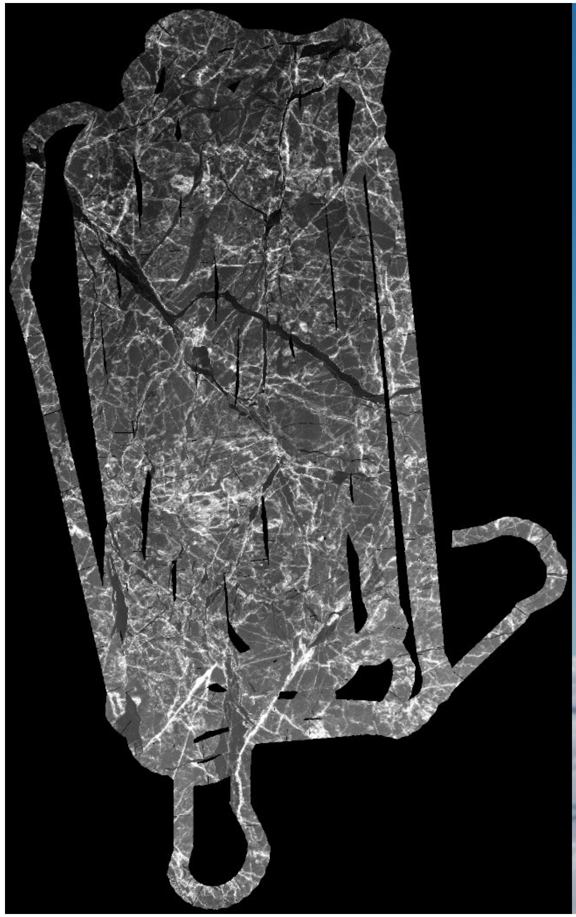
II. MOSAiC

Multidisciplinary drifting **O**bservatory for the **S**tudy of **A**rctic **C**limate

TerraSAR-X Dual Pol Data

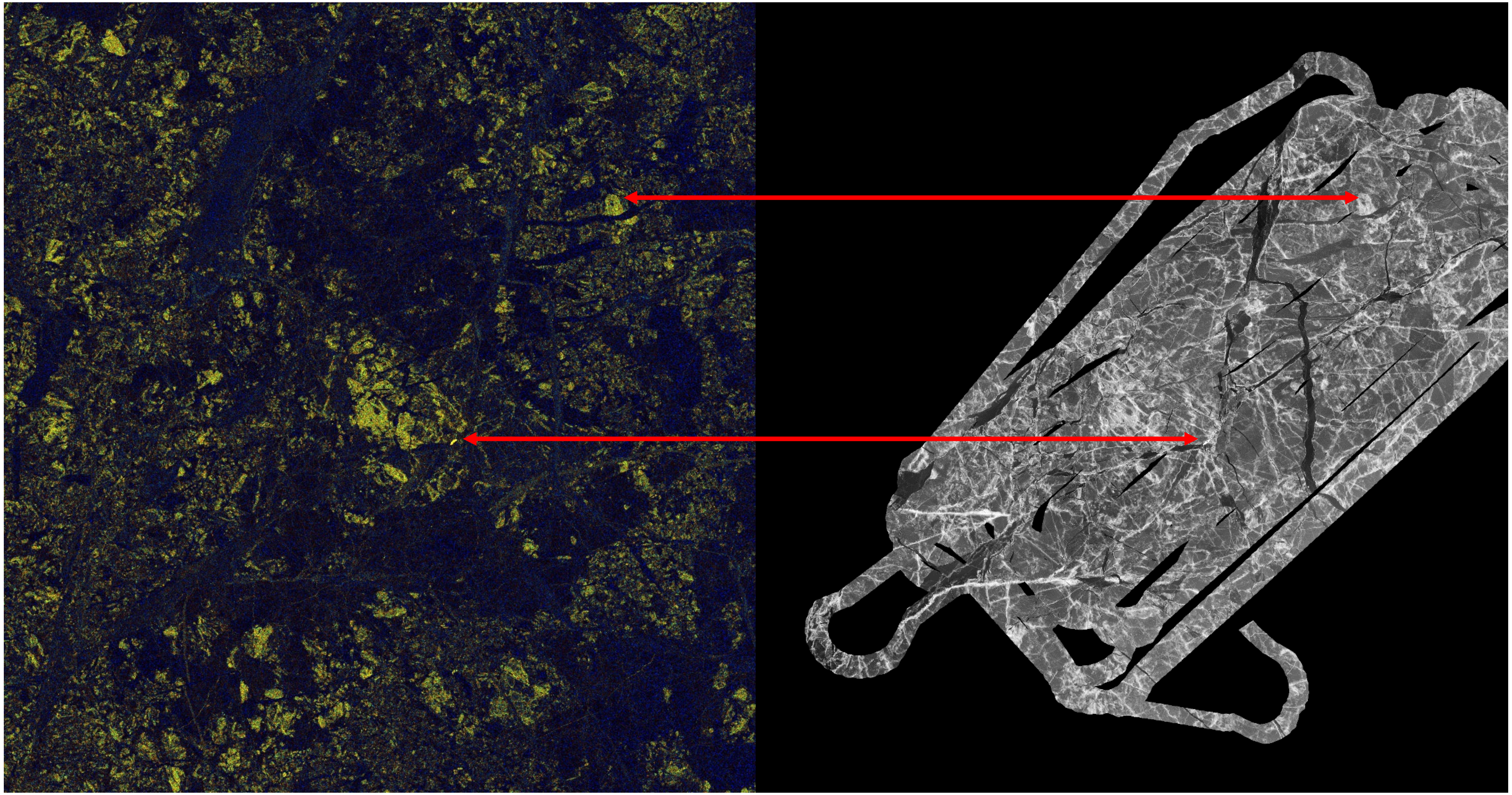


Airborne Laser Scanner

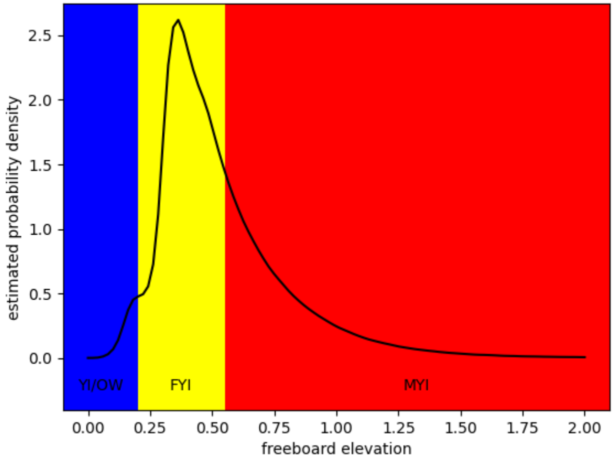


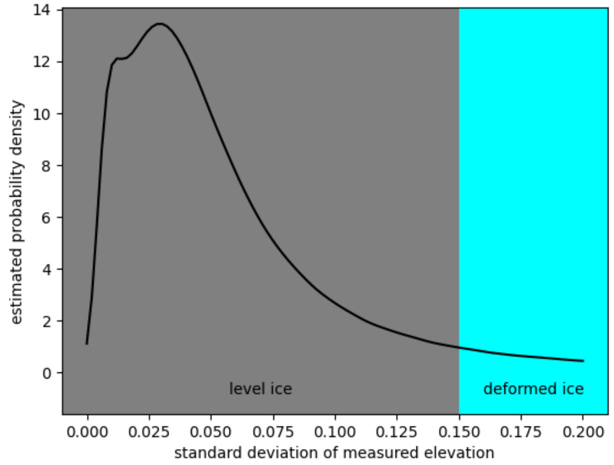
ALS measurement, 08.04.2020

Drift Correction Results



Deriving Ice Types from ALS Freeboard Measurement





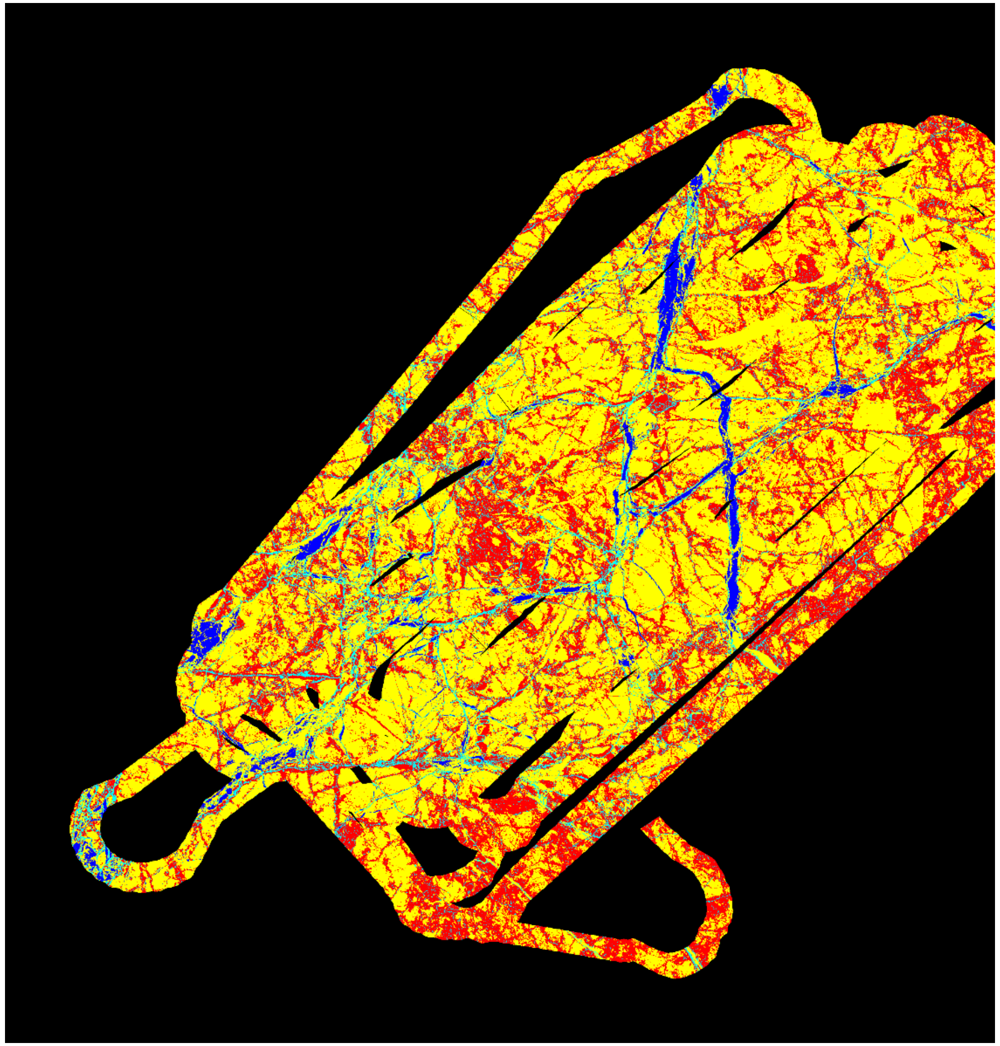


Image Segmentation Model

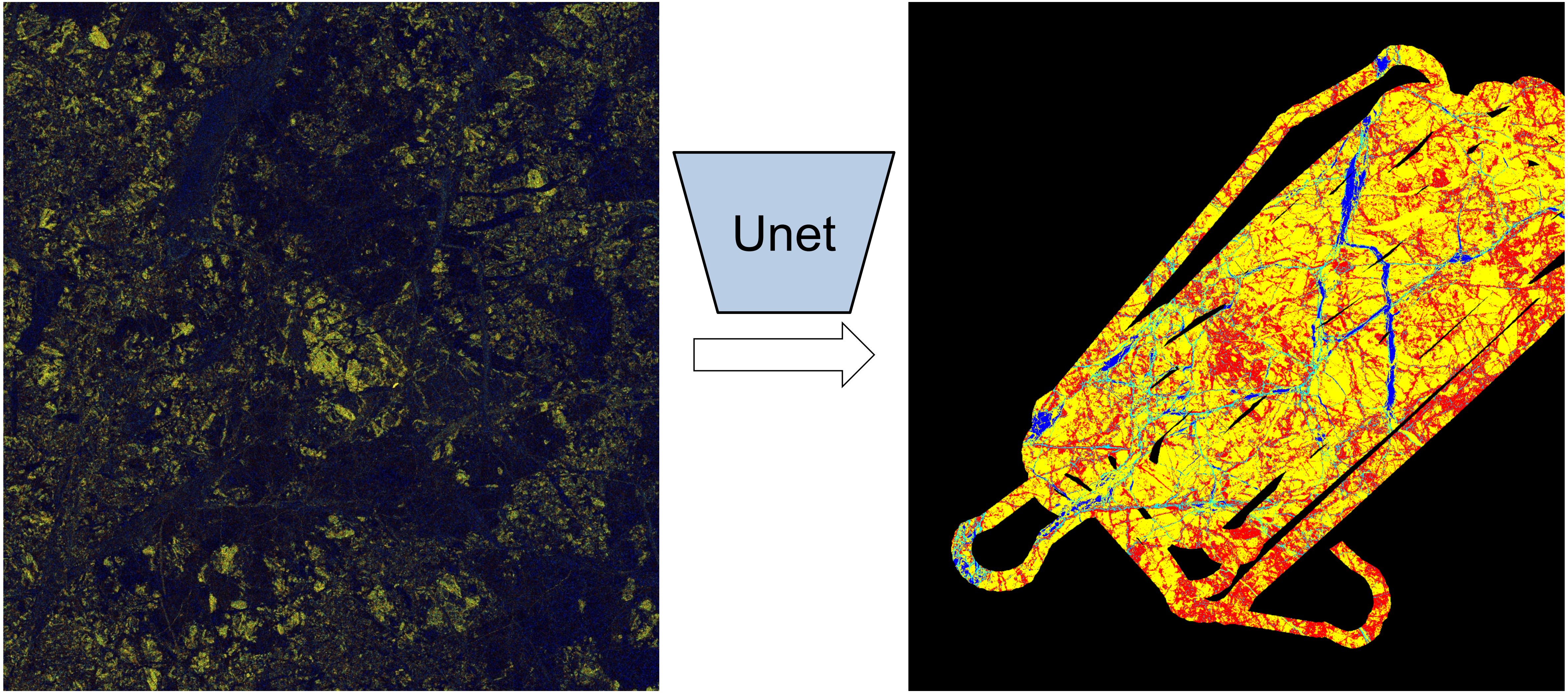
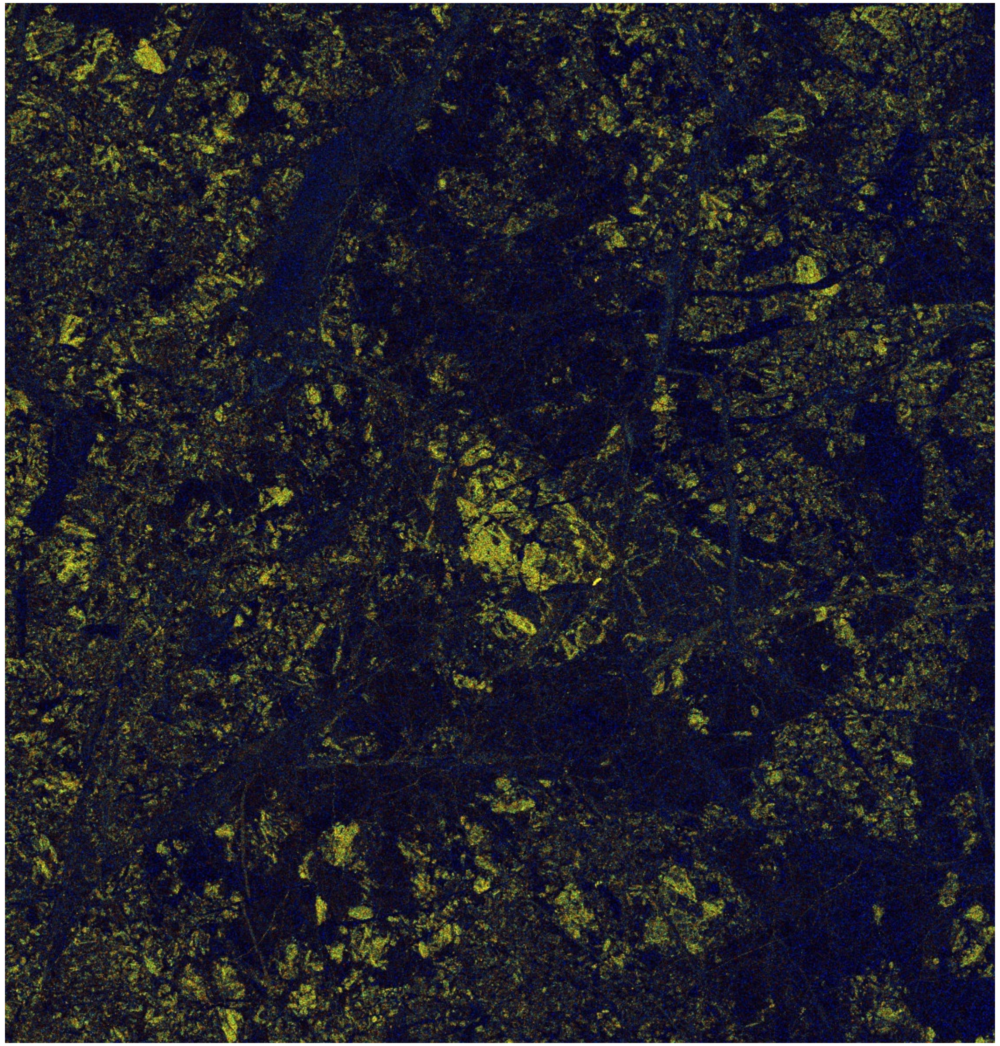
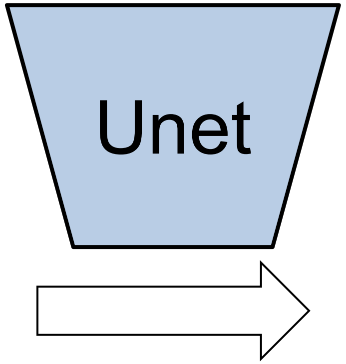
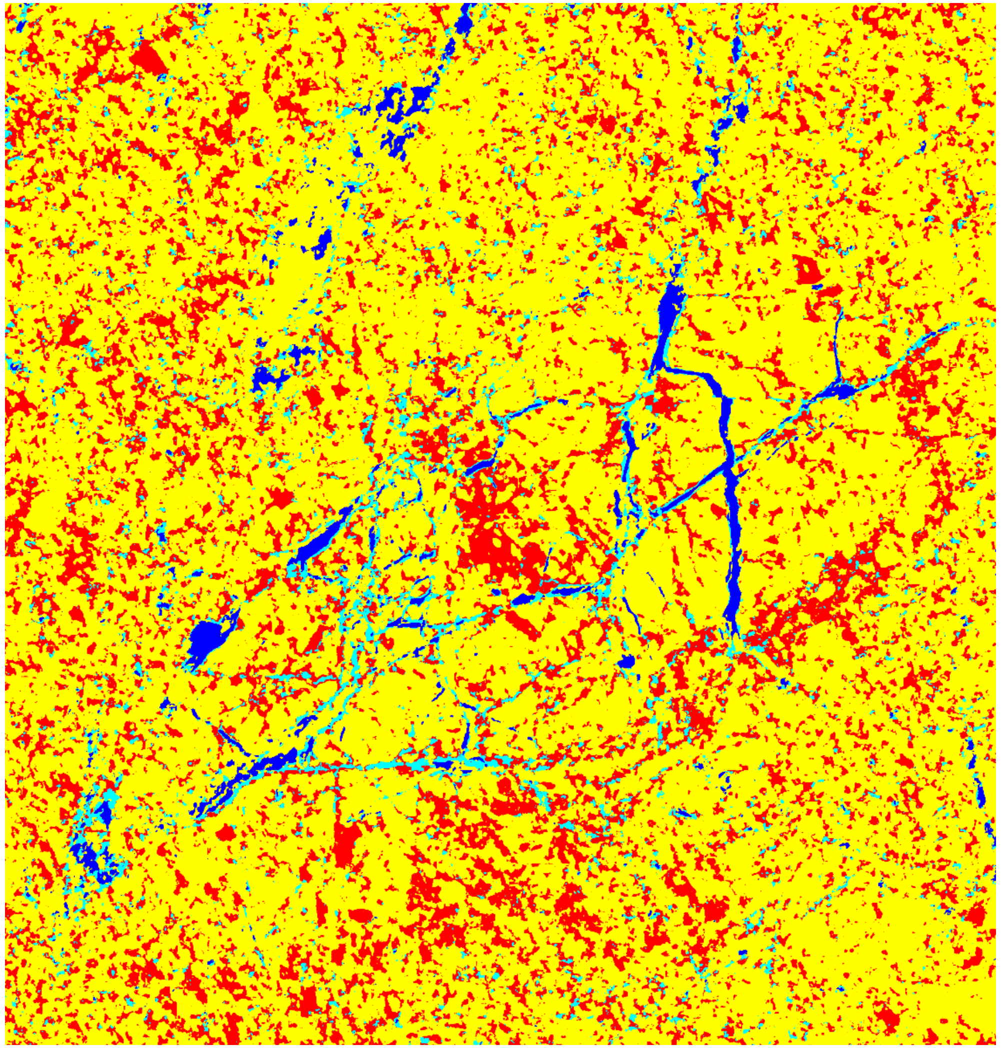


Image Segmentation Model

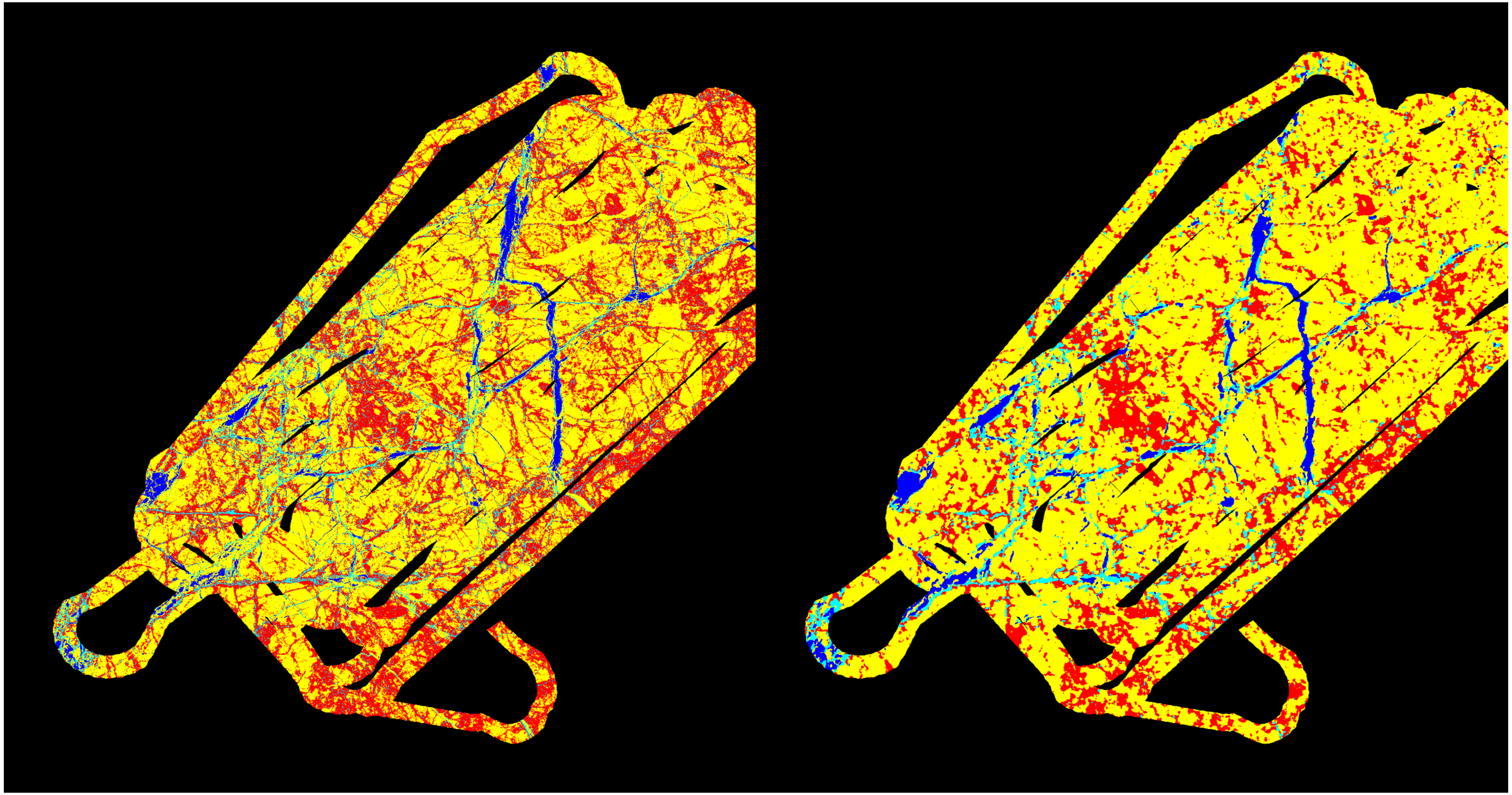






ALS Labels

SAR Predictions



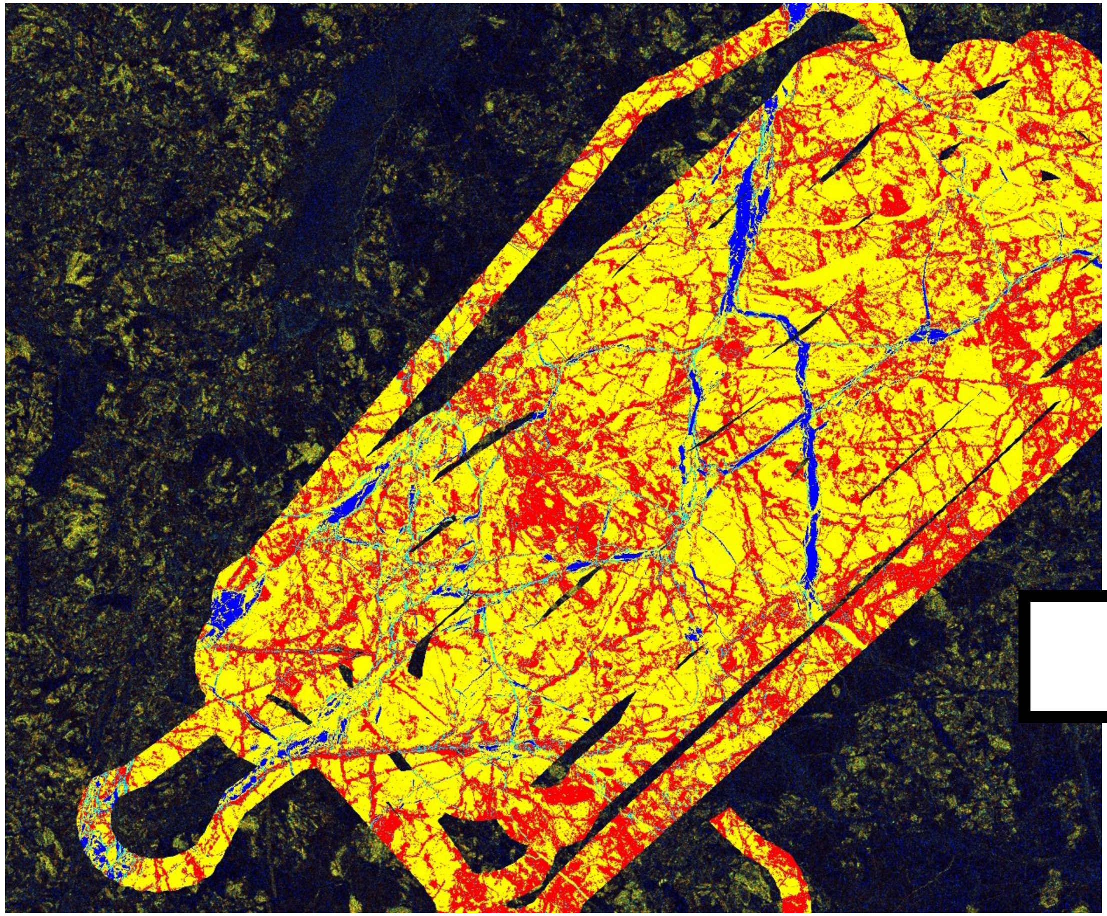
III. How can we extrapolate our retrieval algorithms to unseen regions?

Problem: Neural networks highly non-linear learning results in poor off-distribution performance.

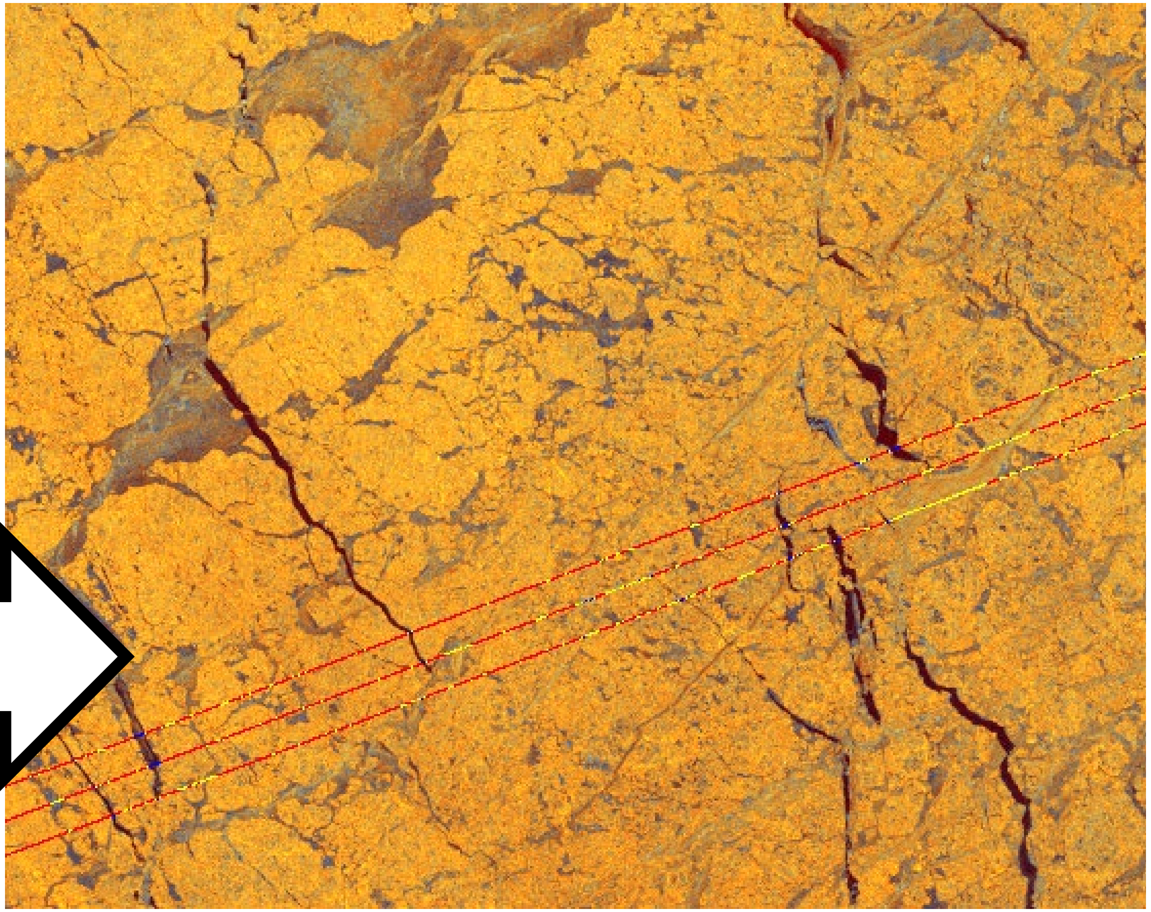
Idea: Use unlabelled data to ‘pad’ distribution for more stable performance across the Arctic.

Execution: Introduce secondary unsupervised learning task (no labels needed).

TerraSAR-X + ALS

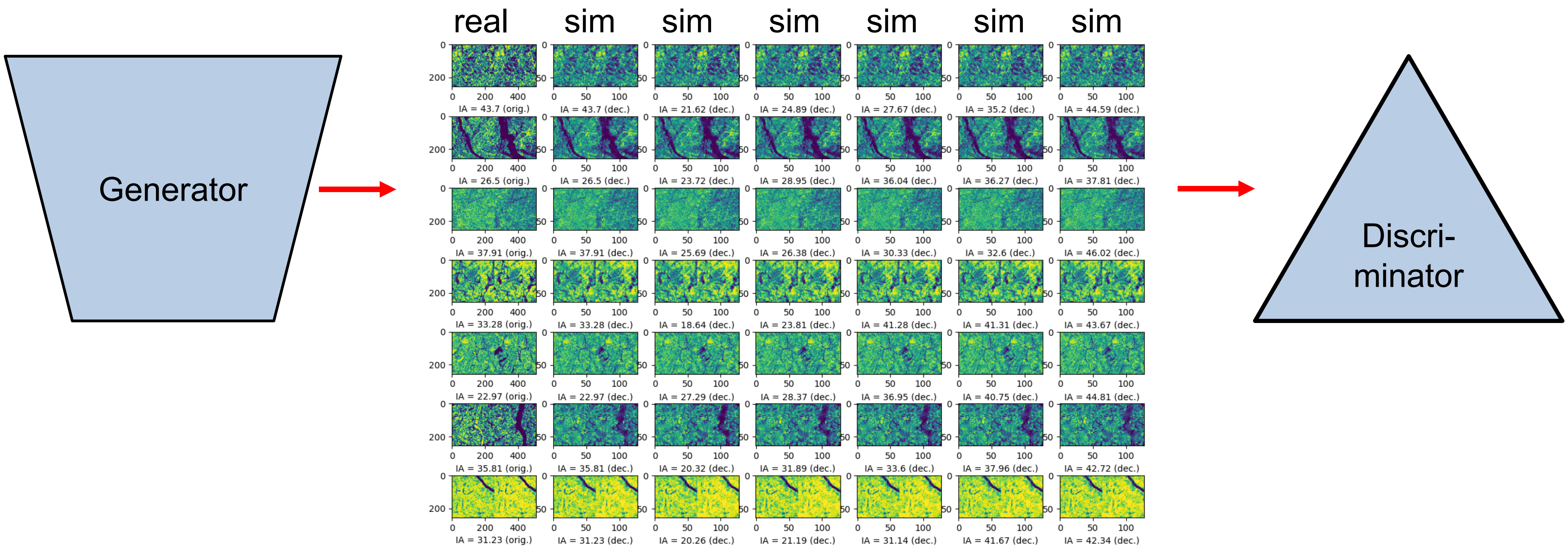


Sentinel-1 + ICESAT2 (Oct, Nov)

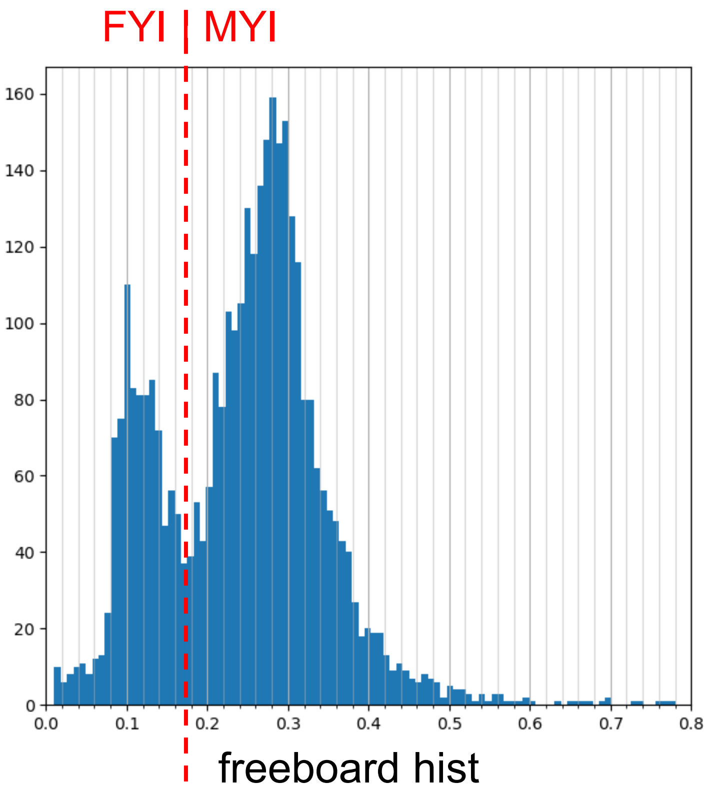


Adversarial Set-Up: Generator vs Discriminator

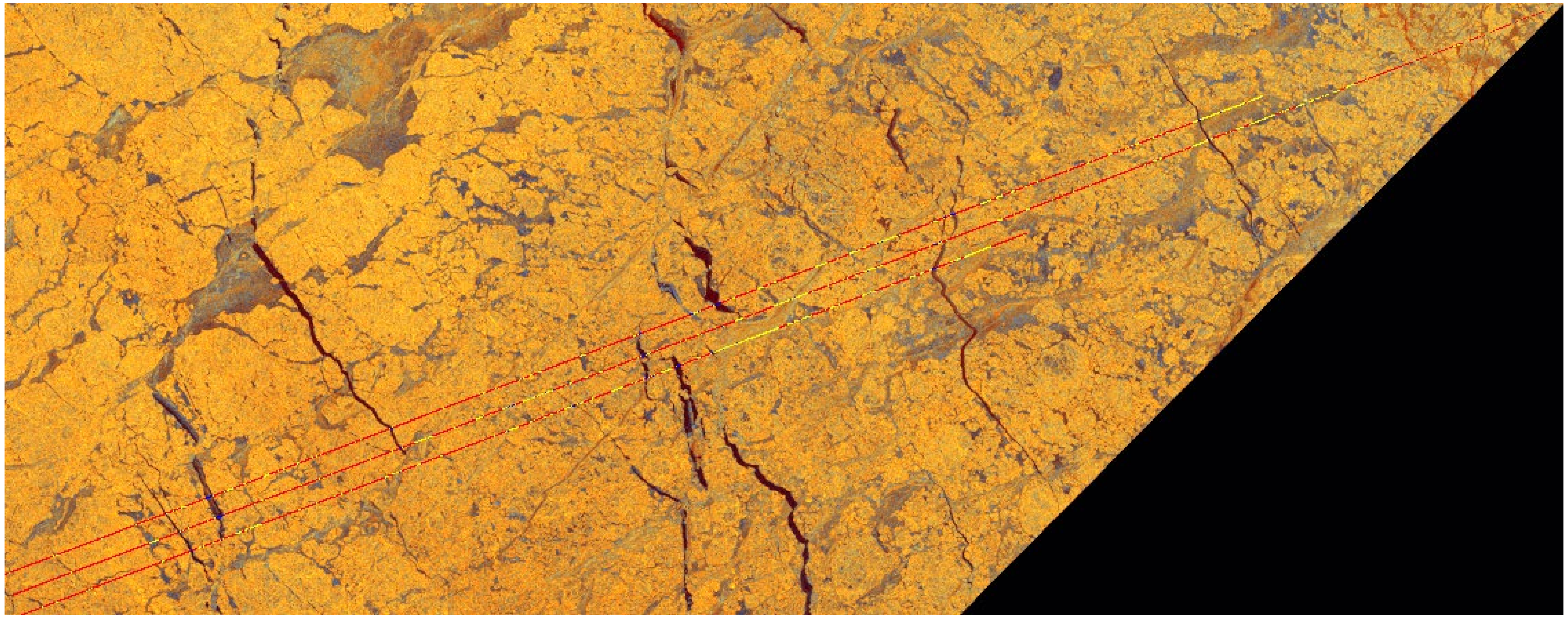
Mahmud et al. 2018, ‘Incidence Angle Dependence of HH-Polarized C- and L-Band Wintertime Backscatter Over Arctic Sea Ice’
Lohse et al. 2021, ‘Incident Angle Dependence of Sentinel-1 Texture Features for Sea Ice Classification’,



Validation with ICESAT2 measurements

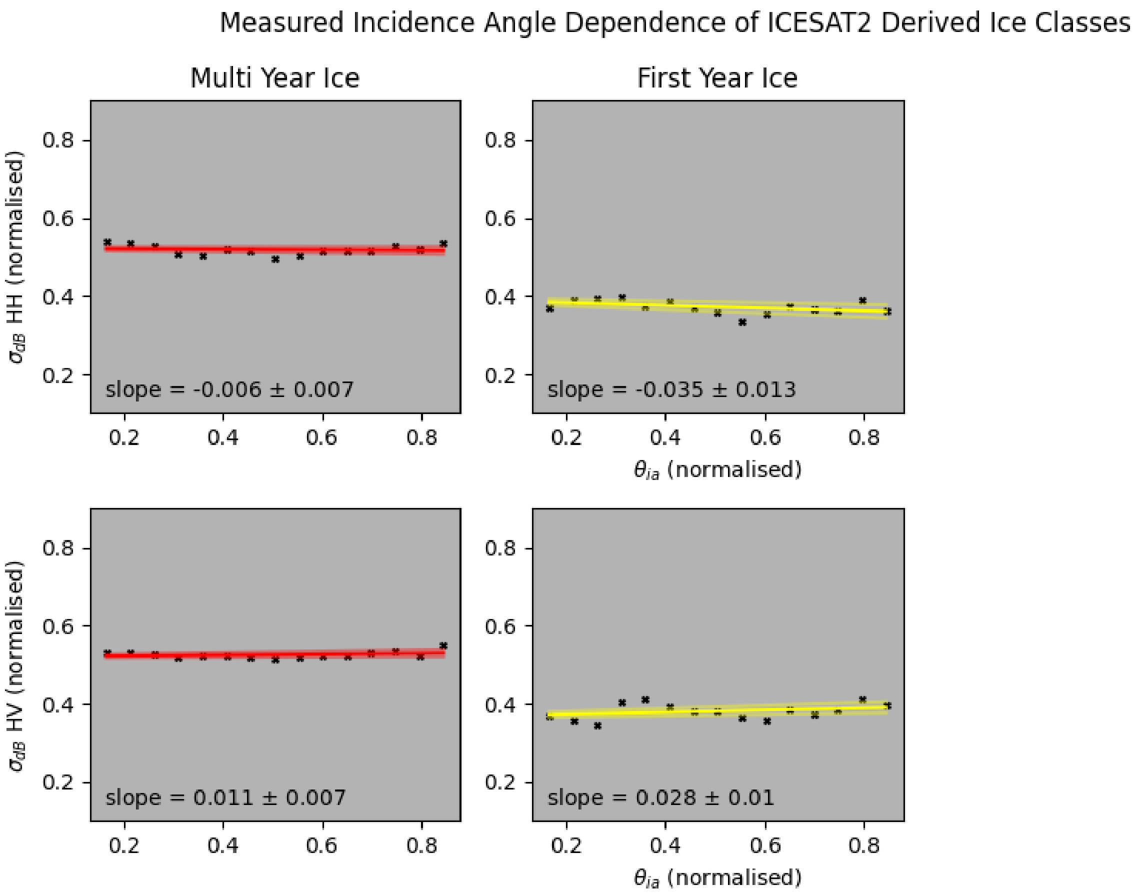


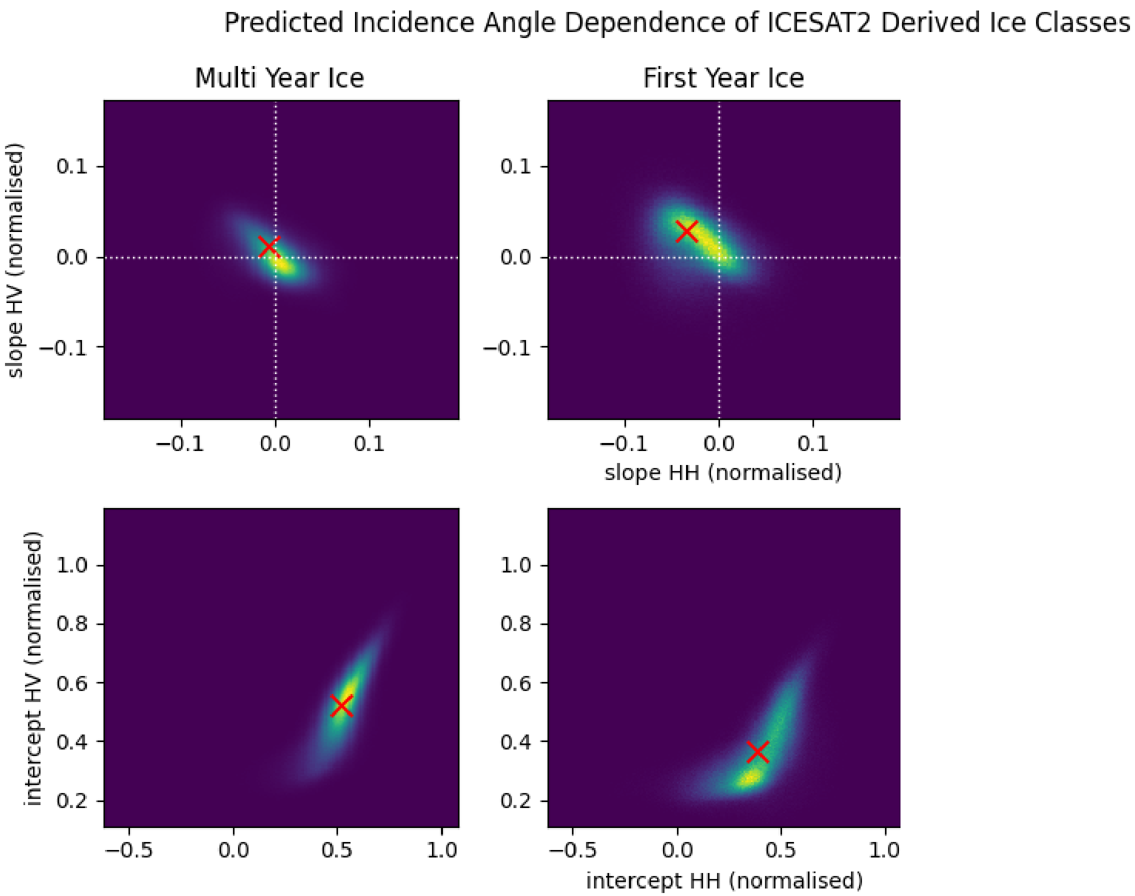
freeboard hist



Sentinel-1 EW + ICESAT2 (2021/11/02), time_delta < 10min

ICESAT2 derived IA dependence vs Model approx. IA dependence





3 Key Questions

I. Why should we not be satisfied with the current state of SAR sea ice charting?

Introduction of human bias, no known relation to important ice properties.

II. How can Topographical data from the MOSAiC mission help?

Establish relations between ice thicknesses and backscatter from collocated measurements.

III. How can we extrapolate our retrieval algorithms to unseen regions?

Leverage unlabelled data and physical constraints.

Acknowledgements

Data used in this research was produced as part of the international Multidisciplinary drifting Observatory for the Study of the Arctic Climate (MOSAiC) with the tag MOSAiC20192020.

TerraSAR-X datasets were acquired via science AO suman$_$OCE3562.

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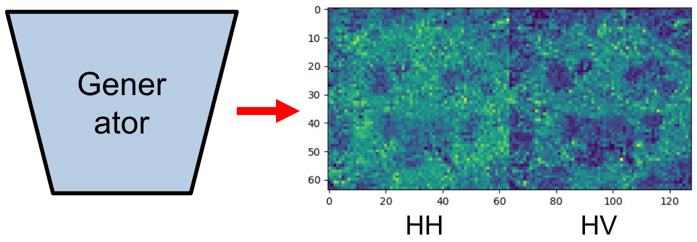
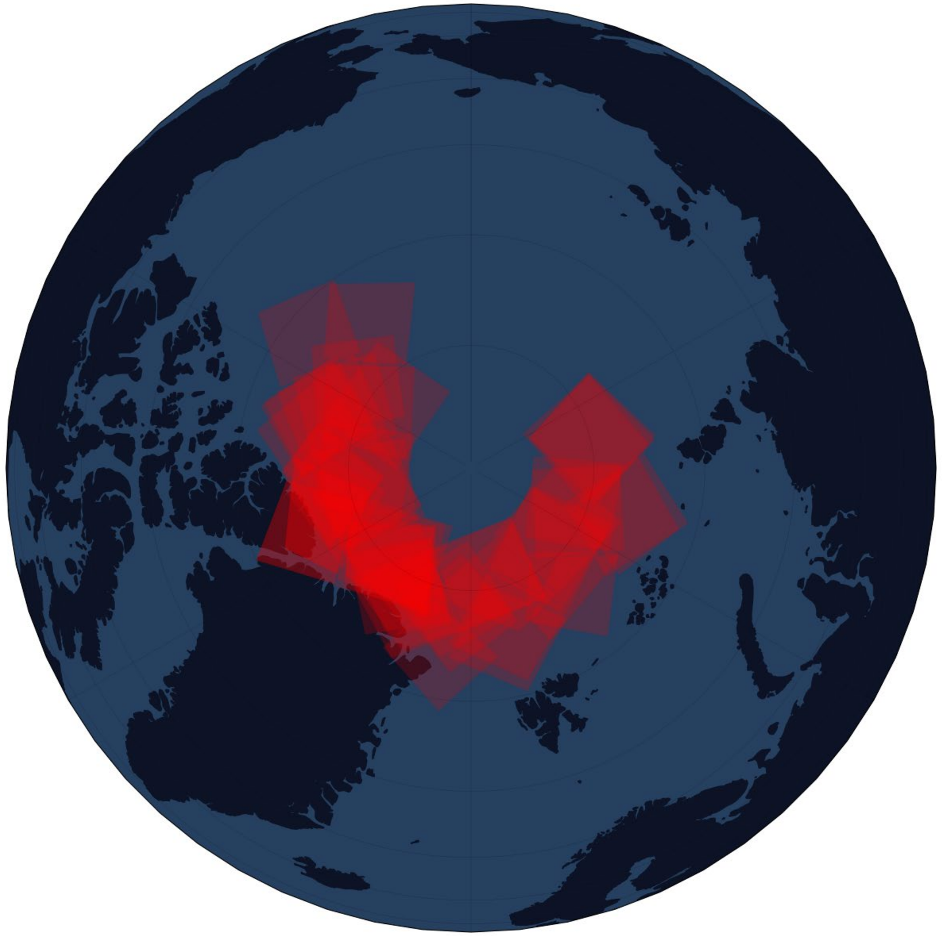
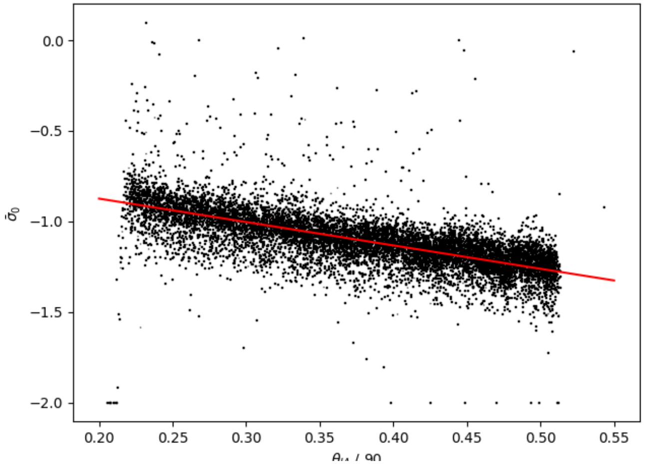
Thank you.



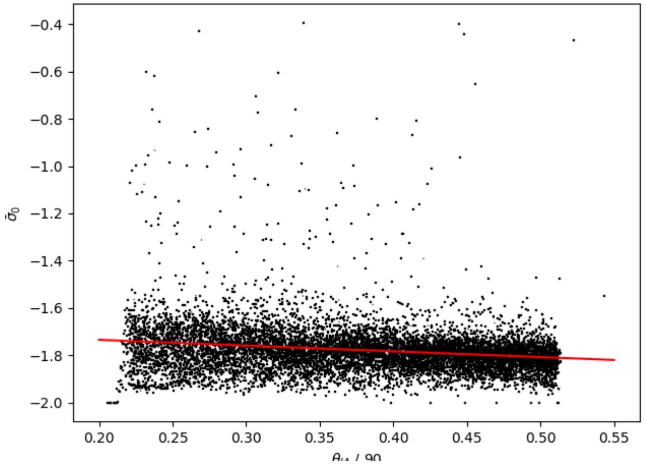
Sentinel 1 Scenes with overlapping ICESAT2 in October and November



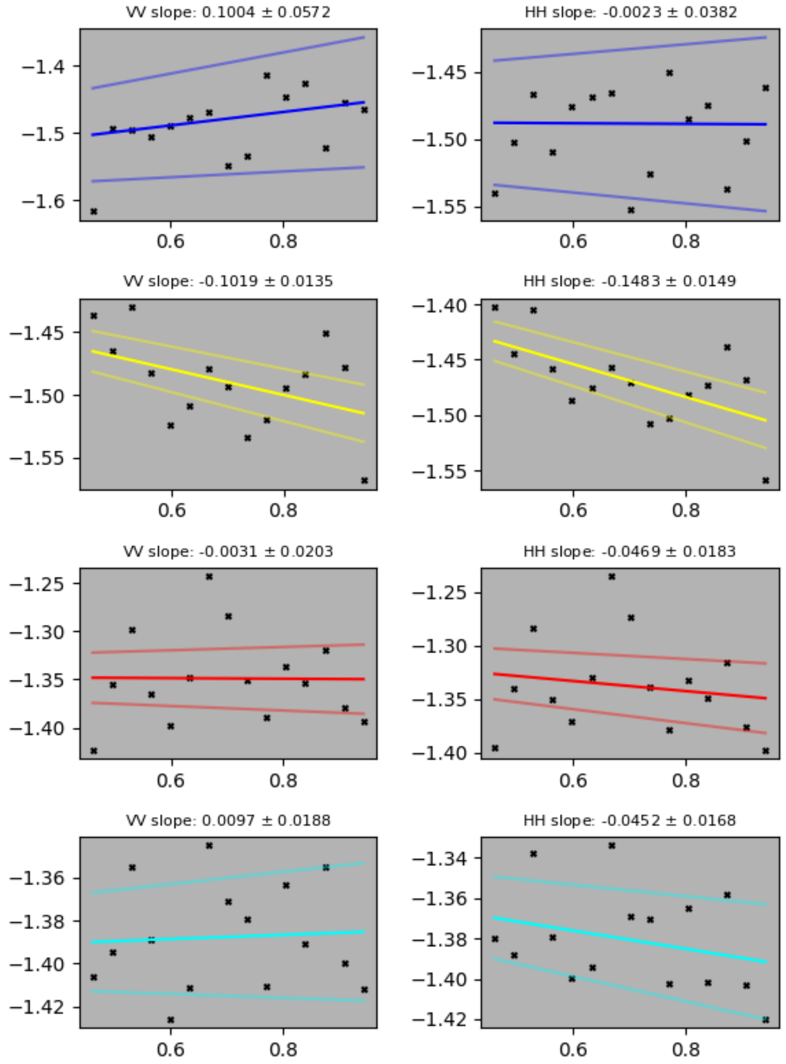
HH IA dependence

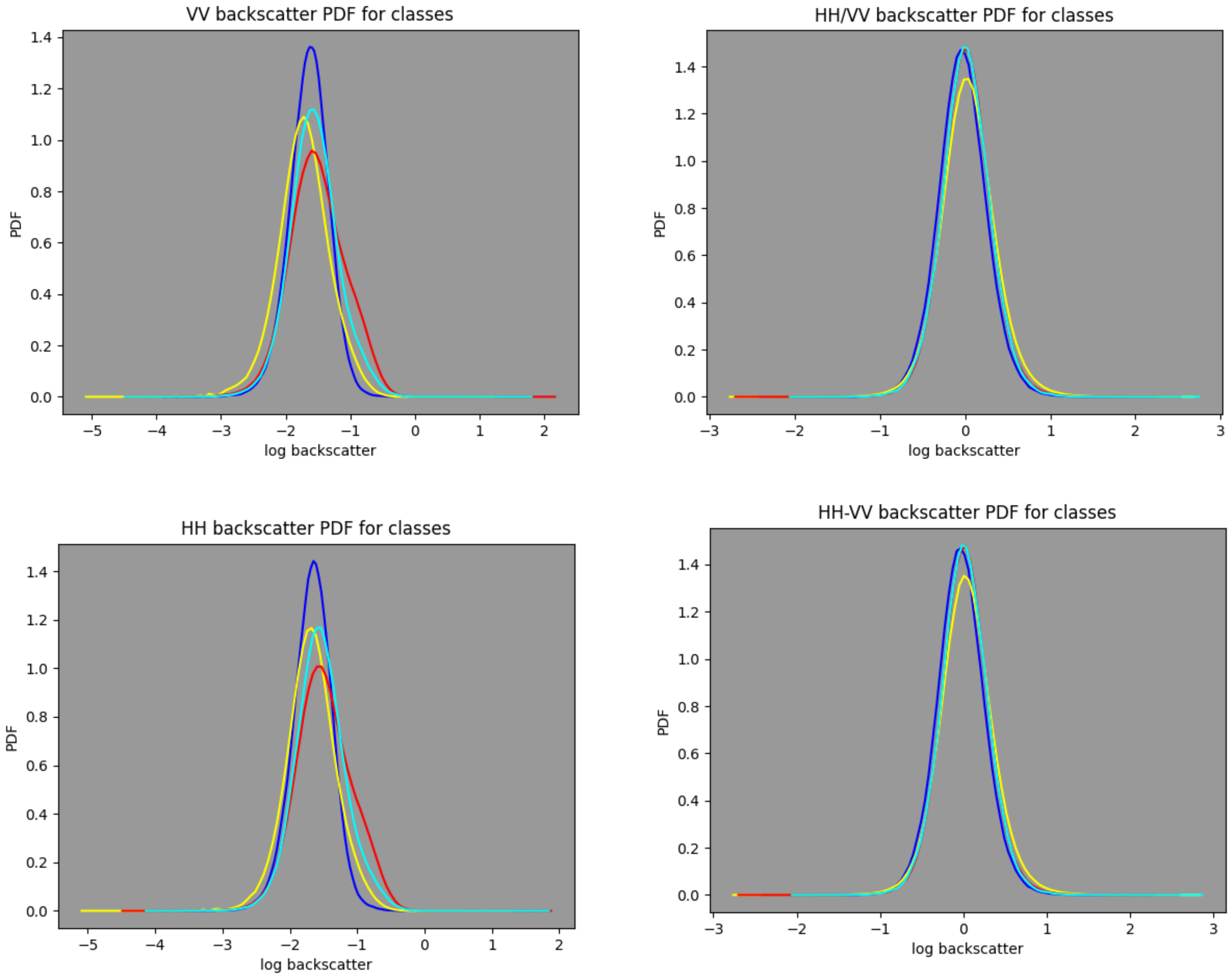


HV IA dependence



TerraSAR-X Ice Type Slopes and Brightness





Network feature space (relative to mean distribution)

Split along the ICESAT2 classes