Seabed 2030 5th SaWPaC Regional Mapping Community Meeting

Deep Learning for seabed classification using SONAR data

Rosa Virginia Garone[1], Tor Inge Lønmo[2], Alexandre Schimel[3], Lasse Løvstakken[4]

1: NTNU (Norwegian University of Science and technology), PhD – rosa.v.garone@ntnu.no
2: NGU (Norges Geologiske Undersøkelse), Underwater Acoustics Scientist
3: Kongsberg Maritime, Senior engineer R&D
4: NTNU (Norwegian University of Science and technology, Professor

12.07.2023

Introduction

- A little bit about myself…

- The aim of the project is:

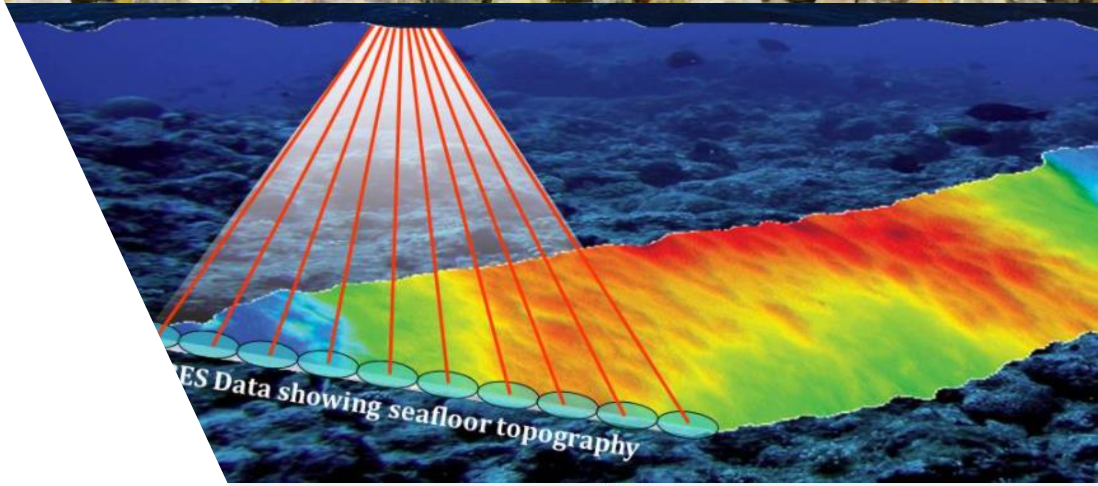
<u>To develop a model which uses semantic segmentation applied to seabed imagery</u>

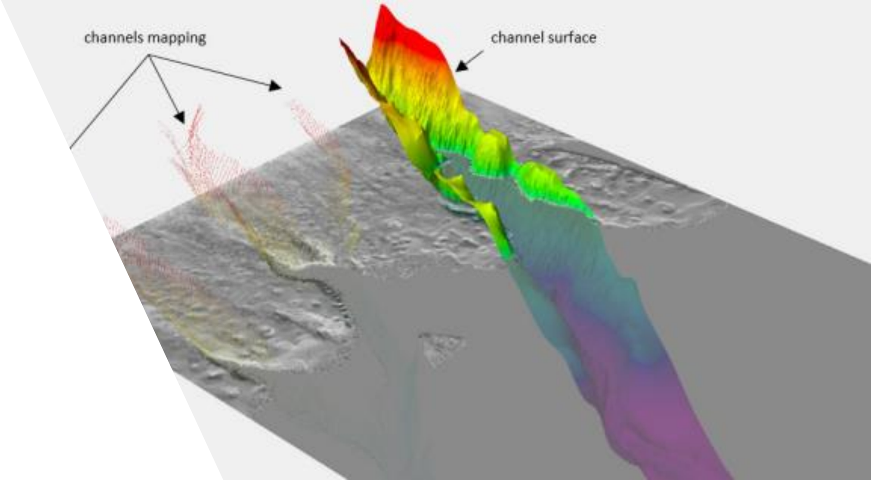
"This PhD project brings together expertise from research institutions and industry to enhance innovation in the field of ultrasounds applied to ocean exploration.

The partners are CIUS/NTNU, Kongsberg Maritime, NGU (Geological Survey of Norway) and NTNU.

CIUS (Centre for Innovative Ultrasound Solutions) aims to develop ultrasounds knowledge and technology.

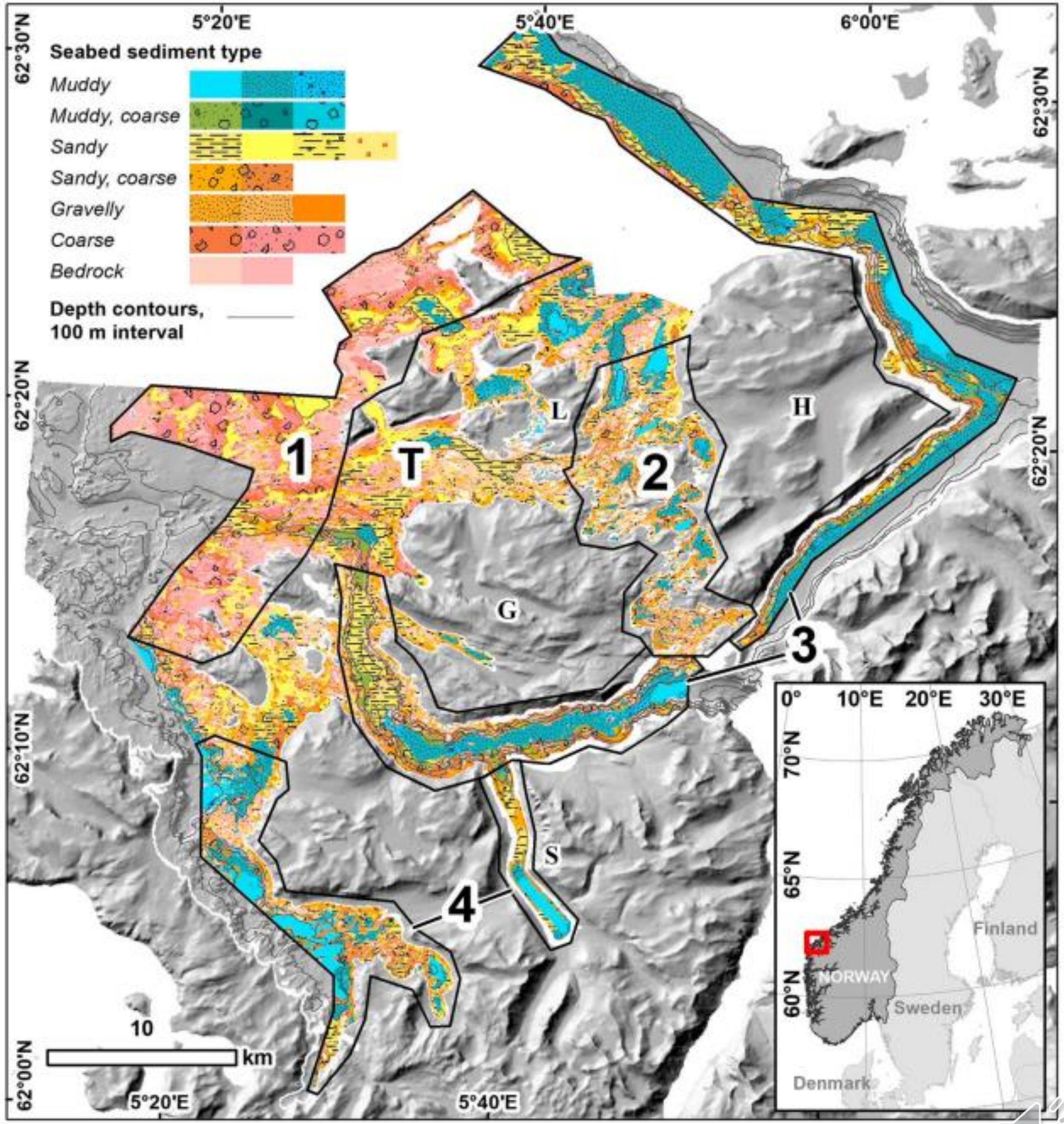
Through the expertise gained in the field of AI for imaging and classification tasks in the medical area, CIUS aims to explore the future potential of ultrasound imaging in various industries".





Study Area, Dataset and Software

- The study region covers the nearshore marine portions of the five municipalities Hareid, Ulstein, Herøy, Sande and Vanylven in the Søre Sunnmøre area (Norway).
- Depth data from MBES surveys covering a depth range of 0.2–636 m. Data gridded to a horizontal resolution of 1x1 m.
- Multibeam backscatter data gridded to 1 × 1 or 2 × 2 m horizontal resolution, depending on sounding density and data quality.
- Expert annotations from the area.
- ArcGis Pro
- Python: TF GPU, Keras, Scipy being the main libraries used.



Sigrid Elvenes , Reidulv Bøe , Aave Lepland & Margaret Dolan (2019) Seabed sediments of Søre Sunnmøre, Norway, Journal of Maps, 15:2, 686-696,
DOI: 10.1080/17445647.2019.1659865

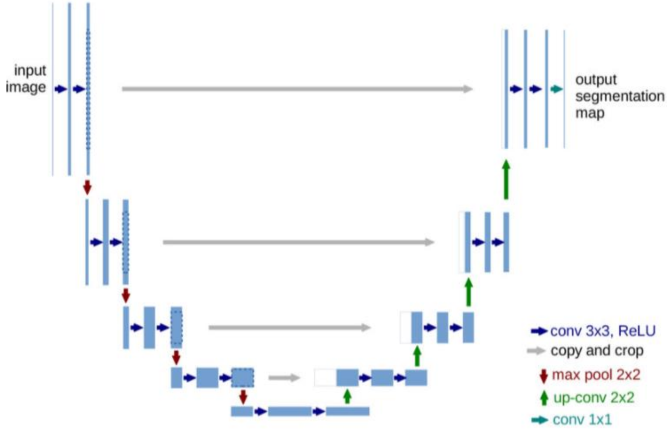
Main Goal: Training a Deep learning network to obtain a model able to replicate/predict the expert annotations.

Source Data		
Multibeam Bathymetry Grid	Multibeam Backscatter Mosaic	Expert Annotations

What do we need to build our model?

A Deep Learning network

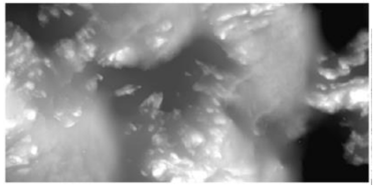
- In our case U-Net. Principally implemented for semantic segmentation and usually applied to biomedical data

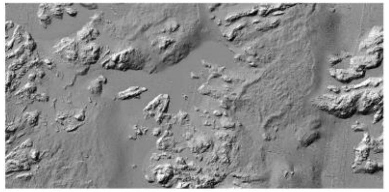


Ronneberger et al., 2015, U-net: Convolutional networks for biomedical image segmentation. International Conference on Medical image computing and computer-assisted intervention p. 234-241.

Features to be used as Input to our network

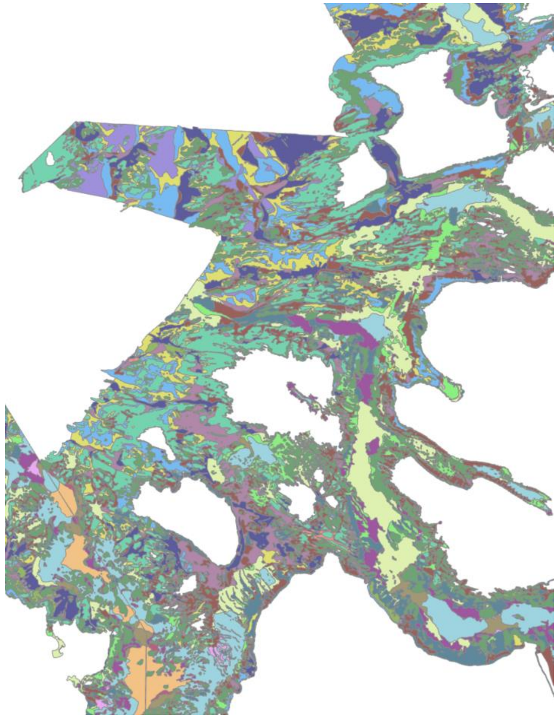
- The Digital Bathymetric Model (DBM)
- The Hillshade Grid modelled from the DBM
- The Backscatter mosaic





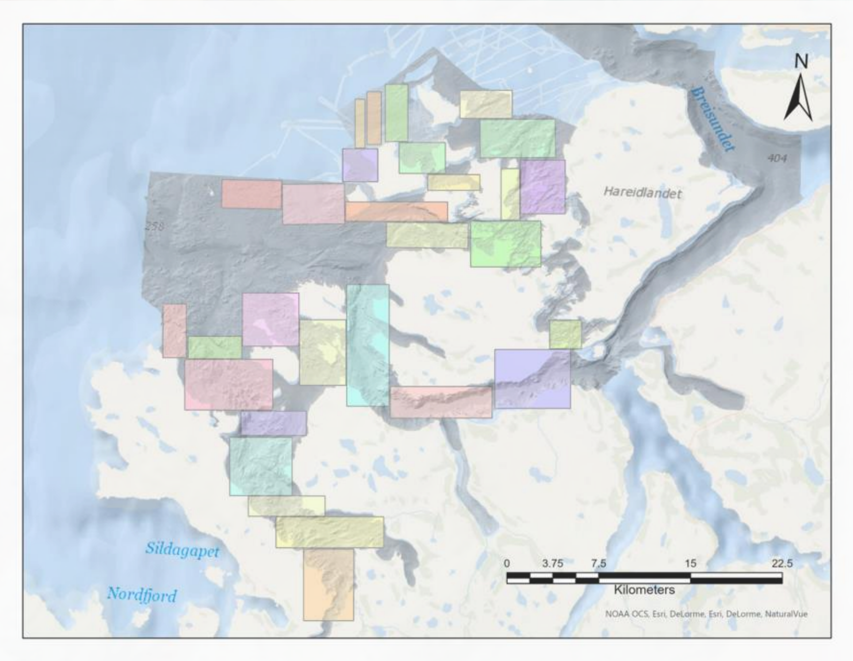
Labels we wish to predict

- Expert annotations



Pre-processing and Network training

- The seabed imagery was sampled using polygons across the total area
- U-Net trained with 4 different data sources: Backscatter, Depth, Slope and Hillshade data
- Several models were trained and evaluated, using both single or combined data sources
- Model evaluation with the Dice score coefficient, Producer's accuracy (PAcc), User's accuracy (UAcc), Accuracy .



The Dice coefficient is: two times the intersection between the ground truth and the predicted mask, divided by the sum of the ground truth and the predicted mask.

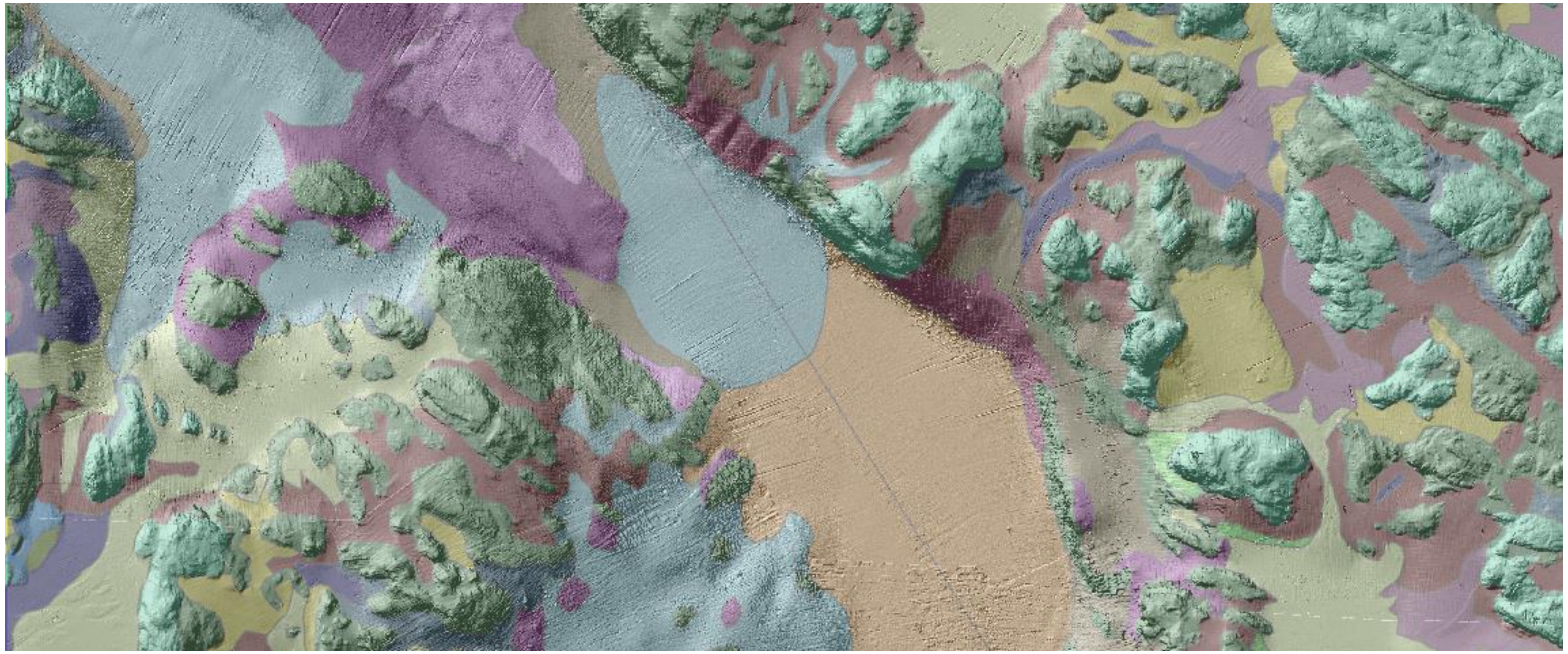
$$\text{Dice} = 2\text{x} \frac{y \cap y_{\_pred}}{y + y_{\_pred}}$$

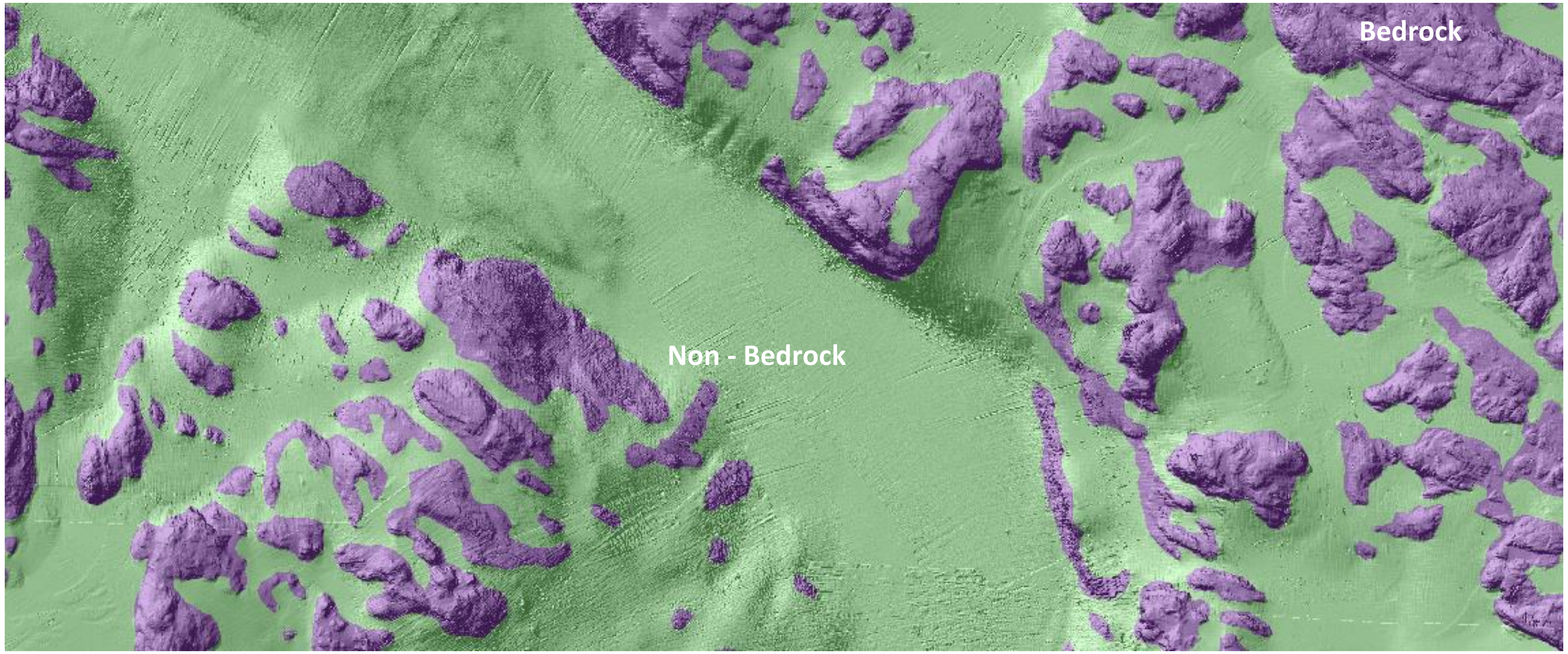
The minimum value that the dice can take is ***0,*** the maximum value that the dice can take is ***1***, which means the prediction is ***99%*** correct.

https://pycad.co/the-difference-between-dice-and-dice-loss/

Conversion from multiple classes to binary classes annotations.

- NGU multi-class annotations were converted into binary-class labels for initial testing.
- The binary classes being Bedrock and Non-Bedrock
- The “Bedrock” class included: ”Bedrock” and “Bedrock covered by fine sediments”
- The Non – Bedrock class included every other category not included into the “Bedrock” one.





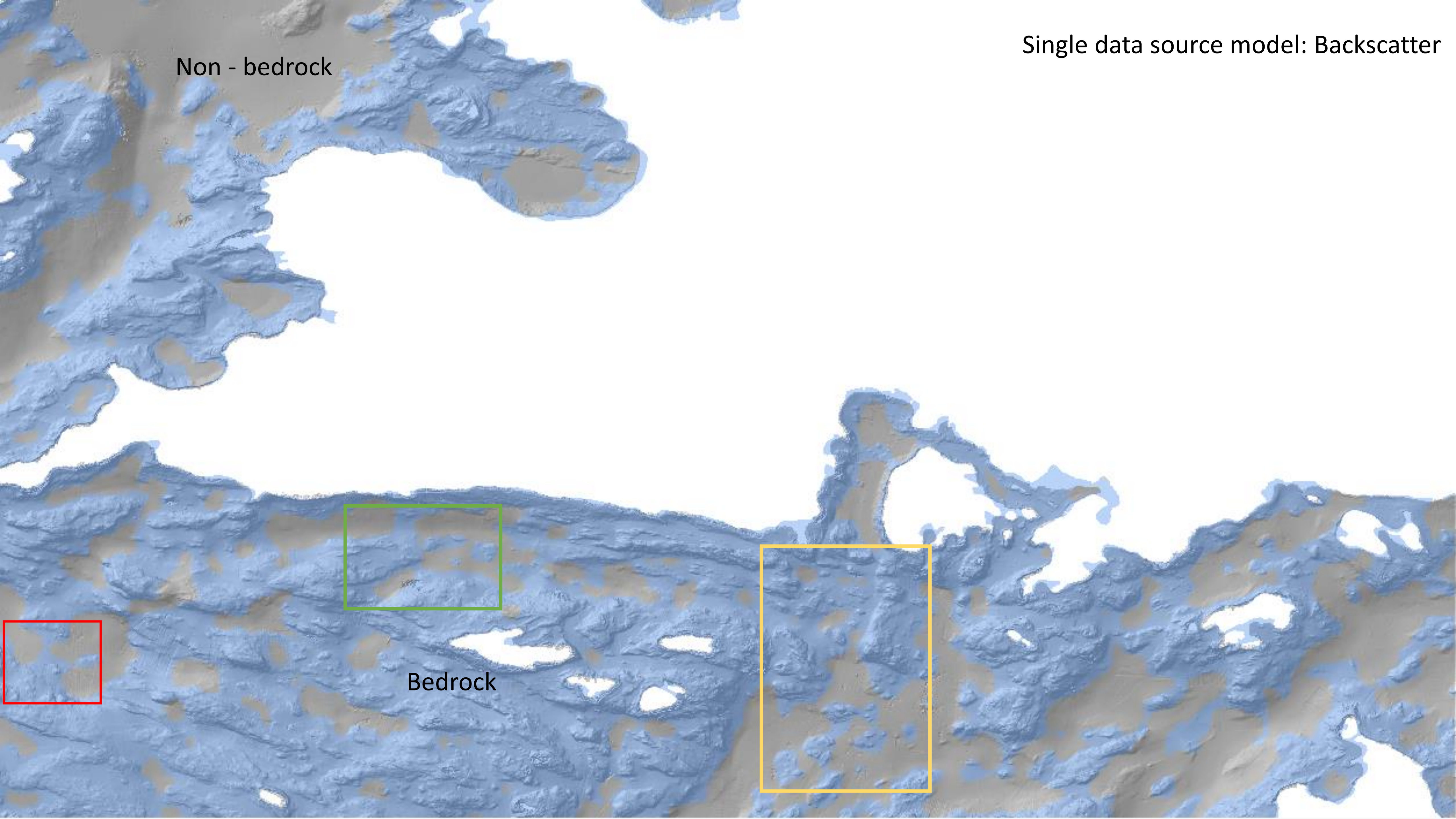
Quantitative Results - Metrics

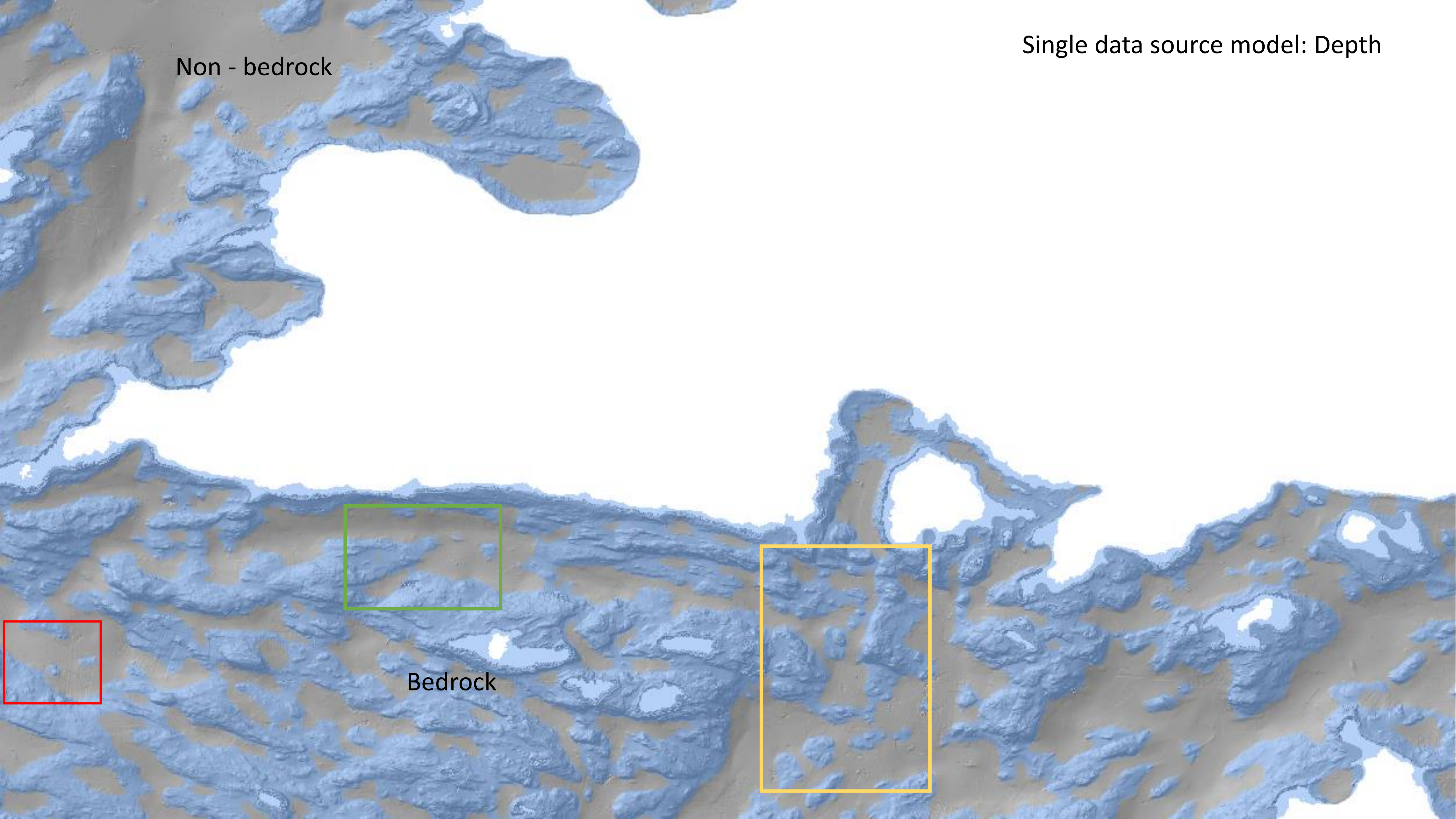
Single – data sources models						
Model Name	Dice Score on test data (DS)	Producer's Accuracy (PAcc)		User's Accuracy (UAcc)		Overall accuracy (Acc)
		Non - Bedrock	Bedrock	Non - Bedrock	Bedrock	
Backscatter model	0.69	0.86	0.63	0.77	0.76	0.77
Depth model	0.79	0.93	0.72	0.83	0.88	0.84
Hillshade model	0.76	0.93	0.66	0.76	0.89	0.81
Slope model	0.80	0.92	0.75	0.85	0.85	0.85

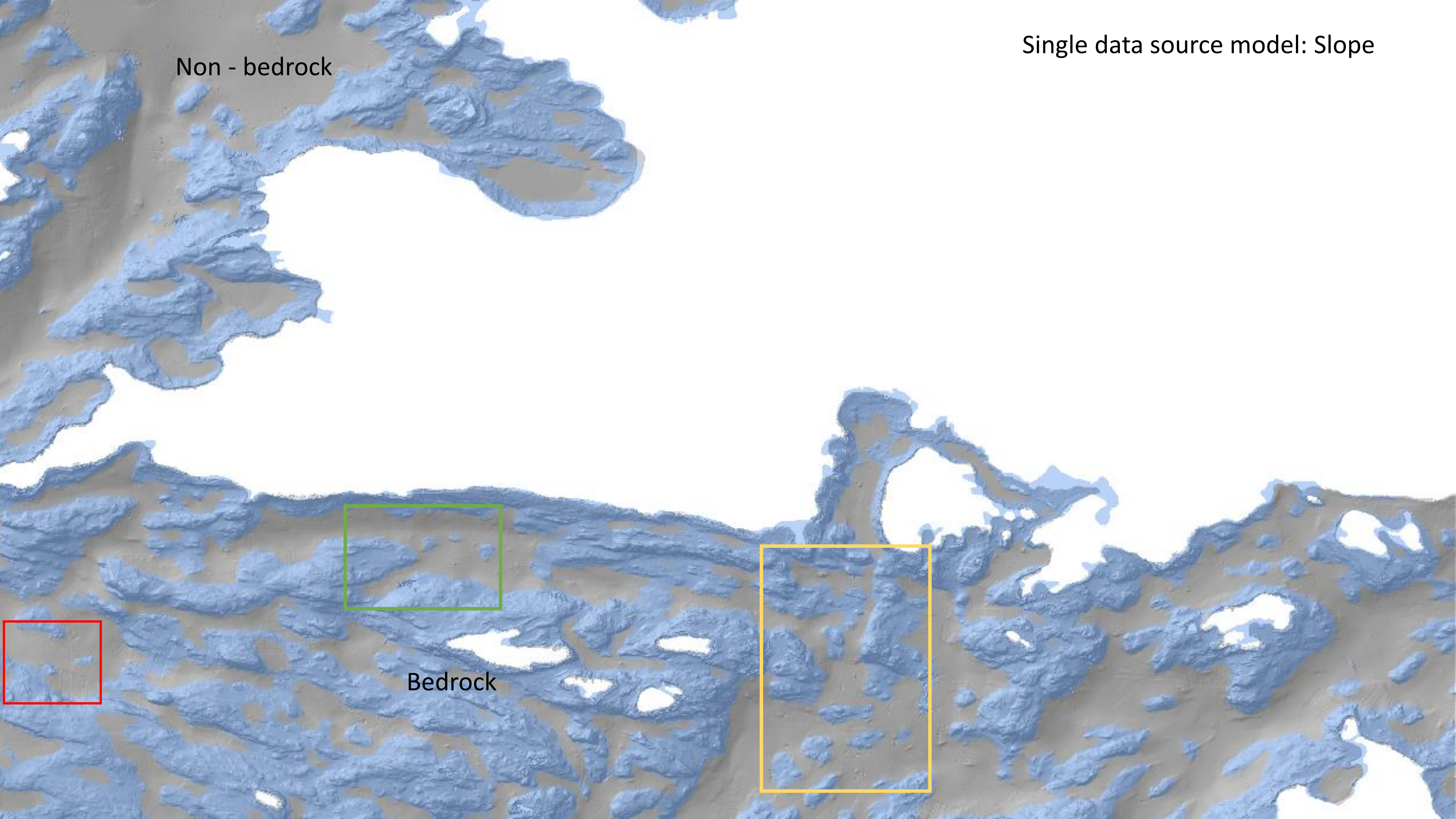
Combined – data sources models						
Backscatter & Depth model	0.74	0.89	0.68	0.80	0.82	0.80
Backscatter & Hillshade model	0.72	0.89	0.65	0.77	0.82	0.79
Backscatter & Slope model	0.74	0.89	0.69	0.81	0.81	0.81
Depth & Hillshade model	0.73	0.81	0.67	0.94	0.82	0.82
Depth & Slope model	0.79	0.92	0.73	0.84	0.86	0.85
Slope & Hillshade model	0.77	0.93	0.69	0.80	0.88	0.82

Visual Results


Original annotations
Non - bedrock
Bedrock


Single data source model: Backscatter
Non - bedrock
Bedrock


Single data source model: Depth
Non - bedrock
Bedrock


Single data source model: Slope
Non - bedrock
Bedrock

What can be concluded observing the metrics and the predictions in figures?

- The models tend to replicate the human annotations very closely
- The depth and the slope models seem to outperform the rest of the models

- The class bedrock is often over predicted → **Misclassification error**

Simplified classes	Original annotated classes	Fraction of pixels predicted as bedrock in relation to the original classes (%)		
		Backscatter model	Depth model	Slope model
Bedrock	Bedrock covered by fine sediments	45.13	52.75	53.9
	Bedrock	18.62	19.92	21.35
Non - Bedrock	Sand, gravel, cobbles	0.25	3.88	3.68
	Sand, gravel, cobbles, boulders	18.14	16.20	15.57
	Muddy sand	1.43	1.10	0.91

Final considerations

- Deep Learning networks showed high potential in replicating human annotations.
- The depth and the slope models are the most suitable ones at reliably predicting the bedrock distribution on the seabed.
- Predictions show the tendency of the models to efficiently delineate and separate topographic features, but also to over-predict the bedrock class.
- The subjectivity of the human interpreter, the acoustic similarities between bedrock and the misclassified classes and data artifacts within the dataset in use, must be accounted for.
- As progress in the field evolve, Deep Learning networks might be used, as support to the human expert geologists, for mapping task routines.
- Next experiments will involve the attempt to explore the potential of Deep Learning in classifying multiple seabed sediment classes.

Thank you for the attention

Any Questions?

Rosa Virginia Garone, PhD NTNU
Contact: rosa.v.garone@ntnu.no