

Analysis of seabed nature supervised segmentations according to input multibeam data formats and levels of processing.

ENSTA

**Irène Mopin, H. Moreau, G. Le Chenadec,
S. Homrani**

Shom

C. Vrignaud, E. Marches

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SeabAId project

Partnership between :

- ENSTA : engineering school (Brest, France)
- Shom : French naval hydrographic and oceanographic institute

Objective:

- Analysis and large-scale exploitation of seafloor acoustic reflectivity from MBES, with the aim of classification and characterisation

Two approaches:

- Physical: analysis of the measurement method and its explainability
- AI: semantic segmentation using deep learning methods

SeabAId
underwater acoustics • machine learning • backscatter



2023-2026

Problem statement

Second approach (AI):

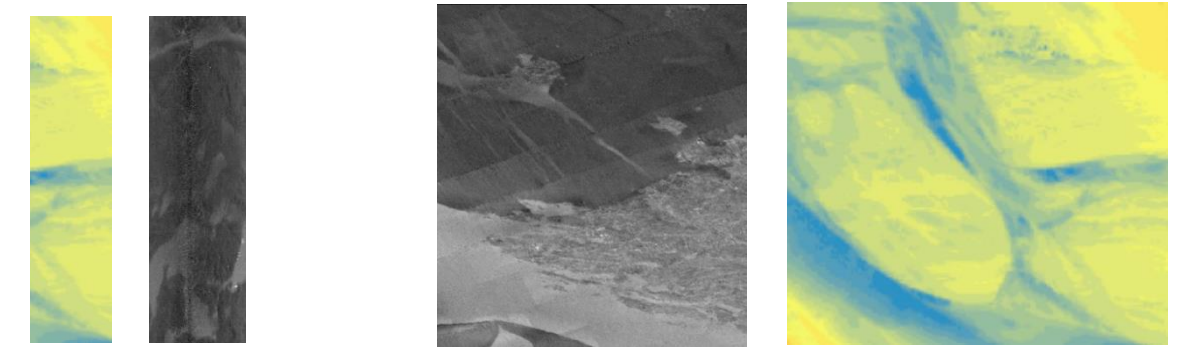
- Semantic segmentation using deep learning methods

Focus of this presentation:

- How the use of different data format and processing impact the result of semantic segmentation?

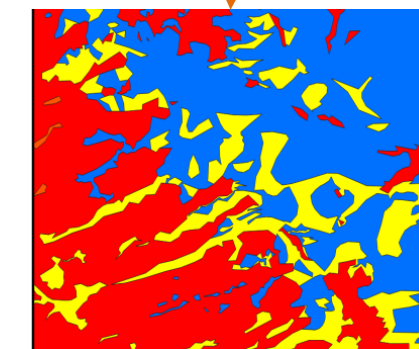
Results from H. Moreau post-doc works

Possible inputs data and formats



Ping-Beam or map

Network



Output

Summary

Survey areas & Dataset.

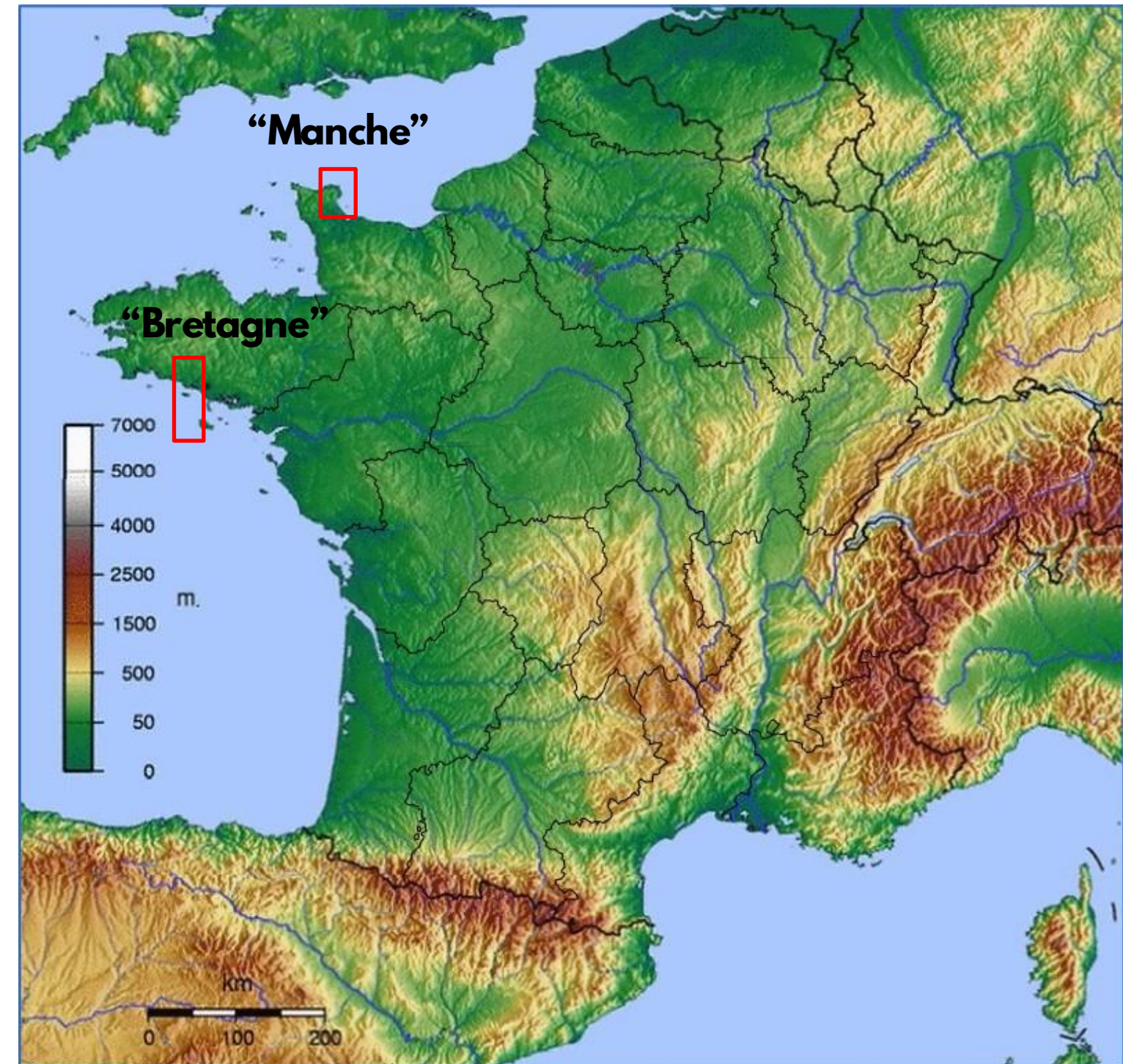
Survey areas

Two survey areas

- « Bretagne »: South of Brittany, close to Lorient
- « Manche »: English Channel, close to Utah Beach

Survey achieved by Shom in 2020-2021 to prepare the implantation of offshore wind farms

- « Bretagne »: start date 2033 – 250 MW
<https://www.pennavel.bzh/>
- « Manche »: start date 2032 – 1,05 GW
<https://parc-eolien-en-mer-manche-normandie.fr/>



Surveys

Focus on one echosounder:

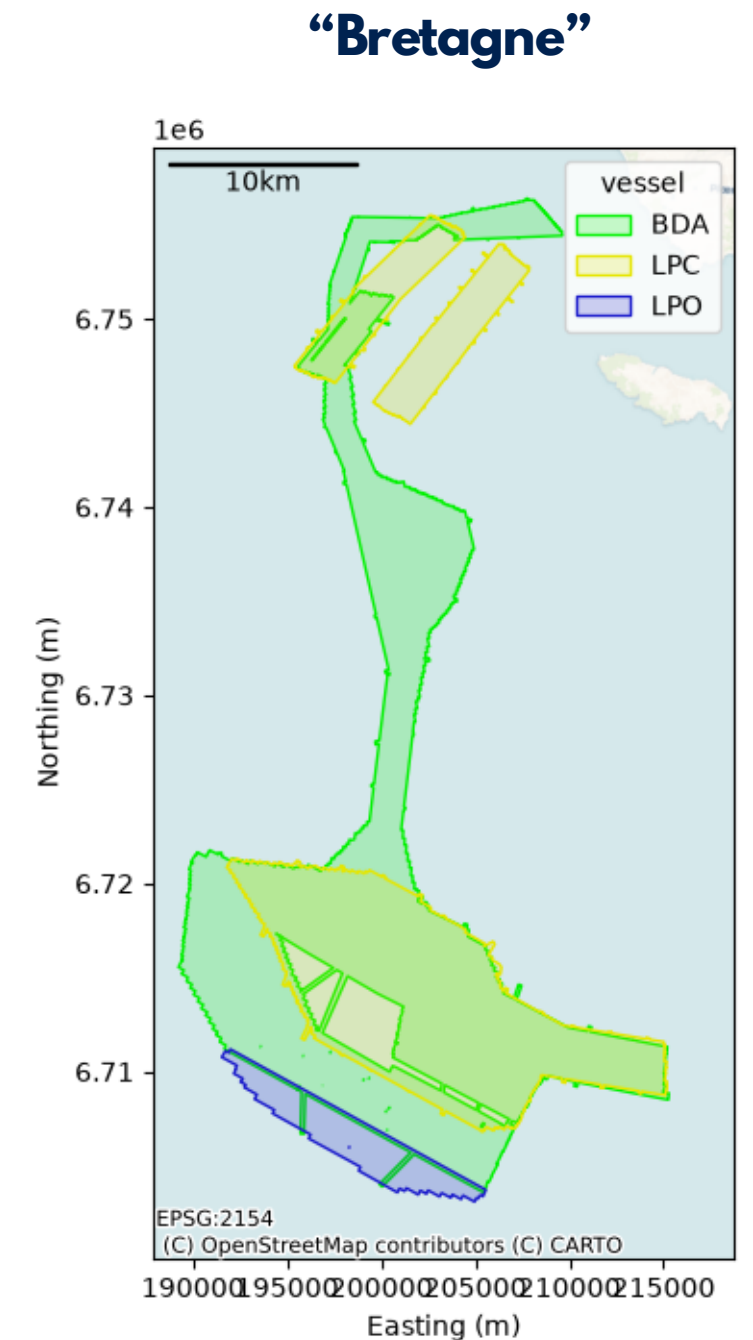
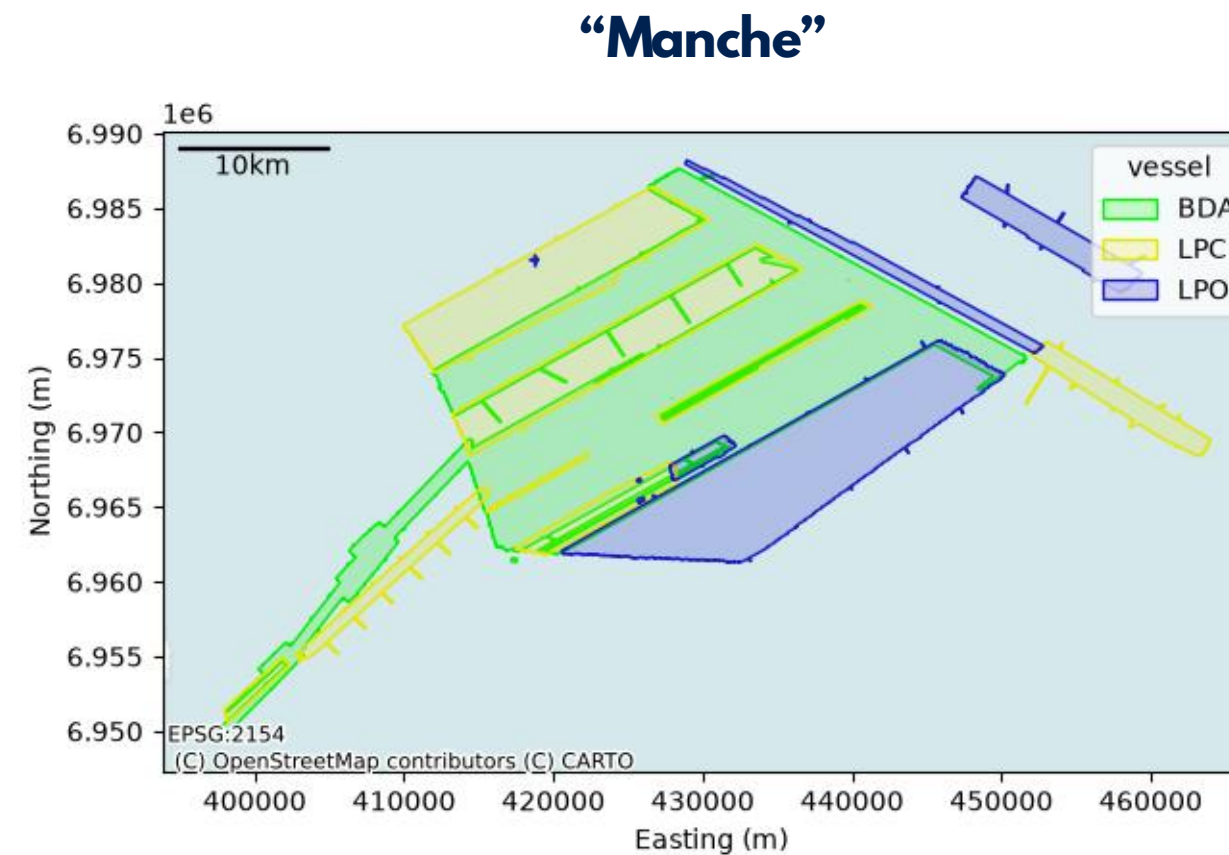
- Kongsberg EM710

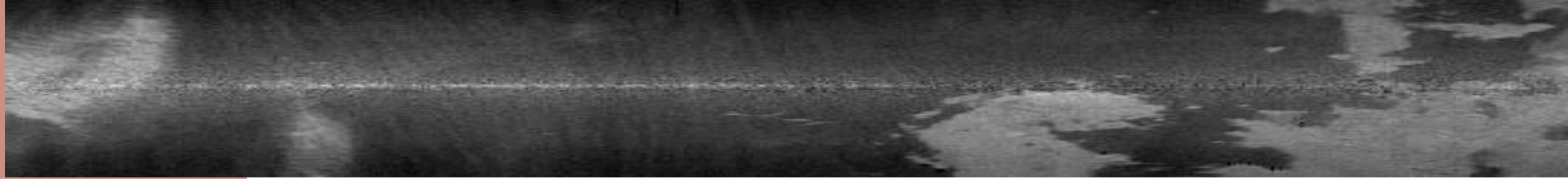
Different survey vessels:

- Borda (BDA)
- Laplace (LPC)
- La Pérouse (LPO)

Parameters of acquisition:

- Dual Swath
- High density Equidistant
- [70-80-70]kHz, [90-100-90]kHz
- 1° / 1°
- Very Shallow





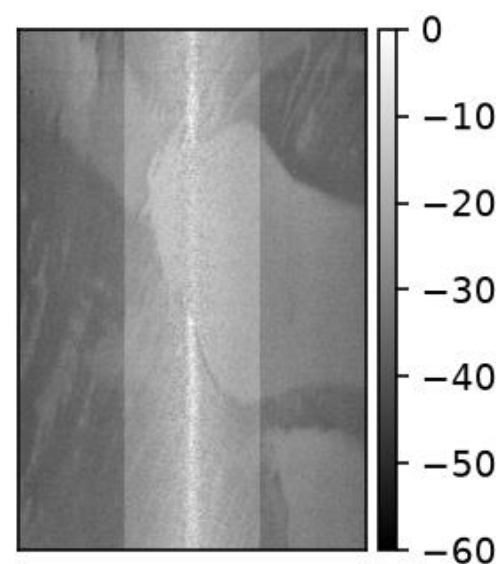
MBES data

Multibeam echosounder data available:

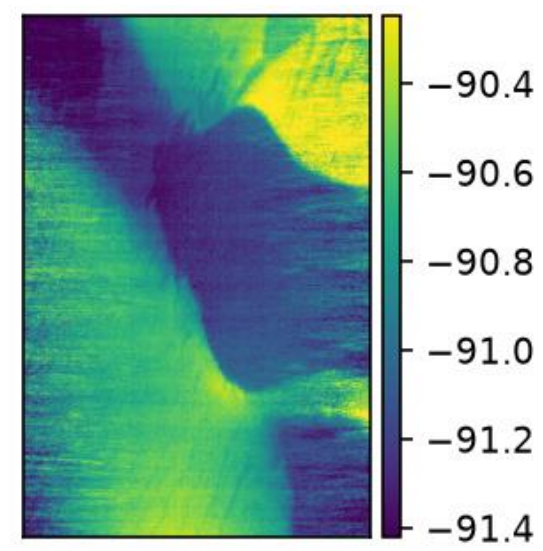
- Bathymetric data or « Depth »: DBM or raw (ping-beam)
- Reflectivity data - « Backscatter »: mosaic or raw (ping-beam)

DBM is provided by Shom (all vessels and MBES combined)

Raw data (ping-beam)

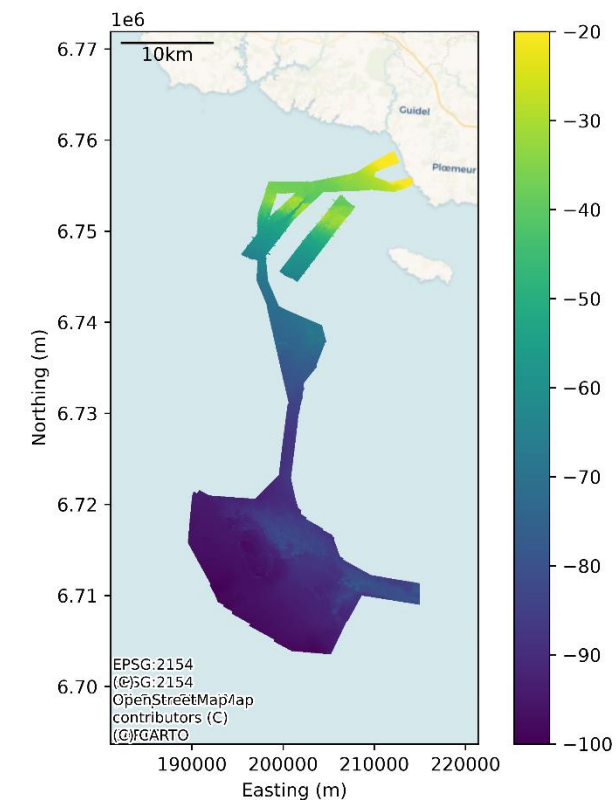


Backscatter



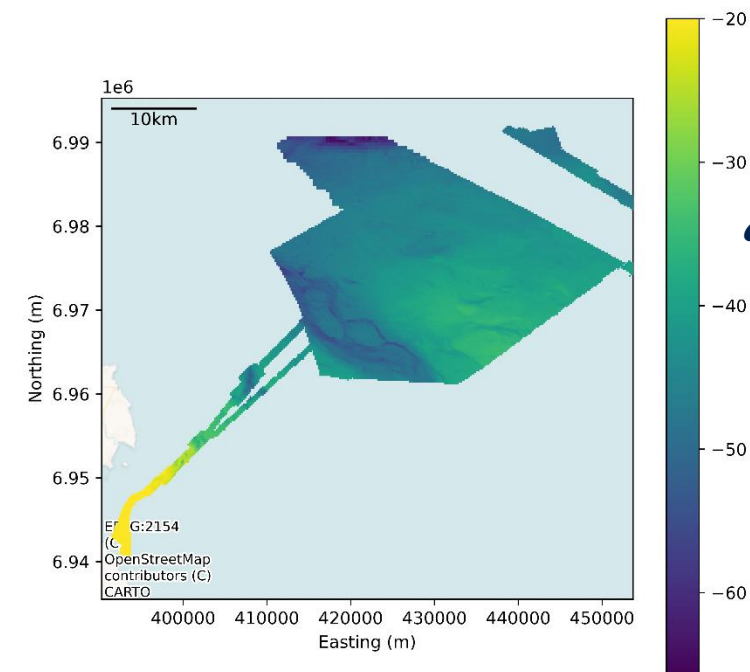
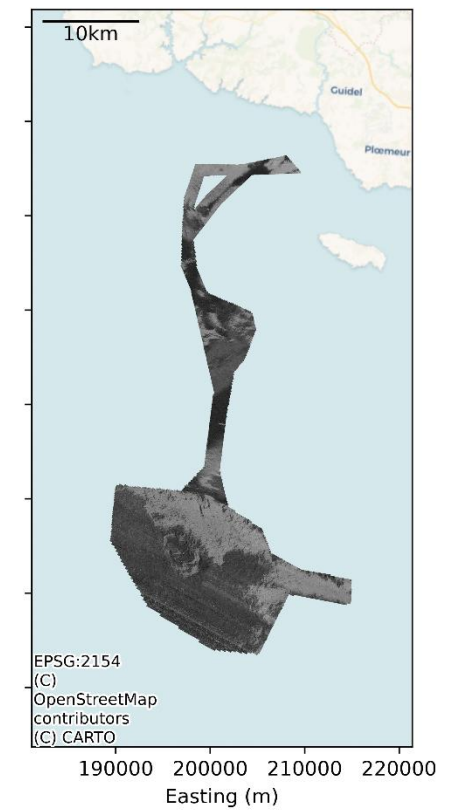
Depth

Digital Bathymetric Model

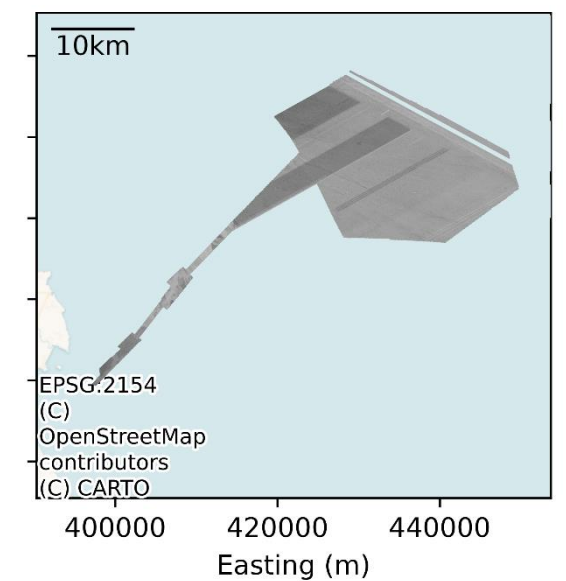


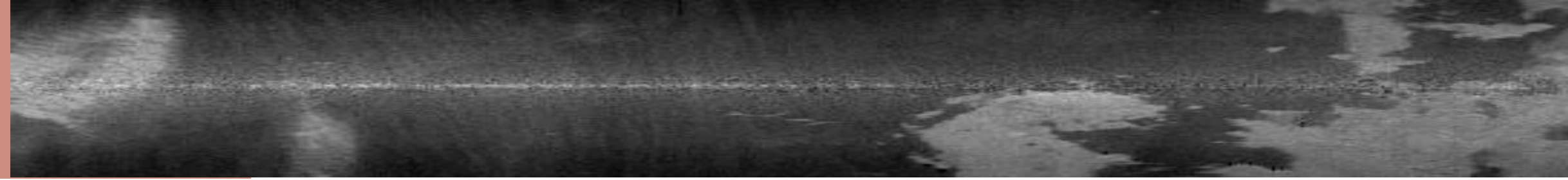
“Bretagne”

Reflectivity map or Mosaic



“Manche”





Seafloor nature map

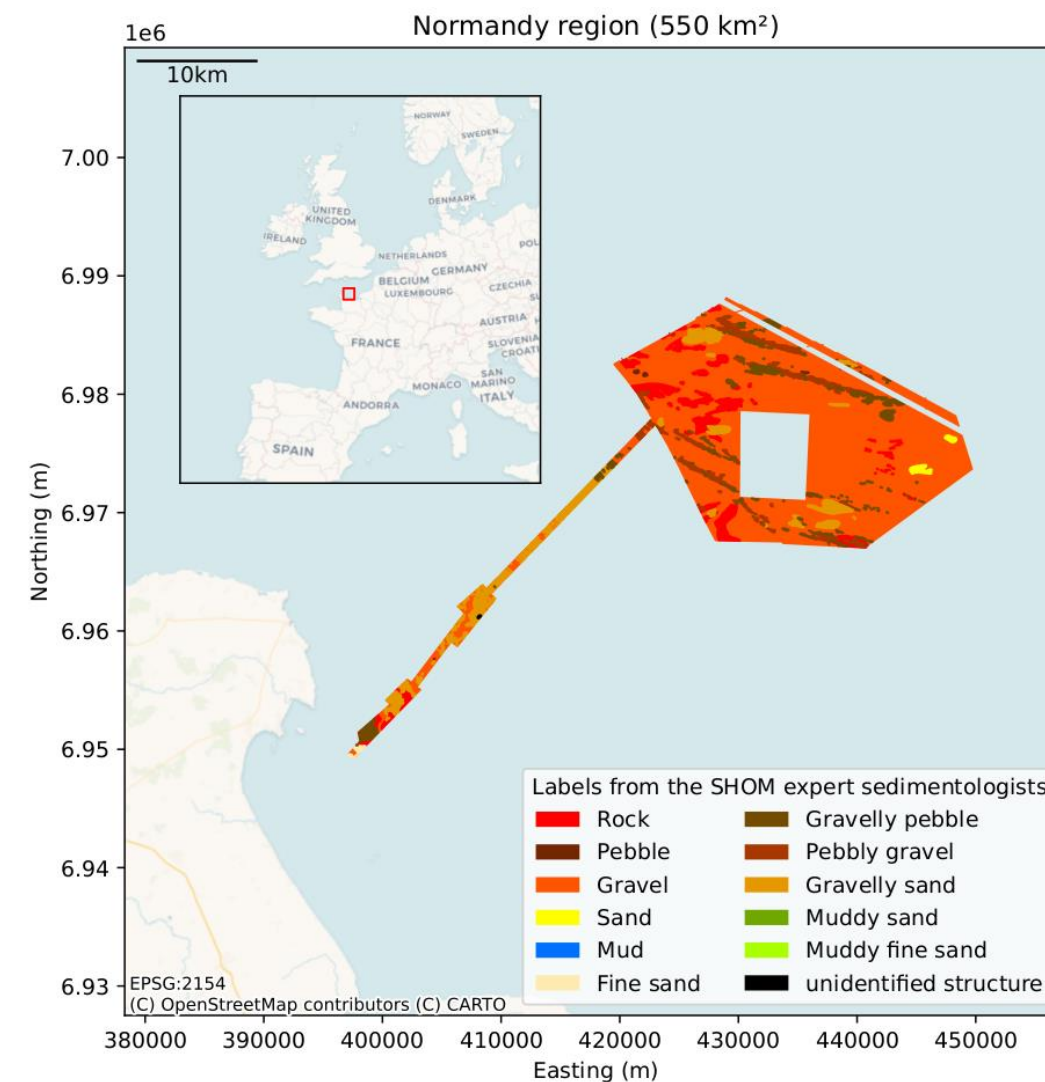
Seafloor nature map is created by Shom experts in sedimentology based on:

- Bathymetric data (DBM)
- Reflectivity map (mosaic)
- Sidescan sonar data (imagery)
- Sub-bottom profiler data
- Samplings
- Expertise

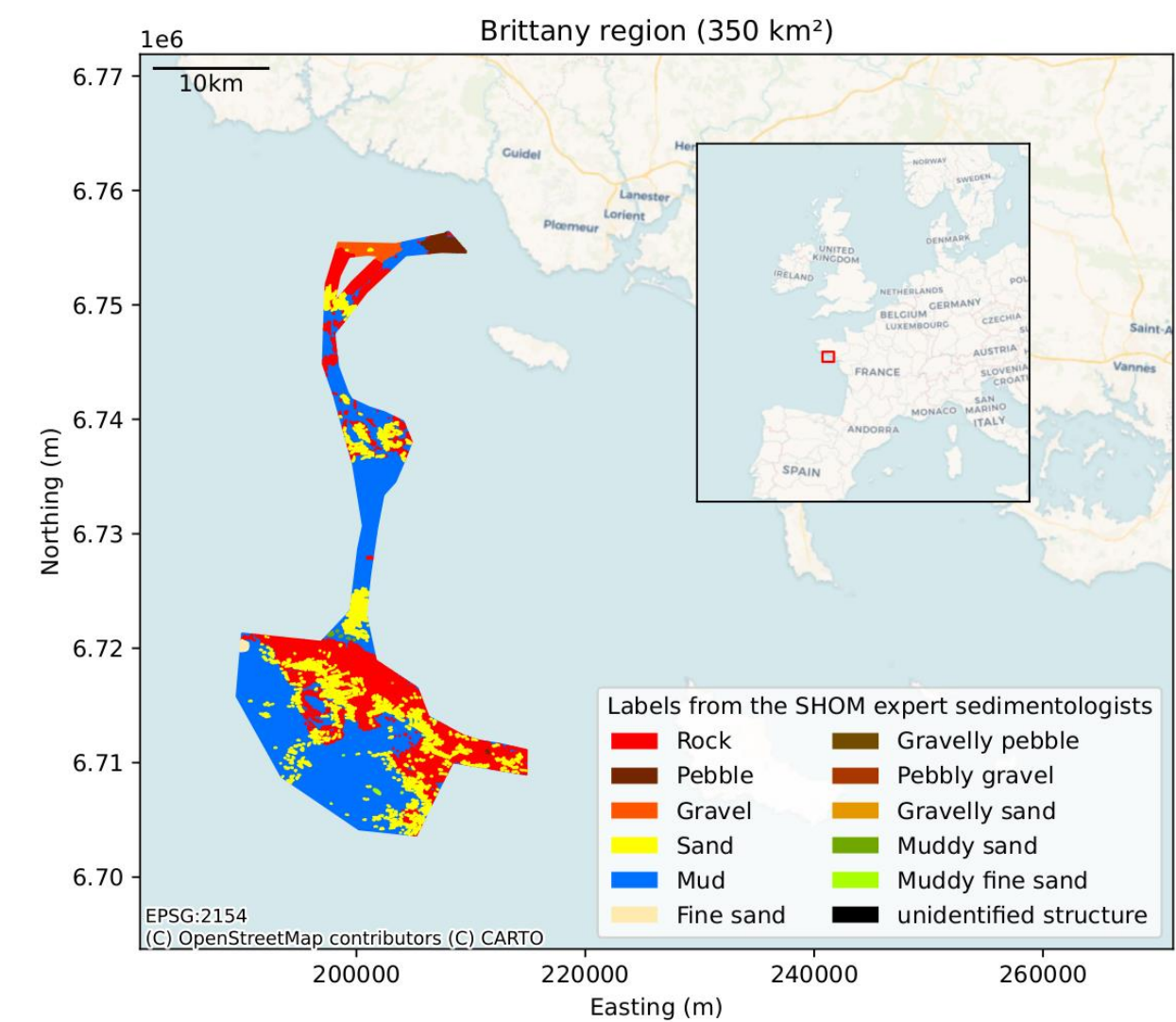
The map is drawn above the mosaic
⇒ At the resolution of the mosaic (1m)

Labels from Shom classification

“Manche”



“Bretagne”



Summary

Method.

Labels fusion

Shom seafloor nature classification includes too much classes

⇒ We merged some to retain 4 classes:

- Rock
- Rough sediment
- Medium sediment
- Fine sediment

original labels				merged labels			
Label	Proportion train	Proportion validation	Prop. test	Label	Proportion train	Proportion validation	Prop. test
Rock	19.70 %	4.31 %	12.31 %	Rock	19.70 %	4.31 %	12.3 %
Pebbles	0.05 %	0 %	6.25 %	Rough sediment	40.41 %	62.25 %	69.46 %
Pebbles with Gravel	1.09 %	0.45 %	2.28 %				
Gravel with Pebbles	1.76 %	0.99 %	1.89 %				
Gravel	37.51 %	60.81 %	59.04 %				
Sand with Gravel	2.78 %	2.09 %	0.29 %	Medium sediment	9.36 %	6.22 %	4.57 %
Sand	3.59 %	4.13 %	2.09 %				
Sand with Mud	0.02 %	0 %	0 %				
Fine Sand	2.94 %	0 %	1.57 %				
Fine Sand with Mud	0.02 %	0 %	0.0004 %				
Mud	30.53 %	27.22 %	13.66 %	Fine sediment	30.53 %	27.22 %	13.66 %

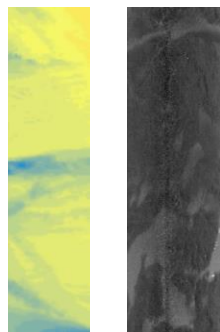
Data preprocessing

Training:

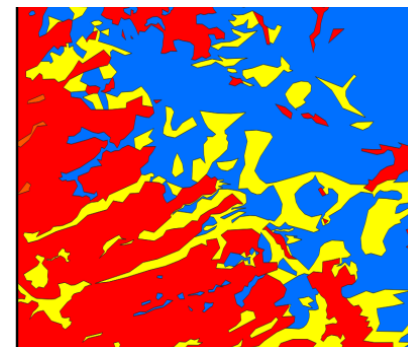
- Use of backscatter and depth data + seafloor nature map

⇒ For ping-beam format : necessary to project the labels

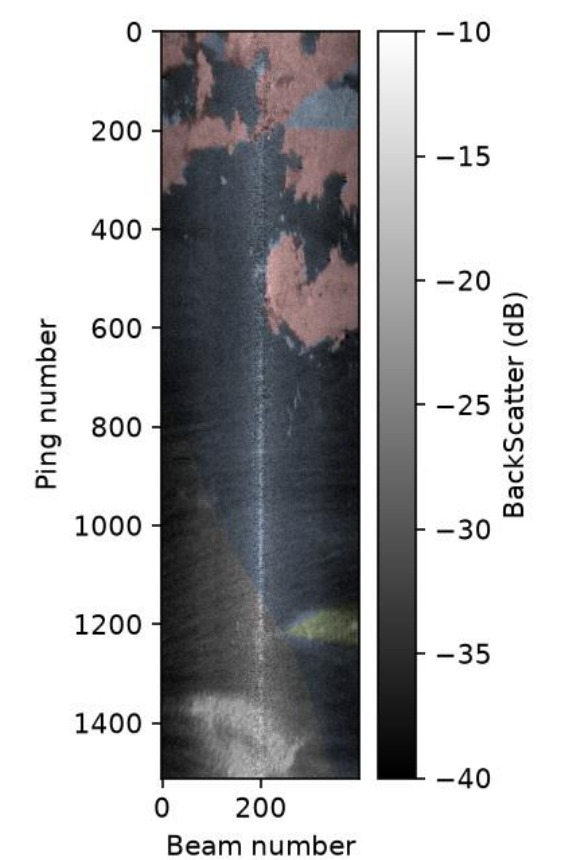
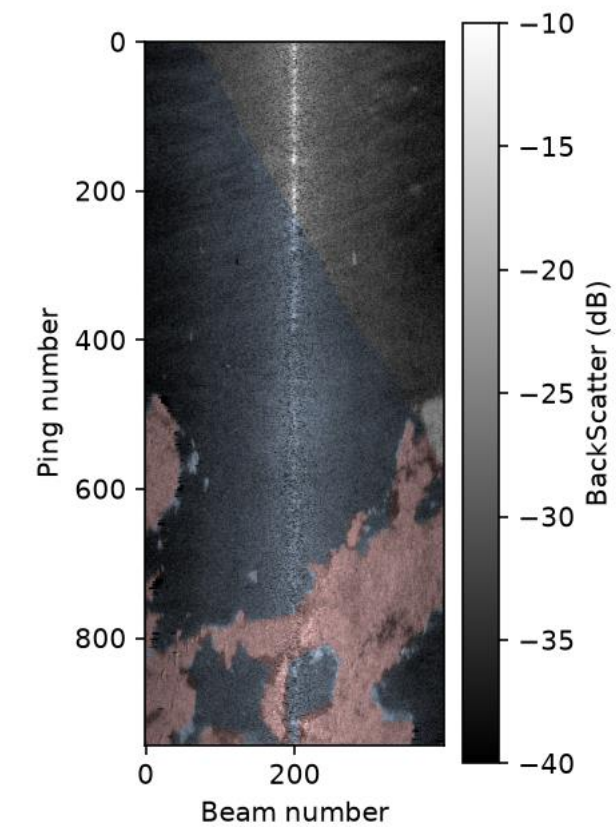
MBES data in ping-beam format



Seafloor nature map



Projected labels

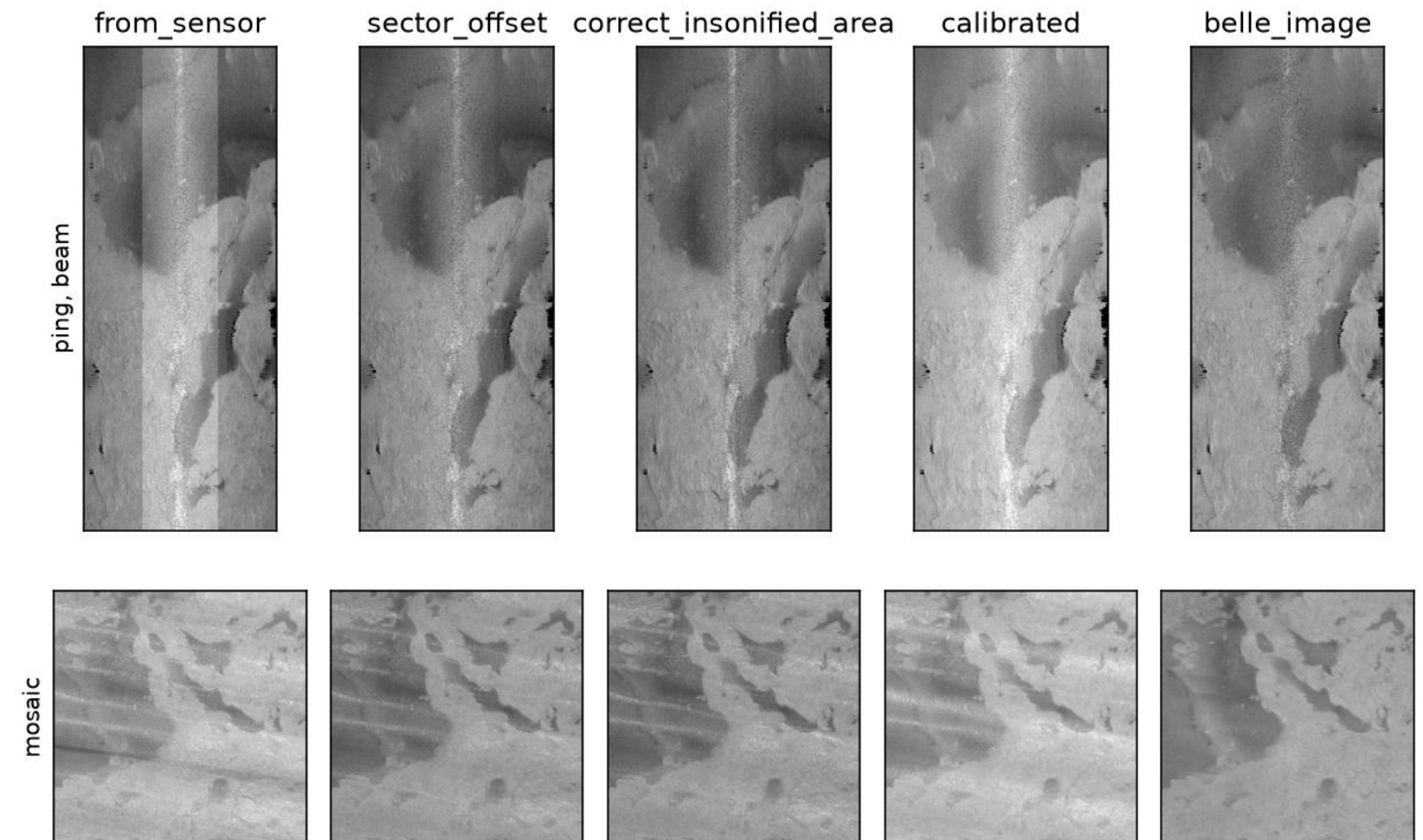


Data preprocessing

Analysis with different level of backscatter processing:

- « From sensor »: raw data (*.all files, Reflectivity datagram)
- « Sector offset »: manual compensation of sectors offsets
- « Corrected insonified area »: with re-calculation of the insonified areas based on the DBM
- « Calibrated »: with Bscorr file issue from calibration of *Carré Renard* (Ifremer)
- « Belle image »: egalisation of levels

All available for ping-beam and map formats



Network

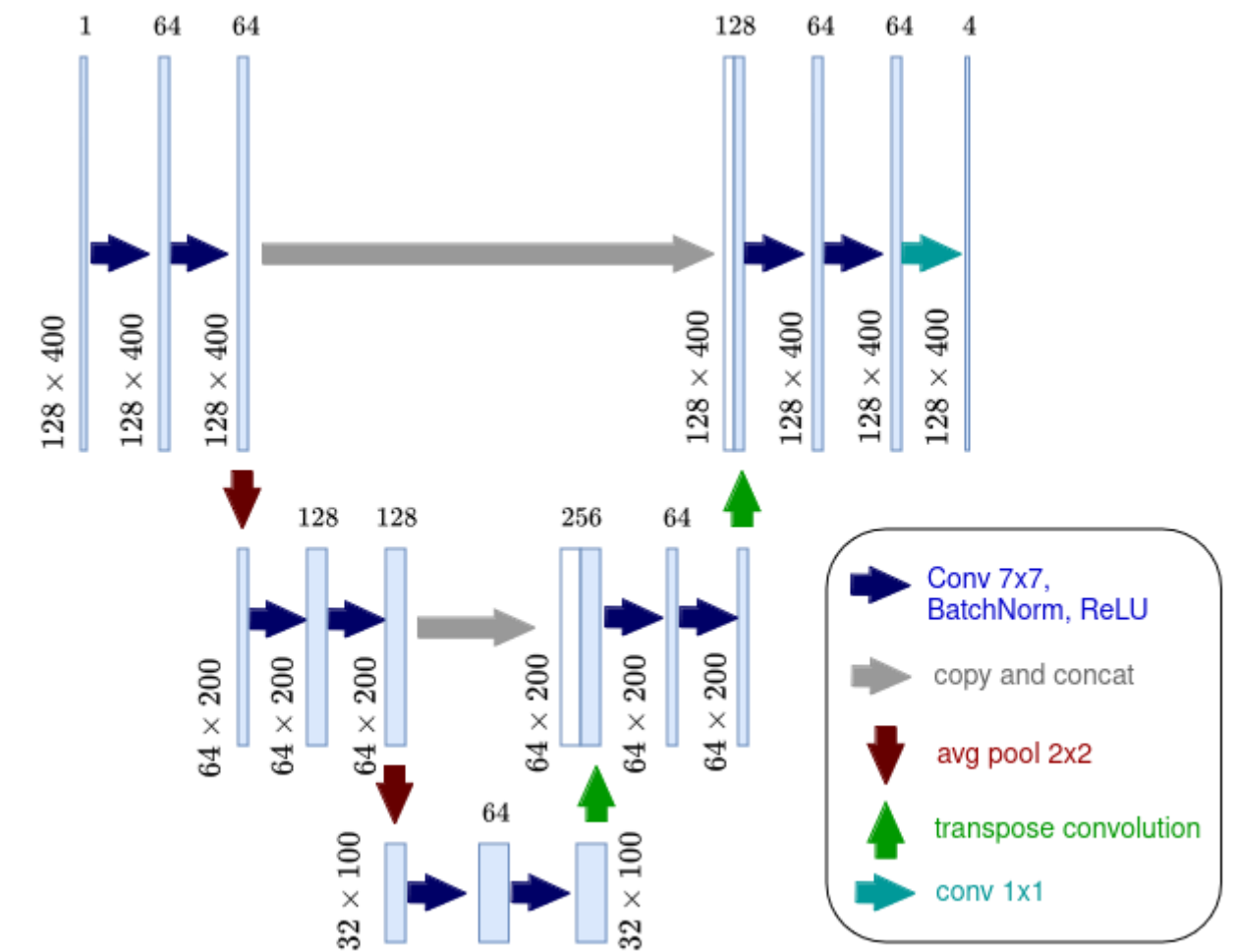
Architecture comparable to a U-net with the same set of hyperparameters for both data formats (ping-beam or map)

Inputs :

- Ping-beam or map data
- Backscatter alone, depth alone, or backscatter + depth

Output :

- Seafloor nature prediction in the format of inputs



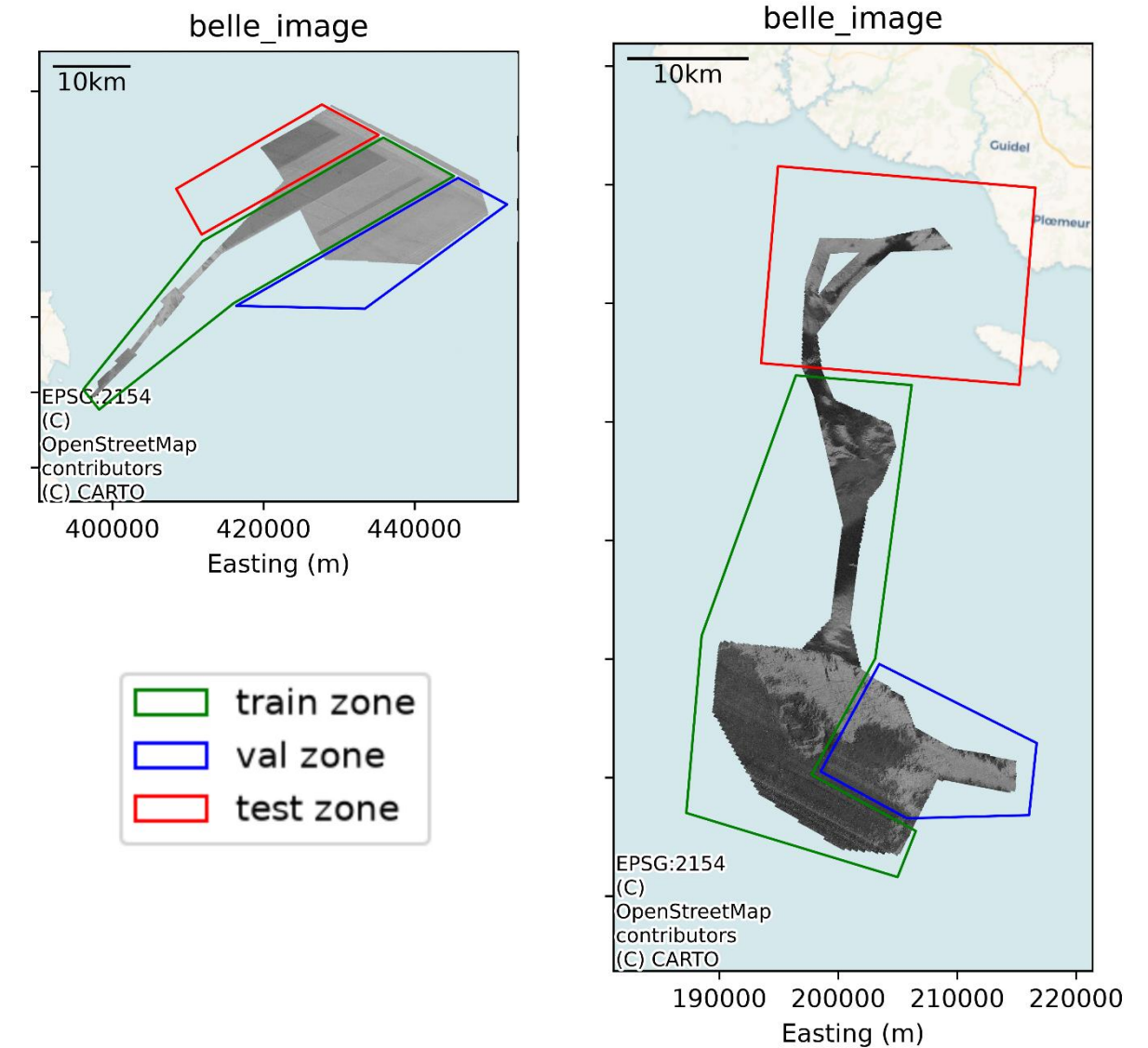
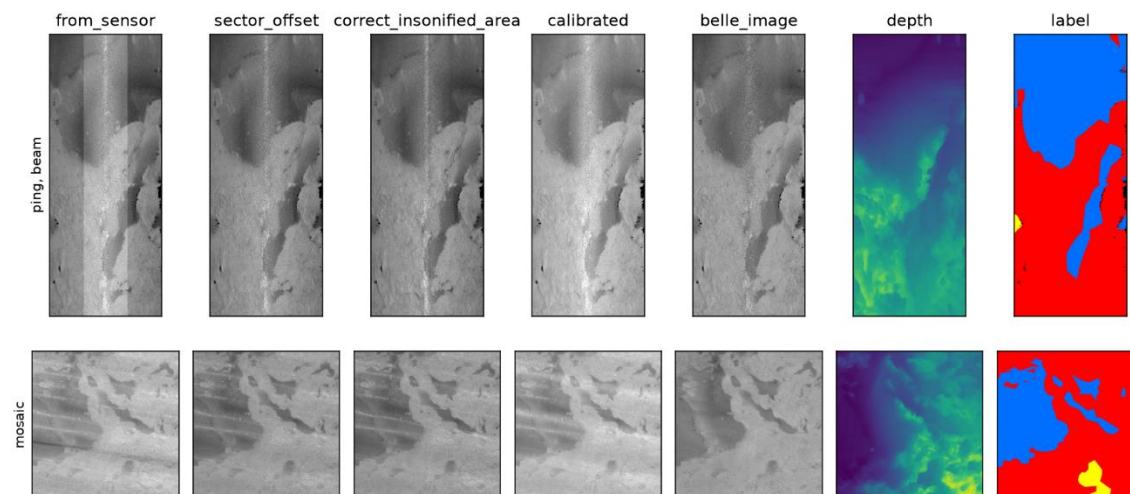
Protocol

Training / Validation / Test on different geographical areas

Training is made using :

- Backscatter data
- Depth data
- Seafloor nature data - projected if necessary (labels)

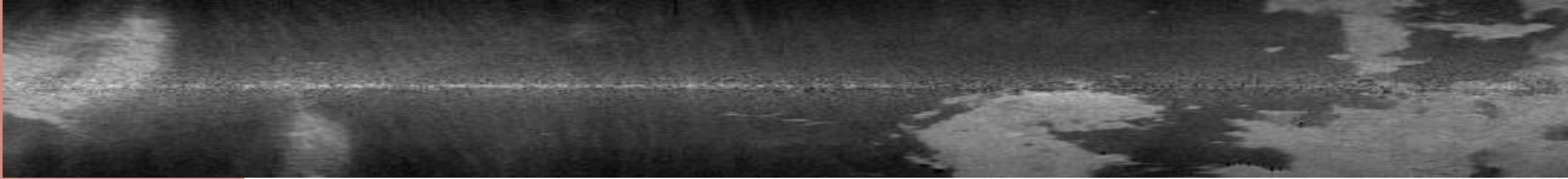
One training is made for each backscatter preprocessing dataset



NB: we only test and evaluate the network on data with the same pre-processing level and format than the training dataset

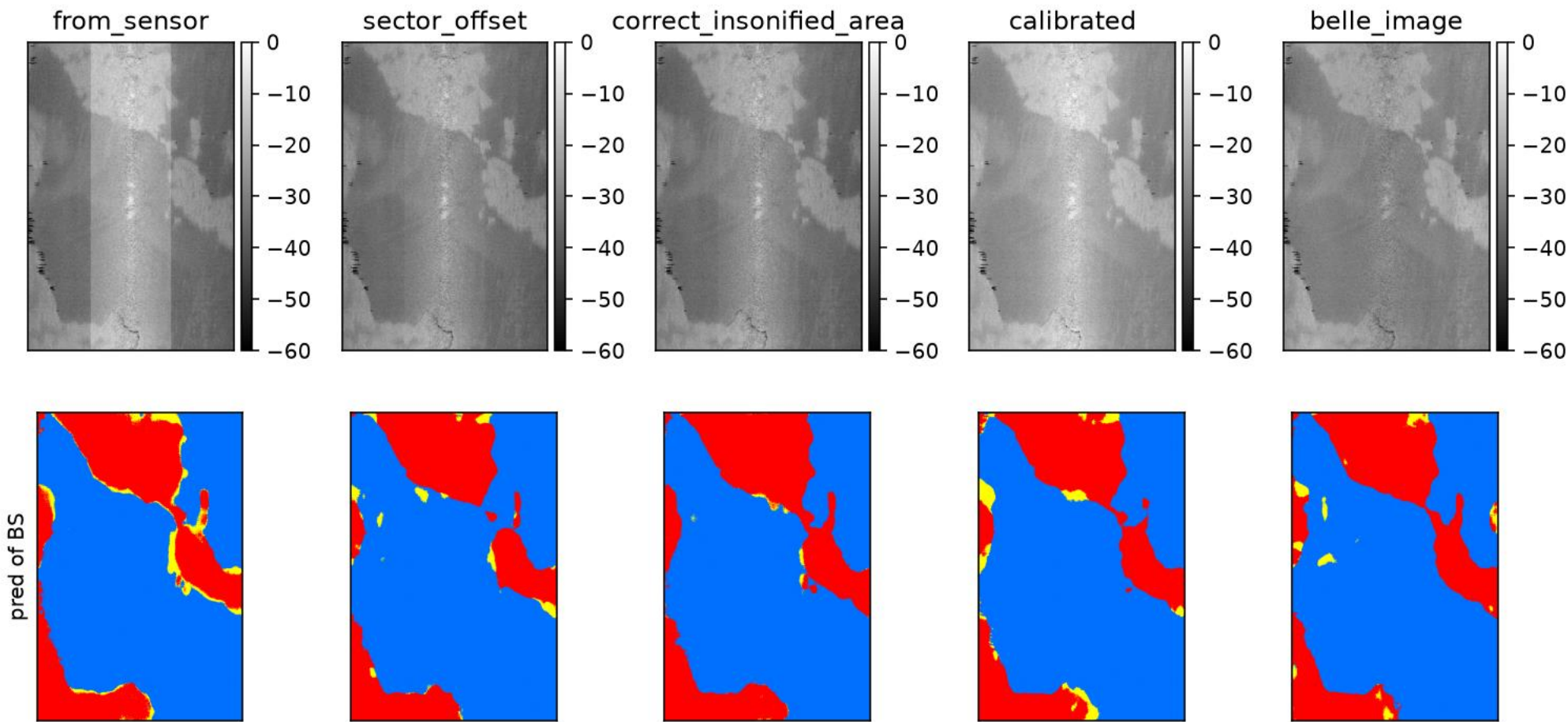
Summary

Results & Discussions.



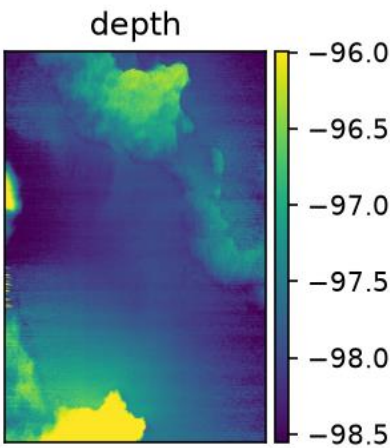
Examples of predictions

Predictions of seafloor nature from ping-beam backscatter

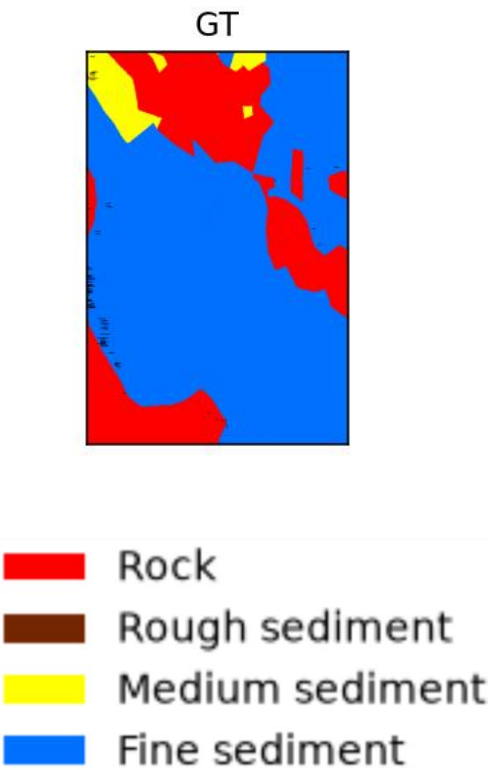


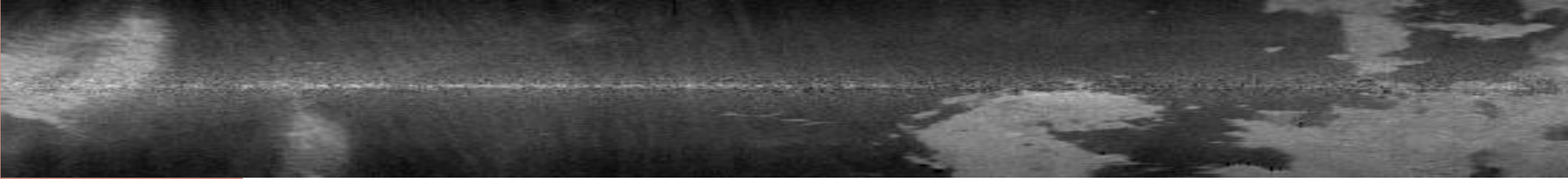
« good »

Associated bathymetry



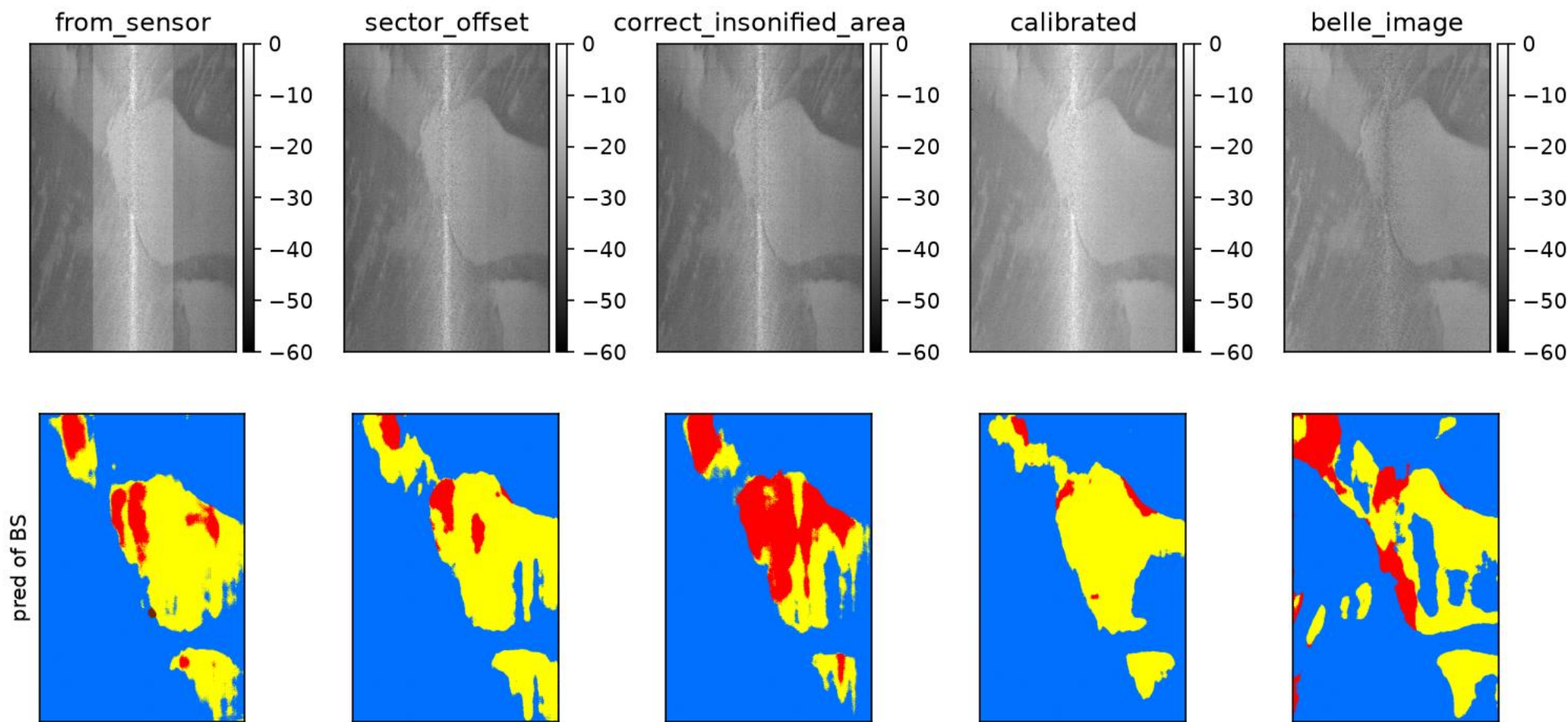
Associated seafloor nature





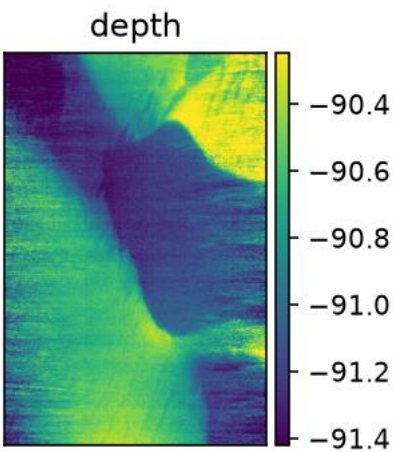
Examples of predictions

Predictions of seafloor nature from ping-beam backscatter

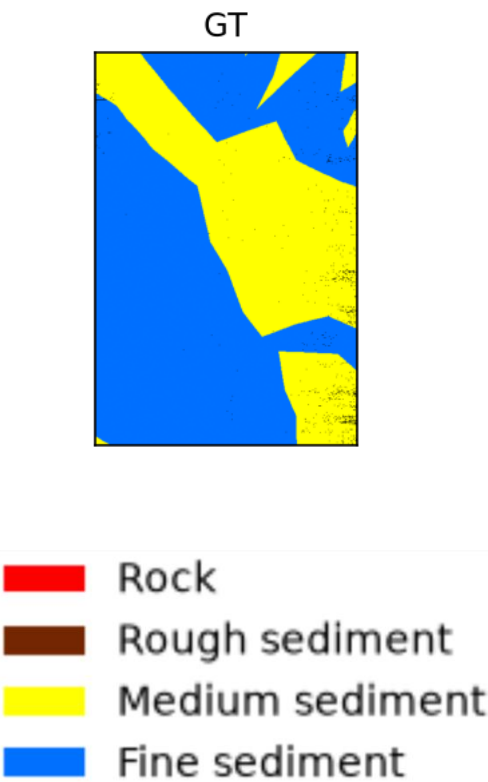


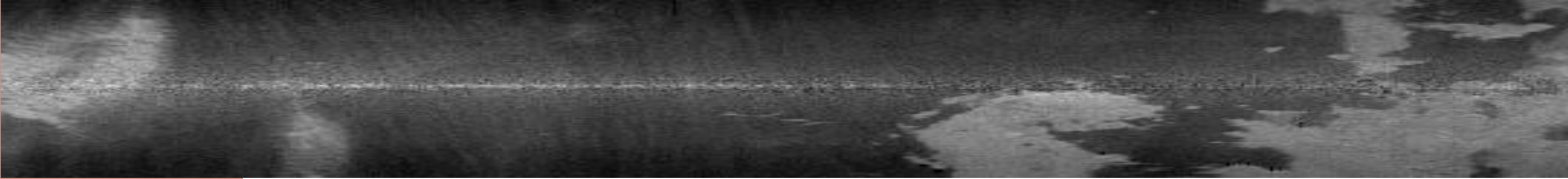
« okay »

Associated bathymetry



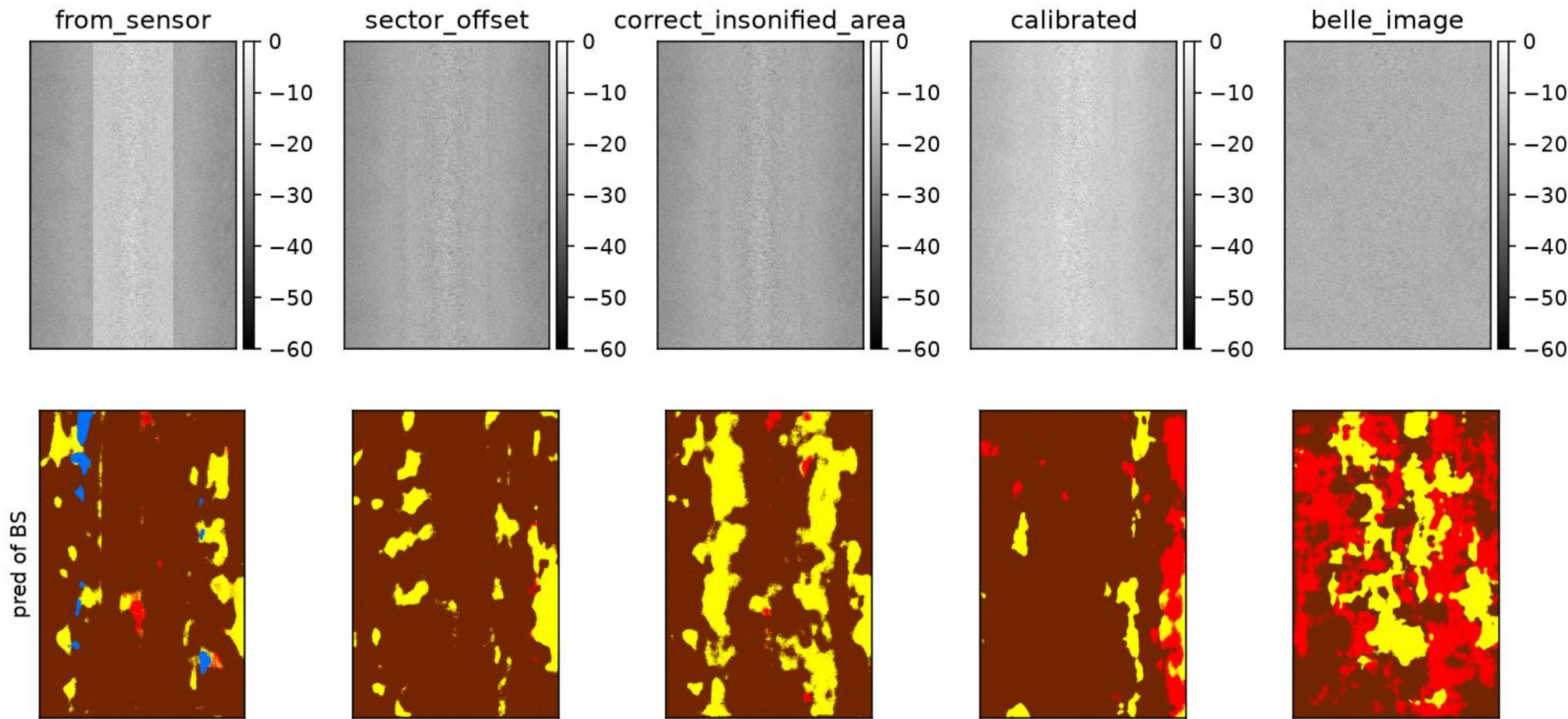
Associated seafloor nature





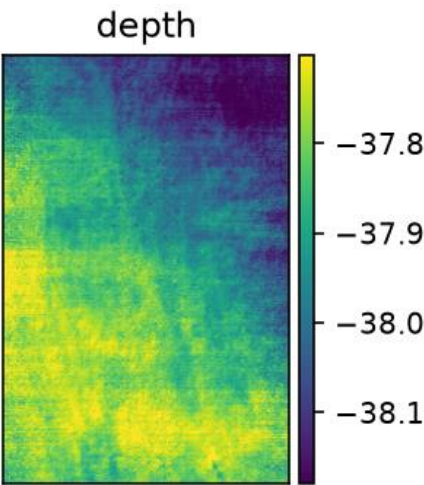
Examples of predictions

Predictions of seafloor nature from ping-beam backscatter

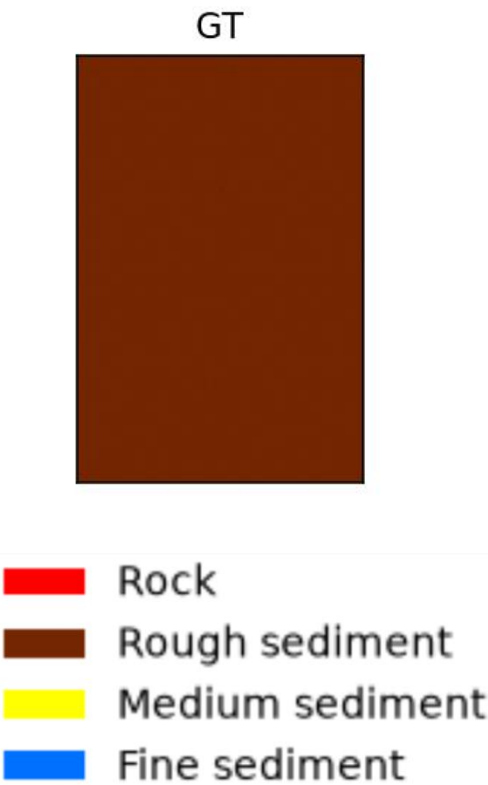


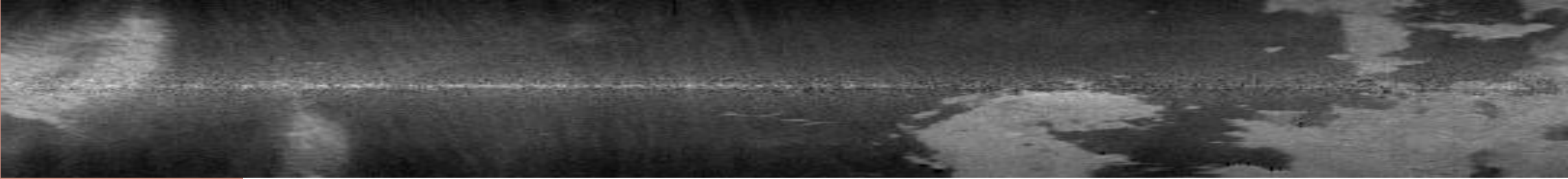
« bad »

Associated bathymetry



Associated seafloor nature

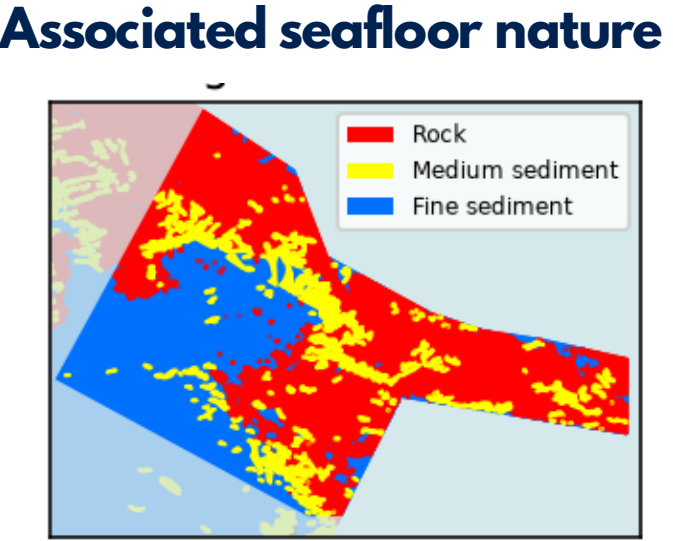
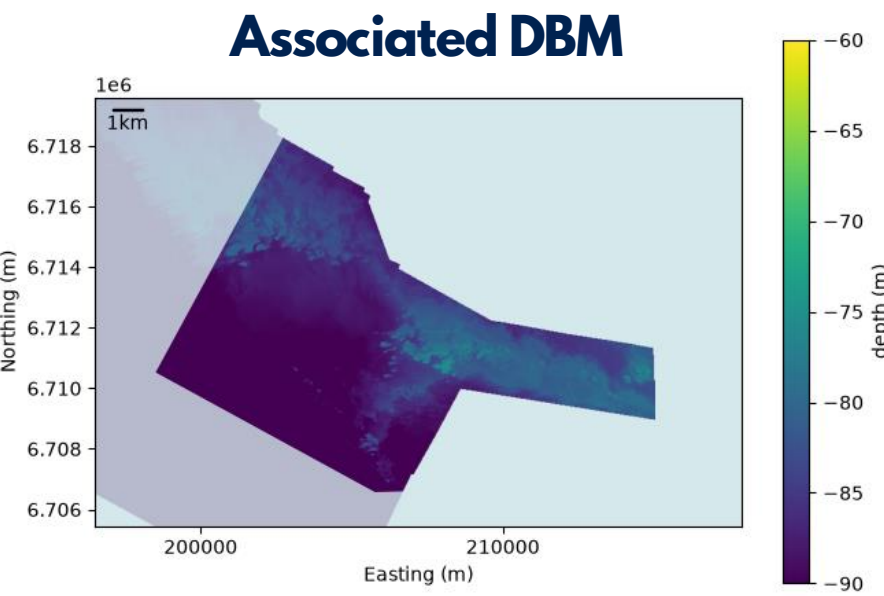
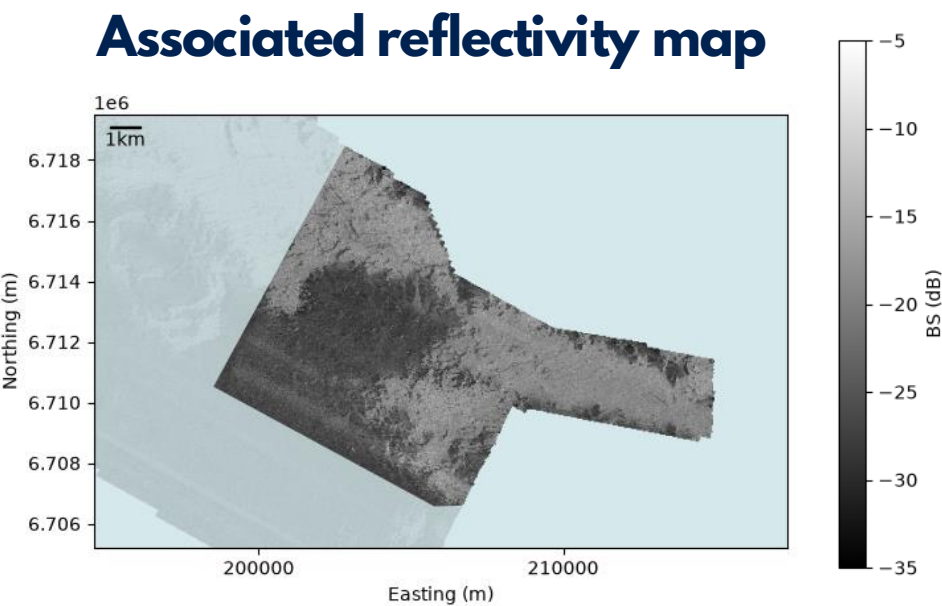
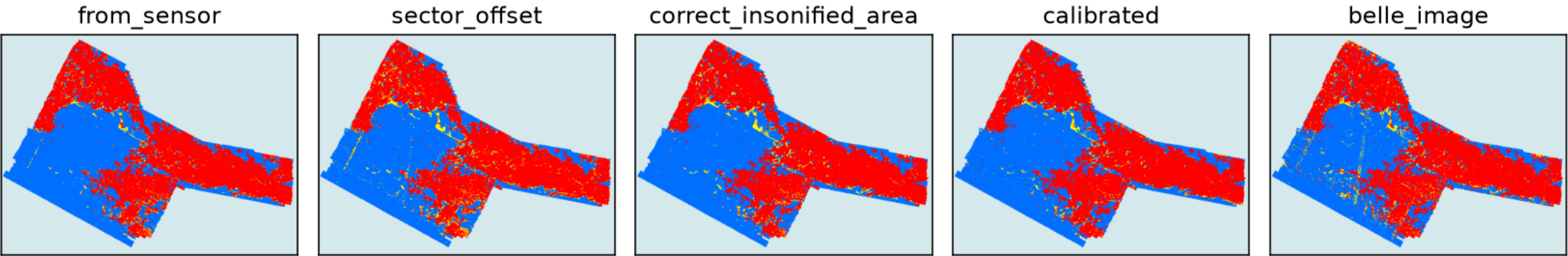


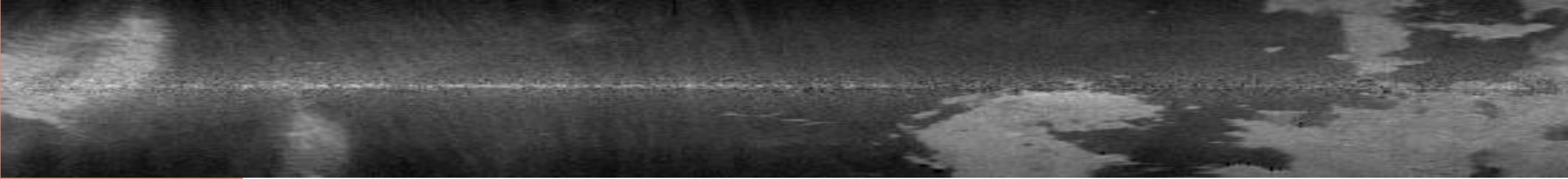


Combined predictions – “Bretagne”



Predictions of seafloor nature from ping-beam backscatter, then mapped

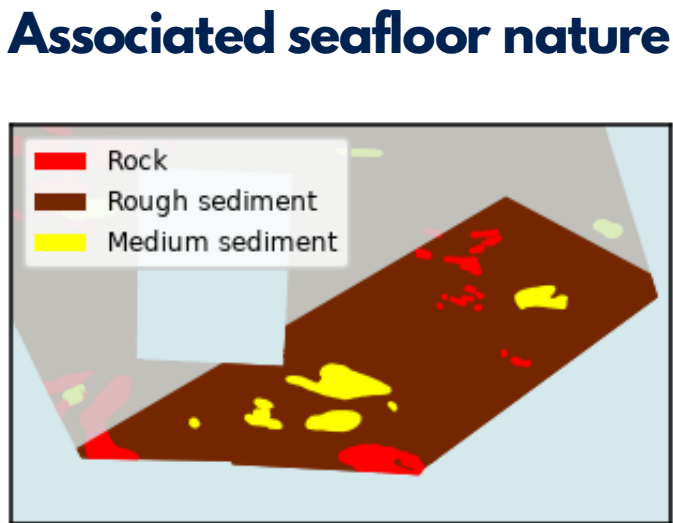
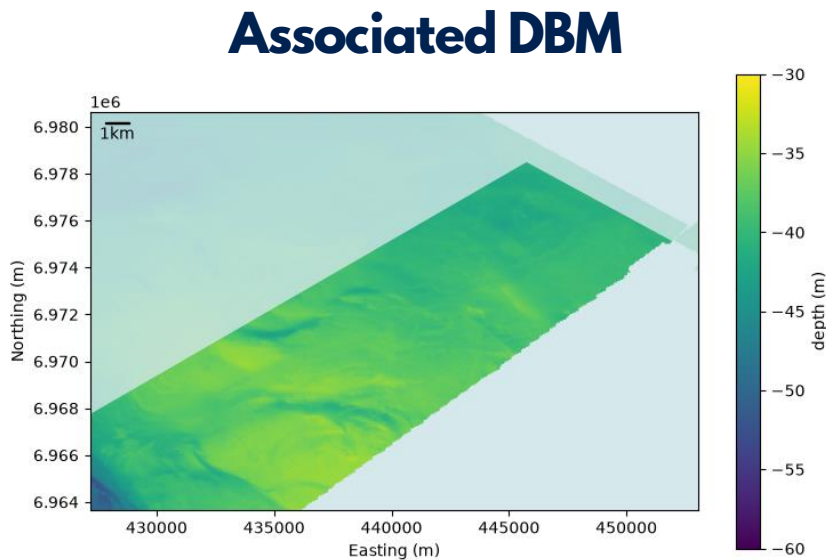
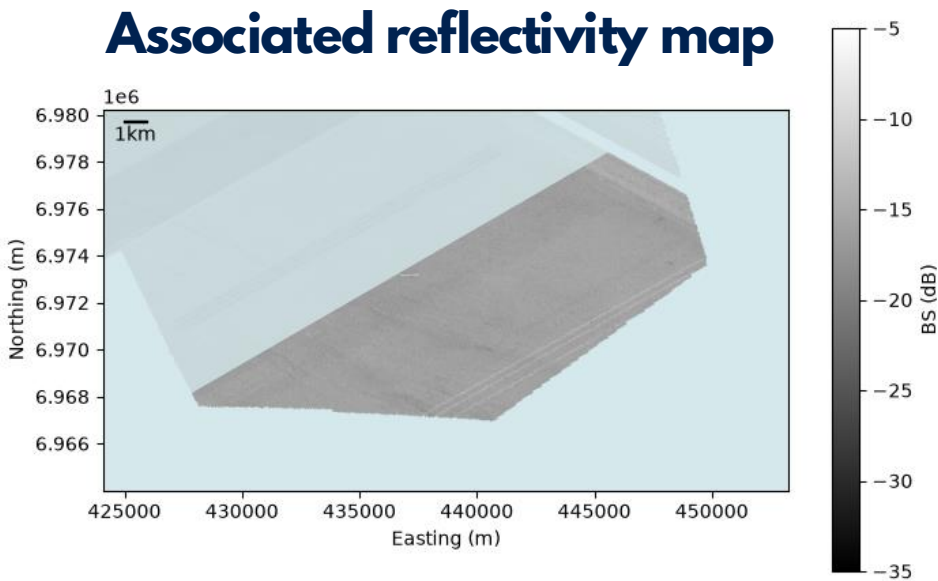
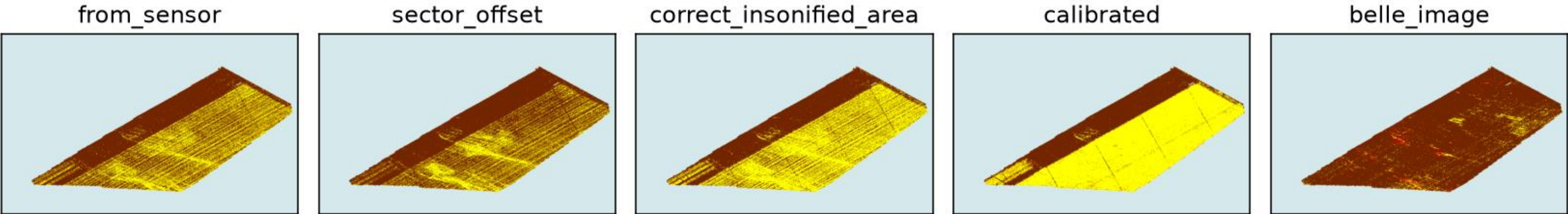


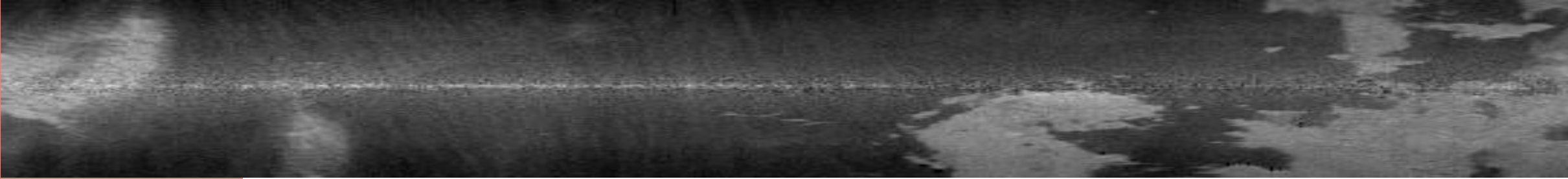


Combined predictions – “Manche”



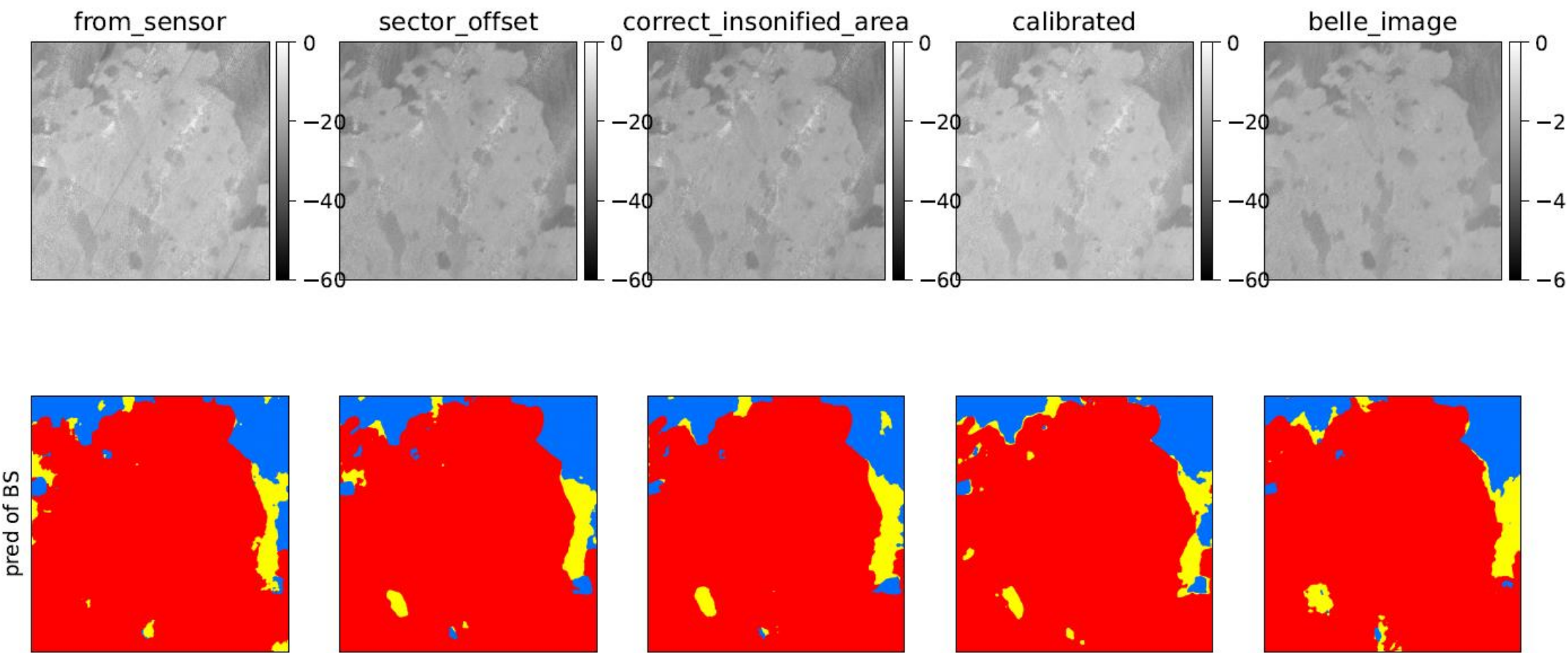
Predictions of seafloor nature from ping-beam backscatter, then mapped





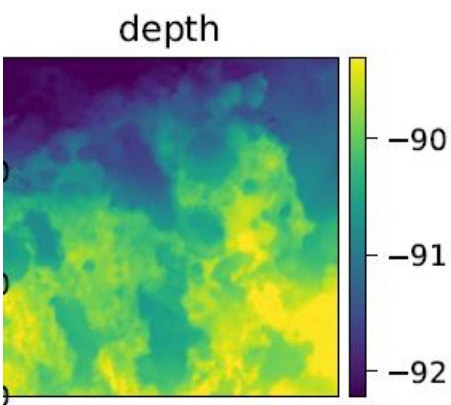
Examples of predictions

Predictions of seafloor nature from **mosaic** backscatter



« good »

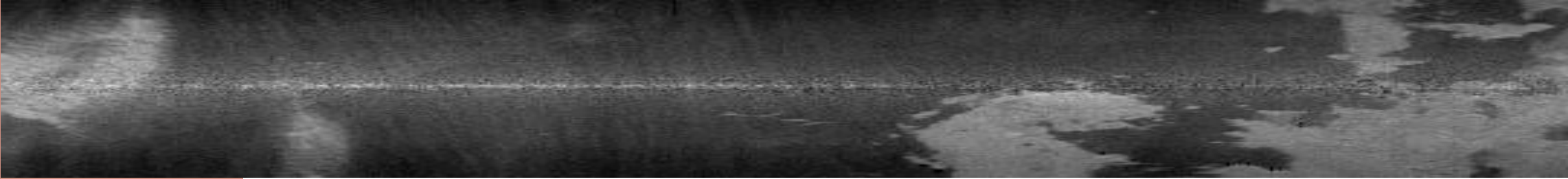
Associated bathymetry



Associated seafloor nature

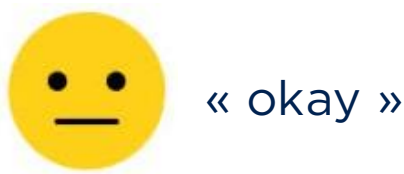
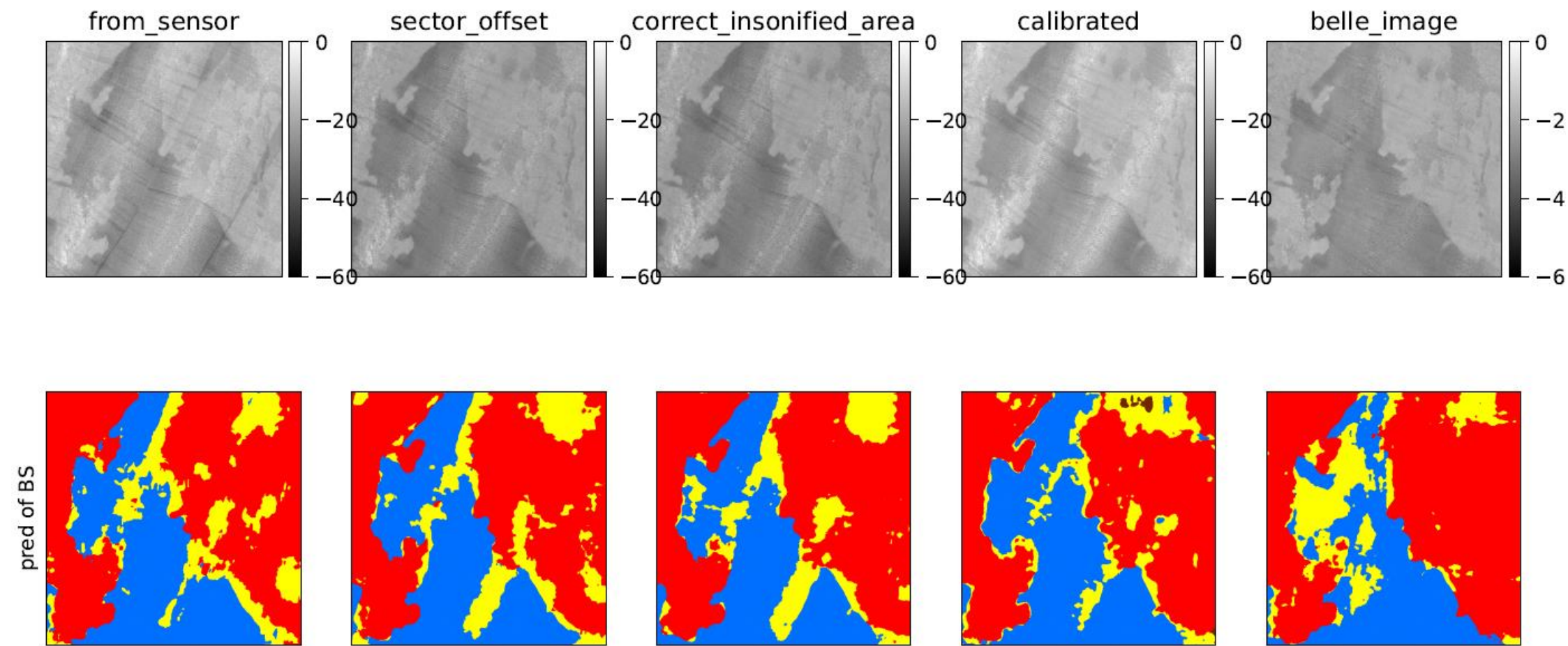


- Rock
- Rough sediment
- Medium sediment
- Fine sediment

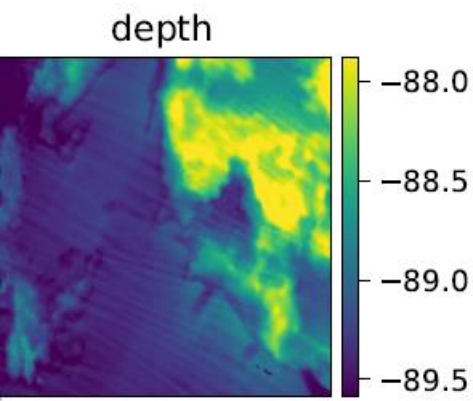


Examples of predictions

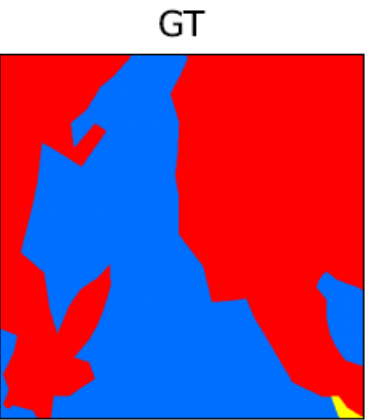
Predictions of seafloor nature from **mosaic** backscatter



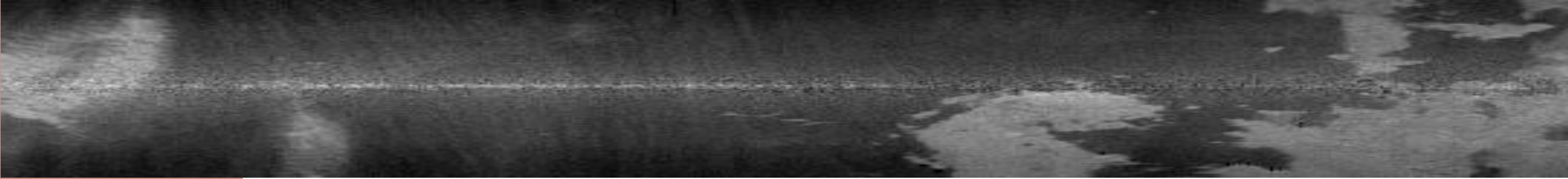
Associated bathymetry



Associated seafloor nature

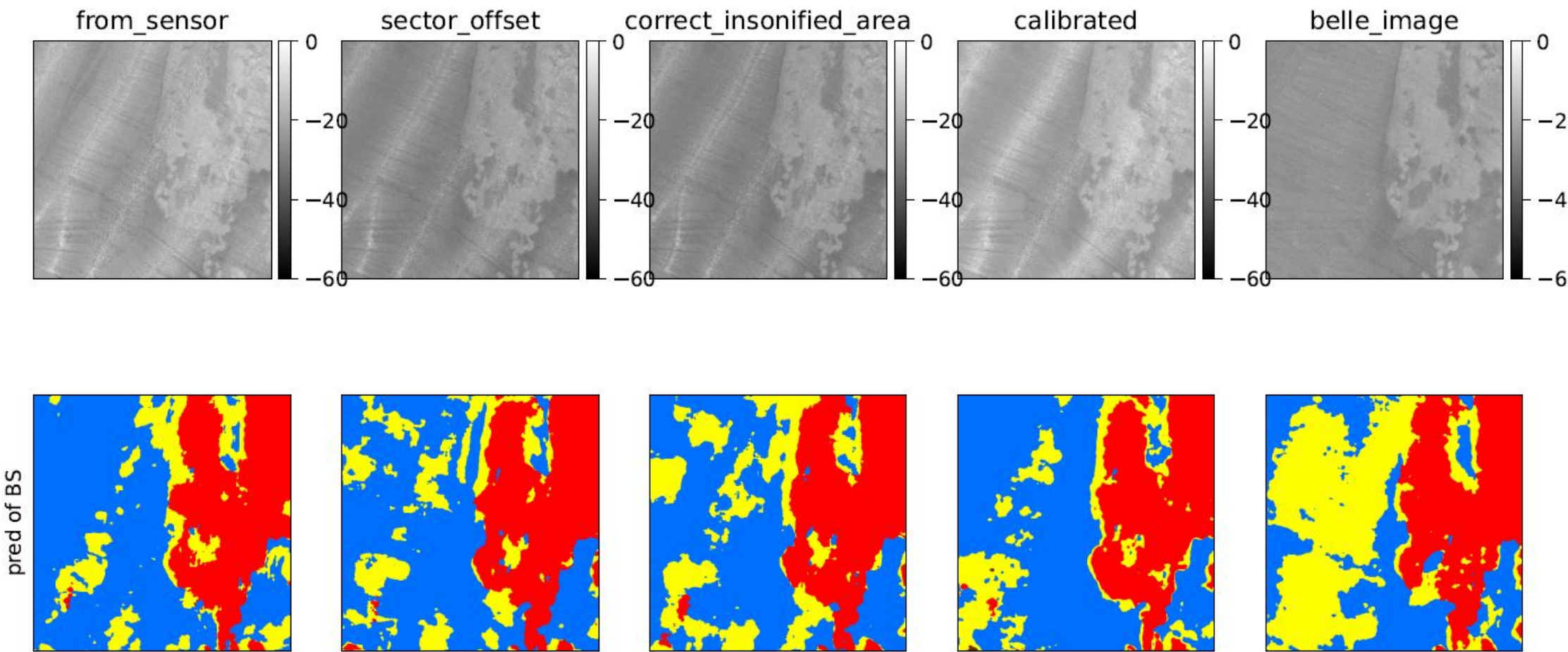


- Rock
- Rough sediment
- Medium sediment
- Fine sediment



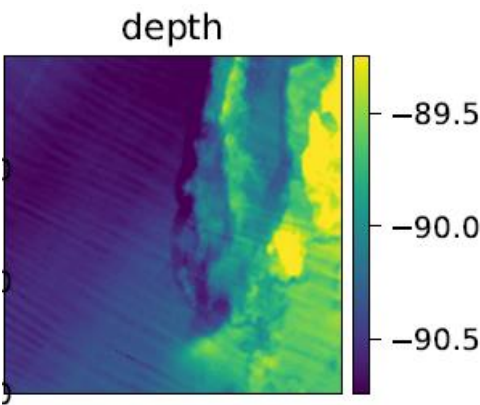
Examples of predictions

Predictions of seafloor nature from **mosaic** backscatter

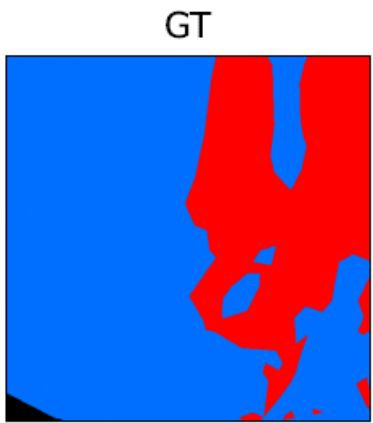


« bad »

Associated bathymetry



Associated seafloor nature



- Rock
- Rough sediment
- Medium sediment
- Fine sediment

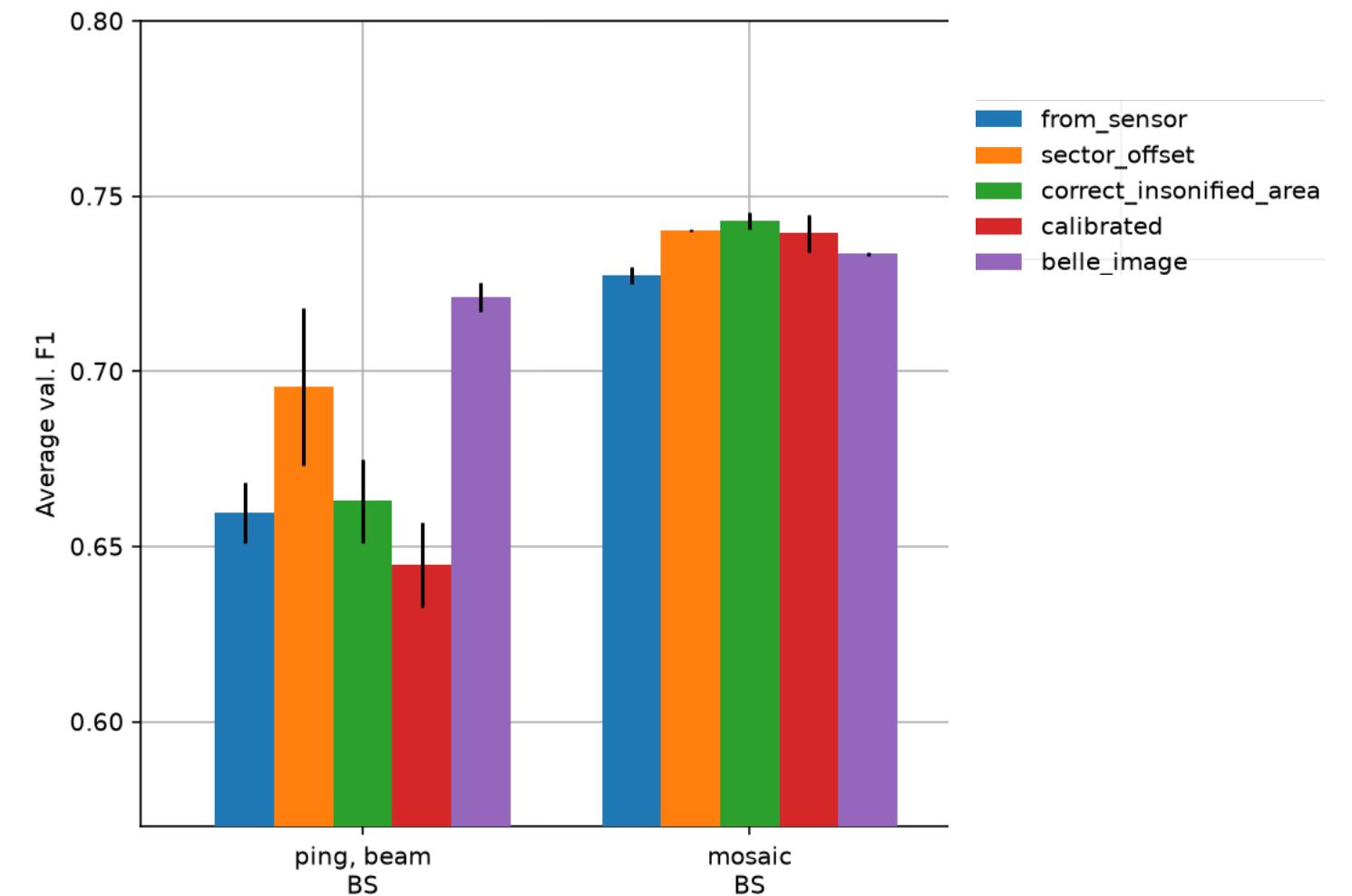
Results in metrics

Results are evaluated by comparing pixels' labels that are predicted and the reference labels (seafloor nature map from Shom)

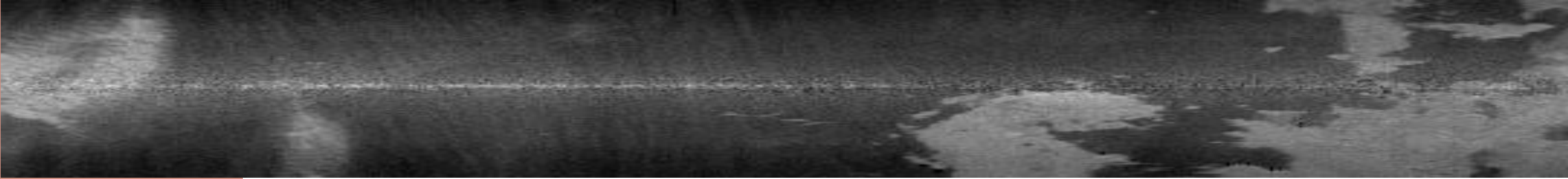
Used metric:

- F1-score
- Standard-deviation measured on 3 evaluations

- Results are better using mosaic (reflectivity map) than ping-beam backscatter
- No difference are observed in results between different pre-process used when inferring from mosaic, the contrary from ping-beam format
- Using « Belle Image » seems better as it results in less standard deviation using ping-beam or mosaic



Backscatter alone



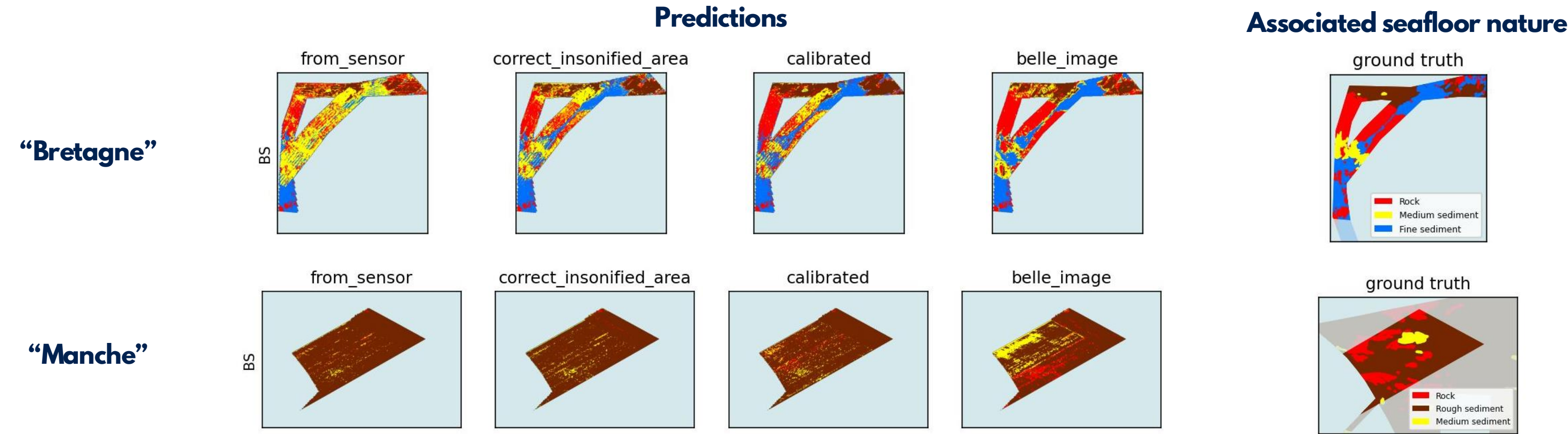
Results in metrics

From validation scores to test scores

- Strong decrease in performance
⇒ difficulties to generalise

F1 score on map format
Backscatter pre-processing : calibrated

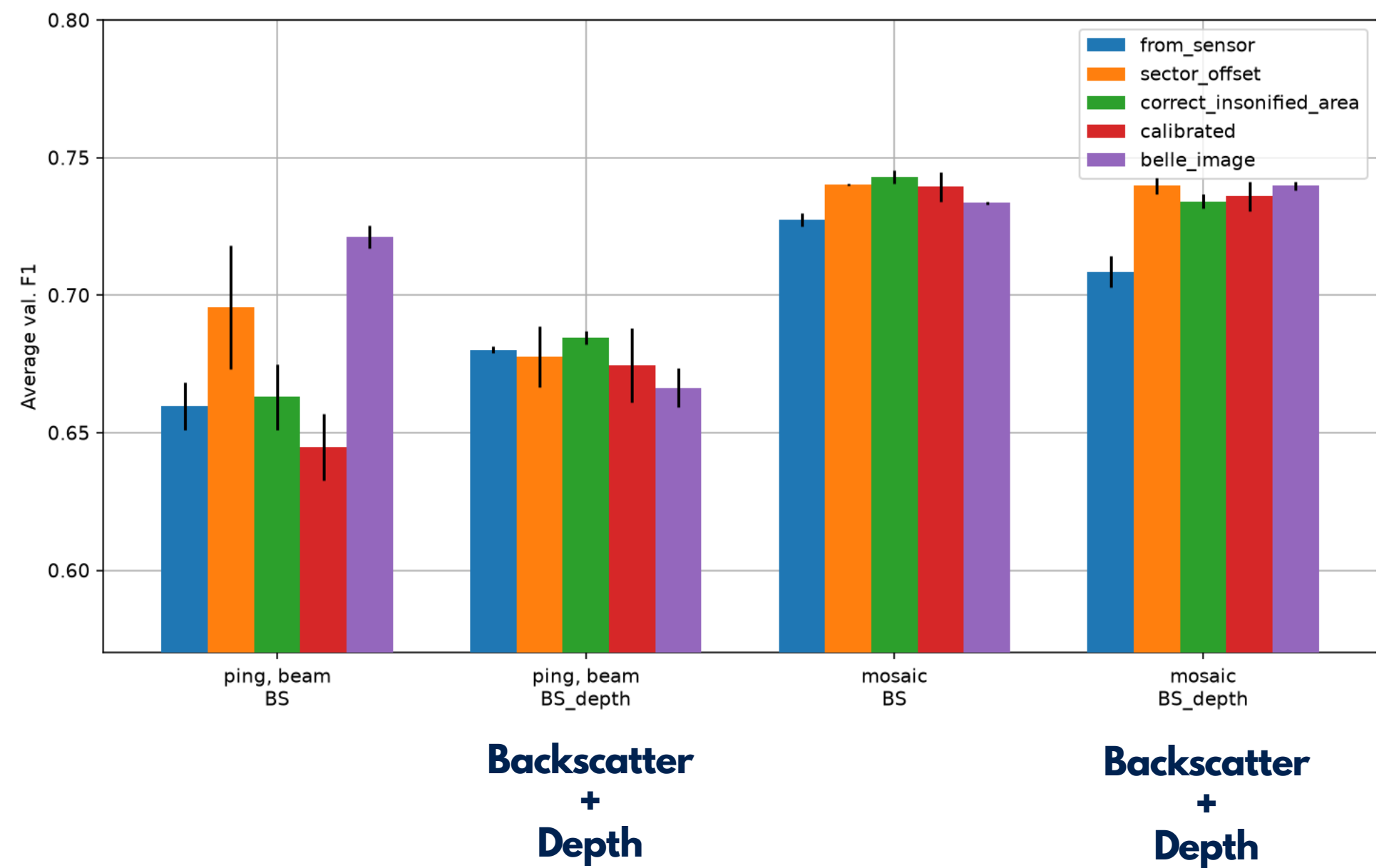
Training	Validation	Test
76.9 +/- 0.6 %	73.9 +/- 0.5 %	53.5 +/- 1.7 %



Adding *depth* to backscatter data

When adding depth data in inputs

- No specific changes using map format
- Using ping-beam format, there seem to be less difference between the results with different backscatter pre-processing



Conclusion & Perspectives.

Conclusions

Comparison of neural network performances when using two different formats (ping-beam or map)

- Shows better results with maps => Very likely due to the format/resolution of the labels (seafloor nature map)

Comparison between pre-processings of backscatter data:

- Shows that calibrated data doesn't stand out **BUT** the network can't generalise to new echosounders or non-identically pre-processed data

Including depth data (soundings) in input with backscatter:

- Doesn't increase significantly the results

Global results are satisfactory

- But generalisation is a specific issue to investigate

Perspectives

Training the network with more seabed variability still with EM710

Compare results using calibrate/uncalibrate backscatter data from different echosounders (EM710, EM2040, etc.)

Use a finest map of labels (e.g. acoustics facies) to be closer to the backscatter variations

Thank you for your attention.

“Belle image” computation

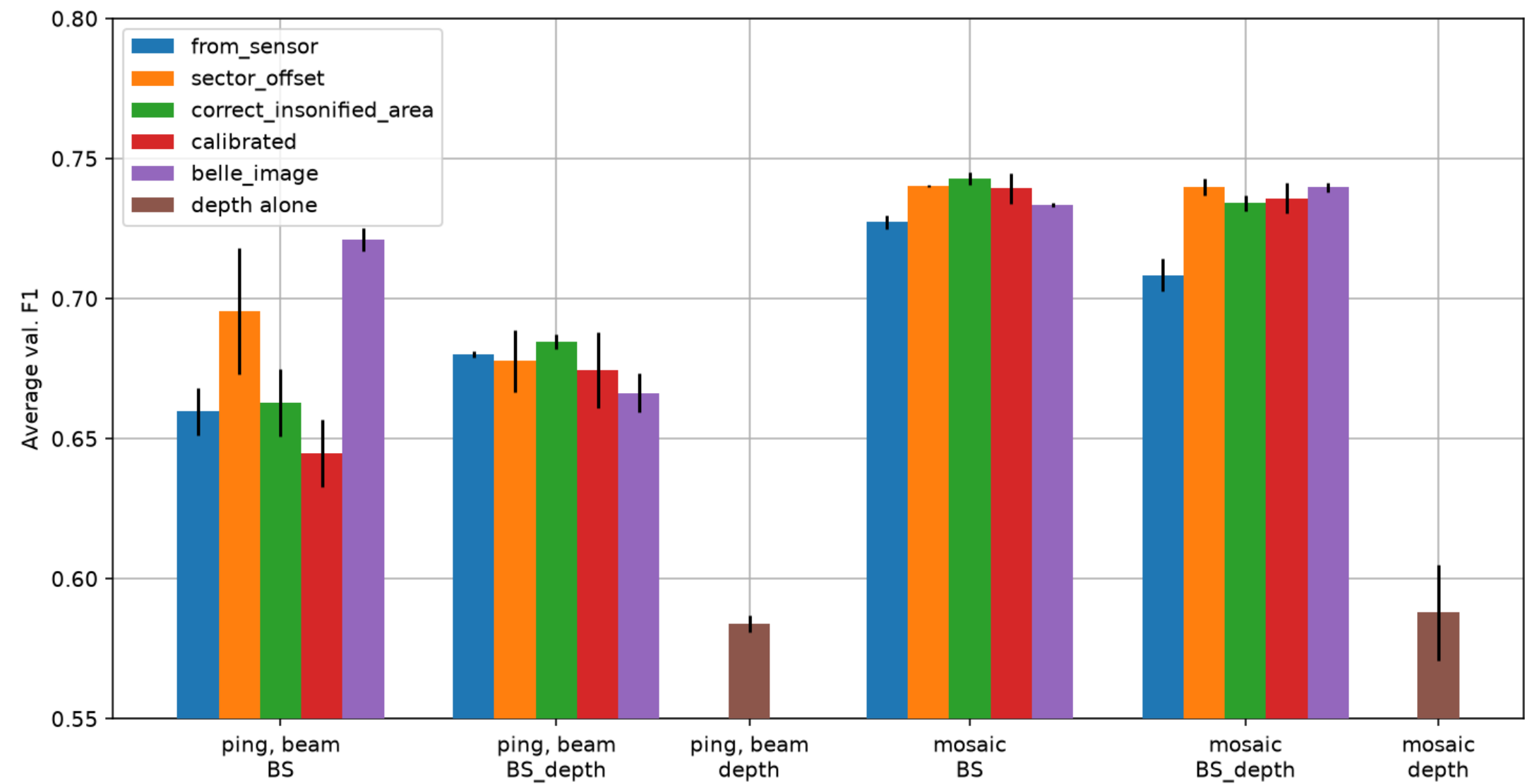
Steps:

1. Compute the mean and standard deviation of the BS values in the patch ;
2. Standardize each beam: for each beam (column), we subtract the per-beam mean and divide by the per-beam standard deviation ;
3. Multiply the values by the global standard deviation we computed in step 1, and add the global mean.

⇒ the computation flattens the angular response curve while keeping the global mean and standard deviation of the BS patch

With “depth” alone

It absolutely doesn't work!



Network details

Hyperparameters :

- We had one set of hyperparameters (and thus, pne architecture) for each of the representation (map and (ping, beam)). However, we found so little differences between the results of each calibration that we keep the same architecture and hyperparameters for all of them.
- The complete protocol of the hyperparameter search (paper in writing) explains how we paid attention to avoid biases in favour of any processing

Training :

- During each training, we train the neural networks with a CrossEntropy Loss, where each pixel is weighted proportionally to the inverse of the class count, in order to offset the imbalanced class distribution.
- We train the neural network for 100 epochs, or until the validation decreases for 20 consecutive epochs (early stopping). We repeat each training three times, changing the random initialization of network weights each time.

Cross-evaluations

Evaluations on different inputs pre-processings than the training

