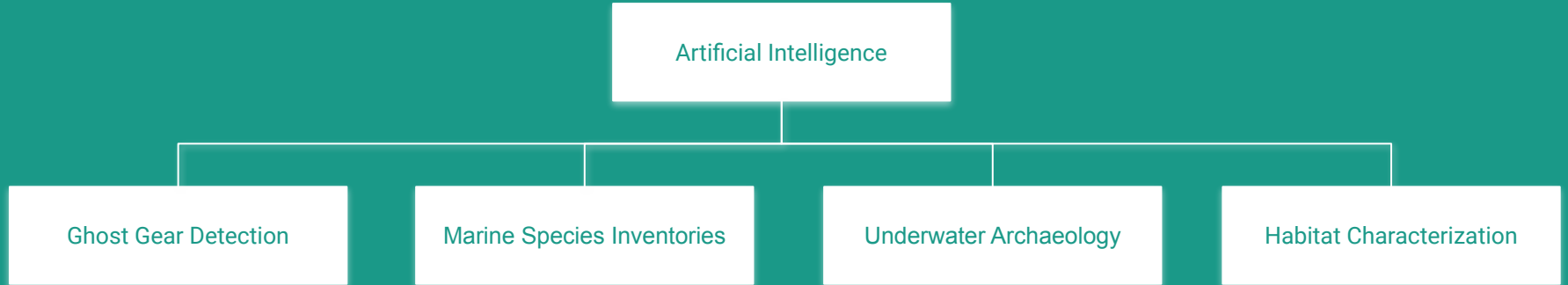




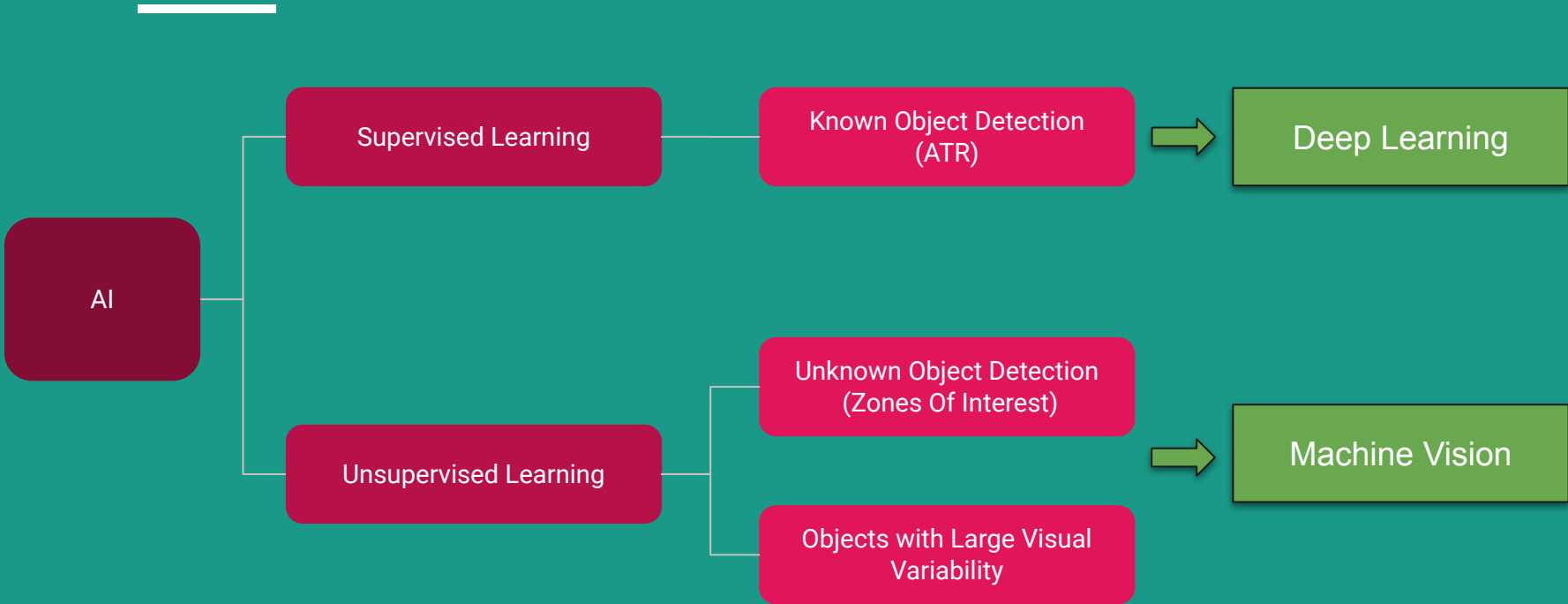
CIDCO

Automating marine inventories using artificial intelligence

AI @ CIDCO



AI methods for object detection





Underwater Object Detection

Detecting Ghost Gear

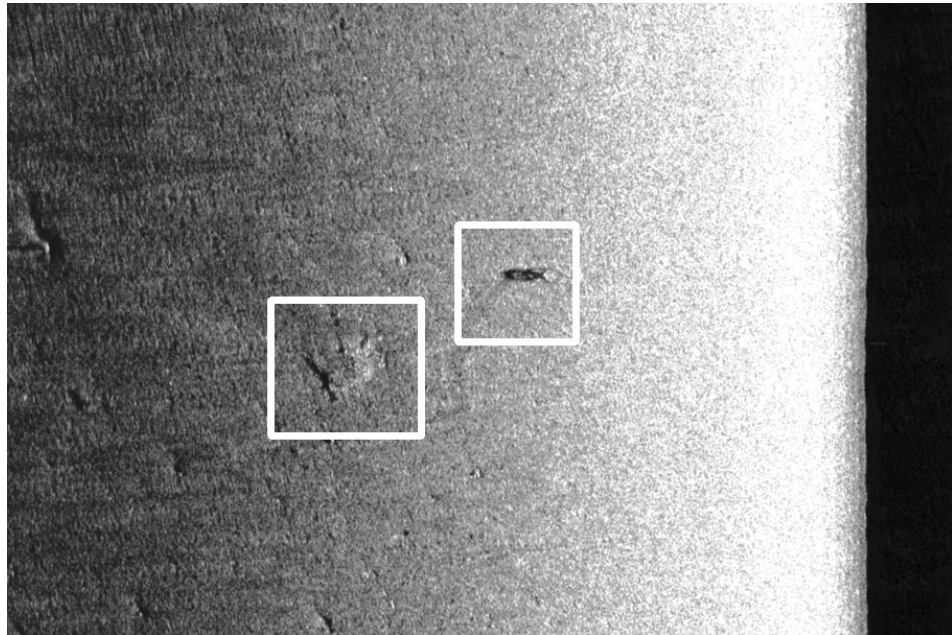




1st Generation: Detecting odd shapes

Nets, long lines and historical traps do not have a regular shape that can be properly turned into a visual signature.

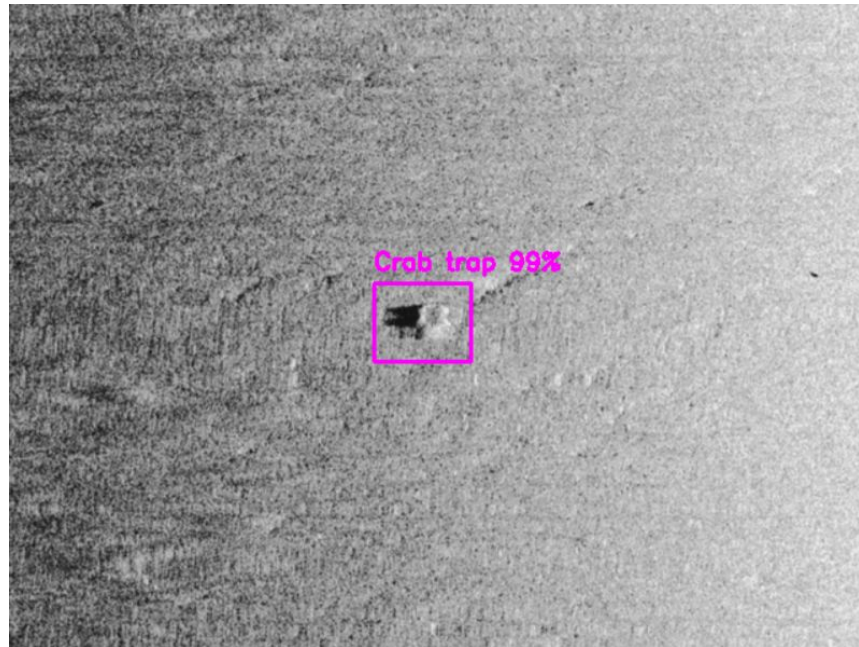
Machine vision algorithms such as (Morissette & Gautier, 2020) address this issue.





2nd Generation: Deep Learning Signatures

Modern crab pots are easily recognisable and have a well-defined geometry that can be exploited through deep learning methods such as (Jocher & AI,2022)





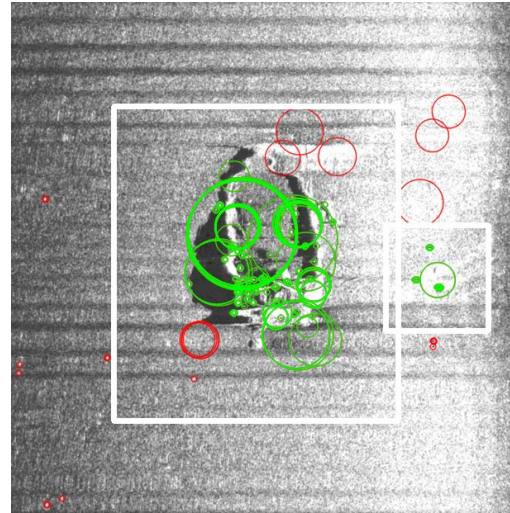
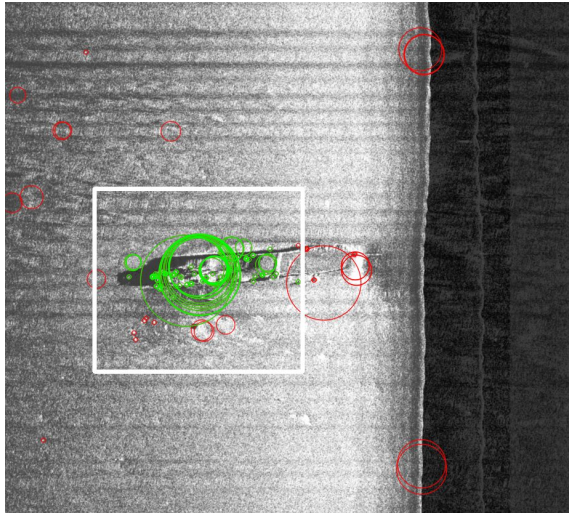
Underwater Object Detection

Underwater Archaeology





Finding Shipwrecks



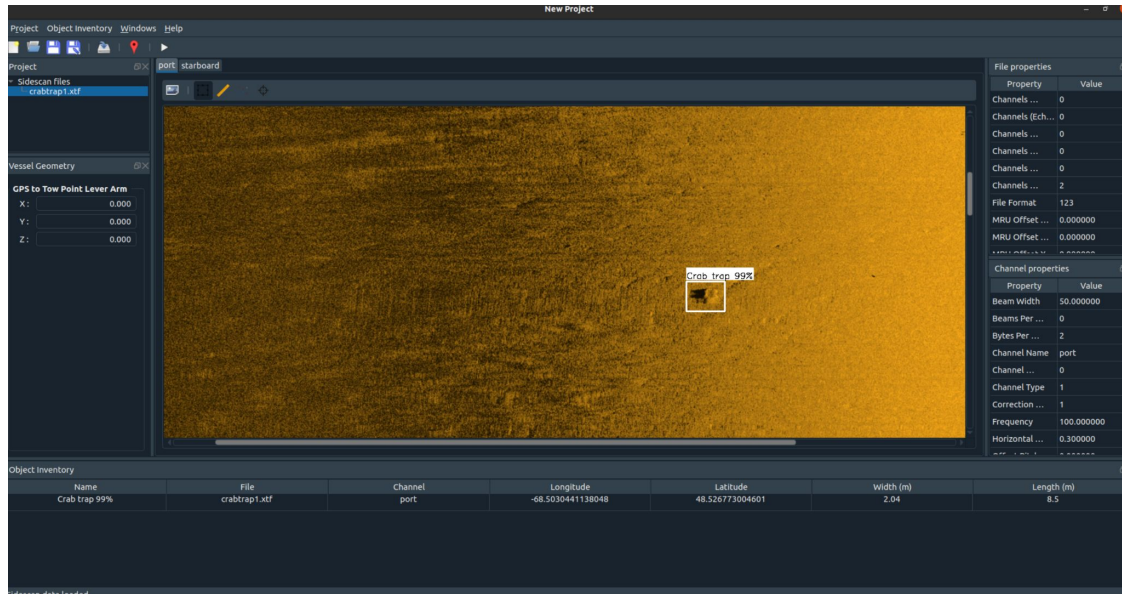
Clusters of visual features left by shipwrecks in sidescan sonar imagery can be identified using machine vision algorithms such as (Morissette & Gautier, 2020).

Open Sourcing SSS & Deep Learning Tools

CIDCO has open-sourced its sidescan data processing tool under MIT license as the OpenSidescan application.

The current version features CIDCO's shipwreck detector.

The next release will feature deep-learning features such as ONNX models for arbitrary object detection.





Underwater Object Detection

Marine Species Inventories





Automated Marine Species Inventories

Godbout's urchins

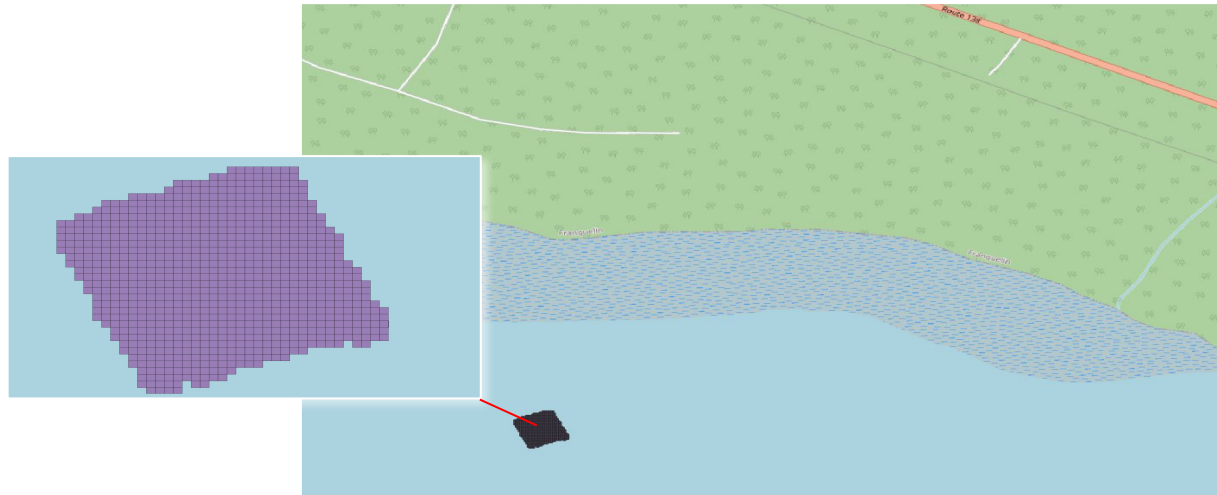
831 orthomosaics

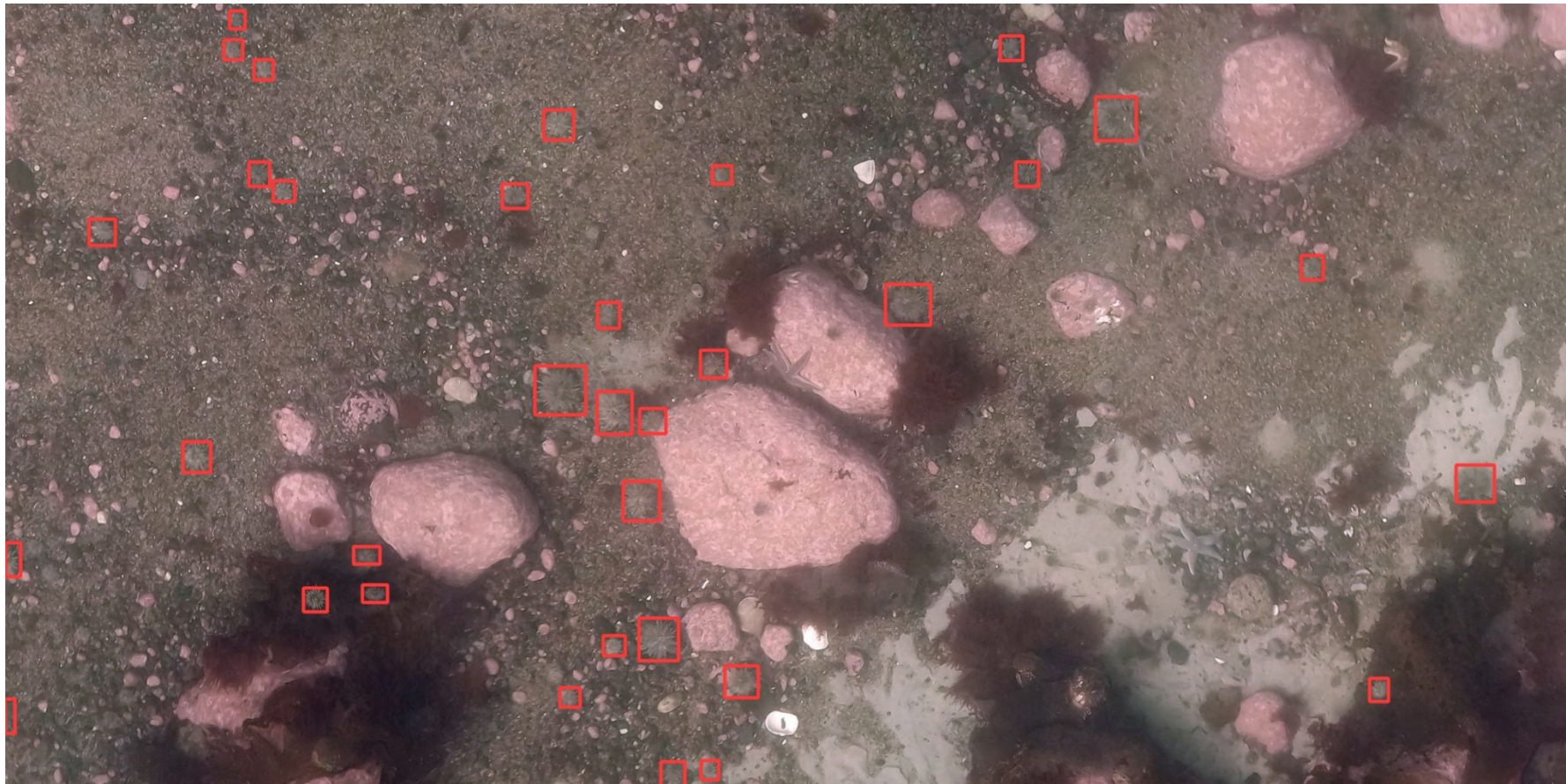
6.858m² per zone

5699m² in total

Detection in 3 minutes

5668 Urchins Detected



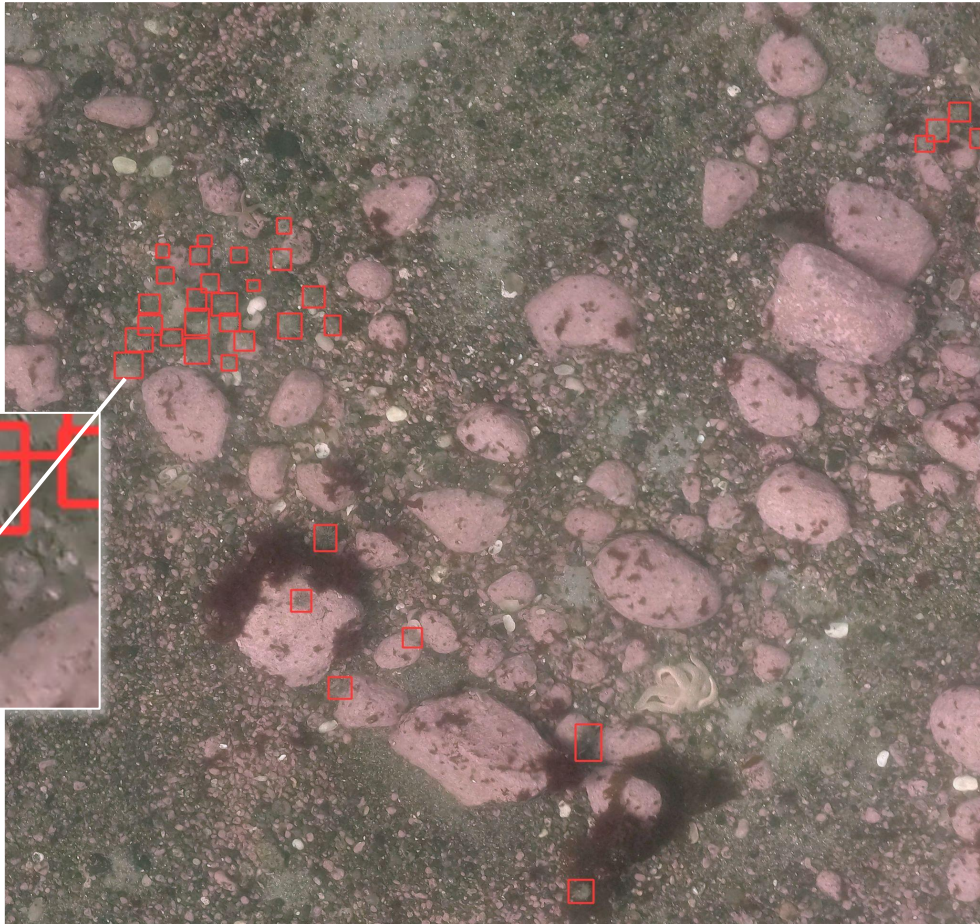
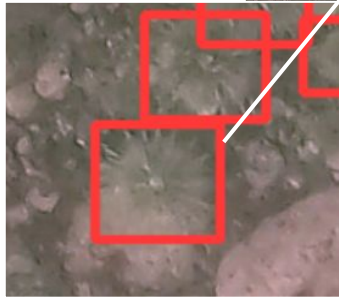




Results

Once trained, the AI can detect more urchins than the **average** human eye and alleviate issues due to contrast, illumination and turbidity.

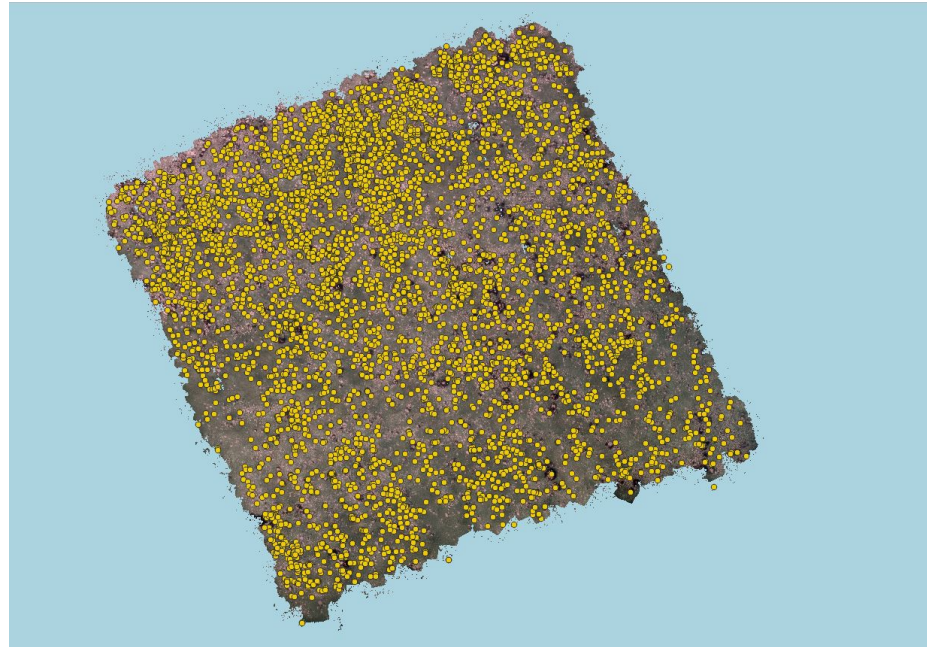
Can you spot them all?





Spatial distribution

The spatial distribution of detected urchins' positions and sizes can be readily exported as a SHP file for further analysis.



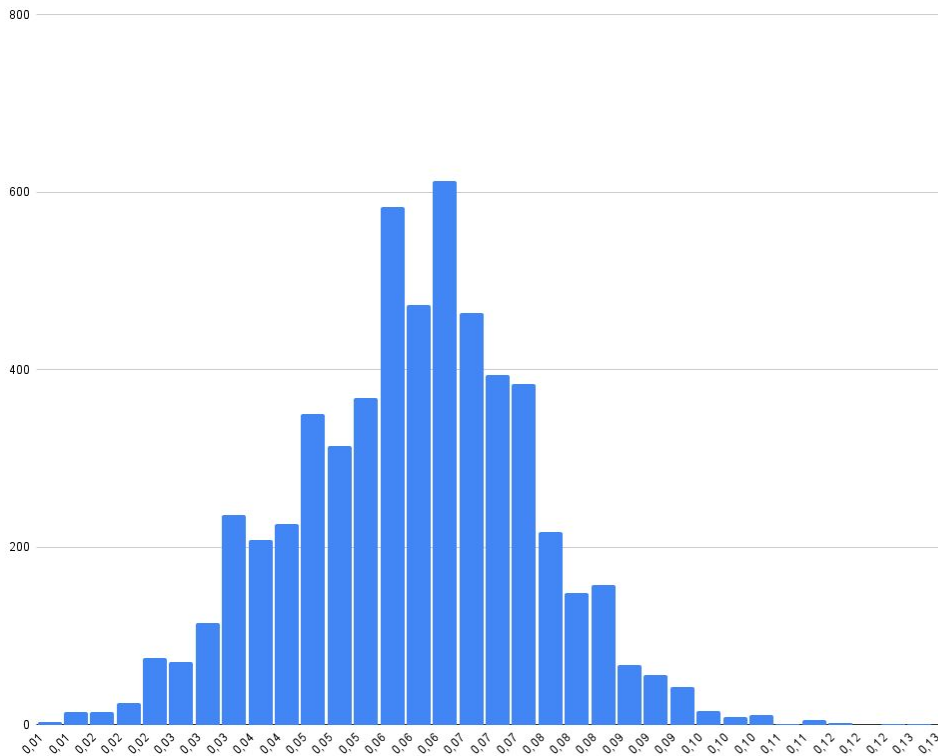


Size

“the shell of the green urchin can reach a diameter of 100 millimeters, with an average between 50 and 60 millimeters”

-DFO-MPO

Grosseurs des spécimens détectés



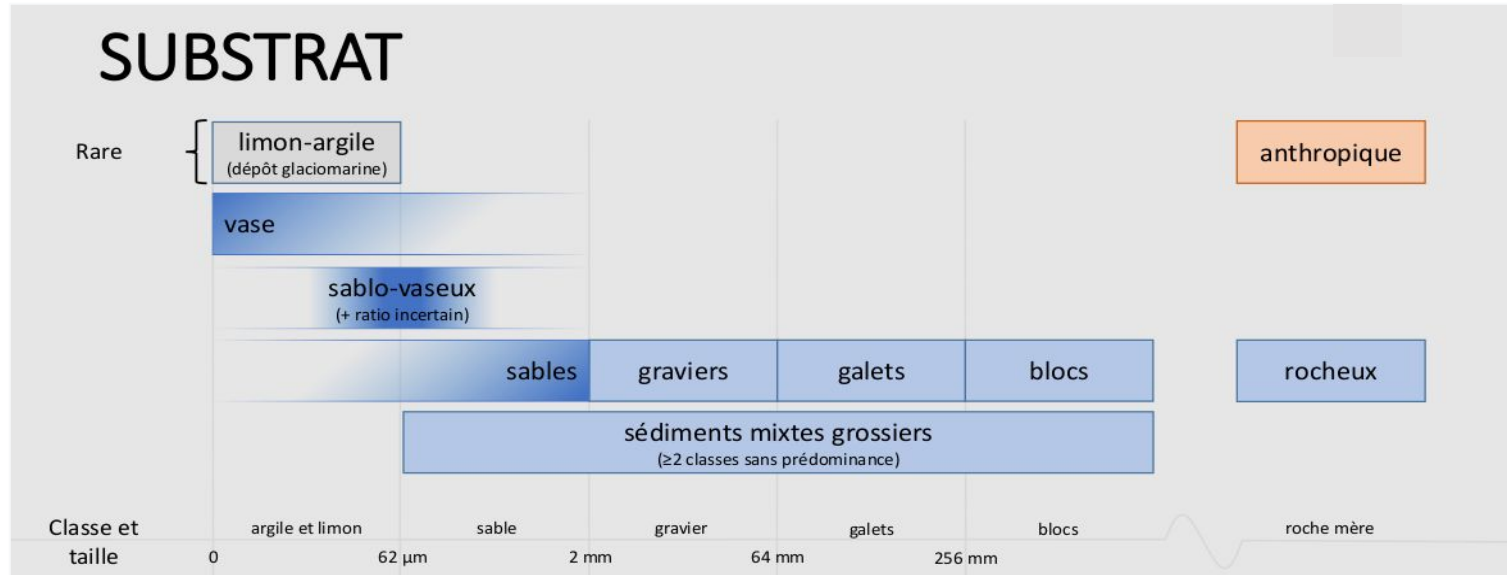


Habitat Characterization

Classifying benthic substrates



Caractérisation des substrats marins



Ground Truth Stations

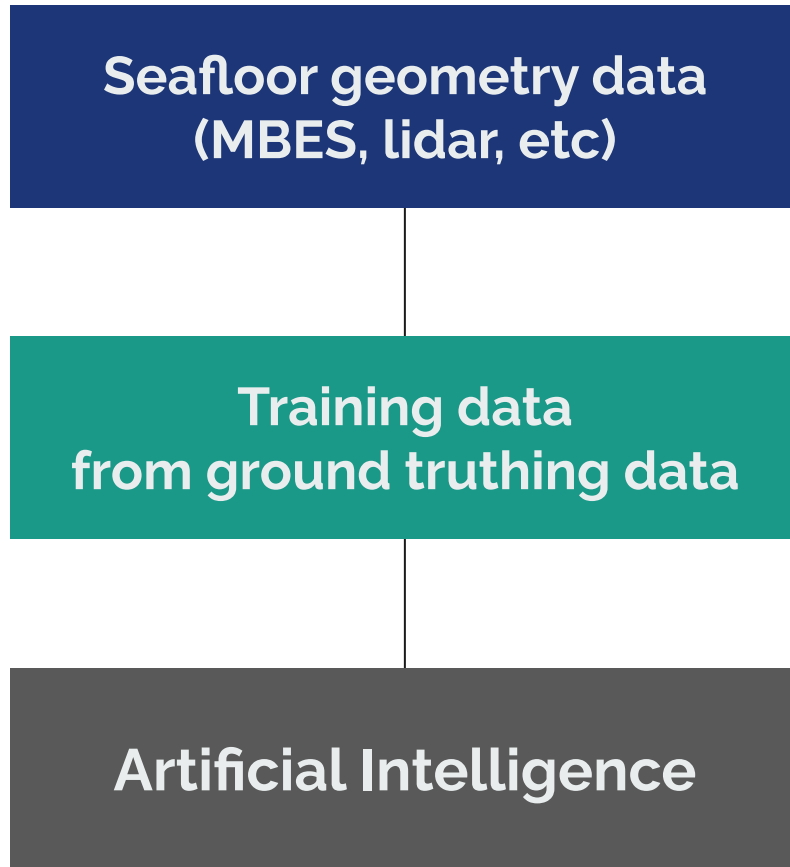



1000 DFO Ground Truthing Stations



Process

Using supervised learning makes it possible to classify benthic habitats using proxy variables derived from seafloor geometry.





Feature Engineering

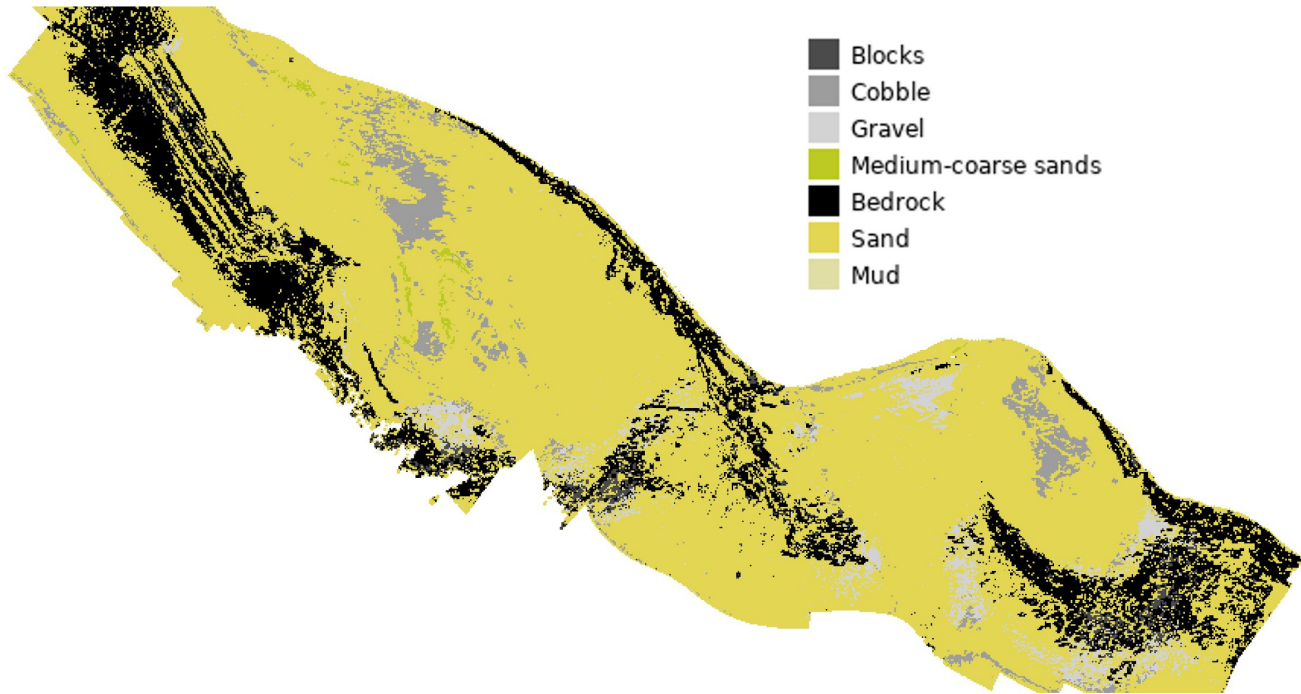
We enrich bathymetric surface data with geomorphometric features

covariance	Sum	$\lambda_1 + \lambda_2 + \lambda_3$
	Omnivariance	$(\lambda_1 \cdot \lambda_2 \cdot \lambda_3)^{\frac{1}{3}}$
	Eigenentropy	$-\sum_{i=1}^3 \lambda_i \cdot \ln(\lambda_i)$
	Anisotropy	$(\lambda_1 - \lambda_3)/\lambda_1$
	Planarity	$(\lambda_2 - \lambda_3)/\lambda_1$
	Linearity	$(\lambda_1 - \lambda_2)/\lambda_1$
	Surface Variation	$\lambda_3/(\lambda_1 + \lambda_2 + \lambda_3)$
	Sphericity	λ_3/λ_1
	Verticality	$1 - \langle [0\ 0\ 1], \mathbf{e}_3 \rangle $
moment	1 st order, 1 st axis	$\sum_{i \in \mathcal{P}} \langle \mathbf{p}_i - \mathbf{p}, \mathbf{e}_1 \rangle$
	1 st order, 2 nd axis	$\sum_{i \in \mathcal{P}} \langle \mathbf{p}_i - \mathbf{p}, \mathbf{e}_2 \rangle$
	2 nd order, 1 st axis	$\sum_{i \in \mathcal{P}} \langle \mathbf{p}_i - \mathbf{p}, \mathbf{e}_1 \rangle^2$
	2 nd order, 2 nd axis	$\sum_{i \in \mathcal{P}} \langle \mathbf{p}_i - \mathbf{p}, \mathbf{e}_2 \rangle^2$
height	Vertical range	$z_{\max} - z_{\min}$
	Height below	$z - z_{\min}$
	Height above	$z_{\max} - z$

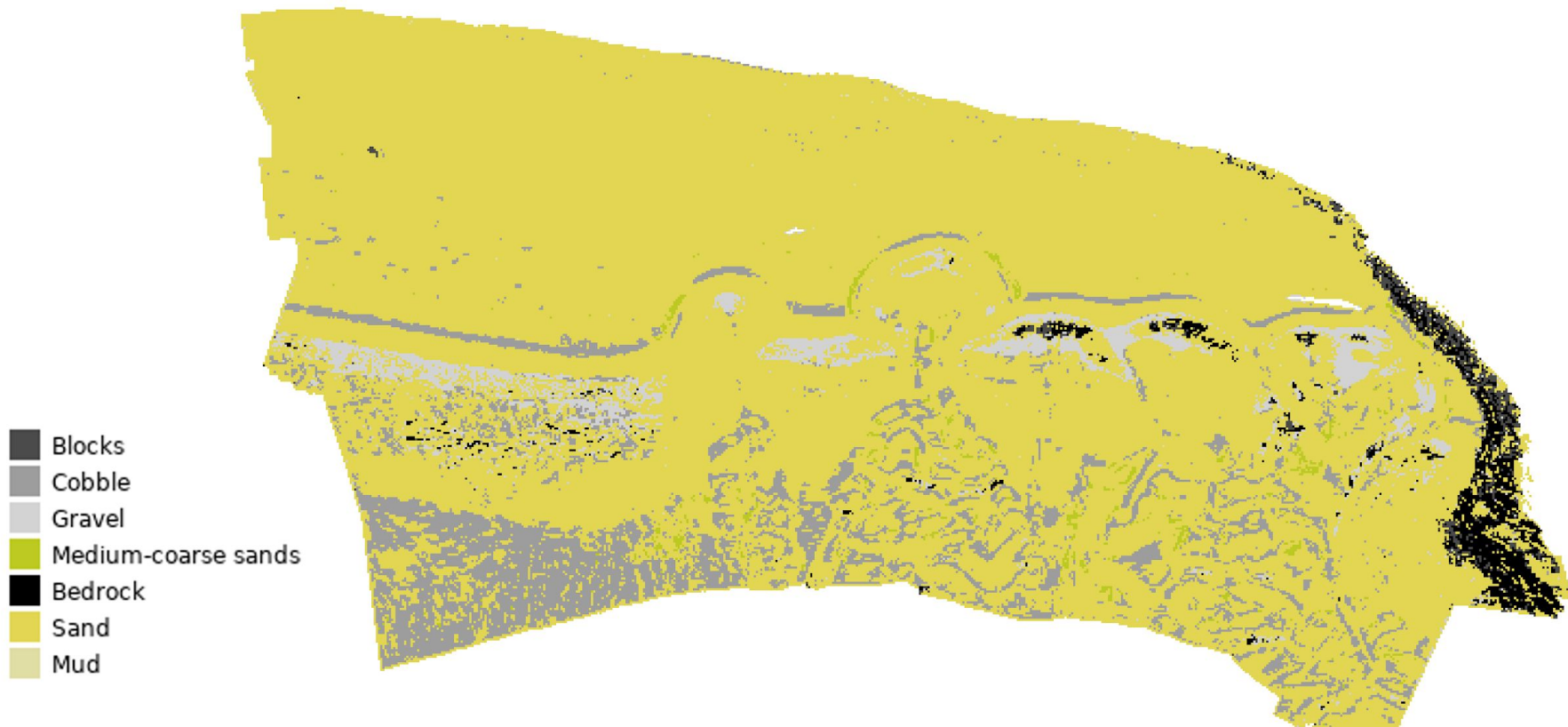


Benchmark results

Algorithm	Average Accuracy (over all classes)
K Nearest-Neighbors	91% (Danger: Overfitting)
Gradient Boosted Trees	90%
Support Vector Machines	83%
Naive Bayes	31%



Baie-des-Anglais, Côte Nord, QC, Canada

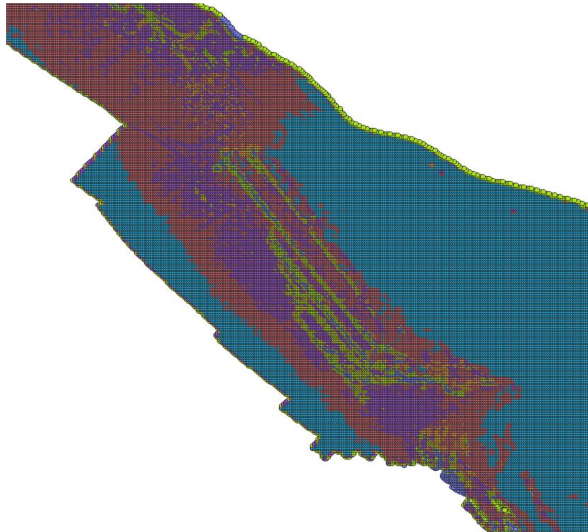


Franquelin, North Shore, QC, Canada

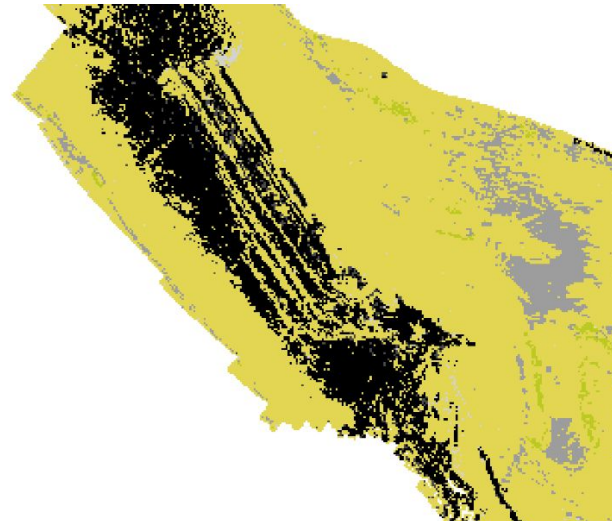


Unsupervised Characterization

Processus Non-supervisé (sans vérité terrain)



Procédé Supervisé (avec vérité terrain)





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Merci