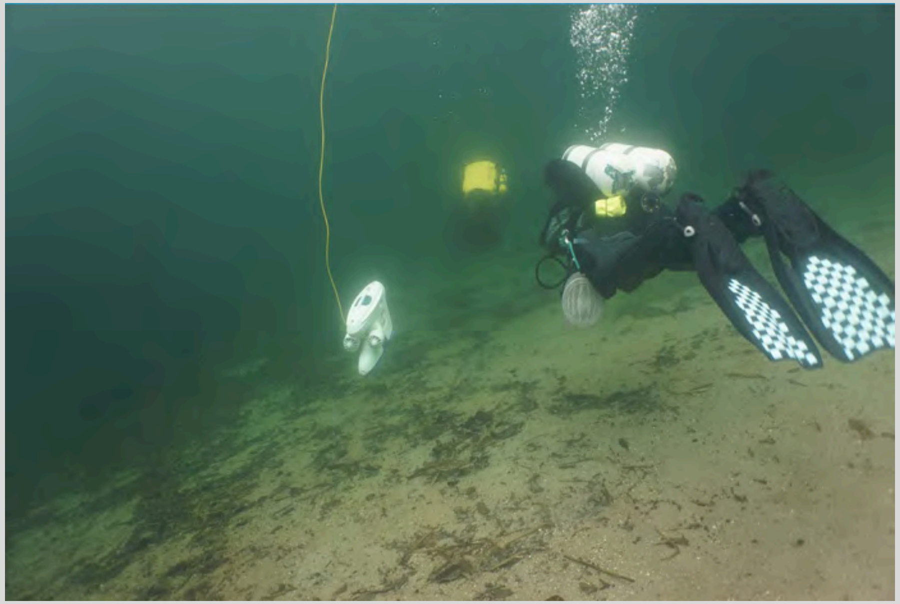
VESSELITY

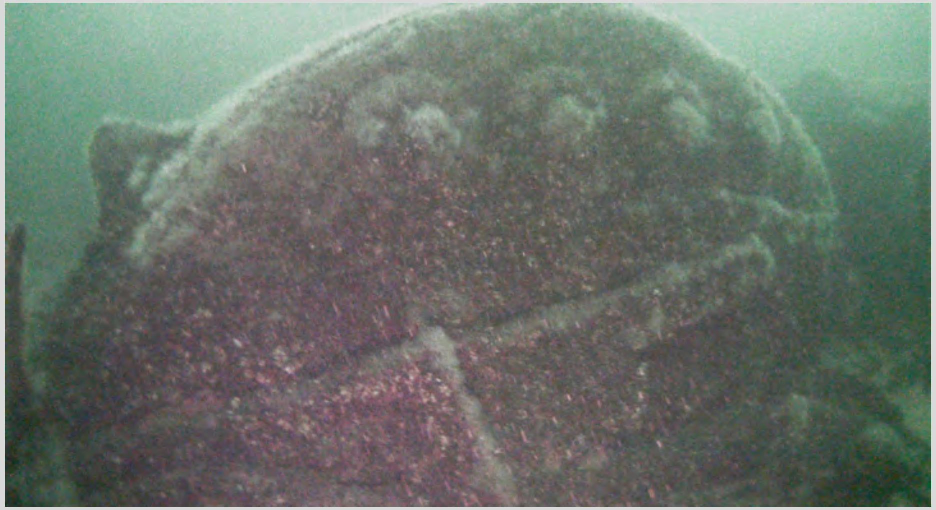
MARITIME ANALYTICS

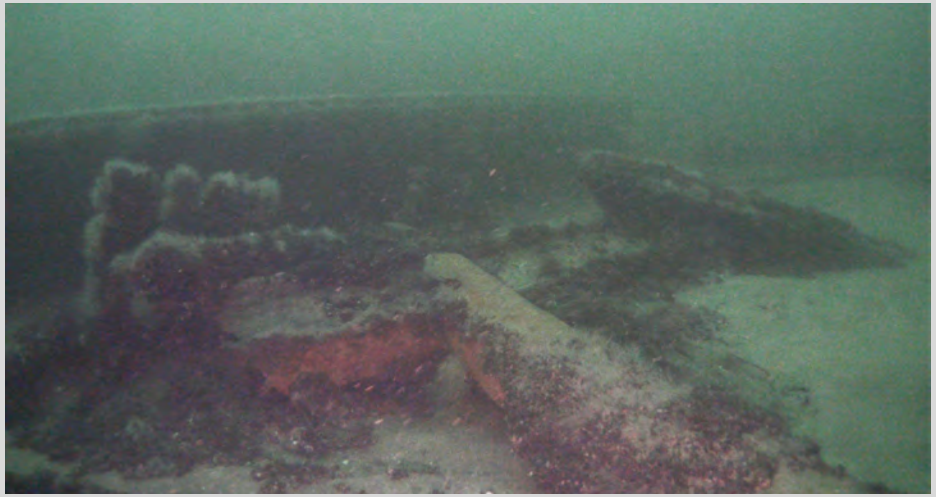
Prologue


EUROPORT
exhibition for
maritime technology
7-10 November 2017
Rotterdam Ahoy



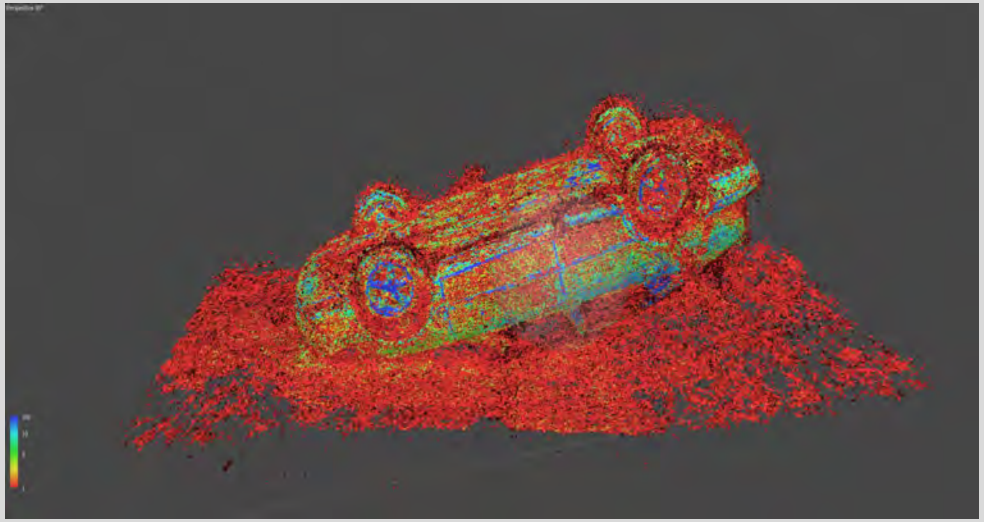
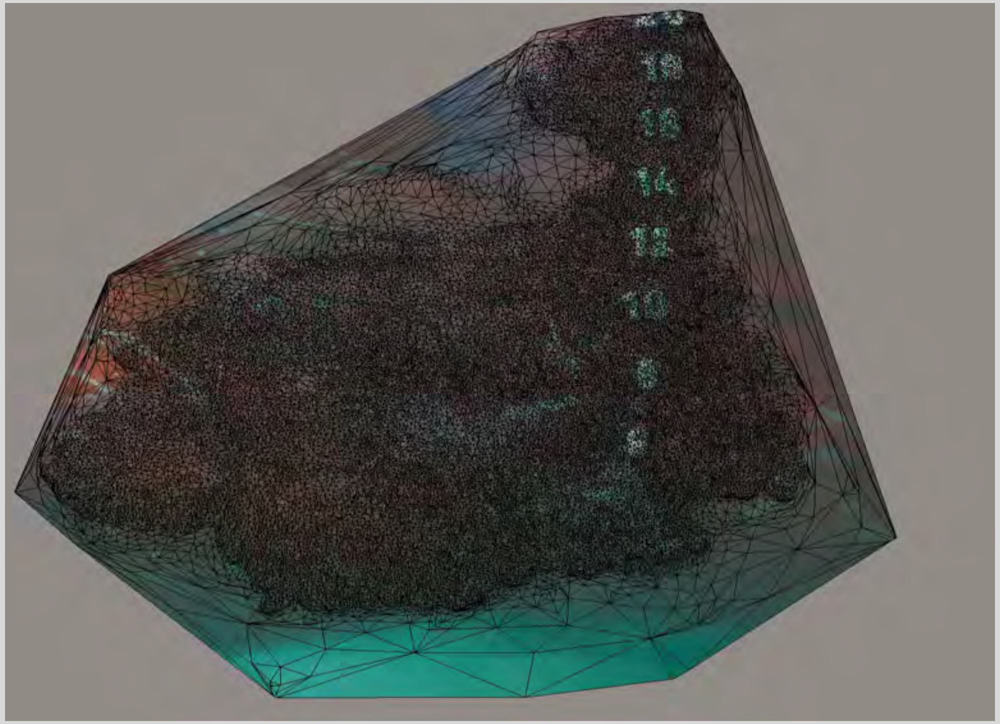
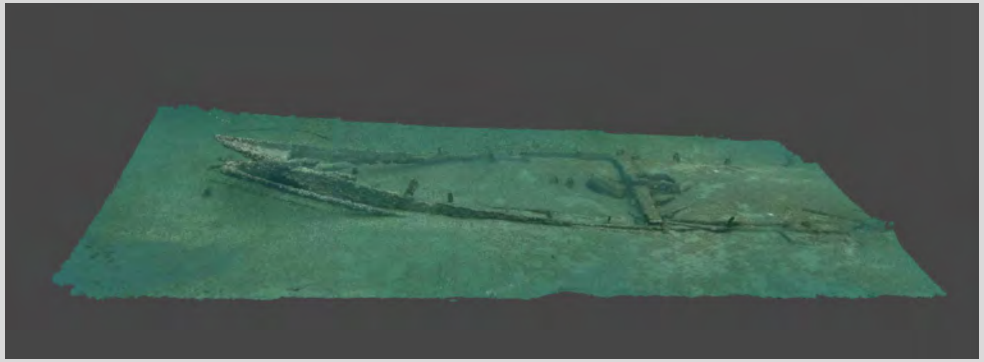
2018



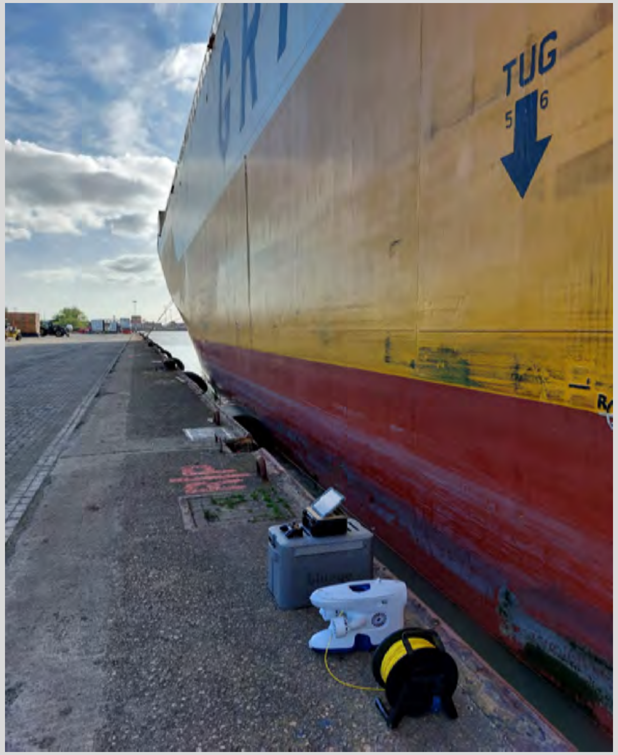


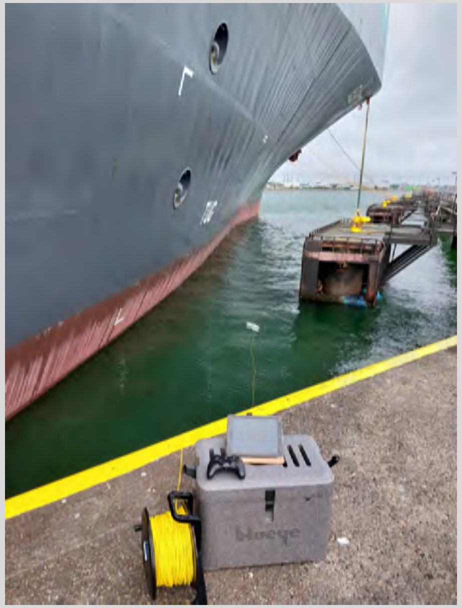
2018

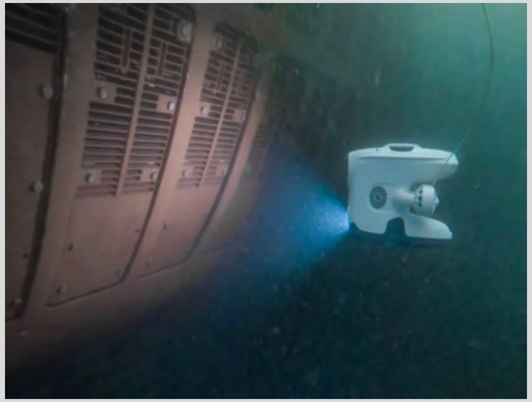
2019

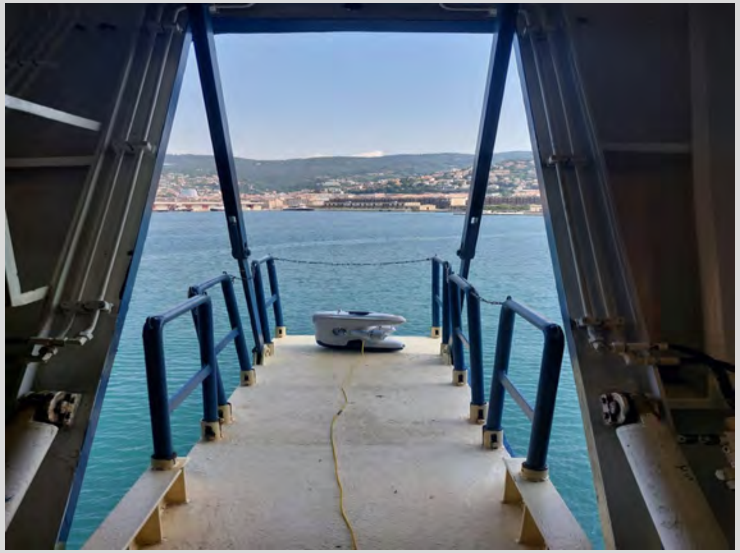





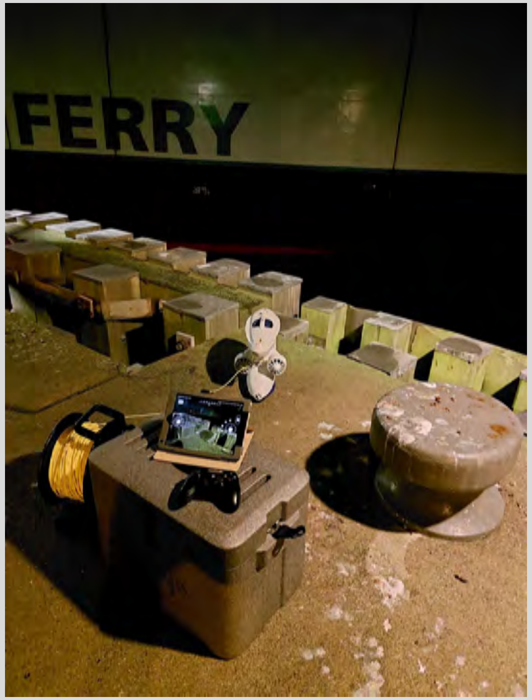

2019



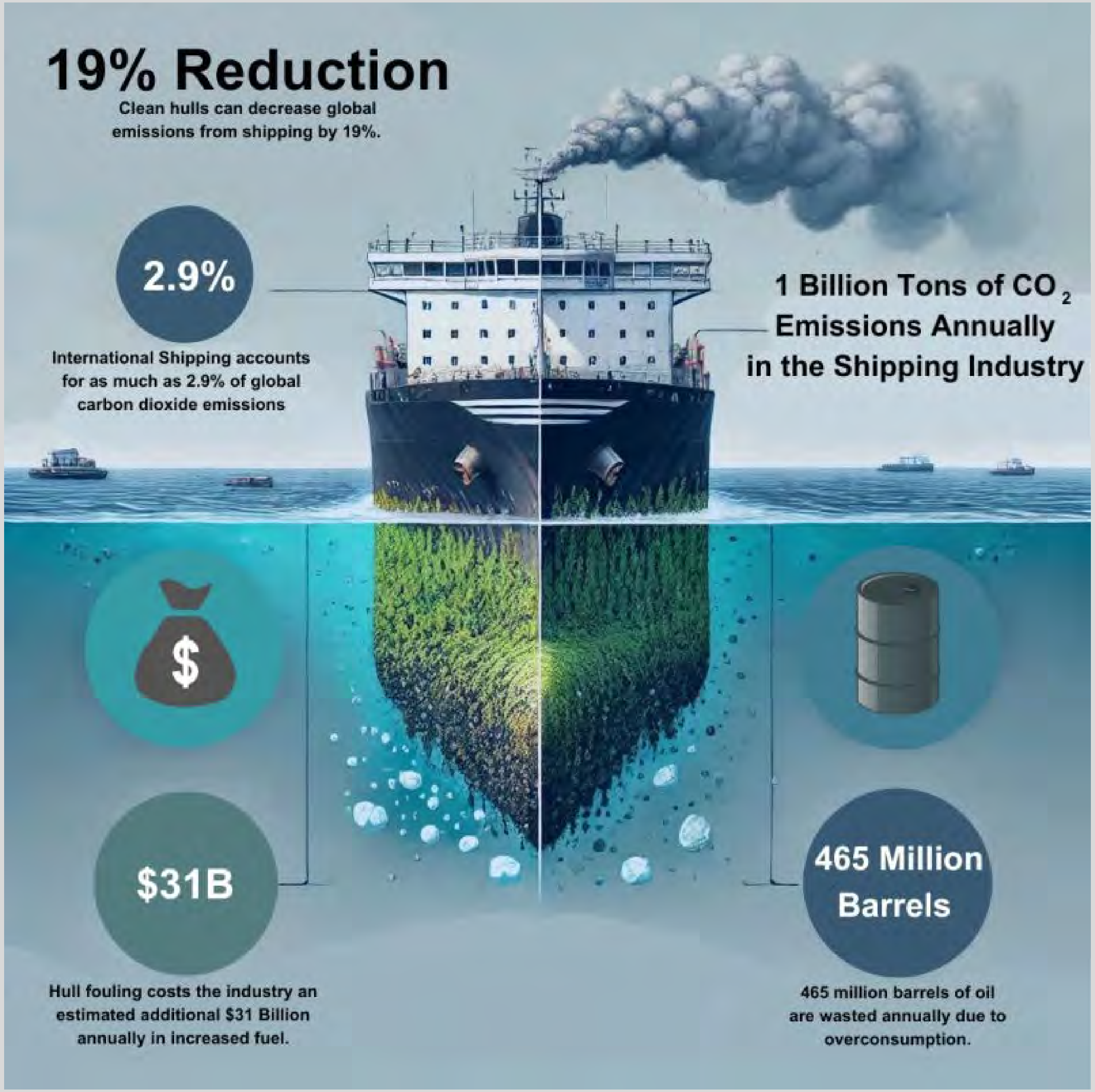






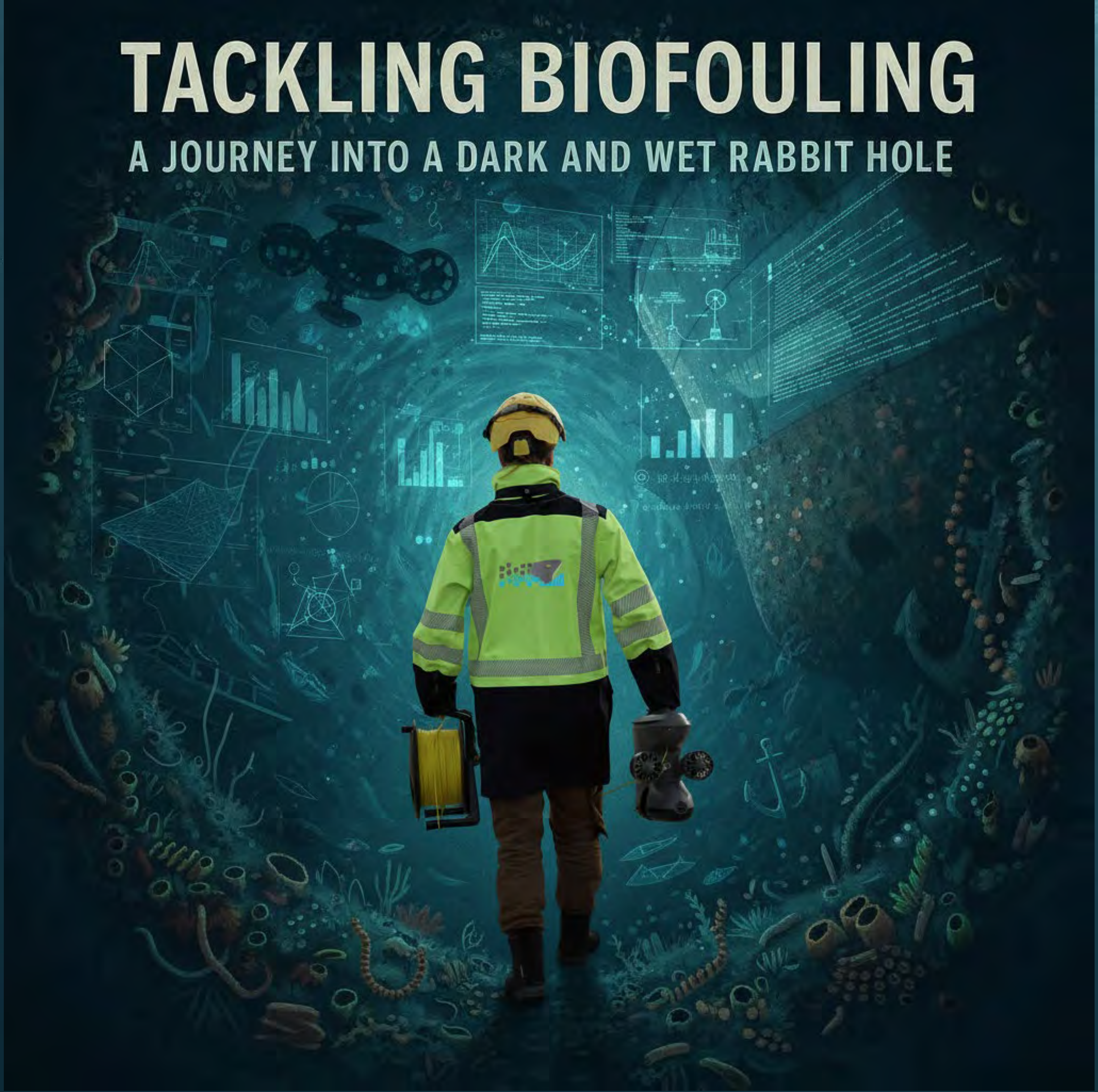


2020


19% Reduction
Clean hulls can decrease global emissions from shipping by 19%.
2.9%
International Shipping accounts for as much as 2.9% of global carbon dioxide emissions
1 Billion Tons of CO_2 Emissions Annually in the Shipping Industry
$
$31B
Hull fouling costs the industry an estimated additional $31 Billion annually in increased fuel.
465 Million Barrels
465 million barrels of oil are wasted annually due to overconsumption.

2 Years B.C. -> Before ChatGPT

2021



Michael Stein
Vesselity Maritime Analytics

Gothenburg
September 10th 2025

Problem Statement and Intention

Fouling is one of the largest unresolved cost driver in shipping where the absence of one single solution has created a huge and diverse market

In order to understand marine fouling in shipping, you require data... a lot of data to contextualize the impact of risk factors before it attaches to the hull

It is our believe, that AI will close the gap in marine fouling research by allowing to optimize the unseen below the water with data science

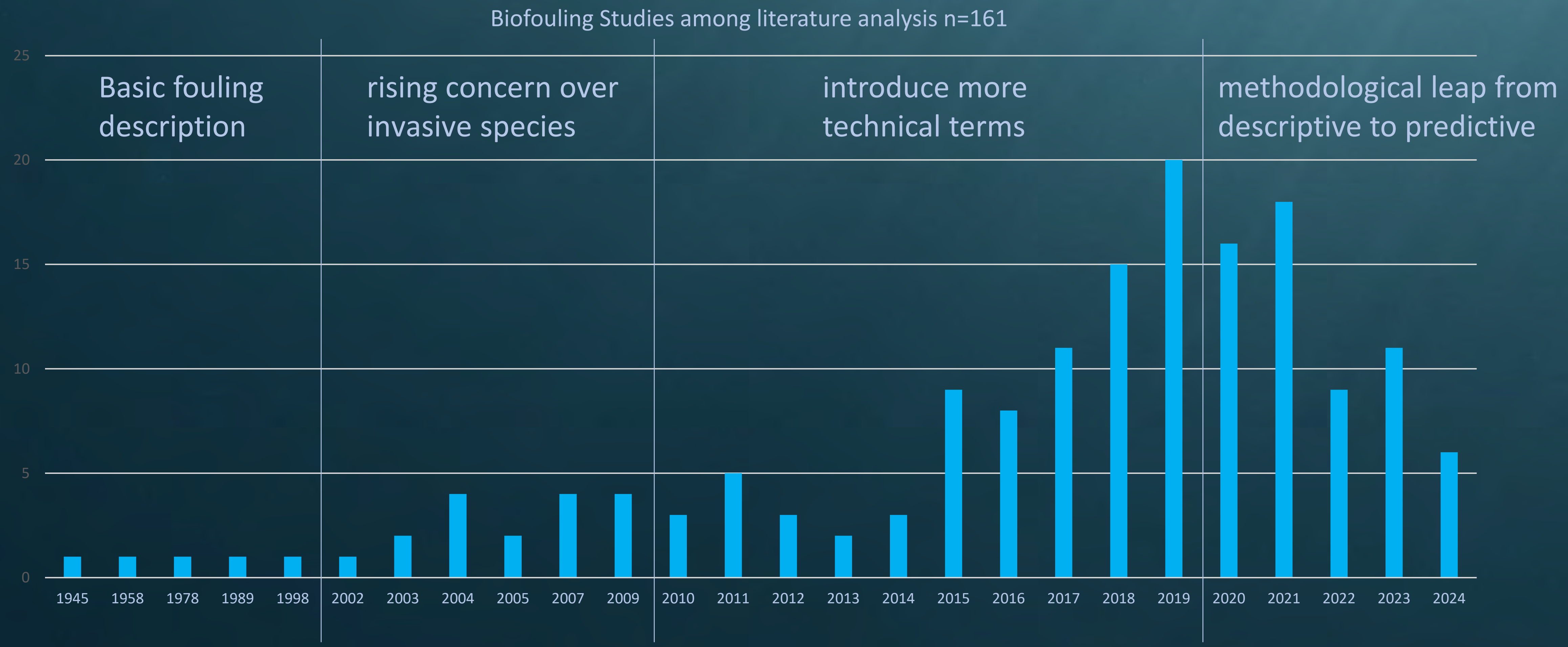
Applying the right AI image segmentation architecture to extract data from visual underwater content is the highest discipline.

Big Questions About Biofouling

1) What kind of fouling is there?
2) How much of what fouling is there?
3) How does the fouling impact the ship performance?
    1) How big is the fouling?
    2) Where is the fouling located?
4) What external factor influenced the fouling to be there?
    1) Can we identify patterns of fouling based on external factors?
    2) Can we measure the effectiveness of anti-fouling paints?
5) Is the fouling invasive?
6) Can we predict biofouling on ships in advance?

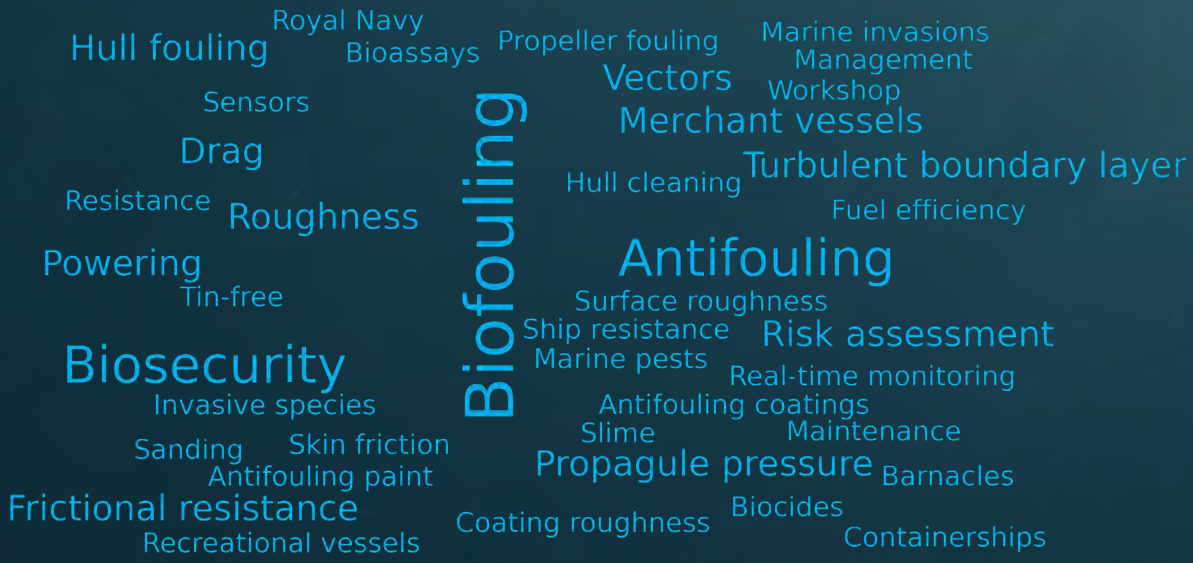
A brief excurse to 80 years of biofouling science

Biofouling Literature Analysis

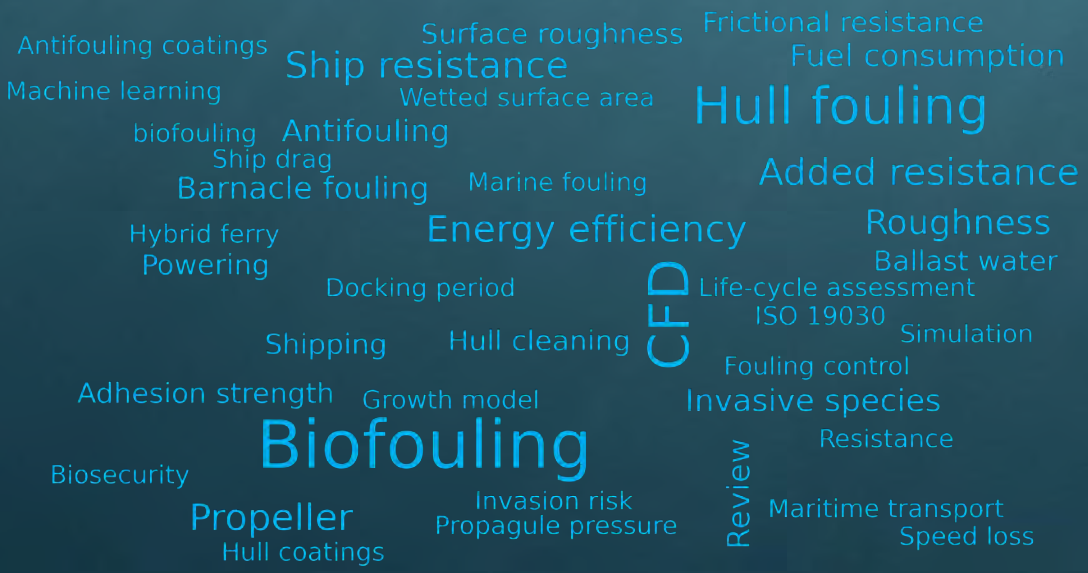


Biofouling Literature Analysis

2000-09



2010-19



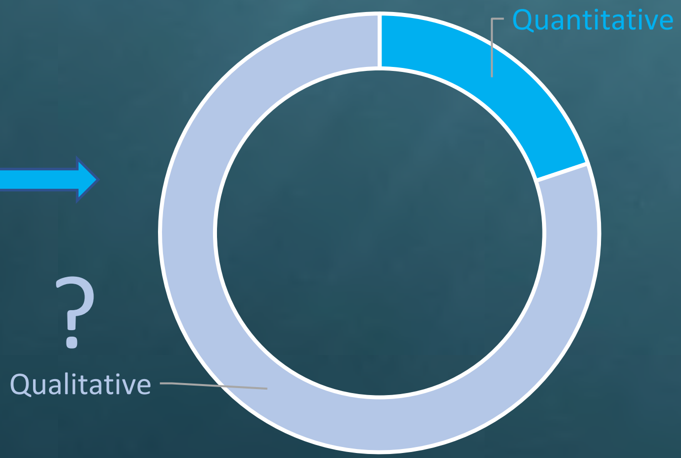
Biofouling Literature Analysis

2020+

Hull fouling
ISO 19030
Energy efficiency
Coatings
Hull roughness
Biofouling management
Deep learning
Biofilm
RANS CFD
Ship hull
Management
Propeller
Barnacle
Power penalty
Hydrodynamics
Marine growth
Baltic Sea
Review
Fuel consumption
Prevention
Biofouling
Non-indigenous species
colonization
biofouling
Antifouling
Performance indicator
Ship resistance
Data analytics
Machine learning
CFD
Image segmentation
Fouling
Monitoring
ROV
KCS
Hard fouling
Heterogeneous roughness
Biosecurity
Barnacle pattern

Biofouling Literature Analysis

- 161 biofouling
- 21 ship coating
- 14 fouling in ports
- 13 underwater image enhancement
- 11 image segmentation underwater



17 studies 1-3 ships ?

15 studies > 5 Ships

Max -> 80 ships

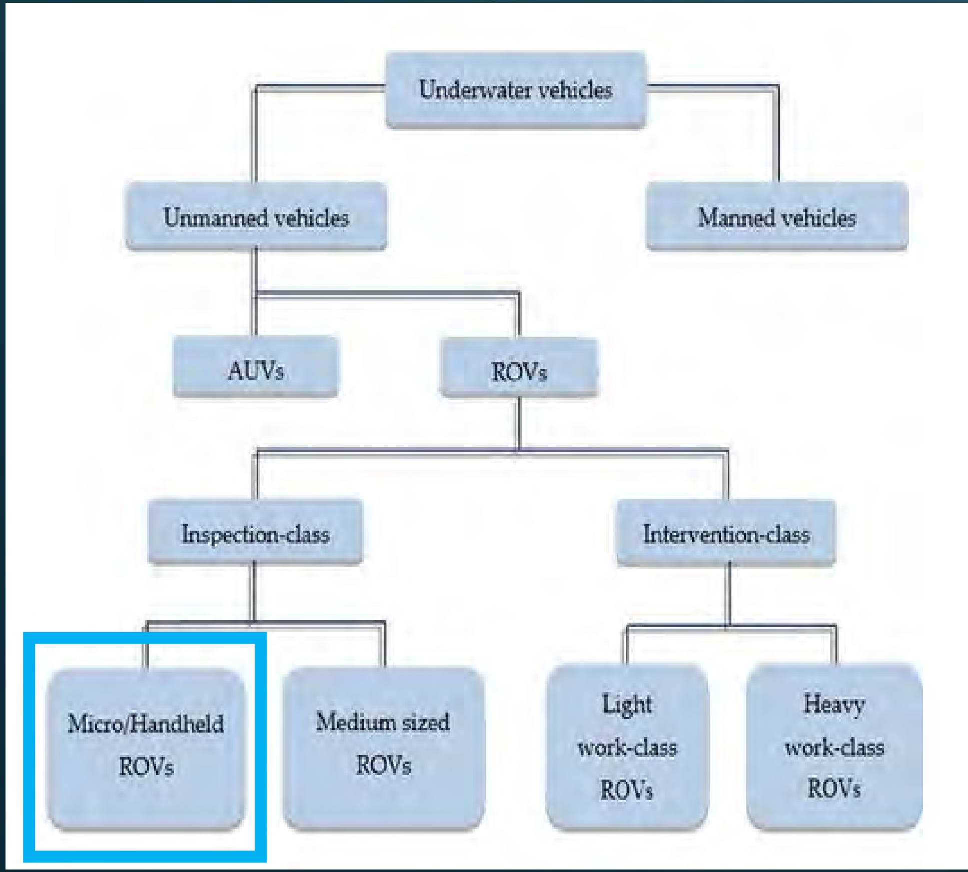
3rd quartile 21 ships

Average 17 ships

SUM 489 Ships

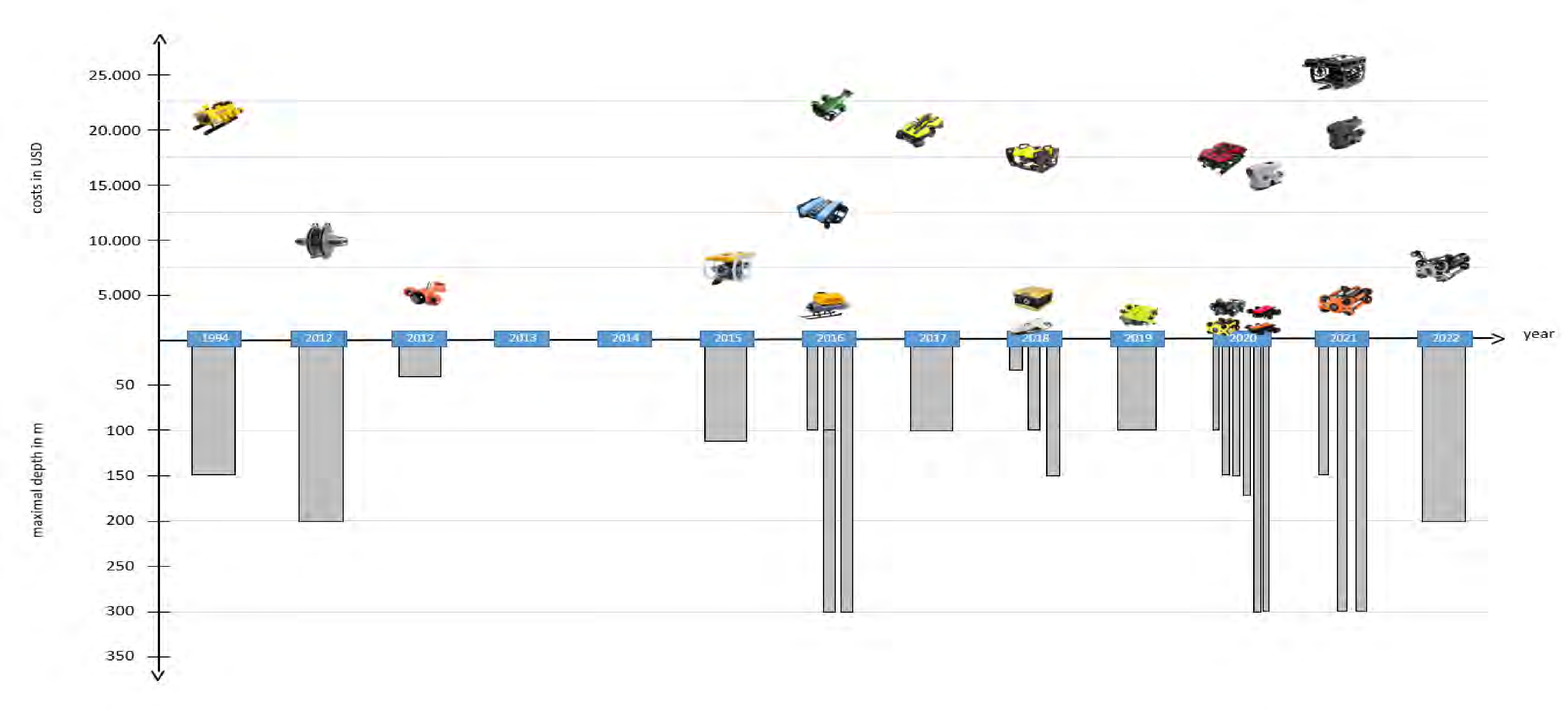
A Brief ROV Market Overview

Micro ROV Overview



Capocci et al. (2017)

Biofouling Literature Analysis



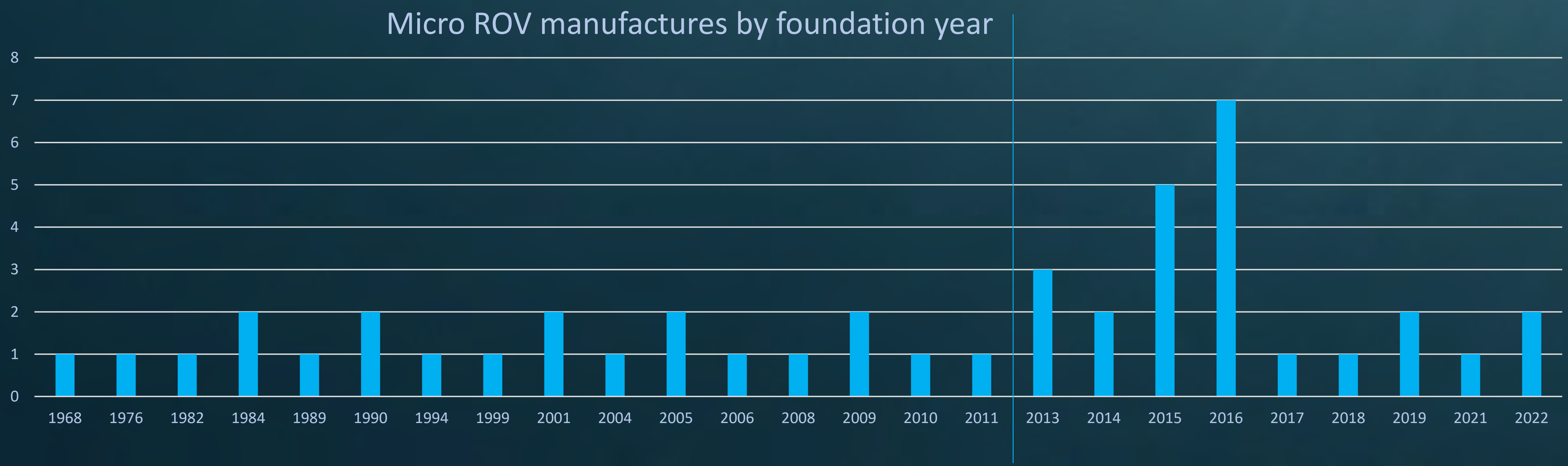
Source: Stein (2023)

Micro ROV Market Overview

Stein (2023) 22 most prominent micro systems

Kingma et al. (2025) 88 ROV Systems micro and intervention class

Complete Market Overview on micro ROV systeme 2025
-> 48 manufacteurs
-> 133 micro ROV systems



Market Observation most predominant ROVs

QYSEA

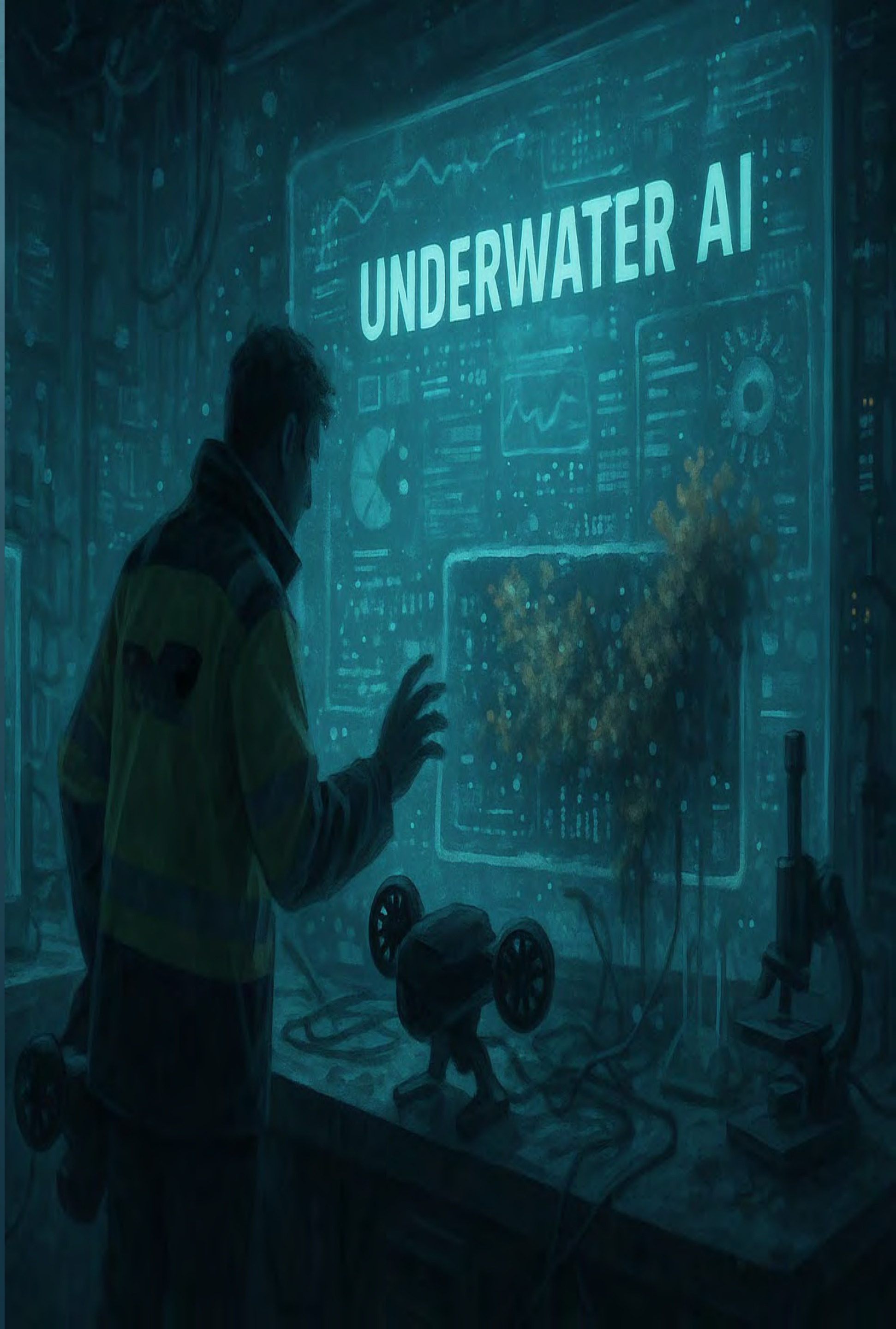
blueye

CHASING

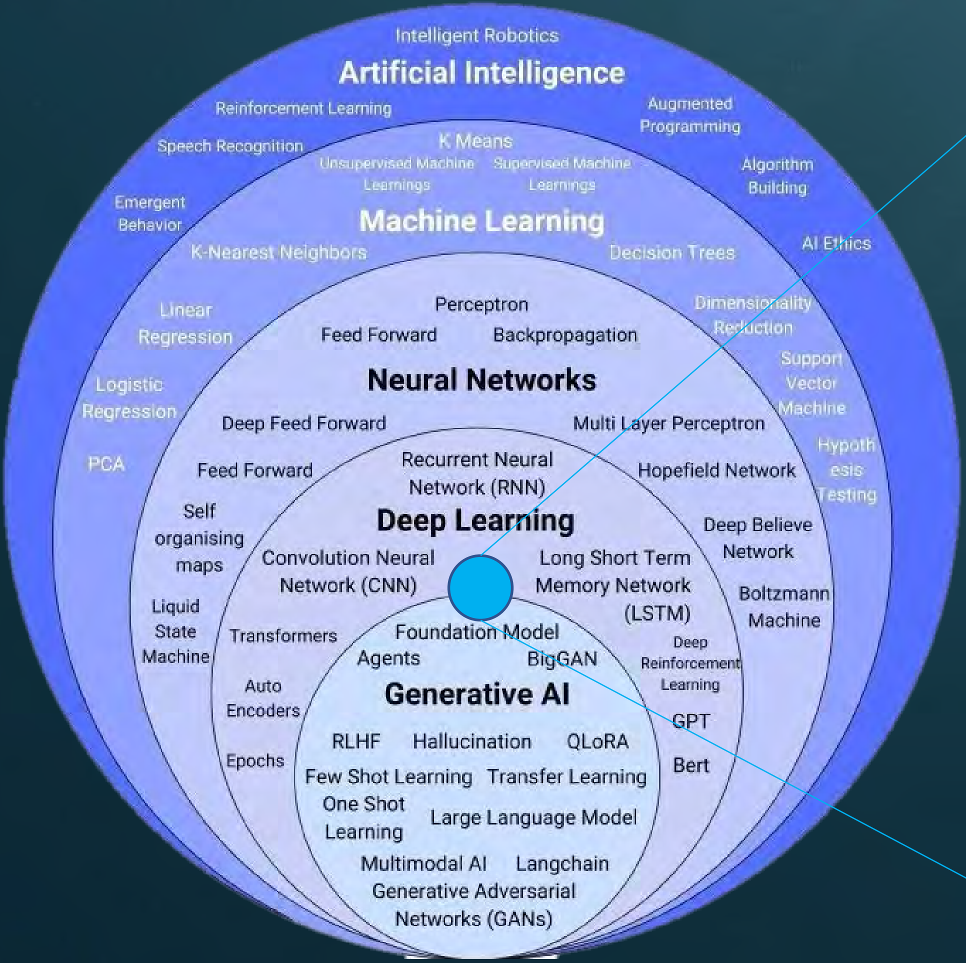
DEEP TREKKER

BlueRobotics

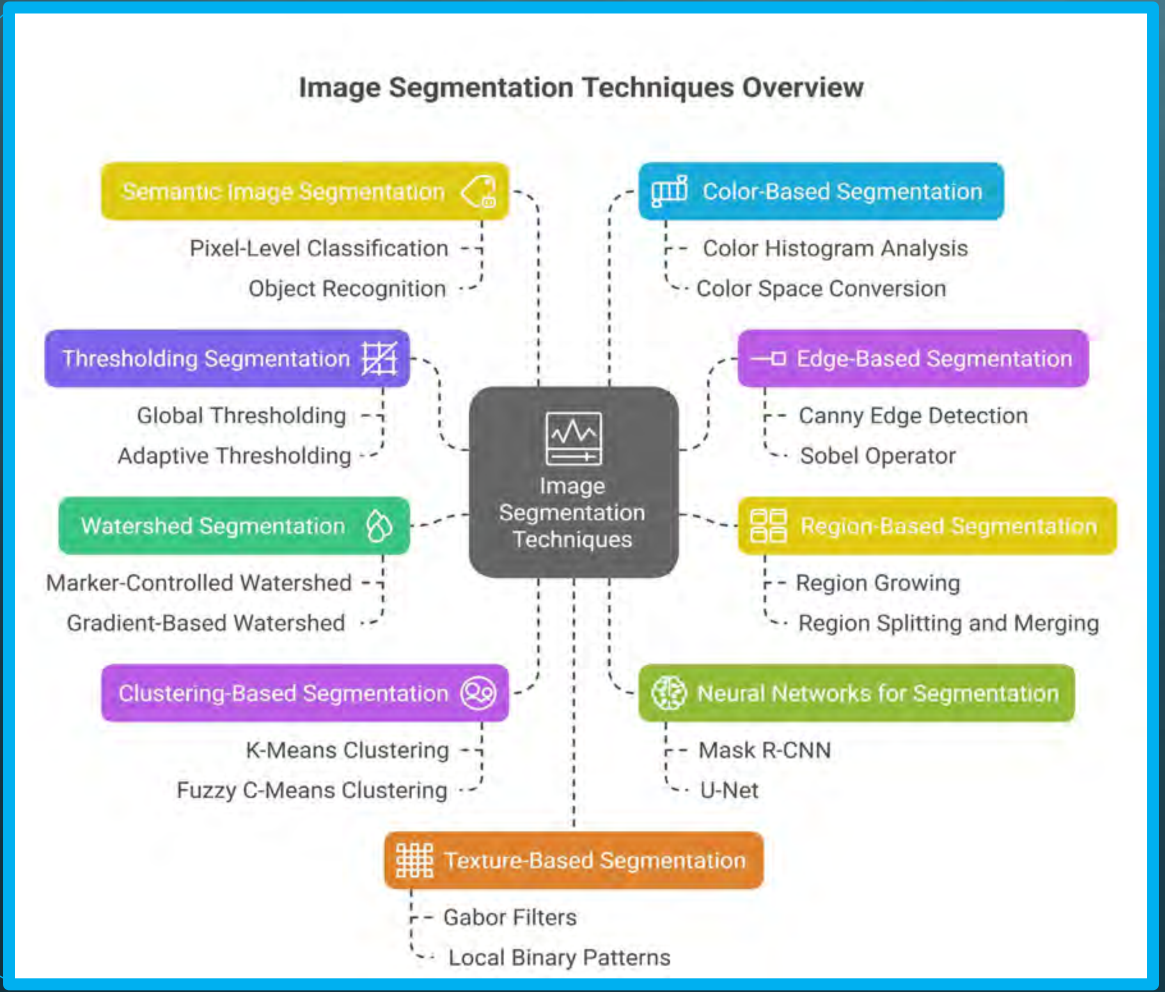
Image Segmentation Architecture Model Comparison



Understand AI **BEFORE** We Talk About It

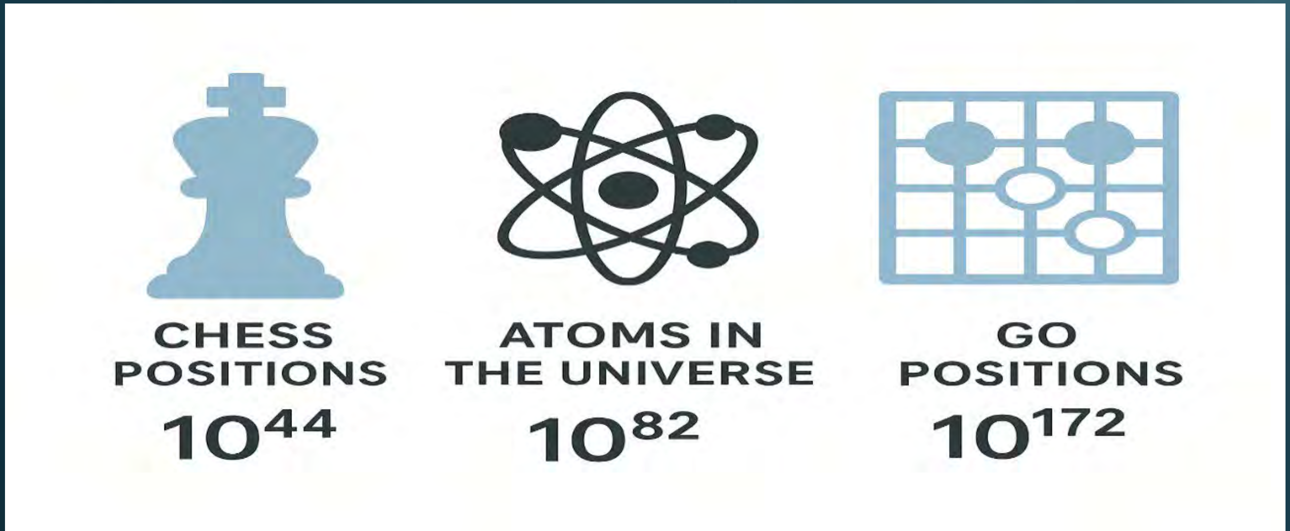


Source: Abdelnaser (2024)



Source. Vadapalli (2025)

Understand The Magnitude



1997
Deep Blue vs. Kasparov

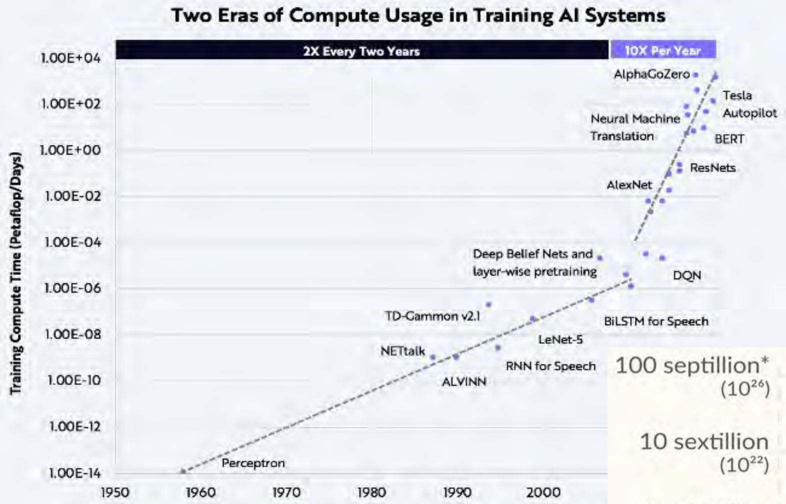
2006
AlphaGo vs. Sedol

25 years ago, successful AI calculation exceeded the handling of amount of atoms in the universe…

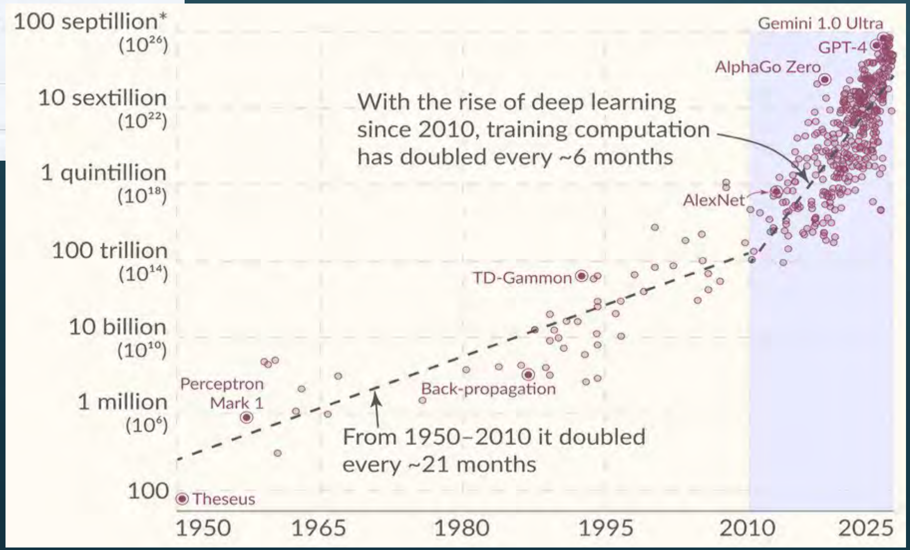
… how hard can it be to predict biofouling growth patterns on tiny box shapes (ships) in a confined space (oceans)…

… if we ask the right questions?

Understand AI **BEFORE** You Talk About It

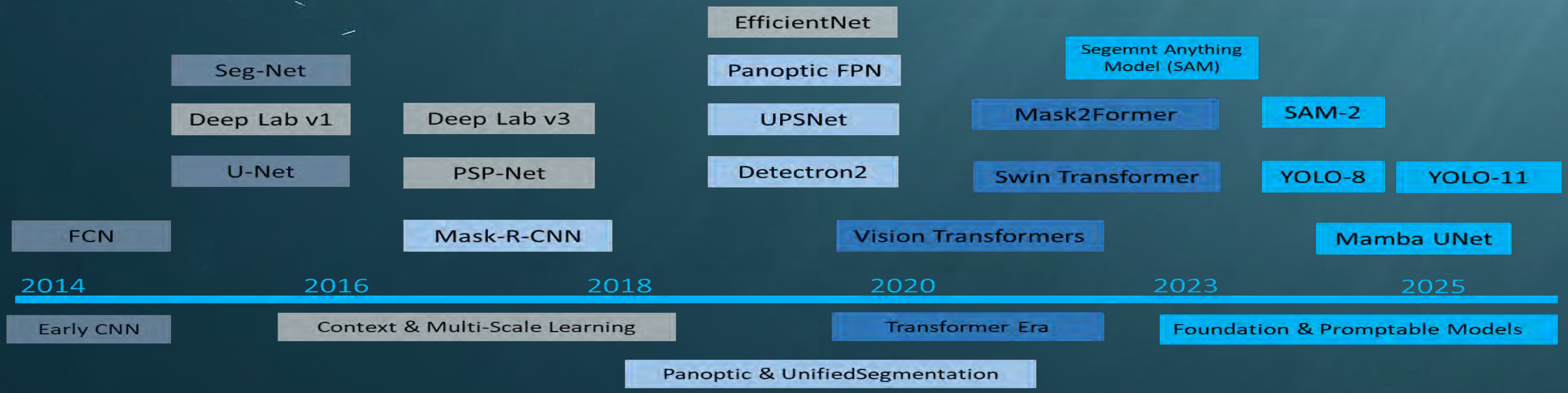


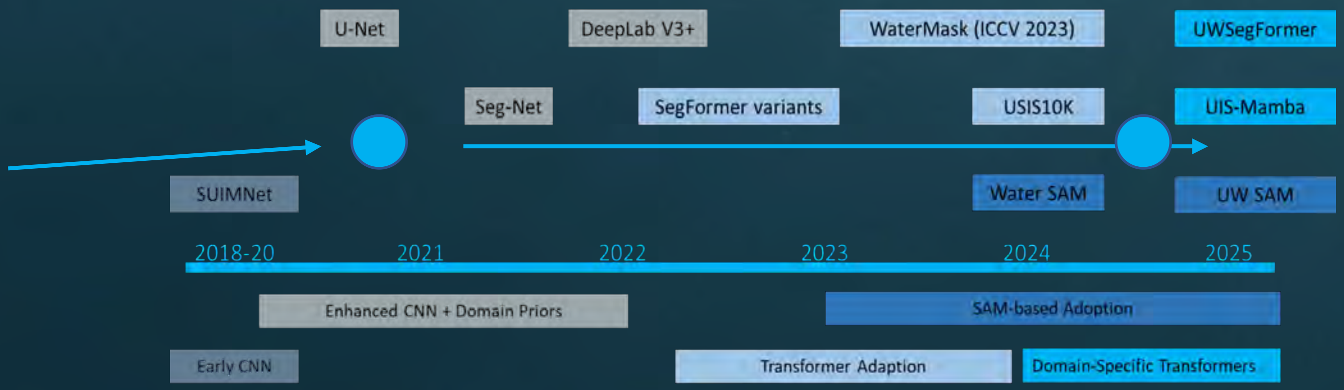
Source:Wang (2020)



Source: Giattino (2024)

Overview of Image Segmentation Architectures





AI Data 2021

	Precision	MIoU	Data
Bloomfield et al (2021)	0.7960	-	10.263
Islan et al. (2020)	0.8697	0.8414	1.525
O'Byrne et al. (2018)	0.9400	0.8700	2.500
Liu & Fang (2020)	-	0.6465	2.237
Our approach	**0.9500**	**0.8500**	**1.128**

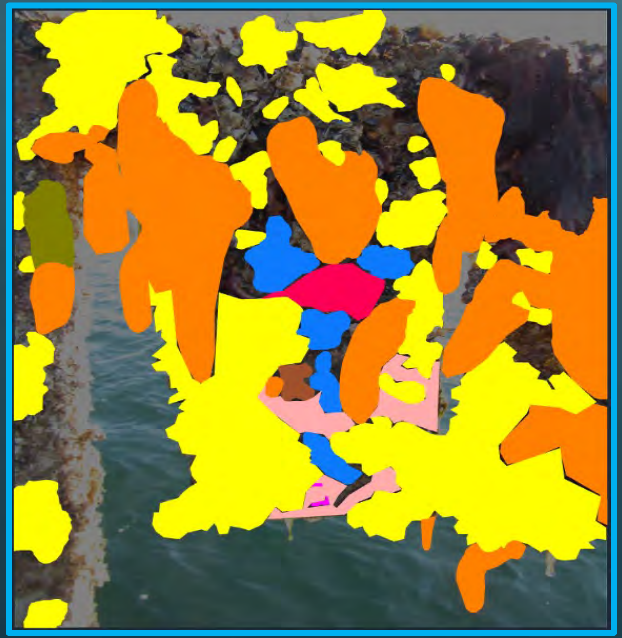
Chin et al (2021) identified a variety of marine growth including lkelp and oysters etc.

Architecture	MIoU*	data
PSPNet	.45	1.128
Simple Unet	.51	
Unet with encoder	.54	
SUIMNet with encoder	.73	
Our approach	**.85**	

Marine Fouling Image Segmentation

Class View

Layer View



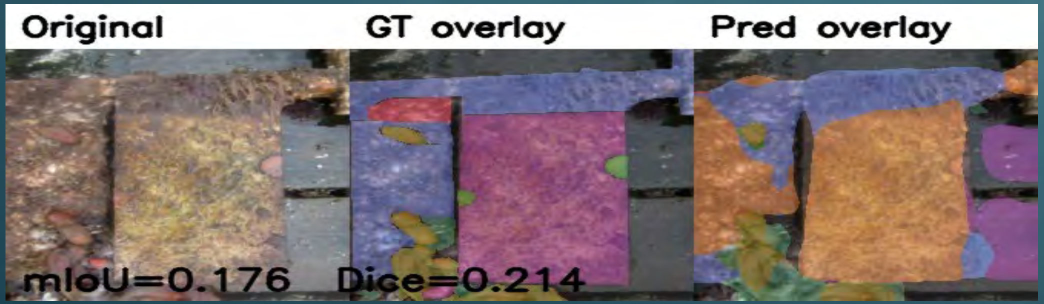
The key to successful underwater AI analysis lies in the labeling of the core training data. This process must be correct, accurate and consistent to achieve valid and robust results.

Technical Demo Examples

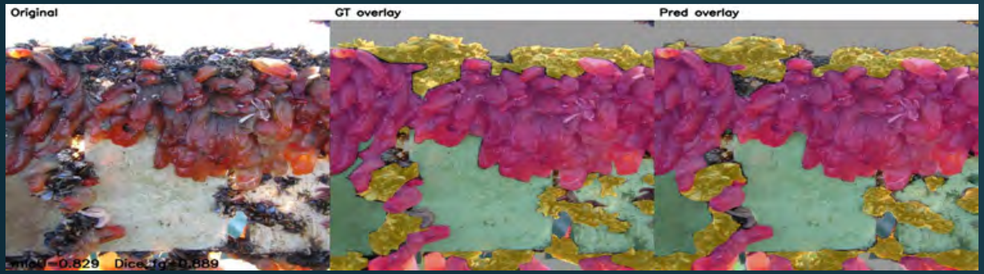
Tunicates

Slime

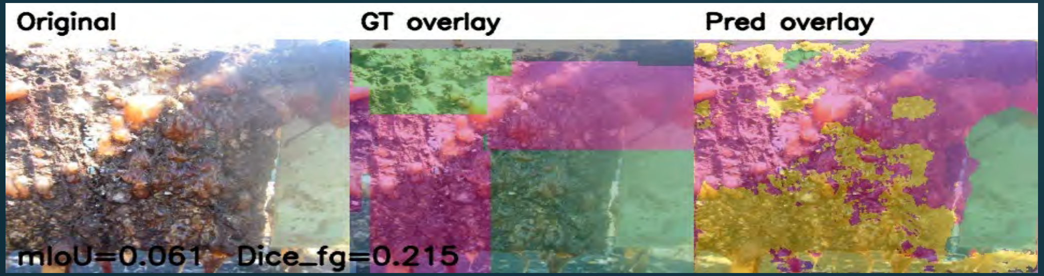
Marine Fouling Image Segmentation



ViT



U-Net

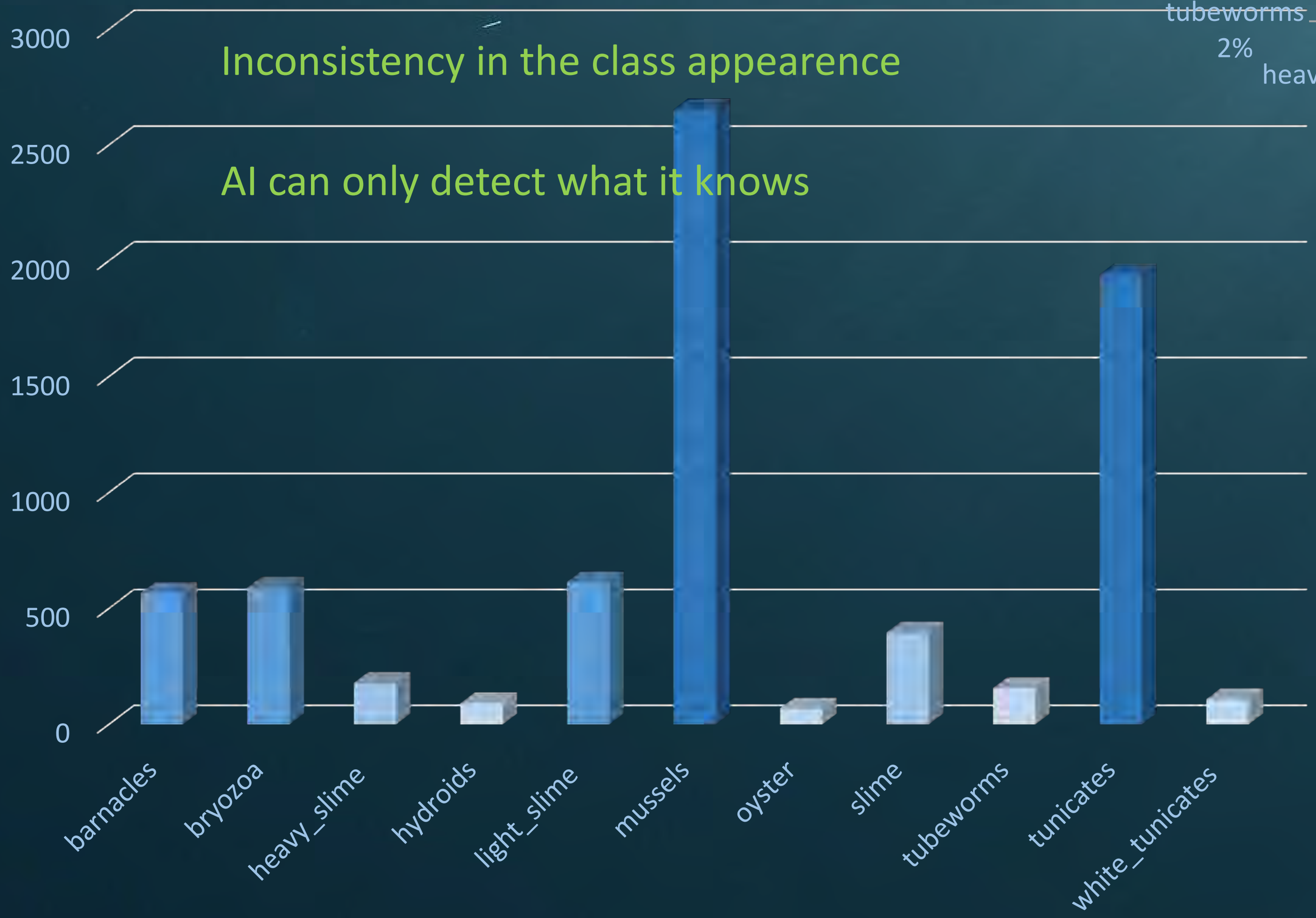


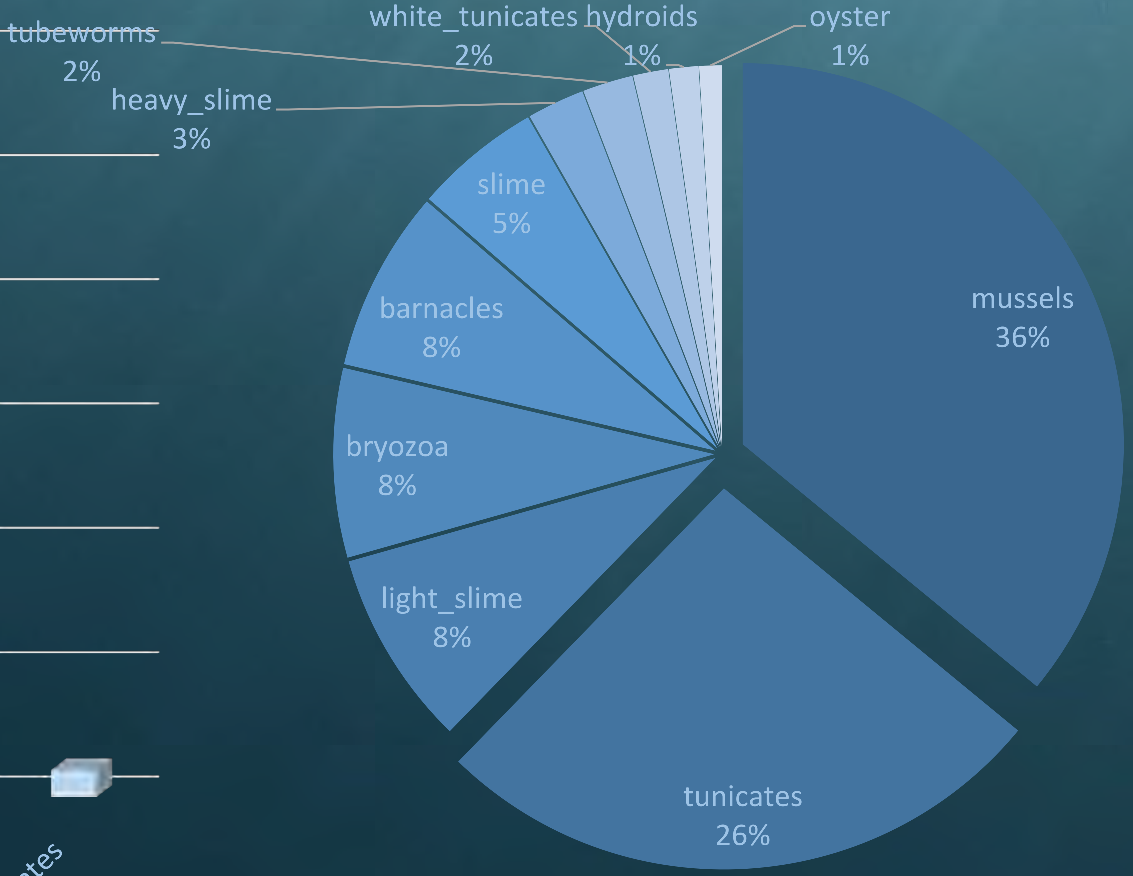
SUIM Net

Labelling classes summary

Inconsistency in the class appearence

AI can only detect what it knows



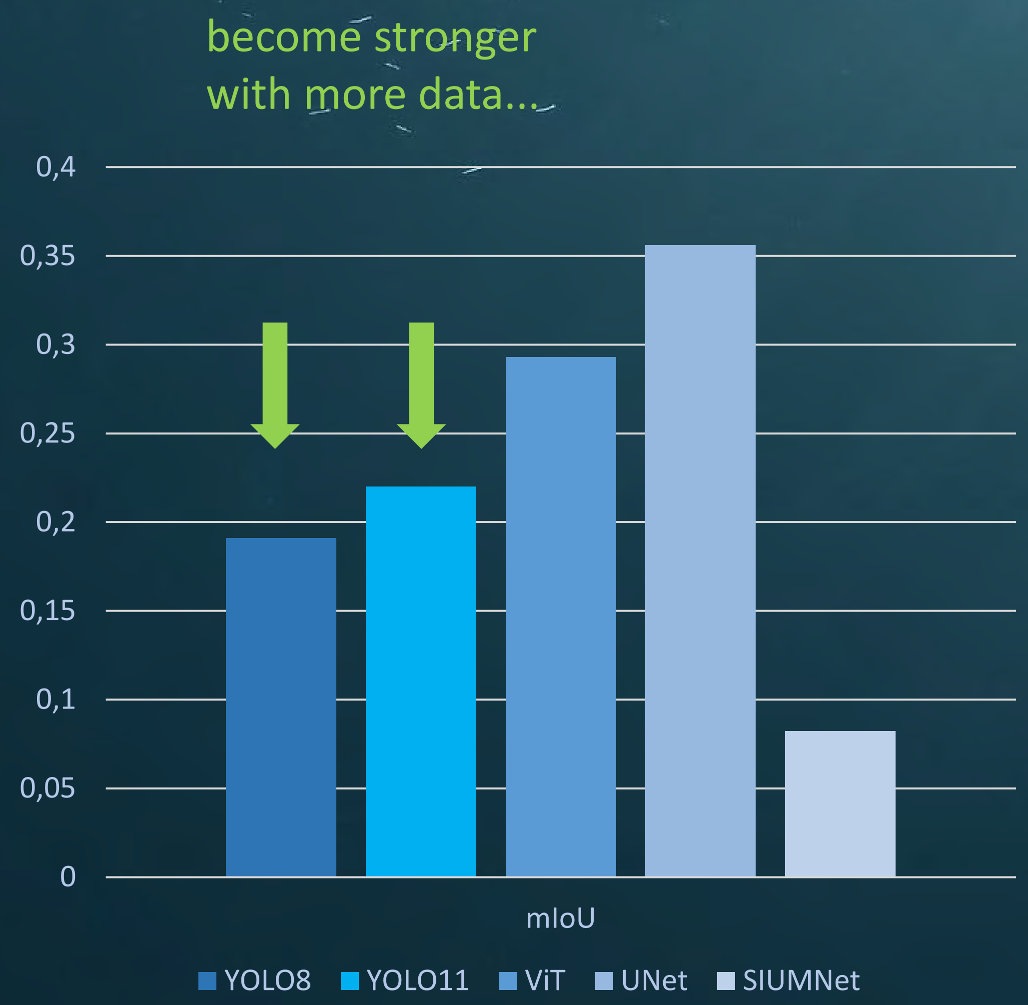


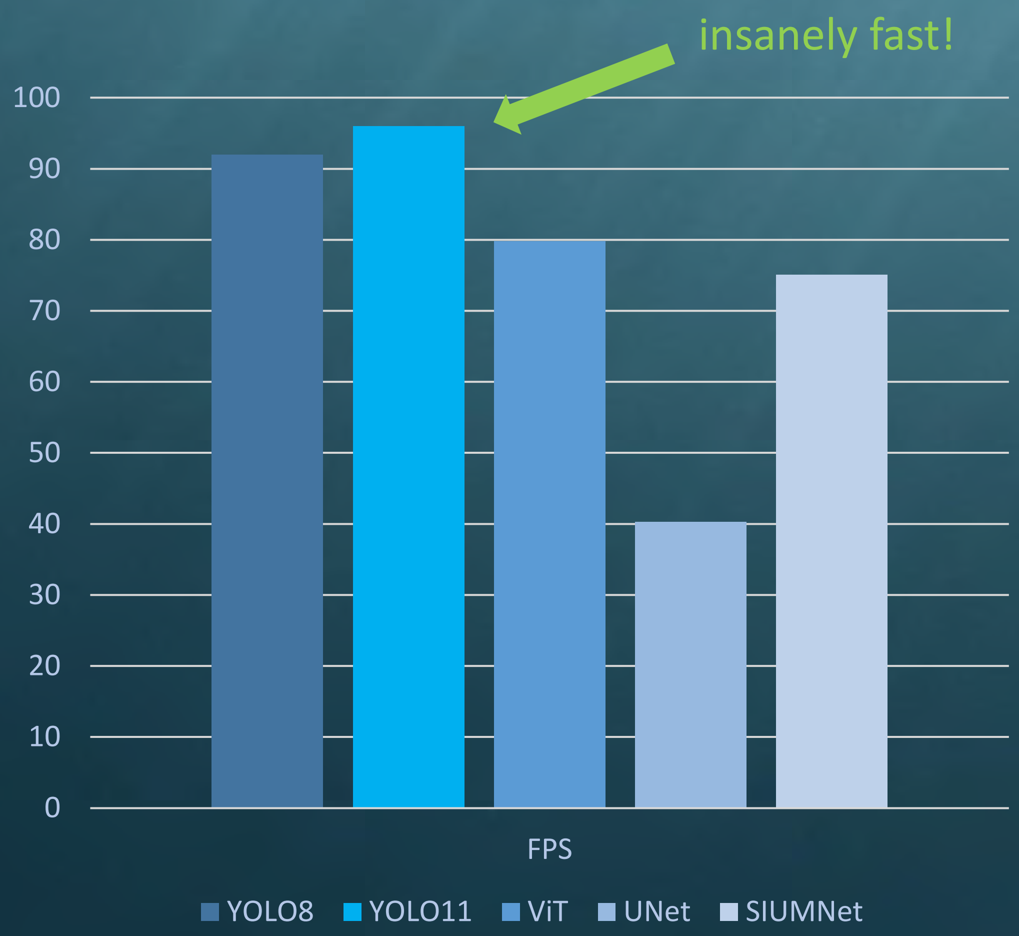
Comparison Summary Label Class

	YOLO 8	YOLO 11	Vision Transformer	UNet	SIUMNet
Year	2024	2025	2020	2015	2018
Global mIoU	0.191000	0.220000	0.293050	0.355979	0.080257
Pixel accuracy	0.335000	0.335000	0.679211	0.756594	-
Average FPS	92.000	96.000	79.811	40.332	75.109
background	0.020000*	0.020000*	0.552615	0.627898	0.105474
Barnacles	0.280000	0.440000	0.278368	0.270012	0.015103
Bryozoa	0.270000	0.500000	0.099924	0.212970	0.000000
heavy_slime	0.200000	0.240000	0.241472	0.266231	0.005831
Hydroids	0.010000	0.120000	0.192138	0.180790	0.055604
light_slime	0.320000	0.410000	0.663962	0.760580	0.293367
Mussels	0.450000	0.290000	0.513417	0.723532	0.275035
Oyster	0.000000	0.000000	0.000000	0.000000	0.000000
Slime	0.170000	0.220000	0.331678	0.468613	0.030817
Tubeworms	0.000000	0.000000	0.000000	0.000000	0.000000
Tunicates	0.580000	0.440000	0.643021	0.761122	0.261727
white_tunicates	0.000000	0.000000	0.000000	0.000000	0.000377

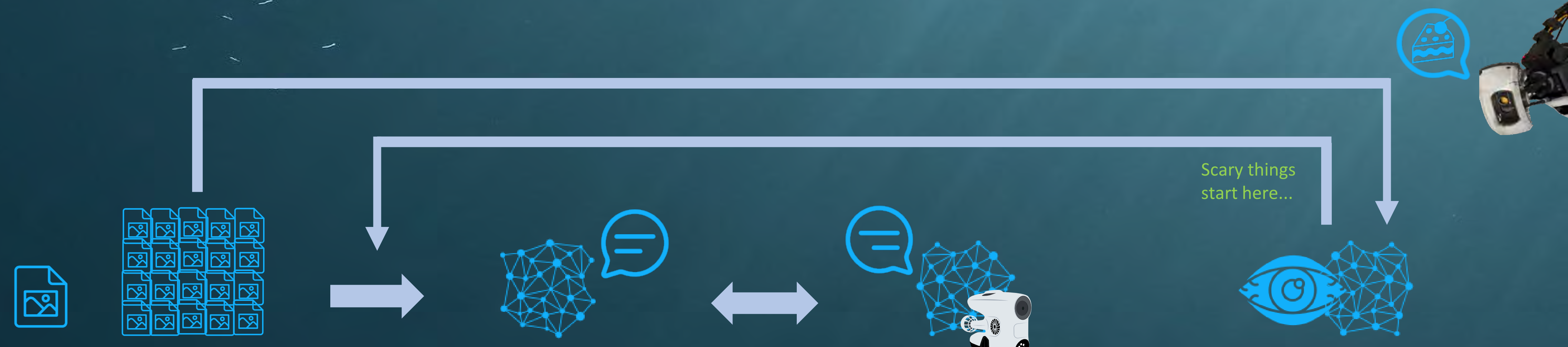
* YOLO ignores the background, non comparible

Comparison Summary Label Class





The AI Solution to Biofouling Management



Largest dataset of labeled biofouling classes from merchant ships

Very Big UNet for label propagation to allow auto labeling

YOLO or faster RCNN for edge-device detection

Synthetic image pipeline for semi-supervised learning

We intent to have the largest underwater image dataset of labeled biofouling on ships

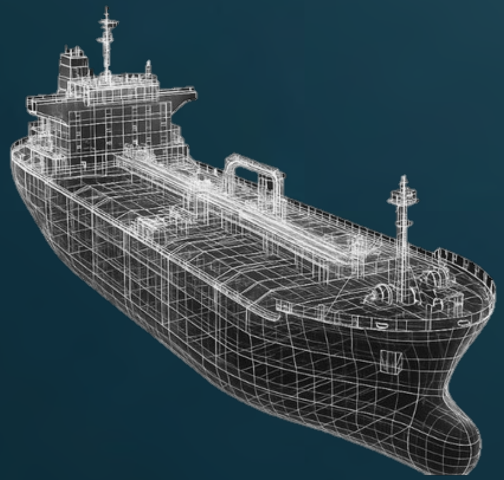
Apply strong but slow Unet characteristics in the labeling process

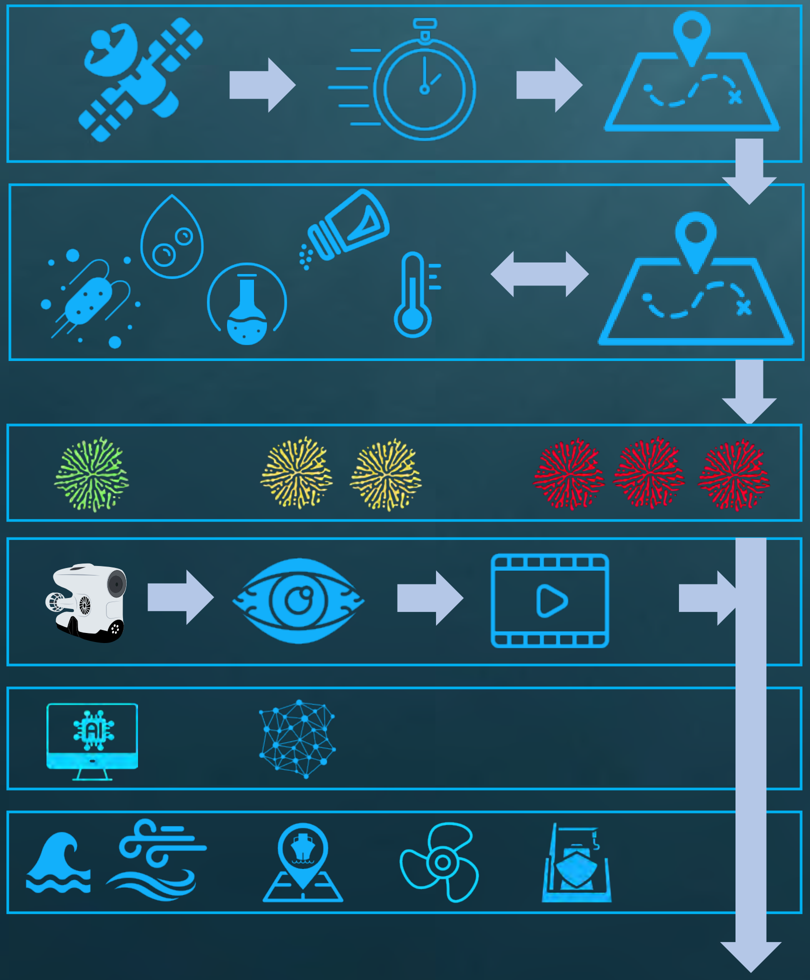
The super fast detection speed will allow for edge device application (ROV, Smartphone)

Solves the limited data issue. System will train itself after a while.

Capturing data to understanding biofouling

Our Approach





Routing Factors

Environmental Factors

Biofouling Risk Factor

Confirming ROV inspection

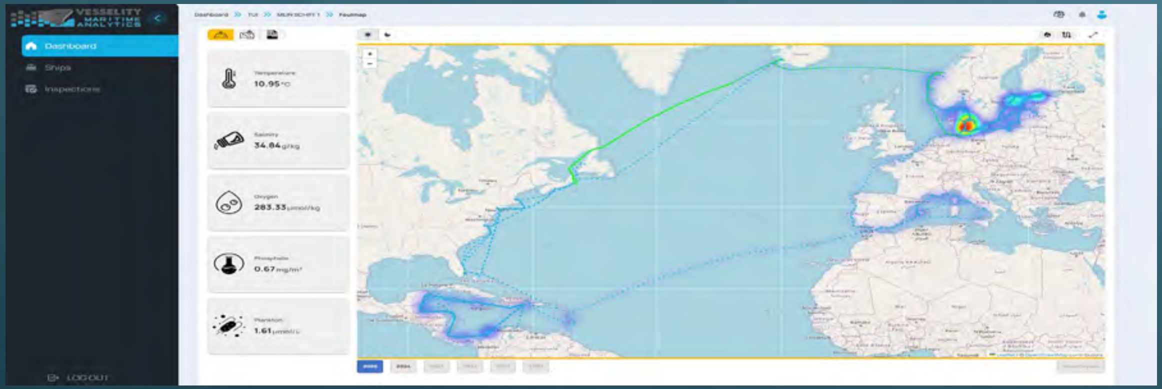
AI Data Extraction

Performance Factors

Updated Greybox Model Approach

Input	Unit
White-box prediction	[kW]
Ship speed	[knots]
Ship direction	[°]
Wave height	[m]
Wave direction	[°]
Wave period	[s]
Wind speed	[m/s]
Wind direction	[°]
Average sea surface temperature	[°C]
Anchorage days since clean ship	[days]
Sailing days since clean ship	[days]
Average ship speed	[knots]
Mean roll	[°]
Mean pitch	[°]
Roll deviation	[$°/s$]
Pitch deviation	[$°/s$]
Output	**Unit**
Fouled ship power	[kW]

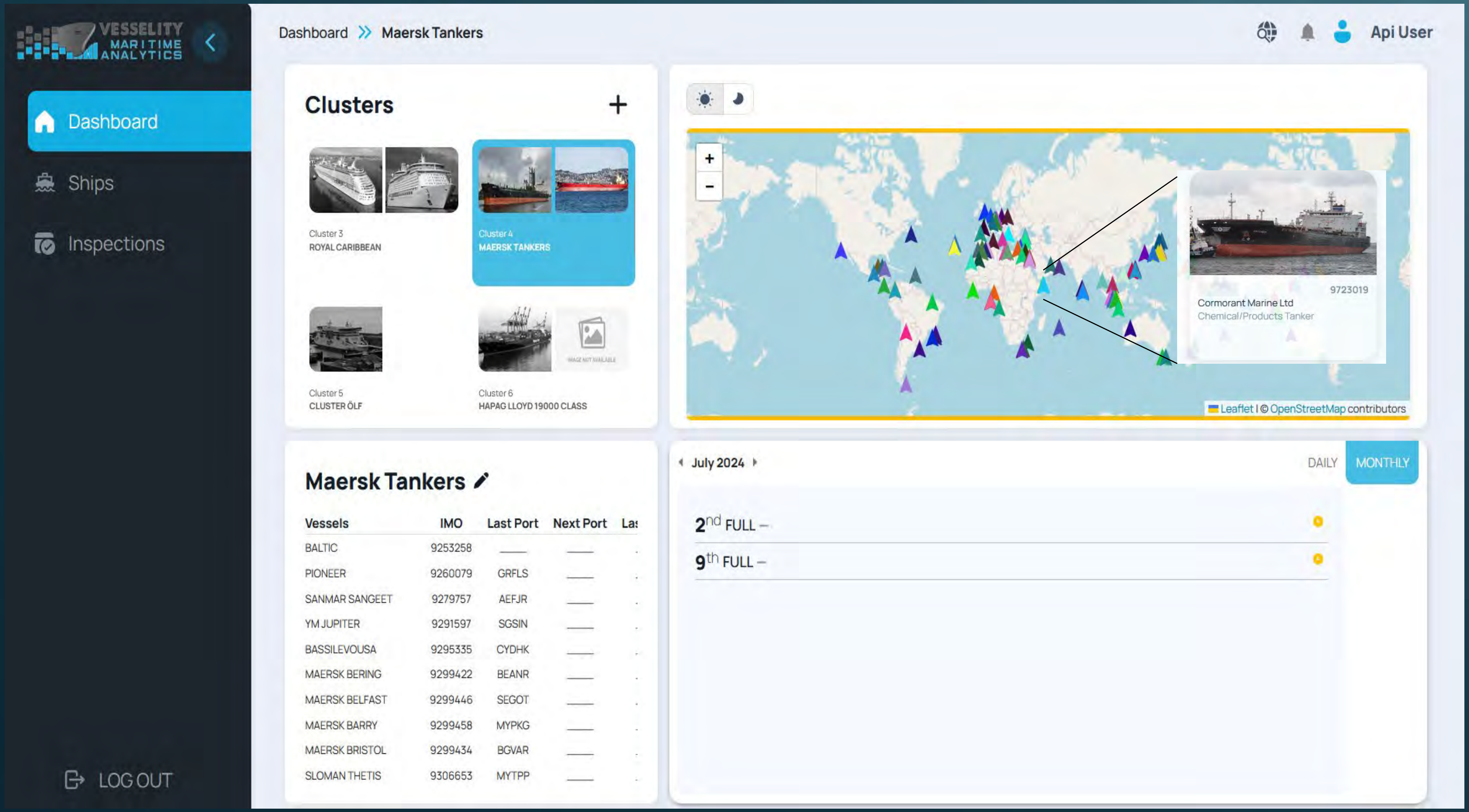
de Haasa et al. (2024)



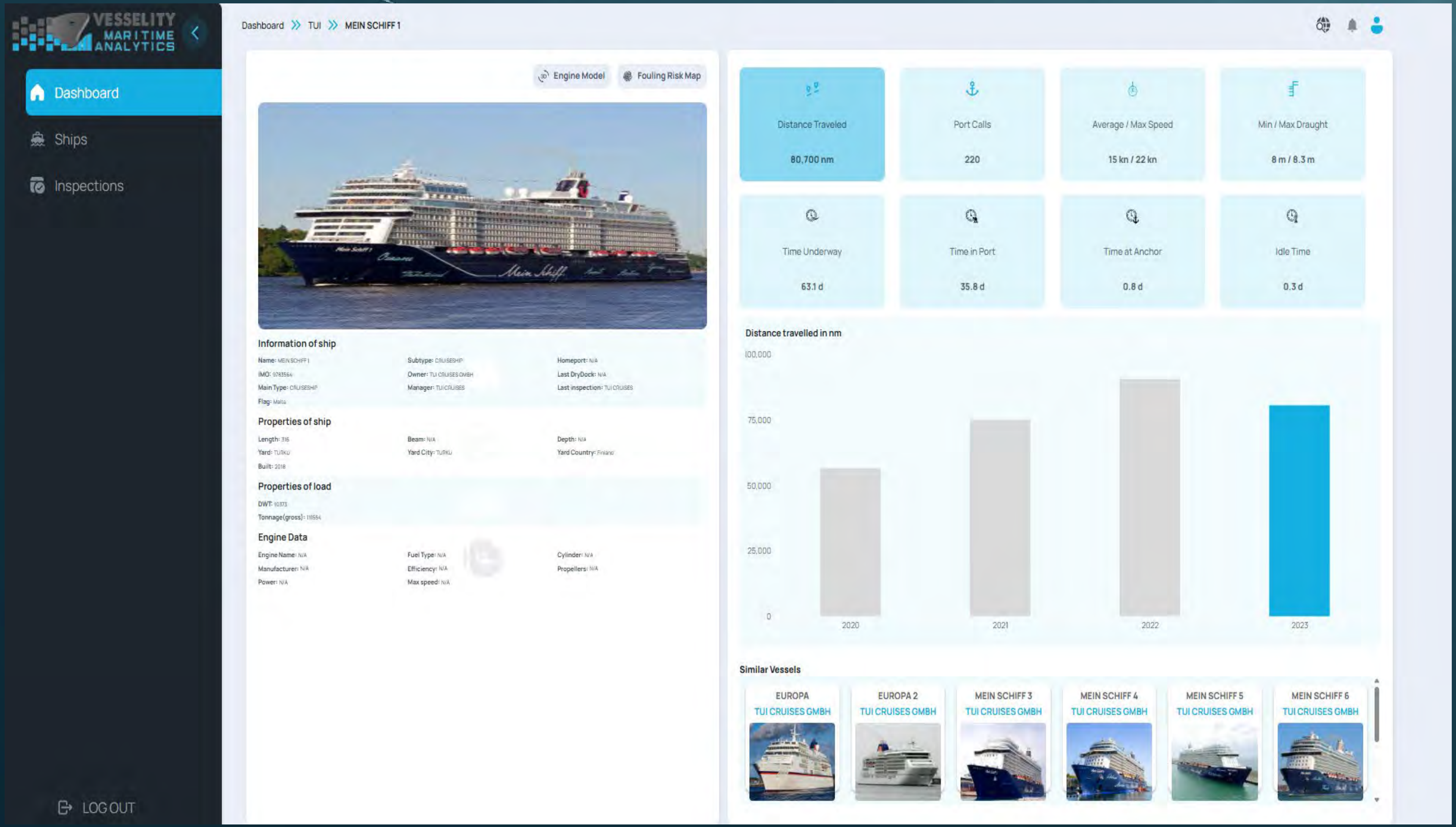
Advanced live routing evaluation based on time and speed

Additional Biofouling Factors
Chlorophyll (mg/m³)
Iron (nmol/L)
Phyto (mg C/m³)
Oxygen (µmol/kg)
Ph
Phytoplankton (mg/m³)
Phosphate (µmol/L)
Silicate (µmol/L)
Salinity (g/kg)
Temperature (°C)

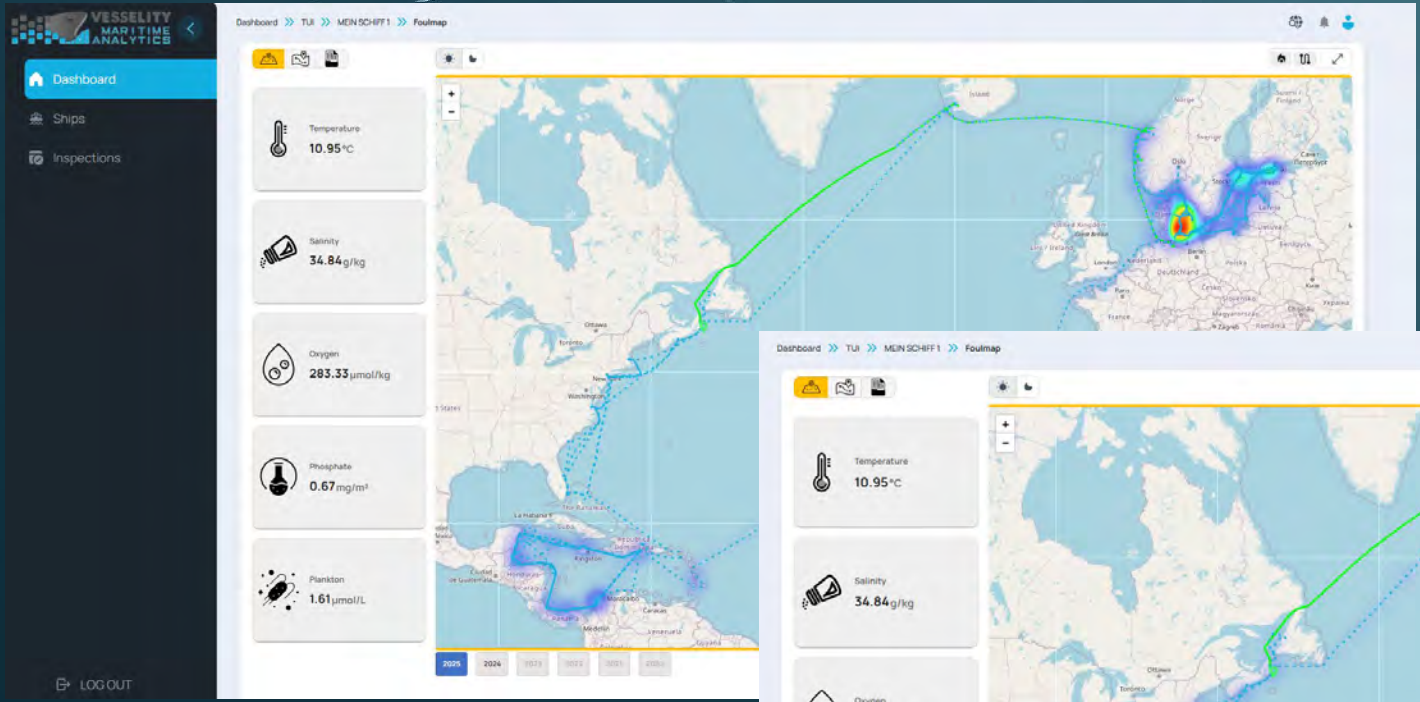
Comparison Summary Label Class

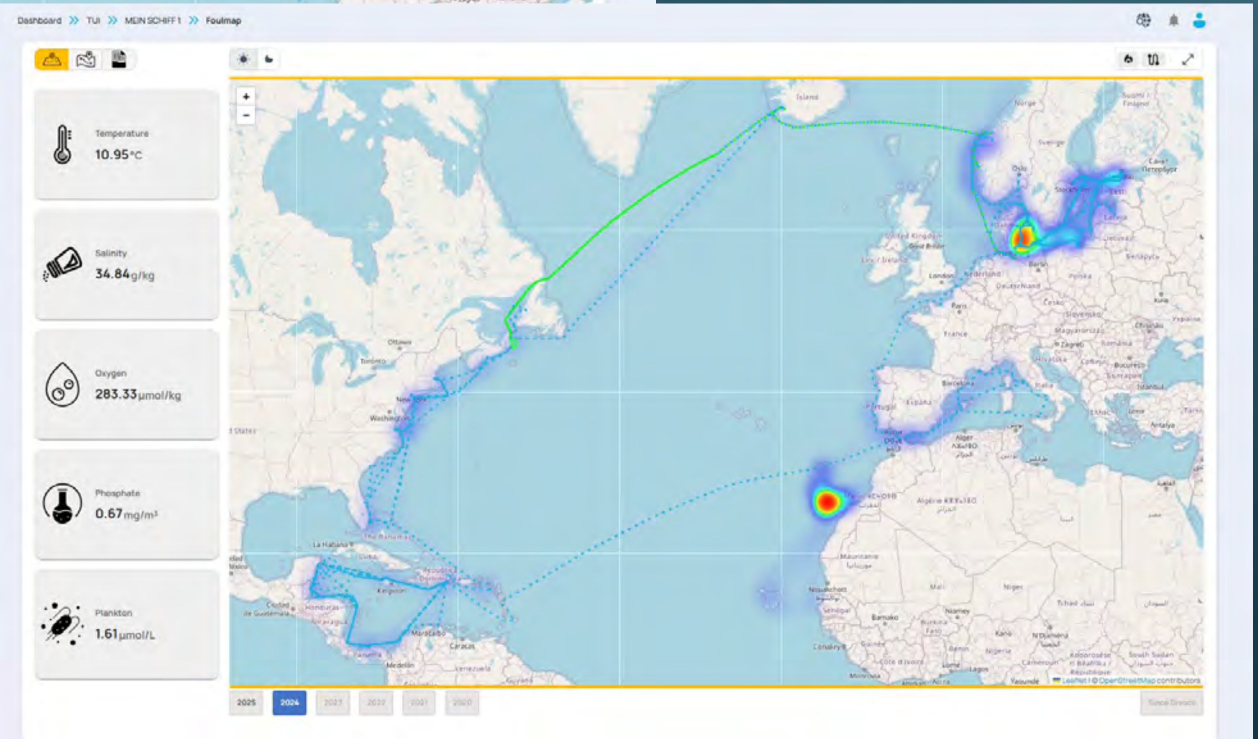


Comparison Summary Label Class

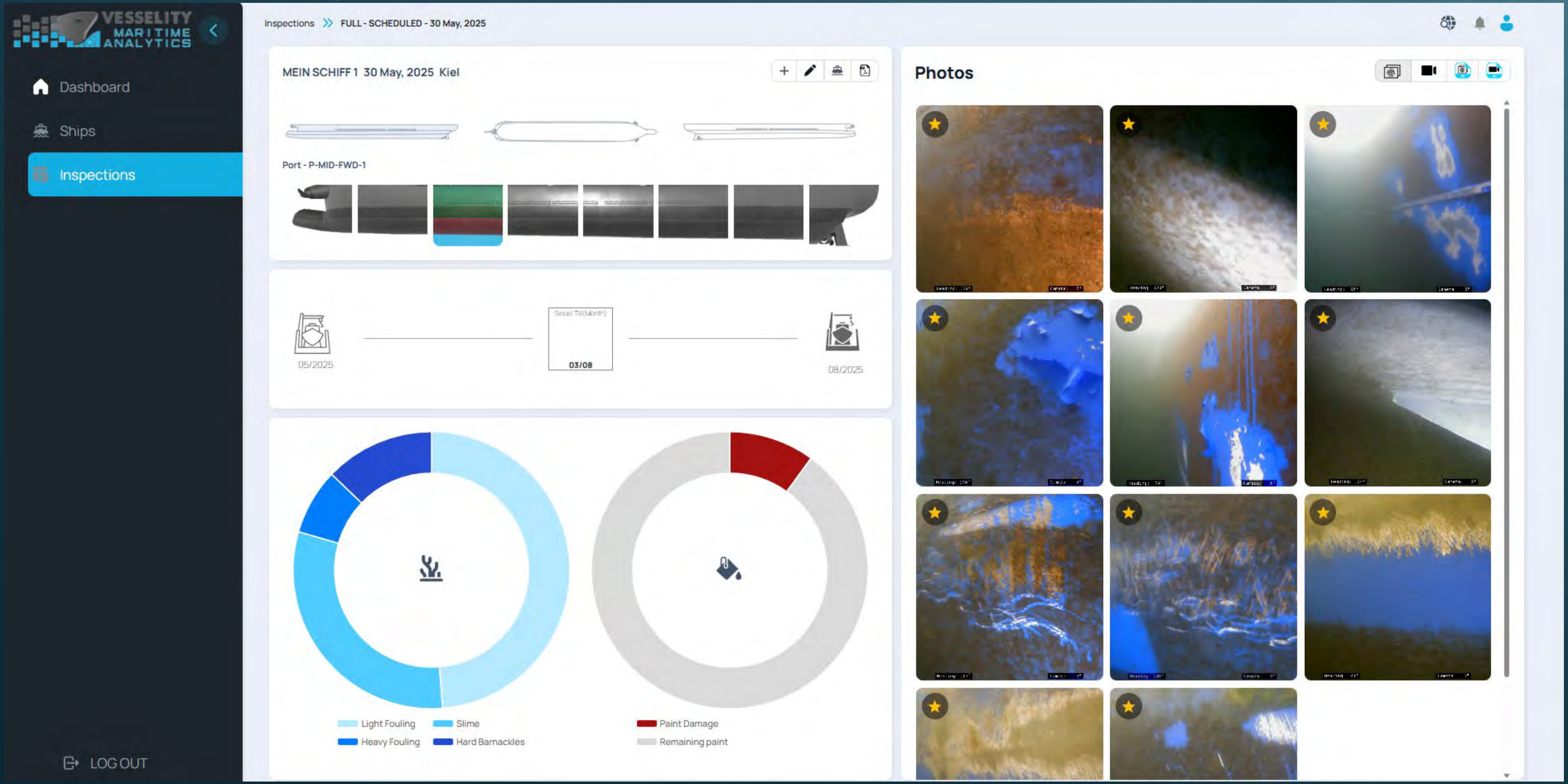


Comparison Summary Label Class

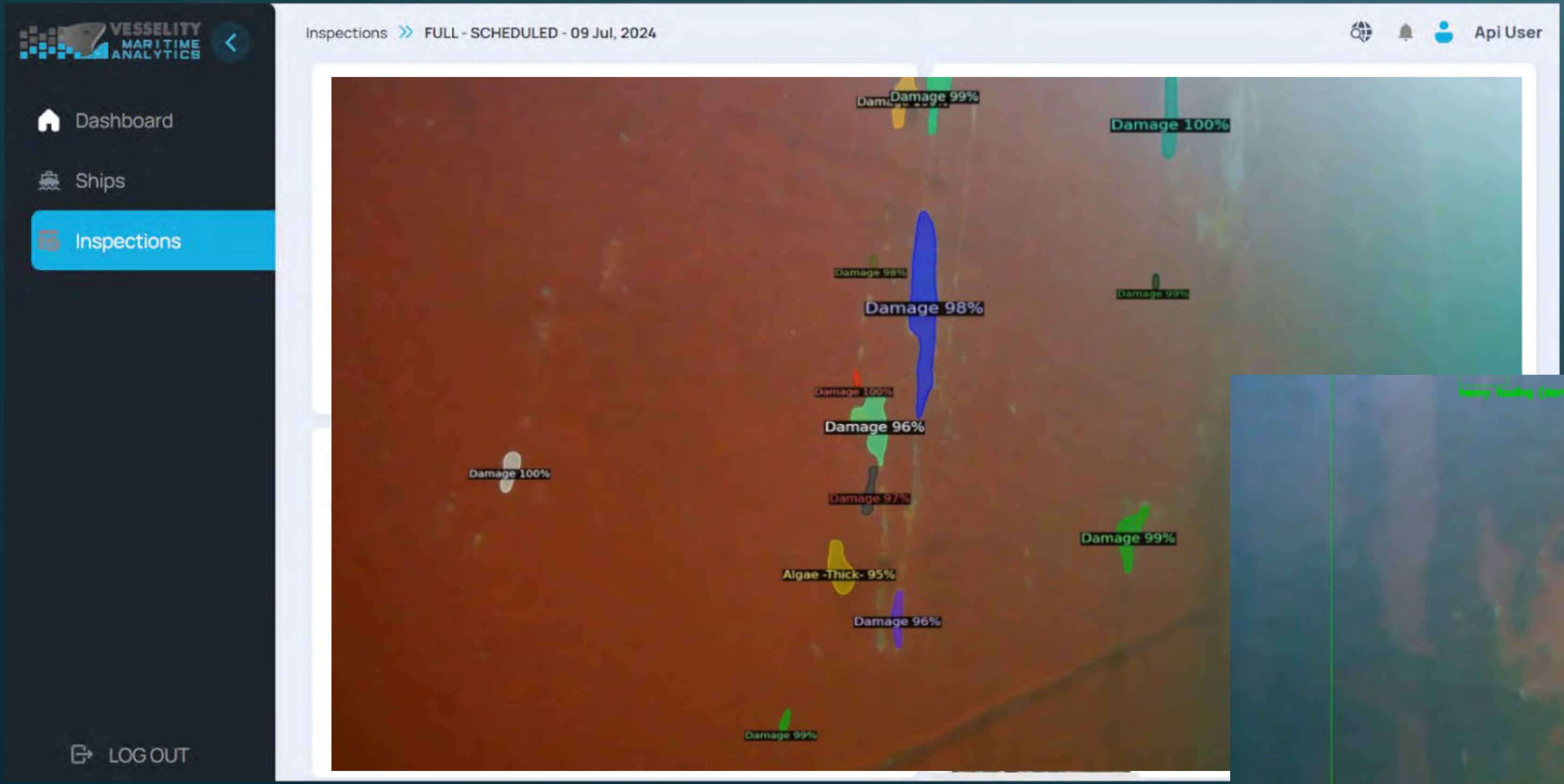




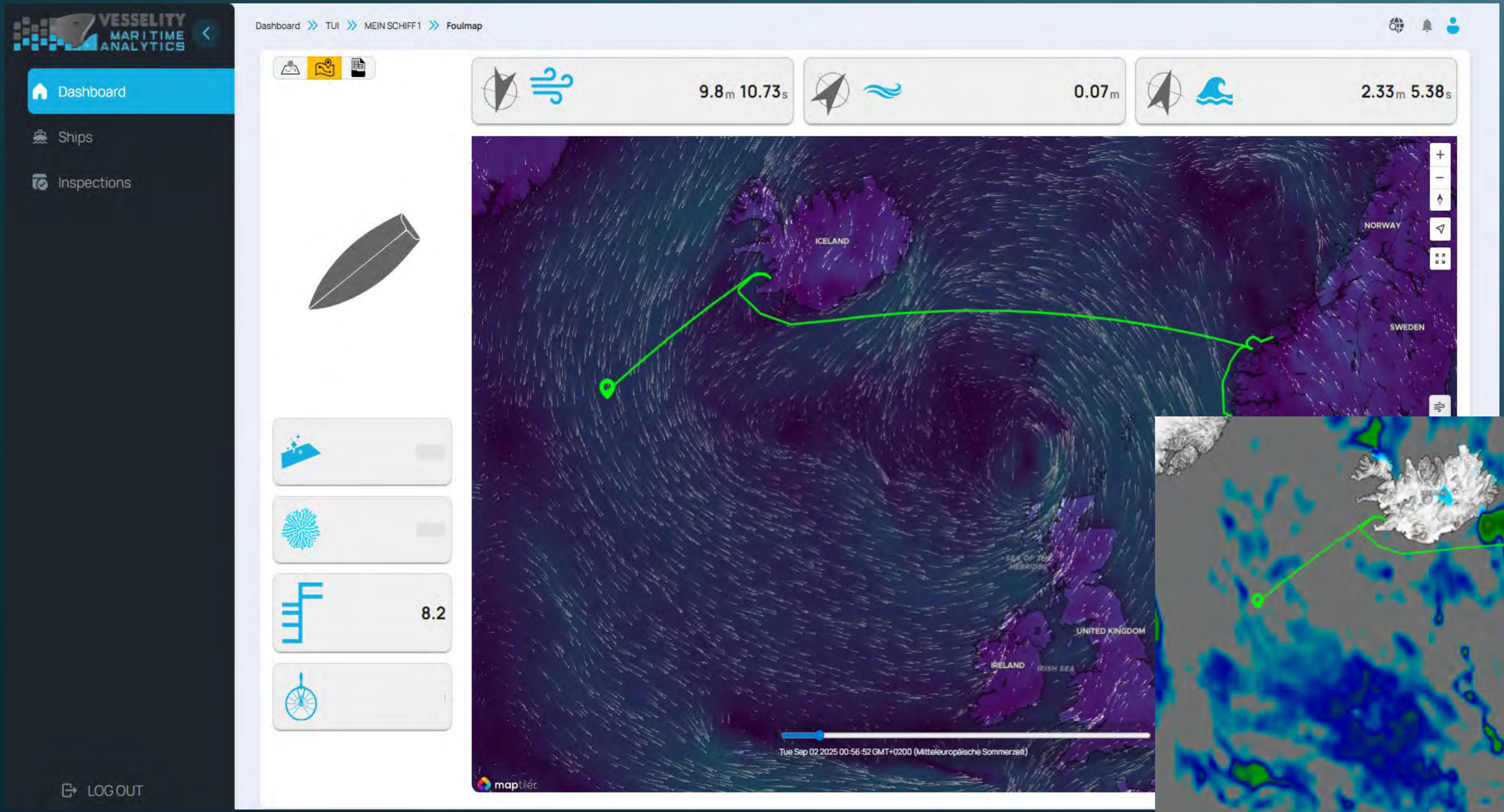
Comparison Summary Label Class

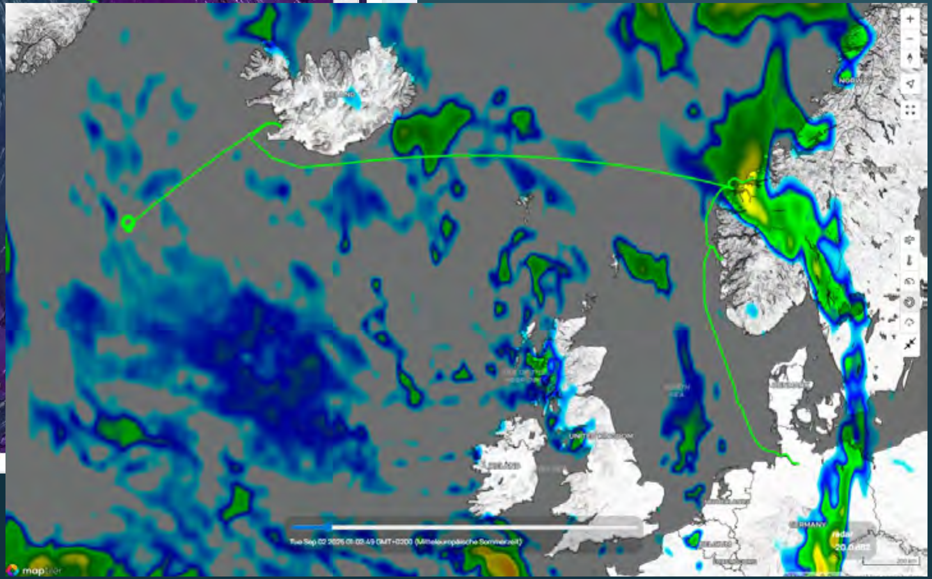


Comparison Summary Label Class



Comparison Summary Label Class





What comes next?

Biofouling Training Image Sythetisation

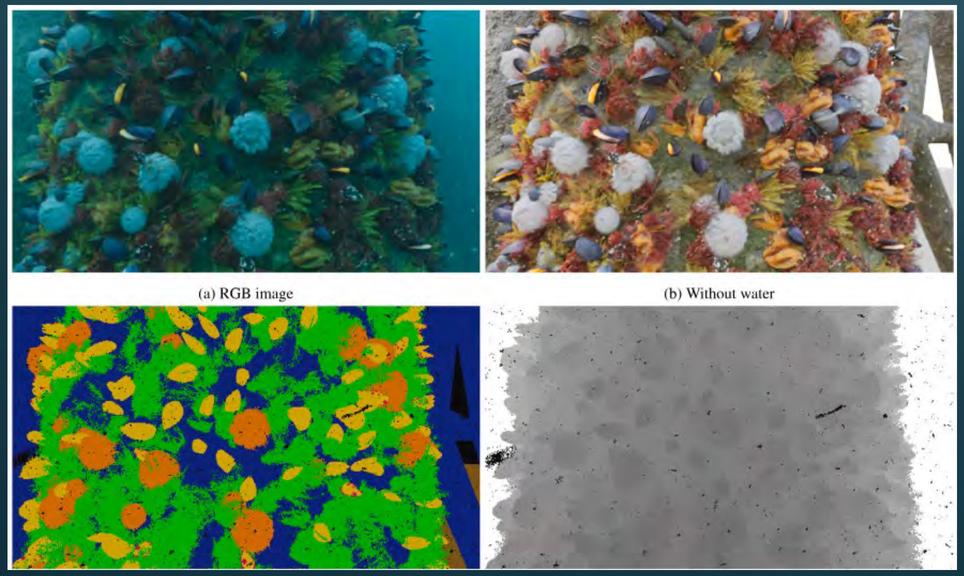
Synthetic image pipeline for semi-supervised learning

Synthetic image pipeline for semi-supervised learning

In the near future, we will have our AI network train itself on synthetic training images of biofouling.

Barbosa and Apolinario (2025)

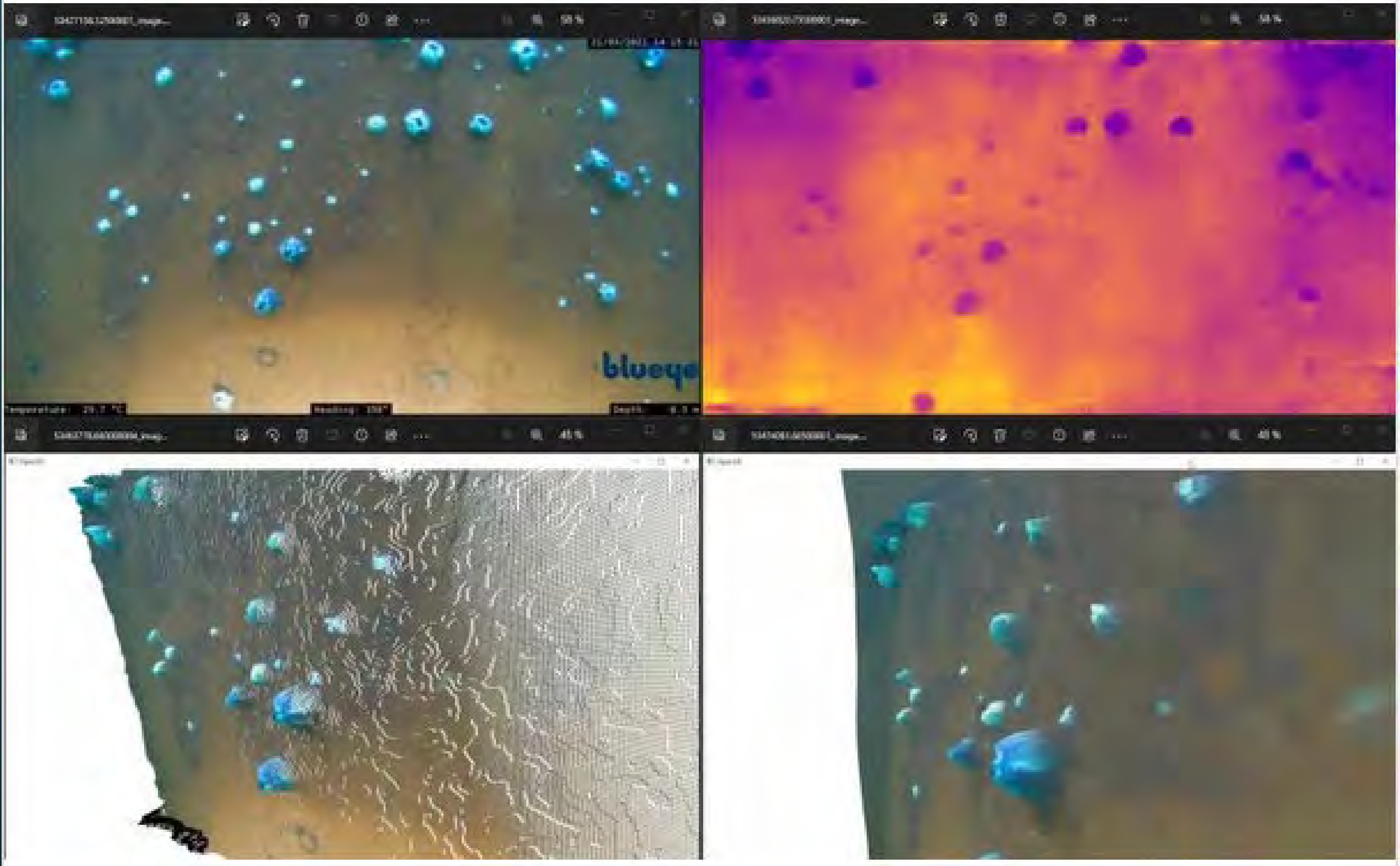
Mai et al. (2024)



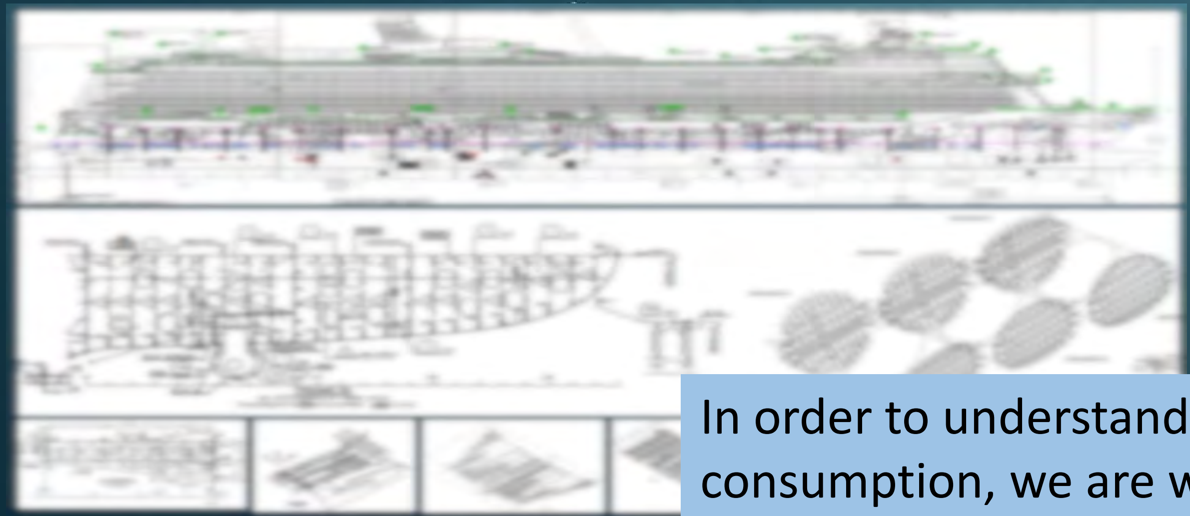
Neural Radience Fields

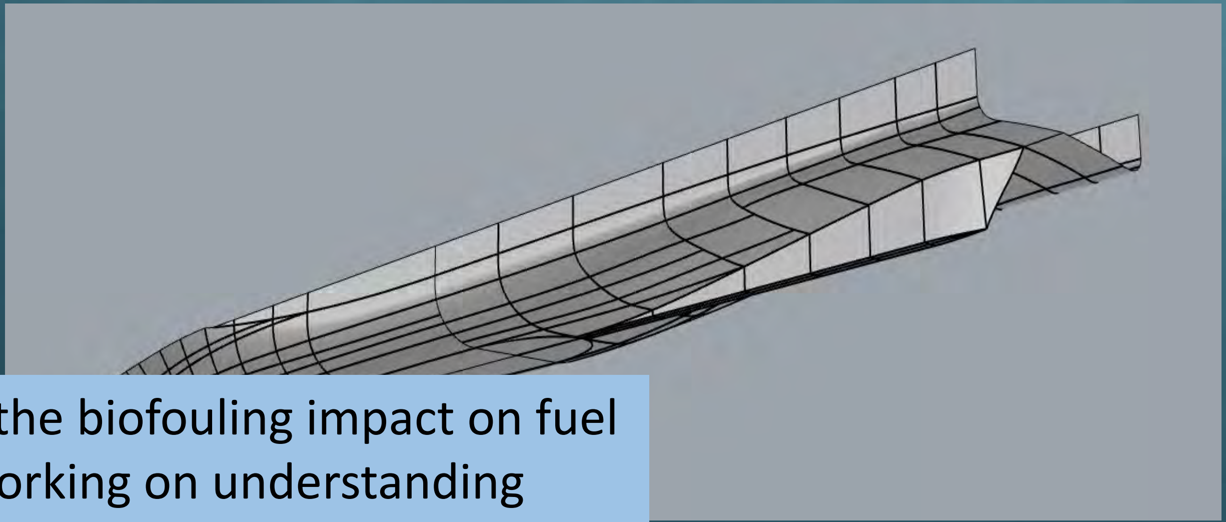
By applying a technique in AI image manipulation called Neural Radience Fields (NeRF) we are able to extract/ estimate 3D depth information from 2D inspection images, by image depth map generation.

With additional research, this will allow us to understand the size of biofouling on a ship hull.

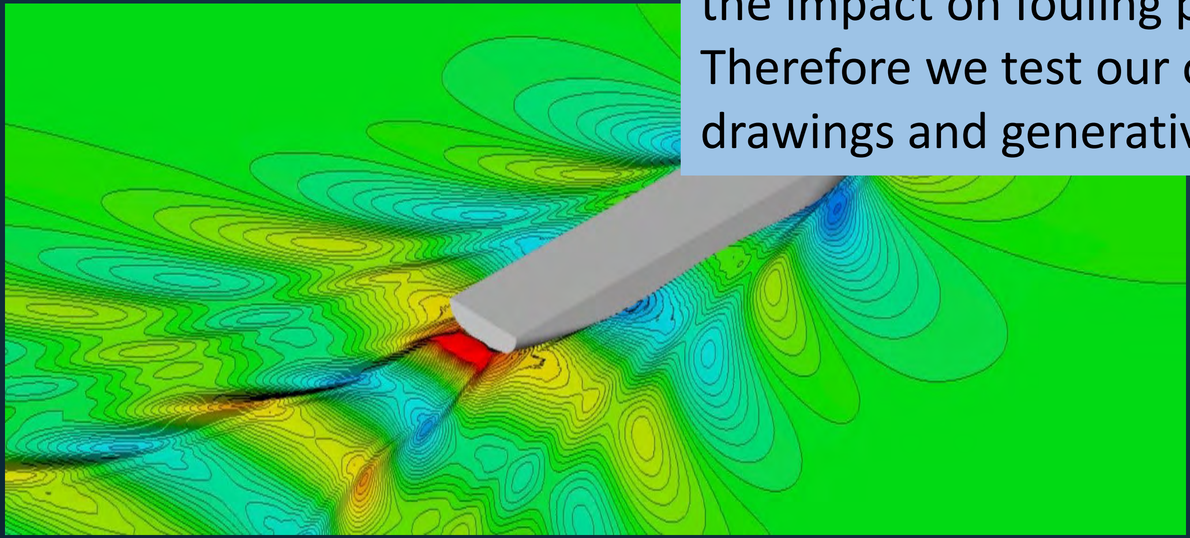


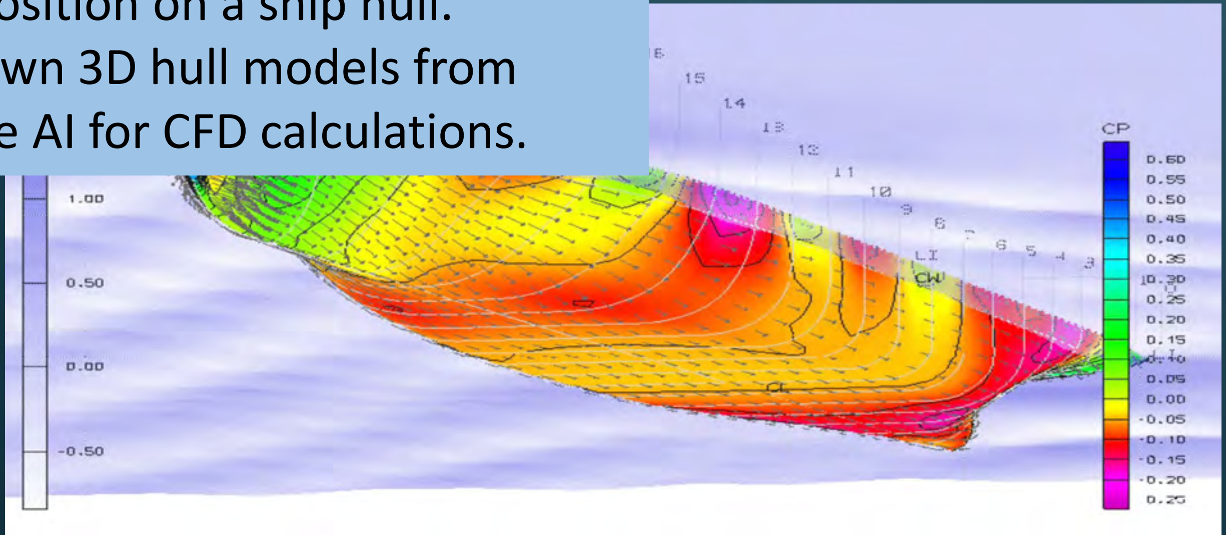
Reverse Engineered CDF Models



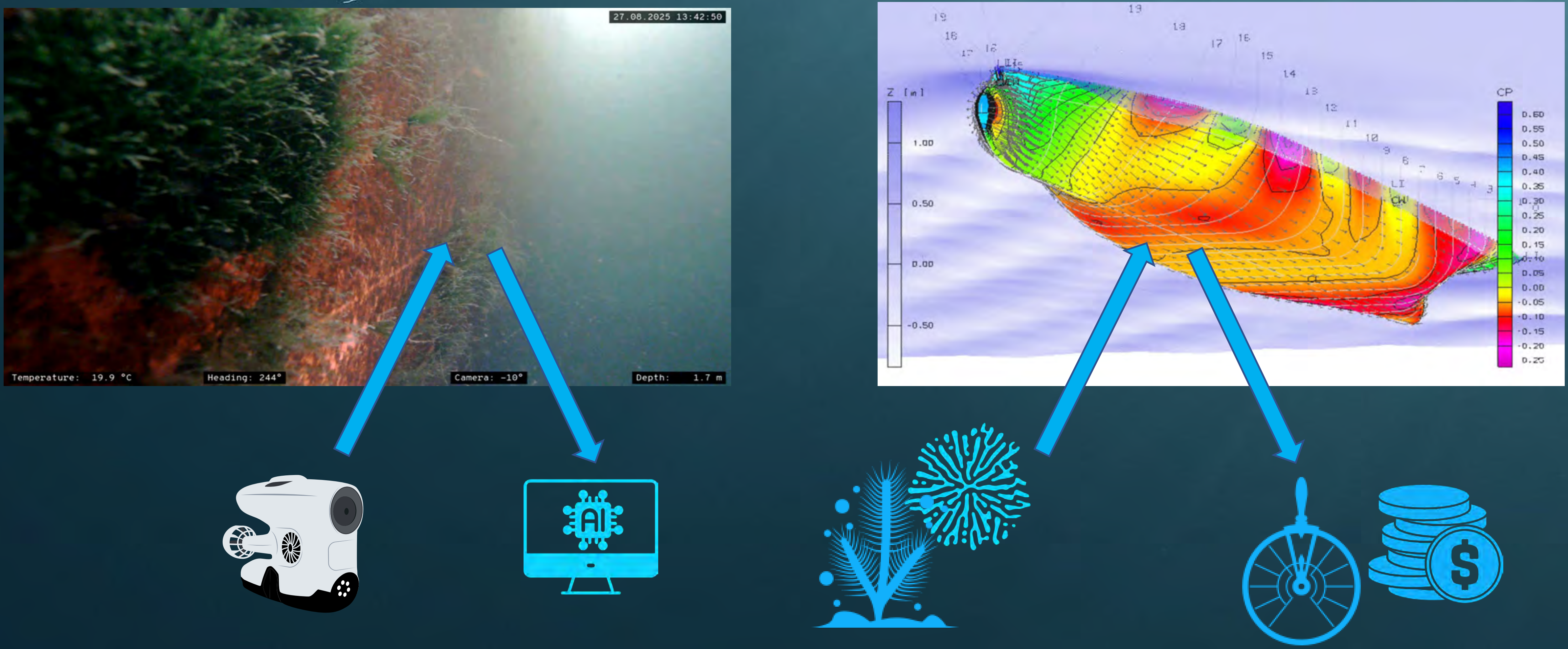


In order to understand the biofouling impact on fuel consumption, we are working on understanding the impact on fouling position on a ship hull. Therefore we test our own 3D hull models from drawings and generative AI for CFD calculations.





SLAM Projection



??? V-SLAM

??? LIFT-SLAM (introduced by Bruno and Colombini, 2021)

Big Questions About Biofouling

1) What kind of fouling is there?
2) How much of what fouling is there?
3) How does the fouling impact the ship performance?
    1) How big is the fouling?
    2) Where is the fouling located?
4) What external factor influenced the fouling to be there?
    1) Can we identify patterns of fouling based on external factors?
    2) Can we measure the effectiveness of anti-fouling paints?
5) Is the fouling invasive?
6) Can we predict biofouling on ships in advance?

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