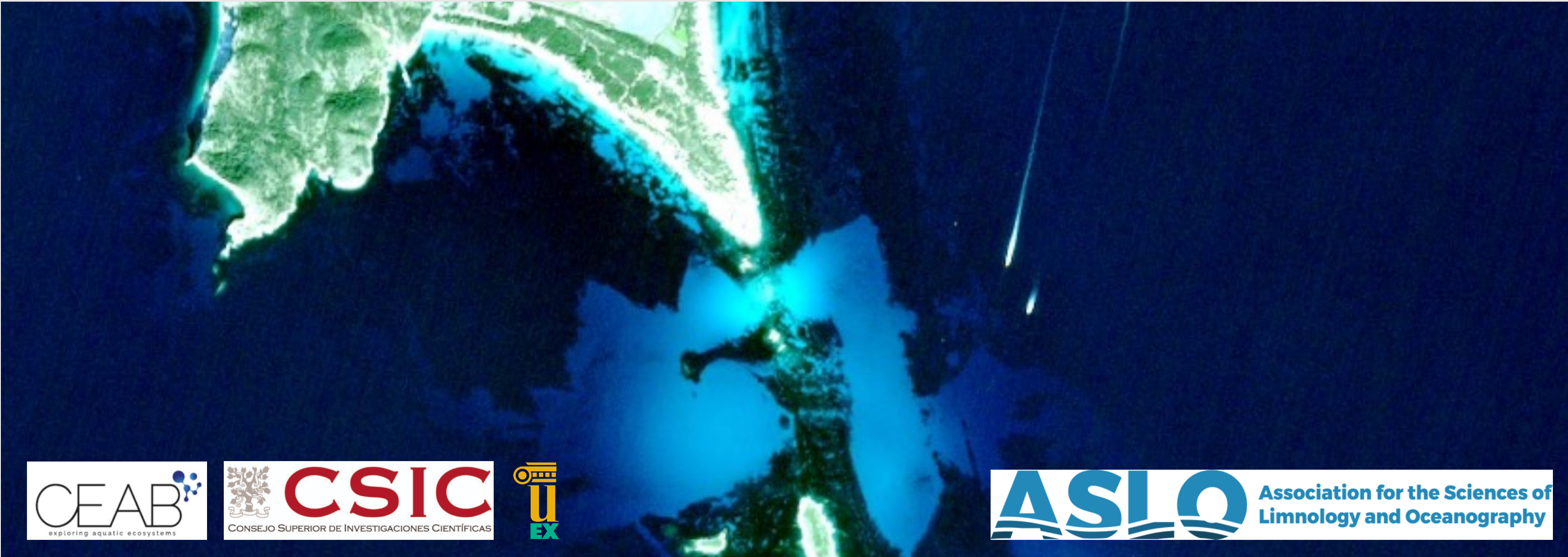
MAPPING UNDERWATER ECOSYSTEMS THROUGH REMOTE SENSING:

NOVEL APPROACHES TO EXPAND THE SCALES OF GLOBAL BIODIVERSITY TRACKING

FERNANDO GARCIA-GONZALEZ (CEAB-CSIC)
JORDI BOADA (CEAB-CSIC)
EMMA CEBRIAN (CEAB-CSIC)
ELIA QUIROS (Extremadura University)



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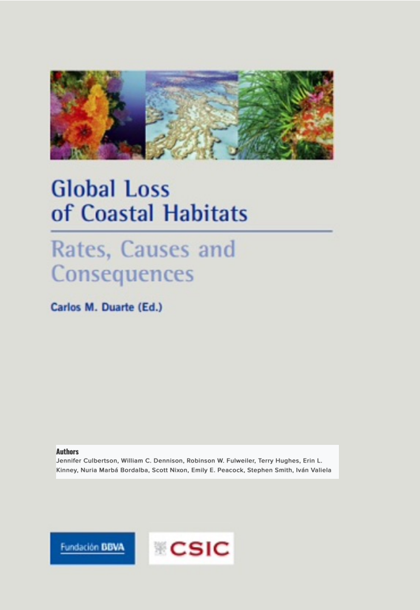
ASLO Association for the Sciences of Limnology and Oceanography

Global loss of coastal habitats



[…] anthropogenic pressures on coastal habitats have led to a sustained global loss of coral reefs, mangrove forests, salt marshes, and seagrass meadows over the past five decades.

(Carlos Duarte, 2009)

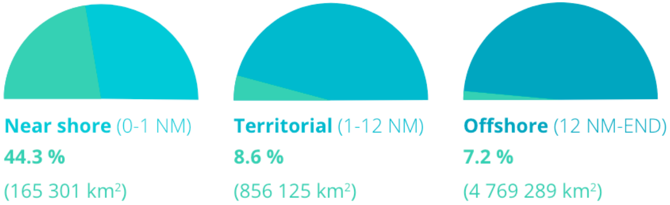
https://www.unep.org/interactives/why-blue-ecosystems-matter/
(UNEP: UN Environment Program 2023)

Expanding monitoring scales

Distribution of MPAs in Europe's seas is skewed towards coastal waters

Distribution of protected area coverage per zone

European Environment Agency

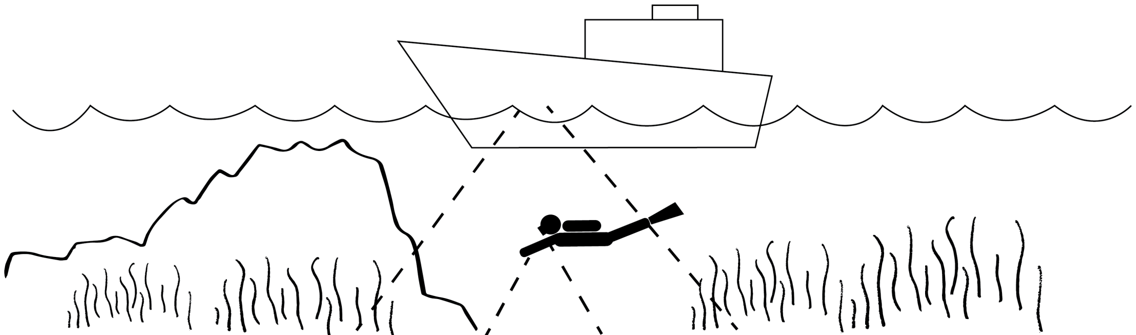


Spatial Analysis of Marine Protected Area Networks in Europe's Seas II, Volume A, 2017. Data from Table 3.6, p. 34.

The "white ribbon"

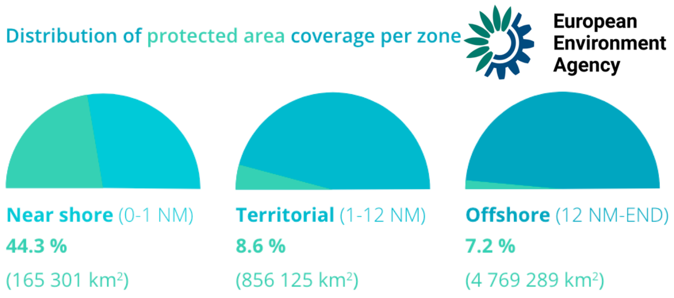
Term coined by the British Geological Survey to designate the nearshore area characterized by the lack of data:

- Too shallow and dangerous for most traditional survey vessels
- Too deep for land-based survey methods.
- Traditionally surveyed by SCUBA diving

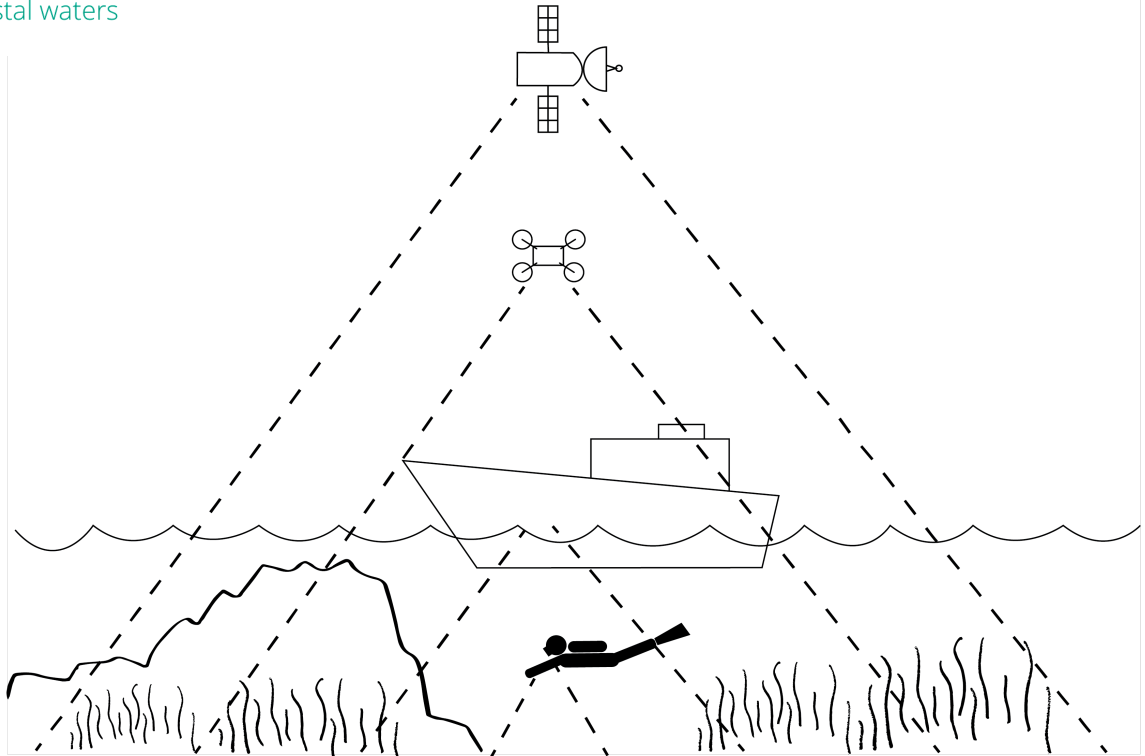


Expanding monitoring scales

Distribution of MPAs in Europe's seas is skewed towards coastal waters

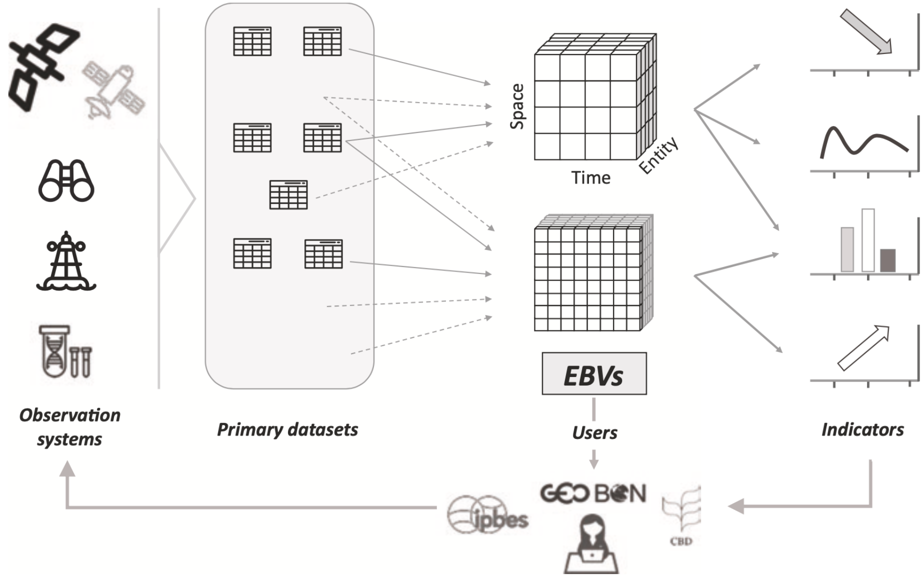


Spatial Analysis of Marine Protected Area Networks in Europe's Seas II, Volume A, 2017. Data from Table 3.6, p. 34.



Essential Variables

Essential Variables (EV) are variables known to be critical for observing and monitoring a given facet of the Earth system.



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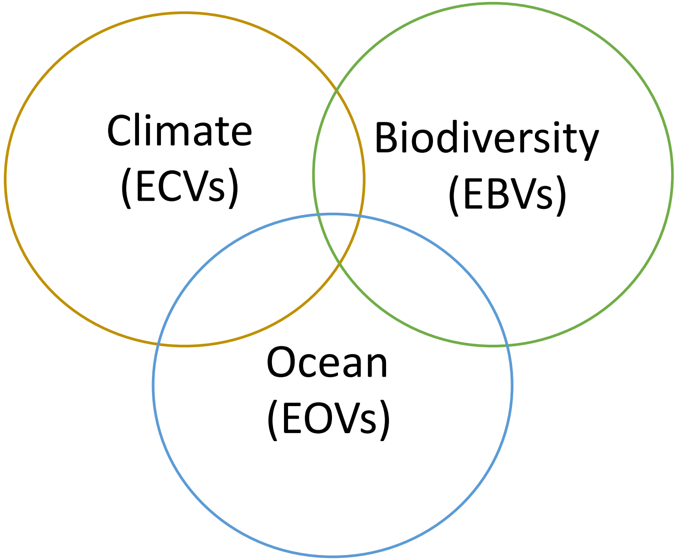

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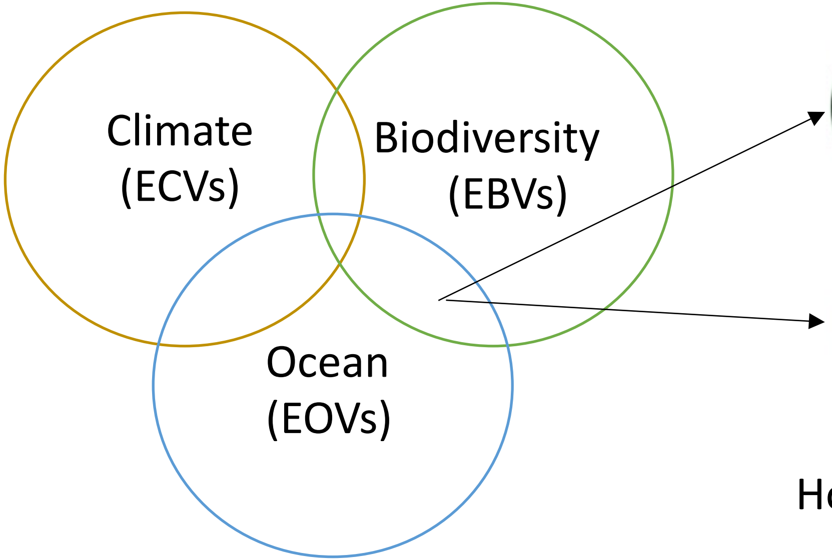
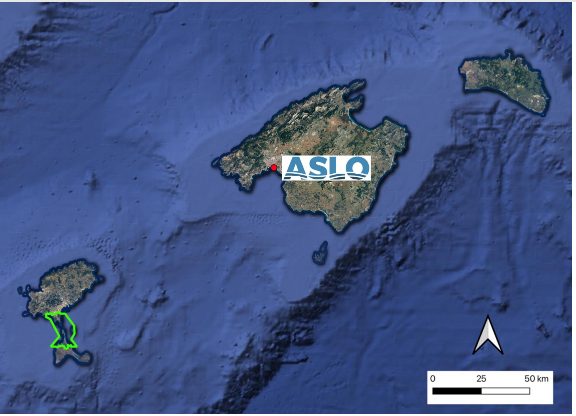


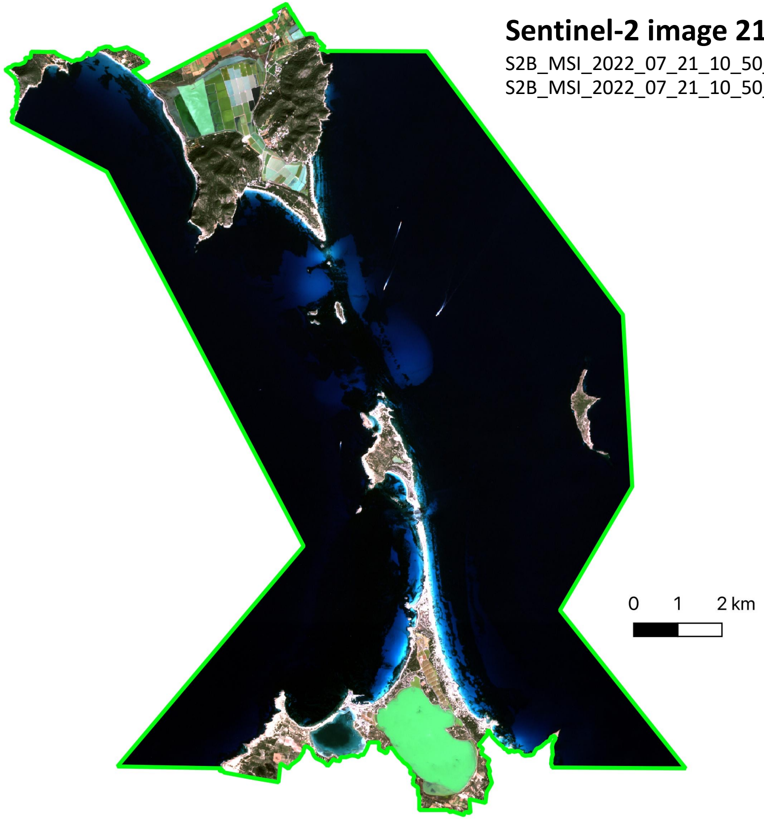
Seagrass cover

Macroalgal canopy cover

How well can be monitored from space?
Case Study Es Freus MPA

“Freus d'Eivissa i Formentera” MPA

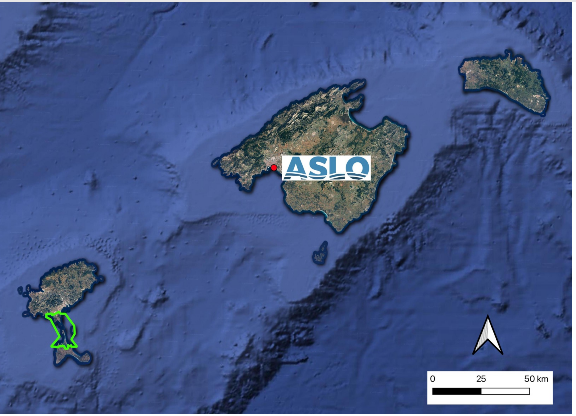


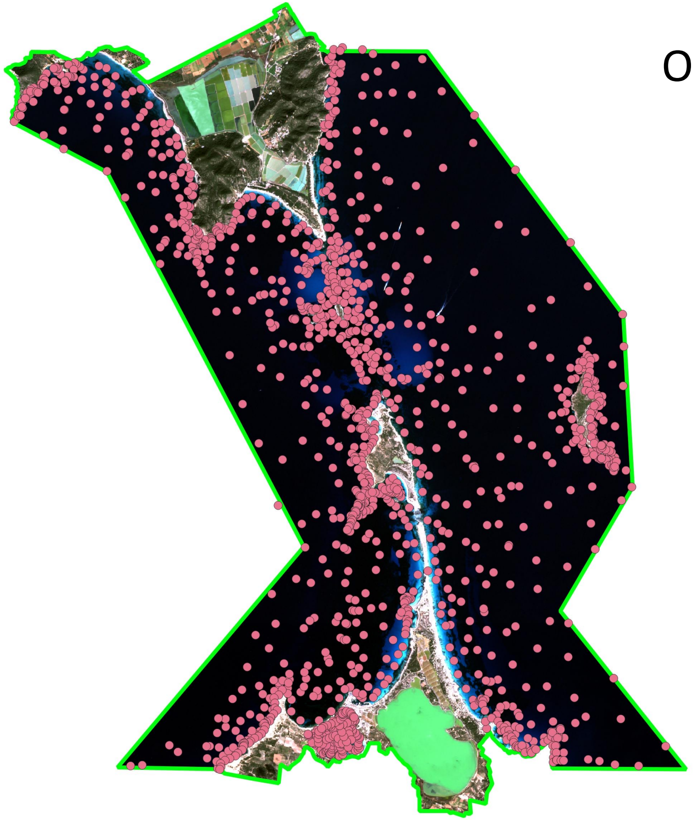


Sentinel-2 image 21st July 2022

S2B_MSI_2022_07_21_10_50_18_T31SCD_L1R
S2B_MSI_2022_07_21_10_50_33_T31SCC_L1R

“Freus d'Eivissa i Formentera” MPA

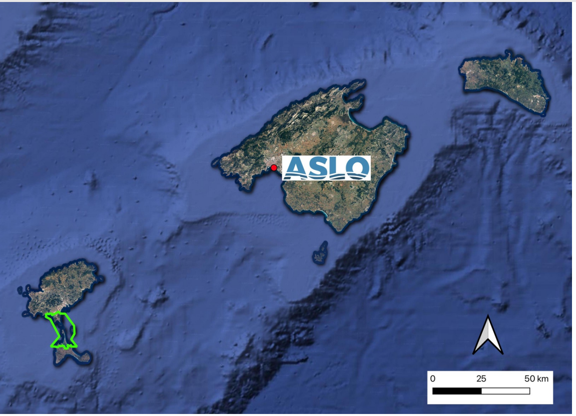


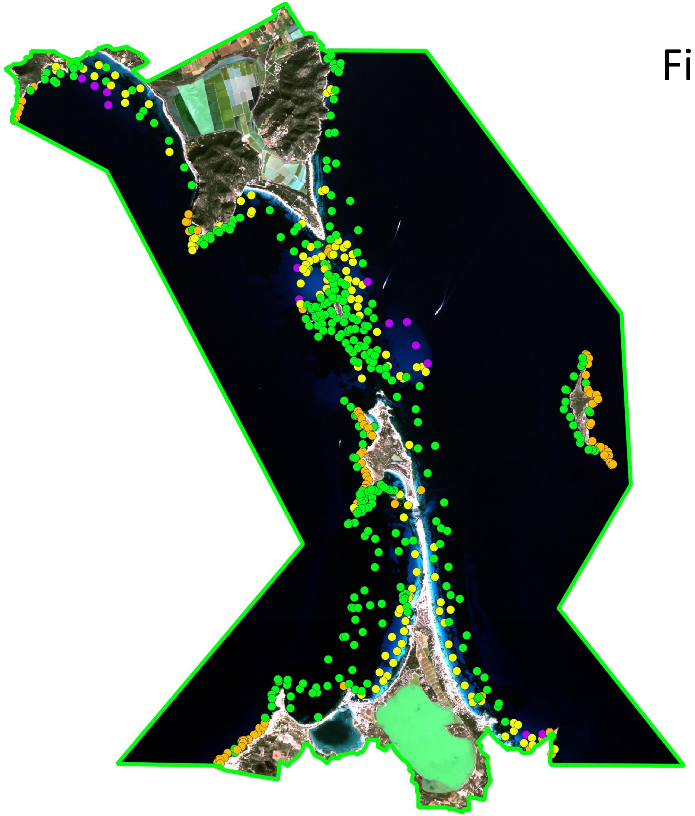


Original validation dataset

- 6 field campaings
- 2000 -2004
- 1450 points
- 0 to 60m
- 28 classes

“Freus d'Eivissa i Formentera” MPA





Final validation dataset

- 0 to 20 m
- Core habitat
- 530 points
- 4 classes

Posidonia oceanica (EUNIS MB252)

Sand (EUNIS MB55)

Photophilic algae (EUNIS MB151)

Cymodocea nodosa (EUNIS MB5521)


TOA B3
TOA B4
TOA B5
+
Z
PREPROCESSING
TRAINING AND CLASSIFICATION
VALIDATION

TOA B3
TOA B4
TOA B5
+
Z

MINISTERIO PARA LA TRANSICIÓN ECOLÓGICA

PREPROCESSING

TRAINING AND CLASSIFICATION

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VALIDATION

ACOLITE ATMOSPHERIC CORRECTION + DEGLINT

LAND MASK

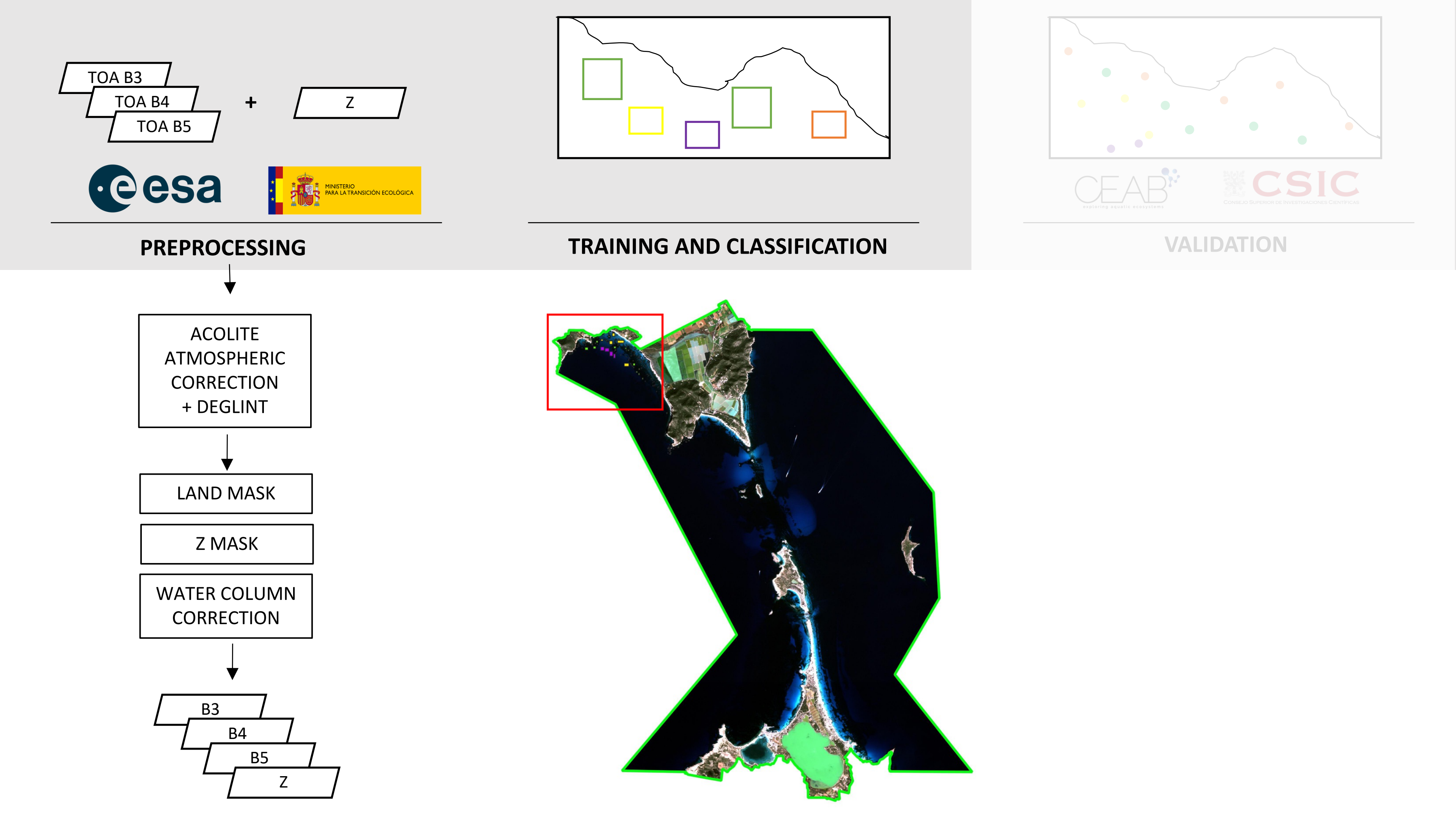
Z MASK

WATER COLUMN CORRECTION

B3
B4
B5
Z

TOP OF ATMOSPHERE REFLECTANCES

BOTTOM OF THE SEA LEAVING REFLECTANCES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esa
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CSIC
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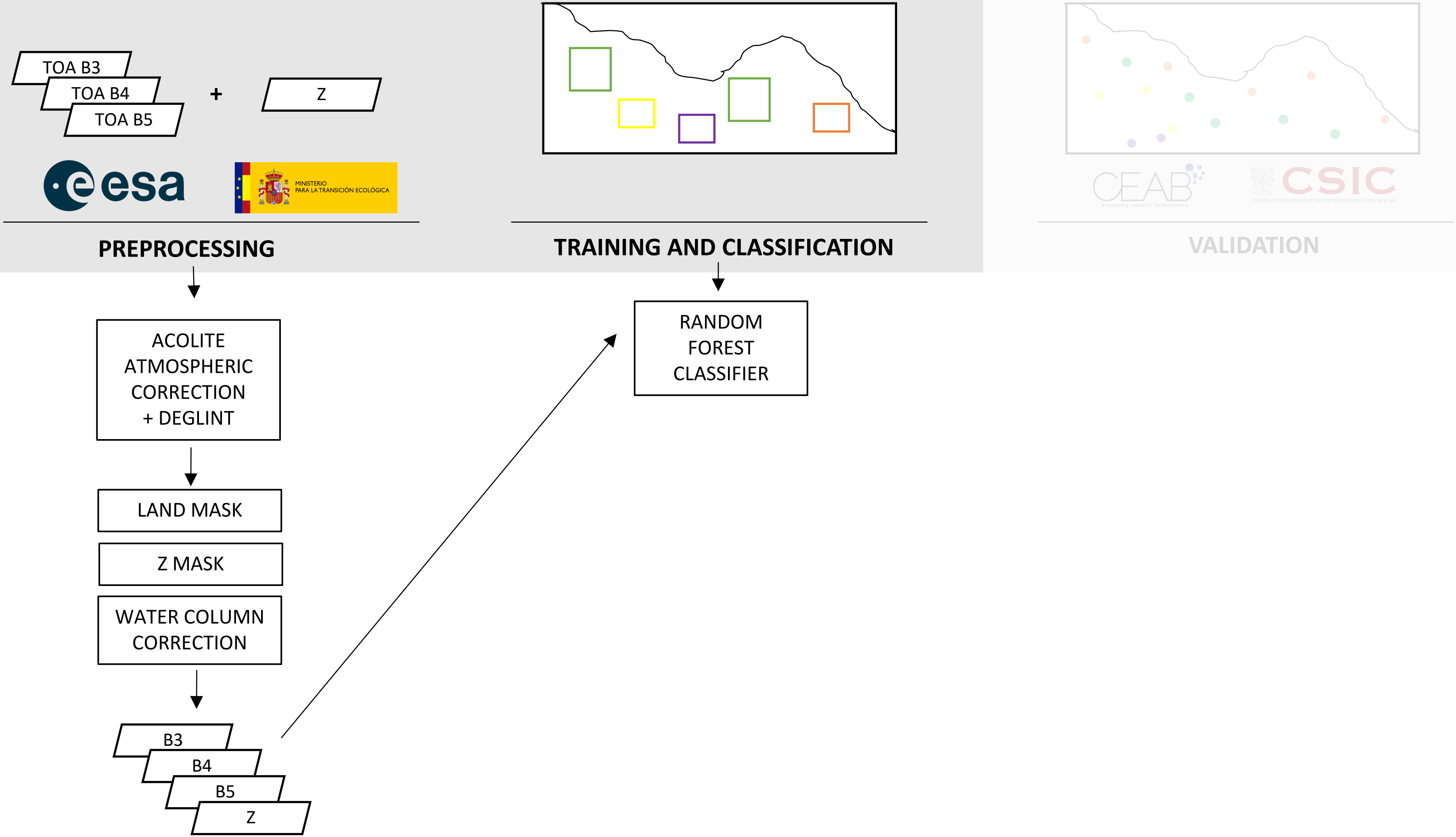
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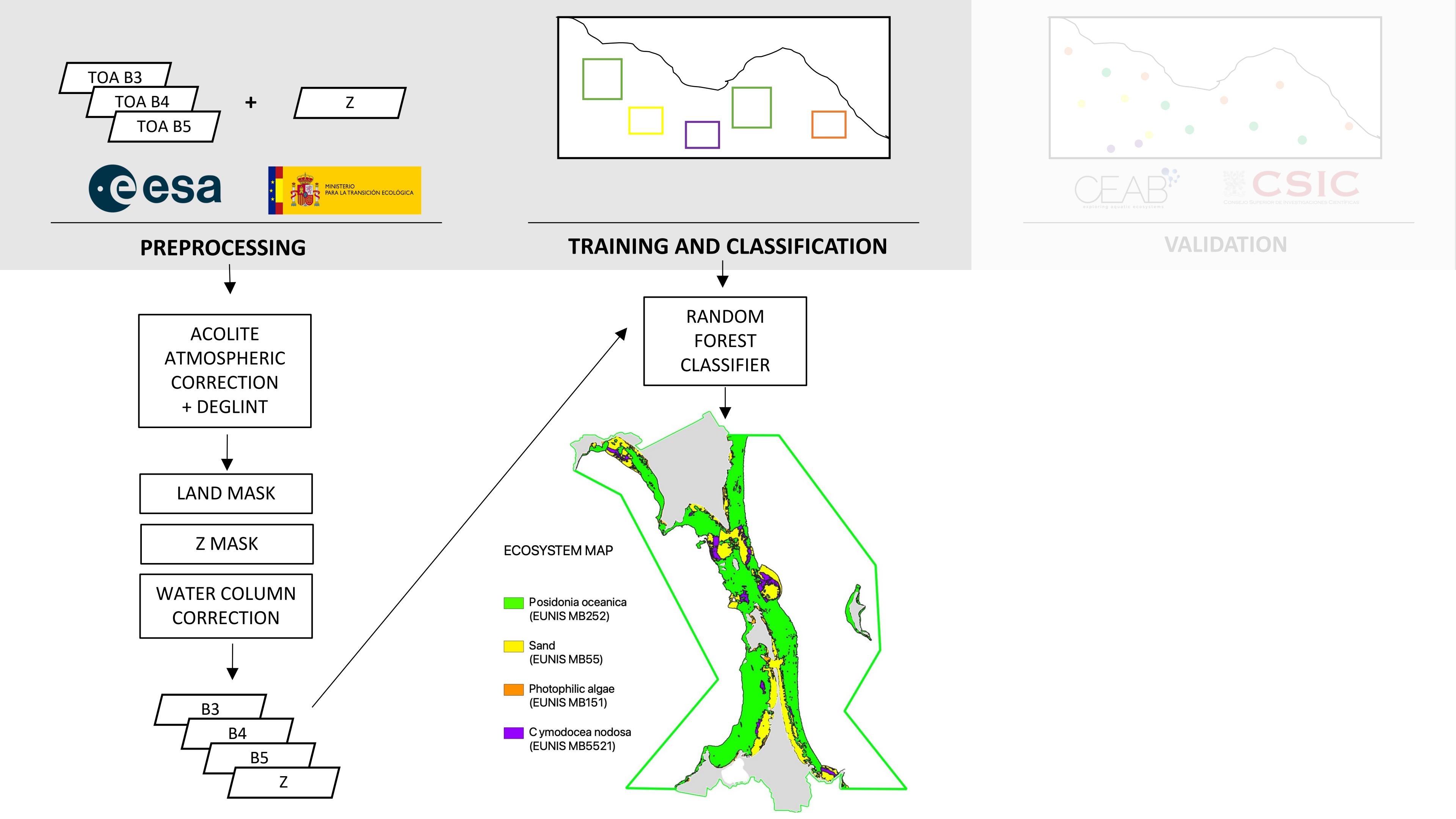
RANDOM
FOREST
CLASSIFIER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CSIC
VALIDATION
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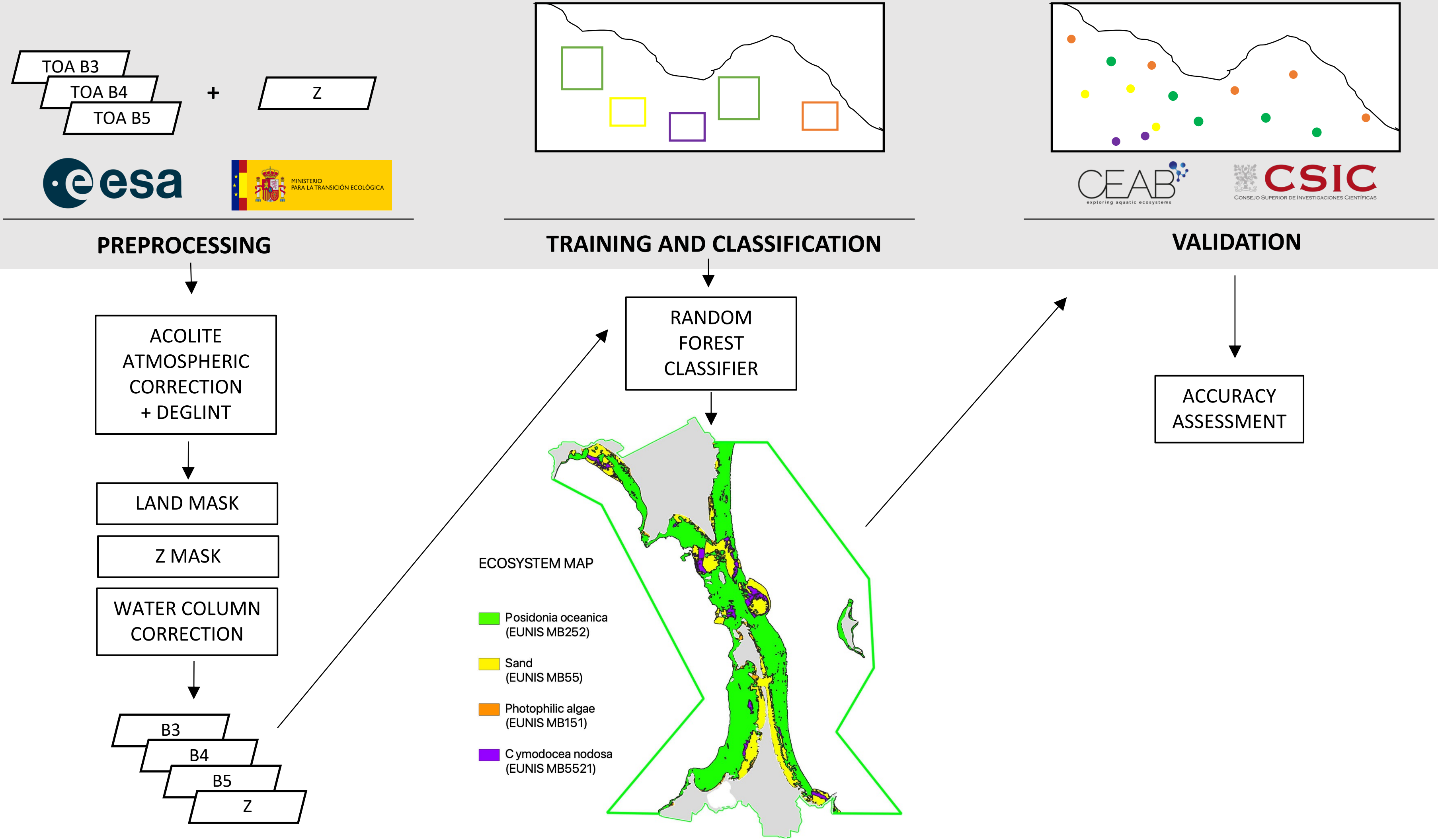
RANDOM FOREST CLASSIFIER
ECOSYSTEM MAP
Posidonia oceanica (EUNIS MB252)
Sand (EUNIS MB55)
Photophilic algae (EUNIS MB151)
Cymodocea nodosa (EUNIS MB5521)



TOA B3
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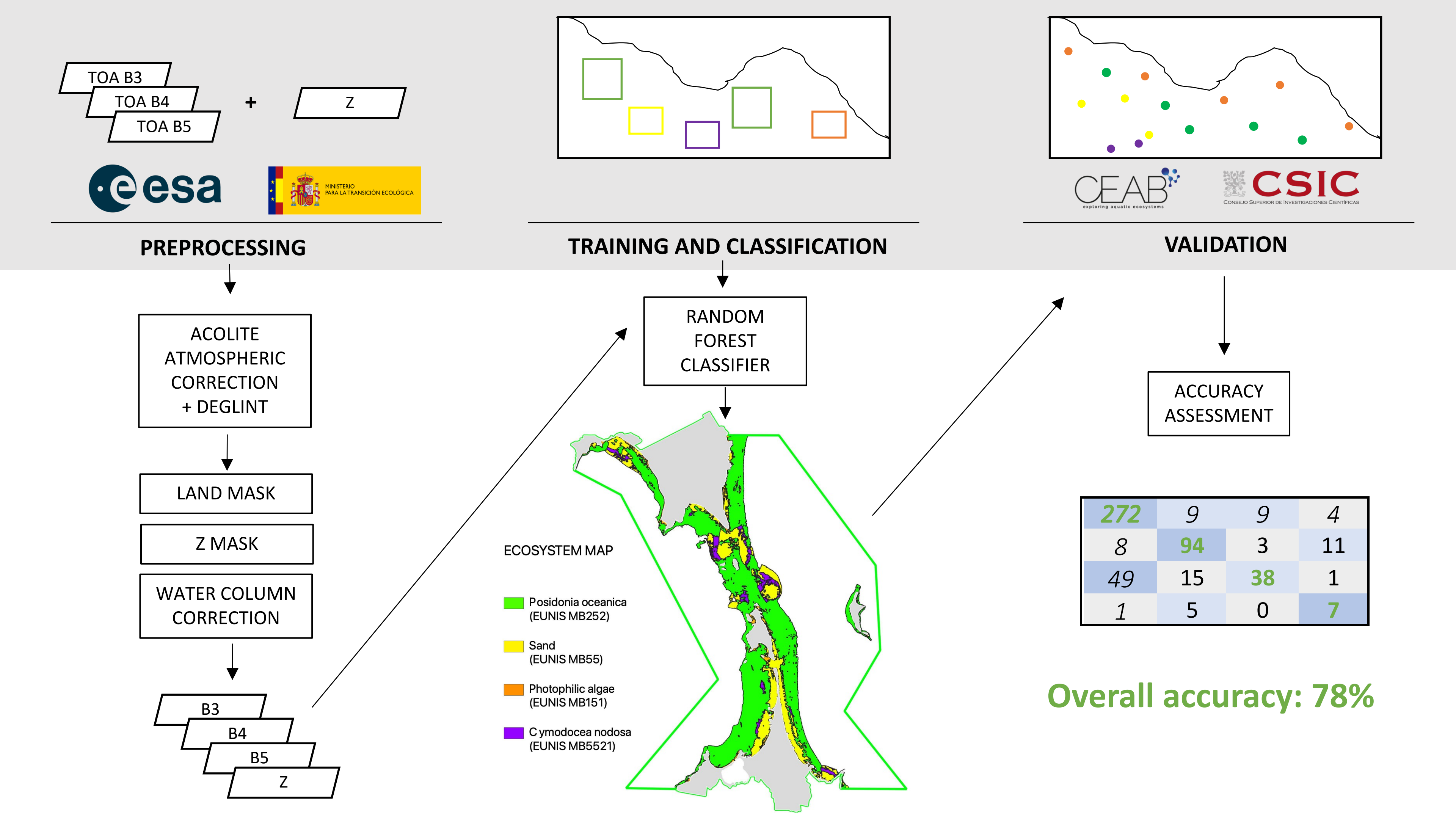
VALIDATION
ACCURACY ASSESSMENT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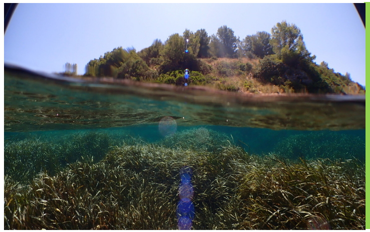
VALIDATION
ACCURACY ASSESSMENT
272 9 9 4
8 94 3 11
49 15 38 1
1 5 0 7
Overall accuracy: 78%

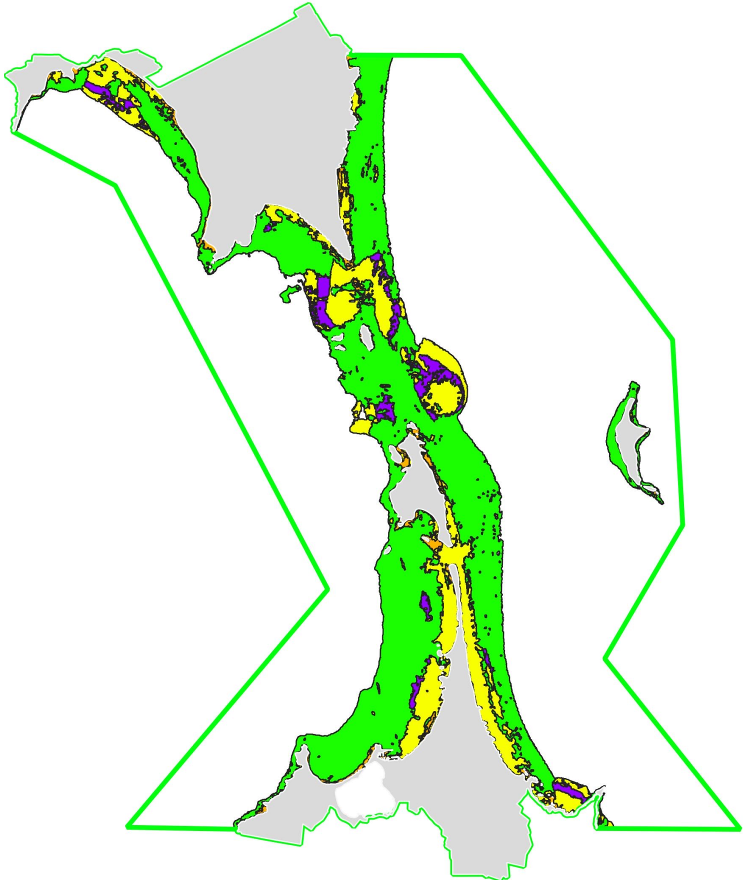
Results



Posidonia oceanica
-Recall (accuracy): 93%
-Precision: 82%

Sand
-Recall (accuracy): 81%
-Precision: 76%

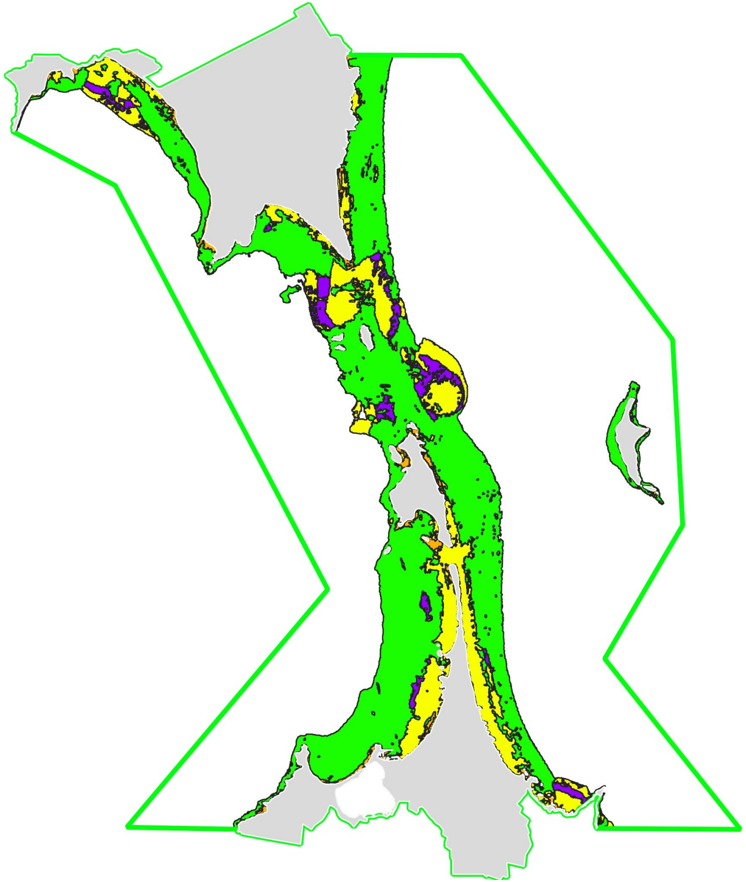
Machine Learning model handles this 2 classes quite well.



Results

Photophilic algae
-Recall (accuracy): 37%
-Precision: 76%

Machine Learning model barely detects this class but when it does the outcome is quite reliable (underestimation of coverage)



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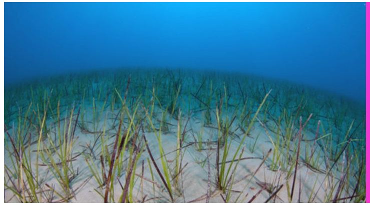
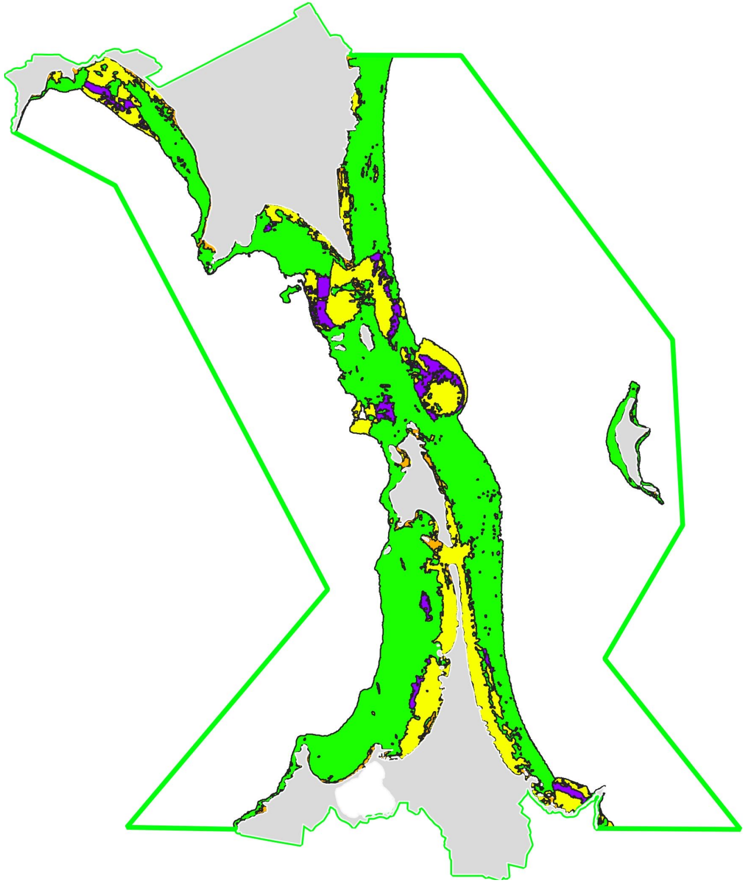


Cymodocea nodosa
-Recall (accuracy): 54%
-Precision: 30%

Machine learning model is able to detect this class but it also mixes it with other classes, particularly sand (overestimation of coverage or ”potential distribution”).



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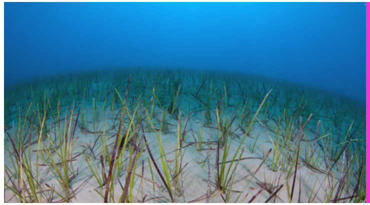

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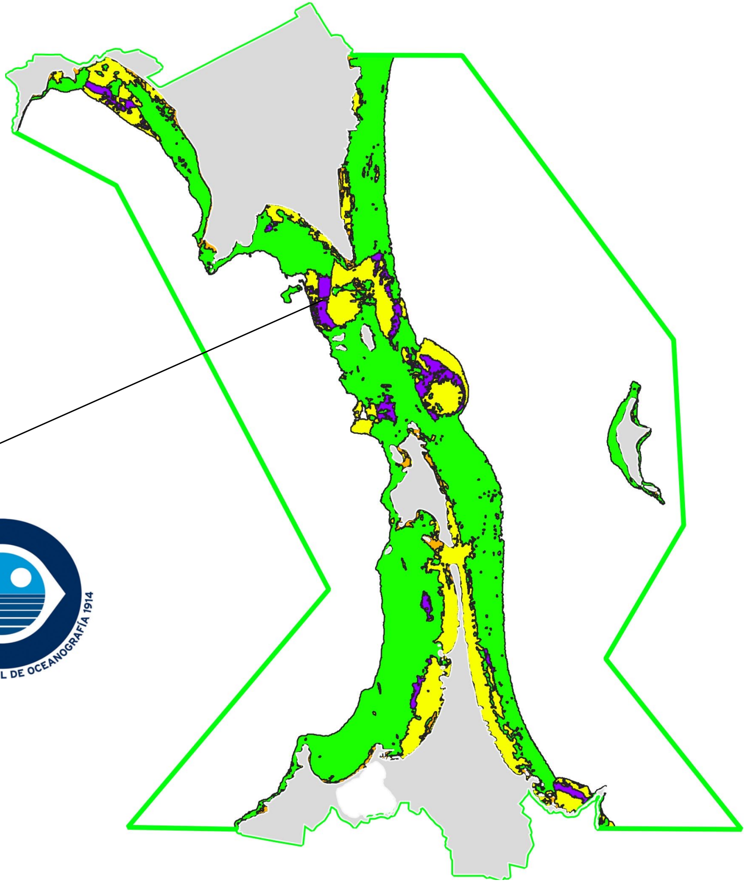
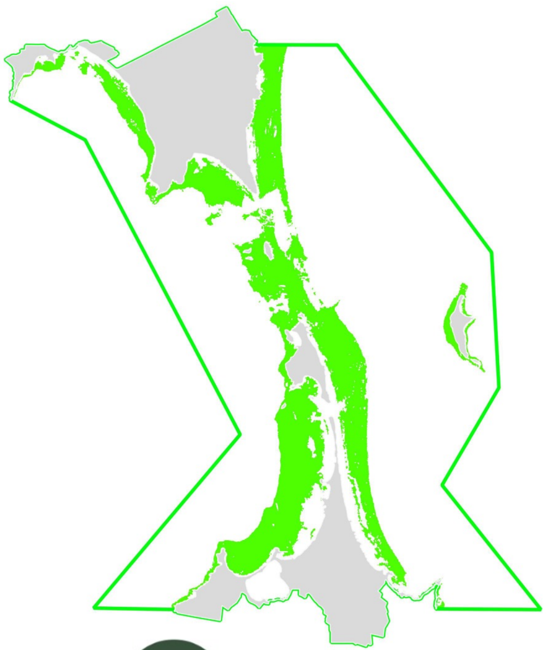


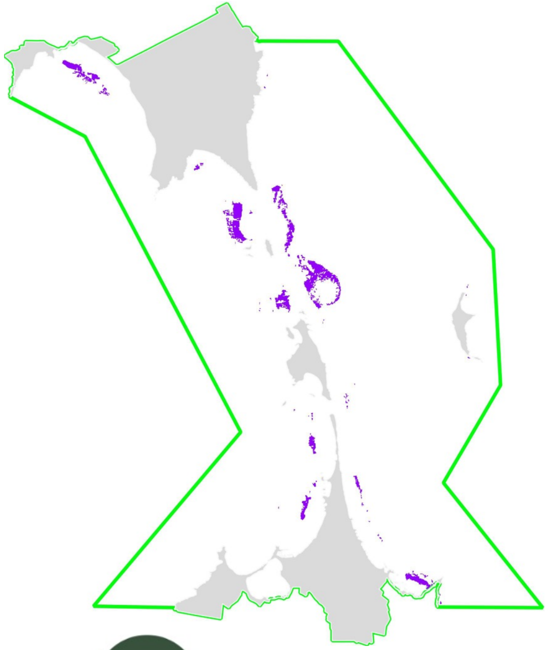
Essential Ocean Variables Estimation



Seagrass

25 km2
(0 to 20m)

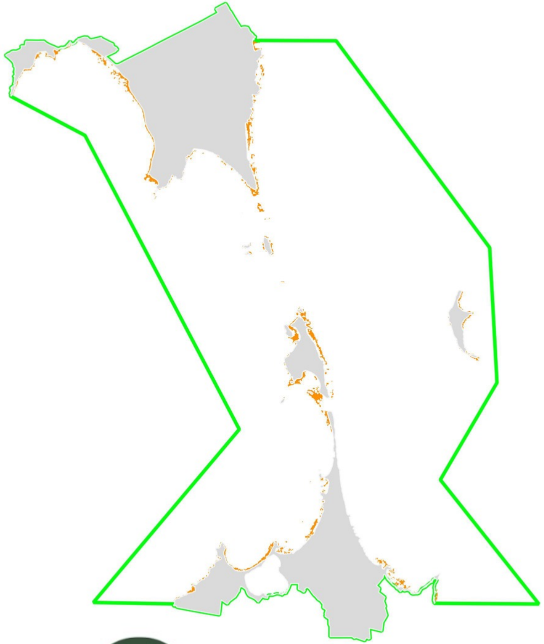
Posidonia oceanica



Seagrass

1.9 km2
(0 to 20m)

Cymodocea nodosa



Macroalgal canopy

1.6 km2
(0 to 20m)

Photophilic algae

Conclusions and future directions

CONCLUSIONS

- RF has been able to extrapolate from a small training area in the corner of the MPA to the full MPA extent

- This is might be a reliable (enough) and scalable methodology (that can be further improved)

- **The methodology allows the upscaling of in situ observations from local to more global frameworks**

Conclusions and future directions

CONCLUSIONS

- RF has been able to extrapolate from a small training area to the full MPA extent
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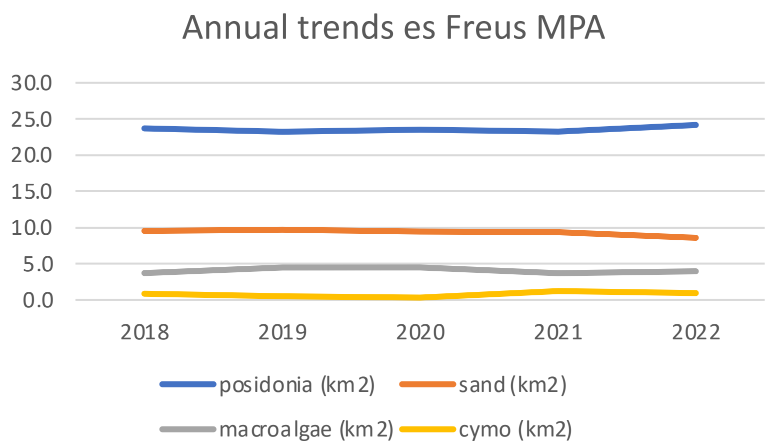
FURTHER DIRECTIONS



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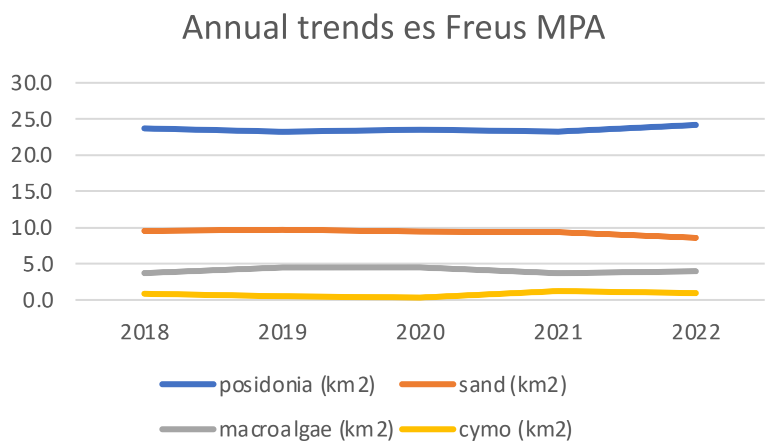
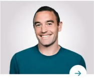


- Narrow the gap and foster collaboration between the RS and Marine Ecology communities

Missing link?

One More Way AI Can Help Us Harness One Of The Most Underutilized Datasets In The World



Kevin Weil
President, Product and Business

Kevin Weil | March 21, 2023

How we tracked the Chinese balloon in satellite data

Satellite data may be one of the most underutilized datasets in the world.

At Planet alone, we have six years of documented history — which means we have over 2,000 images on average for every point on earth's landmass. This dataset at high resolution never existed before Planet came along and created it.

OPEN ACCESS Freely available online — PLOS ONE

High-Resolution Satellite Imagery Is an Important yet Underutilized Resource in Conservation Biology

Sarah A. Boyle[1]*, Christina M. Kennedy[2], Julio Torres[3], Karen Colman[4], Pastor E. Pérez-Estigarribia[5], Noé U. de la Sancha[6]

[...] Generally, the collection of field data for the classification of remote sensing of aquatic habitats is expensive, time-consuming, and sparse today. More efforts should be driven towards allocating funding for accurate and high resolution in situ data and/or advocating the sharing of open datasets that would permit regional to global projects. The search for open access data on seagrass from relevant data repositories reveals a high number, however a fraction of these are potentially suitable for use in the remote sensing domain. Therefore, it is mandatory to urge a collaborative action between seagrass and remote sensing scientists, which will galvanize the development of a protocol that could be easily adapted in any seagrass bioregion for the designation of accurate and well documented with metadata, in situ data for seagrass mapping using the present workflow.

Traganos, D.; Aggarwal, B.; Poursanidis, D.; Topouzelis, K.; Chrysoulakis, N.; Reinartz, P. Towards Global-Scale Seagrass Mapping and Monitoring Using Sentinel-2 on Google Earth Engine: The Case Study of the Aegean and Ionian Seas. *Remote Sens.* **2018**, *10*, 1227

MISSING LINK

Why have researchers been unable to define a standard set of biodiversity variables to monitor from satellites? Because of inadequate access to satellite data; uncertainties in the continuity of observations; and temporal and spatial limitations of satellite imagery. The problem is exacerbated by a lack of communication between the ecology and remote-sensing communities.

Skidmore, A., Pettorelli, N., Coops, N. *et al.* Environmental science: Agree on biodiversity metrics to track from space. *Nature* **523**, 403–405 (2015)

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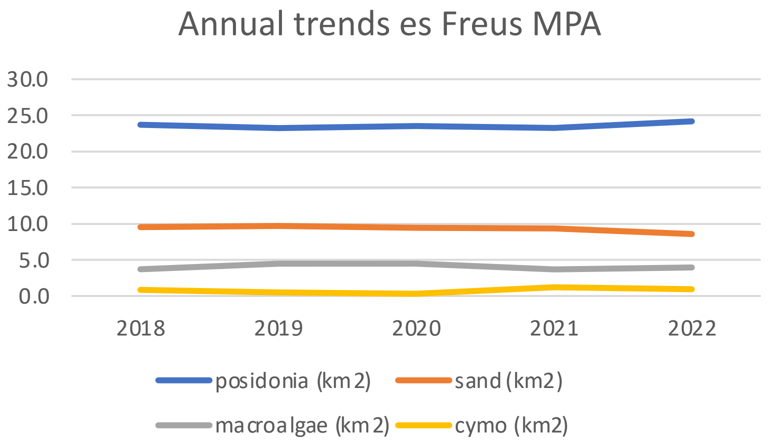

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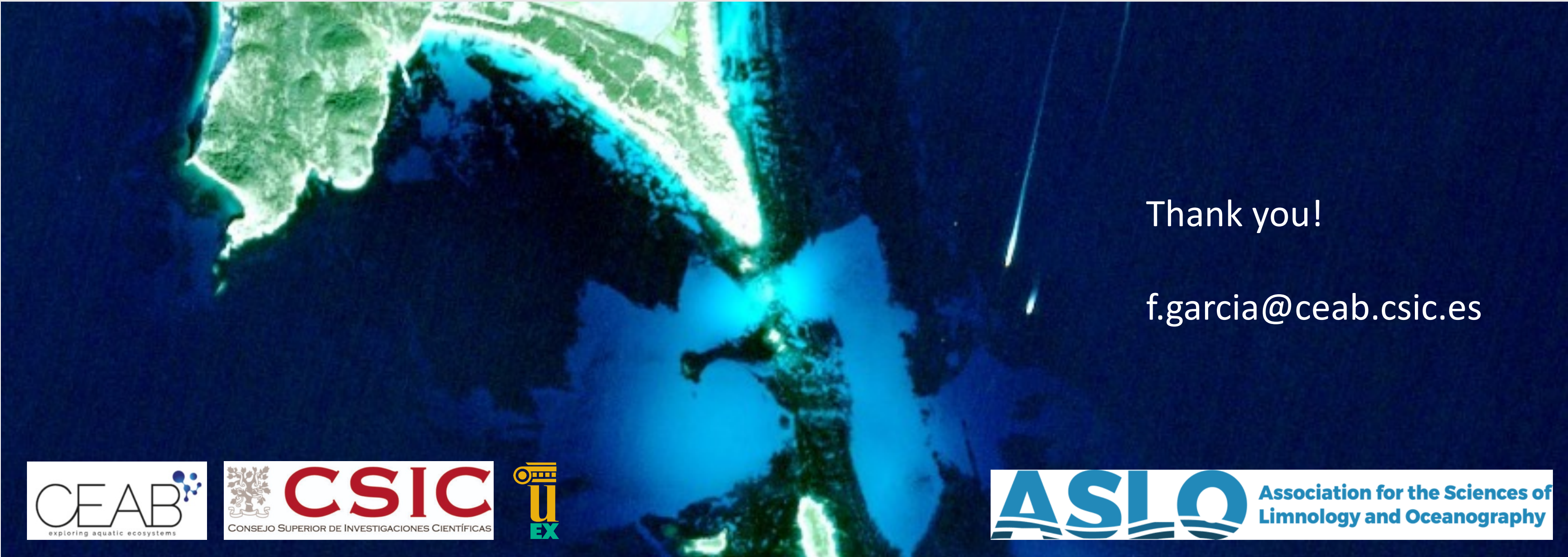

Thank you!

f.garcia@ceab.csic.es

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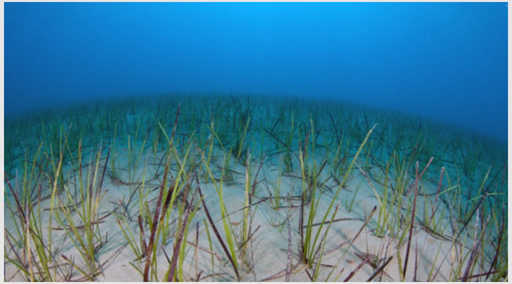
UEX
ASLO Association for the Sciences of Limnology and Oceanography

Accuracy assesment



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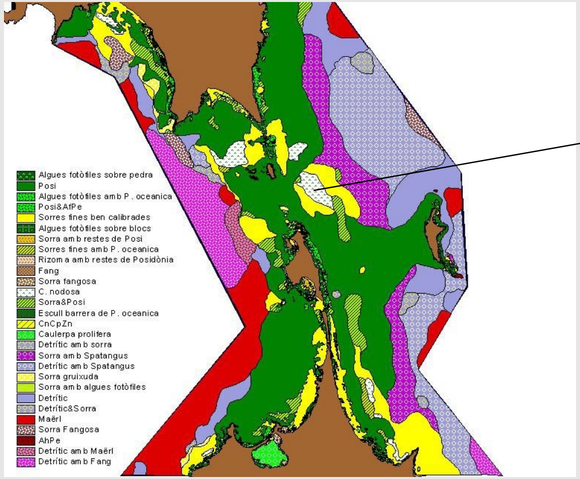

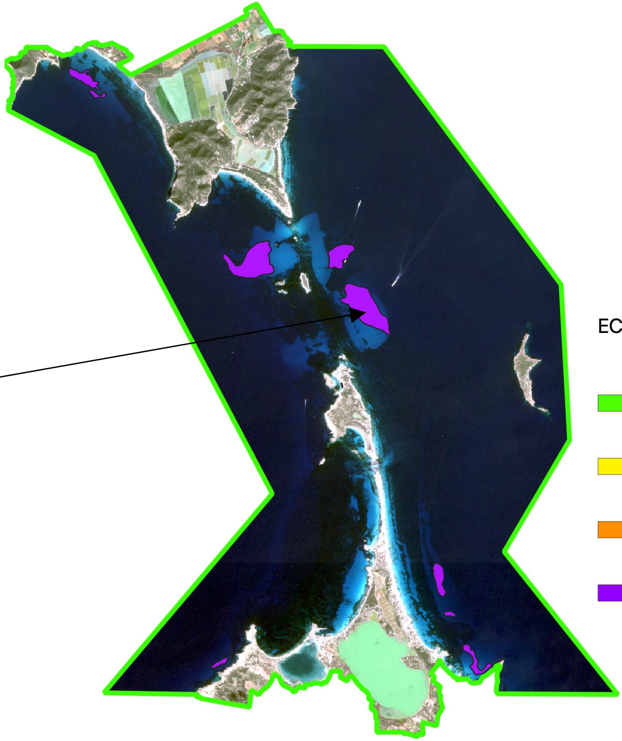

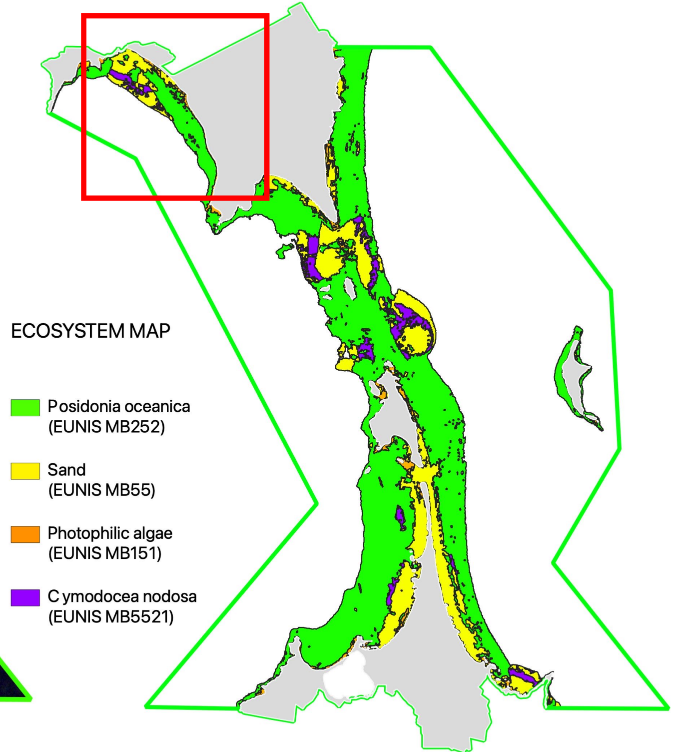

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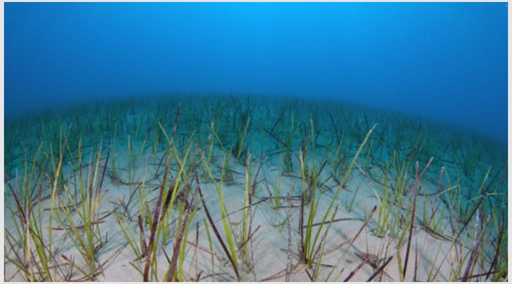

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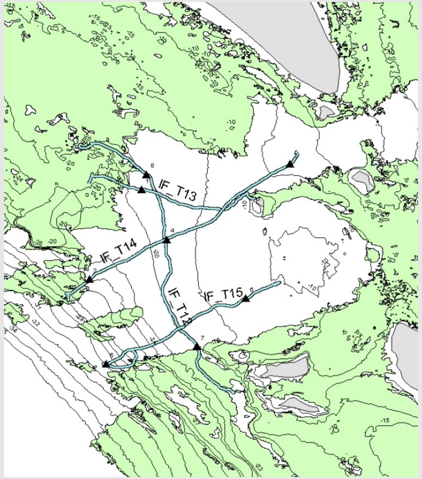
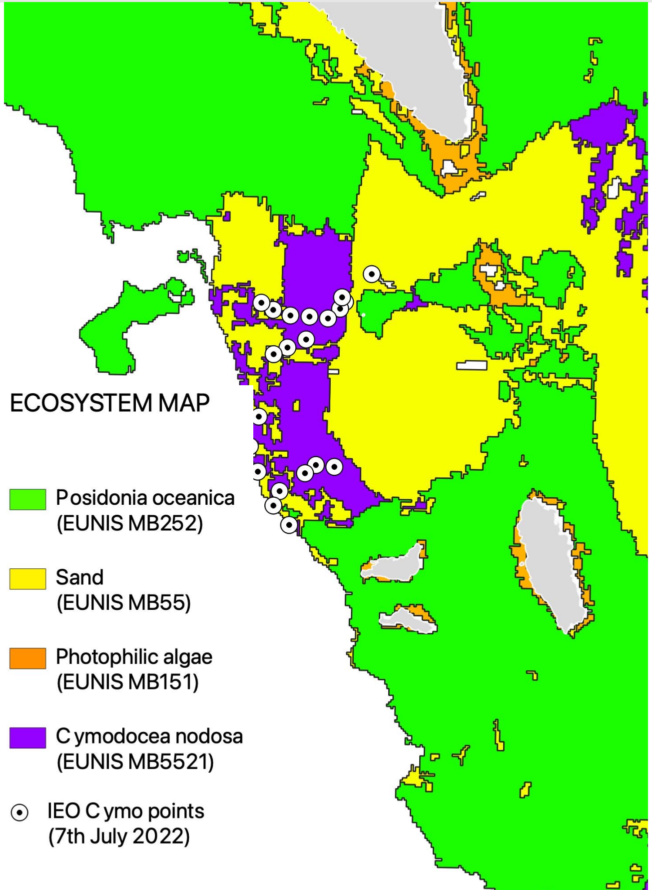


Marine Strategies Seagrass Campaing
Camara trawl transects
7th July 2022 (3 weeks prior to S2 image)

"Potential distribution"



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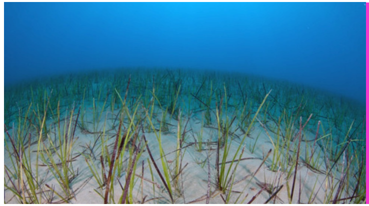

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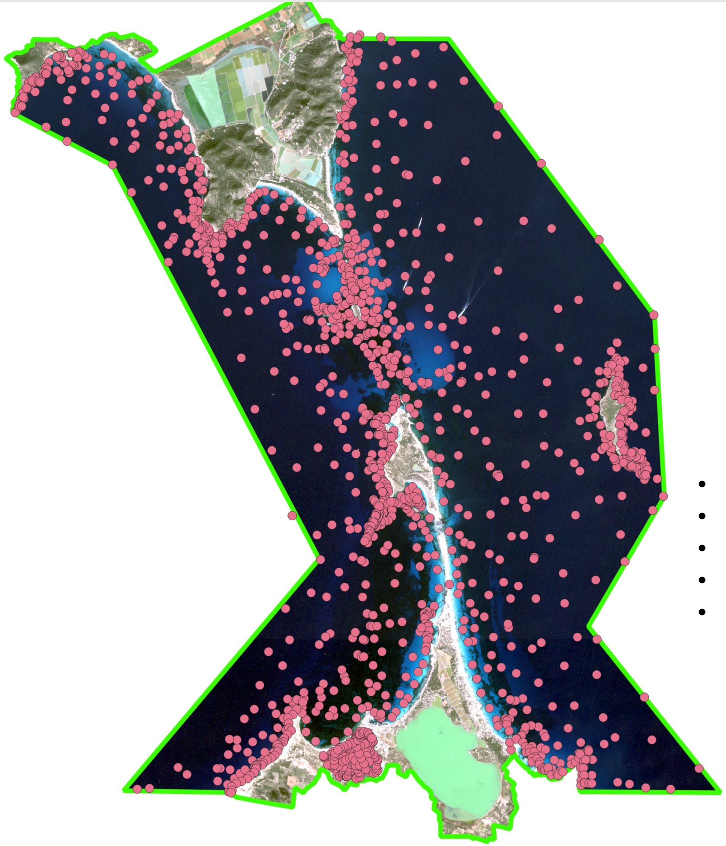
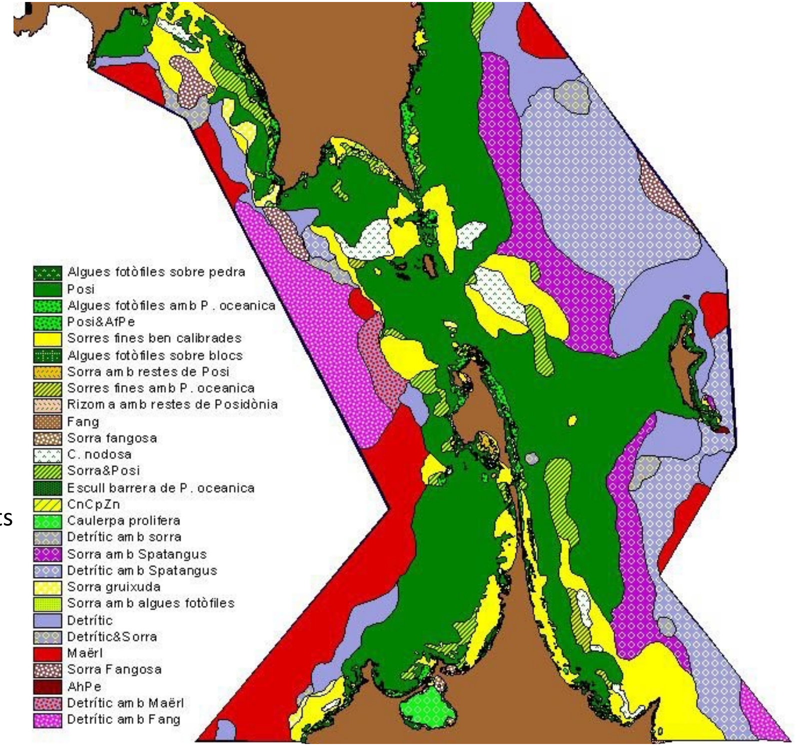
Machine learning model is able to detect this class but it also mixes it with other classes, particularly sand (overestimation of coverage or ”potential distribution”).

Fieldwork



- 6 field campaings
- 2000 -2004
- 1450 validation points
- 0 to 60m
- 28 classes



https://www.caib.es/sites/reservesmarines/es/descripcion-876/

Photophilic algae
-Accuracy: 37%
-Precision: 76%

Cymodocea nodosa
-Accuracy: 54%
-Precision: 30%

Posidonia oceanica
-Accuracy: 93%
-Precision: 82%

Sand
-Accuracy: 81%
-Precision: 76%