

MAPPING UNDERWATER ECOSYSTEMS THROUGH REMOTE SENSING:

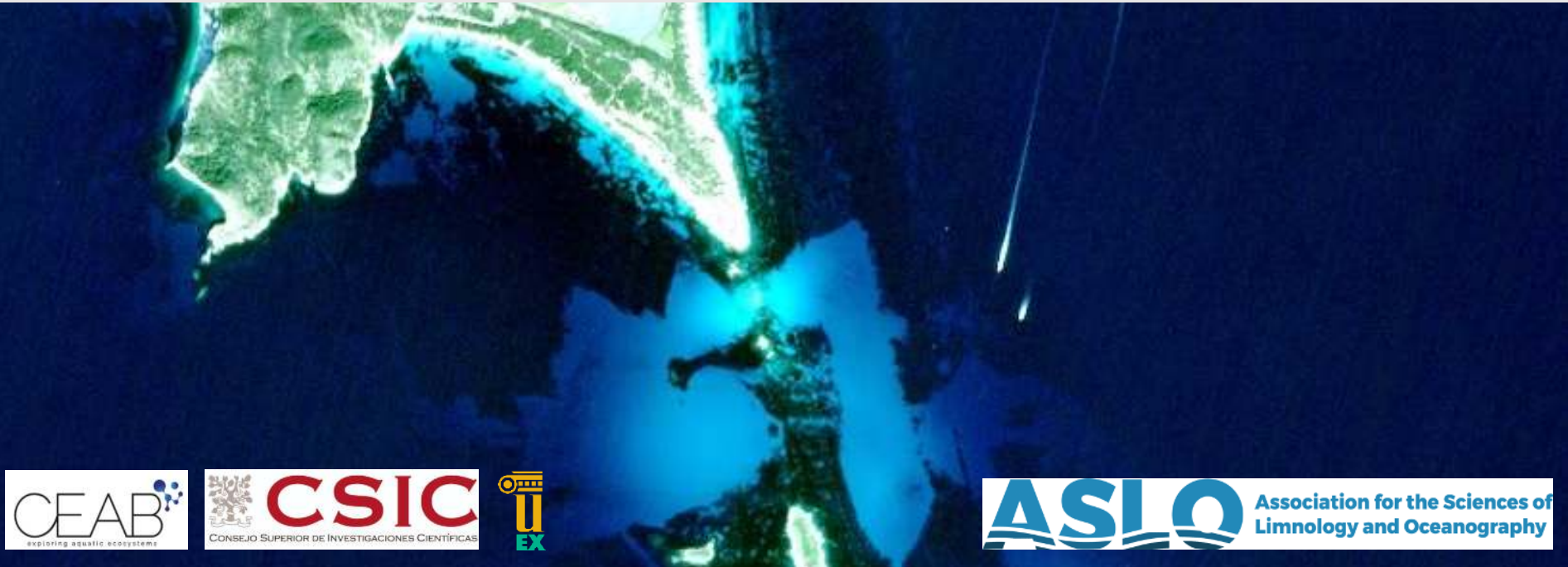
NOVEL APPROACHES TO EXPAND THE SCALES OF GLOBAL BIODIVERSITY TRACKING

FERNANDO GARCIA-GONZALEZ (CEAB-CSIC)

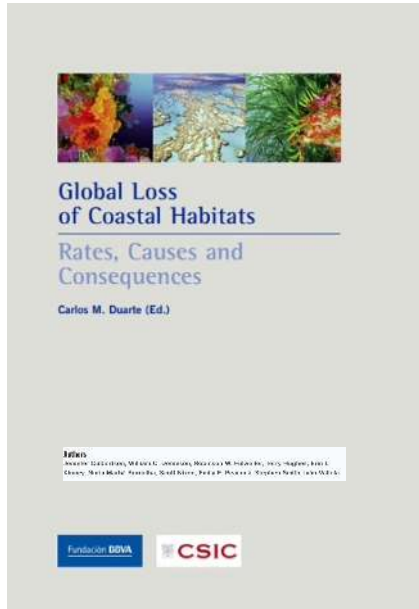
JORDI BOADA (CEAB-CSIC)

EMMA CEBRIAN (CEAB-CSIC)

ELIA QUIROS (Extremadura University)



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

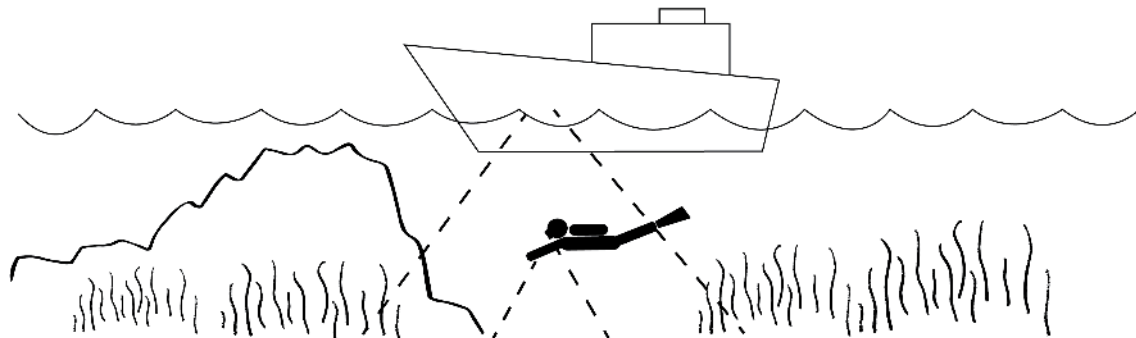


Spatial Analysis of Marine Protected Area Networks in Europe's Seas II, Volume A, 2017. Data from Table 3.6, p. 34.

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

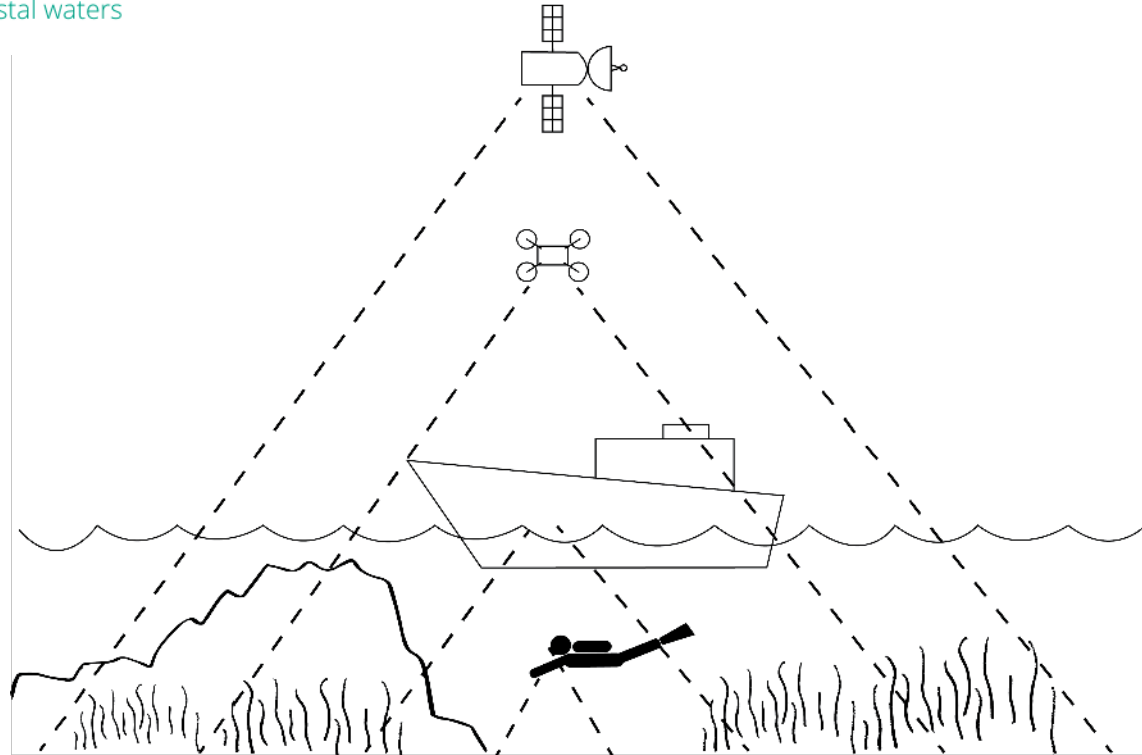


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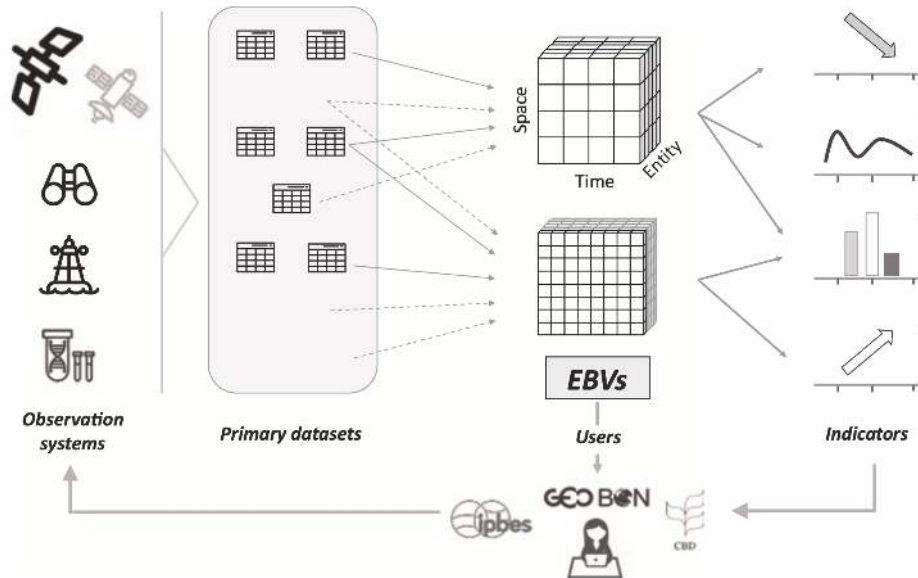


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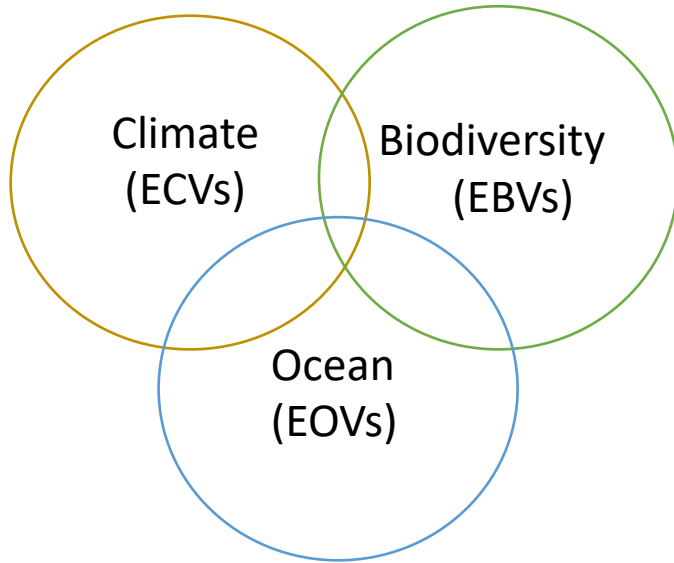
Essential Variables

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



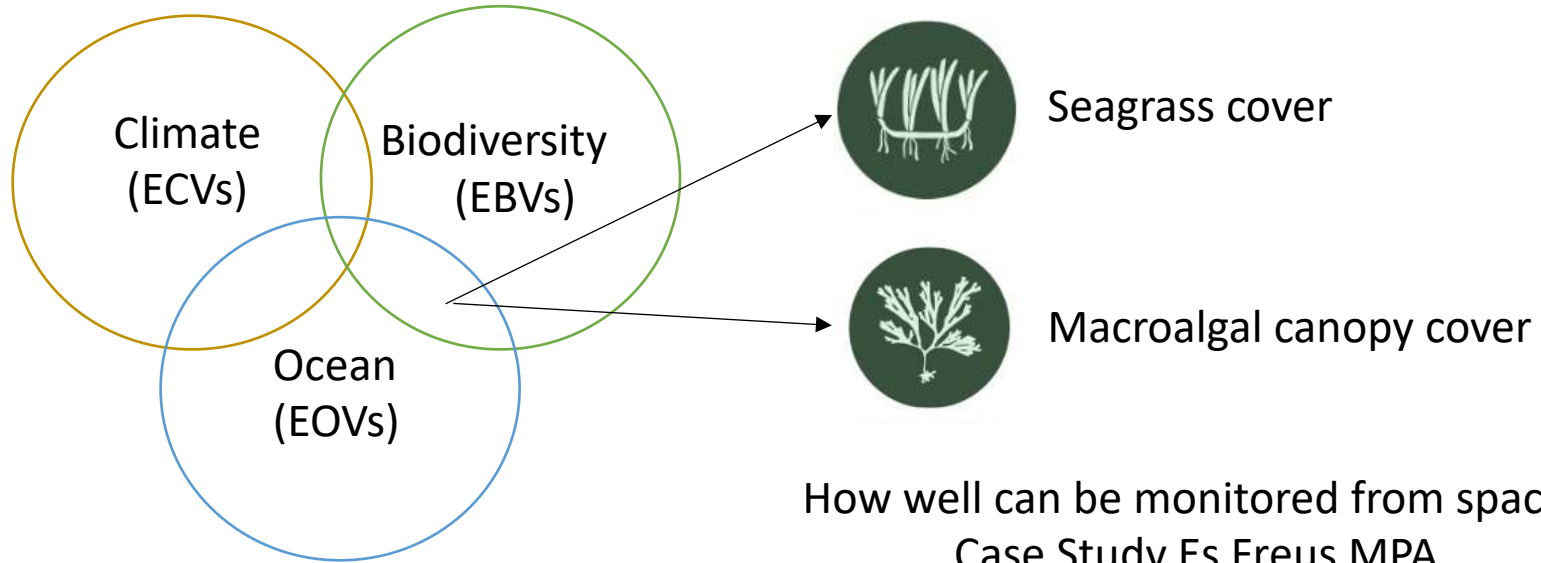
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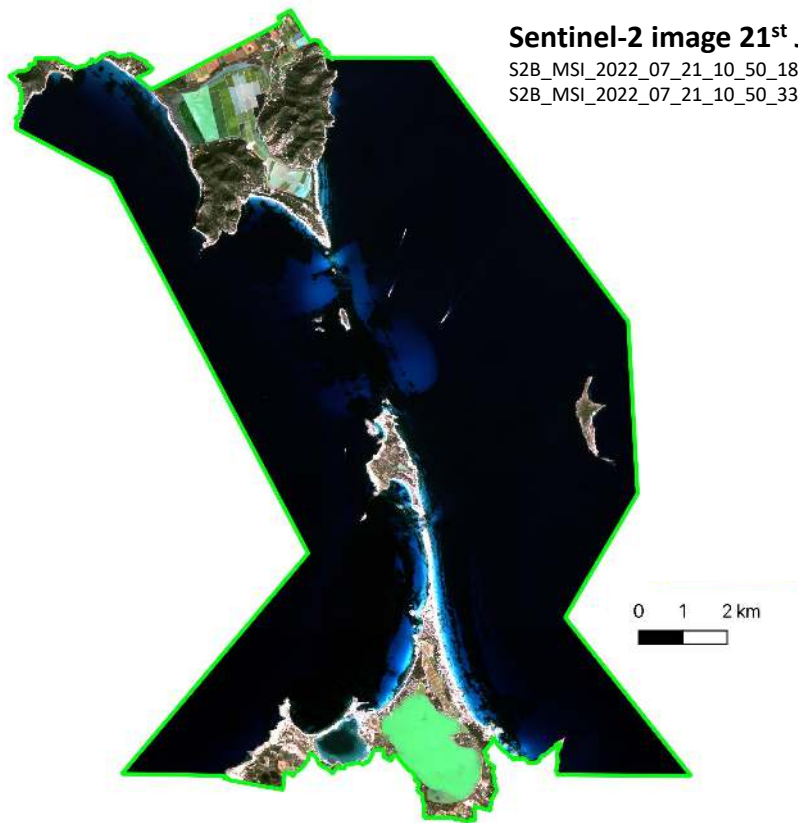


Essential Variables

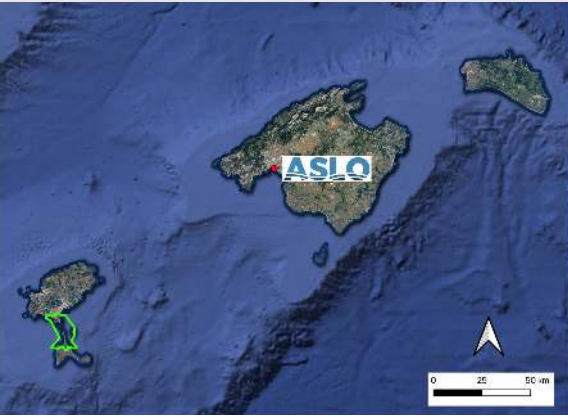
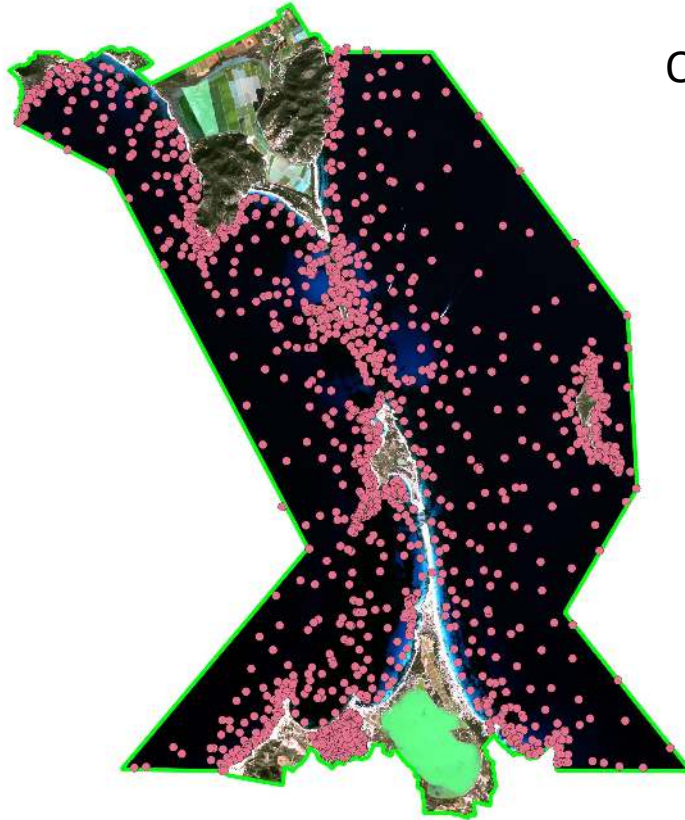
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“Freus d'Eivissa i Formentera” MPA



“Freus d'Eivissa i Formentera” MPA

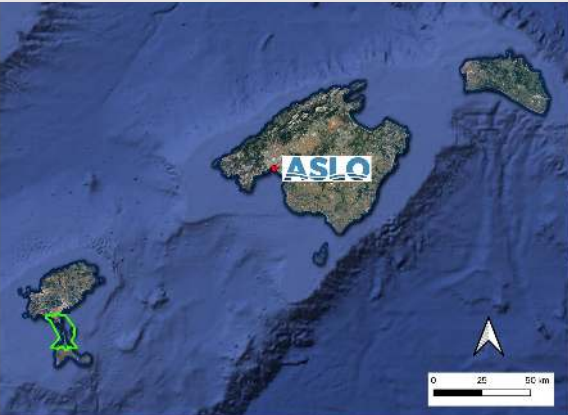
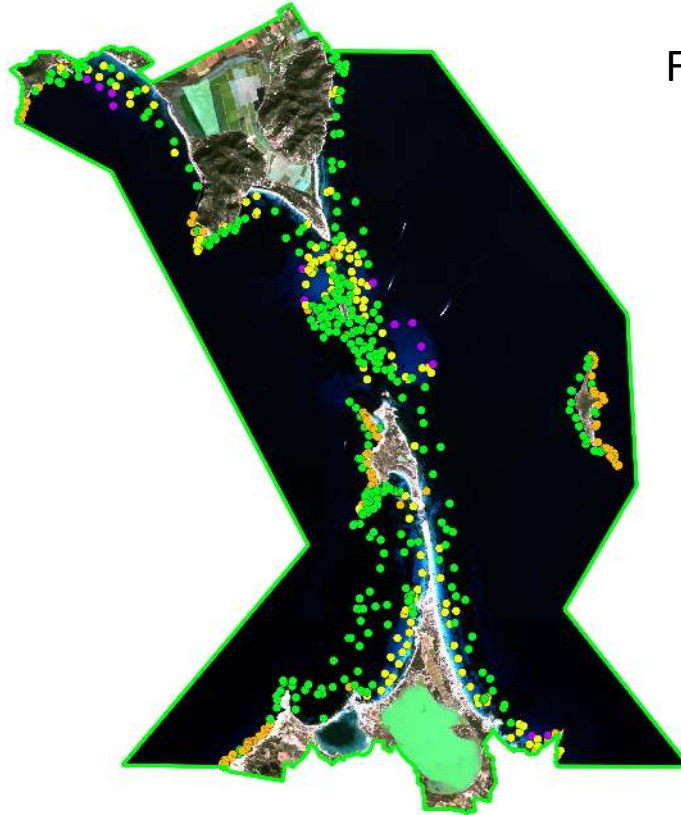


Original validation dataset



- 6 field campaigns
- 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)



PREPROCESSING



TRAINING AND CLASSIFICATION



VALIDATION



PREPROCESSING

ACOLITE
ATMOSPHERIC
CORRECTION
+ DEGLINT

LAND MASK

Z MASK

WATER COLUMN
CORRECTION

B3

B4

B5

Z



TRAINING AND CLASSIFICATION



VALIDATION



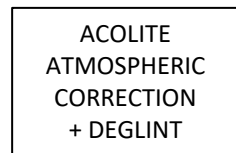
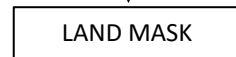
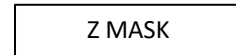
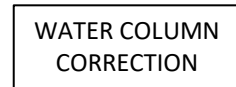
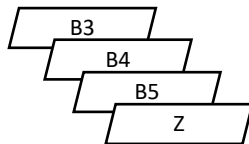
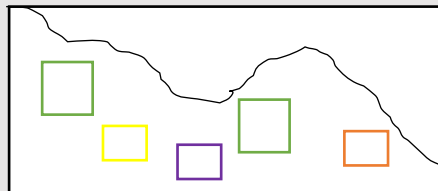
TOP OF ATMOSPHERE REFLECTANCES



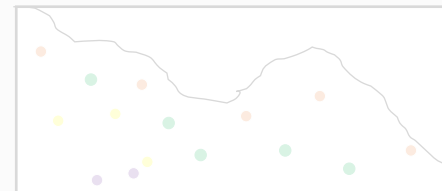
BOTTOM OF THE SEA LEAVING REFLECTANCES



PREPROCESSING



TRAINING AND CLASSIFICATION



VALIDATION





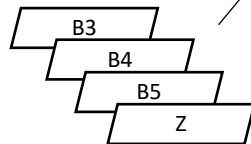
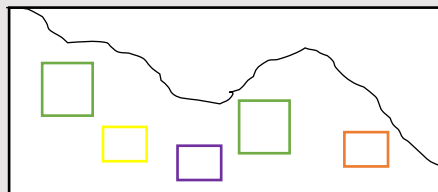
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CORRECTION



TRAINING AND CLASSIFICATION

RANDOM
FOREST
CLASSIFIER



VALIDATION



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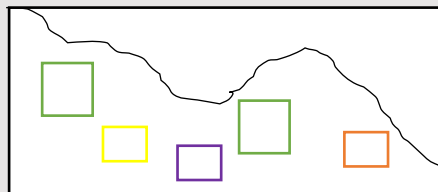
WATER COLUMN
CORRECTION

B3

B4

B5

Z

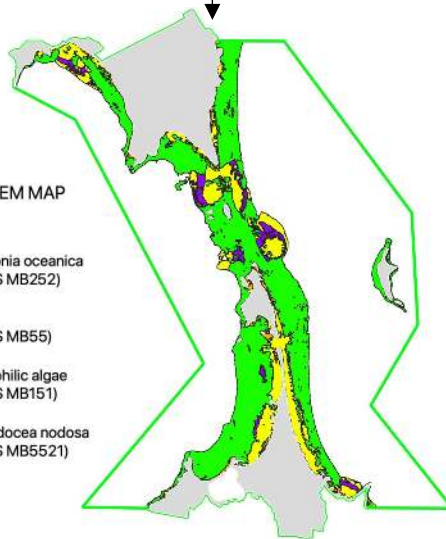


TRAINING AND CLASSIFICATION

RANDOM
FOREST
CLASSIFIER

ECOSYSTEM MAP

- Posidonia oceanica
(EUNIS MB252)
- Sand
(EUNIS MB55)
- Photophilic algae
(EUNIS MB151)
- Cymodocea nodosa
(EUNIS MB5521)



VALIDATION



PREPROCESSING

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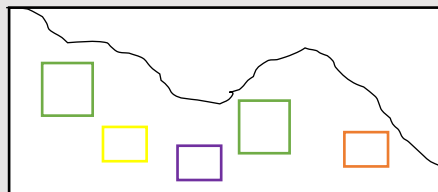
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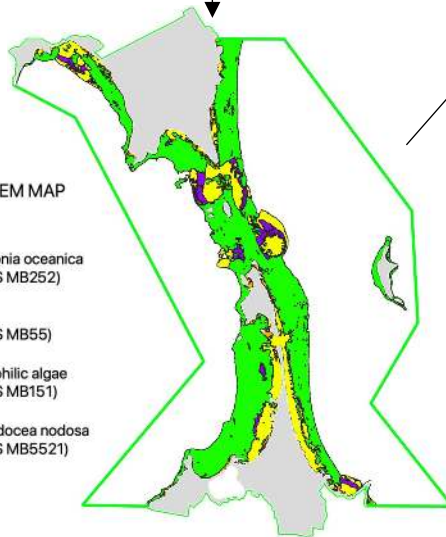
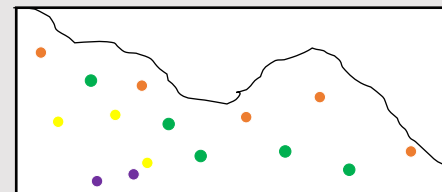


TRAINING AND CLASSIFICATION

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FOREST
CLASSIFIER

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VALIDATION

ACCURACY
ASSESSMENT



PREPROCESSING

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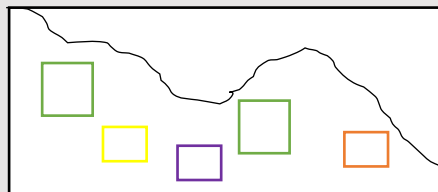
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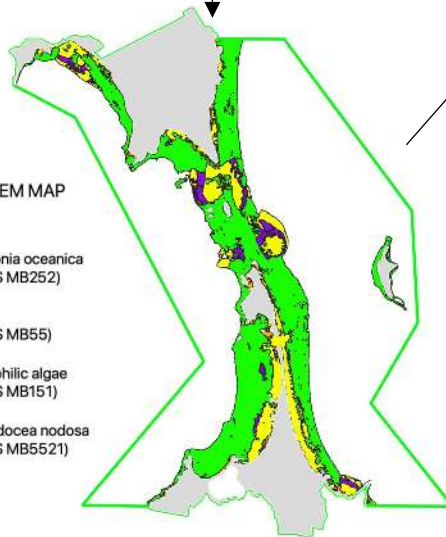
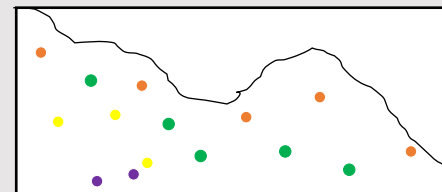


TRAINING AND CLASSIFICATION

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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%

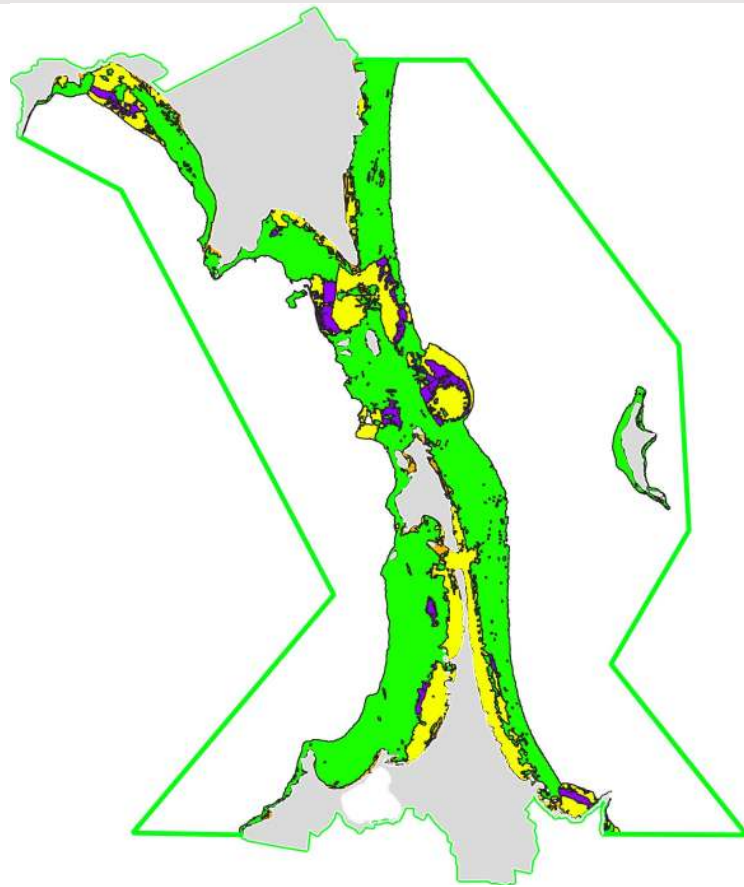


Sand

-Recall (accuracy): 81%

-Precision: 76%

Machine Learning model handles this
2 classes quite well.

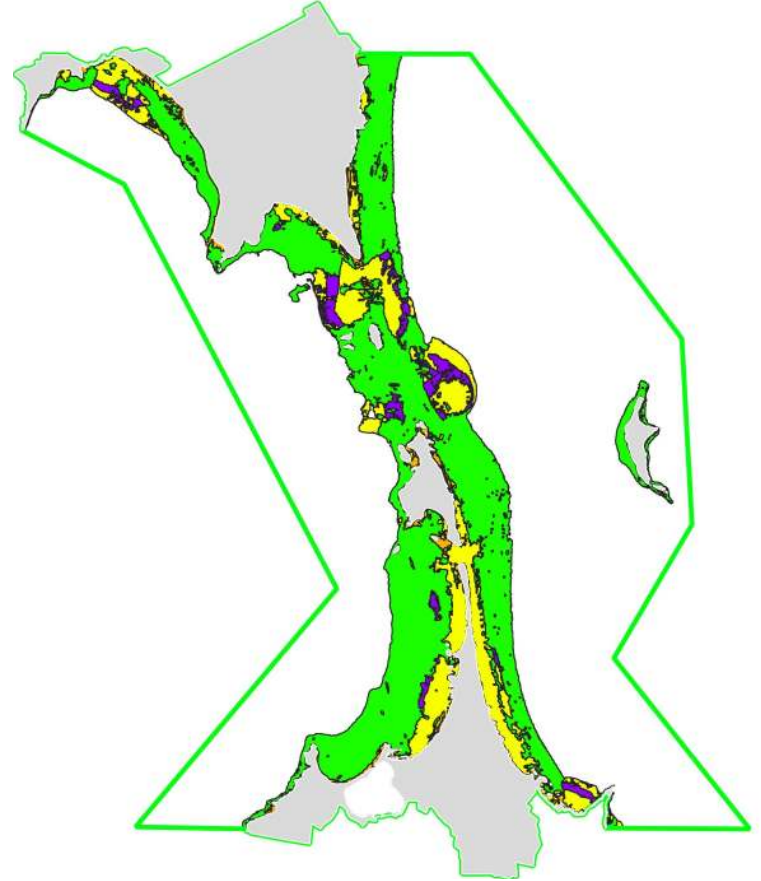


Results



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)

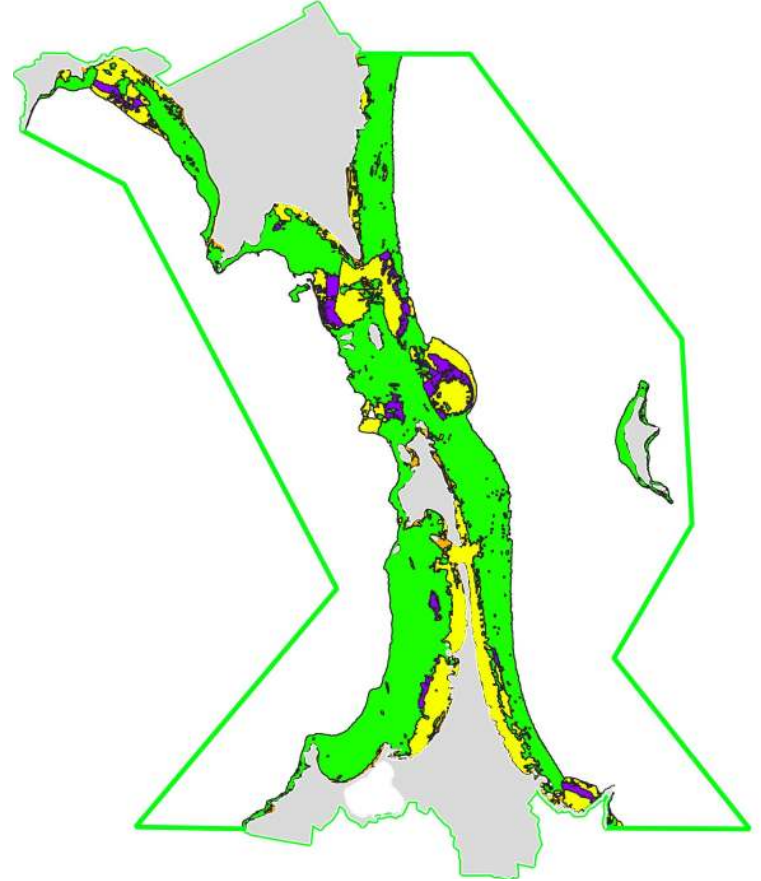


Results



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

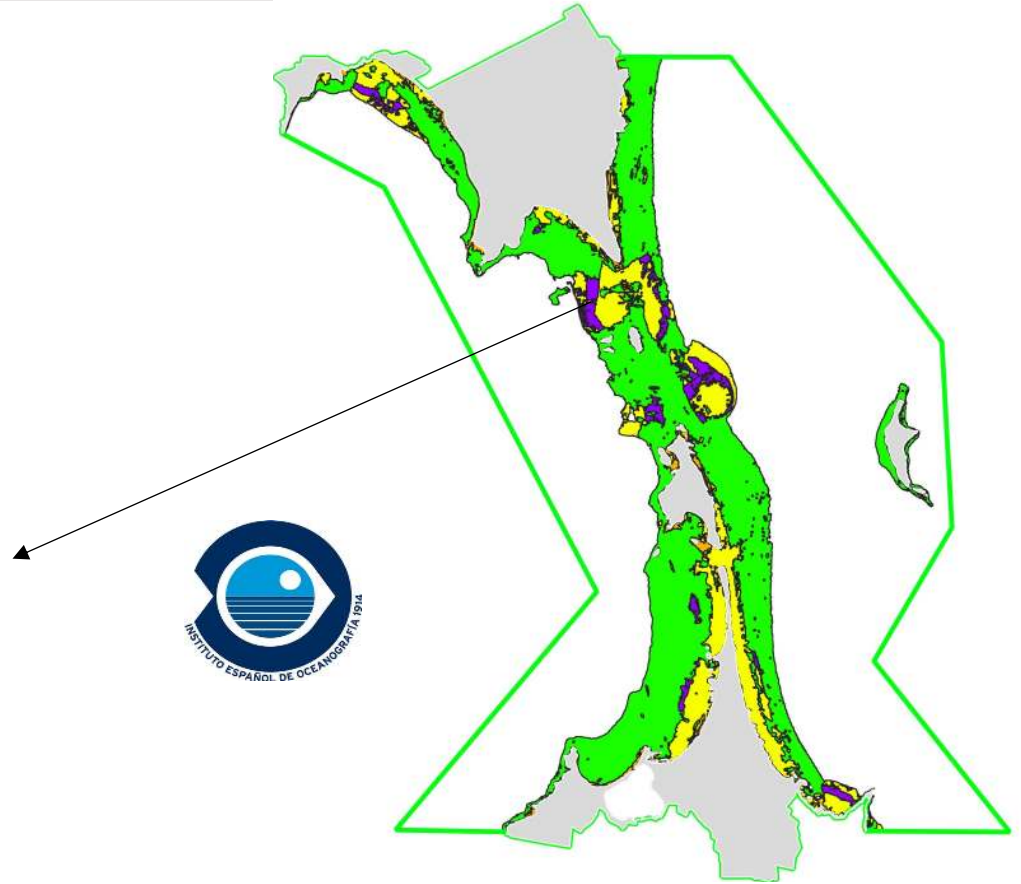
Machine learning model is able to detect this class but it also mixes it with other classes, particularly sand (overestimation of coverage or "potential distribution").



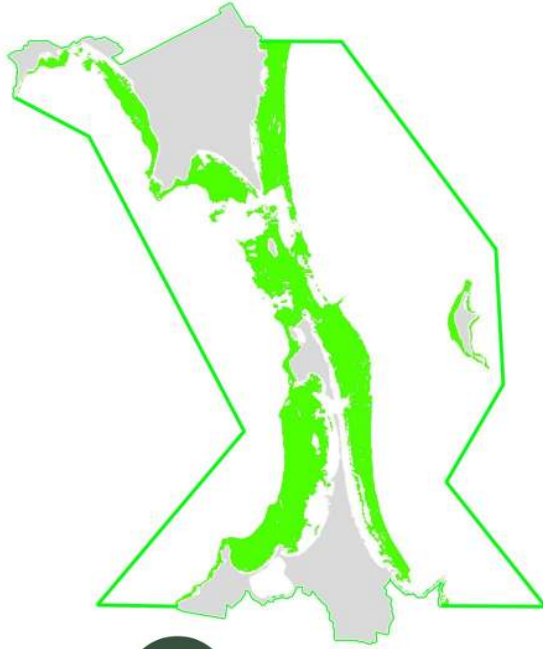
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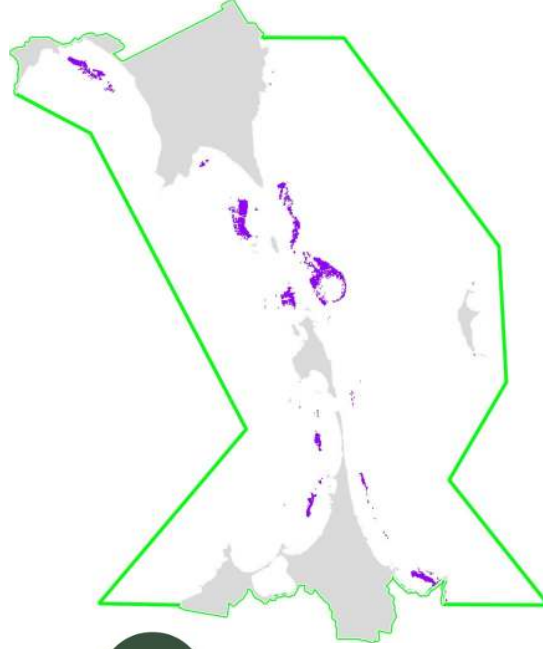
Essential Ocean Variables Estimation



Seagrass

25 km²
(0 to 20m)

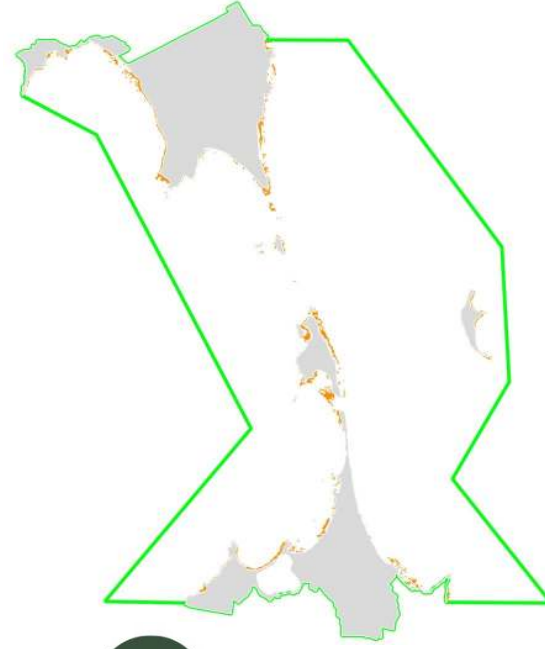
Posidonia oceanica



Seagrass

1.9 km²
(0 to 20m)

Cymodocea nodosa



Macroalgal
canopy

1.6 km²
(0 to 20m)

Photophilic algae

Conclusions and future directions

CONCLUSIONS

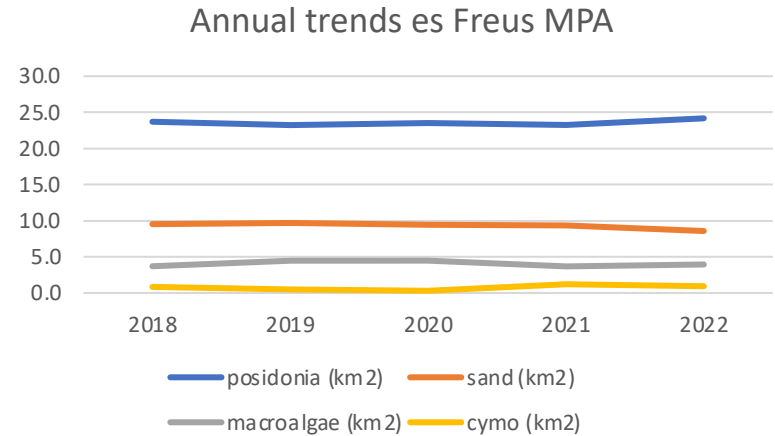
- RF has been able to extrapolate from a small training area in the corner of the MPA to the full MPA extent
- This might be a reliable (enough) and scalable methodology (that can be further improved)
- **The methodology allows the upscaling of in situ observations from local to more global frameworks**

Conclusions and future directions

CONCLUSIONS

- RF has been able to extrapolate from a small training area to the full MPA extent
- This is a reliable and scalable methodology (that can be further improved)
- **The methodology allows the upscaling of in situ observations from local to more global frameworks**

FURTHER DIRECTIONS

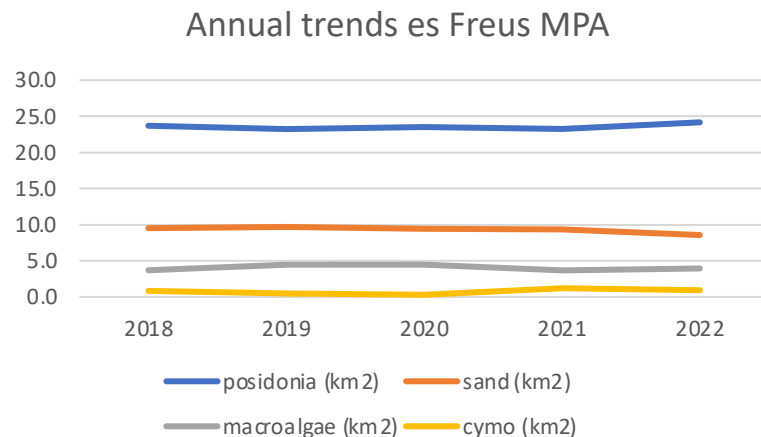


Conclusions and future directions

CONCLUSIONS

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FURTHER DIRECTIONS



- **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 Well | March 21, 2023

Kevin Well
Principal, Tracelink
AI/ML

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



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

Sarah A. Boyle^{1*}, Christina M. Kennedy², Julio Torres³, Karen Colman⁴, Pastor E. Pérez-Estigarribia⁵, Noé U. de la Sancha⁶

[...] 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.

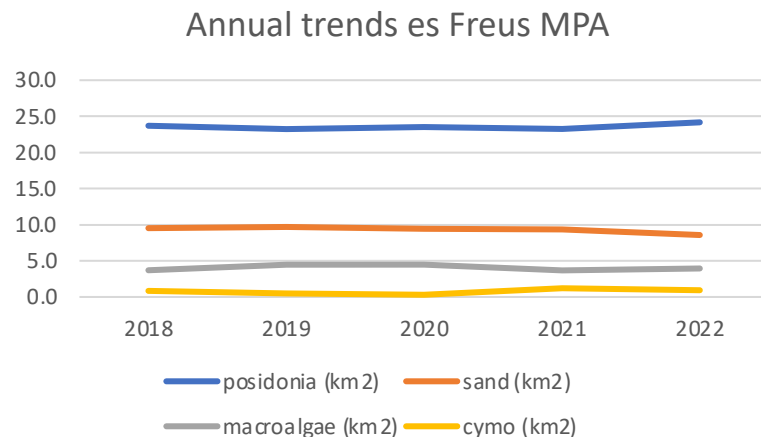
Skidmore, A., Pettoirelli, N., Coops, N. *et al.* Environmental science: Agree on biodiversity metrics to track from space. *Nature* **523**, 403–405 (2015)

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

FURTHER DIRECTIONS



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Thank you!

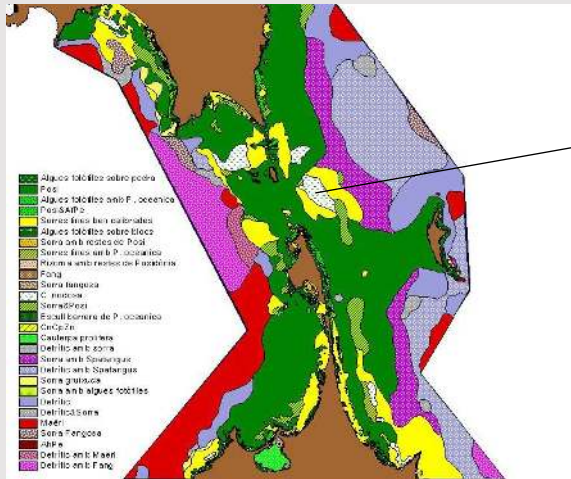
f.garcia@ceab.csic.es



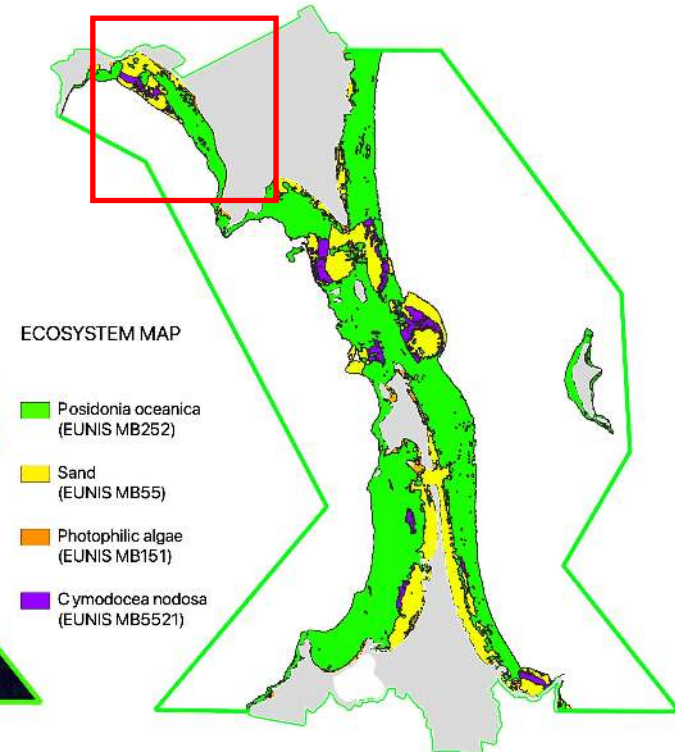
Cymodocea nodosa

-Accuracy: 54%

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Accuracy assesment



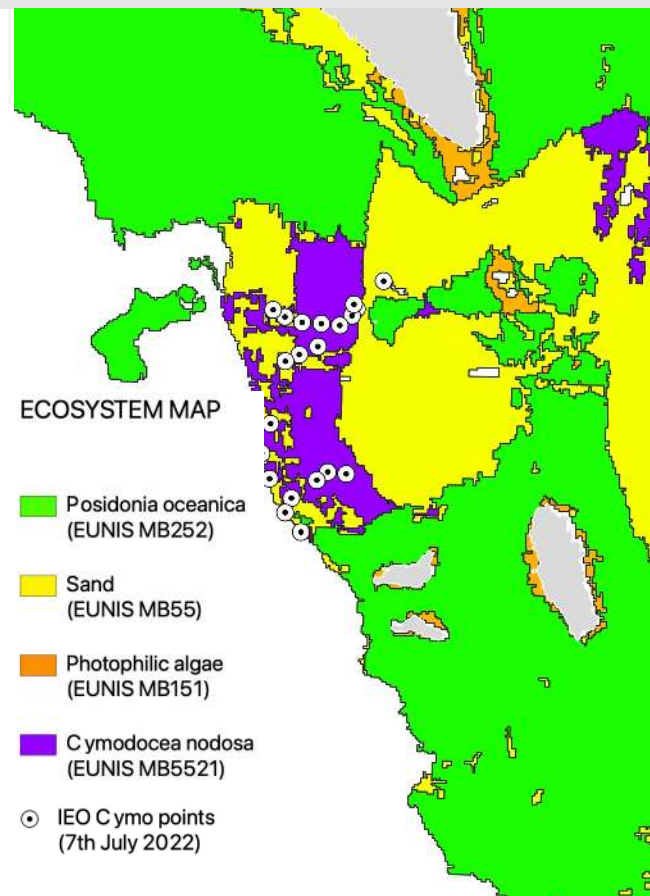


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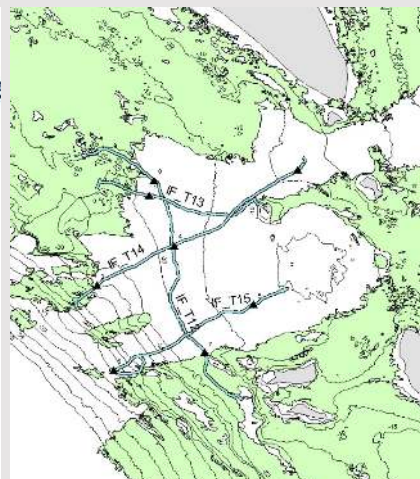
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Accuracy assesment



“Potential distribution”



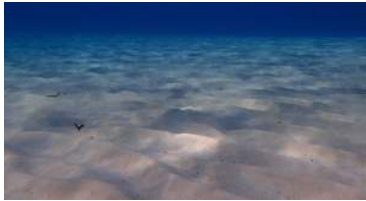
Marine Strategies Seagrass Campaign
 Camara trawl transects
 7th July 2022 (3 weeks prior to S2 image)

Results



Posidonia oceanica

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



Sand

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



Photophilic algae

-Recall (accuracy): 37%
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Cymodocea nodosa

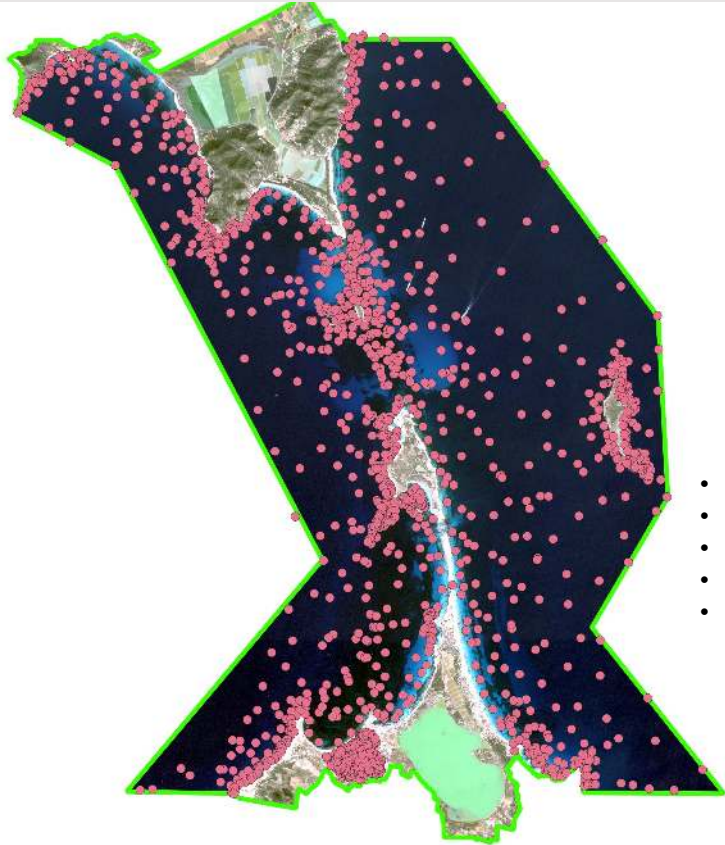
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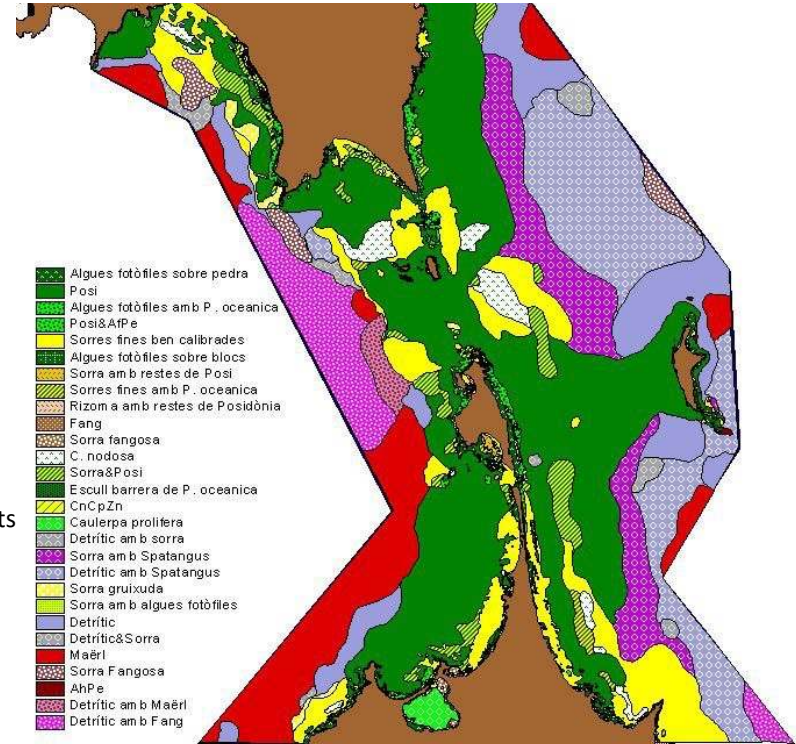
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Fieldwork



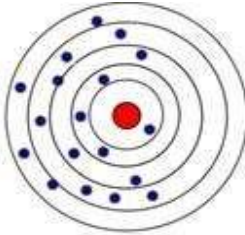
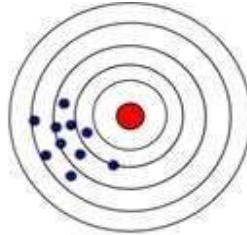
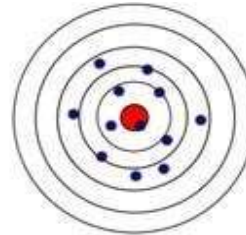
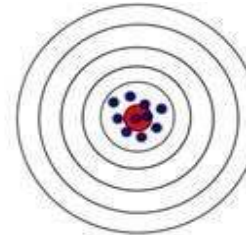
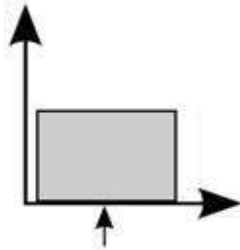
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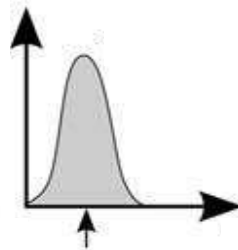
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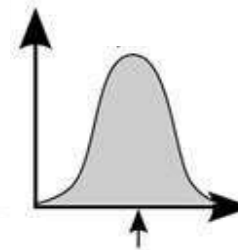
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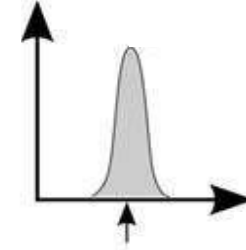
✗ Accuracy
✗ Precision



✗ Accuracy
✓ Precision



✓ Accuracy
✗ Precision



✓ Accuracy
✓ Precision