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A CLOUD-BASED COASTAL EARTH OBSERVATION FRAMEWORK FOR REGIONAL SEAGRASS ENVIRONMENT MAPPING ACROSS THE EASTERN AFRICAN COASTLINES

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INTRODUCTION

- Seagrasses provide a multitude of ecosystem services such as blue carbon sequestration, coastal protection, as well as biodiversity maintenance, however, they are underappreciated and underestimated
- The coastlines of East African countries (Kenya, Tanzania, Mozambique, and Madagascar) are inhabited by 11 seagrass species belonging to the Tropical Indo-Pacific bioregion
- Seagrass species in East Africa are facing loss and degradation due to climate change, over-fishing, coastal development, and coastal eutrophication
- Our aim is to present an end-to-end cloud-based tool to map the seagrass meadow extents in East Africa as a decision-support system for scientists, policy makers, and governments, and as a base for blue carbon accounting and sustainable development.

MATERIALS AND METHODS

Multi-temporal Satellite Data Synthesis

1. Multi-temporal Analytics
   - Cloud masking
   - 20th percentile approach
   - S2 L2A SR archive (28/03/2017—20/04/2020)
2. Land and Optically Deep Water Masking
   - Otsu (1979)-based thresholding
   - Above-surface R_{rs} reflectance transformation

Reference Data

Self-labeled turbid zone

Field-collected SDB data points

Benthic habitat data points

Turbidity Processor

- Spectral unmixing using polygons based on 50-m buffers of self-labeled data points

Satellite-derived Bathymetry Processor

1. Unsupervised k-means clustering
2. Satellite-derived bathymetry modelling
   - Lyzenga (1985)
   - Stumpf et al (2003)
   - SVM regression (Burges, 2008)
3. Accuracy assessment (R^2, MAE, RMSE)

Seagrass Classification Framework

1. „Soft" Classification

Seagrass probability mapping with Random Forest machine learning algorithm (Breiman, 2001)

2. „Hard" Classification
   - Binary class mapping of the seagrass presence and absence based on the probability thresholding
   - Accuracy assessments (overall accuracy, producer's accuracy, user's accuracy, F1-score)

RESULTS AND DISCUSSIONS

Accuracy scores

PA: Producer's Accuracy
UA: User's Accuracy
OA: Overall Accuracy
NS: Non-seagrass
SG: Seagrass
TZ: Turbid Zone
CW: Clear Water

Seagrass mapping		
Metric	Class	Score
	NS	99
PA	SG	47
	NS	84
UA	SG	92
	NS	91
F1-score	SG	62
OA (%)		85

Turbid zone mapping		
Metric	Class	Score
	TZ	87
PA	CW	97
	TZ	96
UA	CW	88
	TZ	91
F1-score	CW	92
OA (%)		92

SDB Cluster-Based Lyzenga	
RMSE	1.64
MAE	1.22
R^2	7.51
Max depth (m)	99.99
Mean depth (m)	7.88
Min depth (m)	-82.20

Seagrass area and depth

	Kenya	Madagascar	Mozambique	Tanzania
Seagrass area (m^2)	679.59	1309.34	1779.30	548.16
Max depth (m)	9.18	22.96	9.23	8.52
Mean depth (m)	2.15	2.06	1.62	1.06
Min depth (m)	-6.79	-49.43	-6.41	-18.23

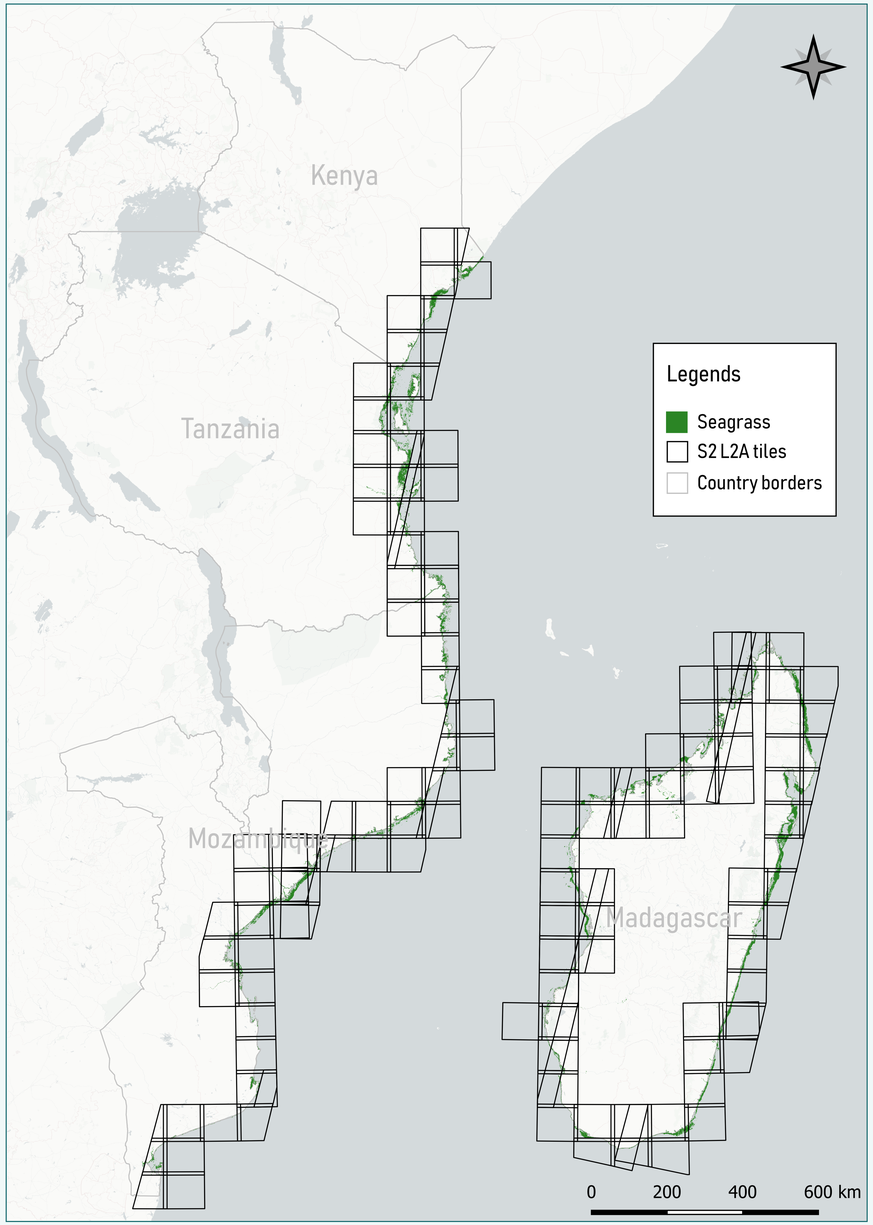

Figure 1. The East Africa (Kenya, Tanzania, Mozambique, and Madagascar) study area, Sentinel-2 L2A coverage, and the mapped seagrass extent

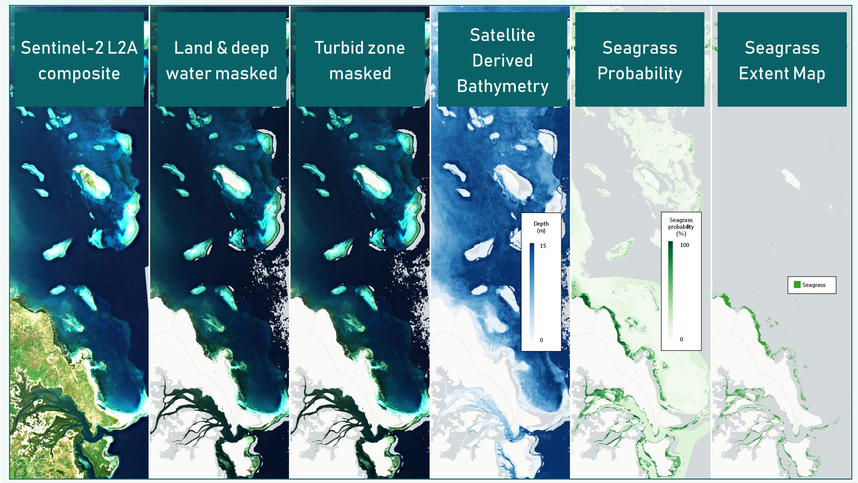

Figure 2. Successive images of the mapping processes and results

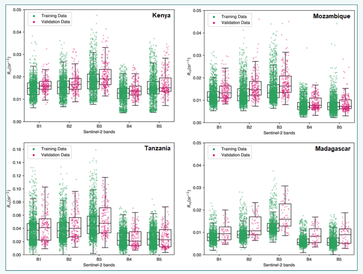

Figure 3. The training and validation data seagrass spectral profiles on the first 5 Sentinel-2 bands

- Seagrass extents were slightly underestimated as shown in UA values which are higher than PA values
- The spectral value boxplot shows Tanzania as the noisiest composite, manifested by large ranges of seagrass reference data across the 5 S2 bands due to turbidity as well as spectral response non-uniformity and parallax effects of the sensor
- SDB modeled with the Cluster-based Lyzenga method has the highest accuracy scores
- Despite the high accuracy scores, , turbid zone detection is highly site-specific depending to the materials of the suspended sediments.

CONCLUSION

- Our cloud-based Earth Observation seagrass mapping framework is scalable and can be applied to map the worldwide seagrass extent thanks to the global Sentinel-2 L2A coverage
- Cloud, land, deep water, and turbid zone masking provides the shallow clear water area for habitat mapping where the light attenuation of the benthic substrate was not hindered

FUTURE STEPS

- Reduction of noise on the satellite image composite
- Improved cloud, cloud shadow, deep water, and turbid zone masking
- Object-based image analysis
- Scaling up the study sites and blue carbon estimation
- Liaison with local and national stakeholders of the study sites for better field data

Promoted talk:
„Serverless is more for blue carbon"
Dr. Dimosthenis Traganos
Sun, 27 Jun, Session SS14

Global Seagrass Watch
SCAN ME

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