Nationwide Seagrass Mapping Using Analysis-Ready PlanetScope Data to Support the Nationally Determined Contributions of Seychelles

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Introduction

Background:

- Seagrass meadows provide many valuable ecosystem services, such as blue carbon sequestration, natural nursery for many marine species, food source, habitat, and so on. For example, the fisheries support at Gran Canaria was estimated to be worth 600,000 € per year (Tuya *et al.*, 2014, de los Santos *et al.*, 2020).
- Seagrasses have been highly threatened in the past century, with global habitat losses of 19.1% (Dunic *et al.*, 2021).
- There is a considerable lack of knowledge on the global seagrass distribution, and spatial data for seagrass habitats is unavailable in many places (Waycott *et al.*, 2009; Dunic *et al.*, 2021).
- As this information is essential for the Blue Carbon Accounting, seagrass mapping is needed.

Situation:

- Seagrasses are usually submerged, so the optical sensors are the most practical approach from space.
- The recent free and high-resolution (4.77 m) Norway's International Climate and Forests Initiative (NICFI) by PlanetScope has a buffer along the shorelines that includes shallow coastal waters. These are where seagrasses can usually be found.
- Our multitemporal approach can be integrated with NICFI images to map seagrasses (Lee *et al.*, 2022).

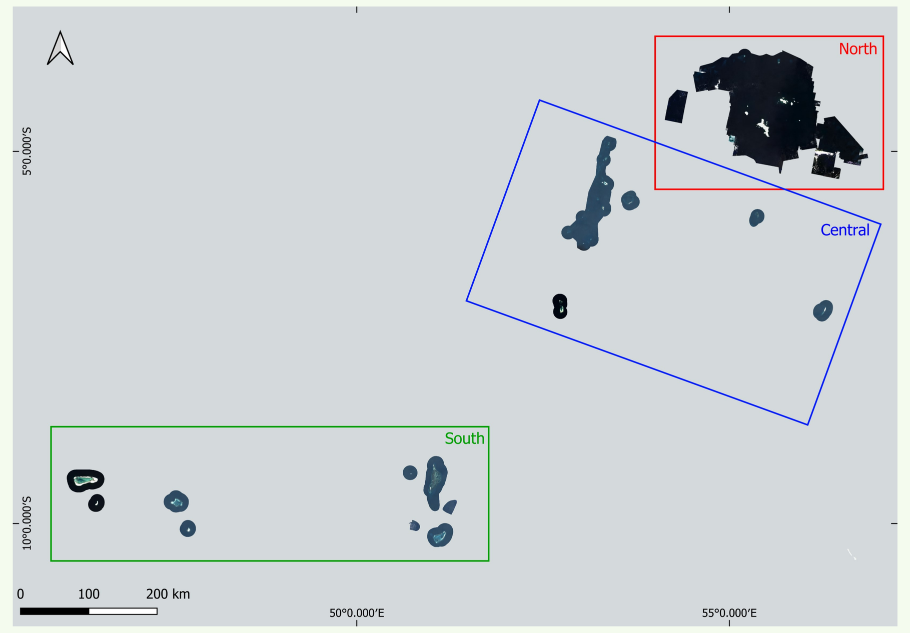


Figure I1. Map of the Seychelles showing the three geographic regions for this study. Basemap: CartoDB Positron.

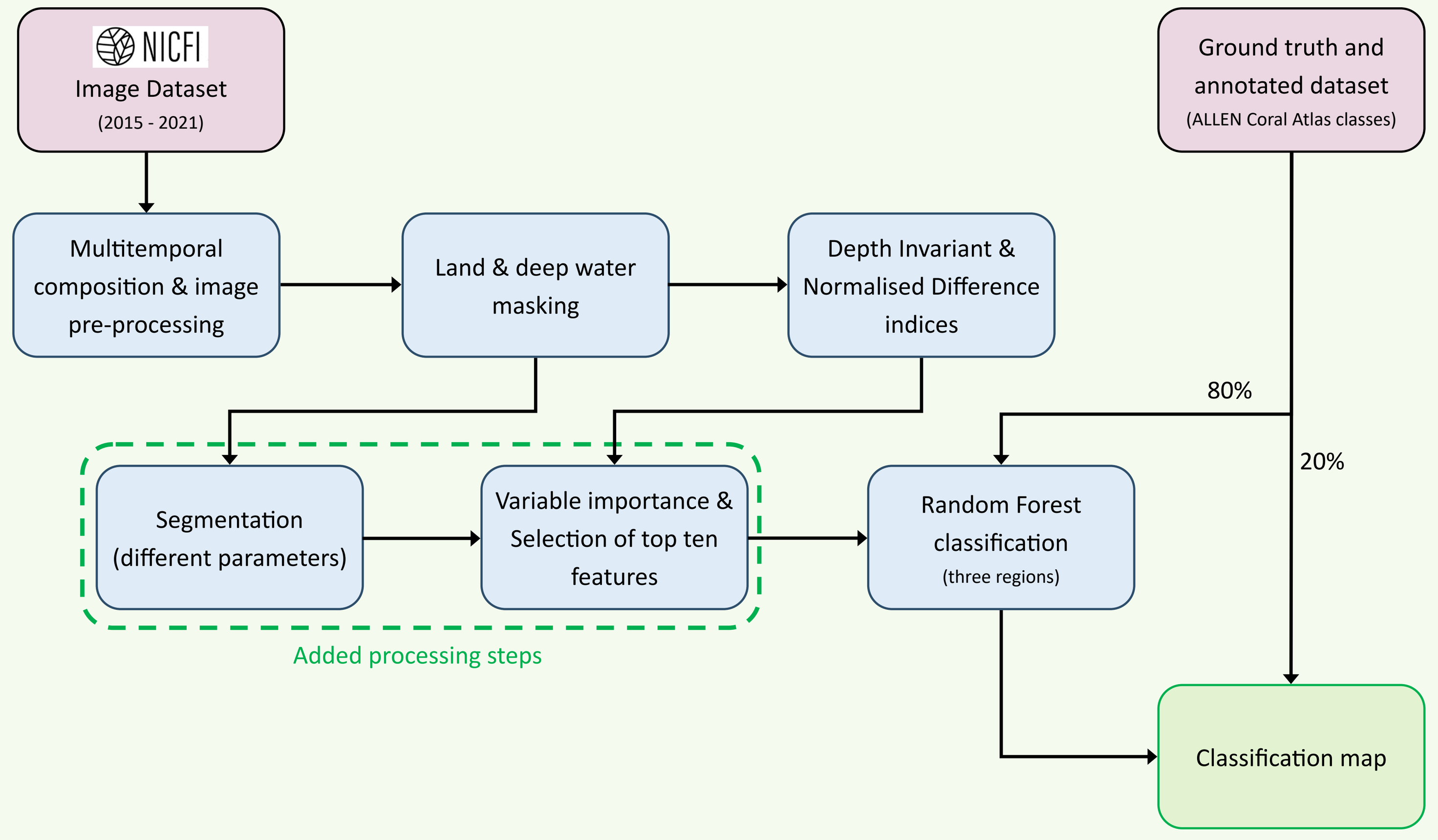
Problem:

- The NICFI has only four spectral bands, which is a limiting factor.
- Owing to accessibility matters, collecting data from all islands has been challenging.
- Classification of seagrass areas is still possible, albeit with some errors (Lee *et al.*, 2022).

Experiment hypothesis:

- Feature generation from existing spectral bands through segmentation would improve the current classification.

Methods & Materials



The authors would like to acknowledge the contributions of many collaborators for the ground truth and expert knowledge-annotated dataset, including the University of Seychelles, Island Conservation Society, School of Science & Centre for Marine Ecosystems Research (Edith Cowan University) and the Pew Charitable Trusts.

Main Message

The classification accuracies for the seagrass maps in the Seychelles are improved in the Central and Southern regions, while having mixed results for the Northern region.

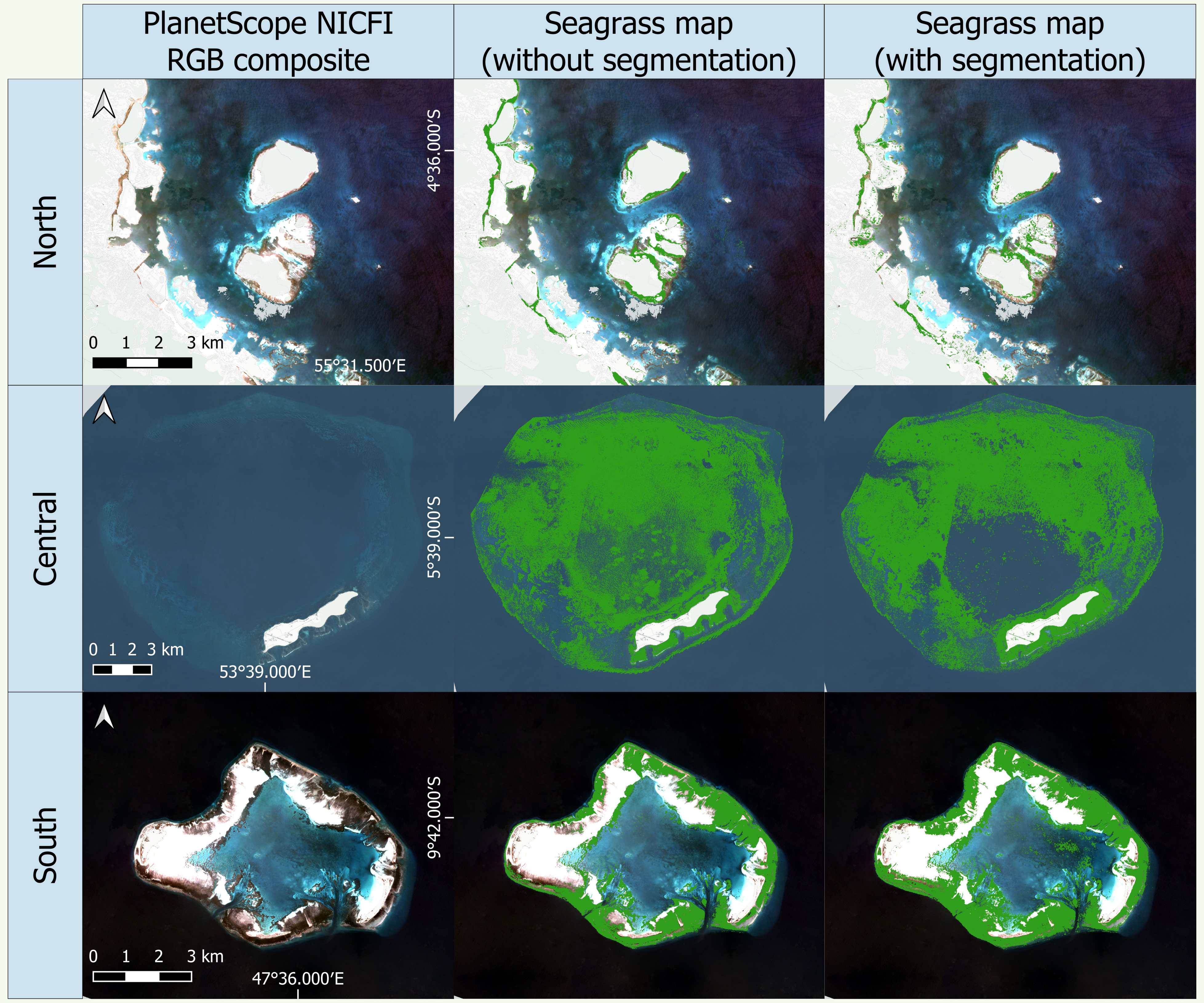


Figure M1. Subset maps comparing the original PlanetScope NICFI images (left) with the seagrass map from the classification without segmentation features (middle) and with segmentation features (right) over the three defined regions. Basemap: CartoDB Positron.

Results & Discussion

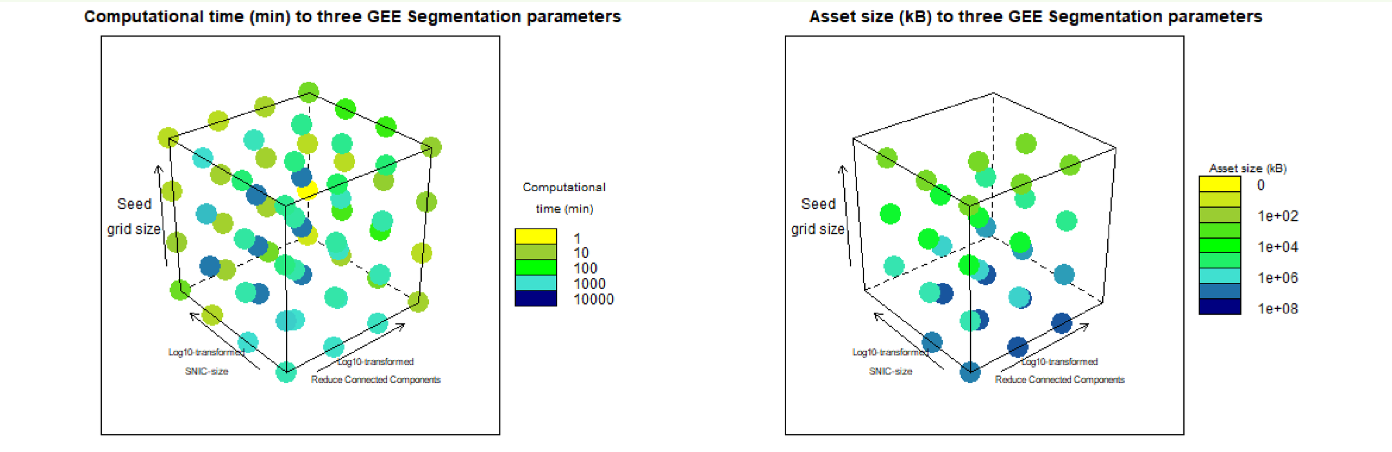


Figure R1. Resource demand in computational time (left) and product asset size (right) with varying parameters. Seed grid size: 5, 10, 15, 20; SNIC size: 10, 100, 1000, 10000; Reduce Connected Components: 10, 100, 1000, 10000.

Table R1. Benchmark classification accuracy for the Seychellois seagrass map (without segmentation features) by region.

Region	North	Central	South
Mean Overall Accuracy	62.70%	62.70%	64.60%
Mean Producer's Accuracy for seagrass class	74.40%	67.80%	63.70%
Mean User's Accuracy for seagrass class	63.80%	86.30%	91.10%

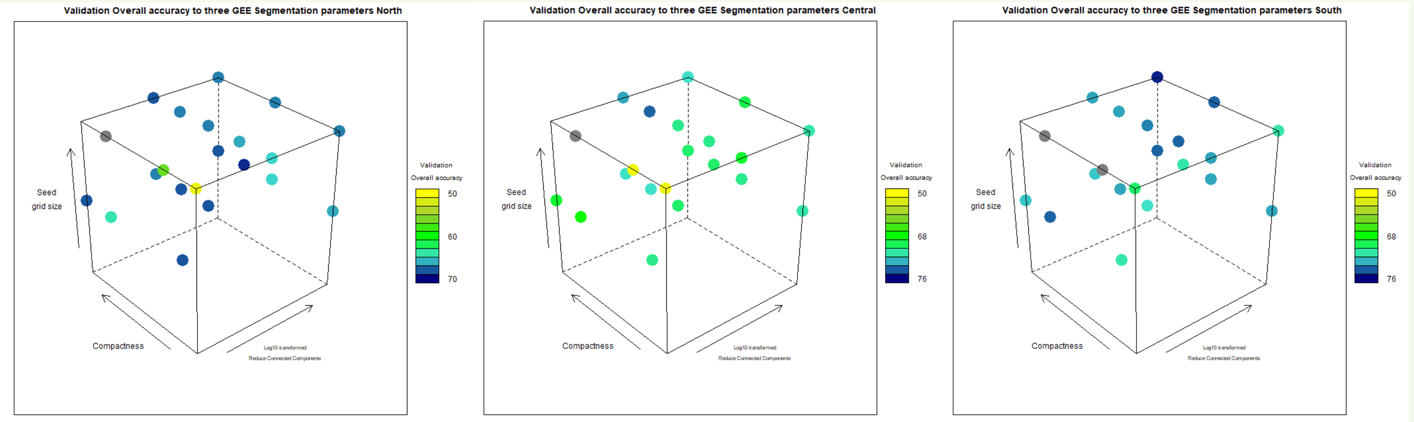


Figure R2. Overall classification accuracy with varying parameters across different regions. Greyed points are invalid. Seed grid size: 5, 10, 15; Compactness: 0, 0.2, 0.4, 0.6, 0.8; Reduce Connected Components: 10, 100, 1000.

Table R2. Best classification accuracy for the Seychellois seagrass map with the corresponding segmentation parameters by region.

Region	North	Central	South
Best Overall Accuracy	69.70%	73.40%	75.70%
Best Producer's Accuracy for seagrass class	62.60%	89.20%	86.90%
Best User's Accuracy for seagrass class	63.90%	77.70%	81.50%
Seed Grid	10	15	15
Compactness	0.6	0.6	0.8
Reduce Connected Component	1000	100	1000

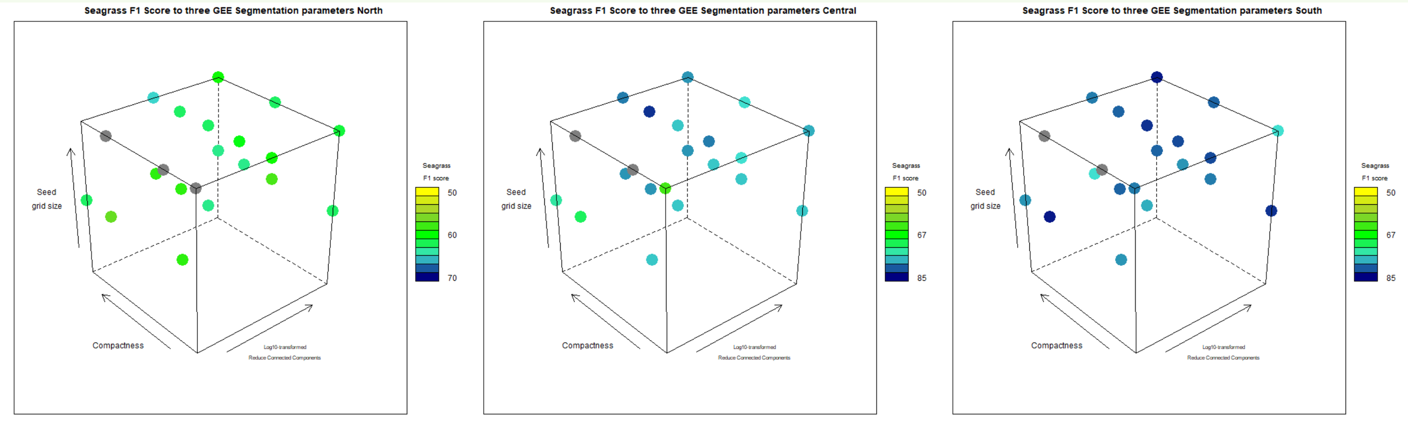


Figure R3. F1 score for the seagrass class with varying parameters across different regions. Greyed points are invalid. Seed grid size: 5, 10, 15; Compactness: 0, 0.2, 0.4, 0.6, 0.8; Reduce Connected Components: 10, 100, 1000.

- There were no significant trends for the seed grid, compactness and reduce connected components parameters (p-values > 0.05), based on their tested range. Nonetheless, the selection criteria could still be augmented by their resource demands as well as feasibility of output.
- Seed grid should be set no lower than 10 in GEE, as the resource costs for the finer resolutions only introduces more noise.
- Although costing more computing resources, reduce connectivity should be set no lower than 100 in GEE, as the image will be patchy.
- Although the performance of compactness seems towards the larger values, there were no significant differences for all three regions.

Table R3. Generalised Linear Regression of the parameters to the classification overall accuracy for the northern region. There were no significant results across all three regions. Regression trends were also similar between regions, except in the South where sdGrd has a slightly positive estimate. rCC: Reduce Connected Components, sdGrd: Seed grid size, Compact: Compactness.

Region	Coefficient	Estimate	Standard Error	t value	Pr (> |t|)
North	(intercept)	0.826	2.597	0.318	0.756
	Log10(rCC)	-0.085	0.932	-0.091	0.929
	sdGrd	-0.033	0.177	-0.186	0.855
	Compact	0.237	0.397	0.598	0.560
	Log10(rCC):sdGrd	0.016	0.064	0.244	0.811
	Log10(rCC):Compact	-0.096	0.144	-0.668	0.516
	sdGrd:Compact	-0.021	0.028	-0.757	0.462
	Log10(rCC):sdGrd:Compact	0.009	0.010	0.834	0.419

Reference

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