Advancements in Shallow Water Remote Sensing

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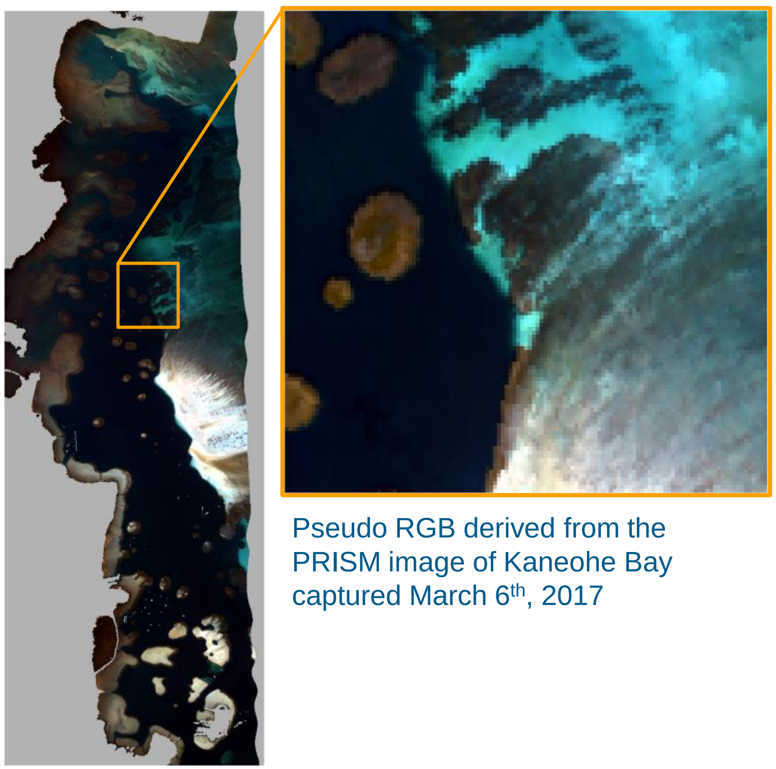
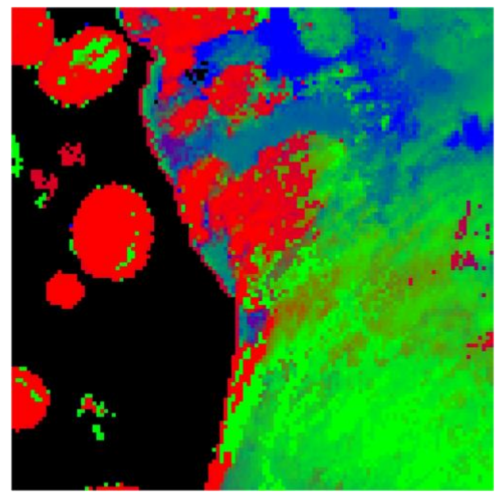
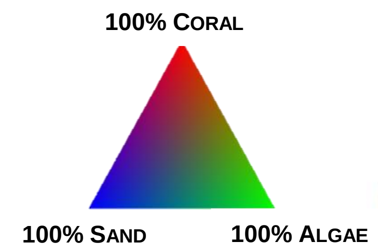
Benthic Classification in Hyperspectral Imagery

- The number of wavebands, narrow bandwidths and high spectral resolution have advanced approaches that can remove the modulating effects of the water column through physics-based inversion models.



Pseudo RGB derived from the PRISM image of Kaneohe Bay captured March 6th, 2017





Derived fractional coverage of coral, algae and sand.

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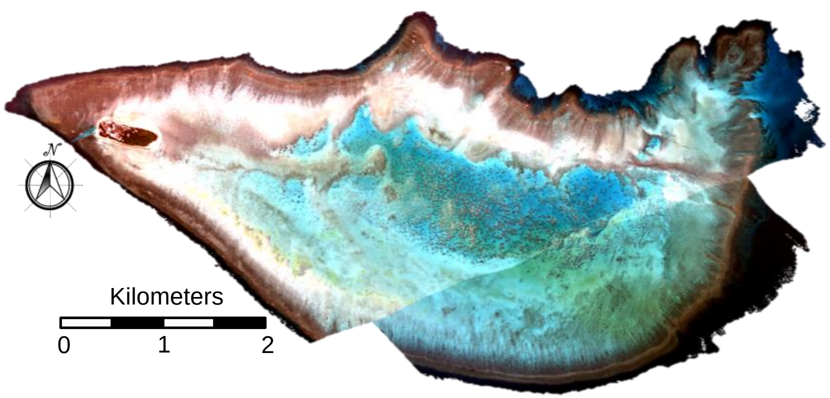
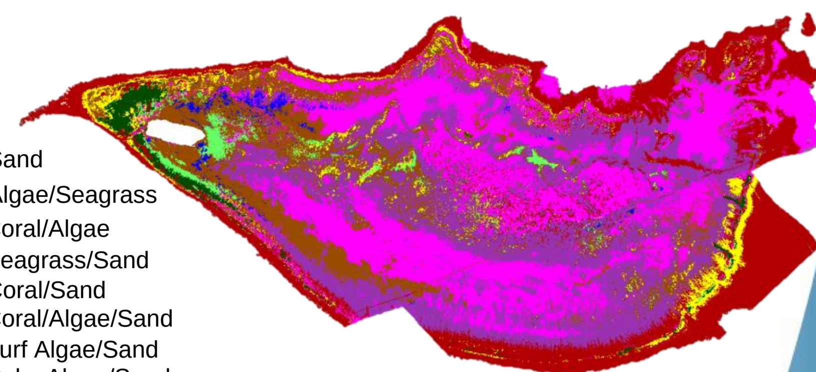
Shortcoming from current approaches

- The bottom reflectance, ρ, is unknown *a priori* yet is a required input to shallow water inversion models.
- Parameterizing ρ as a linear mix of one (or more) benthic endmembers enables iterating of different endmember pairs, and the selection of the pair that produced the best result (Brando et al., 2009).
- Endmember <u>pairs</u> are not constrained – assumes any bottom substrates are possible anywhere in an image



Pseudo RGB derived from the PRISM image of Heron Reef captured September 17th, 2016



Benthic classification map produced from a variant of the BRUCE inversion model (Garcia et al., 2018)

Overall accuracy of 57%

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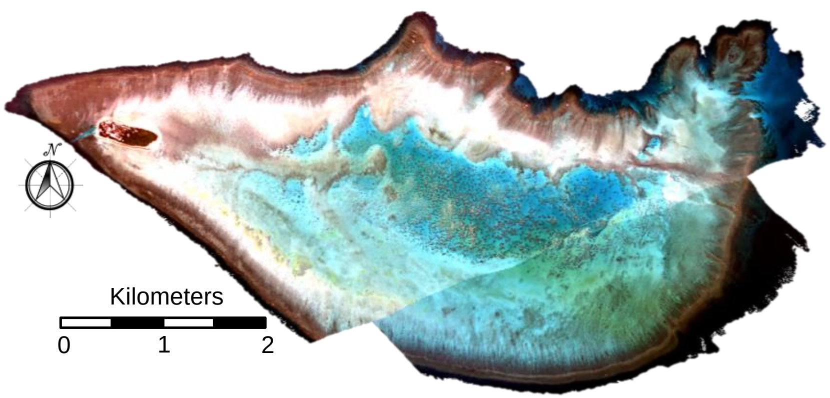
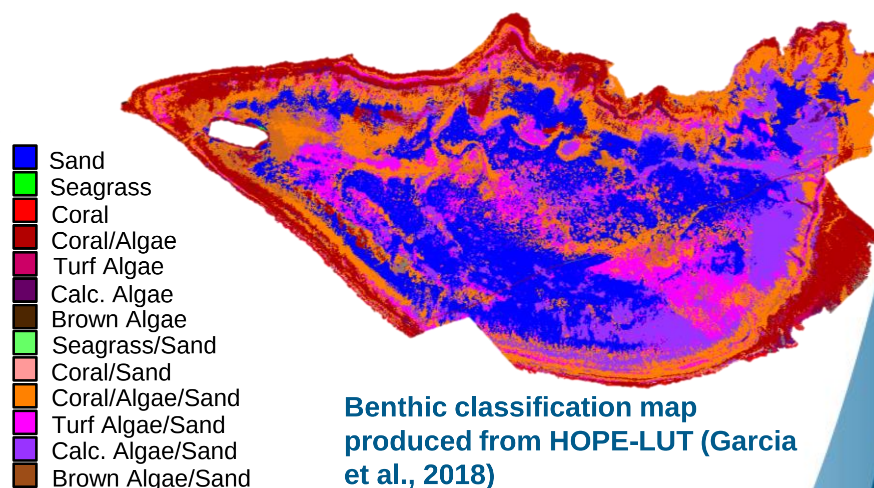
Potential Solution

- Traditional approach isn't always accurate and very time consuming;
- Development of a structured hierarchical object-based classifiers is an active field of research in multispectral remote sensing (e.g. Roelfsema et al., 2013; 2018)
- Improvements were made by developing R_{rs}-based classifiers, aided by depth, to predetermine the likely benthic endmembers (Garcia et al., 2018).



Pseudo RGB derived from the PRISM image of Heron Reef captured September 17th, 2016



Benthic classification map produced from HOPE-LUT (Garcia et al., 2018)

Overall accuracy of 74%

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Future directions in Benthic Classification

- HOPE-LUT from Garcia et al. (2018) trained Mahalanobis-based classifiers from a LUT of R_{rs}
- Machine learning approaches are attractive approaches as they find patterns and relationships in the data.
- Extensive application in Remote Sensing and in field vision.
- However, more effort required in selecting the best approach, fine tuning abstract parameters (specific vs. global), and time consuming training the classifiers.

(Left) Normalized Error Matrix from a subset of an *in situ* R_{rs} dataset.

These classification accuracies were produced from a variant of HOPE-LUT, where gradient boosted regression trees where used in a multiple expert classifier system.

Depth ≤ 5 m	Seagrass	Algae	Coral	Mud	Sand	User's acc.
Seagrass	**0**	0	0	0	0	N/A
Algae	0.49	**92.30**	5.33	0.00	1.88	92.30
Coral	0.23	11.79	**85.90**	1.44	0.62	85.90
Mud	0	0	0	**0**	**0**	N/A
Sand	0.20	5.56	7.32	0.00	**86.92**	86.92
Producer's Accuracy	N/A	84.2	87.1	N/A	97.2	**Overall: 88.4**

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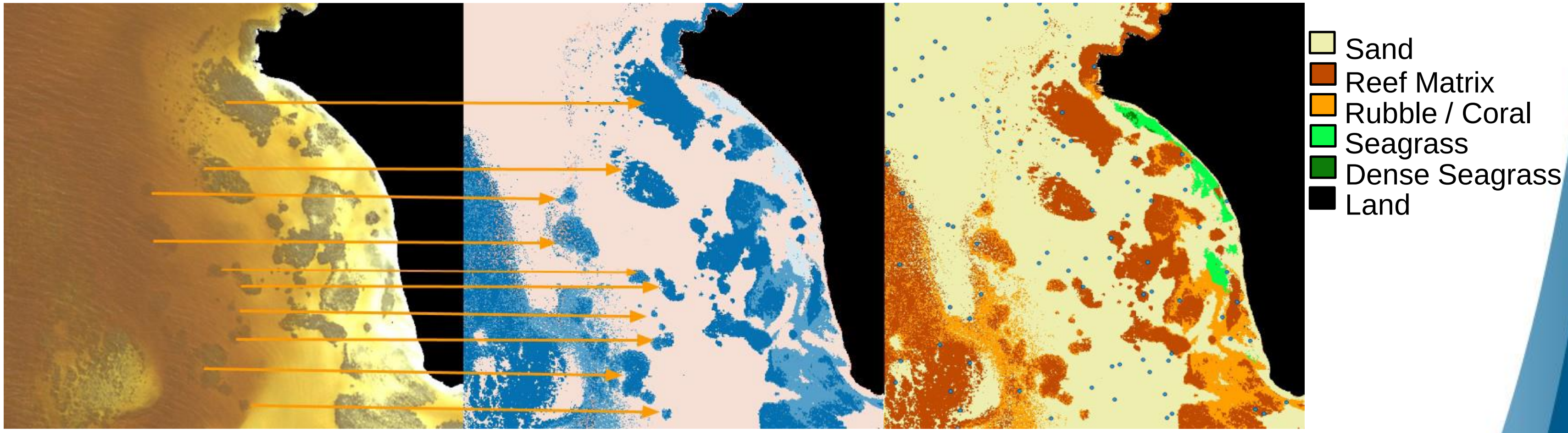
Future directions in Benthic Classification

- Quality of outputs from inversion models and R_{rs}-based classifiers are dependent on quality of input image (atmospheric/sunglint correction, SNR) and spectral library (global vs. local).
- Inversions and R_{rs}-based classifiers are not a complete solution as they work independently of the spatial arrangement of reflectances.
- Including spatial information will improve the selection of endmembers

Marrable et al. (2014)



SPOT-5 image of a portion of Lizard Island GBR, 2009

Unclassified image after super-pixel clustering

Classified image, with validation points. Overall accuracy of 77.5%

Curtin University

Future directions in Shallow Water Remote Sensing

- Parameterizations of the bottom reflectances yield different results [Jay et al., 2017; Petit et al., 2017].

1) $\rho = B\rho^*$ [Lee et al., 1999]

2) $\rho = B_1\rho_1^* + B_2\rho_2^* + B_3\rho_3^*$ [Klonowski et al., 2007]

3) $\rho = S_1 f_1 \rho_1 + S_2 B_2 \rho_2 + S_3 B_3 \rho_3$ [Klonowski, 2015]

4) $\rho = f_1\rho_1 + f_2\rho_2$ [Brando et al., 2009; Hedley et al., 2009]

5) $\rho = f_1\rho_1 + f_2\rho_2 + f_3\rho_3 + f_4\rho_4$ [Petit et al., 2017]

6) After inversion, rearrange the shallow water equation so that ρ is a function of R_{rs} [Hedley et al., 2018]

A community-driven dataset

- The validation of newly developed algorithms utilize a combination of the following:
  1. Comparison with field-, LIDAR- or navigational map-based depths;
  2. Comparison from a simulated R_{rs} dataset;
  3. Comparison with limited field-based IOPs, and;
  4. Benthic classification accuracy either from local expert knowledge or field data.

- Validation from different sources, regions-of-interest, environmental conditions make it difficult to compare between shallow water inversion models, without substantial effort from the community (e.g. Dekker et al., 2011)

- Datasets such as NOMAD exist for ocean color algorithm development and validation – however such a dataset is absent for shallow water environments

An Optics Dataset for Shallow Water Remote Sensing

- As part of NASA's CORAL project, temporal and spatial coincident IOPs and L_w, E_s were measured in situ at 6 different coral reefs, resulting in ~200 matchups.

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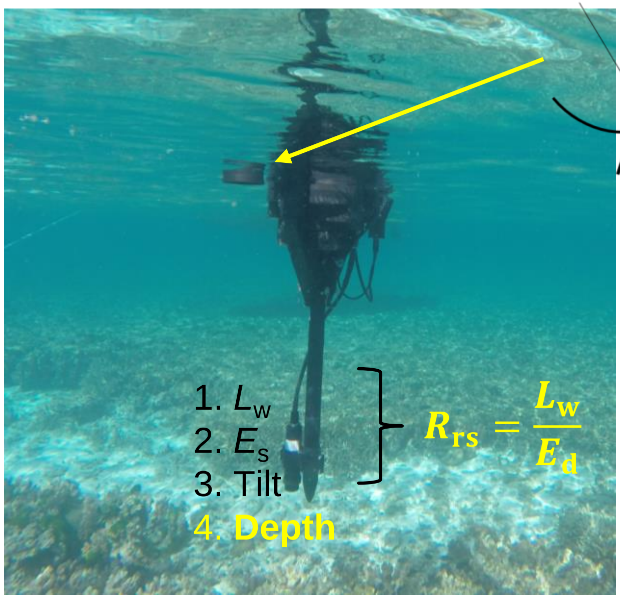
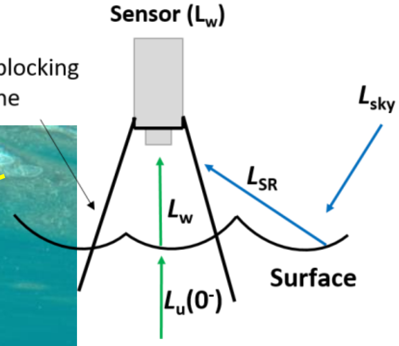
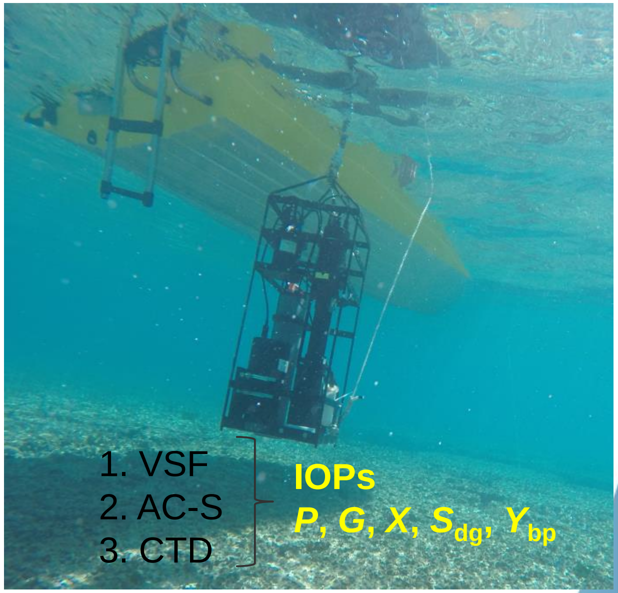




Additional data:
1. GoPro Images
2. GPS coordinates
3. Tilt/Telemetry

IOP Package



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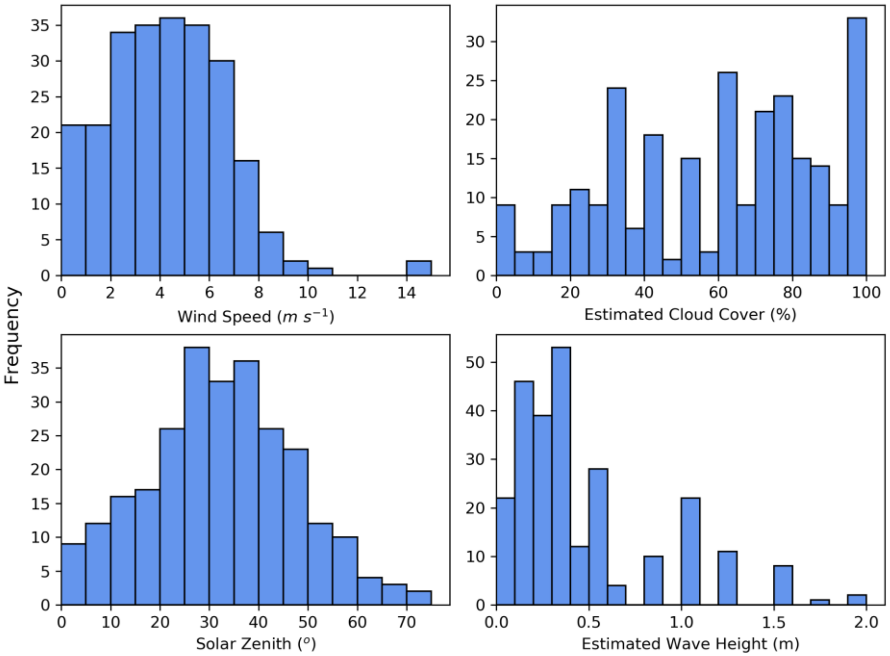

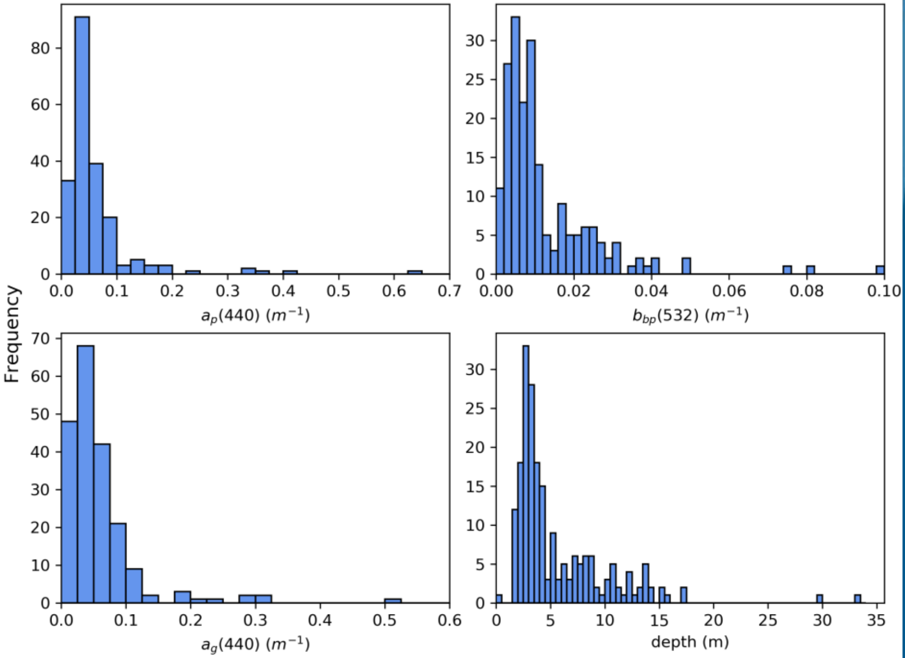

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Summary

- Substantial improvements in benthic classification by constraining the inversion to the likely benthos;
- Spectral classifiers can be enhanced with the use of advanced techniques such as multiple expert systems and machine learning approaches;
- Utilizing spatial context information can further aid benthic classification and such combined (spatial & spectral) should be utilized further;
- The shallow water remote sensing community requires an *in situ* R_{rs} dataset that has coincident depth, IOPs, and bottom substrate information to enable intercomparison between approaches.