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National

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Challenges

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Satellite and machine learning for monitoring our coastal environments

Background & Objectives



PART 1: Estuarine water health



Water Optical Properties



A comprehensive monitoring system needs less labour-intensive and more efficient techniques.





Based on the long-term water optical results from the satellite monitoring, classify estuaries with similar conditions for consistent management.



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PART 1: Estuarine water health

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Methods Sites

Raglan



PART 1: Estuarine water health



- 13 sites in total.
- Ranging from relative pristine ecosystems (Mahurangi) to urban-influenced estuaries (Manukau).
- The sediment sources also vary (e.g. uniform black sands in Raglan and a mixture of rocky and sandy shores in Whangarei.





PART 1: Estuarine water health

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Three categories were classified: highly impacted, moderately impacted and less impacted;

We observed a strong correlation between dominant wavelength and K_d Blue.

Estimate K_d Blue values in deep waters where L's model is not applicable.



Validation

PART 1: Estuarine water health





Findings:

High-level match up with other classification/score

The satellite derived dominant wavelength and Kd can be two useful indicators at scale to monitor estuarine

BHMS: Benthic health model scores PAR: Photosynthesis active radiation light ETISB: Estuary trophic index susceptibility bands



Background & Objectives



PART 2: Estuarine vegetation health



Distribution and monitoring (Zostera muelleri)



60 years ago

10 years ago





PART 2: Estuarine vegetation health





Gross primary productivity (GPP)



PART 2: Estuarine vegetation health



The optimal values for hyperparameters of random forests (validation with fivefold cross-validation):

Number of trees: 280; Min sample split: 4; Min sample leaf: 4; Max depth: 9

The classification report using random forests.

Class	Precision	Recall	F1-Score	Support	
				(Sample numbers)	
Sparse	0.86	0.91	0.89	20912	
seagrass					
Dense	0.97	0.97	0.97	32301	
seagrass					
Sandflats	0.92	0.94	0.93	16178	

The overall accuracy is 0.96. 70% of pixels for training and 30% for testing.







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PART 2: Estuarine vegetation health

Validation for optimal hyperparameters

80% (400) for training, 10% (50) for validation and 10% (50) for testing.

Model	Hyperparameters	Optimal	Validation	
		values	MSE	R ²
ANN	Activation function	Relu	0.023	0.625
	Number of hidden layers	2		
	Number of neurons	10		
	Learning rate	0.01		
SVR	Kernel function	rbf	0.024	0.612
	Gamma	0.1		
	С	13		
RFR	Number of estimators	20	0.021	0.644
	Max depth	10		
	Min samples leaf	1		
	Min samples split	4		



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----1:1 line

Seagrass coverage distribution



PART 2: Estuarine vegetation health





Gross primary productivity of seagrass and MPB

PART 2: Estuarine vegetation health

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Projection of sea level rise



PART 2: Estuarine vegetation health









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What can we do with satellite data and machine learning?

- Monitor the estuarine water optical properties at scale in the long term;
- Manage the estuaries with similar conditions;
- Evaluate estuarine vegetation health based on their distribution and percentage cover;
- Predict the potential effects of sea level rise and climate changes on coastal environments;

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Acknowledgements





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Data available:



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