Using UAVs and object-based image analysis for coastal habitat mapping

Paula Lightfoot[1]

Prof. N. V. C. Polunin[1], Dr C. L. Scott[2] and Dr C. Fitzsimmons[1]

[1] Newcastle University, [2] Natural England

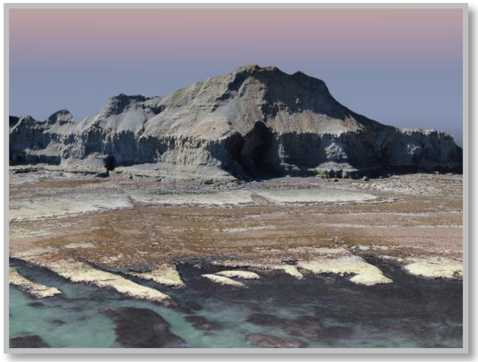
Introduction

PhD research 2014-2017:

"Object-based mapping of temperate marine habitats from multi-resolution remote sensing data".

Four projects in North Sea Marine Protected Areas:

1. Using object-based image analysis (OBIA) to map seabed habitats from acoustic data.



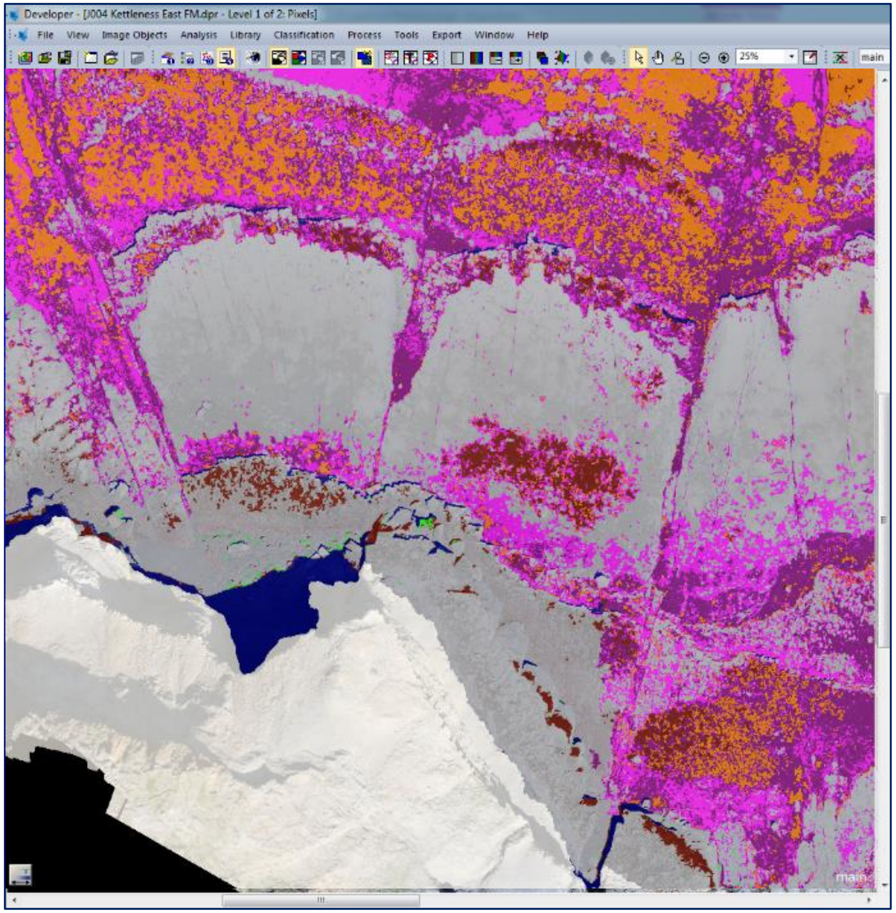
2. Measuring rocky shore rugosity using photogrammetry of UAV imagery.

3. Using OBIA to map intertidal habitats from UAV imagery.

4. Detecting change in intertidal habitats from multi-temporal aerial and LiDAR data using OBIA.

Object-based image analysis (OBIA)

User creates automated workflows to **segment** and **classify** layers of imagery, producing GIS-ready outputs.

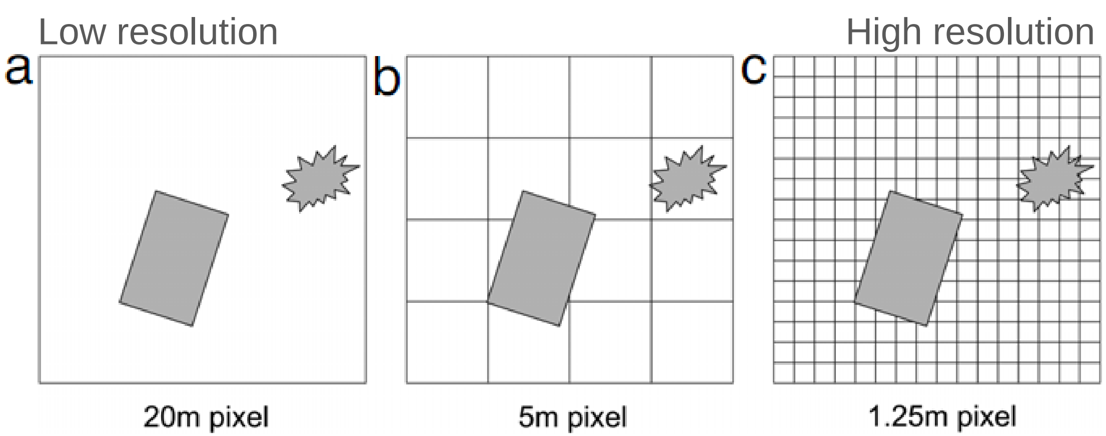


Background to OBIA

- An increasingly popular method of interpreting remote sensing data since around the year 2000. (Blaschke *et al*, 2014)
- OBIA methods are likely to play a key role in UK habitat monitoring. (Medcalf *et al*. 2015)
- The application of OBIA to marine data is in its infancy but shows potential. (Lucieer *et al*. 2013, Diesing *et al*. 2016)

Benefits of OBIA

- Remote sensing data is becoming available at ever higher resolution – objects of interest may be larger than individual pixels. Grouping pixels to form objects avoids the ‘salt-and-pepper’ effect produced by pixel-based classification.
- Objects have more properties than single pixels do:
  - Mean, mode, max, min, standard deviation, skewness etc of spectral values.
  - Geometric features e.g. shape, size, orientation.
  - Texture, e.g. rugosity.
  - Context and hierarchy – relation to neighbour objects, super-objects, sub-objects.
- This enables users to integrate their ecological knowledge and contextual information into the segmentation and classification process.



Blaschke *et al*, 2010

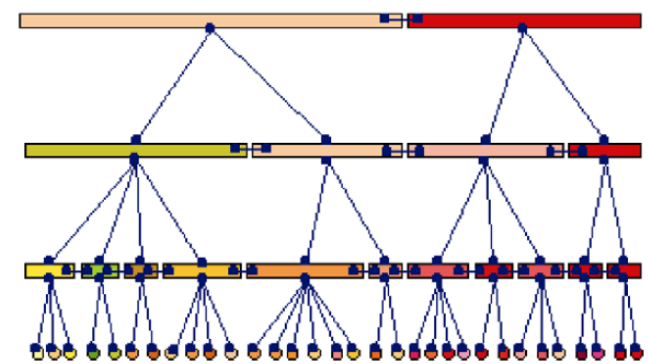
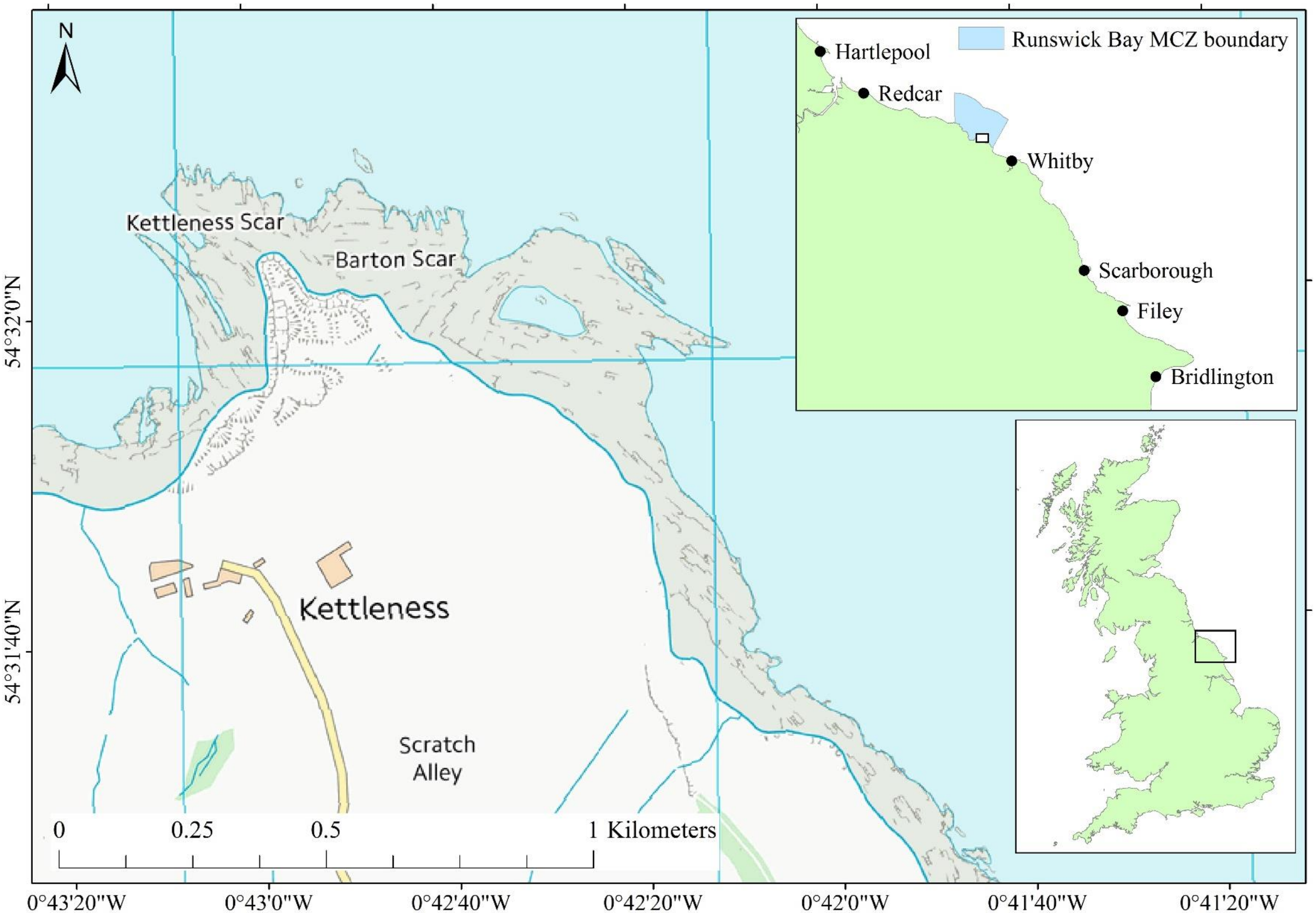


Fig. 3. Four-level hierarchical network of image objects in abstract illustration.

Benz *et al*, 2004

Study site

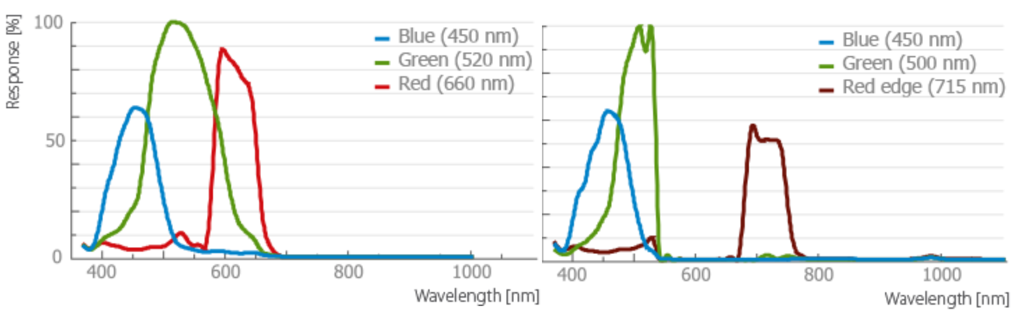
Kettleness headland in Runswick Bay Marine Conservation Zone, North Yorkshire



Data Collection

UAV imagery

- 17 flights between April - September 2015 using a senseFly eBee.
- Sensors:
  - ➢ Canon IXUS 127 HS 16.1 megapixels (RGB)
  - ➢ Canon Powershot ELPH 110 16.1 megapixels (Red Edge)
- 1,500 images captured:
  - ➢ Ground sampling distance 0.04 m
  - ➢ 60% lateral overlap, 75% forward overlap
  - ➢ Perpendicular intersecting flight lines
  - ➢ Ground Control Points (GCP) ~35 per km^2



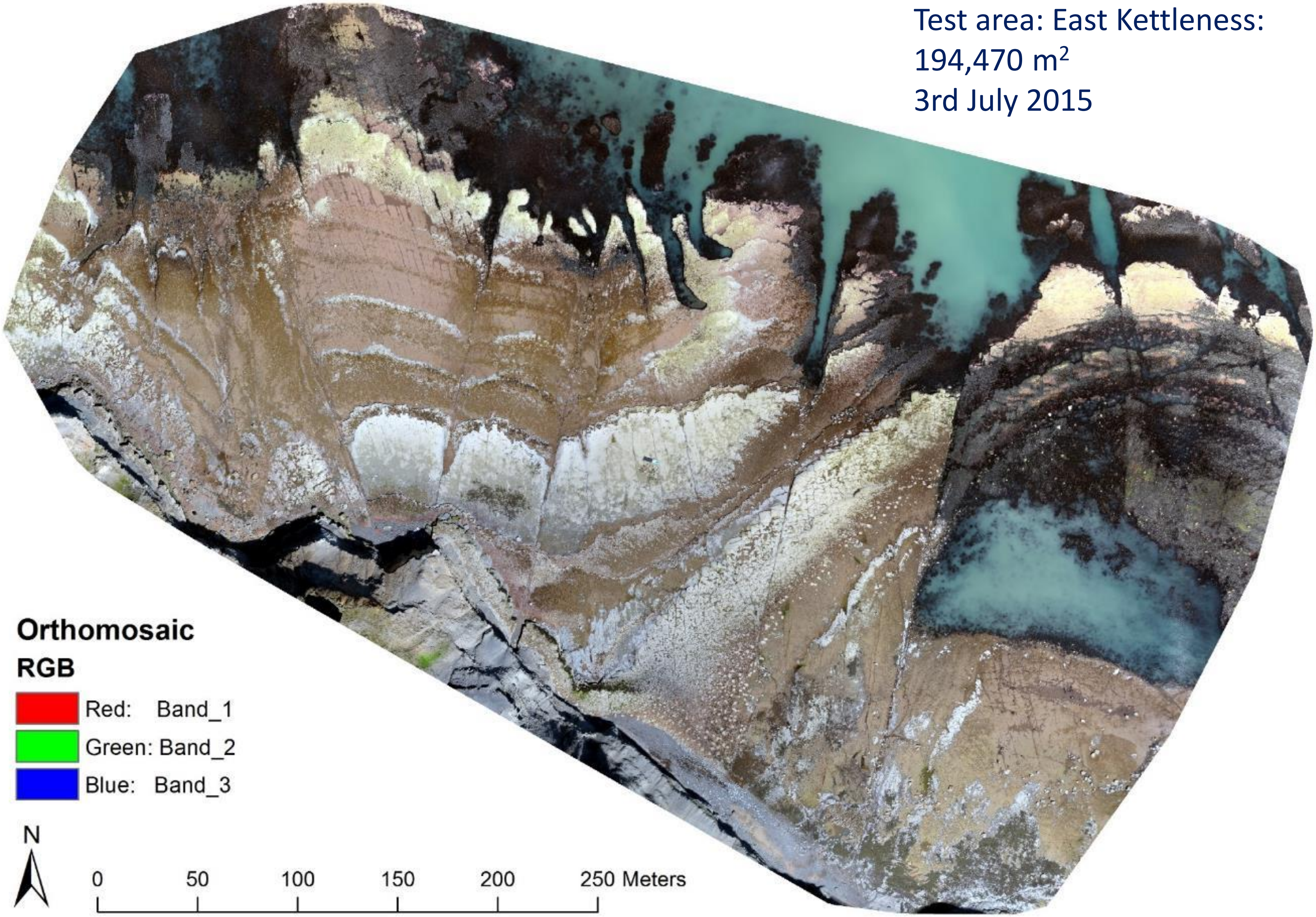
Canon S110 RGB and red edge camera specifications (senseFly, 2014)

Ground truth data

- Random sampling stratified by shore height.
- Faunal and algal cover and habitat class (*n* = 264)
- Marine Habitat Classification for Britain & Ireland v15.03 (Connor *et al*, 2004)
- Ground truth and GCP coordinates recorded using Leica Viva GS15.

UAV Data Processing

Test area: East Kettleness:
194,470 m^2
3rd July 2015



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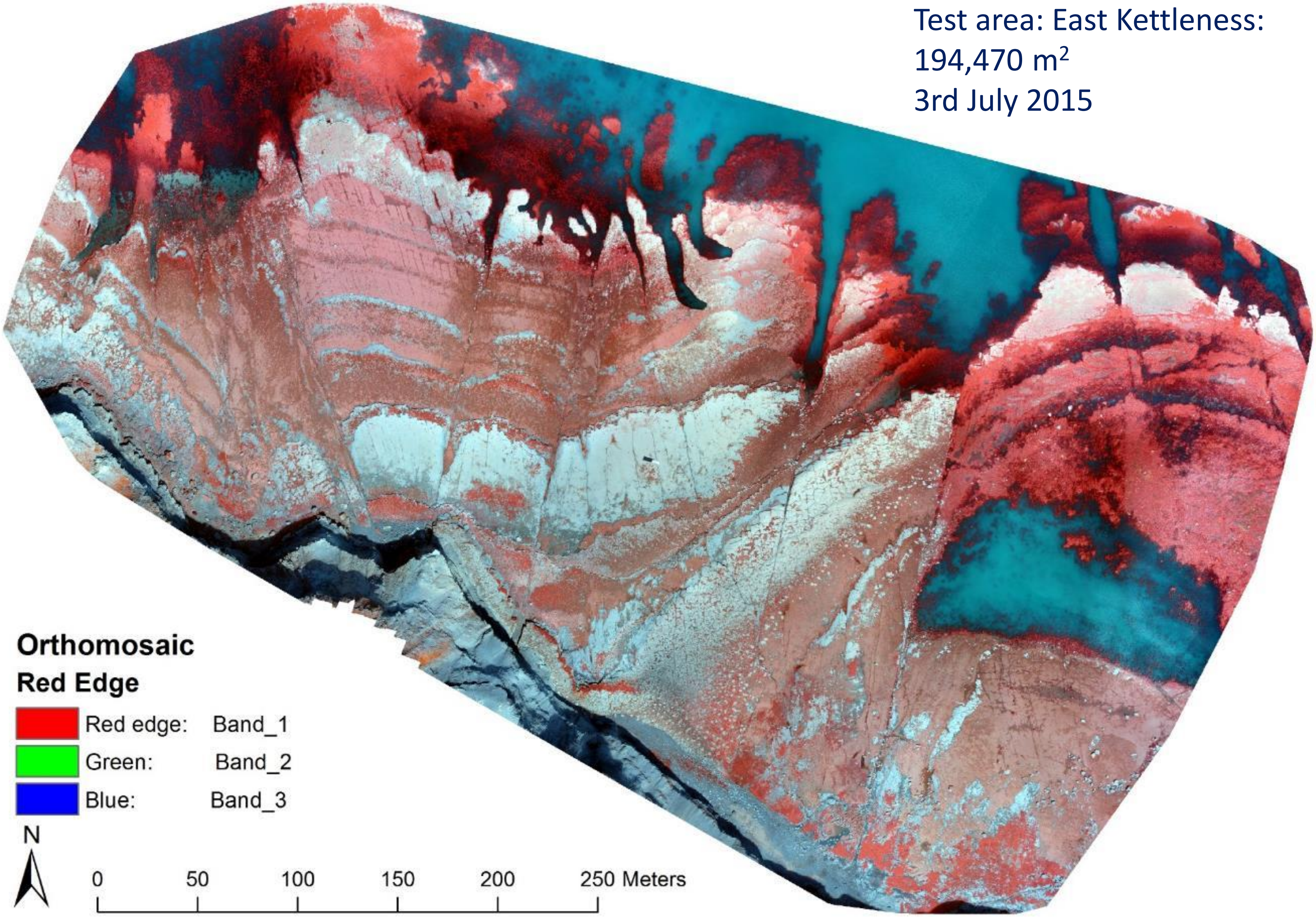

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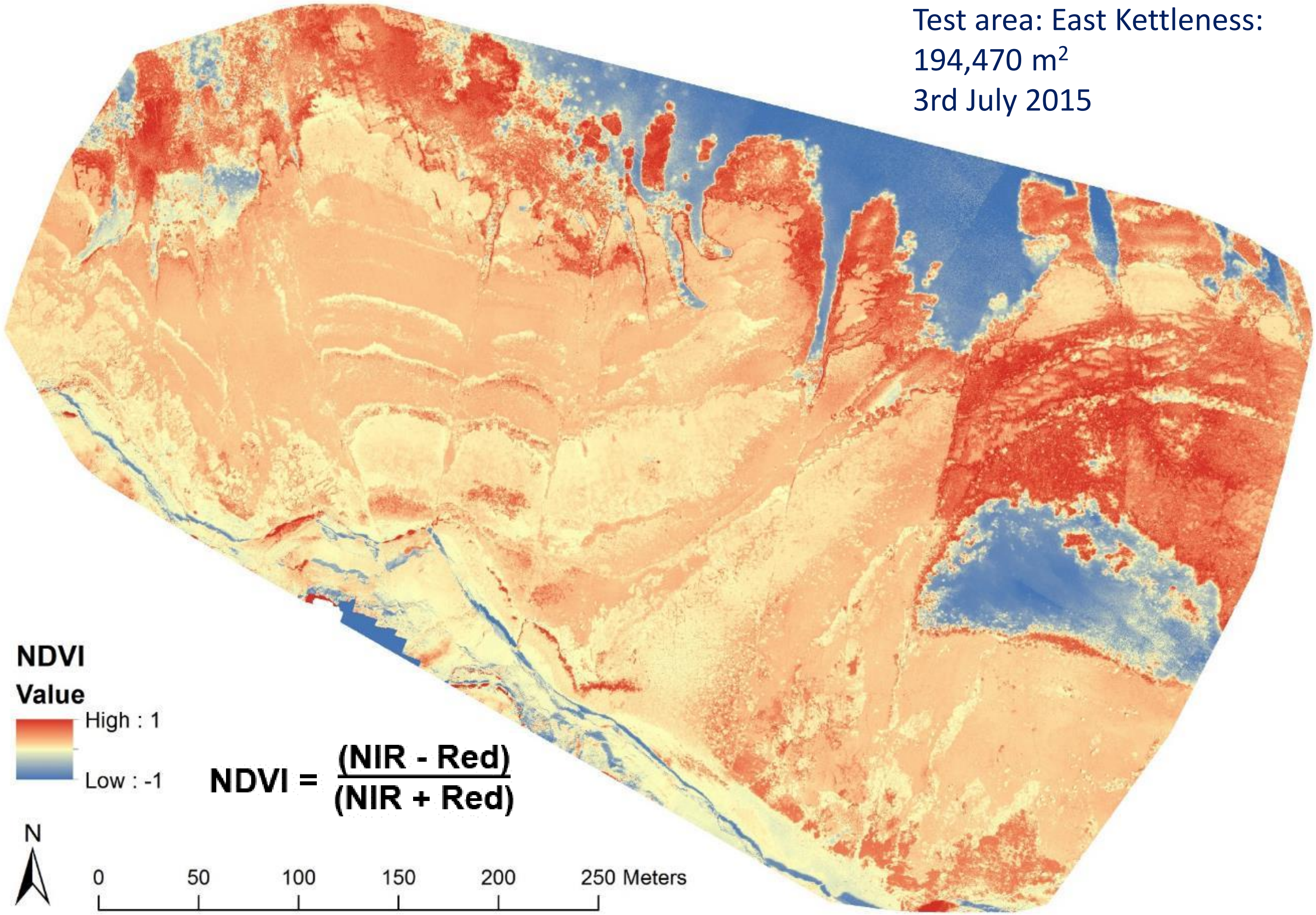

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

UAV Data Processing

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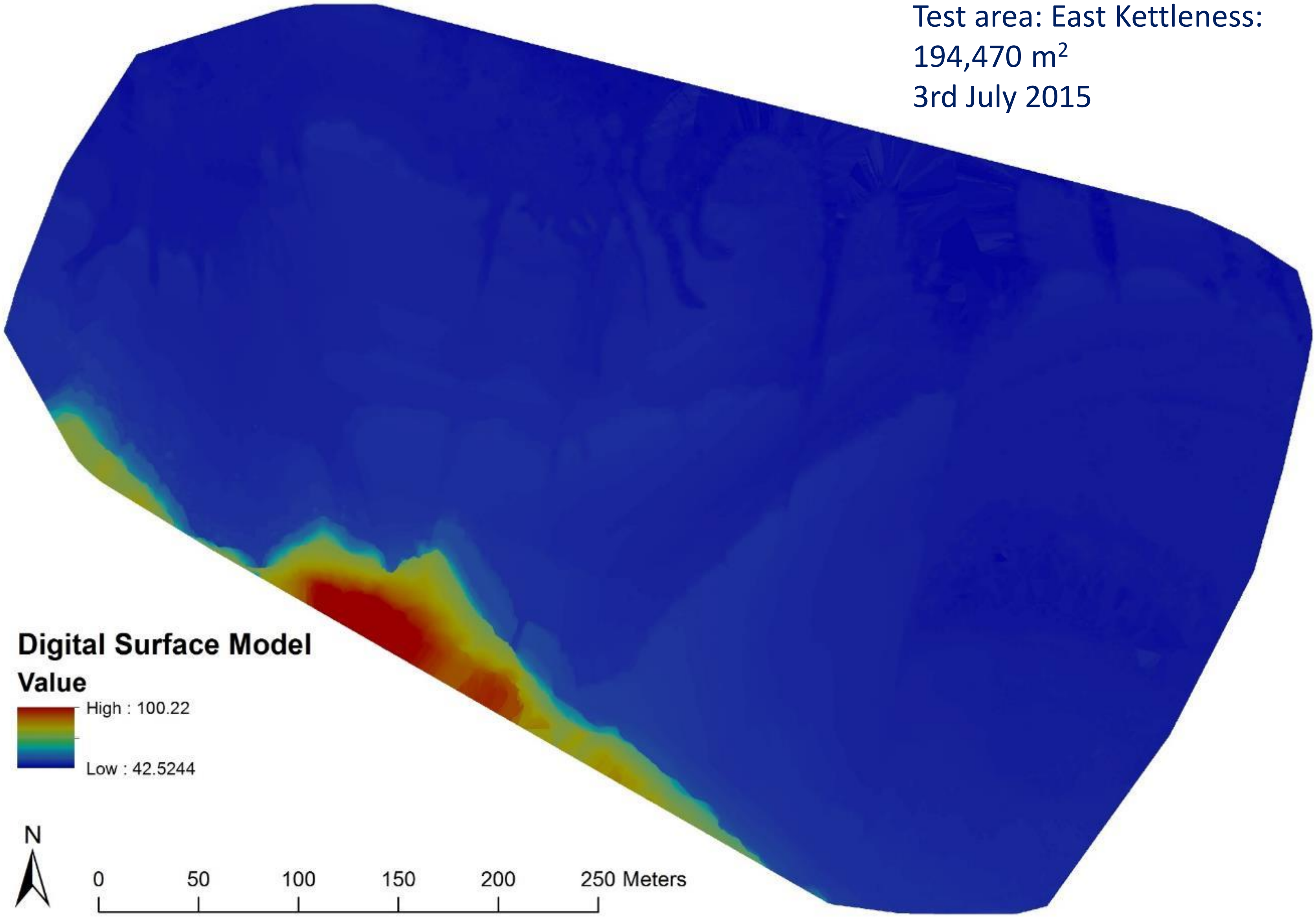

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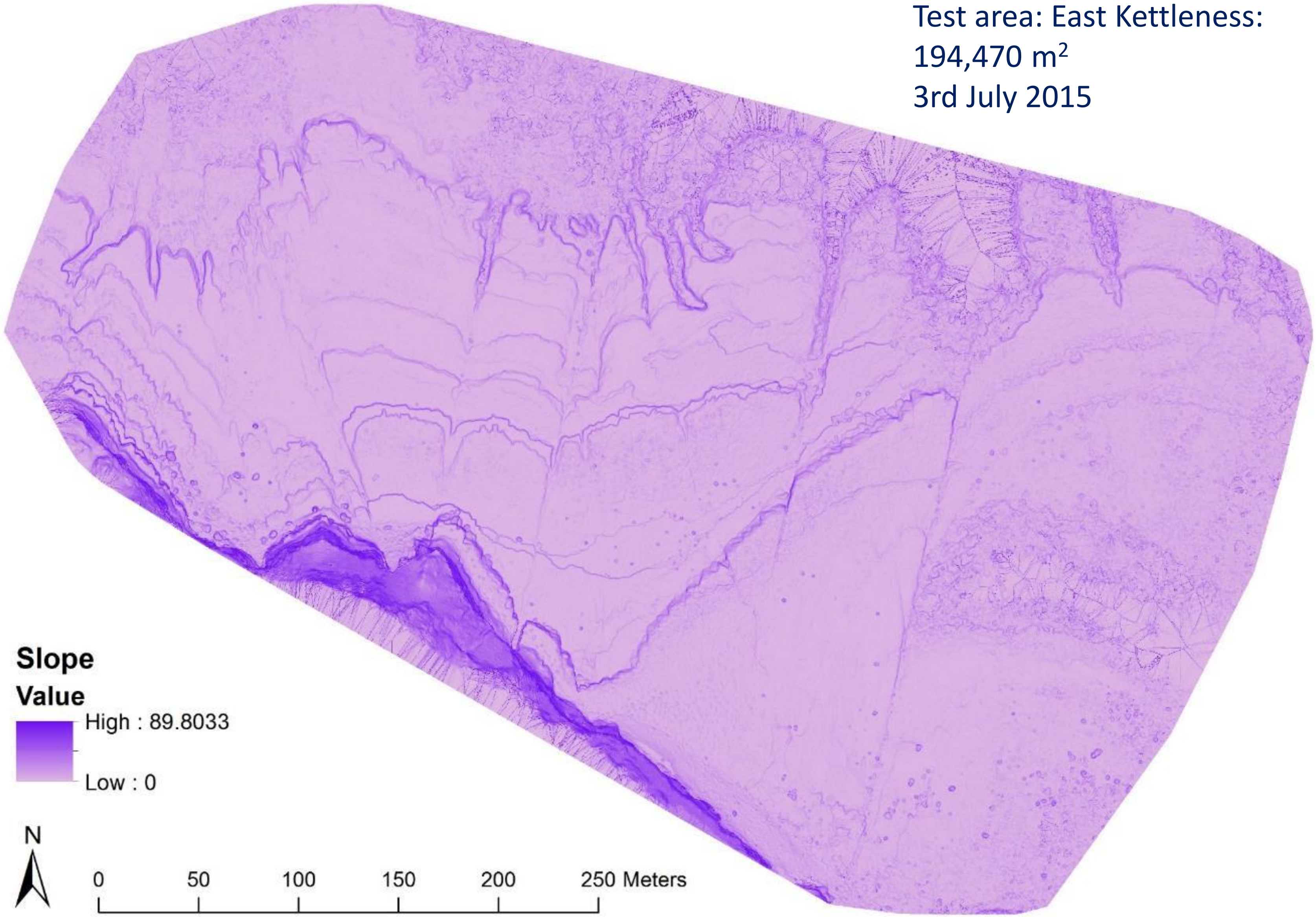


OBIA workflows

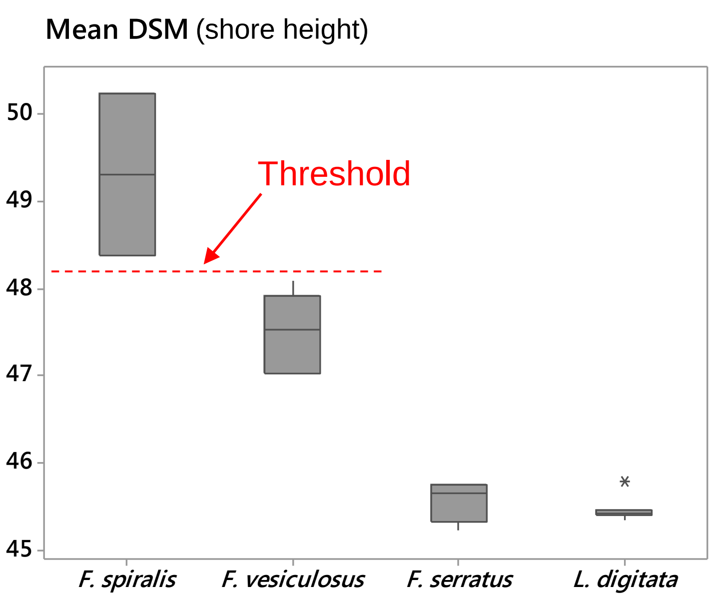
OBIA workflows created in eCognition Developer

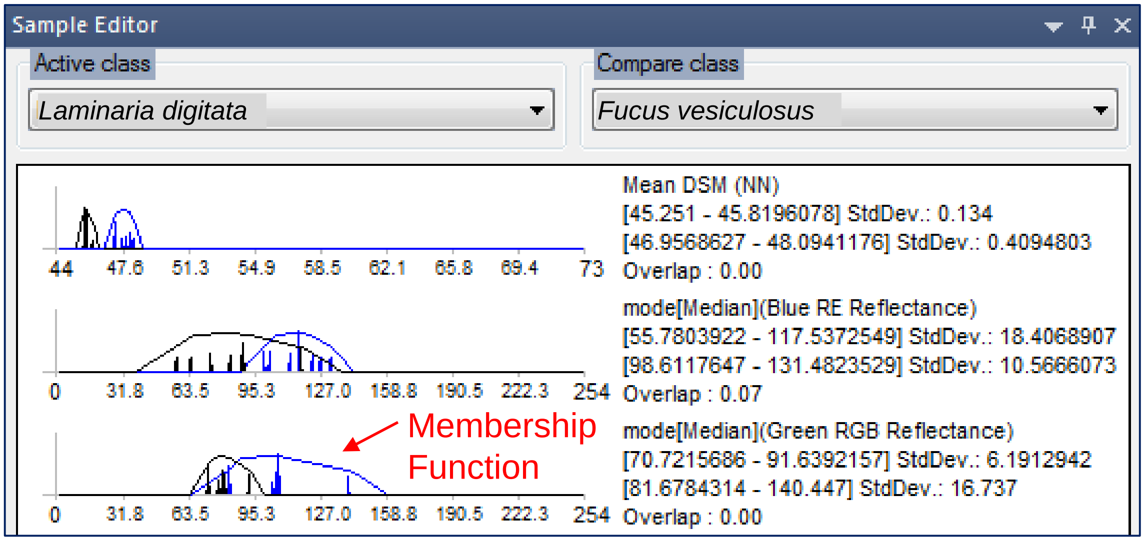
Three classification approaches:

- Standard Nearest Neighbour
- Random Forests (Breiman, 2001)
- Knowledge-based rules using thresholds and membership functions

Two sets of training samples

(2-fold cross validation)





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Two sets of training samples

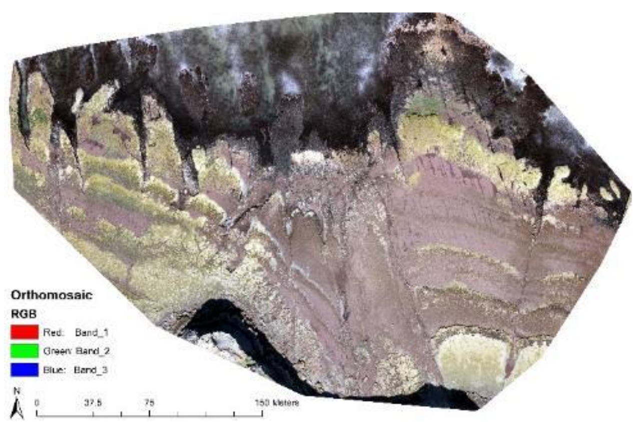
(2-fold cross validation)

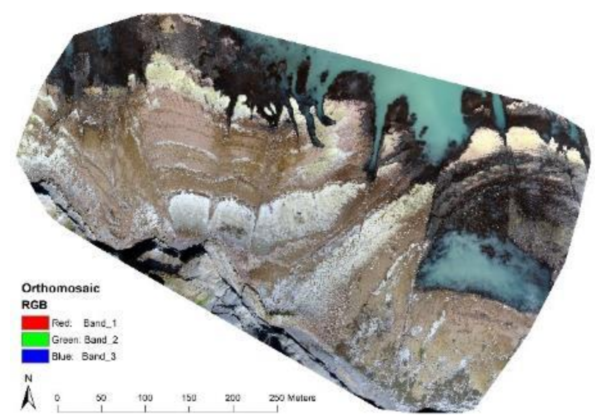
Two levels of thematic resolution:

- Broadscale habitats – red, green or brown algae, barnacles/bare rock
- Biotopes

Two datasets:

- Kettleness East, July 2015
- Kettleness West, Sept. 2015

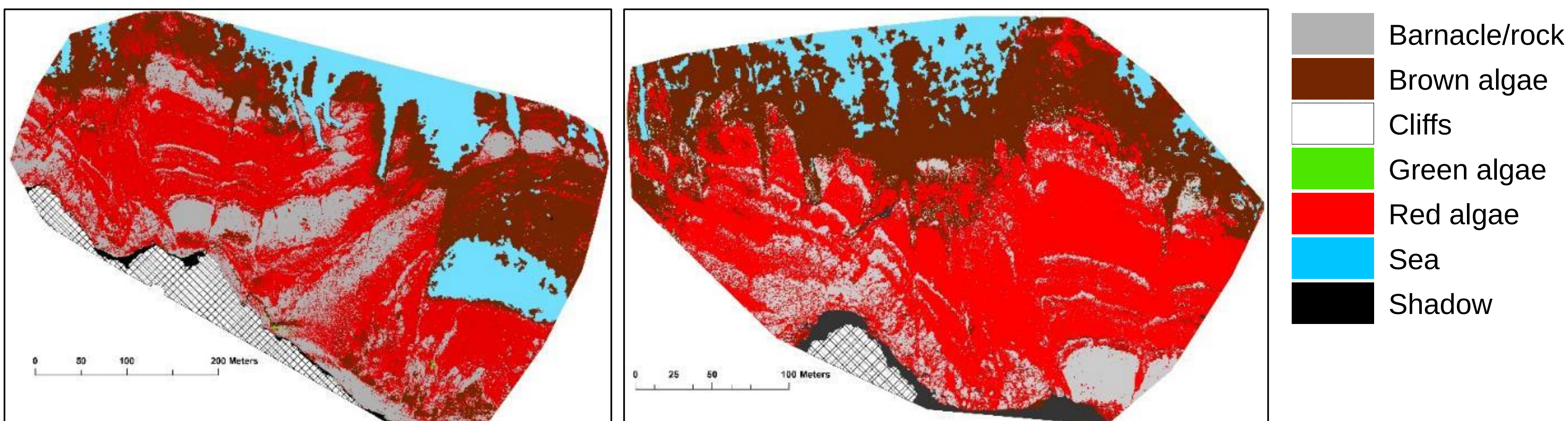




Results – broadscale maps

		Overall Accuracy	Kappa	Balanced Error Rate
Dataset 1 (July 2015)	Standard Nearest Neighbour (training samples a)	80%	0.67	14%
	Standard Nearest Neighbour (training samples b)	85%	0.76	44%
	Random Forests (training samples a)	95%	0.91	27%
	Random Forests (training samples b)	90%	0.83	10%
	Knowledge-based rules	84%	0.73	38%
Dataset 2 (Sep. 2015)	SNN (training samples a)	77%	0.62	19%
	SNN (training samples b)	87%	0.77	27%
	Random Forests (training samples a)	68%	0.46	48%
	Random Forests (training samples b)	88%	0.80	32%
	Knowledge-based rules	80%	0.67	28%

Example – broadscale habitat maps produced using the knowledge-based OBIA workflow:

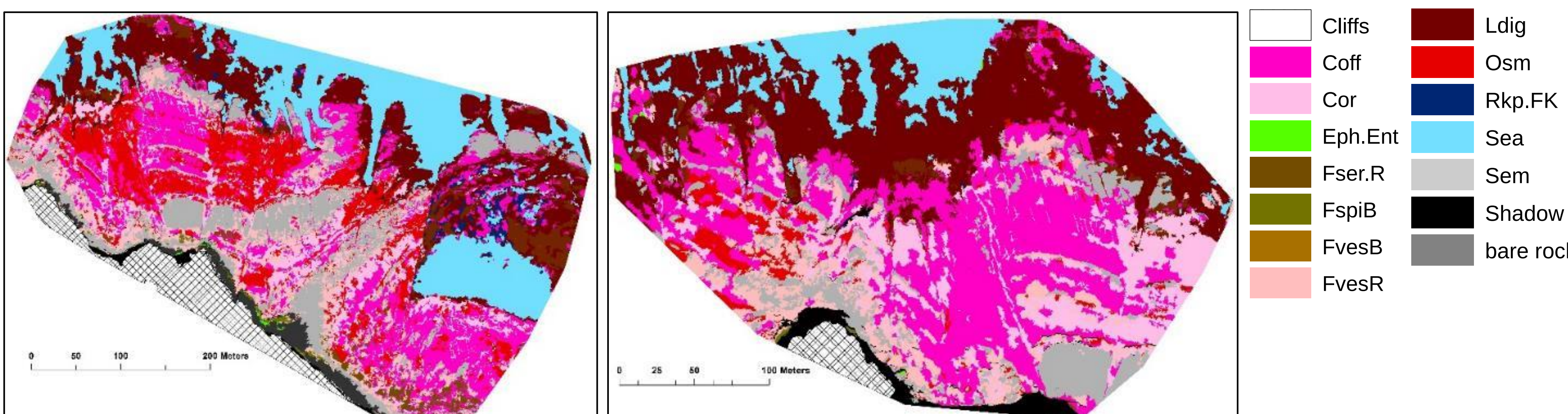


Results – biotope maps

		Overall Accuracy	Kappa	Balanced Error Rate
Dataset 1 (July 2015)	Standard Nearest Neighbour (training samples a)	41%	0.35	68%
	Standard Nearest Neighbour (training samples b)	56%	0.48	51%
	Random Forests (training samples a)	66%	0.60	27%
	Random Forests (training samples b)	63%	0.57	51%
	Knowledge-based rules	70%	0.66	24%
Dataset 2 (Sep. 2015)	SNN (training samples a)	28%	0.10	77%
	SNN (training samples b)	27%	0.12	76%
	Random Forests (training samples a)	59%	0.48	47%
	Random Forests (training samples b)	54%		
	Knowledge-based rules	31%		

Low accuracy due to misclassification of *Osmundea* as *Corallina* caused by a change in this species' spectral signature from July to September (bleaching).

Example – biotope maps produced using the knowledge-based OBIA workflow:

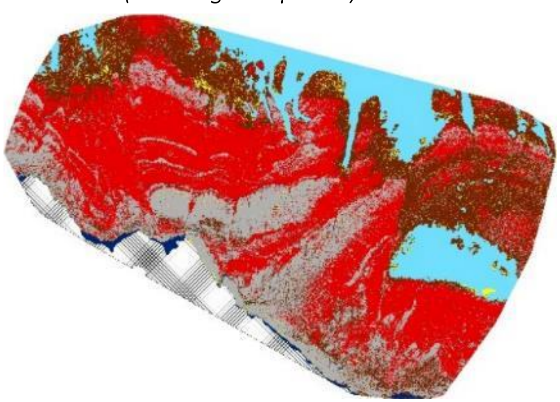


Results – consistency

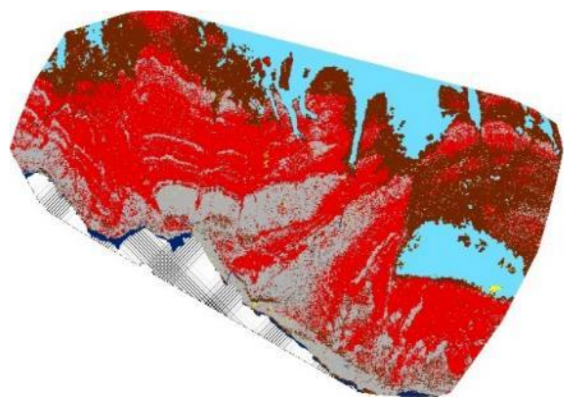
	Percentage of map area with the same classification in both maps	
Dataset and thematic scale	**Standard Nearest Neighbour**	**Random Forests**
Dataset 1: Broadscale habitat map	79%	92%
Dataset 2: Broadscale habitat map	74%	83%
Dataset 1: Biotope map	32%	62%
Dataset 2: Biotope map	23%	72%

Dataset 1 (Kettleness east, July 2015)

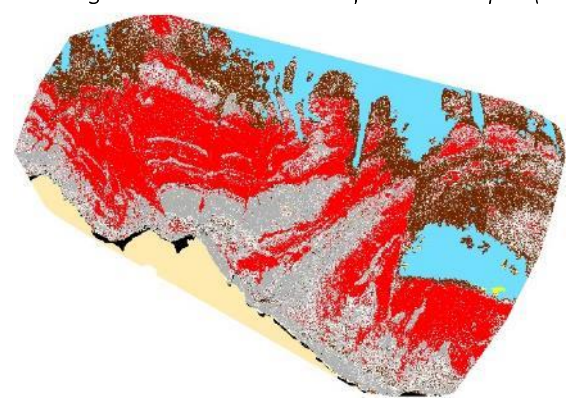
SNN (training samples A)



SNN (training samples B)

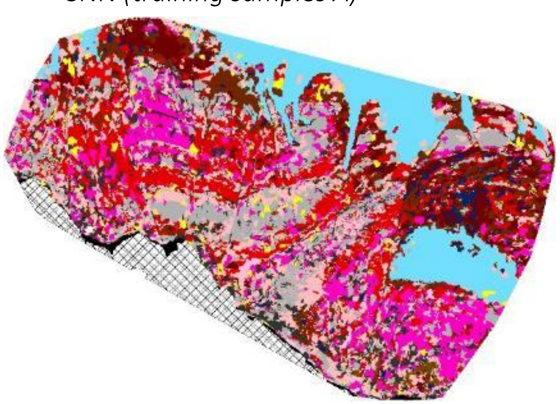


*Agreement between map A and map B (**79%**)*

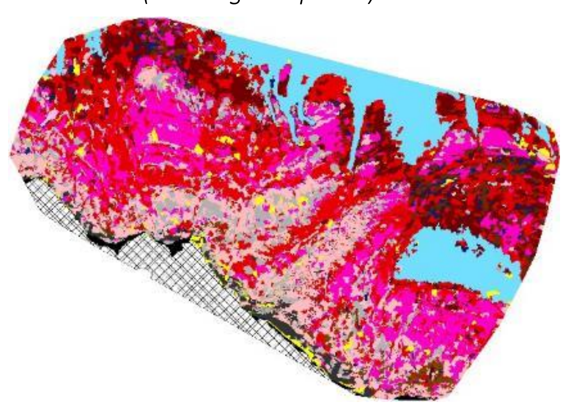


Dataset 1 (Kettleness east, July 2015)

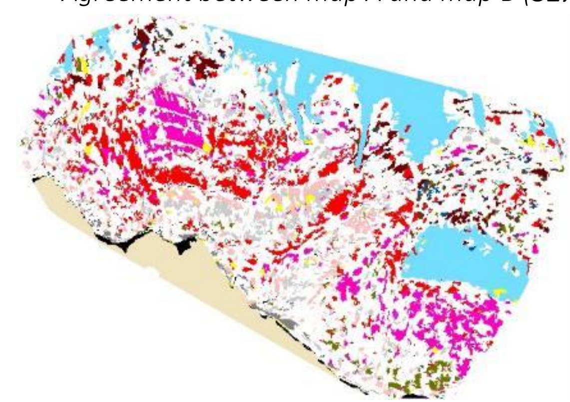
SNN (training samples A)



SNN (training samples B)



*Agreement between map A and map B (**32%**)*



Conclusions

- OBIA of UAV imagery has great potential for mapping and monitoring temperate rocky shore habitats.
- OBIA of UAV imagery produces accurate, consistent broadscale habitat maps.
- Biotope mapping is possible, but accuracy and consistency vary with classification approach and sampling protocol.
- Biotope map accuracy could be improved by:
  - Refining knowledge-based OBIA workflows to allow for seasonal change
  - Improving sampling strategy to increase samples of locally rare habitats
  - Reducing ground sampling distance
  - Capturing multispectral imagery.

Using UAVs for MSc teaching

NATURAL ENGLAND

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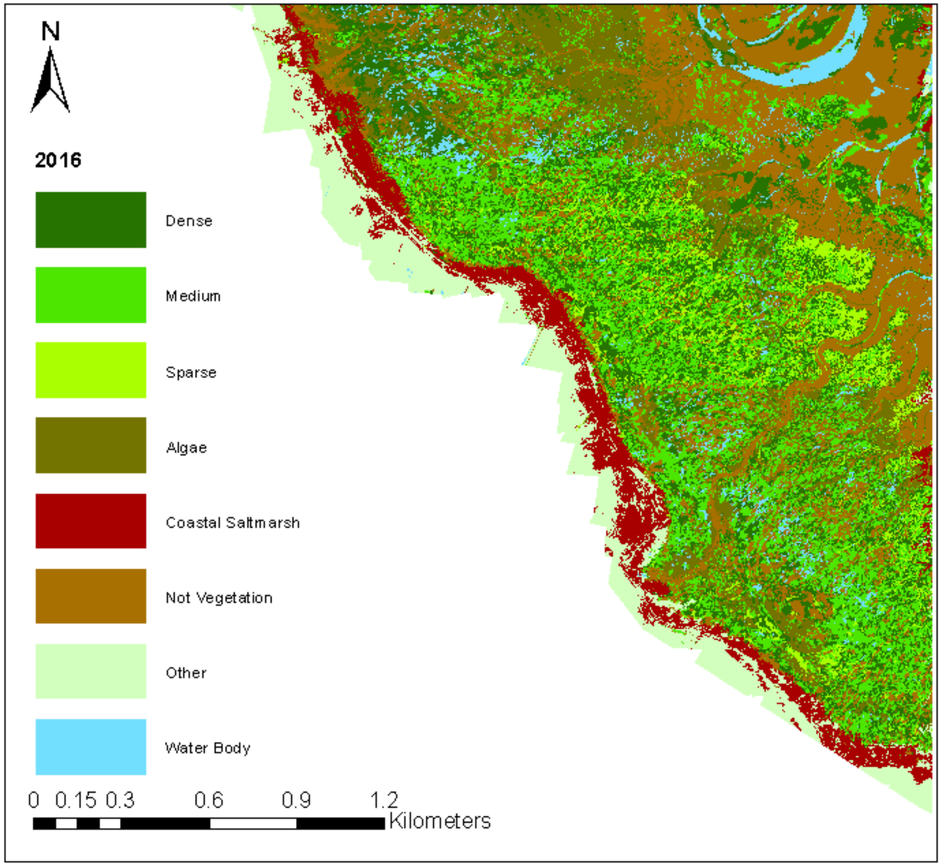
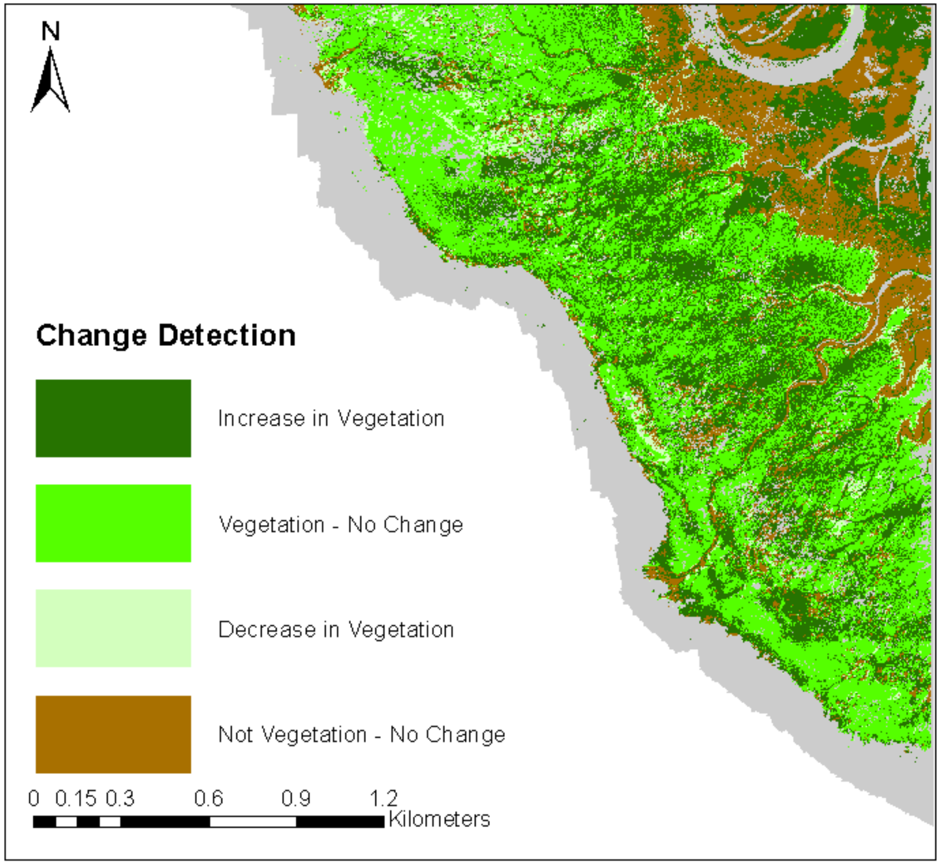
Object-based image analysis methods developed for mapping and monitoring change in extent and distribution of habitats on Lindisfarne National Nature Reserve.



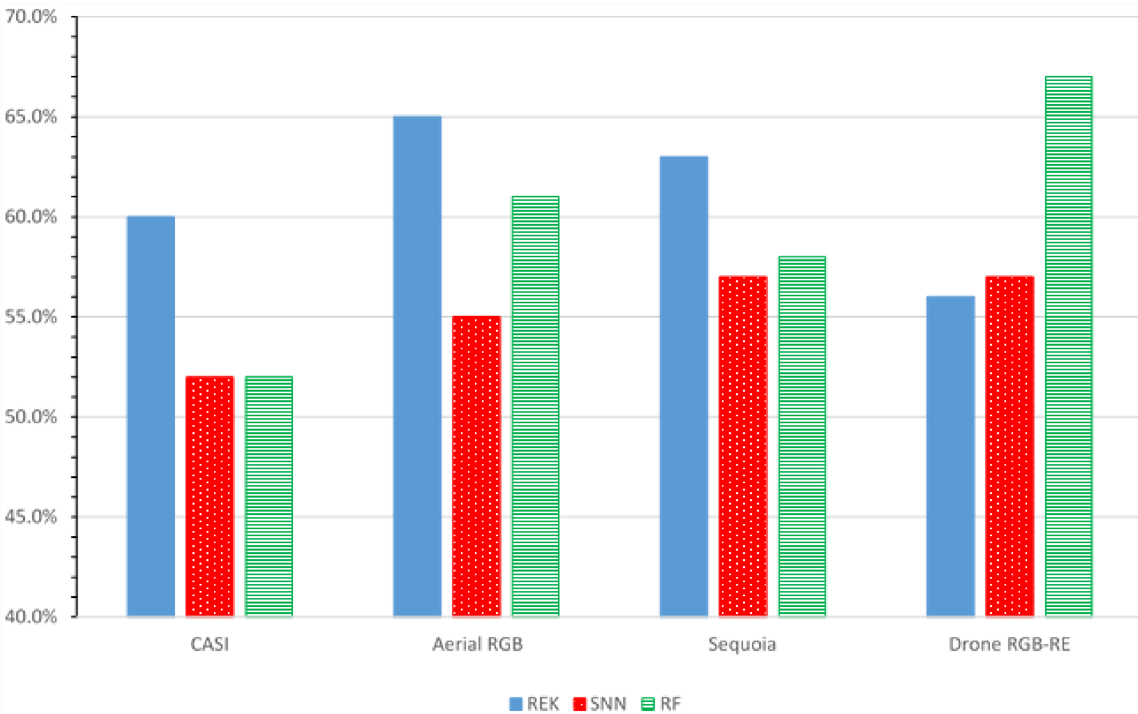


Vegetation density could be mapped from 3-band UAV imagery (78% overall accuracy), but separating seagrass from green algae proved challenging.

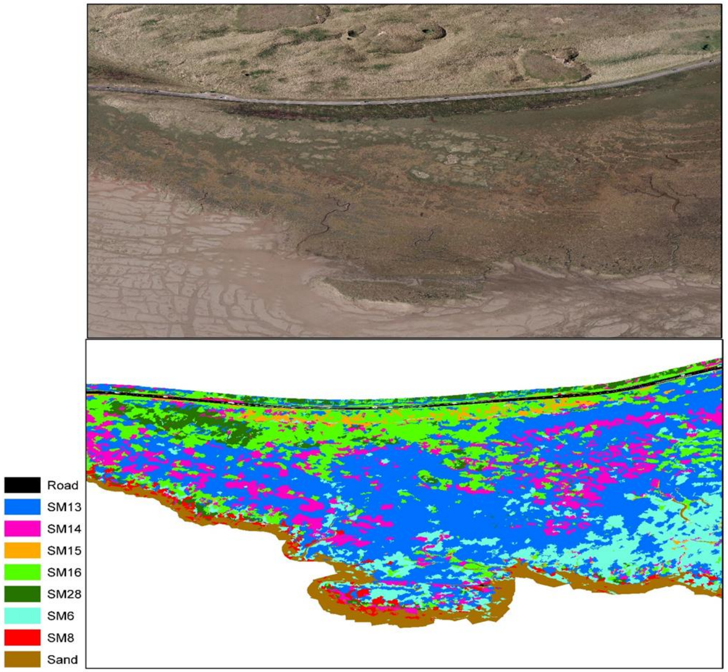
Hannah Gray, MSc International Marine Environmental Consultancy, 2017.

Using UAVs for MSc teaching

Comparison of four sensors, two platforms and three object-based image analysis approaches for mapping saltmarsh vegetation communities on Lindisfarne.



Overall accuracies of the 12 saltmarsh habitat maps produced by rules based on ecological knowledge (REK), standard nearest neighbour (SNN) and random forest (RF)



Comparison of aerial RGB (top) and a model produced using SNN algorithms and Sequoia imagery (bottom).

OBIA of aerial and UAV imagery produced saltmarsh community maps with up to 67% overall accuracy. Random forest classification of 4-band UAV imagery produced the best results.

Harry Garside, MSc International Marine Environmental Consultancy, 2018.

Collaboration and Next Steps

- Regional knowledge-transfer workshop in March 2018 for 50 researchers and practitioners.
- NE North East Area Team and Newcastle University have purchased equipment. Staff are training for PfCO.
- Consultation summer 2018:
  - Natural England North East Area Team and EEOS
  - Durham County Council
  - North and East Yorkshire Ecological Data Centre
  - North Eastern Inshore Fisheries & Conservation Authority
  - Northumberland Inshore Fisheries & Conservation Authority
- Identified requirements for regional marine and coastal applications.
- Currently seeking funding for collaborative research and development.

Thank you!
Any Questions?

Newcastle University

Thanks to:

NATURAL ENVIRONMENT RESEARCH COUNCIL

NATURAL ENGLAND

NORTH & EAST YORKSHIRE ECOLOGICAL DATA CENTRE

UKEOF
ENVIRONMENTAL OBSERVATION FRAMEWORK

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