Roughness metrics as indicators of oyster reef health + Multiscale mapping

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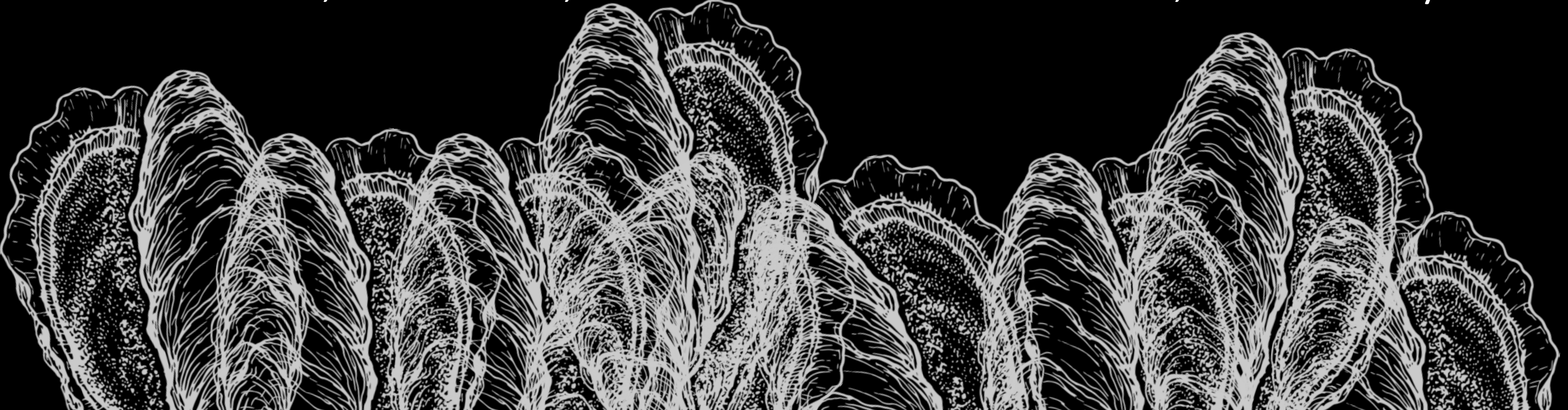
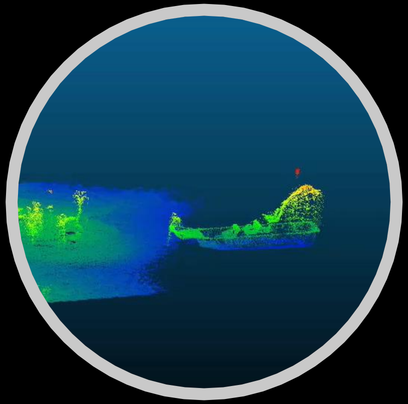
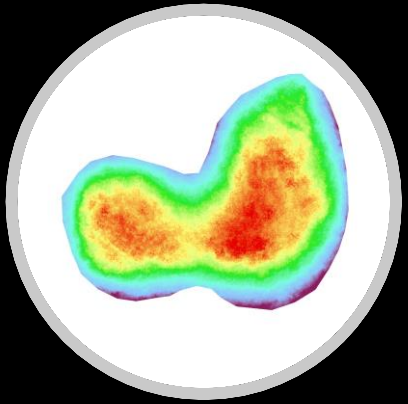


Background and Objective

Sampling challenges



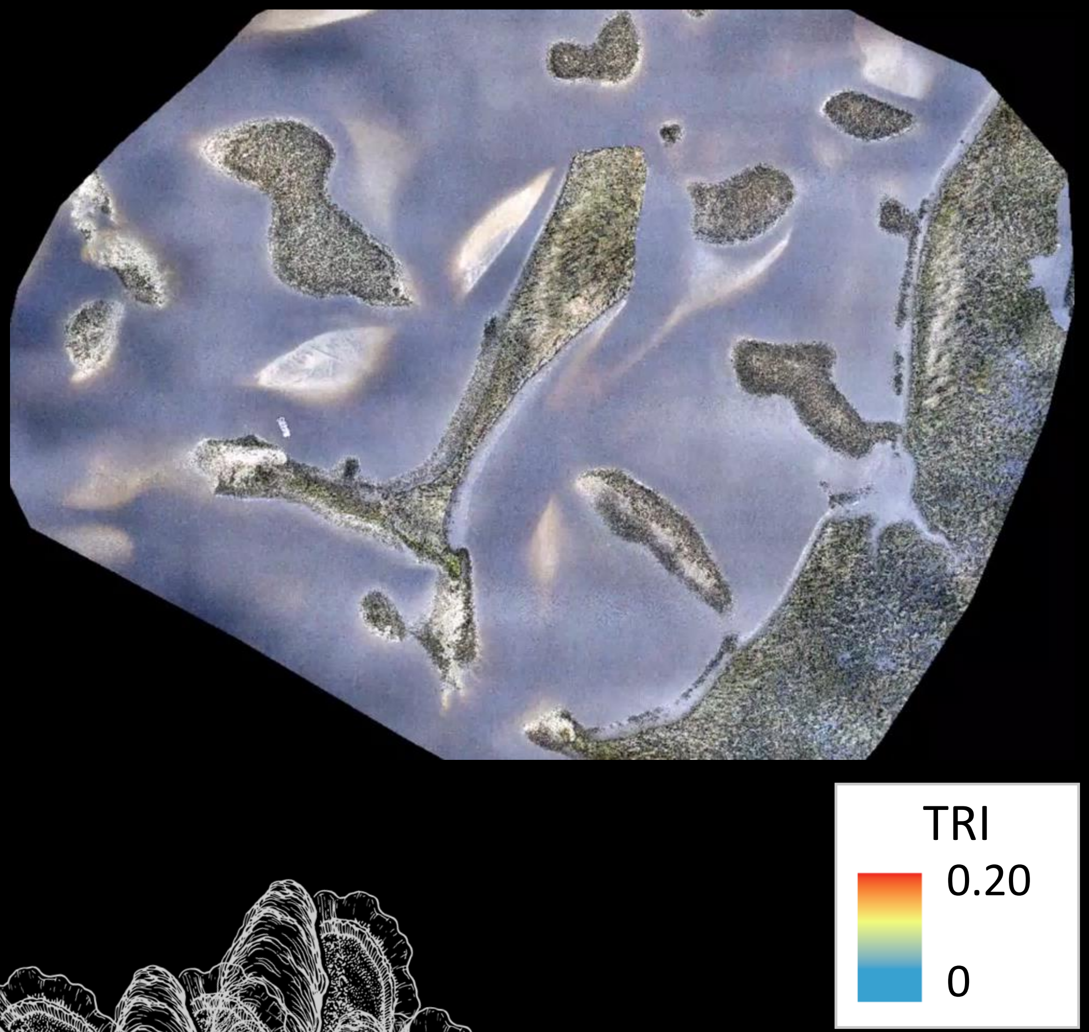
Drone lidar data



Roughness metrics as indicators of health

Approach

- Perform oyster counts
- Survey area using lidar equipped drone
- Generate digital surface model from lidar point cloud
- Derive roughness metrics
- Develop models relating live oyster counts to roughness metrics



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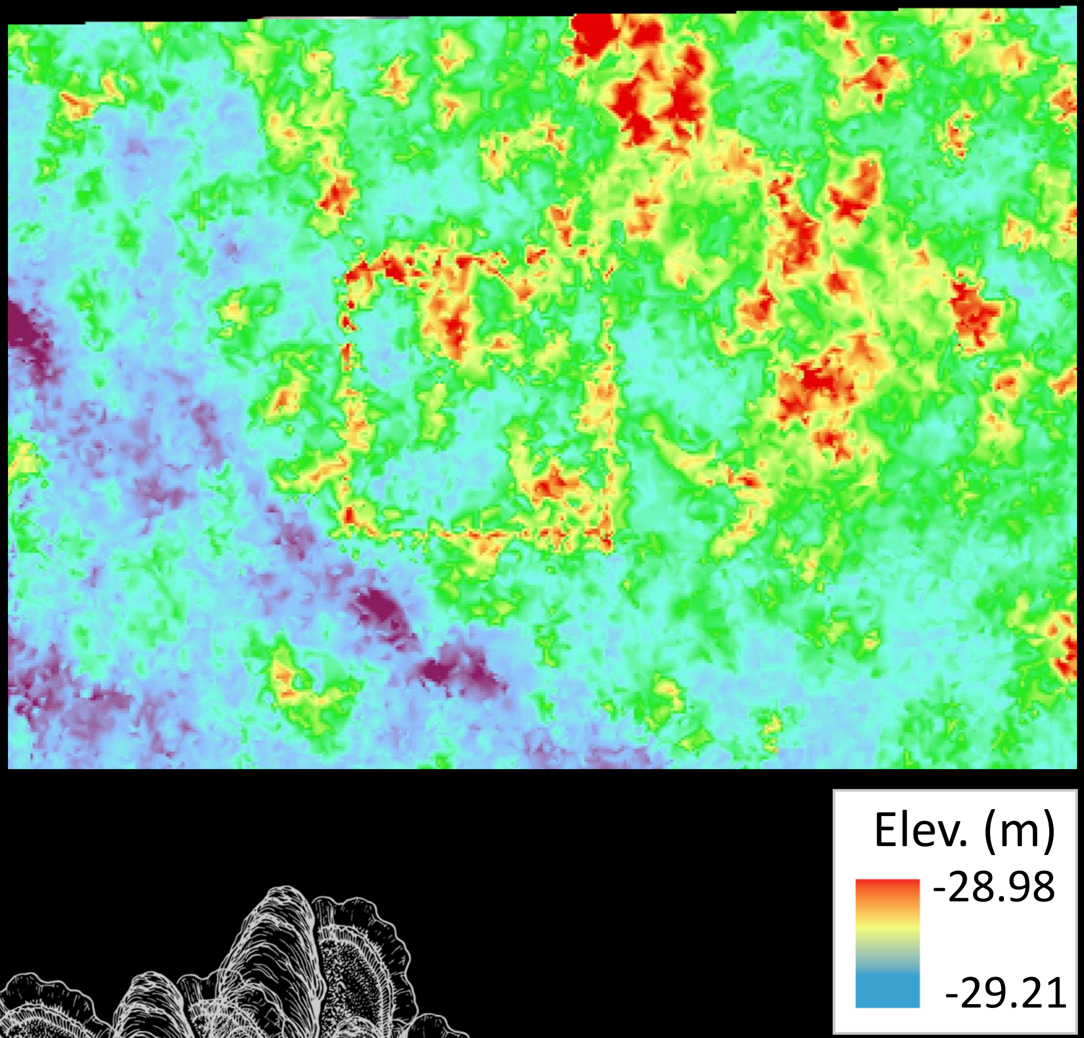

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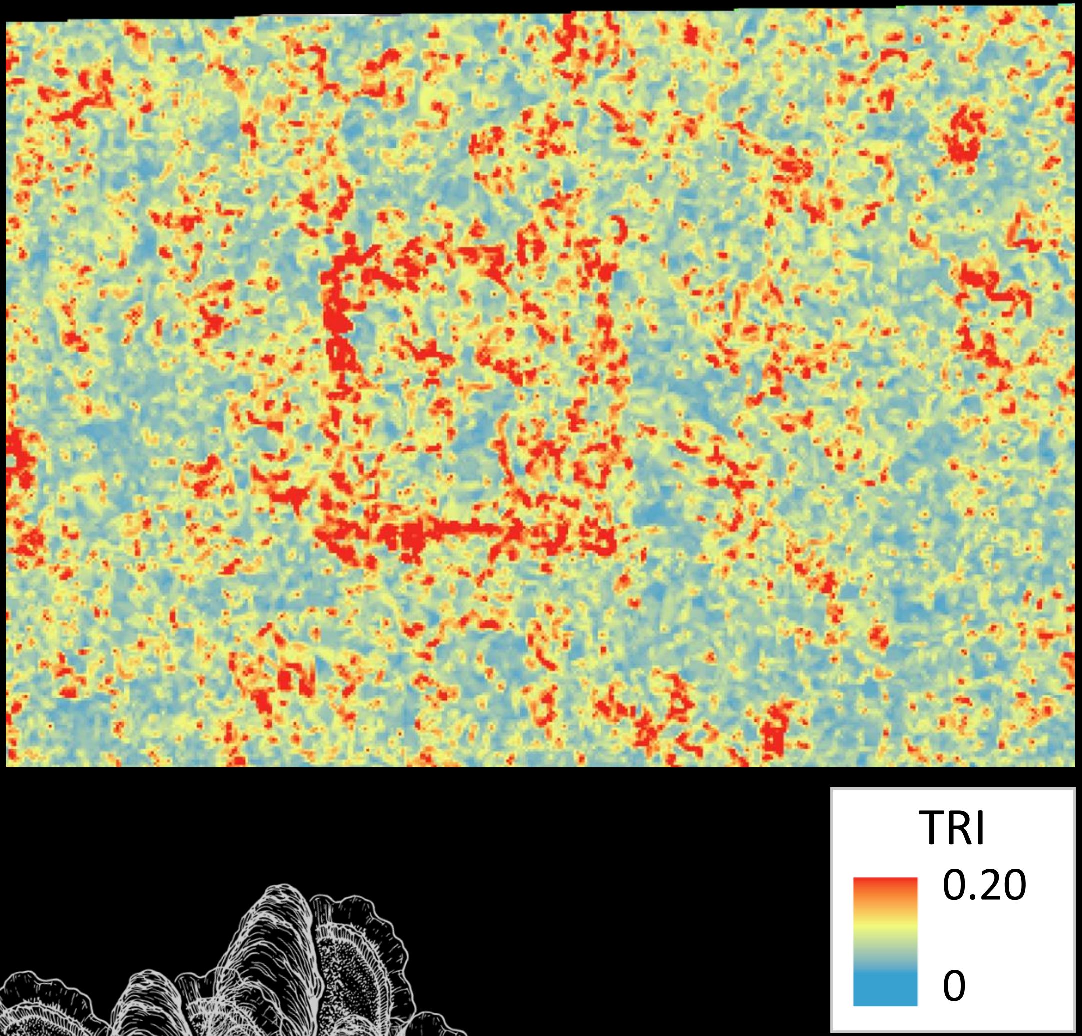
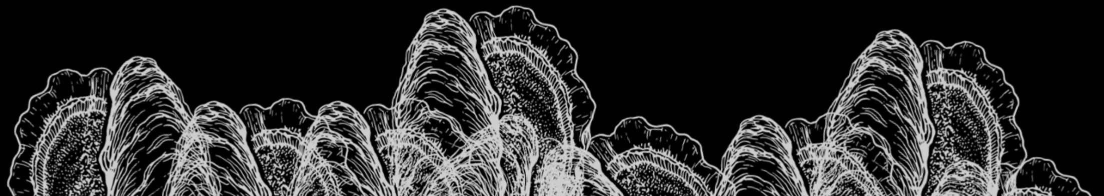


Results and Conclusions

- 4 of 60 variables produced statistically significant models
  - Skewness, kurtosis, skewness of magnitude, volume
- Roughness metrics can inform oyster monitoring
- Limitations
  - Small sample size
  - One study site

Metric	P-value	AIC
Skewness of elevation values	0.011	44.17
Kurtosis of elevation values	0.048	45.09
Skewness of multiscale roughness	0.019	44.72
Volume	0.015	44.09



Multiscale Habitat Mapping

- 3-band (red, green, blue) imagery

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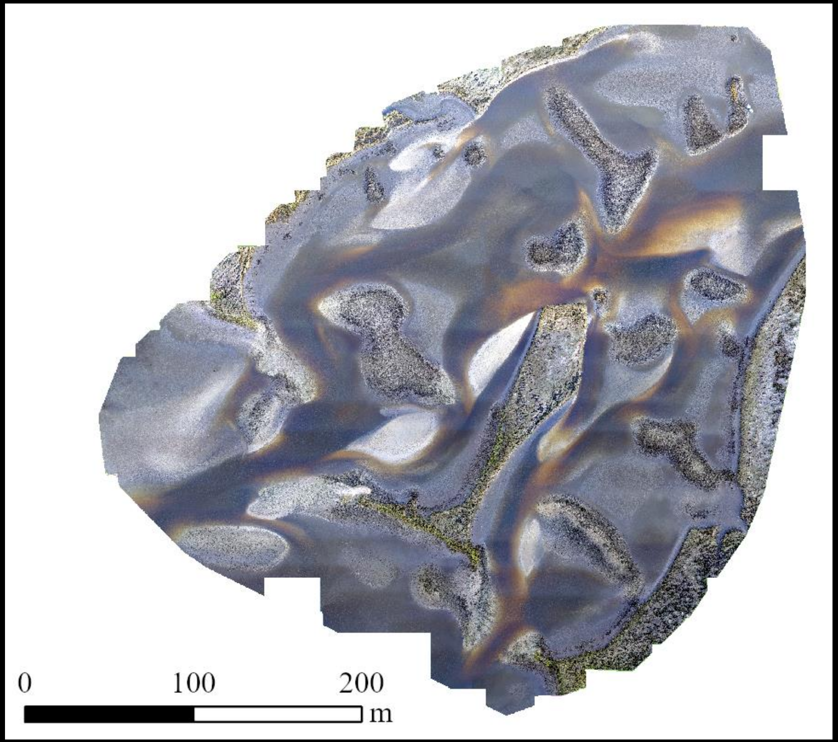
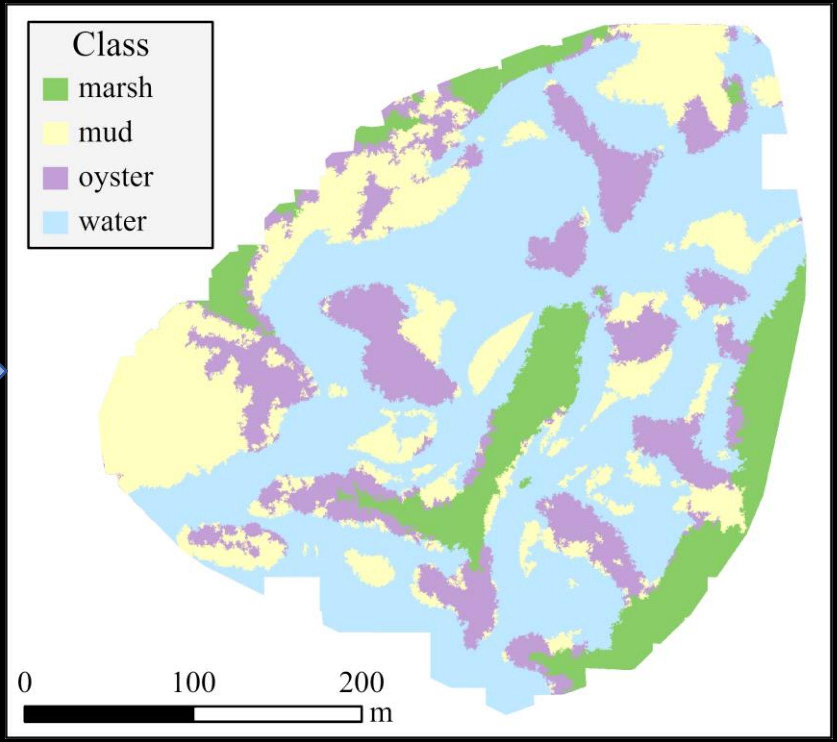
- Utility of habitat maps



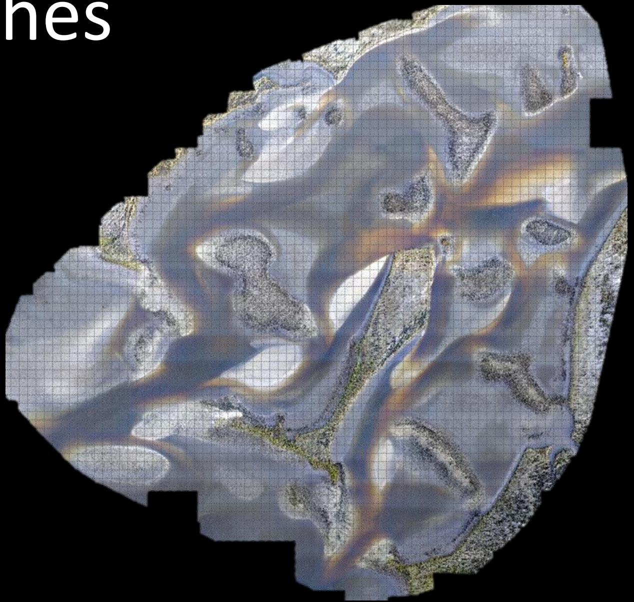


Multiscale Habitat Mapping

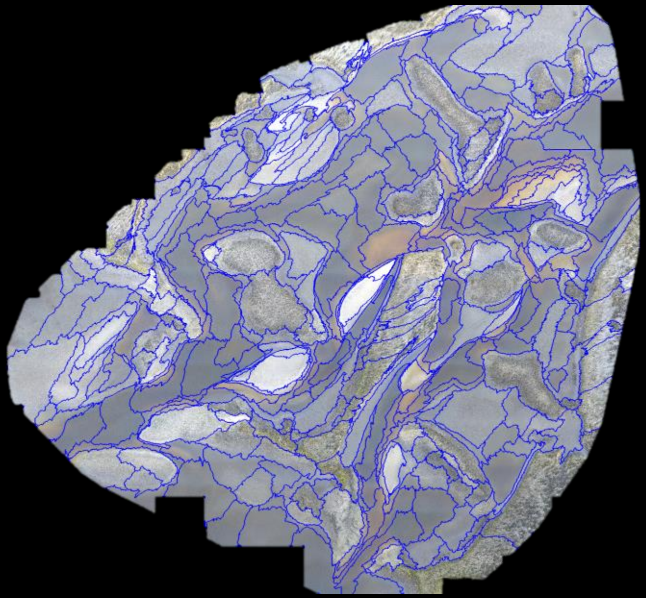
- 3-band (red, green, blue) imagery
- Utility of habitat maps
- Importance of scale
  - Processing considerations
  - Scale is process and habitat specific

Objectives

- Determine optimal imagery resolutions to map intertidal habitats with a high level of accuracy using geographic object-based image analysis
- Assess the improvement in classifications by using multiscale approaches



Traditional pixel-based



Object-based

Approach

Collect imagery → Generate orthomosaic and DSM → Resample products → Optimize segmentation parameters → Segment and classify each resolution

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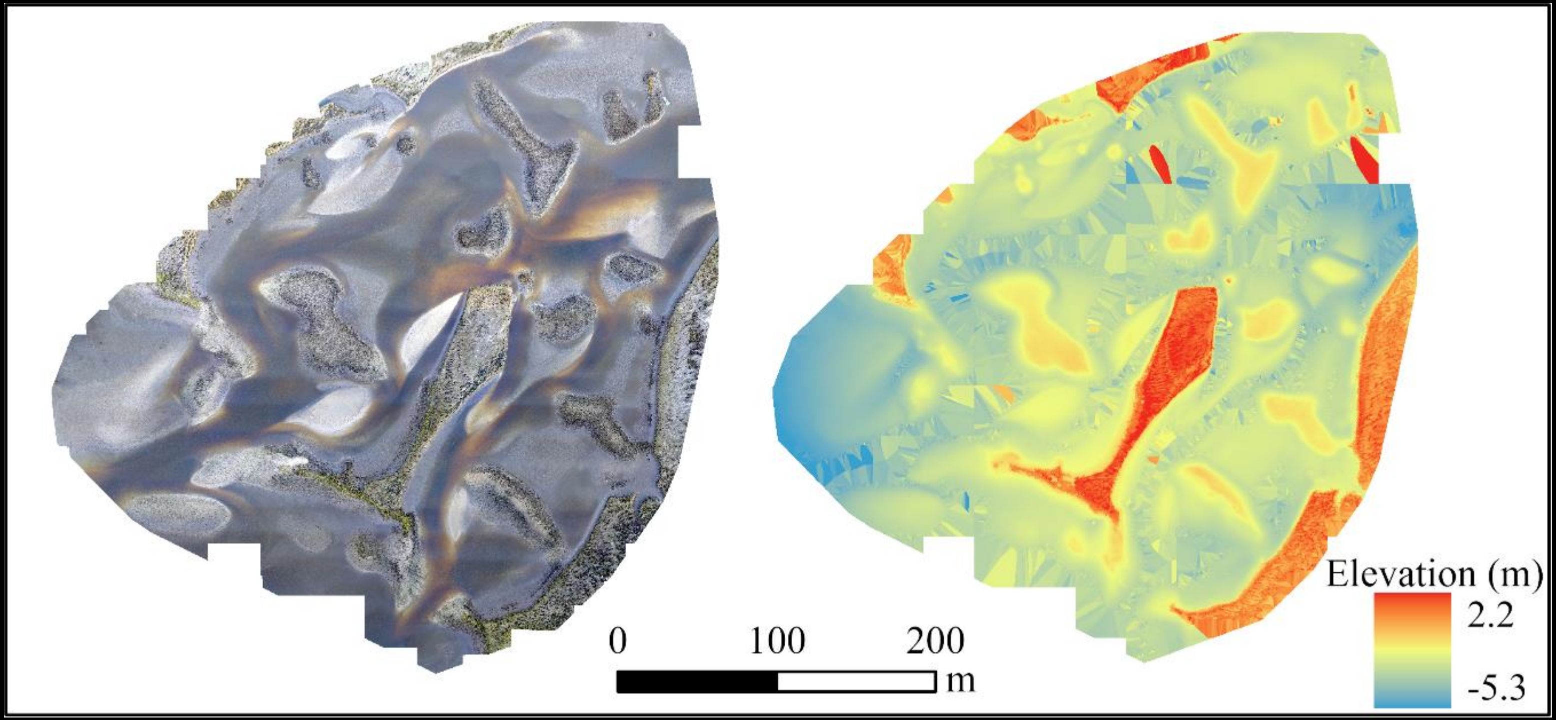

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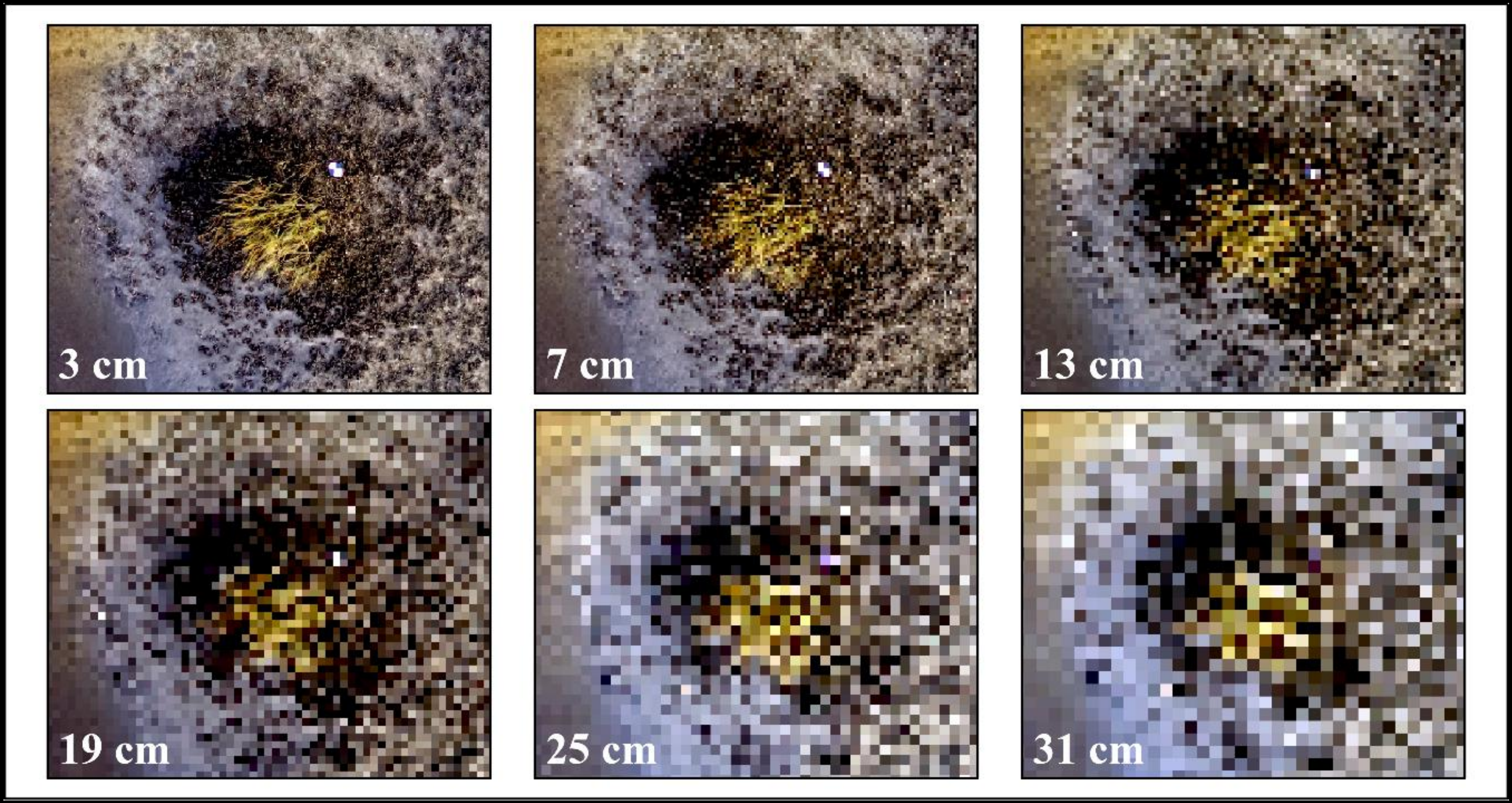

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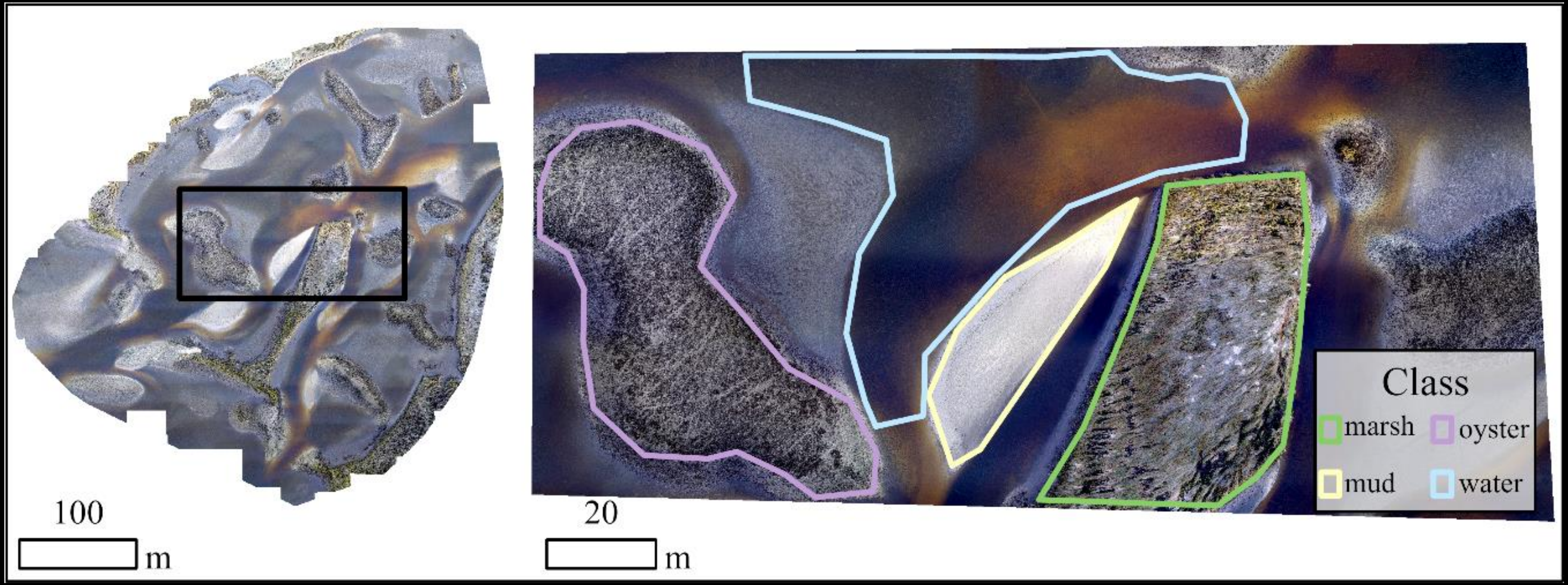

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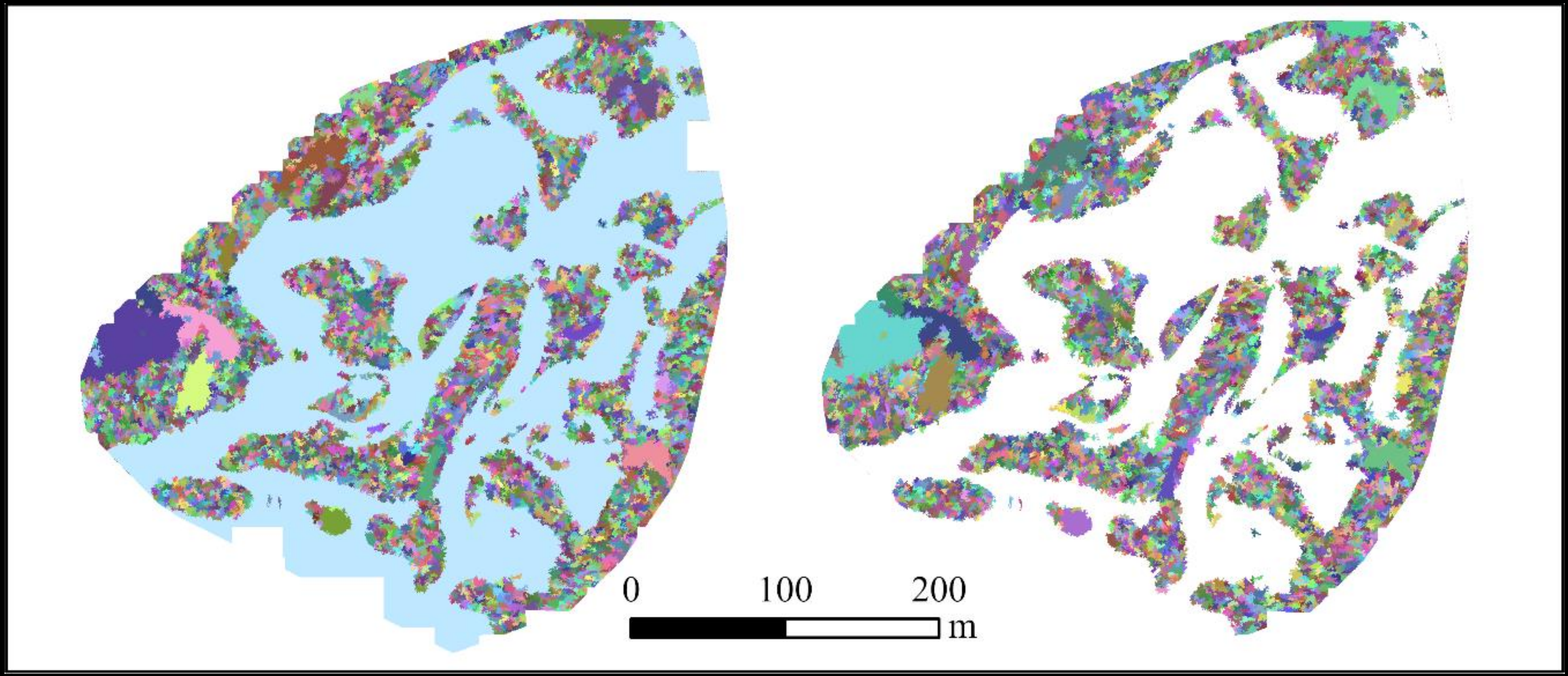
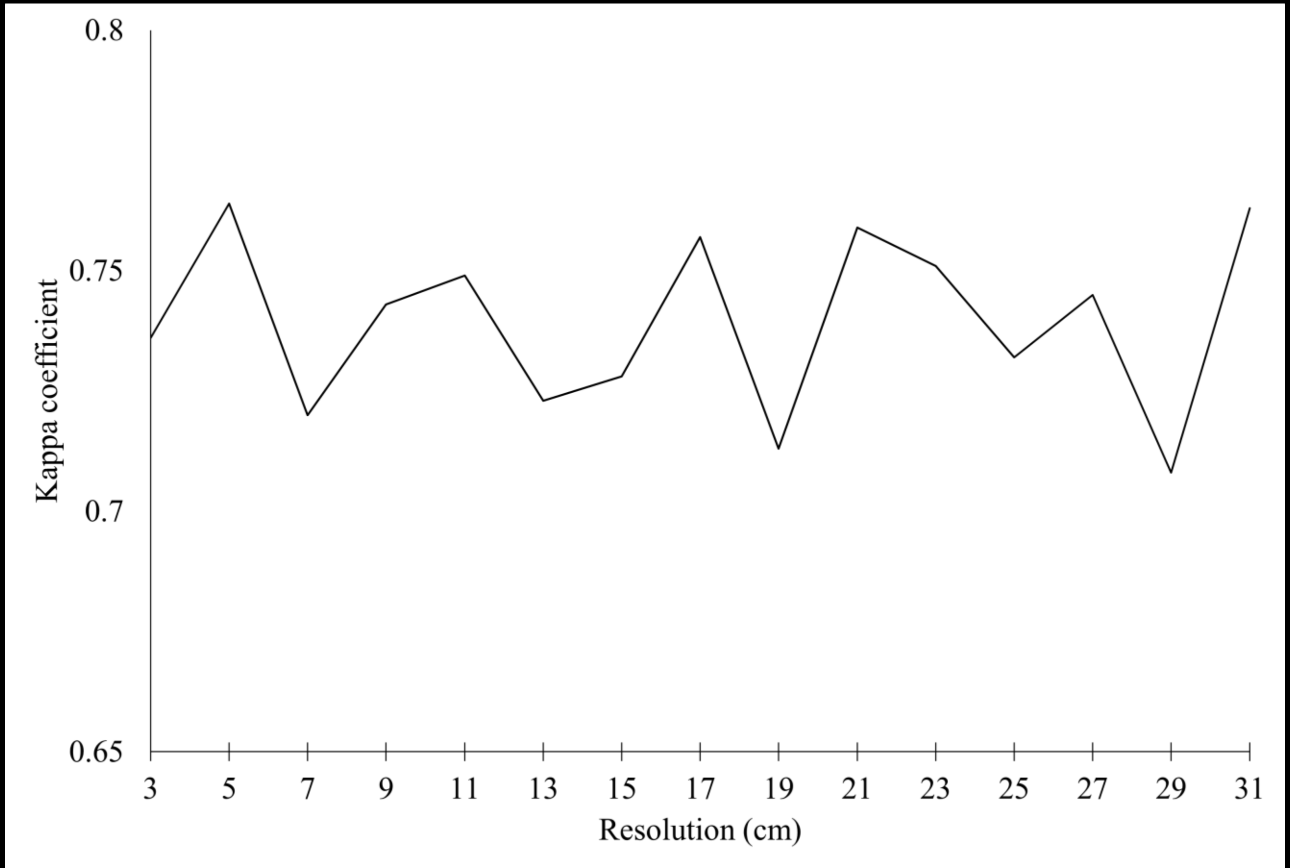


Classification Performance

- Classification accuracy
  - Kappa coefficient
  - User's accuracies
- Variation in classifications



Classification Performance

- Classification accuracy
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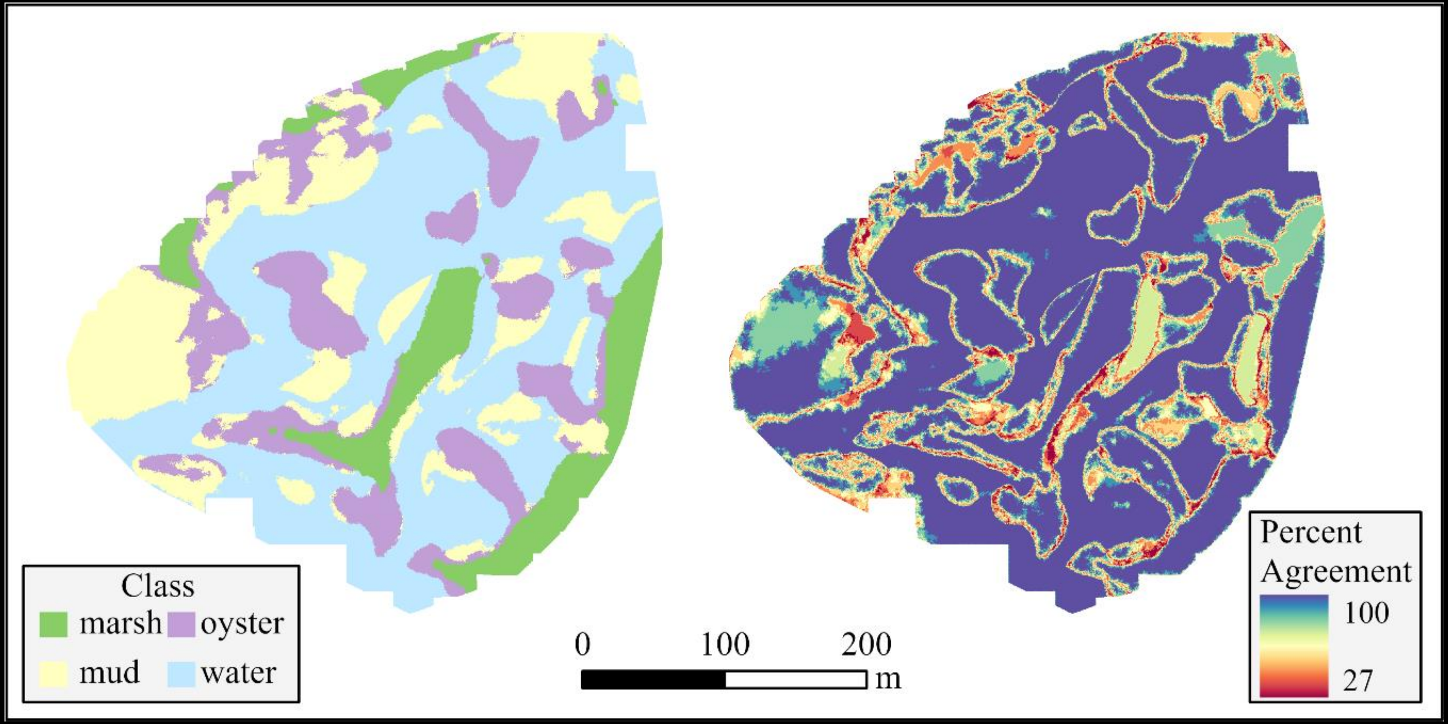
  - User’s accuracies
- Variation in classifications

Class	Highest User’s Accuracy
Marsh	96% (23 cm)
Mud	86% (3 cm)
Oyster	84% (29 cm)
Water	86% (5 cm)

Multiscale classifications

- Classification including best performing resolutions:
  - 3 cm, 5 cm, 23 cm, 29 cm



Kappa=0.821 Kappa=0.778

Class	User's Accuracy
Marsh	89%
Mud	88%
Oyster	86%
Water	75%

Conclusions

Very fine resolutions did not result in higher classification accuracy

Classification performance indicated that the optimal observation scale is habitat specific

Multiscale approaches allow for higher accuracy classifications

This workflow allows for reliable, semi-automated monitoring

Questions?

Acknowledgements: Connor Bass, Brad Ennis, Audrey Jordan, Carter Kelly, Natalie Stephens, João Gonçalves