Using drones to monitor coastal habitats in the Big Bend

Michael Espriella, Vincent Lecours, Peter Frederick, Edward Camp, Ben Wilkinson

School of FOREST RESOURCES & CONSERVATION
SFRC

UF | IFAS
UNIVERSITY of FLORIDA

Florida’s Big Bend Intertidal Habitats

- Mudflats
- Salt marshes
- Oyster reefs

Florida Climate Institute

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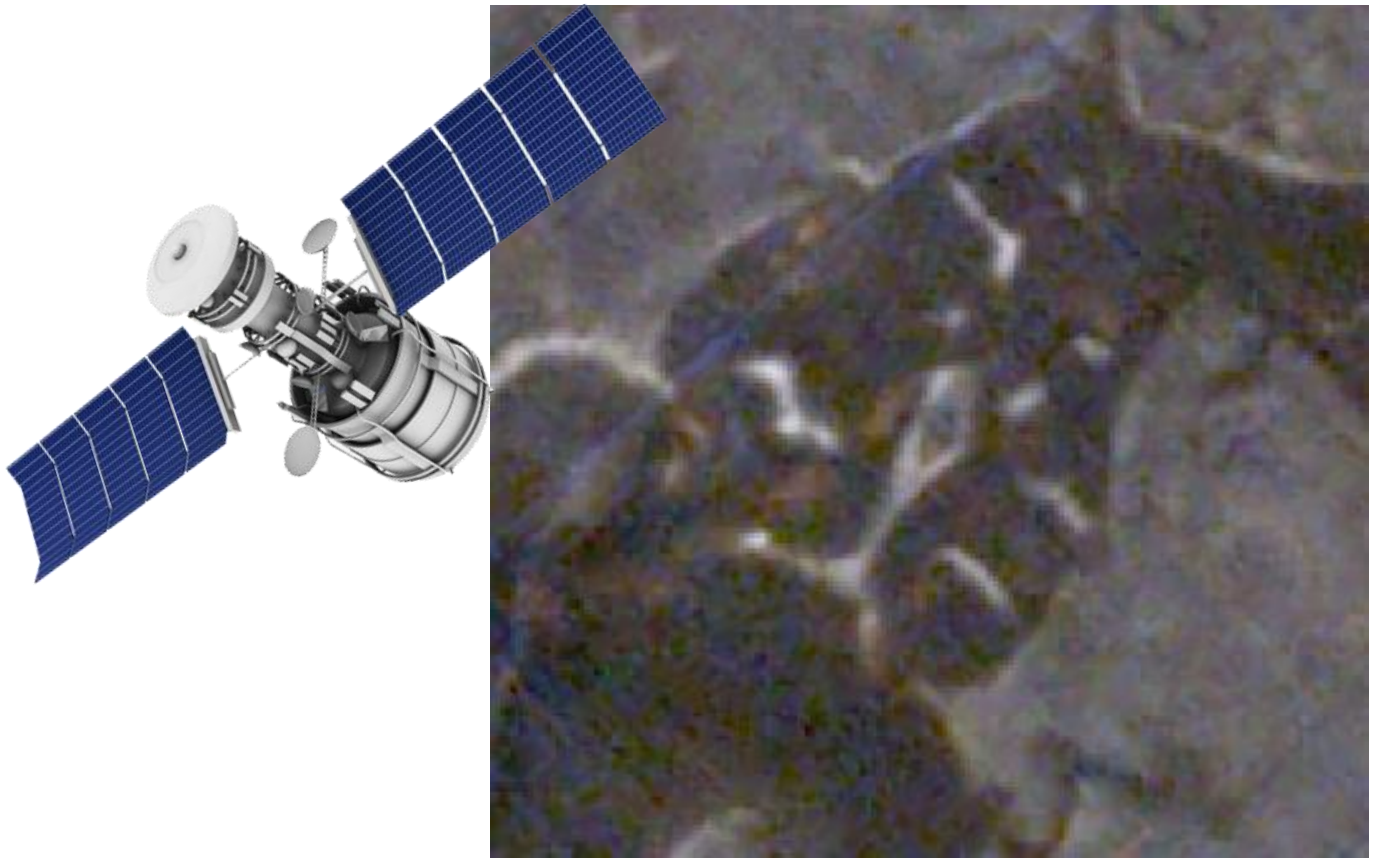
- Sampling challenges
- Remote sensing alternatives



Objective

- Develop a semi-automated and repeatable workflow to monitor changes in intertidal habitats in a cost-effective way

Imagery Collection & Processing

- Collect RGB imagery of Little Trout Creek using a UAS

sensor

GPS, motion sensor, flight computer

DJI Inspire 2

control unit

Operator/pilot

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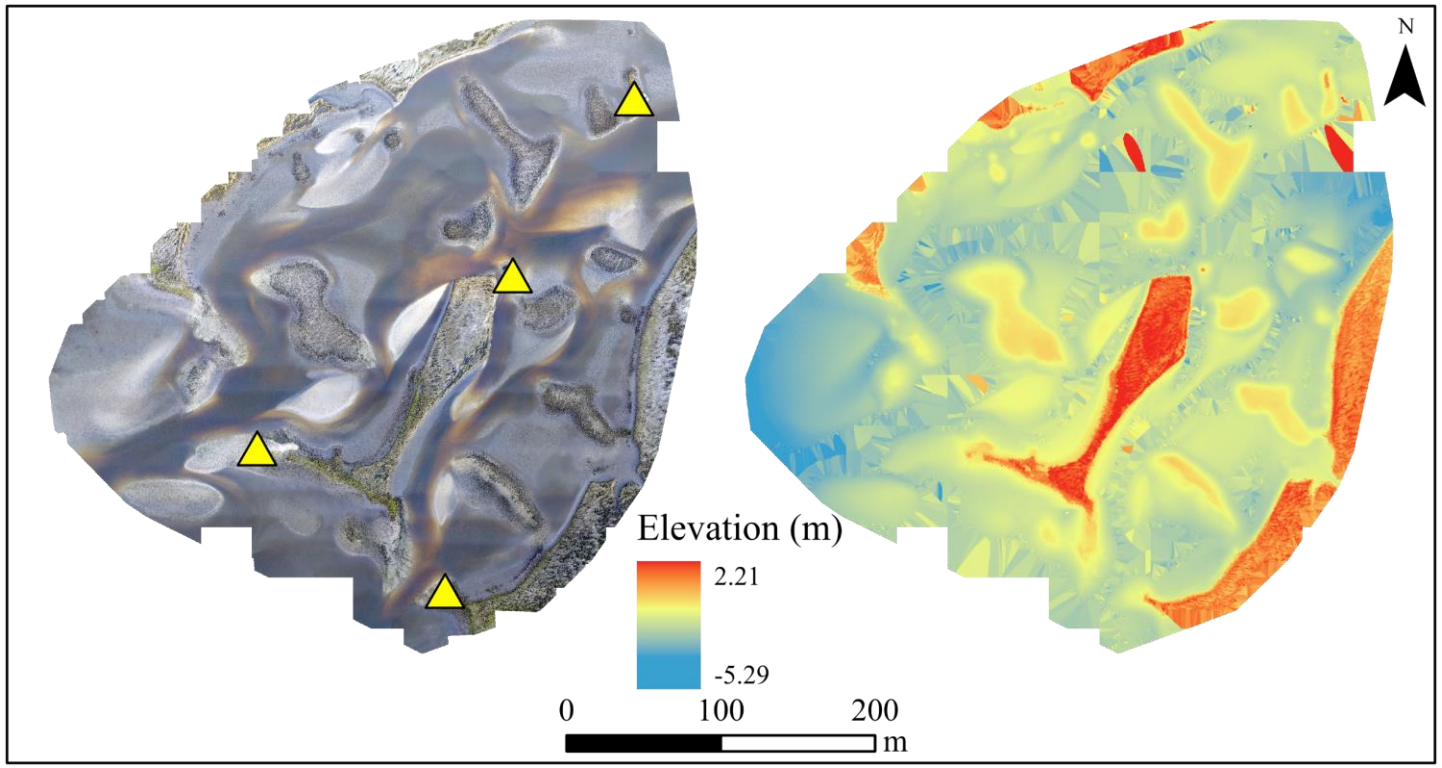
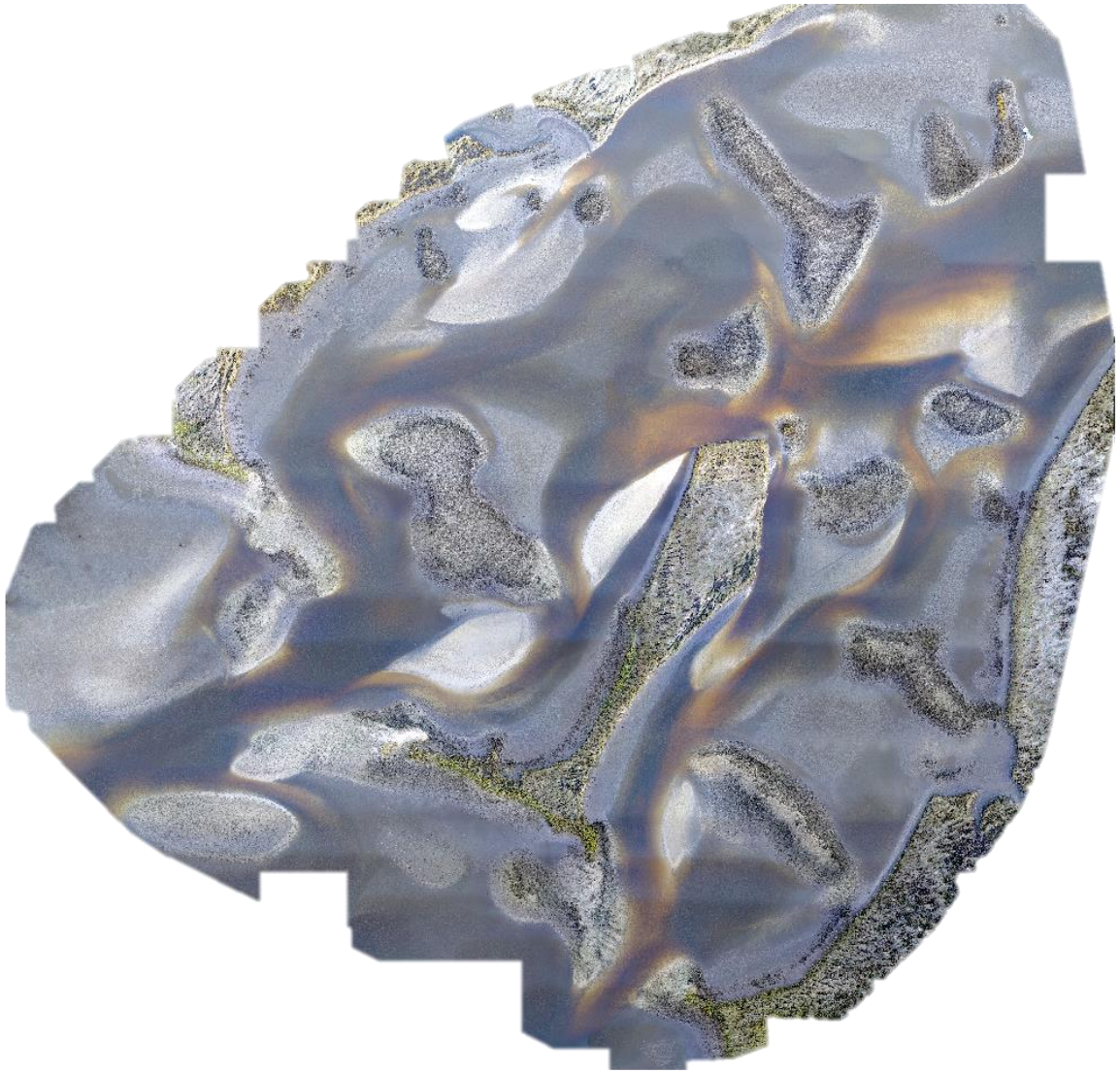
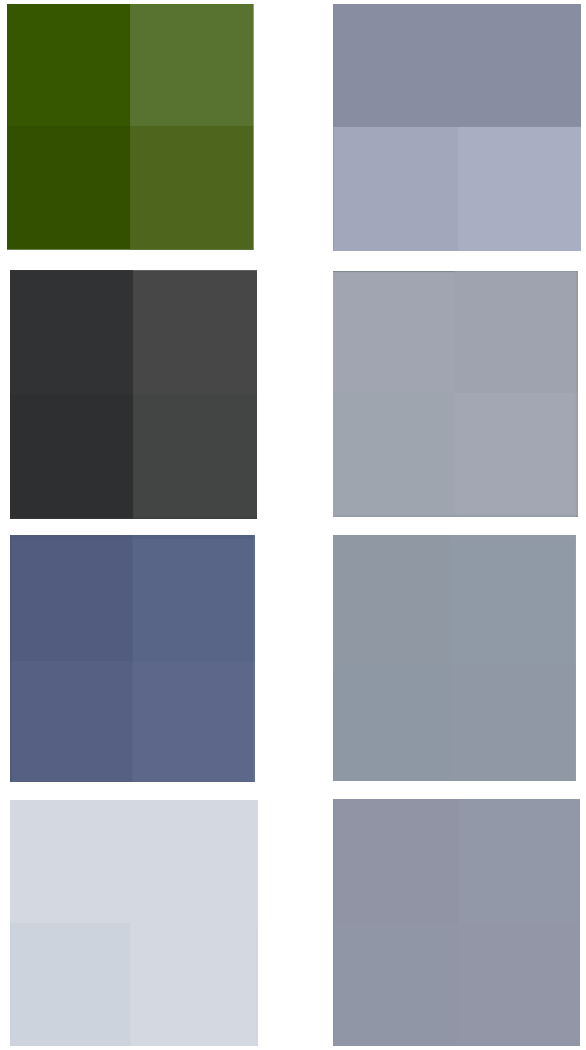
- Generate a mosaic and digital surface model (DSM)





Pixel-Based

- Marsh
- Oyster
- Water
- Mud



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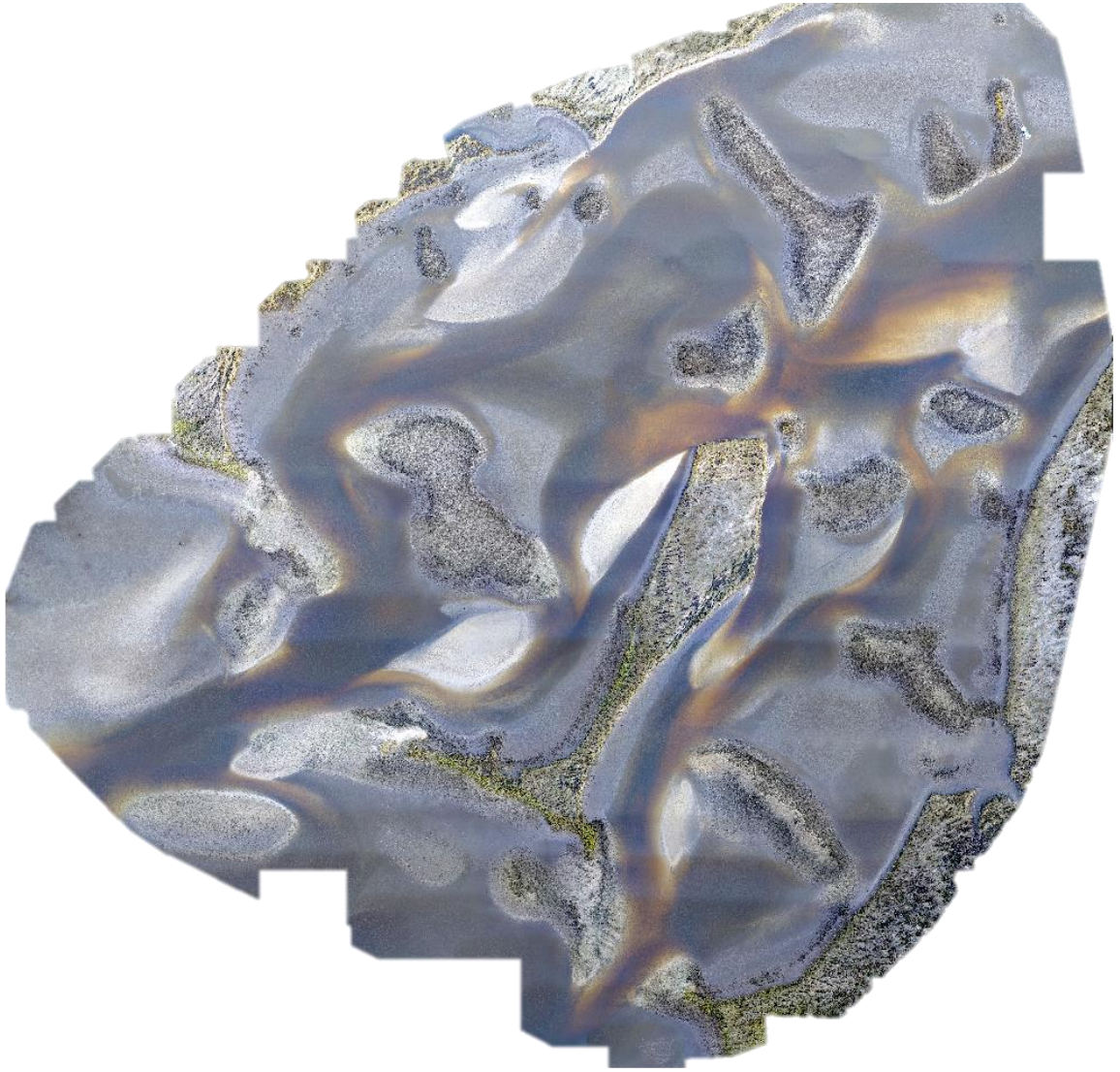

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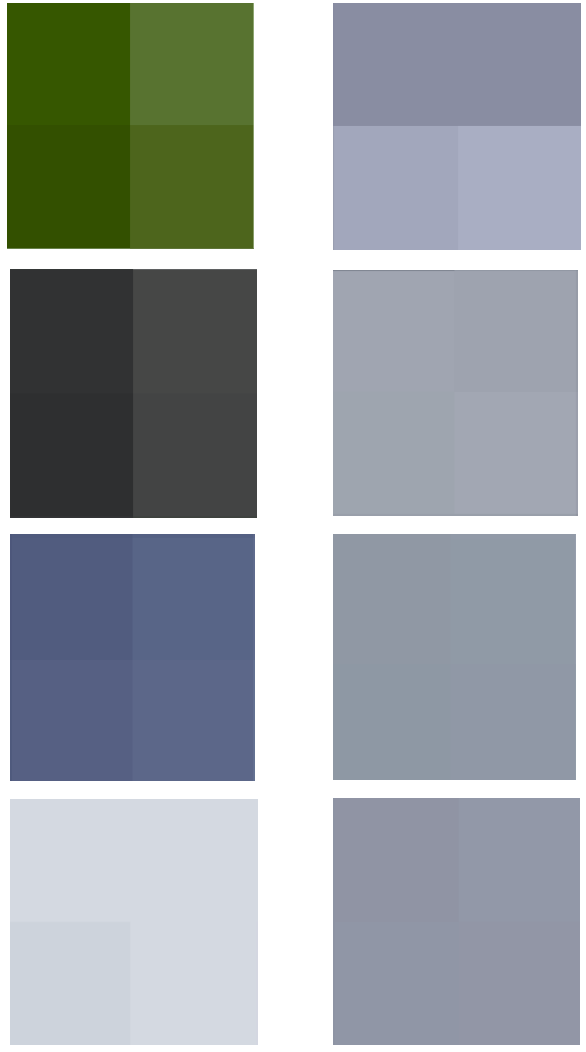

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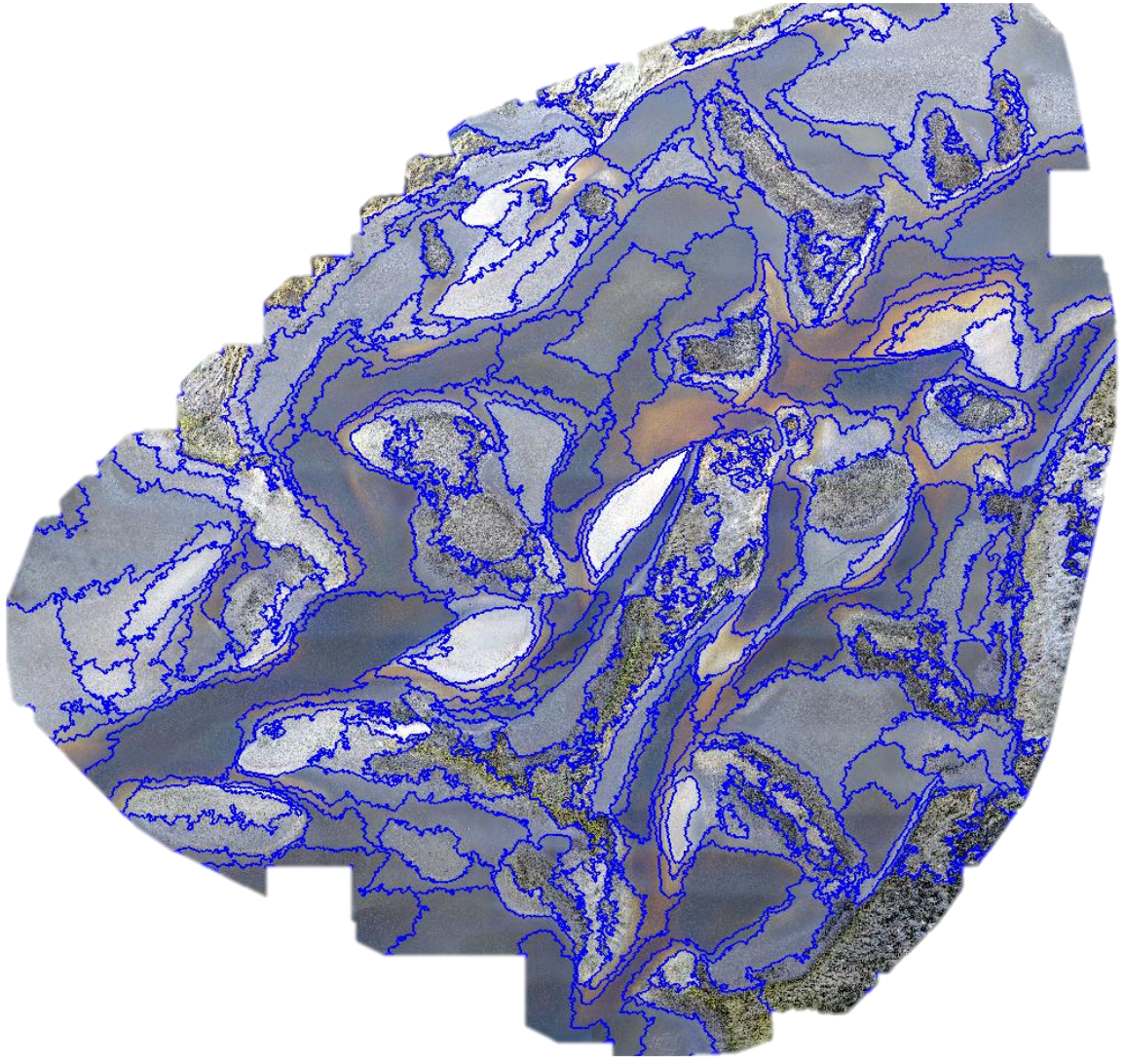

Water masking and segmentation

- Intertidal habitats and surrounding water look very similar to the computer

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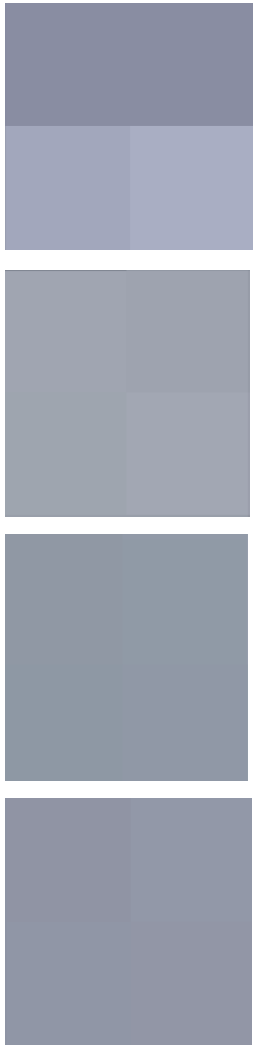
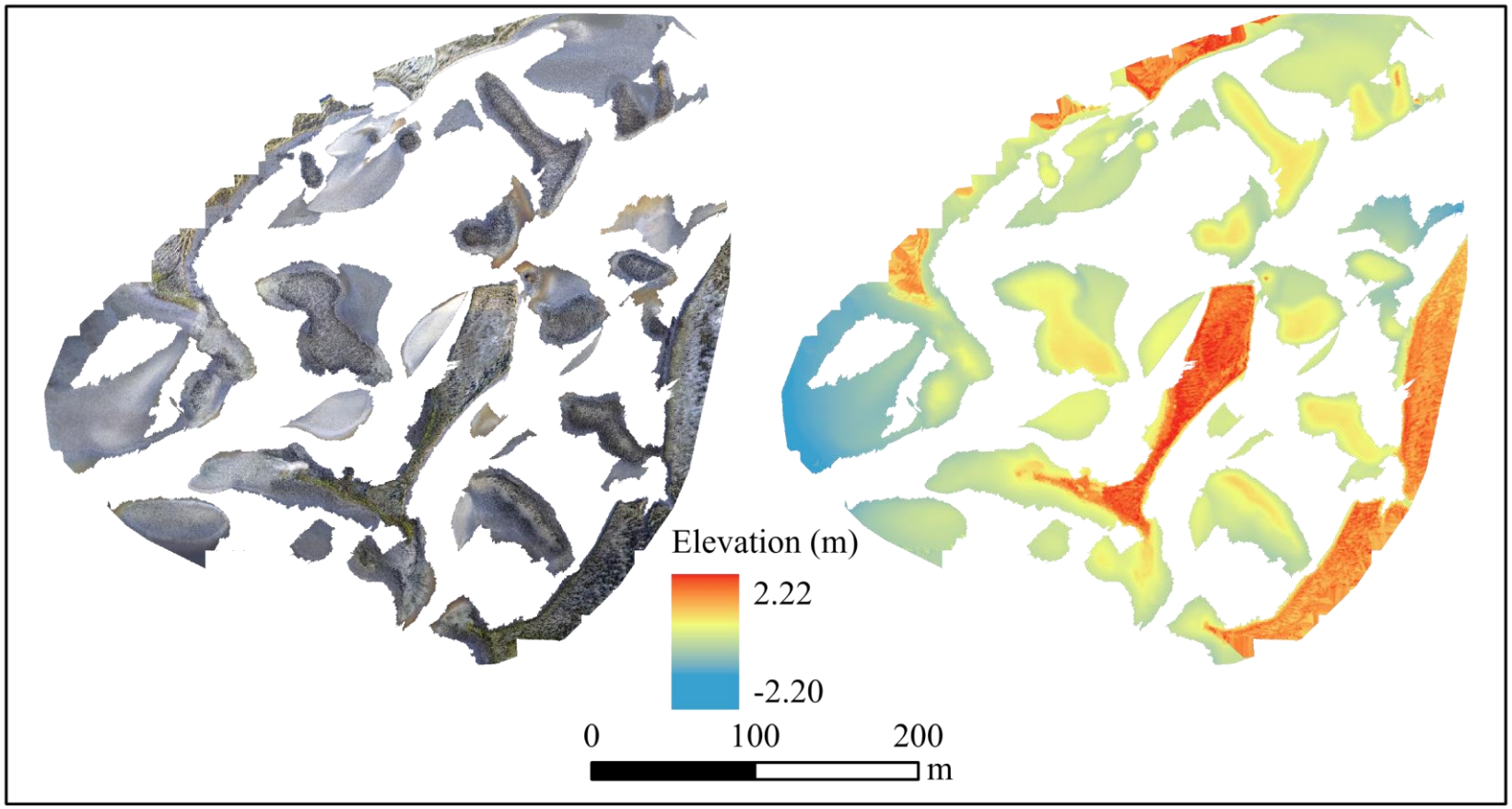


Water masking and segmentation

- Intertidal habitats and surrounding water look very similar to the computer
- Elevation data and a water index were used to mask water from the scene



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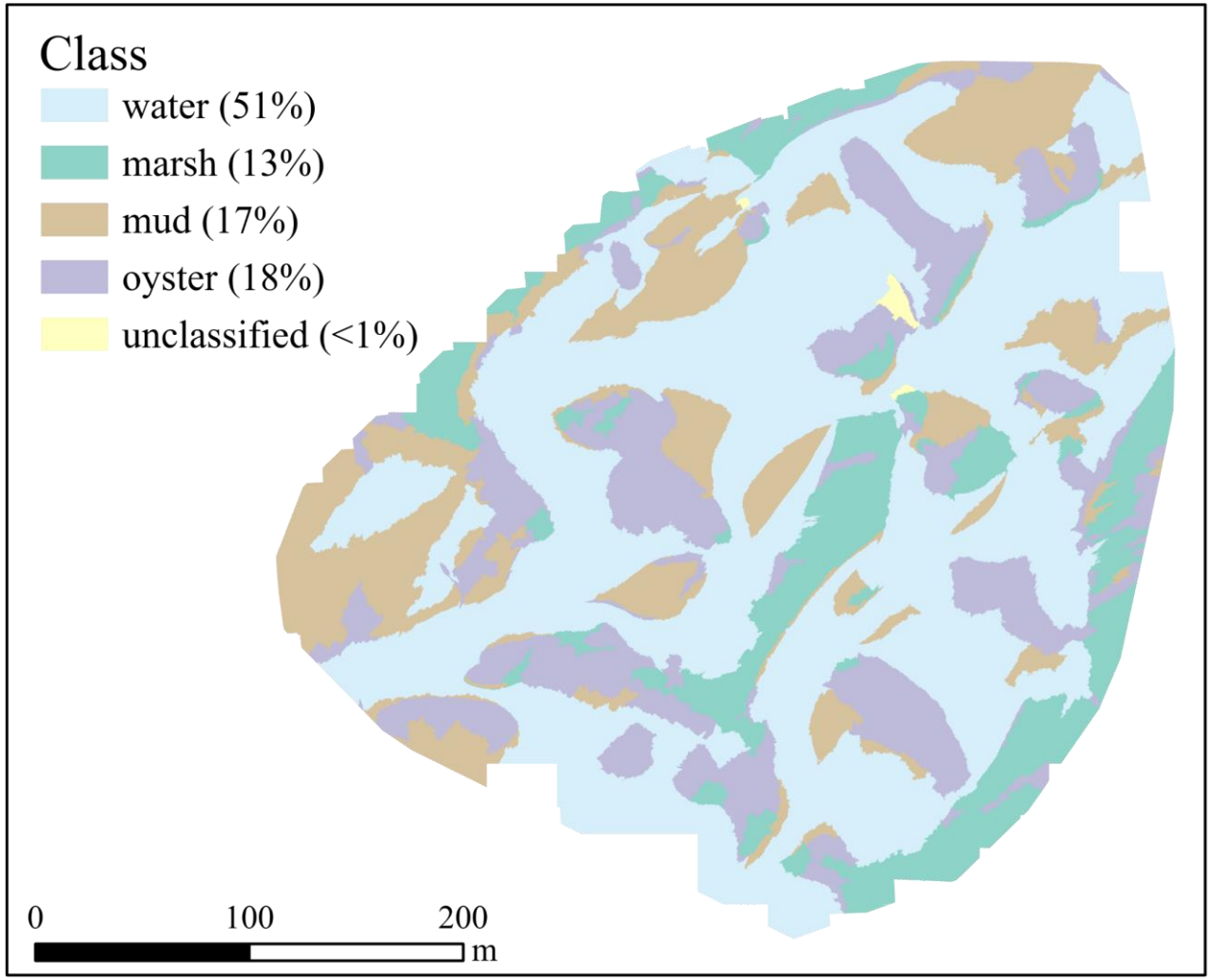
- 31 variables were included in a feature-space analysis
- A classification algorithm within eCognition used the information from the samples to classify the remaining objects

Classification



Accuracy Assessment

Overall accuracy: 79%

		Actual Habitat				
		Oyster	Marsh	Mud	Water	User Accuracy (%)
Classified Habitat	Oyster	133	33	14	6	71.51
	Marsh	17	130	2	1	86.67
	Mud	6	3	119	17	82.07
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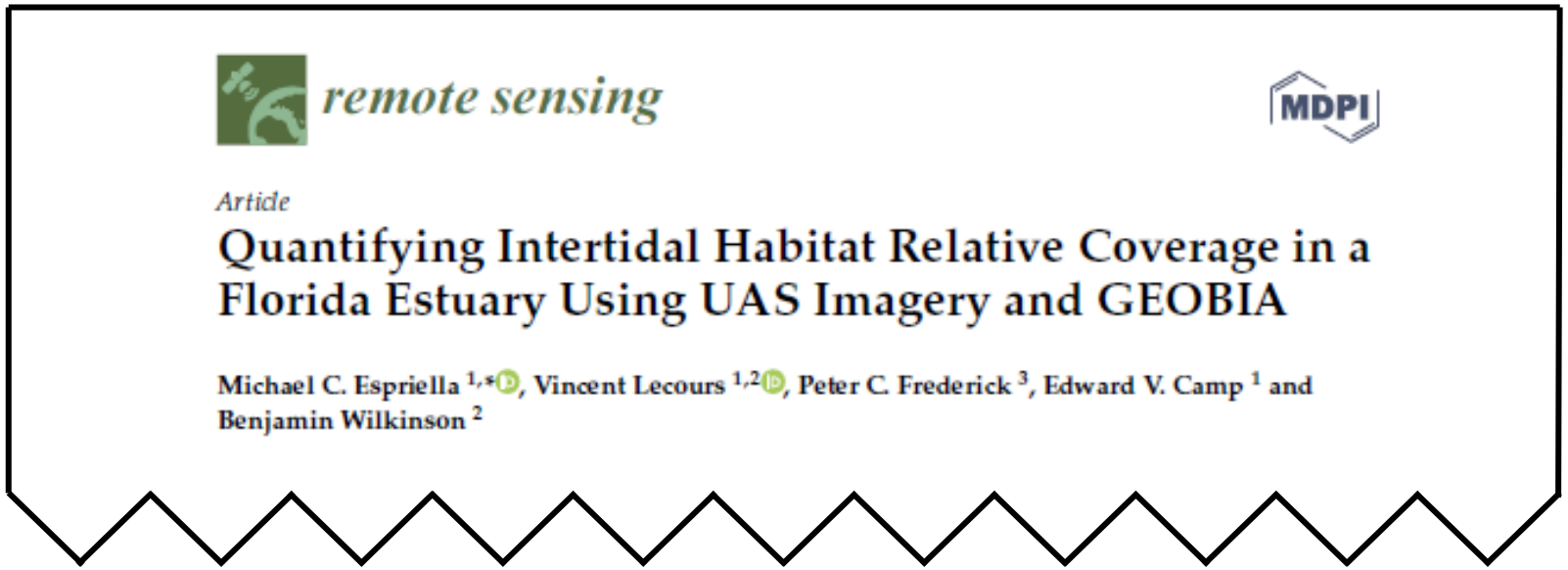
- Geometric attributes at varying scales can improve classification accuracy
- The workflow developed allows for consistent monitoring



Questions?

Acknowledgements

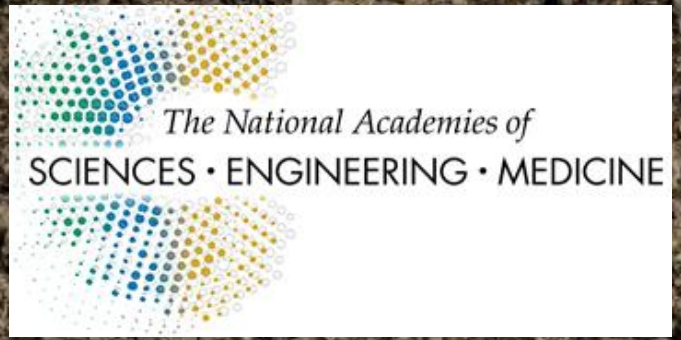
Data collection:

Steve Beck

Andrew Ortega

Sean Denney

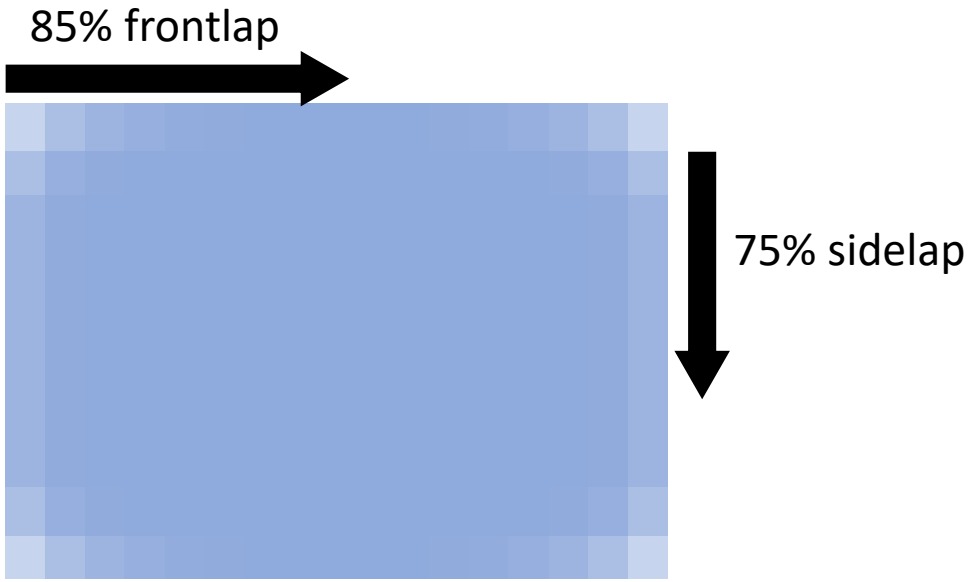
Lindsey Garner



Imagery Collection & Processing

- Collect overlapping imagery of Little Trout Creek using a UAS

DJI Inspire 2



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	Producer Accuracy (%)	80.12	78.31	71.69	85.54	