Satellite Derived Seagrass Update

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V. Hill, J. Li, R. Zimmerman

- Problem: Monitoring of seagrass change is difficult and costly.

- Action: Quantify seagrass w/ machine learning and satellite data.

- Result: Semi-automated method to quantify seagrass area, leaf area, and carbon with new quality controls for CDOM, turbidity, and glint.

- Impact: Larger scale quantification of seagrass change.

Mapping seagrass at a national scale

Maxar's WorldView-2 and WorldView-3 satellites

Image source: Maxar.com

Pros:

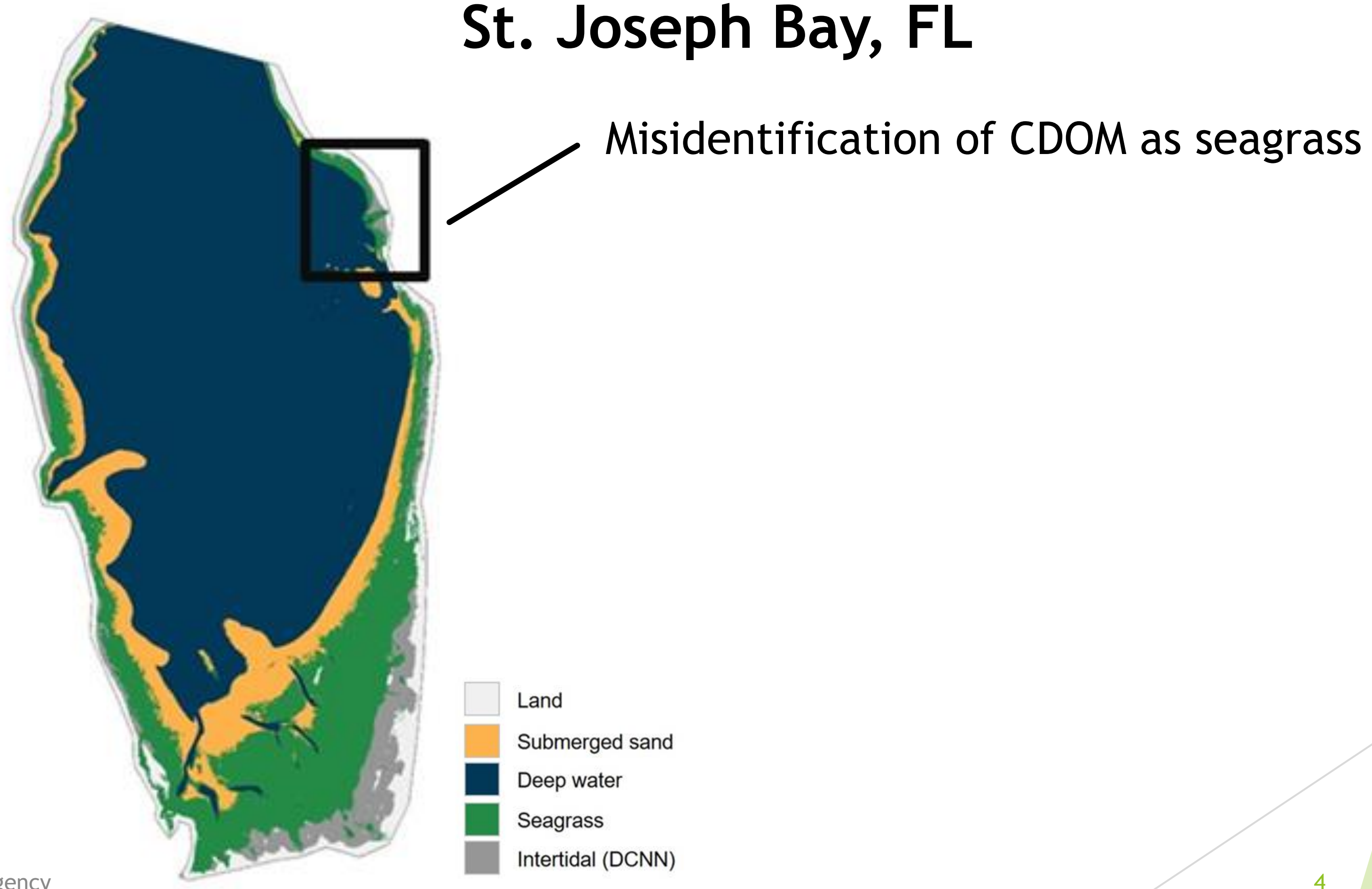
- High spatial resolution (< 2m)
- 8 multispectral bands to help differentiate spectrally similar classes (e.g., seagrass versus benthic algae)

Cons:

- Imagery available either in archives or by tasking the satellite

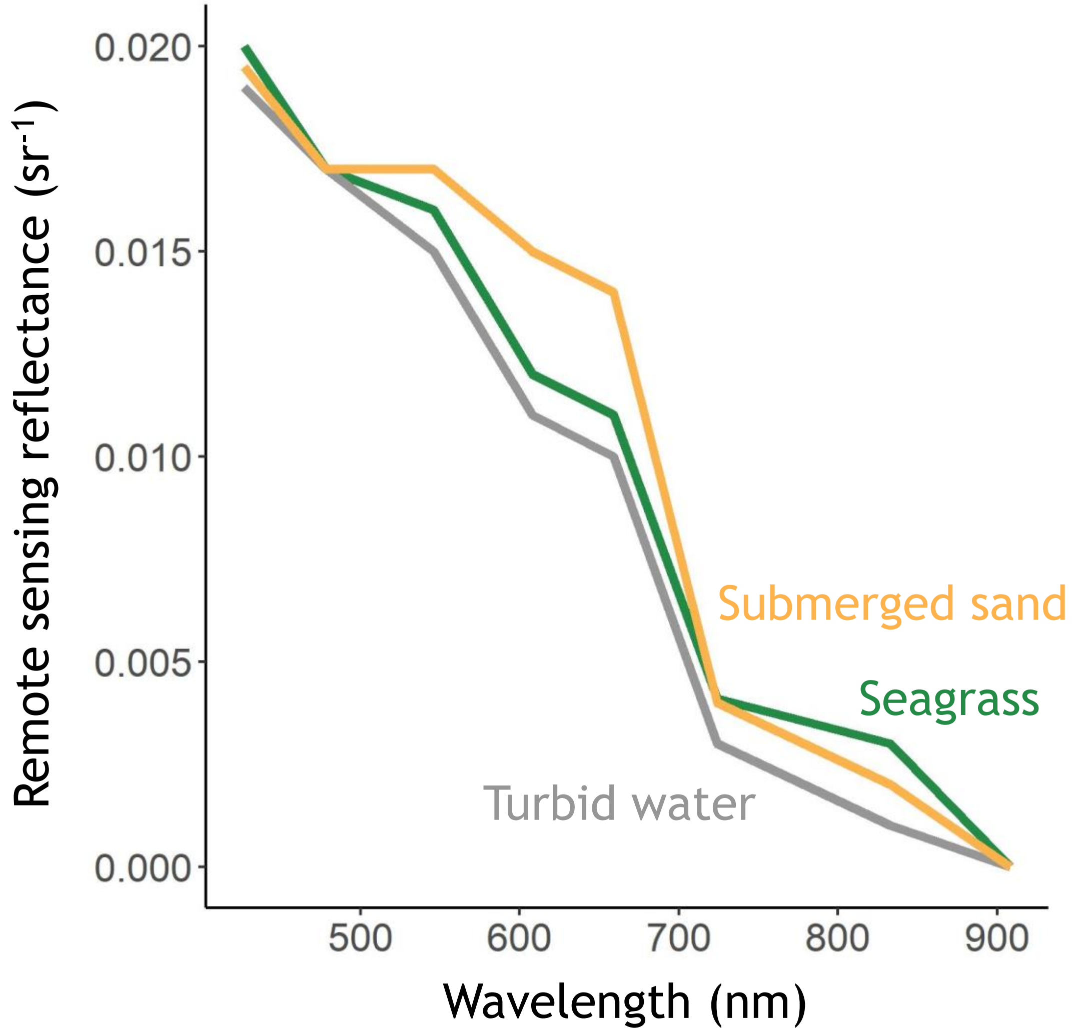
Mapping seagrass at a national scale

St. Joseph Bay, FL



Coffer et al., 2021, *Rem. Sens. Environ.*

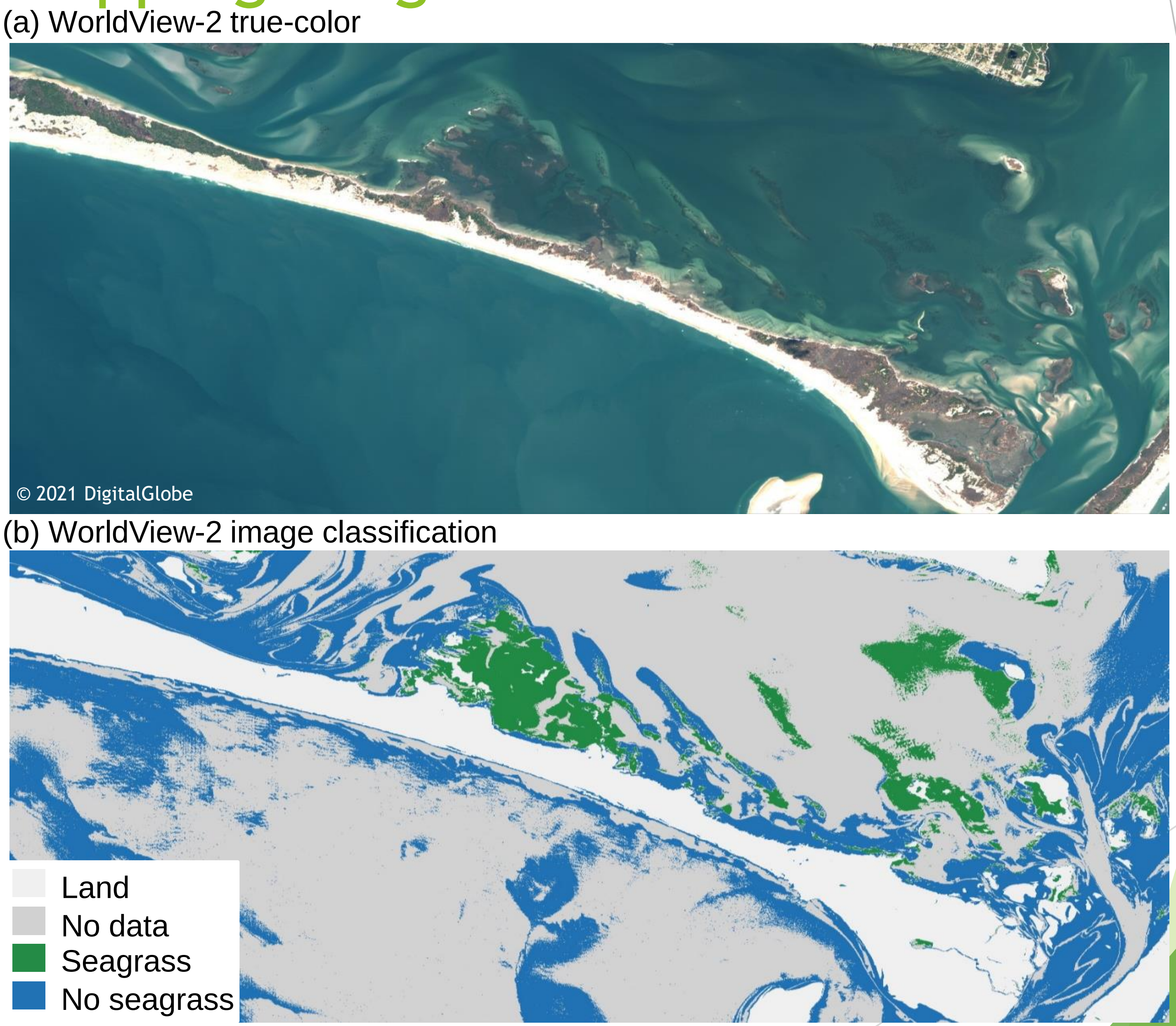
Mapping seagrass at a national scale



- Turbid water and seagrass have similar spectral shapes, which can confuse the classification algorithm
- We have created a **quality control flag** to identify pixels in which water quality conditions prevent characterization of the substrate

Mapping seagrass at a national scale

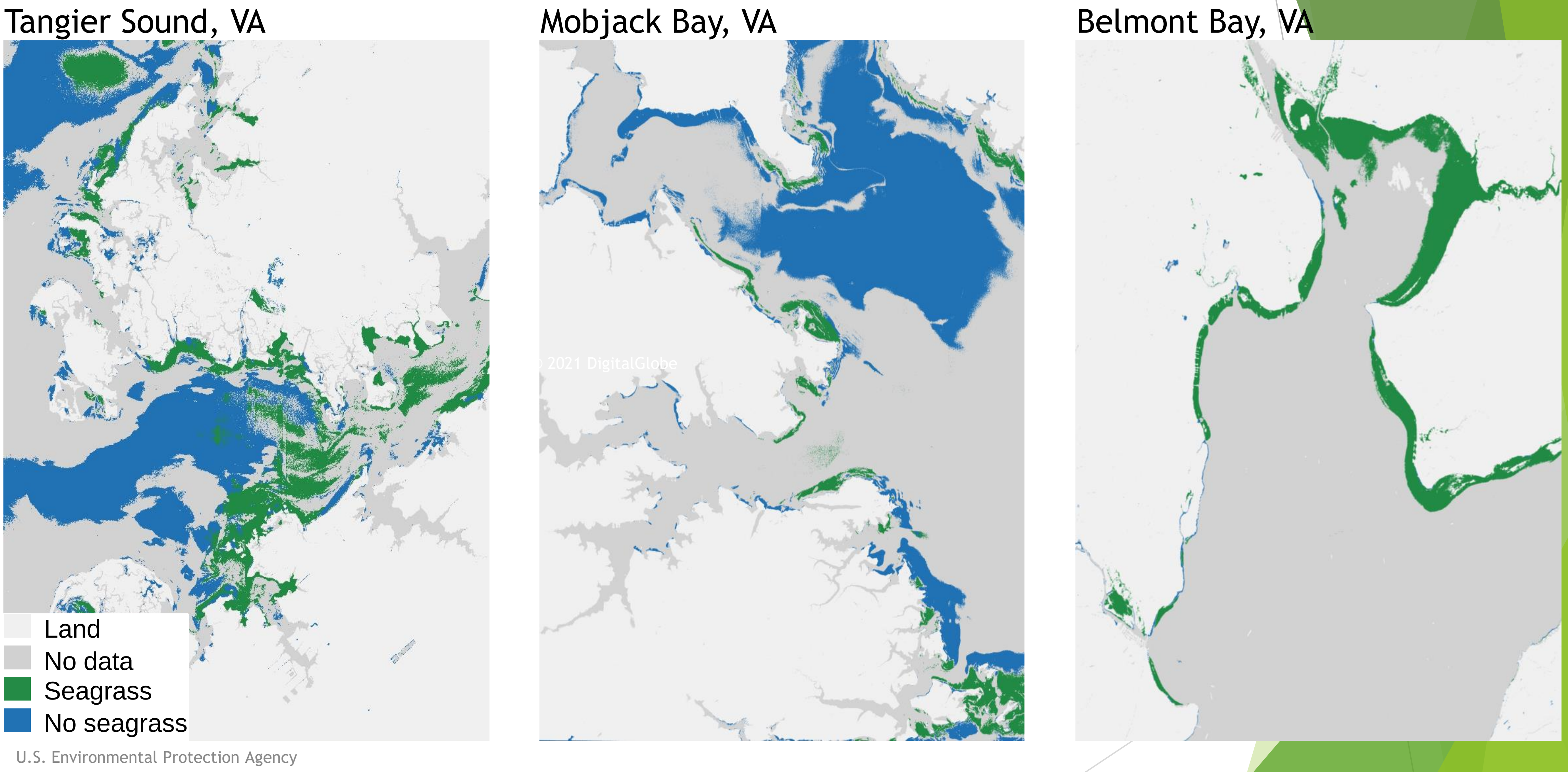
Back Sound, NC



Coffer & Graybill et al., *in prep., J. Environ. Manage.*

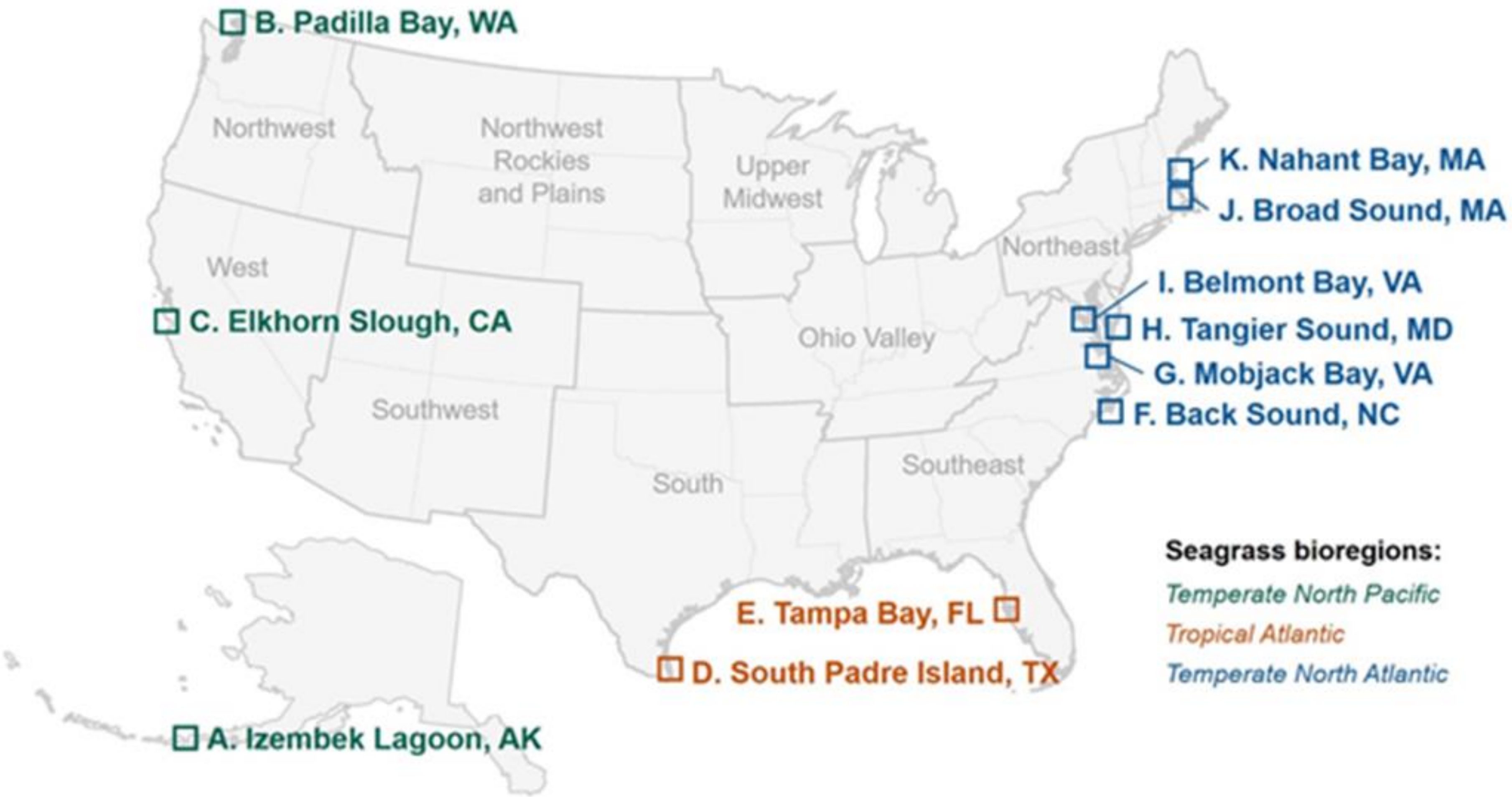
Mapping seagrass at a national scale

WorldView-2 image classifications



Coffer & Graybill et al., *in prep., J. Environ. Manage.*

Mapping seagrass at a national scale



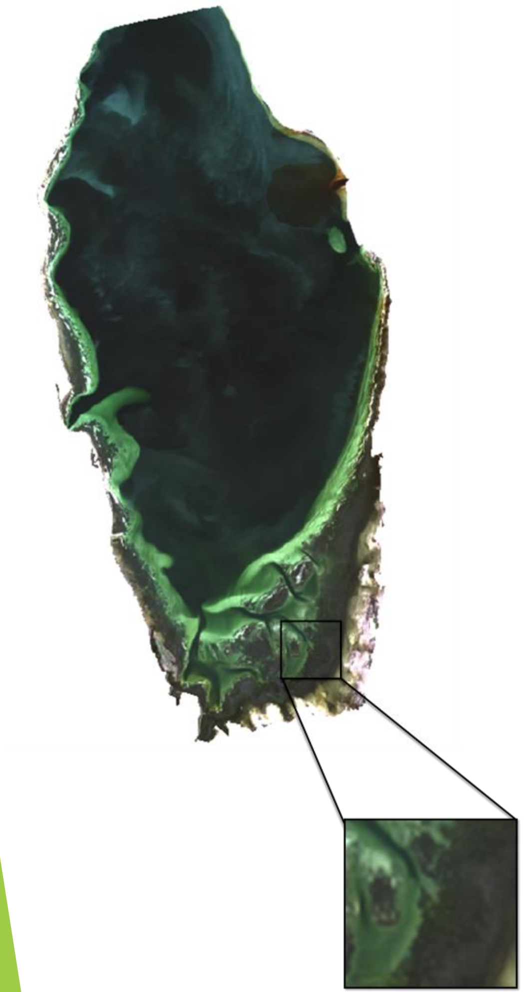
Coffer & Graybill et al., *in prep., J. Environ. Manage.*

Mapping seagrass at a national scale

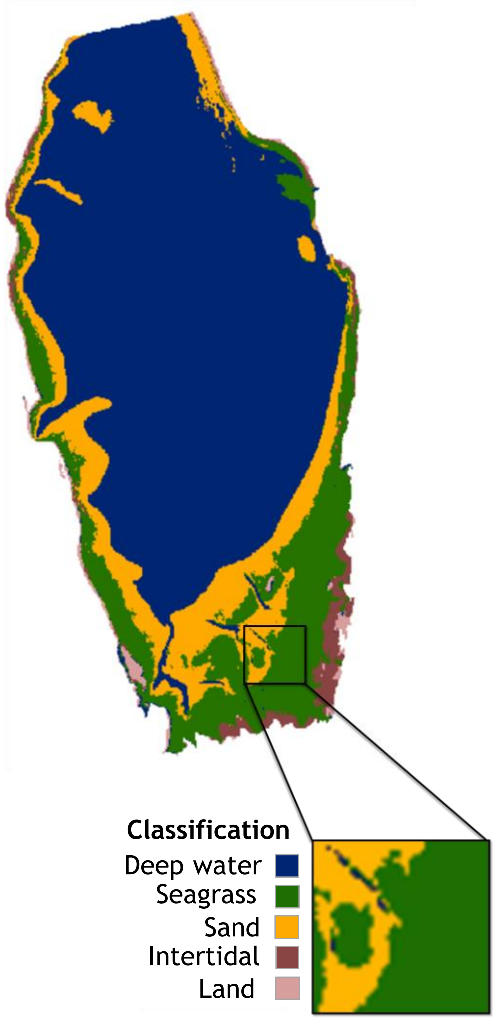
- Able to **differentiate spectrally similar** seagrass and turbid water
- When substrate is visible, seagrass can be mapped with **strong agreement** against field data
- When substrate is not visible, results can inform **satellite targeting** or **field data prioritization**

Seagrass LAI conversion

1. Automated standardized processing of 31 Landsat scenes

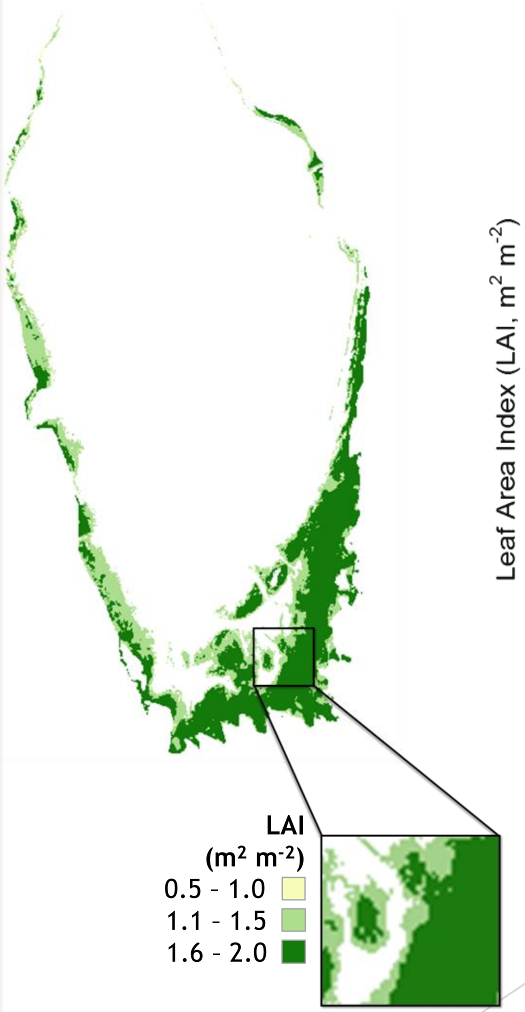


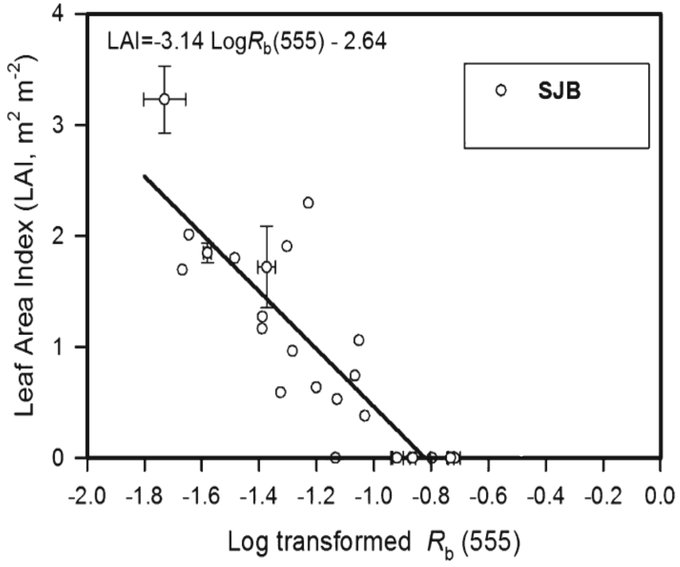
2. Image classified using machine learning



90-96% agreement *with aerial imagery and high-resolution satellite imagery*

3. Leaf Area index (LAI) estimated from optical conditions



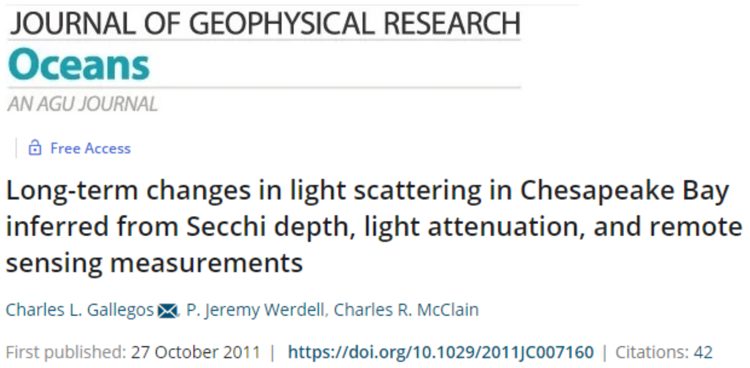


Lebrasse et al., *In Review*, Estuaries and Coasts.

Seagrass LAI conversion

Measurements needed:

- Bottom reflectance (R_b) of seagrass – modeled from reflectance in the green band
- LAI measurements



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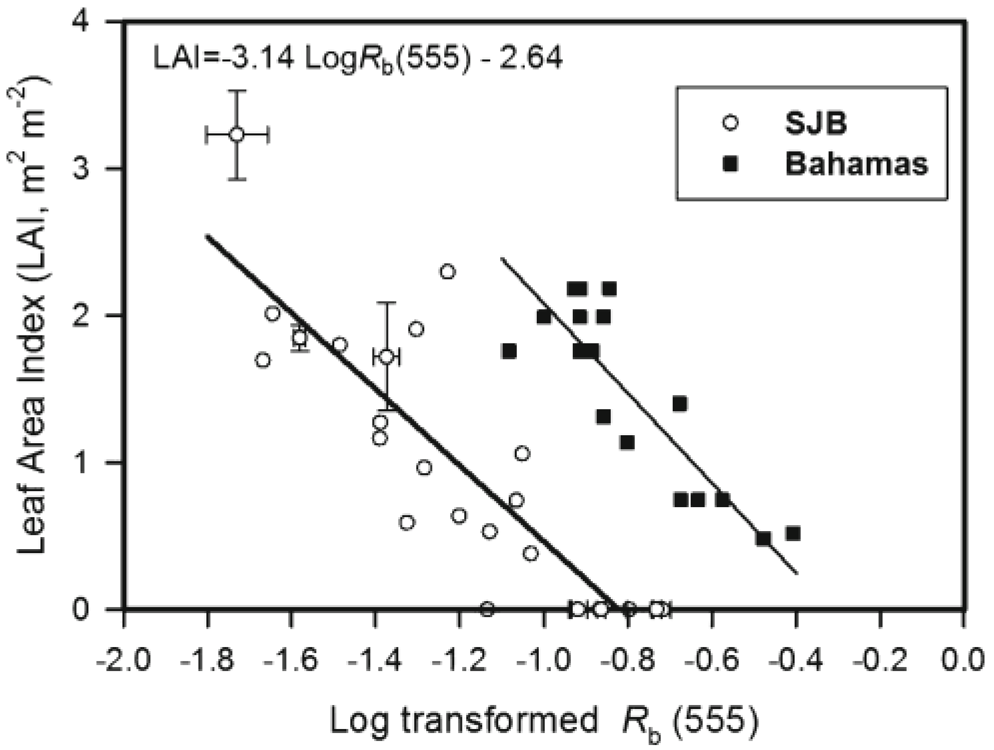
Long-term changes in light scattering in Chesapeake Bay inferred from Secchi depth, light attenuation, and remote sensing measurements

Charles L. Gallegos, P. Jeremy Werdell, Charles R. McClain

First published: 27 October 2011 | https://doi.org/10.1029/2011JC007160 | Citations: 42

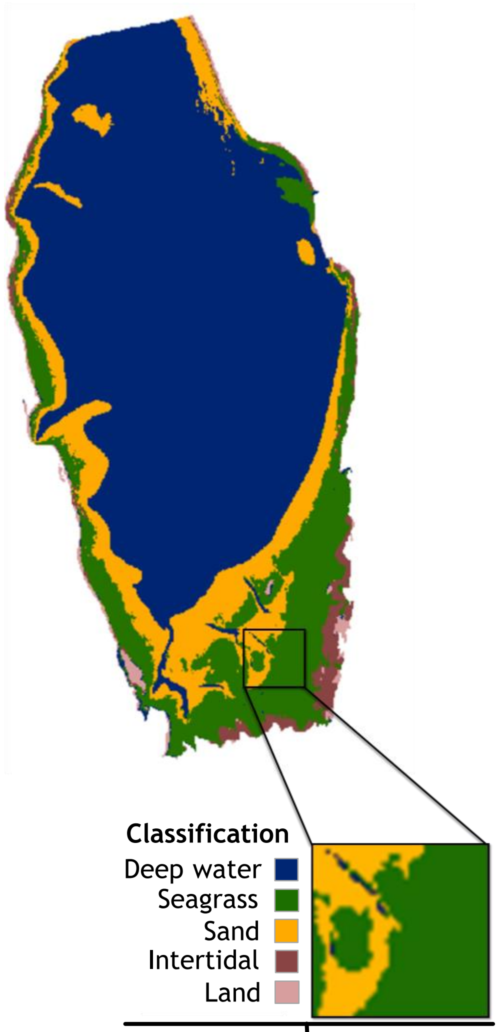


Approach tested both in the Bahamas (Dierssen et al. 2003) and St. Joseph Bay (Hill et al. 2014) – highlighting applicability to other areas such as the Chesapeake Bay

LAI-carbon conversion

1. Automated standardized processing of 31 Landsat scenes

2. Image classified using machine learning



__90-96% agreement__ with aerial imagery and high-resolution satellite imagery

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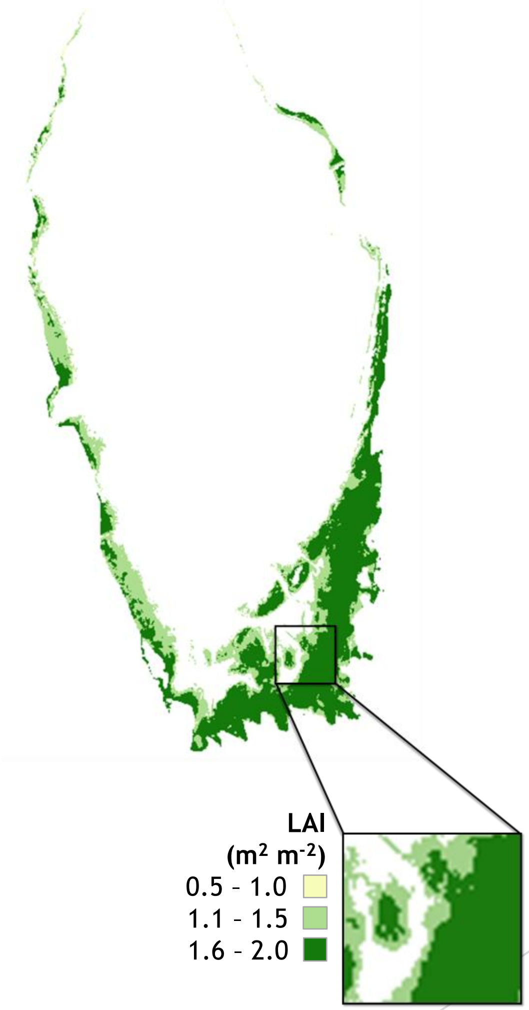
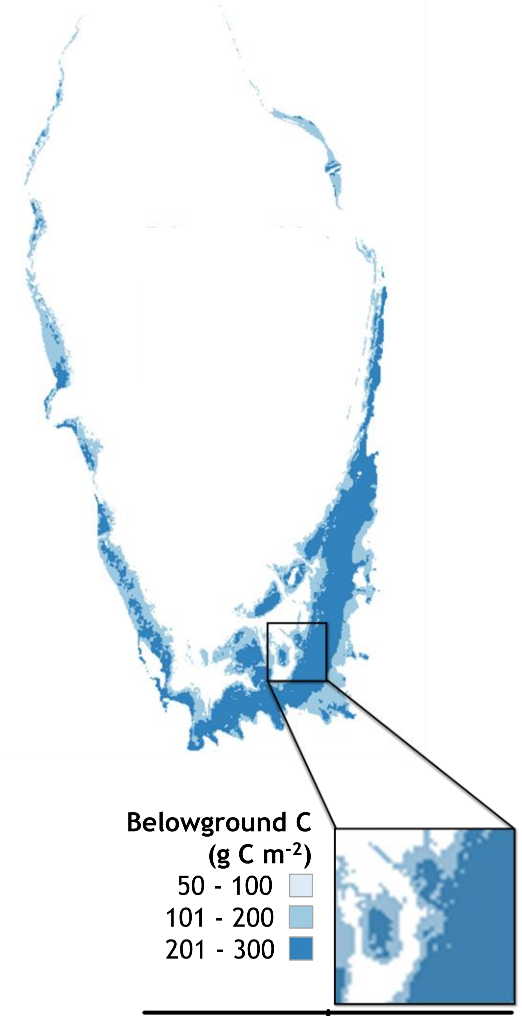
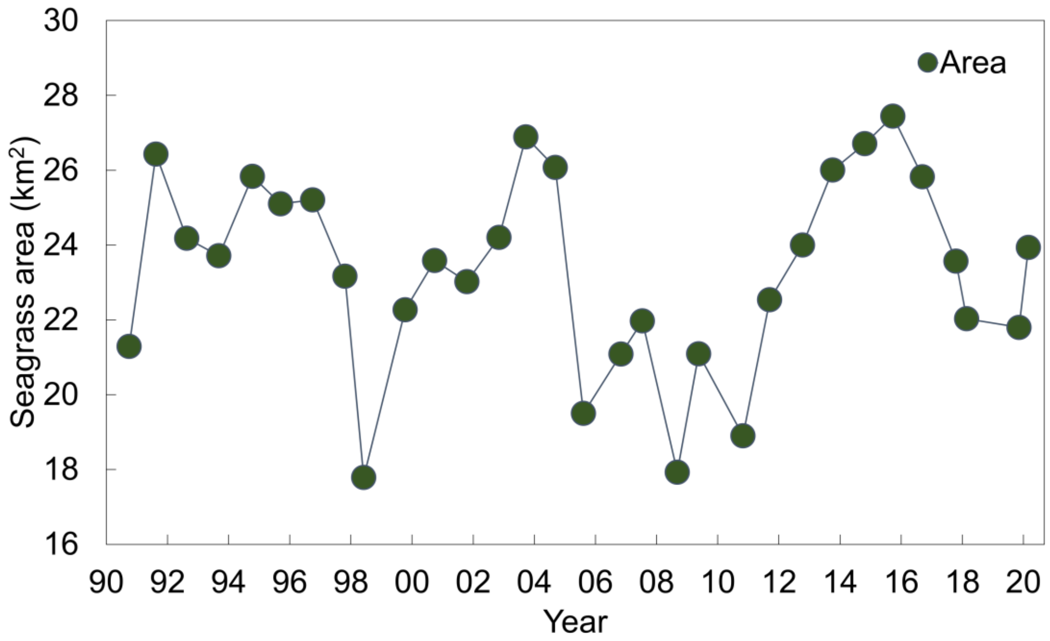


4. Scalar conversion of LAI to belowground carbon (C)

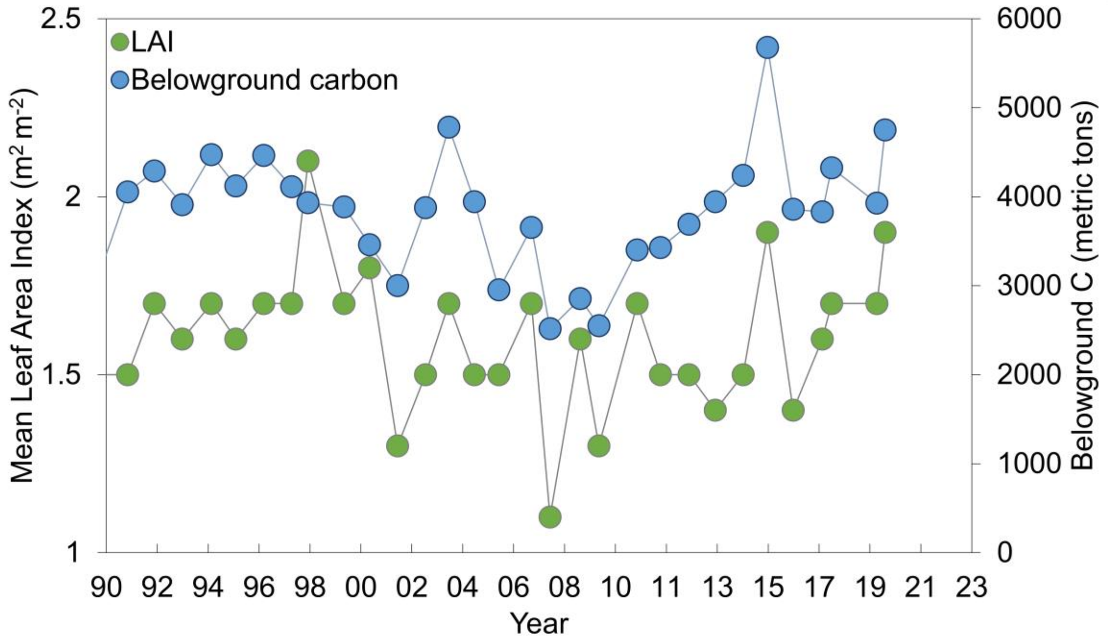


__4400 metric tons of belowground C__ held in St. Joseph Bay over 30 years

30-year time series of seagrass extent, LAI and carbon



No trend in seagrass area (μ = 23.3±3 km^2, τ = 0.09) over the 30-year period.



No trend in LAI *(μ = 1.6±0.3, τ = -0.13)* ***or belowground C*** *(μ = 4400±500, τ = 0.01) over the 30-year period.*

- ❑ **Six seagrass declines between 2004 and 2020 followed the four tropical storms and two hurricanes that passed over St. Joseph Bay,** although seagrass recovered quickly following these disturbances.
- ❑ **Interannual variability in seagrass and BGC in St. Joseph Bay was unrelated to the El Niño Southern Oscillation, North Atlantic Oscillation, or temperature.**

Lebrasse et al. (In Review) *Estuaries and Coasts*

30-year time series of seagrass extent, LAI and carbon

- Adaptation of a semi-automated processing regime to 30 years of publicly-available imagery
- Seagrass LAI and carbon calculations on a time series of images
- Forecasts suggest environmental and climate pressures are ongoing – Time series as a baseline against which to monitor future change in seagrass communities

Exploring the potential of alternative satellite platforms

Planet Labs' PlanetScope Constellation

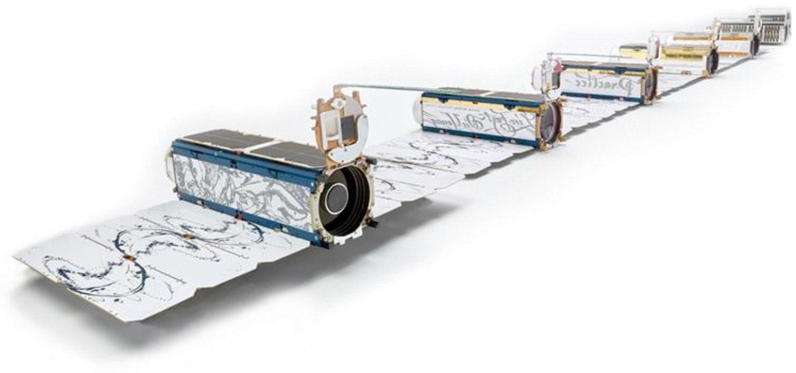


Image source: Planet.com

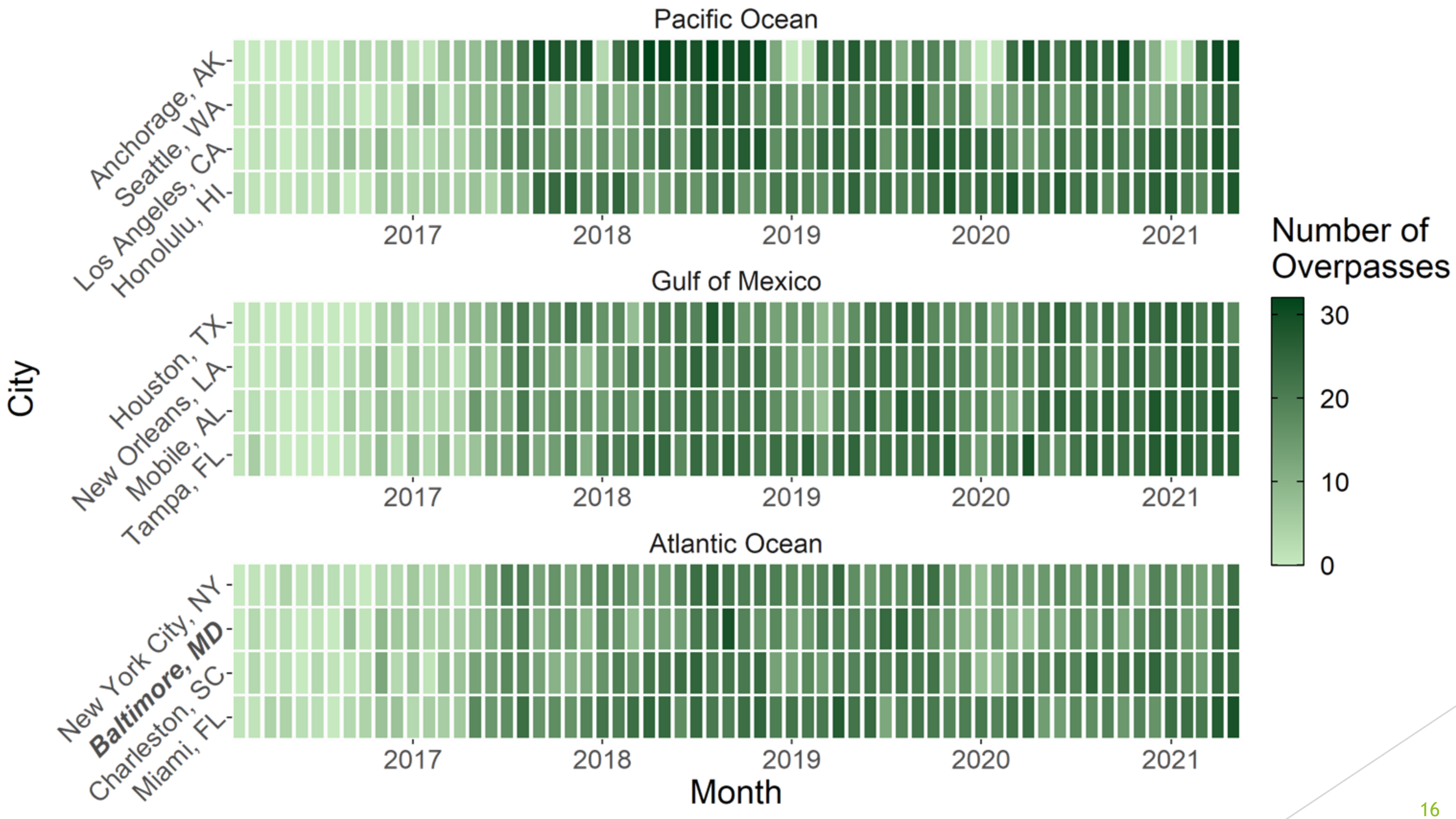
Pros:

- High spatial resolution (~3.7 m)
- High temporal resolution (near daily revisit time)

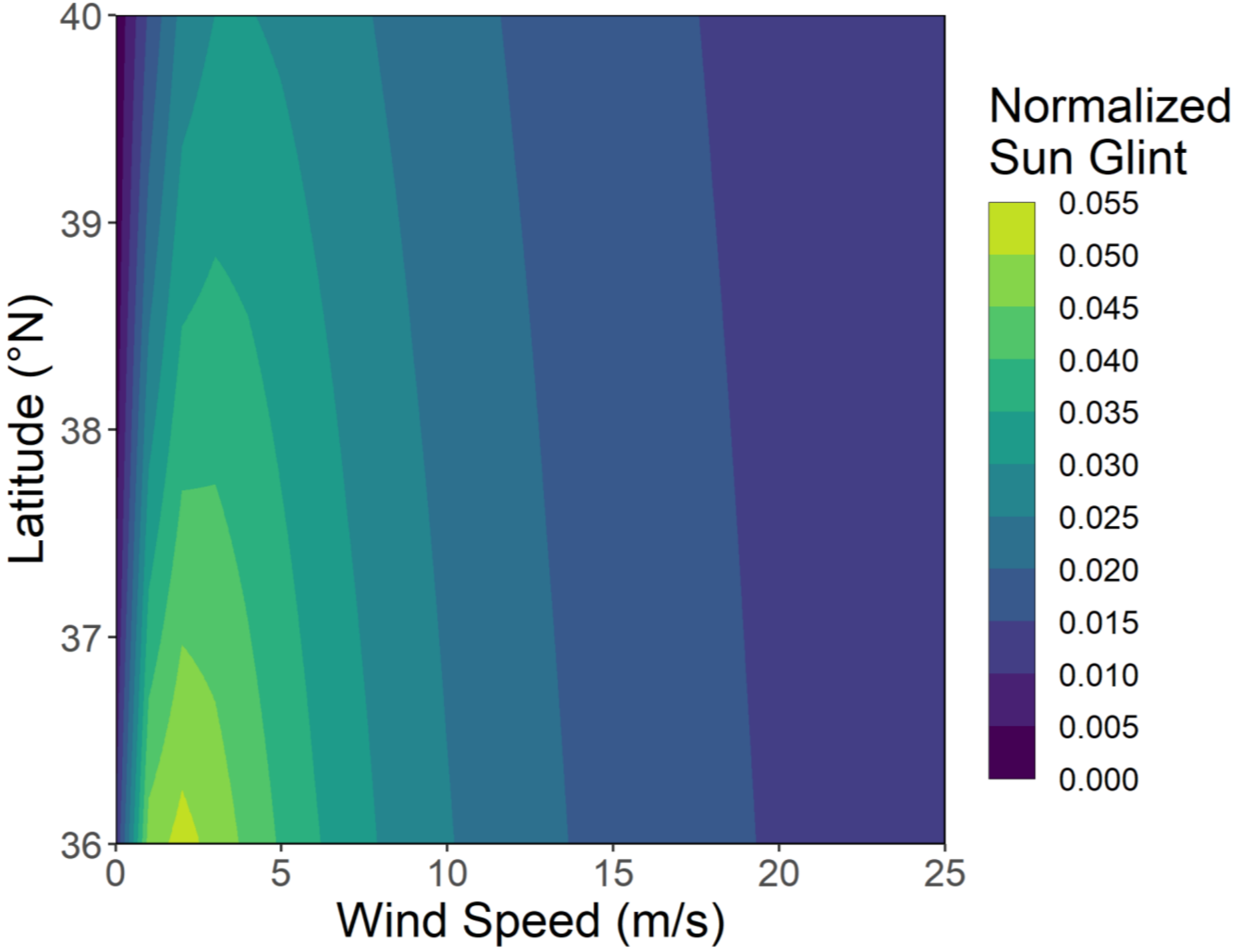
Cons:

- Nadir viewing angle is sensitive to sun glint
- Less bands than WorldView and Landsat to help differentiate spectrally similar classes

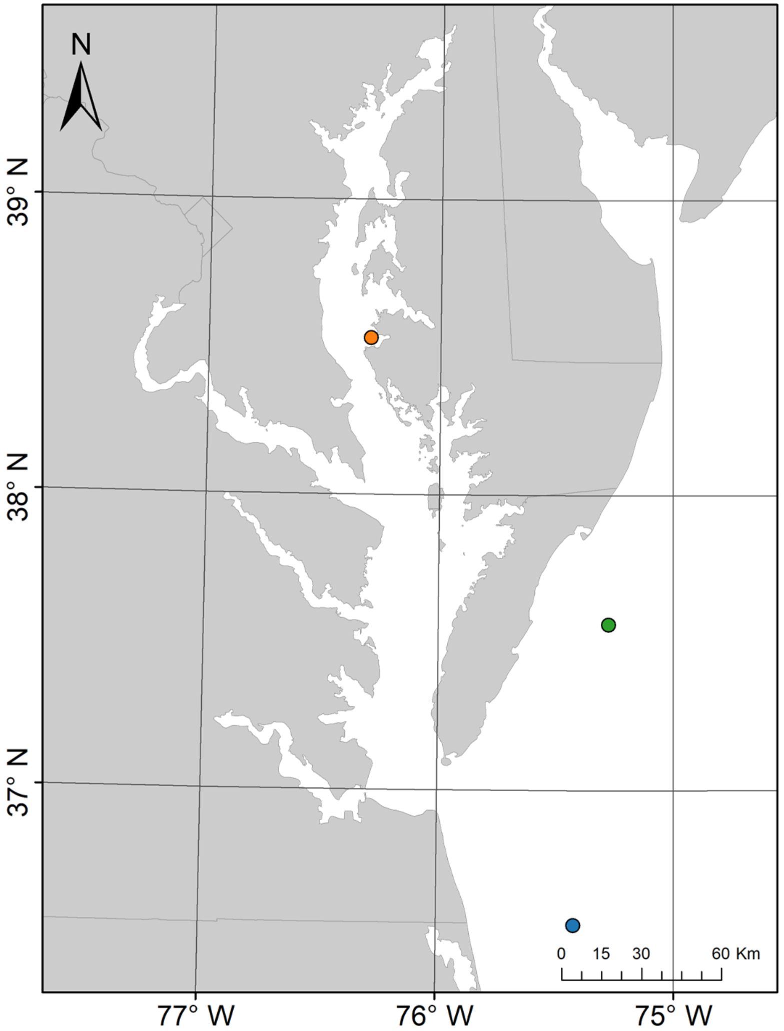
Overpass frequency has increased to provide near daily coverage

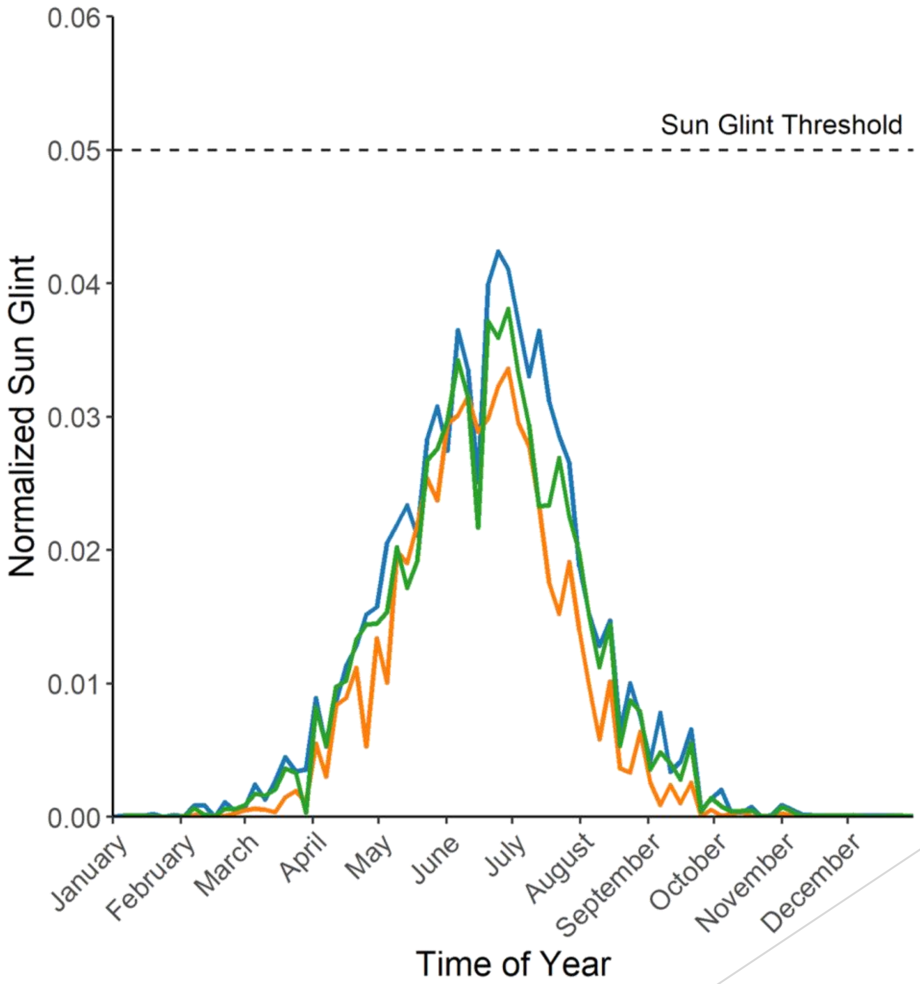


Sun glint potential can be modeled

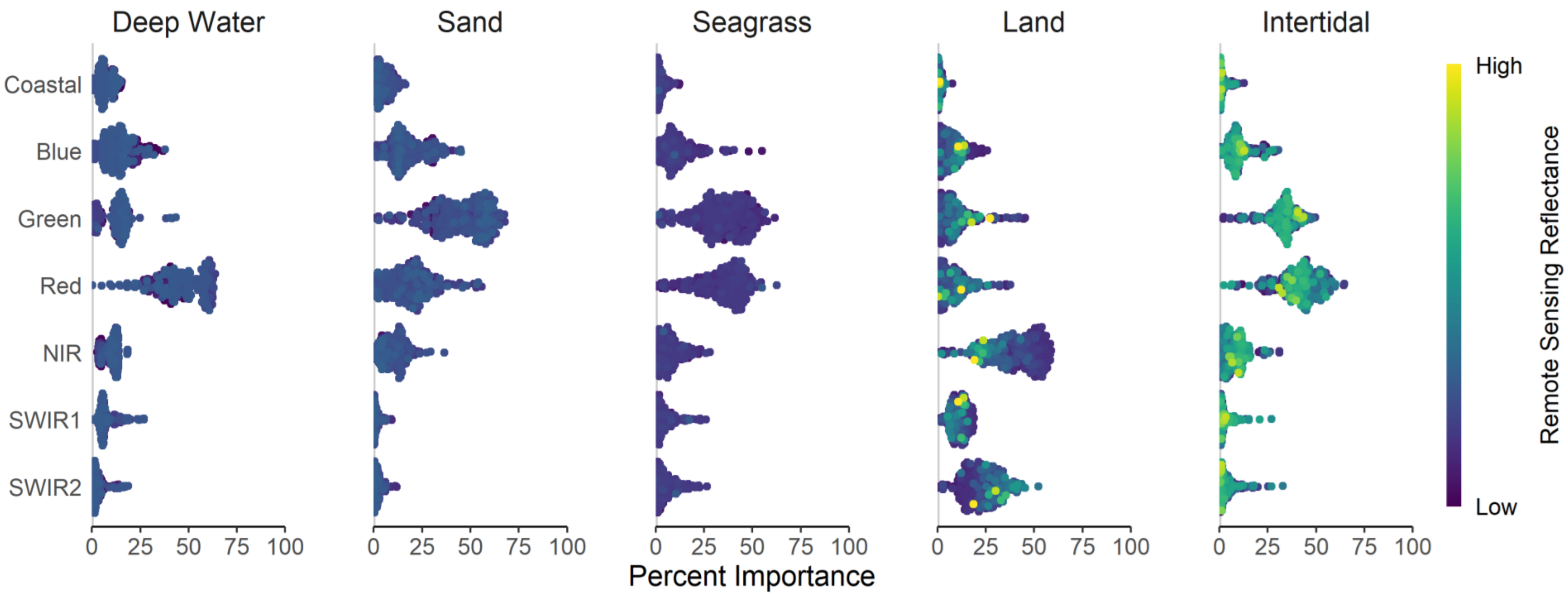


Maximum sun glint that would be observed by PlanetScope at three locations in and around the Chesapeake Bay in 2020





Band importance for image classification of seagrass



Exploring the potential of alternative satellite platforms

- As the PlanetScope constellation has grown, overpass frequency has increased to near daily coverage
- Past, present, and future sun glint conditions can be modeled to ensure image quality even for satellite platforms like PlanetScope that are sensitive to sun glint
- Bands that are commonly provided by remote sensing platforms (Green, Red, and NIR) are the most important for the image classification of seagrass

Looking forward

- Semi-automated process with machine learning & high-resolution satellite data
- Seagrass, leaf-area, carbon
- Demonstration at multiple locations across US
- Solutions for quality flagging increases use of imagery
- Additional platforms potentially increase coverage

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