Prototype for an SAV Blue Carbon Observatory the Chesapeake Bay

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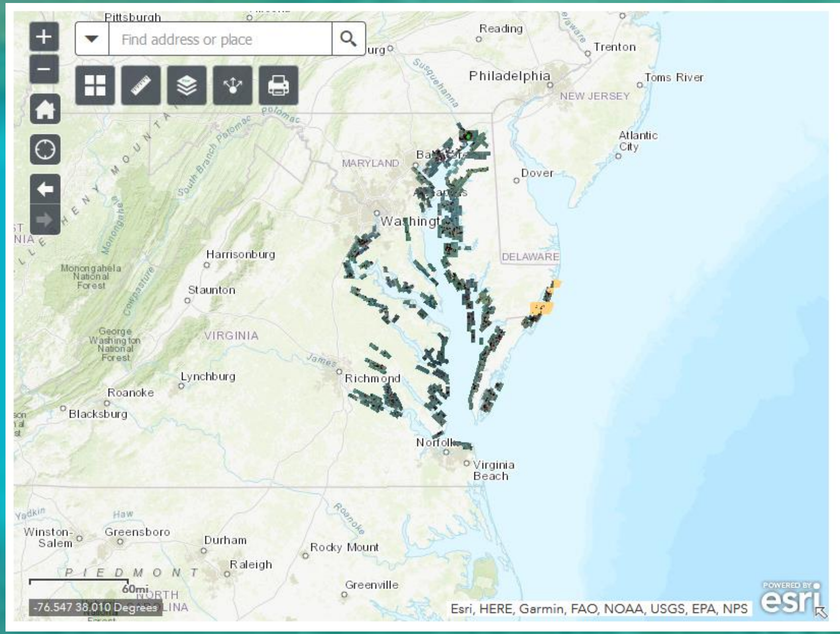
Chesapeake Bay SAV Workgroup Fall 2022 Meeting

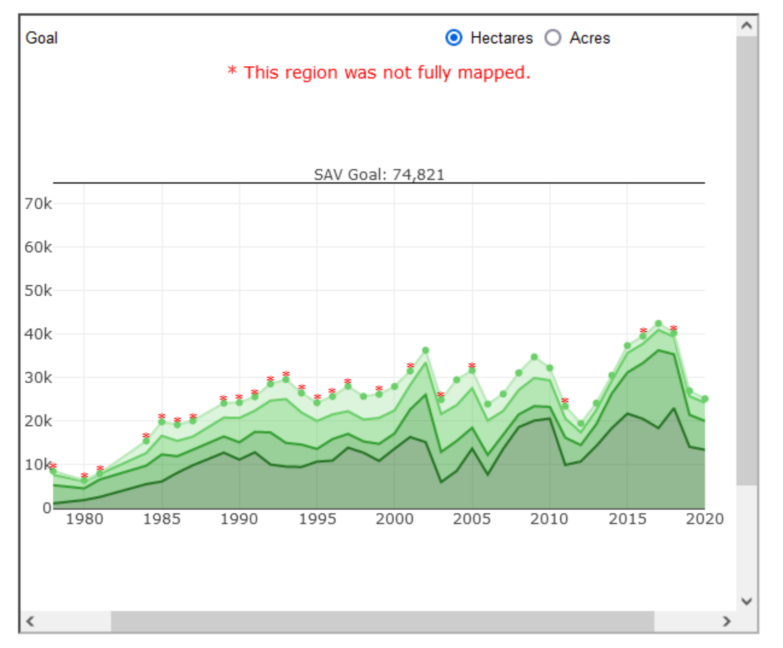
1 Nov 2022

“Blue Carbon” emphasizes the role of aquatic vascular plants in the carbon cycle

- But global estimates of this importance are highly uncertain
- Less than 10% of SAV resources have been mapped quantitatively across the globe
- Mapping submerged plants is technically & logistically challenging
- SAV abundances & distributions are
  - temporally dynamic on seasonal time scales
  - spatially dynamic on meter spatial scales

The Chesapeake Bay SAV mapping effort provides the longest continuous record of SAV distribution & relative abundance anywhere in the world



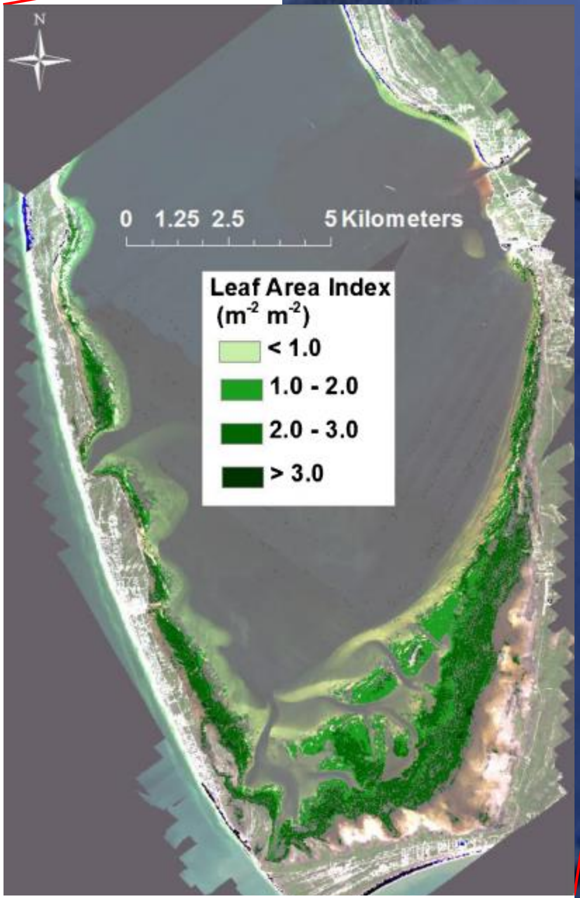


These data ara critically important management & science

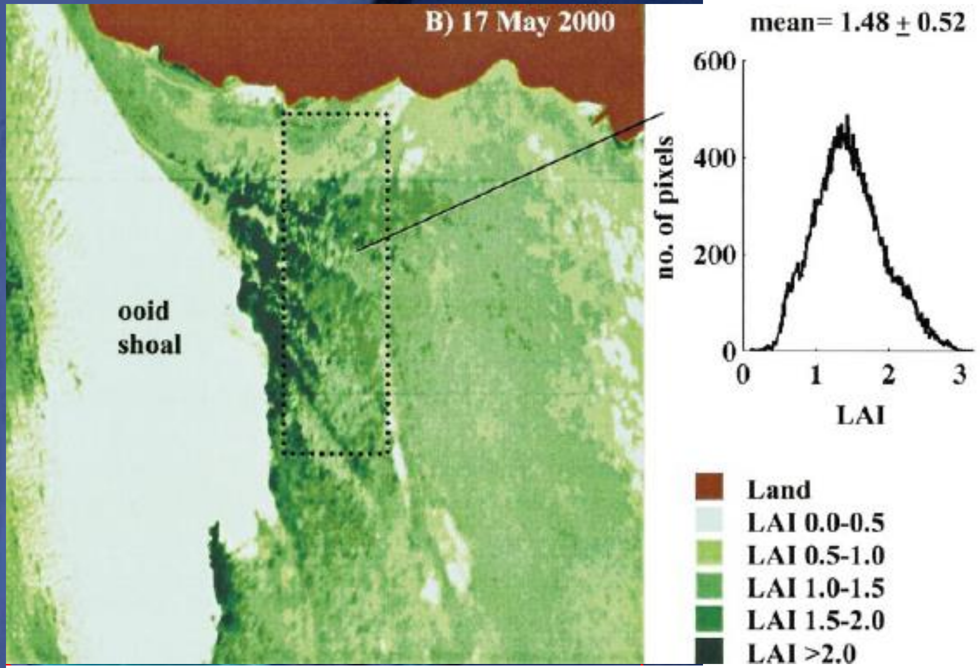
Traditional survey methods face challenges

- Frequency and scale of the surveys is limited
  - High operational costs
  - Labor & equipment intensive
  - Complex logistics
- Radiometrically uncalibrated imagery limits the ability to employ machine learning that can automate the mapping process
- Estimates of absolute abundance required for quantifying coastal biogeochemistry and Blue Carbon cannot be retrieved reliably from semi-quantitative maps of relative abundance

Seagrass extent and abundance can be mapped with high fidelity from aircraft carrying hyperspectral sensors

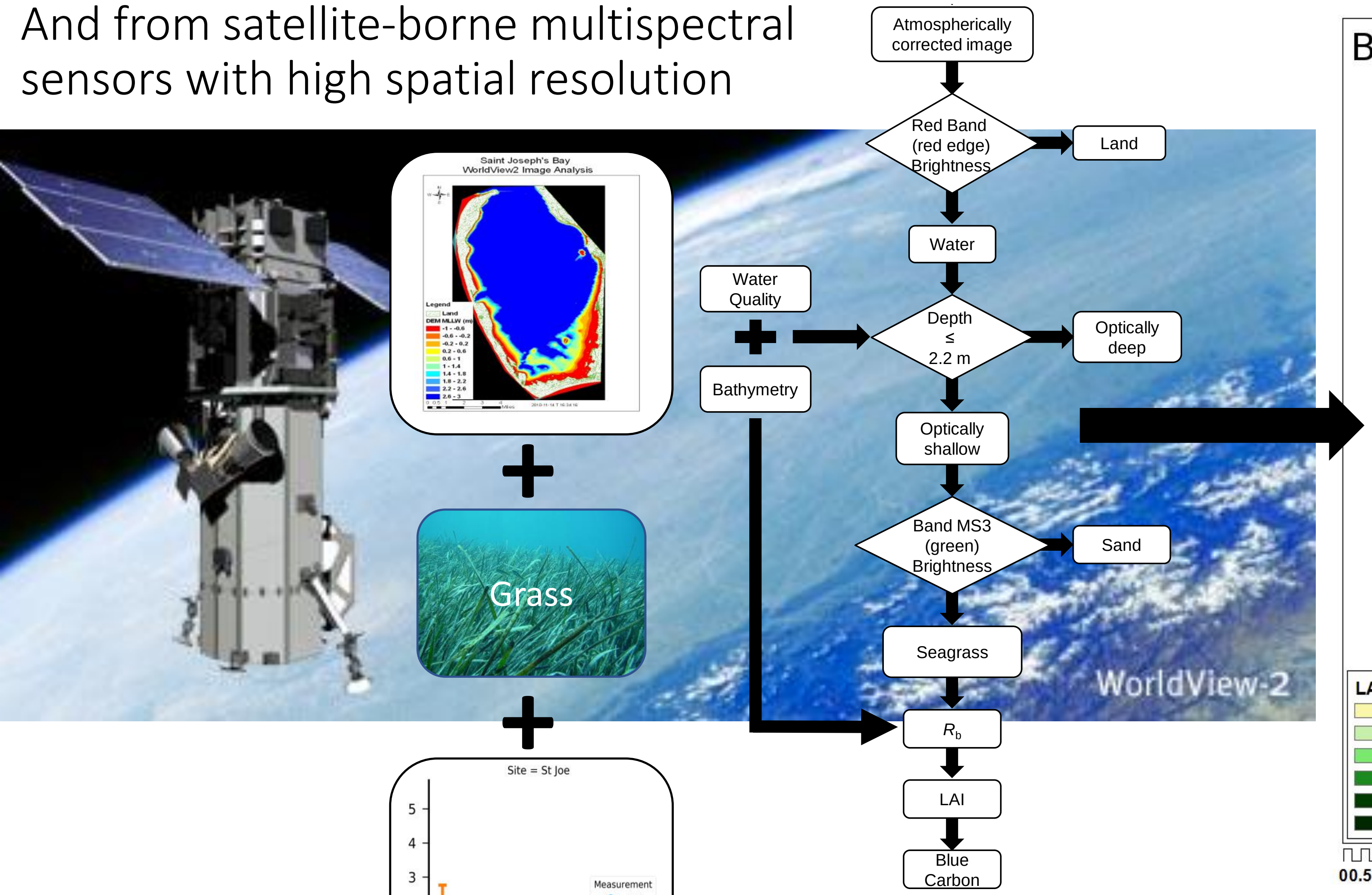


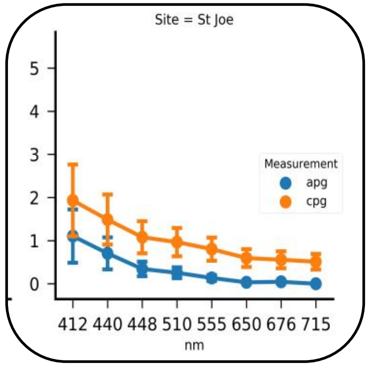
Hill, V.J., R.C. Zimmerman, W.P. Bissett, H. Dierssen, and D.D. Kohler. 2014. *Estuaries and Coasts* 37: 1467-1489.

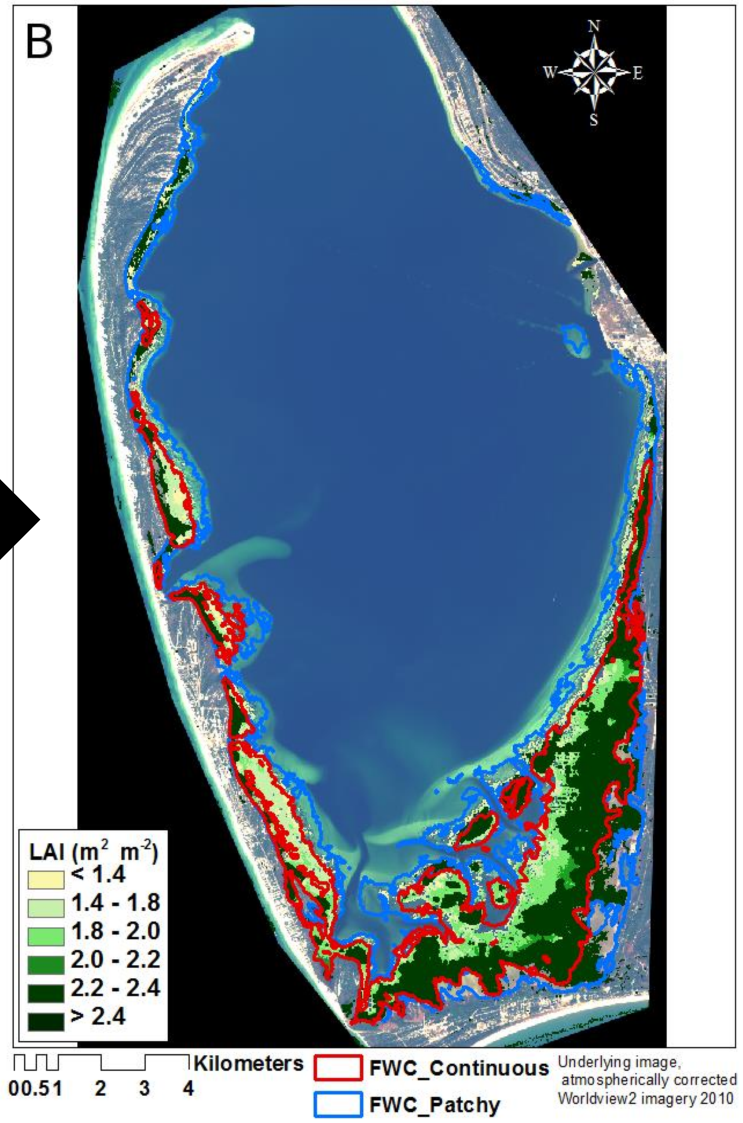


Dierssen, H., R. Zimmerman, R. Leathers, T. Downes, and C. Davis. 2003. *Limnol. Oceangr.* 48: 444-455.

And from satellite-borne multispectral sensors with high spatial resolution

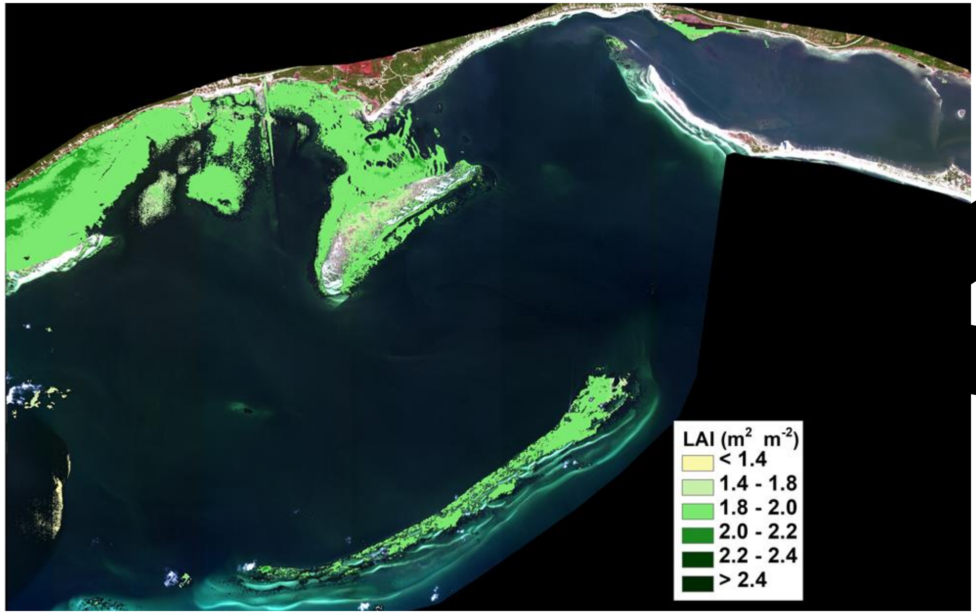






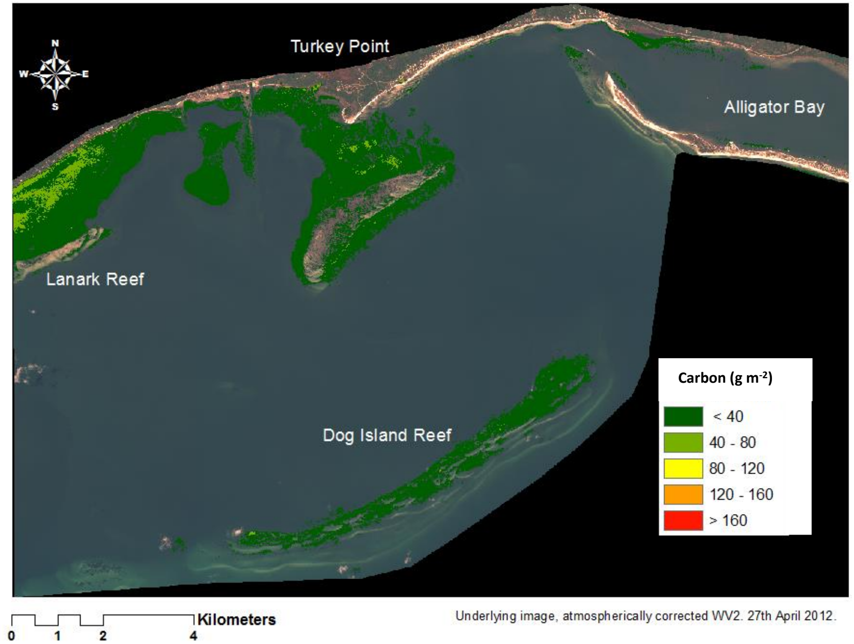
Bissett, W., R. Zimmerman, V. Hill, and D. Kohler. 2011. Saint Josephs Bay Aquatic Preserve Imaging Spectroscopy: Florida Department of Environmental Protection. Office of Coastal and Aquatic Managed Areas. Contract No RM055.

And Seagrass carbon can be derived from the LAI maps

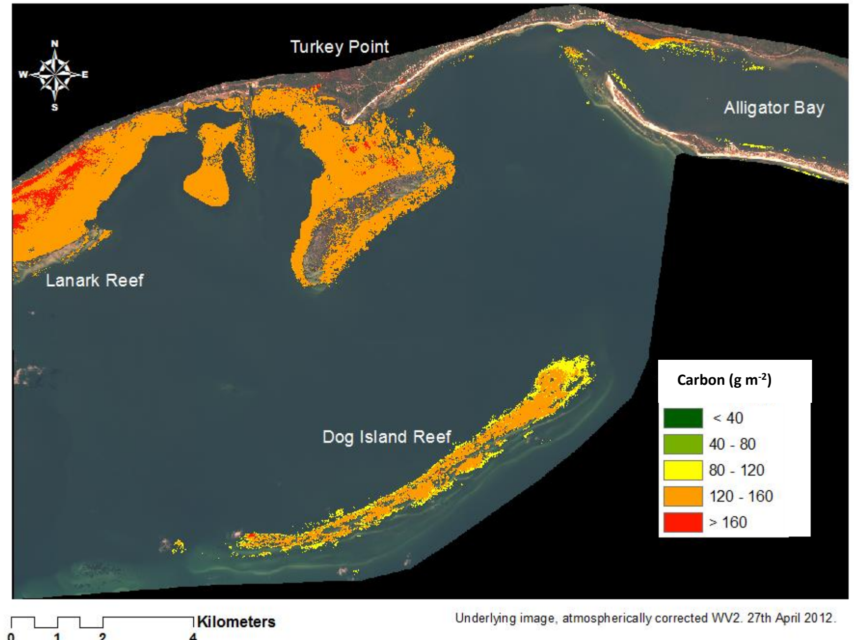


St. George Sound, FL

Above-ground biomass



Below-ground biomass



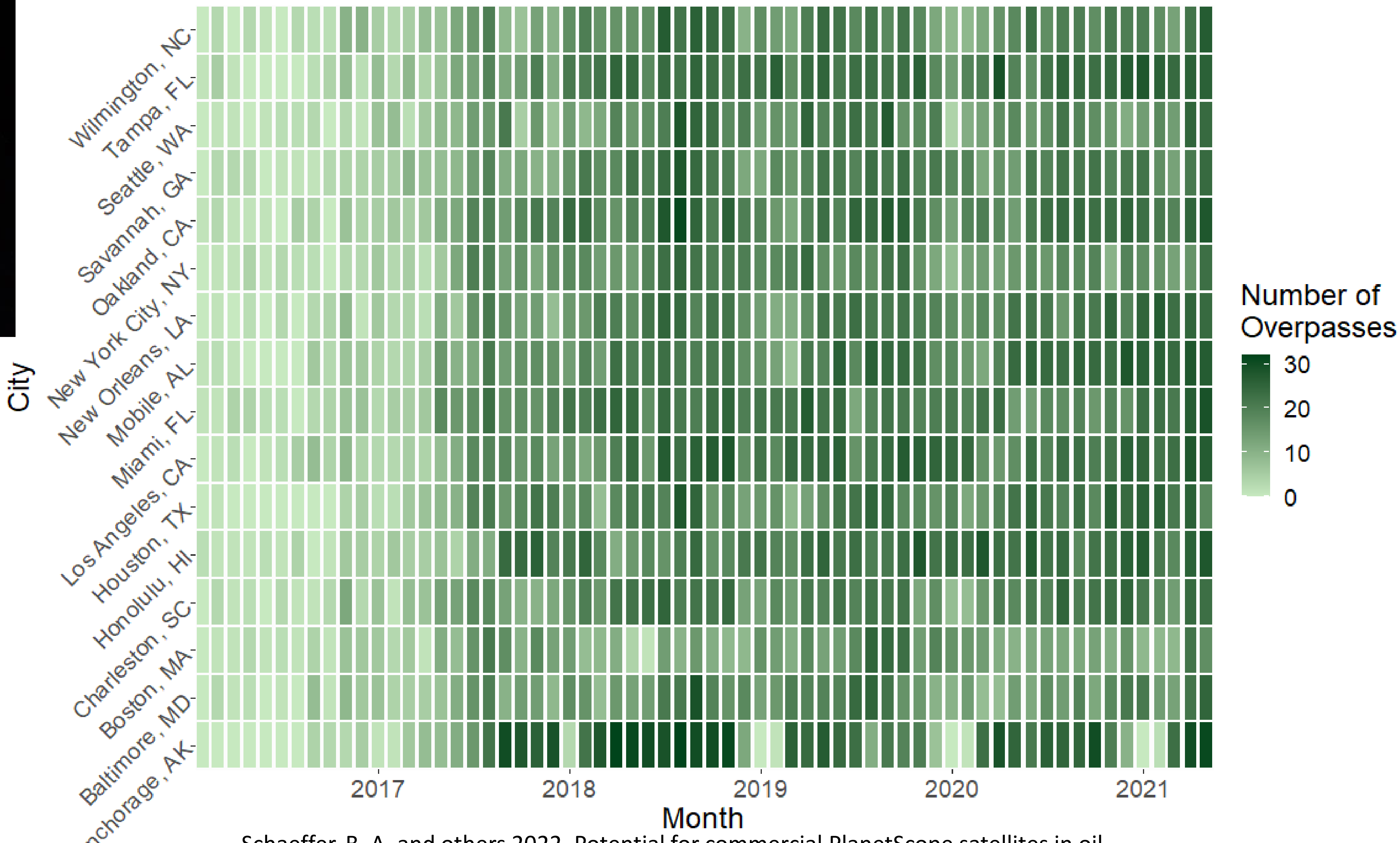
The Opportunity – Satellite Remote Sensing

- Can satellite remote sensing replace or at least augment aerial surveys?
- Can machine learning algorithms be used to automate the classification process?
- Can we generate more quantitative abundance data useful for biogeochemical modeling and estimating Blue Carbon resources?

Tremendous advances in satellite remote in the last decade

Sensor	Operator	Bands	Nadir Spatial Resolution (m)	Operational Status	View Angle	Swath (km)	Coverage	Repeat Cycle	Radiometric Calibration	Atmospheric Correction	Data Availability
LandSat	NASA/USGS	4 Vis 1 NIR	30 multi 15 pan	L5+ since 1984	Nadir	185	Global	16 Days	User-applied	Use-applied	**Public**
Sentinel	ESA	4 Vis, 3 Red Edge, 3 NIR	10	S-2A in 2015	Nadir	290	Global	10 Days	Provided	Provided	**Public**
WorldView 2,3	Maxar	5 Vis, 1 Red Edge 2 NIR, Pan	WV2: 1.8 Multi 0.46 Pan WV3: 1.24 Multi 0.31 Pan	WV2: Since 2009 WV3: Since 2014	Taskable	WV2: 16.4 WV3:13.1	Requires Tasking	Infrequent, requires tasking	User-applied	User-applied	**Propreitary** Free through NGA for limited academic research
Dove PlanetScope	Planet	3 Vis, 1 Red Edge, 1 NIR	3.9	Since 2017	Nadir	5	Global Land Mass, Daily Image	Daily	Provided	Provided	**Propreitary** Free through NGA and Planet for academic research

Dove PlanetScope images per month

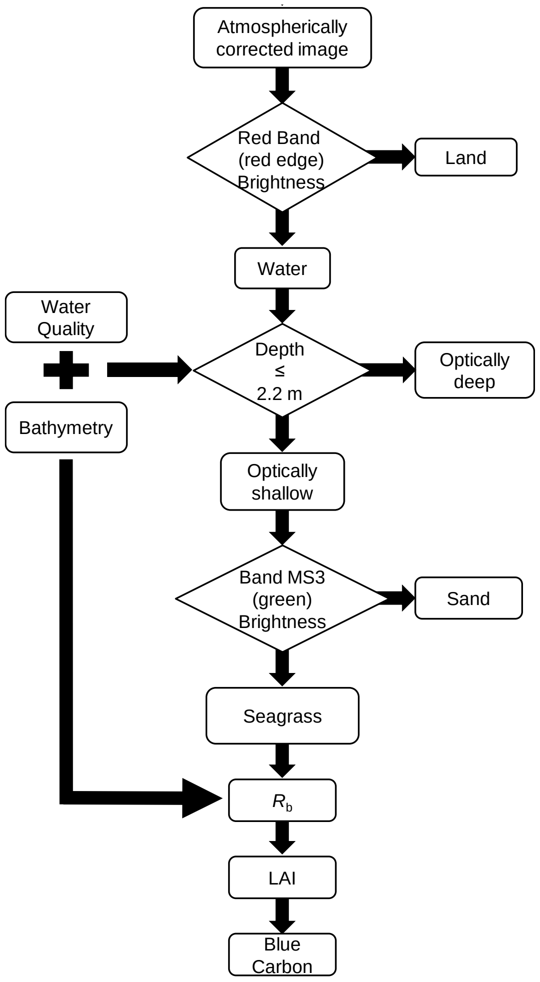


- Daily global coverage eliminates tasking logistics
- Availability of radiometrically calibrated and atmospherically corrected images simplifies the processing
- The on-line catalog is easy to use

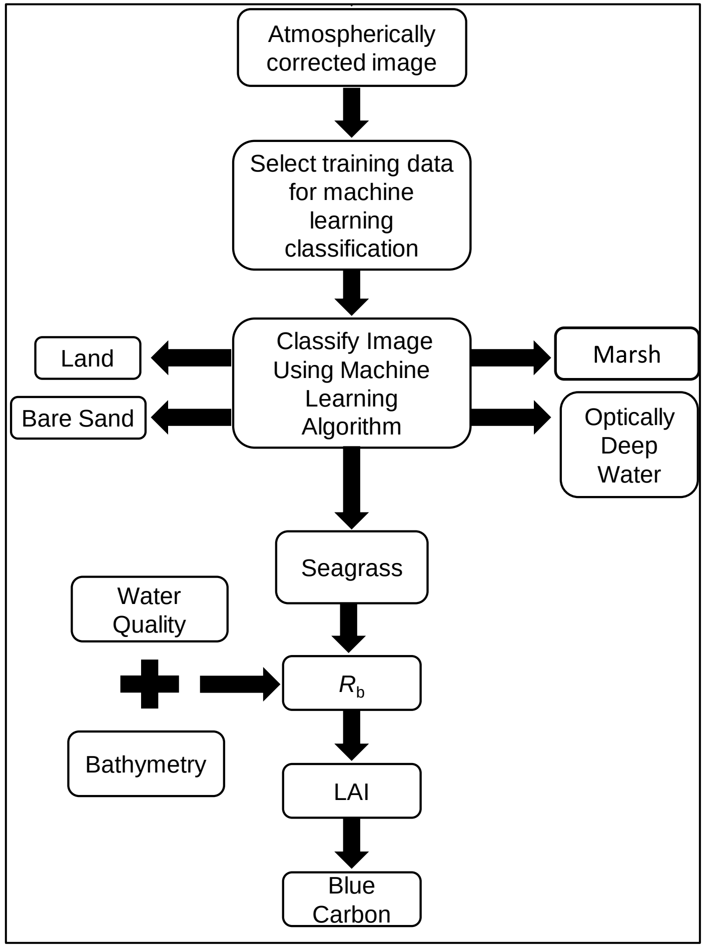
Schaeffer, B. A. and others 2022. Potential for commercial PlanetScope satellites in oil response monitoring. Marine Pollution Bulletin **183: 114077.**

Can we train machine learning algorithms to classify SAV in these complex coastal waters?

Physics-based classification:

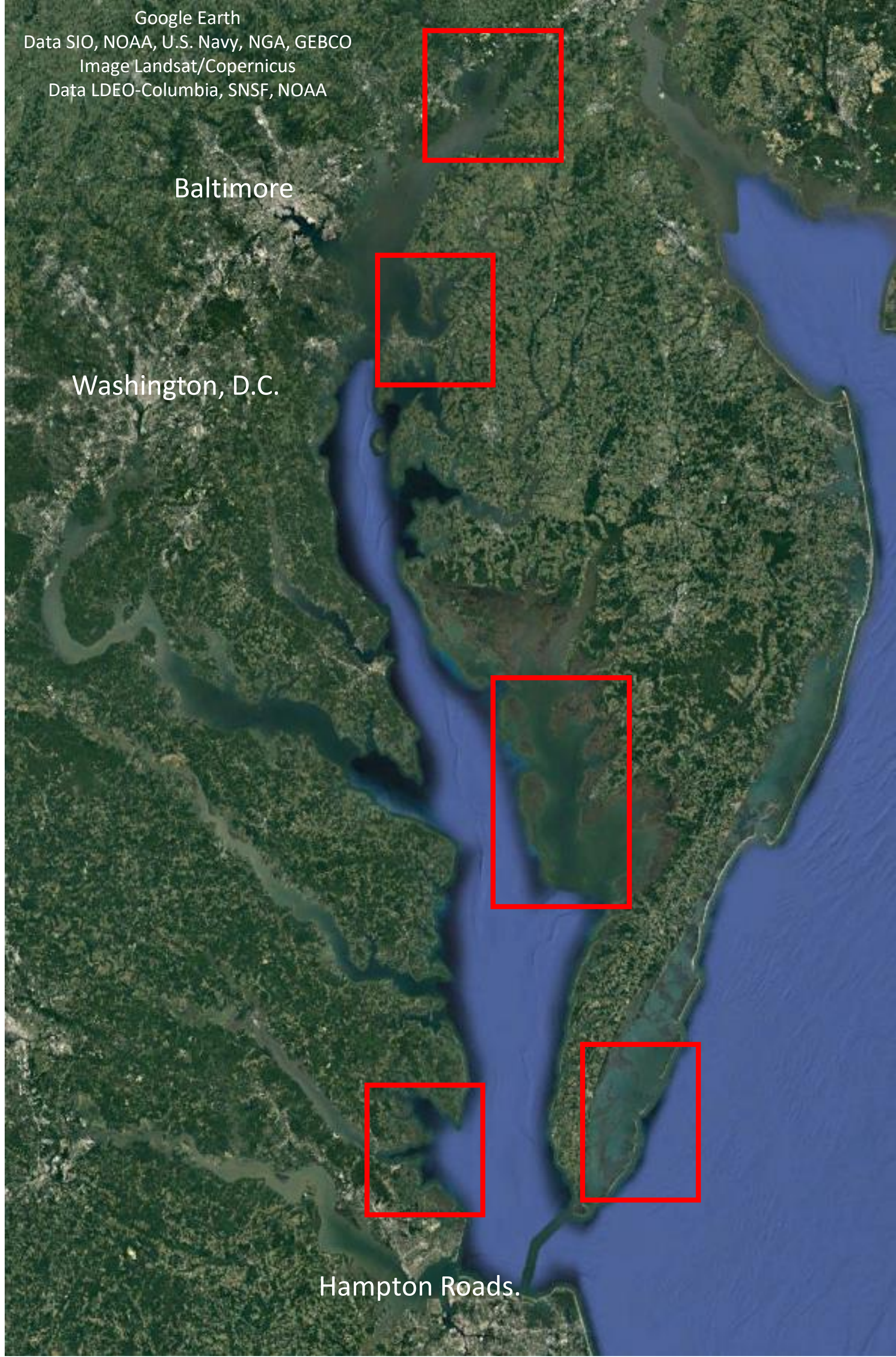


Machine learning classification:



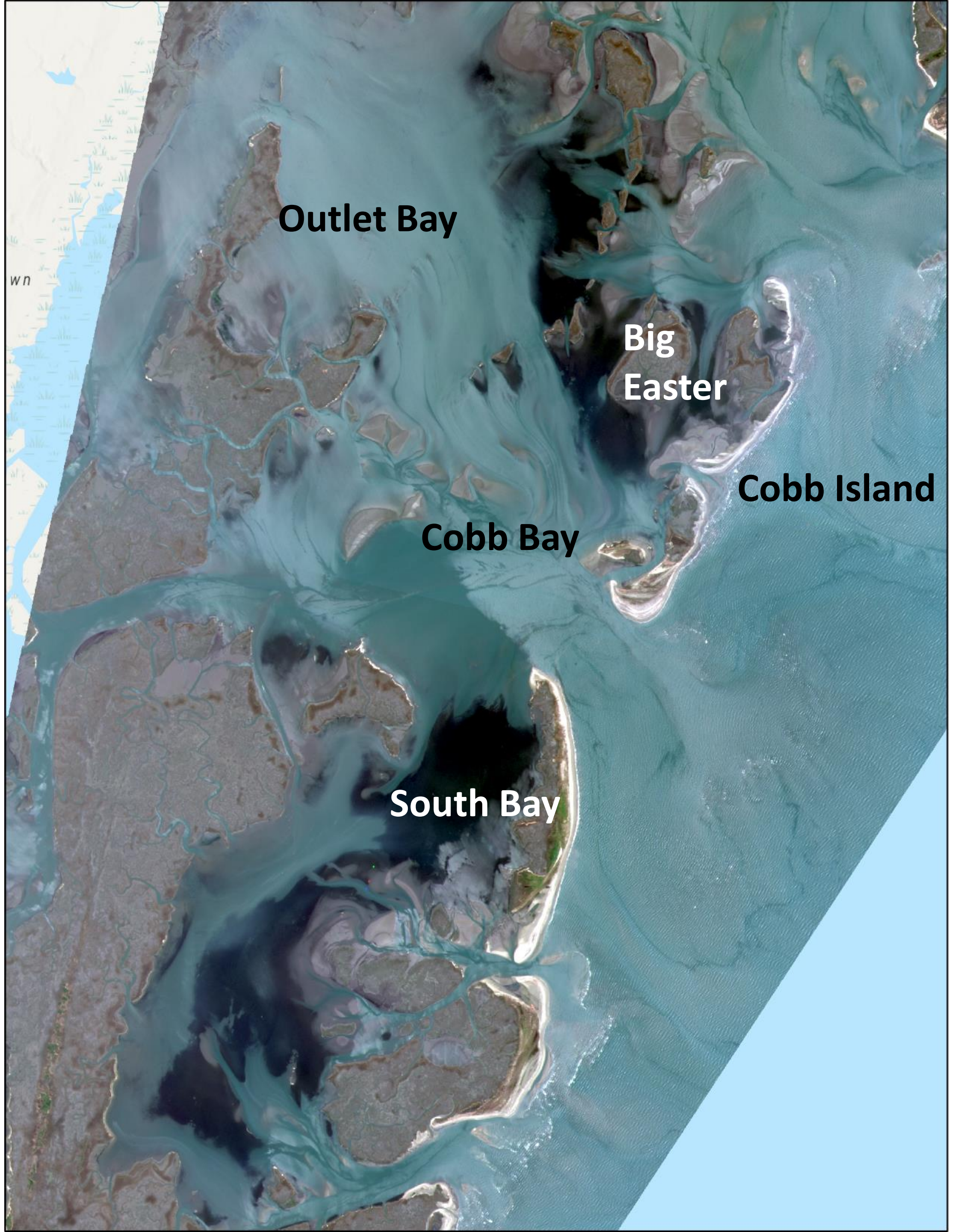
Can machine learning algorithms be used to automate the classification process for SAV in Chesapeake Bay?

- Five different locations
  - Highly turbid oligohaline upper Bay
    - Susquehanna Flats - large stable meadow of *Valisneria americana*
    - Chester River – small & variable patches of SAV (multiple spp.) along river banks
  - Moderately turbid mesohaline central Bay
    - Smith and Tangier Islands – variable patches of SAV (*Ruppia americana* and *Zostera marina*)
  - Polyhaline York River
    - Goodwin Island & Mobjack Bay – variable meadows of *Ruppia americana* and *Zostera marina*
    - *Less turbid than upper*
  - Oceanic coastal lagoons
    - South Bay – extensively restored meadow of *Zostera marina*
    - Highest salinity, lowest turbidity



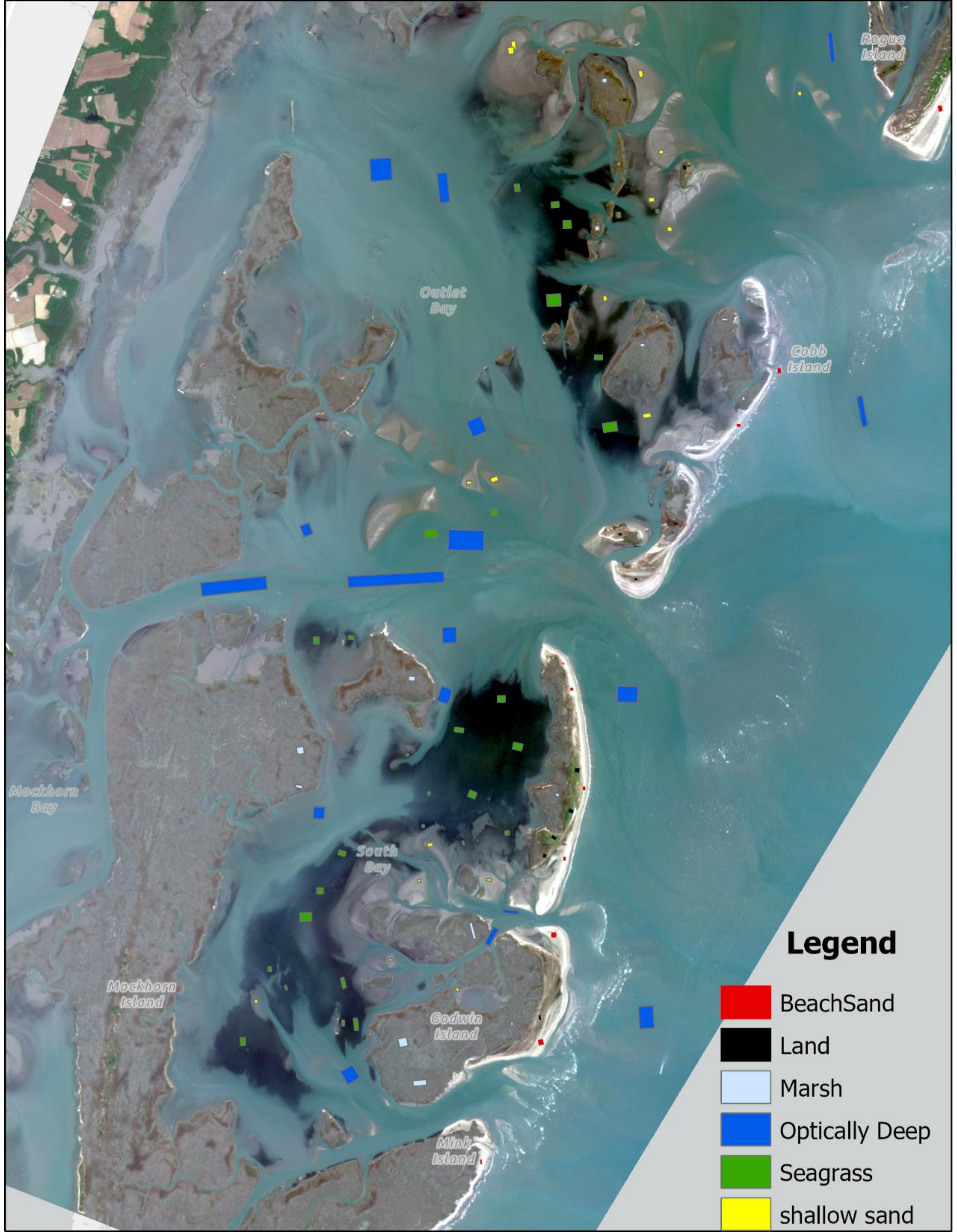
South Bay & Spider Crab

- Planet passes every day, often multiple passes from different sensors.
- Images good for seagrass identification.
  - Low tide
  - Low turbidity
  - Low cloud cover.

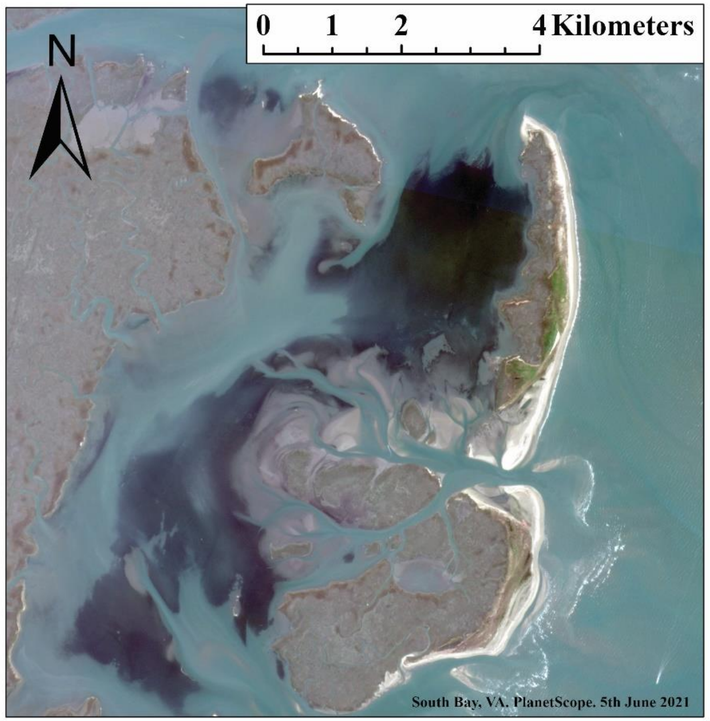


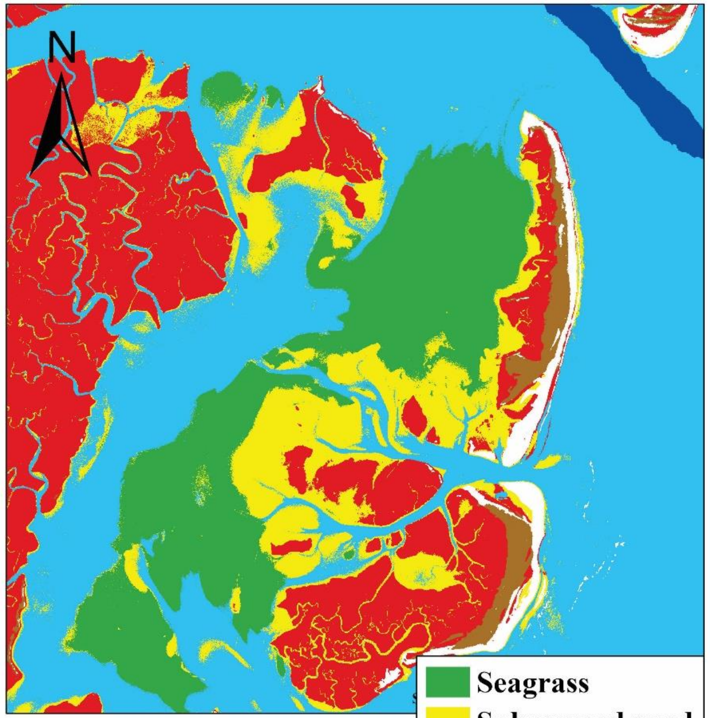
Training the ML model

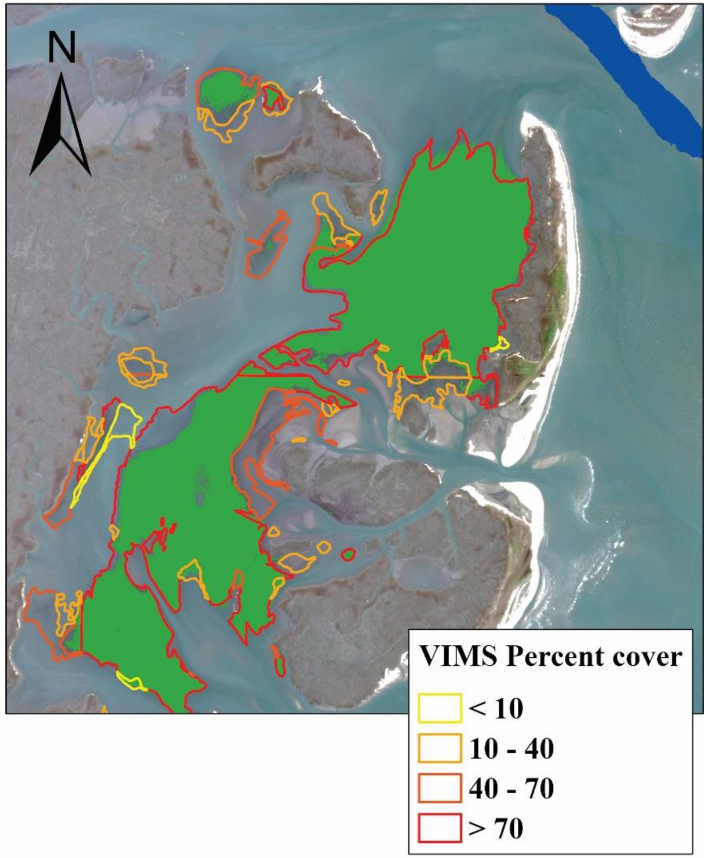
- Identify training patches for each target
    - Beach
    - Land
    - Marsh
    - Optically deep
    - Seagrass
    - Shallow sand
- Include DEM (bathymetry) as a factor in training



Classification of individually trained image

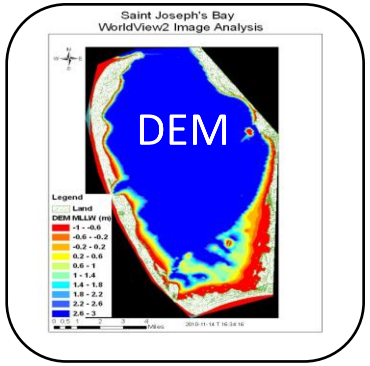


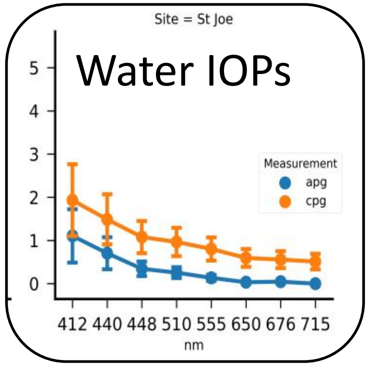




We are training the model with the expectation that we will be able classify a new image without additional training

From distribution to density

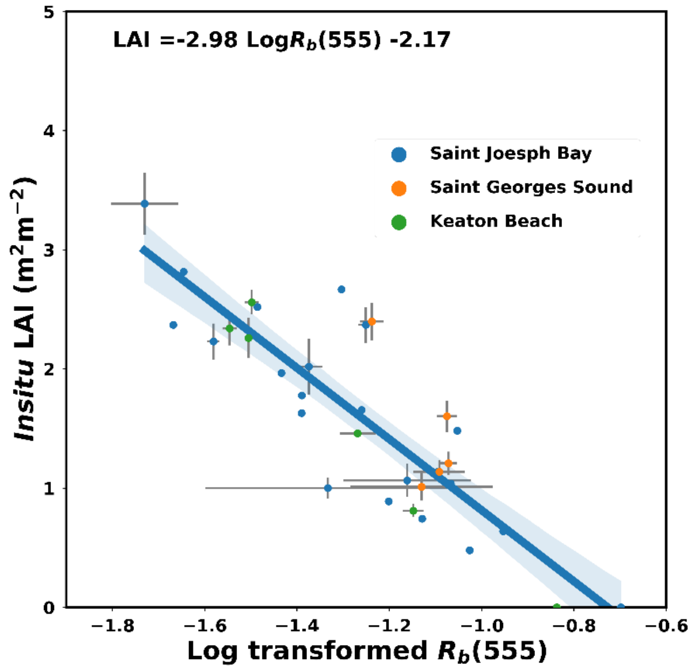




- ***<u>Atmospherically corrected</u>*** R_{rs} from imagery
- $Q_b = E_u(z_b)/L_u(z_b) = \pi$
- K_{Lu} & K_d from *Hydrolight* using measured IOPs
- Water depth, DEM + tide

$$R_b = \frac{R_{rs} Q_b}{t} \frac{\exp\left[-K_{Lu} z_b\right]}{\exp\left(K_d z_b\right)}$$

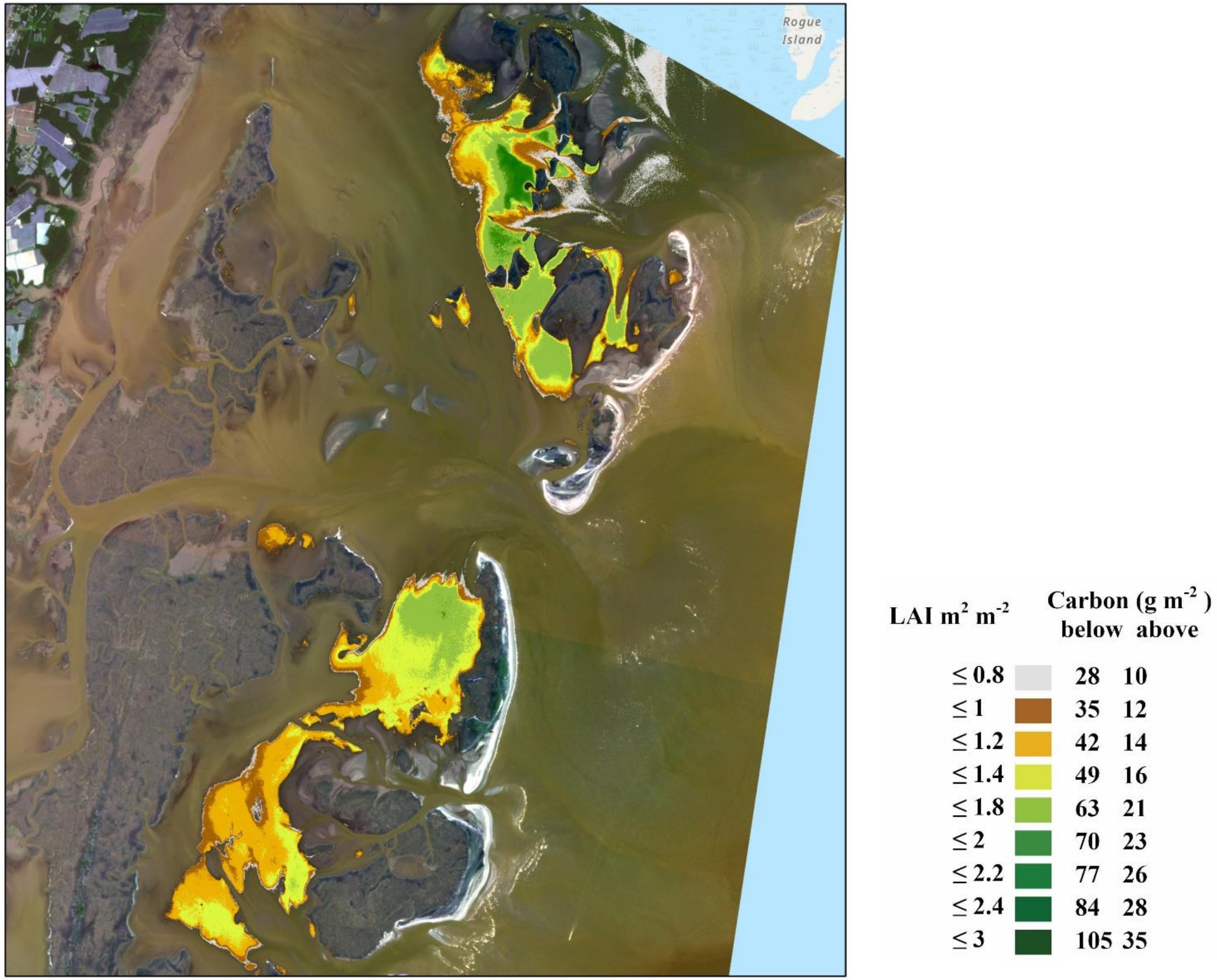
- z_b – bottom depth from acoustic survey
- t – air/sea transmittance of $L_u(0.54)$



Hill, V. J., Zimmerman, R. C., Bissett, P., Dierssen, H. M., & Kohler, D. (2014). Evaluating Light Availability, Seagrass Biomass, and Productivity Using Hyperspectral Airborne Remote Sensing in Saint Joseph's Bay, Florida. *Estuaries and Coasts, 37*. doi:DOI: 10.1007/s12237-013-9764-3.

Dierssen, H., R. Zimmerman, R. Leathers, T. Downes, and C. Davis. 2003. Remote sensing of seagrass and bathymetry in the Bahamas Banks using high resolution airborne imagery. Limnol. Oceangr. **48: 444-455.**

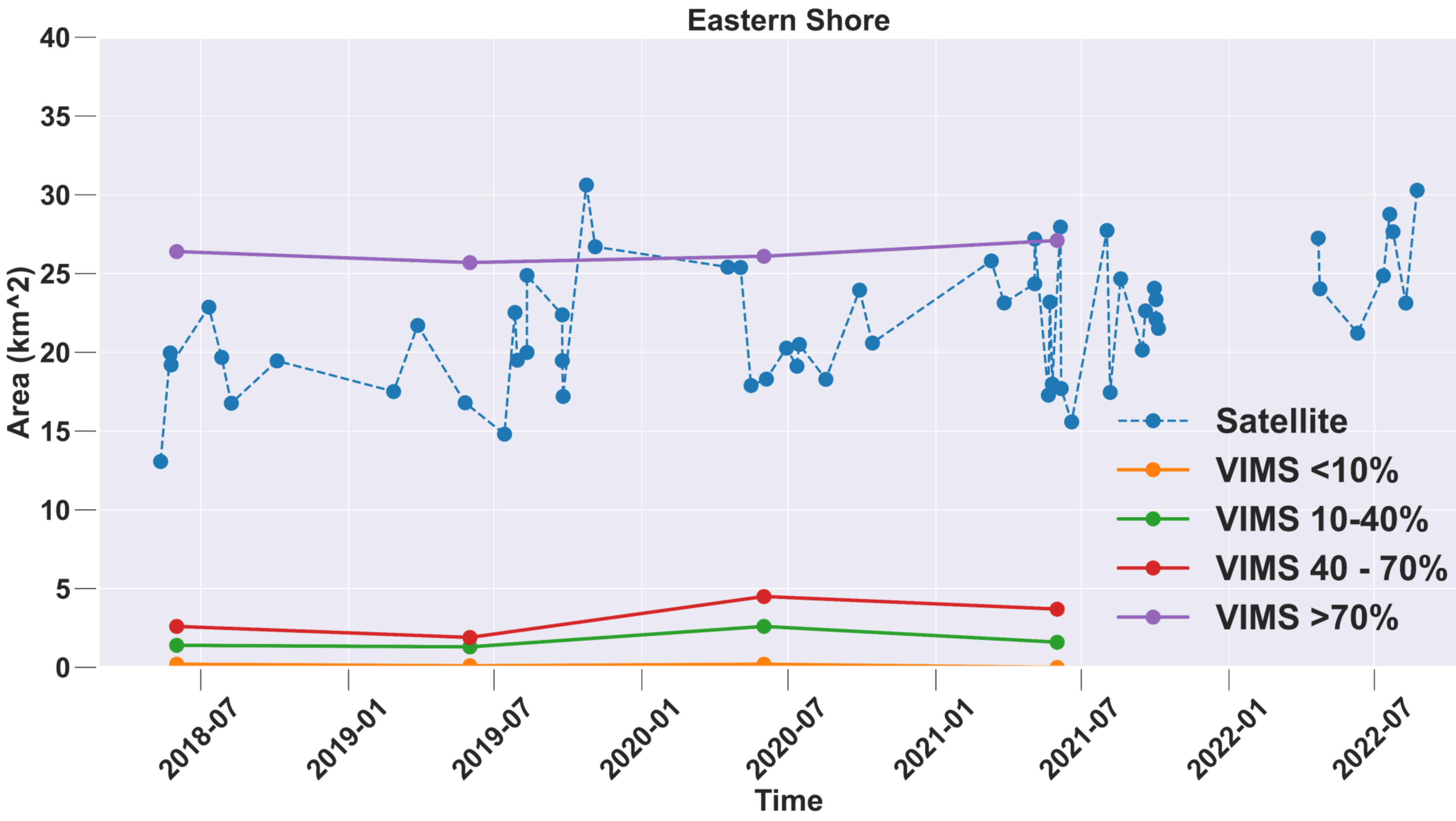
Density and above ground carbon



Number of useful images of the Eastern Shore 2018-2022

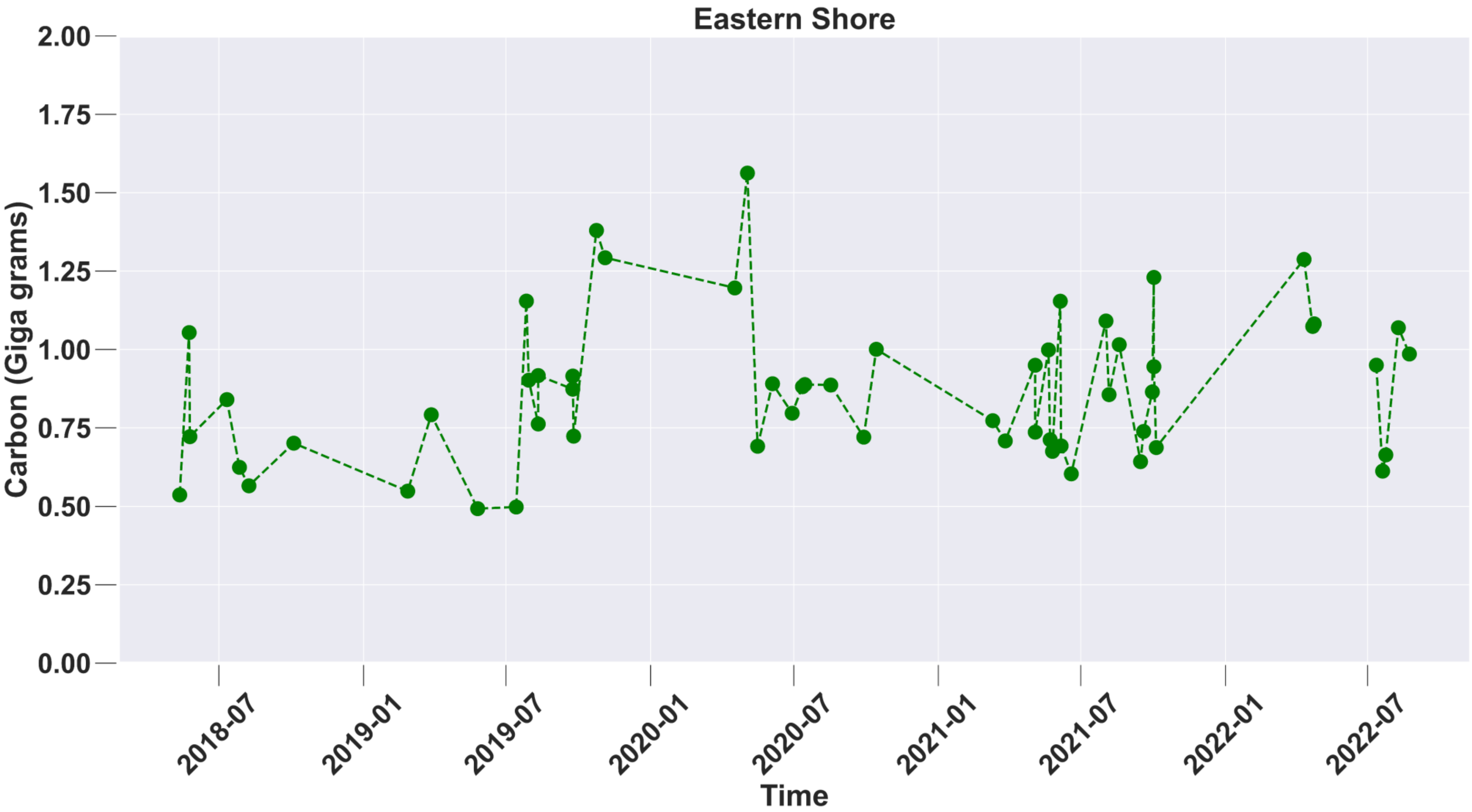
Year	Jan-Mar	April-June	July-Sept	Oct-Dec	Total
2018	1	3	3	1	**8**
2019	2	1	7	2	**12**
2020	0	5	5	1	**11**
2021	2	7	7	2	**18**
2022	0	4	6	NA	**10**

Total SAV area:
Compare pixel based and polygon based approach



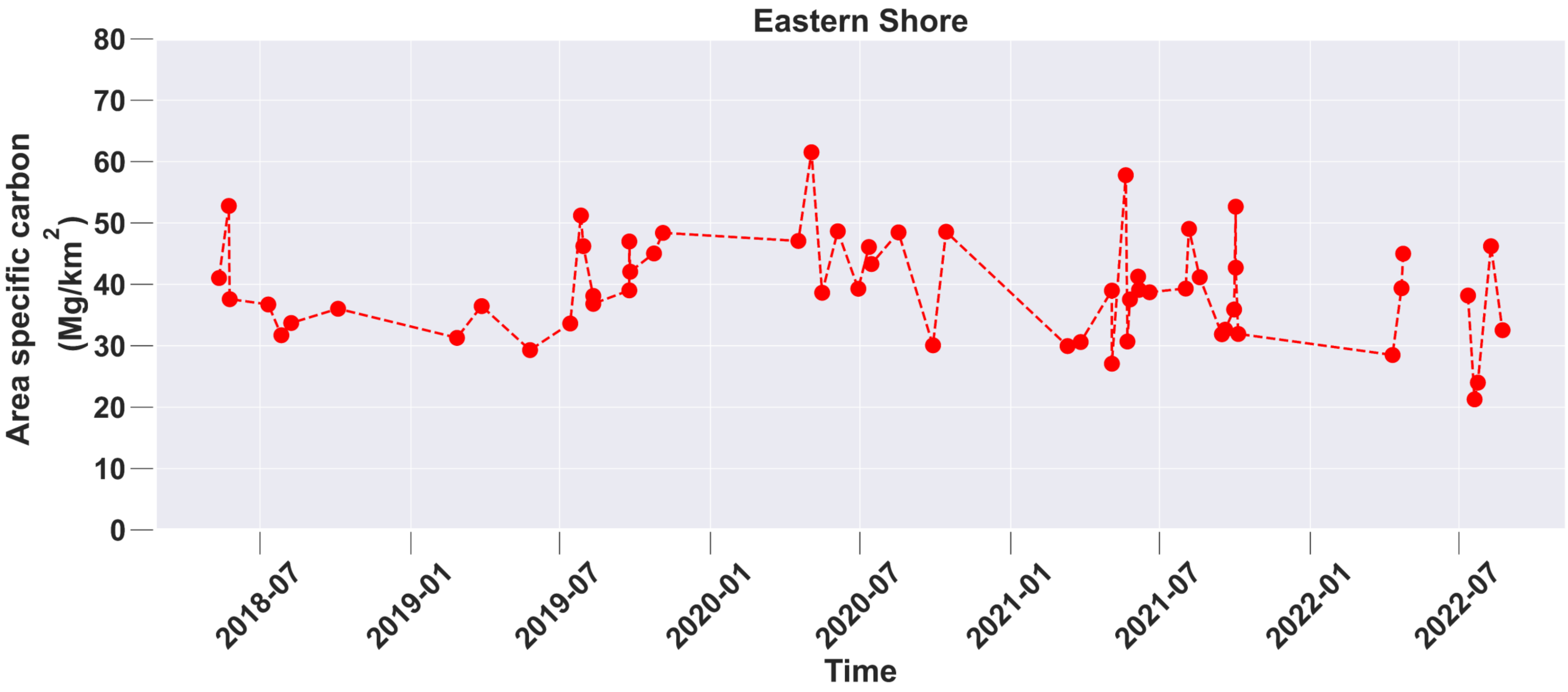
Total above ground carbon

Differences in carbon is due to variation in SAV area.

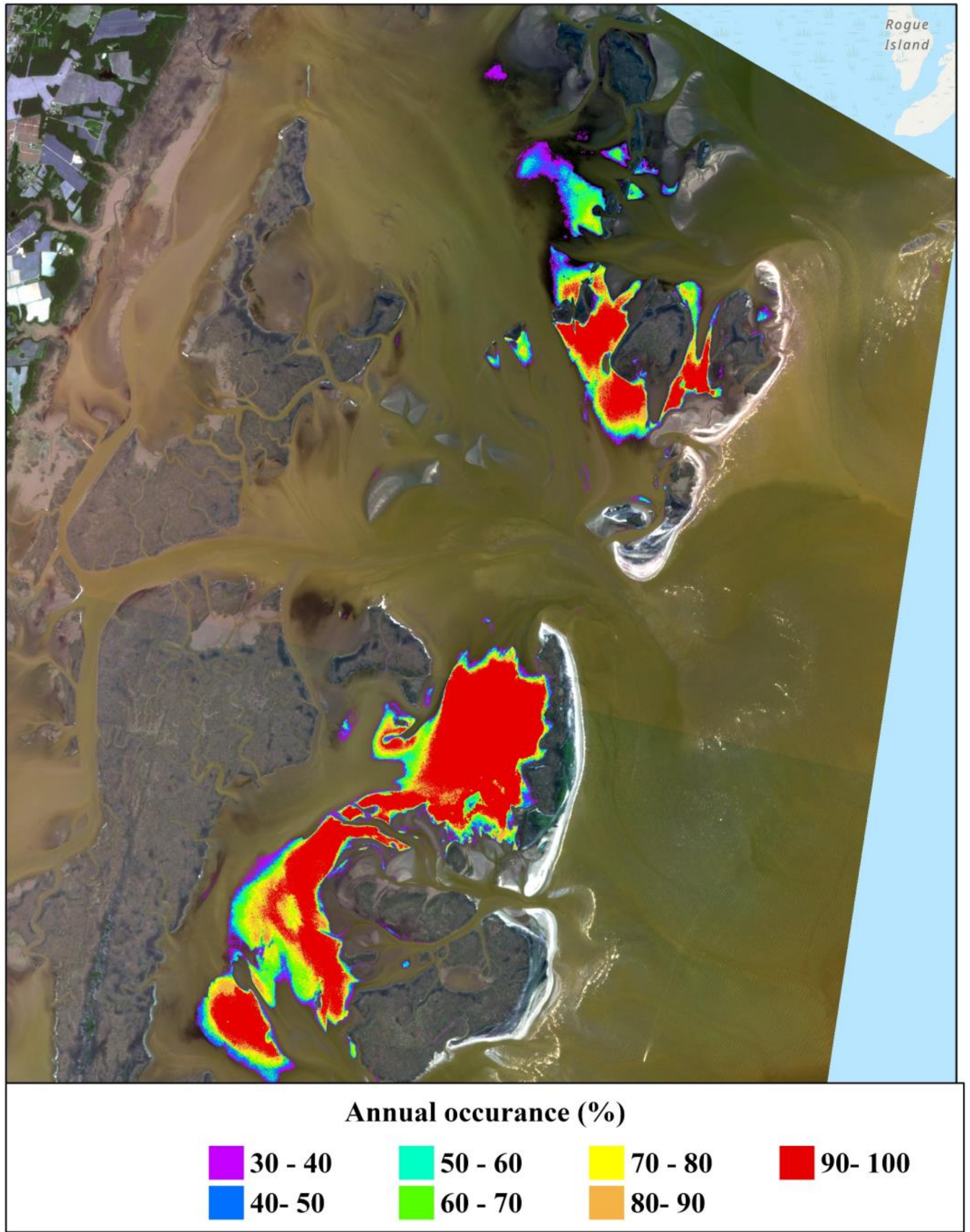


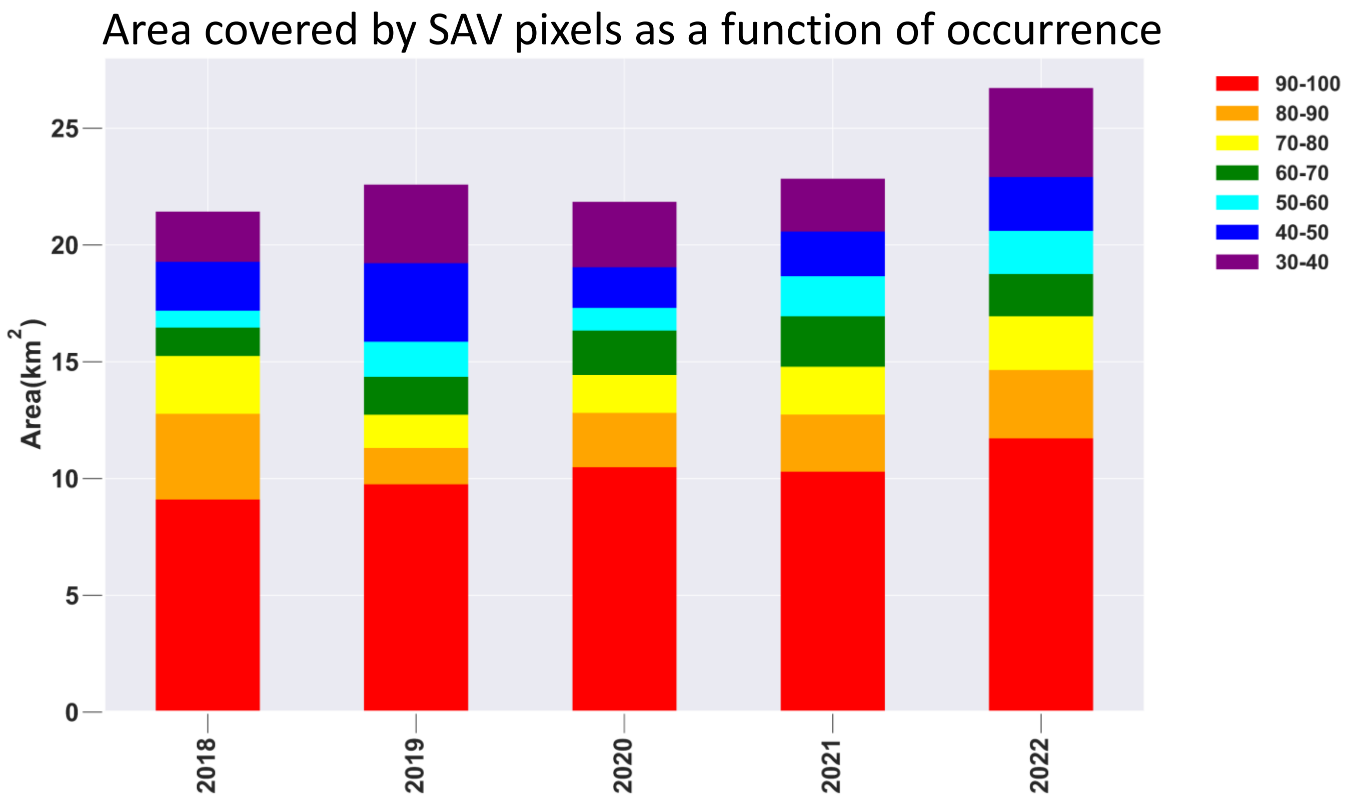
Area specific carbon

Average density of the beds 39.5 Mg km^2

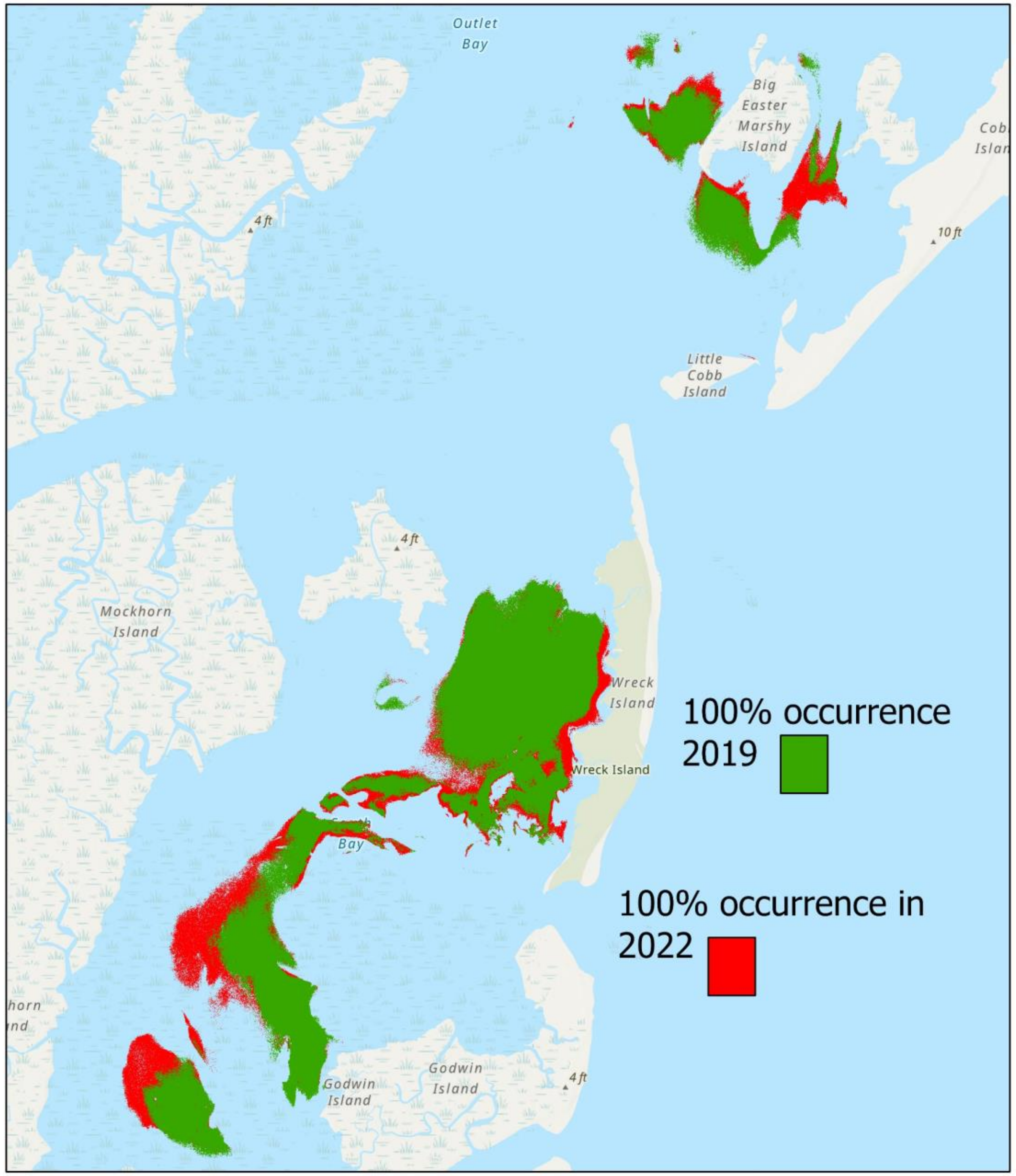


Annual occurrence that an imaged pixel was classified as SAV





Area of 90-100% occurrence is increasing



We can detect areas that have increased in density. They show up as changes in 100% occurrence

Goodwin Island

Smaller and less dense SAV meadows dominating the polyhaline environment Goodwin Islands cover an area ~ 1 km^2.
Standing plant biomass = 0.034 Gg of carbon.
Living carbon density = 34 Mg km^2.

Susquehanna Flats

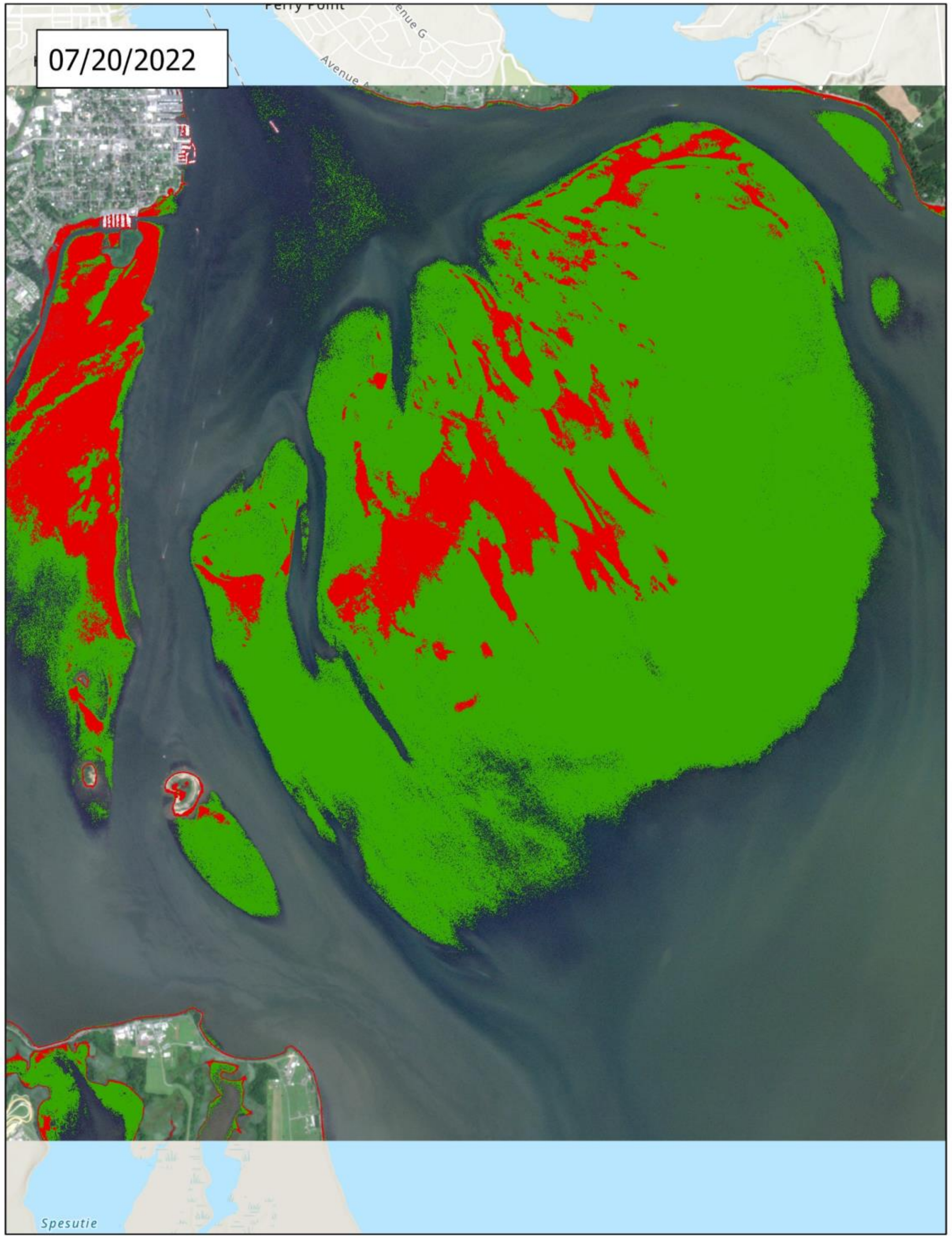
SAV meadow in the tidal fresh habitat of Susquehanna Flats covers an area of 29.3 km^2
Standing plant biomass = 2.11 Gg of carbon
Living carbon density = 70 Mg km^{-2}.

Susquehanna Flats 2022

Susquehanna Flats

Susquehanna Flats

FAV=floating vegetation.
Emergent canopy of the SAV



Susquehanna Flats

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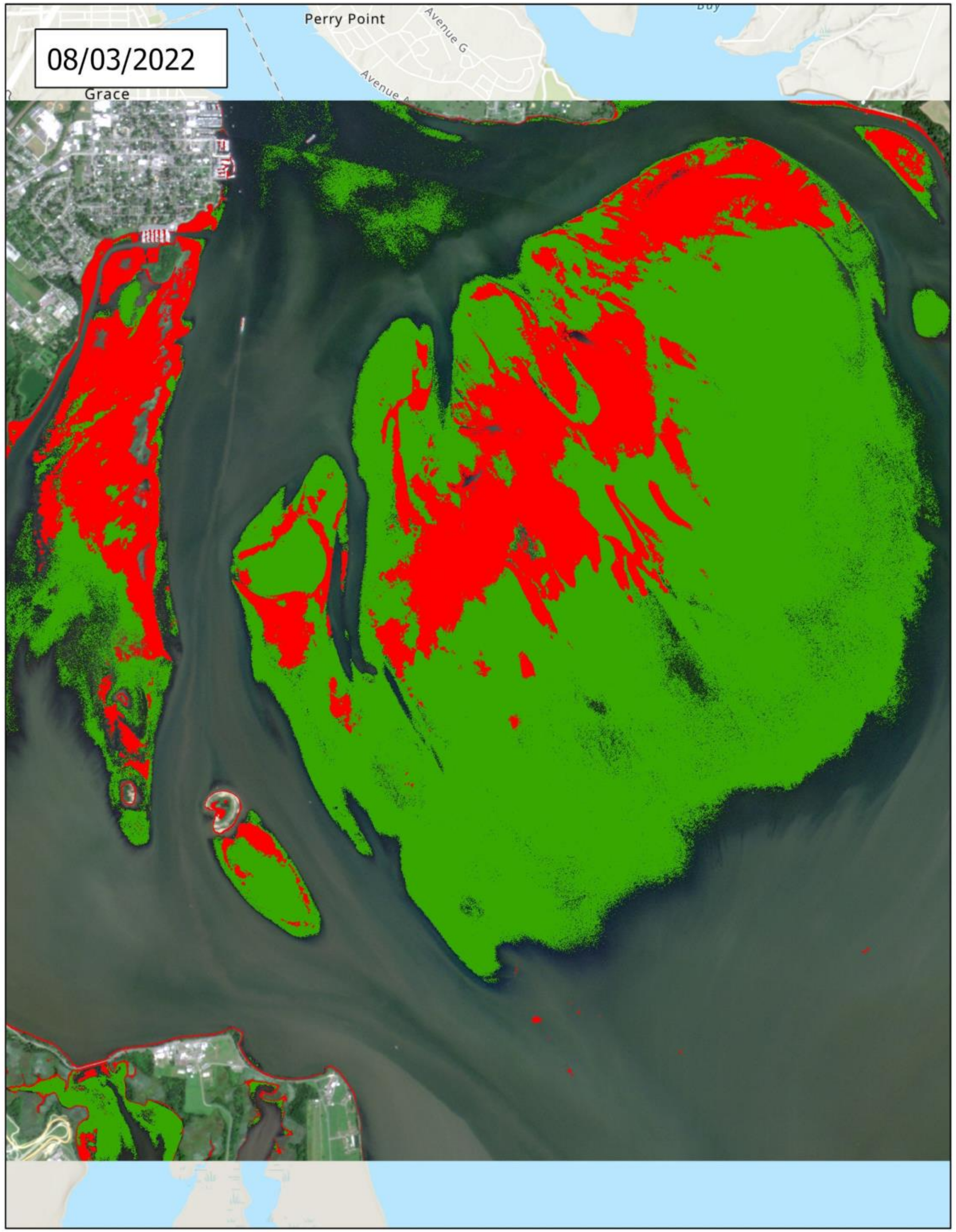

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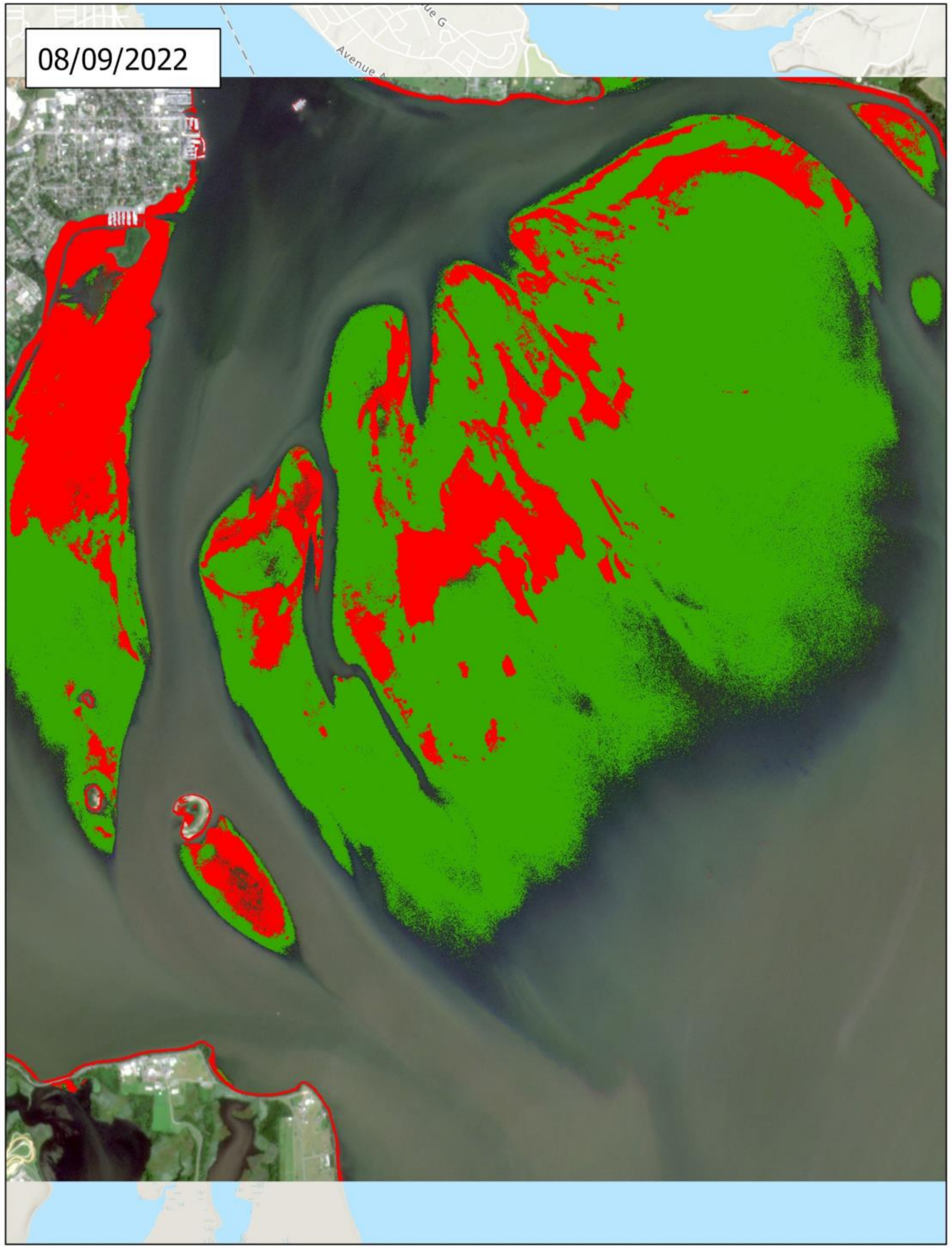

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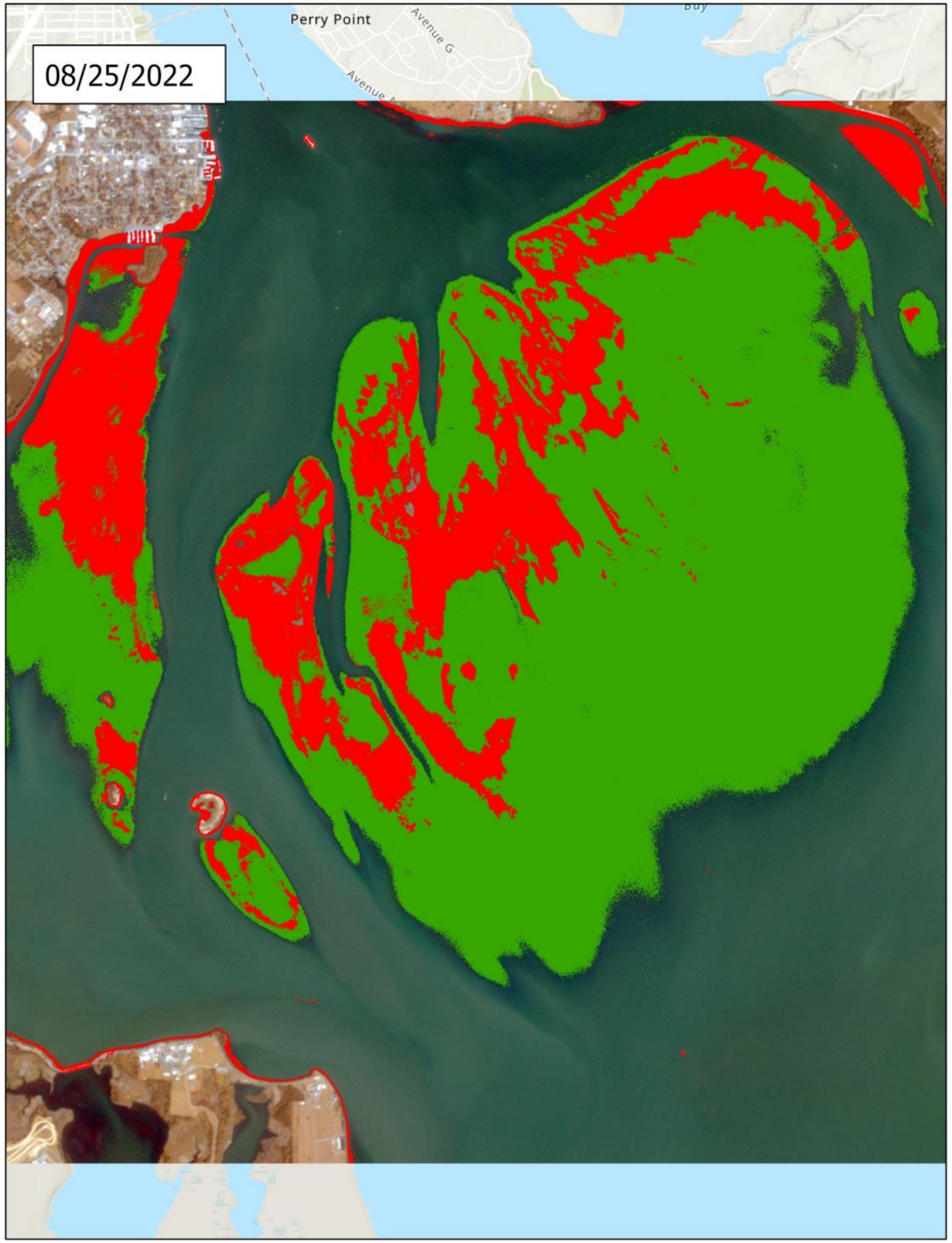

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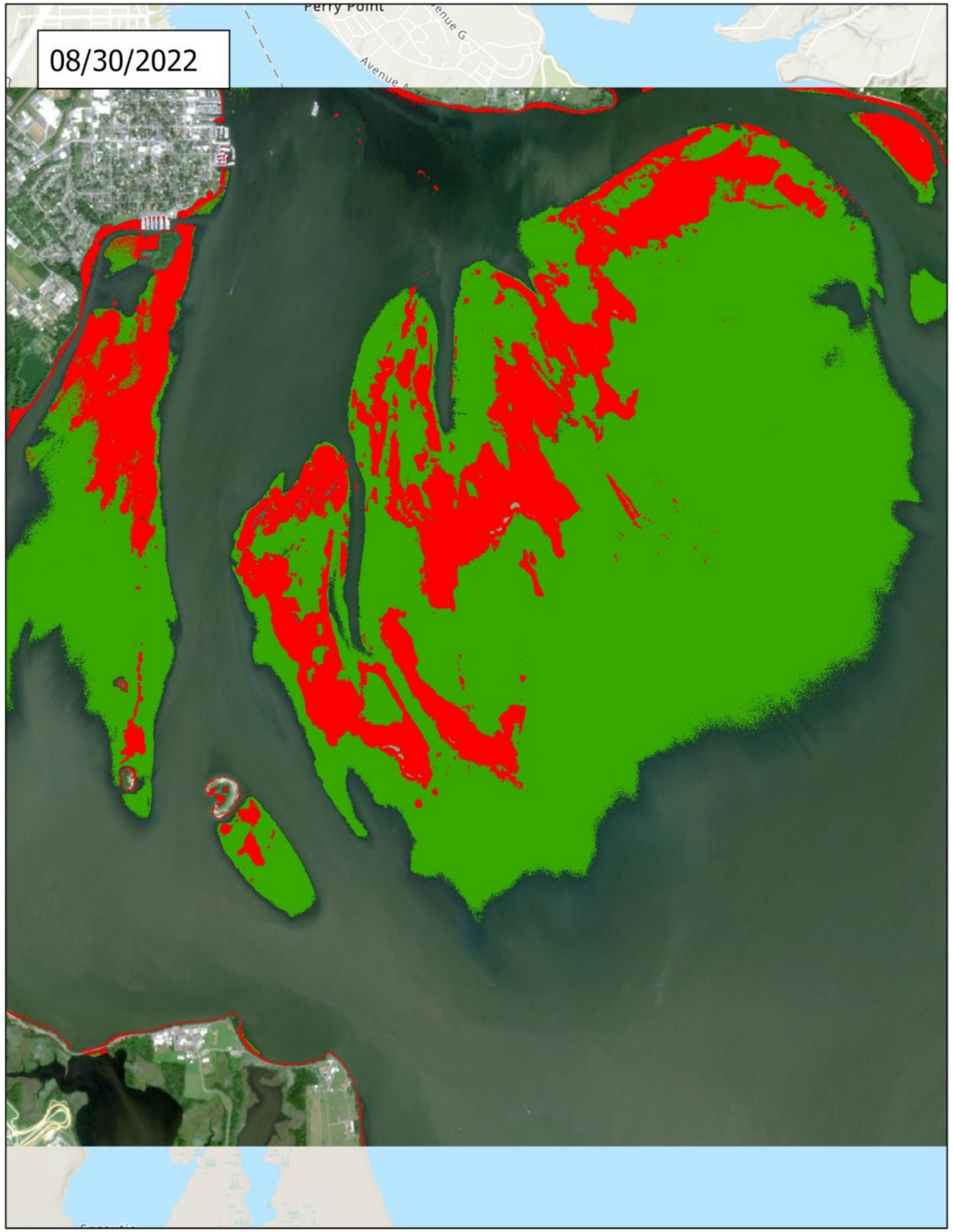

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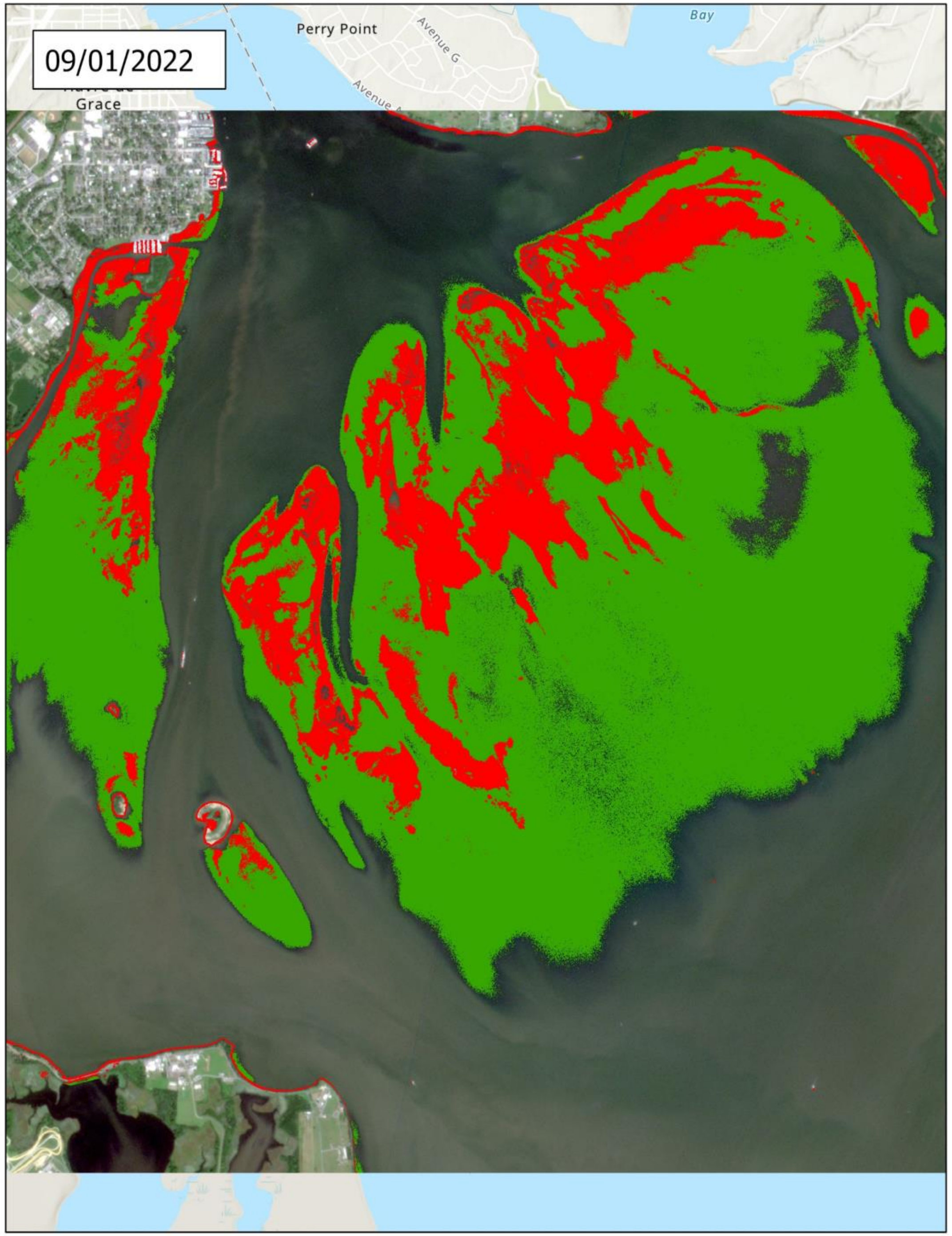

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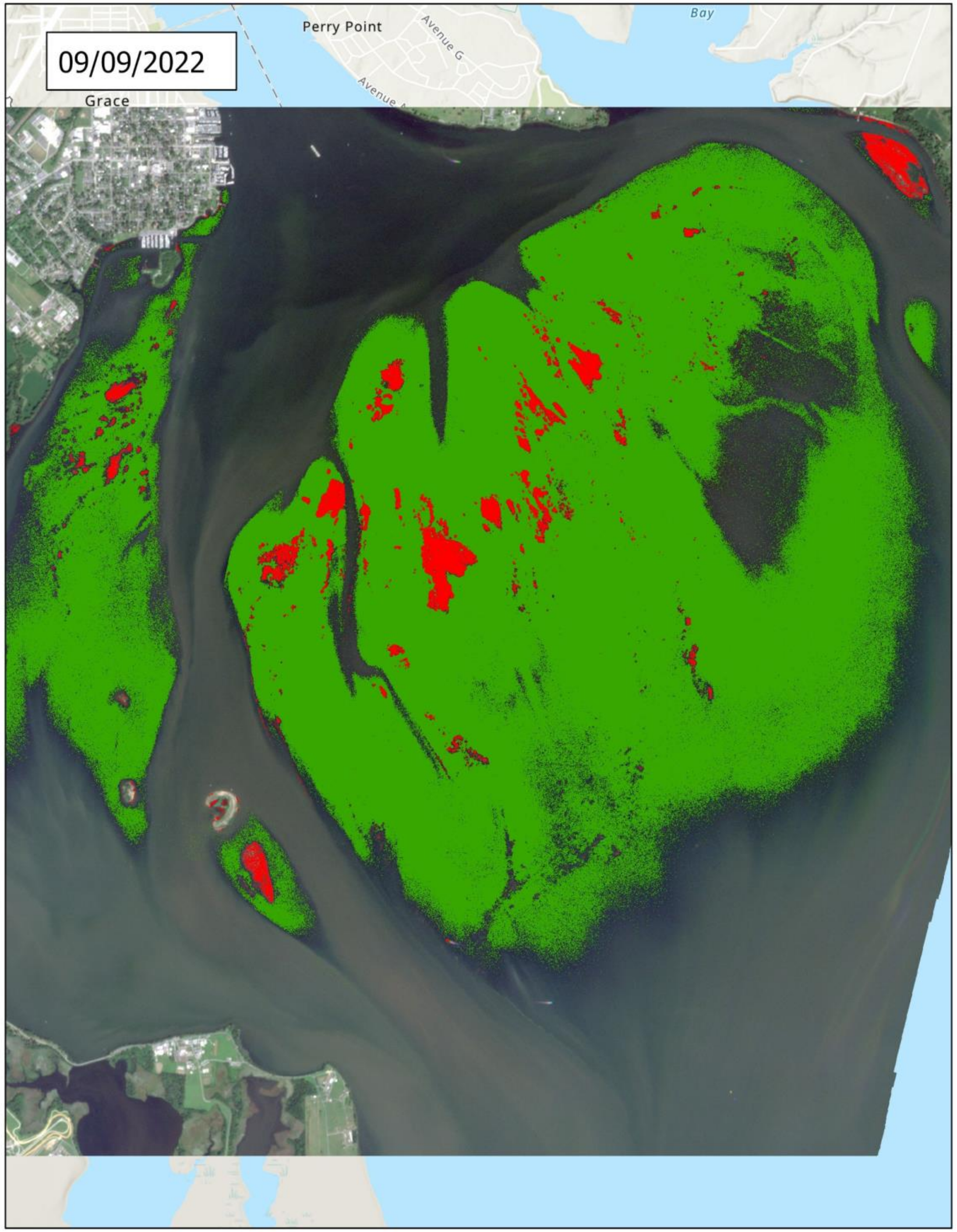

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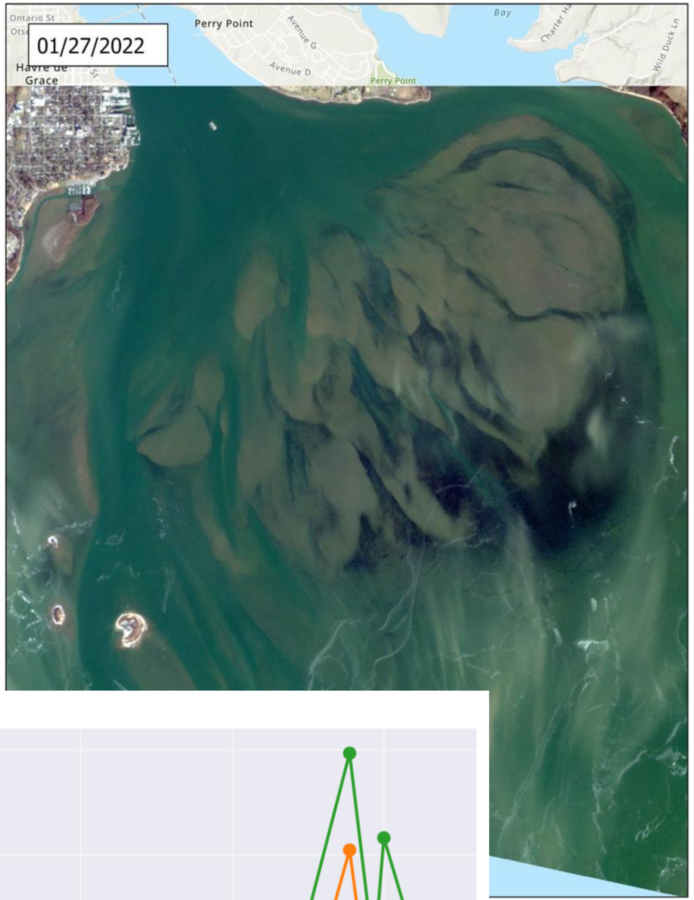

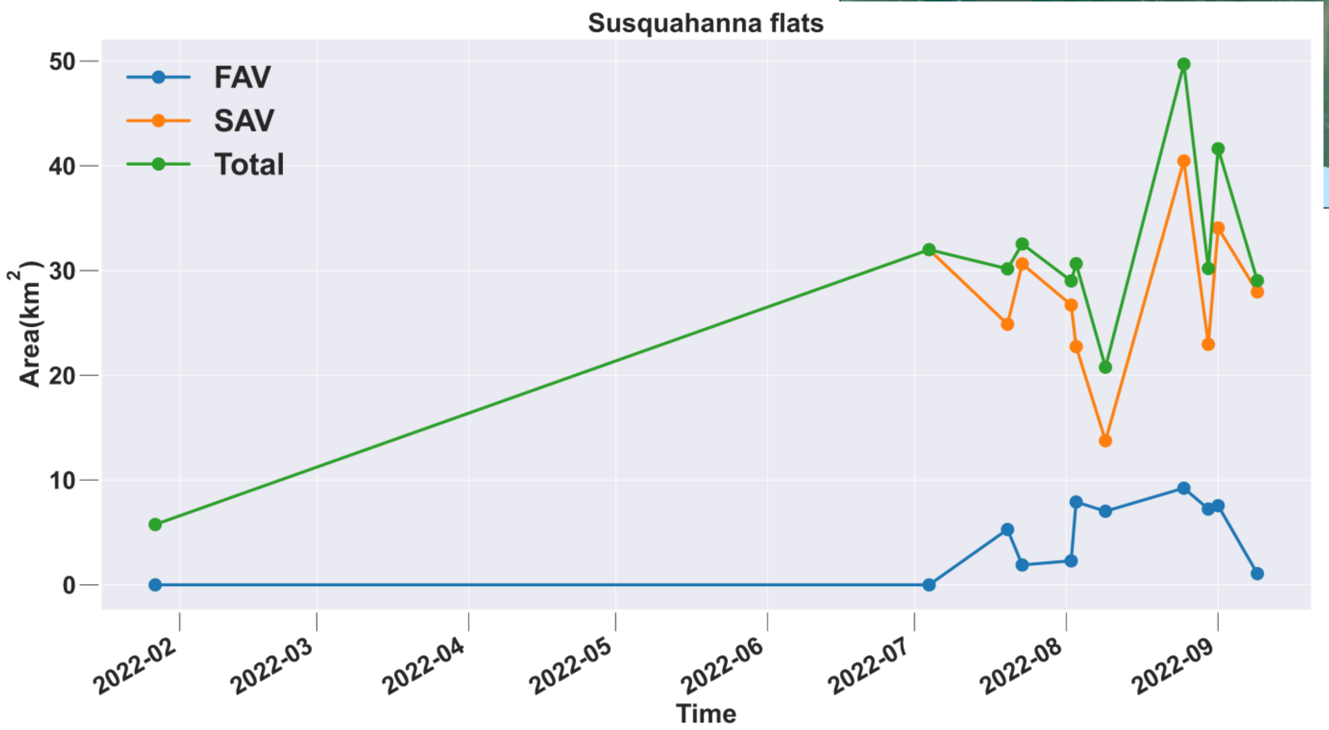

Area SAV on Susquehanna Flats increased from Wintertime 5.7 km^2 to 50 km^2 in the summer

Final remarks

- Our ML model has been successful in classifying images without prior training – tested on 2021 images
- 5 years of PlanetScope imagery from the Eastern Shore is providing SAV presence, density and carbon.
    - As well as analysis of changes in density.
- Our processing workflow has been successfully applied to other areas in the Chesapeake Bay.