Estimating stocks and spatial variability of soil blue carbon in Delaware salt marshes using Landsat imagery

Daniel Warner, Ph.D. – Delaware Geological Survey

Kari St. Laurent, Ph.D. – NOAA NCCOS

Thomas McKenna, Ph.D. – Delaware Geological Survey

John Callahan, Ph.D. – NOAA COOPS

Blue carbon in Delaware

Carbon stored in marine and estuarine environments, like tidal salt marshes (mangroves, sea grass beds)

- These ecosystems store disproportionately large amounts of carbon

Delaware has A LOT of tidal salt marshes

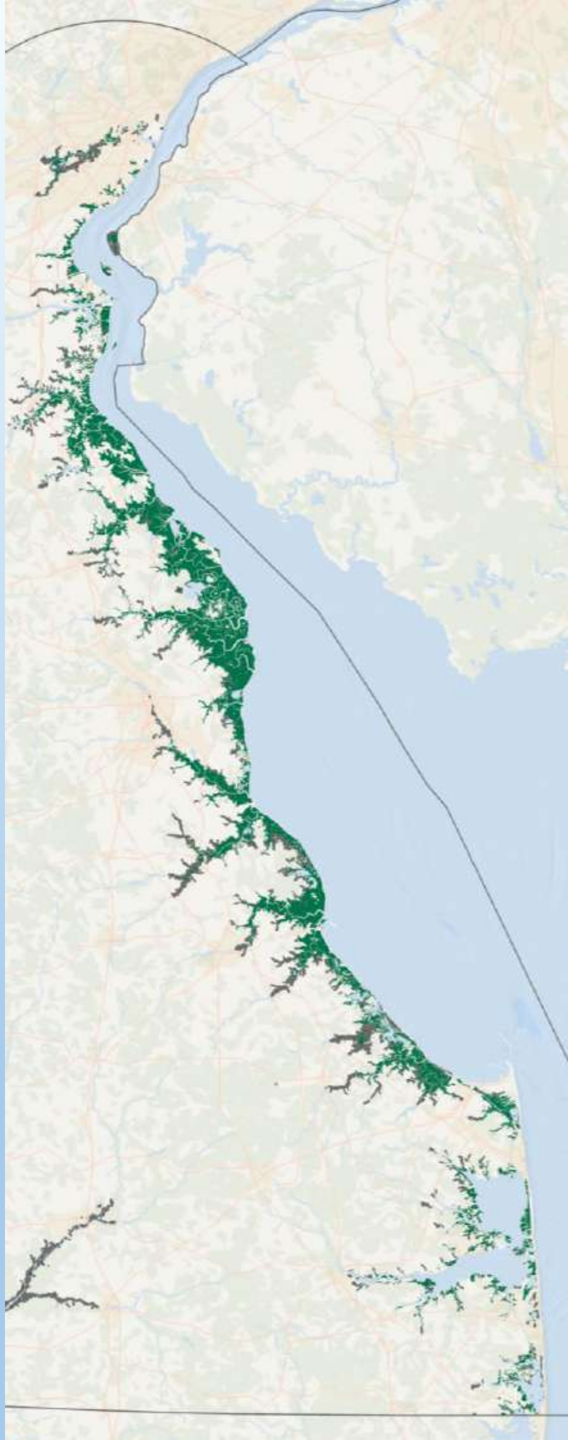
- ~7% of state land area
- We also have ambitious greenhouse gas reduction goals

Management strategies to enhance carbon sequestration and preserve stored carbon could help the state reach its goals

- ...and enhance many other ecosystem services as well

This talk focuses on carbon in **soil organic matter (SOM)**

- The inorganic fraction is also substantial and actively researched



Salt marsh soil development

Salt marshes are very young and they evolve very quickly, geologically speaking

Understanding spatial distributions of SOM in marsh soils is important for:

- Improving stock estimates
- Identifying hot and cold spots

Spatial distributions are driven by:

- Vegetation density and productivity
- Inundation cycles
- Erosion and deposition

Challenges for mapping tidal wetland soils

Sampling wetland soils is hard

- Soft soils → hard to walk and carry equipment
- Spatially heterogeneous → we need a lot of samples

Traditional soil maps often represent all tidal wetland soils as one or two classes

- Insufficient for mapping SOM distributions

Can we use remote sensing data to better map salt marsh SOM with limited soil samples?

Soil sampling

Soil cores in marshes along St. Jones River and Blackbird Creek, DE: near channel, interior, and fringe

Triplicate cores during growing season

- 1-meter sectioned 0-30, 40-60, 70-90 cm

Soils analyzed for SOM density and carbon content

- Bulk density, loss on ignition, and elemental analysis
- SOM was 22-28% organic carbon

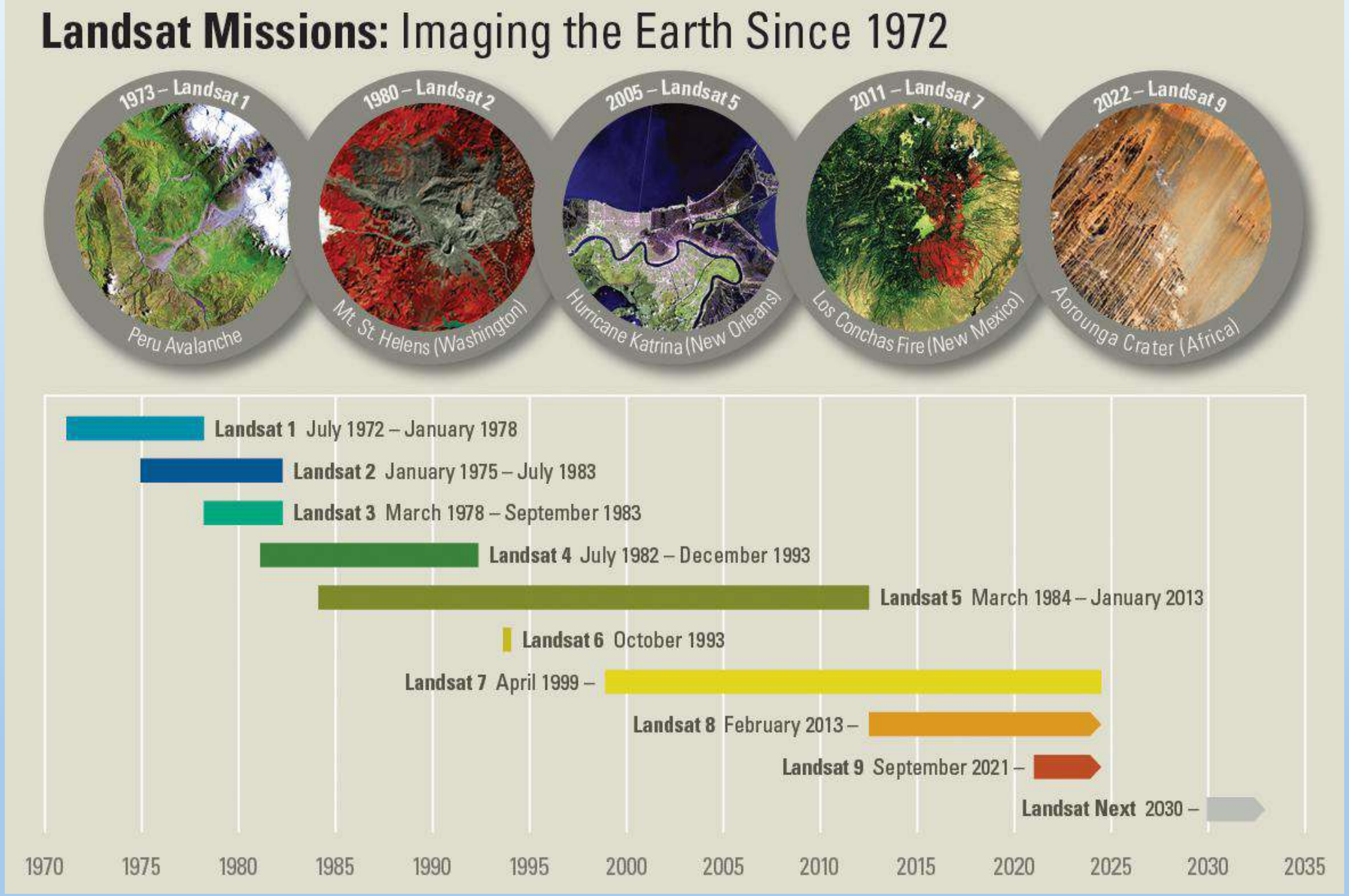
Landsat

Landsat is a long-term satellite imagery program

- Over time resolution and wavelengths have changed

Landsat 8 (16-day return):

- Operational Land Imager
  - Visible spectrum
  - Shortwave IR
- Thermal Imager
  - Longwave IR



From NASA

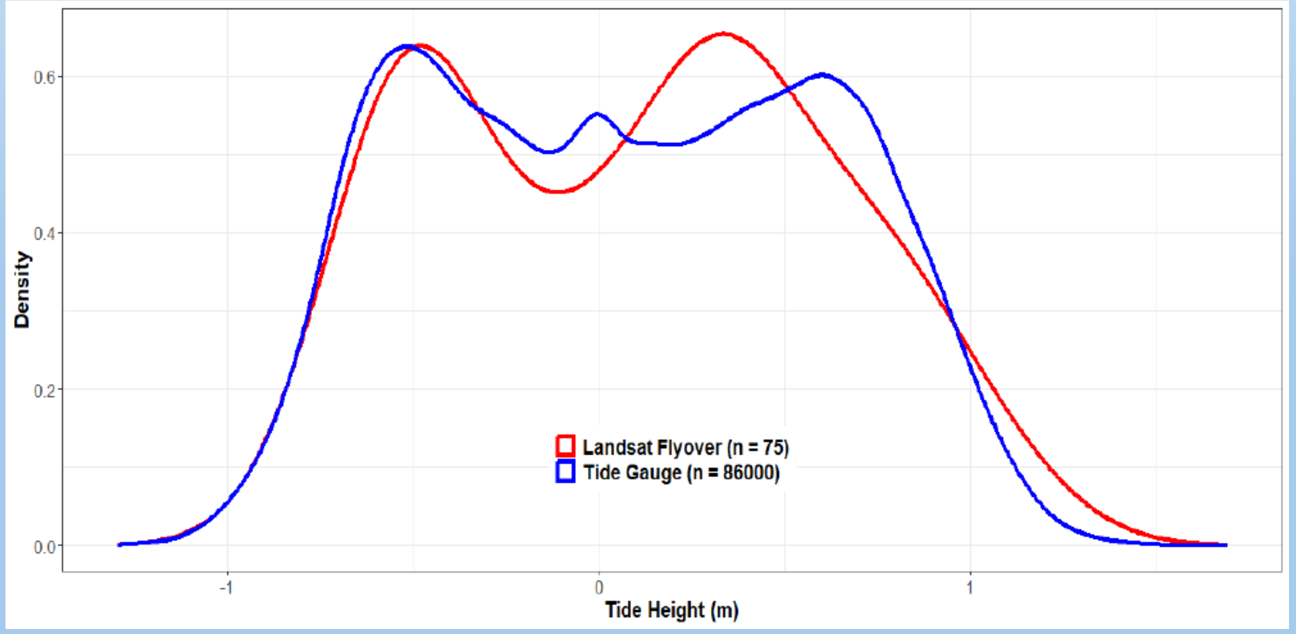
Landsat imagery

10 years of Landsat-8 images reflect seasonal and tidal changes across marshes (75 total)

$$NDI = \frac{(band1 - band2)}{(band1 + band2)}$$

Spectral indices:

- NDVI: Normalized difference vegetation index
- MNDWI: Modified Normalized difference water index
- NPV: Non-photosynthetic vegetation index



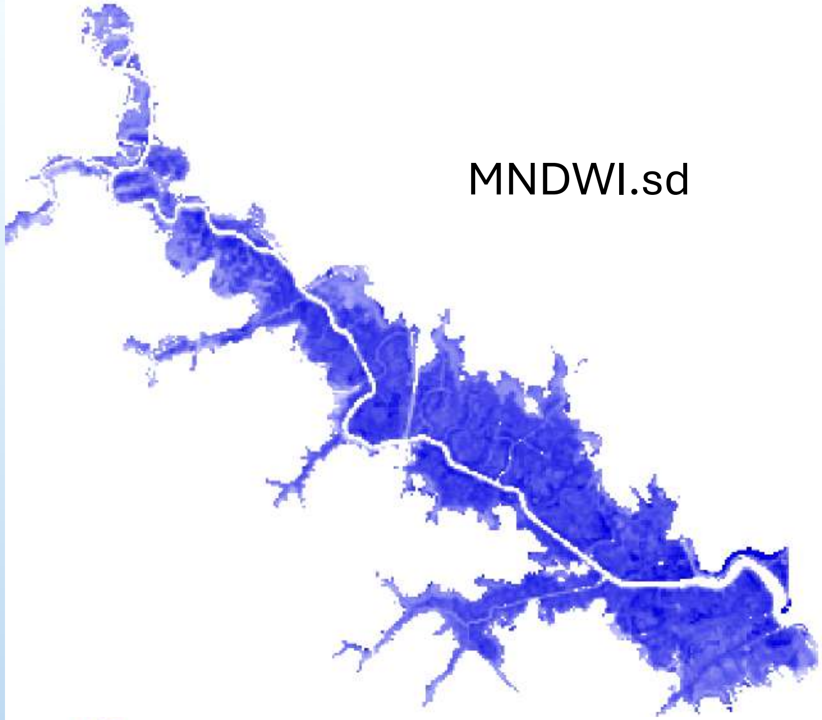
Landsat through time

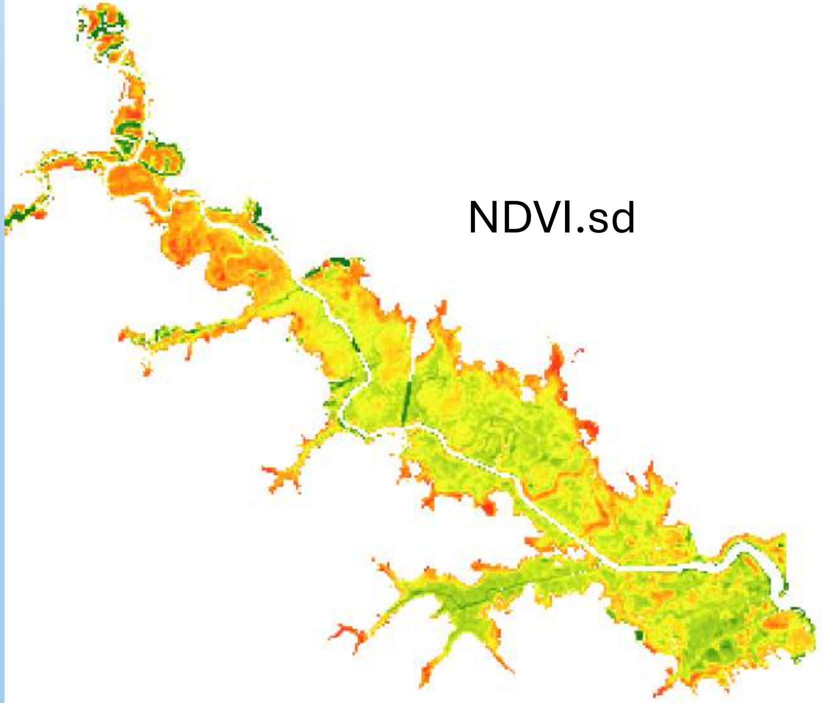
For each Landsat pixel and spectral index, we calculated:

- Mean
- Standard deviation
- Minimum and maximum

By extracting statistics for each pixel, we get a sense of both the average condition through time (e.g., vegetation type) as well as variability (e.g., seasons, tides)

Pixels corresponding to sample locations were extracted

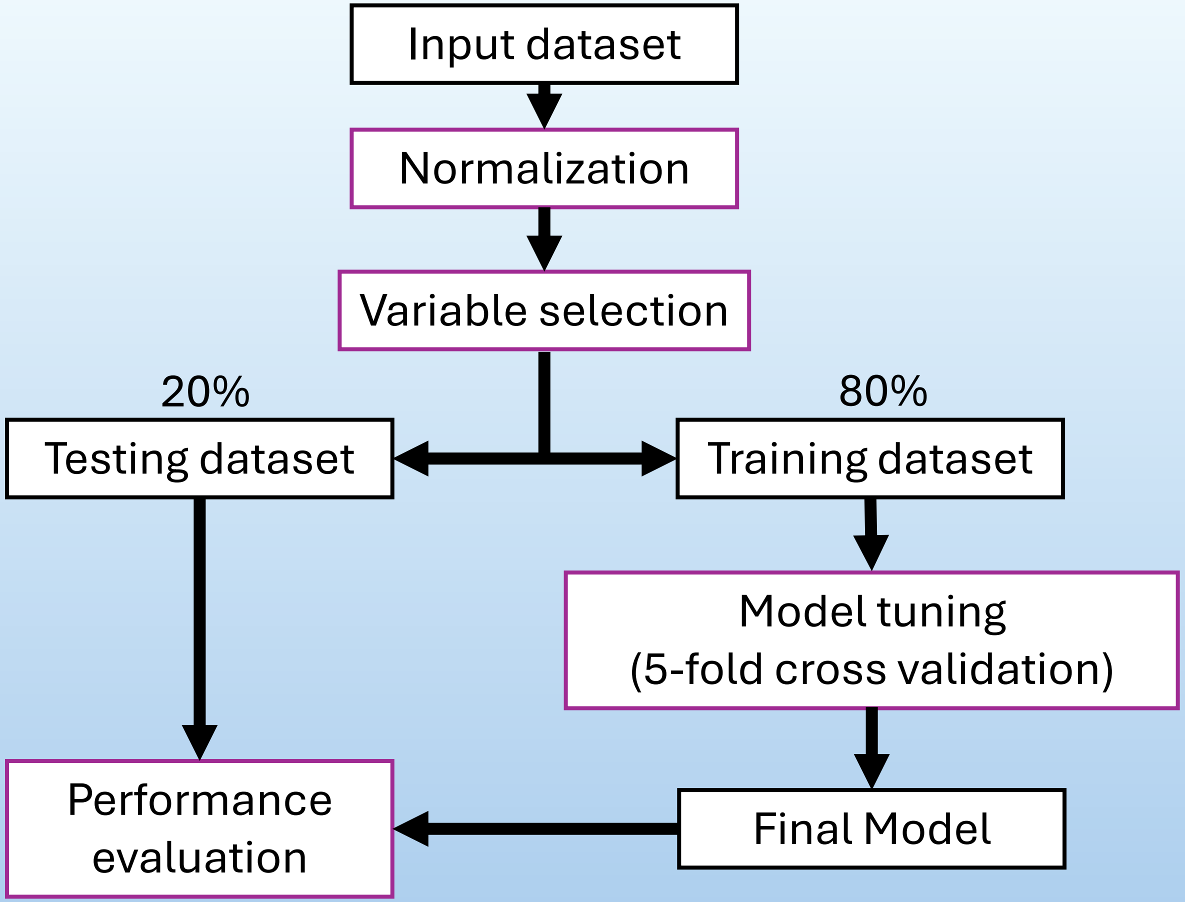




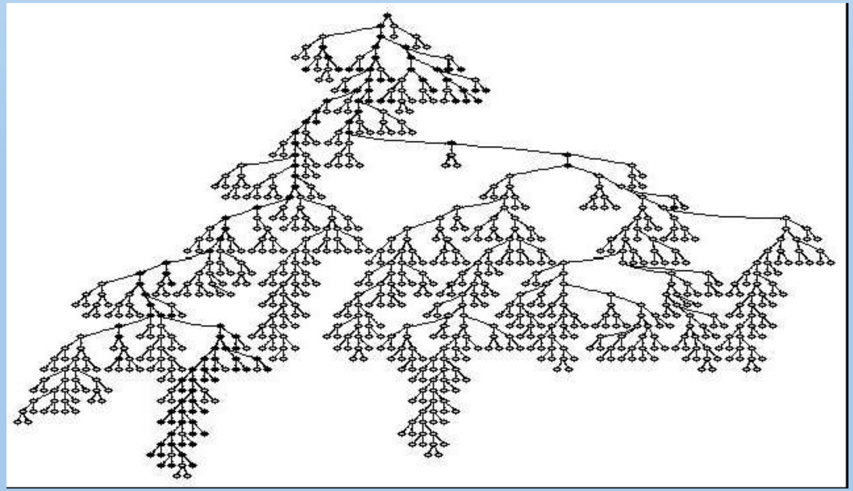
Model fitting

This study used a gradient boosted trees algorithm (xgboost) to predict SOM density in the top 30 cm of soil

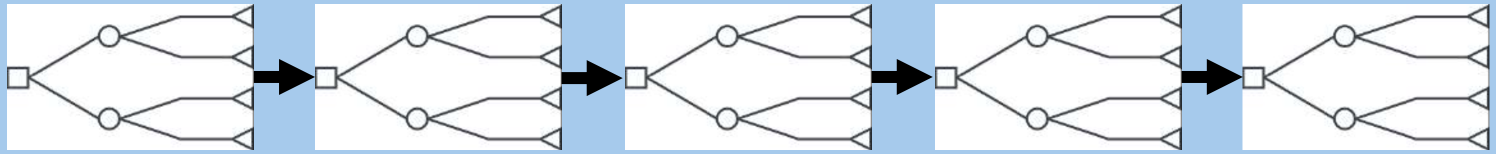
- Other models were tested



Decision tree (easy to overfit)



Gradient boosted trees: a sequence of weak trees trained on the residual error of the previous tree



Model performance

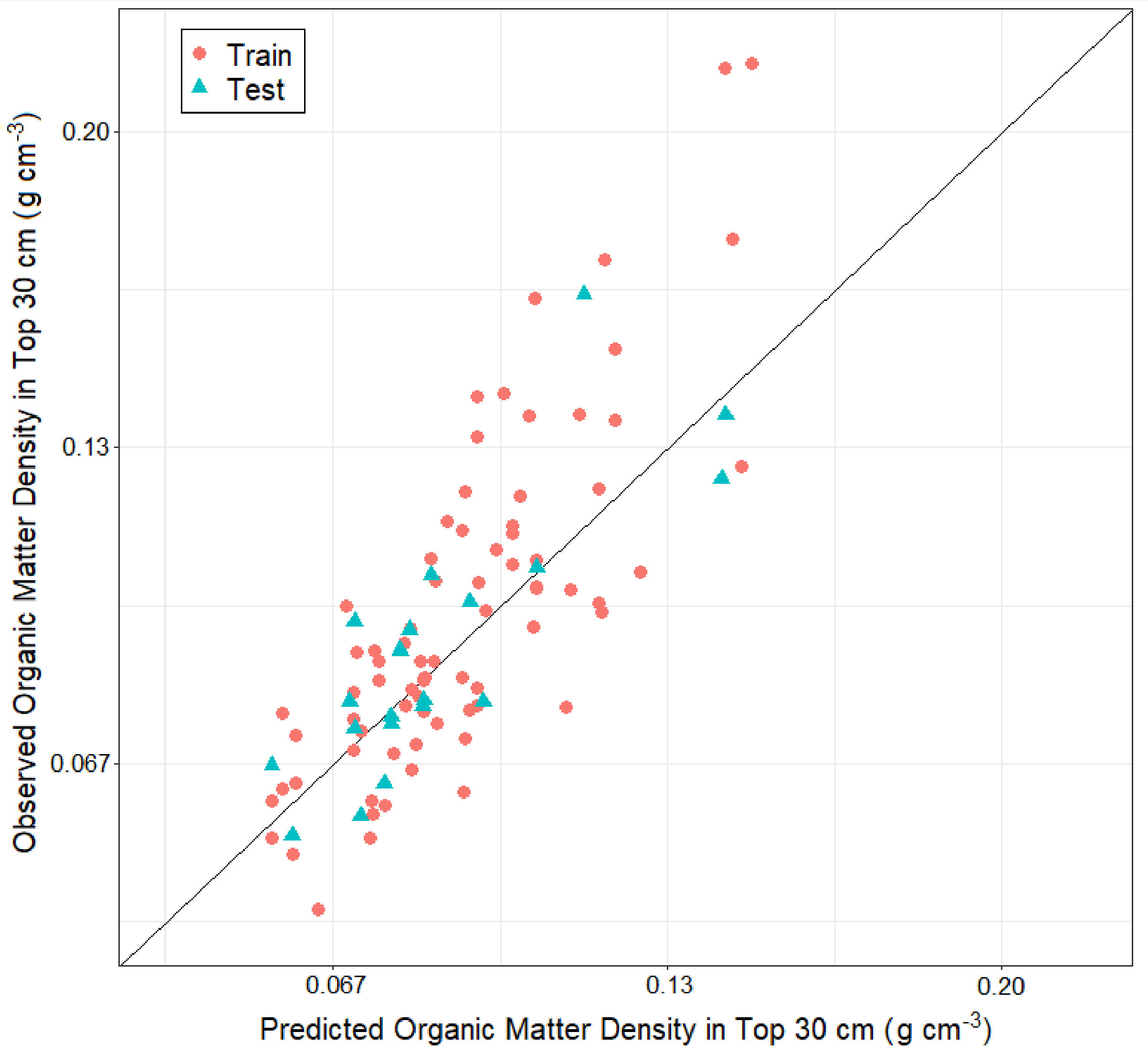
Final predictors:

- NPV.mean (Non-photosynthetic veg index)
- NDVI.SD (Vegetation index)
- MNDWI.SD (Water index)

Testing set R-squared was 0.67

- Very good!

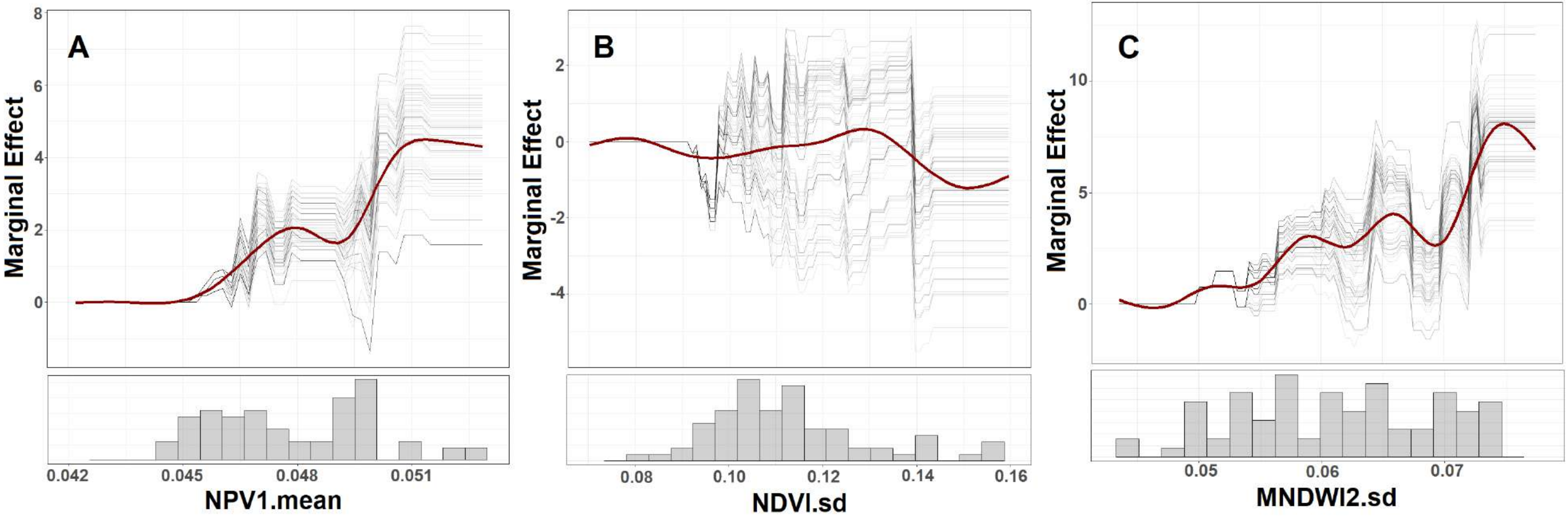
No significant relationships found between satellite data and SOM in deeper soil layers...



Evaluating the model

Variable effects in machine learning can be difficult to understand

- Models are data-driven rather than process-based
- Plotting individual variable effects on model predictions can help



Interpreting variable effects

Mean of non-photosynthetic veg index (+)

- Indicative of biomass accumulation on marsh platform
- Pixels that indicate a higher mean dead biomass have higher soil organic matter densities

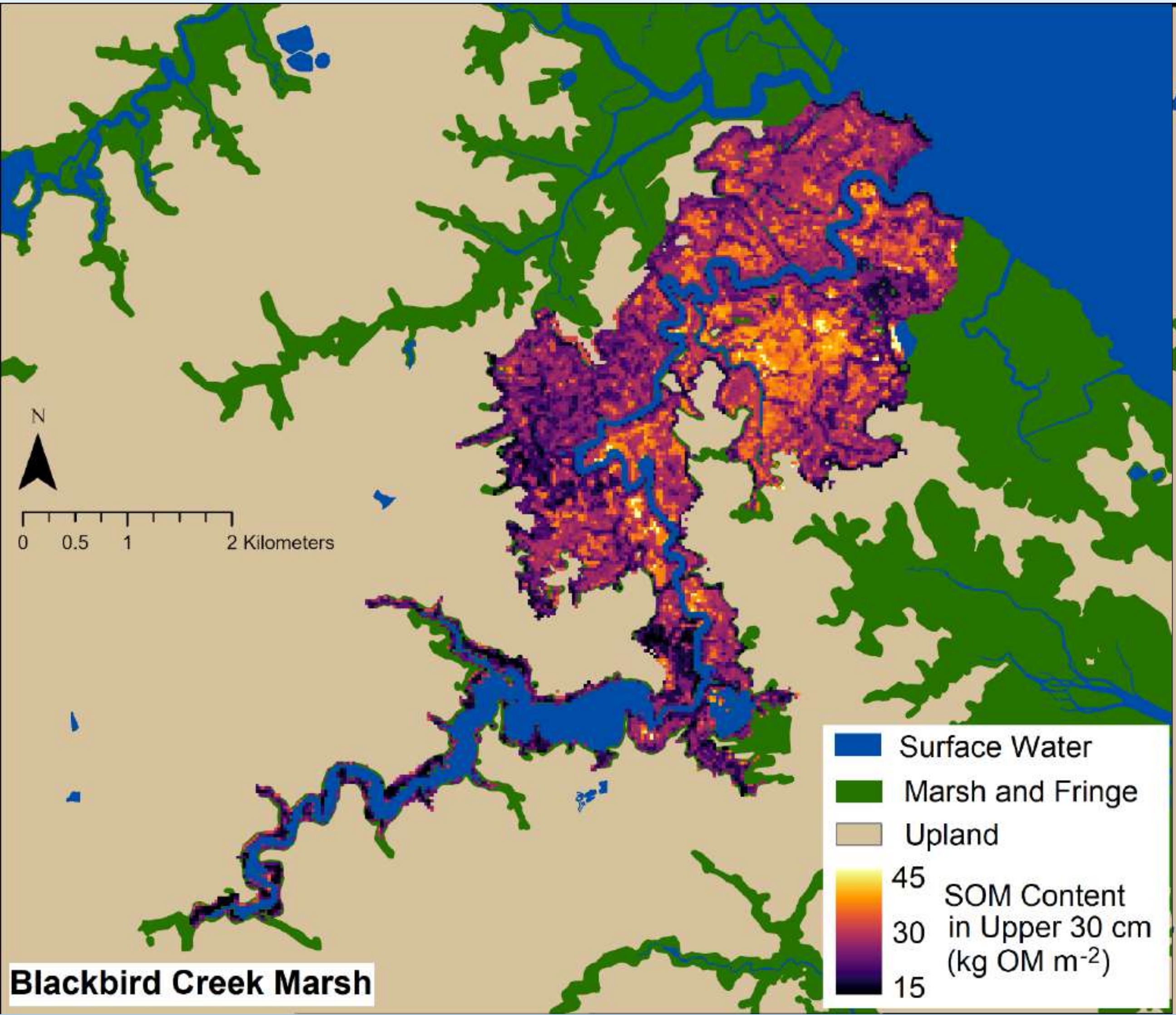
Standard deviation of MNDWI (+)

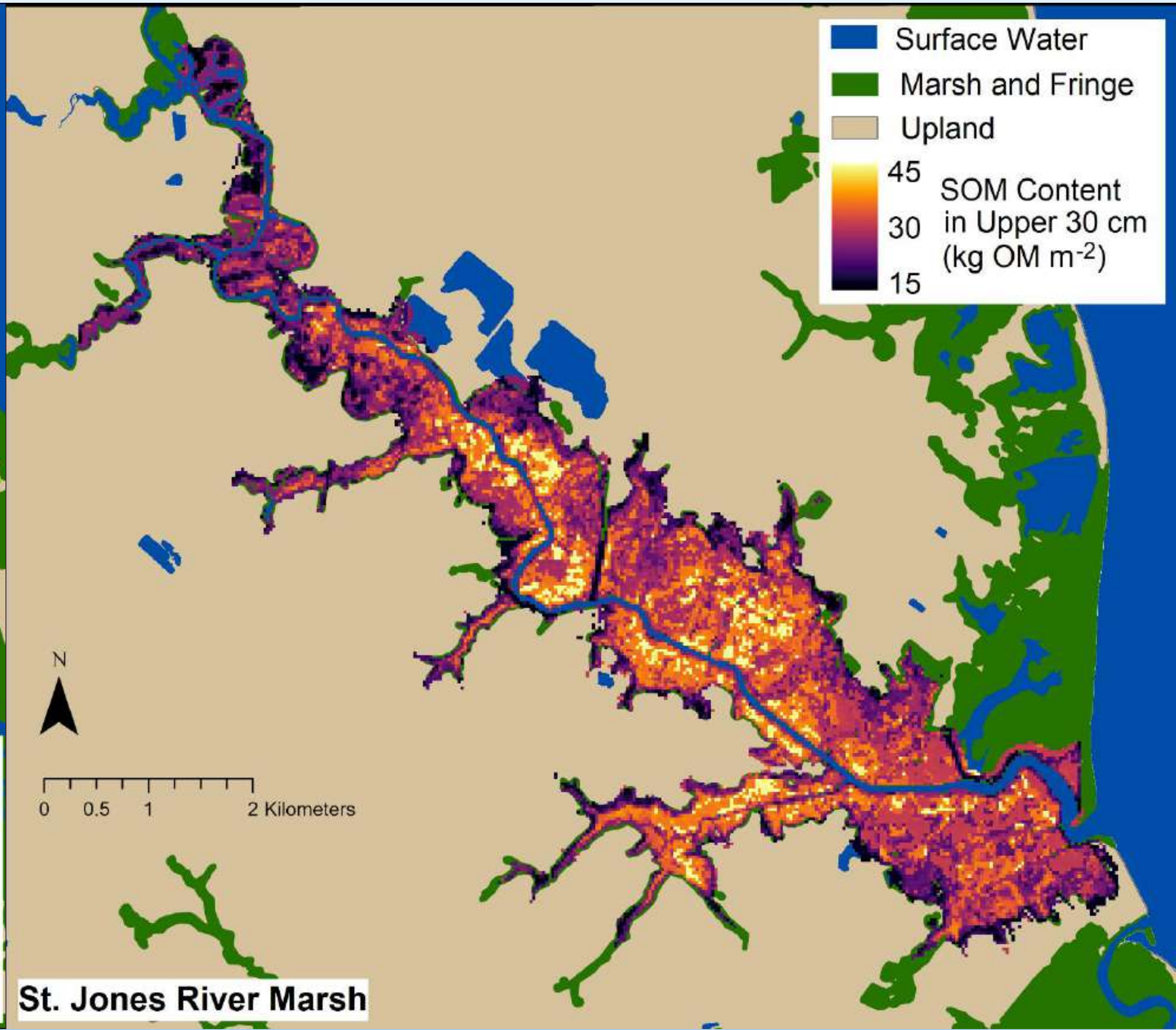
- Indicative of inundation variability of marsh platform
- Pixels with greater variability in surface water inundation status have higher soil organic matter densities

Standard deviation of NDVI (??)

- Indicative of seasonal variability of vegetation greenness
- This showed different effects across samples

Model predictions





57-90 Gg SOC

75-118 Gg SOC

Totals across wetlands

There is lots of organic carbon in just the top 30 cm of these two wetlands:

- 133 - 208 Gigagrams SOC
- 490,000 – 760,000 metric tons of CO_{2EQ}

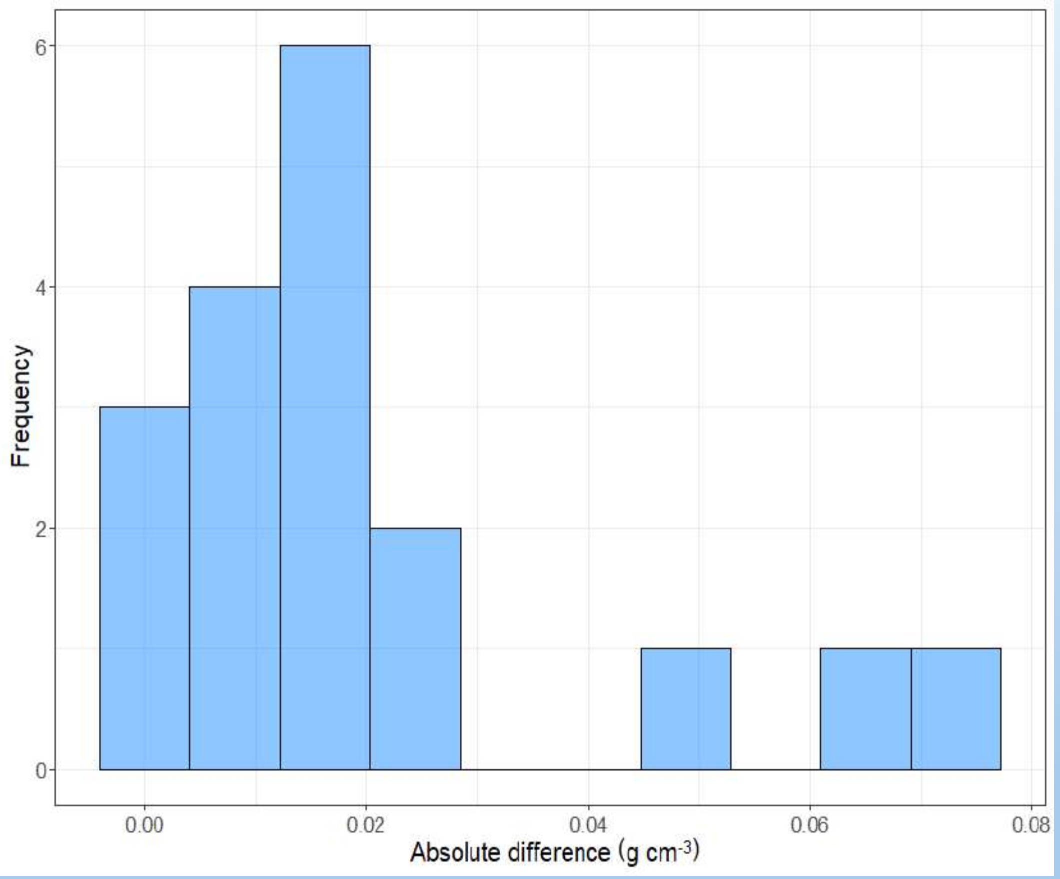
We know these soils can be several meters thick or deeper

- High vertical heterogeneity in C stocks – we found no relationships with surface

Issue of resolution

Spatial representation:

- Landsat pixels are 30x30 m
  - Our cores are collected 3x in ~1x1 m plots
  - How do we account for this?
- We looked at 18 Landsat pixels with 2 or more core locations inside
  - Sub-pixel heterogeneity generally low in uniform vegetation/topography pixels (<20%)
  - High in areas with hummocky topography and mixed vegetation classes (>50%)



Future directions

Depth

- Lots of carbon is stored in deeper layers
- Can we use longer Landsat records?

Coverage

- Can we build a baseline blue carbon inventory for the state of Delaware?

Resolution

- Landsat is 30x30 m, a soil core is much smaller
- Can we use other products (LiDAR, NAIP imagery, high-res satellites) to resolve smaller scale heterogeneity?

Thank you!

If you are interested in this work or other coastal wetland collaborations, please reach out: warnerdl@udel.edu

Contents lists available at ScienceDirect

Remote Sensing Applications: Society and Environment

journal homepage: www.elsevier.com/locate/rsase

Leveraging a decade of Landsat-8 spectral records for mapping blue carbon storage in tidal salt marshes

Daniel L. Warner[a,*], Kari St Laurent[b], Thomas K. McKenna[a], John Callahan[c]

[a] Delaware Geological Survey, University of Delaware, Newark, DE, USA
[b] National Oceanic and Atmospheric Administration, National Ocean Service, National Centers for Coastal Ocean Science, Silver Spring, MD, USA
[c] National Oceanic and Atmospheric Administration, National Ocean Service, Center for Operational Oceanographic Products and Services, Silver Spring, MD, USA