Marsh Species Classification using Remote Sensing Data

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Introduction:

Marsh plants and their Importance:

- Low-lying, waterlogged areas of land between land and sea, known as *salt marshes,* prevent erosion of land and protect against extreme weather events
- Marsh plants mediate accretion (i.e. the building of surface elevation relative to sea-level) by capturing sediment suspended in water and contributing to root tissue below the surface
- As sea levels rise, marshes accrete elevation to keep pace. Given accelerating sea level rise, will marshes be able to keep pace?
- Understanding how plant cover and distribution changes over time is one part of to understanding how accretion may vary across a landscape
- **Goal of project:** to classify species type by calibrating satellite imagery of a marsh in the Chesapeake Bay to estimated plant cover data
  - Understand how species cover changes over time
  - Quantify how classification errors in change across species and time

Figure 1. Smithsonian Environmental Research Center Marshland

SERC Marsh used for experiment in Chesapeake Bay.

Ground Truth Data Types:

RTK Data

- Homlquist *et al.* 2021
- Single year
- Large spatial extent
- Costly to collect
- 2016 only

Satellite:	Ground Truth:
2015	
2016	2016
2017	
2018	
2019	

Marine Geo Data

- Whigham *et al.* 2020
- Multi year dataset
- Smaller spatial extent
- Easier to collect
- 2015-2018

Satellite:	Ground Truth:
2015	2015
2016	2016
2017	2017
2018	2018

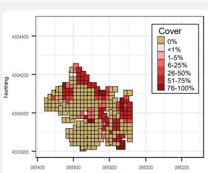


Figure 2. 2016 *Phragmites australis* RTK distribution

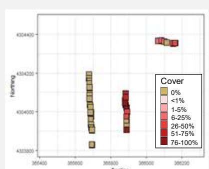


Figure 3. 2016 *Phragmites australis* Marine Geo distribution

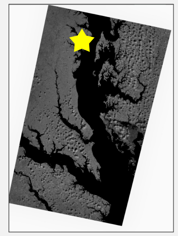
Citations

Holmquist J, Riera J, Schile-Beers L, Megonigal JP (2021). Elevation and vegetation data for the Global Change Research Wetland, Summer 2016. The Smithsonian Institution. Dataset. https://doi.org/10.25573/serc9589337.v1

Whigham D, Holmquist J, Ogburn M, Goodison M, McFarland L, Megonigal JP (2020). Dataset: 2015-2018 USA-MDA TMON Marsh Biomass Surveys. The Smithsonian Institution. Dataset. https://doi.org/10.25573/serc.12636404.v2

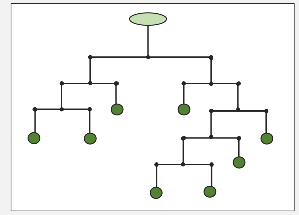
Methodology

1. Acquire Landsat & Cover Data



Landsat ARD Data Downloaded and paired with Ground Truth Datasets.

2. Fit Ordinal Forest Models



Inputs include: Landsat surface reflectance bands and calculated vegetation indices (NDWI, NDVI, EVI)

3. Develop Weighted Error Measure using Pascal's Triangle

Prediction \ Reference	0	1	2	3	4	5
0	131.000	9.338	2.338	0.000	0.000	0.000
1	2.668	1.000	0.000	0.501	0.000	0.000
2	1.169	2.668	12.000	7.337	0.668	0.000
3	0.000	0.668	0.667	16.000	12.673	0.167
4	0.000	0.000	0.668	4.002	20.000	5.336
5	0.000	0.000	0.000	0.000	3.335	4.000

```
        1
       1 1
      1 2 1
     1 3 3 1
    1 4 6 4 1
  1 5 10 10 5 1
```

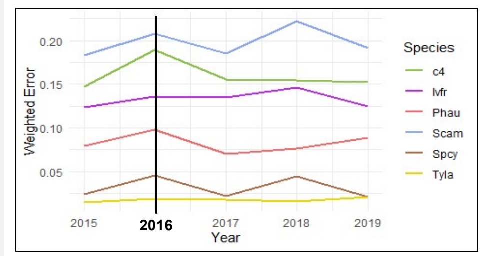
Weighs the "correctness" of classes nearer to the true class higher. Proportions of correctness normally distributed using Pascal's Triangle.

Results & Conclusions:

How stable is species cover in Marshes?

- By looking at yearly weighted error compared to a single year, we can assess the stability of the marsh over 5 years
- Use RTK cover data to build Random Forest (collected in 2016)
- Weighted error does not change consistently with year since 2016.
- No strong conclusion that there is much change in the marsh composition within this time range
- Furthermore, RTK data is costly in price and time to gather. Our results suggest that these data may not need to be collected often to capture changes in species distribution and cover.

Figure 4. Weighted Error by rtk species, 2015-2018



Can we classify species cover correctly?

- What is the overall accuracy of our model? Is it reasonable to assume that we can classify species correctly with the ordinal forest model?
- Use Marine Geo yearly data to build Random Forest
- Average weighted error across species and years = 0.1022
- Model can be used to classify species type for further analyses.
- *Schoenoplectus americanus* and *Phragmites australis* classified with the least amount of error

Year	scam	phau	sspa	disp	ivfr
2015	0.0974	0.0426	0.1459	0.0802	0.1819
2016	0.0651	0.0504	0.0876	0.2121	0.2265
2017	0.0376	0.0525	0.175	0.1627	0.2152
2018	0.0147	0.0353	0.0366	0.1051	0.0203
Avg.	**0.0537**	**0.0452**	**0.111275**	**0.140025**	**0.160975**

Figure 5. Pop Abundance Prediction, Scam 2015-2018