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TAKING THE PULSE OF OUR PLANET FROM SPACE

# Mapping Aboveground Biomass and Carbon in Salt Marshes across the Contiguous United States

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#### Salt marsh



**Environment commonalities** Tidally inundated Low energy Salinity Variation Tidal characteristics Climate Soil Hydrology Sediment Fauna Regional sea level



#### Salt marsh significance



#### Salt marsh

- Carbon sequestration
- Nursery habitat
- Water quality (denitrification and filtering of pollutants)
- Wave attenuation
- Approximately \$10,000 per hectare
  - Tidal mudflats \$1,942 per hectare (Barbier *et al.* 2011)



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#### Salt marsh carbon

- In the CONUS, 75% of blue carbon is found within estuarine emergent wetlands (Hinson et al. 2017).
- Carbon burial
  - Estimated
    - 4.8±0.5 87.2±9.6 Tg C yr<sup>-1</sup>
      (Mcleod et al. 2011)



### Status and change – coastal wetlands



 Historic Wetland losses since 1700 AD are estimated to be as high as 87% (Davidson 2014)





## Science questions

What is the distribution of salt marsh aboveground biomass across the CONUS? What drives this variation (climate, geomorphology, direct anthropogenic change, sea level rise)?

### Data outputs

Update salt marsh extent to 2020 and 10 m spatial resolution CONUS wide map of aboveground biomass



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AGB prediction

- 3 machine learning algorithms (xgboost, random forest, SVM), 2 Scales 10 and 30 m, and stable vs complete training dataset
- Hypertuned
- Evaluated with test data from two sites, one completely unused in training

Extent prediction:

- Three machine learning algorithms estimate spatially a low, medium and high extent
- Confidence interval and accuracy following methods of Olofosson et al. (2014)



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#### Time series stability – AGB results

Plum Island, MA

221.5

232.3

Validation

Type 1

(n=17)

RMSE

373.04

344.5



- All training data from Byrd et al. 2018 were evaluated for time series stability.
- Two metrics of stability trend following biomass samples and breaks for additive season and trend (BFAST)
- Absolute trends of 0.05 were then analyzed with ٠ BFAST finding all these experienced a break following data collection.
- Two AGB models were trained and compared using

Site

n

Validatio

(n =8)

RMSE

107.33

194.2

Georgia

Validatio

(n =158)

RMSE

301.0

326.1

n

n

723

984

Training

set

**Stable** 

e

Complet





Overall accuracy: 96.3% CONUS extent: 14,491 ± 1,736.75 km<sup>2</sup>

Uncertainty from accuracy assessment: 3175.6 km<sup>2</sup>

Uncertainty from machine learning: 3473.5 km<sup>2</sup>





### **CONUS Aboveground biomass**





\*

10

#### Aboveground biomass (2015-2020)



Total AGB 8.32 (7.15-9.35) Tg Average Carbon 255.7 g C m<sup>2</sup>



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### Analysis of AGB drivers



- Average AGB in 3 x 3 km
- Machine learning model (xgboost)
- Shapley calculated and analyzed to determine drivers of AGB across the CONUS.

Data Type	Variable	Resolution	Sensor	Source
Climate	August Temp/Precipitation	250 m	NA	PRISM Climate Data
Tidal/Elevation	Relative tidal elevation, tidal amplitude, RSLR	30 m	Various LiDAR	Holmquist and Windham-Myers 2021
Water	Seasonal, Water, New Seasonal	30 m	Landsat	Pekel et al. 2016
Land cover	NLCD classes	30 m	Landsat	Wickham et al. 2021
Ocean Color	Diffuse Attenuation Coefficient, Chlorophyll	750 m	VIIRS	NOAA CoastWatch/Ocea nWatch

### Major Drivers Aboveground biomass





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#### East coast drivers of aboveground biomass



#### **Takeaways:**



- In salt marsh AGB was 8.32 (7.15-9.35) Tg in 2020
- The 10 m spatial resolution allows for finer scale determination of these loss areas and repeat monitoring
- Machine learning uncertainty can be derived spatially informing management and carbon monitoring
- RSLR between 3-5 mm yr<sup>-1</sup> increase AGB but rates >5 mm yr<sup>-1</sup> reduced AGB
- AGB response to climate and RSLR suggest that these ecosystems response to climate change will be complex

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