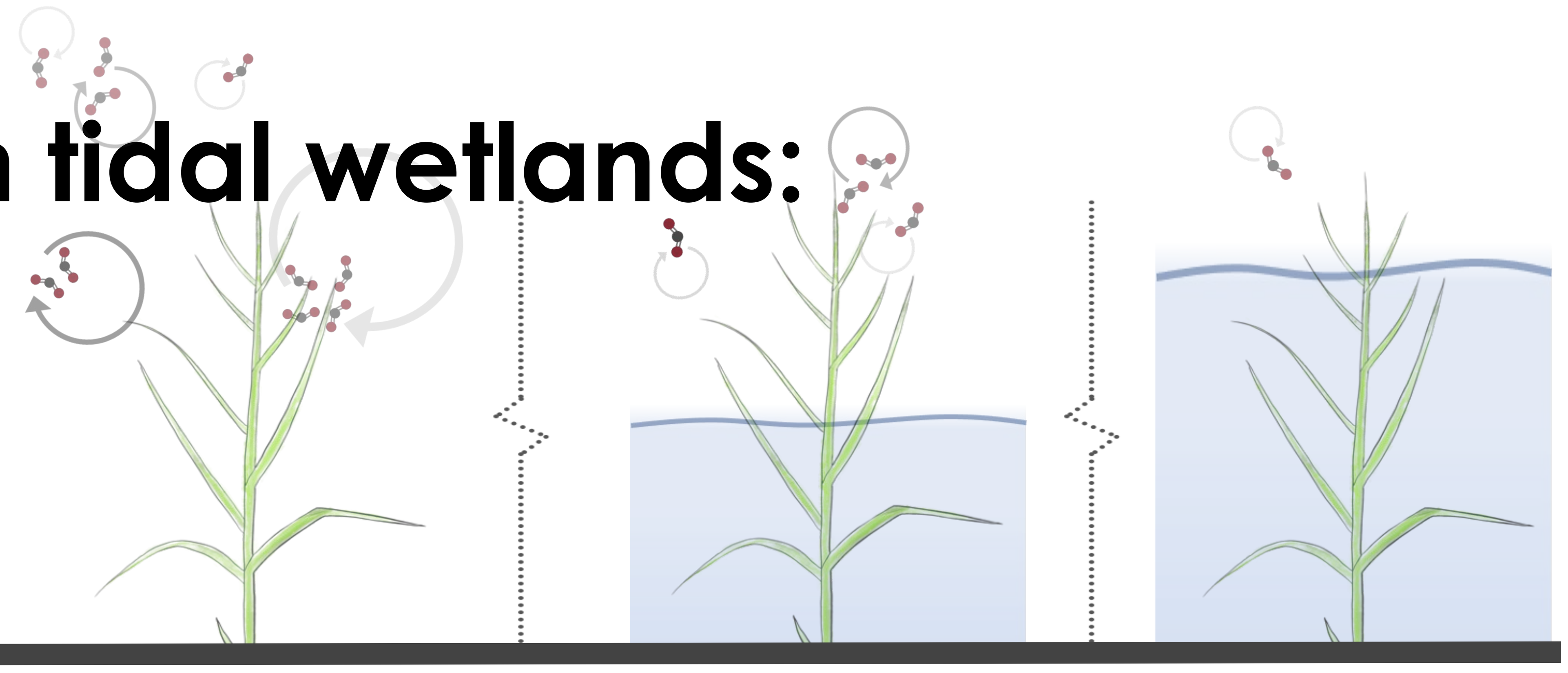
Dynamic emergent leaf area in tidal wetlands:

Implications for Blue Carbon



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INTRODUCTION

Tidal wetlands store carbon, known as blue carbon, at rates that are an order of magnitude greater than comparable terrestrial systems. However, most primary productivity models cannot be applied to tidal systems, as they ignore important spatiotemporal dynamics caused by tidal inundation. Our study is the first to provide a ready mechanism for incorporating important changes in tidal salt marsh leaf area into carbon models, which will help account for tidally influenced changes in carbon assimilation rates. Using open-source satellite data, we show how the emergent leaf area changes at short timescales due to semidiurnal inundation. Our study will help reduce uncertainty in productivity modeling and enhance the accuracy of blue carbon storage components in future global carbon budget studies.

Objectives

1. Measure and model the vertical profile of canopy LAI for *Spartina alterniflora.*
2. Spatially predict emergent LAI through time capturing the tidal cycle.
3. Link spatial emergent LAI to eddy covariance flux tower footprint predictions and CO_2 fluxes.
4. Scale emergent LAI to 10-m Sentinel-2 surface reflectance data to determine if it could be modeled from satellite data at the needed spatial and temporal scales.
5. Compare emergent LAI estimations to commonly used LAI products (MODIS 500-m 8-day; MYD15AH2) to highlight uncertainties in LAI products for tidal wetlands.

METHODS

Emergent leaf area

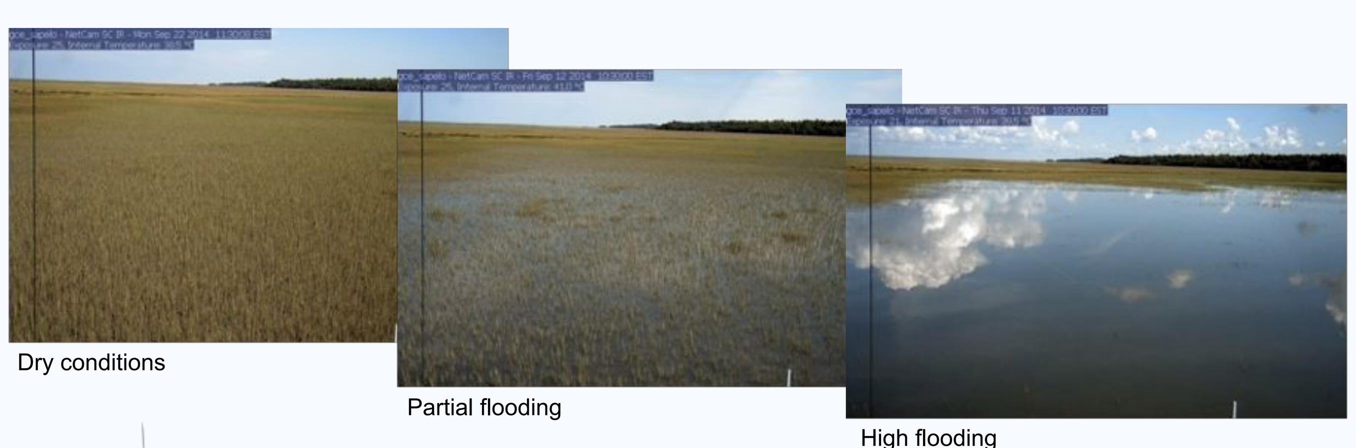
1. We measured plot level leaf area index (LAI) collected in a *Spartina alterniflora* tidal marsh at the Georgia Coastal Ecosystems Long Term Ecological Research (GCE-LTER).
2. We modeled canopy LAI vertical profiles using Weibull Type-1 3-parameter distribution functions.
3. We used LAI profiles, elevation (DEM), water table height, and a marsh habitat distribution map to spatially predict emergent LAI at 1 m^2 across tidal cycles near the GCE-LTER flux tower.

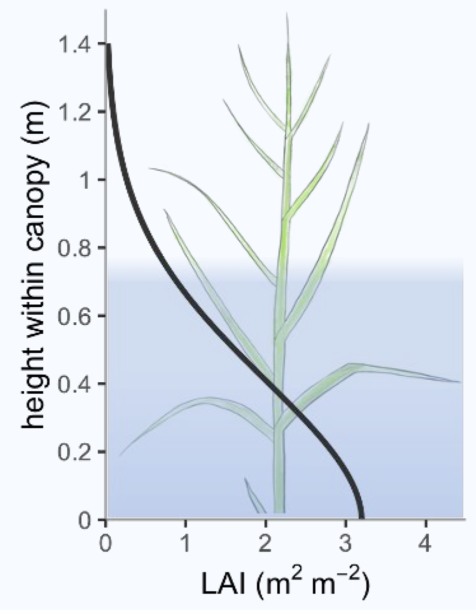
Eddy covariance (EC) net ecosystem exchange (NEE)

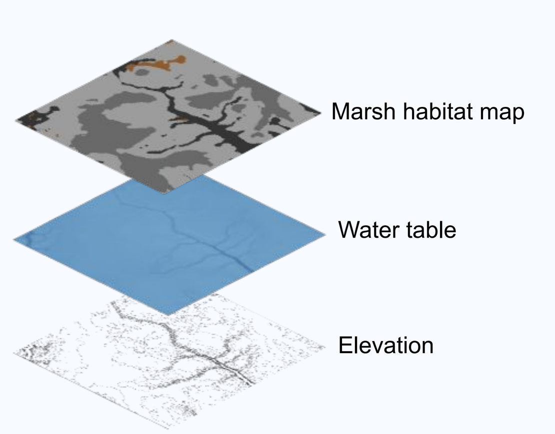
4. We linked spatial estimations of emergent LAI with EC flux tower footprint predictions (FFP), representing the CO_2 flux source areas, and measured NEE from June through October.

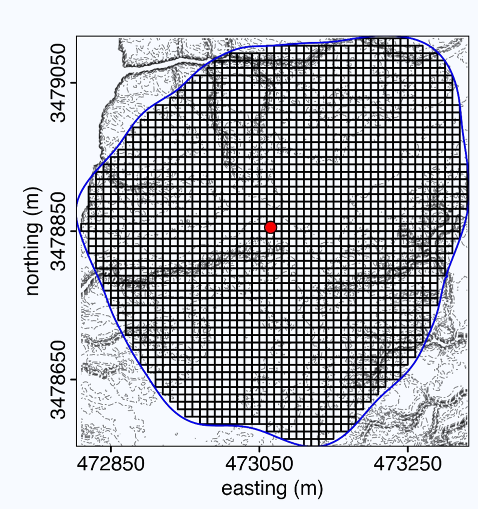
Satellite estimation of emergent leaf area

5. We scaled spatial predictions of emergent LAI to 10-m Sentinel-2 surface reflectance data (5-day returns) and used vegetation indices to model emergent LAI using linear regression.
6. We scaled emergent LAI estimations to match MODIS 500-m 8-day LAI product (MYD15AH2) for comparison.





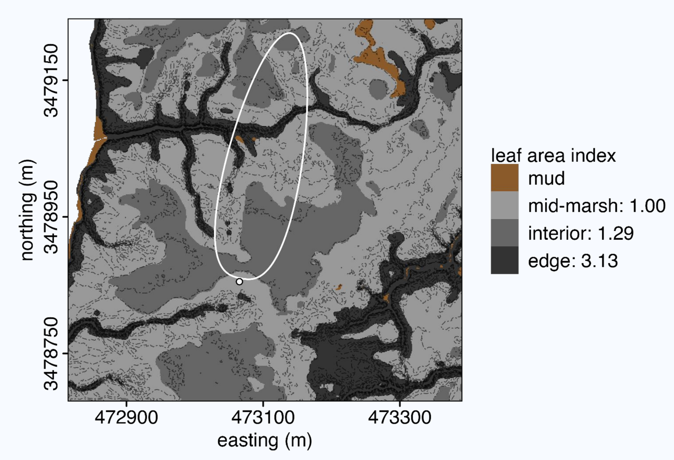




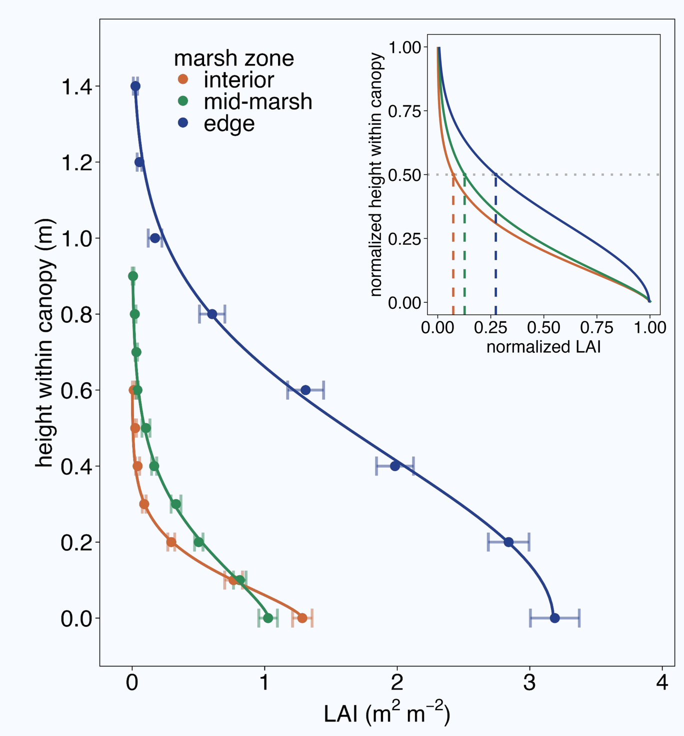
RESULTS

Leaf area index (LAI)

Canopy LAI varied across an elevation gradient from tall and sparse canopies with high LAI found at low elevation marsh edges, to shorter and denser canopies with lower LAI in the higher elevation marsh interior. Mid-marsh canopies had the lowest LAI but intermediate canopy heights and densities.

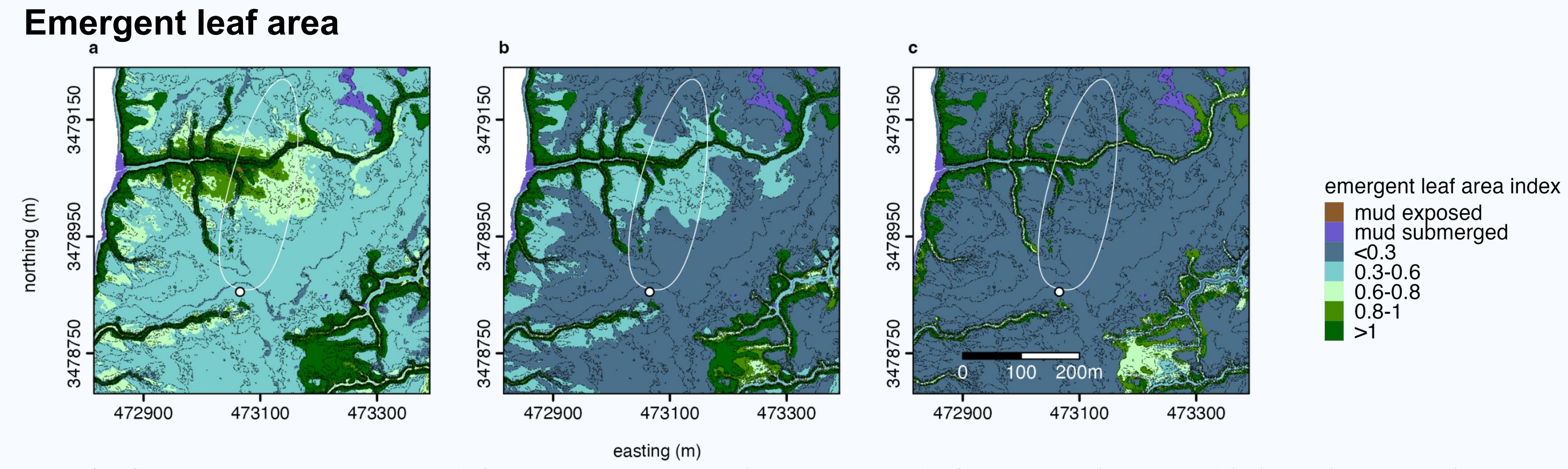


Map showing marsh canopy types and their LAI.



Canopy profiles of leaf area index (LAI) for interior (orange), mid-marsh (green), and edge (blue) canopies.

Emergent leaf area

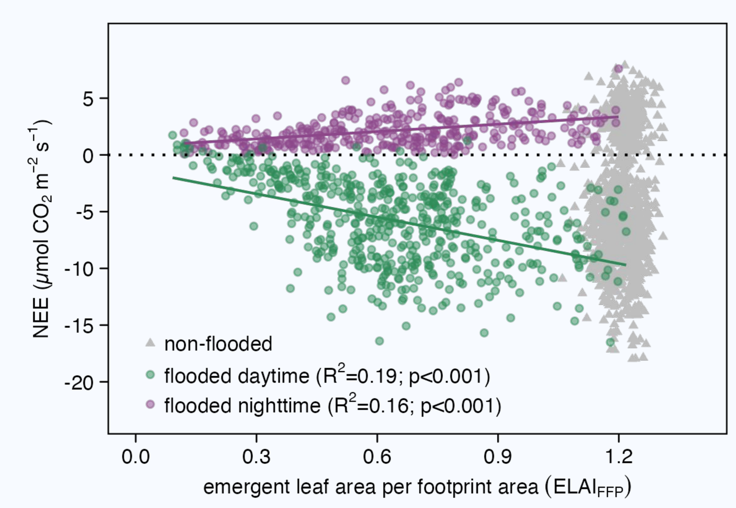


Maps of the flux tower area illustrating the emergent leaf area under three tide heights: **a**) 0.25m relative to soil surface at the tower (1.25 m NAVD88), **b**) 0.50m (1.3 m NAVD88), and **c**) 0.75m (1.55 m NAVD88). Mudflats are represented as exposed or submerged. White oval is an example 30min flux footprint prediction (2020-06-15 19:30 UTC+0), white point is the flux tower location, and dashed lines are 0.1 m elevation contours.

Net ecosystem exchange (NEE)

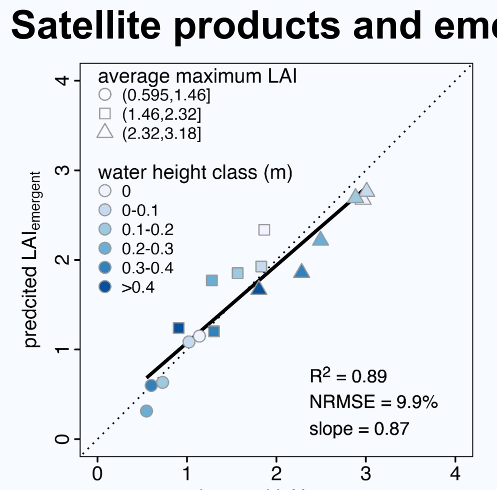
Daytime EC flux tower net ecosystem exchange (NEE; µmol CO_2 m^{-2} s^{-1}) grouped by classes of emergent leaf area index per flux footprint prediction ($ELAI_{FFP}$). The column titled *Significance from >1 (no flooding)* are p-values from pairwise Wilcoxon rank sum tests indicating each flooded group's difference from conditions with no flooding.

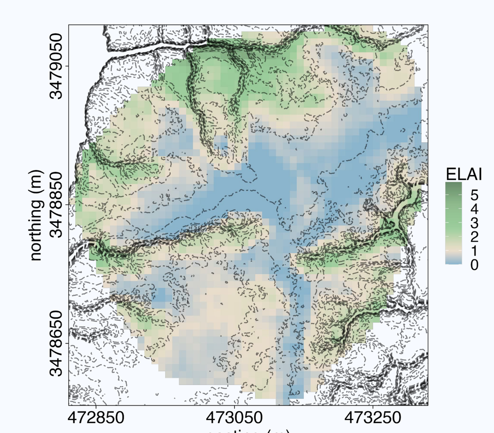
$ELAI_{FFP}$	NEE mean ± SE	Minimum	Maximum	Significance from >1 (no flooding)
<0.3	-0.93 ± 0.25	-6.28	1.74	<0.001
0.3-0.6	-4.91 ± 0.25	-14.29	0.68	<0.001
0.6-0.8	-6.53 ± 0.25	-16.40	0.33	0.09
>0.8	-7.64 ± 0.33	-16.51	1.25	0.04
>1 (no flooding)	-6.97 ± 0.11	-17.99	1.58	-



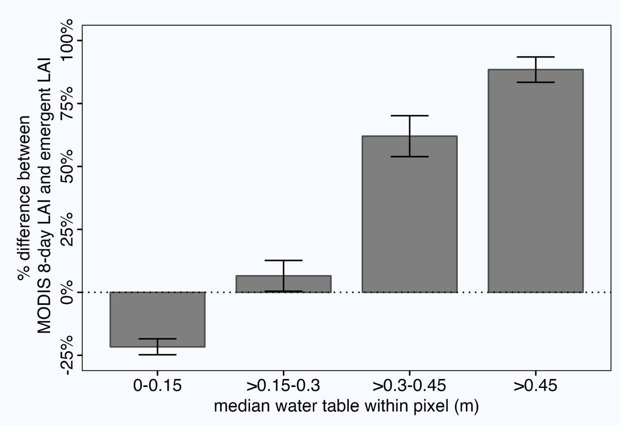
Net ecosystem exchange (NEE) as a function emergent leaf area index per footprint area ($ELAI_{FFP}$). Green points are for daytime measurements with tidal flooding, purple points are nighttime measurements during tidal flooding, and gray triangles are measurements during non-flooded periods. Lines are linear regression fits to the tidal flooding data only separated by daytime and nighttime.

Satellite products and emergent leaf area





Performance plot and fit metrics for predicting emergent LAI with Sentinel-2 derived near-infrared reflectance of vegetation (NIRV). Map showing emergent LAI predictions for September 5, 2020, with a mean water table height of 0.16 m (range: 0-1.19 m) above soil surface.



The percent differences between MODIS 8-day LAI estimates (MYD15AH2) and pixel averaged emergent LAI across water table heights relative to the soil surface for three MODIS pixels around the study location. Error bars represent standard errors.

Conclusions

1. Salt marsh canopy leaf area varies three-fold for areas meters apart
2. Tidal flooding at short timescales alters emergent leaf area, reducing carbon flux
3. Emergent leaf area can be predicted using remote sensing data at high resolution
4. The MYD15A2H LAI product exhibits high uncertainty in salt marshes

Citation

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