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# 1. Abstract

The NOAA National Estuarine Research Reserve System (NERRS) and surrounding communities need a verifiable, spatially explicit forecasting model of tidal marsh response to sea level rise (SLR) to address the potential impacts of SLR on coastal ecosystems and dependent wildlife species. The Marsh Equilibrium Model (MEM) is a one-dimensional mechanistic elevation-based soil cohort model that models marsh elevation change based on feedbacks between field-measured organic (plant biomass) and inorganic (suspended sediment) inputs. Working at Rush Ranch, a San Francisco Bay NERR site, we tested the feasibility of obtaining two important MEM inputs, peak biomass and annual average suspended sediment concentration (SSC), from Landsat 8-based maps of SSC and aboveground biomass. We tested the sensitivity of MEM to remotely sensed inputs as compared to field measured inputs, and to error associated with the remote sensing inputs. We produced a biomass map of Rush Ranch that applied the Wide Dynamic Range Vegetation Index (WDRVI)  $(\rho_{NIR}*0.2 - \rho_R)/(\rho_{NIR}*0.2 + \rho_R)$  to fully vegetated pixels and the simple ratio index ( $\rho_{Red}/\rho_{Green}$ ) to pixels with a mixed signal of vegetation and water. RMSE for top 90<sup>th</sup> percentile biomass values was 326 g/m<sup>2</sup>. We also produced a time series of SSC with a single band semianalytical model based on local mass specific absorbing and scattering properties  $(R^2 = 0.66, RMSE = 3.38 mgL^{-1})$ . Comparison of Landsat 8 and field-based MEM inputs found no significant difference in projections across 95% of the marsh plain area at 100 years, with both projections illustrating a subtle "sinking" of the marsh. Integration of remote sensing data would transform MEM into a spatial model for forecasting coastal marsh vegetation distributions to aid regional decision making.



#### Figure 1. Study Area

Rush Ranch, a San Francisco Bay National Estuarine Research Reserve site, in Suisun Marsh, CA. We are integrating remote sensing data with the Marsh Equilibrium Model to produce regional forecasts of marsh response to sea level rise, using the NERR site as a reference marsh.

## 2. Marsh Equilibrium Model

Testable

MEM is a one-dimensional mechanistic elevation-based soil cohort model that models marsh elevation change based on feedbacks between field-measured organic (plant biomass) and inorganic (suspended sediment) inputs (Morris et al. 2002).



Two most important inputs, peak biomass and suspended sediment concentration, may be derived from remote sensing.

# Remote Sensing of Vegetation and Aquatic Parameters for Modeling Coastal Marsh Response to Sea Level Rise

## 3. Remote Sensing of Aboveground Biomass

During summer 2014, within 48 Landsat pixels, we sampled biomass in 6 regularly distributed 0.1 m<sup>2</sup> sample plots to estimate average biomass per pixel. Biomass averages for Landsat pixels ranged from 0 to 1600 g/m<sup>2</sup>. We built a multi-temporal dataset from 6 Landsat 8 scenes and matched field data collected within 7 days of image data. The biomass model input to MEM is peak biomass. To assess the error in predicting biomass in high biomass plots, we calculated RMSE for measured biomass values in the top 90<sup>th</sup> percentile of the biomass distribution (Byrd et al. 2014).

#### **Biomass Model**

- Produced a rule-based model that applied the Wide Dynamic Range Vegetation Index (WDRVI)  $(\rho_{NIR}*0.2 - \rho_R)/(\rho_{NIR}*0.2 + \rho_R)$ (Mishra et al. 2012) to fully vegetated pixels and a simple ratio index ( $\rho_{\text{Red}}/\rho_{\text{Green}}$ ) to pixels with a mixed signal of vegetation and water (Table 1).
- Fraction vegetation cover (FVC) was calculated using a highresolution vegetation map produced by the California Department of Fish and Wildlife.
- A biomass map (Figure 2) was produced according to the equation:
- If FVC>0.90 then biomass =  $exp^{(4.97*WDRVI+7.57)}$  and if 0.50<FVC<0.90 then biomass =  $exp^{(-5.29*\rho_{Red}^{-}/\rho_{Green}^{-} + 12.52)}/FVC$
- RMSE for the 90<sup>th</sup> percentile plots (plots >1100 g/m<sup>2</sup>) = 326 g/m<sup>2</sup>. Peak biomass in August 8 scene: 2040 g/m<sup>2</sup>.



## Figure 3. Time Series of Landsat 8 SSC (mg/L)

September 23, 2013 June 19, 2013 September 7, 2013 December 12, 2013 October 9, 2013 October 25, 2013 60 March 18, 2014 December 28, 2013 50 January 13, 2014 May 21, 2014 May 5, 2014 April 19, 2014

Because the MEM input parameter is annual average suspended sediment concentration (SSC), we used twelve Landsat 8 scenes to generate a time series of SSC for Suisun Bay and neighboring tidal channels. Images were converted to surface water reflectance according to Vanhellemont and Ruddick (2014) and Gordon and Wang (1994). Band 4 atmospherically corrected reflectance data was highly correlated with the in-water radiometric measurement of reflectance ( $R^2 = 0.86$ , RMSE = 0.0007 sr<sup>-1</sup>).

#### **SSC Model**

- mg/L

Table 2. Landsat 8 SSC Model









### Figure 2. Aboveground Plant Biomass at **Rush Ranch**

## Table 1. Landsat 8 Biomass Models

	R <sup>2</sup>	n	RMSE
omass) ~ WDRVI	0.56	38	217.4 g/m <sup>2</sup>
omass*FVC) ~ $\rho_{Red} / \rho_{Green}$	0.57	47	207.7 g/m <sup>2</sup>

• We calibrated a single band (band 5, 865nm) semi-analytical model of ocean reflectance (Nechad et al. 2010) with 7 in situ SSC samples collected on May 5 at the time of a Landsat 8 overpass. • The absorption coefficient for sediment in the study site was measured using an AC-9 spectrophotometer.

Mass specific absorption: 0.0104 m<sup>2</sup>g<sup>-1</sup> at 865nm.

Mass specific scattering was determined by fitting the model to the 7 SSC-reflectance match-ups collected on May 5th.

Mass specific scattering: 0.0125 m<sup>2</sup> g<sup>-1</sup> at 865nm.

• We used the final model (Table 2) to generate a time series of SSC. Annual average SSC value for channels around Rush Ranch = 30

Semi-analytical model	R <sup>2</sup>	RMSE	<i>In situ</i> SSC range (mg/L)
SSC (mg/L) = $1715\rho_{b5}/(1-\rho_{b5}/0.1179)$	0.66	3.38	37.8 – 52.8
$\rho_{b5}$ = reflectance at band 5 (865 nm)		mg/L	(n=7)

# 5. Sensitivity Analysis of Remote Sensing Data with MEM

We tested MEM3.76 sensitivity to remotely sensed inputs of peak biomass and annual average SSC, compared to field measured inputs (Schile et al. 2014) and to error associated with remotely sensed data. Data were run for 0-300cm initial elevations (n=31 elevations) at a single rate of SLR (100 cm by 2100). Response curves (trend surface analysis) were generated for each model run. The elevation curve responses were compared using matched pair analyses (DF: 1, 30) and significant diversion points were identified at p<0.05, p<0.01 and p<0.001. Based on these differences in linearity, boundaries (in cm) were determined to illustrate significant diversions from field-based inputs.

#### Figure 5. MEM sensitivity to remote sensing error Figure 4. Vegetation maps at 100 years for field and remote sensing **MEM** inputs 2 2 2 <del>2 2 2 2 2 2 2 2</del> 2 2 2 2 **Remote Sensing Data** Elev 220 cm Elev 20 cm Elev 120 cm y1 y10 y20 <del>y30 y40 y50 y60</del> y70 y80 y90 y100 1 2 2 2 <del>2 2 2 2 2 2 2</del> 8 8 8 Elev 240 cm Elev 140 cm Elev 40 cm 1 y10 y20 y<del>30 y40 y50</del> y60 y70 y80 y90 y100 5 4 4 4 4 4 4 4 4 4 4 1222222222222 Elev 160 cm Elev 60 cm y1 y10 y20 <del>y30 y40 y50 y60</del> y70 y80 y90 y100 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 22222222222 Elev 80 cm Elev 180 cm Elev 280 cm 3 Y1 Y10 Y20 Y30 Y30 Y50 Y60 Y70 Y80 Y90 Y10P marsh habitats mudflat low marsh high marsh -SSC +11% —SSC -11% —BM +16% —BM -16%



## 6. Coastal Management Applications

A spatial version of MEM would generate robust, regional projections coastal marsh distributions. These projections would aid habitat conservation planning for special-status wildlife species, and aid conservation planning for coastal ecosystem services, such as carbon sequestration and protection of coastal communities.

# 7. Acknowledgements

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Table 3. Inputs for MEM analysis

Data Source	SSC (mg/L)	Peak biomass (g/m <sup>2</sup> )
Field	37	2400
RS	30	2040
<b>RS+RMSE</b>	30	2366
Biomass		
<b>RS-RMSE</b>	30	1714
Biomass		
<b>RS+RMSE SSC</b>	33.38	2040
<b>RS-RMSE SSC</b>	26.62	2040

• RS inputs were 11-16% lower than field inputs (Table 3) so led to lower rates of accretion. Model performance was insensitive (p>0.05) to differences across 95% of the marsh plain. • At 100 years, projected elevations in this dominant marsh zone (180-200cm NAVD) were less than 5cm different from field-sourced projections, with both projections illustrating a subtle "sinking" of the marsh platform to lower in the tidal frame (Figure 4).

• From the marsh edge to upland (80-200cm), biomass variability had a larger influence than SSC variability, but SSC variability strongly altered mudflat responses (0-80cm; Figure 5).



Soil carbon in coasta wetlands. Photo: Steve Crooks



The endangered salt marsh harvest mouse (Reithrodontomys raviventris). Photo: Isa Woo