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**Abstract**

A spatially-explicit model (Hydro-MEM model) that couples astronomic tides and *Spartina alterniflora* dynamics was developed to examine the effects of sea-level rise on salt marsh productivity in northeast Florida. The hydrodynamic component of the model simulates the hydroperiod of the marsh surface driven by astronomic tides and the marsh platform topography, and demonstrates biophysical feedback that non- uniformly modifies marsh platform accretion, plant biomass, and water levels across the estuarine landscape, forming a complex geometry. The marsh platform accretes organic and inorganic matter depending on the sediment load and biomass density which are simulated by the ecological-marsh component (MEM) of the model and are functions of the hydroperiod. Two sea-level rise projections for the year 2050 were simulated: 11 cm (low) and 48 cm (high). Overall biomass density increased under the low sea-level rise scenario by 54% and declined under the high sea-level rise scenario by 21%. The biomass-driven topographic and bottom friction parameter updates were assessed by demonstrating numerical convergence (the state where the difference between biomass densities for two different coupling time steps approaches a small number). The maximum coupling time steps for low and high sea-level rise cases were calculated to be 10 and 5 years, respectively. A comparison of the Hydro-MEM model with a parametric marsh equilibrium model (MEM) indicates improvement in terms of spatial pattern of biomass distribution due to the coupling and dynamic sea-level rise approaches. This integrated Hydro-MEM model provides an innovative method by which to assess the complex spatial dynamics of salt marsh grasses and predict the impacts of possible future sea level conditions.

1 **Keywords:** salt marsh; hydrodynamics; Timucuan marsh system; sea-level rise; marsh equilibrium  
2 model (MEM); Hydro-MEM model

### 3 **1. Introduction**

4 Coastal salt marsh systems provide intertidal habitats for many species (Halpin, 2000; Pennings and  
5 Bertness, 2001), many of which (e.g., crabs and fish) have significant commercial importance. Marshes  
6 also protect shorelines by dissipating wave energy and increasing friction, processes which subsequently  
7 decrease flow energy (Knutson, 1987; Leonard and Luther, 1995; Möller and Spencer, 2002; Shepard et  
8 al., 2011). Salt marsh communities are classic examples of systems that are controlled by and in turn  
9 influence physical processes (Silliman and Bertness, 2002).

10 Studying the dynamics of salt marshes, which are characterized by complex inter-relationships  
11 between physics and biology (Townend et al., 2011), requires the coupling of seemingly disparate  
12 models to capture their sensitivity and feedback processes (Reed, 1990). Furthermore, coastal  
13 ecosystems need to be examined using dynamic models, because biophysical feedbacks change  
14 topography and bottom friction with time (Jørgensen and Fath, 2011a). Such coupled models allow  
15 researchers to examine marsh responses to natural or anthropogenic changes in environmental  
16 conditions. The models can be divided into landscape scale and fine scale models based on the scales for  
17 projecting vegetation productivity. Ecosystem-based landscape models are designed to lower the  
18 computational expense by expanding the resolution to the order of kilometers and simplifying physical  
19 processes between ecosystem units (Fagherazzi et al., 2012). These models connect different drivers  
20 including hydrology, hydrodynamics, water nutrients, environmental inputs and integrate them in a large  
21 scale model (Clough et al., 2010; Costanza and Ruth, 1998; Costanza et al., 1990; Craft et al., 2008; Fitz  
22 et al., 1996; Martin et al., 2002; Martin et al., 2000; Park et al., 1986; Park et al., 1989; Reyes et al.,  
23 2000; Sklar et al., 1985). However, fine scale models with resolutions on the order of meters can provide

1 more realistic results by including different feedback mechanisms. Most relevant to this work is their  
2 ability to model the response in marsh productivity to a change in forcing mechanisms (e.g., sea-level  
3 rise-SLR) (Allen, 1997; Hagen et al., 2013; Kirwan and Murray, 2007; Marani et al., 2013; Mariotti and  
4 Fagherazzi, 2010; Morris et al., 2002; Mudd et al., 2004; Reed, 1995; Schile et al., 2014; Stralberg et al.,  
5 2011; Tambroni and Seminara, 2012; Temmerman et al., 2003).

6 Previous studies have shown that salt marshes possess biological feedbacks that change relative  
7 marsh elevation by accreting organic and inorganic material (Baustian, 2012; Kirwan and  
8 Guntenspergen, 2012; Morris et al., 2002; Patrick and DeLaune, 1990; Reed, 1995; Turner et al., 2000).  
9 SLR also will cause salt marshes to transgress, but extant marshes may be unable to accrete at a  
10 sufficient rate in response to high SLR (Donnelly and Bertness, 2001; Warren and Niering, 1993)  
11 leading to their complete submergence and loss (Nyman et al., 1993).

12 Salt marsh systems adapt to changing mean sea level through continuous adjustment of the  
13 marsh platform elevation toward an equilibrium (Morris et al., 2002). Based on long-term measurements  
14 of sediment accretion and marsh productivity, Morris et al. (2002) developed the Marsh Equilibrium  
15 Model (MEM) that links sedimentation, biological feedback, and the relevant time scale for SLR. Marsh  
16 equilibrium theory holds that a dynamic equilibrium exists, and that marshes are continuously moving in  
17 the direction of that equilibrium. MEM uses a polynomial formulation for salt marsh productivity and  
18 accounts explicitly for inputs of suspended sediments and implicitly for the in situ input of organic  
19 matter to the accreting salt marsh platform. The coupled model presented in this manuscript incorporates  
20 biological feedback by including the MEM accretion formulation as well as implementing a friction  
21 coefficient effect that varies between subtidal and intertidal states. The resulting model not only has the  
22 capability of capturing biophysical feedback that modifies relative elevation, but it also includes the  
23 biological feedback on hydrodynamics.

1            Since the time scale for SLR is on the order of decades to centuries, models that are based on  
2 long-term measurements, like MEM, are able to capture a fuller picture of the governing long-term  
3 processes than physical models that use temporary physical processes to extrapolate long-term results  
4 (Fagherazzi et al., 2012). MEM has been applied to a number of investigations on the interaction of  
5 hydrodynamics and salt marsh productivity. Mudd et al. (2004) used MEM coupled with a one-  
6 dimensional hydrodynamic component to investigate the effect of SLR on sedimentation and  
7 productivity in salt marshes at the North Inlet estuary, South Carolina. MEM has also been used to  
8 simulate the effects of vegetation on sedimentation, flow resistance, and channel cross section change  
9 (D'Alpaos et al., 2006), as well as in a three-dimensional model of salt marsh accretion and channel  
10 network evolution based on a physical model for sediment transport (Kirwan and Murray, 2007). Hagen  
11 et al. (2013) coupled a two-dimensional hydrodynamic model with the zero-dimensional biomass  
12 production formula of Morris et al. (2002) to capture SLR effects on biomass density and simulated  
13 human-enhanced marsh accretion.

14            Coupling a two-dimensional hydrodynamic model with a point-based parametric marsh model  
15 that incorporates biological feedback, such as MEM, has not been previously achieved. Such a model is  
16 necessary because results from short-term limited hydrodynamic studies cannot be used for long-term or  
17 extreme events in ecological and sedimentary interaction applications. Hence, there is a need for  
18 integrated models, which incorporate both hydrodynamic and biological components for long time  
19 scales (Thomas et al., 2014). Additionally, models that ignore the spatial variability of the accretion  
20 mechanism may not accurately capture the dynamics of a marsh system (Thorne et al., 2014), and it is  
21 important to model the distribution at the correct scale for spatial modeling (Jørgensen and Fath, 2011b).

22            Ecological models that integrate physics and biology provide a means of examining the  
23 responses of coastal systems to various possible scenarios of environmental change. D'Alpaos et al.

1 (2007) employed simplified shallow water equations in a coupled model to study SLR effects on marsh  
2 productivity and accretion rates. Temmerman et al. (2007) applied a more physically complicated  
3 shallow water model to couple it with biological models to examine landscape evolution within a limited  
4 domain. These coupled models have shown the necessity of the interconnection between physics and  
5 biology; however, the applied physical models were simplified or the study area was small. This paper  
6 presents a practical framework with a novel application of MEM that enables researchers to forecast the  
7 fate of coastal wetlands and their responses to SLR using a physically more complicated hydrodynamic  
8 model and a larger study area. The coupled Hydro-MEM model is based on the model originally  
9 presented by Hagen et al. (2013). This model has since been enhanced to include: spatially dependent  
10 marsh platform accretion, a bottom friction roughness coefficient (Manning's  $n$ ) using temporal and  
11 spatial variations in habitat state, a "coupling time step" to incrementally advance and update the  
12 solution, and changes in biomass density and hydroperiod via biophysical feedbacks. The presented  
13 framework can be employed in any estuary or coastal wetland system to assess salt marsh productivity  
14 regardless of tidal range by updating an appropriate biomass curve for the dominant salt marsh species  
15 in the estuary. In this study, the coupled model was applied to the Timucuan marsh system located in  
16 northeast Florida under high and low SLR scenarios. The objectives of this study were to (1) develop a  
17 spatially-explicit model by linking a hydrodynamic-physical model and MEM using a coupling time  
18 step and (2) assess a salt marsh system long-term response to projected SLR scenarios.

## 19 **2. Methods**

### 20 **2.1. Study area**

21 The study area is the Timucuan salt marsh, located along the lower St. Johns River in Duval County in  
22 northeastern Florida (Figure 1). The marsh system is located to the north of the lower 10–20 km of the  
23 St. Johns River, where the river is engineered and the banks are hardened for support of shipping traffic

1 and port utility. The creeks have changed little from 1929 to 2009 based on surveyed data from National  
2 Ocean Service (NOS) and the United States Army Corps of Engineers (USACE), which show the creek  
3 layout to have remained essentially the same since 1929. The salt marsh of the Timucuan preserve,  
4 which was designated the Timucuan Ecological and Historic Preserve in 1988, is among the most  
5 pristine and undisturbed marshes found along the southeastern United States seaboard (United States  
6 National Park Service (Denver Service Center), 1996). Maintaining the health of the approximately 185  
7 square kilometers of salt marsh, which cover roughly 75% of the preserve, is important for the survival  
8 of migratory birds, fish, and other wildlife that rely on this area for food and habitat.

9         The primary habitats of these wetlands are salt marshes and the tidal creek edges between the  
10 north bank and Sisters Creek are dominated by low marsh, where *S. alterniflora* thrives (DeMort, 1991).  
11 A sufficient biomass density of *S. alterniflora* in the marsh is integral to its survival, as the grass aids in  
12 shoreline protection, erosion control, filtering of suspended solids, and nutrient uptake of the marsh  
13 system (Bush and Houck, 2002). *S. alterniflora* covers most of the southern part of the watershed and  
14 east of Sisters Creek up to the primary dunes on the north bank, and is also the dominant species on the  
15 Black Hammock barrier island (DeMort, 1991). The low marsh is the more tidally vulnerable region of  
16 the study area. Our focus is on the areas that are directly exposed to SLR and where *S. alterniflora* is  
17 dominant. However, we also extended our salt marsh study area 11 miles to the south, 17 miles to the  
18 north, and 18 miles to the west of the mouth of the St. Johns River. The extension of the model  
19 boundary allows enough space to study the potential for salt marsh migration.

## 20 **2.2. Overall model description**

21 The flowchart shown in Figure 2 illustrates the dynamic coupling of the physical and biological  
22 processes in the model. The framework to run the Hydro-MEM model consists of two main elements:  
23 the hydrodynamic model, and a marsh model with biological feedback (MEM) in the form of an ArcGIS

1 toolbox. The two model components provide inputs for one another at a specified time step within the  
2 loop structure, referred to as the coupling time step. The coupling time step refers to the length of the  
3 time interval between updating the hydrodynamics based on the output of MEM, which was always  
4 integrated with an annual time step. The length of the coupling time step ( $\Delta t$ ) governs the frequency of  
5 exchange of information from one model component to the other. The choice of coupling time step size  
6 affects the accuracy and computational expense of the Hydro-MEM model which is an important  
7 consideration if extensive areas are simulated. The model's initial conditions include astronomic tides,  
8 bottom friction, and elevation, which consist of the marsh surface elevations, creek geometry, and sea  
9 level. The hydrodynamic model is then run using the initial conditions and its results are processed to  
10 derive tidal constituents.

11         The tidal constituents are fed into the ArcGIS toolbox, which contains two components that were  
12 designed to work independently. The "Tidal Datums" element of the ArcGIS toolbox computes Mean  
13 Low Water (MLW) and Mean High Water (MHW) in regions that were always classified as wetted  
14 during the hydrodynamic simulation. The second component of the toolbox, "Biomass Density," uses  
15 the MLW and MHW calculated in the previous step and extrapolates those values across the marsh  
16 platform using the Inverse Distance Weighting (IDW) method of extrapolation in ArcGIS (i.e., from the  
17 areas that were continuously wetted during the hydrodynamic simulation), computes biomass density for  
18 the marsh platform, and establishes a new marsh platform elevation based on the computed accretion.

19         The simulation terminates and outputs the final results if the target time has been reached,  
20 otherwise time is incremented by the coupling time step, data are transferred and model inputs are  
21 modified, and another incremental simulation is performed. After each time advancement of the MEM  
22 and after updating the topography, the hydrodynamic model is re-initialized using the current elevations,  
23 water levels, and updated bottom friction parameters calculated in the previous iteration.



1           The size of the coupling time step, i.e. the time elapsed in executing MEM before updating the  
2 hydrodynamic model, was selected based on desired accuracy and computational expense. The coupling  
3 time step was adjusted in this work to minimize numerical error associated with biomass calculations  
4 (the difference between using two different coupling time steps) while also minimizing the run time.

### 5 **2.2.1. Hydrodynamic model**

6 We used the two-dimensional, depth-integrated ADvanced CIRCulation (ADCIRC) finite element  
7 model to simulate tidal hydrodynamics (Luettich et al., 1992). ADCIRC is one of the main components  
8 of the Hydro-MEM model due to its capability to simulate the highly variable tidal response throughout  
9 the creeks and marsh platform. ADCIRC solves the shallow water equations for water levels and  
10 currents using continuous Galerkin finite elements in space. ADCIRC based models have been used  
11 extensively to model long wave processes such as astronomic tides and hurricane storm surge  
12 (Bacopoulos and Hagen, 2009; Bunya et al., 2010) and SLR impacts (Atkinson et al., 2013; Bilskie et  
13 al., 2014). A value-added feature of using ADCIRC within the Hydro-MEM model is its ability to  
14 capture a two-dimensional field of the tidal flow and hydroperiod within the intertidal zone. ADCIRC  
15 contains a robust wetting and drying algorithm that allows elements to turn on (wet) or turn off (dry)  
16 during run-time, enabling the swelling of tidal creeks and overtopping of channel banks (Medeiros and  
17 Hagen, 2013). A least-squares harmonic analysis routine within ADCIRC computes the amplitudes and  
18 phases for a specified set of tidal constituents at each computational point in the model domain (global  
19 water levels). The tidal constituents are then sent to the ArcGIS toolbox for further processing.

20           Full hydrodynamic model description including elevation sources and boundary conditions can  
21 be found in Bacopoulos et al. (2012) and Hagen et al. (2013). The model is forced with the seven  
22 dominating tidal constituents along the open ocean boundary located on the continental shelf that  
23 account for more than 90% of the offshore tidal activity (Bacopoulos et al., 2012; Hagen et al., 2013).

1 Placement of the offshore tidal boundary allows tides to propagate through the domain and into the tidal  
2 creeks and intertidal zones, and simulate non-linear interactions that occur in the tidal flow.

3 To model future conditions, sea level was increased by applying an offset of the initial sea  
4 surface equal to the SLR across the model domain to the initial conditions. Previous studies introduced  
5 SLR by applying an additional tidal constituent to the offshore boundary (Hagen et al., 2013). Both  
6 methods produce an equivalent solution; however, we offset the initial sea surface across the entire  
7 domain as the method of choice in order to reduce computational time.

8 There is no accepted method to project SLR at the local scale (Parris et al., 2012); however, a  
9 tide gauge analysis performed in Florida using three different methods gave a most probable range of  
10 rise between 0.11 and 0.36 m from present to the year 2080 (Walton Jr, 2007). The U.S. Army Corps of  
11 Engineers (USACE) developed low, intermediate, and high SLR projections at the local scale, based on  
12 long-term tide gage records ([http://www.corpsclimate.us/ccaceslcurves\\_nn.cfm](http://www.corpsclimate.us/ccaceslcurves_nn.cfm)). The low curve follows  
13 the historic trend of SLR and the intermediate and high curves use the National Research Council (NRC)  
14 curves (United States Army Corps of Engineers, 2011). Both methodologies account for local  
15 subsidence. We based our SLR scenarios on the USACE projections at Mayport, FL (Figure 1c), which  
16 accelerates to 11 cm and 48 cm for the low and high scenarios, respectively, in the year 2050. The low  
17 and high SLR scenarios display linear and nonlinear trends, respectively and using the time step  
18 approach helps to capture the rate of SLR in the modeling.

19 The hydrodynamic model uses Manning's  $n$  coefficients for bottom friction, which have been  
20 assessed for present-day conditions of the lower St. Johns River (Bacopoulos et al., 2012). Bottom  
21 friction must be continually updated by the model due to temporal changes in the SLR and biomass  
22 accretion. To compute Manning's  $n$  at each coupling time step, the Hydro-MEM model utilizes the  
23 wet/dry area output of the hydrodynamic model as well as biomass density and accreted marsh platform

1 elevation to find the regions that changed from marsh (dry) to channel (wet). This process is a part of the  
2 biofeedback process in the model: Manning's  $n$  is adjusted using the accretion, which changes the  
3 hydrodynamics, which in turn changes the biomass density in the next time step. The hydrodynamic  
4 model, along with the main digital elevation model (Figure 3) and bottom friction parameter (Manning's  
5  $n$ ) inputs, was previously validated in numerous studies (Bacopoulos et al., 2009; Bacopoulos et al.,  
6 2012; Bacopoulos et al., 2011; Giardino et al., 2011; Hagen et al., 2013) and specifically Hagen et al.  
7 (2013) validated the MLW and MHW generated by this model.

### 8 **2.2.2. ArcGIS toolbox**

9 This element of the Hydro-MEM model is designed as a user interface toolbox in ArcGIS (ESRI, 2012).  
10 The toolbox consists of two separate tools that were coded in Python v2.7. The first, "Tidal Datums,"  
11 uses tidal constituents from the preceding element of the Hydro-MEM model loop, the hydrodynamic  
12 model, to generate MLW and MHW in the river and tidal creeks. MLW and MHW represent the average  
13 low and high tides at a point (Hagen et al., 2013). The flooding frequency and duration are considered in  
14 the calculation of MLW and MHW. These values are necessary for the MEM-based tool in the model.  
15 The Tidal Datums tool produces raster files of MLW and MHW using the data from ADCIRC  
16 simulation and a 10 m Digital Elevation Model (DEM). These feed into the second tool, "Biomass  
17 Density," to calculate MLW and MHW within the marsh areas that were not continuously wet during  
18 the ADCIRC simulation, which is done by interpolating MLW and MHW values from the creeks and  
19 river areas across the marsh platform using IDW. This interpolation technique is necessary because very  
20 small creeks that are important in flooding the marsh surface are not resolved in the hydrodynamic  
21 model. IDW calculates MLW and MHW at each computational point across the marsh platform based  
22 on its distance from the tidal creeks, where the number of the nearest sample points for the IDW  
23 interpolation based on the default setting in ArcGIS is twelve. This method was used in this work for the

1 marsh interpolation due to its accuracy and acceptable computational time. The method produces lower  
2 water levels for points farther from the source, which in turn results in lower sedimentation and  
3 accretion in the MEM-based part of the model. Interpolated MLW and MHW, biomass productivity, and  
4 accretion are displayed as rasters in ArcGIS. The interpolated values of MLW and MHW in the marsh  
5 are used by MEM in each raster cell to compute the biomass density and accretion rate across the marsh  
6 platform.

7 The zero-dimensional implementation of MEM has been demonstrated to successfully capture  
8 salt marsh response to SLR (Morris, 2015; Morris et al., 2002). MEM predicts two salt marsh variables:  
9 biomass productivity and accretion rate. These processes are related; the organic component of the  
10 accretion is dependent on biomass productivity, and the updated marsh platform elevation is generated  
11 using the computed accretion rate. The coupling of the two parts of MEM is incorporated dynamically in  
12 the Hydro-MEM model. MEM approximates salt marsh productivity as a parabolic function

$$13 \quad B = aD + bD^2 + c \quad (1)$$

14 where  $B$  is the biomass density ( $\text{g}\cdot\text{m}^{-2}$ ),  $a = 1000 \text{ g}\cdot\text{m}^{-2}$ ,  $b = -3718 \text{ g}\cdot\text{m}^{-2}$ , and  $c = 1021 \text{ g}\cdot\text{m}^{-2}$  are  
15 coefficients derived from bioassay data collected at North Inlet, SC (Morris et al., 2013) and where the  
16 variable  $D$  is the non-dimensional depth, given by

$$17 \quad D = \frac{MHW - E}{MHW - MLW} \quad (2)$$

18 and variable  $E$  is the relative marsh surface elevation (NAVD 88). Relative elevation is a proxy for  
19 other variables that directly regulate growth, such as soil salinity (Morris, 1995) and hypoxia, and Eq. 1  
20 actually represents a slice through n-dimensional niche space (Hutchinson, 1957).

21 The coefficients  $a$ ,  $b$ , and  $c$  may change with marsh species, estuary type (fluvial, marine,  
22 mixed), climate, nutrients, and salinity (Morris, 2007), but Eq. 1 should be independent of tide range

1 because it is calibrated to dimensionless depth  $D$ , consistent with the meta-analysis of Mckee and  
2 Patrick (1988) documenting a correlation between the growth range of *S. alterniflora* and mean tide  
3 range. The coefficients  $a$ ,  $b$ , and  $c$  in Eq. 1 give a maximum biomass of  $1088 \text{ g/m}^2$ , which is generally  
4 consistent with biomass measurements from other southeastern salt marshes (Dame and Kenny, 1986;  
5 Darby and Turner, 2008; Hopkinson et al., 1980; Schubauer and Hopkinson, 1984), and since our focus  
6 is on an area where *S. alterniflora* is dominant, these constants are used. Additionally, because many  
7 tidal marsh species occupy a vertical range within the upper tidal frame, but sorted along a salinity  
8 gradient, the model is able to qualitatively project the wetland area coverage including other marsh  
9 species in low, medium, and high productivity. The framework has the capability to be applied to other  
10 sites with different dominant salt marsh species by using experimentally-derived coefficients to generate  
11 the biomass curves (Kirwan and Guntenspergen, 2012).

12 The first derivative of the biomass density function with respect to non-dimensional depth is a  
13 linear function, which will be used in analyzing the Hydro-MEM model results, is given by

$$14 \quad \frac{dB}{dD} = 2bD + a \quad (3)$$

15 The first derivative values are close to zero for the points around the optimal point of the  
16 biomass density curve. These values become negative for the points on the right (sub-optimal) side and  
17 positive for the points on the left (super-optimal) side of the biomass density curve.

18 The accretion rate determined by MEM is a positive function based on organic and inorganic  
19 sediment accumulation (Morris et al., 2002). These two accretion sources, organic and inorganic, are  
20 necessary to maintain marsh productivity against rising sea level; otherwise marshes might become  
21 submerged (Baustian, 2012; Blum and Roberts, 2009; Nyman et al., 2006). Sediment accretion is a  
22 function of the biomass density in the marsh and relative elevation. Inorganic accretion (i.e., mineral

1 sedimentation) is influenced by the biomass density, which affects the ability of the marsh to ‘trap’  
2 sediments (Mudd et al., 2010). Inorganic sedimentation also occurs as salt marshes impede flow by  
3 increasing friction, which enhances sediment deposition on the marsh platform (Leonard and Croft,  
4 2006; Leonard and Luther, 1995). The linear function developed by Morris et al. (2002) for the rate of  
5 total accretion is given by

$$6 \quad \frac{dY}{dt} = (q + kB)D \quad \text{for} \quad D > 0 \quad (4)$$

7 where  $dY$  is the total accretion (cm/yr),  $dt$  is the time interval,  $q$  represents the inorganic contribution to  
8 accretion from the suspended sediment load and  $k$  represents the organic and inorganic contributions due  
9 to vegetation. The values of the constants  $q$  (0.0018) and  $k$  ( $2.5 \times 10^{-5}$ ) are from a fit of MEM to a time-  
10 series of marsh elevations at North Inlet (Morris et al., 2002) modified for a high sedimentary  
11 environment. These constants take both autochthonous organic matter and trapping of allochthonous  
12 mineral particles into account for biological feedback. The accretion rate is positive for salt marshes  
13 below MHW; when  $D < 0$  no accumulation of sediments will occur for salt marshes above MHW  
14 (Morris, 2007). The marsh platform elevation change is then calculated using the equation

$$15 \quad Y(t + \Delta t) = Y(t) + dY \quad (5)$$

16 where the marsh platform elevation  $Y$  is raised by  $dY$  meters every  $\Delta t$  years.

### 17 **3. Results**

#### 18 **3.1. Coupling time step**

19 In this study, coupling time steps of 50, 10, and 5 years were used for both the low and high SLR  
20 scenarios. The model was run for one 50-year coupling time step, five 10-year coupling time steps, and  
21 ten 5-year coupling time steps for each SLR scenario. The average differences for biomass density in  
22 Timucuan marsh between using one 50-year coupling time step and five 10-year coupling time steps for

1 low and high SLR scenarios were 37 and 57  $\text{g}\cdot\text{m}^{-2}$ , respectively. Decreasing the coupling time step to 5  
2 years indicated convergence within the marsh system when compared to a 10-year coupling time step  
3 (Table 1). The average difference for biomass density between using five 10-year coupling time steps  
4 and ten 5-year coupling time steps in the same area for low and high SLR were 6 and 11  $\text{g}\cdot\text{m}^{-2}$ , which  
5 implied convergence using smaller coupling time steps. The Hydro-MEM model did not fully converge  
6 using a coupling time step of 10 years for the high SLR scenario, and a 5 year coupling time step was  
7 required (Table 1) because of the acceleration in rate of SLR. However, the model was able to simulate  
8 reasonable approximations of low, medium, or high productivity of the salt marshes when applying a  
9 single coupling time step of 50 years when SLR is small and linear. For this case, the model was run for  
10 the current condition and the feedback mechanism is subsequently applied using 50-year coupling time  
11 step. The next run produces the results for salt marsh productivity after 50 years using the SLR scenario.

### 12 **3.2. Hydrodynamic results**

13 MLW and MHW demonstrated spatial variability throughout the creeks and over the marsh platform.  
14 The water surface across the estuary varied from -0.85 m to -0.3 m (NAVD 88) for MLW and from 0.65  
15 m to 0.85 m for MHW in the present day simulation (Figure 4a, Figure 4d). The range and spatial  
16 distribution of MHW and MLW exhibited a non-linear response to future SLR scenarios. Under the low  
17 SLR (11 cm) scenario, MLW ranged from -0.74 m in the ocean to -0.25 m in the creeks (Figure 4b),  
18 while MHW varied from 1 m to 0.75 m (Figure 4e). Under the high SLR (48 cm) scenario, the MLW  
19 ranged from -0.35 m in the ocean to 0.05 m in the creeks (Figure 4c), and from 1.35 m to 1.15 m for  
20 MHW (Figure 4f).

21 The same spatial pattern of water level was exhibited on the marsh platform for both present-day  
22 and future conditions with the low SLR scenario, but with future conditions showing slightly higher  
23 values consistent with the 11 cm increase in MSL (Figure 4d, Figure 4e). The MHW values in both

1 cases were within the same range as those in the creeks. However, the spatial pattern of MHW changed  
2 under the high SLR scenario; the water levels in the creeks increased significantly and were more evenly  
3 distributed relative to the present-day conditions and low SLR scenario (Figure 4d, Figure 4e, Figure 4f).  
4 As a result, the spatial variation of MHW in the creeks and marsh area was lower than that of the present  
5 in the high SLR scenario (Figure 4f).

### 6 7 **3.3. Marsh dynamics**

8 Simulations of biomass density demonstrated a wide range of spatial variation in the year 2000 (Fig. 5a),  
9 and in the two future scenarios (Figure 5b, Figure 5c), depending on the pre-existing elevations of the  
10 marsh surface and their change relative to future MHW and MLW. The maps showed an increase in  
11 biomass density under low SLR in 90% of the marshes and a decrease in 80% of the areas under the  
12 high SLR scenario. The average biomass density increased from  $804 \text{ g}\cdot\text{m}^{-2}$  in the present to  $994 \text{ g}\cdot\text{m}^{-2}$  in  
13 the year 2050 with low SLR, and decreased to  $644 \text{ g}\cdot\text{m}^{-2}$  under the high SLR scenario.

14 Recall that the derivative of biomass density under low SLR scenario varies linearly with respect  
15 to non-dimensional depth. Figure 6 illustrates the aboveground biomass density curve with respect to  
16 non-dimensional depth and three sample points with low, medium, and high productivity. The slope of  
17 the curve at the sample points is also shown, depicting the first derivative of biomass density. The  
18 derivative is negative if a point is located on the right side of the biomass density curve, and is positive  
19 if it is on the left side. In addition, values close to zero indicate a higher productivity, whereas large  
20 negative values indicate low productivity (Figure 6). The average biomass density derivative under the  
21 low SLR scenario increased from  $-2000 \text{ g}\cdot\text{m}^{-2}$  to  $-700 \text{ g}\cdot\text{m}^{-2}$  and decreased to  $-2400 \text{ g}\cdot\text{m}^{-2}$  in the high  
22 SLR case.

23 Sediment accretion in the marsh varied spatially and temporally under different SLR scenarios.  
24 Under the low SLR scenario (11 cm), the average salt marsh accretion totaled 19 cm or 0.38 cm per year



1 (Figure 7a). The average salt marsh accretion increased by 20% under the high SLR scenario (48 cm)  
2 due to an increase in sedimentation (Figure 7b). Though the magnitudes are different, the general spatial  
3 patterns of the low and high SLR scenarios were similar.

4 Comparisons of marsh platform accretion, MHW, and biomass density across transect AB spanning  
5 over Cedar Point Creek, Clapboard Creek, and Hannah Mills Creek (Figure 1d) between present and  
6 future time demonstrated that acceleration of SLR from 11 cm to 48 cm in 50 years reduced the overall  
7 biomass, but the effect depended on the initial elevation (Figure 8a-d). Under the low SLR, accretion  
8 was maximum at the edge of the creeks, 25 to 30 cm, and decreased to 15 cm with increasing distance  
9 from the edge of the creek (Figure 8a). Analyzing the trend and variation of MHW between future and  
10 present across the transect under low and high SLR showed that it is not uniform across the marsh and  
11 varied with distance from creek channels and underlying topography (Figure 8a, Figure 8c). MHW  
12 increased slightly in response to a rapid rise in topography (Figure 8a, Figure 8c).

13 The change in MHW, which is a function of the changing hydrodynamics and marsh topography,  
14 was nearly uniform across space when SLR was high, but when SLR was low, marsh topography  
15 continued to influence MHW, which can be seen in the increase between years 2020 and 2030 (Figure  
16 9c, Figure 9d). This is due to the accretion of the marsh platform keeping pace with the change in  
17 MHW. The change in biomass was a function of the starting elevation as well as the rate of SLR (Figure  
18 9e, Figure 9f). When the starting marsh elevation was low, as it was for sites 1 and 2, biomass increased  
19 significantly over the 50 yr simulation, corresponding to a rise in the relative elevation of the marsh  
20 platform that moved them closer to the optimum. The site that was highest in elevation at the start, site  
21 3, was essentially in equilibrium with sea level throughout the simulation and remained at a nearly  
22 optimum elevation (Figure 9e). When the rate of SLR was high, the site lowest in elevation at the start,  
23 site 1, ultimately lost biomass and was close to extinction (Figure 9f). Likewise, the site highest in

1 elevation, site 3, also lost biomass, but was less sensitive to SLR than site 1. The site with intermediate  
2 elevation, site 2, actually gained biomass by the end of the simulation when SLR was high (Figure 9f).

3 Biomass density was generally affected by rising mean sea level and varying accretion rates. A  
4 modest rate of SLR apparently benefitted these marshes, but high SLR was detrimental (Figure 9e,  
5 Figure 9f). This is further explained by looking at the derivatives. The first-derivative change of biomass  
6 density under low SLR (shaded red) demonstrated an increase toward the zero (Figure 10). Biomass  
7 density rose to the maximum level and was nearly uniform across transect AB under the low SLR  
8 scenario (Figure 8b), but with 48 cm of SLR biomass declined (Figure 8d). The biomass derivative  
9 across the transect decreased from year 2000 to year 2050 under the high SLR scenario (Figure 10),  
10 which indicated a move to the right side of the biomass curve (Figure 6).

11 Comparisons between using the coupled model and MEM in isolation are given in Table 2  
12 according to total wetland area and marsh productivity for both the coupled Hydro-MEM model and  
13 MEM. The Hydro-MEM model exhibited more spatial variation of low and medium productivity for  
14 both the low and high SLR scenarios (Figure 11). Under the low SLR scenario there was less open  
15 water and more low and medium productivity, while under the high SLR scenario there was less high  
16 productivity and more low and medium productivity.

17 To qualitatively validate the model result, infrared aerial imagery and land cover data from the  
18 National Land Cover Database for the year 2001 (NLCD2001) (Homer et al., 2007) were compared with  
19 the low, medium, and high productivity map (Figure 12). Within the box marked (a) in the aerial image  
20 (leftmost figure), the boundaries for the major creeks were captured in the model results (middle figure).  
21 Additionally, smaller creeks in boxes (a), (b) and (c) in the NLCD map (rightmost figure) also were  
22 represented well in the model results. The model identified the NLCD wetland areas corresponding to  
23 box (a) as highly productive marshes. Box (b) highlights an area with higher elevations, shown as forest

1 land in the aerial map, and categorized as non-wetland in the NLCD map. These regions had low or no  
2 productivity in the model results. The border of the brown (low productivity) region in the model results  
3 generally mirrors the forested area in the aerial and the non-wetland area of the NLCD data. A low  
4 elevation area identified by box (c) consists of a drowning marsh flat with a dendritic layout of shallow  
5 tidal creeks. The model identified this area as having low or no productivity, but with a productive area  
6 marsh in the southeast corner. Collectively, comparison of the model results in these areas to ancillary  
7 data demonstrates the capability of the model to realistically characterize the estuarine landscape.

#### 8 **4. Discussion**

9         Geomorphic variation on the marsh platform as well as variation in marsh biomass and their  
10 interactions with tidal flow play a key role in the spatial and temporal distribution of tidal constants,  
11 MLW and MHW, across an estuarine landscape. Tidal flow is affected because salt marsh systems  
12 increase momentum dissipation through surface friction, which is a function of vegetation growth  
13 (Möller and Spencer, 2002; Möller et al., 1999). Furthermore, the productivity and accretion of sediment  
14 in marshes affect the total area of wetted zones and, as a result of higher SLR projections, may increase  
15 the width of the tidal creeks, and some areas that are currently covered by marshes might convert to  
16 open water. Also, as the level of water increases, water can flow with lower resistance in the tidal creeks  
17 and circulate more freely through the marshes, thus leading to less spatial variability in tidal constants  
18 within the creeks and over the marsh platform. During the high SLR scenario, water levels and flow  
19 rates increased and bottom friction was reduced. This reduced the spatial variability in MHW in the  
20 creeks and across the marshes. Further, as SLR increased, MHW in the marshes and creeks converged as  
21 energy dissipation from the marshes decreased. These energy controls are fundamental to the  
22 geomorphological feedbacks that maintain stable marshes. At the upper end of SLR, the tidal constants

1 are in more dynamic equilibrium, where at the lower end of SLR, the tidal constants are sensitive to  
2 subtle changes where they are in adjustment towards dynamic equilibrium.

3 Marsh productivity is primarily a function of relative elevation, MHW, and accretion relative to  
4 SLR. SLR affects future marsh productivity by altering elevation, relative MHW, and their distributions  
5 across the marsh platform (i.e., hydroperiod). SLR also affects the accretion rate due to the biological  
6 feedback mechanisms of the system. The Hydro-MEM model captured this relationship by updating  
7 accretion at each coupling time step based on data-derived biomass curve (MEM). Biomass density  
8 increased under the low SLR scenario as a result of the dynamic interactions between SLR and  
9 sedimentation. In this case, the low SLR scenario and the marsh system worked together to increase  
10 productivity and are in agreement with the predicted changes for salt marsh productivity in response to  
11 suggested ranges of SLR in recent study (Cadol et al., 2014).

12 For the low SLR scenario, the numerator in Eq. 2 decreased with increasing accretion while the  
13 denominator increased; the point on the horizontal axis of the biomass curve moved to the left, closer to  
14 the optimum part of the curve (Figure 6). For the high SLR scenario, the numerator's growth outpaced  
15 that of the denominator in Eq. 2, and the non-dimensional depth increased to a higher value on the right  
16 side of the graph (Figure 6). This move illustrates the decrease in salt marsh productivity from the  
17 medium to the low region on the biomass density curve. In our study, most of the locations for the year  
18 2000 were positioned on the right side of the biomass curve (Figure 6, Figure 5d). If the location is  
19 positioned on the far right or left sides of the biomass curve, the first derivative of biomass productivity  
20 is a small negative or large positive number, respectively (Figure 6). This number characterizes the slope  
21 of the tangent line to the curve at that point on the curve. The slope will approach zero at the optimal  
22 point of the curve (parabolic maximum). Therefore, if the point transitions to the right side of the curve,  
23 the first derivative will become smaller, and if the point moves to the left side of the curve, the first

1 derivative will become larger. Under the low SLR scenario, the first derivative showed higher values  
2 generally approaching the optimal point (Figure 5e). As shown in Figure 6, the biomass density  
3 decreased under the high SLR scenario and the first derivative also decreased as it shifted to the right  
4 side of the biomass density curve (Figure 5f).

5 D'Alpaos et al. (2007) found that the inorganic sedimentation portion of the accretion decreases  
6 with increasing distance from the creek, which in this study is observed throughout a majority of the  
7 marsh system, thus indicating good model performance (Figure 7a, Figure 7b). Figure 8a and Figure 8c  
8 further illustrate this finding for the transect AB (Figure 1d), showing that the minimum accretion was in  
9 the middle of the transect (at a distance from the creeks) and the maximum was close to creeks. This  
10 model result is a consequence of the higher elevation of inland areas, and decreased inundation time of  
11 the marsh surface, rather than a result of a decrease in the mass of sediment transport.

12 Spatial and temporal variation in the tidal constants had a dynamic effect on accretion and also  
13 biomass density (Figure 8a, Figure 8b). The coupling between the hydrodynamic model and MEM,  
14 which included the dynamics of SLR, also helped to better capture the salt marsh's movements toward a  
15 dynamic equilibrium. This change in condition is exemplified by the red area in Figure 10 that depicted  
16 the movement toward the optimum point on the biomass density curve.

17 Although the salt marsh platform showed increased rates of accretion under high SLR, the salt  
18 marsh was not able to keep up with MHW. Salt marsh productivity declined along the edge of the creeks  
19 (Figure 8d); if this trend were to continue, the marsh would drown. The decline depends on the  
20 underlying topography as well as the tidal metrics, neither of which are uniform across the marsh. The  
21 first derivative curve for high SLR (shaded green) in Figure 10 illustrates a decline in biomass density;  
22 however, marshes with medium productivity due to higher accretion rates had minimal losses (Figure  
23 9f) and the marsh productivity remained in the intermediate level. The marshes in the high productivity

1 zone descended to the medium zone as the marshes in the lower level were exposed to more frequent  
2 and extended inundation. As a result, in the year 2050 under the high SLR scenario, the total salt marsh  
3 area was projected to decrease, with salt marshes mostly in the medium productivity level surviving  
4 (Figure 5c, Figure 5f). The high SLR scenario also exhibits a tipping point in biomass density that  
5 occurs at different times based on low, medium or high productivity, where biomass density declines  
6 beyond the tipping point.

7         The complex dynamics introduced by marsh biogeomorphological feedbacks as they influence  
8 hydrodynamic, biological, and geomorphological processes across the marsh landscape can be  
9 appreciated by examination of the time series from a few different positions within the marshes (Figure  
10 9). The interactions of these processes are reciprocal. That is, relative elevations affect biology, biology  
11 affects accretion of the marsh platform, which affects hydrodynamics and accretion, which affects  
12 biology, and so on. Furthermore, to add even more complexity to the biofeedback processes, the present  
13 conditions affect the future state. For example, the response of marsh platform elevation to SLR  
14 depends on the current elevation as well as the rate of SLR (Figure 9a, Figure 9b). The temporal change  
15 of accretion for the low productivity point under the high SLR scenario after 2030 can be explained by  
16 the reduction in salt marsh productivity and the resulting decrease in accretion. These marshes, which  
17 were typically near the edge of creeks, were prone to submersion under the high SLR scenario.  
18 However, the higher accretion rates for the medium and high productivity points under the high SLR  
19 compared to the low SLR scenario were due to the marsh's adaptive capability to capture sediment. The  
20 increasing temporal rate of biomass density change for the high, medium, and low productivity points  
21 under the low SLR scenario was due to the underlying rates of change of salt marsh platform and MHW  
22 (Figure 9). The decreasing rate of change for biomass density under the high SLR after 2030 for the

1 medium and high productivity points, and after 2025 for the low productivity point was mainly because  
2 of the drastic change in MHW (Figure 9f).

3 The sensitivity of the coupled Hydro-MEM model to the coupling time step length varied  
4 between the low and high SLR scenarios. The high SLR case required a shorter coupling time step due  
5 to the non-linear trend in water level change over time. However, the increased accuracy with a smaller  
6 coupling time step comes at the price of increased computational time. The run time for a single run of  
7 the hydrodynamic model across 120 cores (Intel Xeon quad core @ 3.0 GHz) was four wallclock hours,  
8 and with the addition of the ArcGIS portion of the Hydro-MEM model framework, the total  
9 computational time was noteworthy for this small marsh area and should be considered when increasing  
10 the number of the coupling time steps and the calculation area. Therefore, the optimum of the tested  
11 coupling time steps for the low and high SLR scenarios were determined to be 10 and 5 years,  
12 respectively.

13 As shown in Figure 11 and Table 2, the incorporation of the hydrodynamic component in the  
14 Hydro-MEM model leads to different results in simulated wetland area and biomass productivity  
15 relative to the results estimated by the marsh model alone. Under the low SLR scenario, there was an  
16 8.2% difference in predicted total wetland area between using the coupled Hydro-MEM model vs. MEM  
17 alone (Table 2), and the low and medium productivity regions were both underestimated. Generally,  
18 MEM alone predicted higher productivity than the Hydro-MEM model results. These differences are in  
19 part attributed to the fact that such an application of MEM applies fixed values for MLW and MHW in  
20 the wetland areas and uses a bathtub approach for simulating SLR, whereas the Hydro-MEM model  
21 simulates the spatially varying MLW and MHW across the salt marsh landscape and accounts for non-  
22 linear response of MLW and MHW due to SLR (Figure 11). Secondly, the coupling of the

1 hydrodynamics and salt marsh platform accretion processes influences the results of the Hydro-MEM  
2 model.

3 A qualitative comparison of the model results to aerial imagery and NLCD data provided a better  
4 understanding of the biomass density model performance. The model results illustrated in areas  
5 representative of the sub-optimal, optimal and super-optimal regions of the biomass productivity curve  
6 were reasonably well captured compared with the above-mentioned ancillary data. This provided a final  
7 assessment of the model ability to produce realistic results.

8 The Hydro-MEM model is the first spatial model that includes (1) the dynamics of SLR and its  
9 nonlinear (Passeri et al., 2015) effects on biomass density, and (2) SLR rate by employing a time step  
10 approach in the modeling rather than using a constant value for SLR. The time step approach used here  
11 also helped to capture the complex feedbacks between vegetation and hydrodynamics. This model can  
12 be applied in other estuaries to aid resource managers in their planning for potential changes or  
13 restoration acts under climate change and SLR scenarios. The outputs of this model can be used in storm  
14 surge or hydrodynamic simulations to provide an updated friction coefficient map. The future of this  
15 model should include more complex physical processes including inflows for fluvial systems, sediment  
16 transport (Mariotti and Fagherazzi, 2010) and biologically mediated resuspension, and a realistic  
17 depiction of more accurate geomorphological changes in the marsh system.

18

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## 6 **References**

- 7 Allen, J.R.L., 1997. Simulation models of salt-marsh morphodynamics: some implications for high-  
8 intertidal sediment couplets related to sea-level change. *Sedimentary Geology* 113, 211-223.
- 9 Atkinson, J., McKee Smith, J., Bender, C., 2013. Sea-level rise effects on storm surge and nearshore  
10 waves on the Texas coast: Influence of landscape and storm characteristics. *Journal of Waterway, Port,  
11 Coastal, and Ocean Engineering* 139, 98-117.
- 12 Bacopoulos, P., Funakoshi, Y., Hagen, S.C., Cox, A.T., Cardone, V.J., 2009. The role of meteorological  
13 forcing on the St. Johns River (Northeastern Florida). *Journal of Hydrology* 369, 55-70.
- 14 Bacopoulos, P., Hagen, S., 2009. Tidal Simulations for the Loxahatchee River Estuary (Southeastern  
15 Florida): On the Influence of the Atlantic Intracoastal Waterway versus the Surrounding Tidal Flats.  
16 *Journal of Waterway, Port, Coastal, and Ocean Engineering* 135, 259-268.
- 17 Bacopoulos, P., Hagen, S.C., Cox, A.T., Dally, W.R., Bratos, S.M., 2012. Observation and simulation of  
18 winds and hydrodynamics in St. Johns and Nassau Rivers. *Journal of Hydrology* 420–421, 391-402.
- 19 Bacopoulos, P., Parrish, D.M., Hagen, S.C., 2011. Unstructured mesh assessment for tidal model of the  
20 South Atlantic Bight and its estuaries. *J Hydraul Res* 49, 487-502.
- 21 Baustian, J.J., Mendelssohn, Irving A., Hester, Mark W., 2012. Vegetation's importance in regulating  
22 surface elevation in a coastal salt marsh facing elevated rates of sea level rise. *Global Change Biology*  
23 18, 3377-3382.
- 24 Bilskie, M.V., Hagen, S.C., Medeiros, S.C., Passeri, D.L., 2014. Dynamics of sea level rise and coastal  
25 flooding on a changing landscape. *Geophysical Research Letters* 41, 927-934.
- 26 Blum, M.D., Roberts, H.H., 2009. Drowning of the Mississippi Delta due to insufficient sediment  
27 supply and global sea-level rise. *Nature Geoscience* 2, 488-491.

- 1 Bunya, S., Dietrich, J.C., Westerink, J.J., Ebersole, B.A., Smith, J.M., Atkinson, J.H., Jensen, R., Resio,  
2 D.T., Luettich, R.A., Dawson, C., Cardone, V.J., Cox, A.T., Powell, M.D., Westerink, H.J., Roberts,  
3 H.J., 2010. A High-Resolution Coupled Riverine Flow, Tide, Wind, Wind Wave, and Storm Surge  
4 Model for Southern Louisiana and Mississippi. Part I: Model Development and Validation. Monthly  
5 Weather Review 138, 345-377.
- 6 Bush, T., Houck, M., 2002. Plant fact sheet. Smooth Cordgrass *Spartina alterniflora* Loisel. USDA  
7 Natural Resources Conservation Service.
- 8 Cadol, D., Engelhardt, K., Elmore, A., Sanders, G., 2014. Elevation-dependent surface elevation gain in  
9 a tidal freshwater marsh and implications for marsh persistence. *Limnology and Oceanography* 59,  
10 1065-1080.
- 11 Clough, J.S., Park, R.A., Fuller, R., 2010. SLAMM 6 beta technical documentation. Waitsfield, VT.
- 12 Costanza, R., Ruth, M., 1998. Using Dynamic Modeling to Scope Environmental Problems and Build  
13 Consensus. *Environmental Management* 22, 183-195.
- 14 Costanza, R., Sklar, F.H., White, M.L., 1990. Modeling Coastal Landscape Dynamics. *BioScience* 40,  
15 91-107.
- 16 Craft, C., Clough, J., Ehman, J., Joye, S., Park, R., Pennings, S., Guo, H., Machmuller, M., 2008.  
17 Forecasting the effects of accelerated sea-level rise on tidal marsh ecosystem services. *Frontiers in*  
18 *Ecology and the Environment* 7, 73-78.
- 19 D'Alpaos, A., Lanzoni, S., Marani, M., Rinaldo, A., 2007. Landscape evolution in tidal embayments:  
20 Modeling the interplay of erosion, sedimentation, and vegetation dynamics. *Journal of Geophysical*  
21 *Research: Earth Surface* 112, F01008.
- 22 D'Alpaos, A., Lanzoni, S., Mudd, S.M., Fagherazzi, S., 2006. Modeling the influence of hydroperiod  
23 and vegetation on the cross-sectional formation of tidal channels. *Estuarine, Coastal and Shelf Science*  
24 69, 311-324.
- 25 Dame, R., Kenny, P.D., 1986. Variability of *Spartina-Alterniflora* Primary Production in the Euhaline  
26 North Inlet Estuary. *Marine Ecology Progress Series* 32, 71-80.
- 27 Darby, F., Turner, R.E., 2008. Below- and Aboveground Biomass of *Spartina alterniflora*: Response to  
28 Nutrient Addition in a Louisiana Salt Marsh. *Estuaries and Coasts* 31, 326-334.
- 29 DeMort, C.L., 1991. The St. Johns River System, in: Livingston, R. (ed.), *The Rivers of Florida*, vol. 83.  
30 Springer New York, pp. 97-120.

- 1 Donnelly, J.P., Bertness, M.D., 2001. Rapid shoreward encroachment of salt marsh cordgrass in  
2 response to accelerated sea-level rise. *Proceedings of the National Academy of Sciences* 98, 14218-  
3 14223.
- 4 ESRI, 2012. ArcMap 10.1, 10.1 ed, ESRI, Redlands, California.
- 5 Fagherazzi, S., Kirwan, M.L., Mudd, S.M., Guntenspergen, G.R., Temmerman, S., D'Alpaos, A., van de  
6 Koppel, J., Rybczyk, J.M., Reyes, E., Craft, C., Clough, J., 2012. Numerical models of salt marsh  
7 evolution: Ecological, geomorphic, and climatic factors. *Reviews of Geophysics* 50, RG1002.
- 8 Fitz, H.C., DeBellevue, E.B., Costanza, R., Boumans, R., Maxwell, T., Wainger, L., Sklar, F.H., 1996.  
9 Development of a general ecosystem model for a range of scales and ecosystems. *Ecological Modelling*  
10 88, 263-295.
- 11 Giardino, D., Bacopoulos, P., Hagen, S., 2011. Tidal Spectroscopy of the Lower St. Johns River from a  
12 High-Resolution Shallow Water Hydrodynamic Model. *The International Journal of Ocean and Climate*  
13 *Systems* 2, 1-18.
- 14 Hagen, S., Morris, J., Bacopoulos, P., Weishampel, J., 2013. Sea-Level Rise Impact on a Salt Marsh  
15 System of the Lower St. Johns River. *Journal of Waterway, Port, Coastal, and Ocean Engineering* 139,  
16 118-125.
- 17 Halpin, P.M., 2000. Habitat use by an intertidal salt-marsh fish: trade-offs between predation and  
18 growth. *Marine Ecology Progress Series* 198, 203-214.
- 19 Homer, C., Dewitz, J., Fry, J., Coan, M., Hossain, N., Larson, C., Herold, N., McKerrow, A., VanDriel,  
20 J.N., Wickham, J., 2007. Completion of the 2001 national land cover database for the counterterminous  
21 United States. *Photogrammetric Engineering and Remote Sensing* 73, 337.
- 22 Hopkinson, C.S., Gosselink, J.G., Parrondo, R.T., 1980. Production of Coastal Louisiana Marsh Plants  
23 Calculated from Phenometric Techniques. *Ecology* 61, 1091-1098.
- 24 Hutchinson, G., 1957. Concluding remarks.: Cold Sprig Harbor Symposia on Quantitative Biology. Yale  
25 University New Haven.
- 26 Jørgensen, S.E., Fath, B.D., 2011a. 10 - Structurally Dynamic Models, in: Sven Erik, J., Brian, D.F.  
27 (eds.), *Developments in Environmental Modelling*, vol. Volume 23. Elsevier, pp. 309-346.
- 28 Jørgensen, S.E., Fath, B.D., 2011b. 11 - Spatial Modelling, in: Sven Erik, J., Brian, D.F. (eds.),  
29 *Developments in Environmental Modelling*, vol. Volume 23. Elsevier, pp. 347-368.
- 30 Kirwan, M.L., Guntenspergen, G.R., 2012. Feedbacks between inundation, root production, and shoot  
31 growth in a rapidly submerging brackish marsh. *Journal of Ecology* 100, 764-770.

- 1 Kirwan, M.L., Murray, A.B., 2007. A coupled geomorphic and ecological model of tidal marsh  
2 evolution. *Proceedings of the National Academy of Sciences* 104, 6118-6122.
- 3 Knutson, P., 1987. *Role of Coastal Marshes in Energy Dissipation and Shore Protection, The Ecology  
4 and Management of Wetlands*. Springer US, pp. 161-175.
- 5 Leonard, L.A., Croft, A.L., 2006. The effect of standing biomass on flow velocity and turbulence in  
6 *Spartina alterniflora* canopies. *Estuarine, Coastal and Shelf Science* 69, 325-336.
- 7 Leonard, L.A., Luther, M.E., 1995. Flow hydrodynamics in tidal marsh canopies. *Limnology and  
8 Oceanography* 40, 1474-1484.
- 9 Luettich, R.A., Westerink, J.J., Scheffner, N.W., 1992. ADCIRC : an advanced three-dimensional  
10 circulation model for shelves, coasts, and estuaries. I: Theory and methodology of ADCIRC-2DD1 and  
11 ADCIRC-3DL. Technical Rep. No. DRP-92-6, U.S. Army Engineer Waterways Experiment Station,  
12 Vicksburg, Miss.
- 13 Marani, M., Da Lio, C., D'Alpaos, A., 2013. Vegetation engineers marsh morphology through multiple  
14 competing stable states. *Proceedings of the National Academy of Sciences* 110, 3259-3263.
- 15 Mariotti, G., Fagherazzi, S., 2010. A numerical model for the coupled long-term evolution of salt  
16 marshes and tidal flats. *Journal of Geophysical Research: Earth Surface* (2003–2012) 115.
- 17 Martin, J.F., Reyes, E., Kemp, G.P., Mashriqui, H., Day, J.W., 2002. Landscape modeling of the  
18 Mississippi Delta: using a series of landscape models, we examined the survival and creation of  
19 Mississippi Delta marshes and the impact of altered riverine inputs, accelerated sea-level rise, and  
20 management proposals on these marshes. *BioScience* 52, 357-365.
- 21 Martin, J.F., White, M.L., Reyes, E., Kemp, G.P., Mashriqui, H., Day, J.J.W., 2000. PROFILE:  
22 Evaluation of Coastal Management Plans with a Spatial Model: Mississippi Delta, Louisiana, USA.  
23 *Environmental Management* 26, 117-129.
- 24 Mckee, K.L., Patrick, W., 1988. The relationship of smooth cordgrass (*Spartina alterniflora*) to tidal  
25 datums: a review. *Estuaries* 11, 143-151.
- 26 Medeiros, S.C., Hagen, S.C., 2013. Review of wetting and drying algorithms for numerical tidal flow  
27 models. *International Journal for Numerical Methods in Fluids* 71, 473-487.
- 28 Möller, I., Spencer, T., 2002. Wave dissipation over macro-tidal saltmarshes: Effects of marsh edge  
29 typology and vegetation change. *Journal of Coastal Research* 36, 506-521.

- 1 Möller, I., Spencer, T., French, J.R., Leggett, D.J., Dixon, M., 1999. Wave transformation over salt  
2 marshes: a field and numerical modelling study from North Norfolk, England. *Estuarine, Coastal and*  
3 *Shelf Science* 49, 411-426.
- 4 Morris, J., 1995. The mass balance of salt and water in intertidal sediments: Results from North Inlet,  
5 South Carolina. *Estuaries* 18, 556-567.
- 6 Morris, J., 2007. Ecological engineering in intertidal saltmarshes. *Hydrobiologia* 577, 161-168.
- 7 Morris, J.T., 2015. Marsh equilibrium theory, ICI-Spartina symposium 2014, p. In Press.
- 8 Morris, J.T., Sundareshwar, P.V., Nietch, C.T., Kjerfve, B., Cahoon, D.R., 2002. Responses of coastal  
9 wetlands to rising sea level. *Ecology* 83, 2869-2877.
- 10 Morris, J.T., Sundberg, K., Hopkinson, C.S., 2013. Salt marsh primary production and its responses to  
11 relative sea level and nutrients in estuaries at Plum Island, Massachusetts, and North Inlet, South  
12 Carolina, USA. *Oceanography* 26, 78-84.
- 13 Mudd, S.M., D'Alpaos, A., Morris, J.T., 2010. How does vegetation affect sedimentation on tidal  
14 marshes? Investigating particle capture and hydrodynamic controls on biologically mediated  
15 sedimentation. *Journal of Geophysical Research: Earth Surface* 115, F03029.
- 16 Mudd, S.M., Fagherazzi, S., Morris, J.T., Furbish, D.J., 2004. Flow, sedimentation, and biomass  
17 production on a vegetated salt marsh in South Carolina: Toward a predictive model of marsh  
18 morphologic and ecologic evolution, *The Ecogeomorphology of Tidal Marshes*, vol. 59. AGU,  
19 Washington, DC, pp. 165-188.
- 20 Nyman, J.A., DeLaune, R., Roberts, H., Patrick Jr, W., 1993. Relationship between vegetation and soil  
21 formation in a rapidly submerging coastal marsh. *Marine ecology progress series. Oldendorf* 96, 269-  
22 279.
- 23 Nyman, J.A., Walters, R.J., Delaune, R.D., Patrick Jr, W.H., 2006. Marsh vertical accretion via  
24 vegetative growth. *Estuarine, Coastal and Shelf Science* 69, 370-380.
- 25 Park, R.A., Armentano, T.V., Cloonan, C.L., 1986. Predicting the effects of sea level rise on coastal  
26 wetlands. *Effects of changes in stratospheric ozone and global climate* 4, 129-152.
- 27 Park, R.A., Trehan, M.S., Mausel, P.W., Howe, R.C., Titus, J.G., 1989. The effects of sea level rise on  
28 US coastal wetlands and lowlands. Office of Policy, Planning and Evaluation, US Environmental  
29 Protection Agency.

- 1 Parris, A., Bromirski, P., Burkett, V., Cayan, D., Culver, M., Hall, J., Horton, R., Knuuti, K., Moss, R.,  
2 Obeysekera, J., Sallenger, A., Weiss, J., 2012. Global Sea Level Rise Scenarios for the US National  
3 Climate Assessment. NOAA Tech Memo OAR CPO, 1-37.
- 4 Passeri, D.L., Hagen, S.C., Medeiros, S.C., Bilskie, M.V., 2015. Impacts of historic morphological  
5 changes and sea level rise on tidal hydrodynamics in the Grand Bay, Mississippi estuary. *Estuarine,  
6 Coastal and Shelf Science*, Submitted.
- 7 Patrick, W.H., DeLaune, R.D., 1990. Subsidence, accretion, and sea level rise in south San Francisco  
8 Bay marshes. *Limnology and Oceanography* 35, 1389-1395.
- 9 Pennings, S.C., Bertness, M.D., 2001. Salt marsh communities. *Marine community ecology*, 289-316.
- 10 Reed, D.J., 1990. The impact of sea-level rise on coastal salt marshes. *Progress in Physical Geography*  
11 14, 465-481.
- 12 Reed, D.J., 1995. The response of coastal marshes to sea-level rise: Survival or submergence? *Earth  
13 Surface Processes and Landforms* 20, 39-48.
- 14 Reyes, E., White, M.L., Martin, J.F., Kemp, G.P., Day, J.W., Aravamuthan, V., 2000. Landscape  
15 modeling of coastal habitat change in the Mississippi Delta. *Ecology* 81, 2331-2349.
- 16 Schile, L.M., Callaway, J.C., Morris, J.T., Stralberg, D., Parker, V.T., Kelly, M., 2014. Modeling tidal  
17 marsh distribution with sea-level rise: Evaluating the role of vegetation, sediment, and upland habitat in  
18 marsh resiliency. *PLOS ONE* 9, e88760.
- 19 Schubauer, J.P., Hopkinson, C.S., 1984. Above- and belowground emergent macrophyte production and  
20 turnover in a coastal marsh ecosystem, Georgia. *Limnology and Oceanography* 29, 1052-1065.
- 21 Shepard, C.C., Crain, C.M., Beck, M.W., 2011. The protective role of coastal marshes: A systematic  
22 review and meta-analysis. *PLoS ONE* 6, e27374.
- 23 Silliman, B.R., Bertness, M.D., 2002. A trophic cascade regulates salt marsh primary production.  
24 *Proceedings of the National Academy of Sciences* 99, 10500-10505.
- 25 Sklar, F.H., Costanza, R., Day Jr, J.W., 1985. Dynamic spatial simulation modeling of coastal wetland  
26 habitat succession. *Ecological Modelling* 29, 261-281.
- 27 Stralberg, D., Brennan, M., Callaway, J.C., Wood, J.K., Schile, L.M., Jongsomjit, D., Kelly, M., Parker,  
28 V.T., Crooks, S., 2011. Evaluating Tidal Marsh Sustainability in the Face of Sea-Level Rise: A Hybrid  
29 Modeling Approach Applied to San Francisco Bay. *PLoS ONE* 6, e27388.

- 1 Tambroni, N., Seminara, G., 2012. A one-dimensional eco-geomorphic model of marsh response to sea  
2 level rise: Wind effects, dynamics of the marsh border and equilibrium. *Journal of Geophysical*  
3 *Research: Earth Surface* 117, F03026.
- 4 Temmerman, S., Bouma, T.J., Van de Koppel, J., Van der Wal, D., De Vries, M.B., Herman, P.M.J.,  
5 2007. Vegetation causes channel erosion in a tidal landscape. *Geology* 35, 631-634.
- 6 Temmerman, S., Govers, G., Meire, P., Wartel, S., 2003. Modelling long-term tidal marsh growth under  
7 changing tidal conditions and suspended sediment concentrations, Scheldt estuary, Belgium. *Marine*  
8 *Geology* 193, 151-169.
- 9 Thomas, R.E., Johnson, M.F., Frostick, L.E., Parsons, D.R., Bouma, T.J., Dijkstra, J.T., Eiff, O., Gobert,  
10 S., Henry, P.-Y., Kemp, P., McLelland, S.J., Moulin, F.Y., Myrhaug, D., Neyts, A., Paul, M., Penning,  
11 W.E., Puijalon, S., Rice, S.P., Stanica, A., Tagliapietra, D., Tal, M., Tørum, A., Voudoukas, M.I., 2014.  
12 Physical modelling of water, fauna and flora: knowledge gaps, avenues for future research and  
13 infrastructural needs. *J Hydraul Res* 52, 311-325.
- 14 Thorne, K.M., Elliott-Fisk, D.L., Wylie, G.D., Perry, W.M., Takekawa, J.Y., 2014. Importance of  
15 biogeomorphic and spatial properties in assessing a tidal salt marsh vulnerability to sea-level rise.  
16 *Estuaries and Coasts* 37, 941-951.
- 17 Townend, I., Fletcher, C., Knappen, M., Rossington, K., 2011. A review of salt marsh dynamics. *Water*  
18 *and Environment Journal* 25, 477-488.
- 19 Turner, R.E., Swenson, E.M., Milan, C.S., 2000. Organic and inorganic contributions to vertical  
20 accretion in salt marsh sediments, in: Weinstein, M., Kreeger, D. (eds.), *Concepts and Controversies in*  
21 *Tidal Marsh Ecology*. Springer Netherlands, pp. 583-595.
- 22 United States Army Corps of Engineers, 2011. Sea-level change considerations for civil works programs  
23 EC 1165-2-212.
- 24 United States National Park Service (Denver Service Center), 1996. Timucuan Ecological and Historic  
25 Preserve, Florida: general management plan, development concept plans. US National Park Service,  
26 Denver Service Center.
- 27 Walton Jr, T.L., 2007. Projected sea level rise in Florida. *Ocean Engineering* 34, 1832-1840.
- 28 Warren, R.S., Niering, W.A., 1993. Vegetation change on a northeast tidal marsh: Interaction of sea-  
29 level rise and marsh accretion. *Ecology* 74, 96-103.
- 30

1 **Figures and tables**

2 Figure 1. Study area and progressive insets. (a) Location of St. Johns river; (b) Location of Timucuan  
3 salt marsh system and lower St. Johns river; (c) Timucuan salt marsh system and tidal creeks. (d) Sub-  
4 region of Timucuan including the location of example transect AB and three biomass sample sites. Site  
5 1 (blue) is in a low biomass productivity region, site 2 (red) is in a medium biomass productivity region,  
6 and site 3 (green) is in a high biomass productivity region. The maps are screen captures of world  
7 imagery in ArcGIS (ESRI, 2012).

8  
9 Figure 2. Hydro-MEM model flowchart. The black boxes show the parameters that are not being  
10 changed and the gold boxes are the parameters that are being changed through simulation. The two main  
11 elements are the big gold boxes which are labeled as hydrodynamic model and ArcGIS toolbox. The  
12 black boxes on the left represent the initial conditions.

13  
14 Figure 3. ADCIRC model input of the Timucuan salt marsh surface elevations. Elevations are referenced  
15 to NAVD88 in meters with blue representing water depths greater than 1 m, greens indicating depths  
16 between 0 m and 1 m, and yellows and browns representative of elevations above 0 m NAVD88.

17  
18 Figure 4. MLW (left column) and MHW (right column) results for the year 2000 (a and d), and for the  
19 year 2050 under low (11 cm) (b and e) and high (48 cm) (c and f) SLR scenarios. Results are referenced  
20 to NAVD88.

21  
22 Figure 5. Biomass density patterns (left column) and its first derivative (right column) in the Timucuan  
23 marsh system. (a) Biomass density in the year 2000; (b) Biomass density in the year 2050 under a low



1 SLR (11 cm) scenario; (c) Biomass density in the year 2050 under a high SLR (48 cm) scenario. Dark  
2 blue represents no biomass density ( $0 \text{ g}\cdot\text{m}^{-2}$ ), yellows are medium biomass density ( $\sim 700 \text{ g}\cdot\text{m}^{-2}$ ), and  
3 reds indicate biomass density of  $1000 \text{ g}\cdot\text{m}^{-2}$  or greater. (d) Biomass density first derivative in the year  
4 2000; (e) Biomass density first derivative in the year 2050 under the low SLR (11 cm) scenario; (f)  
5 Biomass density first derivative in the year 2050 under the high SLR (48 cm) scenario.

6

7 Figure 6. Change in the biomass productivity curve under different SLR scenarios. The colors selected  
8 are based on the scale in Fig. 5. (a) is a selected geographical point from the Timucuan marsh system in  
9 the year 2000 that falls within the medium productivity range of the curve; (b) is the same geographical  
10 location (a), in the year 2050 under high SLR (48 cm) and has moved to the low productivity range of  
11 the curve; (c) is the same geographical location (a) in the year 2050 and under low SLR (11 cm) and has  
12 moved to the high productivity region.

13

14 Figure 7. Fifty years (year 2050) of salt marsh platform accretion following (a) 11 cm of SLR and (b) 48  
15 cm of SLR.

16

17 Figure 8. Changes in elevation, MHW, and biomass along a transect (see Fig. 1d for location of transect)  
18 for the low (11 cm) (a and b) and the high (48 cm) (c and d) scenarios. (a and c) Gray shaded area shows  
19 the elevation change between years 2000 (orange line) and 2050 (black line); red shaded area represents  
20 the increase in MHW between years 2000 (magenta line) and 2050 (red line). (b and d) The dark green  
21 (yellow) shaded area shows an increase (decrease) in biomass density between years 2000 (blue line)  
22 and 2050 (red line).

23

1 Figure 9. Changes in salt marsh platform elevation in (a) and (b), MHW in (c) and (d), and biomass  
2 density in (e) and (f) are displayed, for the low SLR (11 cm) and the high SLR (48 cm) scenarios  
3 respectively, for locations of low, medium, and high productivity as shown in Fig. 1d (indicated as Sites  
4 1, 2, and 3).

5  
6 Figure 10. Changes in the first derivative of biomass density along a transect between years 2000 and  
7 2050. Red shaded area shows the change of the first derivative of biomass density between the year  
8 2000 (yellow line) and the year 2050 (red line) under a low SLR (11 cm) scenario; green shaded area  
9 demonstrates the change in the first derivative of biomass between the year 2000 (yellow line) and the  
10 year 2050 (green line) under a high SLR (48 cm) scenario.

11  
12 Figure 11. Biomass density patterns between using MEM (a and c) and Hydro-MEM model (b and d)  
13 under the low SLR scenario (a and b) and the high SLR scenario (c and d). The marshes with  
14 productivity less than  $370 \text{ g}\cdot\text{m}^{-2}$  are categorized as low, between  $370 \text{ g}\cdot\text{m}^{-2}$  and  $750 \text{ g}\cdot\text{m}^{-2}$  are categorized  
15 as medium, and more than  $750 \text{ g}\cdot\text{m}^{-2}$  are categorized as high productivity.

16  
17 Figure 12. Figure. Qualitative comparison maps. From left to right, infrared aerial map of Timucuan  
18 sub-region (Fig. 1d) from January 7, 1999 (USGS Digital Orthophoto Quadrangles), model generated  
19 map of open water, and low, medium, and high productivity regions, and wetland coverage area in the  
20 National Land Cover Database for the year 2001 (NLCD2001).

1  
2 Table 1. Model convergence as a result of various coupling time steps.  
3  
4 Table 2. Comparisons of areal coverage by landscape classifications following 50-yr simulations with  
5 high and low SLR using a coupled Hydro-MEM model vs. a direct application of a spatially-distributed  
6 marsh equilibrium model (MEM) run without hydrodynamics. The marshes with productivity less than  
7  $370 \text{ g}\cdot\text{m}^{-2}$  are categorized as low, between  $370 \text{ g}\cdot\text{m}^{-2}$  and  $750 \text{ g}\cdot\text{m}^{-2}$  are categorized as medium, and more  
8 than  $750 \text{ g}\cdot\text{m}^{-2}$  are categorized as high productivity.

Figure 1

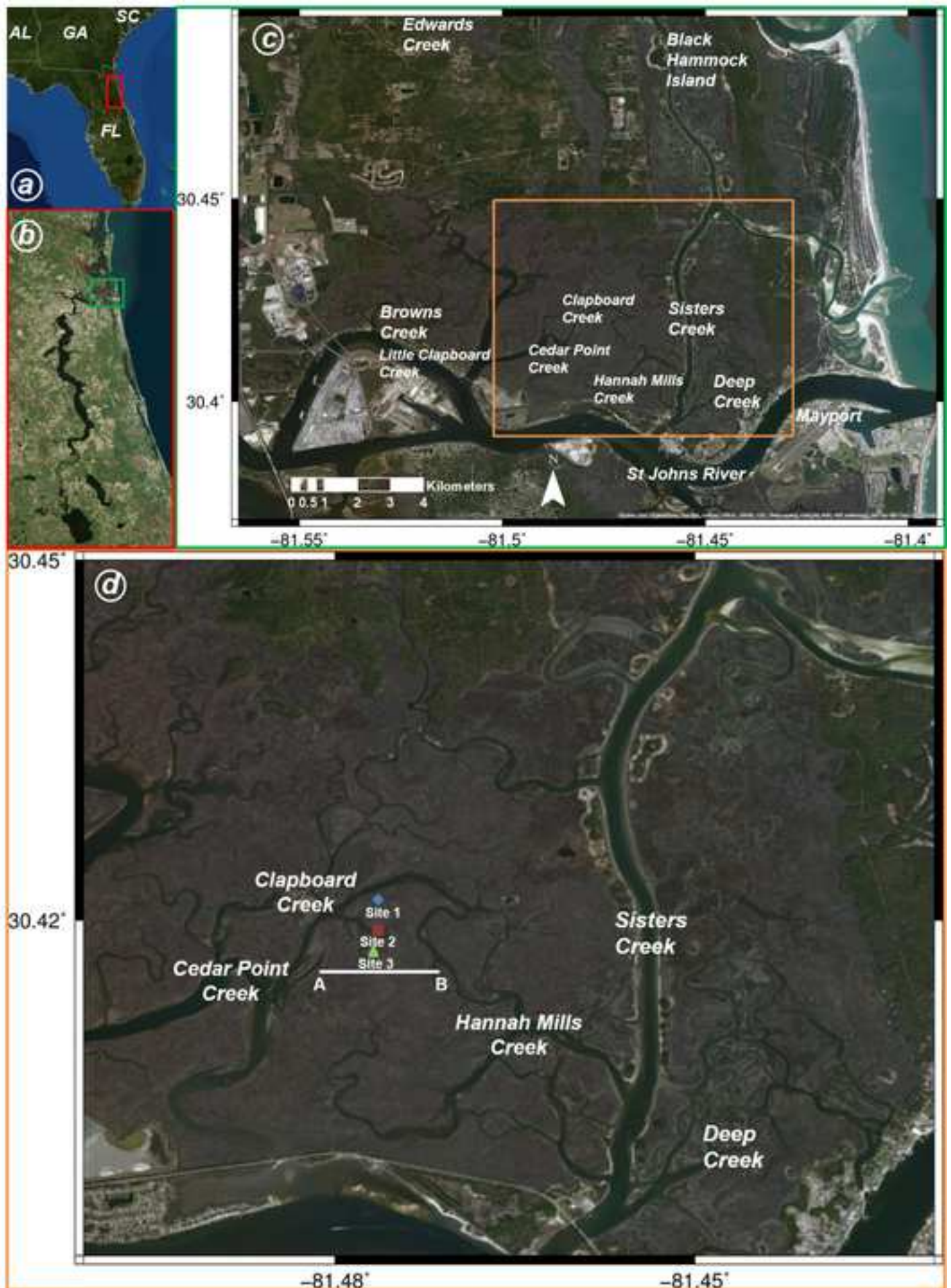


Figure 2

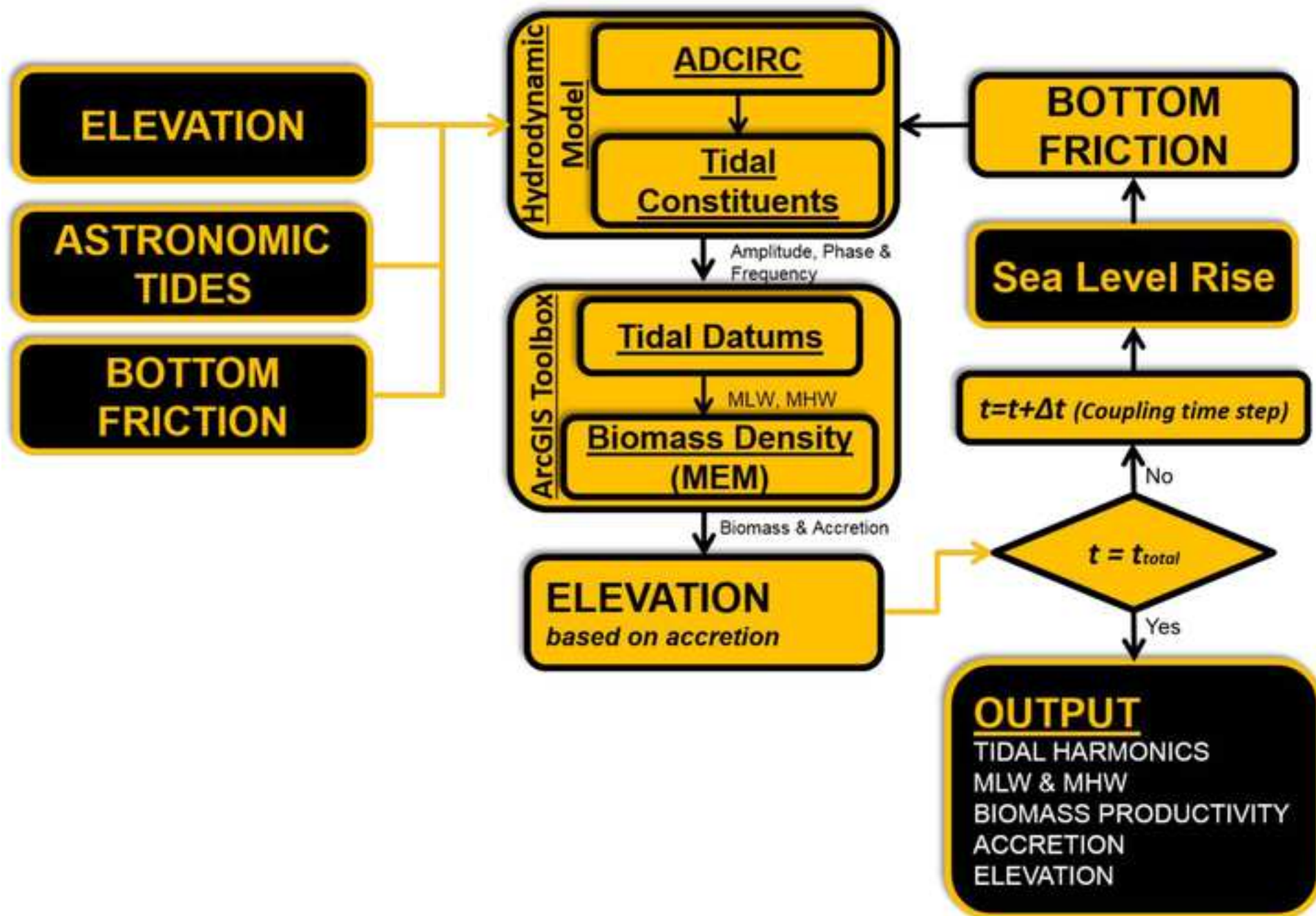




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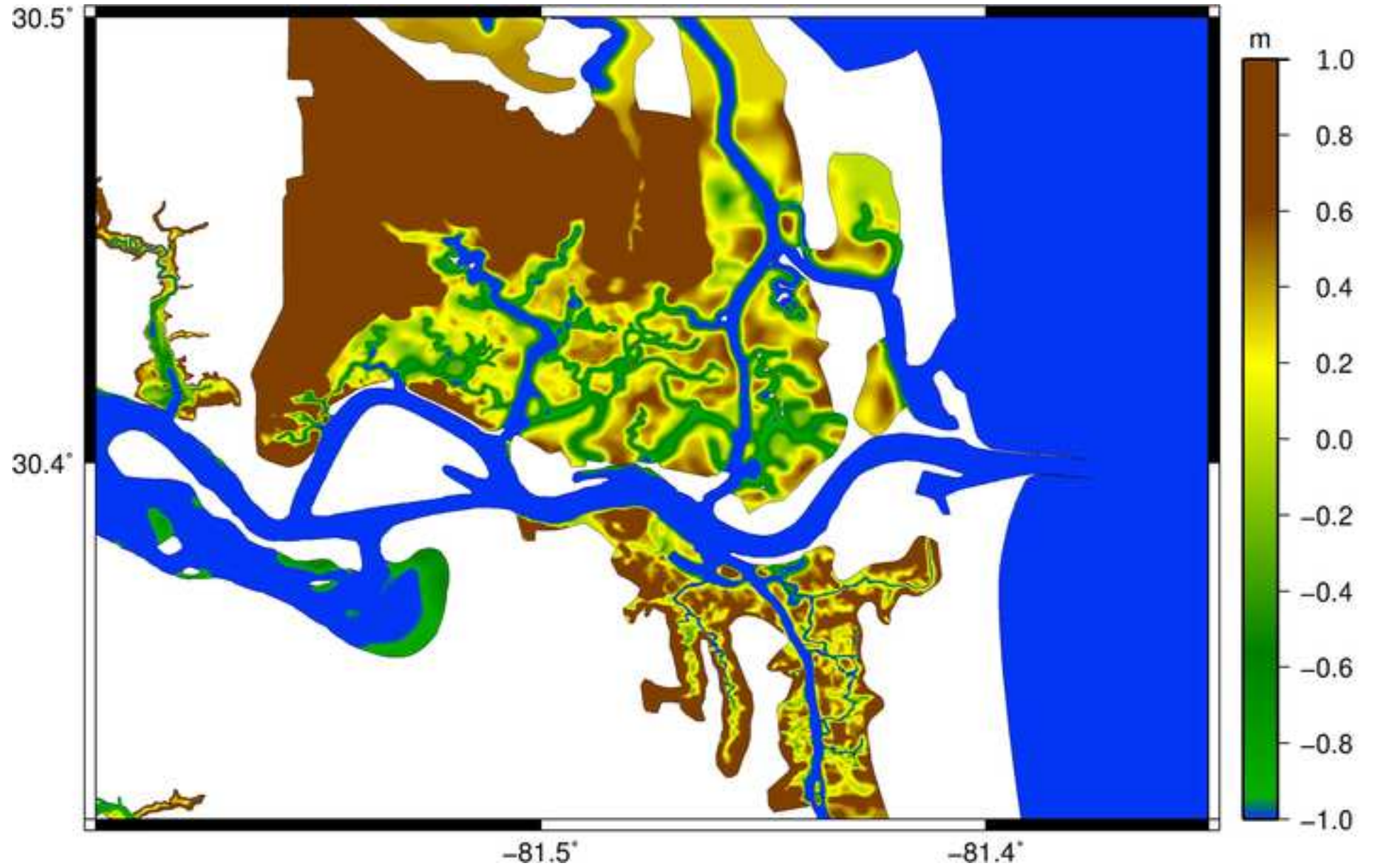


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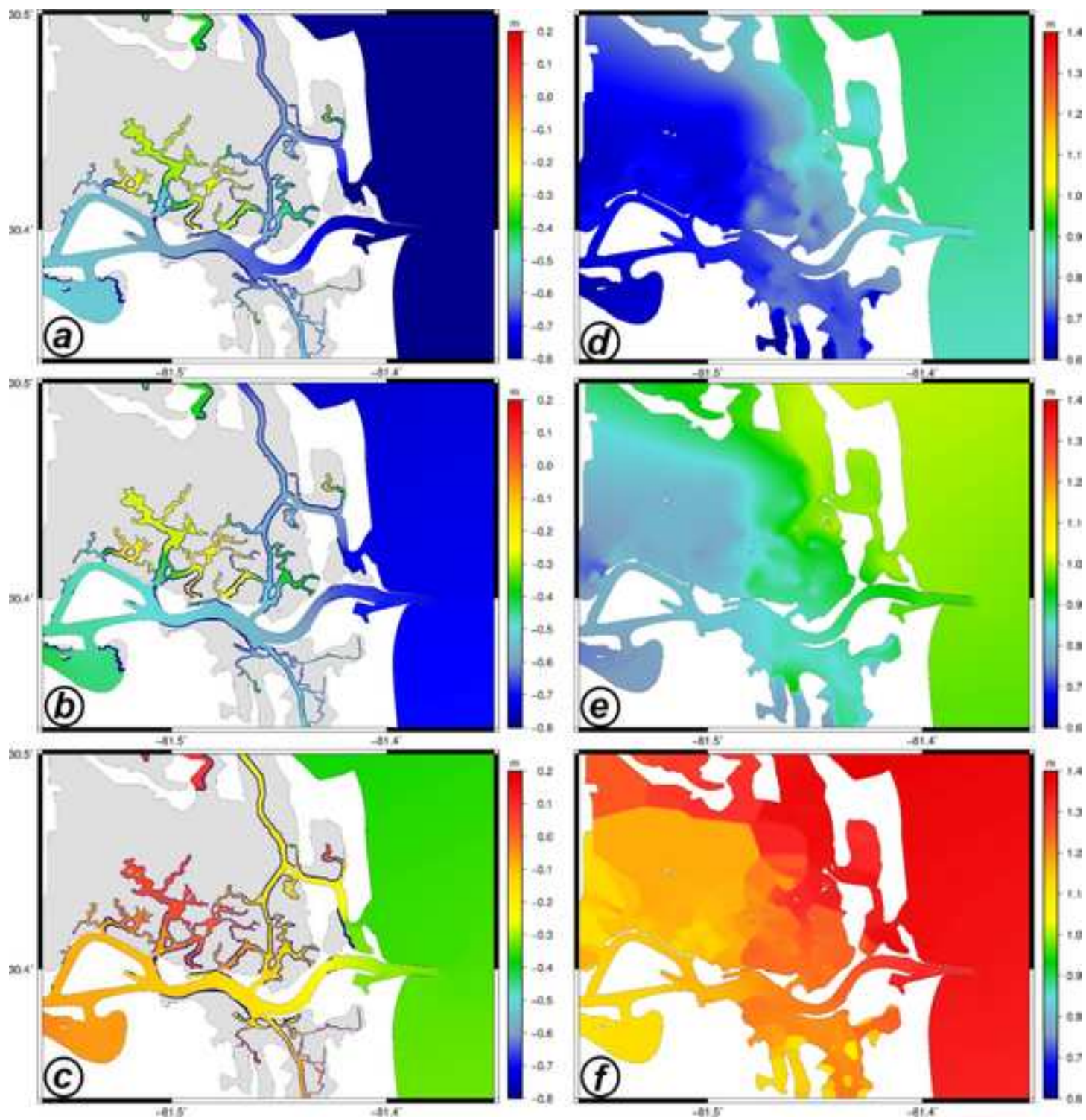




Figure 5

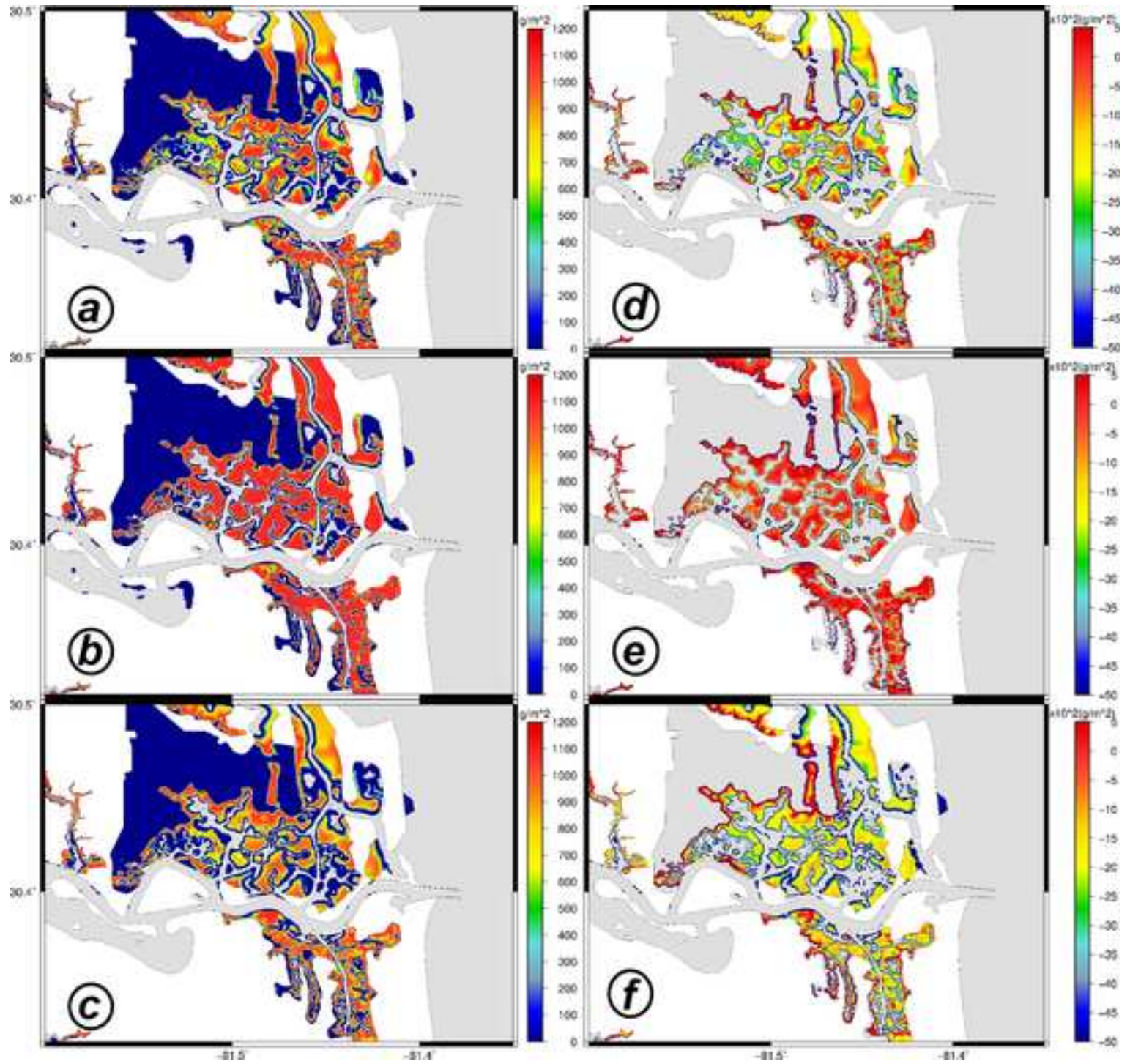




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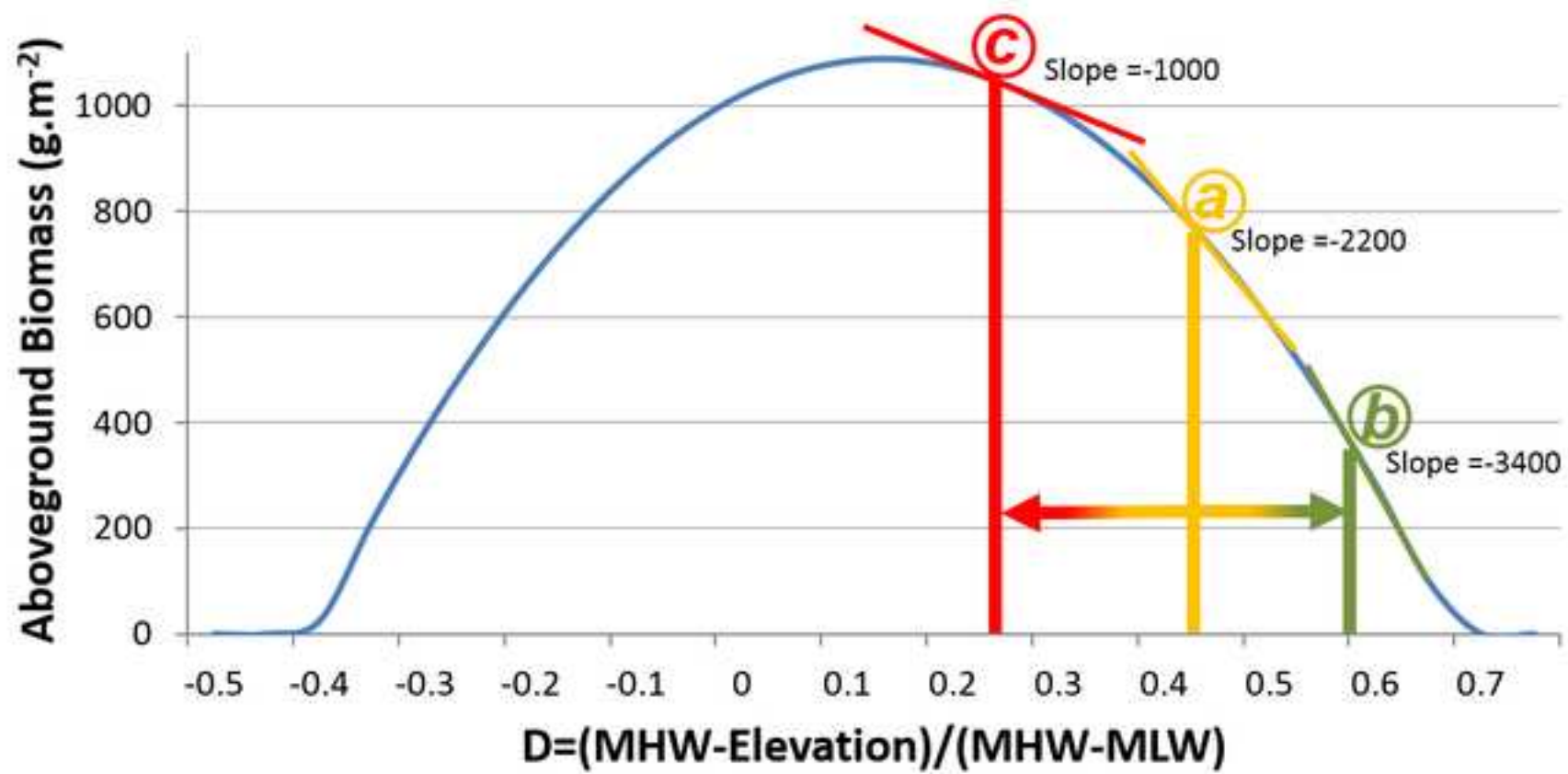


Figure 7



Figure 8

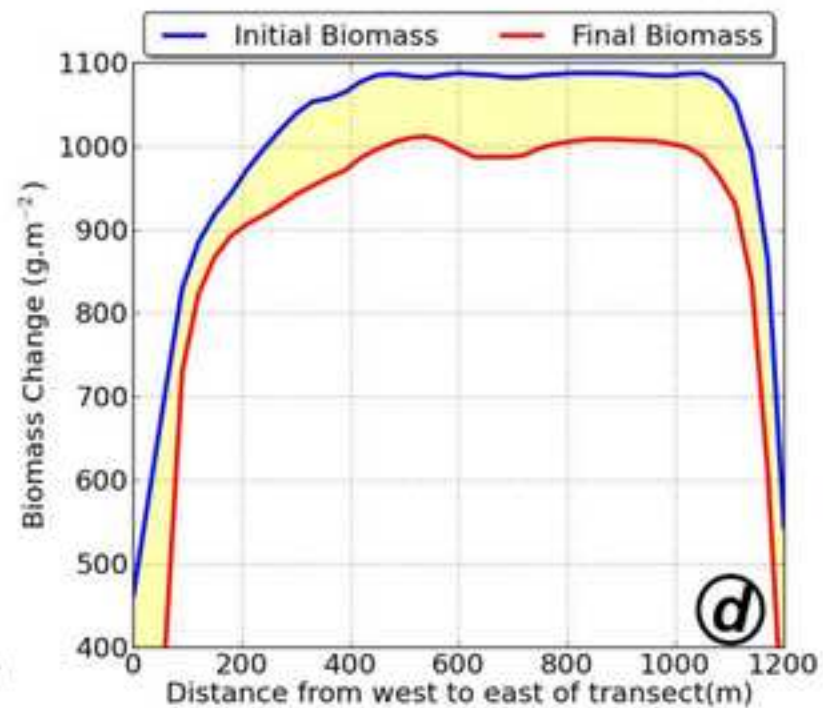
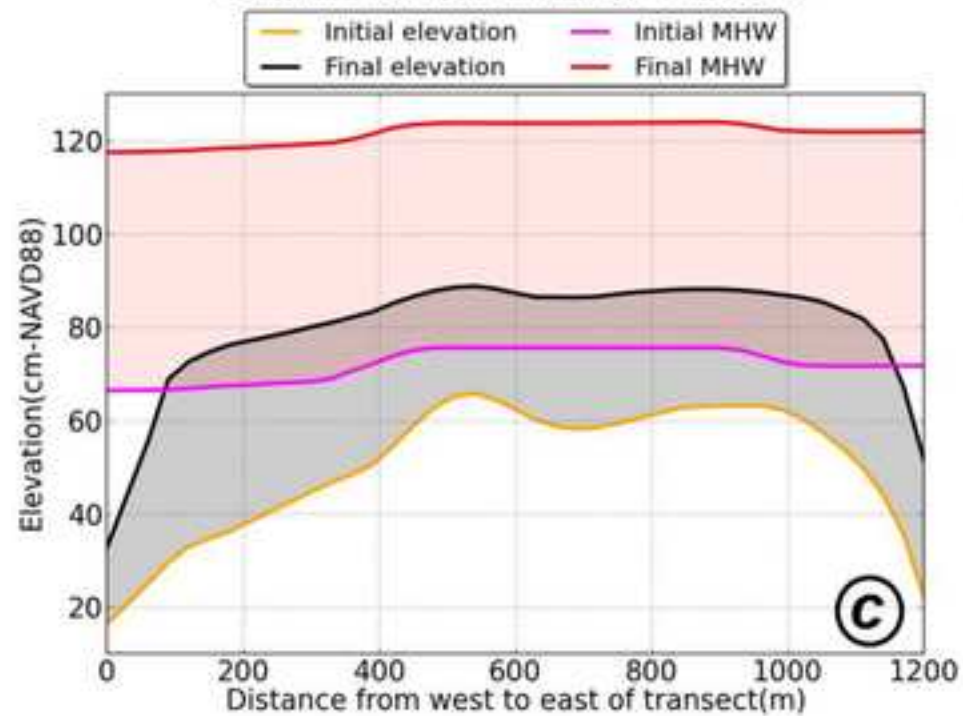
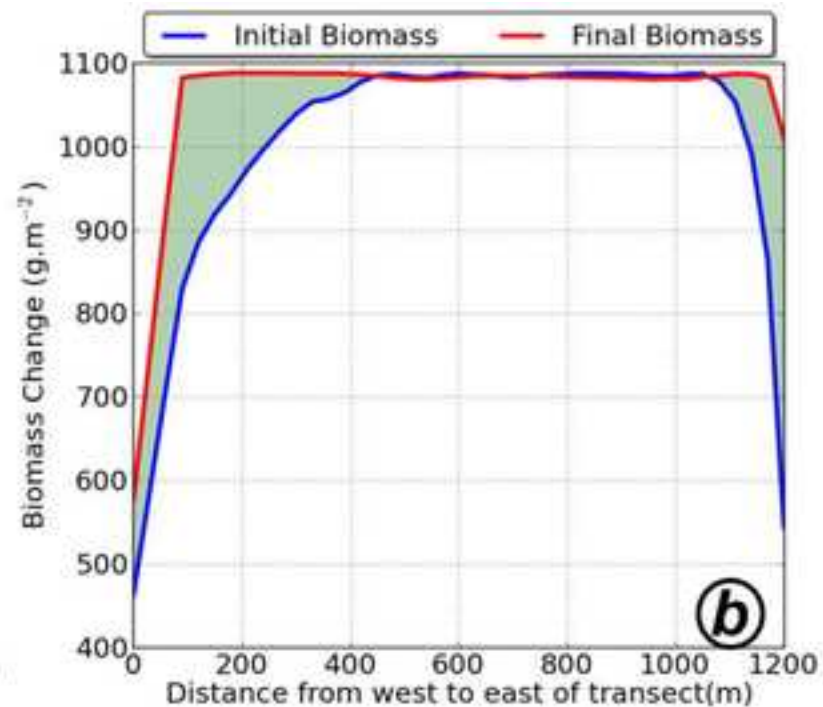
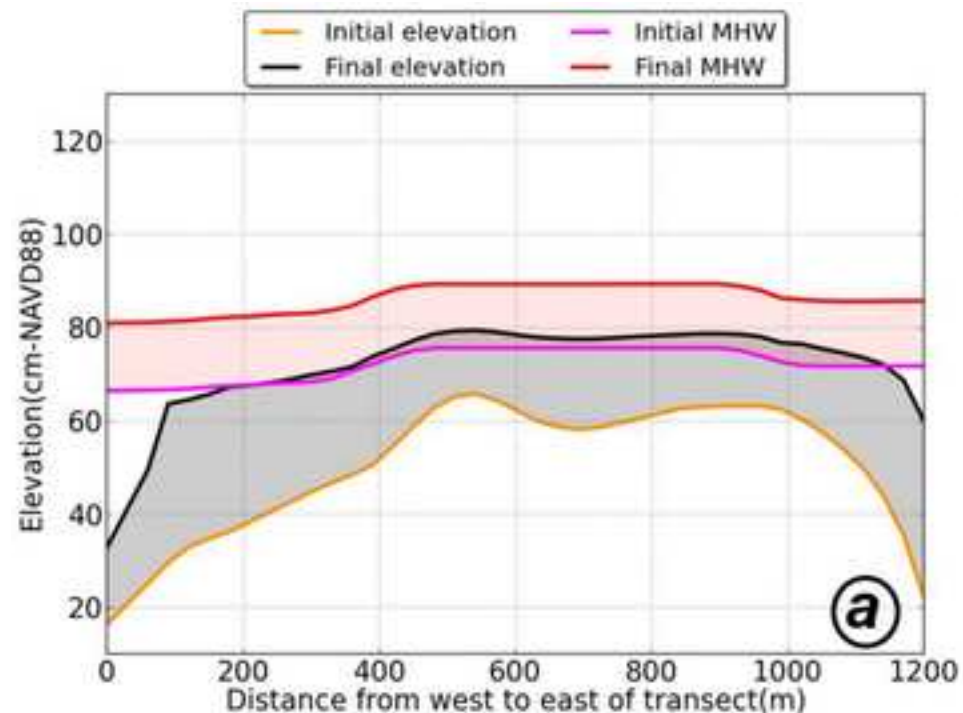


Figure 9

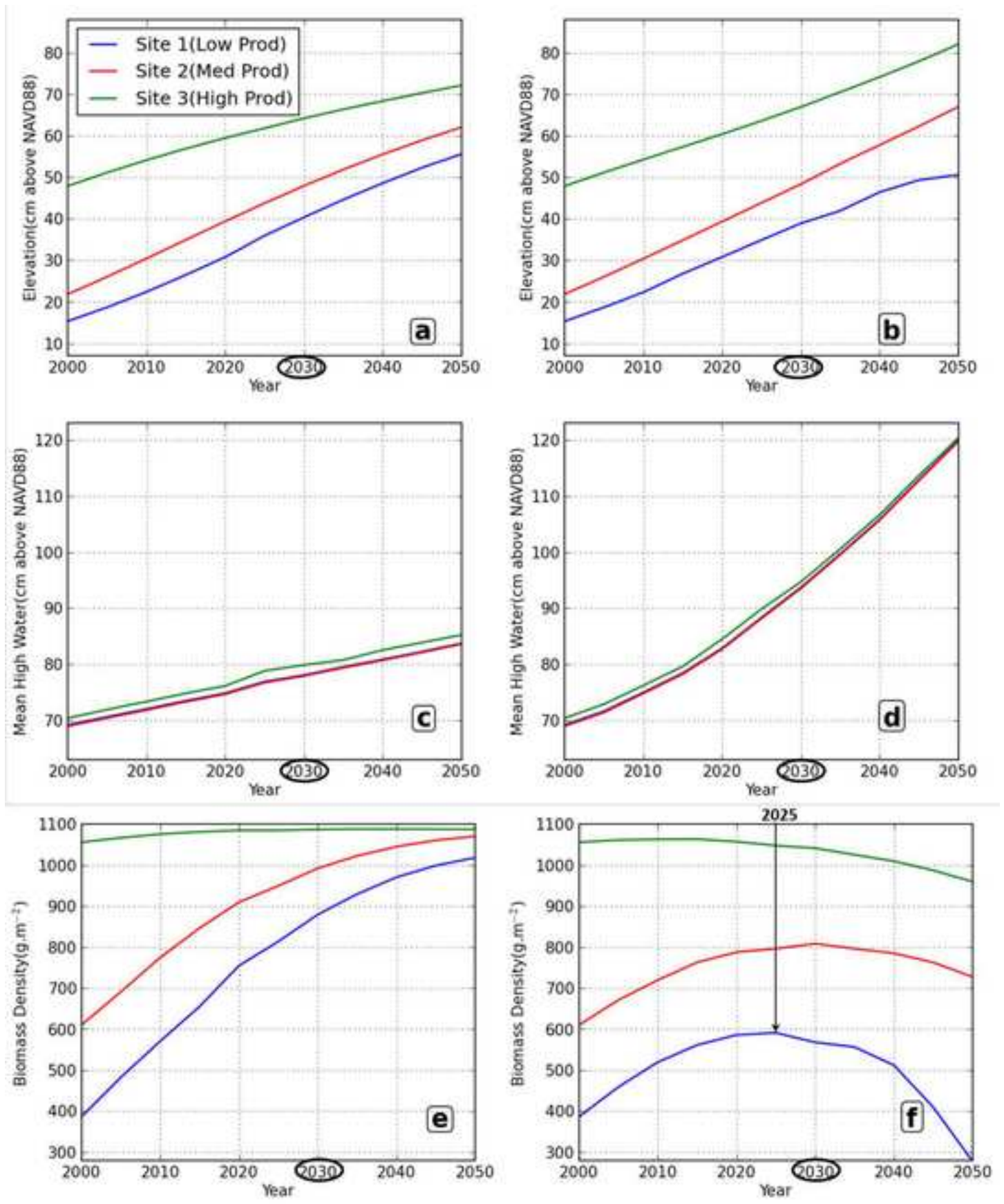




Figure 10

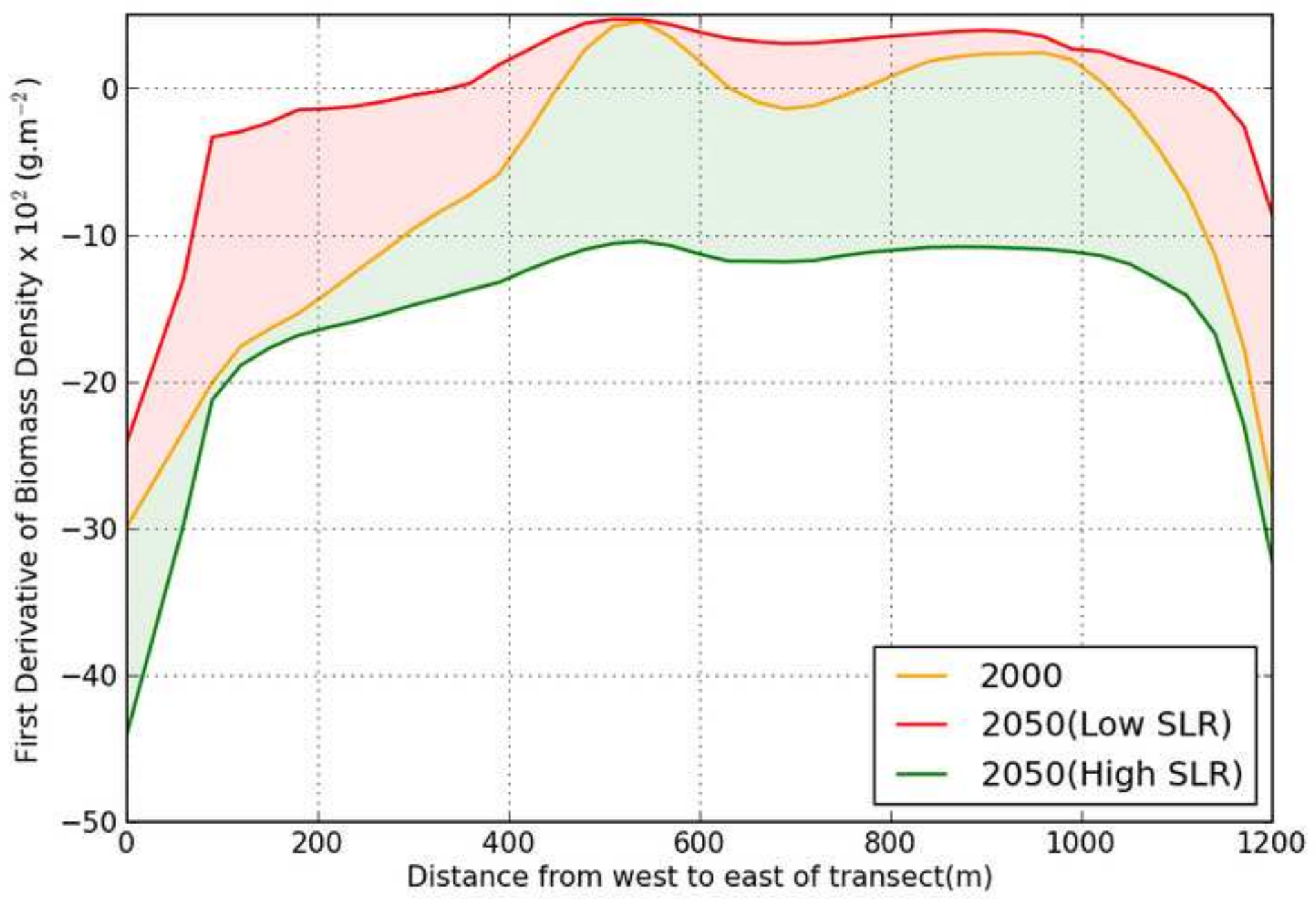


Figure 11

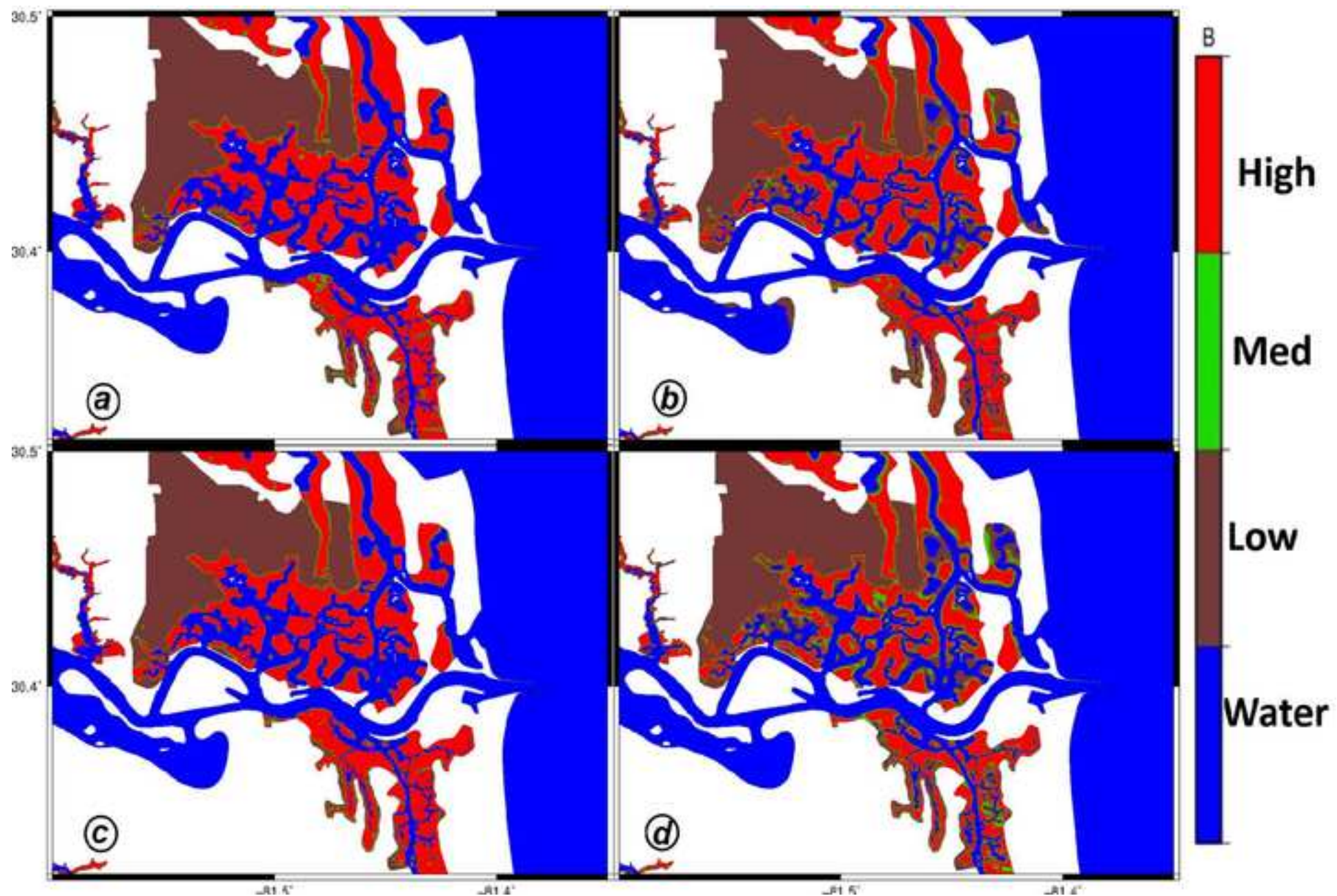
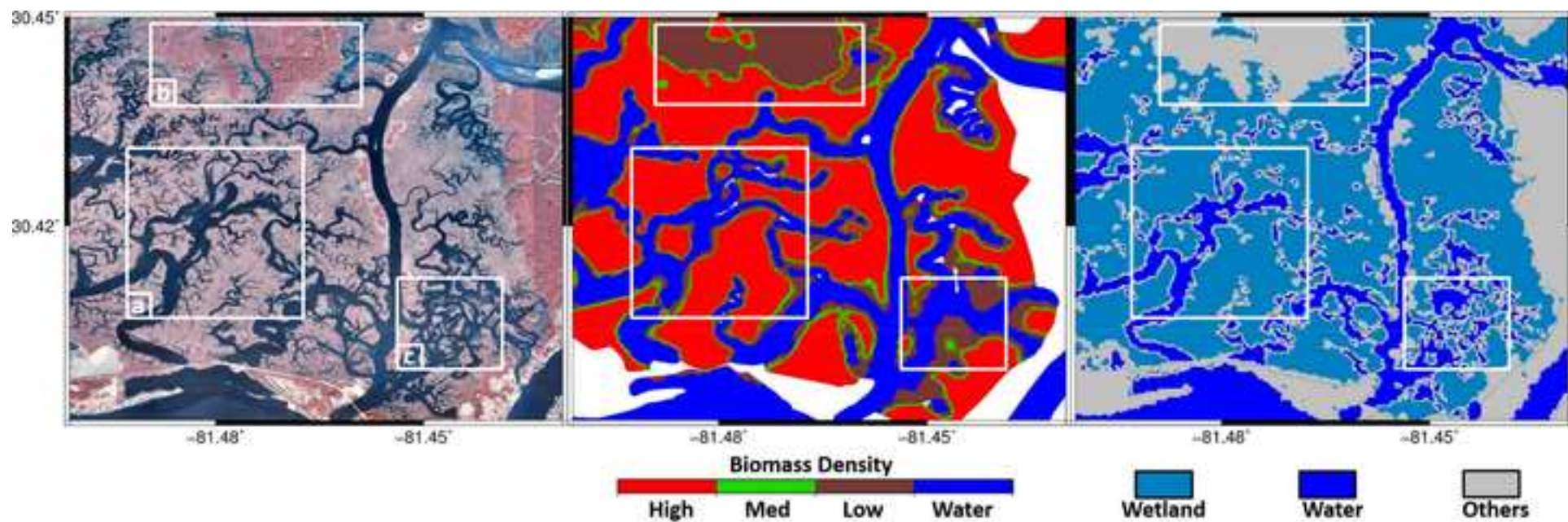




Figure 12



**Table 1**

Number of Coupling Time steps	Coupling time step	Biomass Density for a sample point* at low SLR (11cm) (g.m <sup>-2</sup> )	Biomass Density for a sample point* at High SLR (48cm) (g.m <sup>-2</sup> )	Convergence at low SLR (11 cm)	Convergence at High SLR (48 cm)
1	50 years	1053	928	No	No
5	10 years	1088	901	Yes	No
10	5 years	1086	909	Yes	Yes

\*The sample point is located at Longitude = -81.4769 and Latitude = 30.4167.



**Table 2**

Models	Area Percentage by landscape classification			
	Water	Low Productivity	Medium Productivity	High Productivity
Hydro-Marsh (Low SLR)	54.4	5.2	6.3	34.1
MEM (Low SLR)	62.6	1.2	1.3	34.9
Hydro-marsh (High SLR)	62.1	6.7	8.8	22.4
MEM (High SLR)	61.0	1.2	1.1	36.7