

2021

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Nunez, Karinna; Zhang, Yinglong J.; Bilkovic, Donna M.; and Hershner, Carl, Coastal Setting Determines Tidal Marsh Sustainability with Accelerating Sea-level Rise (2021). *Ocean & Coastal Management*, 214, 105898.

doi: [10.1016/j.ocecoaman.2021.105898](https://doi.org/10.1016/j.ocecoaman.2021.105898)

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1 **Coastal Setting Determines Tidal Marsh Sustainability with Accelerating Sea-level Rise**

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42 **HIGHLIGHTS:**

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- 44 • Enhanced TMM advances the understanding of sea-level rise impacts on tidal marshes
- 45 • TMM accounts for geomorphology, sediment supply, vegetation, and human factors
- 46 • TMM elucidates the effects of coastal settings on the evolution of tidal marshes

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63 **Abstract**

64 There is an increasing concern over how accelerated rates of sea-level rise (SLR) will
65 impact tidal marsh ecosystems. The present study evaluates the potential impacts of SLR on
66 marsh sustainability using the Tidal Marsh Model (TMM) with the addition of a new vegetation
67 algorithm within the SCHISM (Semi-implicit Cross-scale Hydroscience Integrated System
68 Model) framework. This new functionality contributes to an improved understanding of how
69 vegetation affects the mean flow velocity and turbulence, and consequently, the sedimentation
70 processes. Using two SLR scenarios (intermediate and extreme SLR rates), we projected the
71 changes in marsh extent over the next 50 years in two representative marsh systems within a
72 subestuary of Chesapeake Bay. Each study site has marshes associated with different physical
73 settings and anthropogenic components: Carter Creek (developed, high topography) vs. Taskinas
74 Creek (natural, low topography, steep banks). Carter Creek experienced a net marsh loss of 7.3%
75 and 60% in the intermediate and extreme SLR scenario, respectively. In some places, due to the
76 local geomorphic settings, marshes were able to migrate inland and offset part of the total loss,
77 whereas marsh transgression was truncated near development and hardened shoreline structures.
78 In Taskinas Creek, marshes are associated with natural lands with steep upland slopes (inhibitor
79 for marsh transgression due to SLR). Marsh net decline was 23.1% (intermediate SLR scenario),
80 and 89.6% (extreme SLR scenario). Marsh transgression was not substantial in this site,
81 suggesting that marsh loss can be primarily attributed to upland bank conditions which prevented
82 marsh migration with accelerated SLR rates. The enhanced TMM provides the highly-resolved
83 simulations of multi-scale processes needed to inform restoration, strategic planning, and
84 monitoring activities to support marsh sustainability in an evolving system.

85

86 **Keywords:** marshes, tidal marsh model, sea-level rise, cross-scale simulation, SCHISM

87 **1. Introduction**

88

89 Tidal marshes are among the most valuable ecosystems in terms of productivity and
90 species diversity. They provide many ecosystem services including shoreline stabilization, water
91 quality improvements, habitat for many organisms, and long-term carbon storage (Allen
92 2000; Fagherazzi et al. 2004; Zedler and Kercher 2005; Barbier et al. 2011). Tidal marshes occur
93 in a broad range of geomorphic settings with different hydrodynamics, sediment sources, and
94 vegetative communities (Titus et al. 2009). Their establishment and persistence are influenced by
95 environmental factors (e.g., temperature, salinity), different landscapes, coastal processes, as
96 well as anthropogenic activities (e.g., nearshore development, shoreline armoring) (Zhu et al.
97 2014; Fagherazzi et al. 2019). Geomorphological processes are responsible for shaping the
98 physical structure of marshes, thus influencing movement of water, sediments, and nutrients
99 (Leonardi and Fagherazzi 2014). These physical processes provide the framework where marsh
100 ecological processes take place.

101 Marsh habitats have the capacity to dynamically change in response to environmental
102 conditions. Climate change drivers will have different effects on tidal marshes. Changes in tidal
103 regimes, storm patterns, sea-level rise (SLR), as well as human activities that respond to climate
104 change will affect marsh ecosystems and influence their future extent and distribution (Raposa et
105 al. 2017; Horton et al. 2018). There is a universal consensus that global sea levels will rise at an
106 increased rate from those in the recent past (Cazenave and Nerem 2004; Rahmstorf 2007; Boon
107 and Mitchell 2015). Rising seas will increase the vulnerability of coastal communities and
108 ecosystems, and as a result, the supporting services they provide (Parris et al. 2012; Hall et al.
109 2016).

110 It is well established that marsh elevation changes in response to SLR (Cahoon and
111 Guntenspergen 2010; Kolker et al. 2010). These habitats have the capacity to adapt to
112 inundations associated with rising sea level by two mechanisms: vertical accretion and horizontal
113 migration (Morris et al. 2002; Kirwan and Murphy 2007; Raposa et al. 2017; Horton et al. 2018).
114 A tidal marsh will be able to persist in the same location if it builds vertically at a rate equal or
115 higher than the rise in sea level (Reed 1995). If the sea level rises faster than the marsh elevation
116 builds vertically, then the marsh will become submerged.

117 Tidal marshes accrete vertically through the deposition of mineral sediments and organic
118 matter accumulation (Morris et al 2002; Fagherazzi et al. 2012). Inorganic sediment sources to
119 the marsh include bank erosion, sediments coming from upland runoff, and tidally delivered
120 sediments. Mineral sediments are deposited on the marsh surface when the marsh is flooded. The
121 inorganic suspended sediment transport and deposition on marshes will be determined by rates of
122 particle settling, tidal range and inundation depth, and vegetation density. These parameters vary
123 spatially; and for that reason, sediment accretion rates will vary depending on the different
124 vegetative communities and the geomorphic settings (Titus et al. 2009).

125 Marshes also have the capacity to respond to SLR conditions by moving horizontally to
126 higher elevations, either to adjacent land or into adjacent waters if they are filled with sediment.
127 In order for the marshes to migrate inland, they need to have an adjacent open space that allows
128 transgression. This natural response of marshes is truncated in many cases due to increased
129 coastal development which utilizes hardened shoreline structures to stabilize the shoreline and
130 protect public lands and private properties from erosion (Titus et al. 2009; Gittman et al. 2015;
131 Hill 2015; Enwright et al. 2016).

132 Marsh plants play an important role in nearshore hydrodynamics (i.e., waves, current
133 velocity and direction, and water levels) in creeks, rivers, estuaries, and coastal regions
134 (Temmerman et al. 2005; D’Alpaos et al. 2007a; Kiss and Jozsa 2014). The interactions between
135 coastal vegetation and nearshore hydrodynamics have been the focus of many studies (e.g.,
136 Gedan et al. 2011; Shepard et al. 2011; Spalding et al. 2014; Sutton-Grier et al. 2015). Coastal
137 marshes have the ability to modify the circulation pattern by being an obstacle to water motion,
138 affecting the mean flow velocity and turbulence, as well as attenuating wave energy by reducing
139 wave heights entering them (Roland and Douglass 2005; Leonard and Croft 2006; Costanza et al.
140 2008; Feagin et al. 2009; Gedan et al. 2011; Anderson and Smith 2014; Marsooli and Wu 2014;
141 John et al. 2015). Correlation between plant density and sediment deposition rates (e.g., Morris
142 et al. 2002; Li and Yang, 2009; Shepard et al. 2011; Ysebaert et al. 2011; Silliman et al. 2015)
143 suggests that the greater the marsh density, the higher the concentration of suspended sediment
144 trapped in the marsh field, and the more resilient the marsh will be to wave energy and SLR.

145 There is an increasing interest among resource managers and decision makers in
146 spatially-explicit assessments of potential SLR impacts on tidal marshes. To that end, different
147 models have been developed and applied to predict marsh spatial extent and future distribution
148 (Morris et al. 2002; McLeod et al. 2010; Mogensen and Rogers, 2018; Alizad et al. 2018).
149 Current models are constrained by the limitations of the two modeling approaches: landscape-
150 scale models and site-specific models. For instance, landscape-scale models (e.g. Sea Level
151 Affecting Marshes Model, SLAMM) use fixed rates during the entire simulation. They simulate
152 general trends over large areas, but usually at a very coarse resolution. Thus, these types of
153 models are not suitable for site-specific research and management uses because scaling down the
154 results to local levels is not feasible, limiting their accuracy and effectiveness to local

155 applications. On the contrary, site-specific models (e.g. Marsh Evolution Model, MEM) are more
156 mechanistic. Several studies have applied site-specific models to evaluate the long-term
157 evolution of marshes under the effect of SLR (e.g., Kirwan and Murray 2007; Mariotti and
158 Fagherazzi, 2010; Alizad et al. 2016). They are applied to simulate responses for a specific site
159 with a particular set of conditions and settings. One of the main limitations of these approaches is
160 the extrapolation of model results to regional levels. Using results from an individual site to
161 generate long-term projections at larger spatial extents is challenging due to the broad range of
162 geomorphic settings across landscapes (Titus et al. 2009; Nunez 2020).

163 To address and overcome many limitations that current marsh models present, we
164 expanded the capability of an existing multi-scale, hydrodynamic marsh evolution model (Tidal
165 Marsh Model [TMM], Nunez et al. 2020) in order to increase our current knowledge of how
166 marshes may respond to changes in sea level in different settings. The TMM has been developed
167 within the SCHISM framework (Semi-implicit Cross-scale Hydroscience Integrated System
168 Model) (Zhang et al. 2016), an open-source, next-generation hydrodynamic modeling system.
169 Some of the unique features the TMM includes are cross-scale simulations, dynamic rates (i.e.
170 rates vary in space and time as determined by changes in the hydrodynamic conditions of the
171 system), semi-implicit time stepping method, and incorporation of anthropogenic stressors.

172 The present study has two main objectives. First, develop, test, and validate via hindcast a
173 new model component in the TMM that captures the interactions between marsh vegetation and
174 hydro/sediment dynamics. The incorporation of a new vegetation algorithm in the TMM will
175 allow for a more accurate simulation of the water flow and turbulence within the marsh.
176 Modeling the feedback between marsh plants and sediment processes allows simulation of the
177 evolution of the tidal marsh platform, calculated with reference to the relative mean-sea level

178 (MSL). Second, apply the enhanced version of the TMM to evaluate the primary processes
179 affecting marsh sustainability in different geomorphic settings over the next 50 years.

180

181 **2. Materials and Methods**

182 **2.1 Study Area**

183 The TMM with the new vegetation algorithm (hereafter TMM_VEG) was tested and
184 applied in two tidal creeks within the York River estuary in the southern region of Chesapeake
185 Bay, Virginia, USA (Figure 1a): Carter Creek (Figure 1b), and Taskinas Creek (Figure 1c).
186 These two creeks were selected because they are characteristic of the western shore of the
187 Chesapeake Bay, capturing the variation in geomorphic settings common in the region. In
188 addition, these study areas were previously evaluated using the TMM without the vegetation
189 algorithm (Nunez et al., 2020), which allowed for direct comparison of model outputs. Carter
190 Creek is located on the northern side of the York River, approximately 22 km from the mouth of
191 the river. Its watershed is characterized mainly by agricultural and residential land uses.
192 Development pressure has resulted in the presence of roads and hardened shoreline structures in
193 direct contact with marsh habitat. The upland bank height ranges between zero and 1.5 m relative
194 to MSL (CCRM 2018), with gentle bank slope of less than 10 degrees (Danielson and Tyler
195 2016). The geomorphic marsh settings in this creek include fringe and embayed marshes. Fringe
196 marshes have a much greater length than width and occur along sections of the shoreline.
197 Embayed marshes are V-shaped marshes that form along the edges and upper reaches of creeks.
198 The dominant marsh plant species (i.e., more than 50% of the marsh areal extent) in this system
199 is *Spartina alterniflora* (CCRM 2018). The total marsh areal extent evaluated in this system was
200 594,888 m².

201 Taskinas Creek is located on the southern side of the York River, approximately 38 km
202 from the mouth of the river. This is a very pristine environment; it is a component of the
203 Chesapeake Bay National Estuarine Research Reserve (CBNERR). In most of this tidal system,
204 the upland bank height is greater than 1.5 m relative to MSL (CCRM 2018), and mostly with a
205 bank slope greater than 30 degrees (Danielson and Tyler 2016). This creek system is
206 characterized by embayed marshes, which are primarily associated with forested and agricultural
207 land uses. In this system, *S. alterniflora* is also the dominant plant species (CCRM 2018). The
208 total marsh areal extent evaluated in this system was 481,576 m².

209

210 **2.2 Tidal Marsh Model (TMM)**

211 The TMM integrates the physical and anthropogenic components needed to simulate and
212 assess the evolution and persistence of tidal marshes as sea level rises. The TMM simulates
213 marsh migration under the combined influence of tides, wind waves, sediment transport,
214 precipitation, riparian land use, shoreline armoring (e.g., bulkhead, riprap), and roads. The model
215 assesses marsh edge changes as well as internal marsh changes due to variations in elevation and
216 sediment supply, which can lead to internal marsh fragmentation.

217 The TMM is connected to three major modules in the SCHISM system: the
218 hydrodynamic core that serves as the foundation of the SCHISM modeling system; the 3D
219 sediment transport model (CSTMS); and the wind wave model (WWM-III) (Figure 2). WWM-
220 III (Roland 2009; Roland et al. 2012) is a community-driven, parallel, and advanced numerical
221 framework that can be applied to study wave-current interaction processes based on unstructured
222 grids. CSTMS is an adaptation from Warner et al. (2008).

223 Unlike existing marsh models (e.g., Clough et al. 2010; Odink 2019), the TMM uses an
224 unstructured grid in the simulations, which allows highly resolved marsh areas (e.g., 1-meter
225 cross-shore, 5-10 meters along-shore for fringe marshes). The application of unstructured grids
226 to coastal processes offers a great advantage. The superior boundary fitting and local refinement
227 ability of unstructured grids make them ideally suitable for nearshore applications involving
228 complex bathymetry, shoreline geometry, and upland slopes. Figure 3 shows the domain of the
229 unstructured grid used for the model simulations. In addition, TMM has the capacity for a much
230 more dynamic simulation (i.e. rates vary in space and time as determined by changes in the
231 hydrodynamic conditions of the system). Finally, the model highly resolves marsh migration due
232 to the incorporation of anthropogenic stressors, such as coastal development and shoreline
233 armoring.

234

235 **2.3 Incorporation of a New Vegetation Algorithm in the Tidal Marsh Model**

236 The original version of the TMM (hereafter TMM_RF) used a bottom **Roughness Factor**
237 (RF) as an indicator of marsh presence (Nunez et al. 2020). Marsh areas were assigned with a RF
238 of 50 mm, while no-marsh areas were designated with a value of 1 mm (Ye et al. 2013).

239 To increase the functionality of the TMM_RF, we incorporated a vegetation algorithm
240 (Appendix A) in the model to evaluate the effects of *Spartina alterniflora* (dominant plant
241 species in the study areas) on currents and turbulence by modifying the barotropic core of the
242 model. This algorithm allows a more accurate simulation of water flow and turbulence within the
243 marsh. The algorithm was included in the model as an optional function in the simulations.
244 When the vegetation algorithm is turned on, the bottom RF used to define marsh presence is

245 uniformly assigned (1 mm). This is because this factor is less important when compared to form
246 drag from vegetation; with the latter being calculated dynamically inside the model.

247 Vegetation is modeled as an internal source of resistant force and turbulence energy
248 (Lopez and Garcia 2001; Su and Li 2002). The model uses a semi-implicit time stepping method,
249 and the effect of vegetation is incorporated *implicitly* to maintain model stability at large time
250 steps. Therefore, the stability is independent of the vegetation parameters, and large shears that
251 can develop around the canopy can be efficiently simulated. In addition to the impact of
252 vegetation on flow structure, marsh plants attenuate waves (Mendez and Losada 2004). Wave
253 attenuation by vegetation is taken into account in the wave model inside SCHISM (Zhang et al.
254 2019).

255 The inundation frequency used by the TMM_VEG is based on the water-surface level
256 predicted by the modeling system to drive inundation and horizontal marsh migration. Relative
257 SLR is explicitly accounted for in all components. The SLR rate is imposed via the boundary
258 condition at the ocean boundary. The calculated elevation and velocity are shared by all
259 components of the model. The code of the model establishes that marshes have the capability to
260 transgress into an area if the sediment bed elevation is within the suitable elevation range, which
261 is from MSL to 1 m above MSL in our study areas. The CSTMS is responsible to dynamically
262 calculate at each time step the sediment bed elevation, simulating sediment deposition, erosion,
263 and transport. Appendices A, B, and C describe the physical and numerical formulations for the
264 TMM_VEG and the supporting models.

265 To be consistent with the TMM_RF simulations and evaluation (Nunez et al. 2020), the
266 TMM_VEG was also validated via hindcasting (past 40 years) using a time step of 75 seconds,
267 and the sediment transport model was run with morphological acceleration (i.e., simulation = 1

268 year; morphological acceleration factor (MAF) = 40). Historic (Moore and Silberhorn 1976;
269 Moore and Silberhorn 1980) and current (CCRM 2018) tidal marsh inventories were employed
270 for the hindcast. The average SLR rate employed for the study areas over the simulation period.
271 for the hindcast was 4 mm yr⁻¹ (NOAA Tides and Currents 2018).

272

273 **2.4 Model Inputs and Outputs**

274 A suite of major inputs needed for the TMM_VEG and supporting models is displayed
275 Table 1. The Tidal Marsh Inventory developed by the Center for Coastal Resources Management
276 (CCRM), Virginia Institute of Marine Science (VIMS) was used to define the current marsh
277 condition for the simulations. The Inventory for the York River is based on a survey conducted
278 in 2010. Marshes were digitized (1:1000 scale) using high resolution, geo-referenced natural
279 color imagery collected in 2009 by the Virginia Base Mapping Program. Marsh boundaries were
280 field checked. This high-resolution dataset was a crucial input in the model to define accurate
281 marsh boundaries.

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291 **Table 1.** Primary input datasets used for the TMM_VEG and supporting models.

| Dataset | Source |
|---|--|
| Historic Tidal Marshes (1:24,000) | Tidal Marsh Inventories – CCRM, VIMS |
| Current Tidal Marshes (Scale: 1:1,000) | |
| Shoreline Structures (Scale: 1:1,000) | Shoreline Inventory – CCRM, VIMS |
| Riparian Land use (distance: 100 ft.) | Shoreline Inventory Program – CCRM, VIMS |
| LIDAR data | United States Geological Survey (USGS) |
| Bathymetry | NOAA and CBNERR, VIMS |
| Bottom Type (grain sizes) | VIMS, Maryland Geological Survey (MGS), and this study - field samples |
| River Input (average daily values) | United States Geological Survey (USGS) |
| Total Suspended Solids (average monthly values) | Chesapeake Bay Program |
| Atmospheric Forcing | North American Regional Reanalysis (NARR) |
| Tides | US East Coast Tidal Database |
| Marsh Plant Data | Field Data – CCRM, VIMS |

292

293 The physical characteristics of marsh plants change seasonally and spatially. In order to

294 reduce model complexity, an average of these characteristics was selected to represent the annual

295 cycle. Average annual values were used because after the plant dies, the stem of *Spartina*

296 *alterniflora* remains in place and acts as a physical barrier, interfering with the water flow and

297 the sedimentation process until it decomposes.

298 To determine the dominant marsh plant species in the study areas, the Tidal Marsh
299 Inventory was used to examine the spatial extent and distribution of marsh plant species (CCRM
300 2018). Spatial analyses were performed in ESRI® ArcGIS 10.6.1 and ArcGIS Pro. Simulations
301 were run using plant data of the dominant plant species in the study areas. *S. alterniflora* physical
302 characteristic, mean values of density, height, and stem diameter were selected to represent the
303 annual cycle, and were input in the vegetation algorithm within the TMM. Marsh plant data (i.e.,
304 stem diameter (mm), plant height (cm), and stem density (stem per m²) were collected to input in
305 the vegetation algorithm (Table 2). Random sampling with quadrats (0.25 m²) was used to
306 measure stem diameter in the study areas within the low marsh section (*Spartina alterniflora*
307 dominated), for a total of 320 counts. Stem diameter was measured with an electronic digital
308 caliper. Marsh plant height and density data were acquired from surveys in the study areas, as
309 well as other *S. alterniflora*-dominated marshes within the York River watershed to acquire an
310 appropriate representation of the *S. alterniflora* characteristics in this river system. Plant surveys
311 consisted of establishing six transects perpendicular to the seaward edge of the marsh at 13
312 marshes. Four quadrats (0.25 m²) were placed along each transect at 1-m intervals from the
313 marsh–estuary edge. Within each quadrat, *S. alterniflora* plant stems were visually counted and
314 the mean height of *S. alterniflora* was recorded for each quadrat sampled (Bilkovic et al. 2017).
315 For this initial version of the TMM_VEG, we assume constant values of plant characteristics.
316 Values of plant height, density, and stem diameter were averaged (i.e., a single value per plant
317 feature) and input in the model.

318

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321 **Table 2** Plant characteristics of *Spartina alterniflora* used as inputs in the TMM_VEG
 322 simulations.
 323

| Plant Characteristics | Average | Standard Deviation | Count |
|---------------------------------|---------|--------------------|---------------|
| Density (stem m ⁻²) | 152 | 25.5 | 39 (quadrats) |
| Height (cm) | 76.8 | 36.0 | 162 (stems) |
| Stem diameter (mm) | 7.93 | 2.14 | 320 (stems) |

324
 325 A great number of outputs are generated by the model, including marsh boundary
 326 evolution, distribution of surface marsh sediments, and changes in elevation of the marsh
 327 platform. Ancillary outputs from the hydrodynamic, sediment, and wind wave modules include
 328 surface and bottom elevations, bed fraction, and wave height, among many others.

329
 330 **2.5 Evaluation of the Enhanced TMM (TMM_VEG)**

331 Model performance with the new vegetation algorithm was assessed by conducting a
 332 hindcast (past 40 years). Historic tidal marsh inventories (Moore and Silberhorn 1976; Moore
 333 and Silberhorn 1980) and current field observations (CCRM 2018) were used for calibration and
 334 verification purposes, focusing on the following aspects: marsh boundary evolution, distribution
 335 of surface marsh sediments, and changes in elevation of the marsh platform. In addition, results
 336 were compared against the TMM_RF outputs to evaluate if there was a significant difference in
 337 model predictions when *Spartina alterniflora* data (TMM_VEG) were used as opposed to a
 338 bottom roughness factor (TMM_RF) for marsh presence.

339 Outputs from the TMM_VEG were exported to the GIS (Geographic Information
340 System) environment using Matlab and Fortran scripts. Spatial analyses were conducted using
341 ESRI® ArcGIS v10.6.1, and ArcGIS Pro.

342

343 **2.5.1 Marsh Boundary Evolution**

344 The code to simulate the evolution of the marsh boundaries incorporates the effects of
345 tides, waves, sediment transport and morphology, sediment sources, riparian land use, and
346 shoreline armoring. To evaluate the marsh boundary model outputs, the historic Tidal Marsh
347 Inventory generated at VIMS in the early 1970s (Moore and Silberhorn 1976, Moore and
348 Silberhorn 1980), was used in the hindcast as the initial marsh conditions for the simulation. The
349 TMM_VEG was run to the present time, and the marsh boundary outputs were then spatially
350 compared with the current Tidal Marsh Inventory (CCRM 2018). In order to statistically quantify
351 the degree to which the TMM_VEG reproduces the observed data, error matrices were created
352 for both study areas. To be consistent with the approach taken by Nunez et al. (2020), these
353 matrices were used to assess the overall accuracy of the model and to calculate the Kappa
354 statistic (formulation in Appendix D), which is a measure of agreement between the model
355 output and the reference data (i.e., the current Tidal Marsh Inventory). Kappa is a robust statistic
356 and is the most commonly reported measure in evaluating model agreement using categorical
357 variables with multiple levels (McHugh 2012, Tang et al. 2015). In each study area, an error
358 matrix was developed by using 100 random sample points within the marshes. These points were
359 used to establish if the current marsh conditions at those locations agree with the conditions
360 predicted by the TMM_VEG. The random points to assess model performance were the same for
361 both types of simulations (i.e., TMM_RF, and TMM_VEG). In that way, model outputs were

362 directly compared. In addition, the spatial extent and distribution of tidal marshes obtained from
363 the TMM_VEG were mapped, and then compared with the spatial extent and distribution of the
364 model output from the TMM_RF.

365

366 **2.5.2 Spatial Distribution of Sediments – Grain Size**

367 The spatial distribution of sediments across the marshes was evaluated in the TMM_VEG
368 simulations to determine if including marsh plant data would modify the type of surface
369 sediment fractions accumulated in the marshes. Marsh surface sediment core data were used to
370 validate output from model runs with and without the vegetation component. In both study areas,
371 sediment cores (diameter: 3.5 cm; depth 8 cm) were collected from 20 transects running
372 perpendicular from the water's edge to the marsh-upland zone. Along each transect, three
373 locations were sampled: the marsh-water interface, in the middle of the marsh, and the marsh-
374 upland interface, for a total of 60 cores. Samples were analyzed for grain size employing sieves
375 (Folk 1980, Poppe et al. 2003). Removal of organic carbon and carbonates were conducted using
376 loss on ignition, and HCl acidification of the dried samples (Dean 1974; Heiri et al. 2001;
377 Santisteban et al. 2004), respectively. The Wentworth scale was employed to classify grain size
378 into gravel (2-4 mm), sand (0.062-2 mm), and mud (i.e., silt and clay) (< 0.062 mm). These
379 sediment fractions were directly compared with model outputs.

380 The ability of the TMM_VEG to reproduce the distribution of the observed marsh surface
381 sediment fractions was evaluated by estimating the Willmott (1982) index of agreement (dr), the
382 mean absolute error of measured values (MAE), the RMSE-standard deviation ratio (RSR), and
383 the coefficient of determination (NSE). Appendix E shows the equations for these statistical
384 performance measures.

2.5.3 Variation in Elevation of the Marsh Platform

The model uses the vertical datum NAVD88 to compute all state variables (e.g., land surface elevation). The changes in elevation (deposition/erosion) were calculated with respect to the initial values. In the study areas, marshes occur within a particular tidal envelope (between MSL and 1m above MSL). MSL (represented by the free water surface) and the land surface elevation vary during the course of the simulation. MSL was adjusted at each model time step by the rate of SLR (i.e., MSL is dynamically calculated). Similarly, land surface elevation was adjusted at each time step through simulation of sediment erosion, transport, and deposition processes. Based on the new MSL and land surface elevations, inundation depth (which equals the difference between the two values) was calculated. The inundation depth was used as a criterion to determine marsh habitat suitability. A new marsh was created in a grid cell if the land surface elevation was between MSL and 1 m above MSL, and at least one adjacent cell was marsh. A marsh grid cell was considered ‘drowned’ if the land surface elevation fell below MSL.

Changes in elevation of the marsh platform were computed in each study area. The TMM_VEG calculates the variation in elevation of the marsh platform during the simulation period (i.e., depth change from initial marsh surface elevation). Based on these variations, major processes (i.e., “erosion” (negative variation), “deposition” (positive variation), “no change” (variation = 0)) were defined along marsh transects.

2.6 Forecasting Tidal Marsh Evolution

SLR scenarios selected for the forecasts were based on NOAA projections (Sweet et al. 2017). To incorporate subsidence rates in southeast Virginia; an average subsidence rate of 3.1 mm yr⁻¹ (Eggleston and Pope 2013) was added to the projections. For this study, two SLR

408 scenarios were considered: “intermediate” and “extreme.” The intermediate scenario is based on
409 semi-empirical models using statistical relationships in global observations of sea level and air
410 temperature. The extreme scenario is based on estimated consequences from global warming
411 combined with the maximum possible contribution from ice-sheet loss and glacial melting
412 (worst-case scenario). For coastal planning purposes, the projection of marsh evolution in each
413 scenario was 50 years (2020-2070). The increase in sea level by the end of the simulation was
414 622 mm in the intermediate scenario, and 1,243 mm in the extreme scenario. These two
415 scenarios bound reasonable expectations and provide a larger difference to examine.

416 The marsh evolution simulations were run with the vegetation algorithm enabled
417 (TMM_VEG) to more accurately assess the water flow and turbulence within the marsh, as well
418 as to better capture the feedback between presence of marsh plants and sediment processes.
419 Vegetation was modeled as an internal source of resistant force and turbulence energy (Lopez
420 and Garcia 2001; Su and Li 2002). In this study, the effect of vegetation on the nearshore
421 hydrodynamics was defined by the presence of the dominant marsh plant species in the study
422 area, *S. alterniflora*. Outputs from the TMM_VEG were exported to the GIS environment using
423 Matlab and Fortran scripts. Spatial analyses were performed using ESRI® ArcGIS 10.6.1 and
424 ArcGIS Pro.

425 Using a process-based morphodynamic model to conduct long-term simulations involves
426 intensive computational time. This is because morphological changes occur over a much longer
427 time period than hydrodynamic changes. A morphological acceleration factor (MAF) was used
428 to decrease the computational time. This approach was presented by Lesser et al. (2004) and
429 Roelvink (2006), and it is widely used for coastal morphodynamic modeling. This factor was
430 applied after all hydrodynamic and sediment transport processes had been computed for each

431 time step. For the present study, we employed morphological acceleration (i.e., simulation = 1
432 year; MAF = 50) using a time step of 75 seconds (based on model calibration).

433

434 **3. Results**

435 **3.1 Evaluation of the Enhanced TMM**

436 **3.1.1 Marsh Boundary Evolution**

437 The TMM_VEG simulated marsh boundary evolution with an overall high accuracy
438 within both study areas (Carter and Taskinas Creeks: 83%, 82% accuracy; Kappa statistic of
439 0.69, 0.68, respectively), which indicates "Substantial Agreement" according to Viera and
440 Garrett (2005). Appendix D shows the error matrices comparing TMM_VEG against field
441 observations for Carter Creek and Taskinas Creek. In addition, matrices developed by Nunez et
442 al. (2020) are displayed to facilitate the comparison of model performances between the two
443 different approaches. When using the vegetation algorithm, error matrices show an improvement
444 in the overall accuracy of the model. The Kappa statistic in each study area fell inside the same
445 category ("substantial agreement") based on Viera and Garrett (2005).

446 Overall, model results were consistent with field observations. The evolution of marsh
447 boundaries derived from both simulations (i.e., with and without the vegetation component)
448 (Figures 4 and 5) reflected the marsh response expected for the study areas during the past 40
449 years. Marsh migration into open areas was well captured, as were the negative effect of
450 shoreline structures and development on marsh persistence as sea level rises. Marsh loss was
451 significant in areas with high fetch and wave energy in Carter Creek, and outside the mouth of
452 Taskinas Creek, by the main stem of the York River. Nevertheless, including the vegetation
453 algorithm led to a predicted marsh loss of about half of what was predicted without the

454 vegetation component. In Carter Creek, the TMM_RF simulated a marsh loss of 91,459.0 m² (net
 455 loss 10.2%), while the TMM_VEG simulated a loss of 43,706.1 m² (net loss 1.9%). In Taskinas
 456 Creek, the TMM_RF simulated a marsh loss of 49,776.3 m² (net loss 7.6%) while the
 457 TMM_VEG simulated a marsh loss of 26,709.3 m² (net loss 3.5%) (Table 3).

459 **Table 3.** Marsh areal extent (m²) after a 40-year simulation (hindcast) using the TMM_RF and
 460 the TMM_VEG in Carter Creek and Taskinas Creek.

| Simulations | Marsh Boundary Categories | | |
|--------------------------|---------------------------------|--------------------------------|---------------------------------|
| | Marsh Gain (m ²) | No Change (m ²) | Marsh Loss (m ²) |
| Carter Creek - TMM_RF | 24,685.8 | 56,9797.4 | 91,459.0 |
| Carter Creek - TMM_VEG | 31,160.8 | 61,7,550.3 | 43,706.1 |
| Taskinas Creek - TMM_RF | 11,735.9 | 452,033.9 | 49,776.3 |
| Taskinas Creek - TMM_VEG | 9,307.8 | 475,100.9 | 26,709.3 |

462

463

464 3.1.2 Spatial Distribution of Sediments – Grain size

465 The TMM_VEG sediment outputs had a strong agreement with field observations for
 466 both study areas. Similar to the TMM_RF simulation, outputs derived from the TMM_VEG had
 467 a good model performance based on the Willmott Modified Index of Agreement and the MAE.
 468 The NSE and RSR statistics fall within the satisfactory agreement category based on Singh et al.
 469 (2004), and Moriasi et al. (2007) (Appendices E and F). There was not a significant difference
 470 between the two model approaches when considering the spatial distribution of grain size
 471 throughout the marsh surface. In the case of this particular model output, adding information
 472 about the physical characteristics of the marsh plant (plant density, plant height, and stem

473 diameter) in the simulation did not substantially change the predictions about the type of marsh
474 surface sediment fractions (i.e., proportion of gravel, sand, and mud throughout the marsh
475 platform).

476 **3.1.3 Variation in Elevation of the Marsh Platform**

477 The simulation with the vegetation algorithm had an overall lower variation in elevation of the
478 marsh platform in both study areas. In Carter Creek, sites along the marsh transects identified
479 with eroded marsh platform had higher values in the TMM_RF simulation than the TMM_VEG
480 simulation (Figure 6), indicating that the vegetation algorithm more successfully captured the
481 reduction of turbulence, and the capacity of the plants to trap sediments, stabilizing the marsh
482 platform. Appendix G displays the change in elevation of the marsh platform along the marsh
483 transects in Carter Creek when using the TMM_RF and the TMM_VEG, respectively. In some
484 of the sites, the amount of marsh platform lost predicted by the TMM_RF was double or higher
485 than the amount estimated when using the TMM_VEG (e.g., site number 7, 13, 28). Inclusion of
486 vegetation led to reductions in both predicted areal marsh loss and vertical loss of the marsh
487 platform. TMM_RF uses an increased bottom roughness factor (Ye et al. 2013) to assign marsh
488 presence. This uniform bottom roughness (used as marsh plant proxy) interferes with the water
489 mean flow velocity and turbulence, affecting sediment deposition patterns. However, the
490 incorporation of marsh plant data in the vegetation algorithm allowed to better capture the
491 deposition of sediment by marsh plant, stabilizing the marsh platform and resulting in a lower
492 erosion. The incorporation of the physical characteristics of the marsh plants from the study
493 areas provided a more realistic environment affecting the hydrodynamics and the sediment
494 processes, producing a better agreement with the field observations. Most of this behavior occurs
495 in the low-marsh sites (i.e., near the marsh-water interface). These sites are exposed to more

496 frequent and prolonged inundation, allowing more exposure to sediment particles. Nevertheless,
497 a considerable difference in the elevation of the marsh platform was also found in one high-
498 marsh site (site 18). This site is located about 20 meters from the marsh-water edge. The
499 TMM_RF simulation estimated almost a three times higher loss in elevation of the marsh
500 platform. In this case, the difference in model outputs can be related to the higher capacity of the
501 marsh plants to capture sediments coming from the upland-marsh interface due to erosion and/or
502 runoff. In the sites where the dominant process was defined as “deposition,” the magnitude of
503 increase in marsh platform elevation did not exhibit a considerable difference between the two
504 model outputs, except for one location (site 20). This site is situated in the middle of a narrow
505 fringe marsh (approximate 5 m wide). The TMM_RF simulation estimated a deposition of 20.2
506 mm in the 40-year simulation, whereas the model output using the vegetation algorithm
507 predicted an erosion of 2 mm during the same simulation period. This discrepancy in model
508 outputs can be attributed to what was happening to the edge of the marsh (i.e., site 19; low-marsh
509 site) during each of the simulations. In the site 19, the simulation using the roughness factor
510 yielded an erosion of the marsh platform of 106.9 mm in the 40-years simulation, whereas the
511 TMM_VEG simulation projected a loss of 41.1 mm. The TMM_RF simulation produced a
512 greater amount of erosion; hence, more sediments were locally available. These sediments could
513 have been then redeposited in the “new” marsh edge, or further into the existing marsh due to the
514 inundation that reached higher elevations (Friedrichs and Perry 2001; FitzGerald and Hughes
515 2019; Wiberg et al. 2020;). As mentioned before, deposition of inorganic sediments by marsh
516 plants plays a critical role in maintaining the marsh platform. Incorporating detailed plant
517 information in the vegetation algorithm provided a higher accuracy in the simulation of sediment

518 movement within the marsh, helping to identify areas where erosion or deposition throughout the
519 marsh platform occurred.

520 A similar pattern was also observed in Taskinas Creek between both simulations.
521 Taskinas Creek presents different hydrodynamics than Carter Creek due to the meandering
522 channels, which result in a particular sedimentation pattern (asymmetrical channel with the
523 deepest part of the channel on the outside of each bend). Both model approaches predicted
524 mostly the same dominant process on the marsh platform (i.e., erosion, deposition, or no change)
525 along the marsh transects. The main exception to this pattern was site 16, located in the low
526 marsh. The simulation using the TMM_RF produced a deposition of 7.0 mm per year, whereas
527 the simulation with TMM_VEG generated a vertical erosion of 11.5 mm per year (Figure 7).
528 Sediment fluxes are not linear functions, so the difference in sediment distribution near this site
529 could have been very different between the two simulations, affecting the local deposition and
530 erosion of the marsh platform. In addition, site 16 is located close to the concave bank, where the
531 stream erodes the sediments, and deposits these and other sediments downstream on the convex
532 bank. This would be the point bar located to the left of site 16. The particular spatial location of
533 this site, as well as differences in sediment fluxes and water flow are some of the reasons that
534 can explain this unique discrepancy. In the case of the deposition process, the magnitude of
535 sediment deposition during the simulation period was either the same for both simulations or a
536 little higher (e.g., site 10) when using the TMM_VEG (due to the enhanced simulation using the
537 vegetation algorithm). Nonetheless, this pattern was not found in sites 13 and 14. This could be
538 attributed to the heterogeneity of the system (i.e., terrain depressions, very narrow marsh
539 channels), which affects plant marsh growth and soil conditions. This particular difference in
540 marsh plant characteristics was not captured by the model due to the underlying assumptions of

541 using only one type of marsh plant community, and assigning constant plant characteristics along
542 the entire marsh. The values of elevation change along the marsh platform in Taskinas Creek are
543 detailed in Appendix G.

544

545 **3.2 Forecasting Tidal Marsh Evolution**

546 In both study areas, the marsh boundary evolution output was a function of the rate of
547 SLR and the subsequent topographic changes resulting from marsh platform accretion. In many
548 cases, especially in the extreme SLR scenario, the overwhelming extent of inundation damped
549 the impact of topography and flow resistance, and the new marsh patterns were mostly
550 dependent on the rate of SLR. The forecast maps (Figures 8 and 9) show that some marshes had
551 good opportunities to increase their extent by migrating into natural areas that today are not
552 regularly inundated, but that are expected to become inundated in the future.

553 In Carter Creek, the intermediate SLR scenario projected a marsh loss of 24.2 %.
554 Nevertheless, several marshes were able to migrate inland (16.9 %) and offset part of this loss;
555 hence, yielding a net marsh loss of 7.3% over the next 50 years. The capacity of marshes to
556 transgress was truncated in some areas due to anthropogenic pressure (development, shoreline
557 structures, and roads). The projected marsh response in the extreme SLR scenario was
558 considerably different. By the end of the simulation period, the initial marsh areal extent was
559 reduced by 89.6%. However, due to the local topography and natural riparian upland, many
560 marshes were able to migrate to higher elevations (29.6%) mainly in areas where forested and
561 scrub shrubs have become inundated, resulting in a net marsh loss of 60.0% (Table 4).

562 In Taskinas Creek, under the intermediate SLR scenario about a quarter of the marshes
563 will be lost, while the vast majority of marshes are expected to be lost under the extreme SLR

564 scenario. The intermediate SLR scenario predicted a marsh loss of 28.8% from the initial marsh
 565 coverage. In few areas, marshes were able to transgress (5.7%). This resulted in a net marsh loss
 566 of 23.1%. The scenario with the extreme SLR rate projected a major extent of inundation. The
 567 initial marsh areal extent decreased by 94.4%. This loss was slightly compensated by some
 568 marsh transgression (5.2%), yielding a net loss of 89.2% (Table 4).

569

570 **Table 4.** Projected marsh areal extent (m²) after a 50-year simulation using an intermediate and
 571 extreme scenario of SLR.

572

| | Marsh Boundary Categories | | |
|--|------------------------------|-----------------------------|------------------------------|
| | Marsh Gain (m ²) | No Change (m ²) | Marsh Loss (m ²) |
| Carter Creek – Intermediate Scenario | 100,766.7 | 450,819.8 | 144,068.2 |
| Carter Creek – Extreme Scenario | 176,442.9 | 61,512.2 | 533,375.8 |
| Taskinas Creek – Intermediate Scenario | 27,518.6 | 342,768.7 | 138,807.3 |
| Taskinas Creek – Extreme Scenario | 25,090.5 | 26,709.3 | 454,866.7 |

573

574

575 **4 Discussion**

576 **4.1 Evaluation of the Enhanced TMM (TMM_VEG)**

577 We presented a new functionality for a high-resolution and highly predictive marsh
 578 evolution model that incorporated physical characteristics of marsh vegetation, topography,
 579 sediment dynamics, hydrodynamics, changing sea levels, and human features. The incorporation
 580 of a vegetation algorithm into the original version of the TMM (TMM_RF) enhanced the
 581 accuracy and predictive capabilities of the model in the majority of the sites evaluated. The effect
 582 of marsh plants on the nearshore hydrodynamics provided a different pattern of sediment
 583 distribution when compared with the TMM_RF simulations, reflecting an improved agreement

584 between model outputs and field observations. The simulation with marsh plant data better
585 captured sediment deposition and erosion by marsh edges, as shown in the marsh boundary
586 evolution analysis. This type of simulation better reflects the current observed marsh extent and
587 distribution. Moreover, the marsh platforms were more stable due to the effect of marsh plants
588 on sedimentation, as indicated in the elevation change analysis. The type of sediment fractions
589 (i.e., proportion of gravel, sand, mud) throughout the marshes did not differ with the
590 incorporation of the vegetation algorithm, which suggests that the type of inorganic sediments
591 deposited on the marsh platform depends more on the type of sediments available in the system
592 rather than the physical characteristics of the marsh plant, and their capacity to capture
593 sediments.

594 The enhanced version of the TMM was tested on typical salt marshes dominated by
595 *Spartina alterniflora*. We have demonstrated that using only plant data of the dominant plant
596 species explains the majority of the variability in the salt marsh systems studied. The vegetation
597 algorithm can be modified to incorporate other plant species with different physical
598 characteristics to represent marshes with a different dominant plant species or marshes with a
599 variety of plant species (e.g., freshwater marshes). Spatially assessing and mapping these plant
600 communities and incorporating these data as inputs in the simulations would likely increase the
601 accuracy of the model outputs for those systems.

602 The development of the model within the SCHISM framework allows for unique model
603 capabilities to be naturally incorporated into the simulations (Nunez et al. 2020). In the original
604 version of the TMM, the authors focused on a 2D barotropic model configuration due to large
605 uncertainties that exist in some marsh process inputs. For processes as complex as marsh
606 migration, it is important to start from a simple approach, investigate the relative importance of

607 contributing factors, and gradually build up model complexity. While the polymorphism in
608 SCHISM allows efficient simulation of marshes in hybrid 2D-3D mode (Liu et al. 2018), the
609 current 2D model already incorporates most of the physics. At this stage, we have achieved with
610 the TMM_VEG an enhanced simulation of changes in marsh position over a 40-year period of
611 observation (hindcast) based on physical processes and factors. A 3D (baroclinic) model that
612 includes salinity and temperature together can further improve the model's predictive capability
613 for the fate of certain marsh species under climate change. Although some sensitivity to grid
614 resolution has been carried out, more analyses on this in the larger context of other uncertainties
615 need to be explored further.

616 The drag coefficient of marsh vegetation increases in a non-linear way with increasing
617 plant density (Nepf, 1999; Meijer 2005), causing attenuation of wave energy and modification of
618 turbulence. The form drag is dependent on the Reynolds number and on the shape, rigidity and
619 orientation of the object. The TMM_VEG simulations assume a constant value for the drag
620 coefficient. The model code could be modified by adding a varying drag coefficient in the
621 vertical column, which accounts for flexible stems. In the absence of site-specific vegetation
622 data, model results show that implementing a constant value for the drag coefficient is a
623 reasonable approach to evaluate marsh evolution at large scales.

624 The main limitation of the current version of the model is the application of the model in
625 areas where the current marsh vertical accretion is dominated by organic deposition. Different
626 plant communities have different photosynthetic and decomposition rates, which can directly
627 affect the plant structure and size as well as the root size and distribution. These characteristics
628 will directly affect the capture of sediments and stabilization of the marsh platform by the roots.
629 Due to the variability of marsh plant communities, primary production, and decomposition rates,

630 along with the lack of widespread spatially explicit biological data, we assume biological
631 processes to be constant. While the current version of TMM_VEG does not include biological
632 processes at the moment in the simulations, when considering scenarios with high rates of SLR
633 and long-term projections, the accelerated rates of SLR will surpass the maximum rates of
634 organic deposition by marsh plants, and the fate of marshes will depend only on the availability
635 of inorganic sediments. The focus of this work was to improve the original TMM performance
636 by incorporating the effect of marsh plants on the nearshore hydrodynamics, leaving the
637 assessment of the biological processes for our next stage of model development.

638

639 **4.2. Forecasting Tidal Marsh Evolution**

640 This study represents an enhanced modeling approach that integrates anthropogenic
641 barriers to marsh migration within a highly-resolved marsh evolution model to simulate realistic
642 marsh sustainability outcomes. The primary drivers of marsh change in different geomorphic and
643 human settings were elucidated from our modeled systems. The application of the TMM with the
644 vegetation algorithm allowed us to develop detailed projections of marsh sustainability in
645 multiple geomorphic settings under different rates of SLR. Across the scenarios evaluated,
646 projections of marsh areal extent vary in both study areas. Major differences in marsh response
647 are mainly attributed to the geomorphic settings, sediment supply, and anthropogenic factors
648 associated with marsh habitats in those tidal systems.

649 Tidal marshes in Carter Creek occur in a higher topography compared to the ones in
650 Taskinas Creek (Danielson and Tyler 2016). Marshes located at a high topography have more
651 time to offset changes in water levels due to SLR through vertical accretion and horizontal
652 migration, which make them more resilient to SLR (Alizad et al. 2018; Fagherazzi et al. 2019).

653 The persistence of marsh habitat in Carter Creek in the intermediate scenario can be attributed to
654 the local topography and the sufficient sediment supply in this region, as well as the capacity of
655 the marsh plants to successfully capture and deposit the available sediments onto the marsh
656 platform, increasing its elevation and offsetting the rate of SLR. In the extreme scenario, the
657 accelerated rate of SLR surpassed the rate of vertical accretion by marsh plants in most of the
658 marshes, leading to marsh loss where landward migration was not possible.

659 In Taskinas Creek, projections of marsh response over the next 50 years were
660 significantly different between the intermediate and extreme scenarios. This can be attributed
661 mainly to the geomorphic setting of this area. Topographic limitations to marsh expansion were
662 more important for this system. Currently, marshes are not only present in a very low elevation,
663 but also are associated with high upland bank height (more than 1.5 m in the majority of the
664 places) and steep slopes, which create an obstacle to inland migration with high rates of SLR.
665 Even though the adjacent upland areas of these marshes are natural, and no anthropogenic
666 stressors are present in this site, the elevated rates of SLR and the physical environment did not
667 allow marshes to migrate horizontally in the majority of places. The estimated area of marsh
668 transgression was almost the same in both forecast scenarios. This suggests that marsh inland
669 migration was mainly truncated by upland bank conditions under accelerated SLR rates. In the
670 extreme SLR scenario, a widespread marsh drowning was observed because migration was
671 limited. The projected sediment supply for this area over the course of the simulation period was
672 not sufficient to increase marsh elevation and to keep pace with SLR.

673 These projections do not take into account changes in land use and shoreline erosion
674 control structures over the next 50 years, which could significantly change the response of tidal
675 marshes with respect to migrating inland as sea level increases. The conflict between marsh

676 inland migration and human activities near the shoreline is likely to become more significant in
677 the future. Coastal zones are densely populated with an increasing trend of development (Small
678 and Nicholls 2003; Neumann et al. 2015), which will directly affect marsh migration pathways.
679 Shoreline erosion control structures located on the landward edge of the marsh not only act as
680 obstacles for marsh transgression, but also represent barriers for sediment exchange between the
681 marsh and the adjacent upland. Sediment supply is a major factor in marsh response to SLR
682 (Van Proosdij et al. 2006; Cahoon and Guntenspergen 2010; Kolker et al. 2010; Mariotti and
683 Fagherazzi 2010) and a key parameter in modeling marsh evolution (Temmerman et al. 2003b;
684 D'Alpaos et al. 2007a; Kirwan et al. 2016), Lateral and vertical marsh changes can be very
685 sensitive to suspended sediment concentrations. In some settings, small differences in sediment
686 supply can lead to marsh accretion, erosion, progradation, or retreat (Mariotti and Carr 2014;
687 Fagherazzi et al. 2012; Kirwan et al. 2010). The ability of marsh plants to trap sediments
688 increases their resiliency to SLR by maintaining an appropriate surface elevation. Nevertheless,
689 the presence of shoreline armoring to protect private properties from erosion as well as damming
690 of rivers have resulted in a decreased suspended sediment concentration in coastal waters (Willis
691 and Griggs 2003; Weston 2014; Currin et al. 2015). High resolution data sets containing the
692 spatial location of shoreline structures should be included as a model input in the TMM_VEG in
693 order to more accurately simulate sediment deposition by marsh plants and marsh transgression.
694 The code of the TMM_VEG has the capacity to be modified in order to incorporate changes in
695 projections of anthropogenic stressors. If these data are available, we recommend including this
696 information in the forecast to more accurately estimate the future location of marsh habitat.

697 The projections obtained in our study sites provide a framework of how other marshes
698 might respond under similar geomorphic settings and human activity. This TMM_VEG is

699 exportable; end users are able to easily access the model and tutorials. It can be used in any
700 marsh system to better predict marsh responses under different sea-level rise scenarios, including
701 estuaries, back-barrier islands, fluvially-dominated deltas, and lagoons. For instance,
702 TMM_VEG has the capacity to model horizontal migration that occurs in marshes behind barrier
703 islands. These systems respond to SLR by migrating toward the mainland when sand is
704 overwashed from the barrier island and rolls over onto the back-barrier marsh. The overwash
705 deposition allows marshes to increase in elevation and migrate (Finkelstein and Ferland 1987;
706 Fitzgerald et al. 2007; Walters et al. 2014). However, at rapid and high rates of SLR, barrier
707 island migration can outpace marsh migration toward the mainland, yielding a significant marsh
708 loss (Deaton et al. 2017). The interactions between back barrier marshes and barrier islands play
709 a significant role in determining how coastal systems will evolve in the future due to SLR.
710 Application of the TMM_VEG to this type of systems as well as other regions, and with different
711 marsh plant species, will be mainly limited by the available input data for the target areas. The
712 refinement of the original version of the TMM to simulate marsh evolution will offer coastal
713 managers and other stakeholders a detailed assessment of the fate of tidal marshes in different
714 settings as sea level rises.

715 The findings produced with the TMM_VEG have other management implications for the
716 Chesapeake Bay region and beyond. Maintaining water quality is one vital service that marshes
717 provide. It is well established that tidal marshes affect water quality by taking up nutrients and
718 trapping sediments (Fisher and Acreman 2004; Mitsch and Gosselink 2007). Excessive loadings
719 of nitrogen, phosphorus, and sediment are of major concern and the focus of the Chesapeake Bay
720 Program, which established total maximum daily loads (TMDLs) (U.S. EPA 2010). To that end,
721 protecting and creating marshes has become especially important for managers trying to achieve

722 water quality goals. Effectiveness in these efforts requires an understanding of how local
723 conditions influence marshes, in particular how the temporal and spatial variation in sediment
724 supply, deposition, and surface erosion can affect the sustainability of these habitats. Because
725 these factors are quite variable in many coastal and estuarine systems, application of a dynamic
726 simulation of marsh evolution with a fine spatial resolution, such as the TMM_VEG, is
727 important for informed management of current and future marsh resources. Furthermore,
728 sedimentation and turbidity are two of the main factors responsible for the decline in populations
729 of North American aquatic organisms (Henley et al. 2010). The capacity of marshes to retain
730 sediments is directly related to their spatial extent and distribution. Understanding how SLR will
731 impact marsh habitats and modify sediment inputs in the system is crucial to maintain and
732 improve water quality and healthy aquatic food webs.

733 There is an increasing trend from coastal managers and planners to assess the cost-benefit
734 of applying different management strategies to protect marsh habitats and the services that they
735 provide (Kassakian et al. 2017; Reguero et al. 2018; Propato et al. 2018; Rezaie et al. 2020).
736 Another important TMM_VEG application is the identification of areas for marsh conservation
737 that contribute to coastal resilience over longer time frames (e.g., protecting a marsh to reduce
738 coastal erosion, flooding, and/or storm surge impacts). TMM_VEG predictions can be combined
739 with ecosystem-valuation assessments to estimate the most cost-effective strategy to support the
740 physical and ecological services that these critical habitats offer. Model outputs can be used to
741 determine areas at high risk to marsh habitat conversion, as well as potential opportunities for
742 marsh preservation and restoration where upland conditions currently allow transgression.
743 Preserving lands that allow marsh transgression should be a high conservation priority. Coastal
744 managers and decision-makers can use these model outputs to improve the long-term

745 effectiveness of conservation and restoration strategies by maximizing the amount of marsh
746 habitat in high-sediment regions, prioritizing sediment allocation, and identifying and prioritizing
747 key upland transitional sites.

748

749 **5 Conclusion**

750 A new vegetation component was successfully developed, tested, and incorporated into
751 the Tidal Marsh Model (TMM) to provide an improved simulation of how marsh plants modify
752 the circulation pattern by being an obstacle to water motion, affecting the mean flow velocity and
753 turbulence, and consequently, sedimentation processes. The application of the TMM with the
754 vegetation algorithm advances the spatial modeling and understanding of dynamic SLR effects
755 on tidal marsh vulnerability. Running the TMM with the vegetation algorithm (TMM_VEG)
756 more effectively captures the lateral and vertical changes of tidal marshes, supporting more
757 accurate assessments of the vulnerability of these important resources under present and future
758 conditions. The new version of the TMM is exportable; it can be used in any marsh system to
759 better predict marsh responses under different SLR scenarios. The model code and technical
760 documentation are publicly available via direct download from the SCHISM website:
761 <http://ccrm.vims.edu/schismweb/>.

762 Managing shoreline systems to sustain the capacity of marshes to provide multiple
763 ecosystem services entails an understanding of the conditions that will affect their survival.
764 Accelerated rates of SLR will stress the ability of marshes to compensate for rising water levels,
765 and marsh drowning may become more widespread. To better understand the effects of SLR and
766 human pressure on marsh evolution, we projected the changes in marsh extent over the next 50
767 years in two representative marsh systems within the Chesapeake Bay using the TMM_VEG to

768 incorporate in the simulations the effects of marsh vegetation on the nearshore hydrodynamic.
769 Model outputs show how different coastal settings, such as nearshore topography, sediment
770 supplies, and anthropogenic factors determine the evolution of tidal marshes as the rates of sea
771 level accelerate.

772 This modeling approach can be used to inform forward-looking management efforts to
773 identify and protect areas where marsh habitats are most likely to be sustainable, as well as
774 preserve opportunities for migration of marsh habitats in an evolving system. These projections
775 provide valuable and necessary information for restoration, strategic planning, and monitoring
776 activities to support marsh sustainability.

777

778 **Acknowledgement**

779 The authors would like to especially thank William Reay, Eduardo Miles, Kory Angstadt, and
780 Dave Stanhope for their support with field-work activities. We would also like to thank the
781 anonymous reviewers whose comments helped improve the manuscript. This paper has a
782 Contribution No. 1039 of the Virginia Institute of Marine Science, William & Mary.

783 **Funding:** This study was supported by the National Oceanic and Atmospheric Administration
784 (grant number NA17NOS4730142), the United States Environmental Protection Agency (grant
785 number CD-96347001-0), the Chesapeake Bay National Estuarine Research Reserve's Rouse-
786 Bottom Fellowship, and the National Science Foundation (grant number 1600131). Any
787 opinions, findings, and conclusions or recommendations expressed in this material are those of
788 the authors and do not necessarily reflect the views of the National Science Foundation.

789 Some simulations used in this paper were conducted using the following computational facilities:
790 (1) Sciclone at the College of William and Mary which were provided with assistance from the

791 National Science Foundation, the Virginia Port Authority, Virginia's Commonwealth
792 Technology Research Fund, and the Office of Naval Research; (2) the Extreme Science and
793 Engineering Discovery Environment (XSEDE; Grant TG-OCE130032), which is supported by
794 National Science Foundation grant number OCI-1053575; (3) the NASA High-End Computing
795 (HEC) Program through the NASA Advanced Supercomputing (NAS) Division at Ames
796 Research Center.

797

798 **Conflicts of interest/Competing interests:** The authors declare that they have no conflict of
799 interest.

800

801 **Code availability:** model code can be accessed at <http://ccrm.vims.edu/schismweb/>

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APPENDICES

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1270 **Appendix A - TMM (RF & VEG) Physical Formulation – Governing** 1271 **equations:** 1272

1273 SCHISM solves the 3D Reynolds-averaged Navier-Stokes equation in its hydrostatic form:

1274 Momentum equation:
$$\frac{D\mathbf{u}}{Dt} = \frac{\partial}{\partial z} \left(\nu \frac{\partial \mathbf{u}}{\partial z} \right) - g \nabla \eta + \mathbf{F}$$

1275 Continuity equation in 3D and 2D depth-integrated forms:
$$\nabla \cdot \mathbf{u} + \frac{\partial w}{\partial z} = 0$$

1276
$$\frac{\partial \eta}{\partial t} + \nabla \cdot \int_{-h}^{\eta} \mathbf{u} dz = 0$$

1277
 1278 Transport equation:

1279
$$\frac{\partial C}{\partial t} + \nabla \cdot (\mathbf{u}C) = \frac{\partial}{\partial z} \left(\kappa \frac{\partial C}{\partial z} \right) + F_h,$$

1280
 1281 Equation of state:
 1282 $\rho = \rho(S, T, p)$
 1283

1284 where

1285
$$\nabla \left(\frac{\partial}{\partial x}, \frac{\partial}{\partial y} \right)$$

- 1286 D/Dt material derivative (s^{-1})
- 1287 (x, y) horizontal Cartesian coordinates (m)
- 1288 z vertical coordinate, positive upward (m)
- 1289 t time (s)
- 1290 $\eta(x, y, t)$ free-surface elevation (m)
- 1291 $h(x, y)$ bathymetric depth (m)
- 1292 $\mathbf{u}(x, y, z, t)$ horizontal velocity, with Cartesian components (u, v)
- 1293 w vertical velocity
- 1294 \mathbf{F} other forcing terms in momentum (baroclinic gradient $(-\frac{g}{\rho_0} \int_z^{\eta} \nabla \rho d\zeta)$,
 1295 horizontal viscosity, Coriolis, earth tidal potential, atmospheric pressure,
 1296 radiation stress)
- 1297 g acceleration of gravity, in (ms^{-2})
- 1298 C tracer concentration (e.g., salinity, temperature, sediment, etc.)
- 1299 ν vertical eddy viscosity, in (m^2s^{-1})
- 1300 κ vertical eddy diffusivity, for tracers, in (m^2s^{-1})
- 1301 F_h horizontal diffusion and mass sources/sinks

1302

1303 As previously stated, a simpler 2D barotropic configuration was used in this study.

1304

1305

1306 ***Particular Case – Evaluation of Marsh Plants on Nearshore Hydrodynamics (TMM_VEG)***

1307 Based on Zhang et al. (2019) the Reynold’s Averaged Navier-Stokes equations are modified by

1308 adding a form drag term due to vegetation:

1309

$$1310 \quad \frac{Du}{dt} = f - g\nabla\eta + m_z - \alpha[u]uL(x, y, z)$$

1311

$$1312 \quad \alpha(x, y) = Di_v N_v C_{DV}/2$$

1313

1314

1315 *Where:*

1316 u = horizontal velocity

1317 D/dt = material derivative

1318 g = gravitational acceleration

1319 η = surface elevation

1320 α = vegetation related variable

1321 m_z = vertical eddy viscosity term

1322 L = vegetation term

1323 Di_v = stem diameter

1324 N_v = vegetation density (number of stems per m^2)

1325 C_{DV} = bulk form drag coefficient (Nepf and Vivoni, 2000) (value used = 1.13)

1326 f = includes a number of explicitly treated terms (e.g., Coriolis, baroclinic pressure
1327 gradient, horizontal viscosity).

1328

1329 Since SCHISM allows ‘polymorphism’ with mixed 2D and 3D cells in a single grid (Zhang et al. 2016),
1330 there are different forms for the vertical eddy viscosity term (m_z).

1331

$$1332 \quad m_z = \begin{cases} \frac{\partial}{\partial z} \left(\nu \frac{\partial u}{\partial z} \right), & 3D \text{ cells} \\ \frac{\tau_w - \chi u}{H}, & 2D \text{ cells} \end{cases}$$

1333

1334

1335

1336 The vegetation term:

$$L(x, y, z) = \begin{cases} \mathcal{H}(z_v - z), & 3D \\ 1, & 2D \end{cases}$$

1337

1338

1339 ν = eddy viscosity

1340

1341 τ_w = the surface wind stress

1342

1343 $H=h+\eta$ is the total water depth (with h being the depth measured from a fixed datum)

1344

$$\chi = C_D |\mathbf{u}|, \quad C_D = \text{the bottom drag coefficient}$$

1346

134 z_v = the z -coordinate of the canopy.

1348 Note that \mathbf{u} denotes the depth-averaged velocity in a 2D region.

1349

13 $\mathcal{H}()$ = the Heaviside step function

1351

1352

$$\mathcal{H}(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

1355

1356 **Appendix B - TMM Numerical Formulation: Geometry and Discretization**

1357 SCHISM-TMM is a finite-element model that uses a flexible unstructured grid (UG). For
1358 the horizontal grid, hybrid triangular-quadrangular (quads) elements are employed to take
1359 advantage of the superior boundary-fitting capability of triangles as well as efficiency/accuracy
1360 of quads in representing certain features (e.g., channels) as needed.

1361 The basic 3D computational unit in SCHISM is a triangular prism or quad prism. Surface
1362 elevations (η) are defined at the nodes, and the horizontal velocities (u, v) are defined at the side
1363 centers and whole levels. The vertical velocity (w) is defined at the element centers and whole
1364 levels, and the tracer concentration (C) is defined at prism center, as it is solved with a finite
1365 volume method. The conformal and non-conformal linear shape functions (Le Roux 2012) are
1366 used for elevations and velocities respectively.

1367 **Boundary Conditions.** The differential equations previously described require initial
1368 conditions (I.C.) and boundary conditions (B.C.). Generally, all state variables (η, u, C) are
1369 specified at $t=0$ as I.C. In addition, some variables are specified at all open lateral boundary
1370 segments (e.g. open ocean, rivers, etc.). At the sea-surface interface, SCHISM enforces the
1371 balance between the internal Reynolds stress and the applied shear stress:

$$1372 \quad \nu \frac{\partial \mathbf{u}}{\partial z} = \boldsymbol{\tau}_w, \quad z = \eta$$

1373 Since the bottom boundary layer is typically not well resolved in ocean models, the no-
1374 slip condition at the sea or river bottom ($u = w = 0$) is replaced by a balance between the internal
1375 Reynolds stress and the bottom frictional stress,

$$1376 \quad \nu \frac{\partial \mathbf{u}}{\partial z} = \boldsymbol{\tau}_b, \text{ at } z = -h.$$

1377 For a turbulent boundary layer, the bottom stress is defined as:

$$1378 \quad \boldsymbol{\tau}_b = C_D |\mathbf{u}_b| \mathbf{u}_b$$

1379 where \mathbf{u}_b is the near bottom velocity.

1380

1381 **Turbulence closure.** The momentum equation and transport equation are not closed and
1382 must be supplemented by turbulence closure equations for the viscosity/diffusivity. SCHISM
1383 uses the Generic Length-Scale (GLS) model of Umlauf and Burchard (2003) with proper I.C.
1384 and B.C. for each differential equation.

1385

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1391 **Appendix C. Main Equations for Supporting Models**

1392 *Suspended Sediment Transport.* Suspended sediment concentrations are computed as
 1393 follows (Pinto et al. 2012):
 1394

1395

$$1396 \quad \frac{\partial c_j}{\partial t} + \nabla_h \cdot (\mathbf{u}c_j) + \frac{\partial[(w - w_{sj})c_j]}{\partial z} = \frac{\partial}{\partial z} \left(\kappa \frac{\partial c_j}{\partial z} \right) + F_h$$

1397 c_j - volume concentration of suspended sediment in class j
 1398 u - horizontal velocity
 1399 κ - eddy diffusivity
 1400 w_{sj} - settling velocity
 1401 F_h - horizontal mixing
 1402

1403 *Spectral Wave Model (WWM-III).* Governing equation for wave action is defined as (Ronald et al.
 1404 2012):
 1405

$$\underbrace{\frac{\partial}{\partial t} N}_{\text{Change in Time}} + \underbrace{\nabla_x (XN)}_{\text{Advection in horizontal space}} + \underbrace{\frac{\partial}{\partial \sigma} (\theta N) \frac{\partial}{\partial \theta} (\sigma N)}_{\text{Advection in spectral space}} = \underbrace{S_{tot}}_{\text{Total Source Term}}$$

1406 where:

1407

$$1408 \quad N_{(t,X,\sigma,\theta)} = \frac{E_{(t,X,\sigma,\theta)}}{\sigma}$$

1409 E = variance density of the sea level elevations
 1410 σ = relative wave frequency
 1411 θ = wave direction
 1412 X = Cartesian coordinate vector (x, y) in the geographical space
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Appendix D. Error matrices (TMM_REF and TMM_VEG)

Table D.1 Error matrices for Carter Creek based on 100 random sample points. The upper matrix displays the model results using the vegetation algorithm (**TMM_VEG**); the lower matrix display model outputs using a roughness factor (**TMM_RF**). Each point was used to evaluate if the current marsh conditions at that location agree with the conditions predicted by the model. Bold numbers in the diagonal represents the counts where model outputs and current conditions agree.

| CARTER CREEK | | CURRENT TIDAL MARSH INVENTORY | | | | |
|---------------------------------------|----------------|-------------------------------|------------|------------|------------|------------------|
| | | No Change | Marsh Gain | Marsh Loss | TOTAL | Commission Error |
| TIDAL MARSH MODEL (TMM_VEG) | No Change | 52 | 2 | 9 | 63 | 0.17 |
| | Marsh Gain | 1 | 9 | 0 | 10 | 0.10 |
| | Marsh Loss | 5 | 0 | 22 | 27 | 0.19 |
| | TOTAL | 58 | 11 | 31 | 100 | |
| | Omission Error | 0.10 | 0.18 | 0.29 | | 0.17 |
| CARTER CREEK | | CURRENT TIDAL MARSH INVENTORY | | | | |
| TIDAL MARSH MODEL (TMM_RF) | No Change | 45 | 2 | 7 | 54 | 0.17 |
| | Marsh Gain | 2 | 8 | 0 | 10 | 0.20 |
| | Marsh Loss | 8 | 0 | 28 | 36 | 0.22 |
| | TOTAL | 55 | 10 | 35 | 100 | |
| | Omission Error | 0.18 | 0.20 | 0.20 | | 0.19 |

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1440 **Table D.2** Error matrices for Taskinas Creek based on 100 random sample points. The upper
 1441 matrix displays the model results using the vegetation algorithm (**TMM_VEG**); the lower matrix
 1442 display model outputs using a roughness factor (**TMM_RF**). Each point was used to evaluate if
 1443 the current marsh conditions at that location agree with the conditions predicted by the model.
 1444 Bold numbers in the diagonal represents the counts where model outputs and current conditions
 1445 agree.
 1446
 1447

| TASKINAS CREEK | | CURRENT TIDAL MARSH INVENTORY | | | | |
|------------------------------------|----------------|--------------------------------------|------------|------------|------------|-----------------|
| | | No Change | Marsh Gain | Marsh Loss | TOTAL | Comission Error |
| TIDAL MARSH MODEL (TMM_VEG) | No Change | 50 | 5 | 7 | 62 | 0.19 |
| | Marsh Gain | 1 | 19 | 0 | 20 | 0.05 |
| | Marsh Loss | 5 | 0 | 13 | 18 | 0.28 |
| | TOTAL | 56 | 24 | 20 | 100 | |
| | Omission Error | 0.11 | 0.79 | 0.35 | | 0.18 |

| TASKINAS CREEK | | CURRENT TIDAL MARSH INVENTORY | | | | |
|-----------------------------------|----------------|--------------------------------------|------------|------------|------------|------------------|
| | | No Change | Marsh Gain | Marsh Loss | TOTAL | Commission Error |
| TIDAL MARSH MODEL (TMM_RF) | No Change | 48 | 5 | 6 | 59 | 0.19 |
| | Marsh Gain | 3 | 16 | 0 | 19 | 0.16 |
| | Marsh Loss | 8 | 0 | 14 | 22 | 0.36 |
| | TOTAL | 59 | 21 | 20 | 100 | |
| | Omission Error | 0.19 | 0.24 | 0.30 | | 0.22 |

1448

1449 Where Kappa statistic (K):

1450

1451
$$K = \frac{N \sum_{i=1}^k x_{ii} - \sum_{i=1}^k (x_{i1} + X x_{+i})}{N^2 - \sum_{i=1}^k (x_{i1} + X x_{+i})}$$

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1457 **Appendix E. Marsh sediment fraction distributions**

1458 Comparison between model outputs and field observations using the roughness factor (RF) to
 1459 determine marsh presence, and the vegetation algorithm (VEG).
 1460

| | | Mean Absolute Error (MAE) | Observations Standard Deviation Ratio (RSR) | Nash Sutcliffe Efficiency (NSE) | Willmott Modified Index of Agreement |
|----------------|------|---------------------------|---|---------------------------------|--------------------------------------|
| | | RF / VEG | RF / VEG | RF / VEG | RF / VEG |
| Carter Creek | Sand | 0.08 / 0.08 | 0.43 / 0.43 | 0.81 / 0.82 | 0.86 / 0.87 |
| | Mud | 0.08 / 0.08 | 0.43 / 0.43 | 0.81 / 0.82 | 0.86 / 0.87 |
| Taskinas Creek | Sand | 0.1 / 0.1 | 0.61 / 0.62 | 0.62 / 0.62 | 0.83 / 0.82 |
| | Mud | 0.1/ 0.1 | 0.61/ 0.62 | 0.62 / 0.62 | 0.83 / 0.82 |

1461

1462 Where:

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n} \sum_{i=1}^n |P_i - O_i|$$

Willmott Modified Index of Agreement (dr)

$$d_r = \begin{cases} 1 - \frac{\sum_{i=1}^n |P_i - O_i|}{c \sum_{i=1}^n |O_i - \bar{O}|}, & \text{when} \\ \sum_{i=0}^n |P_i - O_i| \leq c \sum_{i=0}^n |O_i - \bar{O}| \\ \frac{c \sum_{i=1}^n |O_i - \bar{O}|}{\sum_{i=1}^n |P_i - O_i|} - 1, & \text{when} \\ \sum_{i=0}^n |P_i - O_i| > c \sum_{i=0}^n |O_i - \bar{O}| \end{cases}$$

Nash_Sutcliffe Efficiency (NSE)

$$NSE = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2}$$

Observations Standard Deviation Ratio (RSR)

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^n (O_i - P_i)^2} \right]}{\left[\sqrt{\sum_{i=0}^n (O_i - \bar{O})^2} \right]}$$

1463

1464 **Appendix F. Interpretation of the model performance measures – Levels of**
 1465 **agreements.**
 1466

| | | | | | | |
|---|----------------------------|-------------------|-------------------|---|-----------------------|--------------------------|
| | Less than chance agreement | Slight agreement | Fair agreement | Moderate agreement | Substantial agreement | Almost perfect agreement |
| Kappa Statistic ¹ | <0 | 0.01-0.20 | 0.21-0.40 | 0.41-0.60 | 0.61-0.80 | 0.81-0.99 |
| | Unsatisfactory | Satisfactory | Good | Very Good | | |
| NSE ² | < 0.50 | 0.50 < NSE < 0.65 | 0.65 < NSE < 0.75 | 0.75 < NSE < 1.0 | | |
| RSR ³ | > 0.70 | 0.60 < RSR < 0.70 | 0.50 < RSR < 0.60 | 0.00 < RSR < 0.50 | | |
| | | Possible values | Optimal value | Preferred values | | |
| MAE ⁴ | | 0 to ∞ | 0 | Low values | | |
| Willmott index of agreement ^{4,5} | | 0 to 1 | 1 | 0.5 to 1.0 ⁶ > 0.8 ⁷ | | |

1467
 1468 Based on: ¹Viera and Garret, 2005; ²Moriasi et al. 2007; ³Singh et al. 2004; ⁴Bennett et al.2013;
 1469 ⁵Willmott et al. 2012; ⁶Machiwal and Jha 2015; ⁷De Jager 1994.
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1478 **Appendix G – Change in Elevation of the Marsh Platform**

1479 **Table G.1** Change in elevation of the marsh platform computed at each sampled point in **Carter**
 1480 **Creek** using the **TMM_RF**. The dominant process is identified in each point along the transects
 1481 (i.e., high marsh = H; medium marsh = M, and low marsh = L).
 1482

| ID (Marsh Cores) | Elevation Change in 40 yrs (mm) | Elevation Change per year (mm/yr) | Location of the core | Dominant Process |
|------------------------|---------------------------------------|--|-------------------------|---------------------|
| 1 | 0.0 | 0.0 | L | no change |
| 2 | 0.0 | 0.0 | M | no change |
| 3 | 0.0 | 0.0 | H | no change |
| 4 | 0.0 | 0.0 | L | no change |
| 5 | 0.0 | 0.0 | M | no change |
| 6 | 0.0 | 0.0 | H | no change |
| 7 | -1131.8 | -28.3 | L | erosion |
| 8 | 4.2 | 0.1 | M | deposition |
| 9 | 0.7 | 0.0 | H | deposition |
| 10 | -134.1 | -3.4 | L | erosion |
| 11 | -861.5 | -21.5 | M | erosion |
| 12 | -710.7 | -17.8 | H | erosion |
| 13 | -832.8 | -20.8 | L | erosion |
| 14 | -300.4 | -7.5 | M | erosion |
| 15 | -687.3 | -17.2 | H | erosion |
| 16 | -253.4 | -6.3 | L | erosion |
| 17 | -223.0 | -5.6 | M | erosion |
| 18 | -529.9 | -13.2 | H | erosion |
| 19 | -106.9 | -2.7 | L | erosion |
| 20 | 20.2 | 0.5 | M | deposition |
| 21 | 0.0 | 0.0 | H | no change |
| 22 | 149.8 | 3.7 | L | deposition |
| 23 | 0.0 | 0.0 | M | no change |
| 24 | 0.0 | 0.0 | H | no change |
| 25 | 0.0 | 0.0 | L | no change |
| 26 | 0.0 | 0.0 | M | no change |
| 27 | 0.0 | 0.0 | H | no change |
| 28 | -776.1 | -19.4 | L | erosion |
| 29 | -5.0 | -0.1 | M | erosion |
| 30 | -118.8 | -3.0 | H | erosion |
| 31 | 234.7 | 5.9 | L | deposition |
| 32 | -0.2 | 0.0 | M | erosion |
| 33 | 0.0 | 0.0 | H | no change |

1483 **Table G.2** Change in elevation of the marsh platform computed at each sampled point in **Carter**
 1484 **Creek** using the **TMM_VEG**. The dominant process is identified in each point along the
 1485 transects (i.e., high marsh = H; medium marsh = M, and low marsh = L).
 1486

| ID (Marsh Cores) | Elevation Change in 40 yrs (mm) | Elevation Change per year (mm/yr) | Location of the core | Dominant Process |
|------------------------|--|--|----------------------------|---------------------|
| 1 | 0.0 | 0.0 | L | no change |
| 2 | 0.0 | 0.0 | M | no change |
| 3 | 0.0 | 0.0 | H | no change |
| 4 | 0.0 | 0.0 | L | no change |
| 5 | 0.0 | 0.0 | M | no change |
| 6 | 0.0 | 0.0 | H | no change |
| 7 | -418.5 | -10.5 | L | erosion |
| 8 | 4.4 | 0.1 | M | deposition |
| 9 | -4.3 | -0.1 | H | erosion |
| 10 | -23.5 | -0.6 | L | erosion |
| 11 | -611.1 | -15.3 | M | erosion |
| 12 | -603.1 | -15.1 | H | erosion |
| 13 | -313.3 | -7.8 | L | erosion |
| 14 | -258.0 | -6.4 | M | erosion |
| 15 | -552.6 | -13.8 | H | erosion |
| 16 | -175.6 | -4.4 | L | erosion |
| 17 | -110.3 | -2.8 | M | erosion |
| 18 | -170.5 | -4.3 | H | erosion |
| 19 | -41.1 | -1.0 | L | erosion |
| 20 | -2.1 | -0.1 | M | erosion |
| 21 | 0.0 | 0.0 | H | no change |
| 22 | 119.2 | 3.0 | L | deposition |
| 23 | 0.0 | 0.0 | M | no change |
| 24 | 0.0 | 0.0 | H | no change |
| 25 | 0.0 | 0.0 | L | no change |
| 26 | 0.0 | 0.0 | M | no change |
| 27 | 0.0 | 0.0 | H | no change |
| 28 | -255.6 | -6.4 | L | erosion |
| 29 | -6.2 | -0.2 | M | erosion |
| 30 | -74.4 | -1.9 | H | erosion |
| 31 | 238.6 | 6.0 | L | deposition |
| 32 | -0.1 | 0.0 | M | no change |
| 33 | 0.0 | 0.0 | H | no change |

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1488 **Table G.3** Change in elevation of the marsh platform computed at each sampled point in
 1489 **Taskinas Creek** using the **TMM_RF** simulations. The dominant process is identified in each
 1490 point along the transects (i.e., high marsh = H; medium marsh = M, and low marsh = L).

| ID (Marsh Cores) | Elevation Change in 40 yrs (mm) | Elevation Change per year (mm/yr) | Location of the core | Dominant Process |
|---------------------|---------------------------------------|--|-------------------------|---------------------|
| 1 | -5.4 | -0.1 | L | erosion |
| 2 | -5.2 | -0.1 | M | erosion |
| 3 | 17.3 | 0.4 | H | deposition |
| 4 | 0.0 | 0.0 | L | no change |
| 5 | 0.0 | 0.0 | M | no change |
| 6 | 0.0 | 0.0 | H | no change |
| 7 | 0.0 | 0.0 | L | no change |
| 8 | 0.0 | 0.0 | M | no change |
| 9 | 0.0 | 0.0 | H | no change |
| 10 | 492.2 | 12.3 | L | deposition |
| 11 | 0.0 | 0.0 | M | no change |
| 12 | 0.0 | 0.0 | H | no change |
| 13 | 305.0 | 7.6 | L | deposition |
| 14 | 177.0 | 4.4 | M | deposition |
| 15 | 0.0 | 0.0 | H | no change |
| 16 | 279.6 | 7.0 | L | deposition |
| 17 | 0.0 | 0.0 | M | no change |
| 18 | 0.0 | 0.0 | H | no change |
| 19 | -387.5 | -9.7 | L | erosion |
| 20 | 0.0 | 0.0 | M | no change |
| 21 | 104.6 | 2.6 | H | deposition |
| 22 | -0.5 | 0.0 | L | erosion |
| 23 | 0.0 | 0.0 | M | no change |
| 24 | 0.0 | 0.0 | H | no change |
| 25 | -559.9 | -14.0 | L | erosion |
| 26 | 0.0 | 0.0 | M | no change |
| 27 | 0.0 | 0.0 | H | no change |

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1495 **Table G.4** Change in elevation of the marsh platform computed at each sampled points in
 1496 **Taskinas Creek** using the **TMM_VEG** simulation. The dominant process is identified in each
 1497 point along the transects (i.e., high marsh = H; medium marsh = M, and low marsh = L).

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| ID (Marsh Cores) | Elevation Change in 40 yrs (mm) | Elevation Change per year (mm/yr) | Location of the core | Dominant Process |
|---------------------------------|--|--|-------------------------------------|-----------------------------|
| 1 | -1.9 | 0.0 | L | erosion |
| 2 | -4.3 | -0.1 | M | erosion |
| 3 | 6.9 | 0.2 | H | deposition |
| 4 | 0.0 | 0.0 | L | no change |
| 5 | 0.0 | 0.0 | M | no change |
| 6 | 0.0 | 0.0 | H | no change |
| 7 | 0.0 | 0.0 | L | no change |
| 8 | 0.0 | 0.0 | M | no change |
| 9 | 0.0 | 0.0 | H | no change |
| 10 | 608.7 | 15.2 | L | deposition |
| 11 | 0.0 | 0.0 | M | no change |
| 12 | 0.0 | 0.0 | H | no change |
| 13 | 157.2 | 3.9 | L | deposition |
| 14 | 68.0 | 1.7 | M | deposition |
| 15 | 0.0 | 0.0 | H | no change |
| 16 | -460.2 | -11.5 | L | erosion |
| 17 | 0.0 | 0.0 | M | no change |
| 18 | 0.0 | 0.0 | H | no change |
| 19 | -432.3 | -10.8 | L | erosion |
| 20 | 0.0 | 0.0 | M | no change |
| 21 | 112.6 | 2.8 | H | deposition |
| 22 | 0.1 | 0.0 | L | deposition |
| 23 | 0.0 | 0.0 | M | no change |
| 24 | 0.0 | 0.0 | H | no change |
| 25 | -307.8 | -7.7 | L | erosion |
| 26 | 0.0 | 0.0 | M | no change |
| 27 | 0.0 | 0.0 | H | no change |

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FIGURES

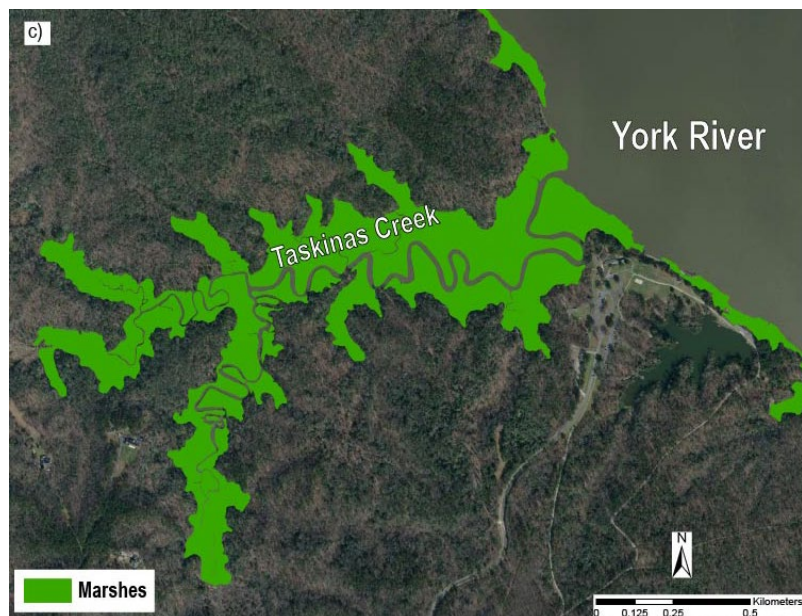
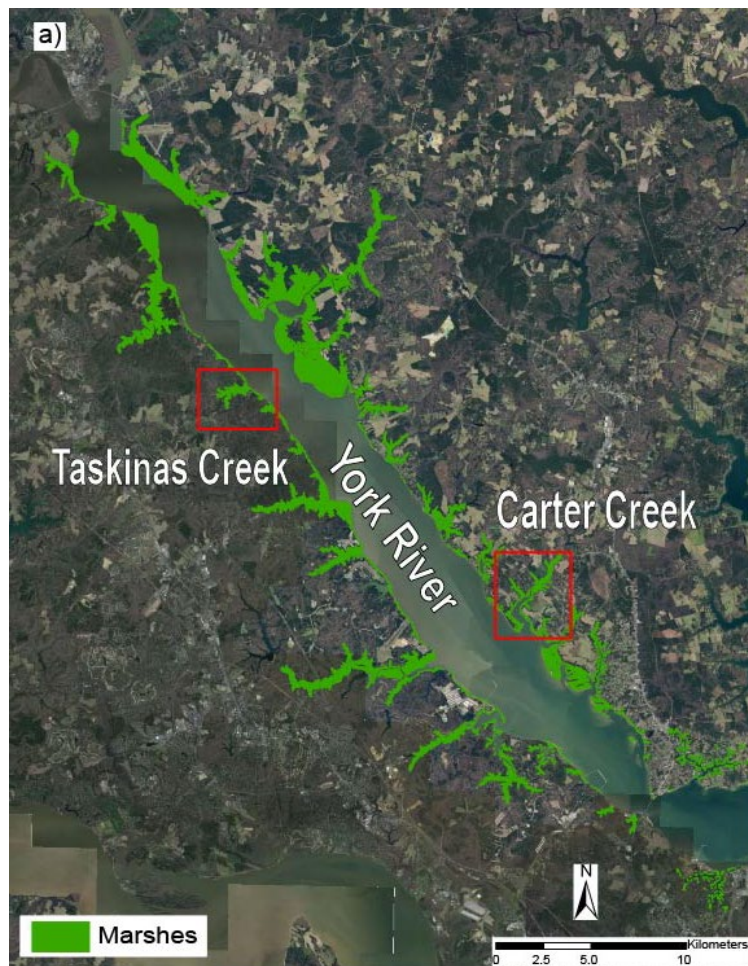


Fig. 1 a) York River system; b) Carter Creek and c) Taskinas Creek: study areas in the York River. Bright green areas represent tidal marshes. Background Image: VBMP2017/VBMP2017 WGS - Virginia Geographic Information Network (VGIN).

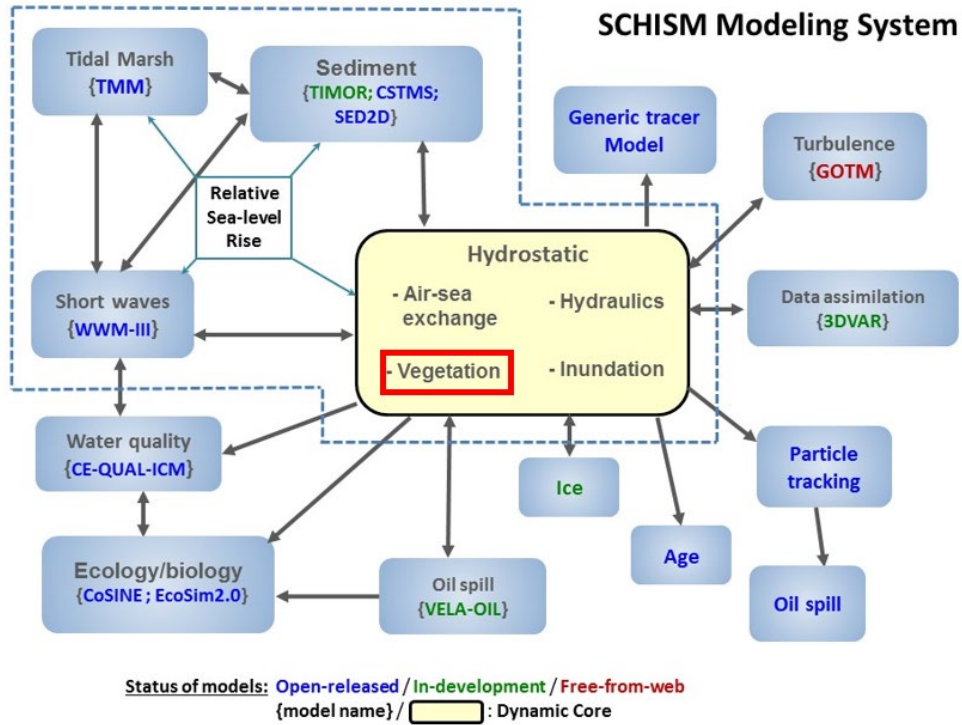


Fig. 2 SCHISM modeling system. The dashed box indicates key components of the TMM. The hydrostatic core serves as the pillar of the system to provide hydrodynamic variables to other models, as well as to facilitate exchange of variables between models in a parallel software environment

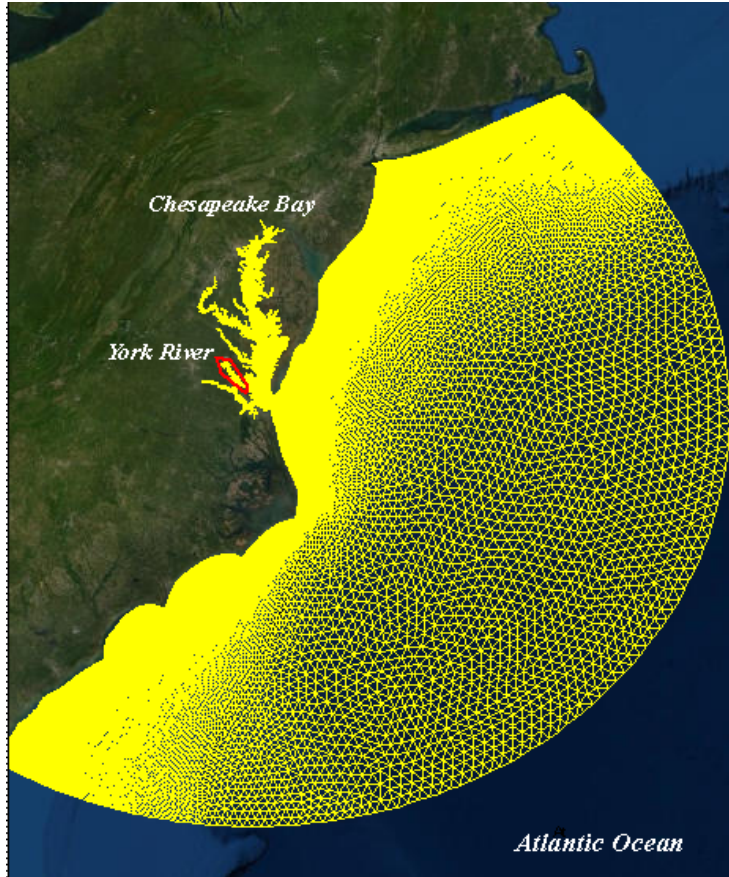


Fig. 3 Domain of the unstructured TMM_VEG grid used for the simulations in Carter Creek and Taskinas Creek. Background Image: ESRI world imagery

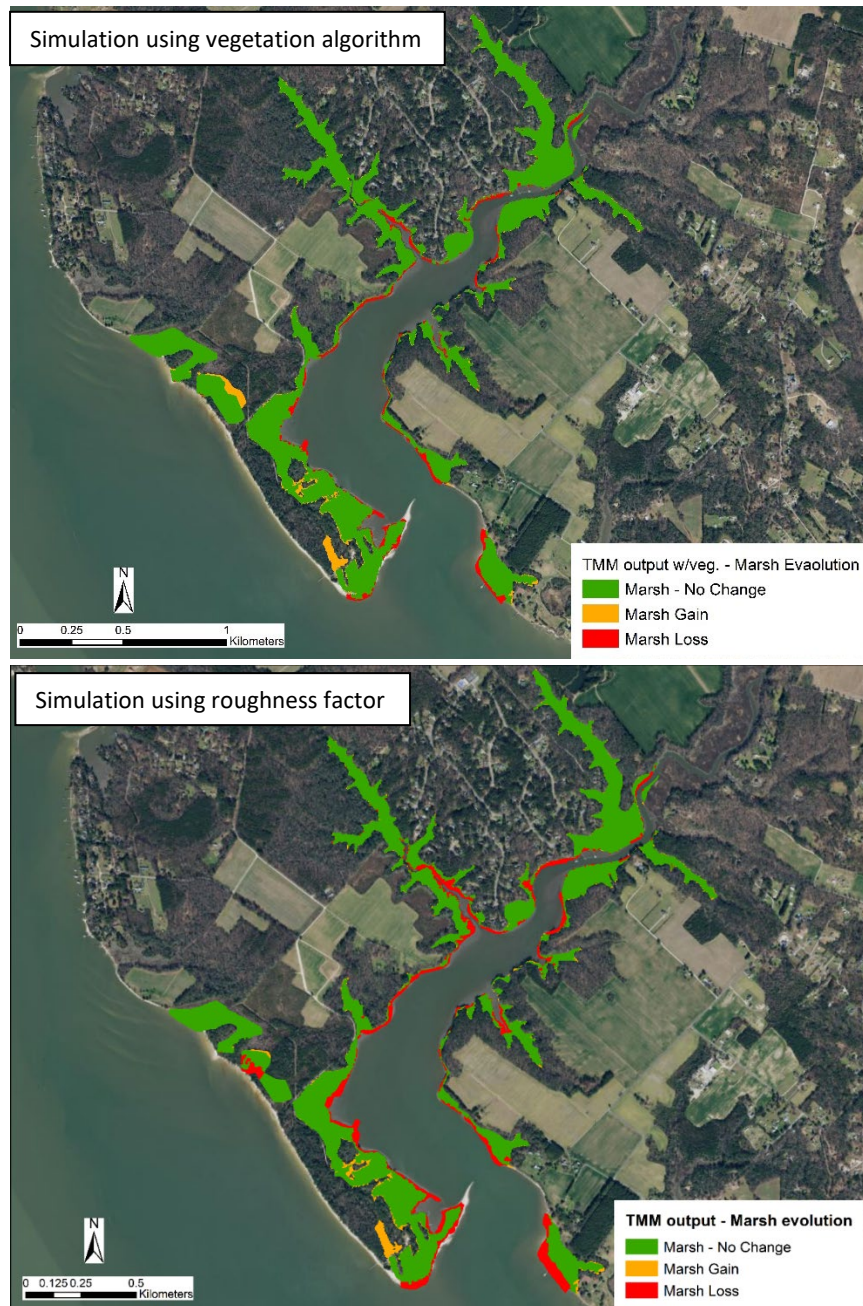


Fig. 4 Comparison of the marsh boundary evolution outputs for Carter Creek – Hindcast outputs: changes in marsh boundary after 40 years of simulation with a sea level rise of 4 mm/yr. Upper panel: **TMM_VEG**, Lower panel: **TMM_RF** simulations. Background image: VBMP2017/VBMP2017_WGS - Virginia Geographic Information Network (VGIN).



Fig. 5 Comparison of the marsh boundary evolution outputs for Taskinas Creek – Hindcast outputs: changes in marsh boundary after 40 years of simulation with a sea level rise of 4 mm/yr. Upper panel: **TMM_VEG**; Lower panel: **TMM_RF** simulations. Background image: VBMP2017/VBMP2017_WGS - Virginia Geographic Information Network (VGIN)

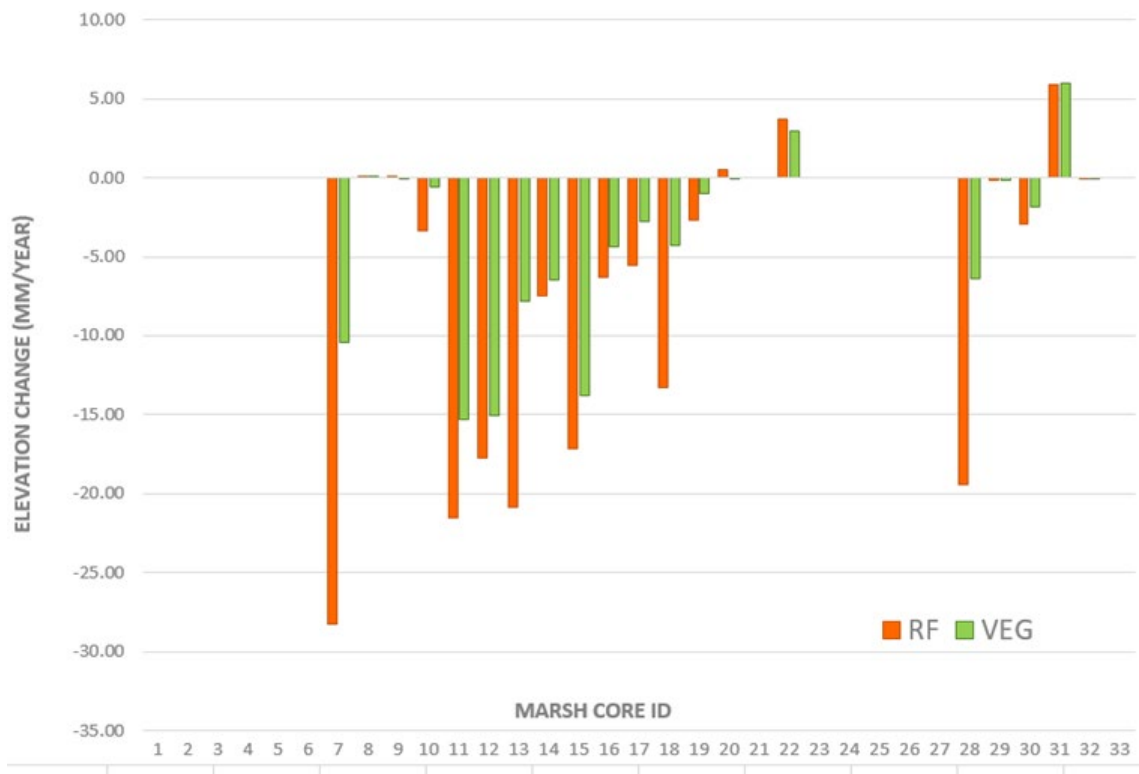


Fig. 6 Comparison of the changes in elevation of the marsh platform between the two simulations using the **roughness factor (RF)** and the **vegetation algorithm (VEG)** during the study period in Carter Creek. Positive numbers denote deposition, negative numbers correspond to erosion, and zero values indicate no change.

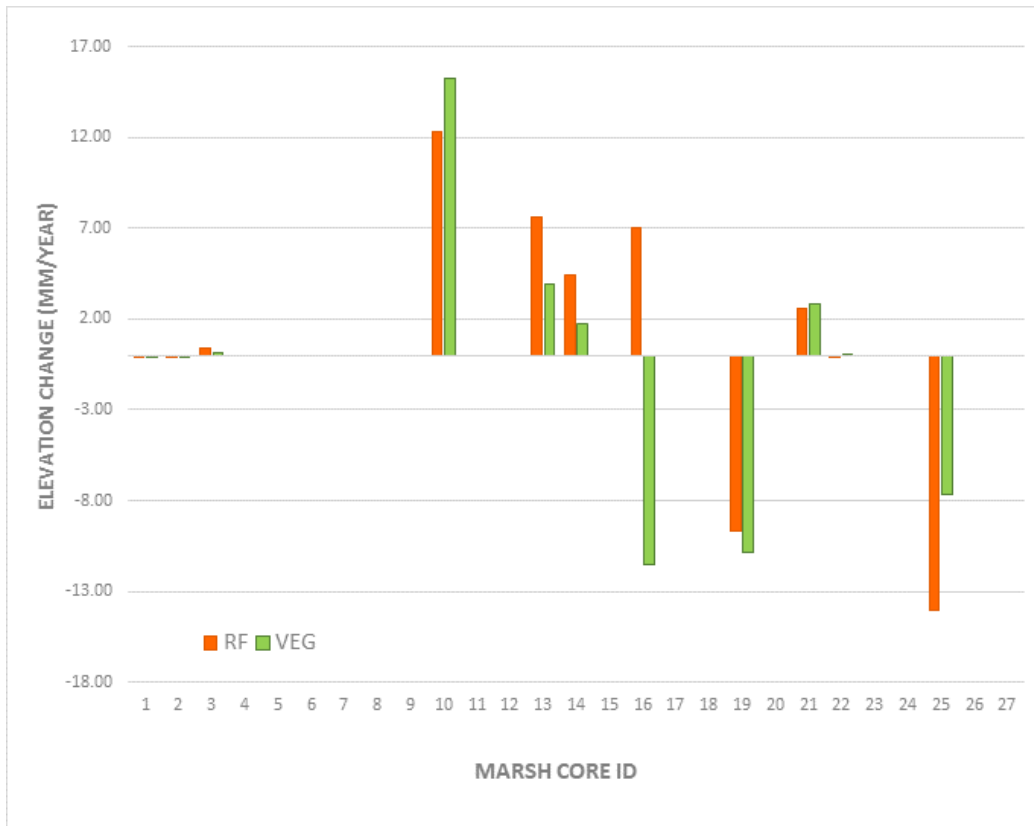


Fig. 7 Comparison of the changes in elevation of the marsh platform between the two simulations using the **roughness factor (RF)** and the **vegetation algorithm (VEG)** during the study period in Taskinas Creek. Positive numbers denote deposition, negative numbers correspond to erosion, and zero values indicate no change.

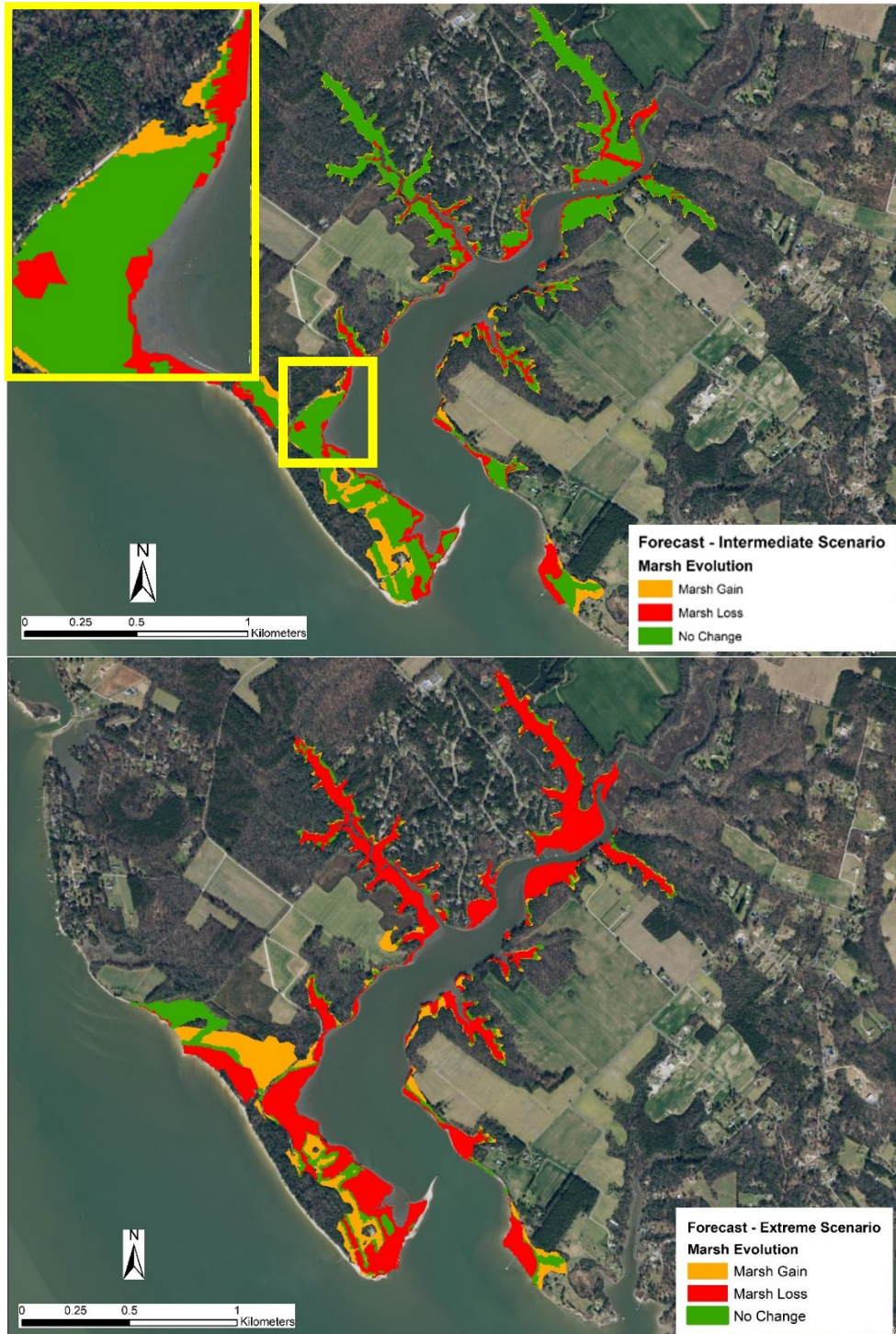


Fig. 8 Marsh boundary evolution output for Carter Creek. Forecast: 50-year simulation (2020-2070). Upper panel **intermediate SLR scenario** (an example of barriers for marsh landward migration is highlighted: presence of a road at the marsh-upland interface). Lower panel: **extreme SLR scenario**. Background image: VBMP2017/VBMP2017_WGS - Virginia Geographic Information Network (VGIN).



Fig. 9 Marsh boundary evolution output for Taskinas Creek. Forecast: 50-year simulation (2020-2070). Upper panel **intermediate SLR scenario**. Lower panel: **extreme SLR scenario**. Background image: VBMP2017/VBMP2017_WGS - Virginia Geographic Information Network (VGIN).