

Microtopographic Variation as a Potential Early Indicator of Ecosystem State Change and Vulnerability in Salt Marshes

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Abstract: As global climate change alters the magnitude and rates of environmental stressors,

predicting the extent of ecosystem degradation driven by these rapidly changing conditions

¹See also the discussion of the local government listed companies in the following section.

spatial variability and heterogeneity – indicators that can serve as potential early warnings of

declining ecosystem resilience. Increased spatial variability in salt marshes at the landscape scale

has been used to quantify the propagation of ponding in salt marsh interiors, but ponding at the

landscape scale follows a state change rather than predicts it. Here, we suggest a novel

application of commonly collected Surface Elevation Table (SET) data and explore millimeter

scale marsh surface microtopography as a potential early indicator of ecosystem transition. We

find an increase in spatial variability using multiple metrics of microtopographic heterogeneity

vulnerable salt marsh communities across the North American Atlantic seaboard. Increasing

microtopographic heterogeneity in vulnerable salt marshes mirrored increasing trends in variance

when a turning point is approached in other alternative stable state systems – indicating that as

warming signals of marsh drowning, and ecosystem transition are observable at small-spatial

scales prior to runaway ecosystem degradation. Congruence between traditional and novel

metrics of marsh vulnerability suggest that microtopographic metrics can be used to identify

hidden vulnerability before widespread marsh degradation. This novel analysis can be easily

25 applied to existing SET records expanding the traditional focus on vertical change to additionally
26 encapsulate lateral processes.

27 Keywords: wetland vulnerability, microtopography, ecosystem state change, sea-level rise
28 Acknowledgements: Primary funding for this work comes from the USGS Ecosystem Mission
29 Area and Climate Research and Development Programs with additional support from the
30 National Science Foundation (#1654374, #1832221, and #2012670). Any use of trade, firm, or
31 product names is for descriptive purposes only and does not imply endorsement by the US
32 Government.

33 **Introduction**

34 Salt marshes provide critical ecosystem services, but are threatened by sea-level rise and
35 diminishing sediment availability that together lead to erosion and marsh submergence
36 (Hopkinson *et al.*, 2012; Temmerman *et al.*, 2013; Kirwan and Megonigal, 2013). Regional and
37 global assessments predict that sea-level rise (SLR) alone could lead to the loss of 20-50% of
38 marshes by the end of the century (Craft *et al.*, 2009; Kirwan *et al.*, 2016). On the other hand,
39 feedbacks between vegetation, inundation, and sediment transport allow some marshes to persist
40 with SLR as stable ecosystems for millennia (Kirwan and Megonigal, 2013). Predicting the fate
41 of tidal marshes to SLR is hotly debated (Kirwan *et al.*, 2016; Schuerch *et al.*, 2018; Tornqvist *et*
42 *al.*, 2021; Saintilan *et al.*, 2022), driven in part by the realization that early warning signals are
43 difficult to detect in systems with non-linear or “catastrophic” transitions (Wilson and Agnew
44 1992; Scheffer *et al.*, 2001).

45 The collapse of salt marshes is often expressed through the runaway growth of
46 unvegetated ponds that consist of shallow depressions filled with standing water and occur

47 within the marsh interior (Mariotti, 2016). The transition between stable, vegetated marsh and
48 unvegetated pond is abrupt, commonly irreversible, and driven by positive feedbacks that
49 separate them into two alternative states (Wang and Temmerman, 2013) Once ponds form,
50 positive biophysical and biochemical feedbacks expand the ponded area, which potentially leads
51 to permanent marsh loss (Stevenson *et al.*, 1985; DeLaune *et al.*, 1994; Mariotti and Fagherazzi,
52 2013; Mariotti, 2016; Himmelstein *et al.*, 2021). As ponds proliferate in the marsh landscape,
53 extensive pond networks decrease wetland stability through enhanced sediment export and
54 reduced sediment trapping (Stevenson *et al.*, 1985; Ganju *et al.*, 2013; Ganju *et al.*, 2017).

55 Salt marsh vulnerability assessments often rely on comparisons between the rate of SLR
56 and point-based measurements of marsh elevation change or vertical accretion rates (Reed 1995;
57 Raposa *et al.*, 2016). While these traditional methods capture vertical stability, they
58 underestimate spatio-temporal variability and neglect lateral processes, such as ponding, erosion,
59 and lateral migration, across the landscape (Kirwan *et al.*, 2016; Ganju *et al.*, 2017). Recent
60 modelling indicates that these neglected lateral dynamics are especially important as biophysical
61 feedbacks maintain marsh stability in the vertical direction but not the lateral direction (Mariotti
62 and Fagherazzi, 2013; Mariotti and Carr, 2014). Therefore, these traditional metrics of wetland
63 vulnerability neglect spatial dynamics that may be more representative of whole-ecosystem
64 resilience and offer clues to impending ecosystem transitions.

65 The Surface Elevation Table (SET) method is a global standard for assessing wetland
66 vulnerability to SLR through the monitoring of vertical elevation change (Cahoon *et al.*, 2006;
67 Webb *et al.*, 2013; Raposa *et al.*, 2016; Jankowski *et al.*, 2017; Saintilan *et al.*, 2022). The
68 method measures elevation change relative to a stable benchmark and is typically paired with an
69 artificial marker horizon (consisting of feldspar, clay, or sand) to capture the suite of biophysical

70 processes contributing to the gain (e.g. accretion, root expansion, soil dilation) and loss (e.g.
71 subsidence, erosion, compaction) of marsh elevation change through time (Callaway *et al.*,
72 2013). SET stations are used extensively; from 1997 to 2017 at least 985 SETs were installed
73 within the state of Louisiana, U.S. (Covington, 2020) and over 1,000 SET stations on the mid-
74 Atlantic U.S. coast were affected by Hurricane Sandy in 2012 (Yeates *et al.*, 2020).

75 SET stations have been utilized in numerous field studies (Baustian *et al.*, 2012;
76 Lovelock *et al.*, 2015; Blum *et al.*, 2021), coordinated wetland monitoring networks (Raposa *et*
77 *al.*, 2016; Jankowski *et al.*, 2017), and global reviews to quantify wetland vulnerability (Saintilan
78 *et al.*, 2022). However, the collected data are underutilized by focusing on solely the vertical
79 component. Because SET stations measure elevation at multiple discrete points within the same
80 local area through time, these stations additionally capture changes in the microtopography of the
81 marsh surface, though this metric is seldom employed or even analyzed (Smith *et al.*, 2022).
82 While the focus on the vertical component of SET records follows traditional understandings of
83 marsh vulnerability to SLR, analyzing changes to the variation within SET records may aid in
84 detecting early warning signals of wetland degradation prior to ecosystem state change.

85 Microtopography, the small scale variation in ground surface height (centimeter to
86 millimeter scale) over short spatial scales (meter scale), in wetland ecosystems is driven by
87 numerous abiotic and biotic drivers as well as the interactions between them (Fig. 1a; Diamond
88 *et al.*, 2021). While these numerous drivers create a spatially complex surface microtopography,
89 climate change imparts directional changes on these drivers to have cascading changes to
90 microtopography (Fig. 1a). Similar dynamics can be seen at the landscape scale, where
91 accelerating rates of SLR are homogenizing not just the landscape diversity of marshes, but also
92 the topography (Mariotti *et al.*, 2020; Schepers *et al.*, 2020). As ponds dominate the landscape,

93 average elevation of the landscape falls because ponds exist as a stable alternative state at lower
94 elevations (Watson *et al.*, 2017; Schepers *et al.*, 2020). However, the distribution of landscape-
95 averaged elevation is non-stationary as the elevation variance of the landscape initially increases
96 during the transition period between alternative stable states (Schepers *et al.*, 2020; Wang *et al.*,
97 2021). We hypothesized that wetland microtopographic variation will similarly increase in these
98 highly vulnerable ecosystems (Fig. 1b). Uniquely, while this variance is likely to follow the same
99 pattern during the “catastrophic”, non-linear transition between alternative states (Wilson and
100 Agnew, 1992; Scheffer *et al.*, 2001), increasing microtopographic variation may serve as an
101 early warning signal of ecosystem state change.

102 To examine whether microtopography can be used as a novel indicator of vulnerability
103 and to explore if microtopographic variation could be an early indicator of ecosystem state
104 change in salt marshes, we analyzed changes in four metrics of microtopographic variation
105 across ~14 years of SET data from 20 SET stations across the U.S. mid-Atlantic coast and
106 Northeast. Here, we show that these four metrics of changing microtopographic variation
107 correlate with traditional metrics of wetland vulnerability and that these microtopographic
108 metrics may be an early warning indicator of state change in wetlands that are likely to be
109 vulnerable to future rates of SLR.

110 **Methods**

111 *Approach*

112 Eight tidal salt marshes along the Atlantic Coast of the United States, ranging across
113 Virginia at the southern extent and Maine at the northern extent, were selected for study.
114 Specifically, we examined salt marshes within Saxis Wildlife Management Area (SX) in

115 Virginia, Fishing Bay Wildlife Management Area (FB8), Blackwater National Wildlife Refuge
116 (BW7), the Smithsonian Environmental Research Center at Hogs Island (HI), and Eastern Neck
117 National Wildlife Refuge (EN) in Maryland, Bombay Hook National Wildlife Refuge (BH) in
118 Delaware, Great Meadows National Wildlife Refuge (GM) in Connecticut, and Rachel Carson
119 National Wildlife Refuge (RC) in Maine (Fig. 2). Within this extent the 50-year averaged rates
120 of SLR ranged from 4.00 mm y^{-1} in Virginia (SX), where rates were twice as high as eustatic
121 rates (~ 2 mm y^{-1}), to 1.90 mm y^{-1} in Maine (RC) (Table 1). Porewater salinity at these sites
122 ranged between 8.9-19.9 ppt (Guntenspergen et al., 2023; Table 1). The unvegetated to vegetated
123 ratio (UVVR) of marsh vegetation within these sites, specifically the 100 m² area surrounding
124 the SET stations, ranged from 0.94, which indicates nearly complete unvegetated marsh, to
125 0.001, indicating near ubiquitous vegetated marsh (Saintilan et al., 2022; Table 1).

126 At each of these reserves, two surface elevation stations (SETs) were installed within salt
127 marshes to monitor elevation changes driven by SLR with the exception of FB8 and BW7 where
128 four SETs each were installed, which are distinguished through the addition of A or D after the
129 site identification labels (Table 1). SET stations are comprised of a deep rod SET marker that is
130 installed deep into wetland soils until reaching refusal to which a receiver is attached. The SET
131 arm can be affixed to the receiver and then rotated to four of eight permanent positions on the
132 receiver. The SET is a portable device that provides repeatable, high-precision measurements of
133 relative elevation change at consistent locations within coastal wetlands. This portable
134 instrument extends horizontally over the marsh surface and from this extended arm, eight pins at
135 fixed points along the instrument are lowered to the marsh soil surface and the heights of those
136 pins above the arm are measured. At the next measurement event, these pins reoccupy the same
137 location on the wetland surface and are measured again. This repetitive measurement monitored

138 through time examines changes to marsh surface elevation. Pin lengths are not measured if the
139 marsh surface is obstructed, such as by wrack deposits or ice deposits. The footprint of an SET is
140 approximately 0.7 m² with pin lengths measured over four ~30 cm subsections of the footprint.
141 See Lynch *et al.*, (2015) for extended details about SET instrumentation.

142 Most SET stations were installed in 2005 with the first measurement taken between July
143 to September of 2005, except for SX, GM, and RC, which were installed in 2006 and were first
144 sampled in March and May of 2006. The eight marshes that we analyzed in this study were
145 established by the U.S. Geological Survey in 2005, to develop a geographically broad network of
146 coastal elevation monitoring stations with standard monitoring protocols to determine how
147 coastal wetland surface elevations respond to sea-level rise and nutrient addition. Because
148 of the long-term nature of the study, sites were established in federal, or state protected preserves
149 which included national wildlife refuges (EN, BW, BH, GM, and RC), state wildlife
150 management areas (FB, SX), and the Smithsonian Environmental Research Center (HI). Only the
151 control plots at each site were chosen for this study. All SETs were monitored with the same
152 frequency for at least 13.5 years with collection dates occurring within 1-2 months of each other
153 across the sites. SETs were measured at least twice yearly until 2008 after which SETs were
154 measured once per year until 2019. SET stations were mostly installed above the site specific
155 mean high water, except for the two SETs at BW7 which were 0.28 to 0.11 m below mean high
156 water and, as sites, had limited land above mean high water. When installed, the dominant
157 vegetation at most sites was either *Spartina patens*, *Distichlis spicata*, or *Schoenoplectus*
158 *americanus* except for at RC where one SET was located within *Glaux maritima*. Vegetation
159 density and changes to both density and species were not recorded through time.

160 *Traditional Vulnerability Metric: Elevation Change Deficit*

161 Elevation change was calculated by averaging the rate of elevation change for each pin
162 (n=28-32) within a SET through time. Cumulative elevation trends were regressed at the pin
163 level to increase precision and to consider serial autocorrelation. This method results in
164 approximately 30 estimates of linear trends that were then averaged to the entire station to get
165 one, average rate of elevation change. Comparison of surface elevation change rates to the rate of
166 local SLR allowed for the calculation of the elevation change deficit (Cahoon *et al.*, 1995). Since
167 the 1990s, elevation change deficits have been the benchmark for determining submergence
168 potentials of wetland ecosystems (Cahoon *et al.*, 1995; Cahoon *et al.*, 2006; Cahoon, 2015;
169 Lovelock *et al.*, 2015; Saintilan *et al.*, 2022; Steinmuller *et al.*, 2022). The general equation for
170 elevation change deficit is:

171 $E_{def} = E_c - SLR$

172 Where E_c is the rate of elevation change (mm y^{-1}) and SLR is the local rate of SLR (SI Table 1).
173 We utilized the 50-year averaged rate of SLR (mm y^{-1}) because it was found to be the greatest
174 predictor of vertical accretion (Saintilan *et al.*, 2022). Rates of SLR were derived from the
175 nearest National Oceanic and Atmospheric Administration (NOAA) tidal gauge with at least a
176 50-year record of sea-level. Typically, a marsh is considered vulnerable if the elevation change
177 deficit is negative, which indicates that the measured elevation change rate is less than the
178 selected rate of SLR. However, it should be noted that the time period over which rates of SLR
179 are calculated can change vulnerability interpretation (Saintilan *et al.*, 2022). For example,
180 elevation deficits calculated with SLR rates averaged over recent, shorter durations are typically
181 more negative (i.e. indicating higher wetland vulnerability) because eustatic SLR rates are
182 generally accelerating.

183 *Novel SET-derived Microtopographic Vulnerability Metrics*

184 Field measurements of microtopography consisted of pin length measurements taken
185 along the SET arm. Our SET arm consisted of eight fixed points approximately 4 cm apart from
186 which pins were lowered to the sediment surface and length was measured. The SET arm was
187 rotated 90 degrees around the anchored center of the SET station and pin length was measured
188 along the arm following each rotation resulting in approximately 32 measures of relative
189 elevation (Fig. 3). Microtopography was quantified using four index measures: random
190 roughness (RR), tortuosity (T), elevation range (ΔH), and the surface area to map area ratio
191 (SA:MA). Random roughness is the standard deviation of all pin readings at a point in time
192 ($\sqrt{\frac{\sum(x_i - x_{\mu})}{n-1}}$) and is the most suitable indicator of water storage in local depressions (Kamphorst *et*
193 *al.*, 2000; Karstens *et al.*, 2016). Generally, random roughness describes the uniformity of the
194 elevation distribution. For the two-dimensional path along each arm, the ratio of the over-surface
195 distance to the corresponding straight-line path is referred to as tortuosity (Moser *et al.*, 2007;
196 Karstens *et al.*, 2016; Smith *et al.*, 2022) and is defined as

$$197 \sum \sqrt{((x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2)}/l$$

198 Where $(x_2 - x_1)$ and $(y_2 - y_1)$ are the respective distance in the x and y direction between
199 adjacent pins, $(z_2 - z_1)$ is the difference in measured pin length, and l is the straight-line path
200 length along the SET arm. This equation produces four tortuosity measurements per SET, one
201 measure of tortuosity along each arm replication, which were then averaged to the plot level. The
202 elevation range (ΔH) was calculated from the difference between the highest and lowest point
203 measured at the SET during a sampling period and represents the magnitude of difference
204 between extremes. SA:MA was calculated in a programming platform (Matlab version R2018b
205 by first using the *griddata* function). This function fits a surface to scattered elevation data by

206 interpolating a surface so that it passes through the data points and interpolates intermediate
207 values according to a triangulation-based natural neighbor interpolation. The interpolated surface
208 consists of a square surface encompassing the extent of the area that the SET arm covers with 32
209 interpolated values along each edge of the square for a total of 1024 interpolated points fitted to
210 the 32 loaded data points (Fig. 3). The surface area of the interpolated surface was then measured
211 (in Matlab using the *delauney* function), which created a 3-D Delauney triangulation from the
212 points within the interpolated surface and returned the indices of the triangles. Using these
213 indices, we then calculated the area of the individual triangles and the cumulative area of the
214 interpolated surface. Finally, dividing the surface area of the interpolated surface to the footprint
215 of the SET produced SA:MA. Tortuosity and SA:MA are both unitless ratios.

216 Microtopography of the marsh surface is likely to be variable between sites based off of
217 local biotic and abiotic factors (Diamond *et al.*, 2021). For example, crab herbivory has been
218 shown to create concave-convex surface formation while vegetation in hummock-hollow
219 formations can preferentially trap sediment and increase surface elevation (Stirling *et al.*, 2007;
220 Qiu *et al.*, 2019). Therefore, to relate microtopography to vulnerability, we focused on the
221 change in microtopography (SI Fig. 1). According to our hypothesis, we expected
222 microtopographic variation to increase as a vulnerable system becomes more degraded (Fig. 1).
223 Therefore to examine this hypothesis, we stipulated that these microtopographic metrics indicate
224 vulnerability if the linear change in microtopographic variation increased significantly during the
225 study period. Across all of these microtopographic metrics, increasing rates of change represent a
226 marsh surface that is generally increasing in roughness. We then compared vulnerability as
227 indicated by these microtopographic metrics to the elevation change deficit to examine the utility
228 of these novel microtopographic metrics as vulnerability indicators. Linear regressions were

229 fitted in Matlab and significance was tested using an F-statistic which tests the significance
230 between two datasets – here the modeled linear relationship and a population showing a null
231 hypothesis (i.e. stable microtopographic variation). Metrics that show significant changes in
232 microtopographic variability were then cataloged in the Marsh Vulnerability Report Card (Table
233 2).

234 **Results**

235 *Traditional Vulnerability Metric: Elevation Change Deficit*

236 Elevation change data from the 20 SET stations indicated that rates of elevation change
237 ranged from -7.8 to 5.9 mm y^{-1} over the duration of the records. Negative rates of elevation
238 change, or elevation loss, were recorded at only two SETs, FB8D4 and BW7D4 (-7.8 and -0.9
239 mm y^{-1} , respectively). All other elevation change rates were greater than zero, indicating
240 increasing surface elevation during the study period. Of these SETs, the average elevation
241 change rate was 3.4 mm y^{-1} ($\pm 1.2 \text{ mm y}^{-1}$, standard deviation) and was greatest at BH2 (5.9 mm
242 y^{-1}) (SI Table 1). The elevation change deficit, the difference between elevation change and the
243 50-year averaged rate of local SLR (SI Table 1), ranged from -11.7 m y^{-1} (FB8D4) to 2.2 mm y^{-1}
244 (BH2) (Fig. 4). Of the 20 SETs, seven had elevation change deficits significantly less than zero
245 (with an average and standard deviation of $-3.9 \pm 2.0 \text{ mm y}^{-1}$), seven SETs displayed elevation
246 change deficits not significantly different than zero ($-0.5 \pm 0.6 \text{ mm y}^{-1}$), and six SETs had
247 significant positive elevation change deficits ($1.5 \pm 0.5 \text{ mm y}^{-1}$) (Fig. 4). Based on these
248 elevation change deficits, we then classify our set of SETs into three categories: “vulnerable”,
249 where elevation change deficit is negative, “steady”, where the elevation change deficit is not
250 significantly different than zero, and “surplus” where the elevation change deficit is significantly
251 positive (Fig. 5).

252 *Novel SET-derived Microtopographic Vulnerability Metrics*

253 Initial measurements of microtopography during the first sampling period indicated
254 significant differences between SETs. For example, RR was highest at BW7D (1.2 mm),
255 approximately 2.5 times rougher than the site with the lowest RR (SX4, 0.5 mm). However, an
256 insignificant relationship was found between initial variability and change in microtopographic
257 variation across all metrics (linear regressions; RR: $R^2=0.07$, p -value = .25; T: $R^2=0.01$, p -
258 value = .62; ΔH : $R^2=0.03$, p -value = .41; SA:MA: $R^2=0.04$, p -value = .37). Sites where
259 microtopographic variability increased significantly were categorized as vulnerable. RR
260 increased at a rate significantly greater than zero across 12 SETs and consequently was the
261 microtopographic metric that identified the greatest number of sites as vulnerable (Fig. 5a; Table
262 2). Tortuosity increased at a significant rate at eight SETs, all of which were also indicated as
263 vulnerable by RR (Fig. 5b; Table 2). At 11 SETs, ΔH increased at a significant rate. However,
264 two of these SETs (HI2 and HI3) were not indicated as vulnerable according to either the
265 tortuosity or RR metrics (Fig. 5c; Table 2). Finally, SA:MA increased at a significant rate at six
266 SETs (Fig. 3; Fig. 5d; Table 2). These SETs were indicated as vulnerable by all aforementioned
267 microtopographic variation metrics. Across all of these microtopographic metrics, positive rates
268 of change are associated with a marsh surface that is increasing in roughness generally (SI Fig.
269 1).

270 **Discussion**

271 *Comparing Microtopographic Vulnerability and Traditional Vulnerability Metrics*

272 Traditional analyses of wetland vulnerability utilizing SET data emphasize elevation
273 change deficits, the difference between the rates of elevation change and local SLR, as a primary

274 indicator of wetland vulnerability (van Wijnen and Bakker, 2001; Cahoon *et al.*, 2006; Kirwan
275 and Temmerman, 2009; Cahoon and Guntenspergen, 2010; Cahoon, 2015). According to this
276 traditional metric, seven of the SETs in this study are highly vulnerable to SLR while the other
277 SETs are keeping pace with SLR (seven SETs) or increasing in elevation faster than the rate of
278 SLR (six SETs) (Fig. 4, Fig. 5, SI Table 1). The collated novel metrics of changing
279 microtopographic variation examined indicated similar results: six of the SETs indicate potential
280 vulnerability according to all four metrics, eight were categorized as potentially vulnerable by
281 one, two, or three metrics, and six were identified as potentially stable ecosystems (Table 2).
282 While a limited sample size prevents the application of significant statistical regressions between
283 the novel and traditional vulnerability metrics, six out of the seven SETs indicated by traditional
284 metrics as highly vulnerable were positively identified as vulnerable by all novel
285 microtopographic metrics (Fig. 6). This result suggests that microtopographic variation can be
286 used to assess vulnerability in those wetlands that are at high risk of drowning from SLR. Of the
287 SETs where the elevation change was approximately equal to the 50-year averaged rate of SLR,
288 five out of the seven SETs were indicated as vulnerable by at least one microtopographic metric
289 (Fig. 5, Fig. 6). This result could indicate that while these sites are keeping up with historic rates
290 of SLR, modern rates may be exceeding marsh stability and increasing ecosystem degradation or
291 an independent driver not captured in our dataset may be affecting microtopography, such as
292 shifts in vegetation or herbivory (Fig. 1). Of the six sites with positive elevation change deficits
293 and not considered vulnerable to SLR, two SETs were categorized as vulnerable by at least one
294 microtopographic metric (Fig. 6). Without additional information regarding biomass density or
295 vegetation shifts, it is impossible to determine if these indicators are false positives or indicators
296 of a hidden vulnerability not captured in the elevation change deficit. For example, because

297 microtopography is greatly affected by vegetation morphology and density, changing
298 microtopography could be driven by SLR induced recovery time reductions or by independent
299 changes in plant community (Bertness *et al.*, 1992; Diamond *et al.*, 2021). Additionally, abiotic
300 drivers like wrack deposition and sediment accumulation can both increase variance or
301 homogenize the marsh surface (Werner and Zedler, 2002). The limitations of this dataset prevent
302 the examination of these co-occurring drivers, but the general congruence between
303 microtopographic and elevation deficit relative to sea-level rise indicates that microtopographic
304 changes can be used as a proxy for wetland vulnerability. A holistic model that integrates both
305 traditional and novel microtopographic metrics as well as information regarding changes in
306 vegetation density and species that affect both metrics may best encapsulate wetland
307 vulnerability. Additionally, examining these changes in SET records that span the entire
308 transition from the vegetated to ponded ecosystem states would better reveal how early
309 microtopography can detect decreased vulnerability and therefore further resolve some of these
310 potential false positives.

311 While the temporal and statistical limitations of this dataset prevent the definitive
312 identification of changing microtopographic variation as an early indicator of imminent state
313 change, we argue that the utility of microtopographic variation extends beyond traditional
314 vulnerability metrics. For example, marshes in Plum Island Estuary, Massachusetts (42.717, -
315 70.826) have low sediment budgets, limited area for landward migration, and negative elevation
316 change deficits – all of which indicate high vulnerability to accelerating SLR (Farron *et al.*,
317 2020; Langston *et al.*, 2020). However, despite this perceived vulnerability, ponding in Plum
318 Island marshes has been historically stable (Wilson *et al.*, 2014) and marsh extent is forecasted to
319 be largely maintained through 2100 (Langston *et al.*, 2021; Farron *et al.*, 2020). Eventually, as

320 the elevation change deficit reduces the elevation capital and lowers the marsh surface within the
321 tidal frame, ponding will likely propagate throughout the landscape (Duran Vinent et al., 2021;
322 Himmelstein et al., 2021), but elevation change deficit cannot predict these sudden changes as it
323 already classified the marsh as vulnerable far prior to a critical ponding threshold (Langston *et*
324 *al.*, 2021). Microtopography, specifically rapid increases in microtopographic variation, could be
325 a more useful early indicator of this sudden state change, which is critical for rapid management
326 actions in preserving these valuable, yet vulnerable ecosystems (Neijnens et al., 2021).
327 Therefore, integrating these traditional metrics with these novel microtopographic metrics could
328 bridge vulnerability assessments examining slow gradual drowning with fine-scale analyses
329 predicting sudden state change.

330 *Temporal and Spatial Scaling of Microtopography*

331 Microtopography is driven directly by abiotic and biotic drivers that are influenced by
332 climate forcing (Diamond *et al.*, 2021). Because of this cascading relationship, changes in
333 microtopographic variation may be more sensitive to alterations to the climate than metrics like
334 average vertical elevation change, which can be affected by events, such as storms and fires, but
335 is a factor of dynamic biophysical feedbacks that operate at the decadal scale (Törnqvist *et al.*,
336 2021). Low-magnitude early indicators of abrupt ecosystem state changes may be homogenized
337 in the decadal sediment record (Fagherazzi *et al.*, 2012). In contrast to this method, high
338 resolution microtopography responds directly to biotic and abiotic changes that portend
339 ecosystem state change, such as slower plant recovery or decreased belowground biomass, and
340 may be valid as an early indicator of ecosystem degradation (Stribling *et al.*, 2007; van Belzen *et*
341 *al.*, 2017; Diamond *et al.*, 2021). However, the high sensitivity of microtopography to these
342 factors creates noise even under stable conditions (Stribling *et al.*, 2007; Harman *et al.*, 2014).

343 Therefore, similar to elevation trends measured using SETs, equilibration time is likely required
344 to assess the magnitude of background fluctuations associated with a naturally variable living
345 marsh surface (Lynch *et al.*, 2015; Blum *et al.*, 2021). While measuring microtopography over
346 decadal periods can reveal general trends, limiting microtopographic variation to annual
347 measurements may overemphasize temporary changes and homogenize short-term
348 microtopographic cycles and negative feedbacks (Smith *et al.*, 2022). Ultimately, the extended
349 application of these microtopographic vulnerability metrics described herein to regional and
350 global SET datasets could potentially strengthen the possibility of microtopography as an early
351 indicator of state change.

352 Elevation change deficits calculated at SET stations have been scaled-up to represent
353 vulnerability of entire ecosystems and regions (Cahoon *et al.*, 2002; Wasson *et al.*, 2019). The
354 spatial dependent nature of microtopographic measurements prevents similar direct scaling, but
355 spatial heterogeneity can be measured at the landscape scale using LIDAR based digital
356 elevation models (or DEMs) (Doughty *et al.*, 2021). For the past 20 years, many studies have
357 used LIDAR to remotely sense ground elevation over large areas, but salt marsh vegetation
358 structure and instrument error make it difficult to detect meaningful differences in elevation
359 across the landscape at the microtopographic scale (Hladik and Alber, 2012). While recent
360 advances in error correction can reduce error – for example reducing mean error from 0.16 m to
361 0.004 m (McClure *et al.*, 2015) – centimeter-scale horizontal resolutions homogenize across the
362 millimeter-scale topography of the marsh surface that SETs quantify. At intermediate spatial
363 scales (1-10 m) various methodologies exist to quantify topography, but coarse vertical
364 resolution (chain length, drone imagery, real-time kinematic global positioning system (RTK-
365 GPS) units), salt marsh vegetation (Terrestrial Laser Scanning), and a lack of long-term datasets

366 currently limits the comparison between this intermediate spatial resolution and the sub-
367 centimeter variance of the marsh surface.

368 The ratio of unvegetated to vegetated marsh (UVVR) has been suggested as an indicator
369 of marsh health where wetland complexes are stable below UVVR values of 0.10 to 0.15
370 (Wasson *et al.*, 2019; Ganju *et al.*, 2022). UVVR is quantified independently of SLR, similar to
371 microtopographic variation (Ganju *et al.*, 2017). However, the sensing of UVVR at the landscape
372 scale necessitates imagery with a coarse horizontal resolution (from 3-30 m), which neglects
373 ponds below this detection threshold (Ganju *et al.*, 2022). While the presence of larger ponds
374 does have implications about ecosystem-scale functions and vulnerability, the formation of large
375 ponds follows rather than precedes ecosystem state change (Duran Vinent *et al.*, 2021). Because
376 of this temporal difference, there is a lack of correlation between UVVR and the novel
377 microtopographic vulnerability metrics (SI Fig. 2). However, as the spatial and temporal
378 resolution of UVVR datasets improves and we assess the spatiotemporal UVVR dynamics,
379 comparisons of changing landscape heterogeneity with changing microtopographic variability
380 may support insights into the spatial scaling of microtopographic vulnerability metrics.

381 *Microtopographic Change as a Potential Early Indicator of Ecosystem Vulnerability*

382 “Critical slowing down” is an early warning signal for impending state changes where
383 the time required for a system to recover from a disturbance lengthens as the magnitude of
384 stressor applied increases and typically results in an increase in spatial heterogeneity and
385 stochasticity under applied stress (van Nes and Scheffer, 2007; Dakos *et al.*, 2008; van Belzen *et*
386 *al.*, 2017). In coastal wetlands, vegetation recovery to disturbance slows with increasing
387 inundation, thereby increasing the risk of marsh degradation (van Belzen *et al.*, 2017). Ponds and
388 stable wetlands display a markedly bimodal elevation distribution with a low proportion of

389 transitional, intermediary states within the marsh landscape and with little potential for
390 unvegetated ponds to become revegetated (Wang and Temmerman, 2013; Watson *et al.*, 2017;
391 Schepers *et al.*, 2020). Given the feedbacks that maintain ponds and marshes at their respective
392 stable equilibria, ponds and wetlands have been proposed to reflect alternative ecosystem states,
393 where early warning signals are critical for forecasting impending state changes prior to
394 landscape-scale changes.

395 While landscape heterogeneity can encapsulate the degree of ecosystem degradation,
396 changes in microtopographic variation potentially precede state change because
397 microtopography is highly sensitive to the abiotic and biotic drivers that experience critical
398 slowing down (van Belzen *et al.*, 2017; Diamond *et al.*, 2021). In wetlands, as vegetation
399 recovery rates decrease with increased inundation stress from rising sea-levels, a greater
400 proportion of the marsh platform is likely in or near a lower elevation degraded state following
401 disturbances (van Belzen *et al.*, 2017; Schepers *et al.*, 2020). Therefore, microtopographic
402 variation is expected to increase with inundation, making microtopography a potential leading
403 indicator of landscape-scale ecosystem state change. While similar fundamental biophysical
404 interactions between vegetation and morphology have been used to examine mechanisms that
405 stabilize marsh resilience to SLR (Kirwan and Megonigal, 2013), this study presents the novel
406 idea that changes in sub-meter scale topography can be used as an early indicator of looming
407 state change that can be detected prior to large scale state changes that would be captured with
408 traditional approaches to assessing wetland vulnerability.

409 *Applying Microtopographic Vulnerability Metrics*

410 While this study only reviewed SET records from 8 salt marshes along the U.S. mid-
411 Atlantic and Northeast coasts, the novel metrics described can be easily applied to existing SET

412 data records without requiring additional data collection or leveraged external variables, such as
413 SLR. Because traditional metrics rely on rates of SLR, the time frame over which SLR is
414 calculated can greatly change the perceived vulnerability of wetlands (Saintilan *et al.*, 2022).
415 Microtopography data collected from SETs can be analyzed within the context of previous
416 wetland conditions thereby making vulnerability relative to historical conditions of the marsh
417 surface rather than to external drivers. Additionally, while this study only examined salt marshes,
418 SETs are widely used in a number of coastal ecosystems, such as mangrove forests (Lovelock *et*
419 *al.*, 2015), tidal freshwater forests (Krauss *et al.*, *in review*), and mud flats (Marion *et al.*, 2009),
420 to quantify ecosystem vulnerability and could be implemented in peatlands where
421 microtopographic formations arise from climate induced feedbacks (Harris *et al.*, 2020). The
422 magnitude of microtopographic variation will differ among the various associated root structures,
423 plant morphologies, and substrate compositions between ecological settings (Diamond *et al.*,
424 2021), but the parabolic change in microtopography exemplified in Figure 1 will likely still
425 apply to ecosystem state transitions within these systems. In general, microtopography will be
426 altered if biotic or abiotic conditions change making this framework widely applicable to other
427 transitions such as fronts associated with the migration of primary consumers (Vu and Pennings,
428 2021), barrier island transgression over back-barrier marshes (FitzGerald *et al.*, 2018), and
429 warming driven vegetation shifts (i.e. shrubification (Mekonnen *et al.*, 2021) and mangrove
430 encroachment into marshes (Osland *et al.*, 2017)). While microtopographic heterogeneity is a
431 seldom used tool to predict or assess vulnerability, it can serve as an ecosystem vulnerability
432 metric that directly reflects key aspects of ecological theory that operate across ecosystem and
433 transition types.

434 *Conclusions and Implications*

435 While traditional applications of SET data have been used to assess wetland vulnerability
436 using a single vertical response parameter of central tendency (e.g., average; van Wijnen and
437 Bakker, 2001; Cahoon *et al.*, 2002, 2006; Kirwan and Temmerman, 2009; Cahoon and
438 Guntenspergen, 2010; Cahoon, 2015), marsh vulnerability should not be determined by a single
439 indicator (Kirwan *et al.*, 2016; Ganju *et al.*, 2017; Wasson *et al.*, 2019). More recent
440 vulnerability indexes synthesize multiple vertical and horizontal stability metrics into a holistic
441 assessment (Raposa *et al.*, 2016; Defne *et al.*, 2020; Ganju *et al.*, 2022); however the spatial
442 scale of these assessments homogenize the marsh surface at the microtopographic scale. Our
443 results indicate a correlation between increasing microtopographic variation and a traditional
444 wetland vulnerability metric (Fig. 6), suggesting that metrics of microtopography may serve as
445 early indicators of marsh degradation. These novel metrics could be applied to the catalog of
446 existing SET data records, which includes globally dispersed datasets that extend up to 30 years
447 into the past (Blum *et al.*, 2021; Saintilan *et al.*, 2022). This application could reveal if changing
448 microtopographic variability can be used as an early indicator of degradation generally. These
449 novel metrics in conjunction with traditional vulnerability metrics that emphasize vertical change
450 can facilitate a holistic assessment of current and predicted marsh vulnerability. Early detection
451 of marsh vulnerability to SLR is critical to predict imminent ecosystem state change and to take
452 management measures before irreversible degradation of these valuable coastal ecosystems
453 occurs.

454 References

455 Baustian, J. J., Mendelsohn, I. A., & Hester, M. W. (2012). Vegetation's importance in regulating surface
456 elevation in a coastal salt marsh facing elevated rates of sea level rise. *Global Change Biology*,
457 18, 3377–3382. <https://doi.org/10.1111/j.1365-2486.2012.02792.x>

458 Bertness, M. D., Gough, L., & Shumway, S. W. (1992). Salt tolerances and the distribution of fugitive salt
459 marsh plants. *Ecology*, 73, 1842–1851. <https://doi.org/10.2307/1940035>

460 Blum, L. K., Christian, R. R., Cahoon, D. R., & Wiberg, P. L. (2021). Processes influencing marsh elevation
461 change in low- and high-elevation zones of a temperate salt marsh. *Estuaries and Coasts*, 44,
462 818–833. <https://doi.org/10.1007/s12237-020-00796-z>

463 Cahoon, D. R. (2015). Estimating relative sea-level rise and submergence potential at a coastal wetland.
464 *Estuaries and Coasts*, 38, 1077–1084. <https://doi.org/10.1007/s12237-014-9872-8>

465 Cahoon, D. R., & Guntenspergen, G. R. (2010). Climate change, sea-level rise, and coastal wetlands.
466 *National Wetland Newsletter*. 32.

467 Cahoon, D. R., Hensel, P. F., Spencer, T., Reed, D. J., McKee, K. L., & Saintilan, N. (2006). Coastal wetland
468 vulnerability to relative sea-level rise: wetland elevation trends and process controls. In J. T. A.
469 Verhoeven, B. Beltman, R. Bobbink, & D. F. Whigham (Eds.), *Wetlands and Natural Resource
470 Management* (pp. 271–292). Springer. https://doi.org/10.1007/978-3-540-33187-2_12

471 Cahoon, D. R., Lynch, J. C., Perez, B. C., Segura, B., Holland, R. D., Stelly, C., Stephenson, G., & Hensel, P.
472 (2002). High-precision measurements of wetland sediment elevation: II. the rod surface
473 elevation table. *Journal of Sedimentary Research*, 72, 734–739.
474 <https://doi.org/10.1306/020702720734>

475 Cahoon, D. R., Reed, D. J., & Day, J. W. (1995). Estimating shallow subsidence in microtidal salt marshes
476 of the southeastern United States: Kaye and Barghoorn revisited. *Marine Geology*, 128, 1–9.
477 [https://doi.org/10.1016/0025-3227\(95\)00087-F](https://doi.org/10.1016/0025-3227(95)00087-F)

478 Callaway, J. C., Cahoon, D. R., & Lynch, J. C. (2013). The Surface Elevation Table–Marker Horizon Method
479 for Measuring Wetland Accretion and Elevation Dynamics. In *Methods in Biogeochemistry of*
480 *Wetlands* (pp. 901–917). John Wiley & Sons, Ltd. <https://doi.org/10.2136/sssabookser10.c46>

481 Craft, C., Clough, J., Ehman, J., Joye, S., Park, R., Pennings, S., Guo, H., & Machmuller, M. (2009).
482 Forecasting the effects of accelerated sea-level rise on tidal marsh ecosystem services. *Frontiers*
483 in *Ecology and the Environment*, 7(2), 73–78. <https://doi.org/10.1890/070219>

484 Dakos, V., Scheffer, M., van Nes, E. H., Brovkin, V., Petoukhov, V., & Held, H. (2008). Slowing down as an
485 early warning signal for abrupt climate change. *Proceedings of the National Academy of*
486 *Sciences*, 105(38), 14308–14312. <https://doi.org/10.1073/pnas.0802430105>

487 Defne, Z., Aretxabaleta, A. L., Ganju, N. K., Kalra, T. S., Jones, D. K., & Smith, K. E. L. (2020). A geospatially
488 resolved wetland vulnerability index: Synthesis of physical drivers. *PLOS ONE*, 15(1), e0228504.
489 <https://doi.org/10.1371/journal.pone.0228504>

490 DeLaune, R. D., Nyman, J. A., & Jr., W. H. P. (1994). Peat Collapse, Ponding and Wetland Loss in a Rapidly
491 Submerging Coastal Marsh. *Journal of Coastal Research*, 10(4), 1021–1030.

492 Diamond, J. S., Epstein, J. M., Cohen, M. J., McLaughlin, D. L., Hsueh, Y.-H., Keim, R. F., & Duberstein, J. A.
493 (2021). A little relief: Ecological functions and autogenesis of wetland microtopography. *WIREs*
494 *Water*, 8(1), e1493. <https://doi.org/10.1002/wat2.1493>

495 Doughty, C. L., Ambrose, R. F., Okin, G. S., & Cavanaugh, K. C. (2021). Characterizing spatial variability in
496 coastal wetland biomass across multiple scales using UAV and satellite imagery. *Remote Sensing*
497 in *Ecology and Conservation*, 7(3), 411–429. <https://doi.org/10.1002/rse2.198>

498 Duran Vinent, O., Herbert, E. R., Coleman, D. J., Himmelstein, J. D., & Kirwan, M. L. (2021). Onset of
499 runaway fragmentation of salt marshes. *One Earth*, 4(4), 506–516.
500 <https://doi.org/10.1016/j.oneear.2021.02.013>

501 Fagherazzi, S., Kirwan, M. L., Mudd, S. M., Guntenspergen, G. R., Temmerman, S., D'Alpaos, A., van de
502 Kopp, J., Rybczyk, J. M., Reyes, E., Craft, C., & Clough, J. (2012). Numerical models of salt marsh
503 evolution: Ecological, geomorphic, and climatic factors. *Reviews of Geophysics*, 50(1).
504 <https://doi.org/10.1029/2011RG000359>

505 Farron, S. J., Hughes, Z. J., & FitzGerald, D. M. (2020). Assessing the response of the Great Marsh to sea-
506 level rise: Migration, submersion or survival. *Marine Geology*, 425, 106195.
507 <https://doi.org/10.1016/j.margeo.2020.106195>

508 FitzGerald, D. M., J. Hein, C., Hughes, Z., Kulp, M., Georgiou, I., & Miner, M. (2018). Runaway Barrier
509 Island Transgression Concept: Global Case Studies. In L. J. Moore & A. B. Murray (Eds.), *Barrier*
510 *Dynamics and Response to Changing Climate* (pp. 3–56). Springer International Publishing.
511 https://doi.org/10.1007/978-3-319-68086-6_1

512 Ganju, N. K., Couvillion, B. R., Defne, Z., & Ackerman, K. V. (2022). Development and Application of
513 Landsat-Based Wetland Vegetation Cover and UnVegetated-Vegetated Marsh Ratio (UVVR) for
514 the Conterminous United States. *Estuaries and Coasts*, 45(7), 1861–1878.
515 <https://doi.org/10.1007/s12237-022-01081-x>

516 Ganju, N. K., Defne, Z., Kirwan, M. L., Fagherazzi, S., D'Alpaos, A., & Carniello, L. (2017). Spatially
517 integrative metrics reveal hidden vulnerability of microtidal salt marshes. *Nature*
518 *Communications*, 8(1), Article 1. <https://doi.org/10.1038/ncomms14156>

519 Ganju, N. K., Nidzieko, N. J., & Kirwan, M. L. (2013). Inferring tidal wetland stability from channel
520 sediment fluxes: Observations and a conceptual model. *Journal of Geophysical Research: Earth*
521 *Surface*, 118(4), 2045–2058. <https://doi.org/10.1002/jgrf.20143>

522 Harman, C. J., Lohse, K. A., Troch, P. A., & Sivapalan, M. (2014). Spatial patterns of vegetation, soils, and
523 microtopography from terrestrial laser scanning on two semiarid hillslopes of contrasting

524 lithology. *Journal of Geophysical Research: Biogeosciences*, 119(2), 163–180.

525 <https://doi.org/10.1002/2013JG002507>

526 Harris, L. I., Roulet, N. T., & Moore, T. R. (2020). Mechanisms for the development of microform patterns

527 in peatlands of the Hudson Bay lowland. *Ecosystems*, 23, 741–767.

528 <https://doi.org/10.1007/s10021-019-00436-z>

529 Himmelstein, J., Vincent, O. D., Temmerman, S., & Kirwan, M. L. (2021). Mechanisms of pond expansion

530 in a rapidly submerging marsh. *Frontiers in Marine Science*, 8.

531 <https://www.frontiersin.org/articles/10.3389/fmars.2021.704768>

532 Hladik, C., & Alber, M. (2012). Accuracy assessment and correction of a LIDAR-derived salt marsh digital

533 elevation model. *Remote Sensing of Environment*, 121, 224–235.

534 <https://doi.org/10.1016/j.rse.2012.01.018>

535 Hopkinson, C. S., Cai, W.-J., & Hu, X. (2012). Carbon sequestration in wetland dominated coastal

536 systems—A global sink of rapidly diminishing magnitude. *Current Opinion in Environmental*

537 *Sustainability*, 4, 186–194. <https://doi.org/10.1016/j.cosust.2012.03.005>

538 Jankowski, K. L., Törnqvist, T. E., & Fernandes, A. M. (2017). Vulnerability of Louisiana's coastal wetlands

539 to present-day rates of relative sea-level rise. *Nature Communications*, 8, Article 1.

540 <https://doi.org/10.1038/ncomms14792>

541 Kamphorst, E. C., Jetten, V., Guérif, J., Pitkänen, J., Iversen, B. V., Douglas, J. T., & Paz, A. (2000).

542 Predicting depressional storage from soil surface roughness. *Soil Science Society of America*

543 *Journal*, 64, 1749–1758. <https://doi.org/10.2136/sssaj2000.6451749x>

544 Karstens, S., Jurasinski, G., Glatzel, S., & Buczko, U. (2016). Dynamics of surface elevation and

545 microtopography in different zones of a coastal Phragmites wetland. *Ecological Engineering*, 94,

546 152–163. <https://doi.org/10.1016/j.ecoleng.2016.05.049>

547 Kirwan, M. L., & Megonigal, J. P. (2013). Tidal wetland stability in the face of human impacts and sea-
548 level rise. *Nature*, 504, Article 7478. <https://doi.org/10.1038/nature12856>

549 Kirwan, M. L., Temmerman, S., Skeehan, E. E., Guntenspergen, G. R., & Fagherazzi, S. (2016).
550 Overestimation of marsh vulnerability to sea level rise. *Nature Climate Change*, 6, Article 3.
551 <https://doi.org/10.1038/nclimate2909>

552 Kirwan, M., & Temmerman, S. (2009). Coastal marsh response to historical and future sea-level
553 acceleration. *Quaternary Science Reviews*, 28, 1801–1808.
554 <https://doi.org/10.1016/j.quascirev.2009.02.022>

555 Langston, A. K., Alexander, C. R., Alber, M., & Kirwan, M. L. (2021). Beyond 2100: Elevation capital
556 disguises salt marsh vulnerability to sea-level rise in Georgia, USA. *Estuarine, Coastal and Shelf
557 Science*, 249, 107093. <https://doi.org/10.1016/j.ecss.2020.107093>

558 Langston, A. K., Durán Vinent, O., Herbert, E. R., & Kirwan, M. L. (2020). Modeling long-term salt marsh
559 response to sea level rise in the sediment-deficient Plum Island Estuary, MA. *Limnology and
560 Oceanography*, 65, 2142–2157. <https://doi.org/10.1002/leo.11444>

561 Lovelock, C. E., Cahoon, D. R., Friess, D. A., Guntenspergen, G. R., Krauss, K. W., Reef, R., Rogers, K.,
562 Saunders, M. L., Sidik, F., Swales, A., Saintilan, N., Thuyen, L. X., & Triet, T. (2015). The
563 vulnerability of Indo-Pacific mangrove forests to sea-level rise. *Nature*, 526, Article 7574.
564 <https://doi.org/10.1038/nature15538>

565 Lynch, J., Hensel, P., & Cahoon, D. (2015). The surface elevation table and marker horizon technique: a
566 protocol for monitoring wetland elevation dynamics. (*No. NPS/NCBN/NRR—2015/1078*).
567 *National Park Service*.

568 Marion, C., Anthony, E. J., & Trentesaux, A. (2009). Short-term (≤ 2 yrs) estuarine mudflat and saltmarsh
569 sedimentation: High-resolution data from ultrasonic altimetry, rod surface-elevation table, and

570 filter traps. *Estuarine, Coastal and Shelf Science*, 83, 475–484.

571 <https://doi.org/10.1016/j.ecss.2009.03.039>

572 Mariotti, G. (2016). Revisiting salt marsh resilience to sea level rise: Are ponds responsible for

573 permanent land loss?: *Journal of Geophysical Research: Earth Surface*, 121, 1391–1407.

574 <https://doi.org/10.1002/2016JF003900>

575 Mariotti, G. (2020). Beyond marsh drowning: The many faces of marsh loss (and gain). *Advances in*

576 *Water Resources*, 144, 103710. <https://doi.org/10.1016/j.advwatres.2020.103710>

577 Mariotti, G., & Carr, J. (2014). Dual role of salt marsh retreat: Long-term loss and short-term resilience.

578 *Water Resources Research*, 50, 2963–2974. <https://doi.org/10.1002/2013WR014676>

579 Mariotti, G., & Fagherazzi, S. (2013). Critical width of tidal flats triggers marsh collapse in the absence of

580 sea-level rise. *Proceedings of the National Academy of Sciences*, 110, 5353–5356.

581 <https://doi.org/10.1073/pnas.1219600110>

582 Mariotti, G., Spivak, A. C., Luk, S. Y., Ceccherini, G., Tyrrell, M., & Gonnea, M. E. (2020). Modeling the

583 spatial dynamics of marsh ponds in New England salt marshes. *Geomorphology*, 365, 107262.

584 <https://doi.org/10.1016/j.geomorph.2020.107262>

585 McClure, A., Liu, X., Hines, E., & Ferner, M. C. (2015). Evaluation of error reduction techniques on a lidar-

586 derived salt marsh digital elevation model. *Journal of Coastal Research*, 32, 424–433.

587 <https://doi.org/10.2112/JCOASTRES-D-14-00185.1>

588 Mekonnen, Z. A., Riley, W. J., Berner, L. T., Bouskill, N. J., Torn, M. S., Iwahana, G., Breen, A. L., Myers-

589 Smith, I. H., Criado, M. G., Liu, Y., Euskirchen, E. S., Goetz, S. J., Mack, M. C., & Grant, R. F.

590 (2021). Arctic tundra shrubification: A review of mechanisms and impacts on ecosystem carbon

591 balance. *Environmental Research Letters*, 16, 053001. <https://doi.org/10.1088/1748-9326/abf28b>

593 Moser, K., Ahn, C., & Noe, G. (2007). Characterization of microtopography and its influence on
594 vegetation patterns in created wetlands. *Wetlands*, 27, 1081–1097.
595 [https://doi.org/10.1672/0277-5212\(2007\)27\[1081:COMAI\]2.0.CO;2](https://doi.org/10.1672/0277-5212(2007)27[1081:COMAI]2.0.CO;2)

596 Neijnens, F. K., Siteur, K., van de Koppel, J., & Rietkerk, M. (2021). Early warning signals for rate-induced
597 critical transitions in salt marsh ecosystems. *Ecosystems*, 24, 1825–1836.
598 <https://doi.org/10.1007/s10021-021-00610-2>

599 Osland, M. J., Feher, L. C., Griffith, K. T., Cavanaugh, K. C., Enwright, N. M., Day, R. H., Stagg, C. L., Krauss,
600 K. W., Howard, R. J., Grace, J. B., & Rogers, K. (2017). Climatic controls on the global distribution,
601 abundance, and species richness of mangrove forests. *Ecological Monographs*, 87, 341–359.
602 <https://doi.org/10.1002/ecm.1248>

603 Raposa, K. B., Wasson, K., Smith, E., Crooks, J. A., Delgado, P., Fernald, S. H., Ferner, M. C., Helms, A.,
604 Hice, L. A., Mora, J. W., Puckett, B., Sanger, D., Shull, S., Spurrier, L., Stevens, R., & Lerberg, S.
605 (2016). Assessing tidal marsh resilience to sea-level rise at broad geographic scales with multi-
606 metric indices. *Biological Conservation*, 204, 263–275.
607 <https://doi.org/10.1016/j.biocon.2016.10.015>

608 Reed, D. J. (1995). The response of coastal marshes to sea-level rise: Survival or submergence? *Earth
609 Surface Processes and Landforms*, 20, 39–48. <https://doi.org/10.1002/esp.3290200105>

610 Saintilan, N., Kovalenko, K. E., Guntenspergen, G., Rogers, K., Lynch, J. C., Cahoon, D. R., Lovelock, C. E.,
611 Friess, D. A., Ashe, E., Krauss, K. W., Cormier, N., Spencer, T., Adams, J., Raw, J., Ibanez, C.,
612 Scarton, F., Temmerman, S., Meire, P., Maris, T., ... Khan, N. (2022). Constraints on the
613 adjustment of tidal marshes to accelerating sea level rise. *Science*, 377, 523–527.
614 <https://doi.org/10.1126/science.abo7872>

615 Scheffer, M., Carpenter, S., Foley, J. A., Folke, C., & Walker, B. (2001). Catastrophic shifts in ecosystems.
616 *Nature*, 413, Article 6856. <https://doi.org/10.1038/35098000>

617 Schepers, L., Brennand, P., Kirwan, M. L., Guntenspergen, G. R., & Temmerman, S. (2020). Coastal marsh
618 degradation into ponds induces irreversible elevation loss relative to sea level in a microtidal
619 system. *Geophysical Research Letters*, 47, e2020GL089121.
620 <https://doi.org/10.1029/2020GL089121>

621 Schepers, L., Kirwan, M. L., Guntenspergen, G. R., & Temmerman, S. (2020). Evaluating indicators of
622 marsh vulnerability to sea level rise along a historical marsh loss gradient. *Earth Surface
623 Processes and Landforms*, 45, 2107–2117. <https://doi.org/10.1002/esp.4869>

624 Smith, A. J., Noyce, G. L., Megonigal, J. P., Guntenspergen, G. R., & Kirwan, M. L. (2022). Temperature
625 optimum for marsh resilience and carbon accumulation revealed in a whole-ecosystem warming
626 experiment. *Global Change Biology*, 28, 3236–3245. <https://doi.org/10.1111/gcb.16149>

627 Steinmuller, H. E., Bourque, E., Lucas, S. B., Engelbert, K. M., Garwood, J., & Breithaupt, J. L. (2022).
628 Comparing Vertical Change in Riverine, Bayside, and Barrier Island Wetland Soils in Response to
629 Acute and Chronic Disturbance in Apalachicola Bay, FL. *Estuaries and Coasts*.
630 <https://doi.org/10.1007/s12237-022-01131-4>

631 Stevenson, J. C., Kearney, M. S., & Pendleton, E. C. (1985). Sedimentation and erosion in a Chesapeake
632 Bay brackish marsh system. *Marine Geology*, 67(3), 213–235. [https://doi.org/10.1016/0025-3227\(85\)90093-3](https://doi.org/10.1016/0025-
633 3227(85)90093-3)

634 Stribling, J. M., Cornwell, J. C., & Glahn, O. A. (2007). Microtopography in tidal marshes: Ecosystem
635 engineering by vegetation? *Estuaries and Coasts*, 30, 1007–1015.
636 <https://doi.org/10.1007/BF02841391>

637 Temmerman, S., Meire, P., Bouma, T. J., Herman, P. M. J., Ysebaert, T., & De Vriend, H. J. (2013).
638 Ecosystem-based coastal defence in the face of global change. *Nature*, 504, Article 7478.
639 <https://doi.org/10.1038/nature12859>

640 Törnqvist, T. E., Cahoon, D. R., Morris, J. T., & Day, J. W. (2021). Coastal wetland resilience, accelerated
641 sea-level rise, and the importance of timescale. *AGU Advances*, 2, e2020AV000334.
642 <https://doi.org/10.1029/2020AV000334>

643 van Belzen, J., van de Koppel, J., Kirwan, M. L., van der Wal, D., Herman, P. M. J., Dakos, V., Kéfi, S.,
644 Scheffer, M., Guntenspergen, G. R., & Bouma, T. J. (2017). Vegetation recovery in tidal marshes
645 reveals critical slowing down under increased inundation. *Nature Communications*, 8, Article 1.
646 <https://doi.org/10.1038/ncomms15811>

647 van Nes, E. H., & Scheffer, M. (2007). Slow recovery from perturbations as a generic indicator of a
648 nearby catastrophic shift. *The American Naturalist*, 169(6), 738–747.
649 <https://doi.org/10.1086/516845>

650 van Wijnen, H. J., & Bakker, J. P. (2001). Long-term surface elevation change in salt marshes: a prediction
651 of marsh response to future sea-level rise. *Estuarine, Coastal and Shelf Science*, 52, 381–390.
652 <https://doi.org/10.1006/ecss.2000.0744>

653 Vu, H. D., & Pennings, S. C. (2021). Directional movement of consumer fronts associated with creek
654 heads in salt marshes. *Ecology*, 102, e03447. <https://doi.org/10.1002/ecy.3447>

655 Wang, C., Schepers, L., Kirwan, M. L., Belluco, E., D'Alpaos, A., Wang, Q., Yin, S., & Temmerman, S.
656 (2021). Different coastal marsh sites reflect similar topographic conditions under which bare
657 patches and vegetation recovery occur. *Earth Surface Dynamics*, 9, 71–88.
658 <https://doi.org/10.5194/esurf-9-71-2021>

659 Wang, C., & Temmerman, S. (2013). Does biogeomorphic feedback lead to abrupt shifts between
660 alternative landscape states?: An empirical study on intertidal flats and marshes. *Journal of
661 Geophysical Research: Earth Surface*, 118, 229–240. <https://doi.org/10.1029/2012JF002474>

662 Wasson, K., Ganju, N. K., Defne, Z., Endris, C., Elsey-Quirk, T., Thorne, K. M., Freeman, C. M.,
663 Guntenspergen, G., Nowacki, D. J., & Raposa, K. B. (2019). Understanding tidal marsh

664 trajectories: Evaluation of multiple indicators of marsh persistence. *Environmental Research*
665 *Letters*, 14, 124073. <https://doi.org/10.1088/1748-9326/ab5a94>

666 Watson, E. B., Wigand, C., Davey, E. W., Andrews, H. M., Bishop, J., & Raposa, K. B. (2017). Wetland loss
667 patterns and inundation-productivity relationships prognosticate widespread salt marsh loss for
668 Southern New England. *Estuaries and Coasts*, 40, 662–681. <https://doi.org/10.1007/s12237-016-0069-1>

670 Webb, E. L., Friess, D. A., Krauss, K. W., Cahoon, D. R., Guntenspergen, G. R., & Phelps, J. (2013). A global
671 standard for monitoring coastal wetland vulnerability to accelerated sea-level rise. *Nature*
672 *Climate Change*, 3, Article 5. <https://doi.org/10.1038/nclimate1756>

673 Werner, K. J., & Zedler, J. B. (2002). How sedge meadow soils, microtopography, and vegetation respond
674 to Sedimentation. *Wetlands*, 22, 451–466. [https://doi.org/10.1672/0277-5212\(2002\)022\[0451:HSMSMA\]2.0.CO;2](https://doi.org/10.1672/0277-5212(2002)022[0451:HSMSMA]2.0.CO;2)

676 Wilson, C. A., Hughes, Z. J., FitzGerald, D. M., Hopkinson, C. S., Valentine, V., & Kolker, A. S. (2014).
677 Saltmarsh pool and tidal creek morphodynamics: Dynamic equilibrium of northern latitude
678 saltmarshes? *Geomorphology*, 213, 99–115. <https://doi.org/10.1016/j.geomorph.2014.01.002>

679 Wilson, J. B., & Agnew, A. D. Q. (1992). Positive-feedback Switches in Plant Communities. In M. Begon &
680 A. H. Fitter (Eds.), *Advances in Ecological Research* (Vol. 23, pp. 263–336). Academic Press.
681 [https://doi.org/10.1016/S0065-2504\(08\)60149-X](https://doi.org/10.1016/S0065-2504(08)60149-X)

682 Yeates, A. G., Grace, J. B., Olker, J. H., Guntenspergen, G. R., Cahoon, D. R., Adamowicz, S., Anisfeld, S. C.,
683 Barrett, N., Benzecry, A., Blum, L., Christian, R. R., Grzyb, J., Hartig, E. K., Leo, K. H., Lerberg, S.,
684 Lynch, J. C., Maher, N., Megonigal, J. P., Reay, W., and Warren, S. (2020). Hurricane Sandy
685 effects on coastal marsh elevation change. *Estuaries and Coasts*, 43, 1640–1657.
686 <https://doi.org/10.1007/s12237-020-00758-5>

687

688 **Tables and Figures**

689 Table 1. Environmental characteristics at the site and SET level for eight tidal salt marshes along
 690 the Atlantic Coast of the United States. Every SET is accompanied with elevation data of the
 691 marsh surface in m in NAVD88 and D, the dimensionless position within the tidal frame where
 692 positive values indicate an elevation greater than mean high water (calculated from mean high
 693 water minus elevation divided by the tidal range (Morris, 2006; Kefelegn, 2019)), and the
 694 dominant vegetation surrounding the plot at the point of installation. Site level characteristics
 695 include regional 50-year averaged rates of SLR (sea-level rise, mm y^{-1}) (NOAA Sea Level
 696 Trends, 2023), porewater salinity (ppt) measured in April to May of 2006, and the ratio of
 697 unvegetated to vegetated marsh surface (UVVR) within 10 ha patches including both SETs at
 698 each site.

State	SET Label	Elevation (m, NAVD88)	D	SLR (mm y^{-1})	Salinity (ppt)	UVVR	Dominant Vegetation
VA	SX2	0.452	-0.68	4.00	17.4	0.07	S. patens
	SX4	0.379	-0.68				D. spicata
MD	FB8A2	0.487	-0.77	3.89	11.4	0.09	S. patens
	FB8A3	0.461	-0.81				S. americanus
	FB8D1	0.402	-1.09	3.89	10.8	0.09	S. patens
	FB8D4	0.413	-0.99				S. patens

	BW7A1	0.169	0.11				S. americanus
				3.89	10.6	0.94	
	BW7A3	0.136	0.23				S. americanus
	BW7D1	0.122	0.28				S. americanus
				3.89	9.6	0.94	
	BW7D4	0.123	0.27				S. alterniflora
	HI2	0.344	-0.55				S. americanus
				3.73	8.9	0.001	
	HI3	0.337	-0.52				S. americanus
	EN2	0.308	-0.42				S. americanus
				3.73	11.2	0.15	
	EN3	0.416	-0.45				S. americanus
DE	BH2	0.914	-0.03				D. spicata
				3.76	13.6	0.16	
	BH3	0.823	0.02				S. patens
CT	GM1	1.329	-0.18				S. americanus
				3.14	16.0	0.42	
	GM3	1.379	-0.2				S. americanus
ME	RC1	1.369	-0.06				D. spicata
				1.90	19.9	0.24	
	RC3	1.348	-0.04				G. maritima

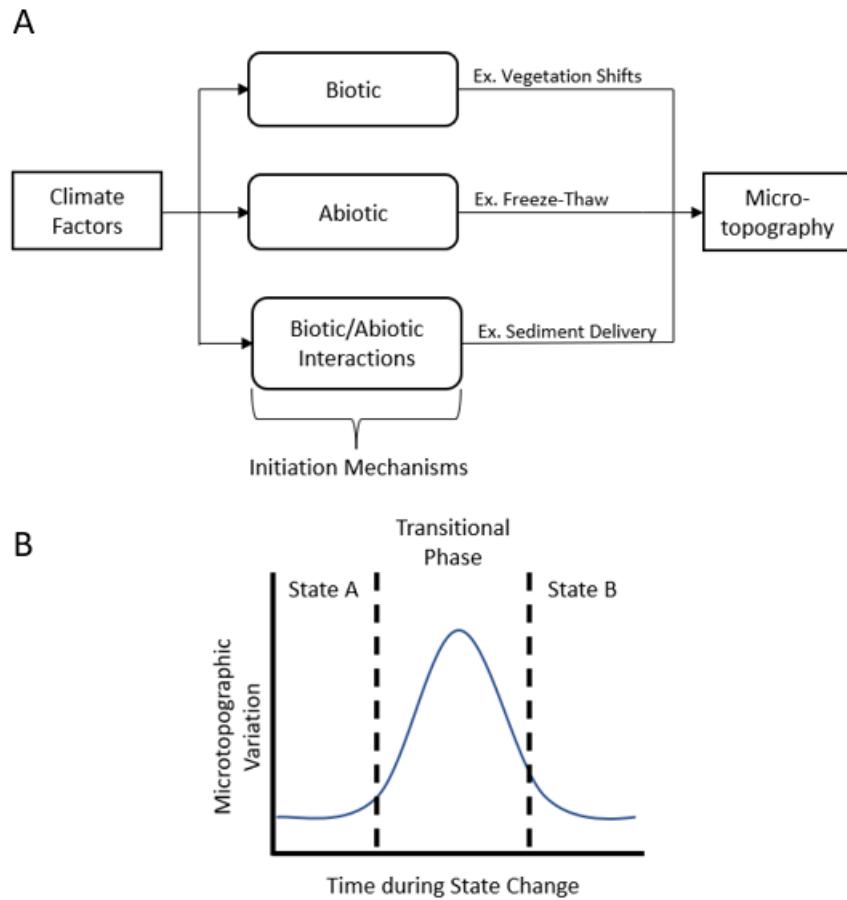
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700 Table 2. Marsh Vulnerability Report Card. A summary table of traditional and microtopographic
 701 vulnerability metrics for eight tidal salt marshes along the Atlantic Coast of the United States.

702 The calculated elevation change deficit (E_{def} , mm y^{-1}) is written out while the table depicts in red
 703 if a microtopographic metric (random roughness (RR), Tortuosity (T), elevation range (ΔH), or
 704 surface area to map area ratio (SA:MA)) detected vulnerability. SETs are grouped within their
 705 respective states and ordered latitudinally from left to right.

	VA		MD												DE		CT		ME	
E_{def}			0.802	FBA2																
RR			-0.201	FBA3																
T			-1.375	FBD1																
ΔH			-11.7	FBD4																
SA: MA			1.49	BWA1																
Total	3	4	0	2	4	4	1	3	1	4	1	1	4	1	0	0	0	4	0	
															2.19	BH2				
															-0.533	HI2				
															-0.762	HI3				
															-2.12	EN2				
															-1.78	EN3				
															0	0	0	0	0	

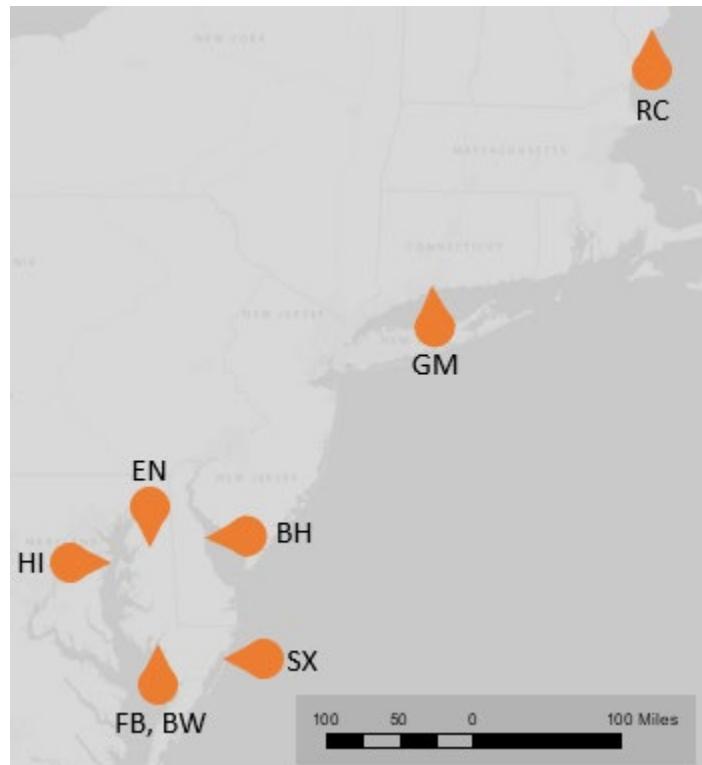
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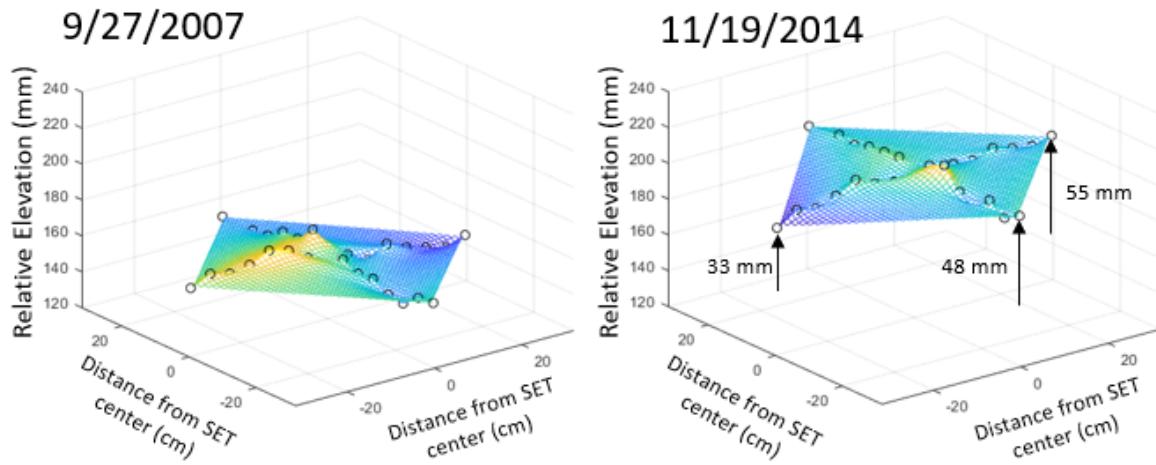
708 **Fig. 1** (a) Conceptual diagram of the influence of climate on microtopographic initiation in
 709 wetlands (adapted from Diamond *et al.*, (2020)). Initiation mechanisms create small-scale
 710 variation in soil elevation. These mechanisms can be modulated by climate factors, such as
 711 elevated atmospheric CO₂ concentrations, warming, and enhanced productivity, that affect biotic
 712 and abiotic drivers of microtopography. (b) Conceptual diagram of increased spatial variation
 713 associated with the transition between two alternative stable states. As a stable ecosystem (State
 714 A) approaches the critical threshold of a state change, spatial variation (e.g. microtopographic
 715 variation, landscape heterogeneity, etc.) is expected to increase and is maximized during the
 716 transitional phase when the reference frame is a mosaic of either alternative states. As the

717 alternative state (State B) dominates the reference frame, spatial variation is expected to decrease
718 to the state's equilibrium conditions.

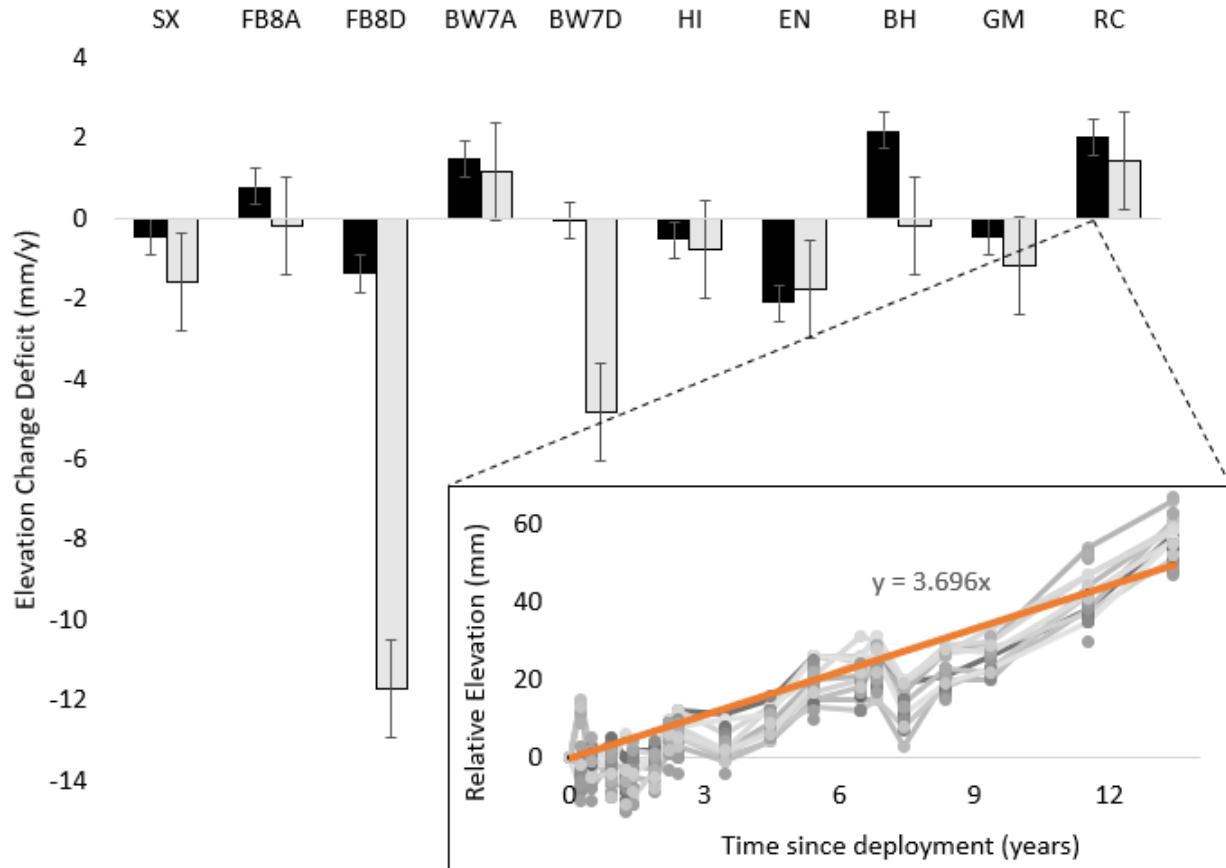


719
720 **Fig. 2** A general map of the mid-Atlantic region of North America showing site names and
721 locations. The southernmost site is in Virginia (SX, Saxis Wildlife Management Area), six sites
722 are located in Maryland (FB, Fishing Bay Wildlife Management Area; BW, Blackwater National
723 Wildlife Refuge; HI, Hog Island at the Smithsonian Environmental Research Center; EN,
724 Eastern Neck National Wildlife Refuge), and one site is located in Delaware (BH, Bombay Hook
725 National Wildlife Refuge), Connecticut (GM, Great Meadows National Wildlife Refuge), and
726 Maine (RC, Rachel Carson National Wildlife Refuge). Each site contains two SET stations,
727 except for FB and BW, which contain four SET stations each.

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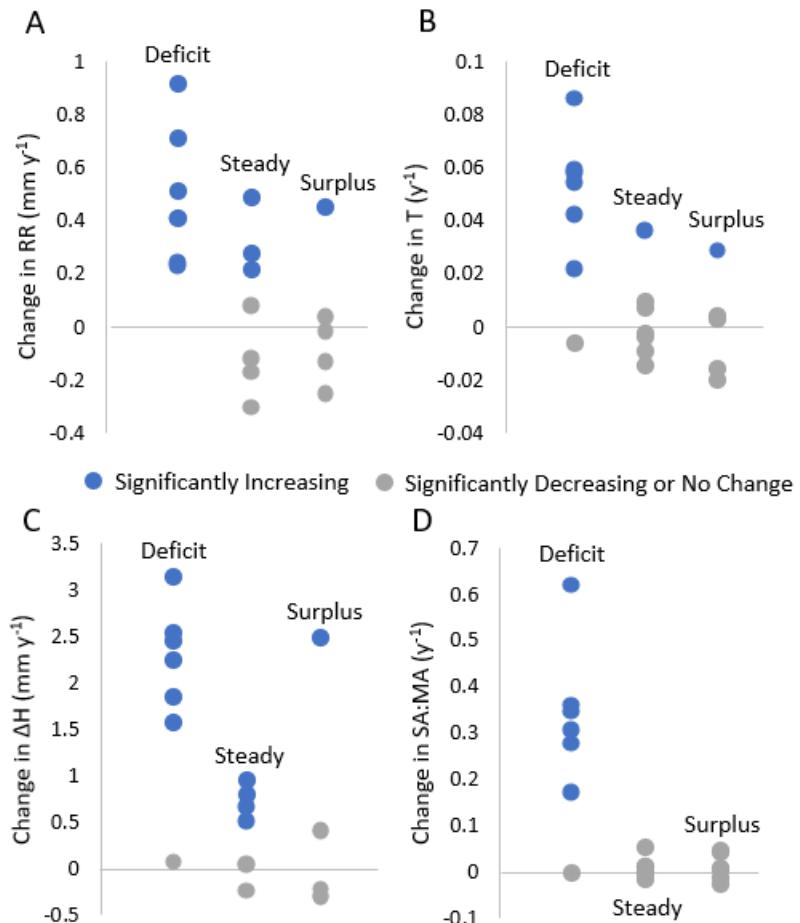
729 **Fig. 3** Interpolated mesh-grid of the marsh surface at BH2 (Bombay Hook National Wildlife
730 Refuge, Maryland, U.S., SET2) on September 27th, 2007 and November 19th, 2014. These
731 interpolated surfaces were created for all SETs during all measurement collections and serve as
732 the surface utilized in the SA:MA microtopographic variability metric. The color of the grid is
733 relative to the height extremes of the marsh surface during each sampling period with the highest
734 point in yellow and the lowest point in blue. The black open circles represent the SET derived
735 measurements from the respective dates that were used to interpolate the surface. Arrows
736 demarcate the change in elevation of identical locations in the marsh surface measured between
737 the two time points.



738

739 **Fig. 4** The elevation change deficits (mm y^{-1}) calculated from the surface elevation tables (SETs)
 740 reviewed in this study. Positive elevation change deficits indicate that the rate of elevation
 741 change is greater than the rate of sea-level rise (SLR) while negative elevation change deficits
 742 indicate that the rate of SLR is greater than the rate of elevation change (see Methods section).
 743 SETs are grouped by site with the respective site abbreviation above the paired stations. These
 744 are then organized from left to right in order of increasing latitude. The gray and black colors of
 745 the bar differentiate the SET stations present within each site and are not representative of any
 746 treatment or applied condition. Elevation change deficit is the difference between elevation
 747 change (mm y^{-1}) and 50-year average rate of SLR (mm y^{-1}). Elevation change at each SET was
 748 determined by averaging the rate of elevation change of each individual pin ($n \sim 30$) across the

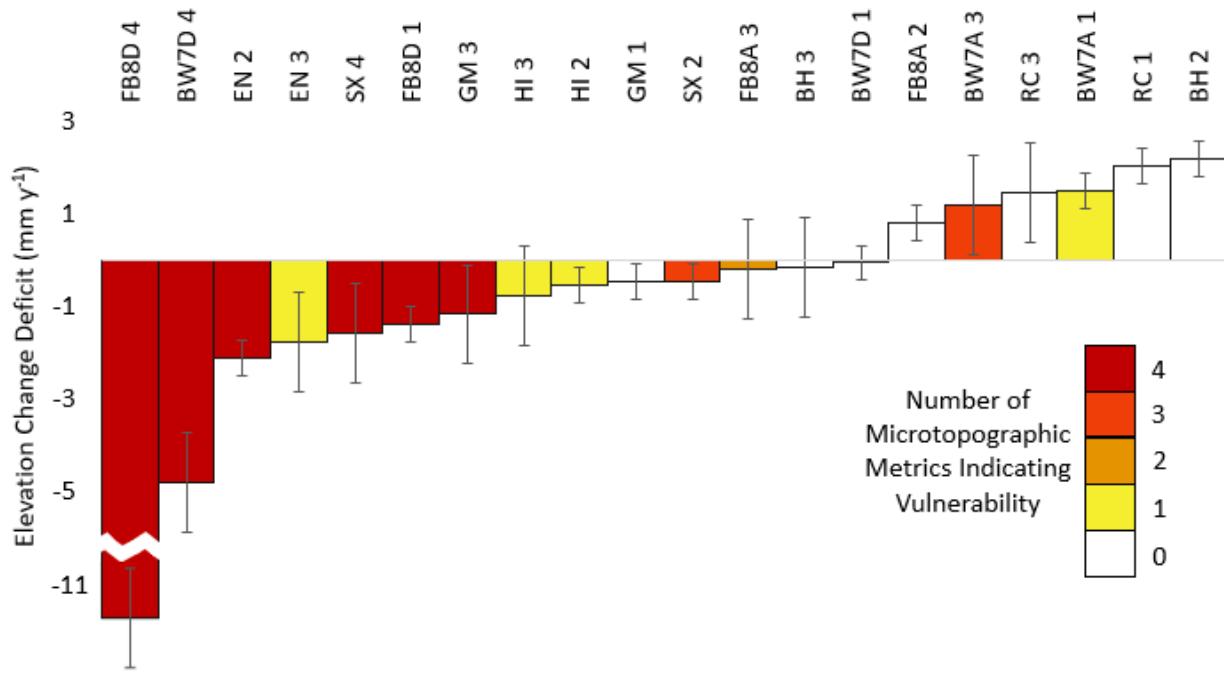
749 time period, exemplified by the inset of SET pin trajectories at RC1 shown in grays with the
 750 calculated average elevation change shown in orange. Error bars within the bar chart represent
 751 the standard deviation of the average elevation change deficit.



752

753 **Fig. 5** Categorical scatterplots of rates of changes of the four microtopographic variability
 754 metrics, (a) random roughness (RR), (b) tortuosity (T), (c) elevation range (ΔH), (d) the surface
 755 area to map area ratio (SA:MA), grouped according to traditional metrics of vulnerability (i.e.
 756 elevation change deficits). The “Deficit” category refers to surface elevation tables (SETs) where
 757 the elevation change was less than the 50-year averaged rate of local sea-level rise (SLR), while
 758 the “steady” and “surplus” categories indicate SETs where the elevation change was not different
 759 or significantly greater than the rate of local SLR. The color of the datapoint represents whether

760 the linear regression calculated for the respective vulnerability metrics is either significantly
761 increasing through time (blue) or decreasing or not significantly changing (both in gray).



763 **Fig. 6** Comparison of traditional vulnerability metrics (elevation change deficit) with the novel
764 microtopographic vulnerability metrics for eight tidal salt marshes along the Atlantic Coast of
765 the United States. Elevation change deficit data are the same data displayed in Fig. 4, but
766 arranged from lowest to highest elevation change deficit with the respective SET label displayed
767 above. Positive elevation change deficits indicate that the rate of elevation change is greater than
768 the rate of SLR while negative elevation change deficits indicate that the rate of SLR is greater
769 than the rate of elevation change (see Methods section). The color of the bars is determined by
770 the number of microtopographic metrics that indicated vulnerability (Table 2). From this, we can
771 see that six of the seven most vulnerable sites identified by traditional metrics are also identified
772 as vulnerable according to every novel microtopographic vulnerability metric. Error bars
773 represent standard error.

