

1 **Upland forest retreat lags behind sea-level rise in the mid-Atlantic coast**

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5

6 **ABSTRACT**

7 Ghost forests consisting of dead trees adjacent to marshes are striking indicators of climate change,  
8 and marsh migration into retreating coastal forests is a primary mechanism for marsh survival in  
9 the face of global sea-level rise. Models of coastal transgression typically assume inundation of a  
10 static topography and instantaneous conversion of forest to marsh with rising seas. In contrast,  
11 here we use four decades of satellite observations to show that many low-elevation forests along  
12 the US mid-Atlantic coast have survived despite undergoing relative sea-level rise rates (RSLRR)  
13 that are among the fastest on Earth. Lateral forest retreat rates were strongly mediated by  
14 topography and seawater salinity, but not directly explained by spatial variability in RSLRR,  
15 climate, or disturbance. The elevation of coastal treelines shifted upslope at rates correlated with,  
16 but far less than, contemporary RSLRR. Together, these findings suggest a multi-decadal lag  
17 between RSLRR and land conversion that implies coastal ecosystem resistance. Predictions based  
18 on instantaneous conversion of uplands to wetlands may therefore overestimate future land  
19 conversion in ways that challenge the timing of greenhouse gas fluxes and marsh creation, but also  
20 imply that the full effects of historical sea-level rise have yet to be realized.

21

22 **Running head:** Upland Conversion Lags Behind Sea-Level Rise

23 **Keywords:** Sea-Level Rise, Forest Mortality, Saltwater Intrusion, Lag Effect, Coastal Wetland,

24 Marsh Migration, Climate Change

25

26 **1. INTRODUCTION**

27 Climate-driven landscape reorganization, manifested in coastal ecosystems as the migration of  
28 marshes into adjacent uplands via sea-level rise, is affecting large sections of the global coast  
29 (Kirwan & Gedan, 2019; McDowell et al., 2022; Osland et al., 2022). This phenomenon is  
30 considered one of the major processes that will fundamentally modify the feedbacks of coastal  
31 ecosystems to global climate (Chen & Kirwan, 2022a; Smart et al., 2020; Smith & Kirwan, 2021;  
32 Valentine et al., 2023; Warnell et al., 2022) and potentially incur large socio-economic  
33 repercussions (Bhattachan et al., 2018; Kirwan & Megonigal, 2013). However, predictions of  
34 coastal ecosystem transformations remain limited by an incomplete understanding of how the  
35 impacts of relative sea-level rise rate (RSLRR) are potentially mediated by spatially variable  
36 environmental drivers.

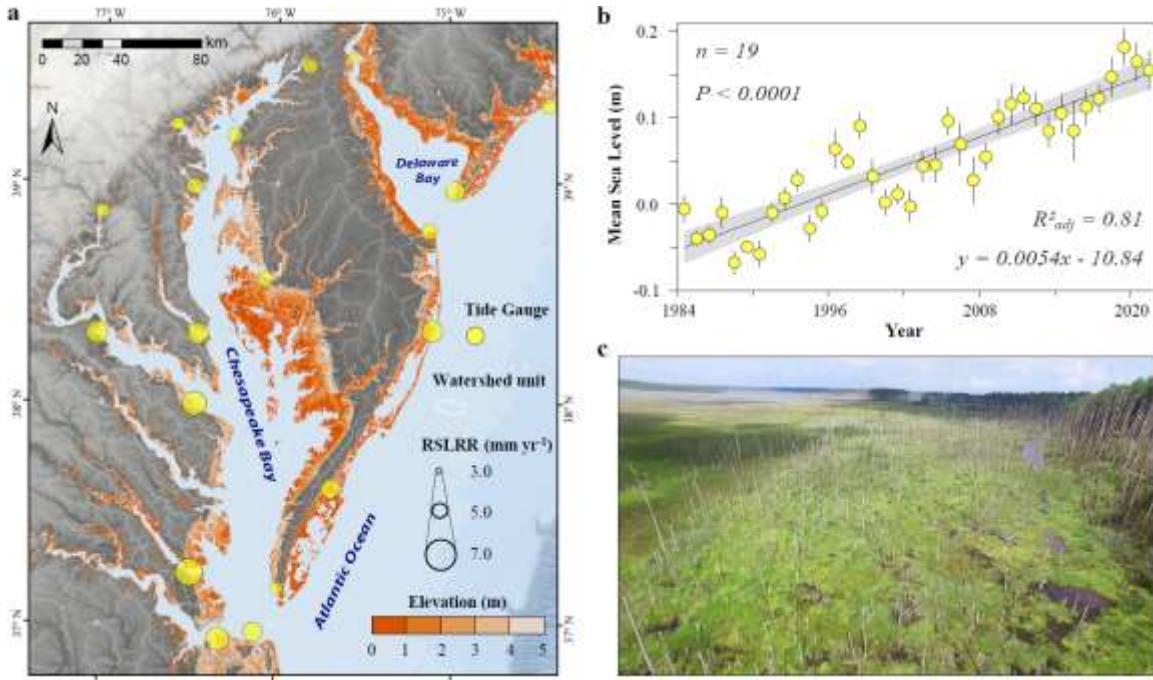
37 Upland forest is generally considered to be highly vulnerable to sea-level rise and saltwater  
38 intrusion (Doyle et al., 2010; Fagherazzi et al., 2019; McDowell et al., 2022). Previous estimates  
39 of coastal forest loss to sea-level rise assume that the positional change of the coastal treeline is  
40 synchronous with rising sea level (Buchanan et al., 2022; Enwright et al., 2016; Haer et al., 2013;  
41 Molino et al., 2022; Osland et al., 2022; Warnell et al., 2022). For example, recent studies based  
42 on modeled tidal datums predict that a 1.0-1.5 m mean global sea-level rise will translate into  
43 hundreds of thousands of hectares of upland forests replaced by salt marshes across the  
44 conterminous US within this century (Osland et al., 2022; Warnell et al., 2022). The resulting loss  
45 of wood production and stimulation of methane emissions contribute to a predicted net increase in  
46 the global warming potential of coastal ecosystems over large regions of the US coast (Baušťan  
47 et al., 2023; Warnell et al., 2022).

48 However, it is unclear to what extent the predicted magnitude of forest loss will be realized, as  
49 multiple lines of evidence suggest that coastal forest retreat may not be synchronized with rising  
50 seas (Chen & Kirwan, 2022b; Schieder & Kirwan, 2019), and that other factors also play a role in  
51 modulating fine-scale patterns of coastal treeline dynamics (Fagherazzi et al., 2019; Poulter et al.,  
52 2009). For example, site-specific stratigraphic reconstructions over the past 2000 years suggest  
53 periods of time where upland conversion was slower (Schieder & Kirwan, 2019) or faster (Miller  
54 et al., 2021) than concurrent RSLRR. These reconstructions are consistent with field observations  
55 of mature trees that persist for decades under chronic flooding and salt stress (Field et al., 2016;  
56 Kirwan & Gedan, 2019; Poulter, Christensen, et al., 2008; Williams et al., 1999), and the paradigm

57 that storms are necessary to facilitate forest retreat (Fagherazzi et al., 2019). Topography,  
58 disturbance, and biotic interactions are all factors previously invoked to interpret site-scale patterns  
59 of coastal treeline dynamics in response to rising seas (Chen & Kirwan, 2022a; Field et al., 2016;  
60 McDowell et al., 2022; Molino et al., 2022; Poulter et al., 2009; Ross et al., 1994; Schieder et al.,  
61 2018; Smith, 2013; Williams et al., 1998, 1999). Nonetheless, it is largely unknown how rates of  
62 coastal treeline retreat will manifest across broad spatial scales that stretch wide gradients of  
63 environmental context (e.g. salinity, disturbance, climate and tidal regime).

64 Here we leverage extensive Landsat satellite images between 1984 and 2020 to explore  
65 landscape-scale patterns, including rates and drivers of both lateral and vertical coastal treeline  
66 retreat along the US mid-Atlantic coast (Fig. 1), a global hotspot for accelerated sea-level rise  
67 (Sallenger et al., 2012). In contrast to static inundation models that assume instantaneous coastal  
68 ecosystem shifts with sea-level rise, we find that only a fraction of upland forests (~40% within  
69 elevations of 0 and 2 m) retreated inland between 1984 and 2020. Moreover, the rate of vertical  
70 forest retreat is merely half of contemporary RSLRR, pointing to a pronounced lag between sea-  
71 level rise and upland conversion that suggests surprising ecosystem resistance.

72



73  
74 **Fig. 1 | Sea-level rise along the mid-Atlantic coast of North America.** **a**, Yellow circles indicate the locations of all  
75 tide gauges ( $n = 19$ ) across the study region, where long-term information in sea level is available (1984–present). The  
76 size of the circles is proportional to the relative sea-level rise rate between 1984 and 2020. Elevation is relative to  
77 NAVD88 (mean sea level in the region). **b**, Regional sea-level rise trend averaged across all tide gauges in the region.  
78 Data shown as mean  $\pm$  1 standard deviation. The mean linear regression trendline is bounded by the 95% confidence  
79 interval. **c**, Drone image showing retreating forest in the Blackwater National Wildlife Refuge taken in 2020 (Image  
80 credit: Tyler Messerschmidt).

81

## 82 2. METHODS

### 83 2.1 Regional context

84 We studied coastal forest migration in response to sea-level rise across the US mid-Atlantic coast  
85 ( $\sim 12,000 \text{ km}^2$ ; Virginia, Maryland, Delaware and New Jersey). This geophysically variable region  
86 encompasses the largest US estuary, the Chesapeake Bay, and the adjacent Delaware Bay (Fig. 1).  
87 Soil texture is relatively homogenous in the region, largely characterized as silt and silt loam  
88 (Walkinshaw et al., 2022). The region was selected because it is a known global sea-level rise  
89 hotspot (Sallenger et al., 2012), and spans strong gradients in salinity, topography, and rates of  
90 relative sea-level rise rate (RSLRR) (Table 1). Moreover, the relatively rural coast of the US mid-  
91 Atlantic represents a great opportunity to observe how sea-level driven landscape reorganization  
92 proceeds across broad scales with minimal anthropogenic obstacles (Molino et al., 2022). Indeed,

93 massive marsh encroachment and forest mortality have been documented across the region over  
94 recent decades concurrent with increasing flooding and saltwater intrusion towards uplands  
95 (Schieder et al., 2018; Smith, 2013; White et al., 2022).

96 To capture the full spatial extent of sea-level rise impact (Chen & Kirwan, 2022a), we included  
97 areas between 0 and 5 m above sea level (relative to NAVD88, the mean sea level in the region)  
98 (Fig. 1). The elevation range extends from permanently flooded lowlands to coastal uplands free  
99 from seawater flooding (Pekel et al., 2016). All elevation data refers to the high precision Coastal  
100 National Elevation Database (CoNED) (Danielson et al., 2018) at 1 m resolution. All sea-level rise  
101 data are observed by long-term tidal gauges (Table 1), accessed from the NOAA Center for  
102 Operational Oceanographic Products and Services (Center for Operational Oceanographic  
103 Products and Services, 2023).

104

105 **Table 1 | Sea-level rise in the US mid-Atlantic region.**

Tide Gauge Station*	NOAA Code	Geolocation	Time-span	RSLRR (mm yr <sup>-1</sup> )	Linear regression statistics
Sewells Point, VA	8638610	36.95° N, 76.33° W	1984-2020	6.30	$R^2 = 0.82 (P < 0.001)$
Chesapeake Bay Bridge Tunnel, VA	8638863	36.97° N, 76.11° W	1984-2017	5.74	$R^2 = 0.79 (P < 0.001)$
Kiptopeke, VA	8632200	37.17° N, 75.99° W	1984-2020	4.66	$R^2 = 0.74 (P < 0.001)$
Yorktown, VA	8637689	37.23° N, 76.48° W	1984-2020	6.85	$R^2 = 0.86 (P < 0.001)$
Wachapreague, VA	8631044	37.61° N, 75.69° W	1984-2020	5.68	$R^2 = 0.79 (P < 0.001)$
Dahlgren, VA	8635027	38.32° N, 77.04° W	1984-2020	6.03	$R^2 = 0.83 (P < 0.001)$
Lewisetta, VA	8635750	37.99° N, 76.47° W	1984-2020	6.86	$R^2 = 0.84 (P < 0.001)$
Solomons Island, MD	8577330	38.32° N, 76.45° W	1984-2020	5.91	$R^2 = 0.86 (P < 0.001)$
Washington, D.C.	8594900	38.87° N, 77.02° W	1984-2020	4.84	$R^2 = 0.59 (P < 0.001)$
Cambridge, MD	8571892	38.57° N, 76.06° W	1984-2020	5.10	$R^2 = 0.81 (P < 0.001)$
Annapolis, MD	8575512	38.98° N, 76.48° W	1984-2020	5.28	$R^2 = 0.76 (P < 0.001)$
Baltimore, MD	8574680	39.27° N, 76.58° W	1984-2020	4.58	$R^2 = 0.76 (P < 0.001)$
Tolchester Beach, MD	8573364	39.21° N, 76.25° W	1987-2020	4.97	$R^2 = 0.65 (P < 0.001)$
Chesapeake City, MD	8573927	39.53° N, 75.81° W	1984-2020	5.13	$R^2 = 0.71 (P < 0.001)$
Ocean City, MD	8570283	38.33° N, 75.09° W	1984-2020	5.95	$R^2 = 0.83 (P < 0.001)$
Lewes, DE	8557380	38.78° N, 75.12° W	1984-2020	5.26	$R^2 = 0.80 (P < 0.001)$
Reedy Point, DE	8551910	39.56° N, 75.57° W	1984-2020	4.18	$R^2 = 0.72 (P < 0.001)$
Cape May, NJ	8536110	38.97° N, 74.96° W	1984-2020	5.81	$R^2 = 0.84 (P < 0.001)$
Atlantic City, NJ	8534720	39.36° N, 74.42° W	1984-2020	5.01	$R^2 = 0.75 (P < 0.001)$

106 \*All sea-level data are available at the NOAA Center for Operational Oceanographic Products and Services (Center  
107 for Operational Oceanographic Products and Services, 2023). The relative sea-level rise rate (RSLRR) is computed  
108 as the slope of linear regression between year and mean sea level.

109

110 **2.2 Landcover mapping**

111 We mapped regional landcover using Landsat satellite images acquired around 1984 and 2020,  
112 and estimated lateral and vertical patterns of coastal forest retreat between 1984 and 2020 (Tables  
113 S1-S2). We did not include an intermediate time-step after taking into account the relatively slow  
114 processes of coastal forest retreat (Chen & Kirwan, 2022b; Schieder & Kirwan, 2019) combined  
115 with comparatively coarse spatial resolution of Landsat images. The extended 36-yr (1984-2020)  
116 time-span allowed us improved confidence in change detection (Chen & Kirwan, 2022a). We  
117 generated two landcover maps (one in 1984 and one in 2020 that include each of six classes: Marsh,  
118 Forest, Farmland, Urban area, Water and Sandbar, Table S1) with special focus on the marsh-  
119 forest boundary using the classification algorithm we developed earlier for accurate mapping of  
120 retreating forest in coastal landscape (Chen & Kirwan, 2022b). It is worth mentioning that ‘Forest’  
121 studied here refers specifically to upland forest (Table S1), and it does not include forested  
122 wetlands (i.e. freshwater swamps). We mapped all upland forests across our study region, which  
123 stretch from higher elevations entirely devoid of seawater inundation to low-lying, salt-intruded  
124 areas at the coastal transgression front where forest species are dominated by relatively salt-  
125 tolerant evergreen trees like Loblolly pine (*Pinus taeda*) and red cedar (*Juniperus virginiana*)  
126 (Brinson et al., 1995; Kirwan et al., 2007). Both maps were created at 30 m resolution using  
127 random forest classifier in R (v. 4.1.1, packages of ‘*caret*’ and ‘*randomForest*’). A detailed  
128 description of our coastal mapping approach can be found in Chen & Kirwan (2022b).

129 Briefly, we complemented the multispectral Landsat satellite images acquired from contrasting  
130 seasons in the year of mapping with a set of phenology metrics derived from the annual Landsat  
131 NDVI time-series for optimal differentiation between encroaching marsh and retreating forest at  
132 the upland-wetland transition (Chen & Kirwan, 2022b). For each mapping, we trained the classifier  
133 with 50% of reference sites collected earlier for different landcover types across the mid-Atlantic  
134 region (Chen & Kirwan, 2022a), and used the remaining sites for validation. All reference sites (~  
135 30,000) were identified according to field campaign, drone images, or high-resolution aerial  
136 images acquired in 1982-1986 (for mapping in 1984) and in 2018-2020 (for mapping in 2020)  
137 (Chen & Kirwan, 2022a), and the sites were divided randomly by landcover type in the ratio of  
138 1:1 for training and validation.

139 The resulting maps were processed further for enhanced accuracy following similar post-  
140 processing steps as addressed in Chen & Kirwan (2022a). First, we assigned all areas where  
141 flooding frequency is identified by Global Surface Water dataset (1984-2020) (Pekel et al., 2016)

142 as greater than 95% to water. Next, areas of potential misclassification of marshes were identified  
143 and removed according to the rules of flooding frequency less than 5% and elevation greater than  
144 2.5 m (upper tidal range of mid-Atlantic (Danielson et al., 2018)). Finally, we manually digitized  
145 all areas (~5% of the study region) precluded from auto-classification due to contamination by  
146 cloud/cloud-shadow in the input Landsat images using high-resolution aerial images following the  
147 approach by Chen, Lara, et al. (2021). The final landcover maps were validated extensively across  
148 the region, which achieved an overall classification accuracy of 92.4% (*Kappa* coefficient = 0.91)  
149 and 94.5% (*Kappa* coefficient = 0.93) for the map in 1984 and 2020, respectively (Table S2).

### 150 **2.3 Coastal treeline and coastal forest retreat**

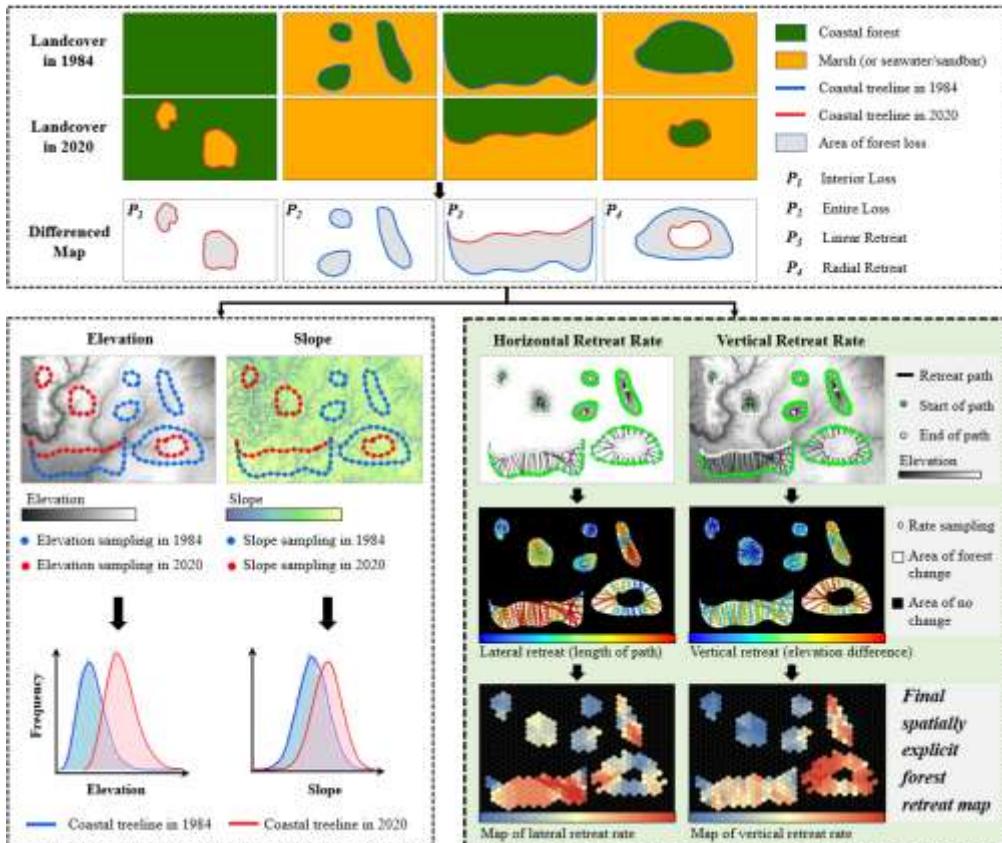
151 Using the landcover maps generated above, we then extracted coastal treelines in 1984 and 2020  
152 following the approach of Chen & Kirwan (2022b). Coastal treelines in this study refer specifically  
153 to the marsh-forest boundary (or in less frequent occasions where coastal forests meet seawater or  
154 sandy shores as commonly seen on barrier islands) (Chen & Kirwan, 2022a, 2022b; Schieder et  
155 al., 2018; Schieder & Kirwan, 2019), and they do not include treelines where forests border human  
156 land use like farmland or urban areas, which were removed prior to analysis. To understand the  
157 spatial distribution and temporal changes of coastal treelines along topography, we systematically  
158 sampled the elevation and slope data along all coastal treelines every 100 m ('Generate Points  
159 Along Line' tool in ArcGIS v10.7) from the CoNED DEM (Danielson et al., 2018) (Fig. 2).

160 We differenced the landcover maps in 1984 and 2020 to identify areas of forest change, and  
161 then estimated rates of lateral and vertical forest retreat based on unique patterns of forest boundary  
162 change. The step by step methodology is illustrated in Fig. 2, modified from the framework in  
163 Chen & Kirwan (2022b) to quantify both lateral and vertical forest retreat. In brief, there are four  
164 patterns of forest loss depending on coastal treeline configuration: Interior loss (P1: emerging  
165 forest loss, treeline present only in 2020), Entire loss (P2: complete patch loss, treeline present  
166 only in 1984), Linear retreat (P3: parallel retreat with conjoint treelines in 1984 and 2020), and  
167 Radial retreat (P4: concentric retreat with disjoint treelines in 1984 and 2020) (Fig. 2). All areas  
168 of forest loss were converted to smoothed polygons ('Smooth Polygon' in ArcGIS v10.7) with the  
169 boundaries classified either as treeline in 1984 or in 2020. In general, forest losses in P1 and P2  
170 are usually small in size, collectively accounting for less than 10% of regional forest loss, with the  
171 remaining 90% areas of forest loss roughly equally represented by P3 and P4.

172 Next, we generated transects running through the polygons to represent paths of forest retreat  
173 (Fig. 2). For forest loss in patterns of P3 and P4, treelines are present in both years to indicate  
174 directional retreat from 1984 to 2020. For these areas, we placed points along all polygon  
175 boundaries at regular distance (100 m), from where we created perpendicular lines ('Create  
176 Perpendicular Lines', ArcGIS v10.7) to intersect the opposite treeline (Fig. 2). Only those  
177 connecting paired treelines were selected as a retreat path, the intersection with the treeline in 1984  
178 was determined as the start of the path, and the intersection with the treeline in 2020 was the end  
179 of the path. Unlike P3 or P4 polygons of paired treelines, the P1 and P2 polygons have a single  
180 treeline, present either in 1984 or in 2020. For each of these polygons, we generated a theoretical  
181 start (P1) or end (P2) point according to the CoNED DEM to direct the path of forest retreat. To  
182 be specific, the start point of the P1 polygon was identified as the location that has the lowest  
183 elevation within the polygon, whereas the end point of the P2 polygon referred to the location of  
184 the highest elevation within the polygon. In the same way, we generated points along boundaries  
185 of P1 and P2 polygons every 100 m, and connected these points with the start or the end point to  
186 represent directional change of forest from 1984 to 2020 (Fig. 2).

187 Finally, we computed the length of each path to represent the magnitude of lateral forest retreat,  
188 and estimated the elevation difference between the start and the end of the path to represent the  
189 magnitude of vertical forest retreat. We then divided the magnitude of lateral/vertical forest retreat  
190 by the years between 1984 and 2020 to calculate the rate of lateral/vertical forest retreat. To allow  
191 explicit representation of forest retreat pattern across the study region, we sampled forest retreat  
192 rate every 100 m along each path across all areas of forest loss, and rasterized the results ('Generate  
193 Tessellation', ArcGIS v10.7) to generate regional forest retreat maps at a spatial resolution of 0.075  
194 km<sup>2</sup> (Hexagon grid, side length of 170 m). The value of each grid is calculated as the mean of all  
195 rate samples inside the grid, and grids outside polygons are assigned to a value of 0 as they  
196 correspond to areas of no forest change (Fig. 2).

197



198

199 **Fig. 2 | Flowchart for quantifying coastal forest retreat.** The approach was modified from the framework developed  
200 in Chen & Kirwan (2022b). See Methods for detailed description of the step by step procedure.

201

## 202 **2.4 Data analysis**

203 We analyzed regional forest retreat rates using multiple linear regression models to identify key  
204 environmental drivers for the dynamic patterns of coastal forest change (Table 2). To explore  
205 whether the environmental controls differ between lateral and vertical forest retreat, we generated  
206 separate models for lateral retreat rate ( $\text{m yr}^{-1}$ ) and vertical retreat rate ( $\text{mm yr}^{-1}$ ). We fitted each  
207 model with the same set of candidate variables that includes observed RSLRR and 24 other  
208 predictors identified from literature as influential for coastal forest retreat (Table 2). Overall, these  
209 variables can be grouped into 5 broad categories: (1) climatic variables, such as precipitation,  
210 growing degree days (Chen & Kirwan, 2022a; Desantis et al., 2007; McDowell et al., 2022; White  
211 et al., 2022); (2) geophysical variables, including sea surface salinity, tidal range, and soil texture  
212 (Kirwan & Gedan, 2019; Molino et al., 2021; Schieder et al., 2018); (3) sea-level rise variables,  
213 such as RSLRR, flooding frequency (Chen & Kirwan, 2022a; Schieder & Kirwan, 2019; White &

214 Kaplan, 2021); (4) landscape metrics, like mean forest patch size, proximity to drainage channels  
215 (Chen, Hu, et al., 2021; Poulter, Goodall, et al., 2008; Raabe & Stumpf, 2016; Smart et al., 2020);  
216 and (5) disturbance variables, including observed storm frequency, and modeled inundation depth  
217 and duration of Hurricane Isabel (Fagherazzi et al., 2019; Ury et al., 2021; White et al., 2022).

218 To be consistent with sea-level rise observation, all data (except for static variables) were  
219 processed to the same time-span (1984-2020) and watershed-scale (HUC10 unit) as defined by the  
220 National Hydrography Dataset Plus (McKay et al., 2019), where the variable value of a certain  
221 watershed was computed as the mean of all forested areas within the watershed. We fitted the  
222 model with all candidate variables, and eliminated unimportant, cross-dependent/correlative  
223 variables in a stepwise manner to achieve a single reduced model that contains only significant  
224 predictors for the response variable (i.e. lateral or vertical forest retreat rate). Model performance  
225 was assessed using the adjusted coefficient of determination ( $R^2_{adj}$ ), and the *Pearson's* correlation  
226 coefficient ( $r$ ) was calculated between the response variable and the set of significant predictors  
227 retained in the final model. All statistical analyses were conducted in R (v. 4.1.1) and significance  
228 was determined at the level of  $p < 0.05$ .

229

230 **Table 2 | Candidate predictors for modeling lateral and vertical forest retreat rate.** The column “Reference”  
 231 refers to prior literatures suggesting relationships between coastal forest retreat and the variables selected.

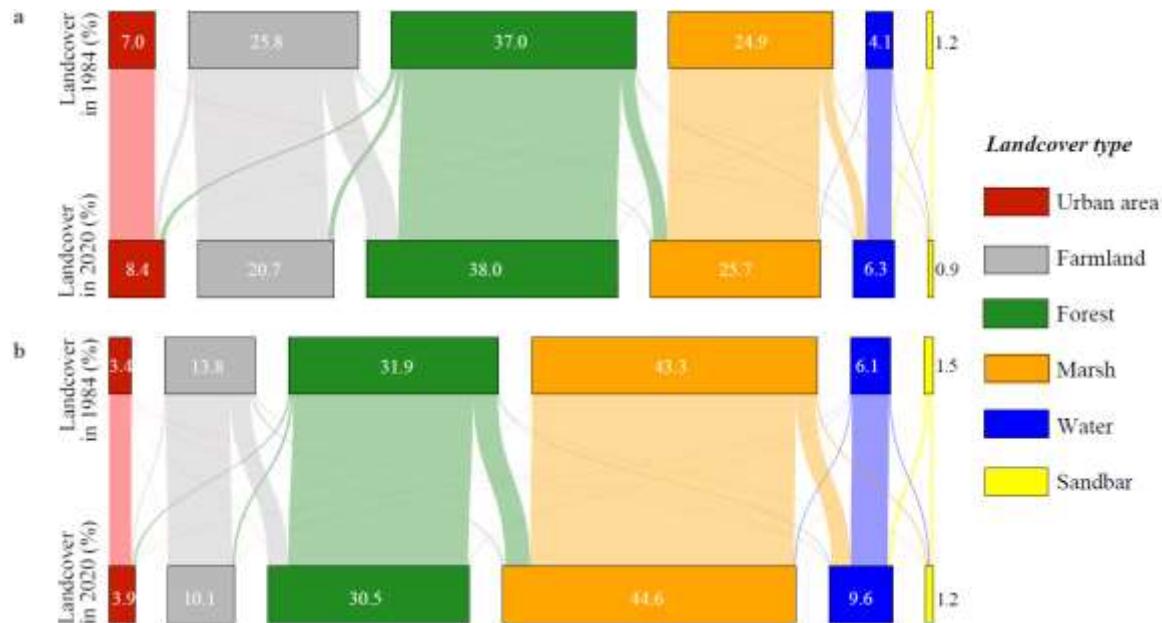
Category	Variable	Description	Data source	Reference
Climatic variables	MAAT	Mean annual air temperature (°C)	30-year normals of PRISM Climate Data (“PRISM Climate Group,” 2020)	Chen & Kirwan (2022a); Desantis et al. (2007); McDowell et al. (2022); Schuerch et al. (2018); White et al. (2022)
	Tmax	Maximum air temperature (°C)		
	TAP	Total annual precipitation (mm)		
	VPD	Maximum vapor pressure deficit (hPa)		
	GDD	Mean annual growing degree ( $\geq 10$ °C) days	Chen & Kirwan (2022a), derived from annual PRISM Climate Data (“PRISM Climate Group,” 2020)	Chen & Kirwan (2022a); Chen & Ye (2014); Langston et al. (2017); Schieder et al. (2018); Smith & Kirwan (2021); Williams et al. (1998)
	$\Delta$ MAAT	Change in annual air temperature (°C) from 1984 to 2020		
	$\Delta$ TAP	Change in annual precipitation (mm) from 1984 to 2020		
	$\Delta$ GDD	Change in annual growing degree days from 1984 to 2020		
Geophysical variables	Elevation	Elevation (meter above sea level)	CoNED DEM (Danielson et al., 2018)	Chen & Kirwan (2022a, 2022b); Chen & Ye (2014); Langston et al. (2017); Schieder et al. (2018); Smith & Kirwan (2021); Williams et al. (1998)
	Slope	Topographical slope		
	TPI	Topographic position index (unitless)		
	Aspect	Aspect (degree)		
	Salinity	Sea surface salinity (psu)	Delaware Bay (Salinity Climatology for the Mid-Atlantic, 2023); Chesapeake Bay (St-Laurent et al., 2020)	Soil properties (Walkinshaw et al., 2022)
	ST	Soil texture (unitless)		
	$R_{tidal}$	Mean tide range (m), computed as the difference in height between mean high water and mean low water		
	FF	Flooding frequency (0-100%) between 1984 and 2020	NOAA Tidal Datums (NOAA Tidal Datums, 2023)	Chen & Kirwan (2022a, 2022b); Fagherazzi et al. (2019); Schieder & Kirwan (2019)
Sea-level rise variables	$\Delta$ FF	Change in flooding frequency from 1984-1999 to 2000-2020		
	RSLRR	Relative sea-level rise rate (mm yr <sup>-1</sup> ) between 1984 and 2020	NOAA Tides & Currents (Center for Operational Oceanographic Products and Services, 2023)	
	PR	Mean proximity to channels (m)	NHDPlus Version-2 (McKay et al., 2019), and Our landcover map in 1984	Poulter, Goodall, et al. (2008); Smart et al. (2020); Ury et al. (2021)
Landscape metrics	MPS	Mean forest patch size (m <sup>2</sup> )		
	Compact	Mean compactness of forest patch (unitless)		
	$S_{frequency}$	Number of tropical storms between 1984 and 2020	NOAA IBTrACS Project (Knapp et al., 2018)	Fagherazzi et al. (2019); Schieder & Kirwan (2019); White et al. (2022)
Disturbance variables	$S_{severity}$	Number of hurricanes between 1984 and 2020		
	$H_{depth}$	Maximum inundation depth (m) by Hurricane Isabel	Storm surge simulation by ADCIRC (Molino et al., 2021)	
	$H_{duration}$	Inundation duration (h) by Hurricane Isabel		

232  
 233 **3. RESULTS**  
 234 **3.1 Coastal landscape reorganization**  
 235 We find that 1320.8 km<sup>2</sup> of the areas between 0 and 5 m NAVD88 underwent landcover change  
 236 from 1984 to 2020, mostly (733 km<sup>2</sup>) driven by human activity (e.g. deforestation), and to a lesser  
 237 degree (587 km<sup>2</sup>) by sea-level rise impacts (e.g. forest transition to marsh, Fig. 3a). However,  
 238 closer examination of patterns of landcover change reveals that human-induced changes largely  
 239 (67.3%) occurred at elevations greater than 2 m, whereas 96% of sea-level induced changes  
 240 appeared at elevations between 0-2 m elevations (Fig. 3b). Thus, we restricted all further analysis  
 241 to 0-2 m above sea level.

242 Within elevations between 0 and 2 m, sea-level rise impacts outpaced human activity as the  
 243 predominant force responsible for over 70% of all coastal landcover change, expressed primarily

244 as forest conversion to marsh ( $223.6 \text{ km}^2$ ) and marsh transition to water ( $171.9 \text{ km}^2$ ), followed by  
 245 farmland loss to marsh and water ( $50.1 \text{ km}^2$ ) (Fig. 3b). In particular, sea-level driven landward  
 246 marsh migration led to the creation of  $257.3 \text{ km}^2$  of new marsh, which overcompensated marsh  
 247 loss at coastal margins and resulted in an overall increase of marsh area of  $78.8 \text{ km}^2$  from 1984 to  
 248 2020 (Fig. 3). In contrast,  $235.7 \text{ km}^2$  of forests were deforested by rising seas from 1984 to 2020.  
 249 In spite of reforestation from abandoned farmland ( $180.8 \text{ km}^2$ ), the total area of coastal forest  
 250 decreased by  $88.7 \text{ km}^2$  (Fig. 3b).

251



252  
 253 **Fig. 3 | Patterns of coastal landcover change in the US mid-Atlantic region from 1984 to 2020.** **a**, Landcover  
 254 change for all areas between 0 and 5 m above sea level. **b**, Landcover change for all areas between 0 and 2 m above  
 255 sea level. Alluvial plots illustrate the direction and magnitude of changes between landcover types. Numbers given  
 256 indicate the percent cover of each landcover type.

257

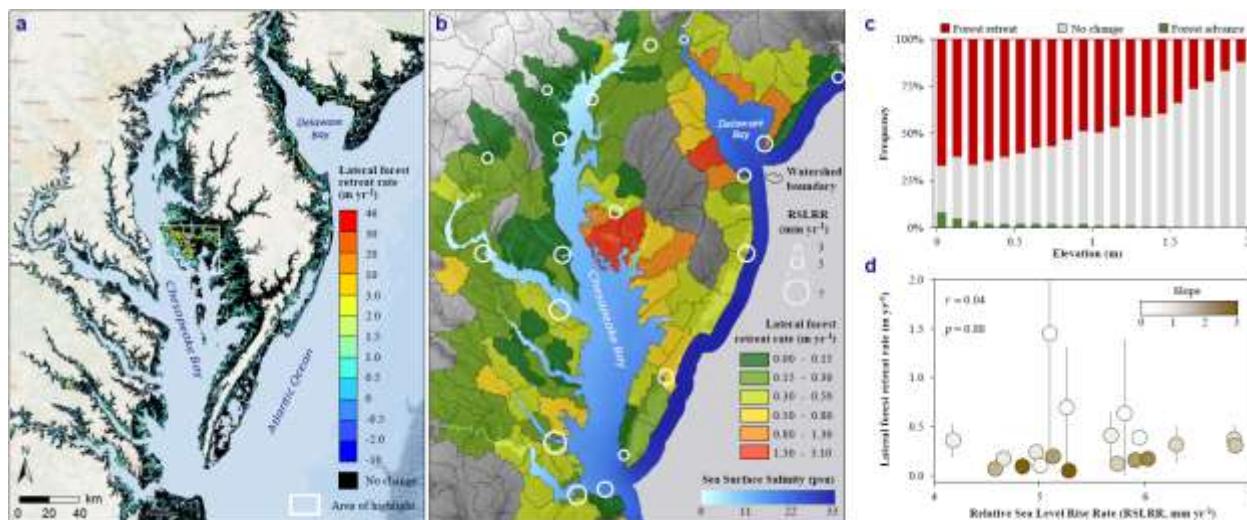
### 258 **3.2 Lateral forest retreat**

259 We detect that coastal forest retreat was widespread across the mid-Atlantic region (Fig. 4 and Fig.  
 260 S1), with an average lateral retreat rate of  $0.67 \pm 0.01 \text{ m yr}^{-1}$  (mean  $\pm$  SE) between 0 and 2 m  
 261 elevations (Fig. 4a). However, not all forested areas retreated with rising seas, and the average  
 262 forest retreat rate exhibited declining trends with elevation ( $r = -0.70, p < 0.001$ , Figs. 4-5). Overall,  
 263 41% of coastal forests retreated, whilst 56% of the forests remain unchanged with the remaining  
 264 3% showing treeline advance (primarily in the Virginia Coastal Reserve due to natural barrier

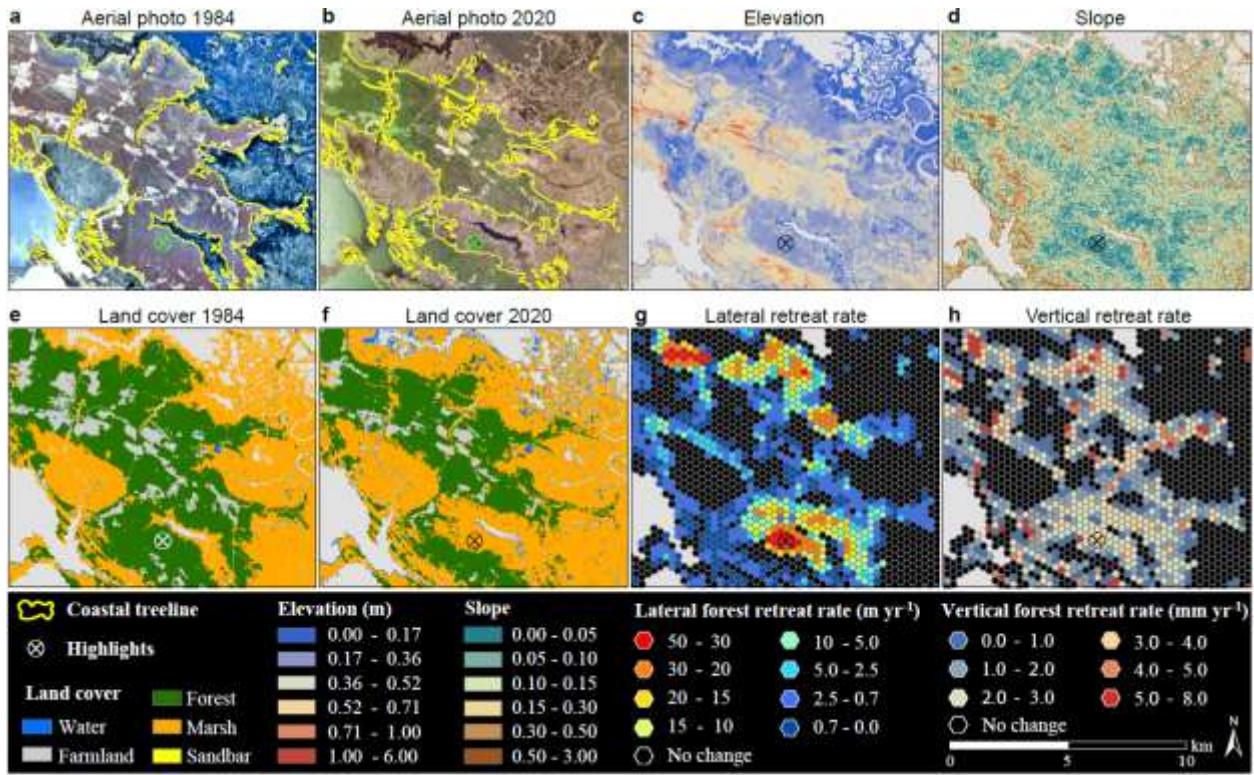
265 island rollover (Deaton et al., 2017)) (Fig. 4c). The proportion of retreating forest decreased rapidly  
 266 from ~70% at elevations below 0.3 m above sea level to ~10% at elevations of 1.9-2.0 m (Fig. 4c).  
 267 Accordingly, lateral forest retreat rates declined from a maximal rate of  $1.93 \pm 0.09 \text{ m yr}^{-1}$  at  
 268 elevations of 0.2-0.3 m to  $0.12 \pm 0.01 \text{ m yr}^{-1}$  at elevations of 1.9-2.0 m.

269 To explore the linkage between spatially-variable lateral forest retreat rate and relative sea-  
 270 level rise rates (RSLRR,  $n = 19$ ) observed in local watersheds, we averaged the spatially-explicit  
 271 map (Fig. 4a) by watershed to generate a watershed-scale forest retreat map (Fig. 4b). Interestingly,  
 272 we do not detect a statistical relationship between lateral forest retreat rate and RSLRR ( $p = 0.88$ ,  
 273 Fig. 4d). The lack of correlation is confirmed by our multiple linear regression model ( $R^2_{\text{adj}} = 0.69$ ,  
 274  $p < 0.001$ , Fig. 6a), suggesting that lateral forest retreat rate is strongly and positively influenced  
 275 by sea surface salinity ( $p < 0.01$ ), and negatively influenced by elevation ( $p < 0.05$ ) and  
 276 topographical slope ( $p < 0.05$ ). Whereas salinity emerges as the most influential variable  
 277 responsible for 38.5% of the variance, topography – the combination of elevation and slope –  
 278 accounts for the majority of overall variance (55.2%) in lateral forest retreat (Fig. 6a).

279



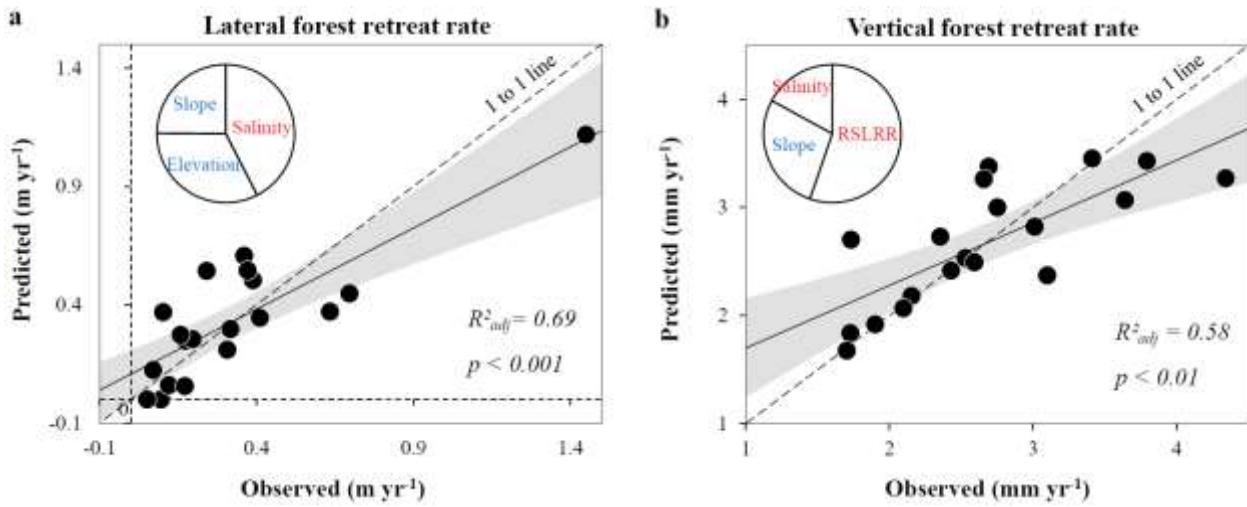
280  
 281 **Fig. 4 | Lateral forest retreat from 1984 to 2020 across the mid-Atlantic region.** **a**, Spatially-explicit map of lateral  
 282 forest retreat rate (resolution  $0.075 \text{ km}^2$ ). Positive values refer to forest retreat, and negative values represent forest  
 283 advance. The white box outlines the Blackwater National Wildlife Refuge, highlighted in Fig. 5. **b**, Watershed-scale  
 284 lateral forest retreat rate (HUC10 units, NHDPlus (McKay et al., 2019)). White circles refer to relative sea-level rise  
 285 rate (RSLRR) recorded by long-term tide gauges in the region. **c**, Histogram showing patterns of coastal forest  
 286 dynamics along elevation. **d**, No statistical relationship between lateral forest retreat and RSLRR. Data shown as mean  
 287  $\pm 1$  standard deviation.



288

289 **Fig. 5 | Regional subset highlighting dynamic patterns of coastal forest retreat in the Blackwater National**  
 290 **Wildlife Refuge.** High-resolution (~1.0 m) aerial photographs in 1984 (a) and 2020 (b) demonstrate variable patterns  
 291 of landward marsh migration and coastal treeline retreat along gradients in elevation (c) and slope (d). The landcover  
 292 maps in 1984 (e) and 2020 (f) were used to create the spatially-explicit maps of lateral (g) and vertical (h) forest retreat  
 293 rate. The elevation and slope data refer to the CoNED DEM (Danielson et al., 2018).

294



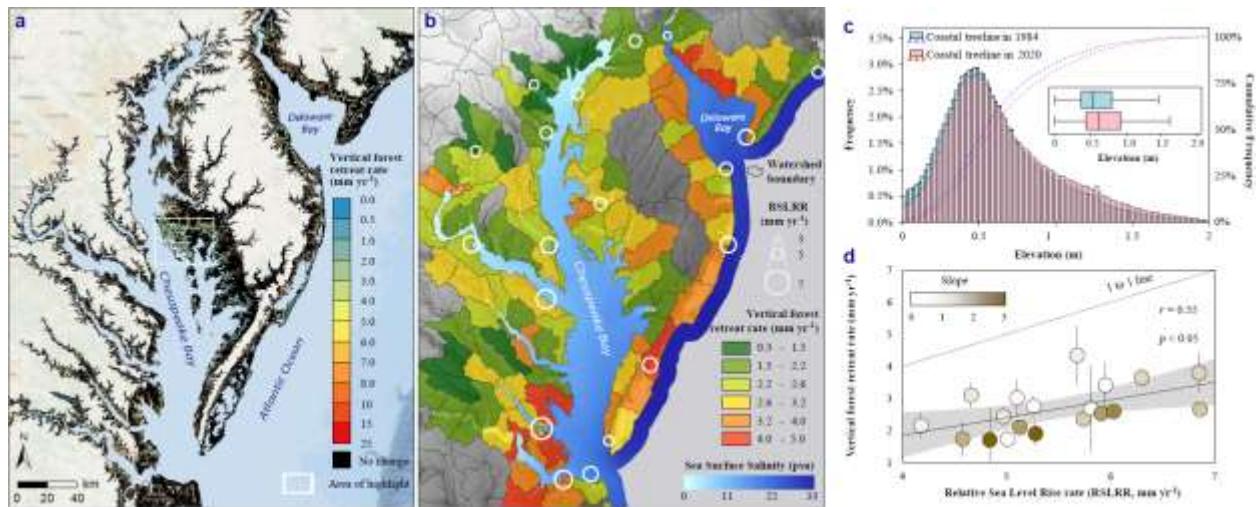
295 **Fig. 6 | Multiple linear regression models for patterns of coastal forest retreat.** Factors responsible for spatially-  
 296 variable patterns of horizontal forest retreat rate (a) and vertical forest retreat rate (b). The mean linear regression  
 297 trendline is bounded by the 95% confidence interval. The inserted pie charts present the relative contribution of each  
 298 variable retained in the model to overall variance, where variables in red represent positive correlation with the  
 299 response variable and variables in blue suggest negative correlation. RSLRR is short for relative sea-level rise rate,  
 300 and salinity refers to sea surface salinity.  
 301

302  
 303 **3.3 Vertical forest retreat**  
 304 Whilst lateral forest retreat is conceptually simple, the rate is heavily influenced by terrain  
 305 attributes (Figs. 4-6). To better isolate the influence of sea level on coastal forest retreat, we then  
 306 created maps of vertical forest retreat (i.e. the upward migration of forest along elevation) between  
 307 1984 and 2020 (Fig. 7). Similar to patterns of lateral forest retreat, vertical forest retreat rates  
 308 varied widely across the mid-Atlantic region (Fig. 7a), and declined with increasing elevation ( $r =$   
 309  $-0.48, p < 0.05$ ). Our multiple linear regression model suggests that RSLRR is the overriding  
 310 variable ( $R^2_{adj} = 0.58, p < 0.01$ ) responsible for 43.1% of the variance in vertical forest retreat (Fig.  
 311 6b). Although slope ( $r = -0.51, p < 0.05$ ) and salinity ( $r = 0.46, p < 0.05$ ) remain significant controls  
 312 shaping the observed patterns of vertical forest retreat, they are secondary to RSLRR, explaining  
 313 21.6% and 13.3% of the variance, respectively (Fig. 6b).

314 Concurrent with rising sea level, the average elevation of the coastal treeline shifted upslope  
 315 from  $0.60 \pm 0.01$  m ( $n = 443,145$ ) above sea level in 1984 to  $0.69 \pm 0.01$  m ( $n = 468,502$ ) above  
 316 sea level in 2020 (Fig. 7c). Notably, the estimated regional mean vertical forest retreat rate of  $2.71 \pm 0.003$  mm  $yr^{-1}$  (averaged across all forested areas between 0-2 m elevations, Fig. 7a) is less than

318 the regional RSLRR of  $5.48 \pm 0.17 \text{ mm yr}^{-1}$  ( $n = 19$ , Table 1). The deficit between forest retreat  
 319 and sea-level rise is reaffirmed by the watershed-scale results (Fig. 7b). We find that although the  
 320 rate of vertical forest retreat is strongly and positively correlated with RSLRR ( $r = 0.55, p < 0.05$ ),  
 321 the vertical forest retreat rate is merely  $48.5 \pm 2.6\%$  ( $n = 19$ , range of 34.6-76.4%) of RSLRR (Fig.  
 322 7d). For instance, as RSLRR increased from  $4.2 \text{ mm yr}^{-1}$  in New Castle, Delaware to  $6.9 \text{ mm yr}^{-1}$   
 323 in Yorktown, Virginia, the corresponding vertical forest retreat rate increased from only  $2.2 \text{ mm}$   
 324  $\text{yr}^{-1}$  to  $3.8 \text{ mm yr}^{-1}$  (Fig. 7b).

325



326 **Fig. 7 | Vertical forest retreat from 1984 to 2020 across the mid-Atlantic region.** **a**, Spatially-explicit map of  
 327 vertical forest retreat rate (resolution  $0.075 \text{ km}^2$ ). White box outlines the Blackwater National Wildlife Refuge,  
 328 highlighted in Fig. 5. **b**, Watershed-scale vertical forest retreat rate (HUC10 units, NHDPlus (McKay et al., 2019)).  
 329 White circles refer to relative sea-level rise rate (RSLRR) recorded by long-term tide gauges in the region. **c**, Elevation  
 330 of coastal treeline shifted upslope from 1984 to 2020. The inserted panel shows the boxplot of coastal treeline  
 331 elevations, where the left and right edges of the box respectively correspond to the first and third quartiles, the center  
 332 line refers to the median, the white point corresponds to the mean, and the whiskers represent data within  $1.5 \times$  the  
 333 interquartile range. **d**, Strong positive correlation between vertical forest retreat rate and RSLRR. The dotted 1 to 1  
 334 line indicates where vertical forest retreat rate equals RSLRR. The mean linear regression trendline (solid line) is  
 335 bounded by the 95% confidence interval. Data shown as mean  $\pm$  1 standard deviation.

337

## 338 4. DISCUSSION

### 339 4.1 Patterns and drivers of coastal forest retreat

340 Sea-level rise caused massive forest loss along the mid-Atlantic coast from 1984 to 2020. Notably,  
341 landward forest retreat appeared up to 10 km away from the coastline, facilitated by interconnected  
342 drainage networks. This finding complements earlier observations in coastal North Carolina  
343 (Poulter, Goodall, et al., 2008; Smart et al., 2020; Ury et al., 2021) and the Gulf of Mexico (Raabe  
344 & Stumpf, 2016), suggesting that legacy wetland management practices may serve as effective  
345 corridors for interior salinization. Nonetheless, the very condition detrimental to forest survival is  
346 conducive to inland marsh migration, which outpaced seaward marsh loss and led to an expansion  
347 of regional marsh area by 2%. Topographic and anthropogenic barriers are well known to limit  
348 marsh migration (Enwright et al., 2016; Molino et al., 2022). Interestingly, we found that with sea-  
349 level rise from 1984 to 2020, the slope at the marsh-forest boundary increased from 0.8 to 1.1,  
350 indicating that forests are retreating into progressively higher topographic slopes, which may slow  
351 marsh transgression in the future.

352 In spite of widespread forest loss over past decades, not all forests retreated with rising seas.  
353 In fact, only ~40% of coastal forests migrated inland between elevations of 0-2 m. Notably, stable  
354 treelines commonly occur in steeply sloped areas even at elevations in which treelines would have  
355 otherwise retreated. While it is intuitive that a gentle slope is favorable to forest migration in the  
356 lateral dimension (Chen & Kirwan, 2022a; Kirwan et al., 2016; Schieder et al., 2018; Smith, 2013),  
357 previous site-based measurements suggest contrasting relationships between topographical slope  
358 and vertical forest retreat (Fagherazzi et al., 2019; Field et al., 2016; Wasson et al., 2013). By  
359 synthesizing data across broad spatial scales, we show that both lateral and vertical forest retreat  
360 are strongly, negatively correlated with slope, highlighting steep terrain as a key asset in mediating  
361 sea-level rise impacts on adjacent uplands.

362 We argue that steep slopes may favor forest persistence in several ways. Aside from posing  
363 direct physical obstacles for marsh encroachment (Kirwan et al., 2016; Smith, 2013), steeper  
364 slopes generally increase the drainage area for forests downslope (Hawthorne & Miniat, 2018).  
365 Thus, forests abutting steep slopes likely receive freshwater subsidies to temper saltwater  
366 intrusion. Moreover, steep slopes minimize the distance that tree roots must extend in the landward  
367 direction to reach freshwater (Messerschmidt et al., 2021). Finally, increasing slopes also tend to  
368 shorten the duration of tidal flooding and enhance soil drainage (Hussein & Rabenhorst, 2001a,  
369 2001b), which lessens salinization and waterlogging conditions.

370 Previous work suggests that increases in salinity and/or soil saturation are the primary drivers  
371 of coastal forest mortality although their effects are difficult to distinguish (McDowell et al., 2022;  
372 Smith & Kirwan, 2021). Both hypoxia and salinity are hypothesized to drive similar mechanisms  
373 of plant mortality, resulting in hydraulic failure and carbon starvation (Krauss & Duberstein, 2010;  
374 McDowell et al., 2022). The range of lateral forest retreat rates that we observed across watersheds  
375 of the mid-Atlantic coast offers empirical support to both hypotheses (Fig. 6), and it also indicates  
376 that coastal topography may interact with these processes (hypoxia, salinization) to dynamically  
377 modify the impacts of sea-level rise on coastal forest survivorship.

378 Interestingly, we find no relationship between rates of forest retreat and patterns of climate  
379 change or disturbance (i.e. storms), both of which are known to influence tree growth and mortality  
380 (Chen & Kirwan, 2022a; McDowell et al., 2022; Ury et al., 2021). Prior dendrochronological  
381 analyses on common coastal forest species (*Juniperus virginiana*) suggest that progressive  
382 increases in sea level suppress the impacts of climate, while strengthening the impact of tidal  
383 flooding on forest growth (Hall et al., 2022). This phenomenon potentially explains why patterns  
384 of forest retreat are not directly linked to climate, even though a warmer and wetter climate boosts  
385 forest biomass at higher elevations (Chen & Kirwan, 2022a). Similarly, although disturbance has  
386 long been regarded as important in shaping forest retreat (Fagherazzi et al., 2019; Schieder &  
387 Kirwan, 2019; Ury et al., 2021), we find no correlations between spatially-variable forest retreat  
388 and the magnitude or duration of Hurricane Isabel, the largest storm to influence the mid-Atlantic  
389 coast since the 1950s. We suspect that stochastic processes like storms may be essential in  
390 explaining coastal forest dynamics at relatively short, local scales (Walters et al., 2021), but the  
391 impacts may average out over long, broad scales – a pattern also seen in the process of barrier  
392 island retreat (Mariotti & Hein, 2022).

### 393 **4.2 Lags with sea-level rise**

394 Vertical forest retreat is strongly correlated with sea-level rise, yet the rate of vertical forest retreat  
395 is merely 35%-76% of RSLRR (Fig. 7). This result, derived from multiple decades of modern  
396 satellite observation, is supported by paleoecological evidence from sediment cores in the region,  
397 which estimated that the magnitude of vertical forest retreat (~2 m) was approximately 60%-80%  
398 that of regional sea-level rise (~2.5-3.5 m) over past millennia (Schieder & Kirwan, 2019). Both  
399 forest retreat rates and RSLRR are accelerating in the mid-Atlantic region (Chen & Kirwan, 2022b;

400 Ezer & Corlett, 2012; Schieder & Kirwan, 2019). However, the average vertical forest retreat rate  
401 we observed between 1984 and 2020 (2.7 mm yr<sup>-1</sup>) most closely resembles the average RSLRR  
402 recorded between 1930-1950 (2.0-3.0 mm yr<sup>-1</sup>) (Ezer & Corlett, 2012), implying that regional  
403 forest retreat lags behind sea-level rise by roughly half of a century. With the ever-growing power  
404 of Earth observation satellite, future studies that utilize higher spatial/temporal resolution images  
405 may help identify the precise lag and potential nonlinearities in the lag effects.

406 We hypothesize that a suite of internal and external mechanisms may be involved that buffer  
407 upland forests from the otherwise acute impacts of sea-level rise. For instance, greenhouse  
408 experiments reveal that tree species commonly found in coastal uplands (e.g. *Pinus taeda*, *P. serotina*) possess physiological traits allowing them to tolerate a range of flooding and low salinity  
409 conditions (Poulter, Christensen, et al., 2008; Williams et al., 1998). Recent study also indicates  
410 that coastal forests can actively adapt to rising seas through morphological plasticity, as reflected  
411 by the distribution of tree roots preferentially towards freshwater sources upslope (Messerschmidt  
412 et al., 2021). Moreover, forested wetlands in other regions accrete vertically through the  
413 accumulation of mineral sediment and organic matter (Craft, 2012; Noe et al., 2016), which may  
414 be amplified in our region by the expansion of *Phragmites australis* into transitioning forests  
415 (Langston et al., 2021).

416 Although forests intruded by seawater generally display reduced tree height and basal area as  
417 compared to intact forests (Krauss et al., 2009; Smith & Kirwan, 2021), remote-sensing  
418 observations and repeated field surveys suggest that many salt-intruded forests did not show  
419 biomass loss over time (Chen & Kirwan, 2022a; White & Kaplan, 2021) and some even exhibited  
420 heightened growth vigor due to enhanced light availability near forest margin (Field et al., 2016).  
421 Other factors, such as biotic interactions encouraging seedling survival (Poulter et al., 2009), the  
422 effects of marsh migration on reducing saltwater intrusion landwards (Guimond & Michael, 2021),  
423 and the capacity of coastal forests to rapidly regenerate and resprout under variable salt stress  
424 (Walters et al., 2021; Williams et al., 1998) may confer additional strength for forest persistence.  
425 Thus, although upland forests may ultimately succumb to wetlands under excessive tidal flooding,  
426 the complete transition may take years to decades to fully realize.

427 Our finding of a lagged response between sea-level rise and forest retreat mirrors findings in  
428 an array of terrestrial and coastal ecosystems, where sizable spatiotemporal misalignment exists  
429 between ecosystem transition and climatic forcing (Rastetter et al., 2021). For instance, the upward

431 shifts of forest fronts in many Arctic and high-mountain regions demonstrate decadal to centennial  
432 timescale lags with climate warming (Alexander et al., 2018; Chapin & Starfield, 1997; Rastetter  
433 et al., 2021). In coastal barrier islands, the rate of barrier retreat is out of equilibrium with  
434 contemporary sea-level rise rate, but rather reflects baseline rates of past centuries (Mariotti &  
435 Hein, 2022). Similarly, marsh accretion rates lag behind accelerating sea-level rise by around 20-  
436 30 years (Kirwan & Temmerman, 2009), and marshes may persist for decades to centuries even  
437 after threshold RSLRR's are exceeded (Törnqvist et al., 2021).

438 Our observations of multi-decadal lags between sea-level rise and coastal forest retreat are  
439 therefore consistent with observations from a variety of earth systems responding to various facets  
440 of climate change. Numerical models of marshes, barrier islands, and terrestrial forests typically  
441 include physiological or geomorphic processes that allow ecosystems to persist under climate  
442 change until certain thresholds are surpassed (Dial et al., 2022; Kirwan & Temmerman, 2009;  
443 Mariotti & Hein, 2022). Yet, models of sea-level driven ecosystem migration are in their infancy,  
444 and typically assume that marshes migrate into adjacent uplands as soon as tidal inundation occurs  
445 (Enwright et al., 2016; Molino et al., 2022; Osland et al., 2022; Warnell et al., 2022). Incorporating  
446 newly emerging processes into numerical models are critical to predictions of coastal vulnerability  
447 and feedbacks with climate (Ward et al., 2020). In the meantime, our finding of a multi-decadal  
448 lag suggests that existing predictions based on static inundation may overestimate land conversion  
449 (Kirwan & Gedan, 2019; Osland et al., 2022), greenhouse gas emissions (Warnell et al., 2022),  
450 and marsh formation (Schuerch et al., 2018) during a given time period, but also suggests that the  
451 effects of historical sea-level rise have yet to be fully realized.

452 **Acknowledgments.** Primary funding for this work comes from the National Science Foundation  
453 (no. 1654374, 1832221 and 2012670, M.L.K.) with additional support from the US Department of  
454 Energy, Office of Biological and Environmental Research Program (DE-SC0021112, M.L.K.),  
455 U.S. Geological Survey Climate Research and Development Program and the U.S. Geological  
456 Survey Coastal and Marine Hazards and Resources Program, and National Natural Science Fund  
457 for Excellent Young Scientists Fund Program (Overseas) (Y.C.). We thank Tyler Messerschmidt  
458 and Alex Smith for their assistance in field validation, and acknowledge Kendall Valentine Cole  
459 for her feedback on the methodology. We appreciate the generosity of Marjy Friedrichs and Pierre  
460 St-Laurent for providing the salinity model output, Grace Molino for curating the tidal range  
461 dataset, and Alfredo Artxabaleta for navigating the ADCIRC Prediction System to provide the  
462 Hurricane Isabel product.

463 **Author Contributions.** Y.C. designed the study, performed the analysis and wrote the initial draft.  
464 M.L.K contributed to the study design and revised the manuscript. Both authors interpreted the  
465 data.

466 **Competing Interests.** The authors declare no competing interest.

467 **Data Availability.** All data will be available in the Virginia Coast Reserve Long-Term Ecological  
468 Research repository.

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