Effects of Shoreline Alteration and Other Stressors on Submerged Aquatic Vegetation in Subestuaries of Chesapeake Bay and the Mid-Atlantic Coastal Bays

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Abstract Submerged aquatic vegetation (SAV) provides many important ecosystem functions, but SAV has been significantly reduced in many estuaries. We used spatial–statistical models to identify estuarine shoreline characteristics that explain variations in SAV abundance among subestuaries of the Chesapeake Bay and mid-Atlantic Coastal Bays. We summarized digital spatial data on shoreline construction, shoreline land use, physical characteristics, watershed land cover, and salinity for each subestuary. We related SAV abundance to shoreline characteristics and other stressors using univariate regression and multivariate models. The strongest univariate predictors of SAV abundance were percent shoreline forest, percent shoreline marsh, the percentage of shoreline that is 5–10 m tall, percent riprap, the percentage of subestuary area <2 m deep, percent herbaceous wetland, and percent shrubland. Shoreline marsh, bulkhead, and shoreline forest had different effects on SAV in different salinity zones. Percent riprap shoreline was the most important variable in a regression tree analysis of all the subestuaries, and percent deciduous forest in the watershed was the most important variable in a separate regression tree analysis on the mesohaline subestuaries. Subestuaries with <5.4 % riprap followed a significantly different temporal trajectory than those with >5.4 % riprap. SAV abundance has increased steadily since 1984 in subestuaries with <5.4 % riprap, but has not increased

since 1996–1997 in subestuaries with >5.4 % riprap. Some shoreline characteristics interact with larger-scale factors like land cover and salinity zone to affect the distribution of SAV, while the effects of other shoreline characteristics are consistent among subestuaries with different salinities or local watershed land covers. Many shoreline characteristics can be controlled by management decisions, and our results help identify factors that managers should consider in efforts to increase SAV abundance.

Keywords Shoreline hardening · Riprap · SAV · Land use change · Shoreline geometry · Landscape analysis

Introduction

Submerged aquatic vegetation (SAV) is an essential part of estuarine and marine ecosystems and provides many important ecosystem services. SAV beds are habitats for juvenile fish, benthic crustaceans, and shellfish (Heck and Thoman 1984; Heck et al. 2003). Waterfowl and wetland mammals forage in SAV (Lubbers et al. 1990). SAV also takes up dissolved nutrients (Wigand et al. 2001), provides oxygen to the water column (Hemminga and Duarte 2000; Lubbers et al. 1990), and slows down water to settle sediments and reduce shoreline erosion (Hemminga and Duarte 2000; Gruber et al. 2011). Because of these important functions, the worldwide decline of SAV is of significant concern (Orth et al. 2006b).

In the Chesapeake Bay, historical reports suggest that SAV was declining through the 1800s (Orth and Moore 1984), and reliable scientific observations document the decline of SAV between the 1930s and 1972 due to a series of negative drivers (Southwick and Pine 1975; Orth and Moore 1984). In the 1930s, wasting disease decimated eel grass beds (Rasmussen 1977). During the 1950s and 1960s, invasive water chestnut (*Trapa natans*) and hydrilla (*Hydrilla verticillata*) outcompeted

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native species (Orth and Moore 1984; Posey et al. 1993) and declining water quality eliminated SAV habitat (Brush and Hilgartner 2000; Orth and Moore 1984). Damage from Hurricane Agnes in 1972 reduced SAV to the lowest spatial extent ever reported in the bay (Orth et al. 2010).

From 1984 to the present, some areas of the bay (such as the Upper Patuxent River) have shown increases in coverage and sustained dense grass beds, but coverage in other areas (such as the Lower Western Shore) has not changed much (Orth et al. 2010). In recent years, there has been little additional recovery and there have been bay-wide declines in SAV (Orth et al. 2010). The current spatial extent of SAV is only a fraction of the area reported early in the twentieth century, and that area was just an unknown remnant of historical highs (Orth and Moore 1984). Understanding the post-Agnes dynamics of SAV in the Chesapeake Bay is critical to developing successful restoration strategies, and the wealth of data available provides the opportunity to integrate diverse potential drivers of SAV to better understand the complex factors controlling SAV spatial extent. The lessons learned from studying SAV in the Chesapeake can be applied in SAV conservation strategies in other estuaries around the world.

SAV is sensitive to changes in water clarity, making it very vulnerable to human activities. Species in the tidal fresh and oligohaline parts of the bay require at least 13 % of incident sunlight reaching their leaves (Table 1), and polyhaline and mesohaline species require at least 22 % (Kemp et al. 2004). Lower water clarity reduces the depth at which SAV beds can grow and reduces the spatial extent of potential SAV habitat. Water clarity is negatively affected by materials delivered from the watershed, including sediments, colored dissolved organic matter (cDOM), and nutrients that drive algae blooms (Gallegos 2001; Gallegos and Bergstrom 2005; Kemp et al.

2004). Fine-scale disturbances such as boat traffic, dredging for shellfish (Orth et al. 2002), herbivory by waterfowl (Tatu et al. 2007), and disturbances by cownose rays also negatively impact SAV (Myers et al. 2007).

While many studies have focused on water quality and light conditions within individual SAV beds, estuarine responses have also been linked to landscape-level drivers like watershed land cover (Comeleo et al. 1996; Dauer et al. 2000; Rodriguez et al. 2007). Li et al. (2007) examined landscape-level correlates of SAV abundance among shallow embayments within Chesapeake Bay. Shallow subestuaries can be treated like replicate units within the larger estuarine ecosystem, and subestuary responses can be strongly driven by activities in their local watersheds. Dominant land cover in the upland watershed was a significant predictor of SAV abundance, which was negatively affected by agriculture and development (Li et al. 2007). Li et al. (2007) found that some properties of the subestuaries themselves, such as fractal dimension of the shoreline and subestuary mouth width, were also significant predictors of subestuary abundance. Although Li et al. (2007) demonstrated strong linkages between SAV abundance and watershed subestuary characteristics, they did not consider shoreline characteristics (like shoreline hardening) directly at the land–water interface.

In this paper, we develop landscape-level models to evaluate the relationship between shoreline characteristics and SAV abundance in subestuaries of the Chesapeake Bay and nearby Atlantic Coastal Bays. Shoreline structures significantly modify and fragment natural habitat, but their impacts on estuarine biota have only recently been studied (King et al. 2005; Seitz et al. 2006; Bilkovic et al. 2006; Weinstein and Kreeger 2000). SAV in this region is concentrated near the shore in shallow water because of light limitation, so alterations to the land–water interface could be particularly damaging to SAV. Shoreline armoring (such as bulkhead and riprap) may increase wave energy bouncing back into the benthos, increasing both bottom scour and the amount of suspended sediments in the water column (Mills and Fonseca 2003; Wright 1995).

We used data on shoreline characteristics from an extensive shoreline survey, which maps many aspects of shoreline condition (especially shoreline hardening) throughout the study area (<http://www.vims.edu/ccrml>). We tested the relationships between single shoreline characteristics and SAV abundance, and we considered multivariate models that combine shoreline characteristics with dominant land cover, salinity zone, and other variables representing physical, chemical, and geometric characteristics that could contribute to spatial variation in SAV abundance among subestuaries.

Table 1 SAV species present in the salinity zones of Chesapeake Bay (after Moore et al. 2000; Orth et al. 2010)

Tidal fresh and oligohaline	Mesohaline	Polyhaline
<i>Vallisneria americana</i>	<i>Ruppia maritime</i>	<i>Zostera marina</i>
<i>Hydrilla verticillata</i> ^a	<i>Potamogeton perfoliatus</i>	<i>Ruppia maritima</i>
<i>Myriophyllum spicatum</i> ^a	<i>Zostera marina</i>	
<i>Elodea canadensis</i>	<i>Zannichellia palustris</i>	
<i>Heteranthera dubia</i>		
<i>Najas guadalupensis</i>		
<i>Najas minor</i> ^a		
<i>Potamogeton crispus</i>		
<i>Potamogeton perfoliatus</i>		
<i>Potamogeton pusillus</i>		
<i>Ceratophyllum demersum</i>		
<i>Zannichellia palustris</i>		

^a Invasive species

Methods

Study Area

We studied 100 subestuaries within the Chesapeake Bay and the Atlantic Coastal Bays of Maryland, Virginia, and Delaware (Fig. 1). Each subestuary had at least one perennial stream flowing into it. We evaluated 141 subestuaries, but dropped systems which had been previously categorized as “no-grow zones” for SAV (USEPA 2003) and also eliminated subestuaries for which key measurements were missing. Mattawoman and Piscataway Creeks in the upper Potomac were excluded because their unusually high SAV abundances are driven by invasive *H. verticillata* (Li et al. 2007).

Boundaries for the subestuaries were taken from a composite of the highest-resolution shoreline layers for the Chesapeake Bay and Atlantic Coastal Bays. The northern half of the Chesapeake was best represented by the Environmental Sensitivity Index shoreline dataset (National Oceanic and Atmospheric Administration, <http://oceanservice.noaa.gov/dataexplorer/datasites/>), and the southern half of the Chesapeake and the Atlantic Bays were best characterized by the shoreline maps described in the “Shoreline Condition” section. For each subestuary, we added a line across the mouth to the composite digital shoreline. This formed a closed polygon representing the water surface of the subestuary. We delineated the local watershed draining to each subestuary by applying automated watershed delineation (ArcGIS 9.3, ESRI, Inc.) to digital elevation maps (Federal Geographic Data Committee FGDC 2001; http://www.ngs.noaa.gov/newsys_ims/shoreline). Coastal plain and low elevation watersheds were manually corrected and checked against US Geological Survey 12-digit or 14-digit unit code boundaries (Baker et al. 2006; Allord 1992; <http://water.usgs.gov/GIS/huc.html>).

Data Sources

Submerged Aquatic Vegetation

The spatial extent and density of SAV were calculated from maps of SAV beds digitized from annual aerial photography for the years 1984–2009, except 1988 (Moore et al. 2000; <http://www.vims.edu/bio/sav>). Beds were classified into five density categories: no SAV, 0 %; very sparse, 0–10 %; sparse, 10–40 %; moderate, 40–70 %; and dense, 70–100 % (Orth et al. 2004).

We created a new map of potential SAV habitat because previous potential habitat maps based on depth have missed some areas actually occupied by SAV (Li et al. 2007), possibly because of the coarse resolution of bathymetric maps and errors in the bathymetric data. We started the new map with the area that is <2 m deep using bathymetry for the Chesapeake Bay (Cohen 1994; <http://www.ngdc.noaa.gov/mgg/bathymetry/maps>) and the Atlantic Coastal Bays (<http://www.ngdc.noaa.gov/mgg/coastal/grddas02/grddas02.htm>).

We removed areas designated as no-grow zones by the Chesapeake Bay Program (CBP) (USEPA 2003), and then added areas where SAV had actually been observed in historical surveys (unpublished spatial data from Maryland DNR) or in the aerial surveys from 1984 to 2009 (see previous paragraphs).

For each subestuary and year, we estimated the SAV coverage as density-weighted percent occupied habitat (DWOH) by summing the density-weighted area across all the observed SAV beds:

$$\text{DWOH} = \frac{\sum A_i D_i}{P} 100, \quad (1)$$

where A_i is the area of observed SAV bed i , D_i is the density observed in bed i , P is the total potential SAV habitat area in the subestuary, i indexes the observed beds in the subestuary, and the factor of 100 converts the number from a fraction to a percentage. Density estimates were simplified by replacing each reported density range with its median value expressed as a fraction (no SAV, 0; very sparse, 0.05; sparse, 0.25; moderate, 0.55; and dense, 0.85). DWOH is the same metric reported as “SAV abundance” in Li et al. (2007). As a weighted ratio of two areas, it is a unitless metric that can range from zero where there is no SAV to 100 % where every bit of potential habitat is occupied by the maximum density of SAV. In this study, the maximum possible value is 85 % because we assigned the median density value 0.85 to the reported “dense” category (see previous paragraphs). We introduced the metric here as “DWOH” to more accurately describe what the metric measures and how it is calculated. In the rest of the paper, we refer to it simply as SAV abundance for ease of reading and consistency with Li et al. (2007).

Shoreline Condition

We summarized the shoreline characteristics of each subestuary using digital shoreline situation maps from the Comprehensive Coastal Inventory Program (<http://www.vims.edu/ccrml>). The inventory reports 31 shoreline characteristics that we used, including adjacent land use (agriculture, forest, marsh, and residential land), erosion status (erosional or not), bank height (0–5, 5–10, 10–30, and >30 m), and vegetative cover of the bank. The inventory also maps structures built upon the shoreline, including recreational structures (docks, boat ramps, or marinas) and shoreline hardening (riprap, bulkhead, groin field, seawall, and breakwater).

Salinity

We estimated the average salinity for each subestuary using salinity measurements from the CBP monitoring program, which collects samples every 2 weeks during the SAV growing

Fig. 1 The study subestuaries and their local watersheds. The subestuaries are in *black* and the watershed for each is *outlined in black* (see *inset*). Note that Atlantic Coastal Bays are not part of the Chesapeake Bay watershed

season of March–October (CBP 2012, <http://www.chesapeakebay.net/data/downloads/>). To create a bay-wide interpolated map of average salinity for each year from 1984 to 2009, we applied inverse distance weighted spatial interpolation (with the shoreline as a boundary) to the growing season salinity data. We intersected the salinity maps with the subestuary boundaries and then averaged across years (1984–2009) to estimate the average growing season salinity for each subestuary. Subestuaries were then categorized as tidal fresh (TF, 0–0.5 ppt salinity), oligohaline (OH, 0.5–5 ppt), mesohaline (MH, 5–18 ppt), or polyhaline (PH, >18 ppt).

Land Cover

Watershed land cover information was summarized from the circa 2000 National Land Cover Dataset, which was derived from Landsat 7 satellite remote sensing imagery (NLCD 2001; 30 m resolution; Homer et al. 2004). For the local

watershed of each subestuary, we summarized total watershed area and the percentages of cropland, herbaceous wetland, total forested land, total developed land, and four subclasses of developed land (open, low, medium, and high) for each watershed. We classified each subestuary system into one of six land cover categories based upon dominant land cover of its watershed: (1) forested (≥ 60 % forest and forested wetland), (2) developed (≥ 50 % developed land), (3) agricultural (≥ 40 % cropland), (4) mixed–developed (15–50 % developed land), (5) mixed–agricultural (20–40 % cropland), and (6) mixed–undisturbed (watersheds which did not fit into categories 1–5) (King et al. 2005, Li et al. 2007).

Subestuary Characteristics

We summarized the subestuary polygons and their intersection (ArcGIS 9.3, ESRI) with the bathymetry

layers (see previous paragraphs) to calculate the metrics describing subestuaries, including the average depth, area, area of shallow (<2 m) water, length from mouth to headwater, shoreline length, mouth width, and fractal dimension of the shoreline, which was calculated as two times the natural logarithm of subestuary perimeter divided by the natural logarithm of subestuary area (Li et al. 2007; Mandelbrot 1982; Milne 1988).

Correlations of SAV Abundance with Shoreline Characteristics and Other Variables

To identify shoreline variables that are significantly related to SAV abundance, we fit a univariate regression model predicting SAV abundance using each potential predictor. We also fit univariate regression models for other variables describing the subestuaries and their watersheds to see if improvements in data resolution would support or overturn previous findings (Li et al. 2007). Predictor variables which did not approximate normal distributions were transformed to reduce heteroscedasticity.

Effects of Salinity and Watershed Land Cover on SAV–Shoreline Relationships

Preliminary explorations suggested that the effects of shoreline variables on SAV abundance might differ among salinity zones or among subestuaries with different dominant land covers. We tested the possibility for four shoreline variables: percent riprap, percent bulkhead, percent marsh, and percent forest. For each of these, we fit a linear model treating the shoreline characteristic as a continuous variable and salinity zone as a categorical variable. A second model was fit in which dominant land cover of the local watershed was the categorical variable. Statistical interactions (shoreline characteristic $\times$ categorical variable) were dropped unless an interaction was statistically significant ($P < 0.05$) or marginally significant ($P < 0.10$). We constructed plots to illustrate any differences in the SAV vs. shoreline characteristic relationships among the salinity zones or dominant land cover types.

Combining Variables to Predict SAV Abundance

We fit multivariate models to test whether combinations of shoreline variables or shoreline variables together with other watershed or subestuary characteristics could explain more of the variation in SAV abundance among subestuaries than could single predictors (see previous paragraphs). We used the Leaps package in R to consider all possible multiple regression models with up to

five independent variables, and we selected the model with the lowest Bayesian information criterion (BIC) score (Weakliem 2004; Anderson 2008). Beginning with the entire suite of variables, we removed some variables that were >60 % correlated with another variable by eliminating the variable in each pair that explained less variance in the univariate analysis (see previous paragraphs). We supplied the remaining predictor variables and their squared values as potential predictors to the Leaps package.

We also considered combinations of possible predictor variables by fitting regression tree models. Tree models are especially sensitive to thresholds and other nonlinear responses that are not well represented by regression models (Maindonald and Braun 2007). Using the RPART library (Venables and Ripley 2002) in R, we constructed a regression tree for all the subestuaries and a separate tree for each salinity zone. Trees were pruned using the 1-standard error (SE) rule to remove splits for which the additional explanatory power was within 1 SE of the minimum cross-validated estimate of error (Maindonald and Braun 2007).

Relationship Between Riprap and Temporal Patterns of SAV Abundance

The first split in the regression tree for all the subestuaries was the percentage of riprapped shoreline, with more riprap resulting in lower SAV area (see the “Results” section). That finding matched our expectation that shoreline hardening would reduce SAV abundance, and the split created two groups of subestuaries: those with >5.43 % riprap and those with <5.43 % riprap. Time series plots suggested that SAV abundance responded very differently through time in these two groups. To test if the temporal patterns of the two groups were significantly different, we applied repeated-measures analysis of variance (ANOVA). High or low riprap was the independent (categorical) variable, and the annual observations of SAV abundance from 1984 to 2009 were the repeated measures of the response. All statistical analyses were performed in the statistical program R (R Development Core Team 2011).

Results

Summary Statistics of the Watershed–Subestuary Systems

The subestuaries ranged between 0.4 and 335 km² in size and between 10.7 and 1,229 km in shoreline length (Table 2). Their associated watersheds were between 9.3 and

Table 2 Shoreline characteristics and other estuary and watershed metrics used in the analyses

Metric	Description	Median value	Maximum value	Minimum value	Standard deviation
Shoreline characteristics					
Height 0–5 m	Percent shoreline in the subestuary that is 0–5 m tall	0.87	1.00	0.32	0.18
Height 5–10 m	Percent shoreline in the subestuary that is 5–10 m tall	0.09	0.34	0.00	0.10
Height 10–30 m	Percent shoreline in the subestuary that is 10–30 m tall	0.02	0.56	0.00	0.10
Height >30 m	Percent shoreline in the subestuary that is >30 m tall	0.00	0.15	0.00	0.021
Shoreline beach	Percent shoreline in the subestuary that is beach	0.06	0.30	0.00	0.07
Shoreline marsh	Percent shoreline in the subestuary that is marsh	0.48	1.00	0.01	0.28
Shoreline agriculture	Percent shoreline in the subestuary that is agriculture	0.00	0.45	0.00	0.11
Shoreline bare	Percent shoreline in the subestuary that is bare land	0.00	0.05	0.00	0.01
Shoreline paved	Percent shoreline in the subestuary that is paved or being used commercially	0.04	0.66	0.001	0.12
Shoreline family	Percent shoreline in the subestuary that is residential (waterfront homes)	0.32	0.77	0.00	0.19
Shoreline forest	Percent shoreline in the subestuary that is forested	0.46	0.96	0.11	0.21
Shoreline grass	Percent shoreline in the subestuary that is grass	0.05	0.64	0.00	0.07
Shoreline erosional	Percentage of shoreline in the subestuary that shows evidence of shoreline erosion	0.05	0.013	1.00	0.28
Boathouse	Density of boathouses in the subestuary (units/km)	0.66	24.55	0.00	3.36
Dock	Density of docks in the subestuary (units/km)	16.23	242.72	0.13	41.67
Ramp	Density of ramps in the subestuary (units/km)	1.18	9.96	0.00	2.055
Marina	Density of marinas in the subestuary (units/km)	0.83	22.99	0.00	4.028
Bulkhead	Percent shoreline in the subestuary that is bulkhead	5.65	48.87	0.00	10.63
Riprap	Percent shoreline in the subestuary that is riprap	6.52	42.41	0.00	8.08
Subestuary characteristics					
Subestuary area	Area of each subestuary (km ²)	11.80	334.00	0.39	39.04
Subestuary length	Length of each subestuary shoreline (km)	81.21	1,229.00	10.73	184.22
Fractal dimension	Subestuary fractal dimension ^a	1.40	1.53	1.27	0.05
Mouth width	Subestuary mouth width (km)	2.10	53.68	0.15	5.64
Subestuary volume	Bathymetric volume of the subestuary (km ³)	0.02	0.35	0.002	0.055
Bathymetric mean	Mean depth of the subestuary (m)	−1.65	−5.14	−0.06	1.06
2 m area	Area within the subestuary that is <2 m deep (km ²)	7.97	295.78	0.38	33.42
Local watershed characteristics					
Barren	Percent barren land in each watershed	0.00	0.00	0.11	0.02
Shrub	Percent shrubland in each watershed	0.02	0.09	0.00	0.02
Grass	Percent grassland in each watershed	0.001	0.01	0	0.00
Pasture	Percent pasture in each watershed	0.06	0.26	0	0.07
Crops	Percent cropland in each watershed	0.17	0.64	0.00	0.15
Herbaceous wetland	Percent herbaceous wetland in each watershed	0.02	0.43	0	0.09
Total wetland	Percent total wetland (woody, herbaceous, forested) in each watershed	0.16	0.72	0.01	0.17
Total forest	Percent forest in each watershed	0.21	0.63	0.02	0.17
Total developed	Percent developed lands in each watershed	0.12	0.91	0.03	0.22
Watershed area	Area of the upland watershed of each subestuary (km ²)	7.78	2,463.00	1.68	349.21

Minor subcategories of variables were excluded from this table for brevity

^a Defined as two times the logarithm (ln) of subestuary perimeter (meters) divided by logarithm (ln) of subestuary area (square meters)

1,686 km² in size. The fractal dimension of the shorelines of the subestuaries ranged between 1.27 and 1.53. Watershed land cover percentages ranged between 5.4 and

79.2 % forest, 0 and 56.8 % cropland, 0 and 51.2 % wetland, and 0.01 and 77.4 % developed lands. SAV abundance ranged from 0.0 to 26.4 %.

Correlations of SAV Abundance with Shoreline Characteristics and Other Variables

Twenty-four predictors were significantly correlated with the SAV abundance (Table 3), far more than the 3 significant relationships we would expect from chance alone when testing 65 correlations with a significance level of $P < 0.05$. However, many of the 24 significant correlations explained a low percentage of the variation in SAV abundance among subestuaries (Table 3). The *positive* predictors which explained the most variation (Fig. 2; all $P < 0.001$) were percent herbaceous wetland in the watershed ($R^2 = 0.16$), percent shoreline forest ($R^2 = 0.14$), percent shrubland in the watershed ($R^2 = 0.13$), and subestuary area <2 m deep ($R^2 = 0.12$). The *negative* predictors that explained the most variation (Fig. 2; all $P < 0.001$) were percent shoreline marsh ($R^2 = 0.17$), percent shoreline 5–10 m high ($R^2 = 0.10$), and percent riprapped shoreline ($R^2 = 0.10$). Land cover variables for the watershed that were expected to be important, such as total

developed land ($R^2 = 0.02$, $P = 0.1$), cropland ($R^2 = 0.01$, $P = 0.4$), and total forest ($R^2 = 0.003$, $P = 0.5$) in the watershed, were not statistically significant. The geometric predictors subestuary area ($R^2 = 0.08$, $P = 0.005$) and subestuary length ($R^2 = 0.05$, $P = 0.03$) had a significant *positive* relationship with SAV, and the size of the subestuary watershed ($R^2 = 0.1$, $P = 0.002$; Fig. 2) and the average depth of the subestuary ($R^2 = 0.05$, $P = 0.02$; Fig. 2) had *negative* relationships with SAV abundance.

Effects of Salinity and Watershed Land Cover on SAV–Shoreline Relationships

We tested whether salinity zone or watershed land cover modified the effects of the percentage of bulkhead, riprap, forested shoreline, and marsh shoreline on SAV abundance. There was a significant interaction between salinity zone and shoreline forest ($P = 0.021$; Table 4), where shoreline forest had positive effects on SAV in the oligohaline and polyhaline zones but not in the mesohaline zone (Fig. 3). There were interactions significant at an alpha of 0.10 between salinity and bulkhead ($P = 0.087$; Table 4) and salinity and marsh shoreline ($P = 0.072$; Table 4). Bulkhead was positively related to SAV in the oligohaline zone, negatively related to SAV in the polyhaline zone, and had no effect on SAV in the mesohaline zone (Fig. 3). Marsh shoreline was negatively related to SAV in all three salinity zones, but the effect was strongest in the polyhaline zone (Fig. 3). We found no significant interactions between land cover and shoreline variables, although there were significant negative impacts of riprap, bulkhead, and marsh on SAV (Table 5).

Combining Variables to Predict SAV Abundance

Some highly correlated variables were eliminated before fitting multivariate models predicting SAV abundance from shoreline variables and other subestuary or local watershed variables (Table 1). We eliminated low and medium developed land, total forested land, total developed land, total wetland, subestuary area, subestuary length, bank height of 0–5 m, and density of boat ramps from the dataset prior to the multiple linear regression. The composite variables (e.g., summed total forest) were highly correlated with the individual subcategories (e.g., deciduous forest) and were poorer predictors than the single categories. The other dropped variables were highly correlated with similar variables. For example, low and medium developed lands were both highly correlated with highly developed land and were worse predictor variables. After removal, 49 different explanatory variables remained for analysis.

Table 3 Significant univariate predictors of SAV abundance

Variable	F value	P value	R ²	Sign
Percent shoreline marsh	20.02	<0.001	0.17	–
Percent herbaceous wetland in the watershed	18.74	<0.001	0.16	+
Percent shoreline forest	15.05	<0.001	0.14	+
Percent shrubland in the watershed	14.59	<0.001	0.13	+
Amount of 2 m deep area	13.08	<0.001	0.12	+
Percent wetland in the watershed	11.81	<0.001	0.11	+
Percent shoreline 5–10 m high	10.70	<0.001	0.10	–
Percent shoreline with riprap	10.57	0.002	0.10	–
Size of the subestuary watershed	10.03	0.002	0.10	–
Percent shoreline 0–5 m high	8.96	0.004	0.09	+
Size of the subestuary	8.36	0.005	0.08	–
Percent barren land in the watershed	7.43	0.008	0.07	+
Percent grass covered land in the watershed	7.32	0.008	0.07	+
Density of docks in the subestuary	6.59	0.012	0.06	–
Percent paved shoreline	6.49	0.012	0.06	–
Percent silt clay	6.31	0.014	0.06	
Density of boathouses	6.23	0.014	0.06	–
Average depth of the subestuary	5.52	0.021	0.05	–
Percent evergreen forest in the watershed	5.47	0.021	0.05	+
Percent wooded wetland in the watershed	5.43	0.022	0.05	+
Percent highly developed land in the watershed	5.15	0.026	0.05	–
Percent shoreline 10–30 m high	5.02	0.027	0.05	–
Length of the subestuary	4.72	0.033	0.05	+
Density of private boat ramps	4.65	0.034	0.05	–

Squared correlations estimate the percentage of explained variance in SAV abundance among 98 subestuaries

Fig. 2 Significant predictor variables that explained the most variance in SAV abundance among subestuaries (Table 3)

Across all possible categories 1–5 variable models, the multiple regression model with the highest BIC score explained 48 % of the variance in SAV abundance ($df=5,92$, $P<0.001$):

$$\begin{aligned} \text{SAV abundance} = & 3.51 + 1.77 \times (\text{percent shrub land}) \\ & + 1.70 \times (\text{percent forested shoreline}) \\ & - 1.62 \times (\text{watershed area}) - 1.14 \times \\ & (\text{percent developed open lands})^2 - 1.30 \times \\ & (\text{percent mixed forest})^2 + \text{error}. \end{aligned}$$

A regression tree model based on three variables explained 40 % of the variation in SAV abundance among subestuaries (Fig. 4a). The percentage of shoreline that had riprap was the first split in the tree, and subestuaries with >5.4 % riprap averaged 2.18 % SAV abundance, while subestuaries with <5.4 % riprap averaged 6.13 % SAV abundance. At the next level of the tree, there were two splits. For subestuaries with more riprap, those with >3.1 % herbaceous wetland cover had more SAV (4.8 % SAV abundance) and those with less herbaceous wetland had less SAV (1.3 % SAV abundance). For subestuaries with less riprap, 12 % cropland in the watershed was the next split. Subestuaries above that threshold had less SAV (3.8 % SAV abundance) and those below that threshold had more SAV (10.1 % SAV abundance).

We also fit a separate regression tree for each salinity zone of the bay, but only the tree for the mesohaline zone remained after applying the 1–SE pruning rule. That tree explained 37 % of the variation among subestuaries (Fig. 4b). The first split is the percent deciduous forest in the watershed (7.3 %) and those subestuaries with less deciduous forest were further subdivided by the average depth of the subestuary basin at 2.5 m. The deeper subestuaries averaged 0.43 SAV abundance and the shallower averaged 2.43 % SAV abundance. Subestuaries with more forest were split into

subestuaries with >0.14 % or <0.14 % shrubland. Watersheds with less shrubland had subestuaries with 2.04 % SAV abundance, whereas those with more shrubland had subestuaries with 5.74 % SAV abundance.

Effects of Riprap on Temporal Patterns of SAV Abundance

We applied repeated-measures ANOVA to compare the change in SAV abundance through time for the two groups of subestuaries identified by the regression tree analysis; those with >5.4 % or <5.4 % shoreline with riprap. The effect of riprap category was highly significant ($F=167$, $df=24$, $P<0.001$). Subestuaries with <5.4 % riprapped shoreline showed a steady increase in SAV abundance throughout the entire time period, but those with >5.4 % riprap do not appear to have increased in SAV abundance since 1996 (Fig. 5). We tested the statistical significance of this apparent difference in temporal pattern by applying the regional Kendall trend test (Hirsch and Slack 1984) to each time series. SAV abundance in subestuaries with less riprap increased significantly from 1996 to 2009 (score=55, $P=0.003$, slope=0.34), while subestuaries with more riprap had no significant trend over that period (score=−23, $P=0.23$, slope=−0.08).

Discussion

This is the first landscape-level analysis to document that shoreline characteristics are significantly related to SAV abundance. We discovered that shoreline conditions, such as shoreline hardening or shoreline land use, can be significant factors explaining differences in SAV abundance among subestuaries. We also demonstrated that the effects of shoreline condition on SAV differed among salinity zones. Finally, we built

Table 4 Results for differences in the effects of shoreline variables among subestuaries in different salinity zones

	Degrees of freedom	Type III sum of squares	Mean squared error	F value	P value
Model	3	323.87	107.96	9.22	<0.001
Error	93	1,088.98	11.71		
Corrected total	96	1,412.85			
Riprap	1	2.0068	2.0068	0.17	0.680
Salinity	2	188.94	94.47	8.07	<0.001
Model	5	379.032	75.81	6.67	<0.001
Error	91	1,033.82	11.36		
Corrected total	96	1,412.85			
Bulkhead	1	3.85	3.85	0.34	0.560
Salinity	2	90.99	45.49	4.00	0.022
Bulkhead×salinity	2	57.11	28.55	2.51	0.087
Model	5	531.35	106.27	10.97	<0.001
Error	91	881.5	9.69		
Corrected total	96	1,412.85			
Shoreline forest	1	99.87	99.87	10.31	0.002
Salinity	2	301.64	150.82	15.57	<0.001
Shoreline forest×salinity	2	128.39	64.2	6.63	0.002
Model	5	490.39	98.078	9.68	<0.001
Error	91	922.46	10.13		
Corrected total	96	1,412.85			
Shoreline marsh	1	237.42	237.42	23.42	<0.001
Salinity	2	198.11	99.057	9.77	<0.001
Shoreline marsh×salinity	2	54.86	27.43	2.71	0.072

The interaction term (shoreline variable×salinity) was significant ($P<0.05$) or marginally significant ($P<0.1$) for bulkhead, shoreline forest, and shoreline marsh. The interaction was not significant for riprap and was removed from that model

models including both shoreline condition and land cover variables, and those multivariate models provide accurate predictions of SAV abundance.

Shoreline Characteristics Affecting SAV Abundance

There were many shoreline characteristics that were significantly related to differences in SAV abundance among subestuaries (Table 2). The amount of shoreline with marsh was the strongest single predictor (explaining 17.6 % of the variation among subestuaries), and it was negatively correlated with SAV abundance. The significant negative effect of shoreline marsh on SAV may seem counterintuitive, especially since herbaceous wetland in the local watershed was the strongest positive predictor of SAV abundance (explaining 16.3 % of the variation among subestuaries). However, there are ways that shoreline marsh can negatively affect SAV even though marsh is a natural ecosystem that often exists in areas of low human impact. Marsh sediments are soft and muddy; so they provide poor substrate for *Zostera marina* and *Ruppia maritima*, which strongly prefer sandier sediments (Orth et al. 2003). Eroding marsh sediments are rarely occupied by SAV (Evamaria Koch, personal communication). Marshes also leach materials that can significantly reduce water clarity, including dissolved

organic carbon, cDOM, and dissolved inorganic carbon (Tzortziou et al. 2008, 2011). The relationship between SAV abundance and percent shoreline marsh is wedge-shaped (Fig. 2); that is, SAV abundance is low in all subestuaries with high percent shoreline marsh, but there is a wide range of SAV abundance among subestuaries with low percent shoreline marsh. A high percentage of shoreline marsh appears to limit SAV in a subestuary, but low percentages of shoreline marsh do not necessarily lead to high SAV abundance because other factors can also affect SAV abundance. The negative correlation between shoreline marsh and SAV abundance indicates that not all natural ecosystems necessarily foster SAV.

The other shoreline characteristics we examined had negative and positive relationships with SAV abundance. Shoreline characteristics that had significant negative associations with SAV abundance included paved shoreline, the density of boathouses, and the density of boat ramps. In contrast, forested shoreline was a significant positive predictor explaining 13.6 % of the variation in SAV abundance. Forested shorelines are associated with reduced levels of human activities (such as agriculture, development, and boat traffic) that can reduce water quality or directly damage SAV beds

Fig. 3 Differences among salinity zones in the relationships of SAV abundance to shoreline variables. The lines are estimated from linear models with salinity zone as a categorical variable (Table 5). Salinity zones are polyhaline (PH), mesohaline (MH), and oligohaline (OH)

(Orth et al. 2006a). Shoreline bank height variables were also strong predictors of SAV abundance, but the percentages of steep banks (5 m tall or higher) were negatively associated with SAV, while the percentage of low banks (0–5 m) was positively associated with SAV. High, steep banks often indicate deep nearshore water with strong currents or wave action, which may yield more eroded sediment that can bury SAV beds and reduce water clarity.

Effects of Shoreline Hardening

The percent of riprap shoreline was an important negative predictor of SAV abundance in both the univariate correlations and the regression tree analysis. Riprap, which is composed of rocks and boulders piled along the shoreline, is commonly used to prevent shoreline erosion, but little is known about how riprap affects near-shore estuarine communities (Weinstein and Kreeger 2000). In our study, shoreline riprap alone explained 10 % of the variation in SAV abundance. Additionally, there could be a critical threshold in riprap prevalence that negatively affects SAV (Figs. 4a and 5). SAV abundance increased smoothly from 1984 to 1996 in subestuaries with both high and low amounts of riprap, but after 1996, SAV levels began to fluctuate markedly from year to year (Fig. 5). Some of the fluctuations in abundance coincide with known disturbances like Hurricane Isabel in 2003 and the unusually hot summer of 2005 that caused SAV die-offs (Orth et al. 2010). In subestuaries with lower percentages of riprap (<5.4 %) shoreline, those fluctuations extended to higher and higher peaks from 1996 to 2000, yielding a continuing upward trend in SAV abundance. In contrast, SAV abundance in subestuaries with higher riprap fluctuated but never surpassed the 1997 high point. Subestuaries with more riprap appear to have poorer resilience, whereas subestuaries with less riprap recover rapidly from temporary declines and continue an overall upward trend throughout the time series. Negative effects of riprap have also been reported in freshwater systems. Relative to unaltered shorelines, riprap in lakes can increase the depth of near-shore water, lower the proportion of organic material in the sediment, and decrease the abundance of aquatic macrophytes and fish (Gabriel 2012). In the tidal fresh zone of the Hudson River, there was no decrease in SAV diversity and abundance adjacent to riprapped shorelines, but exotic and undesirable species were more prevalent adjacent to altered than natural shorelines (Strayer et al. 2012).

The act of installing riprap is a major disturbance. Once installed, riprap significantly alters the land–water interface, a major determinant of the health of a water body (Living Shoreline Summit Steering Committee 2006). Riprap is a hard, angular structure that can reflect waves more strongly than shallow natural shorelines (Kraus and Pilkey 1988), so the riprap can increase the wave energy the benthos receives. Increased wave energy can combine with tidal currents to suspend fine sediments and decrease light (Wright 1995). Sediment movement can also harm or kill SAV by burying grass beds (Marba et al. 1994; Paling et al. 2003; Mills and Fonseca 2003). When wave energy is high enough, SAV beds can completely disappear (Dan et al. 1998). Despite the presumed role of waves, we found no relationships between wave energy and SAV in our present analyses. Li et al. 2007 found that wave energy was an important component of the

Table 5 Results for differences in the effects of shoreline variables among subestuaries with different upland land use types

	Degrees of freedom	Type III sum of squares	Mean squared error	F value	P value
Model	6	229.94	38.32	2.93	0.012
Error	91	1,191.027	13.088		
Corrected total	97	1,420.97			
Riprap	1	134.17	134.17	10.25	0.002
Land cover	5	89.03	17.81	1.36	0.25
Model	6	205.15	34.19	2.56	0.025
Error	91	1,215.82	13.36		
Corrected total	97	1,420.97			
Bulkhead	1	109.38	109.38	8.19	0.005
Land cover	5	90.66	18.13	1.36	0.25
Model	6	314.94	52.49	4.32	0.001
Error	91	1,106.026	12.15		
Corrected total	97	1,420.97			
Shoreline forest	1	219.18	219.18	18.03	<0.001
Land cover	5	122.39	24.48	2.01	0.084
Model	6	336.83	56.14	4.71	<0.001
Error	91	1,084.14	11.91		
Corrected total	97	1,420.97			
Shoreline marsh	1	241.064	241.064	20.23	<0.001
Land cover	5	91.58	18.32	1.54	0.19

The interaction term (shoreline variable×land cover) was significant ($P<0.05$) or marginally significant ($P<0.1$) for bulkhead, shoreline forest, and shoreline marsh. The interaction was not significant for riprap and was removed from that model

regression tree models they built for predicting SAV abundance. They used wave data from a very coarse coastal vulnerability map of the entire US Atlantic Coast (Thieler and

Hammar-Klose 1999), while we used higher-resolution maps of predictions from a widely used wave exposure model (WEMO; Malhotra and Fonseca 2007). The WEMO may

Fig. 4 Regression trees predicting SAV abundance for all subestuaries (a) and for mesohaline subestuaries only (b). The numbers at each branch are the split point for the predictor variable, the mean SAV abundance, and the number of subestuaries. The direction of the carrot sign at each split indicates which way you follow the tree for higher or lower values of the predictor. Trees for the tidal fresh, oligohaline, and polyhaline zones (not shown) were not significant

Fig. 5 Effect of riprap on SAV abundance over time. Dashed black line with closed diamond points shows the change in SAV abundance (mean $\pm$ SE) for subestuaries with <5.4 % riprapped shoreline from 1984 to 2009. Solid black line with closed squares shows the change in SAV abundance (mean $\pm$ SE) for subestuaries with >5.4 % riprapped shoreline from 1984 to 2009

not function well in subestuaries and near the shore where the SAV beds occur because the model was designed for predicting wave energy in the main channel of the Bay.

Surprisingly, the prevalence of bulkhead, another common type of shoreline hardening, was not an important univariate predictor of SAV abundance. We expected that bulkheads might have even stronger impacts on SAV than riprap because bulkheads are vertical walls that are even less like natural shoreline than riprap. We did observe some marginally significant effects of bulkhead when we accounted for differences among salinity zones (Table 3). Bulkhead had a negative effect on SAV abundance in the polyhaline zone, little effect in the mesohaline, and a surprising positive effect on SAV abundance in the oligohaline zone (Fig. 3). These different patterns may reflect the strong effect of salinity on the SAV species that are present (Moore et al. 2000; Table 4) and the different responses of the SAV species to stressors. Bulkhead may be positively associated with SAV in the oligohaline because the invasive SAV species (*H. verticillata* and *Myriophyllum spicatum*) common in the fresher part of the bay can thrive in deeper water and degraded habitat adjacent to bulkhead (Moore et al. 2000; Batiuk et al. 2000; Li et al. 2007; Orth et al. 2010). Similarly, SAV abundance may respond more strongly to other shoreline variables in the polyhaline zone (stronger negative response to marsh and stronger positive response to forest; Fig. 3) because the polyhaline zone is dominated by eelgrass (*Z. marina*), which has higher light requirements than species occurring in fresher waters (Kemp et al. 2004). More research is needed to better understand how the different SAV species respond to changes in habitat and water quality caused by human land use and shoreline alteration.

Effects of Watershed Characteristics

The multivariate models for predicting SAV abundance included both shoreline variables and watershed land cover variables. In the multiple regression model, three of the four included variables were watershed characteristics (watershed area and the percentages of shrub, developed open, and mixed forest land cover). Particularly, important predictors of SAV that have not been previously identified included the proportions of herbaceous wetland, shrubland, open developed land, and mixed forest in the local watershed.

Both agriculture and development increase the amounts of nutrients and sediments that enter streams and estuaries (Allan et al. 1997; Walsh et al. 2005). We identified the amount of highly developed land as a significant negative predictor of SAV abundance. Development increases impervious cover, sewage, and automobile activity. Impervious cover reduces water infiltration so that storm water enters streams carrying high loads of sediment and contaminants (Paul and Meyer 2001; Walsh et al. 2005). High-velocity storm water also erodes stream channels, further increasing the sediment load in the water (Paul and Meyer 2001; Walsh et al. 2005). In subestuaries, the elevated sediment and contaminant loads increase suspended solids, reduce light penetration, and bury SAV beds (Gallegos 2001; Kemp et al. 2004). Sewage and automobile nitrogen emissions both increase subestuary nutrient levels and fuel observed algae blooms that further decrease light penetration (Anderson et al. 2002; Paerl et al. 2001). Negative impacts on water quality in the upland watershed decrease water quality in the receiving subestuaries and degrade benthic communities (Hale et al. 2004; Li et al. 2007). Surprisingly, percent cropland was not identified as a significant negative predictor of SAV, even though fertilizer and manure contribute nutrients that might negatively impact SAV (Allan et al. 1997). Subestuaries dominated by agriculture did have lower average SAV abundance than other watersheds (Table 3), and percent agriculture was also an important split in the regression tree analysis.

The positive correlation of forested land types is consistent with past reports (Li et al. 2007). Herbaceous wetland and shrubland in the watershed were significant positive predictors of SAV abundance that were not previously identified (Li et al. 2007). The addition of 15 Atlantic Coastal Bay subestuaries and six more years of SAV data than Li et al. (2007) likely gave us the power to detect the effects of other factors. These land cover types are a small proportion of the watershed area; however, they may be more important than their respective areas. Herbaceous wetland provides a number of ecosystem services, most notably filtering water by removing contaminants and dissolved nutrients and increasing water infiltration (Whigham et al. 1988; Johnston et al. 1990; Hogan et al. 2004). Functioning wetlands likely improve water quality in subestuaries and increase the potential for good SAV habitat.

Effects of Subestuary Characteristics

Many characteristics of the subestuary itself can affect SAV abundance. Li et al. (2007) reported that variables indicative of shoreline complexity, watershed inputs, and tidal exchange of water with the larger estuary are related to SAV abundance. Like Li et al. (2007), this analysis identified system size (subestuary area and watershed area) as significant predictors of SAV abundance; however, Li et al. (2007) identified fractal dimension (a measure of shoreline complexity) as a significant predictor, while this analysis did not. Here, we used an updated shoreline (Fig. 6) that is much more detailed than before (Li et al. 2007), but the subestuaries were not equally affected by the update. In subestuaries that are truly complex, the updated shoreline better represented that complexity and fractal dimension increased. For other subestuaries with

truly simple shoreline, fractal dimension was similar in the new and old maps.

Average subestuary depth also emerged here as a significant predictor of SAV abundance. This result might seem trivial because SAV grow in shallow water, but it was actually unexpected because the measure of SAV abundance (Eq. 1) *already* accounts for depth by expressing abundance normalized to the amount of potential habitat (which largely reflects the area of shallow water, see the “Methods” section). The correlation of abundance with depth suggests that, besides providing more potential habitat area, shallow systems may also support higher SAV abundances in other ways. Shallow subestuaries could have reduced wave energy relative to subestuaries with deep basins because wave velocity and energy decrease as waves enter shallow water (Segar and Segar 2007). In subestuaries with deep water adjacent to potential habitat, SAV beds may be exposed to strong wave

Fig. 6 High-resolution and low-resolution shoreline data. *Black* the revised high-resolution shoreline used in this analysis. *Gray* the shoreline data used previously (Li et al. 2007)

energy during storms. In contrast, in subestuaries with large expanses of shallow water, wave energy may be significantly reduced by the time it reaches potential SAV habitat.

Future Research

Future work should seek to understand the mechanisms driving the correlative relationships observed here. For example, it is tempting to conclude that riprap has a direct, negative effect on SAV, but there are several alternative explanations for the observed negative correlation. Riprap is strongly correlated with human activity in a watershed and could be acting partially as a proxy for decreases in water quality associated with human activities. This may also be true for the other shoreline alteration variables, such as the density of boat ramps or marinas. Furthermore, riprap is often installed to reduce shoreline erosion in areas with naturally high wave energy, so riprap may simply be correlated with higher wave energy. Paired comparisons of adjacent altered and unaltered shorelines next to one another and their effects on SAV would help resolve the independent effects of these correlated stressors.

We need more research on the effect of shoreline alteration on SAV. One future study design that would address many of the issues raised previously would be to include spatial analyses focused on SAV abundance directly adjacent to riprapped and other shoreline types. Direct field measurements of the density and species of SAV adjacent to different shoreline types would also complement and strengthen the spatial analyses. Furthermore, water quality data collected within the near-shore environment where SAV grows would further help draw connections between land use change and water quality in the subestuaries. Finer-scale analyses focused on the SAV beds, potential habitat, and water quality directly adjacent to different types of shoreline would help determine the mechanistic relationship between SAV and shoreline alteration. At a minimum, analysis at the scale of individual shoreline segments will help distinguish between actual effects of shoreline alteration and impacts that are the result of correlation with human activities in the subestuary and watershed.

Management Implications

Our analysis suggests that current variation in SAV abundance among the subestuaries is related to many natural and anthropogenic factors and that shoreline development and shoreline hardening, particularly riprap, are negatively related with SAV abundance. Our study supports the small but growing literature, suggesting that riprap has a negative impact on estuarine biota and may reduce biodiversity while promoting exotic or undesirable species (Balouskus and Targett 2012; Gabriel 2012; Strayer et al. 2012). This work suggests that avoiding additional shoreline hardening and restoring currently

hardened shoreline could benefit subestuary health. Currently, new riprap, bulkhead, and other hardened shorelines are being discouraged in favor of living shoreline approaches (Living Shoreline Protection Act 2008), but the effects of living shoreline relative to natural or hardened shorelines remain poorly studied. Our findings could also help direct SAV restoration efforts to areas that are best suited to regrowing SAV. For example, the observed negative effects of shoreline marsh suggest that SAV restorations should not be located in systems with extensive marshes even though those systems might seem relatively undisturbed. Also, it might make sense to approve riprap projects in a system that our models suggest is unlikely to support SAV, while preventing riprap installation in high-quality subestuaries where the installation could shift predicted SAV abundance to lower levels. The findings from the Chesapeake Bay and mid-Atlantic Coastal Bays could also provide initial guidance for managing less-studied estuaries outside the mid-Atlantic Region.

Our work also suggests that SAV restoration goals should be reexamined. For the Chesapeake Bay, the initial tier 1 goal is to restore SAV to all locations where it was mapped from 1971 to 1990 (Batiuk et al. 1992). The more ambitious tier 2 goal would restore SAV to all water <1 m deep (excluding “no-grow zones” thought to be inherently unsuitable for SAV), while the tier 3 goal targets all water (except the no-grow zones) up to 2 m deep (Batiuk et al. 2000). These three goals require SAV coverages of 460, 653, and 2,504 km², respectively. In 2011, SAV coverage was 255 km². SAV have also been observed within the no-grow zone, suggesting that some of that area may not be completely inhospitable to SAV. Our analysis identified some natural characteristics, particularly the presence of shoreline marsh, which negatively impact SAV. Even if all negative human impacts were removed, some areas, like those next to marshes, might still not support healthy SAV beds. SAV decline is a complex problem and SAV recovery will require multipronged solutions applied to watersheds, shorelines, and the estuary itself.

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