Wetlands
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MARSH RESILIENCE SUMMIT

Rapid Land Cover Change in a Submerging Coastal County

Keryn B. Gedan[1] · Rebecca Epanchin-Niell[2] · Man Qi[1,3]

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Abstract

Sea level rise is reshaping the coasts, allowing coastal habitats such as tidal marshes to migrate inland. To predict where changes will occur, it is critical to understand the factors that influence land cover transition. Here, we test the influence of land cover type on land cover transition. We hypothesized that marsh migration may vary by upland land cover type, due to dominant plant species' differences in salinity and inundation tolerance. Additionally, the response of people may make specific land cover types more likely to be protected from transition. We measured land cover change in high resolution aerial imagery over the relatively short period of 2009 to 2017 in coastal Somerset County, Maryland. In logistic models of land cover transition, we found that 'agricultural land' and 'scrub shrub wetland / forested wetland' cover classes were more likely to transition to 'emergent wetland' than 'forest/scrub shrub' or 'urban or built-up land' cover classes, after controlling for elevation and distance to shore, two well-known predictors of marsh migration. Over only 8 years, loss of upland area in the county totaled 6.1 km^2, of which 5.7 km^2 was agricultural land. This represents a loss of over 2% of the farmland in the county, the majority of which converted to emergent wetland during the study period.

Keywords Land use · Land use and land cover change · Sea level rise · Saltwater intrusion · Marsh migration · Upland conversion · Forest retreat · Transgression

Introduction

Accelerated sea level rise is having a marked impact on coastal ecosystems. One of the most striking effects of sea level rise is the transition of uplands to tidal wetlands and open water (Smith 2013; Smith et al. 2017; Schieder et al. 2018; Kirwan and Gedan 2019). The process of transition from uplands to tidal marsh has been termed marsh migration and has been observed in a variety of upland habitat types, from forests (Smith 2013; Raabe and Stumpf 2016; Langston et al. 2017) to farmland (Gedan and Fernández-Pascual 2019) to freshwater swamps (Craft 2012; Middleton 2016) to suburban lawns (Anisfeld et al. 2017; Anisfeld et al. 2019).

Characteristics of the landscape are important determinants of the timing and pace of upland transition (Tully et al. 2019). Two of the most important of determinants of transition are the elevation and slope of the uplands adjacent to shore. Low elevation areas are the first to be affected, and shallow sloping areas experience more rapid transition due to the greater reach of even small increases in sea level (Smith 2013; Schieder et al. 2018). Additionally, storm surge and saltwater intrusion that kill upland vegetation can precipitate upland transition to marsh (Williams et al. 1999; Kearney et al. 2019). Other factors that influence groundwater levels, such as hydrologic connectivity linking uplands and tidal waters through ditches and canals (Bhattachan et al. 2018a), riverine freshwater inputs (Raabe and Stumpf 2016), groundwater extraction (Michael et al. 2017), and precipitation and drought (Williams et al. 2003), can also influence saltwater intrusion and upland transition.

One landscape factor that has rarely been considered as a determinant of upland transition to marsh is upland land cover type, and that is the focus of this study. In one explicit consideration of upland land cover type, Anisfeld et al. (2017) found no difference in the rate of marsh migration into

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✉ Man Qi
manqistar@gmail.com

1 George Washington University, 800 22nd St. NW, Washington, DC 20052, USA

2 Resources for the Future, 1616 P St NW, Washington, DC 20036, USA

3 Key Laboratory of Geographical Process Analysis & Simulation of Hubei Province/College of Urban and Environmental Sciences, Central China Normal University, Wuhan 430079, China

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wooded areas relative to suburban lawns. However, evidence from forests, the most commonly studied upland land cover type in marsh migration research, supports the hypothesis that land cover type will play an important role in determining transition rates. Smith (2013) observed that forest type, for example, affected the pace of transition in Delaware Bay, with higher rates of transition observed in Atlantic white cedar (*Chamaecyparis thyoides*) than in mixed hardwood forest, even after controlling for upland slope. A greater rate of change in white cedar forests may reflect higher susceptibility to salinity stress and mortality of the dominant canopy tree species, or it could reflect differences in hydrology (i.e. water table level and flooding regime) between forest types.

Furthermore, human interventions have great potential to alter the way upland land cover types transition by either slowing or accelerating change. The installation of tide gates, levees, or berms can prevent tidal influence and slow change, or fail suddenly and cause rapid change to marsh or open water. Terracing or surface regrading to raise the elevation of the land could also prevent upland conversion of areas in the so-called “accommodation space”, where marsh migration is predicted to occur. Lastly, land management practices, such as timber harvest, might affect the water budget of forests or remove relict trees and alter light conditions in areas where forest regeneration has already ceased (“the persistent zone”, Kearney et al. 2019), and thereby promote conditions that are likely to favor upland transition to marsh. Most marsh migration will occur on privately-owned, rural lands given their prevalence in coastal areas. For example, along the east coast of the United States, 96% of lands within 1 m of sea level are rural and 65% are privately held (Epanchin-Niell et al. 2017). The behavior of landowners and development of coastal land use policy remain among of the most uncertain factors in predicting upland conversion of wetlands due to sea level rise, as well as some of the most important factors in shaping tidal wetland area in the future (Epanchin-Niell et al. 2017; Field et al. 2017; Schuerch et al. 2018; Kirwan and Gedan 2019). Local zoning, regulations, and incentive programs will interact with landowner preferences, beliefs, and capacities to affect choices that encourage or discourage wetland migration onto their land (Titus et al. 2009; Field et al. 2017).

In this study, we investigated land cover transitions in a rapidly submerging county on the coast of the Chesapeake Bay over a short time period of 8 years. Using high resolution aerial imagery, we classified land use and land cover change from 2009 to 2017 to detect land use transitions and determine the effect of initial upland land cover type on the probability of upland transition. We also investigated the effect of other known landscape predictor variables, namely elevation and distance to shoreline, and their interaction with upland land cover type in determining transition to marsh.

Methods

Study Area

Somerset County, Maryland on the Lower Eastern Shore of the Chesapeake Bay was selected as the study region due to the high rate of land use transition that has been observed there in recent years and attributed to rapid relative sea level rise (Johnson et al. 2017). Rates of sea level rise in the northeastern US are increasing at three to four times the global average (Sallenger et al. 2012) and are locally exacerbated in the southern Chesapeake Bay by land subsidence rates of greater than 1 mm/year (Eggleston and Pope 2013). The authors have several ongoing field research projects there (Epanchin-Niell et al. 2018; Gedan and Fernández-Pascual 2019). Somerset County has 3183 km of sinuous shoreline surrounding numerous tidal creeks and rivers, including the Wicomico, Manokin, Big Annemessex, and Pocomoke Rivers that feed into the Chesapeake Bay. To target the area of the county most affected by sea level rise and coastal fringe saltwater intrusion (sensu Werner et al. 2013), we defined our study area as the landward region within 2 km horizontal of the highest observed tide (Max Tide during the National Tidal Datum Epoch (NTDE), 1983 through 2001). Elevation of the max tide was based on the datum of the closest tide gauge station, Bishops Head, MD (NOAA Tides & Currents Station #8571421). We used Lidar-based DEM data for Somerset County (MD DNR 2019) to extract the elevation contour of the max tide (0.992 m NAVD88) and create a 2 km buffer. Somerset County DEM (NAVD88) was collected in 2012 and has a vertical accuracy of 0.157 m in open terrain, and 0.267 m in all land cover categories combined. The study region buffer area totaled 625.43 km^2 and included the western portion of the county, the urban area of Princess Anne, MD, and a reach of the Pocomoke River that extended into the eastern half of the county (Fig. 1). Loblolly pine (*Pinus taeda*) is the dominant forest tree in the area. In addition to upland land areas, the study area included vast areas of tidal marsh and a smaller area of open water that were below the max tide line.

Spatial Imagery Data

The National Agriculture Imagery Program (NAIP) program provides statewide, high-resolution imagery during the growing season of every other year. The earliest NAIP images available for Maryland with complete spectral information (four spectral bands: near infrared, red, green, and blue) were collected in August 2009. June 2017 was the most recent available image. NAIP imagery has a spatial resolution of 1 m and a horizontal accuracy of 6.0 m. From our observation of error in 67 stable features (e.g. road intersection and building corners) from across the study area, there is a horizontal offset of 2.96 ± 1.65 m between images from 2009 to 2017.

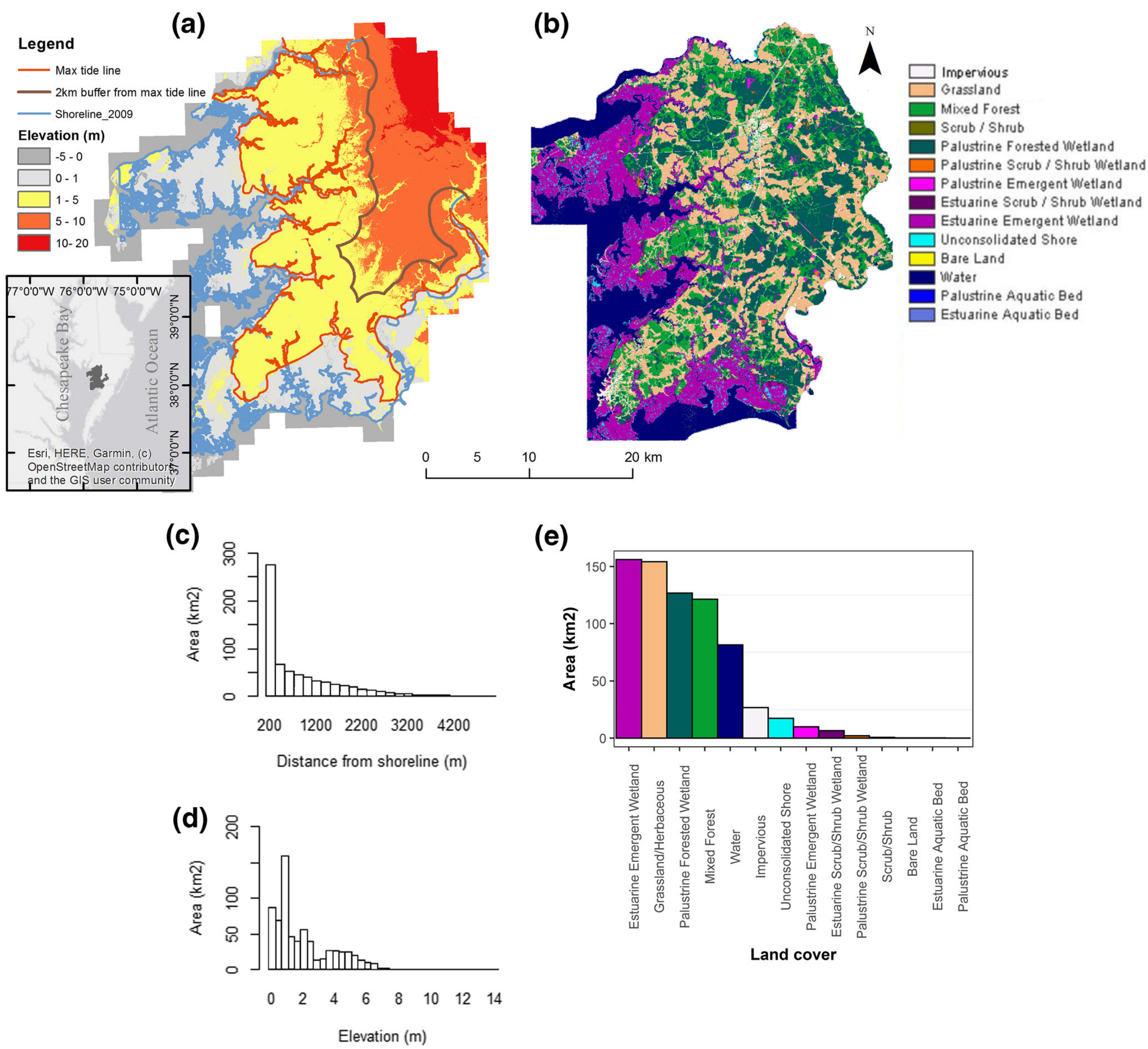


Fig. 1 Maps of the study area, Somerset County, Maryland, showing **a** elevation from a 2012 DEM and the 2009 shoreline (*blue line*), highest observed tide (Max Tide) (*red line*), and 2 km buffer from Max Tide (*brown line*) which defined the extent of land cover classification. **b** land cover in 2013 (Data source: NOAA Coastal Change Analysis Program (C-CAP) Regional Land Cover Database https://coast.noaa.gov/). Inset shows the location of Somerset County within the Chesapeake Bay. Histograms in **c** and **d** show the distribution of distance from the 2009 shoreline and elevation (relative to NAVD88), respectively, within the study area. **e** Area of each C-CAP land cover class in Somerset County derived from panel **b**

One disadvantage of using NAIP data for classification is the high heterogeneity of images at fine scale spatial resolution, which can be challenging for classification algorithms. Additionally, processing time of these images is much greater due to the amount of data in even a relatively small study area such as ours. However, one advantage of using high resolution imagery is the ability of the human eye to detect land use cover types and validate classifications. Additionally, as opposed to coarser imagery such as Landsat, very fine scale changes can be detected.

Image Classification

We used a combination of automated classification and post-classification manual checking and review to interpret land cover from the NAIP images. The land cover types in our study area mainly included agricultural land, such as cropland, orchards, poultry houses, irrigation canals, and ponds; urban or built-up land, such as houses, lawns, highways, power infrastructure, towns, and commercial complexes; upland forest; estuarine and palustrine wetlands; and water bodies (see Fig.

1b, e). The land cover classes we used in this study were based on Anderson (1976). Class names were adopted from the land use and land cover classification system developed by NOAA's Coastal Change Analysis Program (C-CAP), which was developed expressly for coastal areas that are a mix of emergent and submergent wetlands and adjacent uplands (Dobson et al. 1995). We classified areas with 30% or greater tree or shrub cover as Forest / Scrub Shrub, whereas in the C-CAP classes, areas must have only 20% or greater tree or shrub cover, respectively, to be classified in these categories. Our classes therefore ended up splitting some of the C-CAP classes. We denote the correspondence of classes with these modifications in Fig. 2.

We ultimately selected six land cover classes, described in more detail below: (1) Forest/Scrub Shrub, (2) Agricultural Land, (3) Urban or Built-up Land, (4) Water, (5) Scrub Shrub Wetland / Forested Wetland, and (6) Emergent Wetland. It should be noted that Agricultural Land had two subclasses during classification, i.e. Bare Agricultural Land and Vegetated Agricultural Land, as agricultural lands can be bare or vegetated depending on the point in the harvest cycle at the time NAIP images were collected. These two subclasses were merged as Agricultural Land during post-classification.

Forest/Scrub Shrub Areas dominated by trees and/or shrubs with tree and shrub coverage of 30% or greater, regardless of tidal regime, salinity level, or understory plant community type.

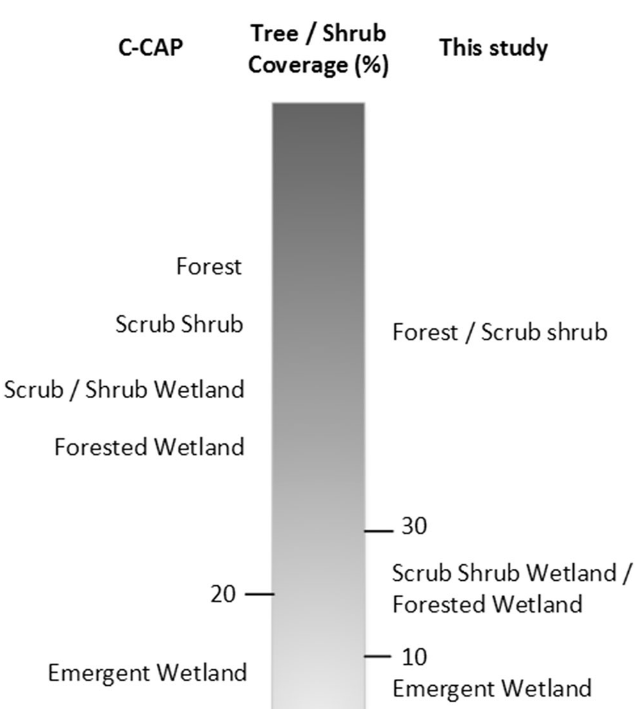


Fig. 2 Comparison between the classes used in this study and the Coastal Change Analysis Program (C-CAP)

Agricultural Land Crop fields, pastures, orchards, groves, vineyards, and nurseries, ornamental horticultural areas, confined feeding operations, farmsteads, holding areas for livestock.

Urban or Built-up Land Areas of intensive use with much of the land covered by structures. Included in this category are residential buildings, cities, towns, villages, commercial and industrial buildings and parking lots, and transportation and power infrastructure.

Scrub Shrub Wetland / Forested Wetland Wetlands with 10 to 30% coverage of woody vegetation, regardless of tidal regime or salinity level.

Emergent Wetland Tidal and nontidal wetlands with at least 30% coverage of emergent plants, emergent mosses or lichens and less than 10% coverage of trees and shrubs.

Water Permanent open water, aquatic bed, streams and canals, lakes, reservoirs, bays and estuaries, ditches and canals, and small ponds for farms.

These classes are here forth referred to by the bolded words for brevity.

For automated classification, we applied the Normalized Difference Water Index (NDWI, McFeeters 1996) and the Difference Vegetation Index (DVI, Richardson and Wiegand 1977) that are sensitive to water and soil background respectively, as well as Normalized Difference Vegetation Index (NDVI, Karnieli et al. 2010) and Ratio Vegetation Index (RVI, Jordan 1969) which are sensitive to normal and high density vegetation coverage respectively, to provide additional information to spectral data for land cover classification. Object-based supervised classification was performed in eCognition Developer 9 based on image textural and spectral characteristics, including spectral indices. First, images were segmented into objects by eCognition multiresolution segmentation algorithm with scale parameter of 100 and equal weights for R, G, B, IR bands. These segmentation parameters were selected after visual comparison of segmentation results of multiple parameter configurations. The selected parameters allowed accurate recognition of boundaries between different feature classes while minimizing the number of features. The 2009 and 2017 images were segmented and classified individually. For each year, we selected a submap (1/10 of study area) that contains all land cover classes as a trial area to train the classifier, and later applied the classifier to the remaining study area.

While training the classifier, two rounds of supervised classification were conducted with each of the segmented subset images using a decision tree algorithm. The decision tree algorithm was selected after visually comparing the performance of several other algorithms, namely k-nearest neighbor, random forest, and support vector machine, in distinguishing the most similar or difficult to distinguish classes in our study system: e.g. 'Vegetated Agricultural Land' versus 'Emergent Wetland', 'Scrub Shrub Wetland / Forested Wetlands' versus 'Emergent Wetland', 'Bare Agricultural Land' versus 'Water' (Fig. S1). We trained the classification algorithm using visually classified areas of our seven land use classes. The first round of classification was supervised using this training dataset. In a second round of classification, we visually detected misclassification by the first round algorithm, and added additional training samples of land use classes that were highly prone to misclassification.

After automated classification, we performed manual review and correction of 100% of the interpreted area of each individual year with incremental screen by screen (working west to east or north to south) qualitative review and corrected misclassified objects at 1:3000 scale with a Minimum Mapping Unit (MMU) for each class as shown in Table 1. Forests under active silviculture were classified as Forest no matter what crown closure percentages they had, following the definition of Forest given by Anderson (1976), and were manually corrected if misclassified during automated classification. All manual corrections were completed in eCognition.

Classification Accuracy Assessment and Change Detection

To assess classification accuracy, we randomly sampled 200 map objects per year from within 2009 and 2017 images and visually determined land cover type. The percentage of correctly classified points indicated the classification accuracy, i.e. Producer's Accuracy (PA). PA was calculated for each land cover class after automated classification and after manual correction.

We measured land cover change within polygons resulting from the intersection of the objects in the 2 years using the thematic change workflow tool in ENVI 93 + IDL85. This approach provides "from-to" information, hereafter called "transition," for all polygons in the theme. We reduced noise by excluding small segments (less than 1000 m^2) that were a result of horizontal inconsistency between years. Landscape transitions were calculated and mapped within ENVI.

Statistical Analysis of Change Patterns

We investigated how observed land cover transitions in Somerset County were explained by two landscape characteristics, elevation and distance to shoreline, which jointly determine the expected reach of changes associated with rising sea levels. Elevation of each object within the classified images was extracted as the median elevation within the DEM of all pixels within the object, and distance was measured between the shoreline (defined as where open water and tidal creeks met any other land cover type within the 2009 classified scene) and the center of each object. We calculated the mean elevation and distance to shoreline of transition area sorted by their original land cover type (i.e. 2009), and compared them with the elevation and distance to shoreline of total area of each land cover type in 2009.

In a separate analysis using area weighted logistic regression, we statistically examined the influence of elevation, distance to shoreline, and upland land cover type on the probability of upland transition to emergent wetland. This enabled us to explicitly test whether initial upland land cover type influenced the rate of marsh migration, controlling for distance and elevation. We limited analysis to the set of objects that were classified as upland land cover (1) Forest, 2) Agricultural Land, 3) Urban Land, or 4) Scrub Shrub Wetland) in 2009. We assigned the binary response variable a value of 1 if the object had transitioned to emergent wetland by 2017 and 0 if it remained as upland in 2017. To focus on the primary region of anticipated change, we consider a focal area for our analysis that only included objects between −1 and 4 m (NAVD88) elevation and distance to shoreline of less than 2 km. We also considered an expanded analysis that incorporated the full span of predominant conditions in the

Table 1 Minimum Mapping Unit (MMU) and Producer's Accuracy (PA). MMU was selected for each class based on the median segment size for the class and the size of misassigned partial segments

	MMU (m^2)	PA of automated classification	PA of manual review
Bare Agricultural Land	100	0.4	1
Emergent Wetland	2000	0.94	0.97
Forest /Scrub shrub	2000	0.95	0.99
Scrub shrub Wetland / Forested Wetland	2000	0.37	0.91
Urban or Built-up Land	200	0.71	0.89
Vegetated Agricultural Land	100	0.71	0.97
Water	100	0.93	0.98
Overall		0.79	0.98

region excluding only extreme elevation and distance values; this analysis included objects with median elevation between −1 and 8 m (NAVD88) and distance to shoreline of less than 4 km.

We used logistic regression because our response variable (transition to emergent wetlands or not) is binary. Furthermore, because objects in our analysis were delineated as contiguous areas of uniform land cover and transition, spatial autocorrelation among objects is avoided. However, objects are non-uniform in size. As such, each observation in our data represents a different sized "population" of locations on the landscape (e.g. different numbers of pixels), so we weighted observations by object size to capture their differential spatial representativeness. Furthermore, we use the sandwich estimator (i.e., Huber and White) of variance to obtain standard errors that are robust to underlying heteroskedasticity. We examine variance inflation factors to ensure that multicollinearity among predictor variables is not a problem. Analyses were conducted in STATA 15.1 (StataCorp 2019), using the *logit* command and *pweights* (probability weights); predicted probability graphs were created using *mgen*.

Results

Accuracy Assessment and Description of the Study Region

The segmentation process identified a total of 109,278 and 104,974 segments in the 2009 and 2017 map areas, respectively, which ranged in area from 1 to 686,920 m^2 (see Fig. S3). The supervised classification achieved an overall PA of 79%, and increased to 98% after manual correction. See the PA of each class and the error matrix in Table 1 and Fig. S1 respectively.

The most common land cover type in the study area in 2009 was forest (39.9%, or 249.23 km^2, Fig. S2). The remaining land cover was primarily emergent wetland, agricultural land, and urban (24.7, 19.1, and 15.4% of area, respectively). Scrub shrub wetland was a smaller component of the landscape, at 0.9%, and water made up less than 0.1% of the scene in 2009.

Land Cover Transitions

We found that 1651 patches comprising a total area of 16.1 km^2, or 2.57% of the total area, transitioned during the study period (Fig. 3). All percentages provided below represent the percentage of the 16.1 km^2 transition area.

One of the most striking changes in the study region during this time was a loss of agricultural land. Agricultural lands were the largest source of change (38.0%) (Table 2 and Fig. 4), whereas very little area transitioned into agriculture (2.5%) (Table 2). Another significant change occurred in emergent wetland area, which increased over the study period. More land transitioned into emergent wetland (39.0%) than into any other land cover class (Table 2). Land transitioning into emergent wetland came predominantly from agriculture (21.7% of all transitions), and secondarily from forest (8.8%) and scrub shrub wetland (6.6%) (Table 2 and Fig. 4). A much smaller percentage of land transitioned out of emergent wetland (15.4%). Most of the land transitioning out of emergent wetland became water (10.6%) (Table 2 and Fig. 4).

Forest area experienced little net change during the study. Land transitioning out of forest (25.9%) approximately equaled land transitioning into forest (25.5%). Scrub shrub wetland behaved similarly; the same proportion of land transitioned out (16.1%) and into (16.5%) scrub shrub wetland. Minimal land transitioned out of urban or water during the study period (3.2 and 1.4% of the transition area, respectively) (Table 2).

Predictors of Land Cover Transitions

Overall, the study region was extremely low elevation, with 71% of the area at less than 2 m (NAVD88) (Fig. S4). Even so, transitions occurred disproportionately at lower elevations and closer to shore after normalizing for skewed distributions in these variables, with 50% of transition area at less than 1 m (NAVD88) and less than 0.56 km from shore (Fig. S5b and S6b). Transitions to emergent wetland and water were most commonly observed at lower elevations and closer distances shore (Fig. S5b).

We observed a divergent pattern in land cover transitions across elevations. Transitions to emergent wetland from any land cover class occurred at low elevation (<1 m NAVD88), whereas transitions to forest from almost any land cover class occurred at higher elevation (>4 m NAVD88, high for this region) (Fig. S6b). Interestingly, transitions from agriculture to forest show the same pattern as transitions from agriculture to emergent wetland; they only occurred at low elevation (Fig. S6b). Lastly, emergent wetland converted to water only at low elevation.

Probabilities of Upland Land Use Types Converting to Emergent Wetland

Logistic regression results demonstrated that elevation is an important predictor of upland conversion to emergent wetland, with low-lying areas having higher probabilities of conversion (Table 3; Fig. 5). Our analysis shows that even when controlling for the effects of elevation and distance to shoreline, upland land use type is an important predictor of conversion. Agricultural land is the baseline land use in the empirical model, such that the effects of each other land use is measured relative to that of agricultural land. Results find that the

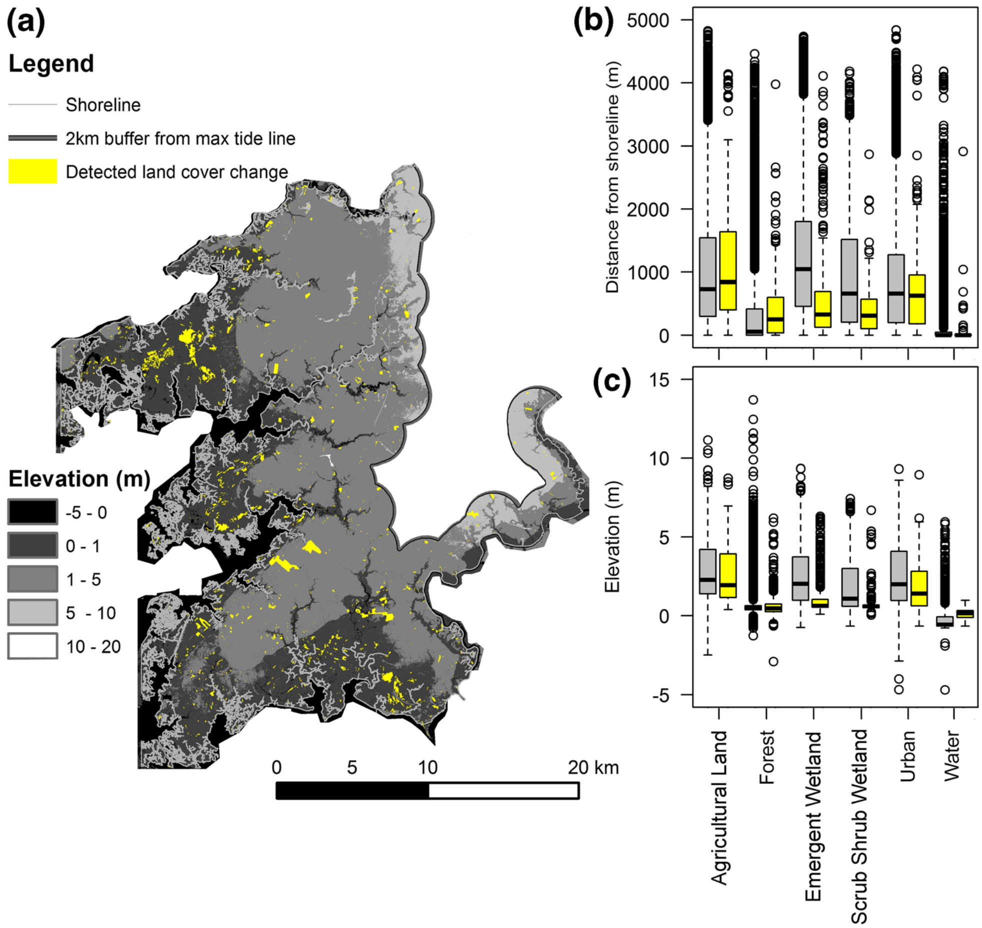


Fig. 3 Distribution of patches that experienced land cover transition from 2009 to 2017: **a** geographic location of transition areas, and **b** distance from shoreline and **c** elevational distribution of each land cover type (*gray*) and subset of patches that transitioned (*yellow*). The 2009 land cover types were referenced when plotting transition areas in **b** and **c**

probability that scrub shrub wetland transitions to emergent wetland is not significantly different from the probability of transition for agricultural land, all else equal, but forest and urban both have significantly lower probabilities of transitioning to emergent wetland (Table 3; Fig. 5).

In our base model (<2 km from shoreline; <4 m median elevation), the VIF was highest for distance (VIF = 4.06) and the coefficient on distance was insignificant, so our preferred model excluded distance (Table 3; Fig. 5). However, coefficients maintain similar magnitudes and have the same significance and sign whether or not distance is included (Table S1). Similarly, in analyses that consider a larger areal extent (i.e., within 4 km of shoreline and < 8 m elevation), the coefficients also maintain similar magnitudes and the same significance and sign, with or without distance included (which is significant and has a negative coefficient when included; VIF = 3.3) (Table S1; Fig. S7). Thus, the findings with respect to effects of elevation and land use on transition to

Table 2 Land cover change type as percentage of 16.1 km^2 transition area (%)

2017 → 2009 ↓	Agriculture	Emergent Wetland	Forest	Scrub Shrub Wetland	Urban	Water	Total (rows)
Agricultural Land	–	21.71	10.85	0.90	4.53	0.04	38.02
Emergent Wetland	0.12	–	3.56	1.03	0.15	10.57	15.44
Forest	1.64	8.77	–	14.43	0.81	0.21	25.85
Scrub Shrub Wetland	0.13	6.60	9.18	–	0.07	0.12	16.10
Urban	0.61	0.58	1.90	0.10	–	0.00	3.20
Water	0.00	1.38	0.01	0.00	0.00	–	1.39
Total (columns)	2.50	39.04	25.50	16.46	5.56	10.94	100.00

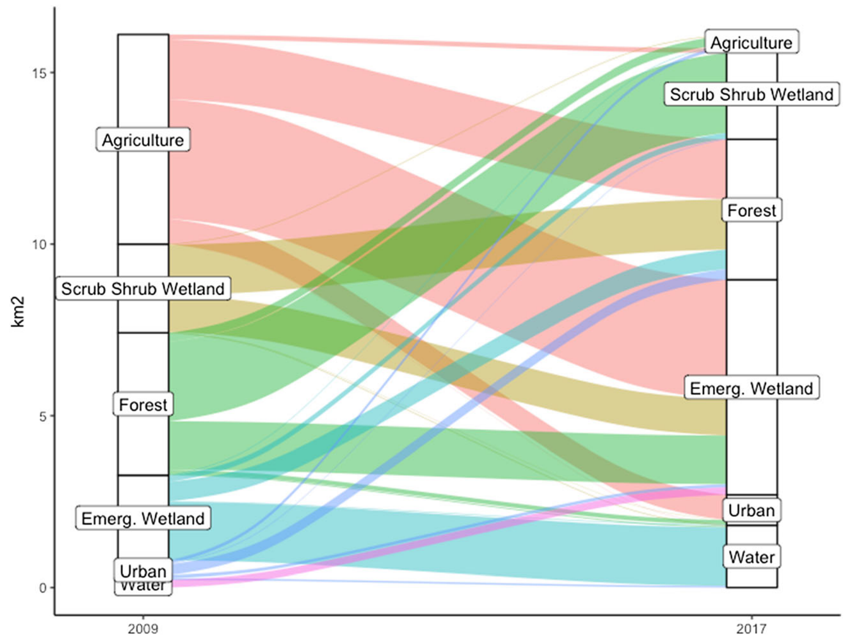


Fig. 4 Alluvial plot of land cover transitions by change class between 2009 and 2017

emergent wetland are qualitatively robust across specifications, and distance has a significant negative effect when a larger range of distance from the shoreline is considered.

Discussion

The land use transitions that we observed occurring over the last decade in Somerset County, Maryland are consistent with predicted marsh migration in response to sea level rise. Emergent wetland area increased, upland area decreased, and upland to emergent wetland transitions were more likely at lower elevation and closer to shore. Importantly, we found that upland land cover type affected the likelihood of transition to emergent wetland. Transition to emergent wetland was more likely for agricultural and scrub shrub wetland areas than for urban or forest areas after controlling for elevation and distance to shore. This is the first study to demonstrate an effect of upland land cover type on marsh migration rates.

Table 3 Logistic regression results predicting probability of upland land cover in 2009 converting to emergent wetland by 2017

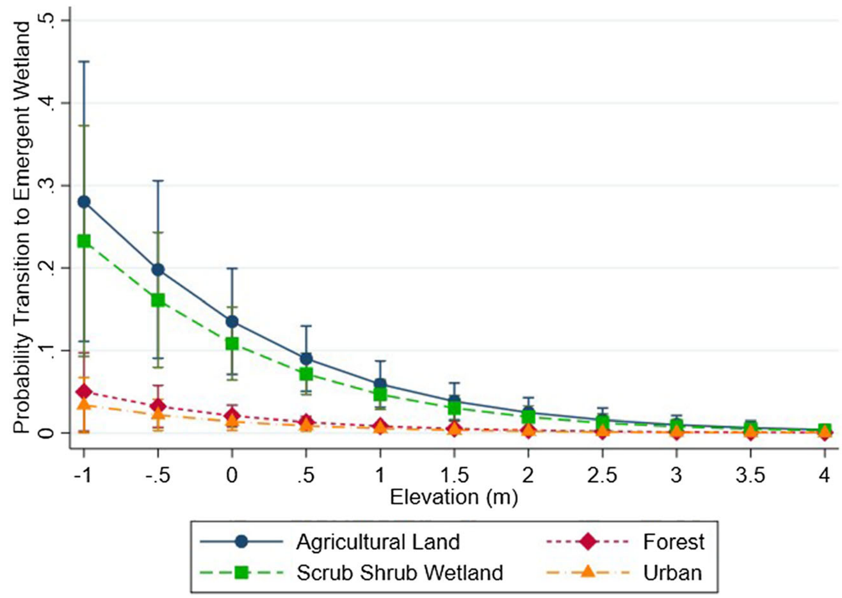
	Coeff.	(s.e.)
Elevation (m)	**−0.914*****	(0.216)
Agricultural Land	–	(.)
Forest	**−2.009*****	(0.336)
Scrub Shrub Wetland	−0.251	(0.310)
Urban	**−2.414*****	(0.4325)
Constant	**−1.856*****	(0.280)
N	36,816	

*** $p < 0.001$

There are a number of reasons why agricultural land may be more likely than forest to transition to marsh. First, crops grown in this region, primarily corn and soy, are more sensitive to salinity and flooding than the predominant forest canopy tree in the region, the loblolly pine *Pinus taeda* (Tanji and Kielen 2002; Conner et al. 2007). One saltwater flooding event may result in enough reduction in crop productivity to cause abandonment of agricultural land, while it may take a more substantial event or repeated events to cause enough tree mortality to convert a forest to a ghost forest (Tully et al. 2019, Fagherazzi et al. 2019). Other possible causes of higher rates of conversion of agricultural uplands than other land cover types (particularly forest, where most coastal landscape change has been observed until now) include sudden failure of protection structures such as tide gates or berms that could result in large areas of agricultural land transition during a single event. Agricultural land use also depends on annual and seasonal management decisions, whereas forest and urban land management generally involve longer term investment decisions such as whether to harvest long-lived trees or construct permanent infrastructure. Additionally, developed, urban lands are more likely to be actively protected from sea level rise encroachment than undeveloped, agricultural lands (Titus et al. 2009).

Another consideration is that some land use types may exhibit more frequent and more reversible land cover transitions than others. For example, agricultural land could be taken out of production and effectively transition to emergent wetland, only to be farmed again in later years if conditions allow. Other land use types might exhibit more unidirectional change. Forest, for

Fig. 5 The probability of upland transition to emergent wetland within the study area is plotted by initial upland land cover type (lines) and elevation above mean sea level (x-axis). *Error bars* show 95% confidence intervals



example, can subsist in the persistent zone until a single climatic event kills adult trees and causes a state change to marsh (Kearney et al. 2019), a transition which is likely to be unrecoverable. Reversible land cover transitions would appear as elevated transition probabilities in time series data.

Scrub shrub wetland matched agricultural land in the probability of transition to marsh (Fig. 5). Scrub shrub wetlands often represent a transitory state between forest and marsh (Conner et al. 2007, Kirwan and Gedan 2019). Much of this area likely would have been classified as forest in earlier decades, and represents the slow conversion of forest, the dominant land use in the county, over time.

The scrub shrub wetland cover class included tidal and non-tidal freshwater swamps with low tree or shrub cover, whereas tidal and non-tidal freshwater swamps with high tree cover were classified as forest (Fig. 2). According to the most recent National Wetlands Inventory data (USFWS 2013), there were 35.77 km^2 of tidal freshwater forested wetlands within our study area and 2.81 km^2 of tidal scrub shrub wetland, for a total of 38.58 km^2. In comparison, we identified a total area of 5.89 km^2 in our 'Scrub Shrub Wetland / Forested Wetland' class in 2009 (Table S2). Given this sizeable difference, we conclude that most areas of tidal freshwater forested wetland in the study area were classified as forest in our study. Tidal freshwater swamps are sensitive to salt stress (Conner et al. 2007, Smith 2013, Middleton 2016). This sensitivity would have raised the transition probability for the forest class, due to their inclusion. Our finding that agricultural land and scrub shrub wetland classes had still higher probabilities of transition than forest, is all the more surprising, then, as the influence of tidal freshwater forested wetlands on the forest class would have reduced the likelihood of observing this difference.

The present rate of sea level rise in the study region is 4.1 mm/yr (NOAA data from 1971 to 2019, Fig. S8A). Sea level increased approximately 6.3 cm from the start of the study period until the end (Fig. S8B). Rates of sea level rise in the Chesapeake Bay are elevated relative to the global average (Boesch et al. 2018) and accelerating (Ezer and Corlett 2012; Boon and Mitchell 2015).

The changes that we observed in land cover were likely affected by this gradual increase in sea level, but additional factors cannot be dismissed in this type of analysis. Other contributors may include overtopping by storm surge or extreme tides and groundwater dynamics that affect saltwater intrusion. Surge from a single storm can salinize groundwater for months or years (Yang et al. 2018), and thereby lead to prolonged land cover change. There was only one major storm impact during the study period. Hurricane Sandy affected the study region in October 2012, causing flooding, saltwater intrusion, and wind damage (Middleton 2016). This storm potentially caused some of the land cover transitions that we observed.

The study period also included a prolonged, extreme drought in summer 2011, with the lowest observed Palmer Drought Severity Index (PDSI) values since 1930 and extreme drought values well below −4 during the growing season months of May, June, and July 2011 (Fig. S9). Drought can cause saltwater incursion into groundwater (Tully et al. 2019) and tree mortality, particularly in areas already affected by gradual sea level rise (Williams et al. 2003). Precipitation was also highly variable during the study period, with the heaviest monthly precipitation on record (13.2 in.) occurring in June 2016 (Fig. S10). Without further analysis, it is impossible to tell if the transitions we observed occurred in a punctuated or gradual manner, and how much resilience, or recovery from disturbance, occurred following a major storm, drought, or wet year. All of these signals – more variable rainfall and drought, more intense storms, and, of course, sea level rise – are results of global climate change.

Changes in Marsh and Upland Land Cover Area

While emergent wetland area experienced a net increase of 3.8 km^2 during this short time period, a substantial amount of emergent wetland loss also occurred; 1.7 km^2 of emergent wetland transitioned to water. These transitions were some of the lowest elevation and closest to shore (Fig. S5 and S6). While not unexpected, this result confirms that emergent wetlands at low elevation are vulnerable to drowning and erosion. These findings also support predictions that despite drowning, marsh migration can offset marsh losses and result in marsh habitat expansion in shallow sloping areas, provided that rates of sea level rise are not extreme, sediment supply is adequate, and upland land use enables migration (Kirwan et al. 2016; Kirwan and Gedan 2019). These findings support policy initiatives that establish and preserve corridors for marsh migration through tools such as voluntary landowner agreements (e.g. transfer or purchase of development rights), land purchases and swaps, and various zoning tools and ordinances (Epanchin-Niell et al. 2017; Spidalieri 2020).

Conversion of upland area to emergent wetland or open water totaled 6.1 km^2. The largest net loss, 5.7 km^2, was from agricultural land cover (Table S2). This amounts to over 2% of the 263.9 km^2 of farmland in Somerset County (USDA NASS 2012). More than half of this lost agricultural land (61%) transitioned to marsh. An additional 31% transitioned to forest. This kind of land transition over a short period represents a significant loss of agricultural productivity for the county, and a hardship for the landowners and farmers who work the land in areas of lower elevation and closer to shore, where effects were concentrated. Such losses are predicted to become common in rural coastal areas of the US (Enwright et al. 2016), for example the Albemarle-Pamlico Peninsula (Bhattachan et al. 2018b). This is one of the first studies to document that these changes are already occurring.

Predictors of Land Cover Change

Interestingly, transitions from agriculture to forest exhibited a similar elevation profile to those from agriculture to emergent wetland. In our experience working in the region with farmers whose land is affected by saltwater intrusion (Epanchin-Niell et al. 2018), conversion of agriculture to forest in low-lying fields is a signal of farm abandonment in response to low productivity from saltwater intrusion. Fallow farmland affected by saltwater intrusion can support woody vegetation within several years of the cessation of farming (Gedan and Fernandez-Pascual 2019). Some of these areas—where conditions permit tree sapling recruitment—could regenerate to forest; in contrast, others, where tree growth is inhibited by salinity and inundation stresses, would convert to marsh (Fagherazzi et al. 2019).

Detection of Change

Our results are based on visual detection of land cover change using a supervised classification algorithm. It is likely that land cover changes which did not substantially shift the spectral signature of an area were missed by this approach. For example, agricultural land transition was only detected when the parcel's spectral signature resembled a scrub shrub wetland, forest, or emergent wetland more than agriculture. Prior to major spectral change, these lands can still visually and spectrally resemble agriculture in high resolution images (KG, personal observation). Effects such as reductions in yield due to saltwater intrusion or recent abandonment would not have been detected in this analysis. We were unable to track these subtler shifts in plant communities, or changes occurring under a forest canopy, what has been termed "invisible migration" (Anisfeld et al. 2019). Therefore, the land cover transitions quantified here should be viewed as a conservative estimate of land cover change.

Most prior mapping studies of marsh migration have been over centennial time scales (e.g. Smith 2013; Raabe and Stumpf 2016; Schieder et al. 2018). We were constrained by NAIP image availability to the very recent past; our study images spanned less than a decade. The high resolution of the NAIP imagery allowed us to detect small changes in the landscape. By adding up all of these small changes, we were able to detect marked change in a short time period, which demonstrates the rapid pace of land cover change in submerging counties in the coastal plain.

Future Directions

These findings have led us in a number of directions to investigate the future of coastal land cover transitions in this region. First, we are investigating changes in cropping and land use decisions on agricultural lands to enhance understanding of the transition paths by which agricultural lands may respond to sea level rise and coastal salinization, as mediated by crop susceptibility and economic factors. In field trials, we are evaluating the suitability of transitioning agricultural lands for production of alternative crops, such as sorghum (*Sorghum bicolor*) and barley (*Hordeum vulgare L.*), and planted wetland restoration species, such as *Spartina patens*. We are also investigating the transition of emergent wetlands to open water during marsh pond expansion (Qi et al. in review). Other future research should seek to disentangle the multiple climate drivers of gradual sea level rise, punctuated storms, heavy precipitation, and drought and to investigate when and in which land cover types transitions are reversible. These questions could be answered by examining land cover changes over annual or semi-annual timescales. Such research will help to inform land management practices and to balance ecological health and human livelihoods that depend on transitioning coastal lands.

Conclusion

We report rapid rates of marsh migration and upland conversion in a low-lying and tidally dissected county in Maryland. Agricultural land and scrub shrub wetland were more vulnerable to conversion to emergent wetland than forest or urban land, after controlling for two important variables in land use transition, elevation and distance to shore. Questions remain about the proximate social, landscape, and climate drivers responsible for this greater vulnerability; these will be the subject of future research. Further insight into variables influencing coastal change can guide the development of policies and land management efforts to promote coastal resilience and improve predictive models of land cover change on the coast.

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References

Anderson JR (1976) A land use and land cover classification system for use with remote sensor data. US Government Printing Office, Washington, DC

Anisfeld SC, Cooper KR, Kemp AC (2017) Upslope development of a tidal marsh as a function of upland land use. Global Change Biology 23:755–766

Anisfeld SC, Kemp AC, O'Connell J (2019) Salt marsh migration into lawns revealed by a novel sediment-based approach. Estuaries and Coasts 42:1419–1429

Bhattachan A, Emanuel RE, Ardon M, Bernhardt ES, Anderson SM, Stillwagon MG, Ury EA, Bendor TK, Wright JP (2018a) Evaluating the effects of land-use change and future climate change on vulnerability of coastal landscapes to saltwater intrusion. Elem Sci Anth 6(1):62

Bhattachan A, Jurjonas MD, Moody AC, Morris PR, Sanchez GM, Smart LS, Taillie PJ, Emanuel RE, Seekamp EL (2018b) Sea level rise impacts on rural coastal social-ecological systems and the implications for decision making. Environ Sci Policy 90:122–134

Boesch DF, Boicourt WC, Cullather RI, et al (2018) Sea-level rise: projections for Maryland 2018. 27 pp.

Boon JD, Mitchell M (2015) Nonlinear change in sea level observed at north American tide stations. J Coast Res 31:1295–1305

Conner WH, Krauss KW, Doyle TW (2007) Ecology of tidal freshwater forests in coastal deltaic Louisiana and northeastern South Carolina. Ecology of tidal freshwater forested wetlands of the southeastern United States. Springer, Dordrecht, pp 223–253

Craft CB (2012) Tidal freshwater forest accretion does not keep pace with sea level rise. Glob Chang Biol 18:3615–3623

Dobson JE, Bright EA, Ferguson RL, Field DW, Wood LL, Haddad KD, Iredale H, Jensen JR, Klemas V, Orth RJ, Thomas JP (1995) NOAA Coastal Change Analysis Program (C-CAP) : guidance for regional implementation

Eggleston J, Pope J (2013) Land subsidence and relative sea-level rise in the southern Chesapeake Bay region. US Geological Survey Circular, 1392, 30 p

Enwright NM, Griffith KT, Osland MJ (2016) Barriers to and opportunities for landward migration of coastal wetlands with sea-level rise. Front Ecol Evol 14:307–316

Epanchin-Niell R, Gedan K, Miller J, Tully K (2018) Saltwater intrusion and coastal climate adaptation: building community resilience. In: Resources for the Future. https://www.resourcesmag.org/archives/saltwater-intrusion-and-coastal-climate-adaptation-building-community-resilience/. Accessed 15 Aug 2019

Epanchin-Niell R, Kousky C, Thompson A, Walls M (2017) Threatened protection: sea level rise and coastal protected lands of the eastern United States. Ocean Coastal Manag 137:118–130

Ezer T, Corlett WB (2012) Is sea level rise accelerating in the Chesapeake Bay? A demonstration of a novel new approach for analyzing sea level data. Geophys Res Lett 39(19):L19605

Fagherazzi S, Anisfeld SC, Blum LK, Long EV, Feagin RA, Fernandes A, Kearney WS, Williams K (2019) Sea level rise and the dynamics of the marsh-upland boundary. Front Environ Sci 7. https://doi.org/10.3389/fenvs.2019.00025

Field CR, Dayer AA, Elphick CS (2017) Landowner behavior can determine the success of conservation strategies for ecosystem migration under sea-level rise. Proc Natl Acad Sci 114:9134–9139

Gedan KB, Fernández-Pascual E (2019) Salt marsh migration into salinized agricultural fields: a novel assembly of plant communities. J Veg Sci 30:1007–1015

Johnson KJ, Needelman BA, Paolisso M (2017) Vulnerability and resilience to climate change in a rural coastal community. Responses to disasters and climate change. ROUTLEDGE in Association with GSE Research, pp 5–14

Jordan CF (1969) Derivation of leaf-area index from quality of light on the forest floor. Ecology 50:663–666

Karnieli A, Agam N, Pinker RT, Anderson M, Imhoff ML, Gutman GG, Panov N, Goldberg A (2010) Use of NDVI and land surface temperature for drought assessment: merits and limitations. Journal of Climate 23:618–633

Kearney WS, Fernandes A, Fagherazzi S (2019) Sea-level rise and storm surges structure coastal forests into persistence and regeneration niches. PLoS One 14:e0215977

Kirwan ML, Gedan KB (2019) Sea-level driven land conversion and the formation of ghost forests. Nat Clim Chang 9:450–457. https://doi.org/10.1038/s41558-019-0488-7

Kirwan ML, Walters DC, Reay WG, Carr JA (2016) Sea level driven marsh expansion in a coupled model of marsh erosion and migration. Geophys Res Lett 43:4366–4373

Langston AK, Kaplan DA, Putz FE (2017) A casualty of climate change? Loss of freshwater forest islands on Florida's Gulf Coast. Glob Chang Biol 23:5383–5397

McFeeters SK (1996) The use of the normalized difference water index (NDWI) in the delineation of open water features. Int J Rem S 17: 1425–1432

MD DNR (2019) MD iMAP: Maryland's mapping & GIS data portal. In: Pre-Defined DEMs. https://imap.maryland.gov/Pages/lidar-dem-download-files.aspx. Accessed 15 Aug 2019

Michael HA, Post VE, Wilson AM, Werner AD (2017) Science, society, and the coastal groundwater squeeze. Water Resour Res 53:2610–2617

Middleton BA (2016) Differences in impacts of hurricane sandy on freshwater swamps on the Delmarva Peninsula, mid-Atlantic Coast, USA. Ecol Eng 87:62–70

Qi M, MacGregor J, Gedan K (in review) Biogeomorphic patterns emerge in marshes during sea level rise-driven pond formation. Limnol Oceanogr

Raabe EA, Stumpf RP (2016) Expansion of tidal marsh in response to sea-level rise: Gulf Coast of Florida, USA. Estuar Coast 39:145–157

Richardson AJ, Wiegand CL (1977) Distinguishing vegetation from soil background information. Photogramm Eng Rem S 43:1541–1552

Sallenger, A.H., Doran, K.S. and Howd, P.A., 2012. Hotspot of accelerated sea-level rise on the Atlantic coast of North America. Nat Clim Chang 2(12):884–888

Schuerch M, Spencer T, Temmerman S, Kirwan ML, Wolff C, Lincke D, McOwen CJ, Pickering MD, Reef R, Vafeidis AT, Hinkel J (2018) Future response of global coastal wetlands to sea-level rise. Nature 561:231–234

Schieder NW, Walters DC, Kirwan ML (2018) Massive upland to wetland conversion compensated for historical marsh loss in Chesapeake Bay, USA. Estuar Coast 41:940–951

Smith JA (2013) The role of Phragmites australis in mediating inland salt marsh migration in a mid-Atlantic estuary. PLoS One 8:e65091

Smith JA, Hafner SF, Niles LJ (2017) The impact of past management practices on tidal marsh resilience to sea level rise in the Delaware estuary. Ocean Coast Manag 149:33–41

Spidalieri K (2020) Where the wetlands are—and where they are going: legal and policy tools for facilitating coastal ecosystem migration in response to sea-level rise. Wetlands. https://doi.org/10.1007/s13157-020-01280-x

Tanji KK, Kielen NC (2002) Agricultural drainage water management in arid and semi-arid areas. FAO, Rome

Titus JG, Hudgens DE, Trescott DL, Craghan M, Nuckols WH, Hershner CH, Kassakian JM, Linn CJ, Merritt PG, McCue TM, O'Connell JF, Tanski J, Wang J (2009) State and local governments plan for development of most land vulnerable to rising sea level along the US Atlantic coast. Environ Res Lett 4:044008. https://doi.org/10.1088/1748-9326/4/4/044008

Tully K, Gedan K, Epanchin-Niell R, Strong A, Bernhardt ES, BenDor T, Mitchell M, Kominoski J, Jordan TE, Neubauer SC, Weston NB (2019) The invisible flood: the chemistry, ecology, and social implications of coastal saltwater intrusion. BioScience 69:368–378

USDA NASS (2012) Census of Agriculture – 2012 Census Publications – State and County Profiles – Maryland. https://www.nass.usda.gov/Publications/AgCensus/2012/Online_Resources/County_Profiles/Maryland/index.php. Accessed 15 Aug 2019

U. S. Fish and Wildlife Service (2013) National Wetlands Inventory website. U.S. Department of the Interior, Fish and Wildlife Service, Washington, DC http://www.fws.gov/wetlands/

Werner AD, Bakker M, Post VE et al (2013) Seawater intrusion processes, investigation and management: recent advances and future challenges. Adv Water Resour 51:3–26

Williams K, Ewel KC, Stumpf RP, Putz FE, Workman TW (1999) Sea-level rise and coastal forest retreat on the west coast of Florida, USA. Ecology 80:2045–2063

Williams K, MacDonald M, Lda Sternberg SL (2003) Interactions of storm, drought, and sea-level rise on coastal forest: a case study. J Coast Res 19:1116–1121

Yang J, Zhang H, Yu X, Graf T, Michael HA (2018) Impact of hydrogeological factors on groundwater salinization due to ocean-surge inundation. Adv Water Resour 111:423–434