Georgia Sea Grant Final Report

Title of project

Incorporating Future Infrastructure Decisions into Salt Marsh Migration Models

Duration of the project

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Name of PIs and co-PIs

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Abstract

Sea level rise affects both coastal development and coastal ecosystems by increasing flooding and erosion. The impacts to human infrastructure and ecosystems are often assessed separately, when in fact they are highly intertwined. Coastal salt marshes may persist under rising seas by migrating landward; however, land management decisions, including armoring coastal properties, may prevent this inland migration, essentially squeezing salt marshes between hard upland barriers and the rising sea. These land management decisions might significantly affect marsh habitat but are not currently accounted for in projections of salt marsh persistence. The goal of this study was to examine the interactions between land management and salt marsh migration under rising sea level. We developed improved modeling tools that specifically account for these interactions to provide more realistic projections of how salt marsh habitat on the Georgia coast might evolve in the future. First, we used a detailed census of existing coastal armoring to develop a logistic regression equation that estimates the probability of armoring for individual coastal parcels. We also simulated future urbanization using the SLEUTH urban growth model. These models were both incorporated into the Sea Level Affecting Marshes Model (SLAMM) to simulate future marsh migration under sea level rise while accounting for urbanization and coastal armoring decisions. We found that sea level rise effects were generally larger than the effects of armoring and urbanization on future salt marsh extent. Armoring and urbanization did restrict salt marsh migration, especially in already developed areas (e.g. the Savannah region). These differences were much smaller for the whole Georgia coast because there are (and are projected to remain) large undeveloped areas where uninhibited marsh migration is allowed. This research provides a more realistic understanding of the interplay

between sea level rise, land management, and salt marsh migration and can inform effective and sustainable coastal management.

Detailed description of your research results

Methods

This research yielded two major outputs. First, was the development of a logistic regression equation that can predict the probability that a coastal parcel will be armored now or in the future. The second output was the development of an integrated modeling approach to incorporate the effects of armoring and future urbanization on salt marsh migration on the Georgia Coast.

Logistic Regression Equation

Study Area

The geographical domain of this study is defined within the six counties that comprise the Georgia coastline: Camden, Glynn, McIntosh, Liberty, Bryan, and Chatham (Figure 1). The Georgia coastline is approximately 100 miles long and includes thirteen barrier islands and nine major estuaries. A defining characteristic of the Georgia coastline is its vast expanse of salt marshes situated in estuarine environments. In comparison to other U.S. coastlines, the Georgia coastline is largely undeveloped. Accordingly, it is home to nearly one-third of all salt marshes along the U.S. Atlantic coastline (Wiegert & Freeman, 1990). Previous research has established that approximately 92% of Georgia's estuarine shoreline is solely or dominantly fronted by salt marsh and approximately 5% of the shoreline is armored (Alexander, 2016).

This study was performed at the scale of individual land parcels. Parcel boundaries and parcel-level tax assessor information were provided by the Coastal Regional Commission (CRC) of Georgia and referenced 2016 computer assisted mass appraisal (CAMA) data. Using ArcMap 10.3.1, we specifically identified shoreline parcels for inclusion in our analysis, as these landowners are directly facing the decision of whether to armor their shoreline. We defined shoreline parcels to be those with dry land (upland) abutting wetland or water habitat. To identify shoreline parcels, we first used the National Wetlands Inventory (NWI)—Estuarine and Marine Deepwater and the NWI—Estuarine and Marine Wetland Habitats (Cowardin et al., 1979) to create a polyline delineating the coastal shoreline; these NWI habitats approximately encompass areas of salt marsh, brackish marsh, estuarine open water, and open ocean. The inland extent of our analysis is bounded by the westernmost extent of either I-95 or U.S. Highway 17, as this is the inland extent of the Georgia Coast Armored Shoreline dataset coverage. (Alexander, 2010)

Based on visual quality assurance checks on the identification of shoreline parcels, we implemented two refinements to our methodology that improved shoreline parcel identification for our purposes. The first removed some inland parcels that were included in multi-part parcels consisting of fully inland, disconnected polygons in addition to polygons associated with shoreline property. The second refinement clipped parcel boundaries to the shoreline polyline so that only dry land was included. Upon creation of these new parcel boundaries, we identified numerous parcels with little of their original area remaining.

We subsequently classified the shoreline type for each parcel to be either 'estuarine' or 'marine' based on whether the centroid of the parcel was nearer the NWI Estuarine and Marine Deepwater sub-classification of E1UBL (Estuarine, Subtidal, Unconsolidated Bottom, Subtidal) or M1UBL (Marine, Subtidal, Unconsolidated Bottom, Subtidal), respectively (Cowardin et al., 1979). Due to the potential for hard armoring to influence salt marsh habitat and migration, we solely included parcels with estuarine shoreline in our analysis. Parcels selected based on the above specified criteria represent a census of estuarine shoreline parcels along the Georgia coastline.

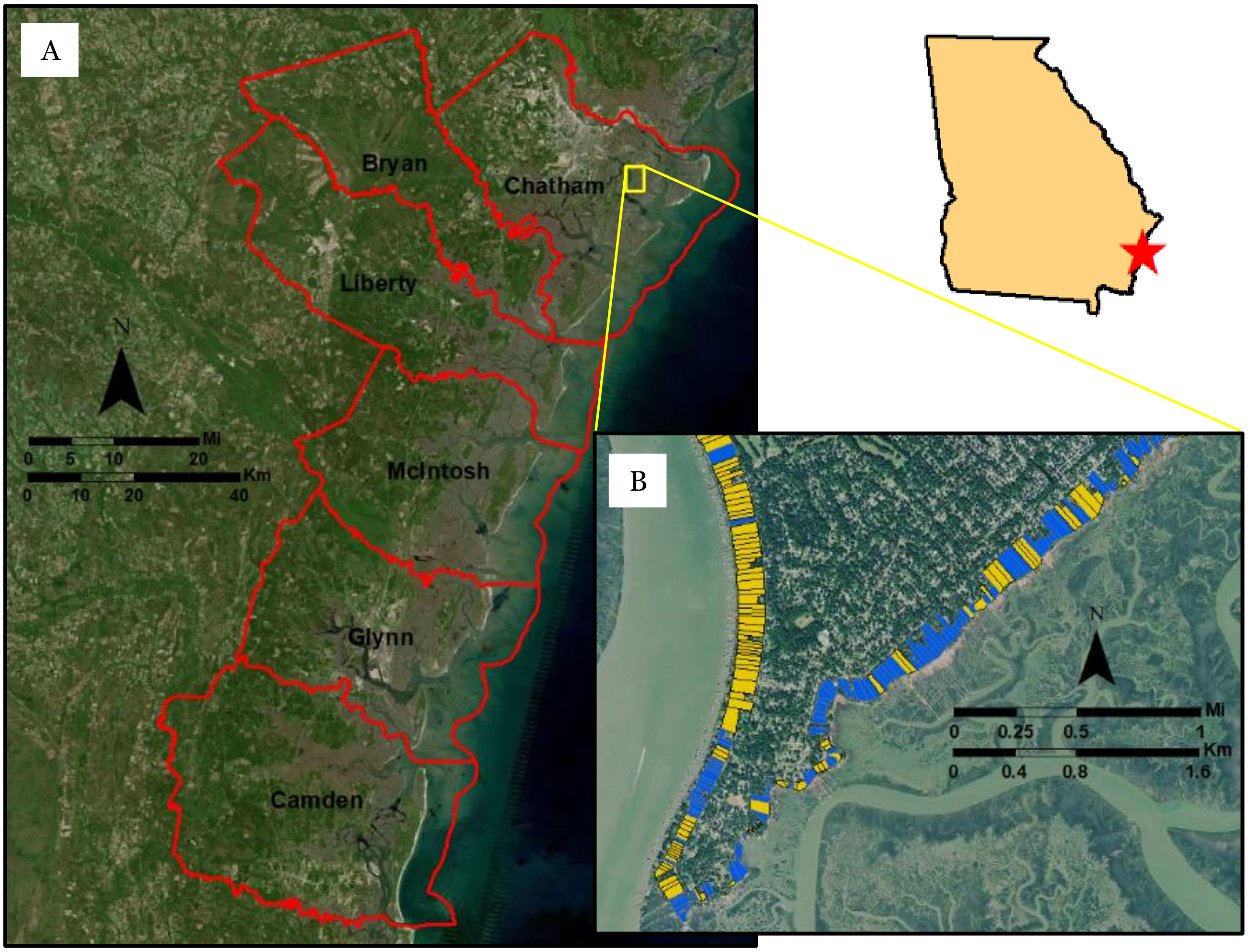

Figure 1. The study area is defined by estuarine shoreline parcels within the six Georgia coastal counties: (A) delineations of each of the six Georgia coastal counties and (B) delineations of individual estuarine shoreline parcels where blue and yellow indicate armoring absence and presence, respectively. Images were generated in ArcGIS Desktop 10.5 using NASA's Web-Enabled Landsat Data (WELD) (DOI: 10.5067/MEaSUREs/WELD/WELDUSYR.001) for (A) and USDA 2017 NAIP Digital Ortho Photo Imagery (DOI: 10.5066/F7QN651G) for (B).

Identifying Armored Parcels

We used a novel, high-resolution dataset (Alexander, 2010; Bulski et al., 2015) to define the distribution of hard armored shorelines throughout the estuarine area of Georgia at the parcel level. Using aerial imagery from 2006 and 2013, combined with extensive field inspection efforts, this dataset identifies the type (bulkhead, revetment, bulkhead and revetment, road causeway, other, unknown) and location of hard armoring structures, using coordinates to define these features as polylines in a Geographic Information System. The armoring structures here have largely been implemented for erosion control purposes, with bulkheads and revetments constituting a majority of the armoring structures (>85%) (Alexander, 2010; Bulski et al., 2015). We did not include road causeways in our analysis because we sought to understand drivers of shoreline armoring emplaced by landowners at the parcel scale. “Soft” armoring approaches such as living shorelines were not considered in this study, as these techniques were outside the scope of the research investigation and their current use is rare along the Georgia coastline.

Methods for identifying parcels with armored shorelines paralleled the approach used to identify shoreline parcels. Armoring polylines were converted into a 1-m grid and then converted into points in ArcMap. CAMA parcel boundaries were then overlaid with these points and the ‘Near’ function was used to identify the nearest parcel to each point; these parcels were coded as being armored. Visual quality assurance checks on associations between individual parcels and armoring structures led us to redefine armored parcels as parcels with an armoring length >25% of their shoreline length. Thus, we estimated the armoring and shoreline lengths for each parcel based on the number of armoring and shoreline points associated with the parcel. We recoded all parcels with an armoring length < 25% of their shoreline length as unarmored.

Attribute Selection and Corresponding Data Collection

Through literature review (Field et al., 2017; Gittman, 2009; Scyphers et al., 2015), application of microeconomic behavioral theory (Gopalakrishnan et al., 2016, 2018; Train, 2009), consideration of the three components of vulnerability (exposure, adaptive capacity, and sensitivity) (IPCC, 2007; KC et al., 2015), and application of local knowledge based on field reconnaissance and informal elicitation of landowner perspectives, we developed a refined list of socio-economic and environmental attributes that we hypothesized to be associated with the presence or absence of estuarine shoreline hard armoring at the parcel level scale along the Georgia coastline (Table 1). For each attribute that we identified, it was necessary for us to obtain parcel-level information representing the attribute of interest either directly or indirectly. We pursued datasets that provided information for the largest number of parcels along the Georgia coastline, and at a scale appropriate for parcel level analysis. We then used descriptor variables to numerically or categorically describe each attribute; in some instances, we identified several descriptor variables to serve as proxies for complex characteristics. Some descriptor variables were directly provided in a dataset at the parcel scale while others required calculation and/or manipulation of a dataset in ArcMap.

All estuarine shoreline parcels were assigned a value for each descriptor variable. In some instances, this required the value of zero to be assigned to parcels with null or missing values. Specifically, the descriptor variables of replacement cost, construction cost, and building area were assigned a value of zero if specified as null in the CAMA data provided by the CRC of Georgia. We determined this methodology to be appropriate for our analysis because a null value indicates an absence of buildings on a parcel, and we are interested in capturing the value of buildings on the parcel through these descriptor variables. The descriptor variables for the shoreline change attribute were also assigned values of zero when historical shoreline change transects did not overlap the original CAMA parcel boundary. The historical shoreline change rate dataset documents the historical rate of shoreline change between ca. 1930–2010 at 50 m intervals along the shore, and in some instances, locations where historical shoreline change rates were assessed occurred outside of the original CAMA parcel boundaries. Historical shoreline change rates were evaluated along prominent waterways, leaving parcels abutting smaller tidal creeks and marshes at the inland extent of the study area without a measure of historical shoreline change. Only limited data were available for smaller creek systems and the naturally meandering nature of these creeks (e.g., erosion on one bank balanced by accretion on the other) makes it impossible to appropriately generalize rates for these systems[58]. We determined that it was most appropriate to estimate the shoreline change values to be zero for parcels that were not associated with a historical shoreline change rate after we applied the methods specified above (Table 1), as these areas are situated in low energy environments where rates of change are low in comparison to ocean front and open fetch settings. We performed extensive spot-checking of all descriptor variables, leading us through several iterations of refining ArcMap commands and calculations.

Table 1. Attributes and corresponding descriptor variables hypothesized to be associated with the presence (+) or absence (-) of hard armoring.

Attribute and Source	**Descriptor Variable**	**Relationship Hypothesis**	**Description** (methodology used for evaluation)
Distance to Shoreline	Distance to Shoreline (m)	-	Shortest distance from the centroid of the parcel area to the shoreline polyline (Cowardin et al., 1979)
Elevation	Elevation (m)	-	Mean elevation of parcel area relative to the North American Vertical Datum of 1988 (NAVD88) (Hladik & Alber, 2012; Hladik & Herbert, 2017)
Slope	Elevation/ Distance To Shoreline	+	Ratio of elevation to distance (each defined above)
Parcel Area (CRC of Georgia)	Parcel Area (km^2)	+	Upland area of the parcel
Shoreline Energy Class	Indicators for Low, Medium, and High Energy	+	Classification of shoreline energy based on shoreline type from the NWI classification:
Shoreline Change*	Minimum Historical Shoreline Change Rate (m/year)	-	Minimum value of the shoreline change rate transects that overlap with the original CAMA parcel boundary (Jackson, 2015)
	Average Historical Shoreline Change Rate (m/year)	-	Average value of the shoreline change rate transects that overlap with the original CAMA parcel boundary (Jackson, 2015)
	Maximum Historical Shoreline Change Rate (m/year)	-	Maximum value of the shoreline change rate transects that overlap with the original CAMA parcel boundary
	Erosion Rate (m/year)	+	Absolute value of the average historical shoreline change rate descriptor variable for values <0
	Accretion Rate (m/year)	-	Value of the average historical shoreline change rate descriptor variable for values >0

Attribute and Source	Descriptor Variable	Relationship Hypothesis	**Description** (methodology used for evaluation)
Influence of Neighboring Armor (Alexander, 2010; Bulski et al., 2015)	Neighbor Armoring (binary)	+	Denotes if a parcel adjoins another parcel that has hard armoring (1) or not (0)
	Distance to Closest Armored Neighbor (m)	-	Distance from the centroid of a parcel area to the centroid of the closest armored parcel area, other than the parcel itself
Parcel Value (CRC of Georgia)	Replacement Cost ($)	+	Replacement cost for buildings on parcel
	Construction Cost ($)	+	Construction cost for buildings on parcel
	Building Area (m^2)	+	Area of buildings on parcel
	Total Value ($)	+	Total value of parcel
Urban Classification (US Census Bureau, 2010)	Housing Unit Density at the Block Scale (hu/km^2)	+	Housing unit count for the block in which a parcel is located, divided by the area (m^2) of that block as given in the census data
	Population Density at the Block Scale (ppl/km^2)	+	Population count for the block in which a parcel is located, divided by the area (m^2) of that block as given in the census data
	Housing Unit Density at the Block Group Scale (hu/km^2)	+	Housing unit count for the block group in which a parcel is located, divided by the area (m^2) of that block group as given in the census data
	Population Density at the Block Group Scale (ppl/km^2)	+	Population count for the block group in which a parcel is located, divided by the area (m^2) of that block group as given in the census data

*The data source for the shoreline change attribute applies negative numbers to rates of erosion and positive numbers to rates of accretion

Logistic Regression Analysis

We performed logistic regression analysis using Stata 15 (Statacorp, 2017) to probabilistically assess the spatial distribution of hard armoring as a function of select descriptor variables (Table 1); the logistic regression model estimates can be used to provide a probability of hard armoring ($0 < p < 1$) on a specified parcel. Model development was directed towards capturing the influential factors in the individual decision to invest in hard armoring (or purchase properties that already had armoring installed). The general form of our model was based on conceptual choice theory, as we viewed the probability of installing hard armoring as a function of perceived risk and benefit, cost and/or ability to pay, and demographic/social factors, including some unobserved effects. Accordingly, we included county-level dummy variables to capture unobserved heterogeneity and we clustered standard errors at the county level.

Our primary regression model specification includes an indicator for hard armoring on a neighbors parcel, geophysical characteristics (distance to the shoreline, elevation, slope, shoreline length, parcel area), shoreline change variables (indicators for medium- and high-energy environments, historical erosion rate), economic characteristics (building value), in addition to the county fixed effects. We tested for the influence neighborhood fixed effects (when information was available) to control for neighborhood-level hard armoring projects (that may be beyond the decisions of individual homeowners). Lastly, we estimated models without the neighboring parcel effect, in order to produce results that might be applied to other locations (under the expectation that neighboring armor indicator may not always be available).

Final model selection was based primarily on variable influence, interpretability, ease of descriptor variable calculation, fidelity to processes supported by theory, and model fit diagnostics. Model prediction accuracy is the in-sample prediction success, using a fitted value of 50% to predict armoring. To assess out-of-sample prediction and sensitivity to the cutoff value for armor prediction, we performed a 10-fold cross-validation and measured the area under the "Receiver Operating Characteristic" (ROC) curve to assess sensitivity and specificity. Sensitivity is the fraction of positive cases that are correctly classified by the logistic regression model, while specificity is the fraction of negative cases that are correctly classified. The ROC curve is the plot of sensitivity versus 1-specificity from a 10-fold cross validation, and area under the ROC is commonly used as a measure of goodness of fit for out-of-sample prediction accuracy. We conducted likelihood ratio tests to assess nested model specifications and used Information Criteria for non-nested assessments. Lastly, we tested the final model for spatial autocorrelation assuming an inverse-distance weighting matrix.

Salt Marsh Migration Modeling

We used the logistic regression model described above to dynamically model the effects of coastal armoring, future urban growth, and sea level rise on salt marsh migration and persistence on the Georgia coast. This modeling effort involved the dynamic coupling of three separate models – logistic regression, SLEUTH urbanization model, and Sea Level Affective Marshes Model (SLAMM) for salt marsh migration. We simulated three NOAA sea level rise scenarios.

The sea level rise scenarios used in this project come from the 2017 NOAA regional scenarios for the Fort Pulaski tide gauge. We evaluated the Intermediate-Low (0.60m/1.97ft from 2000-2100), Intermediate (1.22m/4.00ft), and Intermediate-High (1.93m/6.33ft) scenarios to cover the probable range of outcomes for the next century. Within each sea level rise scenario, we examine marsh migration under high and low shoreline armoring intensity scenarios, with and without future projected urbanization, and finally with no armoring at all and no protection of existing urban land to establish a baseline marsh migration scenario without deliberate human interference.

SLAMM serves as the core framework for modeling sea level rise and marsh migration. SLAMM simulates sea level rise and the processes of marsh accretion, erosion, and conversion to other land covers. The model requires three spatial inputs: a digital elevation model (DEM), land use classification raster, and slope (based on the DEM). We used a 10m resolution vegetation-corrected DEM for the Georgia coast (Herbert, 2015), a land classification raster derived from the most recent National Wetlands Inventory (NWI) vector dataset, and a slope raster derived from the DEM. Other SLAMM parameters include the global sea level rise scenario to be applied, local marsh accretion parameters, and protection scenarios which prohibit designated land cover types from being converted to wetlands. SLAMM can optionally account for local sea level rise by extrapolating the difference between historical local and global sea level rise into the future, but for this effort it is assumed that local and global sea level rise are equal. We ran SLAMM in 10-year increments, while dynamically adjusting the input land cover rasters for each timestep to account for areas which are modeled to become newly armored or urbanized, and subsequently protecting those areas from wetland conversion in future timesteps.

Shoreline armoring is evaluated at the beginning of each timestep using the logistic regression equation described above. Of the 15 total variables, 9 are held constant over time and 6 are newly evaluated at the beginning of each timestep. The 6 dynamic variables are:

1. whether a neighboring parcel is armored [0/1],
2. the distance from the parcel centroid to the SLAMM-derived shoreline for that timestep [m],
3. the mean parcel elevation from the SLAMM DEM [m above NAVD88],
4. the slope variable, computed as the quotient of parcel elevation and distance to shoreline [m/m],
5. whether the parcel has a medium-energy shoreline [0/1], and
6. whether the parcel has a high-energy shoreline [0/1], with shoreline energy classifications defined in terms of SLAMM land cover classifications.

The remaining constant parcel attributes are:

1. the natural log of the original parcel shoreline length [ln(m)],
2. the original parcel area after clipping to NWI polygon-derived shoreline [km^2],
3. the average historical erosion rate of the parcel shoreline [m/yr],
4. the value of any buildings within the parcel [$\$/m^2$], and
5. binary variables based on the county the parcel is in

Parcel shoreline lengths and areas are held constant because they were originally evaluated using the boundaries of the polygons produced in the 2006 National Wetlands Inventory, which offers a considerably higher degree of precision than the shoreline which must be constructed from the SLAMM land cover outputs in subsequent timesteps. The SLAMM-based shoreline can be estimated by finding the boundary between dry land and water or wetlands. Because the SLAMM shoreline is derived from the SLAMM land cover rasters, which have resolutions of 10x10 meters, the resulting shoreline is often quite jagged and not well suited for clipping parcel boundaries or calculating a new shoreline length. However, the SLAMM-derived shoreline is used to evaluate the distance to shoreline parameter (and thus parcel slope, which strongly influences armoring probability), in order to model the driving influence of inland marsh migration on property owners' decision to armor. For the edge cases where the SLAMM-derived shoreline nearly intersects the parcel centroid, resulting in very high parcel slopes, slope values are post-processed such that the maximum permissible value is 95th percentile slope (0.0911 [m/m]) used to construct the original logistic regression.

The armoring regression equation predicts a probability of armoring for each coastal parcel in Georgia. However, these probabilities must then be used to determine whether or not the parcel is actually armored. What constitutes the "right" amount of armoring is open to interpretation, and serves as the basis for the different "armoring intensity" scenarios used in this modeling effort. The scenarios are constructed by starting with the known armoring rate from 2006-2013, which is calculated from the fine-scale armoring census of shoreline armoring structures by Clark Alexander et al.. In that dataset of 13,566 parcels, 2,736 were armored as of their 2006 census, while 3,136 had been armored by 2013, meaning 400 parcels were armored over the course of 7 years. This corresponds to a yearly armoring rate of 0.528%. This is used as the armoring rate for the first timestep (2010-2020), and is either reduced or increased by 10% per timestep to define the low and high armoring scenarios, respectively. The amount of armoring is therefore assumed based on past armoring rates, but the spatial location of armoring is directly predicted from the logistic regression equation. As a result, in the low armoring scenario, an average of 5884, or 43% of total parcels are armored at some point in the simulation. For the high armoring scenario, those numbers are 8452 and 62%, respectively. However, not all of these parcels are armored for the duration of the simulation. We have also developed an armoring removal equation which is evaluated for each armored parcel each timestep, and is a function of mean parcel elevation and weighted by total parcel value.

As the sea level rises, one would assume that there is some threshold at which the effort involved in maintaining armoring infrastructure becomes too great, and the armoring is abandoned or removed. Due to a lack of rigorous study on the conditions which lead to armoring removal, abandonment, and/or dilapidation, a simple elevation-based function is developed to evaluate such processes. The function assumes (1) that there is some mean parcel elevation threshold above which armoring removal will never be considered, and (2) that there is some other, lower mean parcel elevation threshold below which armoring removal is certain. Between the lower and upper elevation thresholds, the probability of armoring removal is assumed to decrease exponentially, with the rate of exponential decay being proportional to the log-transformed total value of the parcel. In other words, a high-value parcel will have a lower probability of armoring removal than a low-value parcel at the same elevation. This is intended to represent the greater incentive to maintain armoring and resist upland retreat for high-value parcel owners relative to low-value parcel owners. However, once the elevation of either a high- or low-value parcel dips below the specified lower threshold, armoring removal is certain regardless of parcel value. For this modeling effort, the lower elevation threshold is assumed to be equal to mean tide level (MTL), and the upper elevation threshold is assumed to be equal to the 30-day inundation elevation, which is called the "salt elevation" parameter in SLAMM. These thresholds are equal to 0 meters above MTL and 1.311 meters above MTL, respectively. The number of parcels which are permitted to un-armor in a given timestep can be restricted in the same manner as the number of parcels allowed to become armored, but for this modeling effort armoring removal is fully unrestricted. The number of parcels which become un-armored is highly sensitive to the sea level rise scenario applied in SLAMM, because SLAMM reduces dry land elevations by an amount equal to the amount of global SLR which is modeled to occur. The percentage of armored parcels which became unarmored by 2100 were found to be 4.2%, 10.6%, and 16.7% for the NOAA Intermediate-Low, Intermediate, and Intermediate-High SLR scenarios, respectively.

Therefore, in each timestep, there is a set of previously-unarmored parcels which become newly armored, and a set of previously-armored parcels which become newly unarmored. In the former case, pixels which overlap with a newly-armored parcel boundary are converted to "developed dry land" in the SLAMM land cover input raster for the current timestep, and are subsequently protected. In the latter case, pixels which overlap with a newly-unarmored parcel are converted from "developed dry land" to "undeveloped dry land", meaning that the parcel is no longer protected from wetland conversion in future SLAMM timesteps. Moreover, parcels which become unarmored are prohibited from becoming armored again in future timesteps.

In addition to new armoring, we also incorporate future projected urbanization using the SLEUTH model from Dr. Keith Clarke at the University of California, Santa Barbara. SLEUTH is named for its inputs – Slope, Land cover, Exclusion, Urban extent, Transportation, and Hillshade. The Slope layer is calculated from a high-resolution 1-m DEM. The Land cover layer is optional for the model to run, and is not used. The Exclusion layer represents areas which are prohibited from development during model execution, where a pixel value of 100 means the cell cannot be developed and a value of 0 means the cell is available for development. Areas corresponding to open water, wetlands, or conservation lands, sourced from the National Wetlands Inventory vector dataset, are coded as 100 and completely excluded. Moreover, cells which correspond to water or wetlands from the most recent SLAMM output are also coded 100 and excluded from being developed. Cells can also be partially excluded, as is the case with cells corresponding to row crop which are coded as 50, while cells representing pasture land are coded as 10, with both being sourced from the 30 meter 2015 Georgia Land Use Trends (GLUT) land cover dataset. Roads are sourced from the US Census Bureau TIGER roads vector dataset. Finally, the urban extent layer is updated each timestep with the new projected urbanization from SLEUTH, assigned using a population projection methodology as described below.

For each timestep, SLEUTH runs and produces a raster with each cell containing a value equal to the percentage chance of urbanization, ranging from 0 to 100. The modeler has to choose a probability threshold cutoff value such that all cells with probabilities greater than that value are coded as urban for the next timestep, and all cells with lower probabilities are not. For this modeling effort, we incorporated county-level population projections from the US Census Bureau to assign urban probability cutoff values for each county at the end of each SLEUTH timestep. Because the Census only provides population projections through 2060, a linear trend is extrapolated through 2100 for the six counties in the study region. To determine the applicable threshold, it is assumed that the ratio between county population and urban extent remains constant through time. Counties which are projected to increase in population will experience a corresponding linear increase in urban extent, whereas counties projected to have zero or negative population growth experience no change in urban extent. This threshold is evaluated and applied to each county at the end of each timestep, and the new urban extent is used as both the Urban input layer for the following SLEUTH timestep and also to reclassify new urban pixels as “developed dry land” in SLAMM to be protected.

The three models – SLAMM, SLEUTH, and the armoring logistic regression equation – are coupled together to dynamically model sea level rise, marsh migration, urbanization, and future armoring in 10-year increments from 2010-2100. The order of operations in a given timestep is to:

1. run SLAMM using initial DEM, slope, and land cover
2. generate the SLAMM shoreline from the previous timestep’s land cover outputs,
3. evaluate new armoring and unarmoring for the current timestep using the logistic regression and SLAMM outputs, and convert newly armored parcels to developed dry land, newly unarmored parcels to undeveloped dry land, in SLAMM NWI inputs for the current timestep,
4. convert new urban land from last timestep’s SLEUTH outputs to developed dry land in SLAMM NWI inputs,
5. execute SLAMM with the updated input land cover layers for the current timestep and process the outputs,
6. exclude new water/wetland pixels from SLAMM NWI outputs from being developed in SLEUTH,
7. execute SLEUTH for the current timestep, and
8. evaluate new urban extent by county using population projection thresholding approach.

Results
Logistic Regression

We identify 13,209 land parcels along Georgia's estuarine shoreline for analysis; these parcels provide a census of armored and unarmored estuarine shoreline parcels. Chatham County comprises the largest number of these parcels (4856, 37%) and Bryan County comprises the fewest (955, 7%). In total, we estimate 2,997 parcels to be armored (23%). Chatham County also comprises the largest number of armored parcels (1473, 49%), whereas Liberty County comprises the fewest (242, 8%). When comparing armoring prevalence among counties, Bryan County has the highest percentage of armored parcels, with 37% of all estuarine shoreline parcels in Bryan County being armored. In total, we estimate 4,004 parcels (30%) to be adjacent to a parcel with existing armoring.

The final selected logistic regression model for describing patterns of hard armoring among estuarine shoreline parcels in Georgia includes the predictor variables shown in Figure 2. The model suggests that the presence of hard armoring on a neighboring parcels is one of the dominant factors in describing patterns of hard armoring. Also important are the historical erosion rate, energy level of the shoreline environment, and shoreline slope.

A likelihood ratio test supported the inclusion of neighborhood fixed effects (Chi-square = 323.476, with 172 degrees of freedom), and this model exhibits a correct classification rate of 88%. Chatham County is used as the reference for county fixed effects. Structure value appears to be best represented by replacement cost per building area, which we term "building value" ($/m^2). The explanatory power of shoreline length is improved by natural logarithm transformation. The urban classification descriptor variables (housing and population density) had inconsistent associations with armoring throughout model development, as well as small marginal effects and minimal influence on classification accuracy; thus, we did not include a measure of urban classification in the final model. The final model (Figure 2) indicates that eight of ten landscape and socioeconomic attributes selected *a priori* are strong predictors of the log-odds of shoreline armoring ($p < 0.1$).

We find that parcel slope (elevation/distance from the shore) has the largest effect on the log-odds probability of hard armoring, with a change in the log-odds value of 3.75 with a marginal effect of 0.33. Thus, a one-unit increase in the slope (from an average of 0.025) increases the likelihood of armoring by 33%. More telling, however, the elasticity of slope is 0.03, indicating that a one-percent increase in slope increases the probability of armoring by only 0.03%. Distance from the shoreline, on its own, has a small negative effect on armoring (marginal effect of -0.0006), while elevation does not have a statistically significant effect (independent of slope).

Also very impactful in the logistic regression model, the "neighbor armoring" coefficient indicates a change in the log-odds average value of 2.32 and a marginal effect of 0.18. Thus, being located next to an armored parcel increases the likelihood of armoring by 18% (holding all other predictor variables constant). This effect may reflect environmental forcings that are common to all parcels in a particular area, spatial spillovers in erosion risk due to installation of hard armoring on neighboring properties, or herding behavior (in which landowners adopt practices they see their neighbors using). To attempt to control for this, we include indicators for medium-energy or high-energy shoreline environments (relative to low-energy) and the historical erosion rate. Model results suggest medium-energy environments have no discernable impact on armoring, but high-energy shoreline environments increase the likelihood of hard armoring by 12%. A one-unit increase in the historical erosion rate increases the probability of armoring by 11%.

Other predictor variables exhibited modest effects in the logistic regression model. A one-meter increase in shoreline length reduces the log-odds by 0.09 (the likelihood of hard armoring by 0.0002 – marginal effect not statistically significant). An additional square-meter of parcel area increases the log-odds of hard armoring by 0.105, with a marginal effect of 0.009. A one-dollar increase in structure replacement cost (per m^2) increases the log-odds by 0.0093, with a marginal effect of 0.0008. Parcels located in Glynn, Liberty, and Bryan Counties are more likely to be armored, controlling for other predictors and neighborhood fixed effects, relative to Chatham County, while parcels in McIntosh County are less likely to be armored. Camden County was no different from Chatham County (all else being equal). The final model showed no evidence of spatial autocorrelation in errors (Moran's Index = 0.000246, p = 0.8125).

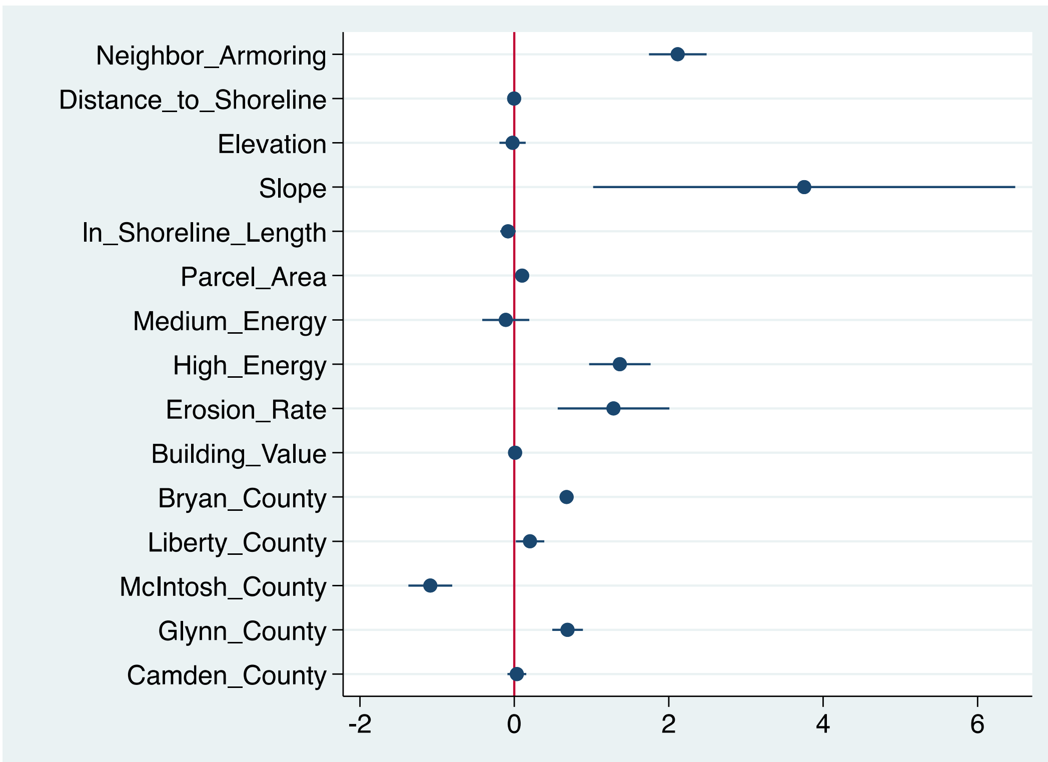

Figure 2. Forest plot of the change in the log-odds of the probability to armor resulting from a unit increase in the predictor variables included in the logistic regression model. Positive values indicate a positive association with hard armoring likelihood and negative values indicate a negative association with hard armoring likelihood. Bars are 95% confidence intervals. Parameter intervals that overlap zero do not significantly influence the probability of hard armoring (at 5% significance level).

Salt Marsh Migration Modeling

We simulated salt marsh migration and loss under three sea level rise scenarios (0.6m, 1.22m, and 1.93m of rise from 2000-2100). We classified salt marshes as both transitional (SLAMM code 7) and regularly flooded (SLAMM code 8) marshes, which broadly includes salt marshes dominated by *Juncus spp.* and *Spartina spp.* There was a net increase in total salt marsh area on the Georgia coast for the two lowest SLR scenarios (Figure 3). However, the highest SLR scenario showed a net loss in salt marsh area by 2100. This is consistent with other research on the Georgia coast that showed that marshes can migrate into new areas, along as the rate of sea level rise is not too high (Herbert, 2015). If sea level rise is too great, the drowning out of new marshes greatly exceeds the creation of new marsh habitat.

The results for scenarios with armoring and urbanization effects show similar trends to the baseline scenario (unimpeded salt marsh migration). However, the simulations that included armoring and urbanization do show less total salt marsh area by 2100 than their baseline counterparts. Differences between the baseline and other scenarios is largest for the highest SLR scenario. Differences among scenarios which included different amounts of armoring and urbanization are relatively small. This suggests that while armoring and urbanization do restrict salt marsh migration, the amount of armoring (that we examined at least) does not have much of an effect. This relatively small effect of armoring and urbanization is apparent for the whole Georgia coast, but there are important regional differences that deserve further exploration.

Much of the Georgia coast is currently undeveloped, and is not expected to experience significant urbanization by 2100. Therefore, there are many areas where salt marsh migration will be relatively unimpeded as sea levels rise. However, currently developed areas are expected to see the most population growth and will therefore experience the greatest effects of shoreline armoring and urbanization on salt marsh loss. For example, salt marsh area in the Savannah region will be significantly smaller by 2100 when the effects of armoring and urbanization are accounted for (Figure 4). At the intermediate-high SLR scenario (1.93m), there will be 57 km^2 less salt marsh habitat in 2100 than there would be if marsh migration was unimpeded (101 km^2 total area compared to 158 km^2).

The spatial patterns of these marsh losses are also significant. Figure 5 shows salt marsh gains, salt marsh loss, and future salt marsh habitat lost to armoring and urbanization for the whole Georgia coast (high armoring + urbanization scenarios). The lowest SLR scenario shows relatively little salt marsh loss overall, which is more than offset by new salt marshes moving inland. The other two SLR scenarios (Intermediate and Intermediate-High), however, show extensive loss of current salt marsh habitat to the west of the barrier islands and even extending significantly inland. The effects of armoring and urbanization can clearly be seen in the more developed parts of the coast (e.g. Savannah and Brunswick areas). Salt marsh losses and gains for the high armoring scenarios with urbanization are shown in Figure 6. Similar to what is seen in Figure 5, salt marsh losses overall increase as SLR increases, as does the amount of lost salt marsh habitat due to armoring and urbanization.

Examining the Savannah region in more detail shows significant effects of armoring and urbanization for all SLR scenarios (Figure 7). There is significant total salt marsh loss in the Intermediate and Intermediate-High scenarios, especially towards the east where the marshes have the greatest benefits in protecting populated areas for waves and storm surge. The largest effects of armoring and urbanization are seen for the Intermediate-High SLR scenario, where salt marsh migration is impeded the most on the barrier islands (Skidaway, Tybee, Wilmington and Whitemarsh), and along the Savannah River (yellow areas on Figure 7). Figure 8 shows salt marsh losses and gains for the high armoring scenarios with urbanization for just the Savannah region. Trends are similar for the whole-coast results (Figure 6), but the relative amounts of salt marsh loss are much greater.

It is unsurprising that armoring and urbanization have the greatest effects on salt marsh migration near developed areas. However, these are also the areas that most benefit from healthy salt marshes for wave attenuation, reduced storm surge, and recreation.

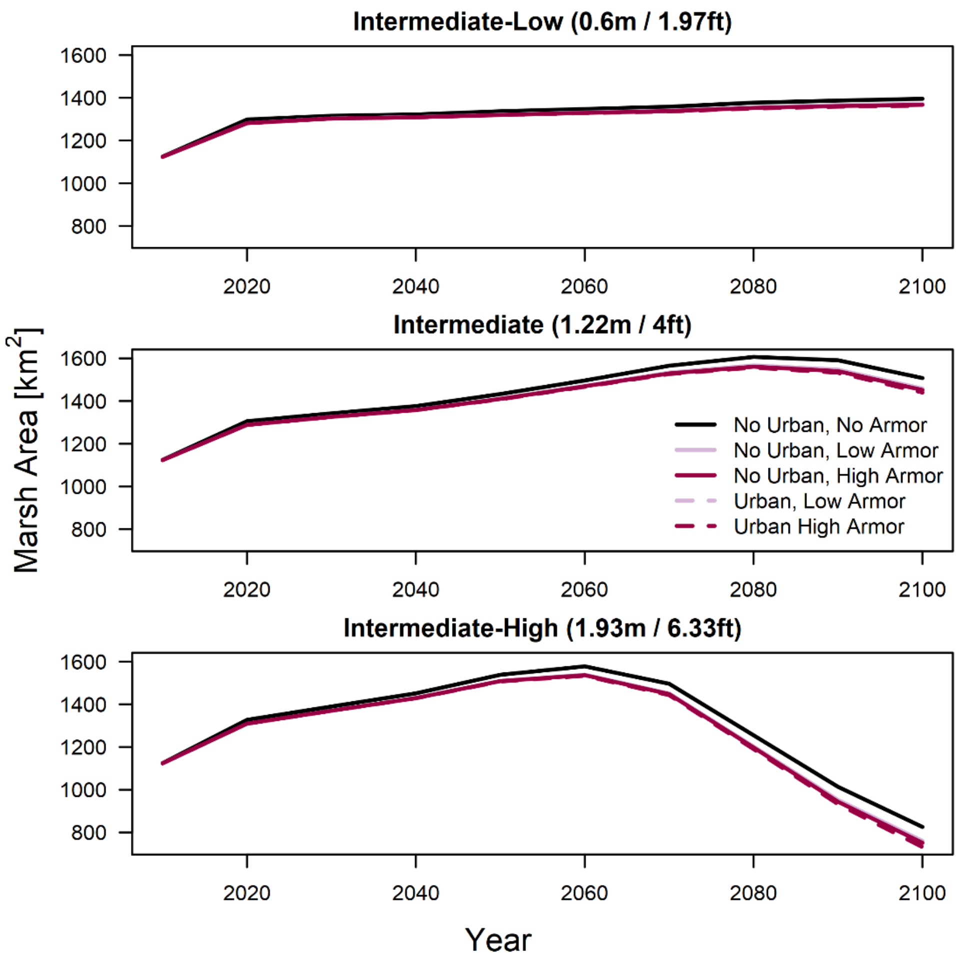

Figure 3. Salt marsh (transitional and regularly flooded) area over time for the three SLR scenarios for the whole Georgia coast. Lines compare the baseline (no urban, nor armor) with scenarios including high and low rates or armoring with and without urbanization.

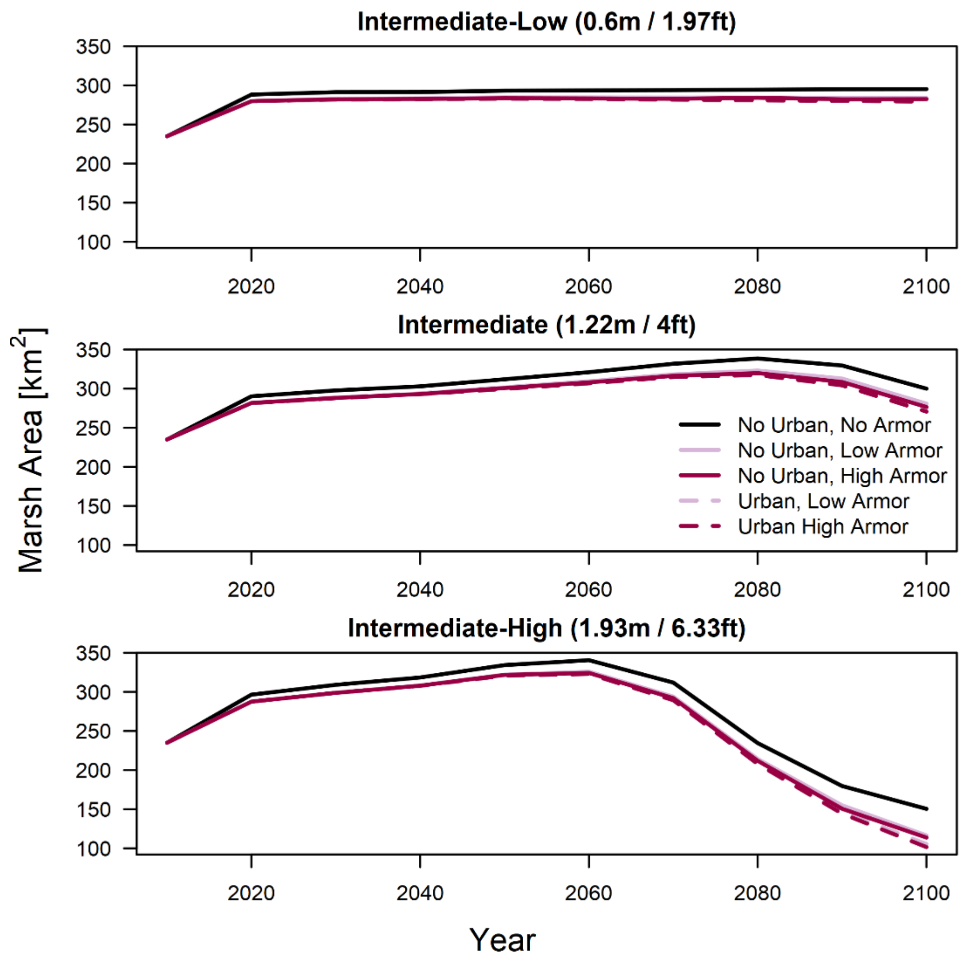

Figure 4. Salt marsh (transitional and regularly flooded) area over time for the three SLR scenarios for the Savannah region. Lines compare the baseline (no urban, nor armor) with scenarios including high and low rates or armoring with and without urbanization.

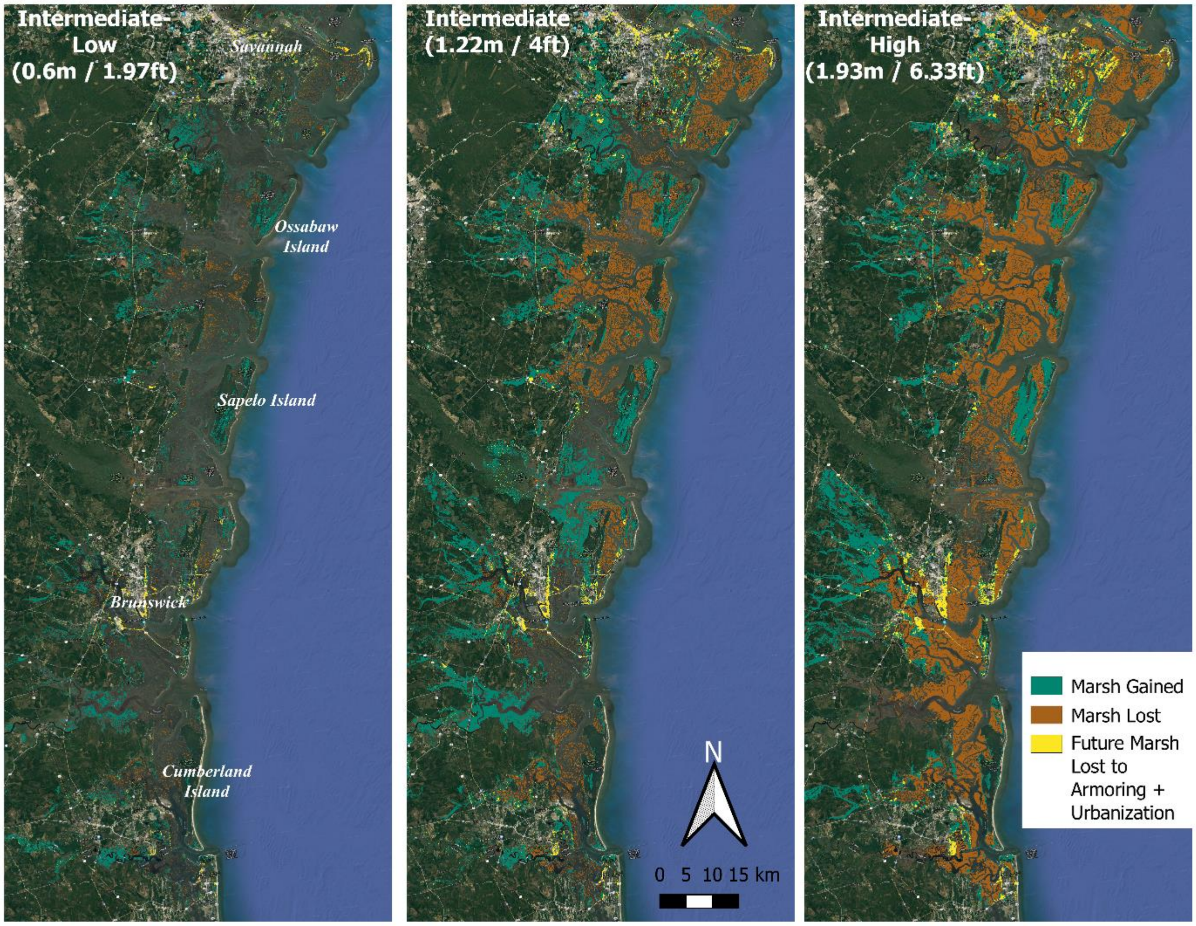

Figure 5. Map of new salt marsh (transitional and regularly flooded) area, lost marsh area, and future marsh area lost to armoring and urbanization for the whole Georgia coast for the three SLR scenarios. Results are from the high armoring scenarios with urbanization.

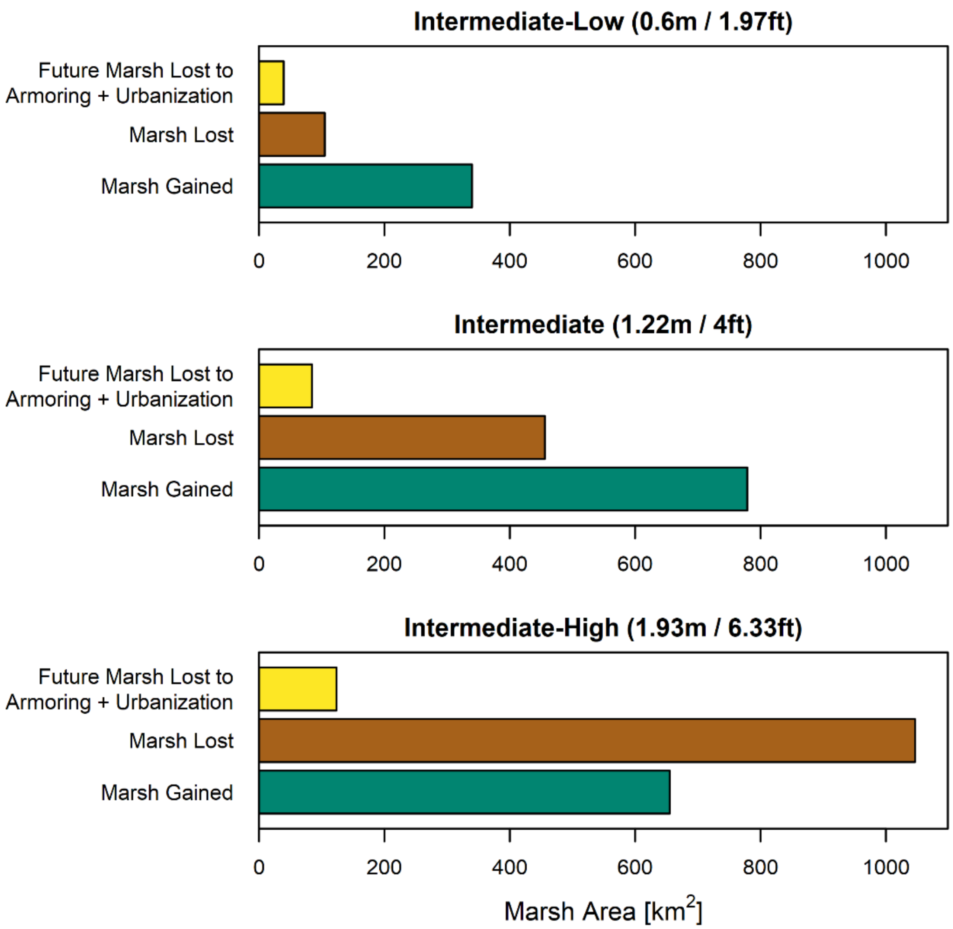

Figure 6. New salt marsh (transitional and regularly flooded) area, lost marsh area, and future marsh area lost to armoring and urbanization for the whole Georgia coast for the three SLR scenarios. Results are from the high armoring scenarios with urbanization.

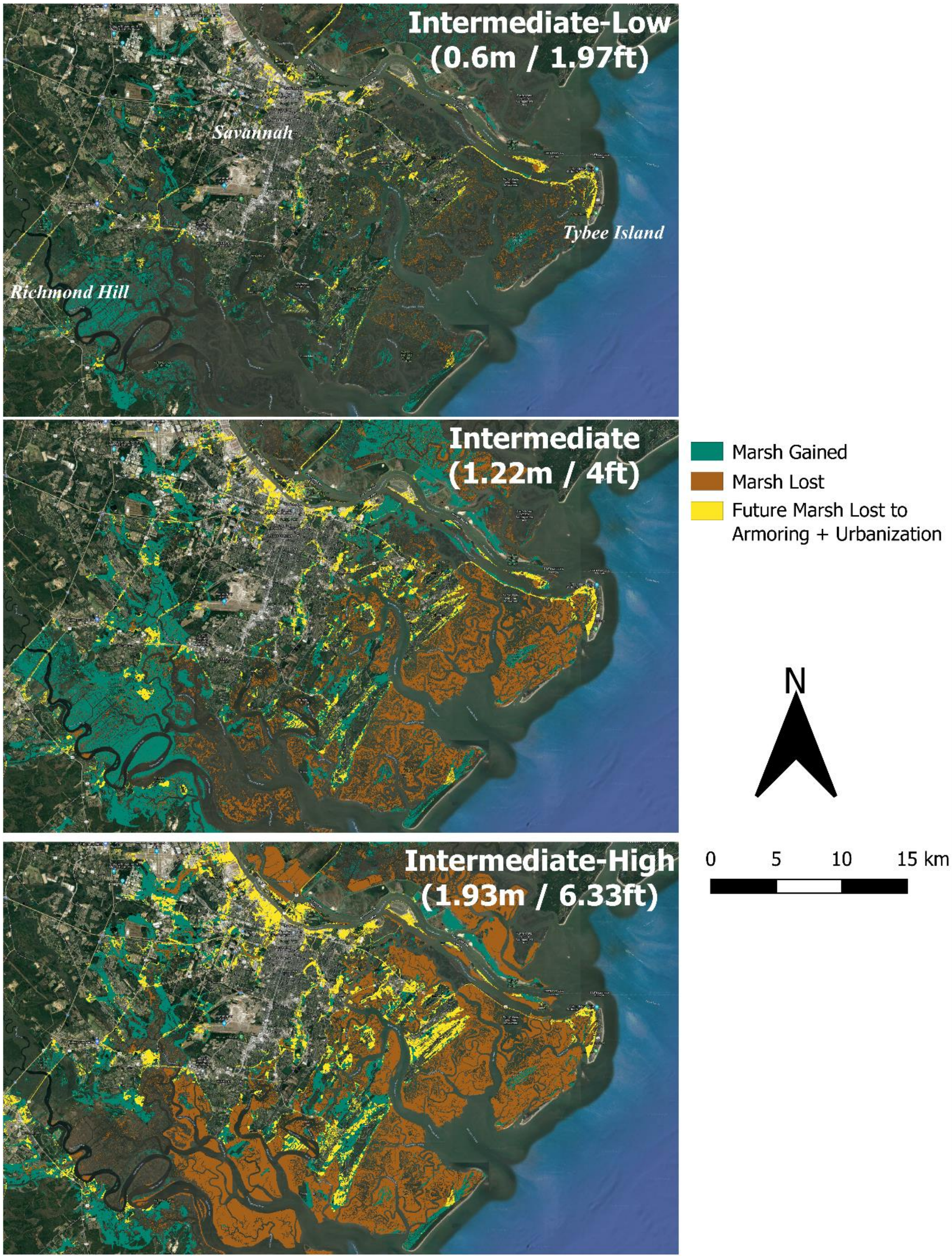

Figure 7. Map of new salt marsh (transitional and regularly flooded) area, lost marsh area, and future marsh area lost to armoring and urbanization for the Savannah region for the three SLR scenarios. Results are from the high armoring scenarios with urbanization.

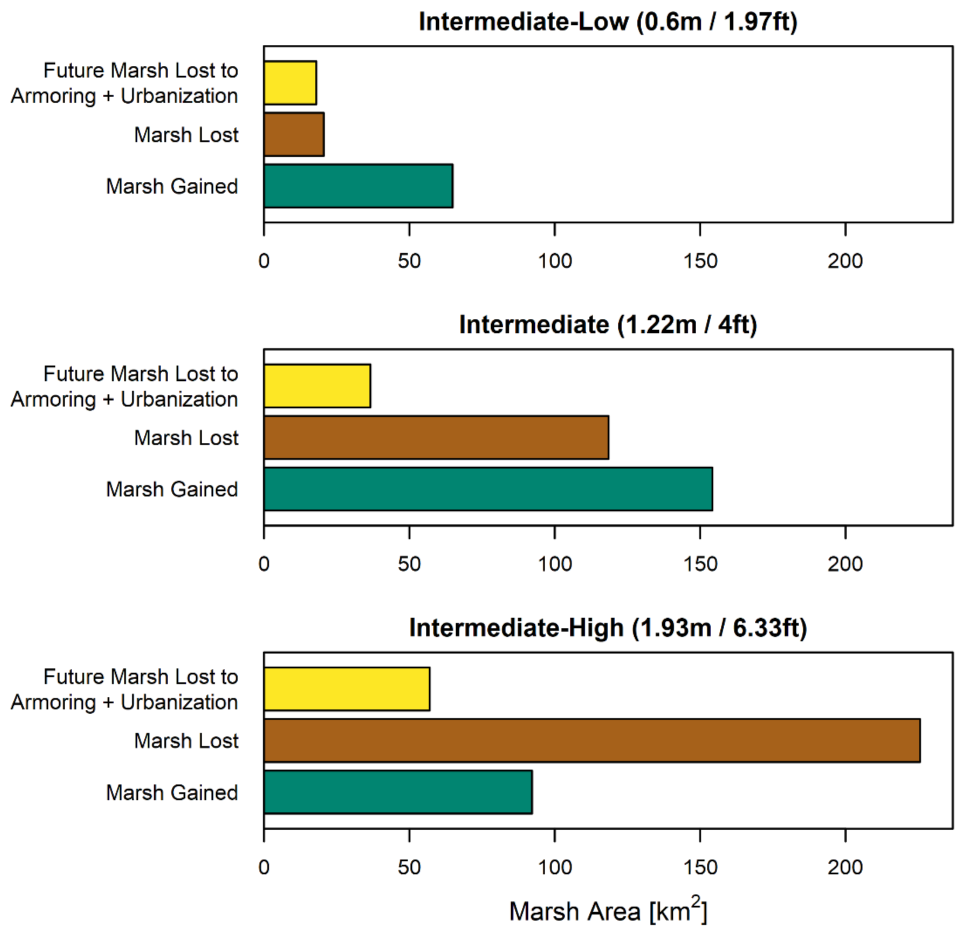

Figure 8. New salt marsh (transitional and regularly flooded) area, lost marsh area, and future marsh area lost to armoring and urbanization for the Savannah region for the three SLR scenarios. Results are from the high armoring scenarios with urbanization.

Potential applications, benefits and impacts of your Sea Grant funded research project

The logistic regression model developed as a part of this research has several important implications and applications. First, this model can be (and has) be used to predict future shoreline armoring on the Georgia coast. This is useful for managers to explore potential future scenarios and how armoring extent may vary between them. Furthermore, the most influential variables selected in the model can help explain when and where shoreline armoring occurs. The neighbor armoring variable had one the largest influences on the probability of armoring – if a parcel is adjacent to one that is already armored, the probability of that parcel having hard armoring increases by 18%. This neighbor effect could be due to a number of factors: peer-pressure among neighbors, adjacent armoring potentially increasing erosion on a landowners shoreline, or simply the fact that specific areas with higher erosion potential will have lots of shoreline armoring. These potential explanations need further research, but understanding that armoring tends to occur in clusters is important for management of shoreline properties.

The salt marsh migration modeling results suggest that, for the whole Georgia coast, the effects of different amounts of sea level rise will be greater than the effects of armoring and urbanization. This is partly because there are large undeveloped areas of the coast that are expected to remain undeveloped and therefore will provide ample opportunity for salt marshes to migrate inland with sea level rise. However, regional results show that currently developed areas (e.g. the Savannah region) will experience much larger salt marsh losses overall and specifically due to armoring and urbanization effects. This is critical because these developed areas are also at highest risk of the negative effects of sea level rise and need the buffering benefits that healthy salt marshes can provide.

The results of this research have a number of direct applications and benefits. Not only does this research improve our understanding of the coupled effects of sea level rise and land use changes on salt marshes, but results can also help coastal managers better manage these complicated and intertwined issues. Protecting salt marshes has a number of ecological, social, and economic benefits. They are important habitat for aquatic and terrestrial species and directly and indirectly support recreational use and tourism. Furthermore, salt marshes are important buffers that protect coastal properties from erosion and storm surge. Effectively managing salt marsh habitat is important and this research will directly inform this management into the future.

The findings of this research will be presented to coastal land managers in November 2020. We will also continue to engage with these and other stakeholders to provide relevant results and outputs that can help improve future management and protection of important salt marsh habitat. This includes sharing data layers to allow stakeholders to analyze local scale impacts of hard armoring on salt marsh migration. Furthermore, these data can be used to identify potential salt marsh migration pathways that should remain unobstructed and potential areas of infrastructure conflict.

Media coverage

None

Publications

Peterson, Nicole E., Craig E. Landry, Clark R. Alexander, Kevin Samples, and Brian P. Bledsoe. 2019. Socioeconomic and environmental predictors of estuarine shoreline hard armoring. *Nature Scientific Reports*. http://dx.doi.org/10.2139/ssrn.3385355

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Undergraduate and graduate students involved

Nicole Peterson – Master's Student, graduated
Paul Coughlin – Master's Student

Project partnerships

Skidaway Institute of Oceanography
UGA Department of Agricultural and Applied Economics

Related projects

None

Awards/Honors

None

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