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Impacts of Projected Sea Level Rise on Diamondback Terrapin Nesting Habitats in Virginia

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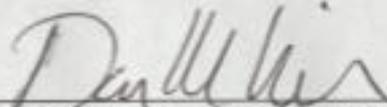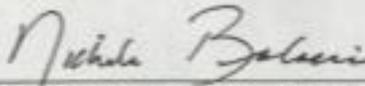The College of William and Mary

by

Holly Funkhouser

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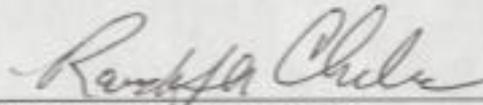
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<u>Abstract</u>

Diamondback terrapins face a variety of ecological and human pressures. As an estuarine species reliant on the availability of optimal nesting sites, the effects of climate change and sea level rise are important to consider when determining appropriate conservation methods for terrapins. My research focuses on the potential impacts of sea level rise on diamondback terrapin nesting locations along tidal shorelines in Virginia. Utilizing GIS and maximum entropy modeling (MaxEnt), I have edited and analyzed spatial data to determine optimal nesting habitats and how these locations will change as rising sea level forces land use shifts. Through my analysis, I determined that essential nesting habitat factors include: distance to beaches, distance to core habitat (the marsh habitat terrapins occupy when not nesting), salinity, and placement of roads. Using this information, I have created a model displaying the current distribution of terrapin nesting habitat throughout Virginia. My results demonstrate how future terrapin nesting habitat will likely decrease across Virginia shoreline. With this information, conservation efforts can be focused on the current terrapin nesting habitat most threatened by rising waters.

Introduction

The diamondback terrapin, *Malaclemys terrapin*, is a turtle species that inhabits estuaries like the Chesapeake Bay. Terrapins feed and reproduce in salt marshes, tidal flats, and estuarine environments ranging from the Gulf coast of Texas to Massachusetts (Carr, 1952). Terrapin populations are threatened by numerous anthropogenic pressures. Historically, terrapins were once considered a culinary delight and the most expensive edible turtle in the world (Carr, 1952). By the early 1900's, the high demand for terrapin meat had led to a massive decline in the species population (Hart & Lee, 2006). Modern terrapin populations are no longer threatened by overharvest because of shifting culinary practices and harvest bans that vary by state; however, the species is vulnerable to other human pressures. Current terrapin threats include, but are not limited to, death by drowning in commercial crab pots (Bishop, 1983; Roosenburg et al., 1997; Dorcas et al., 2007), roadkill mortality (Wood & Herlands, 1997), and increased predation by synanthropic predators such as racoons (*Procyon lotor*) and crows (*Coryus brachyrhynchos*) (Seigel, 1980; Feinberg & Burke, 2003). A recent terrapin conservation concern is the impact of sea level rise on diamondback terrapin nesting habitat (Hunter et al., 2015; Woodland et al., 2017), but the subject is limited in the scientific literature. Human driven global climate change and subsequent sea level rise has increasingly dominated broad scientific conversations of conservation. Uninhibited global climate change and sea level rise threaten essential terrapin habitat in terrestrial, estuarine, and wetland ecosystems (Hoegh-Guldberg et al., 2018). Consideration of how sea level rise will impact diamondback terrapin nesting habitat is imperative to the future of the species and in guiding conservation efforts.

Terrapins have a unique wedge-shaped carapace with the marginal scutes behind the bridge slightly rounded upwards; additionally, the terrapin head and tail are not striped, but

mottled (Carr, 1952). Terrapins are sexually dimorphic, with females larger than the males (Tucker et al., 1995). Like other turtles, terrapins have temperature dependent sex determination; eggs incubated at higher temperatures are female and eggs incubated at lower temperatures are male (Jeyasuria et al., 1994). Terrapin courtship and mating takes place in the water, when both the air and water temperatures are approximately mid-70º F (Brennessel, 2006). Terrapins spend most of their lives in the water (Carr, 1952), but females venture onto land to nest. Understanding the many components of terrapin nesting habitat is essential to creating a holistic current and future nesting model. Unfortunately, the size and status of terrapin populations in Virginia are unknown, and the location and extent of high-quality nesting habitats have never been determined.

Terrapin core habitat—geographic areas where terrapins feed, swim, and mate—and terrapin nesting habitat are not mutually exclusive, but they also are not identical. That said, there are environmental components common to both core habitat and nesting habitat, the primary example being salinity. As previously stated, terrapins inhabit brackish waters and possess physiological and behavioral adaptations that allow them to tolerate salty water, including both the presence of secretory glands (Dunson, 1970) and low tissue permeability to salts (Dunson, 1970; Robison & Dunson, 1976). Terrapins are dependent on an occasional source of freshwater (Brennessel, 2006), however, and can take in rainwater rapidly (Davenport & Macedo, 1990). Salinity is an important component of terrapin habitat that helps delimit the range of terrapin occurrences—both in the water and on land.

The most important component of terrapin nesting habitat is the substrate. Female terrapins lay their eggs on land, typically in sandy, non-vegetated soils (Brennssel, 2006). Beaches provide the ideal substrate for female terrapins to lay their eggs. Terrapins' preference

for sandy soils could be influenced by the ease of nesting in sand and the increased gas exchange possible for eggs laid in the larger particle substrate (Roosenburg, 1994 and Brennssel 2006). Additionally, female terrapins display high nest site fidelity (Roosenburg, 1994; Szerlag-Egger & McRobert, 2006) and tend to nest on the same beaches each year. Given the importance of sandy substrates for terrapin nesting and nest site fidelity, the possible re-distribution and/or loss of suitable nesting beaches due to sea level rise is a concern.

Terrapin core habitat is another important component of understanding future terrapin nesting. Terrapins spend most of their lives in the water where they feed and mate. Occasionally, terrapins will bask on land, but nesting female terrapins are the only individuals that spend a significant time on land. Terrapin occupancy is influenced by habitats with $\geq$ 10% of marsh within a 750-m neighborhood or area, $\leq$ 17% armored shoreline within a 1-km neighborhood, $\leq$ 20% of agriculture within a 500-m neighborhood, $\leq$ 33% low-density housing within a 270-m neighborhood and $\leq$ 9 active crab pots within a 270-m neighborhood (Isdell et al., 2015). Terrapins have high fidelity to certain creeks; they stay within and around the same creeks each year (Gibbons et al., 2001). Given terrapin fidelity to nest sites and waters, it is important to consider how terrapin core habitat may impact nesting habitat.

In some regions, terrapins preferentially nest along road sides, perhaps because roads are local topographic high points where soils are exposed to full sun and are well-drained. Terrapins nesting near roads has never been fully explored, but numerous studies have examined general nesting behavior. In some salt-marsh habitats, ideal nesting habitat has been destroyed by industrialization and development; sandy shoulders of roads may provide the only nesting habitat (Wood & Herlands, 1997). Unfortunately, nesting along major highways increases female terrapin road kill and mortality and hatchling mortality (Wood & Herlands, 1997). With the

likelihood that human development and habitat degradation will continue, roads are an important aspect of terrapin nesting habitat to consider.

The negative effects of roadkill, crab pot mortality, and raccoon predation on terrapin populations have been explored in detail, but climate change impacts have not been studied as extensively. A warming climate could increase nest temperatures above the pivotal range for sex determination in terrapin hatchling, thereby increasing the relative number of females in populations (Burke et al., 2014). In Georgia, terrapins were found to be highly vulnerable to sea level rise given their reliance on nesting beach habitat and salt marshes (Hunter et al., 2015). In the Maryland section of the Chesapeake Bay, historically used terrapin nesting locations were projected to decrease by 80% by 2100 (Woodland et al., 2017). Sea level rise and terrapin nesting has not been previously examined for Virginia, where many different changing environmental variables must be incorporated into the analysis.

Global climate change drives sea level rise through thermal expansion of seawater and freshwater input from melting land ice (Nicholls & Cazenave, 2010). In the United States north east and gulf coast by 2050, sea level in Norfolk, Virginia are projected to rise by about 0.49 m by 2050 (Boon et al., 2015). Sea level rise impacts on coastal environments have been explored through numerous research studies. Coastal beaches and marshes—which are important to terrapin nesting habitat—will likely be negatively impacted by rising levels (Deaton et al., 2017; Mitchell et al. 2017), although some researchers predict marsh gains globally (Kirwan et al., 2016). Additionally, rising sea level will influence salinity ranges in the Chesapeake Bay (Hong & Shen 2012; Hilton et al. 2008). Collectively, changes in these environmental variables with ongoing sea level rise are expected to influence the distribution and extent of terrapin nesting habitat.

My research aims to better understand how environmental variables, such as beaches, terrapin core habitat, salinity, and proximity to roads influence terrapin nesting habitat. Here, I aim to examine how sea level rise will change these environmental variables in Virginia over the next 80 years, toward the goal of using my results for future terrapin conservation.

Methods

Two software programs, ArcGIS® v10.4.1 (ESRI, 2016) and MaxEnt version 3.4.1 (Philips et al.), were used to conduct the project analysis (Figure 1). The first program I used is a geographical information system known as ArcGIS, operated by the Environmental Systems Research Institute (ESRI). ArcMap, the central application used in ArcGIS, was used to gather, edit, and analyze spatial data. The resulting data were then exported as ASC files and imported into the second program called maximum entropy modeling (MaxEnt). MaxEnt is a machine learning program that uses environmental spatial data and species spatial data to construct the probability of species habitat. MaxEnt is a well established method for determining species distribution modeling using presence only data (Elith et al., 2006; Phillips et al., 2006; Phillips & Dudik, 2008). The program can produce numerous outputs. Select outputs essential for this study include: omission/commission graphs, receiver operating characteristic (ROC) curves, spatial models, response curves for each variable, and jackknife graphs of regularized training gain. MaxEnt is unique because it can operate using only species presence data and can project the model into other geographic or temporal locations. MaxEnt's capabilities are important given the limited data available for the analysis and the goal of considering climate change.
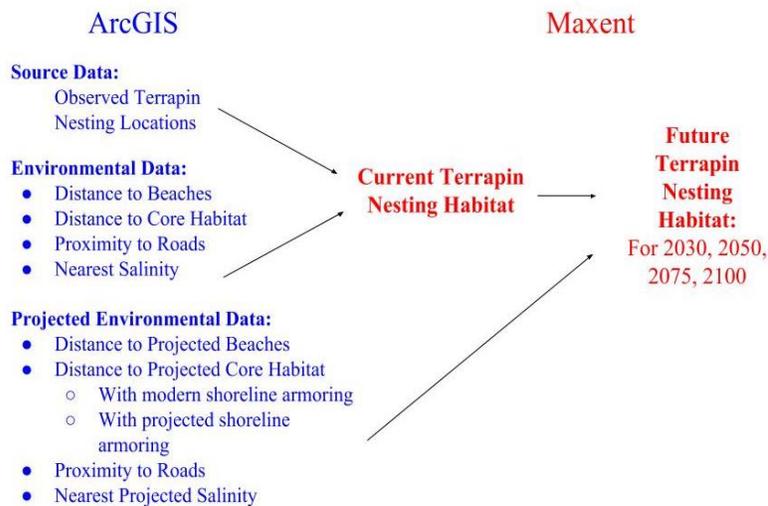
Figure 1: The flowchart displays each component of the methods. The analysis in blue was conducted in the mapping program ArcGIS® v10.4.1 (ESRI, 2016). The analysis in red was conducted in the machine learning program, MaxEnt (Philips et al.).

The study area of my project included all of Virginia, USA's shoreline. This area includes but is not limited to: the Virginia side of the Chesapeake Bay, the tidal regions of the James River, York River, Rappahannock River, Potomac River, and the Virginia Eastern Shore. The methods can be divided into three steps: (1) sample data: terrapin nesting observations, (2) environmental data: current terrapin nesting habitat, and (3) environmental data: projected terrapin nesting habitat. In each step, data were gathered, edited, and analyzed in ArcMap® 10.4.1 and then imported into MaxEnt version 3.4.1 (Figure 1).

Sample Data: Terrapin Nesting Observations

Terrapin nesting data were obtained from a variety of sources. A terrapin observation point shapefile, consisting of 2,187 Virginia terrapin observations—including nesting and water observations—were extracted from a large data set consisting of about 5,700 points (Egger, 2016; Northern Diamondback Terrapin). Due to the absence of observation type (i.e., nesting, basking, or water), the original compilers of the data were contacted to confirm nesting observations. Of the original 2,187 points, 1,118 were nesting locations. Among the nesting

locations, some sites were over-represented, such as Goodwin Islands, which contained 1,006 points of the 1,118 nesting points in Virginia. To account for this bias in the sample data, the Near tool in ArcGIS was used to remove points that were within 30m of each other. Additionally, Goodwin Islands were physically observed in ArcMap, and six points were manually added to six distinct clusters that were lost using the Near tool using the Edit function, to ensure some representation. The final sample data consisted of 58 confirmed, unbiased terrapin nesting points throughout Virginia.

Environmental Data: Current Terrapin Nesting Habitat

To determine the impact of sea level rise on terrapin nesting habitat, the current nesting habitat needed to be determined. The environmental layers, used to establish terrapin nesting habitat include: cost distance to core habitat, cost distance to beaches, nearest salinity, and proximity to roads. The environmental layers were created from data files of tidal marshes, estuarine beaches, salinity, roads, shoreline armoring, and land use.

Core Habitat

A study published by Isdell et al. (2015) determined terrapin occupancy, hereby referred to as core habitat, in a portion of the Chesapeake Bay. The study outlined the necessary factors that can be used to define terrapin core habitat. Core habitat was found to consist of $\geq 10\%$ of marsh with in a 750m neighborhood, $\leq 17\%$ armored shoreline in a 1000m neighborhood, $\leq 20\%$ of agriculture in a 500m neighborhood, $\leq 33\%$ low-density housing in a 270m neighborhood, and ≤ 9 active crab pots in a 270m neighborhood (Isdell et al., 2015). The core habitat model only examined a subsection of the Chesapeake Bay estuary, but the core habitat definition can be used to expand the original model to include all Virginia tidal shoreline.

The data for terrapin core habitat were obtained from the Virginia Institute of Marine Science Shoreline Inventory (marshes and armored shoreline) and the 2011 National Landcover Database (development and agriculture) (Center for Coastal Resources Management, 2017; Homer et al., 2015). Due to the unavailability of active crab pot spatial data—for both the present and future scenarios—I excluded it from the analysis. I defined the projection for each layer as NAD 1983 UTM Zone 18N and set the cell size to 30m. Next, I created binaries of the core habitat data using the Reclassify tool in ArcMap, where the environmental data equaled 1 and all other data equaled zero. Thus, the resulting layers were: (1) marsh binary: marshes = 1 and surrounding data = 0, (2) armored binary: armored shoreline = 1 and surrounding data = 0, (3) developed: developed = 1 and surrounding data = 0, and (4) agriculture = 1 and surrounding data = 0. The binaries allow for the analysis of the variable percentages in their determined neighborhoods. I ran a focal mean using the Focal Statistics tool in ArcMap to get the proportion of each core habitat variable within the neighborhood distance specified by Isdell et al. (2015). The resulting rasters were reclassified to binaries based on the thresholds identified by Isdell et al. (2015) such that a value of 1 indicates that a cell met the conditions, and 0 indicates that it did not. I used the Raster Calculator tool in ArcMap to sum the reclassified binaries and identified areas where all core habitat conditions were met (sum = 4) as core terrapin habitat.

The finalized core habitat environmental layer was then input into the Cost Distance tool in ArcMap. The Cost Distance tool calculates the cumulative cost of moving from any cell to a source cell. A cost raster and a source raster are used in the cost distance calculation. In my analysis, the source raster is the core habitat layer and the cost raster is a layer of surrounding water and 250 m inland. The cost raster was created by making a 250-m buffer of the shoreline and using the Mosaic to Raster tool in ArcMap to combine the buffer and water. The cost raster

was given a set cost of one for every cell; thus, making distance the only cost of moving through the environment, and restricting movement to the water and riparian zone.

Beaches

Beaches were the next environmental layer considered in my analysis. Beaches are an important environmental variable in my analysis, because terrapins prefer nesting in sandy substrate (Brennessel 2006). The beaches polygon shapefile was obtained from the Virginia Institute of Marine Science shoreline inventory (Center for Coastal Resources Management, 2017). The shapefile did not encapsulate all undeveloped island beaches in the Chesapeake Bay, including Goodwin Islands. I edited the original shapefile to reflect the most recent conditions (2017) using aerial photography (ESRI et al., 2016) at a spatial resolution of 0.30-m from the years 2009-2012 and the editing tool in ArcMap. The completed beaches shapefile could then be used in a cost distance analysis.

Roads

Proximity to roads were the next environmental variable considered in my analysis. The roads layer was obtained from the Virginia Geographic Information Network (VGIN, 2016). I clipped the roads to the study area using the Extract by Mask tool and created a 30m buffer using the ArcMap buffer tool. I then created a binary of near roads and not near roads. Areas near roads and in the 30m buffer were given a value of 1. Areas not near roads and outside of the 30m buffer were given a value of zero.

Salinity

Salinity was the next environmental layer considered in the terrapin nesting habitat model. Diamondback terrapins are an estuarine turtle species, meaning they inhabitant waters

that are brackish (Carr, 1952). Occasionally, terrapins will venture in to fresh water or salt water environments, but they preferentially stay in brackish waters. Therefore, for terrapin nesting habitat, salinity is an important environmental consideration. The salinity layer used for my analysis was interpolated by the Chesapeake Bay Program and created with datasets from the Chesapeake Bay Program, Virginia DEQ, Maryland DNR, and NOAA World Ocean (Chesapeake Bay Program, 2017). Water salinity restricts diamondback terrapin range of habitat. Terrapins can be found near brackish water, whether nesting on land or swimming. However, the goal of my study is to examine nesting habitat on land and the salinity values needed to be projected. To project salinity on land, the Euclidean Allocation tool in ArcGIS was used. The Euclidean Allocation tool calculates, for each cell, the nearest source based on the euclidean distance. The distance was restricted to 250m. Therefore, within a maximum distance of 250m, the water salinity value closest to each land cell was assigned to that cell.

Prior to export from ArcMap, all environmental layers were masked to remove water area from the potential predictive surface, thereby minimizing bias in MaxEnt's model accuracy assessments.

Environmental Data: Projected Terrapin Nesting Habitat

In order project future terrapin nesting habitat in the years 2030, 2050, 2075, and 2100, I developed a future environmental layer for each environmental variable except for roads—core habitat, beaches, and salinity—in ArcMap. Due to the absence of spatially explicit guidance on future road creation and abandonment. I opted to use the current distribution of roads for all future scenarios.

Projected Core Habitat

The future core habitat environmental spatial layer is comprised of projected marsh, agriculture, development, and armored shoreline. The spatial data for future marsh, agriculture, and development (for the years 2030, 2050, 2075, and 2100) were obtained from the Virginia Institute of Marine Science (Mitchell, 2018). For these three layers, I used the same methods utilized in the current core habitat environmental layer. I took each raster, formed a binary, and used the Focal Statistics tool in ArcGIS (utilizing the neighborhoods defined by Isdell et al., 2015). However, the armoring raster required additional analysis.

Like roads, projected armoring is difficult to predict. However, Isdell (2014) established the only known equation for the likelihood of future armoring in the Chesapeake Bay. Given its low predictive power and high uncertainty of future development, I decided to create two future core habitat environmental layers (i.e. two scenarios) for each time interval. The first scenario used spatial layer used projected armoring (based off Isdell's model) and the second used current armoring. I created the projected armoring layer from the equation

$$\text{Equation 1: } p(Hardening) = \frac{1}{(1+e^{-(-1.50+0.0004x_1+0.41x_2+4.10x_3-6.69x_4}},$$

where X_1 = housing density$_{90m}$, X_2 = proportion of agriculture$_{180m}$, X_3 = proportion of low urban$_{180m}$, and X_4 = proportion of marsh$_{270m}$. Except for housing density, all of variables were included in the future land use change obtained from the Virginia Institute of Marine Science. The housing density layer was obtained from the Environmental Protection Agency and it's a part of the Integrated Climate and Land-Use Scenarios (U.S. EPA, 2010). For my analysis, I used the baseline housing density projection. The baseline housing density projection estimates a medium fertility, domestic migration and net international migration for each time frame (U.S.

EPA, 2017). The housing density categories are set to values 1-4 and 99 (Table 1). The housing

density utilized in Isdell et al.'s equation operates with the measurements housing units per km^2.

Therefore, I converted the housing units per hectare to housing units per km^2 and reclassified

each category to the median value (Table 1). I created binaries of the other three variables used

in the equation and then used the Focal Statistics tool in ArcMap to create neighborhoods for

each of the variables—housing density, agriculture, low urban, and marsh. The equation and

variables were input into the Raster Calculator tool in ArcMap and a projected armoring layer

was produced. I then used the Extract by Mask tool in ArcMap to extract the armoring within a

30m buffer of current shoreline (the distance was determined based on the cell size). Isdell's

equation produces a probability of shoreline armoring (2014). To account for this, the resulting

raster was reclassified using the Reclassify in ArcMap to create a binary; values greater than 0.5

were reclassified to 1 and values less than 0.5 were reclassified to 0. Finally, I used the Focal

Statistics tool in ArcMap given the equation for core habitat from Isdel et al. 2015.

Each of the layers—projected armoring, marsh, agriculture, and development—for each

of the future years, were exported as ASCII files after the water had been removed from the

analysis.

Housing Density Categories	Raster Values	Housing Units per hectare	Reclassified Housing Units per km^2
Commercial/Industrial	99	NA	NoData
Urban	4	9.884 - >24.71	1729
Suburban	3	1.236 - 9.884	556
Exurban	2	0.062 - 1.236	64
Rural	1	0.062 - <=0.005	3

Table 1. The table displays how each housing density raster cell value (U.S. EPA, 2010) was reclassified in ArcMap.

Projected Salinity

Future sea level rise is expected to influence the future salinity of the Chesapeake Bay. The projected salinity of the Chesapeake Bay has been addressed by two studies. The first study found that a sea-level rise of 0.3 m will increase the salinity of the Chesapeake Bay by 0.5ppt (Hong & Shen 2012). The study also found that, as sea level rises 1.0 m, changes in salinity range from 1.2 to 2.0ppt (Hong & Shen, 2012). However, another study estimated a salinity change in the Chesapeake Bay of 0.4 to 12ppt by 2100 (Hilton et al., 2008). Given 0.49m increase in sea level by 2050 for the Chesapeake Bay (Boon et al., 2018), I assumed a general increase of 0.5 ppt for each time step would simulate how changing salinity could impact future terrapin habitat. This estimate would be considered within the projections by Hong and Shen (2012) and an underestimate by Hilton et al (2008).

To account for an increase in salinity of 0.5 ppt (therefore, 2030 = +0.5ppt, 2050 = +1ppt, 2075 = +1.5ppt, 2100 = +2ppt). I used the Euclidean Allocation tool in ArcGIS to calculate, for each cell, the nearest source based on euclidean distance. I then used the raster calculator four separate times to add 0.5, 1, 1.5. or 2 to the current salinity raster. Thus, resulting in salinity projections for 2030, 2050, 2075, and 2100. Next, I used the ArcGIS Con tool to cap the salinity at standard salt water, 35ppt. The Extract by Mask tool in ArcGIS was used to remove the water from the analysis from each layer. The resulting four raster layers were exported as ASC files.

Projected Beaches

The data for the future beaches environmental layer were obtained from Virginia Institute of Marine Science (Mitchell, 2018). Beaches from each time (2030, 2050, 2075, and 2100) were extracted from the future datasets. Like the current beach environmental layer, I created a cost

distance raster using the cost surface layer. Once again, the water was masked from the analysis.

These steps were repeated for each time interval. The four future environmental layers for both

scenarios were exported as ASC files.

All environmental and sample data were then imported in the machine learning program,

MaxEnt version 3.4.1 (Philips et al.). The MaxEnt settings include: random test percentage =

20%, maximum number of background points = 10,000, replicates = 20, replicated run type =

bootstrap, and maximum iterations = 5,000. With these specifications, MaxEnt preforms 20

replicates with the bootstrapping technique—the training data are chosen by sampling with

replacement from the from the terrapin presence locations, the sampling equals the number of

presence locations (Phillips, 2017). Additionally, 20% of the source data are used to create a

random sample of test points to validate the model. I ran MaxEnt a total of nine separate times.

The first run determined optimal nesting habitat and included a test percentage of the sample

data. Four of the runs determined projected nesting habitat in 2030, 2050, 2075, 2100 and

included projected armoring. The last four runs determined projected nesting habitat but included

current armoring rather than projected.

The resulting current diamondback terrapin nesting habitat model, created in MaxEnt,

displays the importance of each environmental variable—distance to core habitat, distance to

beaches, salinity, or proximity to roads. Simplified, MaxEnt produces a probability that a species

is present in a given environment (Elith et al., 2011). In MaxEnt, f(z) is the probability density of

environmental covariates in the study area and f1(z) is the probability density of environmental

covariates across random locations in the study area (Elith et al., 2011). MaxEnt uses the

occurrence data (terrapin nesting observations) and the background sample data (10,000

randomly sampled background locations within the VA study area) to estimate the ratio f1(z)/

f(z) (Elith et al., 2011). To accomplish this, MaxEnt makes an estimate of f1(z) consistent with

the terrapin nesting occurrences and it selects the one closest to f(z) (Elith et al., 2011). The

distance from f(x) is the relative entropy (measure of distance between two distributions)

regarding f1(z); therefore, MaxEnt is minimizing relative entropy or maximining entropy (Elith

et al., 2011).

<div align="center">**<u>Results</u>**</div>

Current Terrapin Nesting Habitat

Overall, my model suggests that terrapins are most likely to nest in areas characterized by

being geographically close to beaches, core habitat, and near brackish waters. While this result

matches the terrapin nesting habitat literature, it was not guaranteed that this result would be

produced. The results of my findings are supported through evaluation of the model via receiver

operating characteristic (ROC) curves, the gain of the model, jackknife graphs, and response

graphs.

The current terrapin nesting model produced a receiver operating characteristic (ROC)

curve with an averaged training area under the curve (AUC) value of 0.935 for the replicate runs,

and a standard deviation of 0.012 (Figure 3). ROC curves are a machine learning technique that

display the power of the model. ROC curves plot the true positive rate on the y-axis and the false

positive rate on the x-axis (Fawcett, 2006) (Figure 2) and they visually display trade-offs

between sensitivity (true positives) and specificity (true negatives) (Fan et al., 2006). An ideal

model has a "cut-off" value where the sensitivity and specificity are both their highest; however,

this is rare and either sensitivity or specificity must experience a tradeoff in favor of the other

(Fan et al., 2006). The area under the curve (AUC) of the ROC curve is a measure of the model's

predictive performance; the AUC value displays the likelihood that a randomly chosen presence

location is ranked higher than a randomly picked background location (Merow et al., 2013). The

closer an AUC value is to 1, the higher predictive power the model contains. Traditionally,

desirable ROC curves contain an AUC value higher than 0.7. Therefore, my AUC value of 0.935

indicates high predictive power. AUC values do have limitations which will be addressed in the
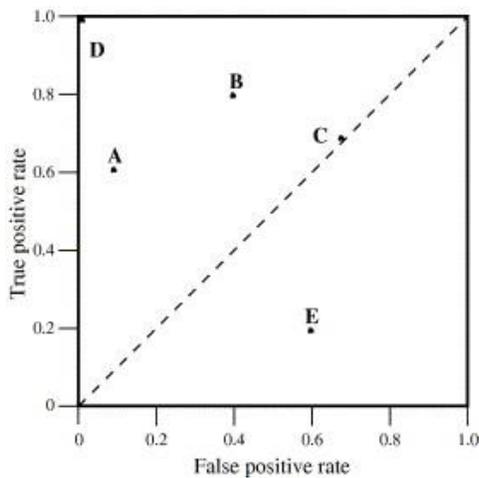
discussion section.

Figure 2: The dashed line represents a random prediction and yields a (0.5, 0.5) point on the graph. Any point, point E in this example, that appears below the dashed line preforms worse than random. Any point above the dashed line, point A and B in this example, performs better than random. Point D represents prefect fit.
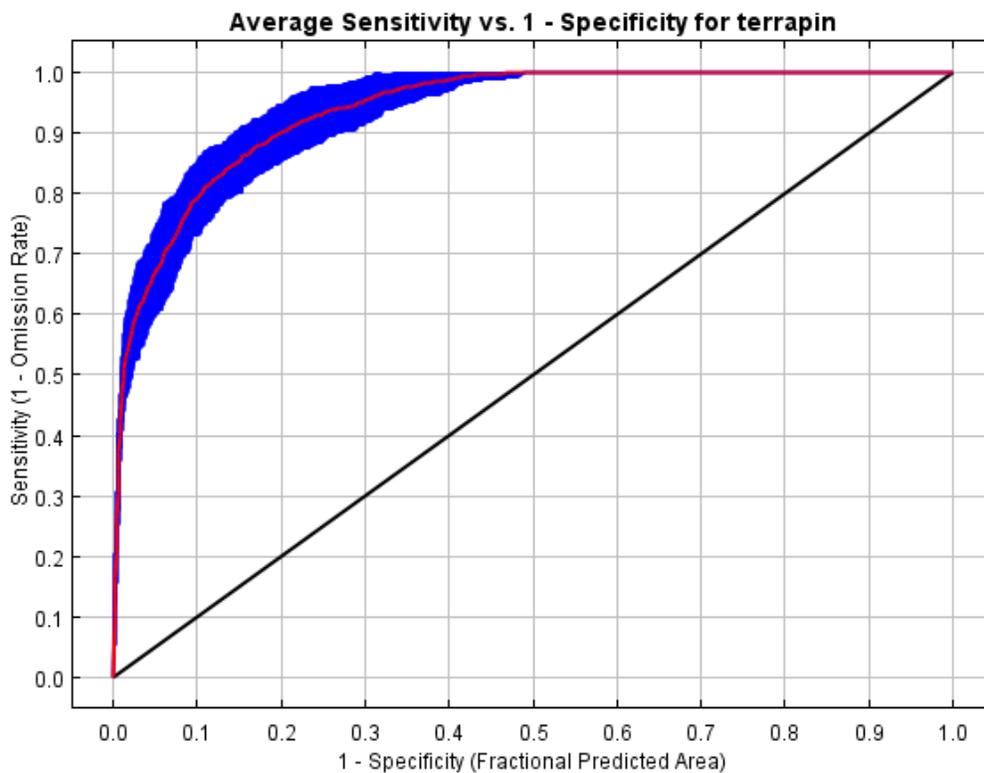
Graph obtained from Fawcett, 2006

Figure 3: The graph displays the Receiver Operating Characteristic (ROC) curve. The true positive rate is on the y-axis and the false positive rate is on the x-axis. The area under the curve (AUC) value equals 0.935, indicating good fit.

In addition to a ROC curve, MaxEnt produces a jackknife graph of the model. The graph displays how the regularized training gain would change given it was only composed of one variable or without a certain variable (Figure 4.b). The gain measures how much higher the predicted probability of occurrence is at the known presence locations compared to the background locations. It is expressed as ln(μpresence/μbackground). The overall gain of my model is 1.8952; therefore, the probability of occurrence at known presence locations is 6.65 ($e^{1.8952}$) times greater than at background locations. Additionally, the model produces an output of the percent contribution and permutation importance of each variable (Figure 4.a). Both the jackknife graph and percent contributions indicate that distance to beaches highly influenced the model. The permutation importance values are calculated by randomly rearranging the values of each environmental variable on training presence and background data. Then the model is reevaluated using the permuted data. The resulting drop is displayed as percentages in Figure 4.a. Although, distances to beaches contain a higher percent contribution percent (58%), distance to core habitat contains a greater permutation importance (46%).

a.

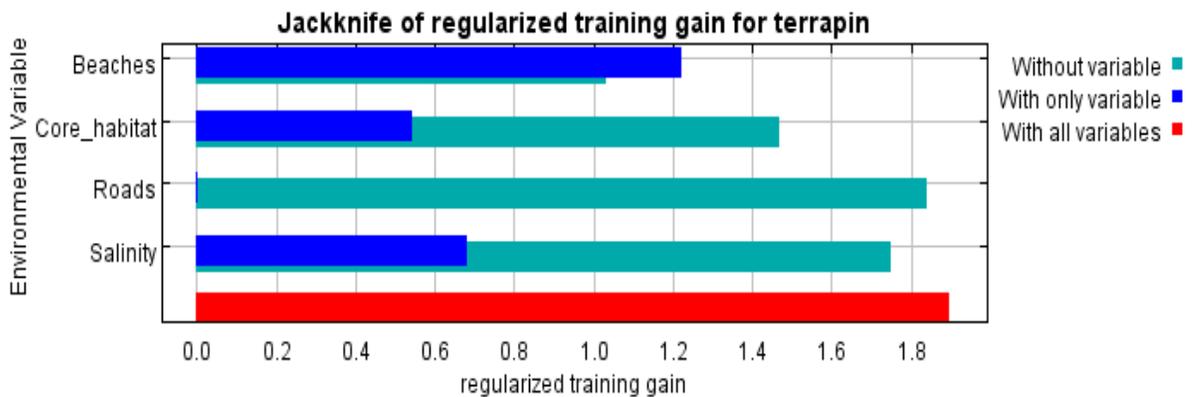| Variable	Percent Contribution	Permutation Importance
Beaches	58	31.6
Core Habitat	26.1	46
Salinity	13	20
Roads	2.9	2.4

b.

Figure 4. These figures display how each environmental variable effects the model. a) The table displays the percent contribution and the permutation importance of each variable. b) The Jackknife graph displays how the regularized training gain in red would change if a certain variable were to be removed (in dark blue) or if the model were to only consist of the variable (light blue).

Interestingly, roads did not have high predictive power individually, but within the context of the other environmental variables, roads contained higher predictive power (Figure 5). Additionally, Figure 5 visual displays how each variable responds to the model. Brackish waters (salinity between about 5ppt -30ppt) had the greatest response for the salinity variable. Areas closer to both beaches and core habitat had the greatest predictive power. The further from beaches or core habitat decreases the likelihood of an area being terrapin nesting.
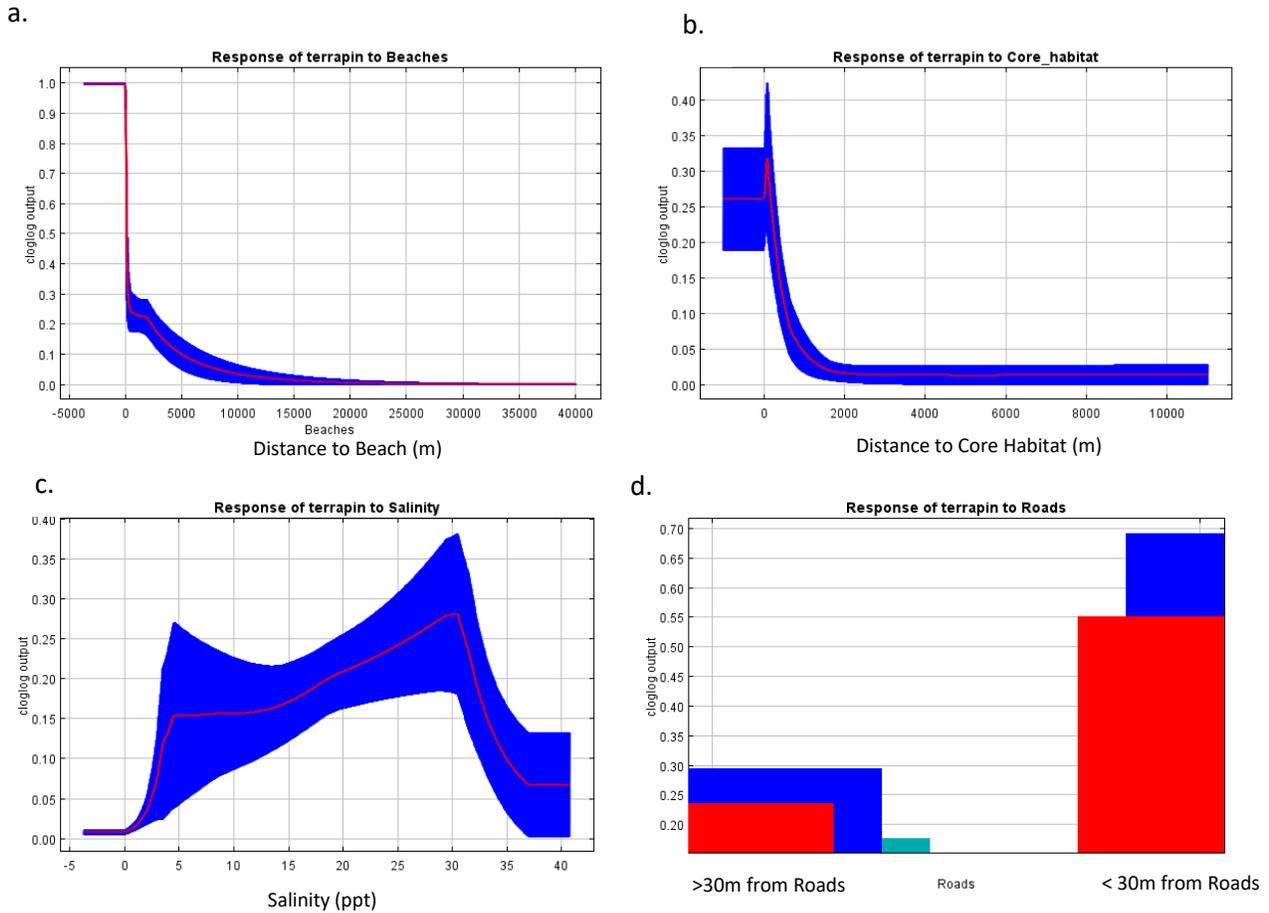
a.

b.

c.

d.

Figure 5. These graphs display how each variable responded to the model. The Y-axis of each graph is the probability of terrapin nesting habitat. The blue area is the standard deviation and the red area is the mean. a) This graph displays how the probability of terrapin nesting decreases with distance from beaches (in meters). b) This graph displays how the probability of terrapin nesting decreases with distance from core habitat (in meters). c) This graph displays terrapin nesting probability given the salinity (in ppt). d) The graph displays how proximity to roads impacts the probability of terrapin nesting.

The terrapin core habitat model (Figure 7) displays probability of terrapin nesting habitat. Areas in dark and light blue display high terrapin nesting probability. Whereas, areas with green and yellow indict low probability of terrapin nesting habitat. Figure 6 highlights areas of the map with high terrapin nesting probability. The Virginia Eastern Shore has several terrapin nesting habitat hot spots. In addition, figure 6 highlights Goodwin Islands—an area of interest, because it

is a well identified terrapin nesting location. Additionally, the Goodwin Islands inset map

displays proximity to roads had moderate predictive power. In areas with low nesting habitat

probability, proximity to roads slightly increases the likelihood that an area will be utilized for
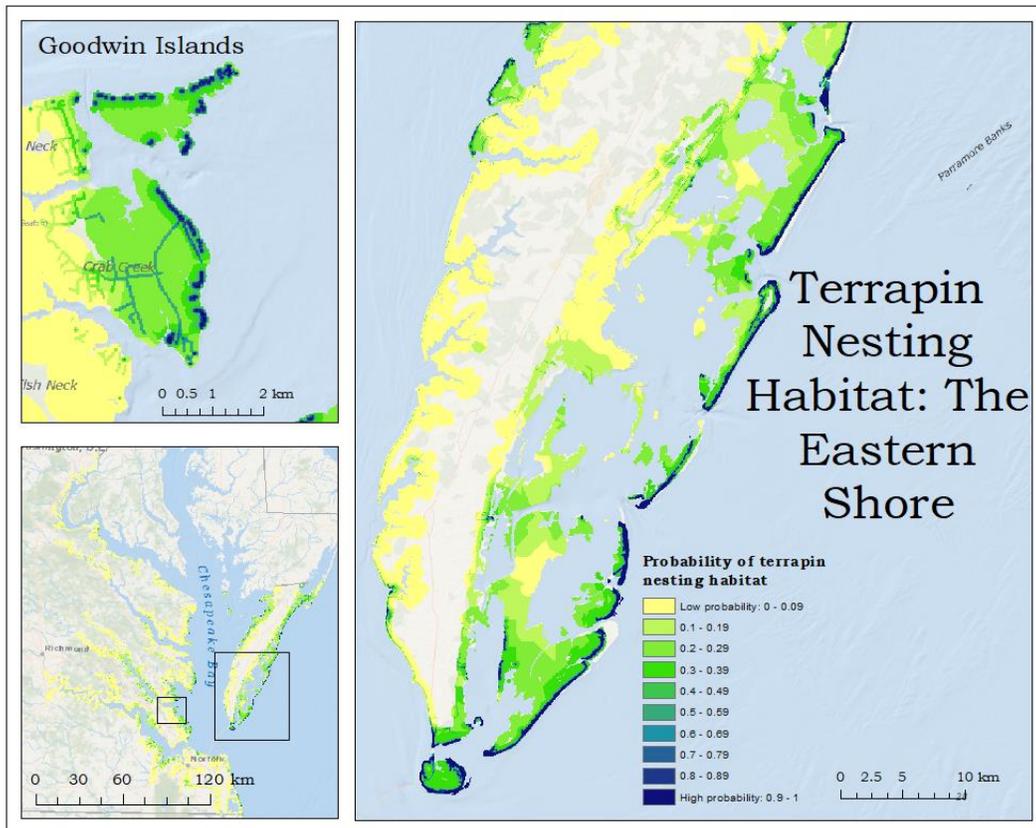
terrapin nesting.

Figure 6. The map displays smaller sections of my study area that were of interest including the VA Eastern Shore and Goodwin Islands.
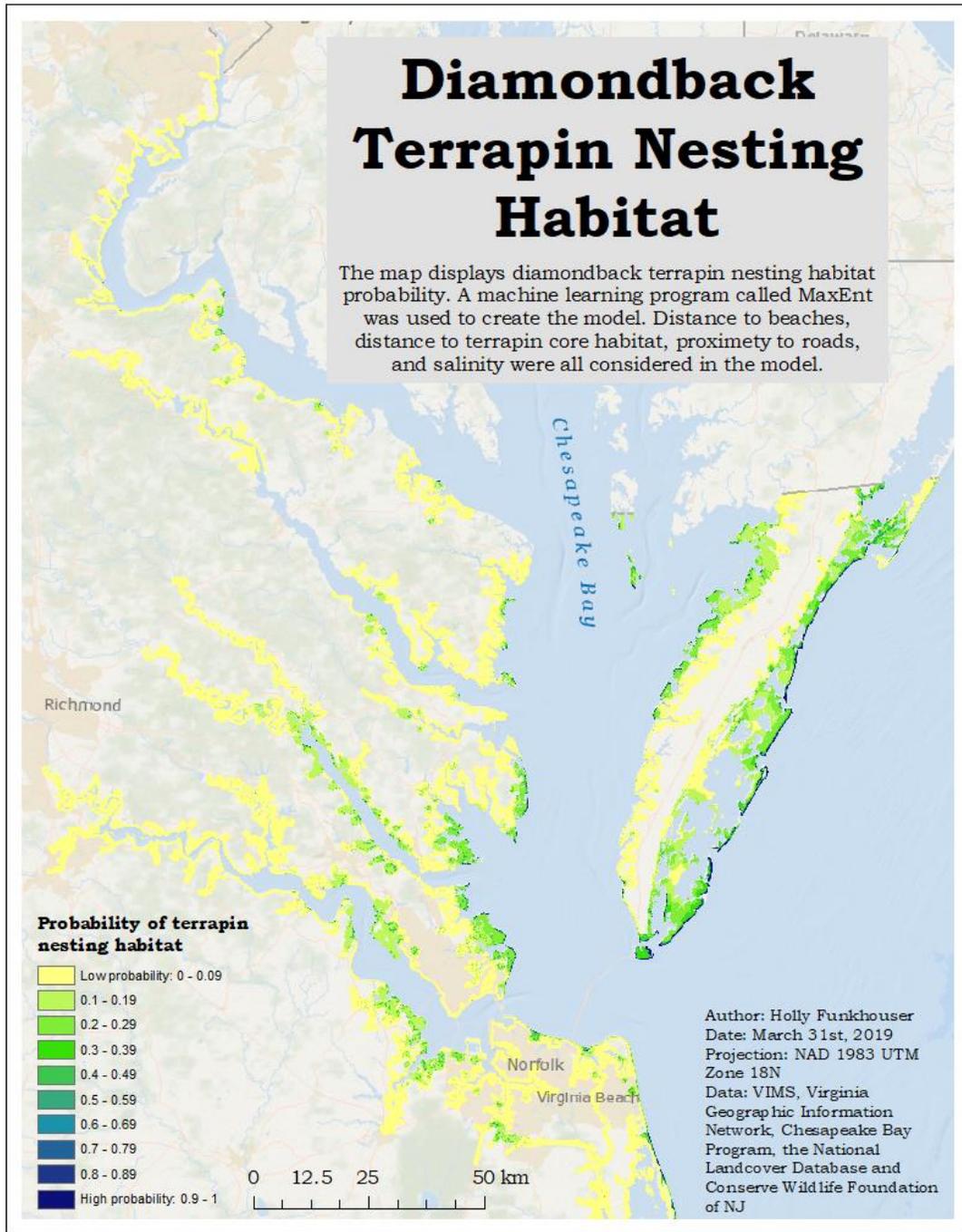
Figure 7. The map displays terrapin nesting habitat probability in Virginia. Areas in blue indicate high nesting probability, Areas in green indicate lower probability, and areas in yellow indicate little to no probability.

Future Terrapin Nesting Habitat

Unfortunately, I discovered that the data used for the future terrapin nesting habitat models was misused. The results from this portion of my research will not be presented. The methods in which the data was analyzed were valid; however, the data itself was incorrect. With the correct data, my methods can be applied to examine future terrapin nesting habitat.

Discussion

My research provides the first inclusive model of terrapin core habitat and optimal current nesting habitat in the entire state of Virginia. Although conditions of terrapin core habitat have been explored and quantified for a portion of the Chesapeake Bay (Isdell et al., 2015), my research greatly expands the geographic area previously studied. The results of my research can inform coastal resource managers developing conservation plans in the 21st century.

Terrapins currently have a relatively broad geographic access to high quality nesting habitat on beaches with minimal proximal development. However, those habitats are unlikely to persist throughout much of Virginia's tidal regions due to the impacts of sea level rise. Exploring the possible causes of and implications for my research results can aid in directing future terrapin conservation.

While the results of my future habitat model are invalid, sea level is predicted to rise and will impact marsh and beach habitat. As sea level continues to rise geographic responses may vary. Researchers have examined the likelihood of beach migration with ongoing erosion and accretion (Glick et al., 2007). While some beaches may be able to migrate landwards, increased armoring and nonlinear trends in sea level rise are continuing concerns. As my results suggest, nesting habitat relies on both distance to beaches and distance to core habitat, i.e., beaches and

marches must retain some connectivity. The combination of increasing sea level, changing

habitat geography, increased shoreline armoring, and development will likely dramatically

decrease the areal extent of future terrapin nesting locations.

Optimal terrapin nesting habitat is distinct from where terrapins choose to nest. Female

terrapins have high nest site fidelity (Roosenburg 1994; Szerlag-Egger & McRobert, 2006). As

optimal nesting locations change and are lost through rising sea level, terrapins may exhibit a

diversity of responses. First, terrapins may travel to a new nesting beach. Terrapins have been

found to greatly increase the time and effort of nesting when encountering shoreline armoring

(Winters et al., 2015), although they have fairly small home ranges to explore, typically less than

2 km (Sheridan et al., 2010). Alternately, terrapins may attempt to nest in suboptimal nesting

locations with more extensive vegetation or closer to human development. Terrapins have been

known to nest in sub-optimal sites including near airports, along roads, and agricultural fields

(Fancoeur, 2013; Wood & Herlands, 1997; Roosenburg, 1994). Human development increases

raccoon predation on terrapin nesting (Roosenburg & Place, 1994). Nesting can also be

negatively impacted by vegetation due either to shading, thereby cooling nest incubation

temperatures and altering terrapin sex ratios (Cook et al., 2017), or to roots invading and

destroying the nesting chamber to access the nutrients in the eggs (Lazell & Auger, 1981;

Feinberg & Burke, 2003). Finally, if female terrapins continue to exhibit nest site philopatry

despite sea level rise, then nests may be flooded during high water events. Terrapins rely on

nesting beaches that are above mean high-water (Brennessel, 2006). I predict that as optimal

terrapin nesting habitat decreases, terrapins will choose suboptimal nesting locations adjacent to

high quality sites lost to sea level rise, rather than not nesting at all. Suboptimal nesting locations

will ultimately lead to decreased nesting success for terrapins. With decreases in optimal nesting

sites due to sea level rise terrapins will be forced to choose nesting sites that will increase egg

mortality and decrease terrapin populations.

Another important consideration is the impact of roads on terrapin nesting locations.

Roads may provide terrapins with nesting habitat (Wood & Herlands, 1997). Within my model,

roads had more predictive power within the context of distance to core habitat, beaches, and

salinity (Figure 5). While roads traverse all coastal Virginia, they may only be important for

terrapin nesting habitat when near terrapin core habitat. One interpretation of this result is that

within terrapin core habitat, if beach habitat is not available, roads are perhaps a decent, open

spaced alternative. If true, this explanation creates additional apprehensions about increased

terrapin roadkill, an already established conservation concern (Wood & Herlands, 1997;

Crawford et al., 2014; Grosse et al., 2011; Szerlag & McRobert, 2007).

The ROC curve and AUC value of my model indicates high predictive power. Several

caveats, however, must be consider with MaxEnt. MaxEnt is well proven in the literature to be a

valid method for determining species distribution modeling using presence only data (Elith et al.,

2006; Phillips et al., 2006; Phillips & Dudik, 2008). When absence data are available, other

modeling techniques are recommended for use (Yackulic et al., 2013). Given the data available

to me, MaxEnt was the best program for my analysis and research goals, with a few limitations.

First, MaxEnt's effectiveness is limited to the predictive power of the environmental variables.

Although the environmental variables used in my project are supported throughout the literature,

other environmental factors not included in the model could have higher predictive power than

any of those chosen. I addressed this limitation through support of the literature and correlation

tests of the chosen environmental variables. Second, MaxEnt uses background points rather than

point absences to create its modeling distribution; therefore, the ROC curve operates to classify

presence vs. background points (Yackulic et al., 2013). To account for the potential model inflation, I excluded the water from the analysis and restricted the model to potential nesting areas on land. Thirdly, sample data bias and the lack of random sampling techniques are often a concern in MaxEnt critiques (Yackulic et al., 2013; Merow et al., 2013). I addressed this limitation in the methods by removing duplicate points and verifying nesting observations. These limitations are valuable to consider in future applications of this research.

The exclusion of active crab pots from the terrapin core habitat model expansion is another limitation to consider. Active crab pots were an important variable in the terrapin core habitat model (Isdell et al., 2015). However, they had a negative impact on the model, meaning by excluding the variable, it inflates the estimate of terrapin core habitat. Given this, my model may be an overestimation of available nesting habitat.

Current terrapin nesting hot spots include areas with beaches such as Goodwin Islands, Fisherman Islands, and the sea side of the Virginia Eastern Shore. The barrier islands on the Eastern Shore assume easy access for nesting female terrapins and do not account for wave action. Wave action could limit the likelihood that female nesting terrapins use Eastern Shore barrier islands. Although, most of the barrier islands are behind extensive marsh habitat and it is possible that terrapins may travel through the marsh habitat to use these nesting beaches. Nesting habitats within the Chesapeake Bay, including Goodwin Islands and tidal creeks on the bay side of the Eastern shore, are dependent on beaches and marsh habitat and are likely to be vulnerable to sea level rise.

My results correspond with the two terrapin nesting habitat and sea level rise studies that were conducted in Maryland and Georgia. In Georgia, the researchers assessed habitat change and their impact on 28 coastal vertebrates; terrapins were found to have high vulnerability due to

their reliance on ocean beaches (Hunter et al., 2015). The Maryland study examined individual

habitats (brackish marsh, estuarine beach, salt marsh, etc.) and compared the area change in these

habitats to known terrapin locations (Woodland et al., 2017). The results from the Georgia and

Maryland study suggest that terrapin nesting habitat will decrease in Virginia. My results build

on these studies by modeling current nesting habitat with the consideration of multiple, core

habitat variables, rather than assuming terrapins only nest on estuarine beaches.

The analytical method I employed using ArcGIS and MaxEnt has implications for future

research. With the appropriate data, my results can be easily transferable to other geographic and

temporal locations. Future researchers can utilize my model to expand to other areas where

terrapins occupy. My current terrapin nesting model provides insight into where terrapins are

currently nesting. Conservation is often limited by species distribution knowledge (Rodriguez et

al., 2007). It is difficult to know how to protect a species if the location of the species is

unknown. The first component of my project, modeling current terrapin nesting habitat, provides

insight into current conservation. Terrapin nests face several conservation issues, outside of sea

level rise, including: animal and plant predation (Seigel, 1980; Lazell & Auger, 1981), and

roadkill (Wood & Herlands, 1997). My research can better aid already established conservation

projects by highlighting areas where terrapins are most likely nesting.

While the results of the sea level rise section of my project were invalid, the methods in

which the data were analyzed is correct. With the correct data, the projected distribution of

terrapin nesting habitat in 2030, 2050, 2075, and 2100, can provide additional implications for

conservation. My research suggests how sea level rise will negatively impact terrapin nesting in

Virginia and builds on the established conservation concerns surrounding diamondback

terrapins.

Conclusions

Terrapin nesting habitat is threatened by rising sea level in Virginia. As nesting habitats shift and are lost, terrapins will likely respond by searching for new nesting sites or settling for suboptimal nesting locations. However, terrapins are opportunistic and have been documented nesting with success in restored habitats (Roosenburg et al., 2014). Terrapin nesting conservation efforts should continue to explore the restoration and creation of terrapin nesting beaches, for example, via creation of dredge spoil islands in proximity to core terrapin habitat. Additionally, future terrapin conservation efforts require focus on preserving current nesting hot spots (i.e. Goodwin Islands, Fisherman Island, and barrier islands along the Eastern Shore) with ecologically viable methods such as living shorelines. Living shorelines are a form of shoreline protection that uses either natural elements or a hybrid approach to increase ecosystem services while protecting shores from erosion (Bilkovic et al., 2016). Ecologically viable shoreline protections will be increasingly crucial for terrapin nesting. Directed conservation efforts are needed as sea level continues to rise and threaten terrapin nesting habitat.

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