THE EFFECT OF ANTHROPOGENIC ACTIVITY ON SEA TURTLE NESTING
AND HABITAT USAGE IN FLORIDA, USA

by
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A THESIS

by

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ABSTRACT

THE EFFECT OF ANTHROPOGENIC ACTIVITY ON SEA TURTLE NESTING AND HABITAT USAGE IN FLORIDA, USA

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Chairperson of Advisory Committee: Robert van Woesik, Ph.D.

Sea turtles have complex life histories that make them difficult to study. Using easily-accessible data, such as nesting and stranding occurrences, can help to efficiently elucidate driving factors in the population dynamics of these imperiled species. The overall goal of the present study was to assess the efficacy of sea turtle protective measures in Florida. To accomplish this goal, two analyses were conducted. The first analysis sought to describe the relationship between nesting numbers of three species of marine turtles, the loggerhead (*Caretta caretta*), green (*Chelonia mydas*), and leatherback (*Dermochelys coriacea*), common in Florida and various anthropogenic and environmental variables. The analysis examined whether these species nest preferentially on beaches with less anthropogenic disturbance, and was accomplished by formulating generalized linear mixed models (GLMM) to predict nesting numbers for each of the study species. The variables used to predict this response variable were (i) the presence of protective
measures, (ii) the presence of access restrictions, (iii) human population of the nearest town, (iv) geographic region, (v) beach angle, (vi) average annual sea surface temperature (SST), (vii) median φ for sediment size, and (viii) presence of lighting ordinance. Beach was analyzed as a random effect in the GLMM. This study also attempted to determine whether sea-turtle strandings in Florida depend on anthropogenic and environmental covariates. This was accomplished by conducting a series of point-pattern intensity analyses on sea-turtle strandings and (i) annual average SST, (ii) gridded human population, and (iii) presence of lighting ordinances. Most notably, the models illustrated a negative relationship between loggerhead turtle nesting numbers and presence of protective measures, and a positive relationship between green sea-turtle nesting numbers and presence of lighting ordinances. It was also found that nesting numbers of both of these species had a negative relationship with population of the nearest town. The notable results of point-pattern intensity analyses identified increased stranding incidence in areas with higher human population and presence of county-wide lighting ordinances. Although lighting ordinances appear to be implemented in optimal locations, the negative relationship between loggerhead turtle nesting numbers and presence of protective measures suggests that protected beaches are in suboptimal locations to aid nesting females. Lack of nesting in highly populated areas suggest that the two more-coastal species exhibit an aversion to cues that signal areas of high human population, whereas increased stranding incidence associated with
areas of high human population density suggests that increased anthropogenic activity does pose a threat to marine turtles. This study underscores the importance of post-establishment assessment of protective measures, as compromises with developers or industry can render these attempts at protecting wildlife ineffective. The negative assessment results of the present study may motivate change to better help target species, while confirmation that measures are effective can secure more support for future efforts.
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CHAPTER I
RATIONALE, OBJECTIVES, RESEARCH QUESTIONS, AND HYPOTHESES

RATIONALE

As with any policy that seeks to improve or change a situation, it is necessary to evaluate the efficacy of conservation policies to determine whether they are indeed protecting the wildlife that they set out to protect. Though it is important to assess human compliance with environmental regulations, target species of such policies are oblivious to the boundaries of areas which humans have designated to protect them. Therefore, no matter how effectively mankind upholds protective measures, they do little to achieve their goal if the protected areas are not placed according to the natural distributions and habitats of the target species (Klein et al. 2015; Margules and Pressey 2000). Because of the dire conservation status of the seven extant sea turtle species (Wallace et al. 2013; Casale and Tucker 2015; Mortimer and Donnelly 2008; Abreu-Grobois and Plotkin 2008; Marine Turtle Specialist Group 1996; Red List Standards & Petitions Subcommittee 1996), many local governments have implemented regulations to reduce anthropogenic impacts on these species. This study will assess whether the regulations and policies that have been implemented to protect sea turtles are effective along the Florida coastline and identify any environmental factors that may be driving sea turtle phenologies and
population dynamics.

Protection regulations include, but are not limited to, lighting ordinances, nightly beach closures, and beach access restrictions (Anderson et al. 2013). Sea turtles are known to return to natal beaches to nest, rather than actively choosing a beach out of suitability (Brothers and Lohmann et al. 2015). Because of this ‘homing’, it is particularly important to assess the spatial overlap between protected areas and natural habitat utilization of sea turtle species. It is also crucial to assess what environmental factors are driving certain aspects of sea turtle life histories and how they are doing so, in order to provide insight into the future of sea turtles and their associated protective measures in the changing environment.

RESEARCH QUESTIONS

The present study seeks to answer the following research questions:

1. Do sea turtles nest preferentially on beaches with less anthropogenic disturbance?

2. Do distributions of sea turtle strandings depend on environmental and/or anthropogenic covariates?
OBJECTIVES

This study examines the relationship between sea turtle nesting and environmental and anthropogenic factors in Florida, as well as the distributions of sea turtle strandings and similar variables that might influence those strandings. The first objective of the present study is to examine the relationship between nesting counts of loggerhead, green, and leatherback sea turtles and anthropogenic and environmental factors. The study then seeks to identify whether environmental and/or anthropogenic covariates are related to the distribution of sea turtle strandings in Florida. Finally, this study attempts to determine how these factors influence sea turtle habitat usage. The overall goal of these two analyses is to assess the efficacy of sea turtle protection measures in the state of Florida.

HYPOTHESES

It is hypothesized that protected areas, and the presence of lighting ordinances, will have a positive association with sea turtle nesting numbers, as they are implemented with the intention of aiding nesting females and hatchlings. It is also hypothesized that human population densities will have a negative influence on nesting numbers, as anthropogenic barriers or disturbances have been detrimental
to turtle nesting. It is also hypothesized that sea turtle strandings will occur more frequently in areas with no lighting ordinances and high human population density. Onshore lighting has been shown to increase hatchling mortality (Mazor et al. 2013), and areas that have higher human population densities are subject to greater impacts from pollution, boating, and fishing activity, which have all been attributed to higher stranding incidence (Casale et al. 2010).
CHAPTER II
SEA TURTLE NESTING AND STRANDING IN FLORIDA

INTRODUCTION

Ever since their arrival on the evolutionary scene, humans have been altering the natural world around them to meet their own survival needs. Anthropogenic impact on the environment has only escalated throughout the course of history as the human population increased. Under natural conditions, approximately nine species are expected to go extinct every century (Ceballos et al. 2015). Researchers at the National Autonomous University (UNAM) have calculated that in the past 100 years alone, nearly 500 species have gone extinct because of anthropogenic impact (Ceballos et al. 2015). This figure does not include the scores of other species whose numbers have been severely reduced directly or indirectly by human activity.

Humans, however, have started to realize their negative impact on the natural world and have formulated conservation measures to reduce or rectify their impact. These conservation measures include the establishment of reserves or protected areas that serve as critical habitat for one or more target species, and include the restriction or prohibition of activities that are known to be harmful to
certain species and their habitats (Anderson et al. 2013). While the establishment of such protective measures is a step in the right direction, their actual success lies in their planning, implementation, and enforcement.

While it is quite clear that inadequate enforcement would prevent a species-protection plan from being successful, it is less clear what effect improper planning or implementation has on the success of such plans. No matter how perfectly species protection measures are enforced, if they are not planned or implemented in places critical for the target species, then these measures do very little to accomplish their goals (Klein et al. 2015; Margules and Pressey 2000). Though errors in reserve design and species protection plans, at the scientific level, are possible, the primary factor contributing to the inadequacy of protective measures is generally opposition to proposed boundaries or regulations.

The ever-growing human population intensifies the stress on natural resources. These resources are often found in areas considered critical habitat for one or multiple species. This spatial overlap between humans and critical resources creates opposition to proposed protective measures, as they often seek to impede land development or resource extraction (Dobson et al. 1997). It is often the case that conservation plans, or existing reserves, will be altered so as not to impede human use. These alterations can strip conservation plans and reserves of their effectiveness by drastically reducing reserve size, excluding critical habitat, or eliminating connectivity of reserve areas (Margules and Pressey 2000). Therefore,
it is important to use not only preliminary research, to ensure that plans are as theoretically successful as possible, but also to analyze their effectiveness after their implementation.

SEA TURTLES

There are seven species of sea turtles alive on Earth today (Figure 2.1). Each of these species belong to one of two families: Dermochelyidae or Cheloniidae. All extant sea turtle species, with the exception of the leatherback (Dermochelys coriacea), belong to the family Cheloniidae. D. coriacea, the loggerhead (Caretta caretta), hawksbill (Eretmochelys imbricata), green (Chelonia mydas), Olive Ridley (Lepidochelys olivacea), and Kemp’s Ridley (Lepidochelys kempii) sea turtles are all considered either vulnerable, endangered, or critically endangered by the International Union for Conservation of Nature (Wallace et al. 2013; Casale and Tucker 2015; Mortimer and Donnelly 2008; Abreu-Grobois and Plotkin 2008; Marine Turtle Specialist Group 1996). The flatback sea turtle (Natator depressus) is currently listed as “Data Deficient”, but was previously listed as vulnerable (Red List Standards & Petitions Subcommittee 1996).
Sea turtles are unique marine organisms in that in addition to their utilization of marine habitat they are also tied to terrestrial habitats. Sea turtles begin life on land and females return to their natal beaches each nesting season to lay their eggs, whereas the rest of their life is spent in the oceans (Antworth et al. 2006). It is currently unclear the extent to which sea turtles travel, and whether those home ranges vary geographically. What is clear is that this complexity in habitat use, and broad geographic home range, can make it difficult to establish conservation plans that accurately encompass the total critical habitat used by sea turtle species. This movement and dual habitat usage makes it imperative that the effectiveness of sea turtle conservation plans are analyzed pre- and post-implementation.
Although it is often difficult to identify critical habitat of sea turtles on a small-scale, Florida beaches are known to be primary nesting grounds for three sea turtle species: green (*Chelonia mydas*), loggerhead (*Caretta caretta*), and leatherback (*Dermochelys coriacea*) sea turtles (Bovery and Wyneken 2015). Because of Florida’s significance in the nesting portion of the sea turtle lifecycle, it makes Florida a notable location to analyze stranding occurrences.

Analysis of stranding data can be difficult to draw conclusions from because many factors contribute to strandings, including where an individual ends up after it is injured or deceased; however, spatial and temporal analyses of strandings can lead to inferences about the major factors that negatively impact sea turtle populations. Hart et al. (2006) modeled the probability of a carcass stranding at increasing distances from shore. The model illustrated that probability of stranding decreases with increasing distance from shore. This relationship makes it acceptable to use local scale attributes of beaches, where strandings occur, to analyze influencing factors, because it can be assumed that these local factors impact a large proportion of the individuals stranded in a given locality.

NESTING MODELS

**TURTLE NESTING AND ENVIRONMENTAL DATA.** The total number of nesting counts, from 2011 to 2015, acquired from the Florida Fish and Wildlife Commission (FWC) ([http://geodata.myfwc.com/datasets](http://geodata.myfwc.com/datasets)) were used as the primary data source (Table A-1). This dataset includes nesting counts for green (*Chelonia*...
mydas), loggerhead (*Caretta caretta*), and leatherback (*Dermochelys coriacea*) sea
turtles at 156 different beach locations throughout 27 counties in Florida. Protected
beaches were designated as such by the presence of wildlife protective
enforcement, such as that found in state and national parks, national seashores, or
wildlife reserves. Restricted beaches were classified as any beach that has access
restrictions, such as nightly beach closures or that require special access permission
that restrict the amount of human traffic on the beach. Protected and restricted data
were acquired from the Parks and Recreation Departments from each county (Table
A-1).

The human population of the nearest town to where the turtle data were
collected was used from the 2010 Census (Table A-1). The population data were
used as a proxy for traffic a given beach would receive (https://www.census.gov).
Beaches were classified by geographical location of the county in which they were
located (Table A-1). The east region was classified as coastal counties from Nassau
to Palm Beach and the southern region included Collier, Monroe, Dade, and
Broward counties (Figure 2.2). The western region was considered from Escambia
to Franklin and Pinellas to Lee (Figure 2.2). There were no data available for the
coastal counties between Franklin and Pinellas because these counties are not
considered sea turtle nesting counties by the state of Florida, and were excluded
from FWC’s survey for this reason (Anderson et al. 2013). Indeed, these counties
support very few beaches (Google Earth, personal observation).
Average annual sea surface temperature rasters of 1 km resolution were accessed from the AVHRR satellite for the NOAA CoastWatch program. Beach angle in degrees was determined using Google Earth (Google Inc.). Sand-grain size data came from the Florida Department of Environmental Protection’s Regional Offshore Sand Source Inventory (ROSSI) database (http://rossi.urs-tally.com/Map). The Krumbein phi scale, a logarithmic scale modification of the categorical Wentworth scale, was used to describe grain size (Krumbein and Sloss 1963). Median $\phi$ values of each beach location were used as the metric for grain size. Because relevant data points did not cover every nesting location, ordinary kriging was used to interpolate a complete raster of median $\phi$ values (Cressie 1990).
Lighting ordinance data were acquired from FWC’s table of Sea Turtle Protection Ordinances Adopted by Counties and Municipalities (myfwc.com/conservation/you-conserve/lighting/ordinances/).

DATA ANALYSIS. To determine whether sea turtles nest preferentially on beaches with low anthropogenic disturbance, a generalized linear mixed model (GLMM) (Bates et al. 2017), was formulated using R (R Core Team, 2017). Each turtle species was analyzed using a separate model. The response variable was the number of nests on a given beach from 2011 to 2015, and the predictive variables, or covariates, were the environmental and anthropogenic variables (Table A-1). Fixed covariates in the models included: (i) the human population of the nearest town, (ii) habitat protection, (iii) habitat restriction, (iv) region, (v) sand-grain size, (vi) sea-surface temperature, (vii) presence or absence of a lighting ordinance, and (viii) beach angle. Beach location was considered a random effect in each of the models. Each of the models operated under the assumption that the human population of the nearest city or town was representative of the relative human impact at a given site. In addition, the models assumed that protected beaches and access restrictions were effectively enforced during the period of data collection, and that protected and restricted variables are independent of one another.

Average sea surface temperature, human population, beach angle, and sand-grain size were numerical data. To improve model fit, these variables were scaled using the ‘scale’ function in R, which subtracts the mean and divides by the
standard deviation. Lighting ordinance, protection, and restriction data were binary, with a value of 1 representing presence and 0 representing absence. Region data were categorical, (West=1, South=2, East=3).

The GLMM was formulated using the function `glmer` from the package ‘lme4’ (Bates et al. 2017). A manual model selection routine was used, since there is no model selection function coded in R for GLMM to date. Models with the lowest Akaike Information Criterion (AIC) were chosen as the final model for each species. Correlation tables, from the package ‘xtables’ (Dahl 2016), were constructed to assess the sensitivity of each variable for each of the three models. A posterior predictive simulation was conducted in R to compare the mean simulated interquartile ranges and actual interquartile ranges to validate each model.

**POINT-PATTERN INTENSITY ANALYSIS**

**DATA ACQUISITION.** Sea turtle stranding data were acquired from Florida Fish and Wildlife Commission (FWC) (http://geodata.myfwc.com/datasets). This data include turtle size data and coordinate locations for stranded sea turtles of all species found on beaches in or in waters surrounding Florida from 1986–2014. These stranding data were overlaid onto rasters for various environmental and anthropogenic covariates. These covariates included average sea-surface temperature for 2011-2014 (NOAA CoastWatch), 5 km-gridded human-population density for 2000 (http://sedac.ciesin.columbia.edu/data/set/gpw-v3-population-density/data-
download), and presence or absence of lighting ordinance
(myfwc.com/conservation/you-conserve/lighting/ordinances/).

**DATA ANALYSIS.** Point-pattern intensity analyses were used to quantify the intensity of the stranding points, given the values of the covariates (Baddeley 2012). The \textit{rhohat} function in the R package ‘spatstat’ (Baddeley 2017) was used to identify patterns in stranding occurrences for average sea surface temperature and human-population density covariates. A local smoothing function was used for the analysis of the gridded population density covariate. Since this function is only appropriate for continuous covariates, the \textit{intensity} function was used to assess the patterns in stranding occurrence related to lighting ordinance presence, a categorical covariate. Though the stranding data spans almost 30 years, it was assumed that the annual average sea surface temperature and gridded human population density covariates did not change appreciably during that time, so a single analysis was performed for each covariate. Additionally, though county-wide lighting ordinances are generally only strictly enforced during nesting season (mid-May to the end of October), stranding occurrences are noted at the time of discovery post-mortem and exact cause of death cannot be identified. Therefore, the entire stranding dataset was utilized for the lighting ordinance point-pattern intensity analysis.
RESULTS

NESTING MODELS

In both the loggerhead and leatherback models, all selected parameters had a significant impact on predicted nesting counts ($p<0.05$) (Table 2.1). In the green sea-turtle model, all variables, except for average sea surface temperature ($p>0.05$), had a significant impact on predicted nesting counts (Table 2.2). Presence of protective measures, population of the nearest town, beach angle, and median φ values (Figure 2.3) were all negatively associated with the nesting counts, in each model in which they were used. In contrast, region, average sea-surface temperature, and presence of lighting ordinance were positively associated with nesting counts in each model in which they were used (Figure 2.4 a-c). It was found that approximately 37% of the surveyed areas was considered protected and had some sort of access restriction (Figure 2.5). Correlation tables revealed that the two most sensitive variables for the green and leatherback models were region and beach angle, whereas the most sensitive variables for the loggerhead model were region and median φ value. Each of the final models chosen performed better than both the minimum and saturation models for all species (Table 2.3). Posterior predictive simulations that ran for 1000 iterations revealed that the mean simulated interquartile ranges and actual interquartile ranges did not differ significantly.
Plotting model outputs identified the central Atlantic coast to be the area where the most nests are predicted to be laid given the present data (Figure 2.6).

Figure 2.3. The relationship between sea turtle nesting counts and scaled median phi values in Florida. Nesting counts modeled for all three species (loggerhead, green, and leatherback sea turtles, respectively) have a negative association with scaled median phi value. This indicates that beaches with coarsely-grained sands will have higher nesting numbers.
Figure 2.4. Plots of coefficients for generalized linear mixed models predicting nesting numbers of (a) loggerhead, (b) green, and (c) leatherback sea turtles in Florida. Coefficients that had a negative association with nesting numbers included median phi value of sand grains (sand), human population of nearest town (humpop), beach angle (angle) and presence of enforcement of protective measures (prot). Coefficients that had a positive association were presence of a lighting ordinance (light), average annual sea surface temperature (avgsst), and geographic region (reg). All coefficients had a significant influence on nesting numbers, except for humpop in the loggerhead model and avgsst in the green sea turtle model; however, their inclusion improved the overall model AIC.
Figure 2.5. Plot of Protected (green) versus Unprotected (white) Beach Locations and Total Sea Turtle Nesting Density in Florida. The area where most of the nests were laid (2011-2015) was on the central Atlantic Coast. Protected beaches account for 37% of the studied area, most of which is located outside of the area where the most nesting activity occurred.
Figure 2.6. Nesting Density Prediction Plots for Loggerhead (a), Green (b), and Leatherback (c) Sea Turtles Based on Model Outputs. Though overall predictions differ, the main locus of sea turtle nesting density in Florida is predicted to be along the central Atlantic coast. The centroid of the leatherback nesting prediction is slightly offset from the coast most likely because most of the variables included in the model were not necessarily tied to the land and seemingly optimal conditions could be found offshore.
Table 2.1. Table of Variables Included in Loggerhead and Leatherback Sea Turtle Nesting Models. Variables included in each generalized linear mixed model are marked with an ‘X’. All variables included in each model were significant, except for human population in the loggerhead model (denoted with an asterisk). This variable was still included, as it improved the model AIC (prot=presence of protective measures; humpop=population of the nearest town; reg=geographic region of beach; angle=beach angle; avgsst=annual average sea surface temperature; sand=median φ sand grain sizes).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Loggerhead</th>
<th>Leatherback</th>
</tr>
</thead>
<tbody>
<tr>
<td>prot</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>humpop</td>
<td>X*</td>
<td></td>
</tr>
<tr>
<td>reg</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>angle</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>avgsst</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>sand</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

Table 2.2. Table of Variables Included in Green Sea Turtle Nesting Model. All listed variables were included in the generalized linear mixed model for green sea turtle nesting in Florida. Variables with a significant impact on nesting numbers are marked with an ‘X’. The non-significant variable was included in the final model, as it resulted in the lowest AIC value. (humpop=population of the nearest town; reg=geographic region of beach; angle=beach angle; avgsst=annual average sea surface temperature; sand=median φ sand grain sizes; light=presence of lighting ordinance).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Significant</th>
</tr>
</thead>
<tbody>
<tr>
<td>humpop</td>
<td>X</td>
</tr>
<tr>
<td>reg</td>
<td>X</td>
</tr>
<tr>
<td>angle</td>
<td>X</td>
</tr>
<tr>
<td>avgsst</td>
<td></td>
</tr>
<tr>
<td>sand</td>
<td>X</td>
</tr>
<tr>
<td>light</td>
<td>X</td>
</tr>
</tbody>
</table>
Table 2.3. Summary Table of Floridian Sea Turtle Nesting Generalized Linear Mixed Models. All models performed better (had a lower AIC) than both the saturation and minimum models for each species. Nest=predicted nesting counts; prot=presence/absence of protective measures; humpop=scaled human population of the nearest town; reg=categorical region; angle=beach orientation angle with respect to ocean; sand=median φ value (grain size metric); light=presence or absence of county-wide lighting ordinance; beach=random effect of beach location.

<table>
<thead>
<tr>
<th>Species</th>
<th>Final Model</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loggerhead (<em>Caretta caretta</em>)</td>
<td>Nest~ (-0.7572)prot + (-0.2327)humpop + 0.8401(reg) + 0.4641(avgst) + (-0.6246)sand + (1</td>
<td>Beach) + 4.1708</td>
</tr>
<tr>
<td>Green (<em>Chelonia mydas</em>)</td>
<td>Nest~ (-0.5117)humpop + 1.3026(reg) + (-0.9993)angle + 0.6082(avgst) + (-1.0006)sand + 2.4064(light) + (1</td>
<td>Beach) + (-3.4877)</td>
</tr>
<tr>
<td>Leatherback (<em>Dermochelys coriacea</em>)</td>
<td>Nest~ 1.3199(reg) + (-2.2737)angle + 0.6265(avgst) + (-0.4424) sand + (1</td>
<td>Beach) + (-3.7894)</td>
</tr>
</tbody>
</table>

POINT-PATTERN INSTENSITY ANALYSIS

The point-pattern intensity analysis for annual average sea surface temperature determined that the majority of sea turtle strandings in the state of Florida from 1986-2014 occurred in areas with median-to-cooler annual average sea surface temperatures (Figure 2.7). The population density portion of the analysis revealed that the majority of sea turtle strandings centered around grid cells with population densities of 1000 or more individuals per 5 km² (Figure 2.8). The intensity analysis of lighting ordinances revealed that most sea turtle strandings occurred in proximity to counties that enforced a county-wide lighting ordinance.
Though the current roster of counties that enforce county-wide lighting ordinances was only completed in 2013, repeated point-pattern intensity analyses across multiple time periods showed no difference in the locations of the highest densities of strandings, so a single analysis was conducted.

Figure 2.7. Annual average sea surface temperature (2011-2014) point-pattern intensity analysis of sea turtle stranding occurrences in Florida. The results of the point-pattern intensity analysis indicate that the majority of sea turtle strandings in Florida between 1986 and 2014 were documented in areas with an annual average sea surface temperature of approximately 24°C.
Figure 2.8. Gridded (5 km$^2$) human population density (2000) point-pattern intensity analysis of sea turtle stranding occurrences in Florida. The results of this point-pattern intensity analysis indicate that most of the sea turtle strandings in Florida between 1986 and 2014 were documented in grid cells with human population densities around 800 people per 5km$^2$.

Figure 2.9. Lighting ordinance presence point-pattern intensity analysis of sea turtle stranding occurrences in Florida. The results of this point-pattern intensity analysis indicate that far more strandings were documented in counties that enforced a county-wide lighting ordinance (shown in yellow) than in counties that do not (dark blue).
DISCUSSION

The first goal of this study was to determine the environmental and anthropogenic factors that influenced the nesting habits of sea turtles in Florida. This was accomplished through the formulation of species-specific GLMMs for the loggerhead, green, and leatherback sea turtles. The models revealed that nesting beach geography strongly impacted nesting numbers. Region was one of the two most sensitive variables in all three models, as was beach angle for the green and leatherback nesting models. Region had a positive impact on nesting numbers. This is unsurprising, since the largest nesting populations of all three species are located on the east coast of the state (Weishampel et al. 2003). Beach angle had a negative association with nesting numbers for green and leatherback sea turtles. This is also unsurprising, as most beaches on the east coast have low values, since due east is located at 90°.

In the present models, average sea surface temperature had a positive relationship with nesting numbers for all models; however, this impact was not significant for the green sea turtle model. Lamont and Fujisaki (2014) determined that loggerhead turtles nesting in northwest Florida began nesting earlier in the year when sea surface temperatures were higher in the months prior to the historical
nurturing season. Earlier nesting led to an extended nesting season, during which more nests were dug. These results suggest that loggerhead turtle nesting behavior is influenced by environmental temperature cues. In contrast, Pike (2009) found that the nesting patterns of green sea turtles at Cape Canaveral, Florida, were not influenced by these same temperature cues. The results of the loggerhead and green models agree with previous findings by Lamont and Fujisaki (2014) and Pike (2009) on the alteration of nesting phenology in two of Florida’s primary nesting sea turtle species.

Findings by Neeman et al. (2015) suggested that local temperatures at lower latitude nesting sites in Costa Rica (both the Caribbean and Pacific coasts) and the US Virgin Islands do not have a direct, significant influence on leatherback nesting behaviors. Yet changes in temperatures at higher latitude foraging grounds, particularly those located in the Gulf of Mexico, have a significant impact on foraging behaviors. Increases in temperature foraging grounds in the Gulf of Mexico have been shown to delay nesting at the lower Caribbean study locations (Neeman et al. 2015).

The relationship between leatherback nesting numbers and temperature in the present study do not directly agree with the findings that the local temperature of nesting sites do not influence nesting behavior (Neeman et al. 2015). The results here are not as directly applicable to the previous study as they are for previous work on loggerhead and green turtles because of the difference in latitude of target
nesting locations. It is possible that temperature variation at the lower latitude nesting sites was not strong enough to elicit a significant effect on leatherback nesting timing, whereas the higher latitude sites near the Gulf of Mexico had more temperature variation and, therefore, had a significant impact regardless of the habitat usage. Additionally, temperature increases in the Gulf of Mexico could serve as a cue that confuses gravid foraging females, causing them to nest initially on nearby Floridian beaches before traveling to lower latitudes to lay their remaining clutches. This could explain the relationship between the delay in nesting season at low latitude nesting sites and temperature increases in the Gulf of Mexico observed by Neeman et al. (2015). In order to investigate this possible explanation for this nesting delay, further study would be needed to determine if sea turtles could be forced by changes in sea surface temperature to nest opportunistically on non-natal beaches.

Median $\phi$ values had a negative influence on nesting numbers for all three models. This relationship suggests that sea turtles prefer beaches with coarse-grained sands, as smaller $\phi$ values are associated with larger grain size. This relationship could be also due to regional differences in sand composition, as beaches on the Atlantic coast of Florida are known to have coarser-grained sands than the beaches of the Gulf coast. It is possible that the coarser-grained sand of the east coast contributes to an optimum range of substratum compactness, which has been determined to be one of the most important factors contributing to nesting
success by Ho-Chang et al. (2007).

It is well-documented that individuals across a variety of species exhibit predator avoidance behavior (Albalat et al. 2016; Perkins et al. 2014; Simpson et al. 2011). These individuals learn to recognize certain cues that are associated with the danger of certain predators. Heithaus et al. (2007) described predator avoidance behavior exhibited in the habitat usage patterns of adult green sea turtles in Shark Bay, Australia. During the months of peak tiger shark activity, healthy adult turtles were observed avoiding the seagrass beds with the most nutrient-dense foliage, which was the location where shark activity was highest. However, during months of tiger shark absence, the turtles were observed foraging in the same seagrass beds that they had previously avoided. These findings suggest that these turtles will forgo ideal foraging grounds in favor of safety. It is possible that turtles exhibit similar trade-off behaviors in other aspects of their lives, such as nesting.

Leatherbacks tend to spend most of their time in pelagic waters, whereas loggerhead and green turtles tend to spend their time relatively close to shore. Human population of the nearest town, a proxy for human activity, had an important negative impact on nesting numbers of both loggerhead and green turtles, whereas human population did not influence nesting numbers of leatherback turtles. It is possible that because loggerhead and green turtles are more frequently exposed to human activity during the open water phases of their lives, they have developed a variation of predator avoidance behavior in response to anthropogenic-based
cues, leading them to avoid nesting on beaches with high surrounding human activity because these are considered high-risk nesting locations. In contrast, leatherbacks may lack the exposure to these anthropogenic-based cues and, therefore, do not have as strong an aversion to nesting on beaches with human influence. This conclusion agrees with the hypothesis presented by Heithaus et al. (2008) which states that pelagic species, specifically leatherbacks, may be less able to alter habitat usage in response to predators than their coastal counterparts.

As expected, the presence of lighting ordinances had a positive influence on nesting numbers of green sea turtles; however, the presence of lighting ordinance did not have a significant influence on loggerhead or leatherback nesting numbers, though the associations were still positive. Artificial lighting has been shown to reduce nesting densities of these three species (Weishampel et al. 2016). The positive influence of lighting ordinances on nesting numbers of green sea turtles and the lack of a negative influence on the other two species suggests that these lighting ordinances are at least aiding nesting females of one species without harming the others. A time-series analysis of nesting numbers of these species before, during, and after the establishment of the present county-wide lighting ordinances might more accurately capture their influence.

Perhaps the most interesting result of the present study is the negative impact of the presence of protected areas on nesting numbers seen in the loggerhead model. Upon further inspection, it was found that approximately 37%
of the surveyed area was considered protected, and included access restriction areas (Figure 2.5). These results suggest that the amount of protected beach area is not the issue, instead, the present protected beaches have been designated in suboptimal locations for protecting nesting loggerhead sea turtles. The area that was predicted to have the most loggerhead nesting activity was the central Atlantic coast (Figure 2.6, a), an area with only a few sparsely interspersed protected beaches. The lack of any significant influence on the green and leatherback sea turtle nesting models further suggests that location of these protected areas is neither suboptimal nor beneficial to nesting females of these two species.

The second objective of the present study was to determine if sea turtle strandings depended on anthropogenic or environmental covariates. This goal was met by performing a point-pattern intensity analysis of historical stranding data and presence or annual average sea surface temperature, presence of county-wide lighting ordinance, and gridded human population density. These point-pattern intensity analyses showed that the majority of stranded individuals were found near high human population densities in counties that enforce a county-wide lighting ordinance. The finding that most strandings occur near areas with high population density was expected, as human activities are known to increase the risk of mortality for sea turtles, as well as other organisms (Schuyler et al. 2014; Barco et al. 2016). Stranding occurrence was highest in areas with population densities around 800 people per 5km², which was notably less than the maximum human
population density. It is possible that this trend appears because of socioeconomic differences between these areas and those with higher human population density, such as the number of boats per capita. The negative relationship between nesting numbers of green and loggerhead turtles and human population suggest that nesting females of these species are able to identify some anthropogenic-based cue(s) that trigger a predator avoidance-like response. The increased stranding incidence near areas of dense human populations, found by the point-pattern intensity analysis, provides support for the implications of these two models. Over 88% of the stranded individuals in the dataset were either loggerhead or green turtles, likely because they are the two most common species of marine turtle in Florida (Bovery and Wyneken 2015); however, this dominance in the dataset means that the implications of the point-pattern intensity analyses apply most directly to these two species.

The finding that most strandings were located in areas with median annual average sea surface temperatures (around 24°C) is also not surprising, as more than half of the individuals were reported in close proximity to the Florida coast, where the annual average sea surface temperature (2011–2014) was no greater than 24°C for over half of the state.

Since more strandings were documented in areas that enforced a county-wide lighting ordinance, it would seem to suggest that the lighting ordinances are ineffective. However, since all but two of the eastern coastal counties and
approximately half of the western coastal counties enforce a county-wide lighting ordinance, this result is likely based on the amount of coastal area that enforces county-wide lighting ordinances. It is also possible that because the counties that have adopted county-wide lighting ordinances are all considered sea turtle nesting counties by FWC (Anderson et al. 2013), and there are simply more sea turtles in the areas surrounding these counties and, therefore, more opportunity for strandings to occur. These results, in conjunction with the positive relationship between nesting numbers and lighting ordinances, would suggest that these ordinances are being enforced in the optimal locations to positively impact the most nesting females and hatchlings.

The findings of these analyses reaffirm some previously suggested environmental influences on sea turtle life histories, while providing some insights into the success of the measures being taken to protect sea turtles. The models suggest that lighting ordinances are indeed aiding in nesting success of females, whereas the locations of protected beaches are subpar. Furthermore, these models provide support for previous findings that suggest that climate change may be resulting in changes in phenologies of sea turtle species. The results of the point-pattern intensity analyses provide further support for the detrimental relationship between high human populations and sea turtle populations and give additional support to county-wide lighting ordinances by reaffirming their locations. Hopefully, further validation of the success of the lighting ordinances will
encourage the remaining sea turtle nesting counties that have yet to establish county-wide lighting ordinances to do so. Additionally, these results may encourage those in charge of the development of sea turtle species protection plans to reevaluate the locations of emphasis for sea turtle protection.
CONCLUSIONS

The results of the present analyses suggest that the factors that have the strongest influence on sea turtles stem from human activity, whether it be from disturbances caused by high human population density or possible long-term implications of global climate change. Results from this analysis support previous studies that suggest that changes in sea surface temperature could alter the phenologies of sea turtle species in the future.

The overall goal of this study was to assess the efficacy of sea turtle protective measures in Florida. The results of this study present a mixed picture of protective measures in place that affect sea turtle populations in Florida. Lighting ordinances appear to be effectively aiding nesting females and have been established in areas where turtle populations are most abundant, whereas designated protected areas seem to be in suboptimal locations, and are unlikely to have a significant influence on these females and their offspring. It may be impractical to increase the amount of protected area where the most sea turtle nesting activity occurs, as it is already a well-developed area. A practical solution could be to increase educational efforts and have stricter on-beach enforcement of state-wide sea turtle regulations during the nesting months in these areas.
Though some aspects of sea turtles’ lifecycle make them difficult to study, analyses that employ readily available data, such as nesting counts and stranding occurrences, are not only efficient and cost-effective, but are able to provide insight into the factors that may influence sea turtle population dynamics. Such analyses can be valuable assessments of conservation efforts and are crucial if humans wish to effectively reduce or reverse their impact on the natural world.


Dahl DB. 2016. Export Tables to LaTeX or HTML. CRAN.


APPENDIX A

R CODE

I. Sand Plot Kriging

A. Kriging Prep
```r
\`
\'{r Kriging Prep}
\'
setwd("C:/Users/Schelli/Documents/MS_Thesis/Nesting/Data/ROSSI")
library(readr)
sand<-read.csv("~/MS_Thesis/Nesting/Data/ROSSI/Sand Grain Full.csv")
sand = sand[which(!duplicated(sand[1:2])), ]

library(rgdal)
xy<-cbind(sand$Longitude, sand$Latitude)
fl<-project(xy, "+proj=utm +zone=17s +ellps=WGS84")
plot(fl)

library(sp)
library(gstat)
FLSP<-SpatialPoints(fl)
FLSP

dx.range <- as.integer(range(FLSP@coords[, 1]))
y.range <- as.integer(range(FLSP@coords[, 2]))
x.range
y.range

#x range= -127517, 888306
#y range= 2691626, 3398054

#x.range <- c(-128000, 88900)
#y.range <- c(2700000, 3400000)

grd <- expand.grid(x = seq(from = x.range[1], to = x.range[2], by = 10845), y =
                   seq(from = y.range[1], to = y.range[2], by = 10845))
```
plot(grd, cex = .4)
points(FLSP, pch = 1, col = "red", cex = 1)

gridded(grd) = ~x+y
medphi<-sand$Median
mp<- data.frame(medphi)
FLNEW<- cbind(coordinates(FLSP), mp)
```{r}
B. Variogram
```{r}
FLvar <- variogram(sand$Median ~ 1, data=FLSP, locations = FLSP)
plot(FLvar)
```{r}
C. Variogram for Spatial Prediction
```{r}
vgm()
FLfit = fit.variogram(FLvar, vgm(nugget=.75, "Gau", psill=1.1,
range=20000),fit.sills = TRUE, fit.ranges = TRUE)
FLfit
plot(FLvar, model=FLfit, as.table=TRUE)
```{r}
```
```
```
```{r}
FLdir<- variogram(sand$Median ~ 1, FLSP, alpha= (0:3)*45)
FLanis<- vgm(2.5, "Gau", range=20000, anis= c(45, 0.3))
plot(FLdir, FLanis)
D. Kriging
```
```{r Kriging and Plot}
KFL <- krig(sand$Median ~ 1, locations=FLSP, newdata=grd, FLfit)
sandkrige <-
  spplot(KFL["var1.pred"],col.regions=colorRampPalette(c('blue','turquoise2' 
  ,'green','yellow','orange','red'))(200),cuts=200,colorkey=T)
KFLr <- raster(KFL)
crs(KFLr) <- "+proj=utm +zone=17s+ ellps=WGS84"
KFLr
plot(KFLr)
```
```{r Extracting Median Phi Values}
setwd("C:/Users/Schelli/Documents/MS_Thesis/Nesting/Data/")
library(sp)
library(rgdal)
nest <- read.csv("FL Nest Full.csv")
locs <- subset(nest, select = c("Beach", "Lat", "Lon"))
coordinates(locs) <- c("Lon","Lat")
proj4string(locs) <- CRS("+proj=longlat +datum=WGS84 +no_defs") # WGS 84
sp <- SpatialPoints(locs)
sanddat <- extract(KFLr,locs, method = "bilinear")
write.csv(sanddat, "med phi.csv")
```

II. Generalized Linear Mixed Model for Sea Turtle Nesting

A. Defining Fixed and Random Effects
```
```{r Defining Fixed and Random Effects}
setwd("C:/Users/Schelli/Documents/MS_Thesis/Nesting/Data")
library(readr)
nest <- read_csv("~/MS_Thesis/Nesting/Data/FL Nest Model.csv")
#Define Fixed and Random Effects
```
Beach<-nest$BeachNo
humpop<-nest$ScaledPopulation
prot<-nest$Protected
rest<-nest$Restricted
ccnest<-nest$ccCount
cmnest<-nest$cmCount
dcnest<-nest$dcCount
meanlen<-nest$meanSurvLength
reg<-nest$Region
angle<-scale(nest$Angle)
light<-nest$Lighting
avgsst<-scale(nest$`Average sst`)
medsst<-scale(nest$`median sst`)
sand<-scale(nest$MedPhi)
```

```r
for all models, continuous variables were scaled to improve fit.
```

B. Testing nesting data for distribution fit

1. Loggerhead distributions
```
```r
library(car)
library(MASS)
qqp(ccnest, "norm")
```
```
```
```
```
```
```
```
```r
cbinom 
```
```
```
```
```
```r
poisson 
```
```
```r
```
2. Green distributions
```{r Green Normal Distribution}
qqp(cmnest, "norm")
```  
```{r Green Lognormal Distribution}
qqp(cmnest, "lnorm")
```
```{r Green Negative Binomial Distribution}
nbinom <- fitdistr(cmnest, "Negative Binomial")
qqp(cmnest, "nbinom", size = nbinom$estimate[[1]], mu = nbinom$estimate[[2]])
```  
```{r Green Poisson Distribution}
poisson <- fitdistr(cnest, "Poisson")
qqp(cnest, "pois", poisson$estimate)
```  
3. Leatherback distributions
```{r Leatherback Normal Distribution}
qqp(dnest, "norm")
```  
```{r Leatherback Lognormal Distribution}
qqp(dnest, "lnorm")
```
```{r Leatherback Negative Binomial Distribution}
nbinom <- fitdistr(dnest, "Negative Binomial")
qqp(dnest, "nbinom", size = nbinom$estimate[[1]], mu = nbinom$estimate[[2]])
```  
```{r Leatherback Poisson Distribution}
poisson <- fitdistr(dnest, "Poisson")
qqp(dnest, "pois", poisson$estimate)
```

Both Loggerhead and Green nesting counts seem to fit Poisson distributions best, while Leatherback fits the negative binomial best.

C. Model Fitting
Since there is no selection routine coded in R for GLMMs, I will be choosing either
forward or backward selection based on whether the saturated model or the minimum model has the lowest initial AIC.

1. Loggerhead Nesting (Caretta caretta)
```
```{r Loggerhead Saturation Model}
library(lme4)
ccsat<-glmer(ccnest~prot+rest+humpop+reg+angle+avgsst+sand+light+(1|Beach),
data=nest, family ="poisson")
summary(ccsat)
```
```
```{r Loggerhead Minimum Model}
ccmin<-glmer(ccnest~1+(1|Beach), data=nest, family ="poisson")
ccmin
```
```
```{r Loggerhead Backward +7 Models,}
#-prot
cc1<-glmer(ccnest~rest+humpop+reg+angle+avgsst+sand+light+(1|Beach),
data=nest, family="poisson")
cc1
# -rest
cc2<-glmer(ccnest~prot+humpop+reg+angle+avgsst+sand+light+(1|Beach),
data=nest, family ="poisson")
cc2
# -humpop
cc3<-glmer(ccnest~prot+rest+reg+angle+avgsst+sand+light+(1|Beach), data=nest, family ="poisson")
cc3
# -reg
cc4<-glmer(ccnest~prot+rest+humpop+angle+avgsst+sand+light+(1|Beach),
data=nest, family ="poisson")
cc4
#-angle
cc5<-glmer(ccnest~prot+rest+humpop+reg+avgsst+sand+light+(1|Beach),
data=nest, family ="poisson")
Lowest AIC resulted from the removal of restricted parameter (1919.828).

```r
}{r Loggerhead Backward +6 Model}

```
The removal of angle yielded the lowest AIC value (1916.8867)
The removal of the light parameter improved AIC value (1916.8867).

```
```

The removal of further parameters failed to improve the model.

Starting from forward selection to see if model is improved at all.
```{r Loggerhead Forward +1 Model}
#prot
cc1 <- glmer(ccnest ~ prot + (1|Beach), data=nest, family = "poisson")
cc1

#rest
cc2 <- glmer(ccnest ~ rest + (1|Beach), data=nest, family = "poisson")
cc2

#humpop
cc3 <- glmer(ccnest ~ humpop + (1|Beach), data=nest, family = "poisson")
cc3

#reg
cc4 <- glmer(ccnest ~ reg + (1|Beach), data=nest, family = "poisson")
cc4

#angle
cc5 <- glmer(ccnest ~ angle + (1|Beach), data=nest, family = "poisson")
cc5

#avgsst
cc6 <- glmer(ccnest ~ avgsst + (1|Beach), data=nest, family = "poisson")
cc6

#sand
cc7 <- glmer(ccnest ~ sand + (1|Beach), data=nest, family = "poisson")
cc7

#light
cc8 <- glmer(ccnest ~ light + (1|Beach), data=nest, family = "poisson")
cc8
```

The minimum model, plus sand yielded lowest AIC value for FS (1932.50)

```{r Loggerhead Forward +2 Model}
#prot
cc41 <- glmer(ccnest ~ sand + prot + (1|Beach), data=nest, family = "poisson")
cc41

#rest
```
The minimum model, plus sand and prot yielded lowest AIC value for FS (1927.3795)

``` {r Loggerhead Forward +3 Model}
#rest
cc451<-glmer(ccnest~rest+sand+prot+(1|Beach), data=nest, family ="poisson")
cc451

#light
cc452<-glmer(ccnest~light+sand+prot+(1|Beach), data=nest, family ="poisson")
cc452

#humpop
cc453<-glmer(ccnest~sand+prot+humpop+(1|Beach), data=nest, family ="poisson")
cc453
```
#avgsst
cc455<-glmer(ccnest~+sand+prot+avgsst+(1|Beach), data=nest, family ="poisson")

# reg
cc456<-glmer(ccnest~+sand+prot+reg+(1|Beach), data=nest, family ="poisson")

```
The minimum model, plus region, prot, and sand yielded lowest AIC value for FS
(1923.6229)
+4 models did not improve the AIC value from backwards selection, therefore
model selection was halted and best model from backwards selection was
chosen.

Final Loggerhead Model is: ccnest~prot+humpop+angle+avgsst+sand+(1|Beach)
```

```
```{r Final Loggerhead Model}
ccfin<-glmer(ccnest~prot+humpop+reg+avgsst+sand+(1|Beach), data=nest, family ="poisson")
summary(ccfin)
install.packages("coefplot")
install.packages("labeling")
library(labeling)
library(coefplot)
coefplot.glm(ccfin)
```

```
```{r Loggerhead Prediction Plot}
predcc<-predict(ccfin)
predspcc<-as.data.frame(cbind(coordinates(nestsp), predcc))
pred = predspcc[which(!duplicated(predspcc[1:2])), ]

library(rgdal)
#xy<-data.frame(cbind(predspcc$lon, predspcc$lat,predspcc))
coordinates(predspcc)<--lon+lat
proj4string(predspcc)<-proj4string(KFLr)# "+proj=utm +zone=17s+
ellps=WGS84")
plot(predspcc)

library(sp)
library(gstat)
FLSP<-SpatialPoints(predspcc)

x.range <- as.integer(range(FLSP@coords[, 1]))
y.range <- as.integer(range(FLSP@coords[, 2]))
x.range
y.range

#x range= -118660, 596263
#y range= 2713405, 3383997

#x.range <- c(-128000, 60000)
#y.range <- c(2720000, 3400000)

grd <- expand.grid(x = seq(from = x.range[1]-100000, to = x.range[2]+100000, by = 12000), y = seq(from = y.range[1]-100000, to = y.range[2]+100000, by = 12000))
coordinates(grd)<-~x+y
plot(grd, cex = .4)
points(FLSP, pch = 1, col = "red", cex = 1)

FLvar <- variogram(predspcc$predcc ~ 1, data=FLSP, locations = FLSP)
plot(FLvar)

vgm()

FLfit = fit.variogram(FLvar, vgm(nugget=1.6, "Gau", psill=6, range=280000),fit.sills = TRUE, fit.ranges = TRUE)
FLfit

plot(FLvar, model=FLfit, as.table=TRUE)

library(raster)
ccpred <- krig(predspcc$predcc ~ 1, locations=FLSP, newdata=grd, FLfit)
ccpred

ccrast<-rasterFromXYZ(ccpred)
crs(ccrast) <- "+proj=utm +zone=17s ellps=WGS84"
require(rgdal)
spTransform(ccrast, CRS("+proj=longlat"))

#pal<-choose_palette()

cols<-colorspace::heat_hcl(200, c=c(35,95), l=c(15,90), h=c(300,75), power=1)
plot(ccrast, col=cols)

library(maptools)
data("wrld_simpl")
flor<-crop(wrld_simpl, c(-88, -79, 24, 31))
llflor<-spTransform(flor, crs(ccrast))
plot(llflor, add=T, col="darkgreen")

2. Green Nesting (Chelonia mydas)
```
{r Green Saturation Model}
library(lme4)
cmsat<-glmer(cmnest~prot+rest+humpop+reg+angle+avgsst+sand+light+(1|Beach), data=nest, family ="poisson")
summary(cmsat)
```

```
{r Green Minimum Model}
cmmin<-glmer(cmnest~1+(1|Beach), data=nest, family ="poisson")
cmmin
```

Saturated model had lowest AIC (1066.682), so I begin with backward selection.

```
{r Green Backward +7 Model}
#-prot
cm1<-glmer(cmnest~rest+humpop+reg+angle+avgsst+sand+light+(1|Beach), data=nest, family ="poisson")
cm1
#-rest
cm2<-glmer(cmnest~prot+humpop+reg+angle+avgsst+sand+light+(1|Beach), 
    data=nest, family ="poisson")

cm2

# -humpop

cm3<-glmer(cmnest~prot+rest+reg+angle+avgsst+sand+light+(1|Beach), 
    data=nest, family ="poisson")

cm3

# -reg

cm4<-glmer(cmnest~prot+rest+humpop+angle+avgsst+sand+light+(1|Beach), 
    data=nest, family ="poisson")

cm4

#-angle

cm5<-glmer(cmnest~prot+rest+humpop+reg+avgsst+sand+light+(1|Beach), 
    data=nest, family ="poisson")

cm5

#-avgsst

cm6<-glmer(cmnest~prot+rest+humpop+reg+angle+sand+light+(1|Beach), 
    data=nest, family ="poisson")

cm6

#-sand

cm7<-glmer(cmnest~prot+rest+humpop+reg+angle+light+(1|Beach), data=nest, 
    family ="poisson")

cm7

#-light

cm8<-glmer(cmnest~prot+rest+humpop+reg+angle+sand+(1|Beach), data=nest, 
    family ="poisson")

cm8

``` removal of prot resulted in lowest AIC (1065.2603).

```
Removal of rest resulted in lowest AIC (1063.8852)

```
## +5 Green Backward Model
# -humpop
cm12 <- glmer(cmnest ~ rest + reg + angle + avgsst + sand + light + (1|Beach), data=nest, family="poisson")

# -reg
cm13 <- glmer(cmnest ~ rest + humpop + angle + avgsst + sand + light + (1|Beach),
               data=nest, family="poisson")

# -angle
cm14 <- glmer(cmnest ~ rest + humpop + reg + avgsst + sand + light + (1|Beach),
               data=nest, family="poisson")

# -avgsst
cm15 <- glmer(cmnest ~ rest + humpop + reg + angle + sand + light + (1|Beach),
               data=nest, family="poisson")

# -sand
cm16 <- glmer(cmnest ~ rest + humpop + reg + angle + avgsst + light + (1|Beach),
               data=nest, family="poisson")

# -light
cm17 <- glmer(cmnest ~ rest + humpop + reg + angle + avgsst + sand + light + (1|Beach),
               data=nest, family="poisson")

```

```r
```
Further removal of parameters failed to improve the model AIC.

Running best model: cmnest~humpop+reg+angle+avgsst+sand+light+(1|beach)

Does forward selection improve the model?

```
{r Green Forward +1 Model}
#prot
cm1<-glmer(cmnest~prot+(1|Beach), data=nest, family ="poisson")

cm1

#rest
cm2<-glmer(cmnest~rest+(1|Beach), data=nest, family ="poisson")

cm2

#humpop
cm3<-glmer(cmnest~humpop+(1|Beach), data=nest, family ="poisson")
```
The addition of reg improved the AIC from the min model (1106.6277)

```r
# Green Forward +2 Model
```

```r
#prot
cm41<-glmer(cmnest~prot+reg+(1|Beach), data=nest, family ="poisson")
```

```r
#rest
cm42<-glmer(cmnest~rest+reg+(1|Beach), data=nest, family ="poisson")
```

```r
#humpop
cm43<-glmer(cmnest~humpop+reg+(1|Beach), data=nest, family ="poisson")
```

```r
#angle
cm44<-glmer(cmnest~reg+angle+(1|Beach), data=nest, family ="poisson")
```
The addition of sand improved the AIC from previous (1082.562)
```r
```
```
The addition of avgsst improved the AIC from previous (1074.7433)

```
```{r Green Forward +4 Model}
#prot
cm4651<-glmer(cmnest~prot+reg+avgsst+sand+(1|Beach), data=nest, family ="poisson")
cm4651

#rest
cm4652<-glmer(cmnest~rest+reg+avgsst+sand+(1|Beach), data=nest, family ="poisson")
cm4652

#humpop
cm4653<-glmer(cmnest~humpop+reg+avgsst+sand+(1|Beach), data=nest, family ="poisson")
cm4653

#angle
cm4654<-glmer(cmnest~reg+angle+avgsst+sand+(1|Beach), data=nest, family ="poisson")
cm4654

#light
cm4655<-glmer(cmnest~reg+avgsst+sand+light+(1|Beach), data=nest, family ="poisson")
cm4655
```

The addition of angle improved the AIC from previous (1068.758)

```
```{r Green Forward +5 Model}
#prot
cm46541<-glmer(cmnest~prot+reg+angle+avgsst+sand+(1|Beach), data=nest, family ="poisson")
cm46541

#rest
cm46542<-glmer(cmnest~rest+reg+angle+avgsst+sand+(1|Beach), data=nest, family ="poisson")
cm46542
The addition of light improved the AIC from previous (1066.1693); however, this is not an improvement from the model found by backward selection.

Final Green Model is: cmnest~humpop+reg+angle+avgsst+sand+light+(1|Beach)

```
```
```
```
# x range = -118660, 596263
# y range = 2713405, 3383997

# x.range <- c(-128000, 60000)
# y.range <- c(2720000, 3400000)

grd <- expand.grid(x = seq(from = x.range[1]-100000, to = x.range[2]+100000, by = 12000), y = seq(from = y.range[1]-100000, to = y.range[2]+100000, by = 12000))
coordinates(grd) <- x+y
plot(grd, cex = .4)
points(FLSP, pch = 1, col = "red", cex = 1)

FLvar <- variogram(predspcm$predcm ~ 1, data=FLSP, locations = FLSP)
plot(FLvar)

FLfit = fit.variogram(FLvar, vgm(nugget=4, "Gau", psill=14, range=200000), fit.sills = TRUE, fit.ranges = TRUE)
FLfit

plot(FLvar, model=FLfit, as.table=TRUE)

library(raster)

cmpred <- krige(predspcm$predcm ~ 1, locations=FLSP, newdata=grd, FLfit)

# cmpred

cmrast <- rasterFromXYZ(cmpred)
cmrast[cmrast < 0] <- 0
crs(cmrast) <- "+proj=utm +zone=17s+ ellps=WGS84"
require(rgdal)
spTransform(cmrast, CRS("+proj=longlat"))

# pal <- choosePalette()
cols<-colorspace::heat_hcl(200, c=c(35,95), l=c(15,90), h=c(300,75), power=1)
plot(cmra$t, col=cols)

library(maptools)
data("wrld_simpl")
flor<-crop(wrld_simpl, c(-88, -79, 24, 31))
llflor<-spTransform(flor, crs(cmra$t))
plot(llflor, add=T, col="darkgreen")

3. Leatherback Nesting (Dermochelys coriacea)
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```
The removal of humpop results in the lowest AIC (537.4525)

```
#-prot
dc31<-glmer(dcnest~rest+reg+angle+avgsst+sand+light+(1|Beach), data=nest, family ="poisson")
dc31

#-rest
dc32<-glmer(dcnest~prot+reg+angle+avgsst+sand+light+(1|Beach), data=nest, family ="poisson")
dc32
```
The removal of light results in the lowest AIC (535.5704)
The removal of rest results in the lowest AIC (533.7721)

```
#-prot
dc3721<-glmer(dcnest~reg+angle+avgsst+sand+(1|Beach), data=nest, family ="poisson")
dc3721

#-reg
dc3722<-glmer(dcnest~prot+angle+avgsst+sand+(1|Beach), data=nest, family ="poisson")
dc3722

#-angle
dc3723<-glmer(dcnest~prot+reg+avgsst+sand+(1|Beach), data=nest, family ="poisson")
dc3723

#-avgsst
dc3724<-glmer(dcnest~prot+reg+angle+sand+(1|Beach), data=nest, family ="poisson")
dc3724

#-sand
The removal of prot results in the lowest AIC (532.7665)

```
{r Leatherback Backward +3 Model}

#-reg
dc37211<-glmer(dcnest~angle+avgsst+sand+(1|Beach), data=nest, family ="poisson")
dc37211

#-angle
dc37212<-glmer(dcnest~reg+avgsst+sand+(1|Beach), data=nest, family ="poisson")
dc37212

#-avgsst
dc37213<-glmer(dcnest~reg+angle+sand+(1|Beach), data=nest, family ="poisson")
dc37213

#-sand
dc37214<-glmer(dcnest~reg+angle+avgsst+(1|Beach), data=nest, family ="poisson")
dc37214
```

The removal of further parameters did not improve the model AIC.

Running best model: dcnest~reg+angle+avgsst+sand+(1|Beach)

Forward selection to ensure this is the best model

```
{r Leatherback Forward +1 Model}

#prot
dc1<-glmer(dcnest~prot+(1|Beach), data=nest, family ="poisson")
dc1

#rest
dc2<-glmer(dcnest~rest+(1|Beach), data=nest, family ="poisson")
```
Best FS model was the addition of angle (552.2627)
Best FS model was the addition of sand (545.8454)
Best FS model was the addition of reg (537.5019)

Model selecton stopped because the best model chosen by backwards selection incorporated 4 parameters and was better than the +3 model.

Final Leatherback Model is: dcnest~reg+angle+avgsst+sand+(1|Beach)

```
```
```r Final Leatherback Model}
library(lme4)
dcfin<-glmer(dcnest~reg+angle+avgsst+sand+(1|Beach), data=nest, family = "poisson")
summary(dcfin)
coefplot.glm(dcfin)
```}
```
```r Leatherback Prediction Plot}
preddc<-predict(dcfin)
predspdc<-as.data.frame(cbind(coordinates(nestsp), preddc))
pred = predspdc[which(!duplicated(predspdc[1:2])), ]

library(rgdal)
coordinates(predspdc)<-~lon+lat
proj4string(predspdc)<-proj4string(KFLr)# "+proj=utm +zone=17s +
ellps=WGS84"
plot(predspdc)
```
```r

library(sp)
library(gstat)
FLSP<-SpatialPoints(predspdc)

x.range <- as.integer(range(FLSP@coords[, 1]))
y.range <- as.integer(range(FLSP@coords[, 2]))
x.range
y.range

#x range= -118660, 596263
```
# y range = 2713405, 3383997
# x.range <- c(-128000, 60000)
# y.range <- c(2720000, 3400000)

grd <- expand.grid(x = seq(from = x.range[1]-100000, to = x.range[2]+100000, by = 12000), y = seq(from = y.range[1]-100000, to = y.range[2]+100000, by = 12000))
coordinates(grd) <- ~x+y
plot(grd, cex = .4)
points(FLSP, pch = 1, col = "red", cex = 1)

FLvar <- variogram(predspdc$preddc ~ 1, data=FLSP, locations = FLSP)
plot(FLvar)

vgm()

FLfit = fit.variogram(FLvar, vgm(nugget=1, "Gau", psill=15, range=180000), fit.sills = TRUE, fit.ranges = TRUE)

FLfit
plot(FLvar, model=FLfit, as.table=TRUE)

library(raster)
dcpredd <- krigge(predspdc$preddc ~ 1, locations=FLSP, newdata=grd, FLfit)

dcrast<-rasterFromXYZ(dcpredd)
dcrast[dcrast < 0] <- 0
crs(dcrast) <- "+proj=utm +zone=17s ellps=WGS84"
require(rgdal)
spTransform(dcrast, CRS("+proj=longlat"))

#pal<-choose_palette()

cols<-colorspace::heat_hcl(200, c=c(35,95), l=c(15,90), h=c(300,75), power=1)
plot(dcrast, col=cols)
image(dcrast, col=cols)
library(maptools)
data("wrld_simpl")
flor<-crop(wrld_simpl, c(-88, -79, 24, 31))
llflor<-spTransform(flor, crs(dcrast))
plot(llflor, add=T, col="darkgreen")

D. Posterior Predictive Simulation

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```
E. Sensitivity Analysis

1. Loggerhead Model
```{r Loggerhead Sensitivity Analysis}
ccsens<-nest[,c(1,8,11,13,17,35,36)] #put in columns used in the model
cccor<-cor(ccsens)
round(cccor, 2)
cccm<-cor(ccsens, use="complete.obs")
lower.tri(cccm, diag=FALSE)
upper.tri(cccm, diag=FALSE)
uppercc<-cccm
uppercc[upper.tri(cccm)]<-
uppercc<as.data.frame(uppercc)
uppercc
lowercc<-cccm
lowercc[lower.tri(cccm)]<-
lowercc<as.data.frame(lowercc)
lowercc
install.packages("xtable")
library(xtable)
print(xtable(uppercc), type="html")
#For visualization as table, put output into HTML viewer at
   http://codebeautify.org/htmlviewer/
```  

2. Green Model
```{r Green Sensitivity Analysis}
cmsens<-nest[,c(1,8,11,20,25,34,35)] #put in columns used in the model
cmcor<-cor(cmsens)
round(cmcor, 2)
cmcm<-cor(cmsens, use="complete.obs")
lower.tri(cmcm, diag=FALSE)
upper.tri(cmcm, diag=FALSE)
uppercm<-cmcm
uppercm[upper.tri(cmcm)]<-
uppercm<as.data.frame(uppercm)
uppercm```
3. Leatherback Model

```r
Leatherback Sensitivity Analysis

dcsens <- c(1, 11, 23, 34, 35, 36) # put in columns used in the model
dcor <- cor(dcsens)
round(dcor, 2)
dccm <- cor(dcsens, use="complete.obs")
lower.tri(dccm, diag=FALSE)
upper.tri(dccm, diag=FALSE)
upperdc <- dcm
upperdc[upper.tri(dccm)] <- ""
upperdc <- as.data.frame(upperdc)
upperdc
lowerdc <- dcm
lowerdc[lower.tri(dccm)] <- ""
lowerdc <- as.data.frame(lowerdc)
lowerdc
install.packages("xtable")
library(xtable)
print(xtable(upperdc), type="html")
# For visualization as table, put output into HTML viewer at
   http://codebeautify.org/htmlviewer/
```

III. Rho Hat Analyses
A. Raster formation

1. Lighting Ordinances
```
library(raster)
#FL Counties Shapefile
us <- getData('GADM', country='USA', level=2)
plot(us)
fl <- subset(us, NAME_1 == "Florida")
plot(fl)
```

###################################################################
###
#Shapefile to Raster Converter
#by Amy Whitehead (https://www.r-bloggers.com/converting-shapefiles-to-rasters-in-r/)
library(maptools)
library(raster)

shp2raster <- function(shp, mask.raster, label, value, transform = FALSE, proj.from = NA,
                       proj.to = NA, map = TRUE) {
  require(raster, rgdal)
  # use transform==TRUE if the polygon is not in the same coordinate system as
  # the output raster, setting proj.from & proj.to to the appropriate
  # projections
  if (transform == TRUE) {
    proj4string(shp) <- proj.from
    shp <- spTransform(shp, proj.to)
  }
  # convert the shapefile to a raster based on a standardised background
  # raster
  r <- rasterize(shp, mask.raster)
  # set the cells associated with the shapfile to the specified value
  r[!is.na(r)] <- value
  # merge the new raster with the mask raster and export to the working
  # directory as a tif file
  r <- mask(merge(r, mask.raster), mask.raster, filename = label, format = "GTiff",
            overwrite = T)
# plot map of new raster
if (map == TRUE) {
  plot(r, main = label, axes = F, box = F)
}

names(r) <- label
return(r)

###

## Creating Mask of State
setwd("C:/Users/Schelli/Documents/MS_Thesis/Nesting/Data/Rho Hat")
light <- read.csv("Light.csv")
library(spatstat)
library(sp)
library(maptools)
library(rgdal)
library(raster)
library(rgeos)
library(stats)
library(rworldmap)
library(maps)
library(RColorBrewer)

# Defining bounding box
x <- c(-79,-79,-88,-88)
y <- c(31,24,31,24)
xy <- cbind(x,y)
S <- SpatialPoints(xy)
bbox(S)

# Identify coordinates
lon <- data.frame(light$Lon)
lon

lon <- data.frame(lon)
lon
lat <- data.frame(light$Lat)
lat
coords = cbind(lon, lat)
coords

# create SpatialPoints
sp = SpatialPoints(coords)

# create a SpatialPointsDataFrame
cc<-data.frame(light$Light)
spdf = SpatialPointsDataFrame(sp, cc)
spdf
spplot(spdf)

#Plotting Florida coastline
e=extent(-87.42732, -80.03288, 24.53098, 30.80007)
data(coastsCoarse)
data(countriesLow)
countriesLow <-spTransform(countriesLow, CRS("+proj=longlat +
datum=WGS84"))
Coast= crop(countriesLow,e)

#Plotting Nesting Density
spdfppp<-as(spdf, "ppp")
summary(spdfppp)

w <- owin(xrange=c(-88,-79), yrange=c(24,31))
NewSppp<-spdfppp[w]

plot(density(NewSppp), main= "Loggerhead Nesting Density")
plot(Coast, add=T)
plot(NewSppp, which.marks="cc", col="white",add=T)

#Converting to raster
nestras=raster(density(NewSppp))
plot(nestras)

#Getting land shapefiles
us<-getData('GADM', country='USA', level=1)
plot(us)
fl<-subset(us,NAME_1=="Florida")
#Plotting density and shapefile together
plot(nestras)
plot(fl, add=T)

#Creating mask to mask land in
landmask=mask(nestras, fl)
plot(landmask); plot(fl, add=T)

# Creating a plain raster of the state.
plain <- shp2raster(shp = fl[grepl(c("Florida"), fl$NAME_2, )],
mask.raster = landmask, label = "Lighting Ordinance", transform = FALSE,
value = 1)

# Designating counties with ordinances as value of 3, the rest as 0.
lightpres <- shp2raster(shp = fl[grepl(c("Bay|Brevard|Broward|Charlotte|Collier|Escambia|Flagler|Franklin|Gulf|Indian River|Lee|Martin|Monroe|Nassau|Palm Beach|Santa Rosa|Saint Johns|Saint Lucie|Volusia|Walton"), fl$NAME_2), ], mask.raster = plain, label = "Lighting Ordinances",
transform = FALSE, value = 3)

#For some reason, a value of 3 works for multiple locations, but not a value of 1

---

2. Population Data
```
library(raster)
setwd("C:/Users/Schelli/Documents/MS_Thesis/Nesting/Data/Rho Hat")
pop.dens <- raster("usads00ag.asc")
projection(pop.dens) <- "+proj=longlat +ellps=WGS84"

e <- extent(-88,-79,24,31)

pop.dens <- crop(pop.dens, e)
```
plot(pop.dens)

```
3. Sea Surface Temperature (2011-2014 Average)
```{r}
setwd("C:/Users/Schelli/Documents/MS_Thesis/Nesting/Data/CoastWatch
     AVHRR SST 1Km/Annual TIFFs/Processed"/
library(readr)
library(raster)
library(sp)
library(rgdal)
sst11<-raster("ProcessedAVHCW_2011001_ANNUAL_MULTISAT_SSTMASK
     ED_EC_1KM.tif")
sst12<-raster("ProcessedAVHCW_2012001_ANNUAL_MULTISAT_SSTMASK
     ED_EC_1KM.tif")
sst13<-raster("ProcessedAVHCW_2013001_ANNUAL_MULTISAT_SSTMASK
     ED_EC_1KM.tif")
sst14<-raster("ProcessedAVHCW_2014001_ANNUAL_MULTISAT_SSTMASK
     ED_EC_1KM.tif")
sstavg<-mosaic(sst11, sst12, sst13, sst14, fun=mean)
plot(sstavg)
```

B. Point-Pattern Intensity Analysis

```{r}
setwd("C:/Users/Schelli/Documents/MS_Thesis/Nesting/Data/Rho Hat")
strand<-read.csv("Strandings.csv")

# Identify coordinates
lon1<-data.frame(strand$X)
lat1<-data.frame(strand$Y)
lat1
cords1 = cbind(lon1, lat1)
cords1
plot(cords1)
sp1 = SpatialPoints(cords1)
spdfppp1<-as(sp1, "ppp")

###############################################################

#Temperature

library(spatstat)
newproj <- "+proj=longlat +datum=WGS84"
pr2 <- projectRaster(sstavg, crs=newproj, res=0.1)
sstim<-as.im(pr2)

Z<- sstim
plot(Z, lwd=2)
contour(Z, add=TRUE)
b<- quantile(Z,probs=(0:4)/4)
Zcut <- cut(Z, breaks = b, labels=1:4)
V<- tess(image=Zcut)
plot(V)
plot(spdfppp1, add=TRUE, pch= "+")
qb<- quadratcount(spdfppp1,tess = V)
qb

plot(rhohat(spdfppp1, sstim))

###############################################################

#Population Density

pr3 <- projectRaster(pop.dens, crs=newproj, res=0.1)
popim<-as.im(pr3)

Z<- popim
b<- quantile(Z,probs=(0:6)/6)
Zcut <- cut(Z, breaks = b, labels=1:6)
V<- tess(image=Zcut)
plot(V)
plot(spdfppp2, add=TRUE, pch= "+")

qb<- quadratcount(spdfppp2, tess = V)
qb

#install.packages("locfit")
library("locfit")
plot(rhohat(spdfppp1, popim, smoother = "local"))

#Subsetting to determine if modern lighting ordinances can be used
strand2013<- subset(strand, strand$YEAR_ >= 2013 )
strand1987<- subset(strand, strand$YEAR_ <= 1987)
lon1<- data.frame(strand2013$X)
lon2<- data.frame(strand1987$X)

lat1<- data.frame(strand2013$Y)
l
lat2<- data.frame(strand1987$Y)

cords2 = cbind(lon1, lat1)
cords3 = cbind(lon2, lat2)

plot(coords2)
plot(coords3)

sp2 = SpatialPoints(coords2)
spdfppp2<- as(sp2, "ppp")
sp3 = SpatialPoints(coords3)
spdfppp3<- as(sp3, "ppp")

#Lighting Ordinances
pr4 <- projectRaster(lightpres, crs=newproj, res=0.1)
lighitim<- as.im(pr4)

Z<- lighitim
b<- quantile(Z,probs=(0:2)/2)
Zcut <- cut(Z, breaks = b, labels=1:2)
V<- tess(image=Zcut)
plot(V)
plot(spdfppp1, add=TRUE, pch= "+")

qb1<- quadratcount(spdfppp2, tess = V)
```R
qb1
qb2 <- quadratcount(spdfppp3, tess = V)
qb2
qb3 <- quadratcount(spdfppp1, tess = V)
qb3

plot(intensity(qb1, image = T))
plot(intensity(qb2, image = T))
plot(intensity(qb3, image = T))
```

```
```
```
```R
# Defining bounding box
x <- c(-79,-79,-88,-88)
y <- c(31,24,31,24)
xy <- cbind(x,y)
S <- SpatialPoints(xy)
```
bbox(S)

# Identify coordinates
lon <- data.frame(nest$Lon)
lon
lon <- data.frame(lon)
lon
lat <- data.frame(nest$Lat)
lat
coords = cbind(lon, lat)
coords

# create SpatialPoints
sp = SpatialPoints(coords)

# create a SpatialPointsDataFrame
cc <- data.frame(nest$NestTot)
spdf = SpatialPointsDataFrame(coords, cc)
spdf = SpatialPointsDataFrame(sp, cc)
spdf
spplot(spdf)

# Plotting Florida coastline
e = extent(-87.42732, -80.03288, 24.53098, 30.80007)
data(coastsCoarse)
data(countriesLow)
countriesLow <- spTransform(countriesLow, CRS("+proj=longlat + datum=WGS84"))
Coast <- crop(countriesLow, e)

# Plotting Nesting Density
spdfppp <- as.spdf, "ppp")
summary(spdfppp)
w <- owin(xrange=c(-88, -79), yrange=c(24, 31))
NewSppp <- spdfppp[w]
plot(density(NewSppp), main = "Total Nesting Density")
plot(Coast, col = "tan", add = T)

# Plotting Nesting Beaches
library(readr)
beaches <- nest
Protected <- subset(beaches, beaches$Protected == 1 & beaches$Restricted == 1)
NP <- subset(beaches, beaches$Protected == 0 & beaches$Restricted == 0)
NP2 <- subset(beaches, beaches$Protected == 1 & beaches$Restricted == 0)
NP3 <- subset(beaches, beaches$Protected == 0 & beaches$Restricted == 1)
NPtotal <- rbind(NP, NP2, NP3)

points(NPtotal$Lon, NPtotal$Lat, col = "white", cex = 1, pch = 20)
points(Protected$Lon, Protected$Lat, col = "green", cex = 1, pch = 20)

...
Table A-1. Table of Data Sets Used. This table contains the data used for both model formulation (white) and point-pattern intensity (blue) analyses in the present study. Data that were utilized in both analyses are shown in purple.

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Title</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prot</td>
<td>Presence of protective measures</td>
<td>binary presence/absence data for enforcement of protective measures on Florida beaches</td>
<td>Data aggregated from Florida County Parks and Recreation Departments</td>
</tr>
<tr>
<td>Rest</td>
<td>Presence of access restrictions</td>
<td>binary presence/absence data for access restrictions (nightly or permanent) on Florida beaches</td>
<td>Data aggregated from Florida County Parks and Recreation Departments</td>
</tr>
<tr>
<td>humpop</td>
<td>Human population of nearest town</td>
<td>counts of human population of town or city closest to a beach</td>
<td>2010 U.S. Census:</td>
</tr>
<tr>
<td>reg</td>
<td>Beach region</td>
<td>categorical geographic region of study beach based on location of county</td>
<td>Regions determined using Google Earth</td>
</tr>
<tr>
<td>angle</td>
<td>Beach angle</td>
<td>numerical beach angle with respect to north in degrees</td>
<td>Angles calculated using Google Earth</td>
</tr>
<tr>
<td>avgsst</td>
<td>Annual average sea surface temperature</td>
<td>numerical average sea surface temperature extracted from raster derived</td>
<td>Rasters from AVHRR satellite for NOAA CoastWatch</td>
</tr>
<tr>
<td>from multiple annual average SST rasters (2011-2014)</td>
<td>Original median $\phi$ values from Regional Offshore Sand Source Inventory:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td></td>
<td></td>
</tr>
<tr>
<td>sand</td>
<td>Median $\phi$ values</td>
<td>numerical median $\phi$ values for a given beach (sand grain size) from kriged rasters</td>
<td></td>
</tr>
<tr>
<td>light</td>
<td>Presence of lighting ordinance</td>
<td>binary presence/absence data for enforced lighting ordinances on Florida beaches</td>
<td></td>
</tr>
<tr>
<td>nest</td>
<td>Sea turtle nesting counts</td>
<td>count data for total nesting numbers of loggerhead, green, and leatherback turtles (2011-2015)</td>
<td></td>
</tr>
<tr>
<td>strand</td>
<td>Sea turtle stranding occurrences</td>
<td>spatial occurrence points of stranded turtles (1986-2014)</td>
<td></td>
</tr>
<tr>
<td>lightpres</td>
<td>Presence of county-wide lighting ordinance</td>
<td>presence/absence raster of county-wide lighting ordinances</td>
<td></td>
</tr>
</tbody>
</table>