SPATIAL AND TEMPORAL MODELING OF SEA TURTLE INTERACTIONS WITH THE PELAGIC LONGLINE FISHERY IN THE WESTERN NORTH ATLANTIC

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The incidental catch of sea turtles, termed bycatch, in the pelagic longline fishery has come to the forefront of issues for fisheries management. Loggerhead (*Caretta caretta*) and leatherback (*Dermochelys coriacea*) sea turtles are both listed on the IUCN red list as endangered or critically endangered. Because of this classification and the frequency of interactions with longline fisheries, it is important to understand the dynamics of these interactions. This study quantifies spatial and temporal patterns of sea turtle distributions to identify potential processes influencing their locations.

A Ripley's K-function analysis was employed to determine spatial and temporal patterns, as well as the space-time interactions, of sea turtle bycatch distributions within the pattern of the pelagic fishery distribution. Results indicate that loggerhead and leatherback sea turtle catch distributions appear to change seasonally, with spatial clustering appearing from July through October. Significant space-time interactions indicate that spatial and temporal patterns are likely changing on a relatively fine scale (1 degree and 1-3 days).

Analysis of bycatch rates of sea turtles in relation to water temperature in three management regions of the Atlantic indicated that the probability of capturing sea turtles varies by temperature and region. The catch rates of swordfish and the bycatch rates of sea turtles were examined in relation to sea surface temperature (SST) and thermal fronts. The results show that all four variables were significant predictors of

the number of loggerhead and leatherback sea turtles captured in the longline fishery for both years. Furthermore, water temperature was also a significant predictor of swordfish catches for both years.

A Bayesian model was constructed incorporating spatial auto-correlation by using the catch information from the preceding day(s) to inform the predictions of where sea turtles may be caught within the fishery for the current day using kriging. These predictions are combined with the predictions based solely on spatial covariates (e.g. SST) in a variance weighted updating model. This final model suggests that with more observed trips, we will likely be able to make near real-time predictions to specify the likelihood of catching sea turtles for a given fishing location.

BIOGRAPHICAL SKETCH

Beth Gardner grew up in Lone Pine, Pennsylvania and went to Allegheny College in Meadville, PA. She received her Bachelors of Science in Math and Environmental Science in May 1999. Upon graduation, she entered the Department of Natural Resources at Cornell University and has not left since! But now, she must finally start a job and for the first time in 20 some years, she will no longer be a student.

Beth is passionate about the environment, equality, equity, and life in general. Beth has a really great dog, Cali, who has been with her since she first came to Ithaca in 1999. Beth likes to hike, play tennis and softball, and enjoys spicy food. As a side note, Beth still feels that people should not be allowed to eat tuna fish in a can. She would classify it as the worst smell ever, followed closely by pickles (first noted in Beth's biographical sketch for her M.S.).

Most people are eagerly groping for some medium, some way in which they can bridge the gap between their morals and their practices.

--Saul Alinsky

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Introduction

Managing and protecting the world's oceans is a difficult task, especially with our lack of knowledge of many pelagic and highly migratory species. Claims have been made that human activities are resulting in the depletion of the world's fish stocks and a significant reduction in the ocean's top predators (Myers and Worm 2003). One issue of fisheries management that has come to the forefront, and is related to all fisheries, is the incidental capture of a species not intentionally targeted, termed bycatch (Hall 1996). In some cases, bycatch can be profitable and sold at markets. However, bycatch can also be time-consuming and harmful to the fishery or the non-target species that are incidentally caught, such as dolphins, pilot whales, sea birds, and sea turtles.

In more recent years, the bycatch of sea turtles in the pelagic longline fishery has become an issue of great concern (Spotila et al. 2000, Lewison et al. 2004, Kobayashi and Polovina 2005). Pelagic longline fishing, where swordfish (*Xiphias gladius*), tunas (*Thunnus spp*.), and sometimes sharks (*Squaliformes*) are targeted, is a large industry worldwide and the economic impacts are considerable. Because of the magnitude of the fishing operation, a single fishing trip of a USA vessel costs roughly thousands of dollars each day to cover expenses. Therefore, fishermen will travel 2000 km or more per trip to find fish. In the USA, the pelagic longline fishery uses gear that typically consists of a single monofilament line, sometimes > 50 km in length. From this single line, hundreds, and possibly thousands, of baited hooks hang vertically in the water column. The pelagic longline fishery fishes in the upper water column of the open seas; generally lines set for swordfish are shallower then the lines set for tuna. This difference in depths appears to substantially affect the bycatch of sea turtles, probably because the turtles spend more of their time in the surface waters.

In the Atlantic swordfish fishery, two species of sea turtles are most affected: the loggerhead (*Caretta caretta*) and the leatherback (*Dermochelys coriacea*). Loggerhead turtles are listed globally as endangered and leatherback turtles are listed as critically endangered on the World Conservation Union Red List of Threatened Species (IUCN 2004). Leatherbacks are pelagic throughout their life and are captured in the fishery as subadults and adults (Watson et al. 2005). Loggerheads, on the other hand, have more distinct oceanic and coastal life stages, beginning with a pelagic, oceanic stage that lasts about a decade. Thus, the loggerheads captured in the open ocean tend to be in an early life stage (Watson et al. 2005). Loggerhead turtles have been known to dive to about 200 m in depth, but spend most of their time in between 0 and 50 m depths. Leatherbacks can dive much deeper than loggerheads, occasionally reaching depths exceeding 600 m, but spend a lot time in the 0 to 50 m depths (Hays et al. 2004). The primary diet of the leatherback is jellyfish and correlations between the two have been documented in the open ocean (Houghton et al. 2006).

With differences in size, diving ability, and foraging behavior, it is not surprising that there are several fundamental differences between the two species with respect to their interactions with the longline fishery. For example, fishermen have reported that loggerheads seem to be caught in groups, whereas leatherbacks tend to be caught individually (personal communication, John Caldwell). Loggerhead turtles appear to be more likely than leatherbacks to take the bait from a longline (Watson et al. 2005). There is a high occurrence of loggerheads directly hooked through the beak or mouth, whereas only a small portion of leatherbacks are hooked in the mouth. Leatherbacks are often hooked externally and a large portion also are entangled in the line.

There have been a number of studies on sea turtle bycatch in the longline fishery (Hoey 1998, Witzell 1999, NMFS 2001, Watson et al. 2005, Gilman et al

2006); however, most have not really questioned the scale at which the data analysis is conducted nor have they really considered the non-linear effects of covariates on the results. In order to more effectively analyze sea turtle bycatch data in the longline fisheries, a main question that must be answered is: what are the appropriate spatial and temporal scales for detecting patterns within the bycatch data and what are the appropriate analytical tools?

This body of work sets out to address this question as well as to better understand the relationships of sea turtle catch rates to oceanic features. Each of the chapters has a different area of focus, from point pattern analysis to analysis of oceanic variables with generalized additive models, aimed at revealing the scales at which the underlying processes may be occurring.

Chapter one analyzes the longline fisheries bycatch data as a spatial point process. The objective of this chapter is to determine if clustering patterns in sea turtle captures existed either spatially or temporally. The results from data in the Northeast Distant waters indicates that sea turtle catches do appear to be clustered spatially on a 1 to 3 day timeframe, which suggests that the underlying mechanism that drives sea turtle distribution patterns may be changing on a similar time scale. Thus, analyses and management actions that correlate bycatch with oceanographic data summarized over longer time frames, such as weekly or monthly, may be inappropriate. Appendix 3 documents the amount of change that occurs in sea surface temperature (SST) over different time frames. The analysis indicates that in certain areas of the ocean, SST for a given location can change by up to 5°C over an 8-day time period. At the same locations, SST changes are much smaller (<1°C) over 2 day time periods. Hence, using oceanic data on a daily basis to analyze daily sea turtle catch data is likely to be more appropriate, and will provide more defined relationships between the two datasets.

Chapter two explores the relationship of sea turtle catches and water temperatures across different spatial regions. Loggerhead sea turtles caught in the Gulf of Mexico may be at a different life or behavioral stages than those caught in the waters of the Grand Banks. If this is the case, the probability of catching a sea turtle at a given temperature may vary by region. The objective of this chapter was to determine if the probability of catching a sea turtle varies by water temperature and by management region. Noting the differences in probability can help to better understand sea turtle dynamics as well as to suggest better management strategies to reduce sea turtle bycatch, such as temperature restrictions on fishing.

Chapter three builds on the former two chapters by analyzing sea turtle and swordfish catch locations in relation to daily SSTs and some related derived variables, such as local differences in SST and distance to thermal fronts. The main objective of this chapter is to find ways to predict sea turtle and swordfish catches based on oceanographic features for which data are readily available, using computed variables that best separate bycatch from target catch. All of these analyses were conducted in a manner that allows for non-linear relationships between independent and dependent variables (Hastie and Tibshirani 1990), which also provided new insight on the patterns of these relationships. SST was found to influence the total catches of both turtle species and swordfish, though other variables, including distance to the smaller thermal front, were only significant predictors for the sea turtle species. Distance to the large thermal front showed potential as an indicator to separate hotspots of sea turtle catches from swordfish.

The final chapter is the capstone of the former and uses the data and determined relationships from the preceding chapters to create a predictive Bayesian model. This chapter incorporates spatial auto-correlation by using the catch information from the preceding day(s) to inform the predictions of where sea turtles

may be caught within the fishery for the current day using kriging (Cressie 1993). Then, these predictions are combined with the predictions based solely on the current day's spatial covariates (SST and other oceanic features) in a variance weighted model. This final chapter suggests that with more data for a given day (e.g. more observed fishing trips), we will likely be able to make near real-time predictions using spatially and temporally explicit modeling to specify the likelihood of catching sea turtles for a given fishing location. For the interested reader, more data visualizations and dataset changes are presented in the appendices (A-F).

The original question we wanted to address was about the appropriate spatial and temporal scales for analyzing sea turtle bycatch data. The results of this work indicate that sea turtles are likely responding to oceanic processes that are changing on fine spatial and temporal scales. This means that to reduce sea turtle interactions with the longline fishery, we must act on a temporal scale of 1 to 3 days, and management or fishing decisions must be made on a smaller spatial scale of less than 100 km. In essence, since fishermen look at each day's remotely sensed data (SST) in order to choose their fishing location, scientists and managers need to do the same in order to make predictions about sea turtle locations.

References:

Cressie, N.A.C. 1993. Statistics for spatial data. John Wiley and Sons, New York.

Gilman, E. et al. 2006. Reducing sea turtle by-catch in pelagic longline fisheries. *Fish and Fisheries*, **7**:2-23.

Hall, M. A., D. L. Alverson, and K. I. Metuzals. 2000. Bycatch: problems and solutions. *Marine Pollution Bulletin* **41**: 204-219.

Hastie, T.J. and R.J. Tibshirani. 1990. Generalized Additive Models. CRC Press. Boca Raton, FL. 336pp.

Hayes, G.C., J.D.R. Houghton, C. Isaacs, R.S. King, C. Lloyd, and P. Lovell. 2004. First records of oceanic dive profiles for leatherback turtles, Dermochelys coriacea, indicate behavioral plasticity associated with long-distance migrations. Animal Behaviour. **67**: 733-734.

Hoey, J. 1998. NEFSC pelagic longline data review and analysis of gear, environmental, and operating practices that influence pelagic longline interactions with sea turtles. Unpublished Report. National Fisheries Institute, Inc., Arlington, VA Final Contract Report NOAA-Contract – 50EANA700063 to National Marine Fisheries Service Northeast Regional Office, Glouster, MA, 32 pp.

Houghton, J.D.R., T.K. Doyle, M.W. Wilson, J. Davenport, G.C. Hayes. 2006. Jellyfish aggregations and leatherback turtle foraging patterns in a temperature coastal environment. *Ecology* **87**: 1967–1972.

International Union for Conservation of Nature and Natural Resources (IUCN). 2004. IUCN redlist of threatened species. Cambridge, UK. Available from http://www.redlist.org/ [accessed October 2006; updated October 2006].

Kobayashi, D.R. and Polovina, J.J. 2005. Evaluation of time-area closures to reduce incidental sea turtle take in the Hawaii-based longline fishery: generalized

additive model (GAM) development and retrospective examination. *NOAA Tech. Memo. NMFS-PIFSC-4* 39p.

Lewison, R.L., S.A. Freeman, and L.B. Crowder. 2004. Quantifying the effects of fisheries on threatened species: the impact of pelagic longlines on loggerhead and leatherback sea turtles. *Ecology Letters* **7**:221-231.

Myers, R.A. and Worm, B. 2003. Rapid worldwide depletion of predatory fish communities. *Nature* **423**: 280-283.

NMFS (National Marine Fisheries Service Southeast Fisheries Science Center). 2001. Stock assessments of loggerhead and leatherback sea turtles and an assessment of the pelagic longline fishery on the loggerhead and leatherback sea turtles of the Western North Atlantic. U.S. Department of Commerce, NOAA Technical Memorandum NMFS-SEFSC-455, 343pp.

Spotila, J. R., R. D.Reina, A. C.Steyermark, P. T. Plotkin, and F. V. Paladino. 2000. Pacific leatherback turtles face extinction. *Nature* **405**:529-530.

Watson, J. W., S. P. Epperly, A. K. Shah, and D. G. Foster. 2005. Fishing methods to reduce sea turtle mortality associated with pelagic longlines. *Canadian Journal of Fisheries and Aquatic Science* **62**: 965-981.

Witzell, W.N. 1999. Distribution and relative abundance of sea turtles caught incidentally by the U.S. pelagic longline fleet in the western North Atlantic Ocean, 1992-1995. *Fisheries Bulletin* **97**:200-211.

Chapter 1

Spatial statistical analysis of bycatch data: patterns of sea turtle bycatch in the North Atlantic

Abstract: Loggerhead (*Caretta caretta*) and leatherback (*Dermochelys coriacea*) sea turtle distributions and movements in offshore waters of the western North Atlantic are not well understood despite continued efforts to monitor, survey, and observe them. Loggerheads are listed globally as an endangered species while leatherbacks are listed as a critically endangered species by the World Conservation Union (IUCN 2004), and thus anthropogenic mortality on these listed species is of elevated interest. One such identified source is the pelagic longline fishery. This study quantifies spatial and temporal patterns of sea turtle distributions to identify potential specific processes influencing their locations. The data examined in this study were from the NOAA Fisheries Atlantic pelagic longline observer program 1992-2003. A Ripley's K-function analysis was employed to determine spatial and temporal patterns, as well as the space-time interactions, of sea turtle bycatch distributions within the pattern of the pelagic fishery distribution. Results indicate that loggerhead and leatherback sea turtle catch distributions appear to change seasonally, with patterns of spatial clustering appearing in the months of July through October; otherwise, the distribution of catches is predominantly random within fishing. However, in certain regions of interest, the loggerhead sea turtle catch distribution shows evidence of temporal patchiness. The space-time interactions indicate that for both species, spatial and temporal patterns are likely different on a relatively finer scale (100 km and 1-3 days). The use of spatial and temporal point pattern analysis, particularly K-function analysis, is a novel way to examine bycatch data that could prove useful to fisheries management.

1. Introduction

Incidental catch of non-targeted species, termed bycatch, is a management concern for all fishing fleets (Hall et al. 2000). One issue facing resource mangers and the fishing industry is the high level of overlap between bycatch species and fishing activity. The nature of the problem is exemplified in the pelagic longline fishery, where baited hooks extend along a line for more than 50 kilometers attracting a variety of targeted and non-targeted species. This persistent problem in the longline fishery, as well as other fisheries, calls for new statistical tools to enable us to separate the target species from bycatch in space and time.

A current area of concern is the bycatch of endangered loggerhead (*Caretta caretta*) and leatherback (*Dermochelys coriacea*) sea turtles in the pelagic longline fishery (Spotila et al. 2000, Lewison et al. 2004a,b, Pinedo and Polcheck 2004). Leatherbacks are pelagic throughout their life and are captured in the fishery as subadults and adults (Watson et al. 2005). Loggerheads, on the other hand, have more distinct pelagic and coastal life stages, beginning with a pelagic stage that lasts about a decade. Thus, the loggerheads captured in the open ocean tend to be in an early life stage (Watson et al. 2005). Due to certain life history traits of sea turtles, especially delayed age until sexual maturity, anthropogenic sources of mortality can have severe impacts on population sizes (Heppell 1998, Heppell et al. 1999). In fact, the bycatch of sea turtles in longline fisheries (predominantly tuna and swordfish) is increasingly cited as a proximate cause for the decline or the failure of loggerhead and leatherback sea turtle populations to recover (Spotila et al. 2000, Lewison et al. 2004a,b, Pinedo and Polcheck 2004). This is confounded by the lack of understanding of sea turtle distributions and movements in pelagic waters, despite continued monitoring efforts in the western North Atlantic (Shoop and Kenney 1992; Epperly et al. 1995; Witzell 1999; Jonsen et al. 2003, James et al. 2005). There is an urgent need for spatially

explicit models to reduce bycatch (Lewison et al. 2004b), and some studies have used pelagic longline observer data to estimate sea turtle catch rates and population changes (Witzell 1999, Lewison et al. 2004b). However, few studies have investigated the spatial and temporal distribution patterns of catch locations with respect to longline fishing, likely because the spatial structure of bycatch and fisheries data presents unique difficulties for analyses.

Bycatch data, where the presence or absence of non-target species in the catch are recorded as a single point for a specific fishing location, can be considered a marked spatial point process (Stoyan 1984). Many tools for examining spatial point process look at the data as independent processes to determine patterns of randomness, clustering, or dispersion (Ripley 1977, Stoyan 1984, Diggle 2003). However, in many biological applications, spatial point processes are actually conditioned upon a different underlying distribution of the process (Kraft et al. 2002; Jolles et al. 2002). For example, the distribution of bycatch locations in the pelagic longline fishery may be conditioned upon the distribution of longline fishing locations. Identifying the spatial distribution of bycatch locations ("marks") as different from the underlying spatial distribution of fishing locations ("events"), may be more insightful for determining if there is a biological mechanism defining contagion, dispersal, or self-organization.

In this study, we apply spatial and temporal statistical techniques to sea turtle bycatch data in the pelagic longline fishery. Space, time, and space-time interactions are examined for both loggerhead and leatherback sea turtles to identify the scale and resolution in which the distributions occur relative to longline fishing locations. Fine scale spatio-temporal interactions may play an important role in influencing the overall sea turtle-fishery dynamics. This application could aid in the predictive ability

of identifying sea turtle locations and to suggest ways of reducing interactions between pelagic longline fisheries and sea turtles.

2. Methods

2.1 Data and study region

The data used in this study were from the NOAA Fisheries Atlantic pelagic longline observer program 1992-2003, managed by the Southeast Fisheries Science Center (SEFSC; Beerkircher et al. 2004). Spatially, the data span from the Gulf of Mexico, to the South Atlantic Ocean, and to the Grand Banks off the coast of Canada (Fig. 1.1). The program typically has observers on 3-5% of the sets made per year. During 2001 - 2003, the SEFSC initiated gear modification experiments directed at the swordfish fishery in the Northeast distant statistical reporting area (NED), which previously had been closed to U.S. pelagic longline fishing. Observer coverage was 100% during the experiments. During the latter two years, the resolution of the data was higher, including detailed data on "sections" or subunits of each haul (Watson et al. 2005). There are generally 7-12 sections for each haul. Such specificity allowed us to examine finer resolution patterns of turtle distribution for this period. This NED experimental dataset extends from July through October in 2002 and 2003, which is the season when the majority of fishing occurs in the NED (a few dates in June and November were also collected depending on the weather and other conditions). Both datasets for this analysis, the pelagic observer dataset (1992-2003) and the NED experiments dataset (2002-2003), contain the latitude, longitude, loggerhead and leatherback turtle catches, and the date. We scored the turtle catch data as 0 for no turtles and 1 for at least one turtle being caught. We used an equidistant conic projection on the latitude and longitude data to calculate distances in kilometers. These variables represent only a subset of the variables collected for both datasets.

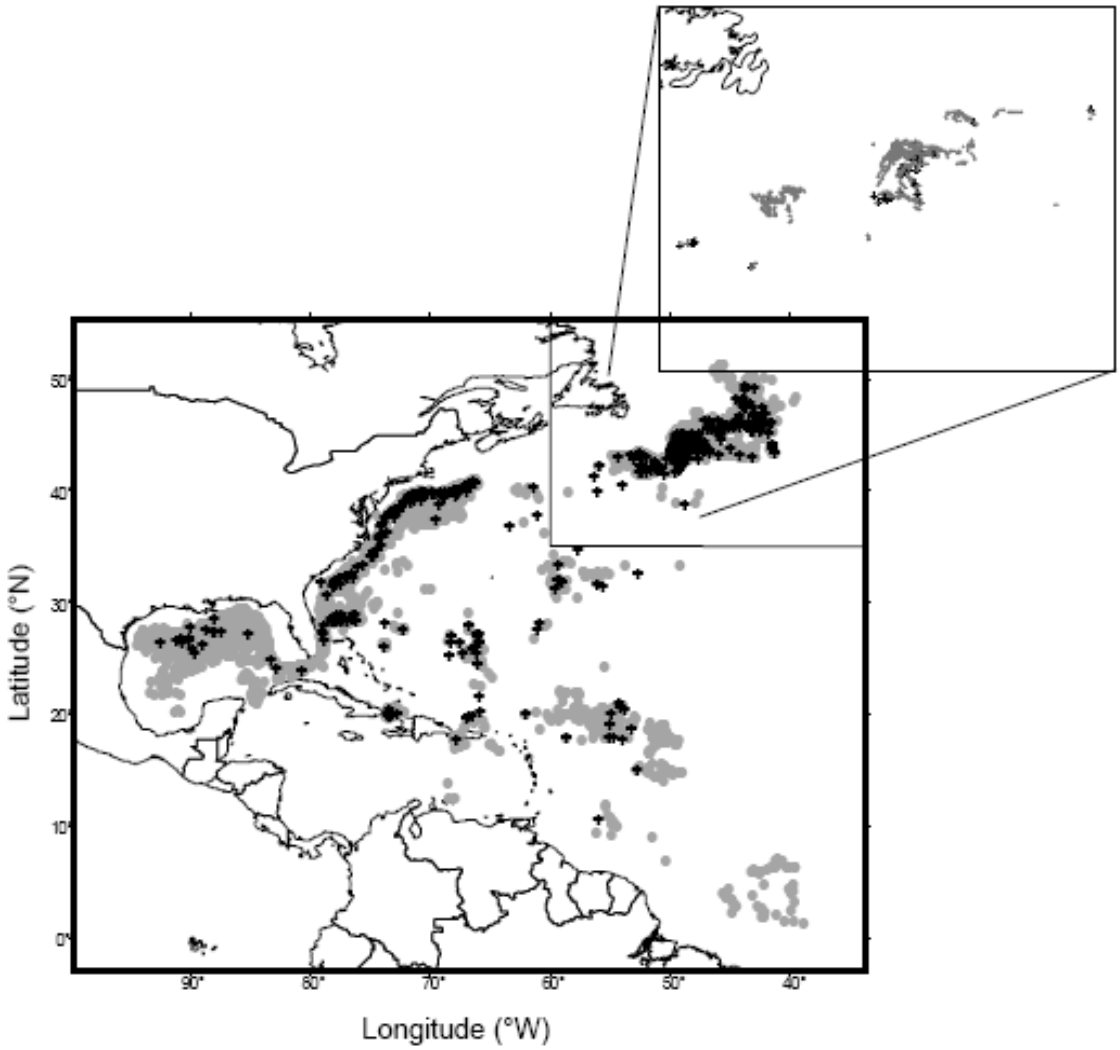

Figure 1.1: Total span of the dataset. The gray points show observed pelagic longline fishing locations whereas the black "+" marks indicate fishing locations with at least 1 loggerhead turtle catch. The rectangle in the upper right corner labeled NED is the Northeast Distant Waters statistical reporting region. Inset: An example of the data from the NED experiment, October 2002 is shown. The points represent each section along a set line (instead of just one point per set); the linear appearance of data can be seen here.

2.2 Model

2.2.1 Spatial K-function

Ripley's (1977) K-function uses an averaging across all observed events to give an approximately unbiased estimator of the expected number of events within a distance *d* of an arbitrary event. The function is given by (combined notation of Cressie 1993 and Gatrell et al. 1996):

$$\hat{K}(d) = (\hat{\lambda}_d N)^{-1} \sum_{i=1}^{N} \sum_{j \neq i}^{N} \frac{I(\| s_i - s_j \| \leq d)}{w(s_i, s_j)}, \; d > 0 \qquad (1)$$

where $\hat{\lambda}_d$ is the intensity of the events, i.e. $\hat{\lambda}_d = N / A$, N is the total number of events, A is the total area, and s_i is the location of event *i*. The weight $w(s_i, s_j)$ is an edge-correction factor equal to the proportion of the circle centered at s_i that is inside the study area. The indicator function $I(\cdot)$ identifies those events s_j that are within a distance *d* of the event s_i. For better visualization of the data, we use a modification, $\hat{L}(d)$, such that

$$\hat{L}(d) = (\hat{K}(d) / \pi)^{\frac{1}{2}} - d, \qquad d > 0 \qquad (2)$$

which transforms the quadratic statistic ($\hat{K}(d)$) into a linear one ($\hat{L}(d)$) that, under the null hypothesis, is a horizontal line that is centered around zero and has a nearly uniform variance across *h*. The square root linearization was suggested by Besag (1977) and subtracting *h* from the root was suggested by Cressie (1993).

Typically the null hypothesis is complete spatial randomness; however, here we know that the locations marked as catching a turtle ("marks") are a subset of the fishing locations ("events"). Fishing locations tend to be clustered along the continental shelf and near oceanic fronts and are not randomly distributed in space (Fig. 1.1). Thus, a model that allows us to identify the spatial distribution of the marks, as differentiated from the non-random spatial distribution of the events on

which the marks occur, would be more meaningful for determining processes, such as contagion or dispersion, than a comparison to complete spatial randomness alone. To test the null hypothesis that marks are distributed randomly within the non-random spatial distribution of events, we use a technique to randomize marks associated with non-random events, thus creating a stochastic prediction envelope of spatial randomness conditioned upon the distribution of fishing. This new estimator (termed adjusted $\hat{L}$) can be written as follows:

$$\hat{L}_m(d) = (\hat{K}_m(d)/\pi)^{\frac{1}{2}} - (\hat{K}(d)/\pi)^{\frac{1}{2}}, \qquad d > 0 \tag{3}$$

$\hat{K}(d)$ is as defined in equation (1) and $\hat{K}_m(d)$ is defined the same but using the marked locations instead of the event locations. Here, under the new null hypothesis of complete spatial randomness of marks (m) conditioned on the distribution of events, the estimator will have a mean of zero and a uniform variance across all values of *h*. One thousand permutations of marks on events were run to create a 95% prediction envelope for testing the significance of $\hat{L}_m(d)$ for each of the sea turtle species catch locations. Spatial clustering is indicated when the adjusted $\hat{L}$ value rises above the prediction envelope; over-dispersion (e.g. less clustering than random or regular) is indicated when the adjusted $\hat{L}$ value falls below the prediction envelope.

2.2.2. Temporal K-Function

The temporal K-function uses an averaging across all observed events to give an approximately unbiased estimator of the expected number of events within a time *t* of an arbitrary event. This function is given by:

$$\hat{K}(t) = (\hat{\lambda}_t N)^{-1} \sum_{i=1}^{N} \sum_{j \neq i}^{N} \frac{I(\| s_i - s_j \| \leq t)}{v(s_i, s_j)}, \; t > 0 \tag{4}$$

where $\hat{\lambda}_t$ is the intensity of the events, i.e. $\hat{\lambda}_t = N/T$, where N is the total number of events, T is the total length of the time series (in days), and s_i is the time of event i. The weight $v(s_i, s_j)$ is the temporal equivalent the spatial edge-correction factor based on the proportion of the time interval centered at s_i that is inside the observed time span (Diggle et al. 1995). The indicator function $I(\cdot)$ identifies those events s_j that are within a time t of the event s_i. Following the same process as above, the estimated K-function is linearized by subtracting $2t$ (because time is one-dimensional, we do not need to take the square root or divide by π). Again, we randomize marks associated with events, thus creating a stochastic prediction envelope of temporal randomness conditioned upon the distribution of fishing. Similar to the estimator above, we have:

$$\hat{L}_m(t) = \hat{K}_m(t) - \hat{K}(t), \qquad t > 0 \tag{5}$$

One thousand permutation of marks on events were run to create a 95% prediction envelope for testing the significance of $\hat{L}(t)$ for each sea turtle species catch locations, or events.

2.2.3 Space-time K-function

By analogy with our previous K-functions, the space-time K-function is an averaging across all observed events to give an approximately unbiased estimator of the expected number of events within a distance d and time t of an arbitrary event. The appropriate edge-corrected function is given by (Diggle et al. 1995, Gatrell et al. 1996):

$$\hat{K}(d,t) = \frac{AT}{N^2} \sum_{i=1}^{N} \sum_{j \neq i}^{N} \frac{I(\| s_i - s_j \| \leq t) I(\| s_i - s_j \| \leq d)}{w(s_i, s_j) v(s_i, s_j)}, \quad t, d > 0 \tag{6}$$

where all of the variables are as previously described. In the case where there is no space-time interaction, $\hat{K}(d,t)$ should be the product of the separate space and time K-functions. Thus, theoretically under the null hypothesis, we expect $K(d,t) = K(d)K(t)$. To examine the space-time interactions, one can use the function:

$$\hat{D}(d,t) = \hat{K}(d,t) - \hat{K}(d)\hat{K}(t) \tag{6}$$

Space-time interactions are indicated by observing peaks on the surface of $\hat{D}(d,t)$, which are unitless, when plotted over space and time (Diggle et al. 1995, Gatrell et al. 1996). To assess the significance of $\hat{D}(d,t)$, the 1000 permutations created for the space and time K-functions were used to calculate $\hat{D}_i(d,t)$ for i=1…..1000. The overall sum of $\hat{D}(d,t)$ over all *d* and *t* was compared to the frequency distribution of the sums of each $\hat{D}_i(d,t)$. If the overall sum of $\hat{D}(d,t)$ is greater than 95% of the simulated values, then we would infer that there is evidence of overall space-time interactions (Diggle et al. 1995). The same permutated $\hat{D}_i(d,t)$ were also used to create a 3-D prediction envelope for examining whether the observed peaks of $\hat{D}(d,t)$ were due to the underlying distribution of fishing or if the peaks might be indicative of further space-time interactions.

2.3 Application

The spatial model was applied to the entire dataset from 1992-2003 to detect broad scale patterns of clustering. All of the years were included in the analysis and the data were grouped together by month to examine trends throughout the year for both loggerheads and leatherbacks. Table 1.1 contains the raw data on the number of sets for each month and the number of turtle catches for each species. Splus spatial module (Insightful Inc. Seattle, WA., Venables and Ripley 1999) was used to calculate the spatial k-function. There are not enough data points to investigate finer temporal scales for this dataset. The number of sections (subunits of a haul) observed and the

number of sea turtles caught in the NED experimental data is higher than the overall dataset from the pelagic observer program (Table 1.2). Given the increased level of data collection for the NED in 2002 and 2003, the spatial, temporal, and space-time models were all applied separately for each year and for both loggerhead and leatherback capture indicators. Here, the data are grouped by season for the spatial analysis, all locations starting in July and running through October are used, instead of looking at individuals month as was done previously. The Splancs package (Rowlingson and Diggle 1993, Bivand and Gebhardt 2000) in R was used to calculate the different k-functions for this analysis.

Table 1.1: Summary of the sea turtles catches for the entire pelagic observer program data from 1992-2003. The data are summarized by month, as was used in the analysis. The loggerhead and leatherback categories indicate the total number of sets where at least one turtle was caught (the total number of catches for both species is higher than what is shown here).

Month	Sets	Loggerheads	Leatherbacks
January	536	25	79
February	582	35	25
March	442	23	30
April	452	19	23
May	575	18	44
June	512	27	41
July	804	48	79
August	925	82	108
September	822	88	111
October	1060	114	114
November	509	25	26
December	311	13	21

Table 1.2: Summary of sea turtle catches for the NED experiment. The Section category is the total number of sections (generally there are 7-12 sections on one line) set for a particular year. The loggerhead and leatherback categories indicate the total number of sections that caught at least one turtle (the total number of catches for both species is higher than what is shown here).

Year	Sections	Loggerheads	Leatherbacks
2002	3910	86	142
2003	4365	66	75

3. Results

The spatial K-function analysis for the entire dataset, including the Gulf of Mexico and western North Atlantic, shows varying spatial patterns across time (Fig. 1.2). Most of the year, both the loggerhead and leatherback turtles display no spatial pattern in catch locations. However, during the months of July – October, the loggerhead results indicate a pattern of spatial clustering (July is shown in Fig. 1.2; August-October results are very similar). The leatherback catches for July – October are similar to the loggerheads, but are not as pronounced and often the adjusted $\hat{L}$ is very close to the upper envelope boundary for the leatherbacks. Two anomalies occur in the leatherbacks results; the first is a pattern of spatial cluster in April across the 500 - 1000 km range, and the second is an indication of over-dispersion in June at the 1100 – 2000 km range.

The spatial results for the 2002 loggerhead sea turtle catches in the NED indicate no patterns of spatial clustering and in 2003 spatial adjusted $\hat{L}$ values for the loggerhead catch locations exhibit patterns of over-dispersion (Fig. 1.3). For

leatherbacks, the spatial adjusted $\hat{L}$ displays evidence of over-dispersion at all distance lags in both years (Fig. 1.3). The temporal K-function results also show changes in the patterns between the species and between years for the loggerheads (Fig. 1.4). In 2002, the temporal adjusted $\hat{L}$ for the loggerheads shows clear evidence of clustering over all time lags; in 2003, the results indicate temporal clustering over 1-3 day time lags and again around 18 day time lag. In both years, the leatherback temporal K-function analysis shows temporal randomness over all time lags.

In examining the plot of $\hat{D}(d,t)$ against space and time, a slight peak in $\hat{D}(d,t)$ at the smallest time and distance lags is evidence of a space-time interaction as the values are above the prediction envelope (Fig. 1.5). For the leatherback catches, the overall space-time interaction values in both 2002 and 2003 were above 95% of the permuted values, supporting the conclusion that there is overall space-time clustering. Examining the plot of $\hat{D}(d,t)$ against space and time for the leatherbacks reveals a similar pattern as seen in the loggerheads (Fig. 1.5). Evidence of space-time clustering exists at the small distance and time lags in 2002 and 2003. Additionally, the plot of $\hat{D}(d,t)$ for the leatherbacks in 2002 provides evidence of more space-time interactions across the middle span of both the spatial and temporal ranges (Fig. 1.5). Without considering $\hat{D}(d,t)$, information on interesting space and time lags would be lost.

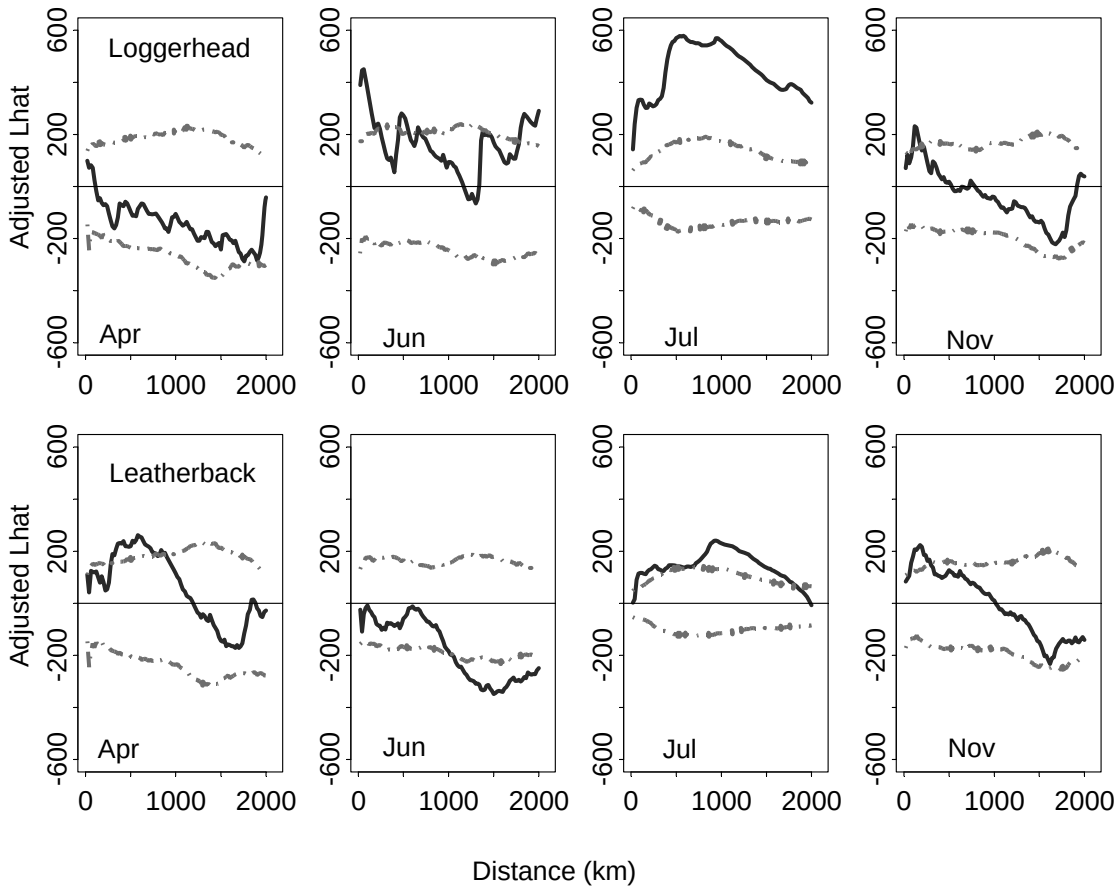

Figure 1.2: Spatial K-function results for the entire dataset. The top row shows the results for loggerheads and the bottom row are the results for leatherbacks, when all years are grouped by month. On all graphs, the x-axis is distance in kms and the y-axis is the adjusted $\hat{L}$ (unitless). Dashed lines represent a randomized prediction envelope; the solid line is the estimated statistic for the catch locations. April, June, and November of the loggerhead analysis indicates the catch locations are randomly distributed as the $\hat{L}$ statistic stays between the bounds of the prediction envelope. In July for both species, and for a section of the leatherback analysis in April, the adjusted $\hat{L}$ statistic rises above the envelope, suggesting spatial clustering of the sea turtle catch locations. The June results for leatherbacks shows the adjusted $\hat{L}$ statistic falling below the prediction envelope at about 1100 km, which indicates spatial patterns of over-dispersion. Patterns for August – October are essentially the same as July (shown above), while December – March are similar to November (shown above).

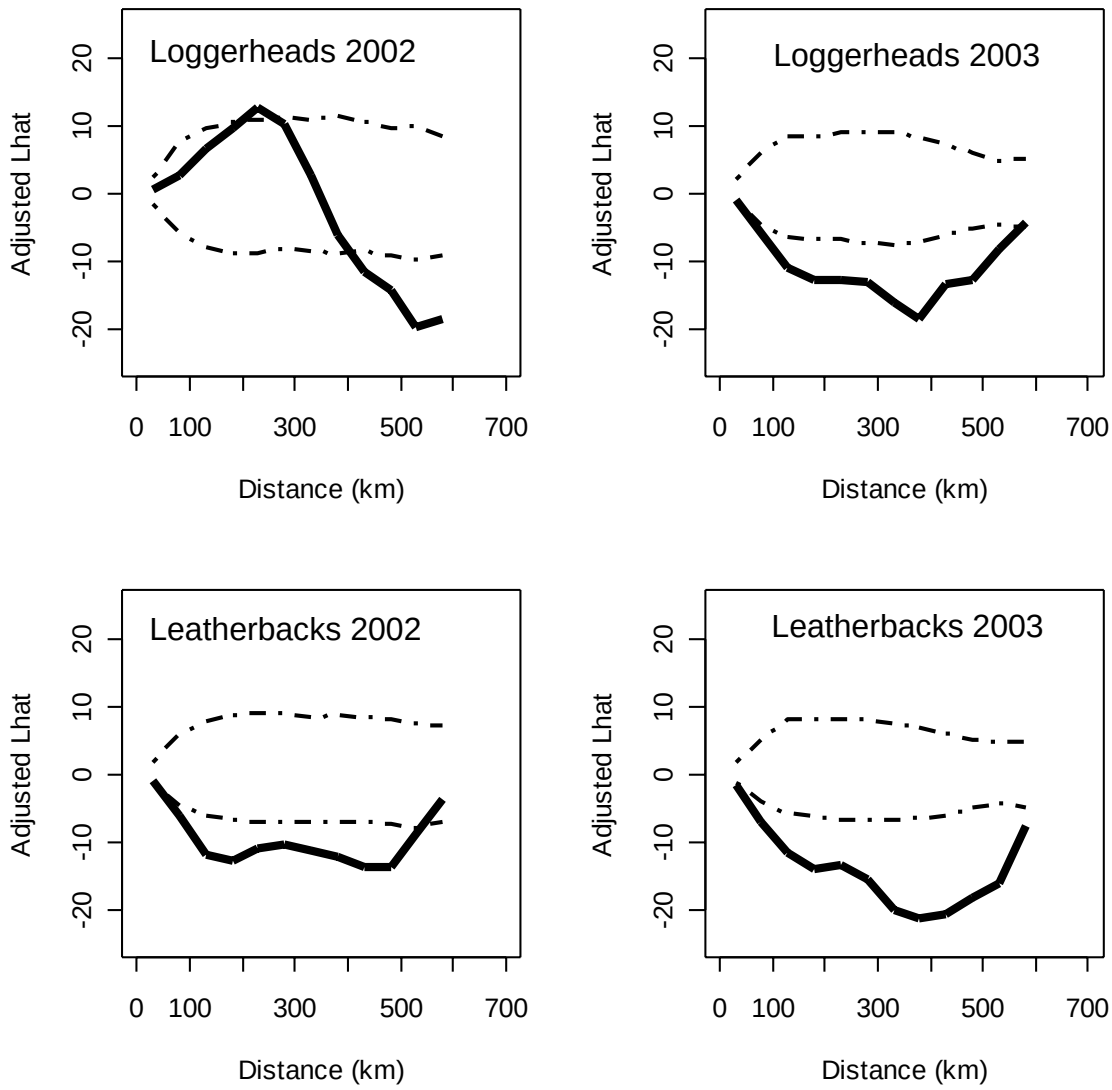

Figure 1.3: Estimated spatial K-function results for the NED experiment data shown as the adjusted $\hat{L}$ on the y-axis and distance (km) on the x-axis. The solid line represents the spatial relatedness of turtle catches while the dashed lines are a simulated prediction envelope showing the range of random turtle catches within the distribution of fishing locations. Both 2002 and 2003 results for the leatherbacks, as well as the 2003 results for the loggerheads indicate patterns of over-dispersion. The 2002 results for the loggerheads indicate a random distribution of the catch locations over a lag of up to 400 km, and then the results display a pattern of over-dispersion between 400 and 600 km.

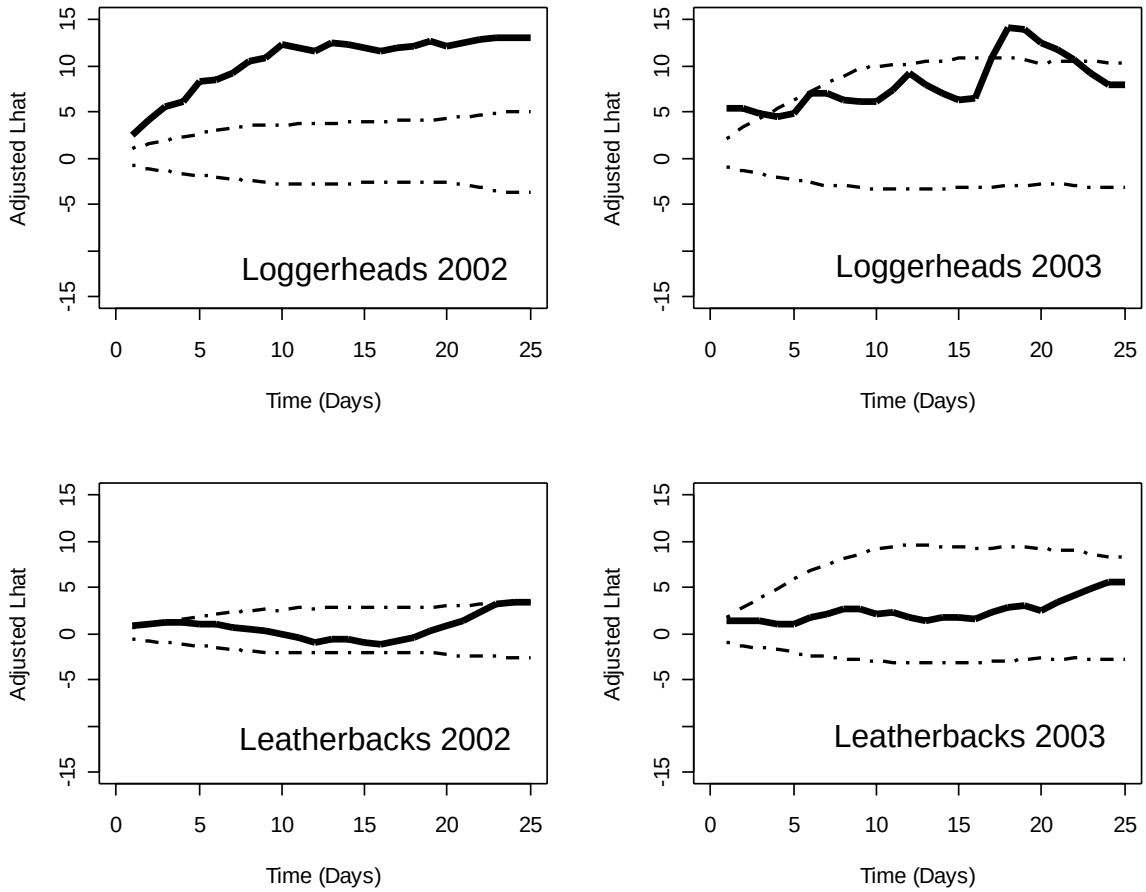

Figure 1.4: Estimated temporal K-function results for the NED experiment data shown as the adjusted $\hat{L}$ on the y-axis and time in days on the x-axis. The solid line represents the temporal relatedness (adjusted $\hat{L}$) of turtle catches while the dashed lines are a simulated prediction envelope showing the range of random turtle catches within the distribution of fishing locations. The 2002 results for the loggerheads indicate temporal clustering over all time lags; in 2003, the results indicate clustering over a 3-4 day time lag. In both years, the results for the leatherbacks show no temporal patterns.

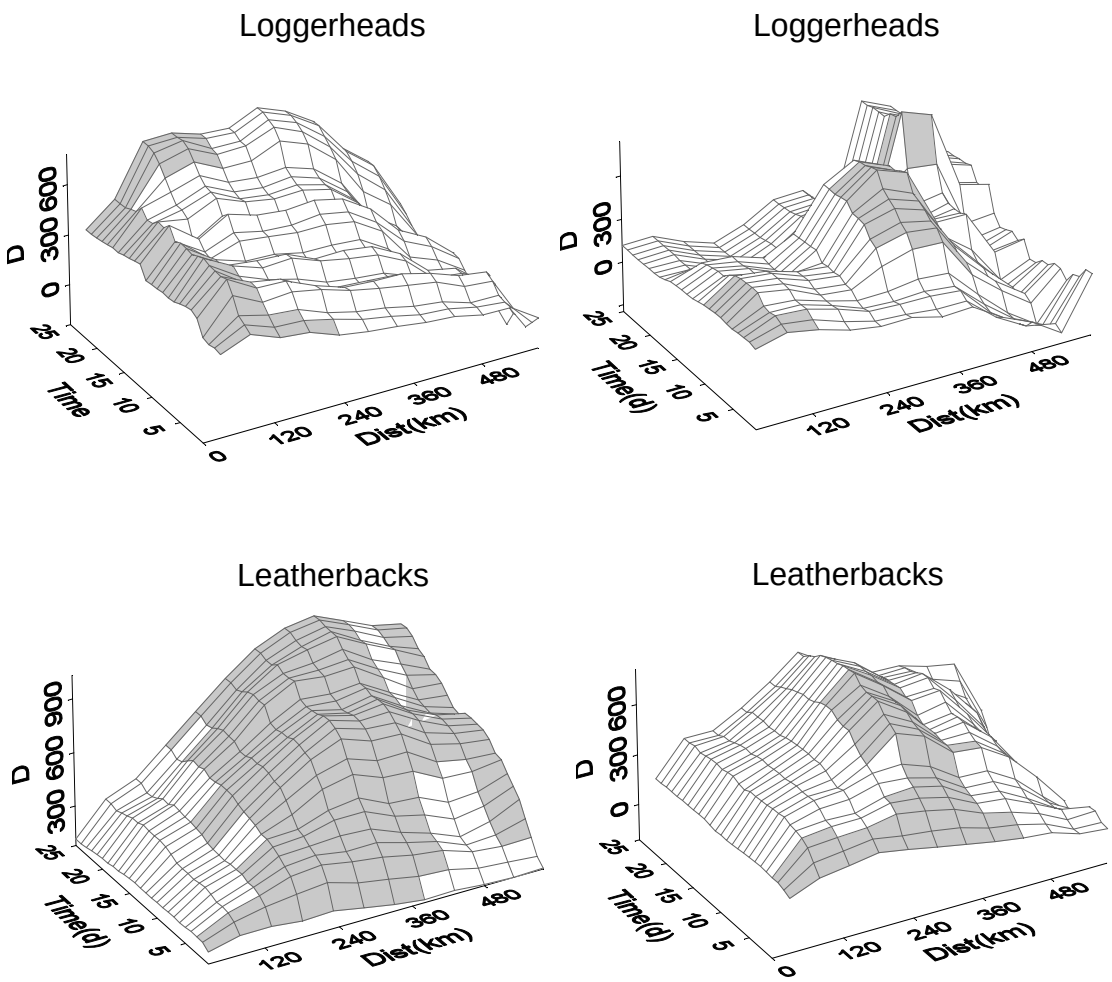

Figure 1.5: Space-time interactions shown as distance (km) on the x-axis, time in days on the y-axis, and $\hat{D}(d,t)$ [unitless] on the z-axis. Evidence of space-time clustering is indicated by positive peaks in $\hat{D}(d,t)$. The dark gray colored blocks show a positive $\hat{D}(d,t)$ value that is also above the maximum value for that time and distance for 100 simulations. The patterns of space-time interactions are different across each year and each species; however for both species in both years, there is support for significant space-time interactions at the small temporal and spatial scales (1- 4 days and 30-200 km).

4. Discussion

Using spatial point pattern techniques applied to bycatch data, we were able to detect clustering and dispersion of sea turtles in both space and time. The broad scale patterns of spatial clustering for the loggerheads during the months of July – October likely represent the opening of fishing in the NED, where turtle catch rates appear higher. The prediction envelope accounts for the underlying distribution of fishing, but given the large number of turtles caught in the NED, the spatial K-function provides support for the overall clustering of turtle catches relative to the fishery. The model's detection of these patterns, which were already recognized but not quantified in this way by the fishing industry, validates the technique employed here and strengthens the perceptions of fishery managers. Combining the data by months across years provides insight at a broad scale, but does not really provide site-specific information regarding the spatial clustering of turtle catches that would be practical for real-time fisheries management.

The spatial results for the NED data suggest that either there is no spatial clustering, or more often, over-dispersion of sea turtle catches. Given the temporal heterogeneity and the space-time interactions indicated by the results, the spatial distribution of sea turtle catch locations is likely changing non-randomly on a short time frame (approximately 1-3 d). In this situation, the spatial K-function would not detect the correct patterns when the data are grouped together over a greater time scale than that of the process. In essence, with more data over a shorter time frame (e.g. daily), the spatial K-function results would likely be more informative.

Loggerhead sea turtles appear to be feeding when they interact with the longline fishery, whereas the behavior of the leatherbacks interacting with the fishery is still unknown (Watson et al. 2005). Regardless of the mechanism, recognizing the temporal clustering of loggerhead catches in the NED region indicates that the

probability of catching a loggerhead on a given day is related to whether or not a turtle was caught on previous days.

The space-time analysis supports the idea that sea turtle catch distributions vary over different spatial and temporal scales. This technique allows us to quantify the space-time interactions and to see the scale at which these interactions are functioning. Although we cannot infer the process from this pattern, the analysis does provide a novel starting point for examining either environmental heterogeneity (e.g. sea surface temperature or eddy formation) that could explain the pattern or allow one to consider biological functions (e.g. foraging) that would produce such a pattern. In quantifying the spatial and temporal distributions of sea turtle catch locations, this study has gone beyond previous analyses of bycatch data and provides insight into the patterns of incidental sea turtle captures.

Inferring a process from a pattern is always a question of judgment and especially so in a dataset such as the longline observer data, where environmental heterogeneity is obviously present. In addition to this problem, the dataset also has high level of variation in mean turtle catch density across the study region. A non-stationary intensity could allow for the K-function to more represent the first-order effects (e.g. a change in the mean) than the interaction of events. Examining a smaller region, such as the NED, helps to account for both environmental heterogeneity and a varying intensity function. This study suggests two things: (1) there is spatial and temporal heterogeneity in the turtle catches and continued finer scale analysis is needed; (2) examination of sea turtle captures is also needed, provided that data can be obtained at finer temporal scales, such as on a daily basis. With more information and a better understanding of the spatial patterns, it may be possible to predict the probability of a sea turtle catch given the information from the previous days of fishing.

As bycatch continues to be an issue for fisheries worldwide, innovative and novel tools are needed to address management and conservation concerns. Applying point pattern techniques, such as those described here, to other datasets could prove to be a powerful tool for fisheries management, conservation, and for better understanding of bycatch distributions for other species of concern.

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References:

Beerkircher, L. R., C. J. Brown, D. L. Abercrombie, and D. W. Lee. 2004. SEFSC Pelagic Observer Program Data Summary for 1992-2002. NOAA NMFS-SEFSC-522: 25 p.

Besag, J. E. 1977. Comment on "Modelling spatial patterns" by B. D. Ripley, *Journal of the Royal Statistical Society* B **39**: 193-195.

Bivand, R. and A. Gebhardt 2000. Implementing functions for spatial analysis using the R language. *Journal of the Geographical Systems* **2**:307-317.

Cressie, N. A. C. 1993. Statistics for Spatial Data, Revised Edition, New York: John Wiley & Sons, Inc.

Diggle, P. J. 2003. Statistical analysis of spatial point patterns. 2nd Edition. New York: Oxford University Press Inc.

Diggle, P. J., A. G.Chetwynd, R Haggkvist, and S. Morris. 1995. Second order analysis of space-time clustering. *Statistical Methods in Medical Research* **4**:124-136.

Epperly, S. P, J. Braun, and A. Veishlow.1995. Sea turtles in North Carolina waters. *Conservation Biology* **9**(2): 384-394.

Gatrell, A. C., T. C. Bailey, P. J. Diggle, and B. S. Rowlingson. 1996. Spatial point pattern analysis and its application in geographical epidemiology. *Transactions of the Institute of British Geographers* **21**: 256-274.

Hall, M. A., D. L. Alverson, and K. I. Metuzals. 2000. Bycatch: problems and solutions. *Marine Pollution Bulletin* **41**: 204-219.

Heppell, S. S. 1998. Application of life-history theory and population model analysis to turtle conservation. *Copeia* **1998**: 367-375.

Heppell, S.S., L. B. Crowder, and T. R. Menzel. 1999. Life table analysis of long-lived marine species with implications for conservation and management. *American Fisheries Society Symposium* **23**: 137-148.

International Union for Conservation of Nature and Natural Resources (IUCN). 2004. IUCN redlist of threatened species. Cambridge, UK. Available from http://www.redlist.org/ [accessed October 2006; updated October 2006].

James, M. C., C. A. Ottensmeyer, R. A. Myers. 2005. Identification of high-use habitat and threats to leatherback sea turtles in northern waters: new directions for conservation. *Ecology Letters* **8**: 195-201.

Jolles, A. E., P. J. Sullivan, A. P. Alker, and C. D. Harvell. 2002. Disease transmission of aspergillosis in sea fans: inferring process from spatial pattern, *Ecology* **83**: 2373-2383.

Jonsen, I. D., R. A. Myers, and J. M. Flemming. 2003. Meta-analysis of animal movement using state-space models. *Ecology* **84**(11): 3055-3063.

Kraft, C. E., P. J. Sullivan, A. Y. Karatayev, L. E. Burlakova, J. C. Nekola, L. E. Johnson, and D. K. Padilla. 2002. Landscape patterns of an aquatic invader: Assessing dispersal extent from spatial distributions. *Ecological Applications* **12**: 749-759.

Lewison, R. L., L. B. Crowder, A. J. Read, and S. A. Freeman. 2004a. Understanding impacts of fisheries bycatch on marine megafauna. *Trends in Ecology and Evolution* **19**(11): 598-604.

Lewison, R. L., S. A. Freeman, and L. B. Crowder. 2004b. Quantifying the effects of fisheries on threatened species: the impact of pelagic longlines on loggerhead and leatherback sea turtles. *Ecology Letters* **7**: 221-231.

Pinedo, M. C. and T. Polacheck. 2004. Sea turtle by-catch in pelagic longline sets off southern Brazil. *Biological Conservation* **119**: 335-339.

Ripley, B. D. 1977. Modelling spatial patterns. *Journal of the Royal Statistical Society B* **39**(2): 172-212.

Rowlingson, B. S. and P. J. Diggle. 1993. Splancs: Spatial point pattern analysis code in S-plus. *Computers in Geosciences* **19**: 627–655.

Shoop, C. R. and R. D. Kenney. 1992. Seasonal distributions and abundances of loggerhead and leatherback sea turtles in waters of the northeastern United Sates. *Herpetological Monographs* **6**: 43-67.

Snyder, J.P. 1978. Equidistant conic map projections. *Annals of the association of American geographers* **68**(3): 373–383.

Spotila, J. R., R. D.Reina, A. C.Steyermark, P. T. Plotkin, and F. V. Paladino. 2000. Pacific leatherback turtles face extinction. *Nature* **405**:529-530.

Stoyan, D. 1984. Correlations of the marks of marked point processes – statistical inference and simple models. *Journal of Information Processing and Cybernetics* **20**(6): 285-294.

Venables, W. N. and B. D. Ripley. 1999. Modern applied statistics with S-Plus, 3rd Ed. Springer, New York. 500pp.

Watson, J. W., S. P. Epperly, A. K. Shah, and D. G. Foster. 2005. Fishing methods to reduce sea turtle mortality associated with pelagic longlines. *Canadian Journal of Fisheries and Aquatic Science* **62**: 965-981.

Witzell, W. N. 1999. Distribution and relative abundance of sea turtles caught incidentally by the U.S. pelagic longline fleet in the western North Atlantic Ocean, 1992-1995. *Fishery Bulletin U.S.* **97**: 200-211.

Chapter 2

Influence of water temperature and ocean region on sea turtle bycatch rates in the Western North Atlantic

Abstract: Loggerhead (*Caretta caretta*) and leatherback (*Dermochelys coriacea*) sea turtles are known to be incidentally caught in the pelagic longline fishery. Both species are protected in the USA and other parts of the world, thus understanding sources of mortality are important. This study aims to quantify the bycatch rates of sea turtles in relation to water temperature and three management regions in the Western North Atlantic. Generalized additive models were used to analyze the data, allowing for non-linear relationships. Results from a deviance goodness of fit test show that water temperature, region, and the interaction term are all significant predictors of the probability of capturing either species of sea turtle. The relationship between probability of capturing a sea turtle and water temperature is non-linear and varies by region. This suggests that management decisions may be more effective if they are spatially-explicit. Including water temperature as a management tool could also help reduce the number of sea turtle – fishery interactions.

1. Introduction

The incidental catch of sea turtles, termed bycatch, in the pelagic longline fishery has come to the forefront as an issue for fisheries management (Lewison et al. 2004, Kobayashi and Polovina 2005). In the USA pelagic longline fishery, a typical set consists of a single mainline (as long as 50 kilometers) with hundreds to thousands of baited hooks hanging vertically. The gear for swordfish is mainly set in the upper 50 meters of the water column which overlaps with the activities of sea turtles. Loggerhead (*Caretta caretta*) and leatherback (*Dermochelys coriacea*) sea turtles are caught on the hooks or entangled in the gear of the longline. Both species are protected by the Endangered Species Act and listed on the IUCN redlist (IUCN 2004). Because of this classification and the number of interactions with the longline fishery, understanding the dynamics of these interactions is of interest (Lewison et al. 2004). Time-area closures, gear modifications and a number of other measures have been implemented to address the rate of sea turtle bycatch in the longline fishery (Gilman 2006). However, more precise measures are warranted to further reduce these undesirable interactions.

Sea turtles are poikilotherms and thus their distributions are influenced by temperature; however, loggerhead and leatherback sea turtles can occur in a broad range of temperatures. In fact, leatherbacks have been observed active in waters ranging from 0°C to 30°C, likely due to their enhanced abilities to preserve and generate heat (Frair et al. 1972). Loggerheads also inhabit a large range of temperatures, though not quite as broad as the leatherbacks, being observed active more commonly in waters >11 °C (Epperly et al. 1995). Despite the vast range of water temperatures where turtles have been observed, most sightings occur between 7 °C and 27 °C, depending on season and region (Shoop and Kennedy 1992, Epperly et al. 1995, Coles and Musick 2000). Coles and Musick (2000) argue that turtles are

constrained by preferred temperature ranges, which vary seasonally, and often their distributions appear to be affected by local temperature conditions.

Specifically, in relation to the pelagic longline fishery, bycatch rates for sea turtles are known to be influenced by water temperature (Hoey 1998, Witzell 1999, NMFS 2001, Shah et al. 2004, Watson et al. 2005). Hoey (1998) found that setting gear in water >20.5 °C (69 °F) appears to increase the probability of encountering a sea turtle. Additionally, a regression tree analysis, which examines the variation around the mean of a variable to identify different classes or separations in data, showed that temperature is an important factor in the rate of bycatch in the northeast distant waters (NED), an area of the open ocean that includes the Grand Banks off the east coast of Canada (NMFS 2001). In concert with these studies as well as the observational and correlation studies mentioned above, a Biological Opinion was issued in 2001 suggesting that fishing practices north of the 35° North Latitude be restricted to only waters with sea surface temperatures cooler than 17.7 °C. These studies set the stage for understanding bycatch rates with respect to temperature using linear and tabular type analysis; however, the relationship of numbers of sea turtles relative to water temperatures may not be linear. For example, studies show that sea turtles tend to spend more time at a given temperature with a diminishing likelihood as the temperature increases or decreases (resulting in a bell-shaped curve around the most preferred temperature, e.g. see Epperly et al. 1995, Polovina et al. 2000). Current linear models will not capture these narrower temperature ranges of increased turtle activity and thus management strategies are not as refined as possible, leaving the *status quo* management strategies with large spatial and temporal blocks as the primary mechanism for reducing sea turtle bycatch.

In addition to temperature, spatial location is also known to influence the bycatch rates within the pelagic longline fishery. The catch rate of sea turtles in the

NED region has been shown to be higher than other regions for both loggerhead and leatherback sea turtles (Hoey 1998, Witzell 1999, NMFS 2001). Specifically, a disproportionate number of interactions occurred in the NED region, including 75% of all loggerhead and 40% of all leatherback interactions recorded from 1990-1996 (Hoey 1998). NMFS (2001) indicated through regression tree analysis that the NED splits from other regions with respect to bycatch rates suggesting the rates vary by region. Thus, fishing in the NED region was restricted for U.S. fisherman from 2001 to 2003. Different bycatch rates could be modeled by region to better understand and improve the large time-area closure management strategies for reducing sea turtle interactions with the longline fishery.

While much is known about the influence of water temperature on sea turtle distributions, no previous studies have examined the impact of water temperature and region on sea turtle interactions with the pelagic longline fisheries. Additionally, the capture rates of various regions have been identified as being different, but the effect has not been quantified. The aim of this study is to combine the space, time, and temperature data into more refined models and increase understanding the dynamics of sea turtle bycatch. The intended objective is to allow for better management decisions, with respect to the influence and interactions of temperature and fishing region, on finer spatial and temporal scales to reduce unwanted sea turtle bycatch within the pelagic longline fishery.

2. Data and Methods

The data used in this analysis are from the NOAA Fisheries Atlantic pelagic longline observer program during 1992-2003 as managed by the Southeast Fisheries Science Center, Miami Laboratory (SEFSC; Beerkircher et al. 2004). The fishery operates throughout the Gulf of Mexico, along the Atlantic Ocean coast of the USA

from south of the equator to the Grand Banks off the coast of Canada (Fig. 2.1). The observer program typically has an individual observer on 3-5% (5-8% in recent years) of the trips per year. The trained observers record data including date, water temperature, and sea turtle catches for each set. These variables, with the modification of making the sea turtle catches binary, were used in this analysis. Other variables collected include gear characteristics, weather conditions, depth, etc., which were not examined here.

For statistical and regulatory purposes, NOAA Fisheries has 11 geographic regions to classify fishing effort for the USA pelagic longline fishery and the year is divided into four seasons (Fig. 2.1; Beerkircher et al. 2004). For this analysis, we examine three different regions: region 7(Northeast Distant, NED), regions 5 and 6 combined (Northeast Coastal, NEC and Mid-Atlantic Bight, MAB – termed NEC), and region 2 (Gulf of Mexico, GOM). These regions were selected in order to compare two different northern regions with the heavily fished Gulf region. All of these regions have been identified as the areas of concentrated loggerhead interactions with the pelagic longline fishery (Williams et al. 1996). In our analysis, we examined two time periods from July – September and from October - December, the two statistical seasons when fishing occurs in all three regions. Because the results were the not statistically different between seasons, the seasonal data were combined for our analysis.

To analyze these data, we scored each set for their loggerhead and leatherback turtle catches (0 for no turtles, 1 for at least one turtle being caught). We then analyzed this data using generalized additive models (GAMs), which are a flexible class of models that allow non-linear effects in the response variable (Hastie and Tibshirani 1990). GAMs use flexible nonparametric smoother functions to quantify the patterns between variables. For this analysis, we used a smoothing spline (denoted

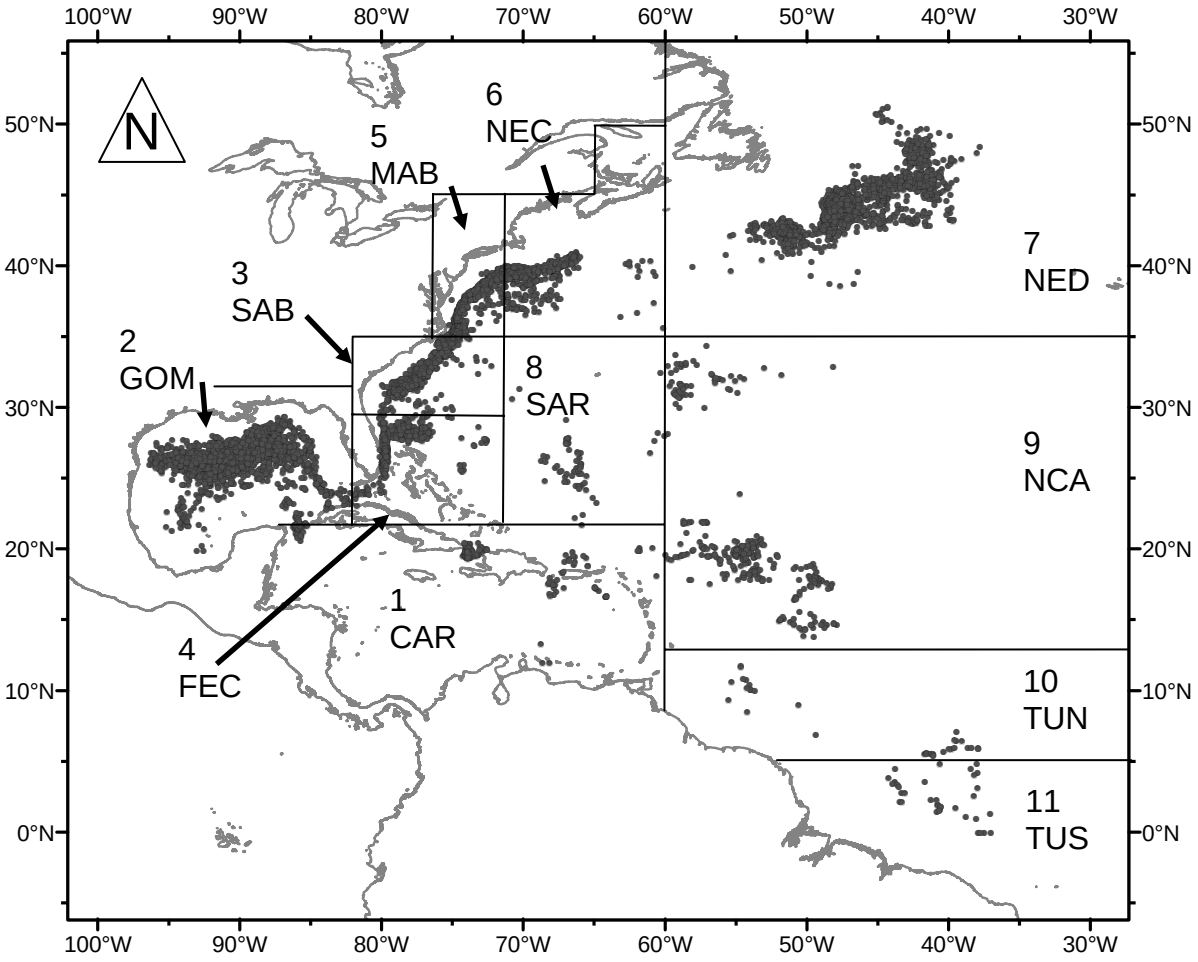

Figure 2.1: The eleven geographic regions used to stratify USA Atlantic Ocean pelagic longline fishing effort. The regions are: 1 Caribbean (CAR), 2 Gulf of Mexico (GOM), 3 South Atlantic Bight (SAB), 4 Florida East Coast, 5 Mid-Atlantic Bight (MAB), 6 Northeast Coastal (NEC), 7 Northeast Distant (NED), 8 Sargasso Sea (SAR), 9 North Central Atlantic ((NCA), 10 Tuna North (TUN), and 11 Tuna South (TUS). The points indicate the pelagic longline fishing locations for 1992-2003.

as *s(·)* in the model). To estimate the probability of catching a turtle (η), we used the presence/absence data for sea turtle captures on each longline set. Because the data are binary, we use a logistic link function within the GAM. The model is set up as follows:

$$\eta = s(temp) + b * region + s(temp) * region$$

where *temp* is the temperature in degrees C, and *region* is a categorical variable indicating one of the three study areas: NED, NEC, or GOM. The structure of the model was designed to analyze temperature, region, and the interactions. The model was individually fit for each species (loggerhead and leatherback), for each of the two statistical seasons, and for all seasons combined. The models were constructed using the software package S-Plus v. 6.2 (Insightful Inc. Seattle, WA.).

3. Results

The temperatures for all fishing locations are shaped similar to a normal distribution (mean = 23.06; standard deviation = 4.77), with a spike at 15-18°C likely due to the high number of fishing locations in at the NED at those temperatures (Fig. 2.2). The total number of turtles caught also displays a bell shaped curve across the temperature range. However, when fishing and turtle catches are separated by region, the distributions of temperatures for fishing and turtle catches differ by area (Fig. 2.3). The distributions likely differ in part because the range of temperatures being fished is different for each region (Table 2.1), which is due to available temperatures in each region varying by latitude and season. The NEC has the widest range of temperatures available throughout the two seasons as opposed to the NED and GOM, based on the temperature where fishing occurs. The distribution of fishing across temperatures also varies by region, with a more normal shape for the NED and NEC and a more uniform shape across temperatures in the GOM. The patterns for both loggerhead and

leatherback turtles are very similar (Fig. 2.3), except there are a higher number of sets catching leatherbacks in the GOM compared to loggerhead turtles (right panel, Fig. 2.3).

The GAM results for both species by season were similar, thus the results were combined for the entire year. A deviance goodness of fit test showed that temperature, region, and the interaction term were significant predictor variables for the probability of catching at least one sea turtle in models for both species (Table 2.2). The probability of catch was near zero at the lowest temperatures for both species in all regions and started to increase as the temperature warms, but the shapes and peaks are different in all regions and by species (Fig. 2.4). The probability of catching at least 1 turtle per set in the NED increased non-linearly with temperature for both species, though the loggerheads reach a maximum probability of 0.58 while the leatherbacks reach a maximum of 0.28. In the NEC, the probability increases then decreases with the peak around 21°C for the loggerhead turtles and 18°C for the leatherbacks (Fig. 2.4). For the GOM, the probability is relatively constant across all local temperature conditions; though this region is unique in that the probability of catching at least one leatherback on a set is higher across all temperatures than that of catching a loggerhead (Fig. 2.4).

Table 2.1: The minimum, mean, and maximum temperatures for all fishing locations in each region.

Region	**Min temp**	**Mean temp**	**Max temp**
NED	10.5	17.2	24.7
NEC	6.0	21.9	30.5
GOM	15.8	26.1	32.4

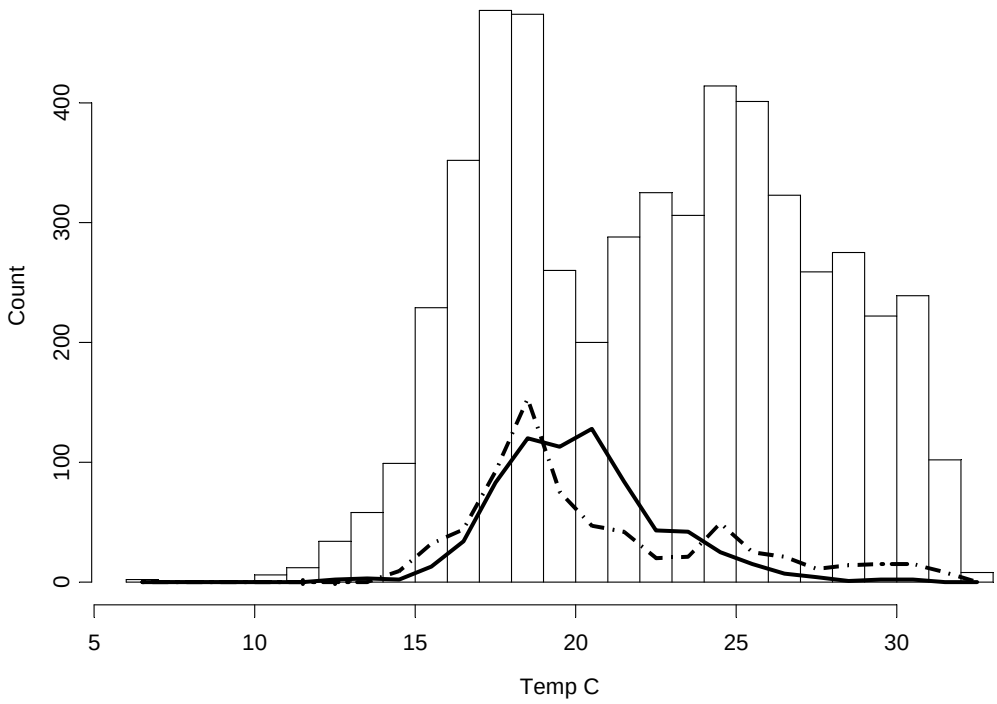

Figure 2.2: Barplot showing the temperatures at which fishing occurs across the entire dataset. The y-axis is the number of fishing hauls set in a shown on the x-axis (degrees C). The solid line is the total number of loggerhead sea turtles caught in each 1 ^{o} increment temperature category. The dashed line is the total number of leatherback sea turtles caught in each 1 ^{o} increment temperature category.

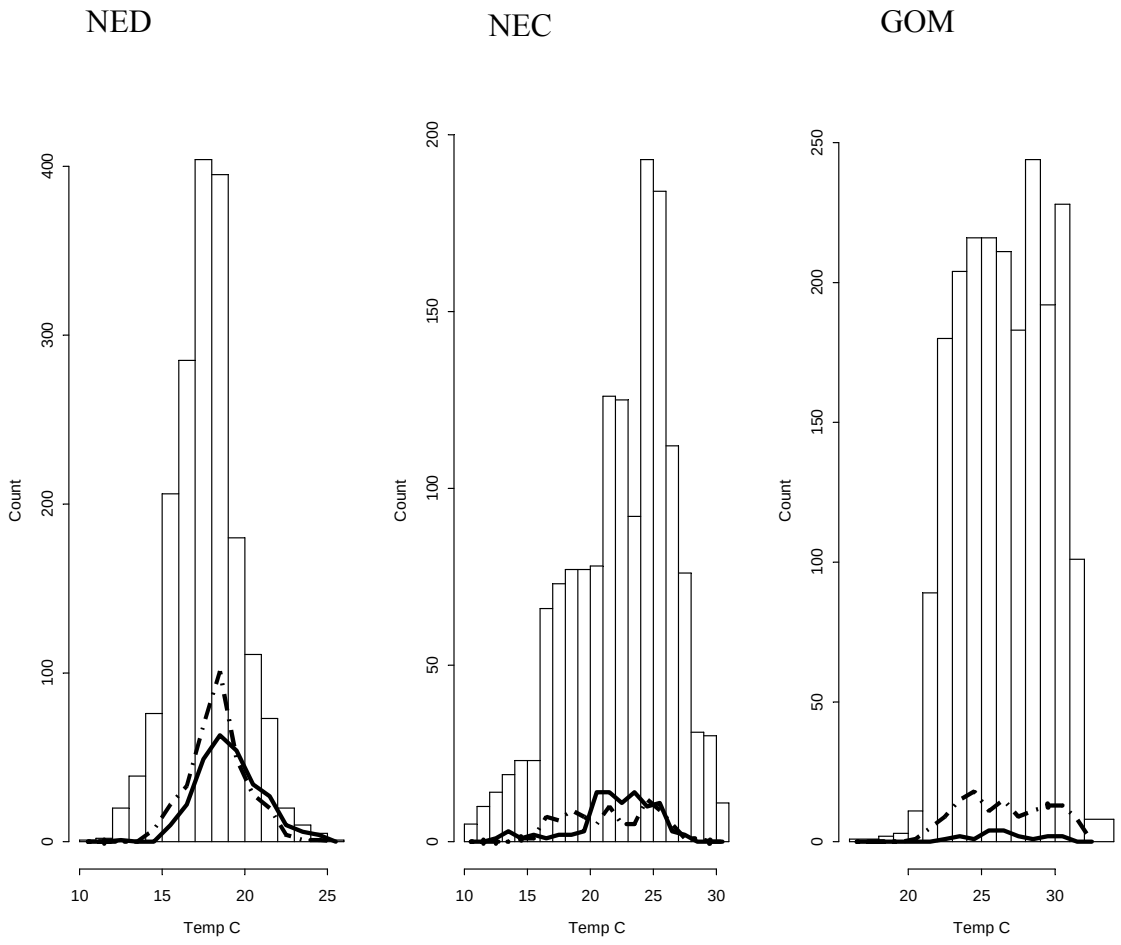

Figure 2.3: Barplot showing the temperatures at which fishing occurs by region (left – NED, middle – NEC, right – GOM). Each bar represents the number of fishing hauls in a 1 ^{o}C increment category. The solid line is the total number of loggerhead sea turtles caught on those hauls in each 1 ^{o}C category. The dashed line is the total number of leatherback sea turtles caught on those hauls in a 1 ^{o}C category. Note the different x and y axes for each panel.

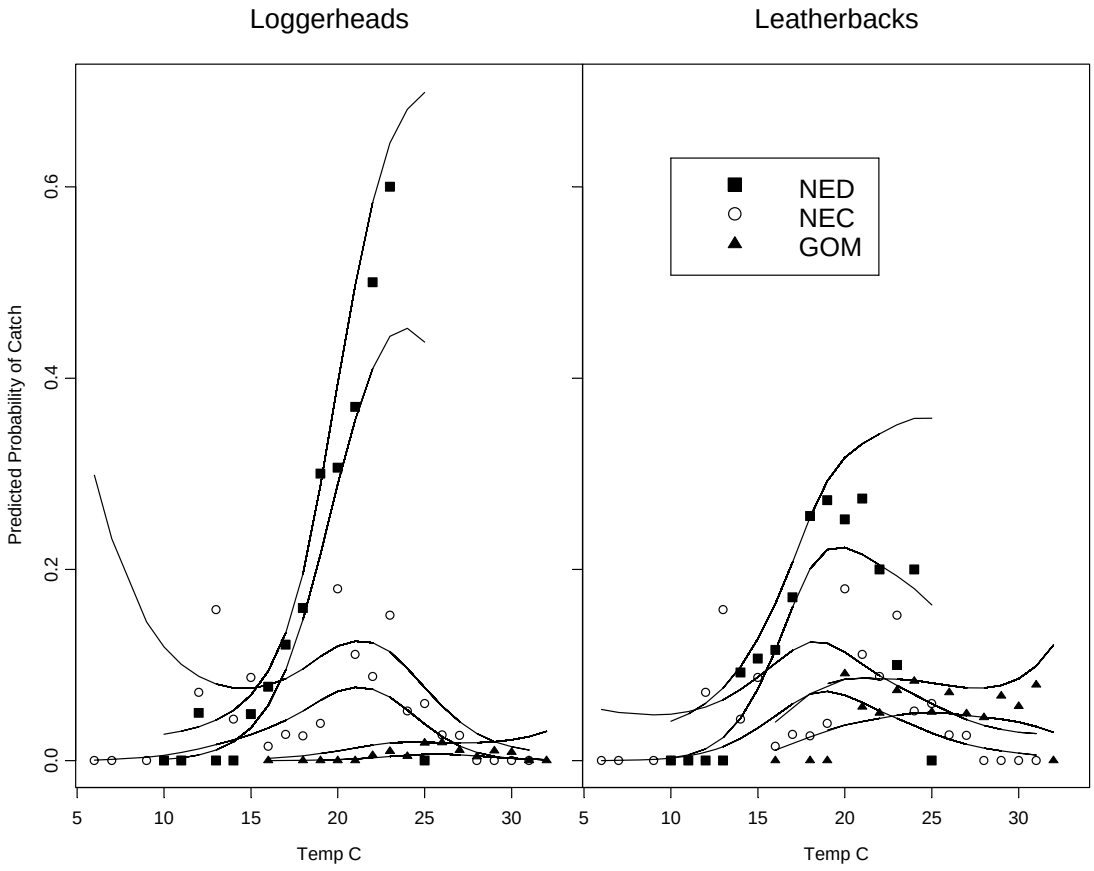

Figure 2.4: GAM results for predicting the probability of catching at least one turtle (y axis) as a function of temperature (x-axis in degrees C). The results are separated by region and species (loggerhead turtles in the left panel, leatherback turtles in the right panel). The points show the data and the lines represent a 95% confidence interval.

Table 2.2: Results for the deviance goodness of fit test for both the leatherback and loggerhead sea turtle models. The residual deviance, degrees of freedom, and p-value are given for each model.

	Deviance	Degrees of freedom	p-value
Loggerheads			
s(temp)	2516.8	3.9	<0.001
s(temp)+region	2320.8	2.0	<0.001
s(temp)+region+interaction	2290.3	2.0	<0.001
Leatherbacks			
s(temp)	3334.9	3.9	<0.001
s(temp)+region	3267.7	2.0	<0.001
s(temp)+region+interaction	3256.8	1.9	0.004

4. Discussion

The application of generalized additive models to temperature data for sea turtles catch probabilities proved very useful. Moreover, the relationship between the probability of catching sea turtles and temperature was not linear in each of the regions examined, and as such, linear models would not be appropriate and likely would not be as informative. For example, a linear model would not show temperature as a significant predictor in the NEC nor would it show temperature as an important factor where the data for all seasons and regions are combined because the shape of the curve is not linear (Fig. 2.2).

A valuable aspect of the GAM approach is that such models allowed us to both examine different relationships and provide a measure of confidence for the probability of catch based on those relationships. However, it is important to note that in certain cases (e.g the cooler temperature predictions for the loggerhead turtles in the NEC), the prediction intervals become quite large. The large intervals could be due to a number of reasons including a high level of variability in the data or a low sample size. For the loggerhead sea turtle predictions in the NEC, there is a relatively

small sample size at the cooler water temperatures. While the prediction interval does get larger, it does not take away from the significance of temperature or region in the analysis and provides a measure of confidence in the predictions which is highly useful in decision making.

There are a few assumptions made in this analysis that are important to consider. One is that each longline set has an equal probability of catching a turtle, which implies that all gear configurations are equally likely to catch sea turtles and that there is no effect of time nor day when a set was made and retrieved. These assumptions are not met perfectly, although there appears to be relatively similar gear type and size across the USA pelagic fleet. This study may be further refined by including variables, like gear characteristics and set time, into the GAM approach used here. Additionally, other variables and environmental features could also be modeled in the framework described above. Another assumption we made is that the probability of catching one turtle is equivalent to catching two or more turtles on a single line. Again, the actual number of turtles caught, as opposed to just the binary scenario examined here, could be modeled using a similar framework. However, the probability of catching at least one turtle appears to be a useful tool in detecting patterns of sea turtle catches relative to fishing.

There are large differences in the temperature conditions in the three regions. Sea turtles in the NED experience different temperature conditions than those in the NEC, which likely contributed to the results indicating that the probability of capturing a sea turtle is influenced by the local temperature conditions. The maximum temperature fished in the NED is almost 6°C cooler than that of the NEC, which is the adjacent geographical region. In the GOM where the temperature range is warmer, the sea turtles are caught more uniformly across all temperatures in contrast to the NEC where the probability of catch declines after a certain temperature. Temperature,

region, and the interaction between the two were all found to be significant predictors in the model. Specifically, because the interaction term is significant, this suggests that the probability of catching sea turtles at a given temperature varies by region. Arguably the sea turtles in the different regions may be at different life stages or are being caught during different behavioral activities. If this is the case, then the management of sea turtles in the different regions may need to be more biologically based to fit the patterns of sea turtle behaviors.

James et al. (2005) suggest that for conservation of sea turtles in the pelagic waters of the Atlantic, modifying fishing practices may be more effective than implementing area closures. In fact, in 2004, gear modifications were required of the U.S. fisherman in order to reduce sea turtle interactions. Our study examined data from 1992-2003, which can be used in future years for comparing the probability of catch after implementation of the gear modifications. Noting the gear modification impacts across regions and temperature ranges will be insightful into the effectiveness of this type of management practice. Thus, the results of this study showing the impact of spatially explicit temperature-dependence on bycatch probabilities are useful as a practical application for management now and as a monitoring tool for future assessment of fishery management effectiveness.

Rules or regulations, such as not allowing fishing above a certain temperature over an entire ocean basin, are likely too broad to be effective for reducing sea turtles catches while not negatively impacting the fishing industry. As such, the use of non-linear models can be a powerful management tool as we move towards more refined mechanisms for reducing sea turtle interactions with the pelagic longline fishery; therefore, highlighting the importance of examining data at more refined spatial scales. The ability to refine the spatial, temporal and temperature scales in which regulations are made could prove to be as effective as altering fishing practices. GAM and other

non-linear models are a good starting place for analytical refinement of fisheries interactions with respect to space and time.

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References:

Beerkircher, L. R., C. J. Brown, D. L. Abercrombie, and D. W. Lee. 2004. SEFSC Pelagic Observer Program Data Summary for 1992-2002. NOAA TECHNICAL MEMORANDUM NMFS-SEFSC-522: 25 p.

Coles, W.C. and J.A. Musick. 2000. Satellite sea surface temperature analysis and correlation with sea turtle distribution off North Carolina. *Copeia*. **2**:551-554.

Epperly, S.P, J. Braun, A.J.Chester, F.A.Cross, J.V. Merriner, and P.A.Tester. 1995. Winter distribution of sea turtles in the vicinity of Cape Hatteras and their interactions with the summer flounder trawl fishery. *Bulletin of Marine Science* **56**(2):547-568.

Frair, W., R.G. Ackman, and N. Mrosovsky. 1972. Body temperature of Dermochelys coriacea: Warm turtle from cold water. *Science* **177**: 791-793.

Gilman, E. et al. 2006. Reducing sea turtle by-catch in pelagic longline fisheries. *Fish and Fisheries* **7**:2-23.

Hastie, T.J. and R.J. Tibshirani. 1990. Generalized Additive Models. CRC Press. Boca Raton, FL. 336pp.

Hoey, J. 1998. NEFSC pelagic longline data review and analysis of gear, environmental, and operating practices that influence pelagic longline interactions with sea turtles. Unpublished Report. National Fisheries Institute, Inc., Arlington, VA Final Contract Report NOAA-Contract – 50EANA700063 to National Marine Fisheries Service Northeast Regional Office, Glouster, MA, 32 pp.

International Union for Conservation of Nature and Natural Resources (IUCN). 2004. IUCN redlist of threatened species. Cambridge, UK. Available from http://www.redlist.org/ [accessed October 2006; updated October 2006].

James, M.C., C.A. Ottensmeyer, R.A. Myers. 2005. Identification of high-use habitat and threats to leatherback sea turtles in northern waters: new directions for conservation. *Ecology Letters* **8**:195-201.

Kobayashi, D.R. and J.J. Polovina. 2005. Evaluation of time-area closures to reduce incidental sea turtle take in the Hawaii-based longline fishery: generalized additive model (GAM) development and retrospective examination. NOAA Tech. Memo. NMFS-PIFSC-4. 39p.

Lewison, R.L., S.A. Freeman, and L.B. Crowder. 2004. Quantifying the effects of fisheries on threatened species: the impact of pelagic longlines on loggerhead and leatherback sea turtles. *Ecology Letters* **7**:221-231.

NMFS (National Marine Fisheries Service Southeast Fisheries Science Center). 2001. Stock assessments of loggerhead and leatherback sea turtles and an assessment of the pelagic longline fishery on the loggerhead and leatherback sea turtles of the Western North Atlantic. U.S. Department of Commerce, NOAA Technical Memorandum NMFS-SEFSC-455, 343pp.

Polovina, J.J., D.R. Kobayashi, D.M. Parker, M.P. Seki, and G.H. Balazs. 2000. Turtles on the edge: movement of loggerhead turtles (*Caretta caretta*) along oceanic fronts, spanning longline fishing grounds in the central North Pacific, 1997-1998. *Fisheries Oceanography* **9**: 71-82.

Shah, A., J. Watson, D. Foster, and S. Epperly. 2004. Experiments in the Western Atlantic Northeast Distant Waters to evaluate sea turtle mitigation measures in the pelagic longline fishery-Summary of statistical analysis. Unpublished data. NOAA Fisheries SEFSC, Miami, FL.

Shoop, C.R. and R.D. Kenney. 1992. Seasonal distributions and abundances of loggerhead and leatherback sea turtles in waters of the northeastern United Sates. *Herpetological Monographs* **6**: 43-67.

Watson, J. W., S. P. Epperly, A. K. Shah, and D. G. Foster. 2005. Fishing methods to reduce sea turtle mortality associated with pelagic longlines. *Canadian Journal of Fisheries and Aquatic Science* **62**: 965-981.

Williams, P., P.J. Annions, P.T. Plotkin, and K.L. Salvini (Complilers). 1996. Pelagic longline fishery-sea turtle interactions: proceedings of an industry, academic and government experts, and stakeholders workshop held in Silver Spring, Maryland, 24-25 May 1994. U.S. Dep. Commerl, NOAA Tech. Memo. NMFS-OPR-7, 77p.

Witzell, W.N. 1999. Distribution and relative abundance of sea turtles caught incidentally by the U.S. pelagic longline fleet in the western North Atlantic Ocean, 1992-1995. *Fisheries Bulletin* **97**:200-211.

Chapter 3

Quantifying the influence of surface temperature and thermal fronts on sea turtle catch locations in the Northeast Distant Waters of the North Atlantic

Abstract: Loggerhead (*Caretta caretta*) and leatherback (*Dermochelys coriacea*) sea turtles are known to be influenced by water temperature and thermal fronts in the ocean. Both species are protected in the USA and in other parts of the world. Consequently, understanding sources of mortality, including that from the pelagic longline fishery, is important. This study aims to quantify the catch rates of swordfish and the bycatch rates of sea turtles in relation to water temperature and thermal fronts. Perhaps more importantly, this study aims to characterize relationships between bycatch rates and oceanic features using a daily scale and to compare the patterns of sea turtle catches with those of swordfish. The Navy Coastal Ocean Model (NCOM) provides daily continuous coverage of sea surface temperatures. From this model spatial temperature changes can be determined and used to detect thermal fronts for each day. To analyze the oceanic data in relation to catch data, we use generalized additive models, which allow non-linear relationships to be quantified. In the western North Atlantic, swordfish, loggerhead, and leatherback catches were analyzed for 2002 and 2003. Results from a deviance goodness of fit test showed that sea surface temperature as well as three derived indicators of thermal fronts were all significant predictors of the number of loggerhead and leatherback sea turtles captured in the longline fishery for both years. Furthermore, water temperature was a significant predictor of swordfish catches for both years, and one derived indicator of thermal fronts was also significant in the year 2003. With near real-time ocean temperature models such as NCOM now available, analysis of these types of oceanographic

features are extremely useful in predicting sea turtle locations, especially with respect to swordfish and other targeted species.

1. Introduction:

Predicting patterns of movement and distribution of species of special concern is one of the primary tools employed by resource managers. In the marine fisheries arena, at the forefront of issues facing managers is the incidental capture of non-targeted species (bycatch). This is exemplified in the pelagic longline fishery where many marine animals of concern, such as the endangered loggerhead (*Caretta caretta*) and critically endangered leatherback (*Dermochelys coriacea*) sea turtles (IUCN 2004), are a large component of the untargeted bycatch (Lewison et al. 2004, Kobayashi and Polovina 2005). Much of the bycatch can be attributed to the nature of longline fishing gear, which in the U.S. fishery typically consists of a mainline often as long as 50 kilometers, with baited hooks numbering in the hundreds to thousands hanging vertically in the water column. Sea turtles and other marine animals can become caught or entangled in the gear. This is especially true for the swordfish (*Xiphias gladius*) fishery and others that concentrate effort in the upper portions of the water column, which is sea turtle habitat. A number of measures have been implemented to address the rate of sea turtle bycatch in the longline fishery and these different approaches have met with varying degrees of success. It is our intent to develop techniques to better predict patterns of sea turtle distributions, and to compare or distinguish these from the target fish with relation to oceanic features such as temperature and thermal fronts. Such refinements in our predictive abilities may be useful in reducing undesired bycatch of sea turtles while minimizing negative impacts to important fisheries.

Included among the numerous management approaches aimed at alleviating the bycatch of sea turtles in the longline fishery are time-area closures and many types of gear modifications (Gilman 2006). Although such management schemes have helped to reduce bycatch, refinements in techniques continue to be warranted. An

important avenue of potential promise is the understanding of associations between sea turtles and specific temperature regimes. Despite the large range of temperatures in which loggerhead and leatherback sea turtles can occur, their distributions are known to be directly influenced by water temperatures (Shoop and Kennedy 1992, Epperly et al. 1995, Coles and Musick 2000).

With advances in the field of remote sensing, sea surface temperatures (SST) derived from satellite imagery have become a useful tool for obtaining synoptic views of the open ocean environment. Using satellite derived data, a number of studies have revealed correlations between sea turtle sightings and SST (Chester et al. 1994, Epperly et al. 1995, Coles and Musick 2000, Polovina et al. 2004, Kobayashi and Polovina 2005). Most of these studies indicated that sea turtles, within their normal distribution ranges, occur at higher frequencies in certain temperatures. This suggests that sea turtles may be more likely to be caught by the longline fishery at certain water temperatures and thus bycatch rates should vary by temperature (Hoey 1998, Watson et al. 2005). This general association between sea turtles and surface temperatures also apparently exists for many targeted fish as SST data are increasingly used by the fishing industry to determine good fishing locations.

Beyond the value of knowing the absolute temperature, discontinuities in temperature that indicate thermal fronts may be more relevant to ocean pelagic fish distributions (Podestá et al. 1993). Such temperature changes likely represent changes in other physical and biological oceanographic factors too, such as salinity, water clarity, and current velocity (Olson and Podestá 1987). Temperature discontinuity may also reflect areas of increased primary production due to the presence of mesoscale oceanic processes (Olson and Backus 1985). In the swordfish fishery, longliners use ocean temperature data to detect the presence of thermal fronts and to identify locations where higher catch rates are expected. It has been reported that very

high swordfish catches per unit effort (CPUE) are associated with proximity to thermal fronts (Podestá et al. 1993).

Evidence is mounting that sea turtles are associated with thermal and chlorophyll fronts (Sakamoto et al. 1997, Polovina et al. 2000, Polovina et al. 2004). The studies to date have depended mainly on the use of Advanced Very High Resolution Radar (AVHRR) or Moderate Resolution Imaging Spectroradiometer (MODIS) to acquire SST data. An acknowledged shortcoming of these data is regions or grid cells on the ocean surface data that contain no information (i.e. no data) caused by cloud cover which satellites could not penetrate on any given day. To overcome the problem of cloud cover, the SST data are composited into 8-day or monthly periods. By compositing the satellite data, a complete picture of SSTs can be achieved with relatively good spatial resolution. However, the loss in temporal resolution could be important in areas of rapid temperature changes, such as the Gulf Stream, known for having strong thermal gradients and consistent dynamic fronts (Podestá et al. 1993). Knowing the daily oceanic features would likely benefit correlation analysis of animal locations, distribution patterns, and movements.

Given that pelagic, oceanic sea turtles may be converging at fronts and that the longline fisheries target swordfish at these fronts, bycatch of sea turtles may be inadvertently high. Our objective in this study was to quantify the influence of SST and thermal fronts, at a higher temporal resolution, in relation to the number of sea turtles caught in the longline fishery. Ideally, we expect to refine existing predictive models to differentiate between areas of high swordfish catch rates and those with high sea turtle bycatch. This information could be used to help reduce bycatch while not unduly impacting the efficiency of catching the target species.

2. Data and Methods:

The data for the sea turtle and swordfish catches used in this study were collected on fishing vessels during gear modification experiments initiated by NOAA's Southeast Fisheries Science Center (SEFSC). During 2001 - 2003, the SEFSC carried out experiments directed at the swordfish fishery in the north central North Atlantic (NED, Fig. 3.1), which otherwise was closed to U.S. pelagic longline fishing. In 2002 and 2003, this NED experimental dataset extends from the end of June through the beginning of November, which is the season when the majority of fishing occurs in the NED (Watson et al. 2005). Observer coverage was 100% during the experiments. During the latter two years, the resolution of the data was higher, including detailed data on "sections" or subunits of each haul (Watson et al. 2005). There are generally 7-12 sections for each haul. During the experiment, there were 3 different hook treatments in 2002 and 4 different hook treatments in 2003. Information was collected on a number of variables during the experiments. Here we make use of the latitude, longitude, number of hooks, treatment, and the number of loggerhead, leatherback, and pounds of swordfish catches per section for 2002 and 2003.

The SST data used in this study were from the Navy Coastal Ocean Model (NCOM), obtained from the Naval Research Laboratory for each day of 2002 and 2003 to coincide with the NED experimental data. NCOM, which provides daily continuous coverage of SST at ≈1/8° latitude resolution, makes use of information from satellites, which can be updated by shipboard and buoy data to make predictions of SST in areas where satellite data are not available for that day. The SST values derived from NCOM, when compared with a satellite-based Pathfinder dataset, had a root-mean-square SST difference of 0.61°C across the global ocean (Kara et al. 2006). Thus, a pixel for which there previously were no data is generally within 1°C of the

actual sea surface temperature recorded using only remote sensed data. The incorporation of NCOM enabled us to achieve greater temporal resolution in our thermally dynamic study area that might otherwise be clouded over.

Based on the daily SST values from NCOM, we used ArcGIS (ESRI Inc.) functions to derive a new set of variables, beginning with a measure of change in temperature (deltaSST). We calculated the maximum change from each center pixel to its surrounding eight neighbors. The value of the computed maximum was then assigned to the center pixel and stored as the variable deltaSST. We used the deltaSST data to create two more variables. A line representing the northern front of the Gulf Stream was calculated for each day by fitting a least cost path through the pixels with the highest values in the deltaSST image. Essentially, this gave the major thermal front for a given day. From the position of this front, we calculated the distance in kilometers to each fishing location creating the new variable, distGS. The final variable we calculated was the distance in kilometers from the nearest pixel with a deltaSST value greater than 1°C to each fishing location. This new variable, dist1C, allowed us to examine the influence of smaller thermal fronts and eddies.

All of the calculated variables were assigned to each section of the fishing haul using the latitude and longitude at the start point of each haul for each section as it was being pulled onto the vessel. We then took the mean from all of the sections and assigned that single value for each variable to the haul. The pounds of swordfish (in thousands) and numbers of loggerhead and leatherback turtles were summed across all the sections of a haul and a single summed value was then assigned to each haul.

To analyze the relationship between sea turtle and swordfish catches and oceanographic features we used generalized additive models (GAMs). As a flexible class of models, GAMs allow non-linear effects in the response variable (Hastie and Tibshirani 1990). These models use nonparametric smoothing functions to quantify

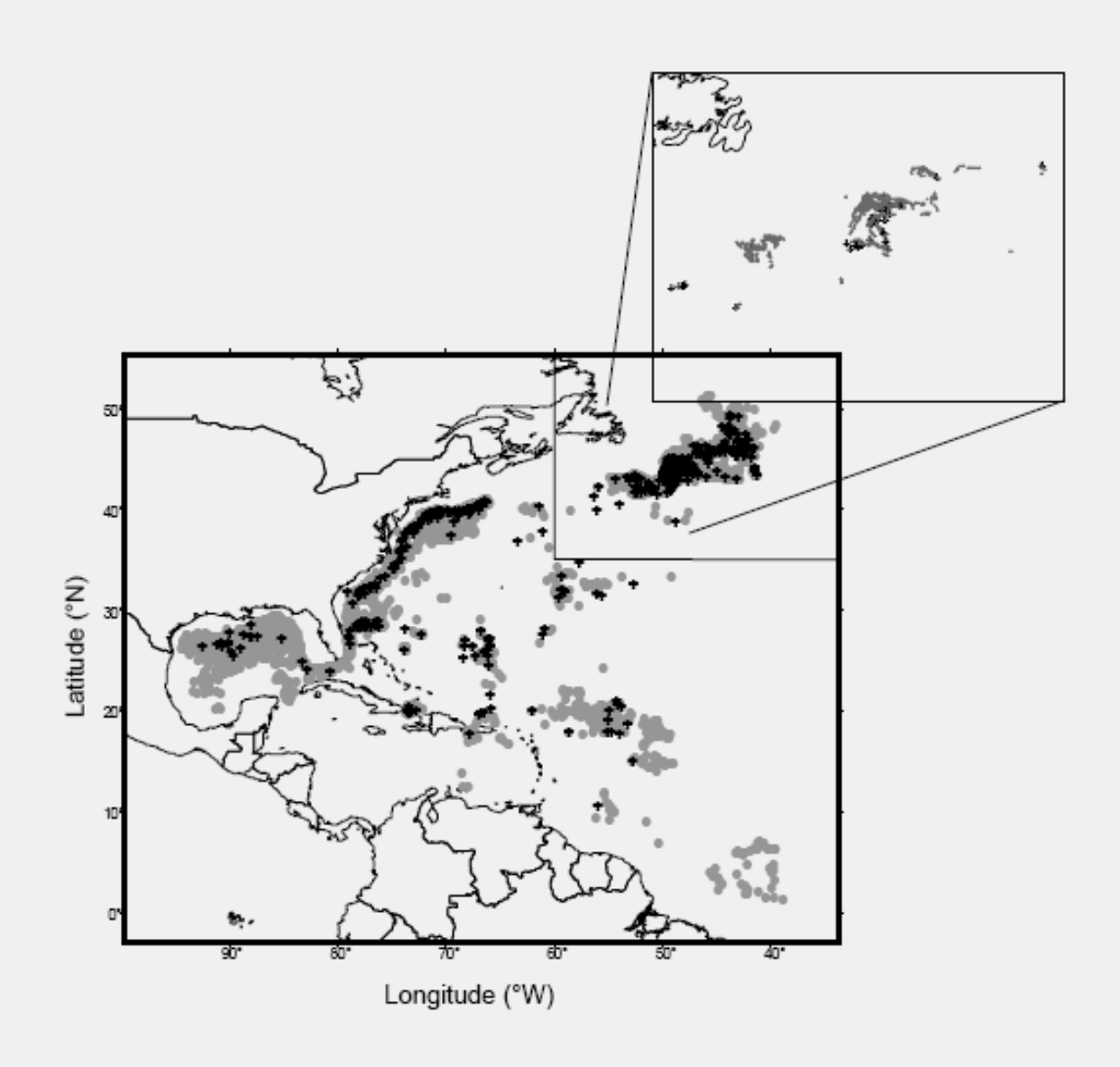

Figure 3.1: Map of the study region. The general area of the study site in the western North Atlantic shown in the lower map and the detailed fishing locations for October 2002 are shown in blown-up map. The 2003 data cover the same region.

the patterns between variables. In this analysis we used the spline option as the smoothing function (denoted as $s(\cdot)$). Because we are analyzing count data (number of sea turtles caught in each haul or thousands of pounds of swordfish), we use a Poisson distribution with a log link function in the all of the models. Thus we define the model as:

$$z \sim Poisson(\eta)$$

where z is the number of sea turtles or pounds of swordfish in each haul. The full model to estimate η is given by

$$\eta = offset(E(c)) + s(ncomSST) + s(deltaSST) + s(distGS) + s(dist1C)$$

where ncomSST is sea surface temperature, deltaSST is a measure of temperature change in near vicinity sea surface temperatures, distGS is the distance to the major thermal front, and dist1C is the distance to the nearest 1°C thermal front. *E(c)* is the expected catch for a given haul, based only on the effort (number of hooks) and the average catch rate by treatment, which is derived as:

$$E(c) = \log(h * \frac{C_T}{H_T})$$

where h is the number of hooks used during a given haul and C_T is the total catch and H_T the total number of hooks in a given treatment (T). Thus, if we were analyzing the swordfish data, C_T would be the total number of pounds of swordfish caught in a given treatment. Watson et al. (2005) found different catch rates between treatments, so *E(c)* is used to adjust for the different catch rates and for the number of hooks used in each haul.

The models were fit for loggerheads, leatherbacks, and swordfish in 2002 and 2003 independently. The GAMs were constructed using the software package S-Plus v. 6.2 (Insightful Inc. Seattle, WA.). Akaike's Information Criterion was used to

select the best model for each species, making use of the number of parameters and the amount of variation explained by the model (Akaike 1973). A deviance goodness of fit test was used to assess the significance of each of the model parameters.

3. Results:

Loggerhead sea turtles - A deviance goodness of fit test indicated that all four variables were significant predictors of loggerhead sea turtle catches for both 2002 and 2003 (Table 3.1). The patterns for the individual components of the GAM (i.e. ncomSST, deltaSST, and dist1C) were very similar in both years for the loggerheads (Figs. 3.2 and 3.3). However, distGS in 2002 shows an increasing trend as distance away from the thermal front increases, but in 2003 the trend is just the opposite (Figs. 3.2 and 3.3). AIC results indicated that the best model for both years included all four of the variables.

Leatherback sea turtles - For the leatherbacks, ncomSST and distGS were both significant in 2002 and 2003 (Table 3.1). The ncomSST shows an increasing trend as temperature increases, which is also similar to the influence of ncomSST on loggerhead catches. However, for the leatherback turtles, dist1C was only significant in 2002, displaying a generally decreasing trend (Fig. 3.4) while dist1C appears almost flat in 2003 (Fig. 3.5). Additionally, deltaSST was only significant in the model for leatherback catches in 2003 and the trends again appear opposite for the two years (Figs. 3.4 and 3.5). Despite the slightly different results for the individual components, the AIC results indicated that the best model for both years included all four of the variables. However, the AIC values were similar for the full model as compared with the model that contained the three significant predictors as determined from the deviance goodness of fit tests.

Table 3.1: Results of the deviance goodness of fit test indicating the significance of each variable for each of the species (loggerhead sea turtles, leatherback sea turtles, and pounds of swordfish).

Year 2002	**ncomSST**	**deltasst**	**distGS**	**dist1C**
loggerheads	**	**	**	**
leatherbacks	**		**	**
swordfish		*		*
Year 2003				
loggerheads	**	**	**	**
leatherbacks	**	**	**	
swordfish	**		*	

* p<.05 ** p<.01

Swordfish – The results from the deviance goodness of fit tests for both years are different for the swordfish. In 2002, dist1C and deltaSST are significant predictors of swordfish catch in pounds (Table 3.1). However, in 2003, ncomSST and distGS were found to be significant predictor variables (Table 3.1). In contrast to the sea turtle results, the AIC for the swordfish analysis indicated that all of the possible models had very similar AIC values. In 2002 the full model had the lowest AIC followed by the null model with the second lowest AIC. In 2003, the model containing ncomSST, distGS, and dist1C had the lowest AIC value. Thus, while deltaSST appears to be significant predictor in 2002, it is not included in the best model for 2003. While ncomSST had a positive relationship with both turtle species, it did not appear to have much influence on the catch of swordfish in either 2002 or 2003 (Figs. 3.6 and 3.7). With the exception of deltaSST in 2002 (Fig. 3.6), none of the variables show any clear positive or negative trends on swordfish catch (Figs. 3.6 and 3.7). And based on the AIC results, none of the models appear to do a very good job at explaining the catch of swordfish in pounds.

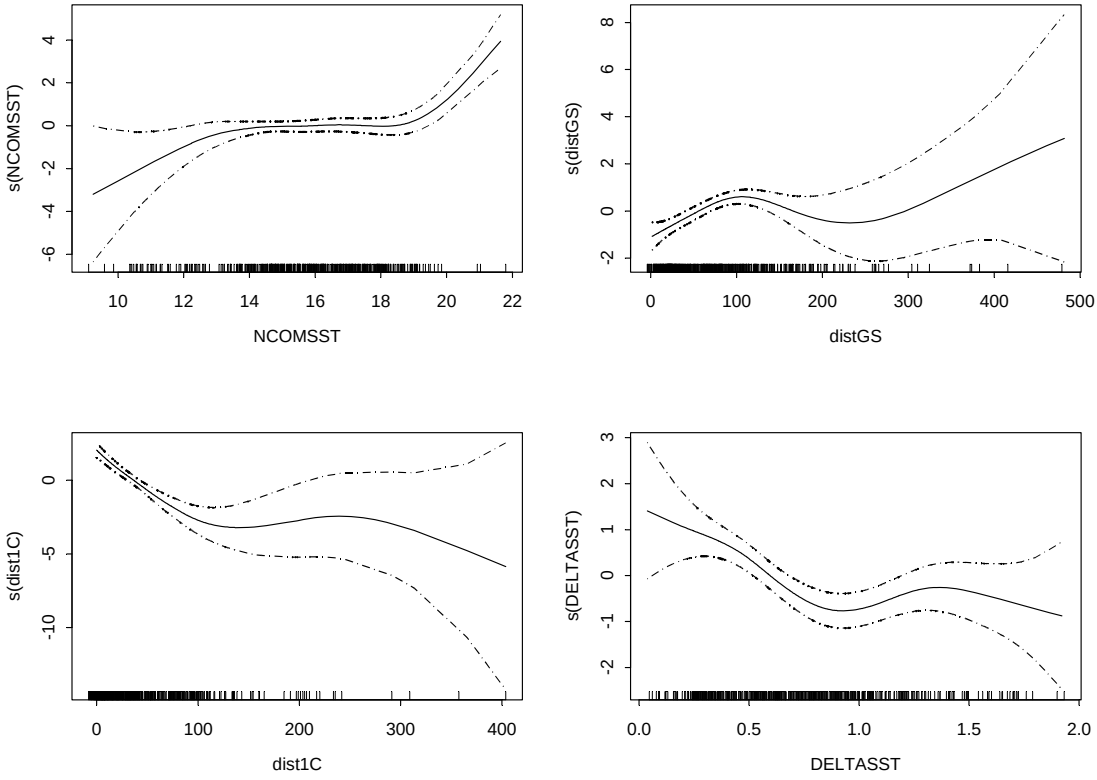

Figure 3.2: Relative influence of each variable in the GAM on loggerhead sea turtle catches in 2002. The variables are: sea surface temperature (NCOMSST), the distance (km) to the major thermal front (DISTGS), distance (km) to the 1°C front (DIST1C), and the change in sea temperature (DELTASST). The lines represent the 95% prediction intervals.

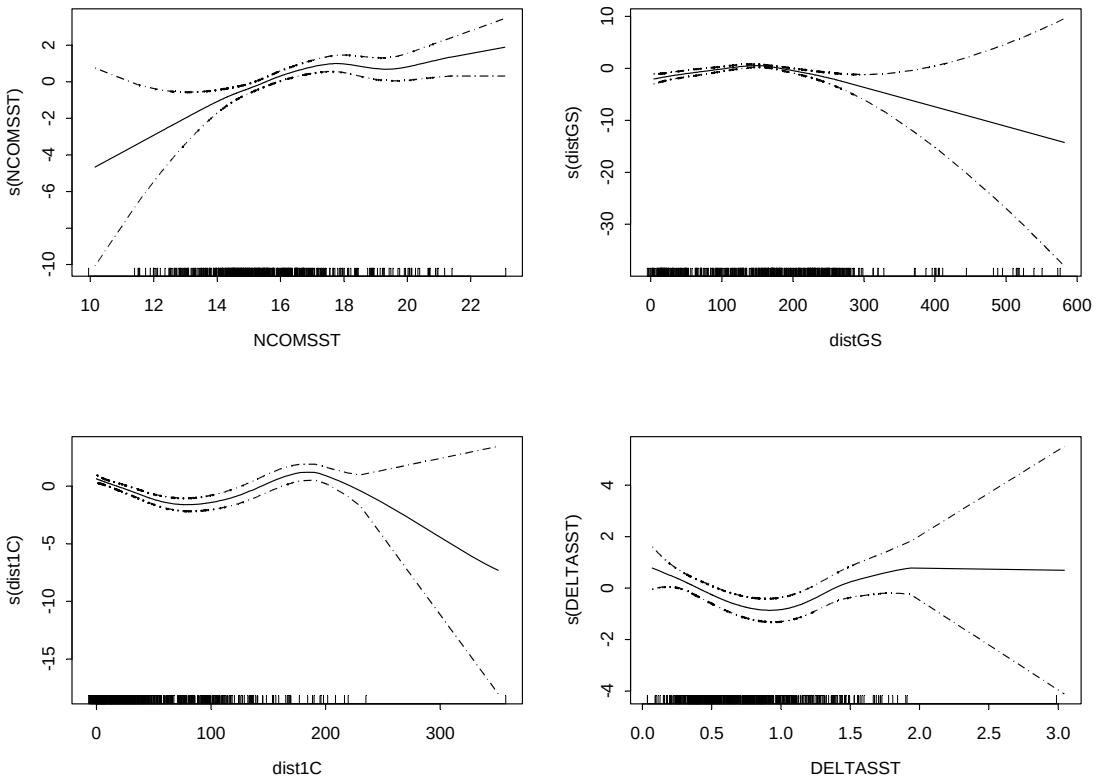

Figure 3.3: Relative influence of each variable in the GAM on loggerhead sea turtle catches in 2003. The variables are: sea surface temperature (NCOMSST), the distance (km) to the major thermal front (DISTGS), distance (km) to the 1°C front (DIST1C), and the change in sea temperature (DELTASST). The lines represent the 95% prediction intervals.

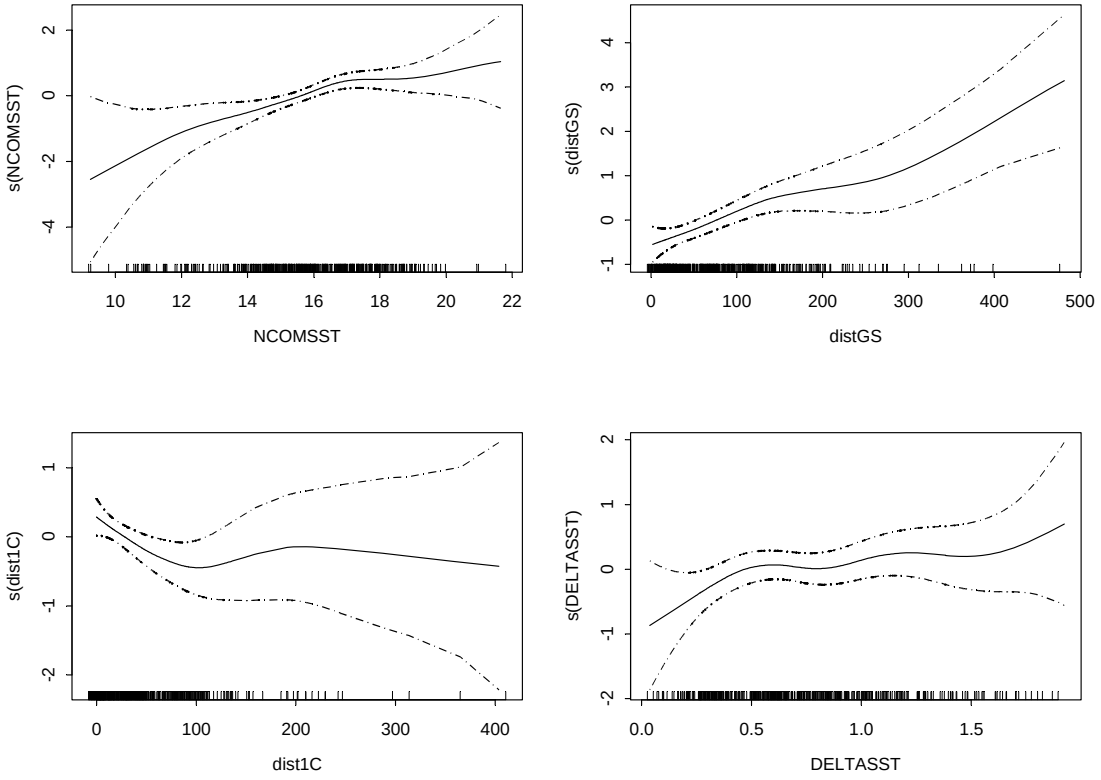

Figure 3.4: Relative influence of each variable in the GAM on leatherback sea turtle catches in 2002. The variables are: sea surface temperature (NCOMSST), the distance (km) to the major thermal front (DISTGS), distance (km) to the 1°C front (DIST1C), and the change in sea temperature (DELTASST). The lines represent the 95% prediction intervals.

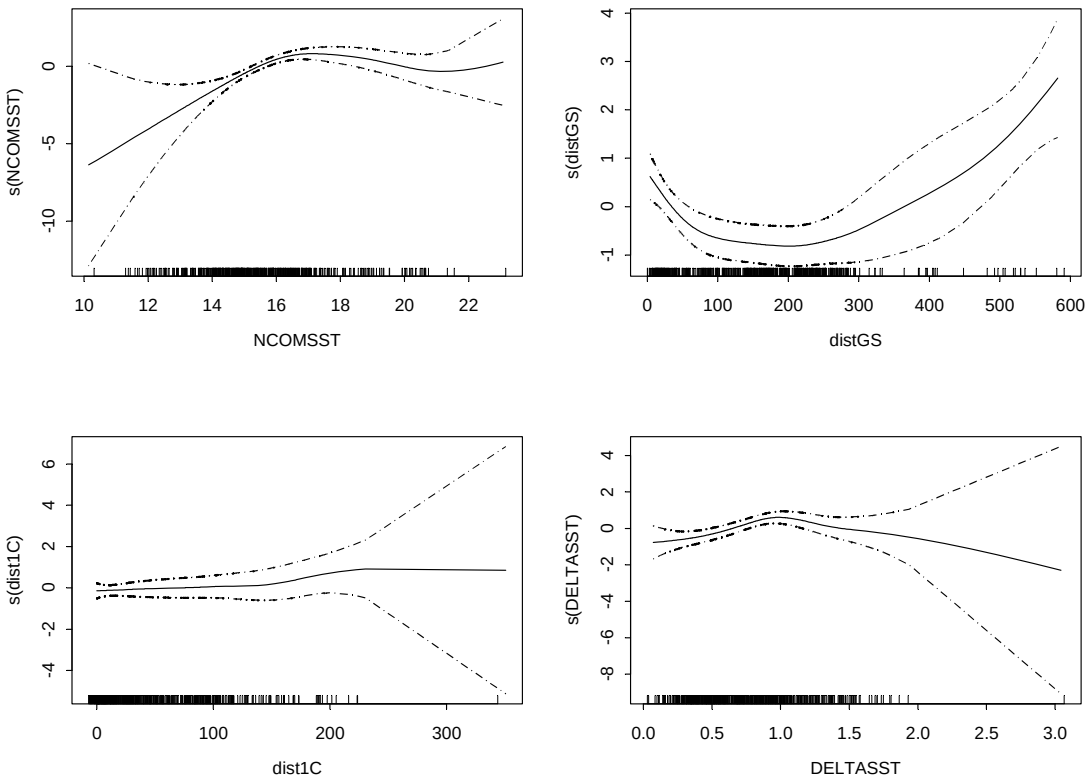

Figure 3.5: Relative influence of each variable in the GAM on leatherback sea turtle catches in 2003. The variables are: sea surface temperature (NCOMSST), the distance (km) to the major thermal front (DISTGS), distance (km) to the 1°C front (DIST1C), and the change in sea temperature (DELTASST). The lines represent the 95% prediction intervals.

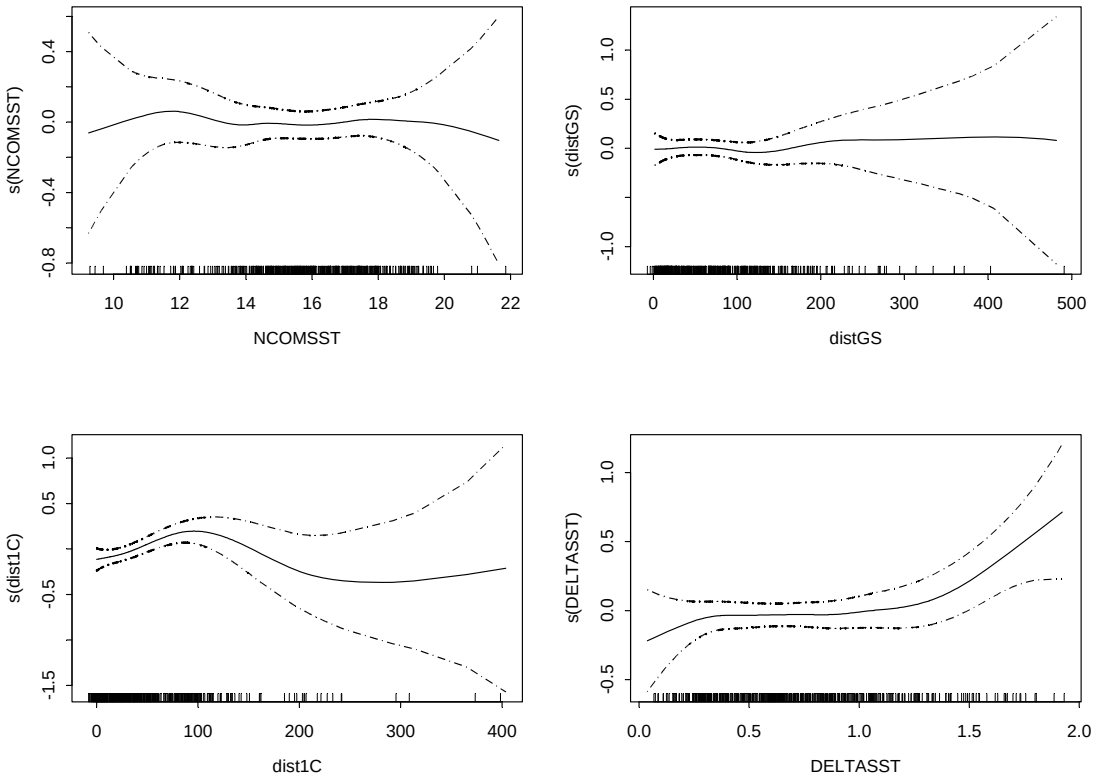

Figure 3.6: Relative influence of each variable in the GAM on swordfish catches (in pounds) in 2002. The variables are: sea surface temperature (NCOMSST), the distance (km) to the major thermal front (DISTGS), distance (km) to the 1°C front (DIST1C), and the change in sea temperature (DELTASST). The lines represent the 95% prediction intervals.

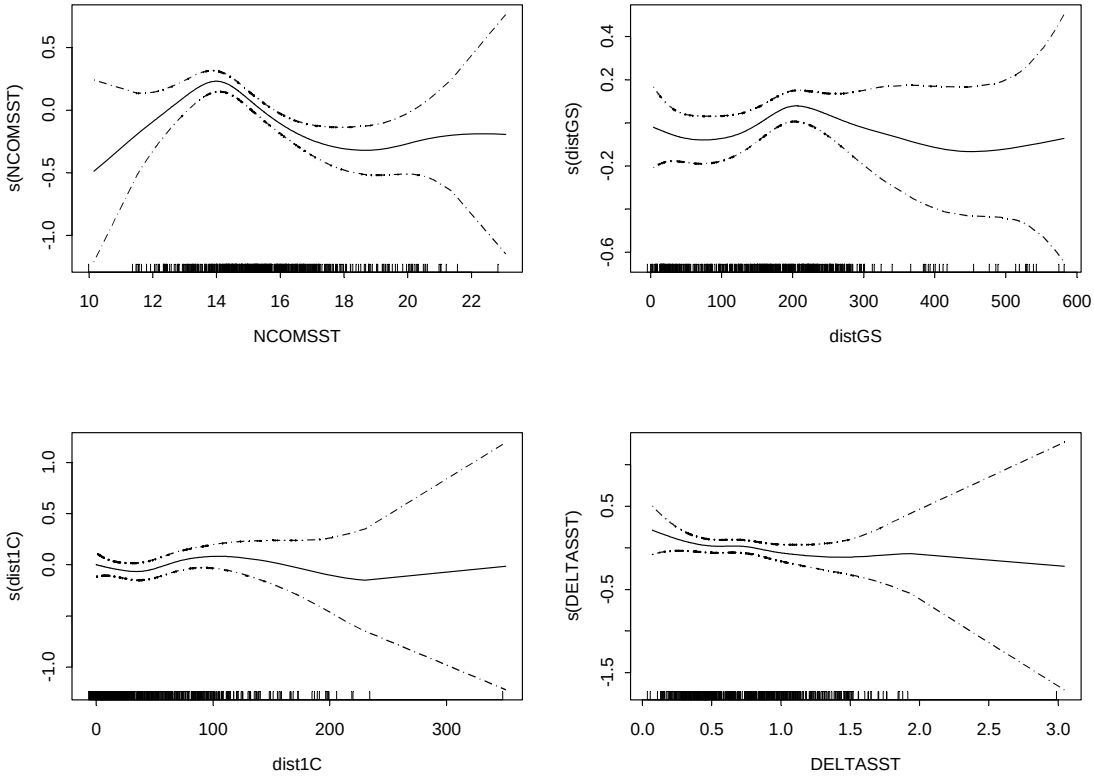

Figure 3.7: Relative influence of each variable in the GAM on swordfish catches (in pounds) in 2003. The variables are: sea surface temperature (NCOMSST), the distance (km) to the major thermal front (DISTGS), distance (km) to the 1°C front (DIST1C), and the change in sea temperature (DELTASST). The lines represent the 95% prediction intervals.

4. Discussion:

The combination of daily SST and better fisheries data (100% observer coverage during this analysis) yielded relationships that were previously unattainable (Olson 2002). The results of this study indicate that the role of oceanic features, such as temperature and thermal fronts, play an important role in the distribution of sea turtle and swordfish catch locations in the western North Atlantic. Furthermore, there appears to be a difference in the occurrence patterns between the three species using calculated oceanic variables derived daily. Based on these results, there may be a better way to maintain the catch rates of target species while simultaneously reducing the undesired bycatch of sea turtles. The also results indicate a year effect, suggesting that management strategies to reduce bycatch may need to be year specific or adaptive.

The NCOM dataset provides daily, continuous coverage for SST which is useful in establishing relationships between fisheries and oceanic features. NCOM overcomes issues of cloud cover and missing satellite by making use of other available data sensors such as shipboard records and buoy data. As the Gulf Stream is an area of high change, with various water masses meeting and persistent fronts, knowing the value of the daily features provides a more appropriate variable for establishing relationships. For example, using an eight-day composite may be misleading regarding the absolute water temperature for a given day or in detecting daily front locations (see Appendix C). NCOM provides oceanographic data for the global ocean on a daily scale with good accuracy on the SST values (Kara et al. 2006).

However, NCOM is a model that predicts the SST for areas where there is cloud cover and where there are missing data by using available information from nearby pixels (Kara et al. 2006). Thus it can be more difficult to detect some small fronts as the model may be “smoothing” the data across areas that are missing data for

that day. Additionally, the spatial resolution for the NCOM data we used in this study is 1/8°, or 14 km/pixel near the mid-latitudes. This resolution was adequate to detect new relationships in this study, but finer spatial resolution (1/32°) is now available, and might be more useful for detecting small thermal fronts near the Gulf Stream and further refining predictive ability. Despite these shortcomings, using the NCOM data to analyze oceanic features on a daily scale proved simple and potentially useful as a management tool.

Another important aspect of this study was using additive models to detect the non-linear nature of the relationships between the catches and environmental covariates. In some situations, using a linear model would not be appropriate for estimating the relationship. For example, in 2003, the relationship between distance to the thermal front (distGS) and catches of leatherbacks takes on a distinct "U" shape which would not be well estimated by a straight line. Thus, equally useful from this analysis is determining what parameters would be adequate to model the effects, such as a quadratic term in the case of distGS and leatherbacks in 2003. Another example is the relationship between ncomSST and the loggerhead sea turtles, with the other variables in the model, which would likely be well modeled with a simple linear component. The GAMs also helped determine which covariates where important predictors in the estimating sea turtle and swordfish catch. However, some caution must be taken when computing p-values associated with the deviance goodness of fit tests and AIC values. According to Hastie and Tibshirani (1990), while the distribution theory for additive models is undeveloped, using the deviance as a way to assess models and their differences still makes sense.

The most important consequence of this study was discovering patterns for the individual components of the GAM, which elucidated differences between all three of the species. As ncomSST increased so did the catch the two sea turtle species, while

the catch in pounds of swordfish did not. Additionally, the distGS, representing the distance from the calculated frontal line, was a significant predictor for both sea turtles species in both 2002 and 2003. Perhaps one of the most interesting results was that the influence of distance to the 1°C front (dist1C) was very different between the loggerheads and swordfish at shorter distances. For fishing locations that were less than 100 km from the 1°C front, the number of sea turtles caught increases as the distance to the front decreases. However, the number of swordfish declined or stayed constant when the distance to the front decreased. When thinking of ways to reduce bycatch while not hindering swordfish catch, this information may prove very useful. For example, loggerhead sea turtle catch could be reduced by not fishing within 100 km of smaller thermal fronts (a value which can easily be calculated from the NCOM SSTs). These types of distinctions and a better understanding of pelagic fishes may start to separate out biological or habitat preferences between the sea turtle species, and ultimately lead to reduced bycatch of sea turtles in the western North Atlantic.

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References:

Akaike, H. 1973. Information theory and an extension of the maximum likelihood principle. International Symposium on Information Theory, 2nd, Tsahkadsor, Armenian SSR; Hungary; 2-8 Sept. 1971. pp. 267-281.

Chester, A.J., Braun, J., Cross, F.A., Epperly, S.P., Merriner, J.V., and Tester, P.A. 1994. AVHRR imagery and near real-time conservation of endangered sea turtles in the western North Atlantic. Proceedings of the WMO/IOC Technical Conference on Space-Based Ocean Observations, September 1993 (WMO/TD-No. 649). Bergen, Norway. P. 184-189.

Coles, W.C. and Musick, J.A. 2000. Satellite sea surface temperature analysis and correlation with sea turtle distribution off North Carolina. Copeia. **2**:551-554.

Epperly, S.P, Braun, J., Chester, A.J., Cross, F.A., Merriner, J.V. and Tester, P.A. 1995. Winter distribution of sea turtles in the vicinity of Cape Hatteras and their interactions with the summer flounder trawl fishery. Bulletin of Marine Science **56**(2):547-568.

Gilman, E. et al. 2006. Reducing sea turtle by-catch in pelagic longline fisheries. Fish and Fisheries, **7**:2-23.

Hastie, T.J. and R.J. Tibshirani. 1990. Generalized Additive Models. CRC Press. Boca Raton, FL. 336pp.

Hoey, J. 1998. NEFSC pelagic longline data review and analysis of gear, environmental, and operating practices that influence pelagic longline interactions with sea turtles. Unpublished Report. National Fisheries Institute, Inc., Arlington, VA Final Contract Report NOAA-Contract – 50EANA700063 to National Marine Fisheries Service Northeast Regional Office, Glouster, MA, 32 pp.

International Union for Conservation of Nature and Natural Resources (IUCN). 2004. IUCN redlist of threatened species. Cambridge, UK. Available from http://www.redlist.org/ [accessed October 2006; updated October 2006].

Kara, A.B, Barron, C.N., Martin, P.J., Smedstad, L.F., and Rhodes, R.C. 2006. Ocean Modelling 11, 376-398.

Kobayashi, D.R. and Polovina, J.J. 2005. Evaluation of time-area closures to reduce incidental sea turtle take in the Hawaii-based longline fishery: generalized additive model (GAM) development and retrospective examination. NOAA Tech. Memo. NMFS-PIFSC-4. 39p.

Lewison, R.L., S.A. Freeman, and L.B. Crowder. 2004. Quantifying the effects of fisheries on threatened species: the impact of pelagic longlines on loggerhead and leatherback sea turtles. *Ecology Letters* **7**:221-231.

Olson, D.B. 2002. Biophysical dynamics of ocean fronts. The Sea. 12:187-218.

Olson, D.B. and Backus, R.H. 1985. The concentrating of organisms at fronts: a cold-water fish and a warm-core Gulf Stream ring. Journal of Marine Research. 43:13-137.

Olson, D.B. and Podestá, G.P. 1987. Oceanic fronts as pathways in the sea. Pages 1-14 *in* W.F. Herrnkind and A.B. Thistle, editors. Signposts in the Sea (Proceedings of a multidisciplinary workshop on marine animal orientation). Tallahassee: Florida State University.

Podestá, G.P., Browder, J.A., and Hoey, J.J. 1993. Exploring the association between swordfish catch rates and thermal fronts on U.S. longline grounds in the western North Atlantic. Continental Shelf Research. **13**:253-277.

Polovina, J.J., Balazs, G.H., Howell, E.A., Parker, D.M, Seki, M.P., and Dutton, P.H. 2004. Forage and migration habitat of loggerhead (*Caretta caretta*) and olive ridley (*Lepidochelys olivacea*) sea turtles in the central North Pacific Ocean. Fisheries Oceanography. **13:1**, 36-51.

Polovina, J.J., Kobayashi, D.R., Parker, D.M., Seki, M.P., and Balazs, G.H. 2000. Turtles on the edge: movement of loggerhead turtles (*Caretta caretta*) along oceanic fronts, spanning longline fishing grounds in the central North Pacific, 1997-1998. Fish. Oceanogr. **9**: 71-82.

Sakamoto, W., Brando, T., Arai, N., and Baba, N. 1997. Migration paths of the adult female and male loggerhead turtles *Caretta caretta* determined through satellite telemetry. Fisheries Science. 63:547:552.

Shoop, C.R. and R.D. Kenney. 1992. Seasonal distributions and abundances of loggerhead and leatherback sea turtles in waters of the northeastern United Sates. *Herpetological Monographs* **6**: 43-67.

Watson, J.W., Epperly, S.P., Shah, A.K., and Foster, D.G. 2005. Fishing methods to reduce sea turtle mortality associated with pelagic longlines. Canadian Journal of Fisheries and Aquatic Science **62**: 965-981.

Chapter 4

A hierarchical spatial model for predicting sea turtle catch locations

Abstract: With bycatch of sea turtles in the pelagic longline fishery continuing to gain attention, new modeling efforts are needed to better predict the probability of capturing sea turtles given the presence of fishing. Both loggerhead (*Caretta caretta*) and leatherback (*Dermochelys coriacea*) sea turtles are protected under the U.S. Endangered Species Act and are listed worldwide on the World Conservation Union (IUCN) Redlist, thus determining ways to reduce sea turtle interactions with the longline fishery is important. A general framework for modeling sea turtle catches with respect to the longline fishery is proposed. The model is comprised of two main components: (1) spatially indexed oceanographic covariates used to predict the prior probability of capturing a sea turtle given that fishing occurs at a specified location; and (2) an updating procedure that characterizes the probability of catching a turtle given that other turtles have recently been caught nearby. The general framework allows for different types of information to be included in the model in a sequential fashion. Here, we use kriging predictions based on the preceding sea turtle interactions to update a Bayesian logistic model based on oceanic covariates. Results indicate that including the kriging predictions improved the predictions from the logistic model alone.

1. Introduction

The incidental catch of non-targeted species is a management concern for all fishing fleets (Hall et al. 2000). One particular area of concern is the bycatch of threatened loggerhead (*Caretta caretta*) and endangered leatherback (*Dermochelys coriacea*) sea turtles in the pelagic longline fishery (Spotila et al. 2000, Lewison et al. 2004, Pinedo and Polcheck 2004, Kobayashi and Polovina 2005). To address this problem, time-area closures, gear modifications and a number of other measures have been implemented to reduce the rate of sea turtle bycatch in the swordfish fishery (Gilman 2006). However, these measures have met with varying degrees of success and informative spatially explicit models are still needed to help further reduce sea turtle bycatch (Lewison et al. 2004).

One comprehensive way to predict the likelihood of sea turtle bycatch in association with longline fishing is through the use of Bayesian hierarchical spatial modeling. Not only does this approach show greater flexibility for modeling complex processes while allowing the inclusion of multiple sources of information, but it also facilitates development of inferential conclusions that are more meaningful in policy discussions due to its probabilistic framework (Ellison 1996).

The model specified here uses a prior predictive component that is based on a spatially indexed covariate model, which is subsequently updated using spatially correlated observations. Generally, the modeling of sea turtle locations has been limited to studies that incorporate only the spatially indexed covariates (sea surface temperature mostly) without regard to the spatial correlation of fishing locations (Chester et al. 1994, Epperly et al. 1995, Coles and Musick 2000, Polovina et al. 2000, Kobayashi and Polovina 2005). Modeling the spatial correlation, in addition to the oceanographic driven trend, permits the use of current information on sea turtle

catches which can then be used to inform the standard predictions acquired from a conventional linear model.

Our objective in this study was to predict the probability of capturing a sea turtle given that fishing is occurring at specific location under a set of specified environmental conditions. Ideally, the model would result in maps that indicate "hotspots" or regions with a high probability of turtle capture on a given day so that the fishery could redirect its fishing effort accordingly. Use of the Bayesian approach allows the model to be easily updated and facilitates the inclusion of prior information on sea turtle catches in a manner that is novel to the current state of the art. This spatially and temporally explicit approach will not only aid fishermen in their effort to avoid sea turtles, it will also allow management agencies to formulate more informed and accurate policies regarding when and where fishing should take place.

2. Model and Methods

For these analyses, a hierarchical modeling approach was employed. To iteratively update predictions based on a model using spatial covariates (oceanic features) with predictions that incorporate spatial correlation of a given set of observations. The sea turtle capture events (i.e. the presence or absence of a catch) given the presence of fishing effort are modeled as Binomial, conditional on a spatially varying intensity process. We define the predictive model as:

$$z_{t,k} \mid \theta_{t,k} = Binomial(1, \theta_{t,k})$$

Where $z_{t,k}$ is the vector of specified fishing locations where we would like to predict turtle capture at time *t* in location *k* and $\theta_{t,k}$ is the associated vector of probabilities of observing a turtle given that fishing is occurring. To emphasize the nature of the updating of the prior predicted probability given oceanographic conditions with the information contained in the observations of sea turtle catch, we can define θ_t as

$$\theta_t = \theta_{t'} + w_t(\psi_t - \theta_{t'})$$

such that $\theta_{t'}$ is the estimated prior probability based on oceanic data collected at time *t* and ψ_t is the subsequent estimated probability from a geostatistical model based on turtle observations taken at time *t-1*. The updating weight matrix is defined as w_t = diag($W_{i,t}$) where the variance-covariance matrix is defined by

$$W_{i,t} = \frac{1/\sigma_\psi^2}{1/\sigma_\theta^2 + 1/\sigma_\psi^2}$$

such that σ_ψ^2 represents the variance associated with the prediction ψ_t and σ_θ^2 represents the variance associated with the prediction $\theta_{t'}$. The cross correlation between ψ_t and $\theta_{t'}$ is assumed to be negligible.

2.1. Spatial Covariates

To characterize the prior probability of a turtle being captured given a fishing event and spatial covariates such as sea surface temperature and distance to the thermal front, a generalized linear regression model with a logit link can be specified as

$$Logit(\theta_{t'}) = X_{t'}\beta$$

where $\theta_{t'}$ is a vector of prior probabilities that a turtle will be caught given a fishing event at time *t'*, $X_{t'}$ is a matrix of spatially indexed oceanographic covariates at time *t'* at each location, and β is a vector of coefficients corresponding to each spatial covariate. To carry this procedure through entirely in a Bayesian context the logistic regression is also estimated using a Bayesian approach. Because information prior to conducting the regression analysis is minimal, all of the hyperparameters, β, for the spatial covariates were given a diffuse normal distribution (i.e. $\beta_j \sim Normal(0,100)$). Note that as information becomes more available, more informed priors can be used (Gelman et al 2003).

2.2. Spatial Correlation

To incorporate the spatial correlation of currently observed sea turtle catches into a larger predictive model, we will use variogram analysis to first model the correlation structure. The variogram is the squared difference of observation values between two points located a certain distance apart. The variogram, $2\gamma(h)$, is estimated as

$$2\hat{\gamma}(h,t) = \frac{1}{|N(h,t)|} \sum_{N(h,t)} \left(Z(s_{i,k}) - Z(s_{j,l})\right)^2$$

where $N(h)$ is the number of observations which are a distance h apart with a certain time t; $s_{i,k}$ and $s_{j,l}$ are fishing locations for a specified time (k,l) and location (i,j) respectively. Thus $Z(s_{i,k})$ is the number of sea turtles captured at fishing location j at time k. The specific form that the variogram takes can typically be summarized by three parameters: the nugget, sill, and range. The nugget represents the small-scale variation of the observation, the sill indicates large-scale variation in the observations, corresponding directly to the largest possible variance for any prediction location, and the range is the distance over which the observations are correlated.

Using the covariance structure from the variogram model, predictions for probabilities of capturing a sea turtle can be made by predicting values at new locations given observations taken at nearby locations. This spatial prediction approach is known as kriging (Matheron 1963, Cressie 1993) and is denoted as:

$$\psi_t = \lambda_t^T z_{t-1}.$$

Because we are predicting the presence or absence of a turtle given the presence or absence of turtles in the surrounding area, ψ_t may be viewed as a vector of predicted probabilities of sea turtle catch specified at a set of n new locations at time t; z_{t-1} is the vector of observed sea turtle catches at time $t-1$; λ_t is a matrix of weights given to

each observation based on the variogram model. The weight given each observation is derived using the correlation between locations based on distance defined as,

$$\lambda_t = k_t^T K_t^{-1}$$

where k_t is the covariance matrix between the target points (new prediction locations) and the observed (fishing) locations and K_t is the covariance matrix between each of the observed (fishing) locations at time t. K_t and k_t are calculated from the correlation structure specified by the variogram which is derived from long term historical observations of the process.

The kriging predictions were made using the Splus spatial module (Insightful Inc. Seattle, WA., Venables and Ripley 1999). After the kriging predictions were estimated and the spatial covariates assigned to all of the locations, the parameter estimates derived made using WinBUGS 1.4 (available online – http://www.mrc-bsu.cam.ac.uk/bugs/), a statistical package conducting Bayesian inference using Gibbs Sampling. The code was written in the R (R Development Core Team 2004) and utilized the R package R2WinBUGS (Sturtz et al. 2005) to execute WinBUGS from within an R session.

2. 3. Data and Application

The sea turtle catch data used in this analysis were collected during gear modification experiments carried out by the Southeast Fisheries Science Center (SEFSC) during 2001 – 2003. The SEFSC initiated experiments directed at the swordfish fishery in the Northeast distant statistical reporting area (NED), which previously had been closed to U.S. pelagic longline fishing. Onboard observers were placed on each vessel in the region during the experiments (Beerkircher et al. 2004). During the latter two years, the resolution of the data was higher, including detailed data on "sections" or subunits of each haul (Watson et al. 2005). There are generally 7-12 sections for each haul. The NED experimental dataset extends mostly from July

through October in 2002 and 2003, which is the season when the majority of fishing occurs in the NED (a few dates in June and November were also collected depending on the weather and other conditions). The dataset includes the latitude, longitude, loggerhead and leatherback turtle catches, and the date for each section of a haul. These variables represent only a subset of the variables collected for the dataset. We scored the sea turtle catches as either 0 for no turtles caught or 1 for at least one turtle caught on a section. Here, we use whether or not a sea turtle was caught, y_t , for the observation model and the latitude and longitude of each trip for calculating the distances used the kriging analysis to estimate $K_{t.}$

Due to the lack of observed fishing locations for any given day, the variogram could not be modeled for each day. The model outlined above has been described such that the variogram is estimated for *t-1* using the observations collected at time *t-1*. However, due to the lack of observed fishing locations for any single day, we modified the process. Thus to calculate K_t, the variogram was applied to the entire data set (around 3 months of fishing observations) and then for each observation at time *t* (a single day), we used the preceding 5 days (*t-1*,….*t-5*) of fishing observations to make the kriged prediction for that observation.

After establishing the covariance structure for the observations, we needed to create target points (or new prediction points) for the kriging analysis. In the NED, we selected a rectangle that encompasses all of the fishing locations and overlaid an evenly spaced grid. From this process, 9792 prediction locations were created and the latitude and longitude for each location was used in the calculation of the k_t matrix. Because of the lack of data for a single day, we estimated the variogram using a month of data and then used the preceding week's observations to make a prediction at the target point for a given day.

The overlaid grid corresponds directly to the centroids of the spatially indexed covariate data, which allowed us to assign the covariates to our predication locations. The spatial covariates used in the analysis are all derived from sea surface temperature (SST) data given by the Navy Coastal Ocean Model (NCOM). These data were obtained from the Naval Research Laboratory for each day of 2002 and 2003 to coincide with the NED data. NCOM, which provides daily continuous coverage of SST at ≈1/8° latitude resolution, makes use of information from satellites, as well as shipboard and buoy data. The SST values derived from NCOM, when compared with a satellite-based Pathfinder dataset, had a root-mean-square SST difference of 0.61°C across the global ocean (Kara et al. 2006).

The spatial covariates used were SST, the change in SST (deltasst), and the distance to a thermal front (dist1c). The deltasst variable was calculated by taking the maximum change from each center pixel to its surrounding eight neighbors. The dist1c values were acquired by calculating the distance from the nearest pixel with a deltasst value greater than 1 °C to each fishing location. Each of the variables and how they were derived are described in more detail in Chapter 3. All of these covariates are spatially indexed and temporally dynamic, hence the appropriate value for the spatial location and day were assigned to both the observed locations and the target points.

In an attempt to measure the fit of the models, we examined Receiver Operating Characteristic (ROC) curves, which are two dimensional measures of the classification performance (Bamber 1975). In particular, the area under of the curve (AUC) was calculated for the ROC of each probability estimate (the kriging estimate, the logistic estimate, and the combined estimate) of capturing a sea turtle for the 483 known observations in 2002. The ROC curves provide a measure of the sensitivity versus the

specificity of the model and the accuracy is measured by the area under the curve (Bamber 1975).

3. Results

The correlation analysis through the use of the variogram indicates spatial correlation over a range of about 100 km when all fishing locations for the year 2002 are combined (see Fig. 4.1). The resulting sill value of 0.003 and nugget value of 0.0, likely indicate low levels of variation due to the high number of observations with zero turtle catches. In contrast, the variogram using October observations alone shows a more pronounced correlation structure (Fig. 4.2). The range parameter for October is 145.57 km, which is larger than that resulting from the global estimates. The sill is 0.03, which is 10 times higher than that realized using the global estimates. The nugget remained at 0.0.

The significant spatial covariates, derived from the logistic regression, were sea surface temperature, sea surface temperature cubed, and distance to the thermal front. The logistic model predictions, based on the oceanographic covariates (Figure 4.3), show a pattern that predominantly matches the sea surface temperature data with the warmer waters in the southwest portion having much higher probabilities than the northern most regions of the study area. These predictions are then updated with the kriging predictions based on spatially correlated data for that same day (panel 2 of Fig. 4.3). The kriging predictions result in a higher probability of turtle capture in areas where turtles were caught in the preceding days, regardless of the spatial covariates which might have indicated otherwise. The absence of turtle catches in zones with high fishing intensity likewise result in lower probability of turtle catch regardless of oceanographic conditions. The updated predictions (panel 3 of Fig. 4.3) show the combined influence of the kriging and logistic predictions. The associated standard

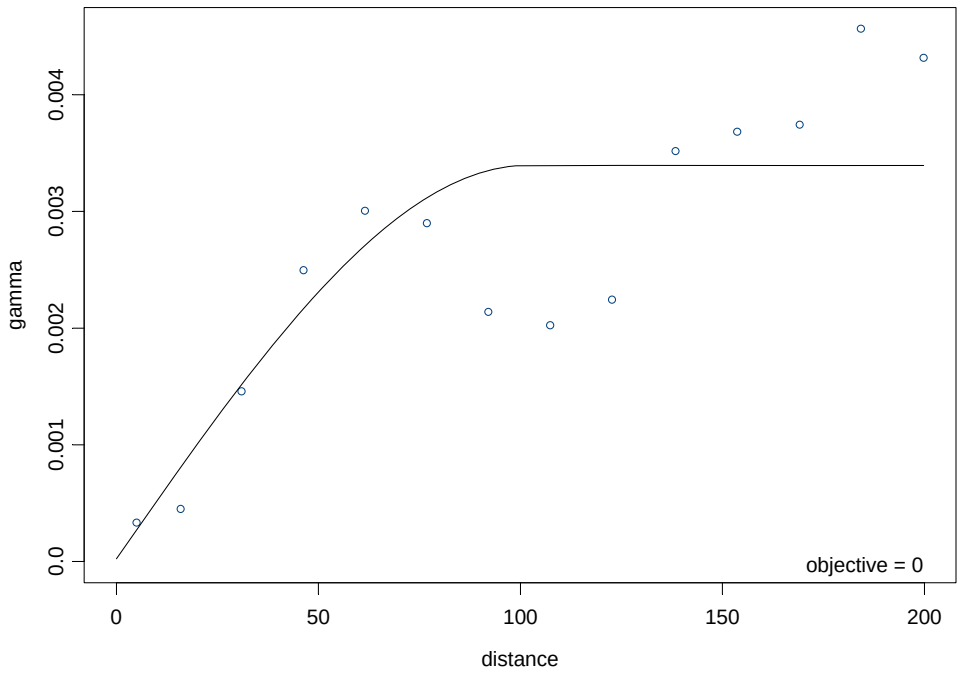

Figure 4.1: Empirical variogram for the whole fishing season of 2002 (July-October). Distance (km) is shown on the x-axis and the calculated gamma value is shown on the y-axis. The line represents the modeled spherical variogram with parameters: nugget = 0.00, sill = .003, and range = 101.67.

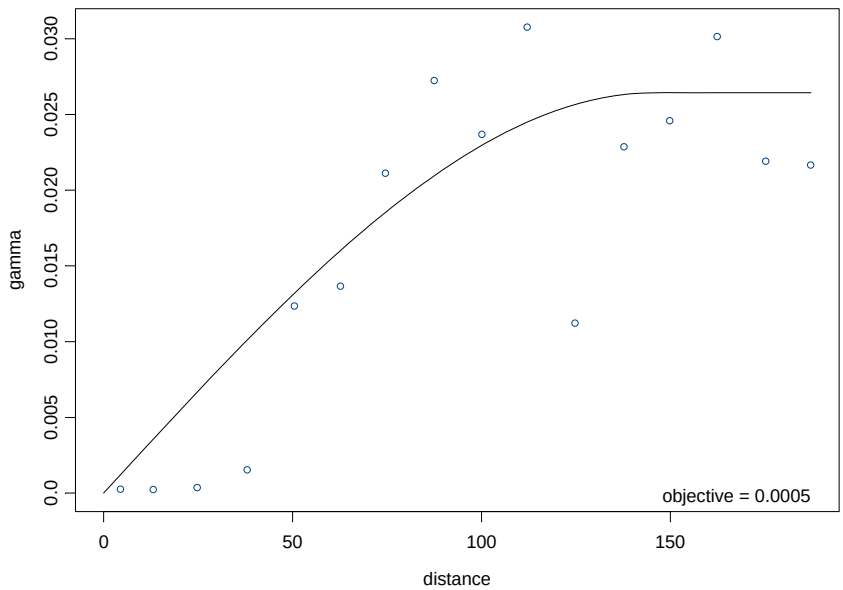

Figure 4.2: Empirical variogram for October 2002. Distance (km) is shown on the x-axis and the calculated gamma value is shown on the y-axis. The line represents the modeled spherical variogram with parameters: nugget = 0.00, sill = 0.03, and range = 145.57.

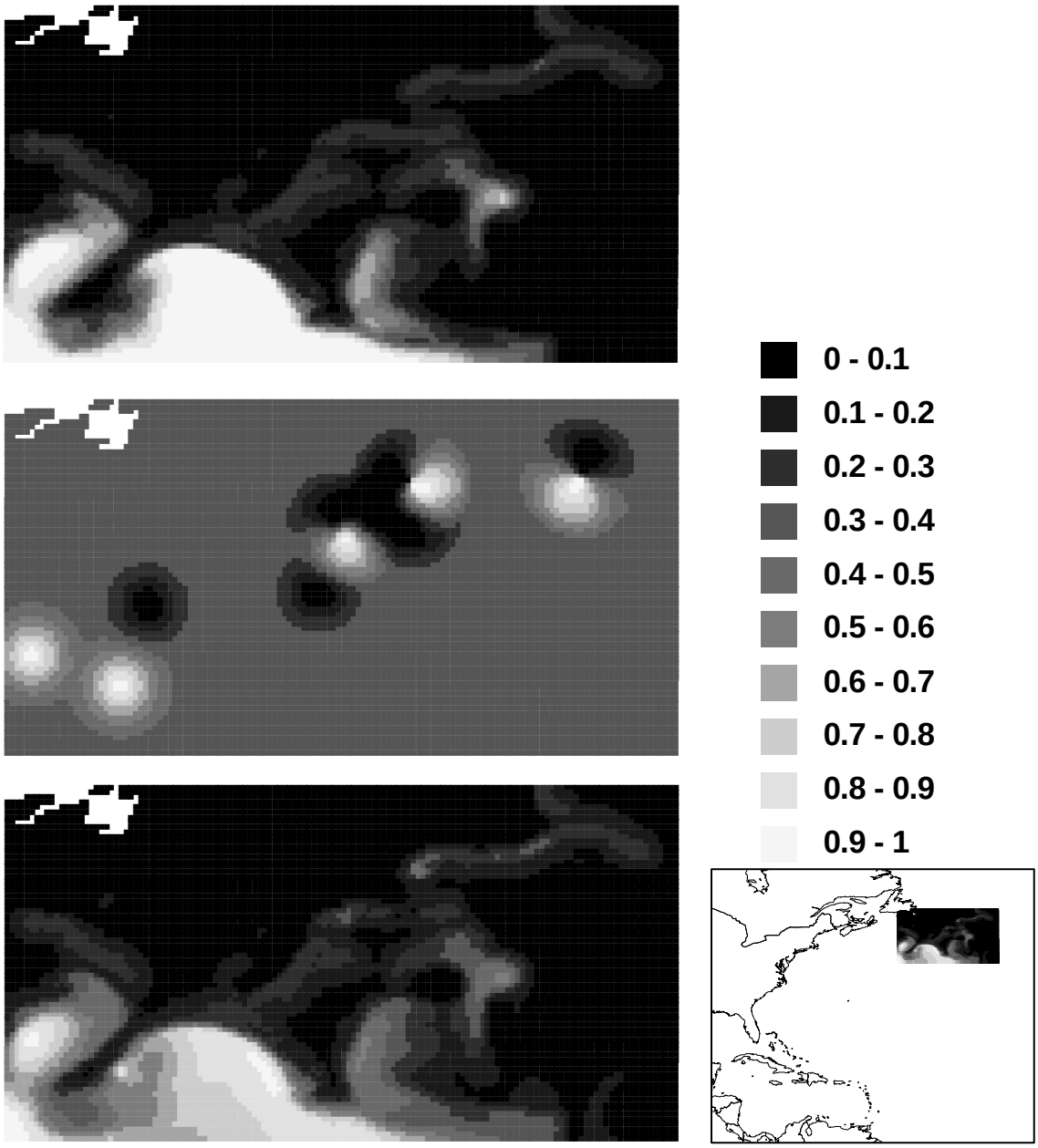

Figure 4.3: Predicted probabilities of loggerhead sea turtle catch for Oct. 15, 2002. The scale is noted to the right side, here the lighter areas indicate a higher probability of catching a sea turtle. The top panel shows the predictions for $\theta_{t'}$ (the logistic model parameter with spatial covariates). The middle panel shows the predictions for ψ_t (the kriging model parameter). The bottom panel shows the updated model predictions, θ_t.

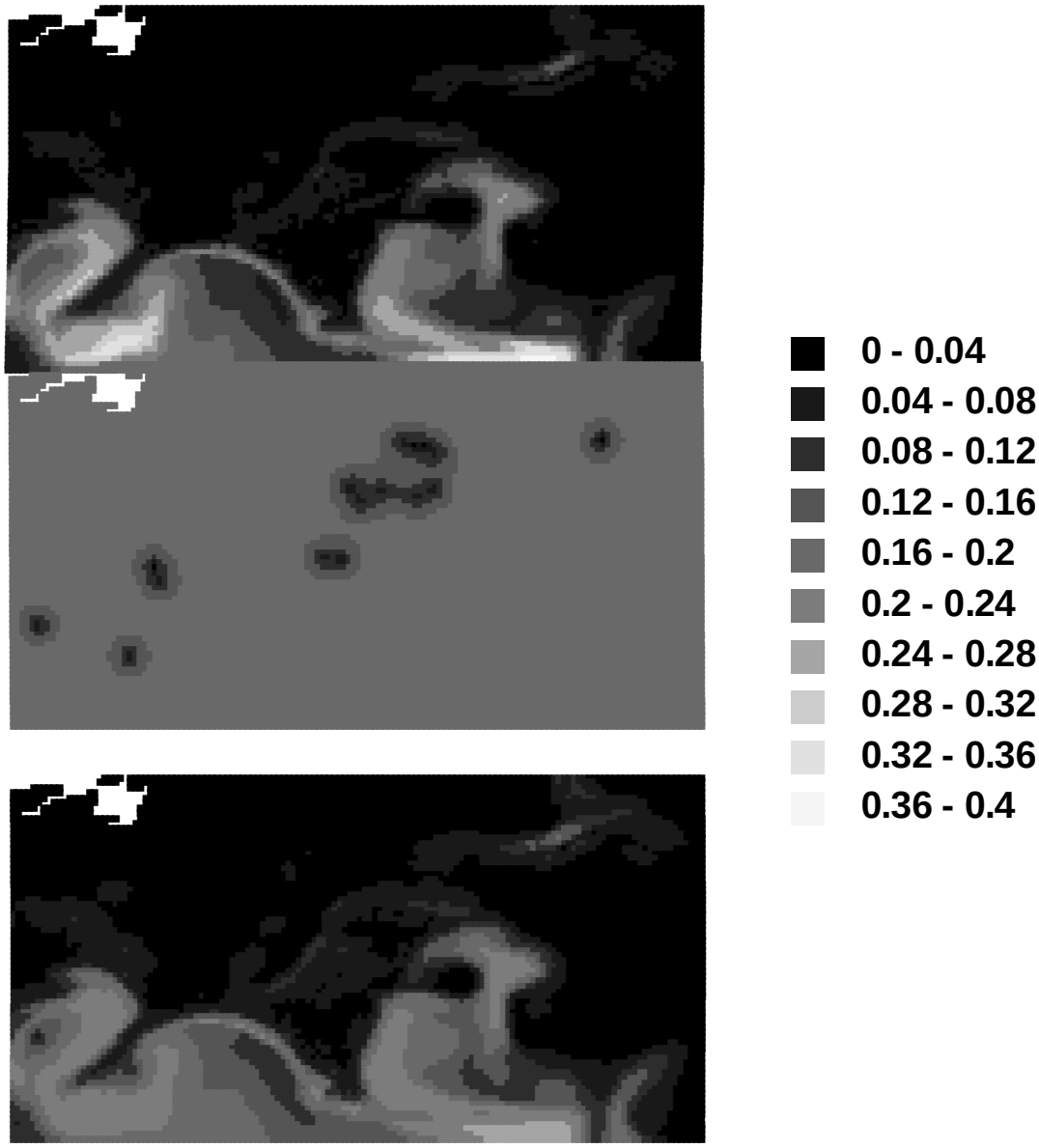

Figure 4.4: Standard deviations of the predicted probabilities of loggerhead sea turtle catch for Oct. 15, 2002. The scale is noted to the right side, here the darker areas indicate less variance in the predications than the lighter areas. The top panel shows the standard deviations for $\theta_{t'}$ (the logistic model parameter with spatial covariates). The middle panel shows the prediction standard deviations for ψ_t (the kriging model parameter). The bottom panel shows the updated model's standard deviations for the predictions, θ_t.

errors for each set of predictions also show the improvement in areas where there is data for the updated model (see Fig. 4.4).

Due to the nature of ROC curves, the AUC values must lie between 0.5 an 1, where 0.5 is considered a poor model and 1 is a very good (optimizing the sensitivity and 1-specificity; Bamber 1975). A model with a value around 0.75 and higher is considered to be a good predictor in ecological studies. The model fitting results from the ROC curve analysis indicate that the kriging and logistic estimators have very similar AUC values (~ 0.72), though the shape of the ROC curve is different. The combined estimator, θ, has the highest AUC value at 0.76, indicating this model does a better job of separating the distributions of sea turtles from non sea turtle catches.

4. Discussion

With this first attempt at combining several sources of information together to create a more informed set of predictions, it is clear that if fully implemented this model could be used to update predictions based on daily oceanographic conditions with actual sea turtle sightings on a real-time basis to make predictions on additional sea turtle capture probabilities. Satellite data describing current oceanographic conditions are readily available daily and the spatial covariate component of the model could easily be analyzed on a daily basis. Additionally, the pelagic longline fishery now has vessel monitoring systems on every ship. This means that the locations of each vessel are recorded each hour and are sent to the National Marine Fisheries Service for archiving and analysis. If fishermen can report sea turtle catch locations daily, the kriging portion of the model could also be run daily and the model predictions then updated appropriately. Hotspot detecting, with self reporting from fishermen, occurs with success in other fisheries (Alaska fisheries). It is reasonable to

think that self-reporting of sea turtle captures in the pelagic longline fishery could also occur and that real-time predictions of sea turtle "hotspots" could be constructed.

The current analysis uses the same observation data for the logistic component and the kriging component. One area where the model could be improved would be in using two separate datasets for each component of the analysis or using a different dataset for the testing the fit of the model. Moreover, instead of using kriging, one could use another technique to incorporate spatial autocorrelation, such as conditional autoregressive models which also assume a Gaussian distribution (Thogmartin et al. 2004).

Despite these shortcomings and the lack of data available for a single day, the updated model is effective at predicting the probability of capturing a sea turtle in the NED given that fishing is occurring. Using the updated information from the previous days fishing locations is a useful tool because it allows us to make more precise predictions in areas where we know fishing is occurring. At the same time, in areas where no fishing is occurring, the variance of the predictions are increased to account for this lack of information. Overall, the Bayesian framework allows the model to be easily updated and facilitates the inclusion of prior information on sea turtle catches in a manner that is spatially and temporally appropriate for understanding sea turtle catch distributions within the pelagic longline fishery. This model is the first step towards making more accurate policies to reduce the bycatch of sea turtles and could easily be applied to other ocean regions and other fisheries.

References:

Bamber D. 1975. The area above the ordinal dominance graph and the area below the receiver operating graph. *Journal of Math Psychology* 12: 387.

Beerkircher, L. R., C. J. Brown, D. L. Abercrombie, and D. W. Lee. 2004. SEFSC Pelagic Observer Program Data Summary for 1992-2002. NOAA NMFS-SEFSC-522: 25 p.

Chester, A.J., Braun, J., Cross, F.A., Epperly, S.P., Merriner, J.V., and Tester, P.A. 1994. AVHRR imagery and near real-time conservation of endangered sea turtles in the western North Atlantic. Proceedings of the WMO/IOC Technical Conference on Space-Based Ocean Observations, September 1993 (WMO/TD-No. 649). Bergen, Norway. P. 184-189.

Coles, W.C. and Musick, J.A. 2000. Satellite sea surface temperature analysis and correlation with sea turtle distribution off North Carolina. *Copeia*. **2**:551-554.

Cressie, N.A.C. 1993. Statistics for spatial data. John Wiley and Sons, New York.

Epperly, S.P, Braun, J., Chester, A.J., Cross, F.A., Merriner, J.V. and Tester, P.A. 1995. Winter distribution of sea turtles in the vicinity of Cape Hatteras and their interactions with the summer flounder trawl fishery. *Bulletin of Marine Science* **56**(2):547-568.

Ellison, A. M. 1996. An introduction to Bayesian inference for ecological research and environmental decision-making. *Ecological Applications* 6(4):1036-1046.

Gelman, A., J.B. Carlin, H.S. Stern, and D.B. Rubin. 2003. Bayesian data analysis second edition. Chapman and Hall, New York, New York, USA.

Gilman, E. et al. 2006. Reducing sea turtle by-catch in pelagic longline fisheries. *Fish and Fisheries*, **7**:2-23.

Hall, M. A., D. L. Alverson, and K. I. Metuzals. 2000. Bycatch: problems and solutions. *Marine Pollution Bulletin* **41**: 204-219.

Kobayashi, D.R. and Polovina, J.J. 2005. Evaluation of time-area closures to reduce incidental sea turtle take in the Hawaii-based longline fishery: generalized additive model (GAM) development and retrospective examination. NOAA Tech. Memo. NMFS-PIFSC-4. 39p.

Lewison, R.L., S.A. Freeman, and L.B. Crowder. 2004. Quantifying the effects of fisheries on threatened species: the impact of pelagic longlines on loggerhead and leatherback sea turtles. *Ecology Letters* **7**:221-231.

Matheron, G. 1963. Principles of geostatstics. Econ. Geol. **58**: 1246-1266.

Pinedo, M. C. and T. Polacheck. 2004. Sea turtle by-catch in pelagic longline sets off southern Brazil. *Biological Conservation* **119**: 335-339.

Polovina, J.J., Kobayashi, D.R., Parker, D.M., Seki, M.P., and Balazs, G.H. 2000. Turtles on the edge: movement of loggerhead turtles (*Caretta caretta*) along oceanic fronts, spanning longline fishing grounds in the central North Pacific, 1997-1998. *Fisheries Oceanography*. **9**: 71-82.

R Development Core Team. 2004. R: a language and environment for statistical computing. R foundation for Statistical Computing, Vienna, Austria.

Spotila, J. R., R. D.Reina, A. C.Steyermark, P. T. Plotkin, and F. V. Paladino. 2000. Pacific leatherback turtles face extinction. *Nature* **405**:529-530.

Sturtz, S., U. Ligges, and A. Gelman. 2005. R2WinBUGS: a package for running WinBUGS from R. *Journal of Statistical Software* 12(3):1-16.

Thogmartin, W.E., J.R. Sauer, and M.G. Knutson. 2004. A hierarchical spatial model of avian abundance with application to cerulean warblers. *Ecological applications* **14**(6): 1766-1779.

Venables, W. N. and B. D. Ripley. 1999. Modern applied statistics with S-Plus, 3rd Ed. Springer, New York. 500pp.

Appendix A

Edits to Section Data - Turtles

The following table shows the edits I made to the section data acquired from Dan Foster at NOAA Fisheries. The section data was collected during the 2002 and 2003 seasons of the Northeast Distant Water gear modification experiment. The species column indicates which turtle species was added to the recorded section (preceding column). Discrepancies appear to have arisen because turtles were not included in the dataset I received if the hook type was unknown. Sometimes one or more turtles were recorded in the dataset already; this is indicated in the comments section. DNE is shorthand for 'does not exist' – I've normally written this when a trip, haul, or section were not present in the section dataset. Sometimes more than one turtle was added to a particular trip and haul; this is indicated in the section column by more than one number being listed (e.g. 3,4 – means one turtle was added to sections 3 and 4), the species will then follow in the respective order.

Trip	**Haul**	**Section (added to)**	**Species**	**Comments**
AO2002	4	3	TLB	
AO2007	4	7	TLB	
AO2007	14	7	TLB	
AO2009	17		TTL	DNE in section dataset
BO2002	2	2	TLB	
BO2002	5	5	TLB	
CO2010	7	1	TLB	1 listed, 1 missing
CO2010	9	1	TLB	
EO3001	4	1	TLB	
IO2007	12	5	TLB	
IO2014	4	3	TLB	
JO2017	2	2	TLB	
JO2017	5	8	TLB	
JO2023	9	7	TLB	
MO1025	5	3,5	TLB, TLB	4 listed, 2 missing

Trip	Haul	Section (added to)	Species	Comments
MO1025	6	1	TLB	1 listed, 1 missing
PO2001	2		TTL	Lat/Long no good for TRIP
RO3001	9	5	TLB	
RO3003	15		TLB	21 listed, 1 missing
SO1045	9	6	TLB	
SO1050	21	5	TLB	
SO1052	17	6	TLB	
TO2003	10	1	TLB	
TO2003	9	8	TLB	DNE in section dataset
TO2008	22	2	TLB	
TO2008	25	2	TLB	
TO2009	12	10	TLB	
UO2001	10	4,9	TLB,TTL	Note blurred on TLB
UO2001	11	4	TLB	
UO2001	12	4	TLB	
UO2001	13	9	TLB	
UO2001	14	6	TLB	
UO3001	4		TLB	6 listed, 1 missing
WO1028	6	8	TLB	
WO1035	13	1	TLB	
XO1012	4	3	TLB	
YO2001	2	6,11	TLB, TLB	

Appendix B

Edits to Section Data – Latitude and Longitude

The following table shows the edits that I made to the section data for 2002 and 2003 acquired from Dan Foster at NOAA Fisheries. Here, I focus on the changes to the latitude and longitude columns of the dataset. The data highlighted in grey indicate where I felt there was a problem (note: sometimes that just means there was blank in the dataset). The numbers highlighted in yellow show the change I made to the dataset. The corresponding Trip, Haul, and Section are given. There are few rows highlighted in light purple which I was unable to really detect the problem, but knew there was something wrong. These rows were deleted from the final analysis.

Trip	Haul	Section	latin	latout	longin	longout	edits	edits
A02002	2	4	47-46.2	47-00.2	42-33.7	42-49.8	48-00.2	
A02002	2	6	47-50.6		42-46.4			
A02002	5	2	47-51.6	47-01.7	42-04.3	42-16.7	48-01.7	
A02002	14	4	45-16.7	44-16.7	47-57.2	47-56.9	45-16.7	
A02003	11	4	44-42.2	44-47.2	45-54.4	45-53.6	45-43.6	
A02007	9	4	45-57.2	46-59.0	44-57.9	44-32.8	45-59.0	
B02001	5	4	43-00.0	43-60.0	50-55.0	50-49.9	43-00.0	
B02002	5	1	46-45.0	46-45.9	45-53.0	45-55.1	46-15.0	46-15.9
B02003	8	2	43-01.5	43-55.4	52-33.3	52-20.5	43-55.4	
C02010	2	7	44-21.1	44-26.9	48-25.1	48-28.6	48-18.6	
C02011	2	2	43-20.4	43-19.5	42-41.9	42-38.5	52-41.9	52-38.5
C02012	9	3	43-00.6	42-47.6	42-46.4	42-41.3	52-46.4	52-41.3
C02012	9	4	43-02.2	42-48.5	52-50.4	42-45.4		52-45.4
C02019	9	1	43-57.2	43-59.4	48-17.5	47-10.7	48-10.7	
C02019	17	2	44-06.6	43-51.6	48-43.0	48-24.4	48-42.4	
D04001	2	3	44-34.0	44-40.4	45-10.9	44-01.9	45-01.9	
D04001	14	6	45-46.5	46-47.6	46-21.8	46-14.3	45-47.6	
I02007	7	7	48-20.1	48-26.8	41-50.7	41-00.7	42-00.7	
I02007	14	7	46-16.1	47-15.1	42-20.6	42-08.5	46-15.1	
I02007	15	2	46-21.9	46-44.5	42-19.6	41-42.1	46-24.5	
I02008	6	5	43-04.8	43-59.9	51-25.5	51-26.4	42-59.9	
I02015	3	2	45-15.7	45-15.5	46-25.1	45-02.1	46-02.1	
I02015	6	1	45-12.4	46-13.5	47-48.4	47-46.6	45-13.5	
I02016	8	3	44-05.6	44-04.6	48-33.6	48-11.0	48-31.0	

J02017	16	4	44-23.5	44-30.9	48-23.3	49-19.2	48-19.2	
Trip	**Haul**	**Section**	**latin**	**latout**	**longin**	**longout**	**edits**	**edits**
J02017	16	5	44-25.3	44-31.3	48-19.6	47-16.8	48-16.8	
J02021	9	4	47-13.0	47-08.0	39-40.0	39-20.0	47-38.0	
J02023	2	6	46-57.0	46-02.0	46-40.0	46-37.0	47-02.0	
J02023	7	2	44-56.0	44-57.0	48-19.0	47-14.0	48-14.0	
J02023	7	8	45-11.0	45-10.0	48-00.0	48-59.0	47-59.0	
M01023	17	4	46-10.2	46-47.8	44-32.4	44-05.3	46-17.8	
M01025	6	4	46-30.5	46-24.5	43-08.5	43-37.9	42-37.9	
P02001	1	1	47-29.2	47-53.4	42-14.6	42-45.0		
P02001	1	2	47-27.4	47-53.4	42-10.6	42-45.0		
P02001	1	3	47-25.1	47-53.4	42-06.0	42-45.0		
P02001	2	3						
P02001	2	4	47-24.3	47-33.5	42-06.0	42-45.0		
P02001	2	5	47-22.4	47-28.5	42-01.7	42-21.5		
P02001	3	5						
P02001	3	6	47-20.5	46-58.9	41-52.1	41-35.1		
P02001	3	7	47-19.8	46-53.9	41-46.1	41-32.8		
P02001	3	8	47-19.6	46-48.9	41-40.6	41-26.5		
P02001	4	5		47-43.2		42-46.7		
P02001	4	6		47-44.5		42-49.9		
P02001	6	6		47-58.2		42-29.7		
P02001	9	1	47-48.1	47-15.0	42-34.2	42-52.7	48-15.0	
R03001	1	5	43-08.2	42-08.5	51-41.6	51-35.9	43-08.5	
S01045	5	1	43-02.6	43-50.2	51-52.2	51-54.0	42-50.2	
S01045	14	4	43-03.1	43-05.4	48-25.3	48-58.3	47-58.3	
S01051	4	5	44-57.8	44-05.4	46-56.7	46-47.3	45-05.4	
S01051	5	5	45-02.4	45-59.2	48-07.8	48-10.8	44-59.2	
S01052	15	9	44-50.8	44-56.2	44-27.8	44-23.8	48-27.8	48-23.8
T02002	4	1	43-28.4	43-24.5	48-53.2	48-34.5		
T02002	8	1	44-40.2	45-44.4	47-31.2	47-55.9	44-44.4	
T02002	8	2	44-38.8	45-43.4	47-27.3	47-53.9	44-43.4	
T02002	8	3	44-41.0	45-45.4	47-23.0	47-53.6	44-45.4	
T02002	8	4	44-43.3	45-47.9	47-20.1	47-57.6	44-47.9	
T02002	8	5	44-47.2	45-49.8	47-20.8	47-02.8	44-49.8	
T02003	5	9		44-34.6		48-45.9		
T02003	6	8	44-35.5		48-42.4			
T02003	9	8	44-33.3		48-33.8			
T02003	11	1	44-38.6	44-49.2	48-22.1	48-00.1	49-00.1	
T02003	15	4	44-26.0	44-37.3	48-18.9	48-48.6	48-18.6	
T02008	10	10	43-54.0	44-58.6	47-55.6	47-54.4	43-58.6	
T02008	23	1	42-59.2	42-00.5	48-17.5	48-16.8	43-00.5	
T02009	10	2	45-56.7	45-00.8	47-17.1	47-08.8	46-00.8	
T02009	10	2	45-56.7	45-00.8	47-17.1	47-08.8	46-00.8	
T02009	15	4	44-55.7	44-00.0	47-24.8	46-58.0	45-00.0	
T02009	15	9	45-03.4	45-01.1	47-04.0	47-54.5	46-54.5	
T02009	15	10	45-06.7	45-03.8	47-03.8	47-57.3	46-57.3	
T02009	23	5	44-11.4	44-13.9	48-01.3	48-58.1	47-58.1	
T02010	5	1	45-15.2	45-15.7	45-05.1	45-59.2	48-05.1	47-59.2

U02001	1	6	46-35.6		43-25.3			
U02001	16	5	43-14.5	43-43.0	51-29.7	51-27.0	43-13.0	
Trip	**Haul**	**Section**	**latin**	**latout**	**longin**	**longout**	**edits**	**edits**
U03002	13	6	45-02.2	45-56.3	48-26.1	48-30.2	44-56.3	
U03003	1	4	44-20.9	44-22.7	45-50.0	48-43.1	48-50.0	
U03003	1	5	44-18.0	44-18.6	44-48.1	44-45.1	48-48.1	48-45.1
U03003	5	8	44-49.2	44-44.2	48-47.9	47-47.5	48-47.5	
U03003	6	9	45-09.9	48-01.1	48-35.3	48-38.8	45-01.1	
U03003	8	9	45-12.7	45-12.6	48-58.1	48-57.1	47-58.1	47.57.1
W01028	9	4	48-33.0	49-54.0	42-37.0	41-56.0	48-54.0	
X01010	16	5	48-26.3	48-33.5	41-50.3	41-00.7	42-00.7	
Y02001	13	6	44-43.2	44-50.2	48-07.7	48-59.6	47-59.6	
Y02001	17	5	44-26.3	44-35.8	48-24.7	47-12.5	48-12.5	
Z02001	7	1	43-23.0	42-21.4	51-43.4	51-43.8	43-21.4	

Appendix C

Analysis of Spatially-explicit Temporal Variation in Sea Surface Temperature

Introduction:

With remote sensing now readily available, there are a number of oceanographic datasets available that offer information on sea surface temperature SST, sea surface height (SSH), chlorophyll-a, etc. These datasets come from a variety of satellites operating at different times. One variable that is of particular interest to marine biologists, especially for sea turtle studies, is SST. Remotely sensed SST allows scientists to gather a lot of information about water temperatures across the ocean. Because of this, SST has been used to correct light based geolocation data (Teo et al. 2004, Shaffer et al. 2005, Nielson et al. 2006), to examine correlations between sea turtle sightings and temperature (Epperly et al. 1995, Coles and Musick 2000, Kobayashi and Polovina 2005), as well as correlations with thermal fronts (Polovina et al. 2000).

Most satellite images contain cloud cover or areas of no data for any given date. This is particularly true in the Gulf Stream region of the Atlantic, where weather fronts cause frequent cloud cover. Due to the cloud cover on daily images, multiple-day composites (8-day or monthly) are often used for the different analyses based on SST. The composite images generally use a mean or most recent data available scheme to fill in the areas of no-data, thereby creating an image or dataset that have more information than that available for a single day. For example, a researcher may know the location of a sea turtle on March 2, and would then use an 8-day SST composite to get an estimate of the SST at that location.

However, most of these studies have been conducted without regard to the daily variability of SST. In areas of the ocean with strong currents, the SST can

change by a few degrees Celsius within a day or two. The aim of this study was quantify temporal changes in sea surface temperatures spatially across standard composite image time frames (8-day and monthly) in the western North Atlantic. We expected to see higher degrees of change in areas associated with the Gulf Stream and less in areas like the Sargasso Sea. The objective was to show that using composite images may not always be appropriate for certain regions in the ocean.

Data and Methods:

The Navy Coastal Ocean Model provides continuous coverage of SST at ≈1/8° latitude resolution at the mid-latitudes. Comparing SST of NCOM with a satellite-based Pathfinder dataset demonstrated that the model has a root-mean-square SST difference of .61° C across the global ocean (Kara et al. 2006). The data were obtained from the Naval Research Laboratory for each day of 2002 and 2003.

To quantify the temporal temperature variation, we examined daily SST scenes from NCOM to estimate variability over 8-day and monthly time periods. This was done by calculating the standard deviation, (using ArcGrid; ESRI Inc.), across the entire Western North Atlantic basin over the different time scales (Figure C.1). We then plot two standard deviations of temperature change which represents bascially 95% of the variation over the time scales analyzed. The figures then show the areas of high temperature change.

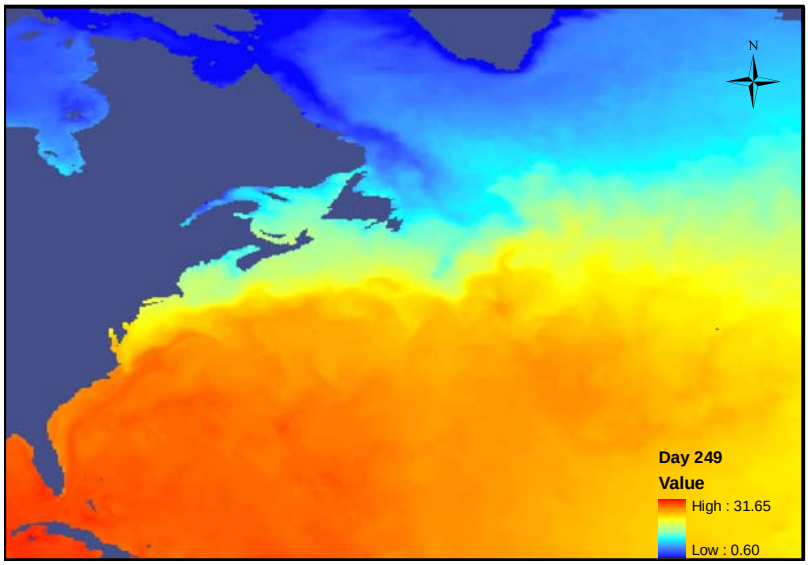

Figure C.1. Navy Coastal Ocean Model sea surface temperature (SST) data for September 8, 2002.

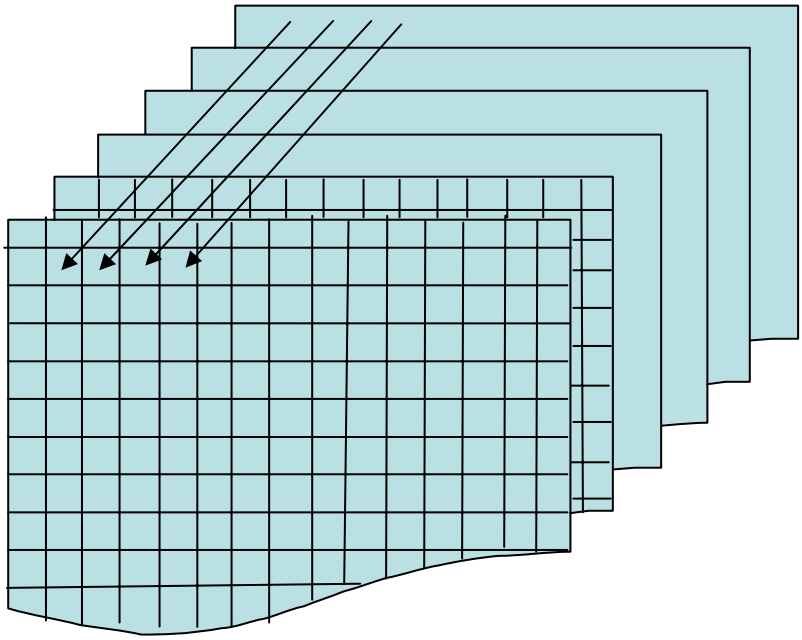

Figure C.2: Essentially, the grids for the time period are stacked as shown here. Then the standard deviation is calculated from the images for each cell over the given number of images (8 images to simulate an 8-day composite).

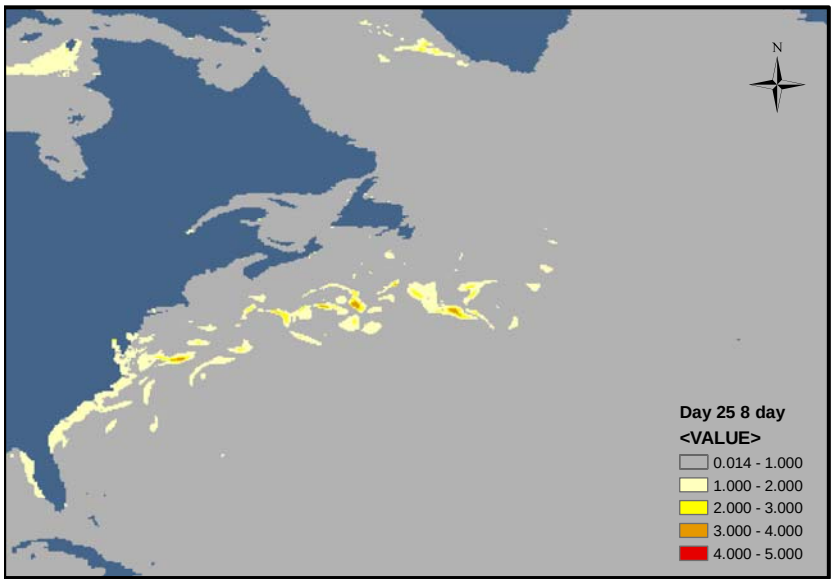

Figure C.3. The calculated standard deviation for each grid cell for an 8-day period starting on January 25, 2002. The gray areas show little variation over the 8 daily images; however, a few locations along the Gulf Stream show changes up to 3-4º C.

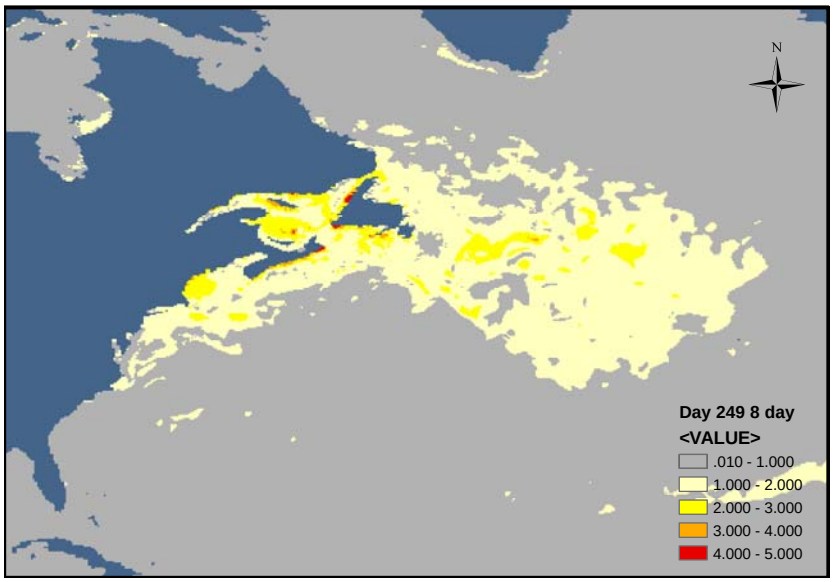

Figure C.4. The calculated standard deviation for each grid cell for an 8-day period starting September 8, 2002, during the fishing season. Areas along the Gulf Stream and near the Grand Banks show variation of 3-4º C. These also are areas where longline fishing efforts are concentrated.

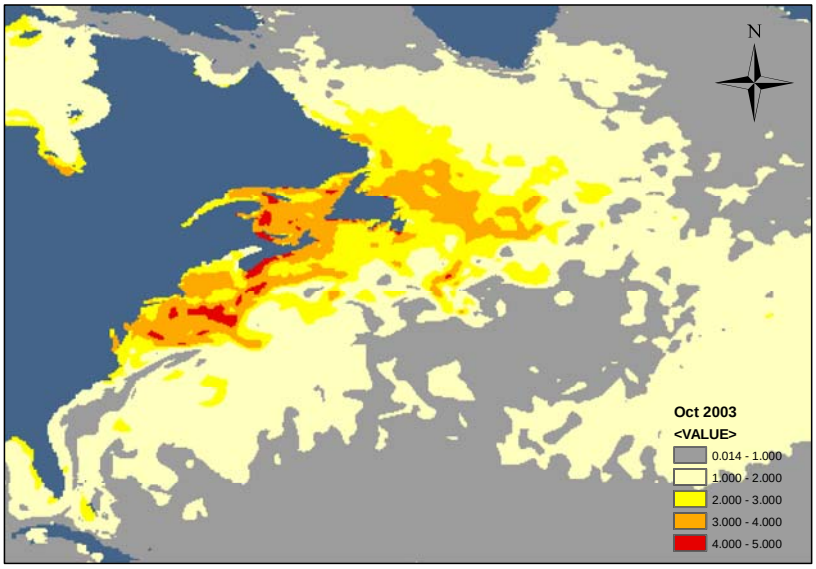

Figure C.5. The calculated standard deviation for each grid cell for the month of October 2003. The grey areas show little variation in SST over the month; however, areas along the coast and gulf stream show changes up to 5º C.

Results:

Preliminary results indicate that, in certain regions of the Western North Atlantic, SST can change greatly within an 8-day period. Many areas have less variation, but regions surrounding the Gulf Stream where fishing efforts are concentrated, vary by as much as 5º C during the peak fishing season. Because of the rapid variation in sea surface temperatures, it is inappropriate to model turtle distributions using 8-day or monthly composite images.

Discussion:

The results suggest that 8-day or monthly composites may not be appropriate when trying to correct geo-locations from satellite tagged animals or in predicting sea turtle locations. Sea turtles are known to be influenced by temperatures; as such, a difference in a few degrees of temperature can affect the probability of finding a sea

turtle in certain locations. The k-function results from chapter 1 indicate that sea turtle distributions are likely changing on a scale of 1-3 days, implying that looking at SST on an 8-day level may be too broad of a scale. This study emphasizes the need for higher resolution data to appropriately analyze loggerhead sea turtle distributions. The Navy Coastal Ocean Model provides very useful daily scenes and is currently improving their spatial resolution. Using daily models such as NCOM may provide a better understanding of loggerhead distributions in relation to key oceanographic features, and may result in improved management decisions that reduce loggerhead interactions with pelagic fisheries.

References:

Coles, W.C. and Musick, J.A. 2000. Satellite sea surface temperature analysis and correlation with sea turtle distribution off North Carolina. Copeia. **2**:551-554.

Epperly, S.P, Braun, J., Chester, A.J., Cross, F.A., Merriner, J.V. and Tester, P.A. 1995. Winter distribution of sea turtles in the vicinity of Cape Hatteras and their interactions with the summer flounder trawl fishery. Bulletin of Marine Science **56**(2):547-568.

Kara, A.B, Barron, C.N., Martin, P.J., Smedstad, L.F., and Rhodes, R.C. 2006. Ocean Modelling 11, 376-398.

Kobayashi, D.R. and Polovina, J.J. 2005. Evaluation of time-area closures to reduce incidental sea turtle take in the Hawaii-based longline fishery: generalized additive model (GAM) development and retrospective examination. NOAA Tech. Memo. NMFS-PIFSC-4. 39p.

Nielsen, A., Bigelow, K.A., Musyl, M.K., and Sibert, J.R. 2006. Improving light-based geolocation by including sea surface temperature. Fisheries Oceanography. **15**(4):314-325.

Polovina, J.J., Kobayashi, D.R., Parker, D.M., Seki, M.P., and Balazs, G.H. 2000. Turtles on the edge: movement of loggerhead turtles (*Caretta caretta*) along oceanic fronts, spanning longline fishing grounds in the central North Pacific, 1997-1998. Fisheries Oceanography. **9**: 71-82.

Shaffer, S.A., Trembley, Y., Awkerman, J.A., Henry, R.W., Teo, S.L.H., Anderson, D.J., Croll, D.A., Block, B.A., and Costa, D.P. 2005. Comparison of light- and SST-based geolocation with satellite telemetry in free-ranging albatrosses. Marine Biology. **147**:833-843.

Teo, S.L.H., Boustany, A., Blackwell, S.B., Walli, A., Weng, K.C., Block, B.A. 2004. Validation of geolocation estimates based on light level and sea surface temperature from electronic tags. Marine Ecological Progress Series. **283**:81-98.

Appendix D

Temperature at Catch by Day

The following two graphs are examples of a data exploration I conducted. I am looking for temperature relationships between hauls with turtle catch and those without but at a smaller spatial and temporal resolution. The objective of this exploration was to see if there was a daily difference in temperatures where turtles were caught versus those where turtles were not captured. No analysis has been conducted but this data exploration suggests that there are trends in the temperature at which sea turtles are being caught when we look at a daily scale.

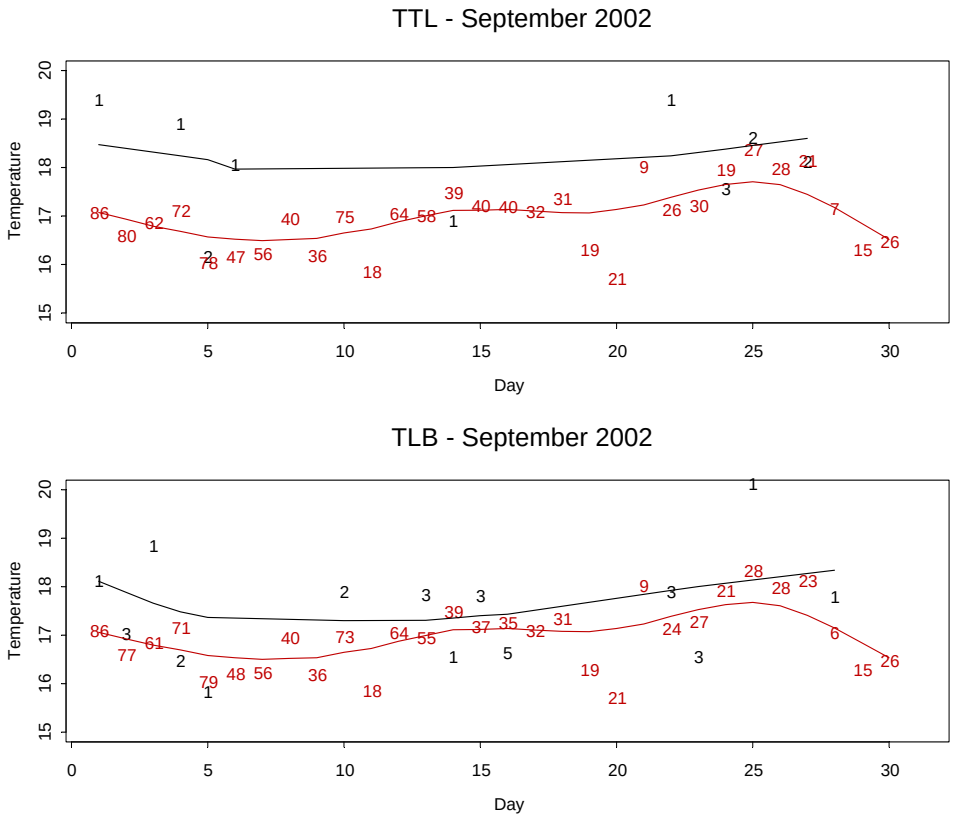

Figure D.1: Data shown for September 2002, the turtle species (TTL – loggerhead; TLB – leatherback) are indicated in the title. The x-axis is the day of the month and the y-axis is the temperature in degrees C. The red points are sections where no turtles were caught; the number indicates the total number of hauls on that day. The black points are sections were turtles were caught; the number here indicates the total number of turtles caught. The black and red lines are just smoothed lines for the mean temperatures.

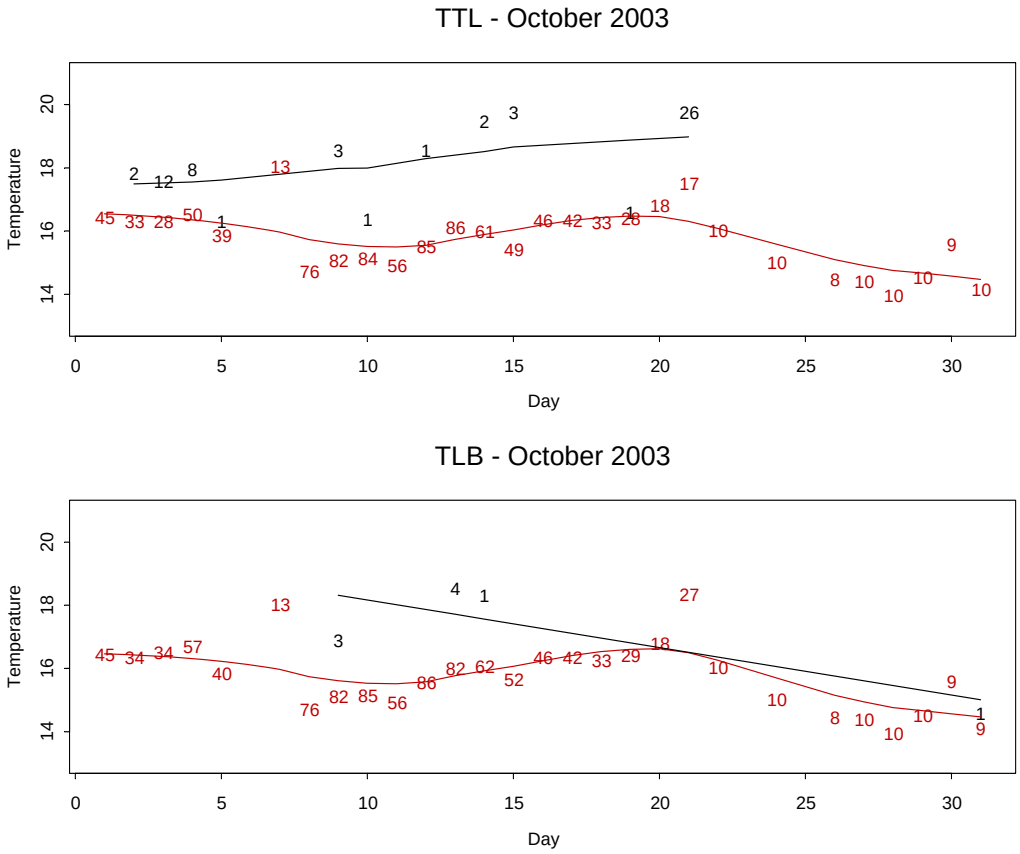

Figure D.2: Data shown for October 2003, the turtle species (TTL – loggerhead; TLB – leatherback) are indicated in the title. The x-axis is the day of the month and the y-axis is the temperature in degrees C. The red points are sections where no turtles were caught; the number indicates the total number of hauls on that day. The black points are sections were turtles were caught; the number here indicates the total number of turtles caught. The black and red lines are just smoothed lines for the mean temperatures.

Appendix E

Spatial Analysis of the Observer Program

One area that I thought I might be useful to examine is the effectiveness of the Observer Program at covering the spatial range and distribution of the pelagic longline (PLL) fishery. Currently the Observer Program uses a random sampling method within spatial and temporal strata defined by the nine management areas in the Atlantic Ocean and four time blocks of the year. The program had aimed for 5% coverage and now targets 8% coverage of the fishery dependent upon effort in each strata.

The objective was to examine the spatial patterns of the observer dataset to see if the observer program is capturing the spatial patterns of the logbook dataset. To do this I am using a modification of a spatial point pattern technique called Ripley's K. The method is the same as that described in chapter one, which allows for the examination of whether the Observer Program was randomly distributed throughout the fishery in a spatially random process.

In this initial analysis, two years (2000 and 2003) were used to look at the spatial coverage of the observer program. Based on the analysis, the over-all ability of the Observer Program to capture the spatial distribution of the PLL fishery appears good. At a certain distance (here shown in decimal degrees), the Observer Program commonly appears over-dispersed (Figures E.1, E.3). This is most likely because there are areas in the Southeast that do not get many observers (Figure E.2). There does appear to be some clustering at smaller scales from January to June in 2000; this may indicate something is occurring with the sampling method. I also believe the reason we see a fair bit of clustering in 2003 is because the NED experiment concentrated more effort in the NED and so there is an unusually high level of

coverage there (Figures E.3, E.4). In general, the Observer program is capturing the spatial patterns and distribution of the PLL fishery pretty well.

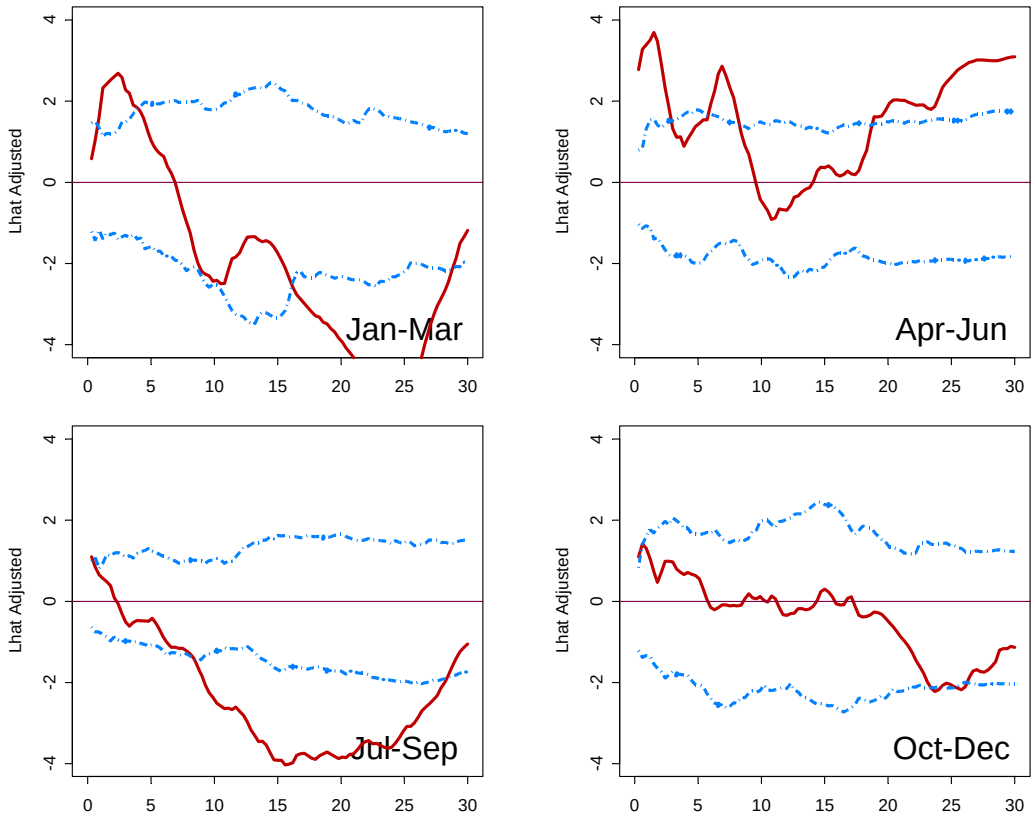

Figure E.1: Lhat adjusted for 2000 by season. Distance in decimal degrees is on the x-axis. There does appear to be some clustering at smaller scales from Jan-Jun. Oct-Dec shows a perfect example of spatial random sampling within the PLL fishery.

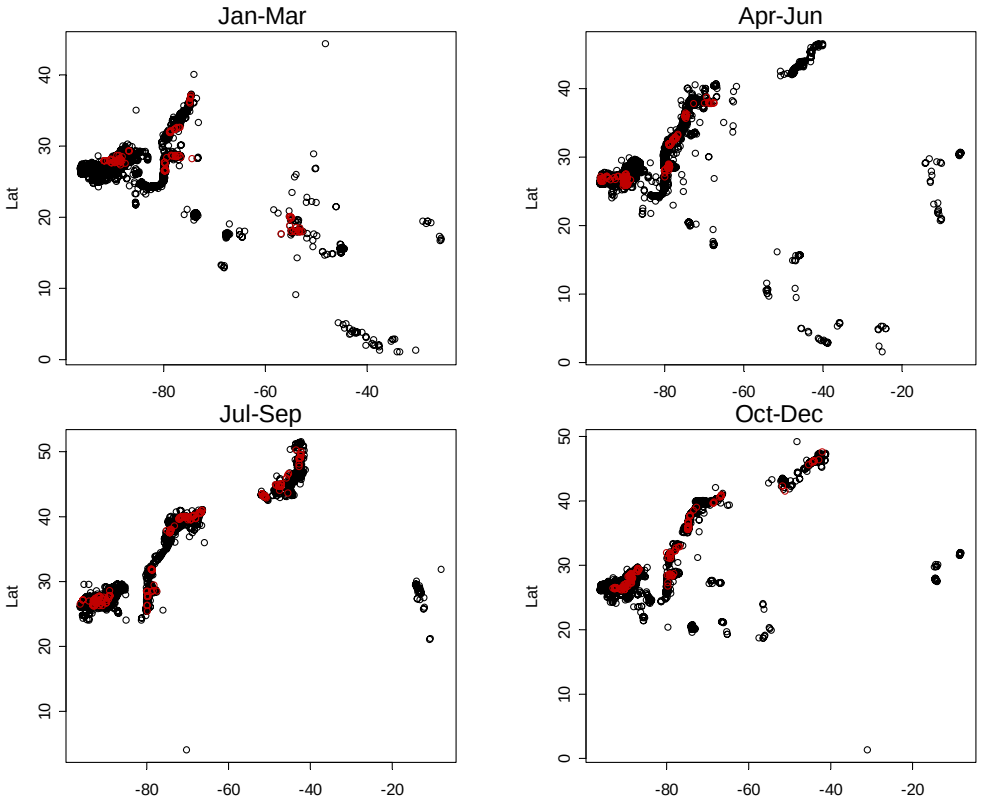

Figure E.2: The spatial locations of the fishery for 2000 by season. Shown in black are the fishing locations and in red are the locations of observed hauls. Latitude on the y-axis, Longitude on the x-axis.

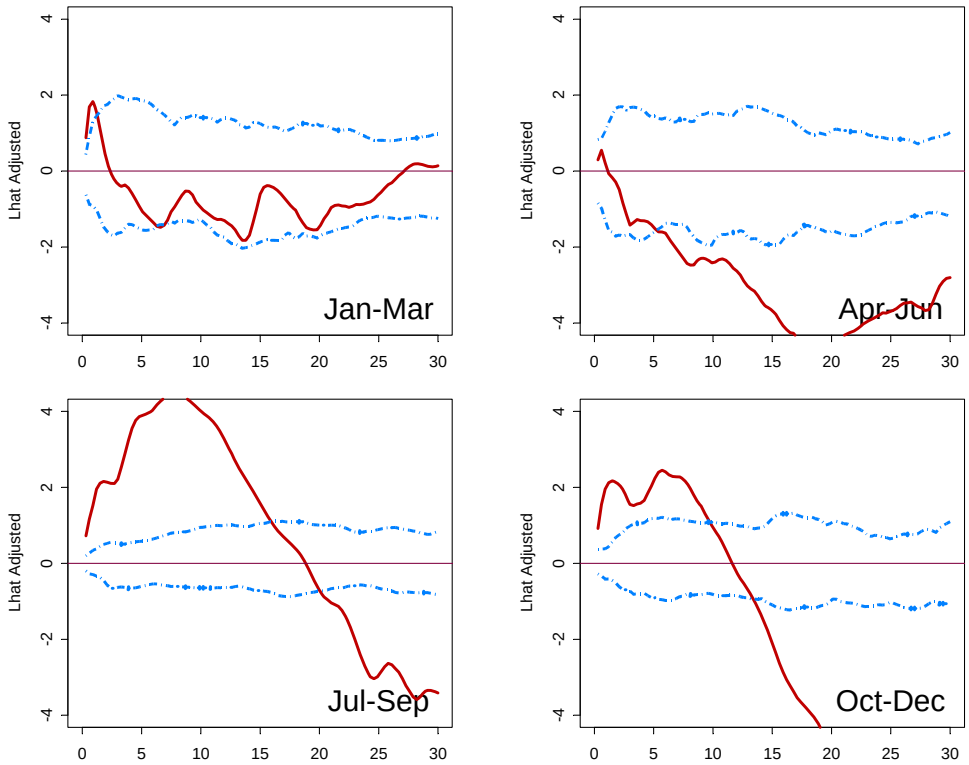

Figure E.3: Lhat adjusted for 2003 by season. Distance in decimal degrees is on the x-axis. There is clustering of the observer program at smaller scales from July – December and then over-dispersion as the distance increases. This is clearly the effect of the experiment in the NED and should indicate that the Lhat can detect these non-random patterns.

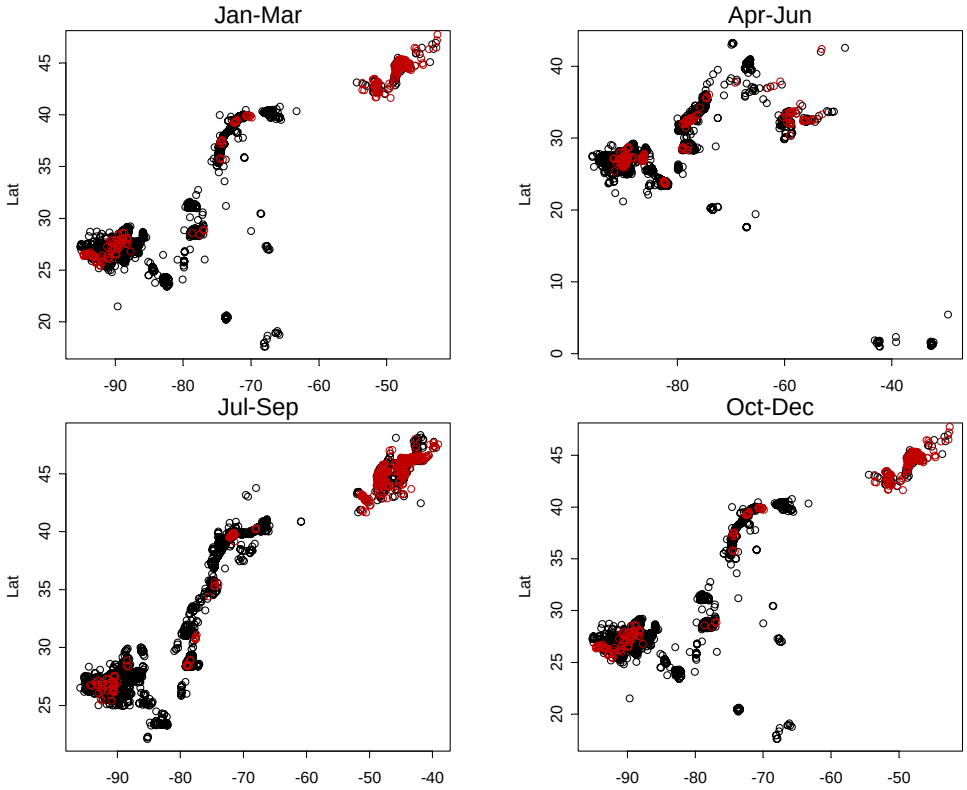

Figure E.4: The spatial locations of the fishery for 2003 by season. Shown in black are the fishing locations and in red are the locations of observed hauls. Latitude on the y-axis, Longitude on the x-axis.

Appendix F

Trellis Graphics for Loggerheads and Leatherbacks in the NED

In addition to the generalized additive model (GAM) results from chapter 3, examining the catches as a function of temperature and distance to the thermal front indicates the strong relationship of SST to loggerhead sea turtle catches with respect to distance to the front. Here, the results show fishing locations in colder waters (lower left panel of the following figures) were confined almost entirely to areas near a thermal front, which increases the difficultly in detecting patterns in SST alone. Nevertheless, locations with sea turtle catches were even closer to a small thermal front or eddy. In the fishing locations in warmer waters, the sea turtle catches still tended to be closer to the thermal fronts but have a greater range of distances than the colder waters. These patterns were similar for the 2003 data for the loggerhead turtles, though the leatherbacks did not display such a pronounced pattern.

Visual analysis through the use of multivariate trellis graphics provided insight into the interaction between absolute sea surface temperature and smaller thermal fronts. Without accounting for thermal fronts, the absolute temperatures can appear to contain no pattern related to sea turtle catches. However, in examining both of these features simultaneously, we can better understand some of the dynamics related to fishing. For example, when a fishing location is in colder SSTs, it is always within close proximity to a thermal front (e.g. see bottom left panel of Fig. F.1). More importantly, when a turtle is incidentally captured in a colder SST, the location is very close to a thermal front. Without paying attention to this interaction of nearness to a front, it would be difficult to understand why some sea turtles are being captured in cold waters too. That is not to say that distance to the front is the only factor influencing sea turtle occurrence. Sea turtles are caught in warmer waters of the NED,

in locations that can be far from a thermal front (e.g. see upper right panel of Fig. F.1). Analyzing both SST and distance to the front, and visualizing the interaction of the two, greatly increased our understanding of sea turtle catch locations and refined our ability to predict sea turtle locations.

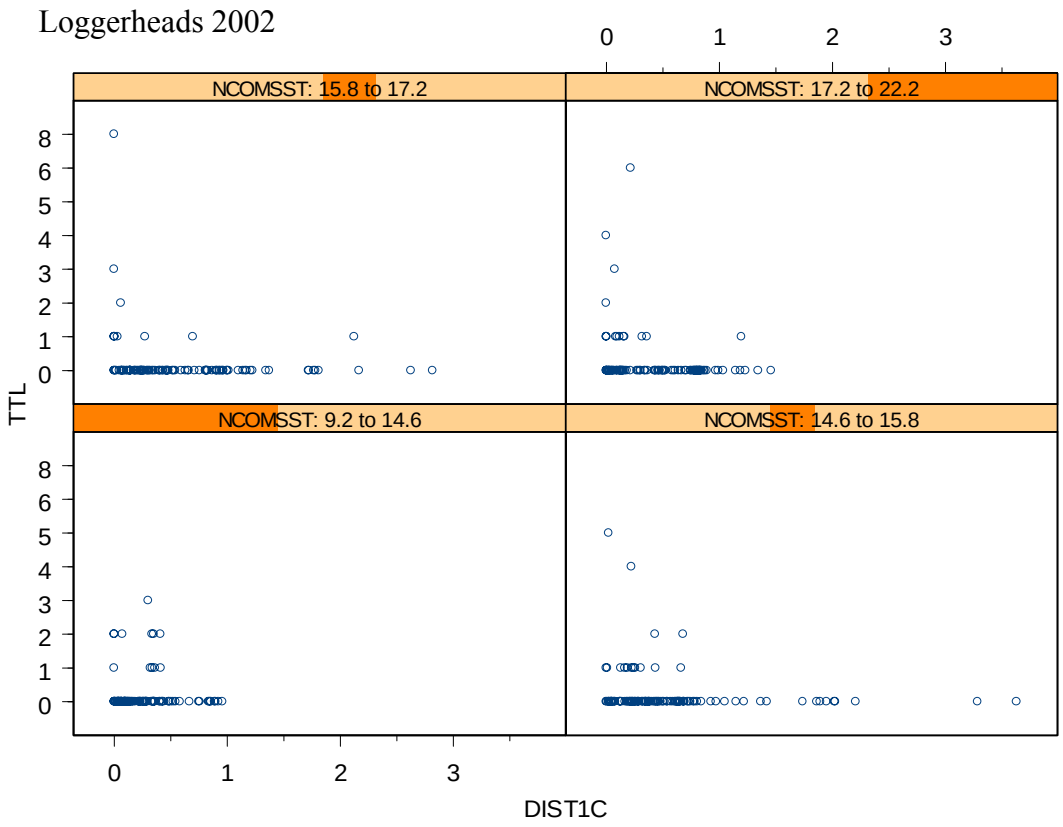

Figure F.1: Loggerhead sea turtle catches as a function of temperature and distance to the nearest location with a temperature difference of >1°C for the 2002 NED data. The x-axis is the distance from fishing locations to the 1 degree thermal front (DIST1C) while the y-axis is the number of loggerheads caught. Each panel represents a sea surface temperature range in °C (NCOMSST), with the coolest temperatures in the lower left panel and the warmest in the upper right. The data here derived from the section data described in Chapter 3 and then summed by haul.

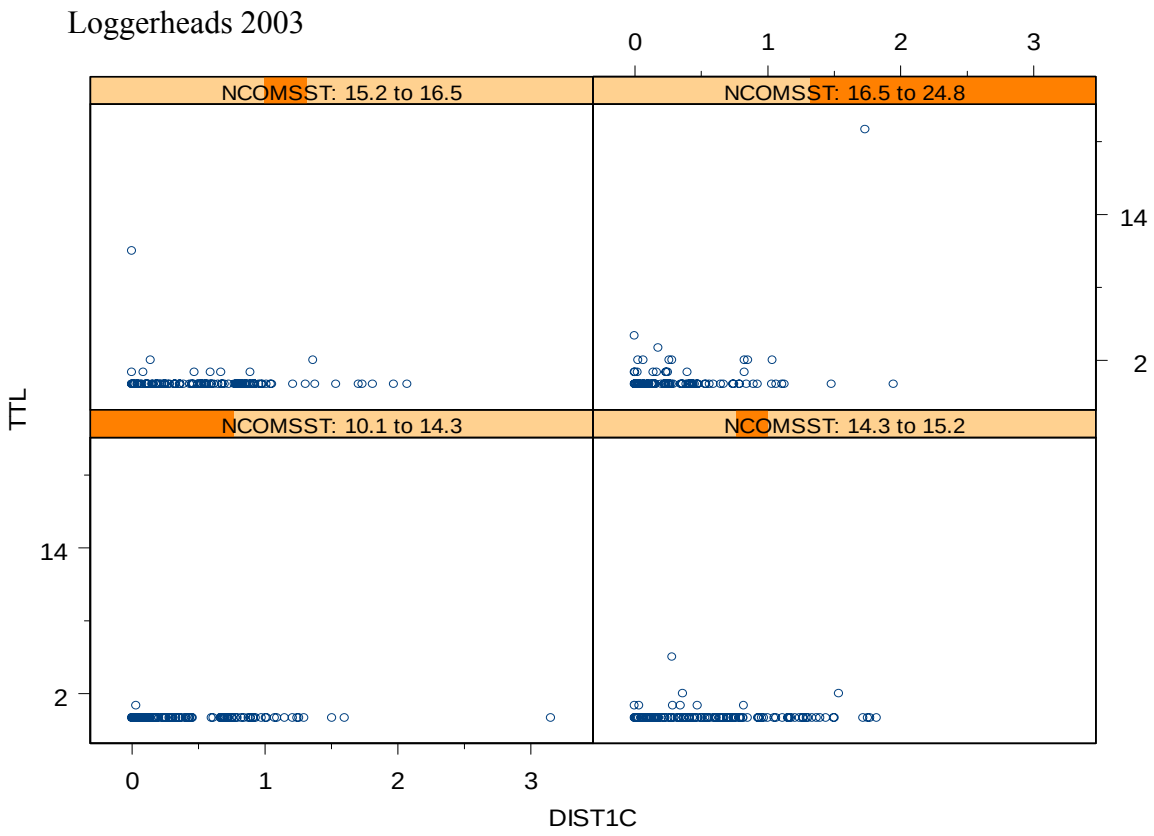

Figure F.2: Loggerhead sea turtle catches as a function of temperature and distance to the nearest location with a temperature difference of >1°C for the 2003 NED data. The x-axis is the distance from fishing locations to the 1 degree thermal front (DIST1C) while the y-axis is the number of loggerheads caught. Each panel represents a sea surface temperature range in °C (NCOMSST), with the coolest temperatures in the lower left panel and the warmest in the upper right. The data here derived from the section data described in Chapter 3 and then summed by haul.

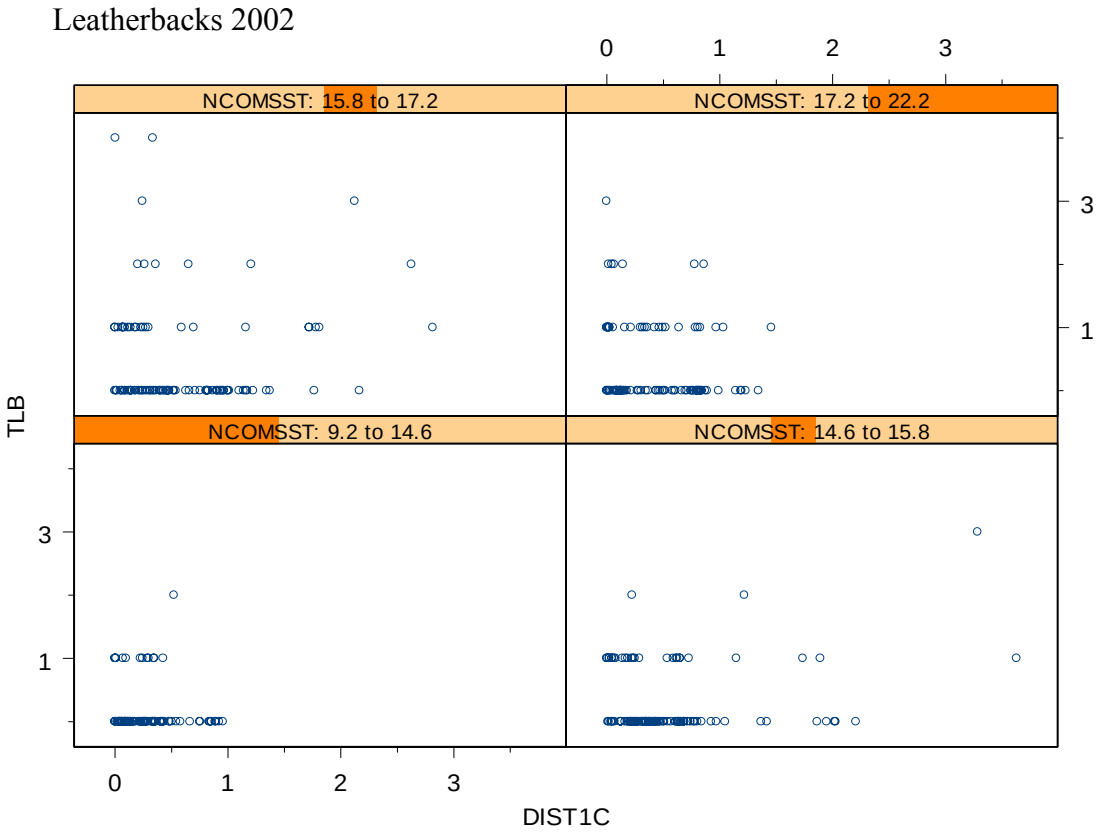

Figure F.3: Leatherback sea turtle catches as a function of temperature and distance to the nearest location with a temperature difference of >1°C for the 2002 NED data. The x-axis is the distance from fishing locations to the 1 degree thermal front (DIST1C) while the y-axis is the number of loggerheads caught. Each panel represents a sea surface temperature range in °C (NCOMSST), with the coolest temperatures in the lower left panel and the warmest in the upper right. The data here derived from the section data described in Chapter 3 and then summed by haul.

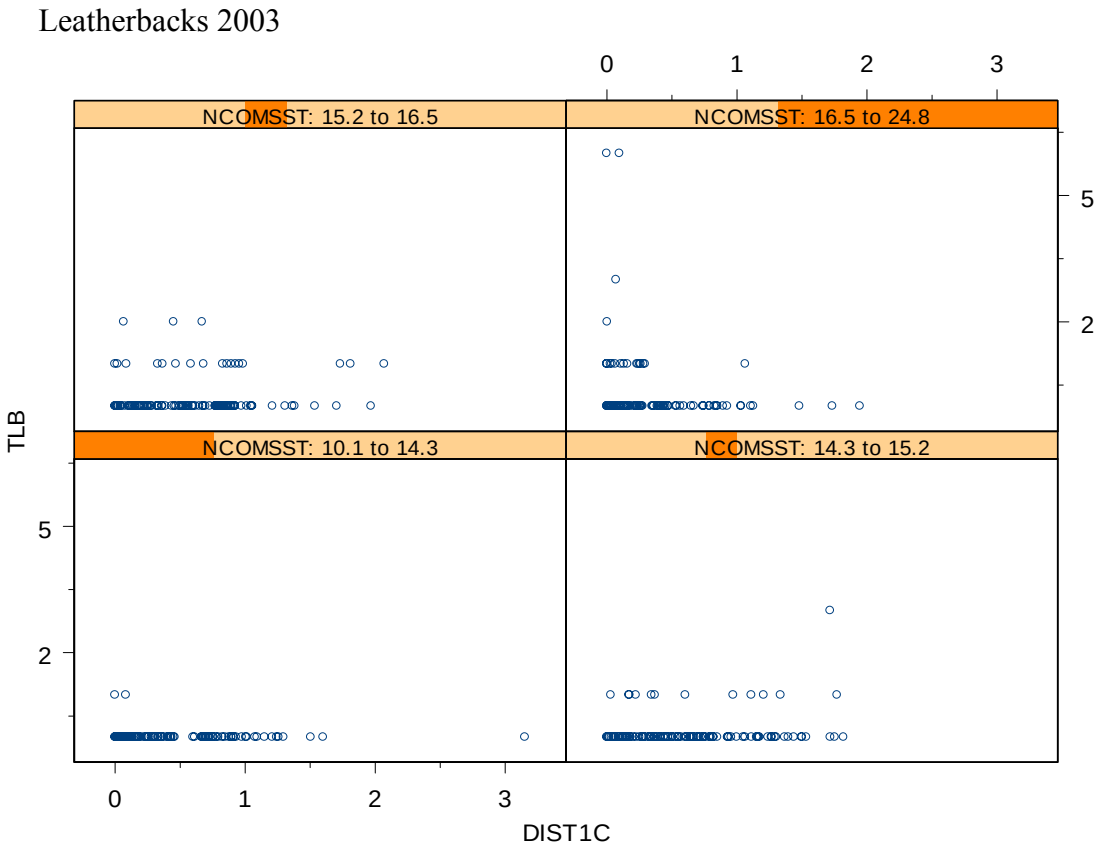

Figure F.4: Leatherback sea turtle catches as a function of temperature and distance to the nearest location with a temperature difference of >1°C for the 2003 NED data. The x-axis is the distance from fishing locations to the 1 degree thermal front (DIST1C) while the y-axis is the number of loggerheads caught. Each panel represents a sea surface temperature range in °C (NCOMSST), with the coolest temperatures in the lower left panel and the warmest in the upper right. The data here derived from the section data described in Chapter 3 and then summed by haul.