

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

Beth Gardner, Patrick J. Sullivan, Stephen J. Morreale, and Sheryan P. Epperly

**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. Loggerhead and leatherback sea turtles are listed as endangered by the World Conservation Union, and thus anthropogenic mortality of these species, including fishing, is of elevated interest. This study quantifies spatial and temporal patterns of sea turtle bycatch distributions to identify potential processes influencing their locations. A Ripley's *K* function analysis was employed on the NOAA Fisheries Atlantic Pelagic Longline Observer Program data to determine spatial, temporal, and spatio-temporal patterns of sea turtle bycatch distributions within the pattern of the pelagic fishery distribution. Results indicate that loggerhead and leatherback sea turtle catch distributions change seasonally, with patterns of spatial clustering appearing from July through October. The results from the space-time analysis indicate that sea turtle catch distributions are related on a relatively fine scale (30–200 km and 1–5 days). The use of spatial and temporal point pattern analysis, particularly *K* function analysis, is a novel way to examine bycatch data and can be used to inform fishing practices such that fishing could still occur while minimizing sea turtle bycatch.

**Résumé :** Les répartitions et les déplacements de la caouanne (*Caretta caretta*) et de la tortue luth (*Dermochelys coriacea*) dans les eaux du large dans la région occidentale de l'Atlantique Nord ne sont pas bien compris, malgré les efforts soutenus pour suivre, inventorier et observer ces tortues marines. Les caouannes et les tortues luths figurent sur la liste des espèces menacées établie par l'Union internationale de la conservation de la nature; c'est pourquoi la mortalité de ces espèces due à des causes anthropiques, en particulier la pêche, est d'un grand intérêt. Notre étude mesure les patrons spatiaux et temporels de la répartition des captures accessoires des tortues marines afin d'identifier les processus potentiels qui influencent cette distribution. Une analyse de la fonction *K* de Ripley faite sur les données du programme des observateurs de la pêche pélagique à la palangre dans l'Atlantique de NOAA Fisheries a permis de déterminer les patrons spatiaux, temporels et spatiotemporels de la répartition des captures accessoires de tortues marines en fonction de la répartition de la pêche commerciale pélagique. Nos résultats indiquent que la répartition des captures de caouannes et de tortues luths change avec la saison, avec des distributions contagieuses en évidence de juillet jusqu'à la fin d'octobre. Les résultats d'une analyse temps-espace montre que les répartitions des captures de tortues marines sont reliées sur une échelle relativement fine (30–200 km et 1–5 jours). L'utilisation d'une analyse spatiale et temporelle selon une structure ponctuelle, et en particulier de l'analyse de la fonction *K*, est une méthode nouvelle d'étudier les données de captures accessoires et peut servir à fournir des renseignements sur les pratiques de pêche de manière à pouvoir poursuivre la pêche, tout en minimisant les captures accessoires de tortues marines.

[Traduit par la Rédaction]

## Introduction

Incidental catch of nontargeted species, termed bycatch, is a management concern for all fishing fleets (Hall et al. 2000). One issue facing resource managers and the fishing

industry is the high level of overlap between the distribution of 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 km, attracting a variety of targeted and nontargeted species. This persistent problem in the longline fishery, as well as in other fisheries, calls for new statistical tools to enable us to separate the target species from undesired bycatch in space and time.

A current area of particular 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; Pinedo and Polachek 2004). Leatherbacks are pelagic throughout their lives 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 an oceanic stage that lasts about a decade. Thus, the logger-

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heads captured in the open ocean tend to be in an early life stage (Watson et al. 2005). Owing to certain life history traits of sea turtles, especially a late age at 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 (*Thunnus* spp.) and swordfish (*Xiphias gladius*)) is increasingly cited as a proximate cause for the decline or the failure to recover of loggerhead and leatherback sea turtle populations (Spotila et al. 2000; Lewison et al. 2004b; Pinedo and Polacheck 2004). The problem is confounded by the lack of understanding of sea turtle distributions and movements in oceanic waters, despite continued monitoring efforts in the western North Atlantic (Shoop and Kenney 1992; Epperly et al. 1995; Jonsen et al. 2003). Because of the widespread nature and the high level of interactions between fisheries and sea turtles, there is an urgent need for spatially explicit models to reduce bycatch (Lewison et al. 2004b). 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. The lack of progress in this area is likely due to the spatial structure of bycatch and fisheries data, which presents unique difficulties for analyses.

Bycatch data, where the presence or absence of nontarget species in the catch is 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 (Jolles et al. 2002; Kraft 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 both for 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. Here, our goals are to identify the scale and resolution of the sea turtle bycatch process occurring within the fishery, which is, in effect, an exploratory data analysis approach. 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. Gilman et al. (2007) suggested that sea turtles may aggregate when foraging, and thus moving a vessel some distance from a location, or not fishing for a certain time, could reduce sea turtle bycatch. Our study aims to address this question, spe-

cifically quantifying how far a vessel would need to move and (or) for how many days to reduce sea turtle bycatch.

## Materials and methods

### Data and study region

The data used in this study were from the National Oceanographic and Atmospheric Administration (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). While the US fishery primarily targets swordfish in the northeast distant statistical reporting area (NED), the longline fishery throughout the western North Atlantic targets a number of other species, including bigeye (*Thunnus obesus*) and yellowfin (*Thunnus albacares*) tuna. 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 NED, which previously had been closed to US pelagic longline fishing. Observer coverage was 100% during the experiments. During the latter two years (2002–2003), the resolution of the data was higher, including detailed data on longline “sections”, which are the length of mainline between high-flyer buoys on each haul (Watson et al. 2005). There are generally 6–10 sections for each haul. Such specificity of location along the longline set allowed us to examine finer resolution patterns of turtle distribution for this period. The NED experiments data set 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 weather and other conditions). For more complete details on the experimental design in the NED, see Watson et al. (2005) and see Hoey and Moore (1999) for details on the regional characteristics of the US Atlantic pelagic longline fishery. Both data sets for this analysis, the pelagic observer data set (1992–2003) and the NED experiments data set (2002–2003), contain the latitude, longitude, loggerhead and leatherback turtle catches (0 for no turtles caught, 1 for at least one turtle caught), and the date. The data are collected per set for the pelagic observer data set and per section for the NED experiments data set. These variables represent only a subset of the variables collected for both data sets.

### Model

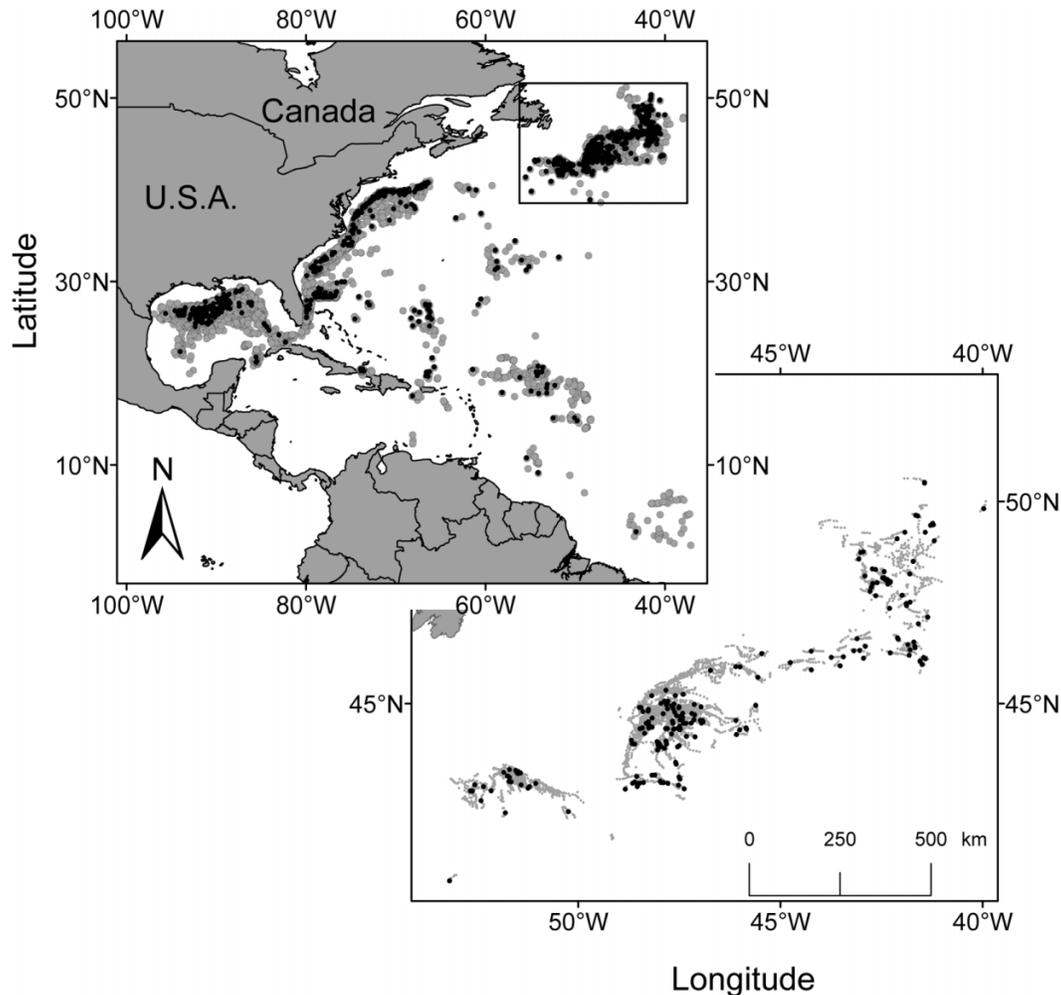
#### Spatial K function

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)

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

where  $\widehat{\lambda}_d$  is the intensity of the events (i.e.,  $\widehat{\lambda}_d = N/A$ ),  $N$  is the total number of events,  $A$  is the total area, and  $s_i$  is the

**Fig. 1.** Upper left panel: total span of the data set. The gray points show observed pelagic longline fishing locations, whereas the black marks indicate fishing locations with at least one sea turtle catch. The upper right inset panel is the northeast distant waters (NED) statistical reporting region. Lower right panel: data from the NED experiment. The points represent each section along a set line (instead of just one point per set): gray points show observed fishing locations, and the black marks indicate fishing locations with at least one sea turtle catch.



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

$$(2) \quad \hat{L}(d) = \left[ \hat{K}(d)/\pi \right]^{\frac{1}{2}} - d, \quad d > 0$$

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

Typically the null hypothesis is complete spatial randomness (Diggle 2003); however, here we know that the locations marked as catching a sea 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). Thus, a

model that allows us to identify the spatial distribution of the marks, as differentiated from the nonrandom 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 (sea turtle captures) are distributed randomly within the non-random spatial distribution of events (fishing locations), we used a permutation test, whereby under a series of simulations the marks were randomly assigned to event locations (i.e., permuted) to create a series of distributions that represent complete spatial randomness conditioned upon the location of the fishing events. Essentially, since we know that fishing locations are not randomly located in space, we are comparing the known sea turtle capture locations with a simulated set of sea turtle captures, which are randomly located within the known fishing locations. One thousand permutations of marks on events were run to calculate a goodness-of-fit test statistic based on Loosmore and Ford (2006) for determining if the observed pattern is different from the null hypothesis. However, to detect if the observed pattern displayed clustering versus overdispersion (e.g., in-

hibition or spatial evenness patterns), we then calculated a new estimator.

This new estimator (termed adjusted  $\widehat{L}$ ) can be written as follows:

$$(3) \quad \widehat{L}_m(d) = \left[ \widehat{K}_m(d)/\pi \right]^{\frac{1}{2}} - \left[ \widehat{K}(d)/\pi \right]^{\frac{1}{2}}, \quad d > 0$$

$\widehat{K}(d)$  is as defined in eq. 1 and  $\widehat{K}_m(d)$  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  $d$ . The same 1000 permutations used for the overall goodness-of-fit test were then used to create a prediction envelope (based on the 95% quantiles) around  $\widehat{L}_m(d)$  for each of the sea turtle species' catch locations. Spatial clustering is indicated when the adjusted  $\widehat{L}$  value rises above the prediction envelope; overdispersion (i.e., evenness) is indicated when the adjusted  $\widehat{L}$  value falls below the prediction envelope. It should be noted that Loosmore and Ford (2006) articulate the incorrect use of the prediction envelope for statistical testing; as such, we use the envelopes and graphs for diagnostic purposes only.

**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

$$(4) \quad \widehat{K}(t) = (\widehat{\lambda}_t N)^{-1} \sum_{i=1}^N \sum_{j \neq i}^N \frac{I(\|h_i - h_j\| \leq t)}{v(h_i, h_j)}, \quad t > 0$$

where  $\widehat{\lambda}_t$  is the intensity of the events (i.e.,  $\widehat{\lambda}_t = N/T$ , where  $N$  is the total number of events,  $T$  is the total length of the time series (in days)), and  $h_i$  is the time of event  $i$ . The weight  $v(h_i, h_j)$  is the temporal equivalent of the spatial edge-correction factor based on the proportion of the time interval centered at  $h_i$  that is inside the observed time span (Diggle et al. 1995). The indicator function  $I(\cdot)$  identifies those events  $h_j$  that are within a time  $t$  of the event  $h_i$ . 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  $\pi$ ). 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

$$(5) \quad \widehat{L}_m(t) = \widehat{K}_m(t) - \widehat{K}(t), \quad t > 0$$

One thousand permutations of marks on events were run to create a 95% prediction envelope for testing the significance of  $\widehat{L}(t)$  for each sea turtle species, catch locations, or events. As with the spatial  $K$  function, envelopes and graphs are used for diagnostic purposes only.

**Space-time K function**

By analogy with our previous  $K$  functions, the space-time  $K$  function is an average across all observed events to give

**Table 1.** Summary of the sea turtle catches for the entire Pelagic Observer Program data from 1992 to 2003.

Month	Sets	Loggerhead		Leatherback	
		<i>n</i>	<i>p</i>	<i>n</i>	<i>p</i>
January	504	25	<0.01	29	0.06
February	556	35	<0.01	23	0.09
March	409	23	0.03	25	0.20
April	434	19	0.29	21	0.12
May	550	18	0.70	38	0.16
June	504	27	0.02	41	<0.01
July	797	48	<0.01	78	<0.01
August	906	81	<0.01	107	<0.01
September	805	88	<0.01	111	<0.01
October	1053	114	<0.01	114	<0.01
November	502	24	0.36	26	0.16
December	307	13	0.11	21	0.03

**Note:** The data are summarized by month, as was used in the analysis. The loggerhead (*Caretta caretta*) and leatherback (*Dermochelys coriacea*) 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). The  $p$  values are based on the overall significance test for spatial patterns; a significant  $p$  value indicates the observed pattern of catches was different than a spatially random pattern based on 1000 simulations.

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)

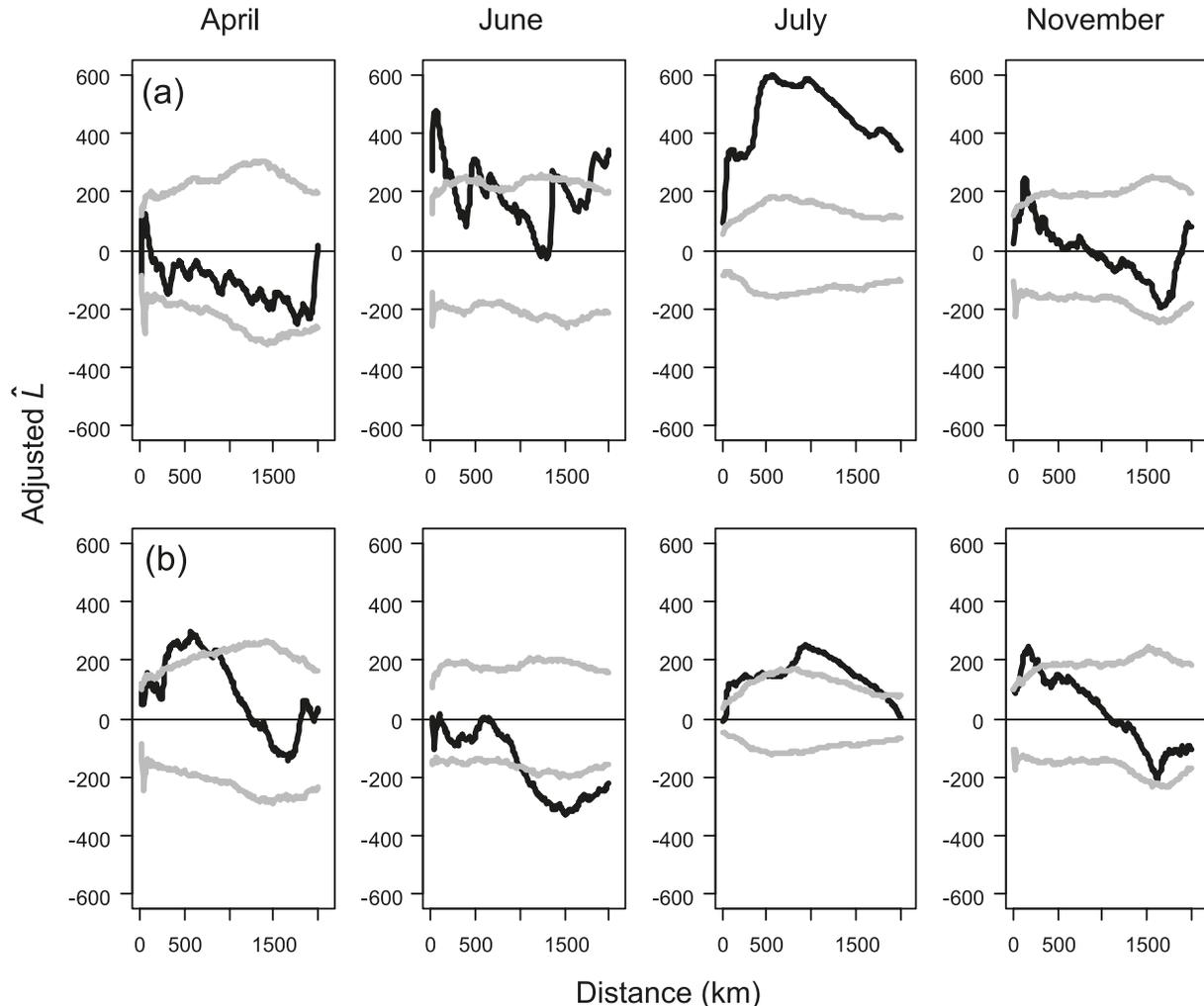
$$(6) \quad \widehat{K}(d, t) = \frac{AT}{N^2} \sum_{i=1}^N \sum_{j \neq i}^N \frac{I(\|s_i - s_j\| \leq d) I(\|h_i - h_j\| \leq t)}{w(s_i, s_j) v(h_i, h_j)}, \quad t, d > 0$$

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

$$(7) \quad \widehat{D}(d, t) = \widehat{K}(d, t) - \widehat{K}(d)\widehat{K}(t)$$

Space-time interactions are indicated by observing peaks on the surface of  $\widehat{D}(d, t)$ , which are unitless when plotted over space and time (Diggle et al. 1995; Gatrell et al. 1996). Space-time clustering implies more than just clustering in space and clustering in time, but specifically that events that are relatively close in space are also relatively close in time. To assess the significance of  $\widehat{D}(d, t)$ , the 1000 permutations created for the space and time  $K$  functions were used to calculate  $\widehat{D}_i(d, t)$  for  $i = 1$  to 1000. The overall sum of  $\widehat{D}(d, t)$  over all  $d$  and  $t$  was compared with the frequency distribution of the sums of each  $\widehat{D}_i(d, t)$ . If the overall sum of  $\widehat{D}(d, t)$  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 permuted  $\widehat{D}_i(d, t)$  were also used to create a 3D

**Fig. 2.** Spatial  $K$  function results for the entire data set. The top row (a) shows the results for loggerhead (*Caretta caretta*) sea turtles, and the bottom row (b) are the results for leatherback (*Dermochelys coriacea*) sea turtles, when all years are grouped by month. On all graphs, the  $x$  axis is distance (km) and the  $y$  axis is the adjusted  $\hat{L}$  (unitless). Grey lines represent a randomized prediction envelope; the black 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 generally stays between the bounds of the prediction envelope. In July for both species and for a section of the leatherback analysis in April and a section of the loggerhead analysis in June, the adjusted  $\hat{L}$  statistic rises above the envelope, suggesting spatial clustering of the sea turtle catch locations. The June results for leatherbacks show the adjusted  $\hat{L}$  statistic falling below the prediction envelope, which indicates spatial patterns of overdispersion. Patterns for August–October are essentially the same as for July, while December–March are similar to November.



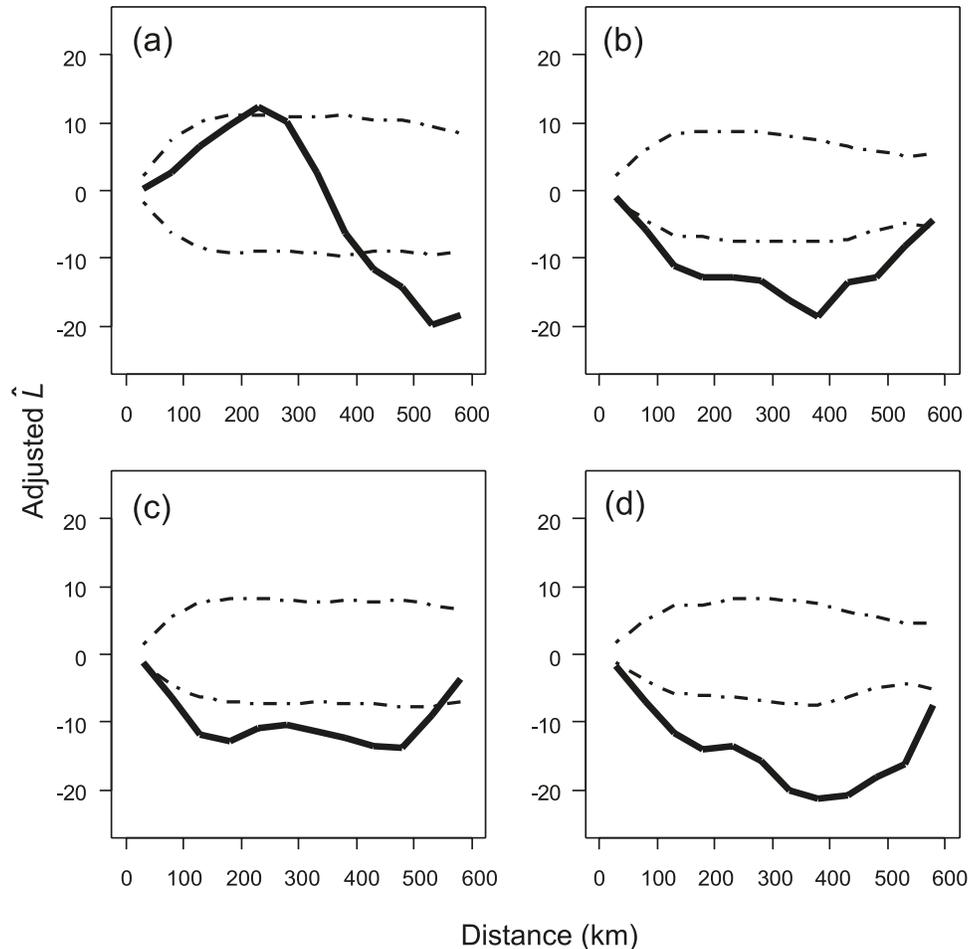
prediction envelope for examining whether the observed peaks of  $\hat{D}(d, t)$  were due to the underlying distribution of fishing or if the peaks might be indicative of further space-time interactions within the fishing pattern. Again, the prediction envelopes are used here to examine the patterns at different spatial and temporal scales; however, because of the confounding of the spatial and temporal scales within the calculation of  $\hat{D}(d, t)$ , the prediction envelopes do not infer statistical significance at each separate  $d$  and  $t$ .

### Application

The spatial model was applied to the pelagic observer data set from 1992 to 2003 to detect broadscale 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 both for loggerheads and leatherbacks. Table 1 contains the raw data on the number of sets for each month and the number of turtle catches for each species. S-PLUS spatial module (Insightful Corporation, Seattle, Washington; Venables and Ripley 1999) was used to calculate the spatial  $K$  function. There are not enough data points of fishing events to investigate finer temporal scales for this data set. The number of sections (which are subunits of a haul) observed and the number of sea turtles caught in the NED experiments data is higher than the overall data set from the Pelagic Observer Program. In 2002, there were 3910 sections, 86 with loggerhead sea turtle captures and 142 with leatherback sea turtle captures. The numbers were similar in 2003, consisting of a total of 4365 sections, 66 with loggerhead sea turtle captures and 75 with leatherback sea turtle captures. Given this increased level of data

**Fig. 3.** Estimated spatial  $K$  function results for the northeast distant waters (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 broken lines are a simulated prediction envelope showing the range of random turtle catches within the distribution of fishing locations. The results are shown for (a) loggerhead (*Caretta caretta*) sea turtles 2002, (b) loggerhead sea turtles 2003, (c) leatherback (*Dermochelys coriacea*) sea turtles 2002, and (d) leatherback sea turtles 2003. Panels b, c, and d indicate patterns of overdispersion, whereas panel a shows more of a random distribution of the catch locations.



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 year for the spatial analysis, and all locations from July through October are used, instead of looking at individual months, as was done previously. In all, there are four analyses being conducted: (i) the spatial  $K$  function on the pelagic observer data set, (ii) the spatial  $K$  function on the NED experiments data set, (iii) the temporal  $K$  function on the NED experiments data set, and (iv) the space–time  $K$  function on the NED experiments data set. The Splanx package (Rowlingson and Diggle 1993; Bivand and Gebhardt 2000) in R was used to calculate the different  $K$  functions for this analysis.

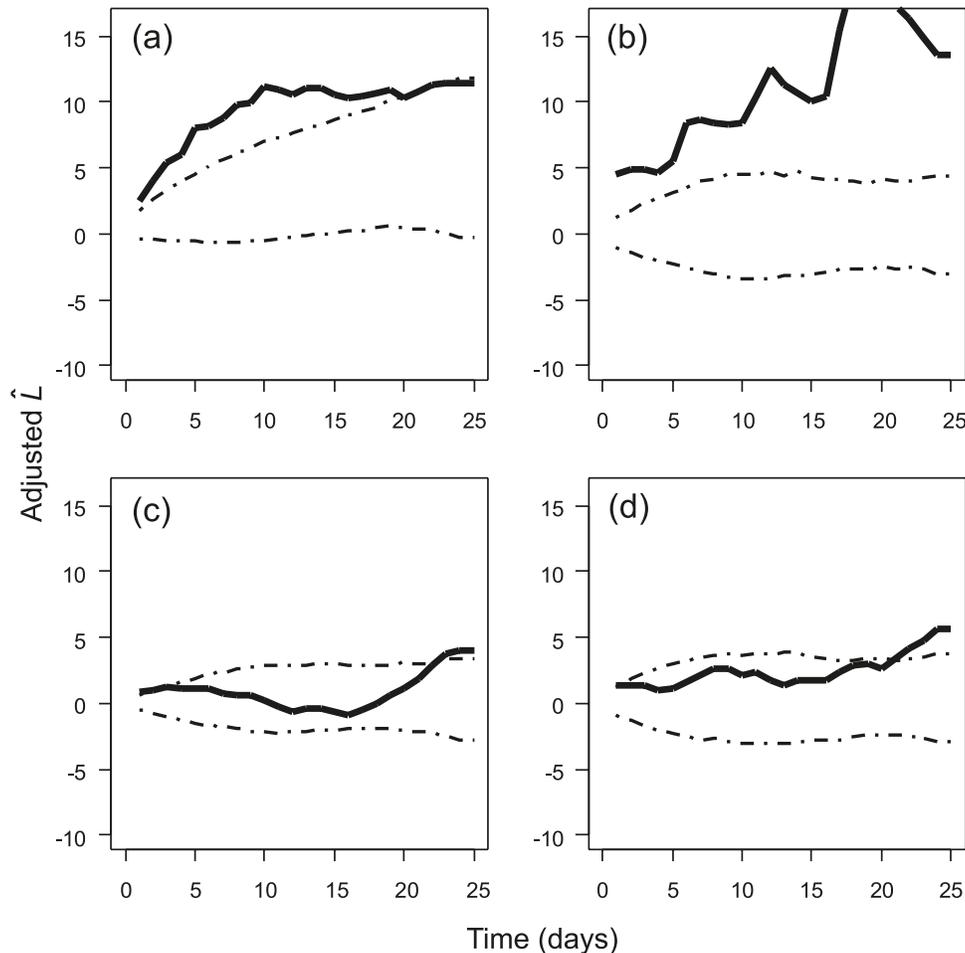
## Results

### Spatial $K$ function — pelagic observer data set

The spatial  $K$  function analysis for the entire data set, including the Gulf of Mexico and western North Atlantic, shows varying spatial patterns across time (Fig. 2).

Throughout most of the year, both the loggerhead and leatherback turtles display some spatial pattern in catch locations that is different from complete spatial randomness (Table 1). These results only suggest that the catch patterns are different from a random pattern; to determine if the patterns are clustered or regular, we examine the plots of the results (Fig. 2). Indeed, during the months of July–October, the loggerhead captures indicate a pattern of spatial clustering (July is shown in Fig. 2; August–October results are very similar). For leatherback catches, the clustering pattern for July–October is similar to the loggerheads, but is not as pronounced; often the adjusted  $\hat{L}$  is very close to the upper envelope boundary for this species. Two anomalies occur in the leatherbacks results: the first is in April when the pattern crosses the upper envelope around 500 km, indicating a change in the spatial clustering and remaining above the envelope until around 1000 km; and the second is the indication of overdispersion in June. The leatherback pattern for June is a good example of a significant result using the Loosmore and Ford (2006) method for testing spatial patterns, where the

**Fig. 4.** Estimated temporal  $K$  function results for the northeast distant waters (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 broken lines are a simulated prediction envelope showing the range of random turtle catches within the distribution of fishing locations. The results are shown for (a) loggerhead (*Caretta caretta*) sea turtles 2002, (b) loggerhead sea turtles 2003, (c) leatherback (*Dermochelys coriacea*) sea turtles 2002, and (d) leatherback sea turtles 2003. Panels a and b indicate temporal clustering over all time lags; however, panels c and d show no clear temporal clustering.



catch pattern is actually more regularly spaced (as opposed to clustered) than the fishing locations.

#### Spatial $K$ function — NED

To look at more fine-scale spatial patterns, we analyzed the spatial  $K$  function for the experiment data from the NED. The spatial results for the 2002 loggerhead sea turtle catches in the NED indicate a pattern of overdispersion at the larger spatial lags ( $p = 0.01$ ), and in 2003, spatial adjusted  $\hat{L}$  values for the loggerhead catch locations exhibit patterns of overdispersion ( $p < 0.01$ ; Fig. 3). For leatherbacks, the spatial adjusted  $\hat{L}$  displays evidence of overdispersion at all distance lags in both years ( $p < 0.01$ ; see Fig. 3).

#### Temporal $K$ function — NED

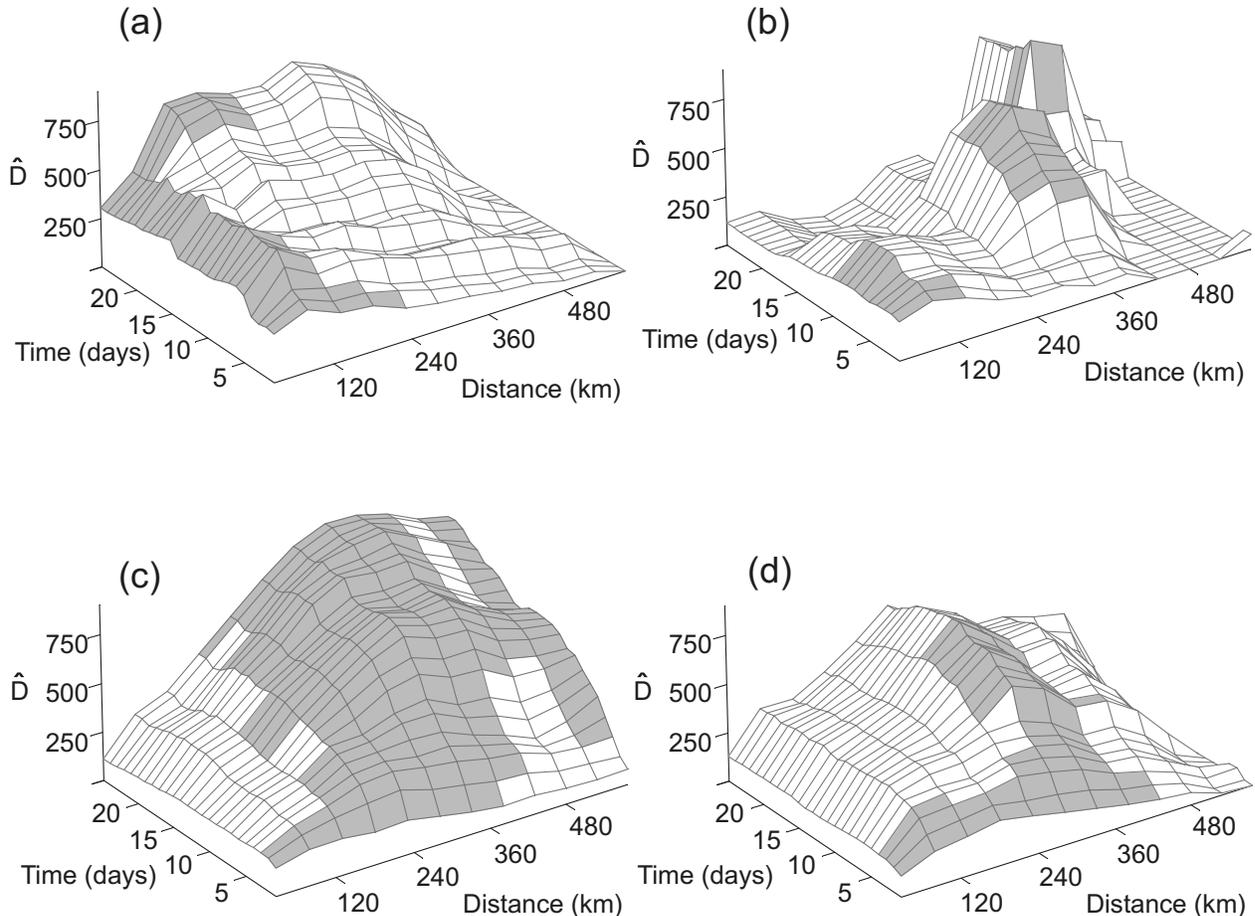
The temporal  $K$  function results also show changes in the patterns between years for the loggerheads and between the species (Fig. 4). In 2002 and 2003, the temporal adjusted  $\hat{L}$

for the loggerheads shows clear evidence of clustering over all time lags ( $p < 0.01$ ). However, in both years, the leatherback temporal  $K$  function analysis shows temporal randomness over all time lags ( $p > 0.05$  for both years).

#### Space-time $K$ function — NED

The overall space-time interactions (i.e., the sum of  $\hat{D}(d, t)$  over all  $d$  and  $t$ ) for the loggerhead catches in both 2002 and 2003 were not significant. For the leatherback catches, the overall space-time interaction value in 2002 was above 95% of the permuted values ( $p < 0.05$ ), supporting the conclusion that there is overall space-time clustering. For 2003, the overall space-time interaction value was above 90% of the permuted values ( $p < 0.10$ ), which is further evidence of clustering in this species, but not at the same significance level. Upon examining the plot of  $\hat{D}(d, t)$  against space and time, the  $\hat{D}(d, t)$  values at the smallest time and distance lags for both species in both years are above the prediction envelopes, which suggests that there

**Fig. 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 shaded blocks show a positive  $\hat{D}(d, t)$  value that is also above the 95th quantile value for that time and distance for 1000 simulations. The results are shown for (a) loggerhead (*Caretta caretta*) sea turtles 2002, (b) loggerhead sea turtles 2003, (c) leatherback (*Dermochelys coriacea*) sea turtles 2002, and (d) leatherback sea turtles 2003. The overall test of space–time clustering was only significant ( $p < 0.05$ ) for the leatherbacks in 2002; however, for both species in both years, we see support, though not statistically significant, for space–time interactions at the small temporal and spatial scales (1–5 days and 30–200 km).



may be space–time interactions at fine scales that are not detected in the overall test of  $\hat{D}(d, t)$  over all  $d$  and  $t$  (Fig. 5). Additionally, the plot of  $\hat{D}(d, t)$  for the leatherbacks in 2002 provides evidence of space–time interactions across the middle span of both the spatial and temporal ranges. This larger span of noted space–time interactions at the individual  $d$  and  $t$  values is reflected in the significant overall test of interactions. The overall test of space–time interactions does not provide insight on how the patterns of clustering or regularity change over different spatial and temporal units. Thus, without considering the plots of  $\hat{D}(d, t)$  as shown in Fig. 5, the potential small-scale space–time interactions would not be detected. To further examine the data, we conducted data exploration and ran the analysis only using a smaller spatial and temporal scale (5 days and 200 km). The results of the overall space–time interaction were significant ( $p < 0.02$ ) for both species and both years at this reduced scale, thus providing more support that there are likely fine-scale space–time interactions occurring in the sea turtle catch patterns. However, care should be taken when considering these results, which stem from data explo-

ration (i.e., data mining) and from a test that was conducted after initial examination of the data.

## Discussion

The results from our space–time analysis support the idea that sea turtle catch distributions vary over different spatial and temporal scales. This technique allowed us to quantify space–time interactions and to detect the scale at which these interactions are functioning in the pelagic longline fishery. Although we cannot infer the nature of the process from the observed pattern, the analysis does provide a novel starting point either for examining environmental heterogeneity (e.g., sea surface temperature or eddy formation) that could explain the pattern or in allowing one to consider biological functions (e.g., sea turtle 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 fisheries bycatch data and provides insight into the patterns of incidental captures and a possible basis from which to reduce undesired bycatch of sea turtles.

Previous studies indicate that modifying fishing practices in various ways, such as gear modifications, may prove effective in reducing sea turtle bycatch (James et al. 2005; Watson et al. 2005; Gilman et al. 2007). In particular, Gilman et al. (2007) suggest that the aggregation of sea turtles at foraging grounds or other areas could result in a higher probability of catching a sea turtle in a set that follows a set in which a sea turtle was caught. This seems to be the case in the NED, where oceanic-stage loggerhead sea turtles appear to be feeding when they interact with the longline fishery (Watson et al. 2005). We detected temporal clustering of loggerhead catches in the NED region; whether they are foraging or not, this indicates that the probability of catching a loggerhead on a given day is related to whether or not a loggerhead sea turtle was caught in previous days.

Additionally, based on the space–time analysis, we would argue that sea turtle captures that are relatively close in space are also close in time. Thus, vessels fishing within 5 days and 200 km of where a sea turtle was caught would likely have a greater chance of interacting with another sea turtle. The results over all space and time (approximately 30 days and 600 km for each species in each year) were not significant, indicating that there are not larger patterns of space–time interactions. Thus when fine-scale patterns of clustering are detected, managers or fishermen could use real-time bycatch data to determine short-term “hotspots”. Such a mechanism would allow for real-time avoidance of much more precise areas to reduce sea turtle bycatch. Conversely, if no space–time patterns were detected, then there would be no basis for requiring fishermen to move to another area after catching a sea turtle, which would be the case in an area where sea turtle foraging grounds are more spread out and habitat preferences are less limited than in the NED.

The broadscale patterns of spatial clustering for the loggerheads during the months of July–October, based on the pelagic observer data set, likely reflect the opening of fishing in the NED, where turtle catch rates appear higher. The test of spatial patterns and the prediction envelopes account for the underlying distribution of fishing, but the spatial  $K$  function provides support for the overall clustering of sea turtle catches relative to the fishery. The model’s detection of these patterns, which have been recognized by the fishing industry but never quantified, validates the technique employed here and strengthens the perceptions of fishery managers. It should be noted that while combining the data by months across years provides insight at a broad scale, such aggregation 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, overdispersion of sea turtle catches within the fishery. Given the temporal heterogeneity and the space–time interactions indicated by the results, the spatial distribution of sea turtle catch locations is likely changing nonrandomly on a short time frame (1–5 days based on the space–time interaction results). 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.

Inferring a process from a pattern is always a question of judgment and especially so in a data set such as the pelagic longline observer data, where environmental heterogeneity is obviously present. In addition to dynamic environmental conditions, the data set also has a high level of variation in mean turtle catch density across the study region. A nonstationary intensity could allow for the  $K$  function to represent more the first-order effects (e.g., a change in the mean) than the interaction of events. In this context, 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: (i) there is spatial and temporal heterogeneity in the sea turtle catch distributions; (ii) further examination of sea turtle captures is 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 in the vicinity.

As bycatch of nontargeted and undesired species continues to be an issue for fisheries worldwide, innovative and novel tools are needed to address management and conservation concerns. The extension of spatial models and the development of new models allows for comparison with other point patterns, such as inhibition processes, which provide more possibilities in testing biologically meaningful hypotheses (Loosmore and Ford 2006). Applying point pattern techniques, such as those described here, to other data sets could prove to be a powerful tool for fisheries management, conservation, and for better understanding of bycatch distributions for other species of concern, all with the ultimate goal of increasing precision of fisheries management decisions.

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