Ecological Applications, 19(4), 2009, pp. 920–930

Mapping the bycatch seascape: multispecies and multi-scale spatial patterns of fisheries bycatch

Rebecca L. Lewison,[1] Candan U. Soykan, and Janet Franklin

Biology Department, San Diego State University, 5500 Campanile Drive, San Diego, California 92182-4614 USA

Abstract. Fisheries bycatch is a worldwide conservation issue. Despite a growing awareness of bycatch problems in particular ocean regions, there have been few efforts to identify spatial patterns in bycatch events. Furthermore, many studies of fisheries bycatch have been myopic, focusing on a single species or a single region. Using a range of analytical approaches to identify spatial patterns in bycatch data, we demonstrate the utility and applications of area and point pattern analyses to single and multispecies bycatch seascapes of pelagic longline fisheries in the Atlantic and Pacific Oceans. We find clear evidence of spatial clustering within bycatch species in both ocean basins, both in terms of the underlying pattern of the locations of bycatch events relative to fishing locations and for areas of high bycatch rates. Furthermore, we find significant spatial overlap in the pattern of bycatch across species relative to the spatial distribution in fishing effort and target catch. These results point to the importance of considering spatial patterns of both single and multispecies bycatch to meet the ultimate goal of reducing bycatch encounters. These analyses also highlight the importance of considering bycatch relative to target catch as a way of identifying areas where fishing effort reduction may help to reduce multispecies bycatch with minimal impact on target catch.

Key words: area pattern; fisheries bycatch; marine mammal; Moran scatterplot; Moran's I; O-ring statistic; point pattern; seabird; sea turtle; spatial analysis.

INTRODUCTION

Bycatch is a conservation concern for fisheries around the world (Kelleher 2005). Also termed "incidental" or "unwanted catch," bycatch includes both discarded individuals of target species and nontarget species. Of particular concern is the bycatch of long-lived oceanic vertebrates, such as sea turtles, seabirds, marine mammals, and sharks (Heppell et al. 2000, Lewison et al. 2004*a*). Studying bycatch of these vulnerable species is challenging due to the relative rarity of bycatch events for these species by individual vessels (Crowder and Murawski 1998) and the paucity of detailed, high-quality data on bycatch (Lewison and Crowder 2007). However, several studies point to the detrimental cumulative effects from bycatch when considered across fleets and gear types (Crowder 2000, Lewison et al. 2004*b*, Tomillo et al. 2007).

Although bycatch is ubiquitous across ocean basins and all types of fishing gear, bycatch of vulnerable species (i.e., those that are impacted by bycatch or have been identified as a species of conservation concern) is not uniformly distributed. By their very nature, spatial location and extent of bycatch are central to management questions and subsequent strategies designed to reduce bycatch (e.g., locations of mandatory mitigation gear/practices and temporary closures or effort redistributions). For example, fleet communication has emerged as a successful method for identifying transient high-bycatch areas (Gilman et al. 2006). Several U.S. fisheries (U.S. North Atlantic longline swordfish fishery, U.S. North Pacific and Alaska trawl fisheries, and U.S. Alaska demersal longline fisheries) use near real-time reporting of bycatch rates to help reduce fisheries bycatch in an efficient, cost-effective manner.

A logical complement to these small-scale, short-term approaches would be an analysis designed to identify underlying spatial patterns in bycatch over longer periods, thereby allowing for the identification of spatially persistent areas of high bycatch. Yet, there have been few analyses along these lines (but see Gardner et al. 2008, Sims et al. 2008). Furthermore, the majority of bycatch analyses focus on a single taxon or species (i.e., sea turtles). These focused studies are critical to understanding potential population-level effects of bycatch from a particular fishery, but fail to capture the full bycatch seascape that includes many species of long-lived oceanic vertebrates encountering multiple gear types as they travel across large marine ecosystems.

Whereas single-species bycatch studies are critical for understanding fisheries impacts on particular populations (Jaramillo-Legorreta et al. 2007), the simultaneous analysis of bycatch events for multiple species more accurately reflects the challenges faced by fisheries management agencies (Hall 1996). Previous research suggests that bycatch management strategies that focus

Manuscript received 1 April 2008; revised 4 August 2008; accepted 20 August 2008. Corresponding Editor: P. K. Dayton.

[1] E-mail: rlewison@sunstroke.sdsu.edu

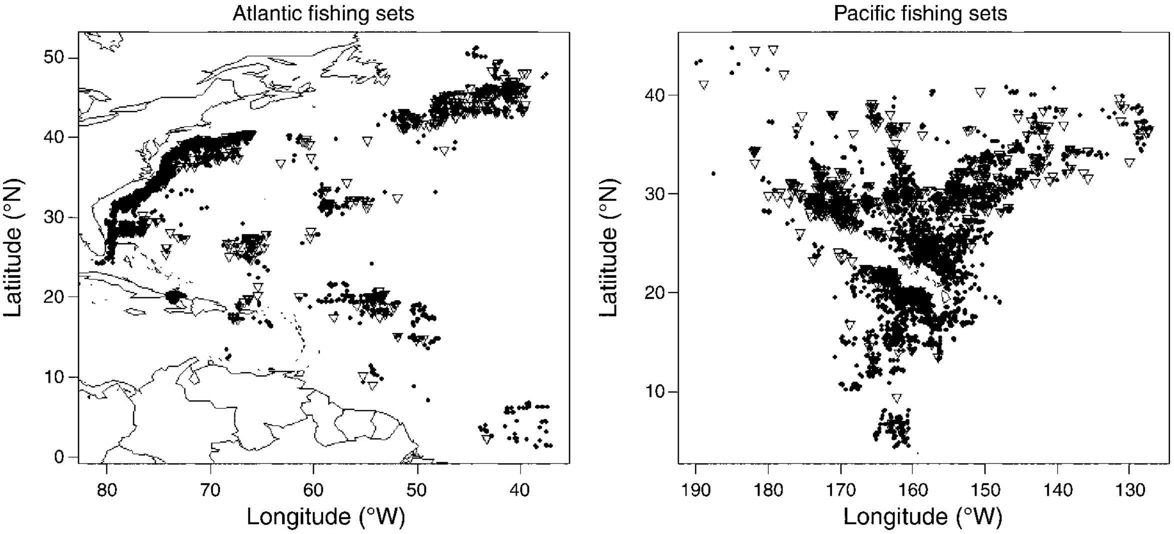

FIG. 1. Distribution of observed fishing sets with bycatch (open triangles) and without bycatch (solid circles) in both the Atlantic Ocean (left) and Pacific Ocean (right). In the Pacific, the Hawaiian Islands are shown near the center of the map.

solely on a single species or taxon may lead to additional bycatch problems (Baum et al. 2003). For instance, closing a fishing ground to reduce bycatch of species A may result in the redistribution of fishing effort in areas that increase bycatch of species B.

Identifying the spatial pattern of bycatch events serves several purposes. It describes spatial locations of persistent bycatch events for a species of conservation concern. If standardized for the distribution of fishing effort, this can point to aggregations of bycatch-impacted species. From a multispecies perspective, spatial analyses can highlight bycatch "hotspots" where fishing gear are encountering multiple vulnerable species. Although there are challenges in hotspot designation (defined as areas that exceed a specified threshold; Kareiva and Marvier 2003), identifying hotspots is an important step to understanding anomalous spatial patterns in complex natural systems and can facilitate efficient and effective conservation planning (Nelson and Boots 2008). From a fisheries management and economic perspective, the distribution of bycatch relative to target catch will influence the effectiveness and costs associated with different mitigation strategies (Hall and Mainprize 2005).

Here we consider the spatial distribution and patterns of bycatch events within and among species, focusing our analyses on sea turtles, seabirds, and marine mammals at a local oceanographic scale (~100–1000 km). We compare the results from multiple analyses that sequentially integrate additional information to explore the differences in utility and potential applications across these methods. These analyses address three questions: (1) Does bycatch occur randomly across fishing locations? (2) Are there spatially persistent areas of high bycatch within or among species? (3) What is the relationship between bycatch and target catch? Our analyses represent a novel application of point and area pattern analyses (Fortin and Dale 2005, Nelson et al. 2006) to the study of bycatch and demonstrate their utility to inform bycatch management and mitigation for vulnerable species and, ultimately, to promote sustainable fisheries.

METHODS

We used National Marine Fisheries Service observer data at the fishing set level from the U.S. Pacific (Hawaiian) and Atlantic pelagic longline fisheries, collected between 1992 and 2005 in the Atlantic (>4000 sets) and between 1994 and 2000 in the Pacific (>3500 sets). Each of the data sets spans 40° or more of latitude and longitude (Fig. 1).

Pelagic longlines consist of a mainline from which secondary lines, called gangions, hang. Hooks are found at the end of each gangion. The mainline is deployed to a specific depth by the number of floats on the line and line weights. The mainline lengths ranged from 6 to 86 km in the Pacific (mean = 38.7 km), from 1 to 60 km in the Atlantic (mean = 24.9 km). The spatial scale of our analyses is based on these gear profiles: we set our minimum spatial lag (1° or ~100 km) to be larger than the maximum length of mainline gear to avoid analyses at a higher resolution than available data. Given the length of longline sets and the large spatial extent of the processes under consideration (biogeographic distributions of marine species, patterns of oceanographic variables), we defined local scale as 100–1000 km. A bycatch event was defined as a fishing set with bycatch of marine mammals, seabirds, or sea turtles. Sharks were excluded from the present study because for the data sets in these analyses, sharks may represent commercially viable catch and thus did not meet our definition of bycatch (see *Introduction*).

For these analyses, we grouped the data over time, treating each gear deployment (fishing set) as an observation. While we were unable to comprehensively test the assumption that the data were stationary over time, dividing the data sets up into two equal-length time periods (seven years in the Atlantic and four years in the Pacific) yielded results similar to those found using the entire data sets. As such, we were able to rule out the existence of major temporal nonstationarity in the data.

Locations of fishing sets and bycatch events can be considered a population of marked points (fishing sets with or without bycatch) and analyzed using point pattern statistics. Alternatively, these point pattern data can be summarized as densities or rates of fishing sets and bycatch events per unit area and analyzed using area pattern statistics. Frequently, spatial ecological data can be viewed in both ways and it is useful to do so (Fortin and Dale 2005). A criterion for choosing between point and area statistics is whether the locations represent a population or a sample. From one perspective the data are a complete census of all observed fishing sets in the time period. Thus, point pattern statistics, which deal with population data, are appropriate. However, it is common and useful to transform point patterns data to area patterns, number of events per sample area, and use area pattern methods to describe their spatial pattern. Although area pattern methods were developed for sample data, they can also be used with population data. Moreover, the fishing sets used in this study can be viewed as a representative sample of all the fishing sets that actually occurred in the time period. Although not every boat has an observer, National Oceanic and Astmospheric Administration (NOAA) observer programs strive to stratify observed vessels across fishing zones.

A major assumption that must be met in spatial analysis is that the underlying data-generating process is stationary, i.e., the parameters do not change over space. Interpreted in the context of this study, the data set would be stationary if fishing effort and bycatch species were distributed evenly across the study area, a clearly unrealistic expectation. However, there are several ways of dealing with nonstationarity: subsetting the data into regions, using local statistics, or using bivariate statistical tests that compare one pattern to an underlying pattern that is not necessarily random. In an exploratory analysis we divided the data into subsets and found no major differences in the results when we divided the Atlantic data into northern (above 35° N) and southern (below 35° N) subregions. We also chose to focus our analyses on spatial patterns that emerge at smaller spatial scales relative to the entire ocean basin. Furthermore, we used a bivariate statistical test for our point pattern analyses and chose a conservative background distribution for our area pattern analyses.

The primary objective of this study was to illustrate the use of complementary methods for describing the spatial distribution and pattern of fisheries bycatch. To that end, we followed a stepwise approach that integrated additional information at each level of analysis. In step 1, we asked whether bycatch events are clustered and at what scales, given the underlying pattern of fishing locations using a bivariate point pattern O-ring statistic (Wiegand and Moloney 2004). Step 2 considered the spatial patterns of standardized bycatch rates (bycatch per unit effort, BPUE) as an area pattern and used the Moran's I statistic (Moran 1948) to assess whether high bycatch areas are clustered and at what scales clusters occur. Step 3 employed these same analyses with data from multiple species, and step 4 considered multispecies bycatch relative to target catch yield.

For steps 1 and 2 we analyzed single-species patterns for each of the four most commonly caught non-fish bycatch species, which together represented 93.9% and 86.5% of all sea turtle, seabird, and marine mammal bycatch individuals in the Pacific and Atlantic, respectively (Appendix A). These were Black-footed Albatrosses (*Phoebastria nigripes*), Laysan Albatrosses (*Phoebastria immutabalis*), loggerhead turtles (*Caretta caretta*), and leatherback turtles (*Demochelys coriacea*) in the Pacific Ocean and loggerhead turtles, leatherback turtles, pilot whales (*Globicephala melaena*), and Risso's dolphins (*Grampus griseus*) in the Atlantic. All aforementioned species have been recognized as species of conservation concern because of mortality due to longline fisheries (NMFS 2001, 2004). The multispecies analyses (step 3) included the aforementioned taxa as well as any other non-fish species recorded as bycatch (Appendix A). In step 4, target catch was defined as the number of swordfish and tuna individuals captured.

Step 1: Does bycatch occur randomly across fishing locations?

The first question treats bycatch as a binary variable (i.e., presence or absence of bycatch in fishing sets) and considers whether bycatch events of an individual species occur as a random subset of all fishing locations across a range of spatial scales. In other words, when we control for the fact that fishing sets are distributed nonrandomly across space, can we detect a nonrandom pattern in the distribution of bycatch events? If so, are these events clustered or overdispersed across different spatial lags? Significant clustering would suggest that certain fishing grounds are more likely to yield a bycatch encounter, whereas significant overdispersion would suggest that bycatch encounters are evenly or regularly distributed among fishing locations.

To address this question, we used the O-ring statistic (also referred to as $g_{12}(r)$, or the neighborhood density function, NDF), testing the null hypothesis that bycatch events are a random subset of all gear deployments. This point pattern statistic calculates the density of events of type B (i.e., bycatch events) across a range of distances r from an arbitrary event of type B, given a nonrandom background distribution of events of type A (i.e., fishing sets). Simulations involving random labeling of points allow for statistical inference by comparing the observed pattern to one that would be expected if the null hypothesis were true (Galiano 1982, Condit et al. 2000, Wiegand and Moloney 2004, Perry et al. 2006). This method is analogous to Ripley's $K_{12}(r)$ with circles of radius r replaced by annular rings with radius r. We chose to use the O-ring statistic in lieu of the more commonly applied Ripley's K statistic because the O-ring statistic focuses attention on specific distance classes, whereas the cumulative K function confounds effects at larger distances with effects at shorter distances (i.e., successive values of Ripley's K are autocorrelated; Wiegand and Moloney 2004, Perry et al. 2006).

We calculated $g_{12}(r)$ for 0.5 decimal degree (~50 km) increments (r) from 1° to 20°, although we focus attention on local patterns from 1° to 10° (~100–1000 km) as the most relevant scale from the perspective of these pelagic fisheries. Values of $g_{12}(r)$ below expectation (deviation from zero) indicate that bycatch events separated by a distance r are more clustered than expected by chance relative to a background spatial pattern determined by the distribution of fishing sets. Conversely, $g_{12}(r)$ values above expectation indicate overdispersion (Appendix B). Values were calculated and compared with simulation envelopes akin to 95% confidence intervals for the expected pattern, estimated by Monte Carlo simulation ($n = 100$), using the R software package "ads" (R Development Core Team 2008).

Due to simultaneous inference, the simulation envelopes generated during this and other steps cannot be interpreted as confidence intervals; the type I error is >5% (Loosmore and Ford 2006). A statistically rigorous approach would be to use an overall goodness-of-fit test (a single summary test statistic) that results in an appropriate alpha level by comparing summed values for the entire data set. However, it is clear from the extremely small P values we obtained that such a test would indicate an overall result that is statistically significant. Such a test does not allow one to determine the scale(s) at which a certain process departs from the null hypothesis, which was our primary objective. We therefore retain the simulation envelopes as a guide for interpreting the scales at which bycatch events cluster.

Step 2: Are high bycatch rates clustered?

The second analysis assessed the distribution of bycatch rates of individual species, BPUE, calculated as the number of bycatch individuals caught divided by the number of hooks deployed. Distinguishing between bycatch rates and events (addressed in step 1) is important because fishing effort (i.e., number of hooks deployed), like fishing sets, may be unevenly distributed. Thus, some areas could have a large number of hooks and very little bycatch, while other areas could have relatively few hooks, but high bycatch. In these areas, bycatch events per vessel may be comparable, but from a bycatch rate perspective, they could differ considerably.

For this analysis we used an area pattern statistic, Moran's I (Moran 1948), a measure of spatial autocorrelation that allowed us to determine whether areas of high bycatch rates are clustered. If high bycatch locations are found near each other more frequently than expected under the null hypothesis of complete spatial randomness (CSR) and low bycatch locations near other low values, then bycatch rates will exhibit positive spatial autocorrelation (Bailey and Gatrell 1995). Because the distribution of bycatch rates is nonnormal and zero-inflated, we estimated the significance of the Moran's I results by simulation. Specifically, bycatch rates were randomly reassigned to fishing sets to determine what a random distribution of bycatch rates would be like. In turn, that distribution, with its pseudo-95% confidence intervals, was compared with the observed results.

Moran's I was calculated for lag distances of 1–10 lags where each lag is 1° (e.g., from 1°–10°, or ~100–1000 km). We used untransformed BPUE rates for this analysis as any transformation or smoothing of values based on neighboring cells (sensu Sims et al. 2008) would potentially inflate spatial autocorrelation among neighboring events. Moran's I was calculated in R using the package spdep (Bivand 2002). In addition to the Moran's I analyses, we also include a Moran scatterplot and map to identify areas where similar bycatch rates are clustered. A Moran scatterplot displays the spatial correlation (local Moran's I value) between a point and its neighbor(s), dividing all points into four categories, each of which is displayed in separate quadrants of the scatterplot (e.g., high bycatch near high bycatch values, high : low, low : high, and low : low). For these analyses, we identified clusters of high-bycatch points as those occurring in the upper right quadrant of the scatterplots (e.g., high : high). Once identified, these points can be located on a map to determine the prevalence and distribution of areas of high bycatch (i.e., possible bycatch rate hotspots). Since our objective was to compare results across methods rather than identify specific locations, we did not attempt to identify statistically significant data points, although this would be possible using local indicators of spatial association (LISA; Anselin 1995).

It is important to note that area pattern statistics such as Moran's I can be calculated for any user-defined set of fishing events and neighborhood distances. The most intuitive comparison is between all bycatch events and all fishing sets included in the data set to determine whether bycatch events cluster with respect to fishing events. However, this metric may be influenced by the nonrandom distribution of fishing effort combined with the large number of zero bycatch events, which may result in clustering of fishing sets without bycatch (i.e., spatial correlation of zero values as a result of spatial autocorrelation in fishing effort). Since this step addressed the question "Do high bycatch rates cluster

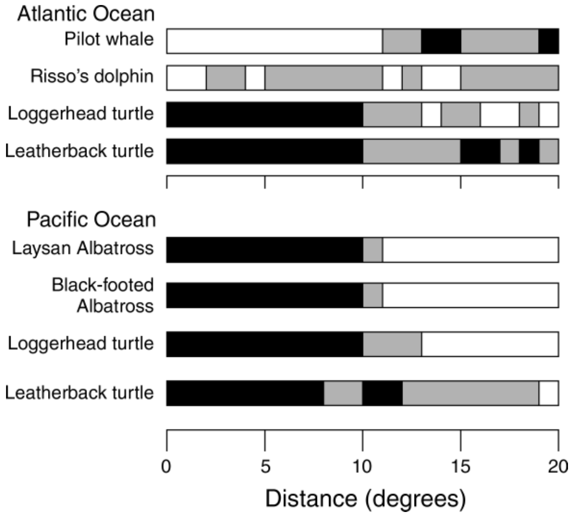

FIG. 2. Point pattern of bycatch based on the O-ring statistic, $g_{12}(r)$, for individual species in each of the ocean basins. Values were calculated at 0.5° increments for distances ranging from 1° to 20°. Gray shading indicates that the distribution of bycatch events relative to all fishing sets does not differ significantly from the null hypothesis of random labeling at that scale, white indicates that it is significantly overdispersed, and black shading indicates that events are significantly clustered.

together?," we focused our analyses only on fishing sets involving a bycatch event. This allowed us to investigate whether high bycatch rates for a species cluster relative to all bycatch events and provided a more conservative analysis of potential clustering. In keeping with our focus on local-scale patterns, we defined a distance-based spatial neighborhood as 1° for the Moran's I analyses and we used the first nearest neighbor for the Moran scatterplots (a 1° radius did not always yield a neighbor value, a requirement for the Moran scatterplot).

Step 3: Pattern analyses of multispecies bycatch

For a multispecies perspective, we repeated the three analyses described above (O-ring statistic, Moran's I, and Moran scatterplot/map) on all species of non-fish bycatch captured in each ocean region (see Appendix A). Previous research has rarely addressed bycatch patterns at the level of community or assemblage. Thus, while the analyses in this step are redundant, the results are not. Indeed, from a manager's perspective, charged with assessing the ecosystem-level effects of fishing, this approach may be more relevant than those reported in steps 1 and 2.

We used the presence or absence of bycatch as a binomial variable for the O-ring analysis and number of bycatch species per unit effort (SPUE), the number of species of bycatch caught divided by the number of hooks deployed, for the Moran's I and Moran scatterplot/map analyses. Species per unit effort offers a simple index of multispecies bycatch that intentionally ignores variation in abundance among species, thus controlling for that variation. These approaches allowed for a multifaceted analysis of bycatch at the community level and facilitated comparison with the single-species patterns described in steps 1 and 2.

In addition to assessing patterns of spatial correlation, we used inverse distance-weighted bilinear interpolation to plot SPUE values on a map using the R software package "akima." In the case of large data sets with many points, interpolation maps can improve visualization of the phenomenon under study. As such they provide a complement to the Moran scatterplot maps for identifying potential bycatch hotspots.

Step 4: Bycatch relative to fishing activity

Target catch per unit effort (CPUE, calculated as number of swordfish and tuna individuals divided by the number of hooks deployed) also varies in space. While this variation has received considerable attention from fishery scientists and fishers alike, it has rarely been related to the distribution of bycatch, particularly at a multispecies level. Do target catch rates and multispecies bycatch rates show similar patterns? Are they correlated? Given that maximizing CPUE is an important fisheries goal and minimizing bycatch is an important conservation goal, we set out to describe the relationship between these two factors. Specifically, we analyzed the standardized number of bycatch species relative to abundance of target catch (SPUE/CPUE). Identifying low values of this metric and whether they cluster together in space is an important step towards maximizing the efficiency of a fishery while minimizing the impact of fisheries on vulnerable species.

For this analysis we calculated the spatial relationships between bycatch and catch by considering the spatial autocorrelation of SPUE/CPUE using Moran's I. We used number of target individuals to represent catch instead of target catch mass because mass data were not available. For this step, we used all sets with nonzero target catch.

RESULTS

Step 1: Does bycatch occur randomly across fishing locations?

Across the two ocean basins we found clear evidence of nonrandom spatial patterns in bycatch events at a local scale for all species examined. For the majority of species, bycatch locations were clustered at smaller distance lags (1°–10°), except for pilot whales and Risso's dolphins in the Atlantic that exhibited overdispersion among bycatch locations, at least at the shortest lags (Fig. 2). Where significant clustering occurred, it was strongest for all species at the shortest distance lag ($d = 1°$ or ~100 km) and declined gradually with increasing distance (Appendix B). Even when we control for the nonrandom distribution of fishing sets, bycatch of sea turtles and albatrosses still displays a

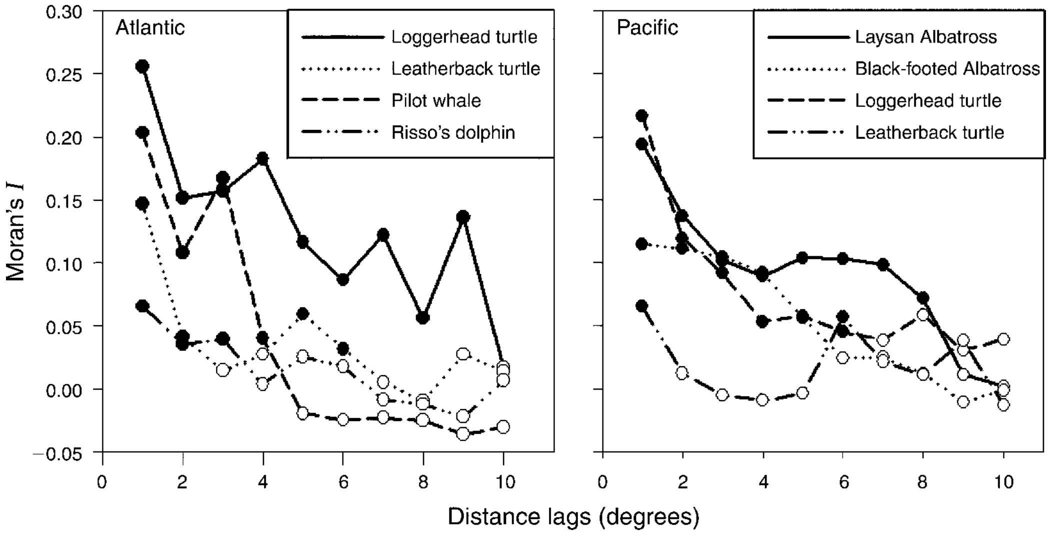

FIG. 3. Autocorrelation of bycatch for individual species in each of the ocean basins. Moran's *I* values were calculated at 1° increments for distance lags ranging from 1° to 10°. Solid circles indicate pseudo-95% confidence intervals that did not overlap zero; open cirlces indicate pseudo-95% confidence intervals that overlapped zero. Values significantly greater than zero indicate positive spatial autocorrelation of bycatch (i.e., clustering), whereas values significantly less than zero indicate negative spatial autocorrelation of bycatch (i.e., overdispersion).

clustered distribution, particularly at small spatial scales, indicating that fishing in certain locations is more likely to result in a bycatch event.

Step 2: Are high bycatch rates clustered?

Bycatch rates (BPUE) analyzed using Moran's *I* showed significant positive spatial autocorrelation for loggerheads and Laysan and Black-footed Albatrosses in the Pacific (Fig. 3). Again, clustering was strongest at the shortest distance lag and declined with distance. Leatherback bycatch, on the other hand, did not show significant spatial patterning beyond the smallest spatial lag. In the Atlantic Ocean, high bycatch levels were clustered to scales of 2° or more for all four species (loggerheads, leatherbacks, pilot whales, and Risso's dolphins; Fig. 3).

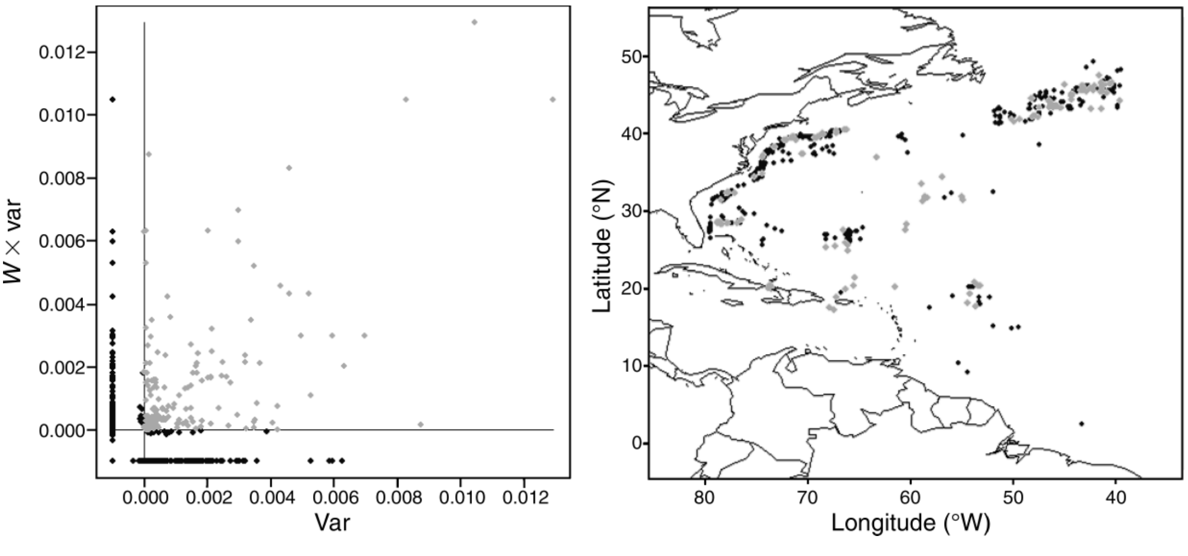

FIG. 4. Moran scatterplot and map for loggerhead turtles in the Atlantic Ocean. The *x*-axis (Var) represents the standardized bycatch rate for a point, while the *y*-axis (*W* × var) represents the standardized bycatch rate for its nearest neighbor. Light gray points in the scatterplot and on the map correspond to observed fishing sets that had above-average values for bycatch per unit effort and whose nearest neighbors also had above-average values (i.e., putative bycatch hotspots). The values in this figure are standardized such that the mean bycatch rate equals zero; hence the line of points at the far left of the graph represents those fishing sets that had zero bycatch, while the line of points at the bottom of the graph represents those nearest-neighbor fishing sets that had zero bycatch.

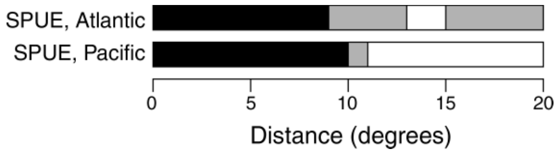

FIG. 5. Point pattern of bycatch based on the O-ring statistic, $g_{12}(r)$, for all bycatch species in each of the ocean basins. See Fig. 2 legend for an explanation of shading schemes. SPUE is species per unit effort.

The Moran's *I* scatterplots and maps (shown for loggerheads in the Atlantic) also depicted the positive spatial correlation among high bycatch events and identified these high bycatch locations (Fig. 4). Similar analyses for other species suggested areas of species-specific high bycatch based on first-nearest-neighbor values (Appendix B). Thus, these analyses reveal that BPUE is spatially clustered, suggesting that regions of high bycatch relative to fishing effort exist at the individual species level.

Step 3: pattern analyses of multispecies bycatch

The point pattern generated by all bycatch species, analyzed using the O-ring statistic, showed significant clustering of bycatch events up to distance lags of 9° or 10° in both ocean basins (Fig. 5). Clustering was strongest at the shortest distance lags (peaking at $d =$ 1° or ~100 km) and declined gradually with increasing distance (Appendix B). In both the Pacific and the Atlantic, Moran's *I* results also suggest positive spatial autocorrelations in SPUE from 1° to 4° or 5° (~100–400 or 500 km; Fig. 6). Therefore, the results at a community level parallel those at the individual species level, suggesting that certain areas are prone to frequent bycatch events and/or high multispecies bycatch rates relative to fishing effort.

In the Atlantic, the interpolated SPUE maps (Fig. 7) identified three primary locations of multispecies bycatch events: Georges Banks (40°–50° N, 40°–50° W), the northern part of the Greater Antilles (20°–30° N, 70°–80° W), and the eastern part of the Lesser Antilles (10°–20° N, 50°–60° W). The Moran scatterplot map (Fig. 7) only picked up two of these locations (Georges Bank and the northern part of the Greater Antilles), but additionally suggested the eastern seaboard of the United States (30°–40° N, 68°–78° W) as an area of high multispecies bycatch. The discrepancy among maps is likely due to low sampling effort in the eastern part of the Lesser Antilles, resulting in isolated high bycatch rate values (recall that we used quadrant *I* of the Moran scatterplot and map, which identifies those areas of high bycatch that are adjacent to other high-bycatch locations). The high-bycatch area identified by the Moran scatterplot map along the eastern seaboard of the United States was absent in the interpolation map. This is likely due to the linear nature of the fishing effort along the eastern seaboard, resulting in many grid cells occurring adjacent to regions with zero fishing effort and bycatch.

The interpolation SPUE map of the Pacific (Fig. 8) highlights three primary locations of multispecies bycatch events: northeast of the Hawaiian Islands (25°–35° N, 135°–145° W), northwest of the Hawaiian Islands (25°–35° N, 165°–175° W), and north-northwest of the Hawaiian Islands (40°–45° N, 160°–180° W). As in the Atlantic, one of these areas (northeast of the Hawaiian Islands) was not identified by the Moran scatterplot and map, also likely as a result of low fishing effort.

Step 4: bycatch relative to fishing activity

Although the focal bycatch species, as measured by SPUE, exhibited clustering in both ocean basins, as shown with the density maps (Figs. 7 and 8), the

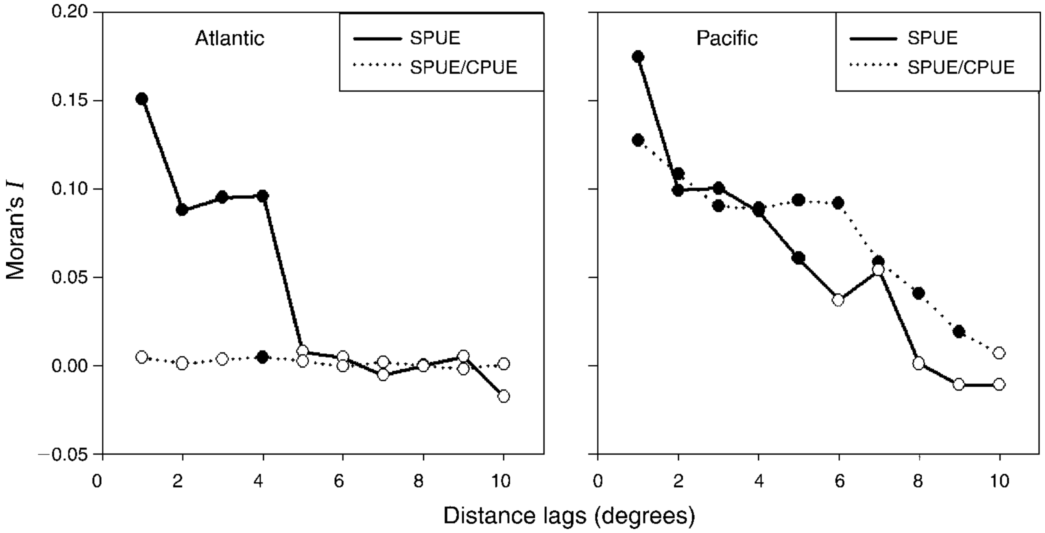

FIG. 6. Autocorrelation of species per unit effort (SPUE) and species vs. catch (SPUE/CPUE) in each of the ocean basins. See Fig. 3 legend for an explanation of fill patterns.

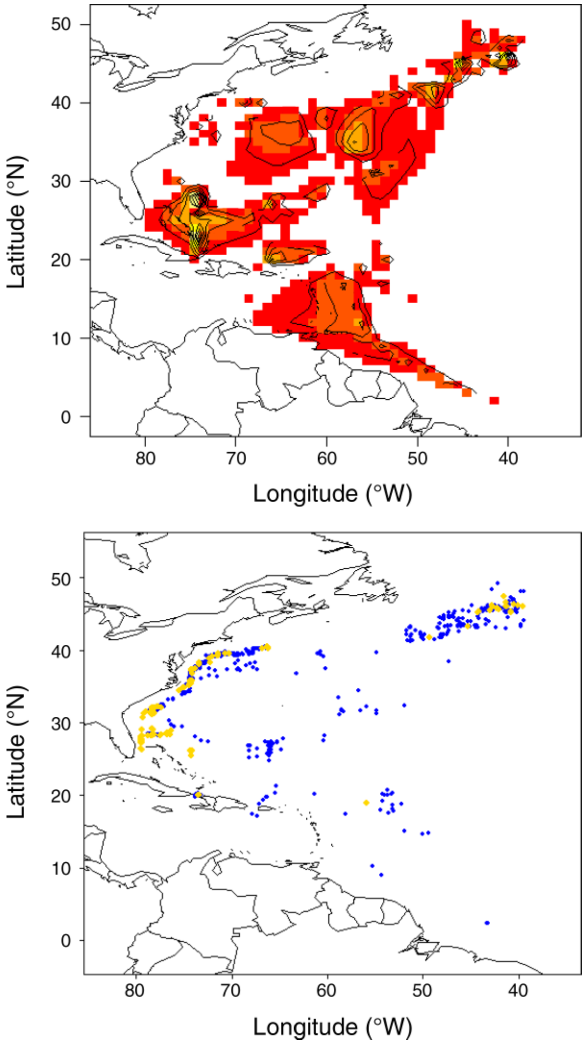

FIG. 7. (Top) Interpolated map and (bottom) Moran scatterplot map of species per unit effort (SPUE) for the Atlantic Ocean. In the interpolated map, the lighter areas have higher SPUE values, whereas the darker areas have lower SPUE values. Yellow points in the scatterplot correspond to observed fishing sets that had above-average values for bycatch per unit effort and whose nearest neighbors also had above-average values (i.e., putative bycatch hotspots).

Moran's *I* analysis for SPUE relative to CPUE indicates clustering in the Pacific, but not the Atlantic. This suggests that areas of high bycatch relative to low target catch cluster in the Pacific Ocean, but not in the Atlantic.

DISCUSSION

The objective of this study was twofold: to explore spatial patterning of bycatch in two major ocean basins and to detail an approach to analyzing spatially explicit bycatch data. To illustrate this, we went through a four-step process that addressed increasingly integrated questions at each level of analysis. In step 1, we tested whether single-species bycatch events were clustered in space with respect to all fishing sets. This required a bivariate analysis that is distinct from the univariate analyses often used in point pattern analysis of ecological data. The distribution of fishing sets in each ocean basin is, in itself, nonrandom, and a univariate analysis (such as a Ripley's *K* function) would be inappropriate because it cannot tease apart the patterns in the distribution of fishing sets from that of the bycatch. A second pitfall that we avoided was the indiscriminate use of Ripley's *K*, because of its tendency to confound effects at larger distances with those at shorter distances (Wiegand and Maloney 2004, Perry et al. 2006). We used the O-ring statistic because it

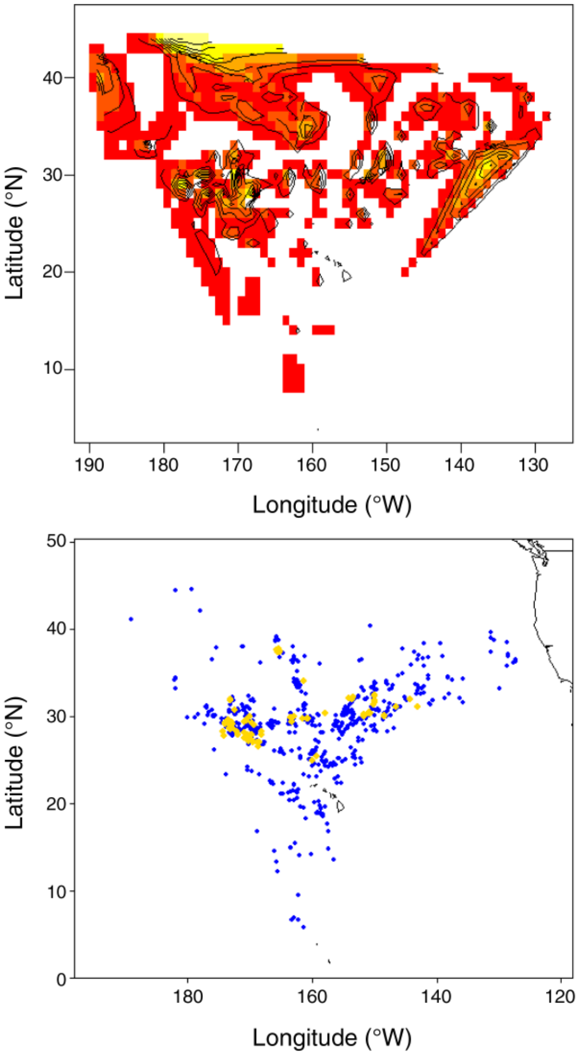

FIG. 8. (Top) Interpolated map and (bottom) Moran scatterplot map of species per unit effort (SPUE) for the Pacific Ocean. In the interpolated map, the lighter areas have higher SPUE values, whereas the darker areas have lower SPUE values. See Fig. 7 for interpretation of the Moran scatterplot map.

calculates correlation based on limited range of distance classes.

Employing these precautionary measures, we found clear evidence of spatial patterns, although the strength and nature of the patterns varied among species. All four of the species examined in the Pacific (Laysan Albatross, Black-footed Albatross, leatherback turtles, and loggerhead turtles) showed strong clustering of bycatch events at scales of 1°–10°. In the Atlantic, sea turtle bycatch displayed strong clustering of bycatch events, whereas pilot whales showed dispersion of bycatch events and Risso's dolphins showed no patterns at most distance lags. The two sea turtles, found in both ocean basins, displayed similar patterns in each basin.

While important, the results of step 1 are not very surprising; researchers who work on bycatch have long known that it is not likely to be a random event. Because the underlying but unknown distribution of bycatch species may be clustered in time and space, step 2 refined this perspective by considering whether high bycatch locations cluster together. Addressing this question required a different statistical approach, one that could accommodate quantitative input variables (e.g., BPUE), such as Moran's *I* and Moran scatterplot maps. The clustering of high bycatch rates is different from the clustering of bycatch events because it points to areas of special concern, areas not only where any bycatch occurs but where high bycatch rates are likely among neighboring bycatch locations. This stepwise approach demonstrates that clustering in bycatch locations does not equate to clustering in bycatch rates. Consider two examples from our study: Risso's dolphin bycatch locations were not clustered, but high bycatch locations were. Conversely, leatherback bycatch events in the Pacific Ocean were clustered, but bycatch rates were not. Bycatch rates for all of the other species did display positive spatial correlation, suggesting that certain regions of the ocean are especially prone to above-average bycatch.

Because multispecies bycatch patterns have rarely been considered, step 3 represents an important extension of the approaches described in steps 1 and 2. Identifying multispecies bycatch areas is a key component to maximizing the efficiency of management strategies while avoiding the promotion of solutions for one bycatch species that imperils another bycatch-impacted species. If bycatch of the different taxa were clustered in space, managers would likely adopt a different mitigation strategy (e.g., a time/area closure) than if bycatch of the different species were dispersed (e.g., gear modification). In our study there was overlap across species, and specific areas of multispecies bycatch were identified in each ocean basin.

For steps 3 and 4 we considered variables that looked at bycatch occurrences across species and taxa weighting the bycatch occurrence for all species equally. Another approach would be to weight bycatch rates by the conservation status of impacted species to focus management actions and strategies on species of greatest conservation concern. A comparison of the interpolated maps and the Moran's *I* scatterplot maps identified congruent areas of multispecies bycatch. However, the Moran scatterplot maps were more likely to detect high-bycatch locations when fishing effort was unevenly distributed (e.g., along the eastern seaboard), while the interpolated maps were more likely to detect high bycatch locations in areas of low fishing effort (e.g., the eastern part of the Lesser Antilles).

In the final step, we incorporated a measure of target catch into our analyses of spatial patterning. Given the importance of fisheries to local and national economies, effective bycatch reduction efforts should minimize negative effects on catch of the target species (Hall 1996). Analyses of the ratio of bycatch species to target catch suggested that, in the Pacific Ocean, there are areas of high bycatch and low target catch, i.e., areas where fishers capture relatively few tuna and swordfish per set, but multiple species of sea turtles, seabirds, and/or marine mammals. While no relationship between the number of bycatch species and the number of target catch individuals emerged in the Atlantic, the pattern may be strengthened if data on target mass, a better proxy for yields and profits, were available rather than number of target individuals. Areas of high bycatch and low target catch point to inefficiencies in the distribution of fishing effort. A preliminary evaluation in the Pacific suggests that if these bycatch areas are temporally persistent, minor spatial restrictions of overall fishing effort (~5–10%) could lead to relatively large reductions in bycatch abundances (~30–40%). From a management perspective, this suggests that spatial closures may be effective for some ocean regions but also points to areas where multispecies bycatch and target catch are not tightly correlated. Although previous research has explored the effects of reductions in fishing effort (Goodyear 1999), the spatial contiguity of these areas was not explored. By identifying underlying spatial patterns, the approach presented here can incorporate both contiguity and fishing efficiency, highlighting areas where it is both biologically and economically reasonable to apply management efforts.

A logical follow-up to the analyses we present here would be to use reserve design tools for incorporating the spatial distribution of bycatch species into time–area closure design. For example, C. D'Agrosa and colleagues (C. D'Agrosa, A. J. Read, P. N. Halpin, and M. A. Hall, *unpublished manuscript*) used a spatial optimization approach to determine how much target catch would be reduced for a given level of bycatch reduction. They found that contiguous time–area closures can reduce bycatch of leatherbacks and blue sharks considerably without much of an effect on target catch.

Our analyses focus on a ubiquitous resource use question: What is the current overlap of resource users (fisheries) and a protected resource (bycatch species)? This question does not, however, address the fundamental question of where critical habitat for bycatch species occurs. Bycatch hotspots have probably changed over time as fisheries have shifted target species and target catch has changed. Additionally, fisheries sample bycatch species only where fisheries operate, which represent a non-random sample of the oceans. As such, estimating the distribution of bycatch and current locations of bycatch hotspots does not necessarily represent pre-exploitation distributions nor does it address habitat suitability.

We believe that the approach described in this study represents a useful starting point for researchers interested in exploring spatial patterns in fisheries bycatch. Whether this approach could be used as a real-time mitigation tool would depend on the presence of adequate on-board observer coverage (Gilman et al. 2006). At present, the fisheries analyzed in this paper have observers on ~5% of fishing trips, as compared with the 100% observer coverage reported for those fisheries that use a fleet communication system to avoid bycatch hotspots. Even then, the data that accrue over a few days or weeks of fishing may be insufficient for these types of data-intensive analyses. Our analytical approach should be considered as one component of a larger framework for analyzing fisheries bycatch in space and time. That framework could include existing fleet communication systems for dealing with and reacting to short-term bycatch hotspots, exploratory spatial analysis of long-term data as demonstrated in this paper, and, ultimately, predictive models that forecast bycatch hotspots using oceanographic data.

A major assumption for all pattern analyses is that the patterns under consideration are stationary, in other words, the processes driving the observed patterns are constant across space and time. In order to minimize the effects of spatial non-stationarity we focused our analyses on relatively small spatial neighborhoods (100–1000 km) and used robust statistical methods. Testing for and dealing with temporal stationarity was beyond the scope of this paper, though we were able to rule out the existence of major temporal trends in the data by subdividing the Atlantic and Pacific data sets into two equal-length periods. Spatial patterns in these subsets were similar to the data set as whole. Nevertheless, if a goal is to apply these results to the future, the assumption of temporal stationarity should be tested explicitly to ascertain whether spatial patterns in bycatch change over time. Finally, an important challenge involves not just testing the aforementioned assumptions and documenting spatiotemporal patterns in bycatch, but also correlating bycatch rates with oceanographic variables such as sea surface temperature, productivity, depth, etc. It is likely that these factors drive the distribution of bycatch species and/or their prey and could be used to forecast areas of likely fisheries–bycatch interactions.

Prioritizing effort, maximizing efficiency, and minimizing costs are mantras in both conservation and fisheries management. Identifying the underlying spatial patterns of fisheries bycatch is a promising way of determining areas of overlap among species of conservation concern and fisheries, a critical step towards developing more efficient conservation strategies designed to protect species diversity. Towards this end, we have presented an approach for the analysis of spatial patterns of bycatch, using data from the U.S. Atlantic and Pacific longline fisheries. Our analyses focused attention on spatial patterning in bycatch events and bycatch rates for individual species of conservation concern, as well as all non-fish bycatch species. Additionally, we linked spatial patterns in bycatch with fishing production and identified areas of low fishing efficiency (i.e., zones in which the ratio of catch per unit effort of the fisheries target is low relative to bycatch per unit effort). By contributing to a more synoptic view of the bycatch seascape, our results illustrate the value of spatial pattern analysis. This approach represents a key component of a larger framework intended to provide a full description of the spatiotemporal distribution of bycatch and the processes that underlie fisheries–bycatch interactions.

Acknowledgments

Many thanks to C. Cot, D. Dunn, J. Moore, C. Safina, M. Sims, and K. Stewart for helpful comments on the manuscript, S. J. Rey for statistical guidance, and A. D. Syphard for GIS advice. This research was supported by a grant from the Gordon and Betty Moore Foundation to Project GloBAL. J. Franklin's participation was supported by a grant from the National Science Foundation (NSF BCS-0452389).

Literature Cited

Anselin, L. 1995. Local indicators of spatial autocorrelation—LISA. Geographical Analysis 27:93–115.

Bailey, T. C., and A. C. Gatrell. 1995. Interactive spatial data analysis. Longman, Harlow, UK.

Baum, J. K., R. A. Myers, D. G. Kehler, B. Worm, S. J. Harley, and P. A. Doherty. 2003. Collapse and conservation of sharks populations in the Northwest Atlantic. Science 299: 389–392.

Bivand, R. 2002. Spatial econometrics functions in R: classes and methods. Journal of Geographical Systems 4:405–421.

Condit, R., et al. 2000. Spatial patterns in the distribution of tropical tree species. Science 288:1414–1418.

Crowder, L. B. 2000. Leatherback's survival will depend on an international effort. Nature 405:881–881.

Crowder, L. B., and S. A. Murawski. 1998. Fisheries bycatch: implications for management. Fisheries 23:8–17.

Fortin, M.-J., and M. R. T. Dale. 2005. Spatial analysis: a guide for ecologists. Cambridge University Press, Cambridge, UK.

Galiano, E. F. 1982. Pattern detection in plant populations through the analysis of plant-to-all-plant distances. Vegetatio 49:39–43.

Gardner, B., P. J. Sullivan, S. J. Morreale, and S. P. Epperly. 2008. Spatial and temporal statistical analysis of bycatch data: patterns of sea turtle bycatch in the North Atlantic. Canadian Journal of Fisheries and Aquatic Sciences 65:2461–2470.

Gilman, E. L., P. Dalzell, and S. Martin. 2006. Fleet communication to abate fisheries bycatch. Marine Policy 30:360–366.

Goodyear, C. P. 1999. An analysis of the possible utility of time–area closures to minimize billfish bycatch by US pelagic longlines. Fisheries Bulletin 97:243–255.

Hall, M. A. 1996. On bycatches. Reviews in Fish Biology and Fisheries 6:319–352.

Hall, S. J., and B. M. Mainprize. 2005. Managing by-catch and discards: How much progress are we making and how can we do better? Fish and Fisheries 6:134–155.

Heppell, S. S., H. Caswell, and L. B. Crowder. 2000. Life histories and elasticity patterns: perturbation analysis for species with minimal demographic data. Ecology 81:654–665.

Jaramillo-Legorreta, J., L. Rojas-Bracho, R. L. Brownell, Jr., A. J. Read, R. R. Reeves, K. Ralls, and B. L. Taylor. 2007. Saving the vaquita: immediate action, not more data. Conservation Biology 21:1653–1655.

Kareiva, P., and M. Marvier. 2003. Conserving biodiversity coldspots—recent calls to direct conservation funding to the world's biodiversity hotspots may be bad investment advise. American Scientist 91:344–351.

Kelleher, K. 2005. Discards in the world's marine fisheries: an update. Food and Agricultural Organization of the United Nations, Rome, Italy.

Lewison, R. L., and L. B. Crowder. 2007. Putting longline bycatch of sea turtles into perspective. Conservation Biology 21:79–86.

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

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

Loosmore, N. B., and E. D. Ford. 2006. Statistical inference using the *G* or *K* point pattern spatial statistics. Ecology 87: 1925–1931.

Moran, P. A. P. 1948. The interpretation of statistical maps. Journal of the Royal Statistical Society B 10:243–251.

Nelson, T. A., and B. Boots. 2008. Detecting spatial hot spots in landscape ecology. Ecography 31:556–566.

Nelson, T., B. Boots, and M. Wulder. 2006. Large-area mountain pine beetle infestations: spatial data representation and accuracy. Forestry Chronicle 82:243–252.

NMFS [National Marine Fisheries Service]. 2001. Endangered Species Act—Section Consultation, Biological Opinion: Reinitiation of consultation on the Atlantic highly migratory species fishery management plan and its associated fisheries. National Marine Fisheries Service, Silver Spring, Maryland, USA.

NMFS [National Marine Fisheries Service]. 2004. Biological opinion on the authorization of pelagic fisheries under the fisheries management plan for the pelagic. National Marine Fisheries Service, Silver Spring, Maryland, USA.

Perry, G. L. W., B. P. Miller, and N. J. Enright. 2006. A comparison of methods for the statistical analysis of spatial point patterns in plant ecology. Plant Ecology 187:59–82.

R Development Core Team. 2008. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ⟨http:/www.r-project.org⟩

Sims, M., T. Cox, and R. Lewison. 2008. Identifying spatial patterns in fisheries bycatch: using models to improve the stability of bycatch estimates and aid fisheries management. Ecological Applications 18:649–661.

Tomillo, P. S., E. Velez, R. D. Reina, P. Rotney, F. V. Paladino, and J. R. Spotila. 2007. Reassessment of the leatherback turtle (*Dermochelys coriacea*) nesting population at Parque Nacional Marino Las Baulas, Costa Rica: effects of conservation efforts. Chelonian Conservation and Biology 6:54–62.

Wiegand, T., and K. A. Moloney. 2004. Rings, circles, and null models for point pattern analysis in ecology. Oikos 104:209–229.

APPENDIX A

Description of the bycatch, target catch, and fishing effort (*Ecological Archives* A019-038-A1).

APPENDIX B

The O-ring statistic, $g12(r)$, vs. time, Moran scatterplots, and Moran scatterplot maps (*Ecological Archives* A019-038-A2).