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Aerial surveys and distribution models enable monitoring of fishing in Marine Protected Areas

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A B S T R A C T

Marine Protected Areas are rapidly becoming a central method for conservation of aquatic resources, but quantifying the success of these reserves in restricting fishing remains a challenge. Monitoring fishing has long been difficult - there are many types of fishers accessing resources in remote places from a diverse set of platforms (e.g., boat types). We used aerial surveys in conjunction with a novel application of species distribution modeling to develop a method for monitoring the change in fisher distributions following the implementation of MPAs. Aerial survey transects were conducted for 3.5 years before and after the implementation of 25 MPAs along the mainland southern California coast in 2012 and resulted in 13,558 vessel observations representing 19 different boat types. We compared actively fishing commercial and recreational vessels with non-fishing vessels to evaluate the use of MPA areas. There was a statistically significant decrease in proportion of vessels observed within MPAs from 17.5% before to 11.4% after MPA implementation, with MPA-implementation, fishing type, and the interaction all predicting the probability of a vessel being observed within MPA boundaries. Distribution models showed both an overall shift in distributions across all boat types and a decrease in predicted probability of habitat suitability of fishing within MPA boundaries after MPA implementation, although results differed among boat types. We illustrate the utility of distribution modeling for evaluating spatial patterns in human activities, providing a powerful tool for conservation biologists and demonstrate the importance of monitoring programs for establishing both baseline and response data needed for adaptive management of marine ecosystems.

1. Introduction

As overfishing continues to increase globally (Pauly et al., 2003), Marine Protected Areas (MPAs) are becoming a widely popular management strategy for protecting critical ecosystems (Edgar et al., 2014, 2007). By restricting harvest of marine resources, MPAs provide a crucial refuge for species and improve overall ecosystem health. Within MPAs, individuals grow larger, population sizes are larger (Lester et al., 2009), and spillover even improves ecosystems outside of MPA boundaries (Gell and Roberts, 2003). Yet, MPAs remain a challenge to study, monitor, and enforce (Agardy et al., 2011), and they frequently fail to fully limit illegal harvesting (Babcock et al., 2010; Edgar, 2011; Mora et al., 2006). They sometimes cover large areas on the open ocean, there is often a lack of baseline data, and traditional reporting structures exist at a different spatial scale than most MPAs. Further the socio-economic impacts of MPAs are difficult to predict (Gell and Roberts, 2003; Hilborn et al., 2006), an important consideration given the high cost of MPAs (Balmford et al., 2004). Novel methods are needed to adequately measure the successes and failures of MPAs for adaptive management. In this study, we use a unique approach integrating baseline research, aerial survey monitoring, and distribution modeling to evaluate shifts in the distribution of fishers following MPA implementation.

Understanding the success of any management approach requires the collection of baseline data prior to implementation, and this is especially true for studying the impacts of MPAs (Edgar et al., 2004). Marine productivity is highly variable and if there is bias as to where MPAs are placed, then outcomes may vary. For instance, MPAs placed in low productivity areas may have little effect on the distribution of fishers, limiting the impact of those MPAs (Edgar et al., 2004). In such cases, baseline data is essential to be able to successfully document these patterns. Further, as ecosystems change over time, it is crucial to continuously monitor MPAs for effectiveness of adaptive management practices (Pomeroy et al., 2005). Thus, to adequately quantify the

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impact of MPAs, it is essential that long-term baseline data are collected.

Aerial surveys provide one approach to overcome the challenges associated with studying management impacts over broad spatial scales and are particularly suited for the study of MPAs where access is limited. This method has long been used in conservation biology to estimate the abundance and distributions of wildlife (Pollock et al., 2006). Here we apply these survey techniques to studying human-related activities in critical ecological habitat. With aerial surveys, we can collect data across large areas in a short amount of time. Further this method has the benefit of providing data on all potential sources of fishing from boats and does not rely on fisher reported data. Although newer technologies, such as vessel monitoring systems, can provide detailed spatially-explicit fishing activities (Gerritsen and Lordan, 2011), implementation of these systems across all potential types of fishing and non-fishing vessels would be cost prohibitive. While aerial surveys can be expensive as well, volunteer supported flight operations can considerably lower the cost of these surveys. LightHawk, a nonprofit organization based in Telluride Colorado, U.S.A., coordinates flights between pilots and scientists. Such organizations represent a new dimension of citizen science, opening new possibilities for research.

Species Distribution Modeling (SDM) (also referred to as Ecological Niche Modeling) is becoming an increasingly popular tool in ecology and conservation (Rodríguez et al., 2007) to study the distribution of organisms. Using spatial locality information for a species in combination with large-scale or global environmental data layers, SDMs can be used to predict a map of the distribution of a species based on underlying environmental variation (Elith and Leathwick, 2009). There many applications of SDMs in conservation biology, such as to identify potential habitat for endangered species reintroductions (Carroll et al., 2003), to estimate changes in species distributions under global climate change (Peterson et al., 2002), or to explore the potential spread of invasive species (Yap et al., 2015; Katz and Zellmer, 2018). SDMs have been used to study the distributions of a broad diversity of organisms, from terrestrial animals (Bryson et al., 2016; Pelletier et al., 2014), birds (McCormack et al., 2010), marine fish and invertebrates (Cheung et al., 2009), plants (Zellmer et al., 2012) and even pathogens (Yap et al., 2015), but have rarely been used to study the distributions of human-related activities. When interacting with the environment, such as through hunting and fishing, humans may likewise have predictable patterns that reflect the underlying environmental conditions that structure the species they utilize. In fact, SDMs have been successfully used to predict the distribution of species based on the environmental conditions of their food resources (Freeman and Mason, 2015). Thus, SDMs may be a useful tool for studying the distribution of human-related activities.

SDMs, and especially those that use a machine learning approach, take advantage of the power within large datasets to let the data determine the model (or set of environmental variables) that best describes the distribution of a species (Olden et al., 2008). This approach is particularly useful when there are a lot of potential contributing variables making it difficult to pre-designate models (Olden et al., 2008). The spatial distribution of fishers is a complex problem with many potential variables contributing (Jalali et al., 2015), thus is well suited for a machine learning SDM approach. Being able to investigate many different predictors allows us to go beyond just understanding how current MPAs structure fisher distributions, and instead determine importance of environmental predictors of where fishing is likely to occur, helping with better design of MPAs in the future.

By design, MPAs should have a significant impact on the distribution of fishers, but what specific impact they have is less clear. By limiting fishing and harvest within specific areas of conservation priority, the implementation of MPAs may result in spreading out the impacts of fishing across the entire region. Alternatively, MPAs may cause compaction in unprotected areas, which may be a significant deterrent to overall conservation of the region (Lester et al., 2009). Others have suggested that no-take MPAs will result in "fishing the line," with fishers locating right outside the boundaries of MPAs to catch spillover (Kellner et al., 2007). These various distributions have different consequences for fish and invertebrate densities across space, and therefore it is important that we understand how MPAs impact fisher distributions (Kellner et al., 2007).

Our goals were thus to 1) determine whether fishers were adhering to MPA boundaries and if there were any differences among fishing or boat types, 2) test whether MPAs impact the distribution of fishers, including their overall distributions and distance from port, and if there were any differences among fishing or boat types and 3) evaluate the potential use of SDMs to investigate the factors impacting the distribution of humans and human-related activities. If MPAs impact the distribution of fishers, then we expect 1) the proportion of actively-fishing boats observed within MPAs will decrease after MPA implementation, 2) there will be decreased overlap between SDMs pre- and post-MPA implementation, and 3) boats will be located either closer or further from port. As a control, we compare vessels on which there was active fishing occurring to non-fishing vessels (vessels that are not used for fishing and were not actively engaging in fishing), which should show no differences before and after MPA implementation, since they should not be directly affected by MPAs.

2. Methods

2.1. Study site

The Southern California Bight (SCB) has had a long history of fishing management, as it is a highly productive marine ecosystem (Horn et al., 2006; Horn and Allen, 1978; Hubbs, 1960; Pondella et al., 2005) located next to one of the largest cities on the west coast of the United States with extensive commercial and recreational fishing (Zellmer et al., 2018). A total of 50 MPAs (known as the South Coast MPAs) have been established in southern California in two efforts, the northern Channel Islands in 2002 and the mainland coast in 2012. Currently there are 25 MPAs on the islands including the southern Channel Islands (established in 2012 as part of the mainland effort) and 25 along the mainland coast. The established MPAs set aside habitat with little to no fishing or marine extraction.

2.2. Aerial surveys

We conducted aerial surveys to collect spatially explicit data regarding the distribution, type and activity of vessels operating in state waters following the implementation of MPAs in the south coast region. These surveys were conducted via two transects along the southern California coast starting in September of 2008 encompassing 2565 km^2, approximately 3.25 years prior to the implementation of MPAs, and continued through September of 2015. During 2008–2013, aerial surveys were flown monthly, and then in 2014 the surveys occurred quarterly. The northern transect ran from Santa Monica Bay north to Point Conception, while the southern transect ran from Santa Monica Bay south to the Mexican border. The aerial surveys covered 19 MPAs along the mainland southern California coast.

Small aircraft capable of high maneuverability and low speeds were used to fly directly over vessels while survey personnel searched for, identified, and recorded data on all vessels spotted within approximately 4.82 km (3 miles) of the shoreline along each transect. The collection of data from small fixed-wing aircraft allow for a transect to be completed in approximately two to two and one half hours depending on number of vessels encountered and other factors e.g., weather, airspace restrictions. Depending on weather conditions, aircraft were flown at an altitude of 152–254 m (500′ to 1000’) and travel at 185–222 km/h (100–120 knots). Volunteer pilots, coordinated by LightHawk, flew the aircraft for each of the surveys.

The survey team consisted of a pilot, spotter, GPS technician and photographer. Some of the planes are incapable of carrying a pilot plus three passengers; in this circumstance, the spotter adopted the photographer role. The spotter directed the pilots' flight path to intersect the vessels on the water, described the type and activity of the vessel at time of contact and directed the GPS technician to enter a point and corresponding information into the computer. When possible, the photographer captured a photograph of the vessel(s) to aid in post flight QA/QC (Quality Assurance Quality Control). The spotter, aided by binoculars or telephoto camera lens, was trained in and familiar with the various boat types and activities in which boaters engage in the south coast region to assure accurate classifications.

The GPS technician recorded the vessel data into a GPS data dictionary along with the date, time, GPS location, and any relevant notes. For each vessel, researchers classified the fishing type (commercial, recreational, or commercial non-fishing; Table S1), identified the boat type (e.g., Sport Fishing Boat; Table S2), and recorded the activity occurring on the boat (e.g., fishing, anchored, in transit). Ideally, vessel positions were not logged until survey planes were directly overhead for highest spatial accuracy. In areas with high vessel density or restricted airspace, where logging vessels individually was infeasible, multiple boats were logged to a single representative point and later extracted using GIS.

2.3. Analyses

To evaluate the impact of MPAs on the distribution of fishing vessels, we 1) evaluated the probability of observations occurring inside or outside MPA boundaries, 2) created distribution models to visualize fishing vessel distributions across the bight, and 3) evaluated the change in distance to nearest port for each observation. We limited our analyses to only boat types that had a least 10 observations both before and after MPA-implementation that were actively fishing (for Commercial and Recreational boats) or not actively fishing (for Non-Fishing boats). The distributions of Non-Fishing boats were used as a control, since the distributions of these vessels should be less impacted by the presence of MPAs. Statistical analyses were completed in R v 3.0.1 (R Development Core Team, 2013).

2.3.1. Summary statistics

We calculated summary statistics for all vessels observed, for both fishing type (Commercial, Recreational, and Non-Fishing Vessels; Table S3) and boat type (Table S4) before and after the implementation of MPAs. The total number of observations for vessels that were actively fishing were also calculated. The proportion of vessels observed within each MPA was determined by taking the number of vessels observed in the MPA divided by the total number of vessels observed for each boat type to account for variation in sampling effort between time periods.

2.3.2. Observations in MPAs

To evaluate the success of MPAs in limiting fishing within their boundaries, we used logistic regression to test whether there was a statistically significant effect of MPA-implementation on the probability of a boat being observed within MPA boundaries. In addition, we tested whether this probability differed between different fishing types and whether there was an interaction between MPA-implementation and fishing type.

2.3.3. Distribution modeling

For a more comprehensive analysis of the impact of MPAs on the distribution of fishers within southern California, we used the locations recorded in the aerial survey data to create distribution models (SDMs) of fishers before and after the implementation of MPAs. SDMs are typically used to construct a map of the variation in predicted probability of habitat suitability for a species based on the observed locations of that species in conjunction with a set of spatially-explicit environmental data layers. This method proceeds by evaluating the environmental conditions at each of the observed locations, building a statistical model to describe the set of environmental conditions that best suit the species, and then extrapolating that model over all regions in the map. We applied this method to each boat type that had at least 10 observations both before and after MPA-implementation that were within the extent of the environmental data. Observations with coordinates outside the extent of the environmental layers were dropped from SDM analyses.

We created all SDMs using MaxEnt v. 3.3 (Phillips et al., 2006) using 19 spatial environmental data layers describing the region, including: bathymetry, 17 biogeophysical variables from the MARSPEC dataset (Sbrocco and Barber, 2013), and presence of MPAs. All variables were treated as continuous variables except for the presence of MPAs, which was categorical. SDMs were trained with a random 80% of the observation data and tested with the remaining 20% of the data. The SDMs were evaluated using the AUC scores, with successful SDMs having scores closer to 1. To quantify whether MPA presence was associated with fisher distributions both before and after MPA implementation, we quantified the proportion of variance explained by each variable to see if the proportion increased following MPA implementation.

We evaluated the change pre- and post- MPA both visually and quantitatively. To visualize the change, we created a new raster layer to describe the change in predicted probability of habitat suitability before and after MPA-implementation by subtracting the pre-SDM from the post-SDM. Values less than zero represent pixels where the predicted habitat suitability decreased after MPA-implementation, while values greater than zero represent pixels where the predicted habitat suitability increased. To quantify whether there was a statistically significant change in the distribution of fishers before and after MPA implementation, we calculated Schoener's *D* values using the ENMeval R package (Muscarella et al., 2014).

To evaluate whether there was an overall shift in fisher distributions or if there were differences between fishing vessel types (e.g., Commercial, Recreational, Non-Fishing vessels) we created summary datasets of 1) all actively fishing vessels, 2) all actively fishing Commercial vessels, 3) all actively fishing Recreational vessels, and 4) all Non-Fishing vessels. The summary SDMs were created by adding together the individual SDMs for each boat type within the fishing category and then dividing by the total number of SDMs added together.

2.3.4. Distance to nearest port

To evaluate whether MPA implementation increased the distance that fishing vessels need to travel, we calculated the distance to the nearest port for each observation. Distances were calculated to a central location at the mouth of each major port along the mainland coast of California using the sp Package in R (Pebesma and Bivand, 2005). Distance to nearest port was then $\log_{10}$ transformed. The data were visually evaluated for equal variances. We used ANOVA to evaluate the significance of MPA implementation, fishing type, and the interaction between MPA implementation and fishing type on the variation in distance to nearest port. We also assessed the statistical significance of MPA implementation on distance to nearest port for each boat type. As variances could not be assumed to be equal between boat types, we conducted Welch's one-way analysis of means for each boat type. We used a sequential Bonferroni adjustment to correct significance values for multiple tests (Rice, 1989).

3. Results

3.1. Summary statistics

There were a total of 13,558 vessel observations over 102 observation days between September 1, 2008 and September 22, 2015 (Tables S1–S2; Fig. S1). Of those observations, 1944 actively fishing Commercial and Recreational vessels and Non-Fishing vessels were observed before the implementation of MPAs on January 1, 2012 and

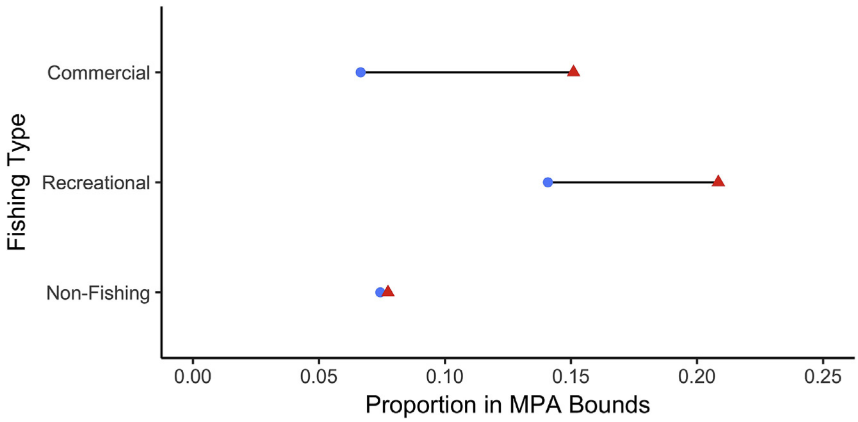

Fig. 1. Proportion of Boats Observed in MPA boundaries before and after MPA-implementation by Fishing Type. Proportion of boats observed inside MPA boundaries before (red triangles) and after (blue circles) MPA-implementation. Only boats types with at least 10 observations before and after MPA implementation were included. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

2838 vessels after implementation for which we had at least 10 observations per boat type for each time period (Tables S3–S4).

3.2. Observations in MPAs

Prior to MPA implementation 17.5% of observations were within the boundaries of MPAs, whereas after MPA implementation 11.4% of observations were within the boundaries of MPAs (Figs. S2–S4). The logistic model indicated that MPA-implementation, fishing type, and the interaction between MPA-implementation and fishing type were all statistically significant predictors of the probability of a vessel being observed within the boundaries of an MPA (Figs. 1–2; Table 1). The proportion of observations within MPA boundaries decreased for both Commercial and Recreational vessels, but remained constant for Non-Fishing vessels (Fig. 1). After MPA-implementation, the proportion of actively fishing Commercial vessels inside MPAs decreased to the proportion of Non-Fishing vessels inside MPAs, while the proportion of actively fishing Recreational vessels inside MPAs decreased but not as low as the Non-Fishing vessels (Fig. 1).

Table 1

Logistic model of the probability of observations occurring inside versus outside MPAs. The logistic model included MPA-implementation, fishing type (Commercial, Recreation, Commercial Non-fishing) and the interaction between MPA-implementation and fishing type.

Variable	Df	Deviance	Resid. Df	Resid. Dev	P-value
MPA	1	36.03	4780	3817	1.945e-09
Fishing Type	2	66.24	4778	3751	4.141e-15
MPA*Fishing Type	2	6.53	4776	3744	0.03829

3.3. Distribution models

The distribution models generally had high AUC scores, with all test scores above 0.93 and all but two (out of 28) training scores above 0.87 (Table S5). Across the entire study area, there were shifts in the distributions of fishers pre- and post-MPA implementation for all fishing and boat types (Table 2, Supplementary Figs. 5–22). Within MPAs specifically, the average change in predicted probability of habitat suitability following the implementation of MPAs for all actively fishing boat types was −0.03, from an average predicted probability of habitat

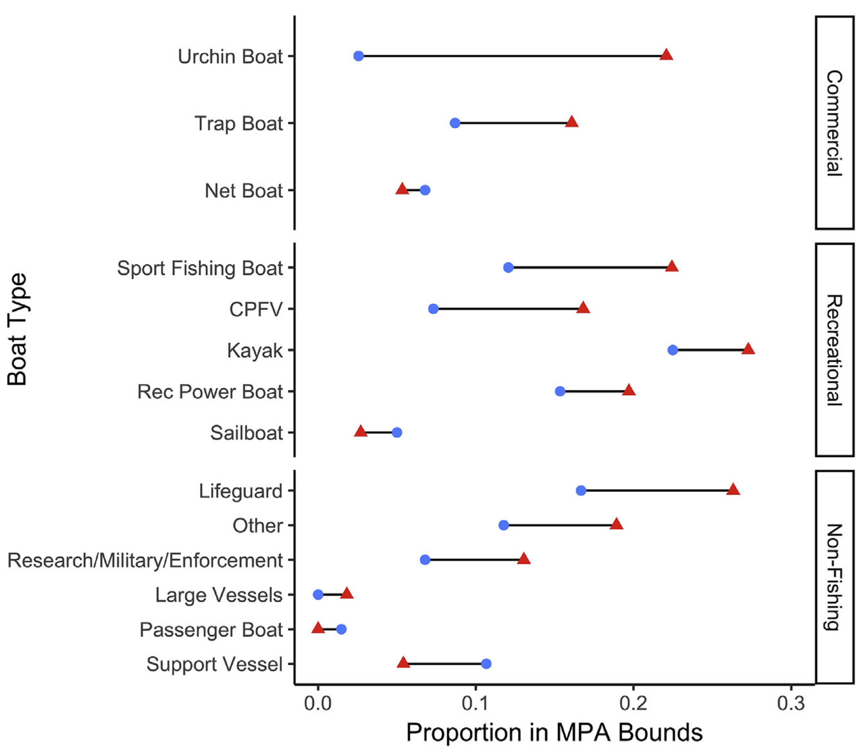

Fig. 2. Proportion of Boats Observed in MPA boundaries before and after MPA-implementation by Boat Type. Proportion of boats observed inside MPA boundaries before (red triangles) and after (blue circles) MPA-implementation. Only boats types with at least 10 observations before and after MPA implementation were included. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Schoener's *D* comparison of overlap in SDMs pre- and post-MPA implementation. No overlap ($D = 0$), complete overlap ($D = 1$). Results are shown for individual boat types and for summarized across fishing types including all commercial, all recreational, all actively fishing boats (Commercial & Recreational), and all commercial non-fishing boats.

Fishing Type	Boat Type	D
Commercial	Net Boat	0.76
	Trap Boat	0.76
	Urchin Boat	0.75
Recreational	CPFV	0.75
	Kayak	0.72
	Rec Power Boat	0.85
	Sailboat	0.67
	Sport Fishing Boat	0.84
Non-fishing	Large Vessels	0.62
	Lifeguard	0.64
	Other	0.69
	Passenger Boat	0.52
	Research-Military-Enforcement	0.68
	Support Vessel	0.70
All Commercial		0.82
All Recreational		0.87
All Non-fishing		0.84
All Fishing		0.87

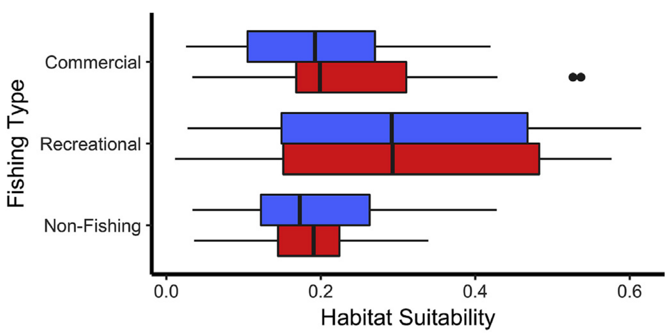

Fig. 3. Predicted probability of habitat suitability inside MPA boundaries before and after MPA-implementation based on Fishing Type. Average predicted probability of habitat suitability was calculated for each MPA by taking the average predicted probability of habitat suitability for all pixels within the boundary of the MPA for each boat type. Pre-MPA (red) and post-MPA (blue) averages are shown. Statistical analyses were not completed due to non-independence. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

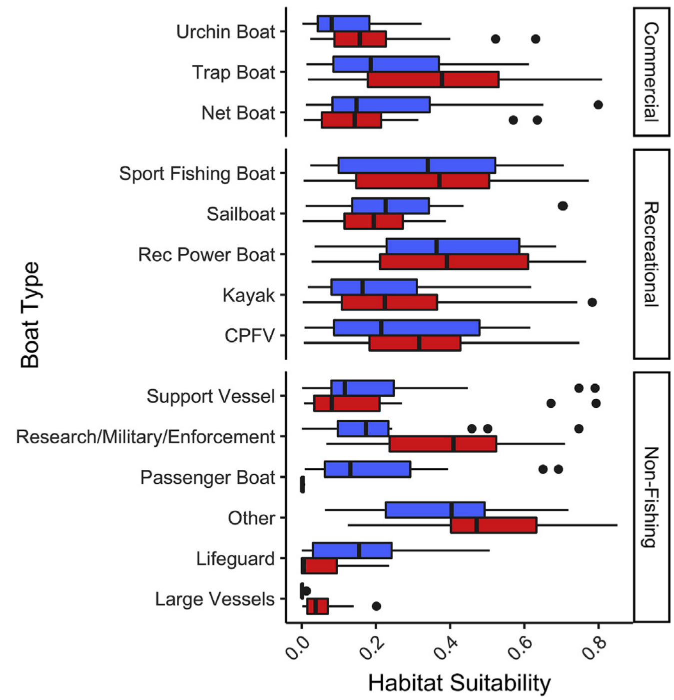

Fig. 4. Average predicted probability of habitat suitability inside MPA boundaries before and after MPA-implementation based on Boat Type. Average predicted probability of habitat suitability was calculated for each MPA by taking the average predicted probability of habitat suitability for all pixels within the boundary of the MPA for each boat type. Pre-MPA (red) and post-MPA (blue) averages are shown. Statistical analyses were not completed due to non-independence. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Results from ANOVA to test whether distance to nearest port is predicted by MPA implementation (MPA) or Fishing type. Distance to port was log 10 transformed.

Variable	Df	Sum Sq	Mean Sq	F-value	P-value
MPA	1	0.1605	0.1605	1.299	0.2545
Fishing Type	2	3.29	1.645	13.31	1.718e-06
MPA*Fishing Type	2	0.2468	0.1234	0.9983	0.3686
Residuals	4776	590.3	0.1236		

suitability of 0.29 before MPA-implementation to 0.26 after (Fig. 3,S19). This change was mostly led by decreases in predicted habitat suitability in MPAs for commercial fishers (−0.05; Fig. 3,S20) more so than recreational fishers (−0.01; Fig. 3,S21). In comparison, for non-fishing boats, the average change in predicted probability of habitat suitability inside MPAs following the implementation of MPAs was 0, from an average predicted probability of habitat suitability of 0.19 before MPA-implementation to 0.19 after (Fig. 3,S22). Different boat types showed varying changes in mean predicted probability of habitat suitability inside MPAs (Fig. 4, S5-S18).

3.4. Distance to nearest port

There was little change in the average distance to port for either commercial or recreational fishers as well as non-fishing boats (Fig. S23). Commercial fishers were on average further from port (10.8 km) than recreational fishers (9.4 km) before and after MPA-implementation. Non-fishing vessels were only slightly further from the nearest port before MPA-implementation (10.2 km) than after (9.2 km). There was neither a statistically significant main effect of MPA-implementation nor an interaction between MPA-implementation and vessel type on the distance to the nearest port, although fishing type was significantly associated with distance to nearest port (ANOVA: $p = 1.7*10^{-6}$; Table 3). When comparing the difference before and after MPA-implementation for each boat type, only Support Vessels showed a statistically significant difference (one-way analysis of means: $p = 0.0009$; Table S6). Support Vessels were on average closer to port after MPA-implementation (12.2 km) than before (14.9 km).

4. Discussion

4.1. Do MPAs successfully reduce fishing?

Quantifying the impacts of management activities on human activities in critical ecological habitat is a challenge because of the complex relationship between humans and environmental resources and requires novel and integrative approaches. Here we test the use of aerial surveys paired with distribution modeling to evaluate the success of MPAs in reducing fishing within MPA boundaries and impacting fishing distributions outside the boundaries. Our results demonstrate that in general, MPAs have been successful in limiting fishing. Overall

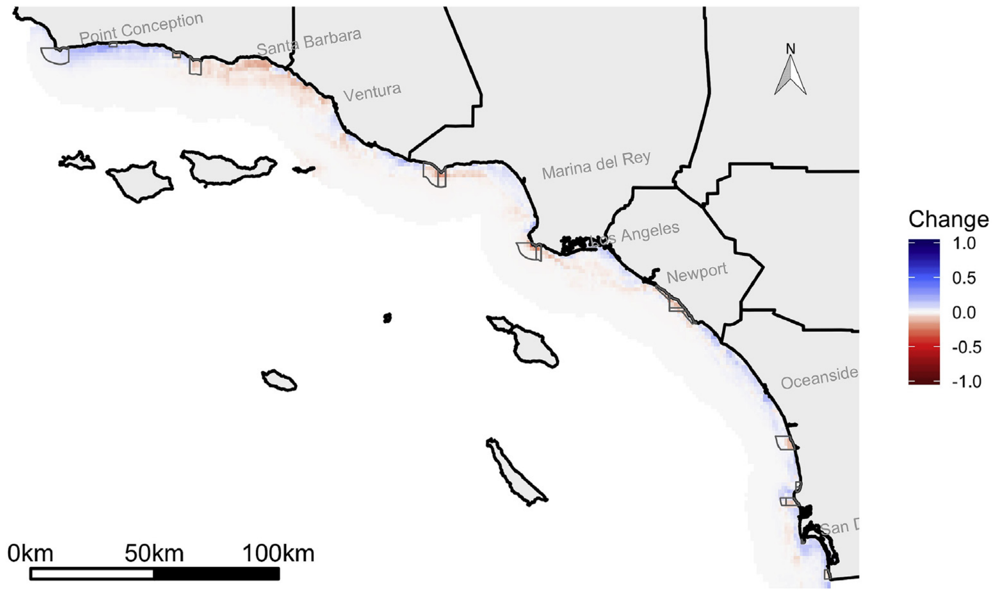

Fig. 5. Change in predicted probability of habitat suitability from SDMs before and after MPA-implementation for all actively fishing Commercial and Recreational vessels combined. Change calculated by subtracting pre-MPA predicted probability of habitat suitability from post-MPA suitability, with increase (blue), decrease (red), and no change (light gray). MPAs were implemented in 2012 (light gray solid lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

there was a decrease in fishing prevalence within MPAs after MPA implementation for both commercial and recreational fishers (Fig. 1; Table 1). Similarly, predicted probability of habitat suitability based on SDMs showed a trend for decreased fishing within MPA boundaries following MPA implementation (Figs. 3 and 5). Despite the difficulty in enforcing fishing and extraction restrictions across large marine areas (Edgar et al., 2004), our results provide some evidence that fishers as a whole appear to be responding as desired.

4.2. *Do MPAs impact Fisher distributions?*

In addition to reduced presence within MPAs, our results further suggest that overall fisher distributions quantitatively shifted. Pre- and post- MPA SDMs differed for all fishers (Table 3; Fig. 5). Interestingly, distributions shifted for all boat types, regardless of whether it was a fishing boat. This result suggests that all boaters, including those on non-fishing vessels, may be responding to the MPAs in some way and is consistent with expectations that MPAs may significantly impact distributions of all boaters beyond just fishers. For example, compaction of fishing vessels outside of MPAs may cause non-fishing boats to shift to new areas. Even if fish are not being harvested on these boats, the presence of boats in these new areas could have negative impacts on marine ecosystems due to disturbance and pollution.

Yet, while all boats showed a shift in their overall distributions, only actively fishing commercial and recreational boats showed a trend toward reduced habitat suitability within MPAs specifically. Commercial boats showed the greatest decrease in predicted probability of habitat suitability within MPAs, which decreased to the same level as non-fishing boats (Fig. 3). Recreational fishing boats had the highest predicted probability of habitat suitability and remained the highest after MPA implementation (Fig. 3). These results suggest that there may be important differences in both usage of MPAs and enforcement of regulations for these groups, and thus may require different approaches to education about MPAs. However, even within these fishing types there was a high amount of variation (discussed below), indicating that the impact of MPAs may vary depending on the specific vessel type. Taken together, these results suggest that the impact of MPAs on boaters is complex and demonstrates the importance of baseline monitoring on individual fishing types to understand vessel-specific impacts.

Since the differences in the SDMs before and after MPA implementation fit our predictions and are in line with results from the observed data, it suggests that we can capture important changes in the distribution of vessels in response to environmental changes. While used extensively for studying the distributions of non-human organisms, few if any studies that we are aware of have used SDMs to study the distribution of specific groups of humans and particularly in the context of environmental pressures. This tool could be a powerful method for conservation biologists to create spatially-explicit models of human impacts on ecosystems and to inform management policies and practices. Our study thus represents a novel use of SDMs to quantify important shifts in the distributions of human activities.

While there were clear associations between MPA implementation and the distribution of vessels inside MPA boundaries, the impacts of MPA implementation on other measures of vessel distribution were less clear. MPAs could potentially force fishers to travel further from ports to access fishing locations, resulting in higher expenditures on fuel. However, our results suggest that on average distance to port did not change for either commercial or recreational boats (Fig. 6). Further there was little evidence for individual boat types of a significant shift in distance to nearest port (Table S6, Fig. 7). The only boat type that statistically significantly shifted over time was Support Vessels ($p = 0.0009$). Thus, while the implementation of MPAs is clearly associated with a shift in fisher distributions, this shift does not appear to simply be shifting fishers further from ports. However, our analyses are restricted to within three miles of the shoreline and do not include fishing along more distant islands. It is therefore possible that if MPA-implementation is shifting fishers outside this three-mile buffer along the mainland or to offshore islands, then we would not be able to detect an effect. Future research should investigate the potential movement of fishers to these more distant locations.

4.3. *Other predictors of Fisher distributions*

Beyond MPA presence, additional variables were associated with the presence of fishing (Table S5). Across all boat types, distance to shore (BIOGEO5; average percent of variance = 45.3) and bathymetry (average = 21.4) were the greatest predictors of vessel presence, and at least one or both was the greatest predictor across most boat types. In addition, slope (BIOGEO6) was a consistent predictor for fishing boats (average = 4.8) and some non-fishing boats. MPA presence was a low predictor for most boat types both pre- and post-MPA (average = 0.6). In contrast, maximum salinity was a consistent predictor for non-fishing boats (average = 9.4). These results suggest that access to fishing sites and quality of habitat where species are found may be contributing to the distribution of fishers across the SCB. These results suggest that SDMs could be used to identify areas where MPAs may have the biggest

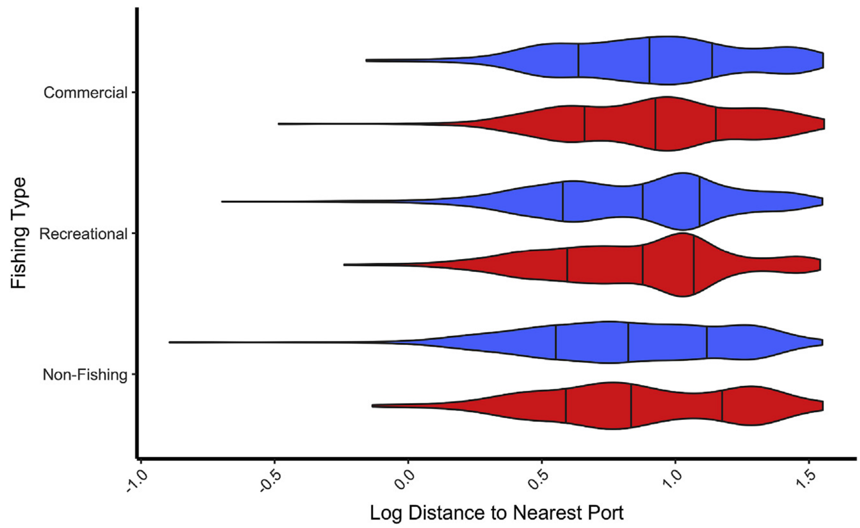

Fig. 6. Change in mean distance to nearest port by fishing type. Pre-MPA (red), Post-MPA (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

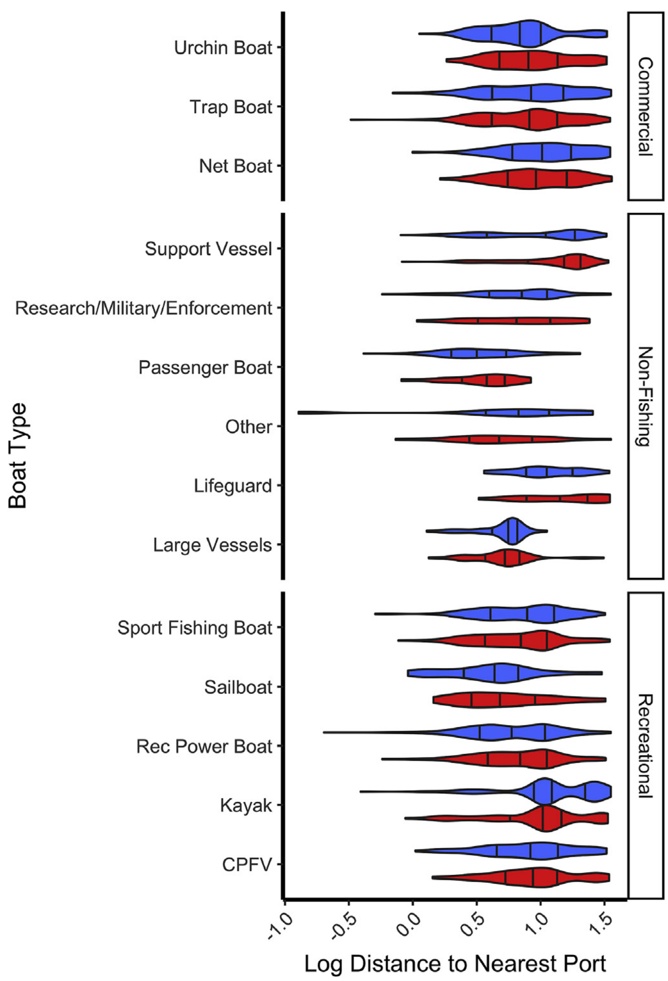

Fig. 7. Change in mean distance to nearest port by boat type. Pre-MPA (red), Post-MPA (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

impact on fishing.

4.4. Variation among fishing and boat types

The success and impact of MPAs depended on the type of boat evaluated (Table 1). We discuss a few of these boats types to illustrate variation in the dataset. Of the actively fishing commercial vessels, urchin fishers demonstrated the greatest response associated with the implementation of MPAs (Fig. 2; Fig. S7), trap boats had an intermediate amount of change (Fig. 2; Fig. S6), and net boats showed the smallest change (Fig. 2; Fig. S5). These differences appear to be due to the initial use of MPA regions before MPAs were implemented, as the total change increases with increasing initial proportion within MPA regions.

For recreational fishers, there was more variability in the magnitude and types of responses to MPA implementation. Both CPFVs (Fig. S8) and Sport Fishing Boats (Fig. S12) showed the largest decrease (Fig. 2). Kayaks (Fig. S9) and Rec Power Boats (Fig. S10) had intermediate decreases while still remaining prevalent within MPAs (Fig. 2). Sailboats had the smallest change although were not present in high numbers in MPA regions to begin with (Fig. 2; Fig. S11). The more varied responses for recreational fishers may stem from greater difficulties in education surrounding MPAs with the diverse types of recreational fishing that occurs.

Together, our results suggest that response of fishers to MPA-implementation is associated with the type of fishing occurring. Commercial fishers showed greater reductions in the proportion of boats observed within MPAs (Fig. 1) and predicted habitat suitability within MPAs (Fig. 3) than recreational fishers. These varied responses may reflect a number of differences inherent to commercial and recreational fishers. One hypothesis is that the costs associated with not respecting the law may be greater for commercial fishers who rely on their catch for their livelihood. Additionally, there may be differences in both education and enforcement among the fishing types. For example, recreational fishers may be more likely to travel from outside the region for fishing opportunities and thus be less familiar with local regulations. Perceptions toward and awareness of MPAs has been linked to visitor profiles, including place of residence (Petrosillo et al., 2007). Future studies should focus on effective measures of education and enforcement for different fisher profiles.

4.5. Caveats

Although the results demonstrate notable differences in fisher distributions and use of MPA areas in conjunction with the implementation of the 25 MPAs in the Southern California Bight, there are limitations to consider with natural experiments such as this one. Alternatively, changes in fisher distributions could be in response to other changes to the region over the time period of the study, such as changes in fish populations and distributions, environmental conditions, or socioeconomic pressures. However, we detected differences in how fishing and non-fishing vessel distributions changed over the course of the study, supporting our initial hypothesis that fisher distributions would be impacted by MPAs. Further, we note that many fishing vessels, although not all, showed similar distributional changes following MPA-implementation, with decreased predicted habitat suitability and observed presence within MPAs, which is suggestive of a response to MPAs rather than environmental or fishing conditions. While our results suggest a role of MPAs in the distribution of fishers in southern California, these external factors are likely to play at least some role in the changes in fisher distributions and use of MPA areas as well. How MPA implementation interacts with external factors such as environmental change should be an important focus of study for future research.

4.6. Conclusions

Evaluating the impact of MPAs on the distribution of fishers is crucial for assessment of management and conservation programs. We used an integrated approach to collect baseline data on the distributions of boaters in southern California and quantify shifts following the implementation of MPAs. Our results demonstrate the utility of both integrative approaches and distribution modeling for studying the response of human activities to management programs. Distribution modeling could be used to study human-environment interactions in a wide variety of scenarios, including but not limited to fishing, hunting, resource extraction, and habitat modification. Further our research highlights the importance of baseline data for conservation, providing the necessary data for evaluating conservation successes and failures.

Conflicts of interest

None.

Contributors

A.J.Z. participated in aerial surveys, conducted statistical analyses, and wrote the manuscript. H.B. conducted aerial surveys, collated data, and contributed to writing the manuscript. I.M. conducted aerial surveys, collated data, conducted statistical analyses, and contributed to writing the manuscript. D.J.P. envisioned the project, analyzed data, and wrote the manuscript. T.F. envisioned the project, conducted aerial surveys, coordinated partners and logistics, analyzed the data, and contributed to writing the manuscript.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.ocecoaman.2018.08.027.

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