Evidence to inform spatial management of a western Pacific Ocean tuna purse seine fishery

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ABTRACT

Fisheries can have profound impacts on co-occurring species exposed to incidental capture, particularly those with life history traits that make them vulnerable to elevated mortality levels. Fisheries spatial management holds substantial potential to balance socioeconomic benefits and costs to threatened bycatch species. This study analyzed observer program data for a western Pacific Ocean tuna purse seine fishery to estimate the effect of the spatial and temporal distribution of fishing on catch rates of target and at-risk species by fitting spatially-explicit generalised additive multilevel regression models within a Bayesian inference framework. Mean field prediction surfaces defined catch rate hotspots for principal market tunas, silky sharks, rays and whale sharks, informing the development of candidate area-based management strategies. Due to sample size limitations, odontocete and marine turtle catch geospatial patterns were summarized using 2D hexagonal binning of mean catch rates. Effort could be focused in two areas within core fishing grounds in the Solomon and Bismark Seas to reduce overlap with hotspots for silky sharks, rays and whale sharks without affecting target catch. Effort could also be shifted outside of core fishing grounds to zones with higher target tuna catch rates that would also reduce overlap with hotspots for at-risk species. However, two tuna warmspots overlapped silky and whale shark warmspots. Sparse and small marine turtle and whale shark hotspots occurred across the fishing grounds. Research on the economic and operational viability of alternative spatial management strategies is a priority. A small subset of sets had disproportionately large odontocete captures. Real time fleet communication and move-on rules and avoiding sets on dolphin schools might reduce odontocete catch rates. Management of informative operational predictors such as set association type and mesh size present additional opportunities to balance catch rates of at-risk and target species. A transition to employing output controls that effectively constrain the fishery would alter the spatial management strategy to focus on zones with the lowest ratio of at-risk bycatch to target tuna catch. Findings inform the design of alternative spatial management strategies to avoid catch rate hotspots of at-risk species without compromising the catch of principal market species.

Keywords: Area-based management tools (ABMTs); bycatch; dynamic spatial management; hotspots

1. INTRODUCTION

There has been growing concern over the sustainability of marine megafauna exposed to bycatch fishing mortality, including species with life histories that make them particularly vulnerable to elevated mortality from anthropogenic threats (Musick 1999; Hall et al., 2017; Jorgensen et al., 2022). Selective fishery removals of pelagic marine apex and mesopredators can alter population and ecosystem size structure, have cascading effects down food webs in some pelagic ecosystems and cause fisheries-induced evolution (Kitchell et al., 2002; Ward and

Myers, 2005; Polovina and Woodworth-Jefcoats, 2013). There has also been increasing attention to risks from bycatch to food, nutrition and livelihood security (Jaiteh et al., 2017; Seidu et al., 2022).

Tuna purse seine fisheries are a substantial anthropogenic mortality source for silky (*Carcharhinus falciformis*) and other species of sharks, including oceanic whitetip sharks (*C. longimanus*), hammerheads (Sphyrnidae) and whale sharks (*Rhincodon typus*). They also capture manta and devil rays (*Mobula* spp.), marine turtles, whales, and mainly in the eastern Pacific Ocean, sets may be made on tuna schools associated with dolphins (Dagorn et al., 2013; Hall & Roman, 2013; Kaplan et al., 2014; Poisson et al., 2014; Lezama-Ochoa et al., 2019; Filmalter et al., 2021).

For some gear types and some taxa of at-risk bycatch, numerous methods are now available that avoid and substantially reduce catch and fishing mortality of bycatch that are also economically viable, practical, safe and support a broad range of approaches for effective compliance monitoring (Gilman, 2011; Poisson et al., 2016; Hall et al., 2017). However, there has been mixed progress in their uptake (Gilman et al., 2014; Juan-Jorda et al., 2018). This includes input and output controls, international trade bans, restrictions on drifting fish aggregating device (FAD) designs to avoid shark and turtle entanglement, restrictions on purse seine set type, handling and release practices and area-based management tools (ABMTs) (Poisson et al., 2016; Hall et al., 2017; Gilman et al., 2022).

Static and dynamic ABMTs hold substantial potential to mitigate threatened species bycatch, including in blue water fisheries (Halpern, 2003; Slooten, 2013; Kaiser et al. 2018, Kenchington et al. 2018; FAO, 2019; Gilman et al., 2019a; Mannocci et al., 2020). Time-area measures for tuna purse seine fisheries adopted by regional fisheries management organizations (RFMOs) have been designed to support management strategies for principal market species (Kaplan et al., 2014; Gilman et al., 2019a; Hilborn et al., 2021). For example, tuna RFMOs have employed seasonal and permanent static closures and seasonal drifting FAD closures to support objectives for managing target species, such as reduced catch and mortality of juvenile tunas, swordfish and bluefin tuna (Gilman et al., 2019a; Hilborn et al., 2021). ABMTs also have the potential to manage threatened species bycatch in purse seine fisheries (Kaplan et al., 2014; Mannocci et al., 2020; Diaz-Delgado et al., 2021). While there is limited empirical evidence of ecological responses to Blue Water spatial management interventions, effects are likely to be strongest for upper trophic level species with certain behavioral and life-history traits, with strong site fidelity and that are highly exploited prior to the ABMT intervention (Le Quesne and Codling, 2009; Claudet et al., 2010; Gruss et al., 2011; Gilman et al., 2019a).

A western Pacific Ocean, Marine Stewardship Council-certified tuna purse seine fishery with vessels flagged to Papua New Guinea (PNG) and the Philippines, composes 17% of regional and 8% of global large scale tropical tuna purse seine vessels (Justel-Rubio and Recio, 2022). The fishery has apparently high silky shark bycatch and captures additional at-risk species including Mobulid rays, whale sharks, cetaceans and marine turtles (SCS, 2020). The fishery adopted a plan to address a condition of Marine Stewardship Council certification on the management of silky shark bycatch by exploring the potential of spatial fisheries management (SCS, 2022).

This study identified the spatial exposure of at-risk and target tuna species to purse seine fishery hazards in the western Pacific Ocean. The study analyzed observer data from PNG and Philippine flagged tuna purse seine vessels to estimate the effect of the spatial and temporal distribution of fishing effort on catch rates of at-risk and target species, with effort conditioned to account for other potentially informative predictors of catch risk based on fitting spatially-explicit generalized additive multilevel regression models within a Bayesian inference framework. Findings identify potential multispecies conflicts from alternative spatial management strategies so that any unavoidable tradeoffs are planned and acceptable (Gilman et al., 2019b). The study objective was to determine if there are temporally and spatially predictable hotspots and coldspots for catch rates of at-risk species and of target tunas to determine if these can be feasibly separated. Findings provide evidence to inform the design of a bycatch management strategy that incorporates spatial management to avoid catch rate hotspots of at-risk species without compromising the catch of principal market species.

2. METHODS

2.1. Data Sources

Observer data were obtained from the Pacific Community and Forum Fisheries Agency Regional Observer Programme. Observer data collection protocols are described in the *Regional Purse Seine Fisheries Observer Workbook* and relevant observer data collection forms (SPC and FFA, 2012, 2018). The compiled dataset comprised the species-specific catch recorded for each set, and 22 continuous and nominal categorical predictors summarized in Table S1 that might be informative of spatial and temporal patterns in the species-specific catch rate. The study sample included 109,396 sets within five zones: the Federated States of Micronesia exclusive economic zone (EEZ) (N=6,204 sets), Gilbert Islands portion of the Kiribati EEZ (N=7,765 sets), Nauru EEZ (N=4,705 sets), PNG EEZ (N=87,713 sets), and Solomon Islands EEZ (N=3,009 sets). These sets were made within 4,859 trips by 157 tuna purse seine vessels flagged to PNG and the Philippines, with sets conducted over ~22 years, between 15 March 2001 and 15 December 2022 (Fig. 1). Sets in other zones of the western and central Pacific Ocean combined, both within EEZs and on the high seas (high seas pockets are closed to purse seine fishing, WCPFC, 2021), contained <6% of available observer data for sets by PNG and Philippine flagged tuna purse seine vessels and were excluded from the study due to too small sample sizes. Fig. 1 summarizes the purse seine set intensity for the 22-year period using a high-resolution 2D hexagon binning approach (Carr et al., 1987) via the `hexbin` R package (Carr et al., 2023).

Six species or species groups considered for inclusion in the study, with sample sizes summarized in Table 1, were: combined principal commercial tuna species (skipjack *Katsuwonus pelamis*, yellowfin *Thunnus albacares* and bigeye *T. obesus* tunas), silky shark, combined species of rays, combined species of odontocetes, whale shark, and combined species of hard-shelled turtles. Records for the weight in metric tonnnes of the catch of commercial tuna species and number of catch of at-risk species were used in the analyses. The fishery primarily targets skipjack and yellowfin tunas and also catches bigeye tuna primarily in associated sets (Table 1). Skipjack tuna accounted for 63.7% of the combined weight of the principal market tuna species, followed by yellowfin tuna (33.6%) and bigeye tuna (2.7%). Of captured rays, 40% were giant manta (*Mobula birostris*), 52% other *Mobula* species, 7% pelagic stingray (*Pteroplatytrygon violacea*), and the remainder (<1%) were not identified to the species level. Of captured hard-shelled turtles, 27% were olive ridley (*Lepidochelys olivacea*), 26% green (*Chelonia mydas*), 19% loggerhead (*Caretta caretta*), 19% hawksbill (*Eretmochelys imbricata*), 6% not identified to the species level, and 2% were recorded as flatback (*Natator depressus*). Of captured odontocetes, 39% were false killer whales (*Pseudorca crassidens*), 13% bottlenose dolphins not identified to the species level (*Tursiops* spp.), 7% common dolphins (*Delphinus delphis*), 6% each of Indo-Pacific (*T. aduncus*), Risso's (*Grampus griseus*), rough-toothed (*Steno bredanensis*) and spinner dolphins (*Stenella longirostris*), and <5% each of other species. Table 1 also reports the proportion of sets with >0 captures by set type and species/taxa. Free school sets had a higher rate of "skunk" sets (sets where the school escaped, with little or no capture) than sets associated with floating objects (Hall & Roman, 2013). Approximately 30% of the sets were skunk sets, and *ca.* 32% of sets contained no target tuna species catch.

The fishery is predominantly a free school set (64% of total sets over the full study period, Table 1). From the first to second half of the study sample time series, anchored FAD sets declined from a mean of 38% to 4%, while free school sets increased from 37% to 77% of annual sets. During the most recent five years, free school sets were a mean of 84.2%, drifting FAD 6.7%, other associated 8.6%, and anchored FAD sets were 0.5% of the total number of sets made per year.

2.2. Statistical Modeling Approach

2.2.1. Workflow synopsis

Our modelling workflow, outlined in more detail below, can be summarised as follows, for four of the species with sufficient catch data (silky shark, tunas, rays, whale shark): (1) identify and extract potentially informative environmental predictors of species-specific catch rate at each of the set-specific geolocations, (2) impute missing values for set-specific predictors such as purse seine net length or set-type using machine learning (ML) based chained imputation procedures due to the very large number of purse seine sets, (3) again due to the large and high dimensional data set, use ML-based predictor screening in terms of predictive performance to explore informative species-specific predictors and potential predictor interactions, (4) fit species-specific spatially-explicit generalised additive multilevel regression models or geoGAMMs to the catch time series data using a Bayesian statistical modelling framework with a reduced selection of predictors informed by the ML-based screening step, (5) evaluate the predictive performance of each geoGAMM using posterior predictive check tests, and then (6) derive from each geoGAMM the spatially resolved catch prediction surface or map to support evidence-informed marine spatial planning. We used 2D hexagonal binning (Carr et al., 1987) to summarise the geospatial pattern in catch rates for the two species groups with sparse data (hard-shelled marine turtles and odontocetes).

2.2.2. Potentially informative predictors

We used macro-scale ocean-climate indicators of the Pacific Decadal Oscillation (PDO) index and Multivariate El Nino Southern Oscillation Index (MEI) as potential environmental drivers known to affect both pelagic fish, cetacean and marine turtle productivity and distributions (Newman et al 2016, Bjorndal et al., 2017; Free et al., 2019). The PDO is a regional climate index based on cyclical variations in north Pacific sea-surface temperature (Newman et al 2016). The MEI is another widely used regional scale ocean-climate index based on sea surface temperature anomalies (Zhang et al., 2019). We sourced the monthly PDO index and the revised bimonthly MEI from NOAA data repositories using the `rsoi` package for R (Albers, 2022). The monthly PDO and MEI index was then matched with the month of each purse seine set — the PDO and MEI time series lagged by 12 months were included to potentially reflect any delay in ocean productivity response to ocean temperature effects (Bjorndal et al., 2017; Reisinger et al., 2022).

Seascape features and ocean depth are related predictors affecting pelagic biodiversity hotspots and tuna fisheries catch rates in the Pacific Ocean (Morato et al., 2010). We sourced the bathymetric depth (depth to seafloor) for the geolocation of each set using Bio-ORACLE v2.0 (Assis et al., 2018) and the `sdmpredictors` package for R (Bosch & Fernandez, 2021). Regional bathymetry mapping shown in Supplemental Material Figure S1 was derived using NOAA bathymetry data (Amante & Eakins, 2009) that were accessed and processed via the `ggOceanMaps` R package (Vihtakari, 2022).

Lunar illumination is known to be informative of tuna catch in the western Pacific region (Gilman et al., 2015), so we sourced predicted moonlight intensity for the date, time and geolocation of each set using the `moonlit` package for R (Śmielak, 2023).

In addition, potentially informative vessel, observer, operational, spatial and temporal predictors of species-specific purse seine catch rates, summarized in Table S1, were included in the ML-based predictor screening steps of the modelling workflow for each species and species group. The most informative identified predictors were then included in the species-specific geoGAMMs. These 16 predictors were available from the observer program dataset. For some of the vessels with missing values for overall length and fish hold capacity in the observer program dataset, values were able to be sourced from WCPFC (2023). The strength of correlation between all continuous predictors (including spatial predictors: longitude, latitude) was explored using the `corrplot` package for R (Wei & Simko, 2021) — this helped determine whether any potential predictors might best be excluded from subsequent models due to potential strong multicollinearity.

Other potentially informative predictors were considered but were not able to be included due to data quality constraints. Explored but excluded predictors included vessel gross weight, vessel engine power, number of crew, number of speedboats, some variables that affect the speed of submerging the net, and vessel owner. Various set type-specific predictors could also not be included due to data quality constraints, including variables specific to free school sets of crow's nest height, use of bird radar and helicopter range (Hoyle et al., 2014), and variables specific to FAD sets such as how drifting FADs were detected (signal from a radio buoy or a satellite buoy attached to the FAD or visual), FAD designs and materials such as the depth and materials of the appendage, and use of instrumentation (e.g., satellite buoy with an integrated echosounder) (Lennert-Cody et al., 2008; Hall & Roman, 2013; Schaefer et al., 2021; Wain et al., 2021).

2.2.3. Machine learning-based missing data imputation

Dealing with missing data in one or more predictors is a major challenge for principled statistical modelling (Little, 1988) and is usually dealt with using some form of model-based imputation prior to fitting the model to be used for inference (Murray, 2018). We used an upset plot approach to visually explore missing data patterns (Lex et al., 2014) and found that ca. 8-9% of purse seine set records were missing one of four predictors of net depth, net length, net mesh size, or set cruise speed, while 4% of sets were missing vessel well capacity and 3% were missing set type. Some sets were missing multiple predictors with, for example, ca. 6% of the sets missing all 4 predictors of net depth, net length, net mesh size and cruise speed. The missing data were not *missing completely at random* (MCAR) as determined with a test for MCAR (Little, 1988: Chi-sq test = 25702, df = 247, $P < 0.0001$) using the `nanair` R package (Tierney & Cook, 2023) — so deleting missing cases or variables in our study is not appropriate but requires modelling the missingness instead to support robust statistical inference (Gelman & Hill, 2006).

It is possible to fit a Bayesian regression-based model using the original data with all predictors and directly estimate the missing data during the model fitting procedure. However, for the very large sample and high dimensional dataset considered here, this sort of measurement-error modelling procedure (Richardson & Gilks, 1993; Goldstein et al., 2018) was not computationally feasible. So, we used a fast multivariate missing data imputation approach based on multiple chained random forests to impute all missing data for all continuous and categorical predictors using the `missRanger` package for R (Mayer, 2021) with the `ranger` R package as the backend (Wright & Ziegler, 2017) where all missing data are simultaneously imputed multiple times until the minimum mean out-of-bag error was found (Mayer, 2021). The chained random forest data imputation model also applied predictive mean matching (Little, 1988) to avoid any imputation with values never present in the original dataset. This imputed dataset now comprised the original 109,396 purse seine sets and 22 predictors but now without any missing values, and was the dataset used in all our subsequent analyses.

2.2.4. Machine learning-based predictor screening

Models using ML approaches are powerful tools for applied predictive modelling in large data settings and make very few assumptions about data structures (Kuhn & Johnson, 2013). The first challenge in our statistical modelling workflow was to determine which ML algorithm was the most applicable for the species-specific catch data. Usually, ML-based applications apply a single prediction algorithm often with little if any specific knowledge domain justification. We used an automatic ML or AutoML procedure (He et al., 2021) in the first instance to explore which prediction algorithm might be best suited for each of the species-specific catch data time series given the 22 potential predictors (Table S1) since there was little evidence of strong correlation between most of the predictors (Figure S2). Specifically, we used the AutoML procedure on the H20.ai platform (H2O.ai, 2022) via the `h2o` (LeDell et al., 2023) and `agua` (Kuhn et al., 2023) R interface packages to: (1) explore, (2) hyperparameter tune, and (3) evaluate a large number of regression or classification (to explicitly address the ‘skunk” sets) models using six prediction algorithm classes (gradient boosting machine, xgboost, distributed random forest, neural nets, generalized linear model, stacked ensemble) and 4 model-specific performance metrics for each species.

Stacked ensemble ML uses a supervised meta-learning algorithm to find the optimal combination of the other five prediction algorithms. We used stacked ensembles as a benchmark to determine which of the other single-class algorithms was as well suited in terms of predictive performance for each species-specific dataset. Stacked ensembles are useful for prediction but very difficult to interpret, which is a major objective of this study, and so we chose the next best performing single-class algorithm for each species that compared adequately with the stacked ensemble class. The performance metrics were MAE, RMSE, R^2, and mean residual deviance for the regression-based models and AUC, accuracy, RMSE, and logloss for the classification-based models (see Kuhn & Johnson, 2013). All ML modelling workflows were applied within the `tidymodels` meta-learning framework for R (Kuhn & Wickham, 2020).

We fitted the appropriate species-specific supervised ML algorithm determined using AutoML to each species-specific catch series using the 22 potentially informative predictors. The response variable (hence *supervised*) in the case of 4 of the 6 species or groups considered here (silky shark, tuna, rays, whale shark) was the recorded set-specific catch with purse seine net length, net volume and vessel length as nonproportional effort proxies (Davies & Jonsen, 2011) being 3 of the 22 potentially informative predictors. We also explored binary data versions for some species based on whether there was either 0 or > 0 set-specific catch modelled with a Bernoulli likelihood, which is a special case of a binomial likelihood but now with a single trial (Congdon, 2003). We then used recent developments in interpretable ML (Lundberg et al., 2020) using SHAP-based summary plots to help derive insight into the predictor functional form and any informative interactions with other predictors. SHAP is an acronym of sorts for Shapley additive feature explanations (Lundberg et al., 2020) where “feature” is a ML term synonymous with the term “predictor”. A SHAP value is the average or expected marginal contribution of that predictor value to the predicted set-specific model outcome while averaging over all other predictors in the model. SHAP values have many desirable properties including being additive so that they sum to the total model output where a higher SHAP value is unambiguously indicative of a more important predictor.

In our context, higher SHAP values imply greater contribution of a specific predictor to the catch rate. A SHAP summary plot then comprises a density summary of the predictive contribution of each predictor included in a model — it is a more robust form of the commonly used variable importance plot (Janitza et al., 2018) but is a marginal effect with the density summarizing the entire 109,396 purse seine set-specific values. SHAP values account for all predictive information in a specific feature that result from interactions and dependencies with other features or predictors in the model. The SHAP summary plots were derived here using (1) the kernelshap R package (Mayer & Watson, 2023) to calculate SHAP values for each of the 109,396 sets within each of the 4 species-specific predictive models followed by (2) SHAP summary visualization using the shapviz R package (Mayer, 2023). Importantly, this predictor screening step of our workflow helped identify the minimal set of meaningful predictors for inclusion in the next more computationally demanding but more inference-focused Bayesian geoGAMM modelling step.

2.2.5. Bayesian statistical modelling approach

We used a Bayesian inference workflow (Gabry et al., 2019) based on spatially-explicit generalized additive multilevel regression models or geoGAMMs (Kammann & Wand, 2003) with the model likelihood based on either a zero-inflated or a distributional (hurdle-type) model structure to account for the purse seine sets with zero-catch ("skunk" sets) conditioned on potential informative covariates or predictors (Kneib et al., 2023: see Schaefer et al., 2021 for an eastern Pacific tuna purse seine fishery modelling example). This Bayesian approach to statistical modelling provides a powerful way to account for uncertainty in the data, the model parameters and the model structure using probability theory (van de Schoot et al., 2021). The Bayesian modelling workflow used here comprised: (1) prior predictive checks to assess the adequacy of the priors used for (2) a robust statistical model accounting for data constraints and potential predictors of catch rates followed by (3) graphical posterior predictive checks of the adequacy of the statistical model(s) fitted to the purse-seine set-specific catch data for each species.

More specifically, we used cubic smoothing splines (Wood, 2006) to account for possible nonlinear functional form of the predictors such as PDO, vessel length and the purse seine net length. The structured spatial effect of the individual purse seine set geolocations was estimated in the geoGAMMs aggregated over all sampling years using a 2D Gaussian Process surface with Matérn covariance kernel (Gelfand & Schliep, 2016). Group-level (or random) effect structures (intercepts-only) included in the models were the identity of the 743 onboard-vessel observers and the identity of the 157 vessels to account for any correlated or observer- and/or vessel-specific heterogeneity in the catch rates not accounted for by the other predictors. Any potential excess zero catch ("skunk" sets) was accounted for explicitly in the models by using a hurdle-negative binomial model likelihood for both the silky shark and ray Bayesian distributional geoGAMMs, a hurdle-lognormal likelihood for the tuna catch weight model and a zero-inflated negative binomial likelihood for the whale shark catch model. The posterior samples for all models were sourced from 4 chains and 2500 iterations after a warmup of 1000 iterations per chain. Therefore, the posterior for each estimate comprised 10,000 samples or draws that were used to derive the 95% quantile-based uncertainty intervals.

These distributional geoGAMMs were fit using the Stan computation engine (Carpenter et al., 2017) using the brms R interface for Stan (Bürkner, 2017) but with the cmdstanr backend (Gabry & Češnovar, 2022). All geoGAMMs were implemented using weakly informative regularizing priors (Lemoine, 2019) with prior predictive graphical summaries used to assess adequacy of the priors (Gabry et al., 2019). Model convergence was assessed using parameter-specific diagnostics such as multiple chain rank plots, bulk and tail effective sample size metrics and a rank-based *Rhat* statistic (Vehtari et al., 2021). All diagnostics reflected convergence of all models used here. Further evaluation of the best-fit-model was assessed using graphical posterior predictive checks (Gelman et al., 2014; Gabry et al., 2019). All inference was then based on the best-fit model.

Throughout the entire study workflow, we used the tidyverse R meta-package (Wickham et al., 2019) for data pre- and post-processing, the terra R package for spatial data processing (Hijmans, 2023), the rnaturalearth (Massicotte & South, 2023) and sf(Pebesma, 2018) R packages for sourcing the regional map data and vector based mapping, and the `ggplot2` R package (Wickham, 2016) for visualizations with the *viridis* color palette from the `colorspace` R package (Zeileis et al., 2019) that was used for SHAP plots and mapped spatial prediction surfaces. The `patchwork` R package (Pedersen, 2022) was used for all multi-panel plot layouts.

3. RESULTS

3.1. Prior Species-specific Predictor Screening

The most appropriate ML algorithm to be applied to each species-specific dataset identified using AutoML was a gradient boosting machine using LightGBM (Ke et al., 2017) for the four explored species (silky shark, tuna, rays, whale shark). The predictive performance for all four metrics using LightGBM was ranked very close to that for stacked ensembles (that comprise a complex mix of both best-in-each-algorithm-class and all algorithms) and far better ranking than for either random forest or XGBOOST (another gradient boosting algorithm) and substantially better than for either a generalized linear model (GLM) or neural nets. ML models with gradient boosting-based regression or classification using the LightGBM engine were then applied to each data catch set for the four species that were identified as best modelled using gradient boosting by AutoML. The performance metric ranking plot for silky shark is shown as one species-specific example in Figure S3. Then, set-specific SHAP-based explanations or predictions were derived for each of those species and summarized in SHAP summary plots to help identify the most important marginal predictor effects of species-specific catch. As one example, we show the SHAP predictor summary plots for skipjack tuna, the main target species, using both a Bernoulli likelihood model (0 or > 0 catch) and the landed weight of the skipjack catch model. These two models combined would be equivalent to a hurdle-lognormal likelihood model in inferential statistical modelling.

The SHAP summary plot for binary set-specific skipjack catch (0,>0) is shown in Figure S4 where the top two predictors in descending order of importance were mean depth to the seafloor and the purse seine net length. Increasing net length results in higher probability of skipjack catch while fishing in deeper waters results in decreasing probability of any skipjack catch (and hence a higher probability of a set with no captured skipjack). The SHAP summary plot for set-specific skipjack catch >0 is shown in Figure S5 where the top 5 predictors were purse seine net mesh size, hour of the day when the skiff was off, the specific vessel, net length and the PDO index in the 12 months prior. Increasing mesh size was associated with higher landed weight of skipjack and decreasing landed weight during the daytime. Importantly, this ML-based predictor screening step helped to identify the minimal set of meaningful predictors for this large and highly dimensional dataset for consideration in the next Bayesian regression modelling step — where different predictor effects were apparent for all four species, revealed using those SHAP summaries.

3.2. Modelling the Expected Species-specific Catch

Expected silky shark catch conditioned on a minimal set of non-spatial potentially informative predictors guided by the prior ML-based predictor screening is shown in Figure 2. Silky shark catch increased over the 22-year period (Figure 2a). Silky shark catch was lower for anchored FAD sets (Figure 2b) — moreover, lower anchored FAD catch occurred during all 4 of the 5-year time periods (Figure 2c), and silky shark catch was higher in drifting FAD and in other associated sets than in free school sets. Silky shark catch was also a significant nonlinear function of both a major ocean productivity proxy (PDO index, Figure 2d) and the set-specific cruise speed (higher set-specific catch increases with vessel cruise speed, Figure 2e). Silky shark catch was not a function of fishing effort measured as purse seine net length (Figure 2f).

The hurdle component (0 vs > 0 catch) of the distributional regression model was a nonlinear function of the purse seine mesh size (Figure 2g) — zero silky shark catch more likely a function of small mesh size. The three posterior predictive check tests for the silky shark distributional geoGAMM with hurdle-negative binomial likelihood were density overlay, maximum prediction and the expected proportion of sets with zero catch. All three predictive check tests reflected adequate silky shark model fit and are shown here as one species-specific example (Figure S6).

Expected tuna catch conditioned on a minimal set of non-spatial potentially informative predictors is shown in Figure 3. The tuna catch was apparently stable over the 22-year period (Figure 3a) but this was not the case when set type was taken into account. Tuna catch increased over the 22-years for all set types other than for anchored FAD sets (Figure 3c). Tuna catch was a significant nonlinear function of the time of the day when initiating a set (based on skiff departure time) with lower catch apparent during the later afternoon and early evening (Figure 3e). Tuna catch was not a function of either PDO (Figure 3d), fishing effort measured as net length (Figure 3f) or net mesh size (Figure 3g). The hurdle component (0 vs > 0 catch) of the distributional regression model was apparently (1) not a significant nonlinear function of fishing effort measured as net volume (Figure 3h) but was apparently (2) a function of the depth to seafloor with higher likelihood of positive catch further from the coast, especially around seafloor depths ca. 2000-2500m, and conversely more likely to have a tuna catch skunk set closer to the coast in areas with shallower depths (Figure 3i).

Expected ray catch (combined catch of various ray species) conditioned on a minimal set of non-spatial potentially informative predictors is shown in Figure 4. The ray catch was not a significant function of the minimal set of informative predictors except perhaps for the hurdle component, where positive catch appears more likely as mesh size increases (Figure 4f).

Expected whale shark catch conditioned on a minimal set of non-spatial informative predictors is shown in Figure S7 and was not a significant function of the minimal set of informative predictors.

3.3. Spatial Prediction Surfaces for Marine Spatial Planning

The geolocation of the purse seine set was a more informative predictor of the catch of all four explored species (silky shark, tunas, rays, whale shark) than most of the non-spatial potentially informative predictors shown in Figures 2-4 and Figure S7. The residual spatial effects for each of the four geoGAMM-modelled species are shown in Figures 5-8.

The geospatial pattern for the silky shark catch that was conditioned on a minimal set of predictors (including set geolocation) indicates that relatively higher catch rates occurred mainly in the PNG EEZ southward in the Solomon Sea and a secondary warmspot (i.e., area with a relatively high, but not the highest, catch rate) was in the Bismarck Sea region off northern PNG centred around Manus Island. However, there were lower silky shark catch rates in the western section of the Solomon Sea and the southern Bismark Sea (Figure 5).

The tuna species geospatial catch pattern on the minimal set of predictors (including set geolocation) indicates that relatively higher model-unaccounted catch occurred in the north-western FSM EEZ at around 10^0N and in the southeastern PNG EEZ, both in areas with relatively low fishing effort (i.e., marginal fishing grounds) (Figure 6). Tuna warmspots straddled the equator in the northwestern zone of the PNG EEZ, Nauru EEZ and western two-thirds of the Kiribati EEZ around the Gilbert Islands, with an apparent warmspot in a marginal part of the fishing grounds in the Coral Sea (Figure 6).

The geospatial pattern for the catch of ray species indicates that relatively higher catches occurred mainly in the southern section of the Solomon Sea spanning the EEZs of both PNG and the Solomon Islands. There was decreasing ray catch rates when moving north and northeast across the study area fishing grounds (Figure 7).

There was little residual geospatial pattern remaining for the modelled whale shark catch rate except perhaps in the southern Solomon Sea in the PNG EEZ and possibly in the Coral

Sea in a marginal section of fishing grounds. A possible warmspot was apparent, following a horizontal band slightly north of the equator within the northern PNG EEZ and zones of the southern FSM EEZ (Figure 8).

There was insufficient catch data for odontocete and hard-shelled marine turtle species, so the catch geospatial pattern of these two groups was summarized using 2D hexagonal binning of the mean catch rate (mean number per set) per hexagon cell to explore any apparent spatial effect. Hard-shelled turtles and odontocetes were very rare capture events, where only 0.6% and 1.4% of sets had one or more hard-shelled turtle or odontocete capture, respectively (Table 1). This explains why most 0.5 x 0.5 degree hexbins have a mean of 0 catch per set (yellow areas of Figures S8, S9). Sparse hard-shelled marine turtle interactions occurred across the fishing grounds, with generally lower catch rates in the PNG EEZ relative to the other zones of the study area (FSM, Solomons, and Nauru EEZs and Gilbert Islands portion of the Kiribati EEZ). Sparse odontocete interactions also occurred across the fishing grounds, with small areas of hot and warmspots scattered throughout the study area.

4. DISCUSSION

4.1. Static and Dynamic Area-based Management

ABMTs hold substantial potential to balance socioeconomic benefits derived from fisheries and costs to at-risk species exposed to bycatch fishing mortality (Gilman et al., 2019a; Mannocci et al., 2020; Lopetegui-Eguren et al., 2022). Mean field prediction surfaces defined catch rate hotspots for principal market tunas, silky sharks, rays and whale sharks, informing the development of candidate static spatial management strategies that reduce catch risk of at-risk species without causing unacceptable costs to catch rates of target species. Focusing effort by the PNG and Philippines purse seine fishery in the western Solomon Sea and the southern Bismark Sea, which are within the core area of the fishing grounds within the PNG EEZ, would reduce overlap with catch rate hotspots for silky sharks, rays and whale sharks without affecting catch rates of target species. Furthermore, shifting effort away from the core fishing grounds in the Bismark Sea and the Solomon Sea: (1) northwards up to but south of the equator in the PNG EEZ, (2) eastwards around the equator in the Nauru EEZ and Kiribati EEZ in the Gilbert Islands, and (3) into a marginal area of the fishing grounds around 10^0N in the western zone of the FSM EEZ would reduce also overlap with catch rate hotspots for silky sharks, rays and whale sharks, and would also increase catch rates of principal market tunas. Two tuna catch rate warmspots overlapped warmspots of at-risk species, for whale sharks in the northwestern zone of the PNG EEZ, and for silky sharks, rays and whale sharks in the Coral Sea in the southeastern PNG EEZ.

Additional research on the economic and operational viability of alternative static spatial management strategies is a priority, particularly for proposed strategies that shift fishing effort to areas that are more distant from ports for smaller vessels that make relatively short trips closer to seaports in PNG. Additional research could also assess the spatial distribution of the size frequency distribution of the principal market tuna catch. Decisions on fishing grounds may be based in part on past behavior and habit, so that despite evidence of higher target species catch rates, and of promising predictors (environmental conditions, physical features) for high catch rates occurring outside historical core fishing grounds, fleet participants may be hesitant to change conventional practices (Davies et al., 2014).

Results did not identify opportunities for temporally dynamic spatial management of target and bycatch catch rates. Time of day of initiating sets was an important predictor for tuna catch rate (declining after about 3pm, Fig. 2d), but not for any assessed at-risk bycatch species. Previous studies that explored time of day effects on attendance at drifting FADs found that target tunas and silky sharks unfortunately make excursions away from the FADs, likely to forage, at similar times (mainly during the night time) (Filmalter et al., 2011; Schaefer and Fuller, 2013; Forget et al., 2015; Restrepo et al., 2016). Temporal predictors at scales of within a month (moon phase), season, and interannual El Nino Southern Oscillation phase did not explain any species-specific catch rates. At a decadal scale, silky shark catch rates were higher with higher PDO index values, with a 12-month lag, reflecting warmer regional SST (Houk et al., 2020). The PDO is associated with north-to-south variability in SST and productivity across the tropical and temperate Pacific Ocean, which can strengthen and weaken responses to ENSO phases (Newman et al., 2016; Houk et al., 2020). Lags in responses in species-specific catch rates to the PDO climate cycle are likely due to delays in ocean productivity, recruitment and biomass responses to ocean temperature effects (Lehodey et al., 1997, 2006; Saba et al., 2007). Silky sharks occur within the upper mixed layer, which extends to about 110 m in the western and central Pacific Ocean (Hutchinson et al., 2015). Variability in the vertical depth distribution of silky sharks in response to PDO phase is not likely explained by PDO, as silky sharks likely occur at shallower depths than most purse seine maximum net depths of about 200 m (Itano et al., 2012) during all PDO phases. Additional research could assess whether locations of species-specific catch rate-defined hotspots, warmspots and coldspots vary by climate cycle phase, which could inform the design of spatially-mobile spatial management strategies where fishery closed areas might vary in location during different climate cycle phases.

A large proportion of total odontocete captures occurred in a small number of sets with relatively numerous captures of dolphin species (common dolphin, false killer whale, bottlenose dolphin, striped dolphin and rough-toothed dolphin). Odontocete captures mainly occurred as multiple captures per set, with 92% of the total captured odontocetes occurring in sets with ≥2 captures per set, and over half of total odontocete captures occurring in 212 outlier sets with between 10 and 120 odontocete captures per set (0.2% of total sets). Real time fleet communication and move-on rules (Gilman et al. 2006; Little et al. 2015; Holland and Martin 2019) and avoiding sets on dolphin schools (unintentional and intentional) might hold potential to reduce odontocete catch rates in this fishery.

Conversely, a large proportion of sets with one or more ray, turtle, whale shark or silky shark capture had relatively few captures per set. Whale shark captures occurred primarily as singletons (1 per set), accounting for 84% of total captures. A third of ray captures occurred as singletons, and 87% of total ray captures occurred in sets with between 1 and 10 ray captures per set. Hard-shelled turtle captures also occurred primarily as singletons, with 85% of total captures occurring as singletons. Half of silky shark captures occurred in sets with between 1 and 14 captures per set, and 30% of total silky shark catch occurred in sets with between 1 and 7 captures per set. Real-time spatial management approaches likely hold less promise for these species with non-clustered interactions. Additional research could be conducted to determine whether there is a higher probability of captures in consecutive sets (i.e., is there a higher probability of a capture in a set that had a capture event in a previous set by that vessel) to explore the potential of species-specific move-on rules.

The geospatial and vertical distributions of pelagic marine predators, and in some cases distributions of different size classes and sexes within species, including when and where they aggregate, are some of the attributes that determine their susceptibility to capture in tropical tuna purse seine and other surface fisheries (Hobday et al., 2011). Industrial purse seine fisheries targeting mainly skipjack and yellowfin tunas, as well as bigeye tuna, occur primarily in the tropics of the eastern Atlantic Ocean, western Indian Ocean and eastern and western Pacific Ocean (Hall & Roman, 2013). Pelagic predator distributions, local abundance and aggregating behavior are defined by environmental variables such as temperature and dissolved oxygen, depth of the thermocline, and availability of their prey (Musyl et al. 2003, 2011; Lopetegui-Eguren et al., 2022). Pelagic predators have different environmental preferences and tolerances (Lehodey et al., 2011; Muhling et al., 2011; Brodziak and Walsh, 2013). Larval and juvenile tunas have a narrower range of environmental variables in which they can live than adults, while optimal temperatures are narrowest and warmest for spawning tunas (Lehodey et al., 2011; Bromhead et al., 2015). Distributions and aggregation behaviors are also determined by physical features that determine biophysical structure. These features include bathymetric structures such as shallow seamounts, reefs, shelf breaks, and islands, atolls and coastal features that create small-scale eddies and fronts (i.e., Island Mass Effect) (Worm et al., 2003; Morato et al., 2010), as well as natural and artificial drifting and anchored floating objects, discussed below. Dynamic hydrographic features also affect distributions and aggregation locations, including currents and frontal systems, upwelling plumes, and eddies (Hyrenbach et al. 2000; Gove et al., 2016). These static and dynamic features structure the distribution of nutrients, levels of primary productivity, and the distributions and aggregations of prey species of pelagic apex predators (Hyrenbach et al. 2000, Vandeperre et al. 2014, Kavanaugh et al. 2016).

4.2. Operational Predictors

Catch composition varies by purse seine set type (Dagorn et al. 2013; Hall & Roman 2013; Peatman et al. 2017; Pons et al., 2023). Set type was found to be an informative predictor only for silky shark catch rate, which was significantly lower in anchored FAD sets than the three other set types, and significantly higher in drifting FAD and in other associated sets (e.g., drifting logs, drifting algae, live and dead large marine organisms, marine debris such as crates, pallets and nets) than in free school sets. Summarized in the Methods section, over the study time series, the fishery has increasingly conducted free school sets, making up a mean of 84% of sets made annually during the most recent five years.

Relative to free-swimming tuna schools chasing prey, sets on relatively slower-moving drifting FADs and logs catch a larger number and weight of nontarget species per set and per unit weight of target tunas (Hall & Roman 2013; Torres-Irineo et al. 2014; Gaertner et al. 2016; Peatman et al. 2017; Lezama-Ochoa et al. 2017; Pons et al., 2023). Shark catch rates, in number or weight of captures per set, are higher in drifting FAD and log sets than in free school sets (Amande et al. 2008, 2010; Clarke et al., 2011; Lopetegui-Eguren et al., 2022). However, when applying a catch rate of the weight of caught sharks per weight of principal market tunas, shark catch rates in school and associated sets are the same order of magnitude (ISSF, 2017). Set type is also an informative predictor of catch rates of principal market tuna species as well as other at-risk species, such as higher Mobulid ray and leatherback turtle catch rates in free school sets compared to associated sets (Dagorn et al. 2013; Hall & Roman 2013). Thus, multispecies conflicts result from managing set type (Gilman et al., 2019b). Not assessed in this study, set type is also an informative predictor of the body size of the catch, where drifting FAD and other associated sets catch smaller fish, including juvenile yellowfin and bigeye tunas, relative to free school sets (Dagorn et al., 2013; Fonteneau et al. 2013; Hoyle et al., 2014; Restrepo et al. 2017).

Sets with a smaller mesh size of the main section of the net were more likely to have no silky shark or ray catch. Mesh size was not an informative predictor for tunas (or whale sharks). This suggests that mesh size might be a manageable operational variable to reduce bycatch risk of silky sharks and rays without posing a cost to economic viability. Mechanistic studies have found that purse seine nets with smaller mesh sizes tend to have slower sink rates, faster drifting speeds, shallower maximum depths, slower pursing speeds, and a different net geometry than nets with larger mesh sizes (Misund et al., 1992, Kim et al., 2007; Hosseini et al., 2011; Widagdo et al., 2015; Tang et al., 2019). Mesh size might be correlated with other gear designs and characteristics that affect catchability (by affecting sink rate, drifting speed, fishing depth, pursing speed, net geometry as well as flow interference) such as the twine material, diameter and density, and net handing ratio and stiffness (Zhou et al., 2019). Purse seine nets with smaller meshes might have lower catch efficiency by increasing the risk of skunk sets and escapement of a portion of encircled schools. Purse seines with smaller meshes might also have a lower risk of entangling some large species, such as documented for sharks and marine turtles in netting used as appendages of drifting FADs (Hall & Roman, 2013; Poisson et al., 2016; Pons et al., 2023) and for dolphins in tuna purse seines (a dolphin bycatch mitigation method for tuna purse seine fisheries uses smaller mesh netting in the upper section of tuna purse seine nets to reduce the risk of entanglement when fishers employ a backdown procedure to release dolphins from the net, Barham et al., 1977; Hall & Roman, 2013).

Vessel cruise speed was an informative predictor for the expected silky shark catch rate. Slower vessel speeds may have a higher probability of skunk sets or catching partial schools, particularly for free school sets (Gaertner et al., 1999; Hall & Roman, 2013). And, faster vessels might have larger searching areas, increasing the probability of encountering a free swimming school or school associated with another vessel's drifting FAD or other type of drifting floating object (Gaertner et al., 1999). This operational variable is unsuitable for bycatch management because restricting vessel speed could impose a large cost to fishing efficiency.

4.3. Input versus Output Controls

The purse seine fishery is subject to input controls of limits on the number of fishing days, number of vessels, number of activated and instrumented drifting FADs, and a FAD seasonal closure (PNA, 2020, WCPFC, 2021), but not output limits. Therefore, a catch rate unit of catch per set as employed in this study (conditioned by all predictors) is appropriate for evaluating alternative bycatch management strategies, including informing spatial management options. Given an objective of minimizing bycatch of at-risk species, selecting fishing zones with lowest at-risk species captures per set would be a suitable spatial management approach under this current management framework with only input controls.

If output controls were used, for either or both target species and at-risk bycatch species, then the ratio of at-risk to target species catch would be appropriate. Under a management framework with a bycatch threshold, zones with the lowest ratio of at-risk species bycatch to commercial species catch would maximize target catch within the constraints of the bycatch limit. With a target species cap, zones with this same low ratio would minimize threatened species catch.

4.4. Catch Data Uncertainty

The observer data collection methods create uncertainty in the purse seine catch records. This includes selectivity bias from grab sampling to estimate the catch of target tuna species - however, since 2008 the observer program has employed a combination of grab and spill sampling to address this selectivity bias (Lawson 2013; Hoyle et al., 2014). Methods employed by observers to estimate the catch of non-target species can also introduce substantial uncertainty (Hutchinson et al., 2015; Briand et al., 2018; Forget et al., 2021). For example, observer sampling protocols to estimate bycatch by counting non-target catch from one brail or counting discards for a sample of catch sorting time and extrapolating linearly to the total number of brails and to total sorting time in a set, respectively, can introduce error (Briand et al., 2018). Observers of the SPC/FFA Regional Observer Programme use visual inspections to estimate the number and weight of bycatch species, as time permits, while sampling the target tuna catch on the upper deck (Itano et al., 2019; Forget et al., 2021). The small sample of non-target catch may be unrepresentative of the underlying catch from the total set, and monitoring only from the upper work deck will result in undercoverage bias as small species and small individuals within species of non-target catch may be detected primarily on the lower well deck (Forget et al., 2021). Observers may have a more difficult time quantifying bycatch on vessels that do not use a hopper to sort catch after brailing onto the deck before the catch goes down a chute to a lower deck for sorting and storage in wells (Poisson et al., 2014; Hutchinson et al., 2015). The SPC/FFA Regional Observer Programme tasks observers with recording the weight or number of each captured non-target species, as well as the number or weight of species of special interest that are observed inside or touching the net that are not subsequently landed on deck (SPC & FFA, 2018). Observers are directed to only record the number of a species that were captured when it is possible for the observer to obtain an accurate count, and observers are to record an estimated weight only when a large volume of a species was captured (SPC & FFA, 2018). As conducted previously to estimate the precision between estimates of target catch through grab and spill sampling (Lawson, 2013), research to identify bias in non-target species-specific observer catch estimates is a priority to produce accurate estimates of catch rates and extrapolated fleetwide magnitudes, especially in purse seine fisheries with low observer coverage rates (Amande et al., 2012). Developments in fisheries electronic monitoring systems used in purse seine fisheries might improve the accuracy of bycatch estimates (Briand et al., 2018; Forget et al., 2021).

4.5. Conclusions

Static and dynamic ABMTs hold substantial potential to balance socioeconomic benefits derived from fisheries and ecological costs to at-risk species exposed to bycatch fishing mortality in blue water fisheries (Gilman et al., 2019a). The PNG and Philippines western Pacific purse seine fishery causes bycatch mortality of several threatened species including silky sharks (Clarke et al., 2018), Mobulid rays (Croll et al., 2015), dolphins (Nelms et al., 2021) and marine turtles (Wallace et al., 2010, 2011).

This study analyzed observer program data to estimate the effect of the spatial and temporal distribution of fishing effort on target and at-risk species-specific catch rates based on fitting spatially-explicit generalized additive multilevel regression models within a Bayesian inference framework. The findings identified areas within existing core fishing grounds where hotspots for silky sharks, rays and whale sharks could be avoided without affecting target catch, and areas outside of the core fishing grounds where there are higher tuna catch rates that would reduce the overlap with hotspots for these same at-risk species. However, the economic and operational viability of these spatial management strategies, especially where effort would be shifted more substantially further away from seaports, needs to be assessed.

Unlike for silky sharks, whale sharks, rays and turtles, a small subset of sets had disproportionately large numbers of odontocete captures. Real time fleet communication and move-on rules, and avoiding sets on dolphin schools, might be effective approaches to mitigate odontocete bycatch.

ABMTs are one of a suite of approaches to manage purse seine bycatch of at-risk species, where an ensemble of measures is often needed to achieve objectives (Selig et al., 2017). Management of significant operational predictors such as set association type and mesh size present additional opportunities to balance catch rates of at-risk bycatch and target species. Introducing fleetwide or vessel-based output controls that effectively constrain the fishery would alter the spatial management strategy to focus on zones with the lowest ratio of at-risk bycatch to target tuna catch. The findings presented here on the spatial exposure of at-risk and target species to this western Pacific Ocean tuna purse seine fishery support the development of evidence-informed policy to apply spatial management as part of an ensemble of complementary bycatch management measures to meet objectives for balancing benefits from target species catch with costs to at-risk bycatch species.

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Supplemental Material

This article includes online supplemental material.

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TABLES

Table 1. Study sample sizes, PNG and Philippines tuna purse seine fishery in the western Pacific Ocean, 109,396 sets, 2001-2022. Catch in metric tonnes for tunas and number for other species/groups. SKJ=skipjack tuna, YFT=yellowfin tuna, BET=bigeye tuna, FAL=silky shark.

Set type (N, number of sets)	Metric	SKJ	YFT	BET	FAL	Rays	Odonto-cetes	Whale sharks	Hard-shelled turtles
Free school (69,984)	Catch	950,887	563,124	20,111	80,411	6,352	2,171	564	378
	% of sets with >0 capture	46.0	40.6	5.2	15.0	4.5	0.6	0.8	0.5
	Catch per set	13.6	8.0	0.3	1.1	0.091	0.031	0.008	0.005
Drifting FAD (9,498)	Catch	273,039	72,601	18,181	23,811	973	1,004	34	77
	% of sets with >0 capture	92.2	89.4	45.7	36.9	6.0	1.8	0.4	0.8
	Catch per set	28.7	7.6	1.9	2.5	0.102	0.106	0.004	0.008
Anchored FAD (13,081)	Catch	178,670	100,071	18,842	8,056	776	1,292	7	81
	% of sets with >0 capture	86.3	87.4	37.9	16.7	3.8	1.4	0.1	0. 6
	Catch per set	13.7	7.7	1.4	0.6	0.059	0.099	0.001	0.006
Other associated (13,238) and set type not recorded (3,595)	Catch	321,804	173,019	17,193	46,444	1,838	2,943	662	180
	% of sets with >0 capture	77.1	78.9	25.4	33.4	5.5	4.2	3.9	0.9
	Catch per set	19.1	10.3	1.0	2.8	0.109	0.175	0.039	0.011
Total (109,396)	Catch	1,724,400	908,815	74,327	158,722	9,939	7,410	1,267	716
	% of sets with >0 capture	59.6	56.3	15.7	20.0	4.7	1.4	1.2	0.6
	Catch per set	15.8	8.3	0.7	1.5	0.091	0.068	0.012	0.007

FIGURE CAPTIONS

Figure 1. **PURSE SEINE SETS.** Geospatial intensity of the 109,396 sets deployed in a PNG and Philippines tuna purse seine fishery over a 22-year period (2001-2022), which is summarized using 2D hexagonal binning with 0.2-degree spatial resolution. The seaward margins of the 5 EEZs included in the study sample are shown by the thin black outlined polygons.

Figure 2. **SILKY SHARK.** Graphical summary of the Bayesian distributional geoGAMM with hurdle-negative binomial likelihood fitted to the silky shark catch data. **Panel a** shows the estimated conditional effect of period (comprising four 5-year time periods) on the set-specific catch rate. **Panel b** shows the conditional effect of the purse seine set type on the catch rate. **Panel c** shows the conditional interaction effect of set type within each 5-year period effect. **Panel d** shows the conditional 12-month-lagged Pacific Decadal Oscillation index effect. **Panel e** shows the conditional effect of set-specific vessel cruise speed. **Panel f** shows the conditional effect of fishing effort using purse seine net length as a fishing effort proxy. **Panel g** shows the conditional effect of purse seine mesh size on catch for the hurdle component. Solid dot=posterior mean, vertical bar = 95% credible interval, solid curve = mean nonlinear trend, shaded polygon = 95% pointwise credible interval.

Figure 3. **TUNAS (skipjack, yellowfin and bigeye tunas).** Graphical summary of the Bayesian distributional geoGAMM with hurdle-lognormal likelihood fitted to the combined tuna species landed weight data. **Panel a** shows the estimated conditional effect of period (comprising four 5-year time periods) on the set-specific catch rate. **Panel b** shows the conditional effect of the purse seine set type on the catch rate. **Panel c** shows the conditional interaction effect of set type within each 5-year period effect. **Panel d** shows the conditional 12-month-lagged Pacific Decadal Oscillation index effect. **Panel e** shows the conditional effect of time of the day when the skiff closed the purse seine net. **Panel f** shows the conditional effect of fishing effort using purse seine net length as a fishing effort proxy. **Panel g** shows the conditional effect of purse seine mesh size. **Panel h** shows the conditional effect of fishing effort using purse seine net volume as a fishing effort proxy on catch for the hurdle component. **Panel i** shows the conditional effect of ocean depth (bathymetry) on set-specific catch for the hurdle component. Solid dot=posterior mean, vertical bar = 95% credible interval, solid curve = mean nonlinear trend, shaded polygon = 95% pointwise credible interval.

Figure 4. **RAYS.** Graphical summary of the Bayesian distributional geoGAMM with hurdle-negative binomial likelihood fitted to the catch data for combined ray species. **Panel a** shows the estimated conditional effect of period (comprising four 5-year time periods) on the set-specific catch rate. **Panel b** shows the conditional effect of the purse seine set type on the catch rate. **Panel c** shows the conditional interaction effect of set type within each 5-year period effect. **Panel d** shows the conditional 12-month-lagged Pacific Decadal Oscillation index effect. **Panel e** shows the conditional effect of fishing effort using purse seine net length as a fishing effort proxy. **Panel f** shows the conditional effect of purse seine mesh size on catch for the hurdle component. Solid dot=posterior mean, vertical bar = 95% credible interval, solid curve = mean nonlinear trend, shaded polygon = 95% pointwise credible interval.

Figure 5. **RESIDUAL SPATIAL EFFECT (silky shark).** Residual spatial effect from the distributional geoGAMM model fitted to the silky shark catch data conditioned on various predictors over the 22-year period (2001-2022). Highlights any geospatial pattern in the silky shark catch not accounted for by the other predictors. The seaward margins of the 5 EEZs covered by this fishery shown by the thin black outlined polygons.

Figure 6. **RESIDUAL SPATIAL EFFECT (skipjack, yellowfin and bigeye tunas).** Residual spatial effect from the distributional geoGAMM model fitted to the combined tuna species landed weight data conditioned on various predictors over the 22-year period (2001-2022). Highlights any geospatial pattern in tuna catch not accounted for by the other predictors. The seaward margins of the 5 EEZs covered by this fishery shown by the thin black outlined polygons.

Figure 7. **RESIDUAL SPATIAL EFFECT (ray species).** Residual spatial effect from the distributional geoGAMM model fitted to the combined ray species catch data conditioned on various predictors over the 22-year period (2001-2022). Highlights any geospatial pattern in ray catch not accounted for by the other predictors. The seaward margins of the 5 EEZs covered by this fishery shown by the thin black outlined polygons.

Figure 8. **RESIDUAL SPATIAL EFFECT (whale shark).** Residual spatial effect from the distributional geoGAMM model fitted to the whale shark catch data conditioned on various predictors over the 22-year period (2001-2022). Highlights any geospatial pattern in whale shark catch not accounted for by the other predictors. The seaward margins of the 5 EEZs covered by this fishery shown by the thin black outlined polygons.

FIGURES

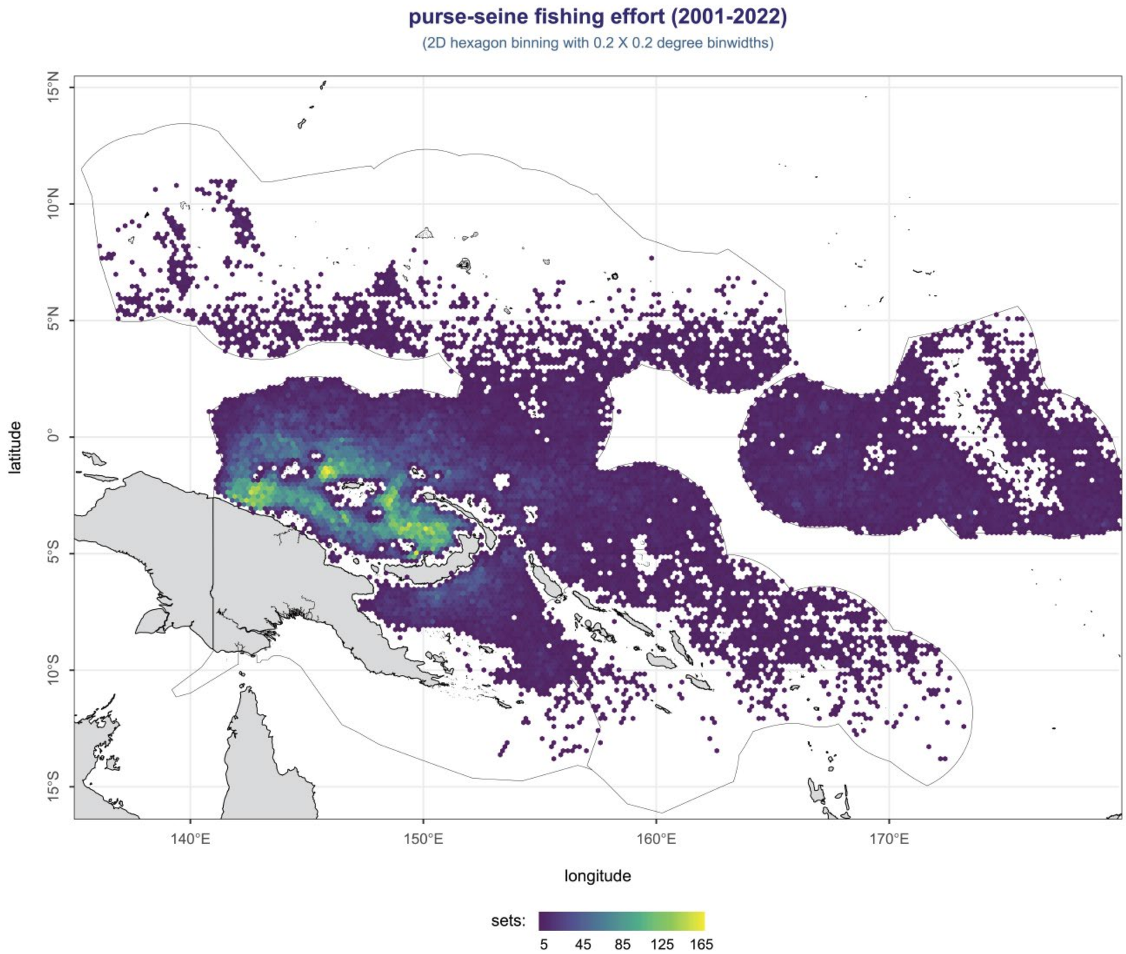

Figure 1

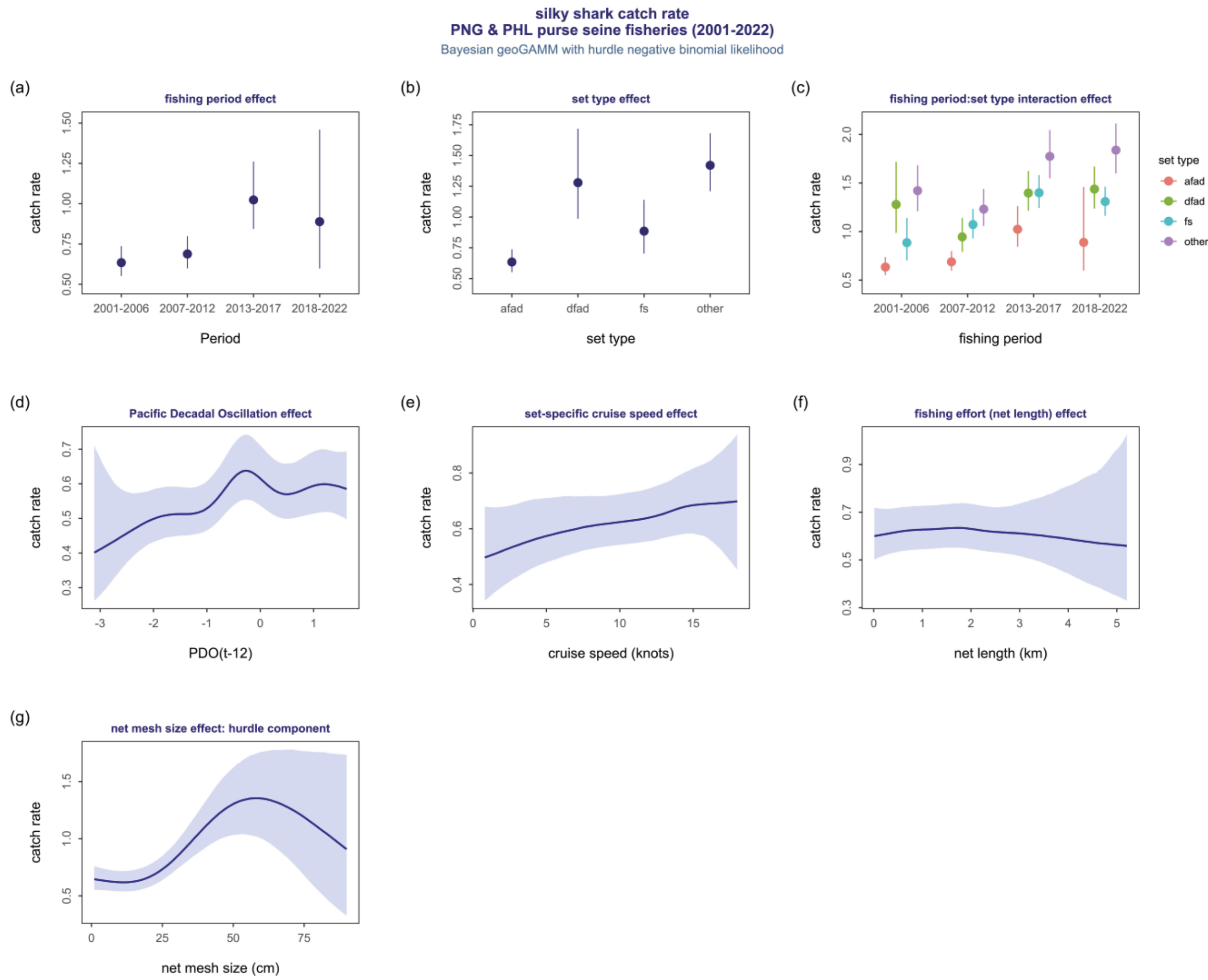
silky shark catch rate
PNG & PHL purse seine fisheries (2001-2022)
Bayesian geoGAMM with hurdle negative binomial likelihood
(a)
fishing period effect
catch rate
2001-2006
2007-2012
2013-2017
2018-2022
Period
(b)
set type effect
catch rate
afad
dfad
fs
other
set type
(c)
fishing period:set type interaction effect
catch rate
fishing period
set type
afad
dfad
fs
other
(d)
Pacific Decadal Oscillation effect
catch rate
PDO(t-12)
(e)
set-specific cruise speed effect
catch rate
cruise speed (knots)
(f)
fishing effort (net length) effect
catch rate
net length (km)
(g)
net mesh size effect: hurdle component
catch rate
net mesh size (cm)

Figure 2

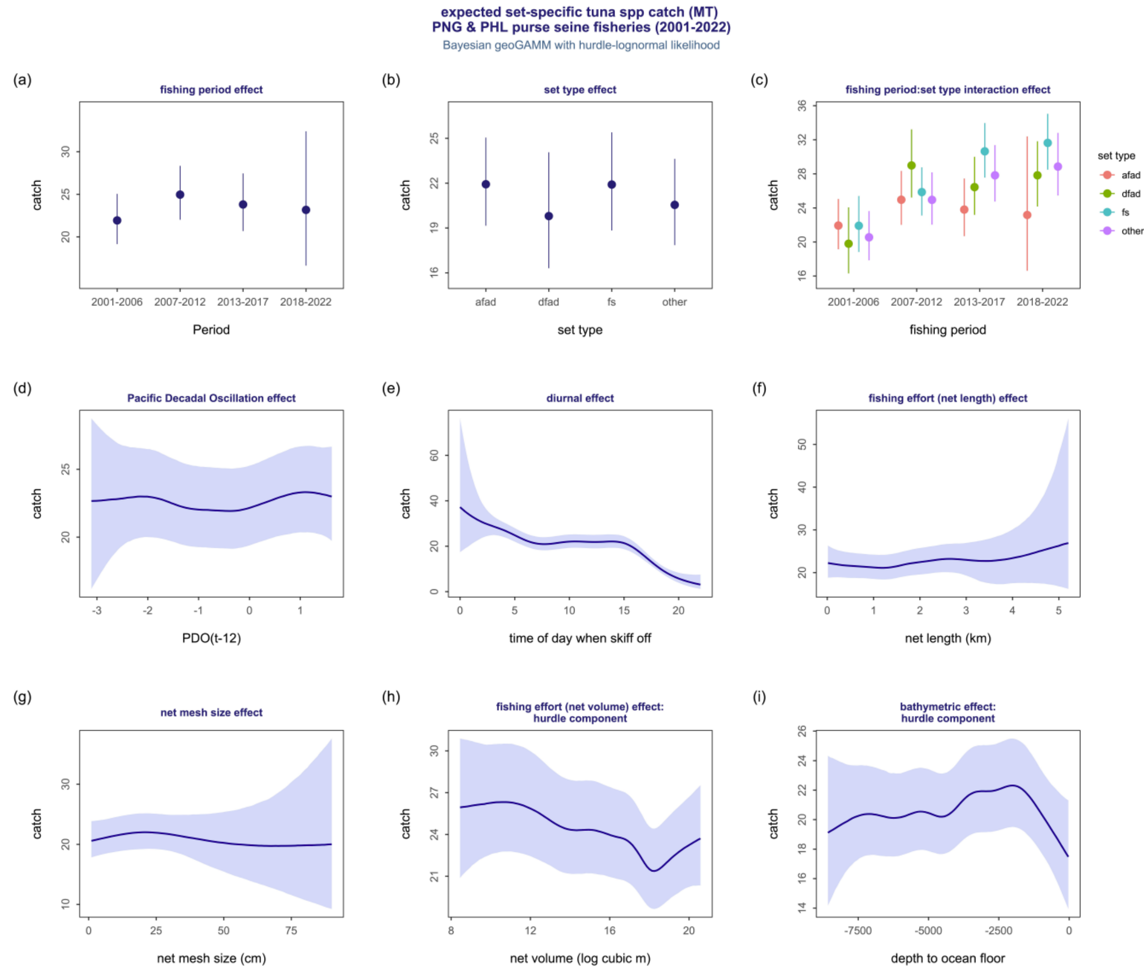
expected set-specific tuna spp catch (MT)
PNG & PHL purse seine fisheries (2001-2022)
Bayesian geoGAMM with hurdle-lognormal likelihood
(a)
fishing period effect
catch
2001-2006
2007-2012
2013-2017
2018-2022
Period
(b)
set type effect
catch
afad
dfad
fs
other
set type
(c)
fishing period:set type interaction effect
catch
set type
afad
dfad
fs
other
fishing period
(d)
Pacific Decadal Oscillation effect
catch
PDO(t-12)
(e)
diurnal effect
catch
time of day when skiff off
(f)
fishing effort (net length) effect
catch
net length (km)
(g)
net mesh size effect
catch
net mesh size (cm)
(h)
fishing effort (net volume) effect:
hurdle component
catch
net volume (log cubic m)
(i)
bathymetric effect:
hurdle component
catch
depth to ocean floor

Figure 3

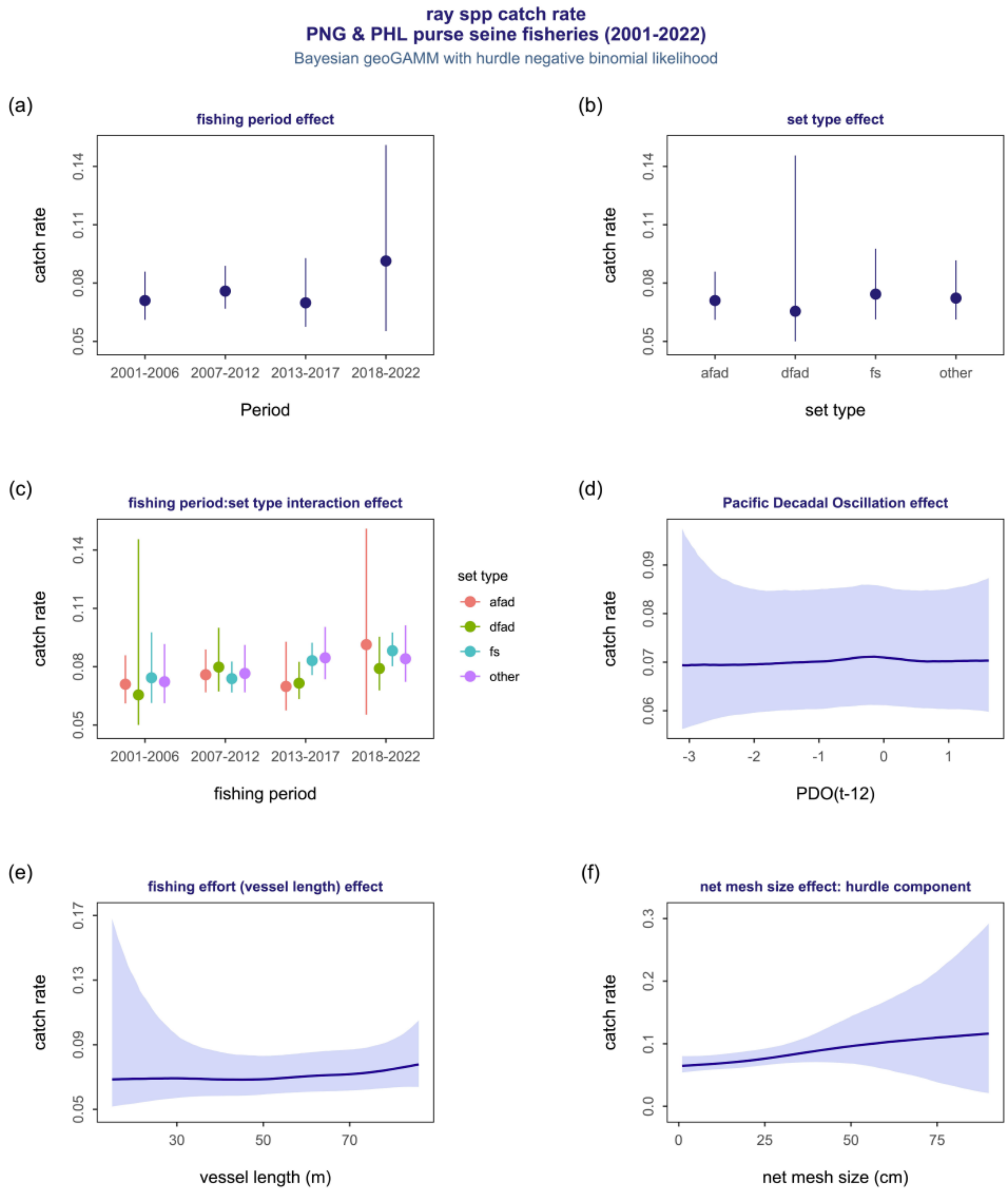
ray spp catch rate
PNG & PHL purse seine fisheries (2001-2022)
Bayesian geoGAMM with hurdle negative binomial likelihood
(a)
fishing period effect
catch rate
0.05
0.08
0.11
0.14
2001-2006
2007-2012
2013-2017
2018-2022
Period
(b)
set type effect
catch rate
0.05
0.08
0.11
0.14
afad
dfad
fs
other
set type
(c)
fishing period:set type interaction effect
catch rate
0.05
0.08
0.11
0.14
2001-2006
2007-2012
2013-2017
2018-2022
fishing period
set type
afad
dfad
fs
other
(d)
Pacific Decadal Oscillation effect
catch rate
0.06
0.07
0.08
0.09
-3
-2
-1
0
1
PDO(t-12)
(e)
fishing effort (vessel length) effect
catch rate
0.05
0.09
0.13
0.17
30
50
70
vessel length (m)
(f)
net mesh size effect: hurdle component
catch rate
0.0
0.1
0.2
0.3
0
25
50
75
net mesh size (cm)

Figure 4

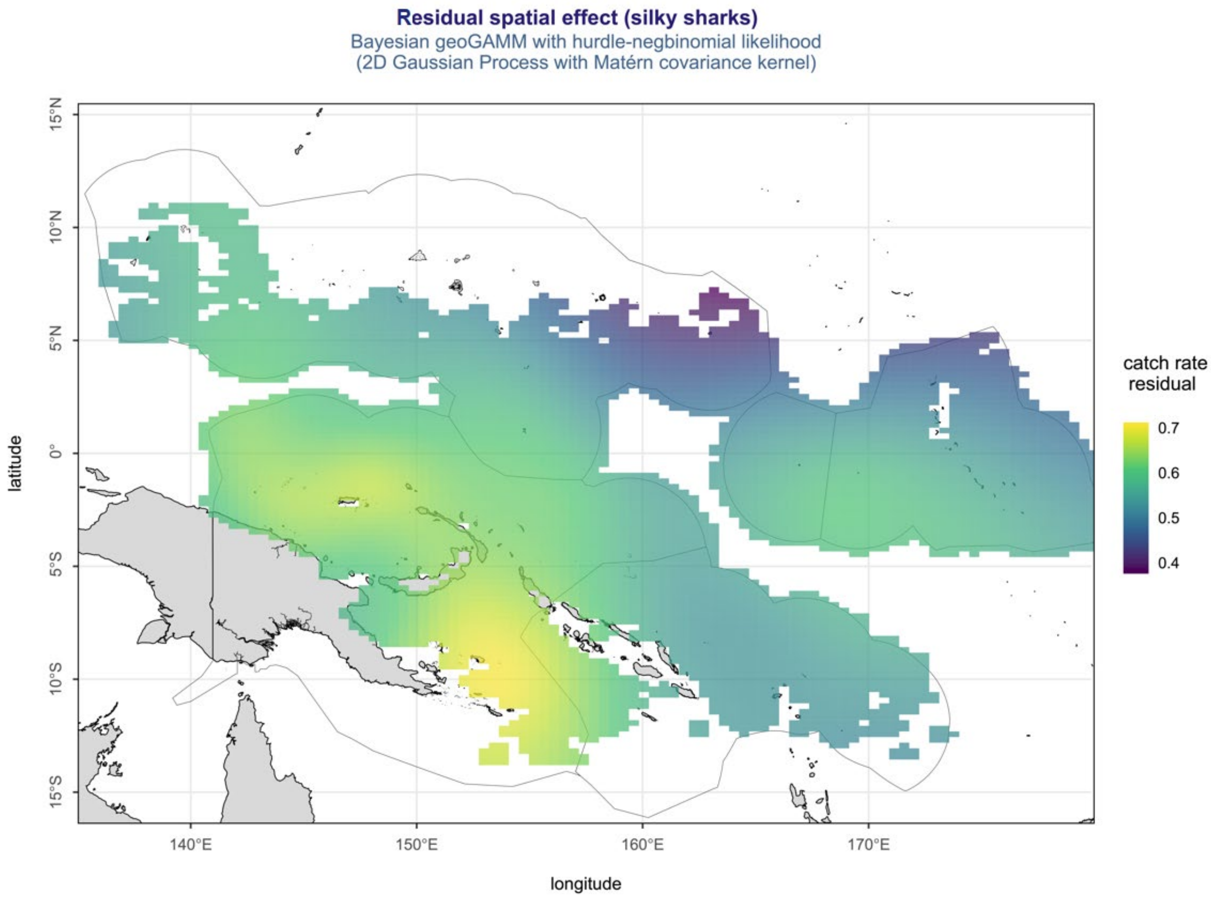
Residual spatial effect (silky sharks)
Bayesian geoGAMM with hurdle-negbinomial likelihood
(2D Gaussian Process with Matérn covariance kernel)
catch rate residual
0.7
0.6
0.5
0.4
latitude
15°N
10°N
5°N
0°
5°S
10°S
15°S
longitude
140°E
150°E
160°E
170°E

Figure 5

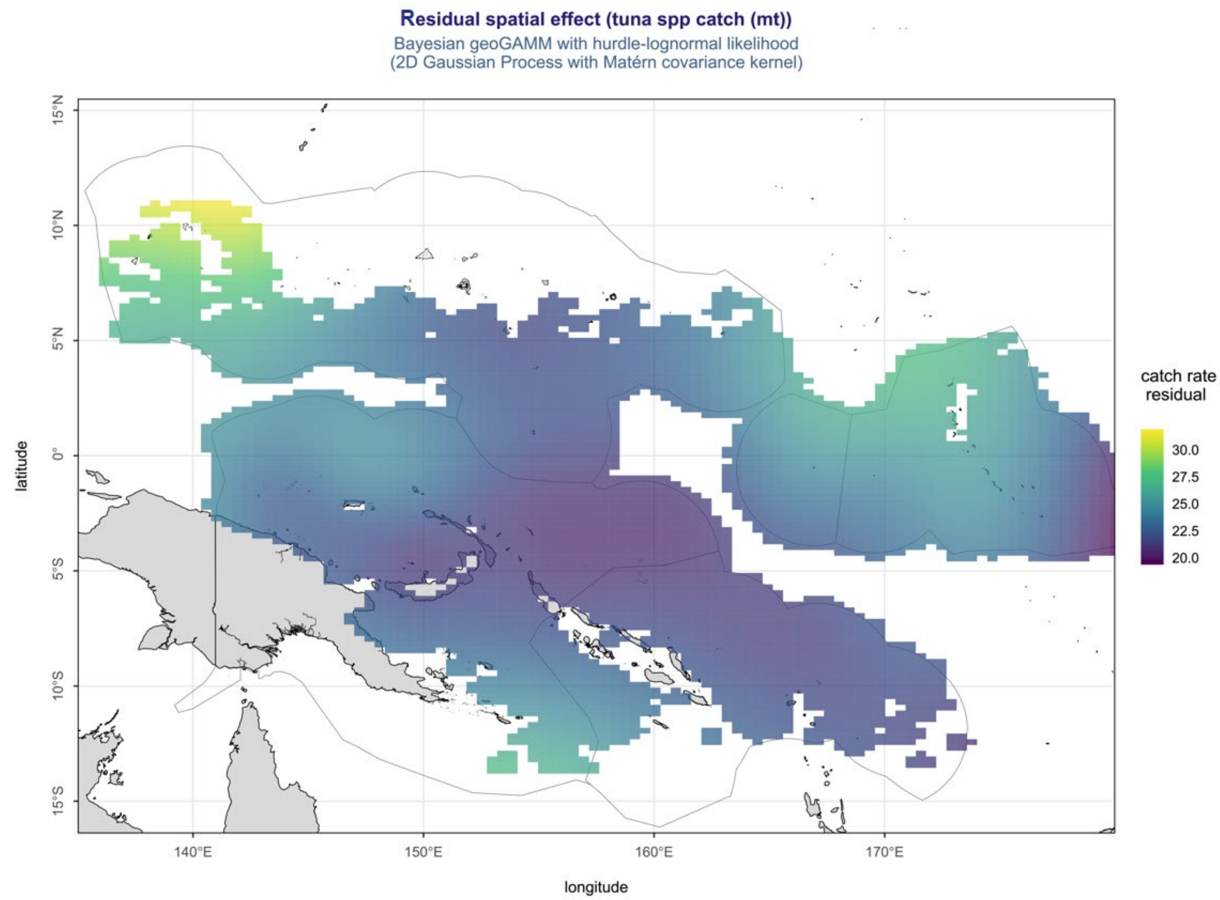
Residual spatial effect (tuna spp catch (mt))
Bayesian geoGAMM with hurdle-lognormal likelihood
(2D Gaussian Process with Matérn covariance kernel)
15°N
10°N
5°N
0°
5°S
10°S
15°S
latitude
140°E
150°E
160°E
170°E
longitude
catch rate
residual
30.0
27.5
25.0
22.5
20.0

Figure 6

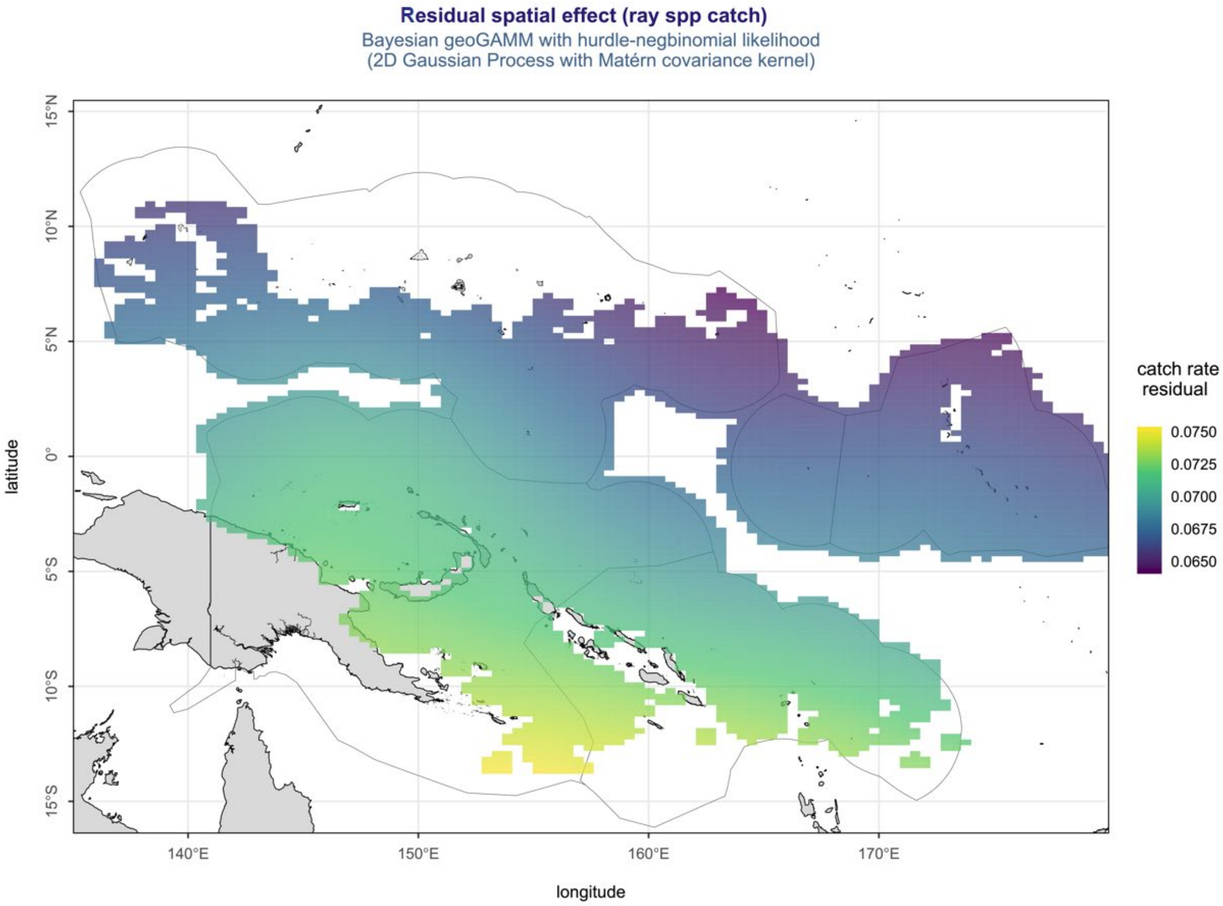
Residual spatial effect (ray spp catch)
Bayesian geoGAMM with hurdle-negbinomial likelihood
(2D Gaussian Process with Matérn covariance kernel)
15°N
10°N
5°N
0°
5°S
10°S
15°S
latitude
140°E
150°E
160°E
170°E
longitude
catch rate
residual
0.0750
0.0725
0.0700
0.0675
0.0650

Figure 7

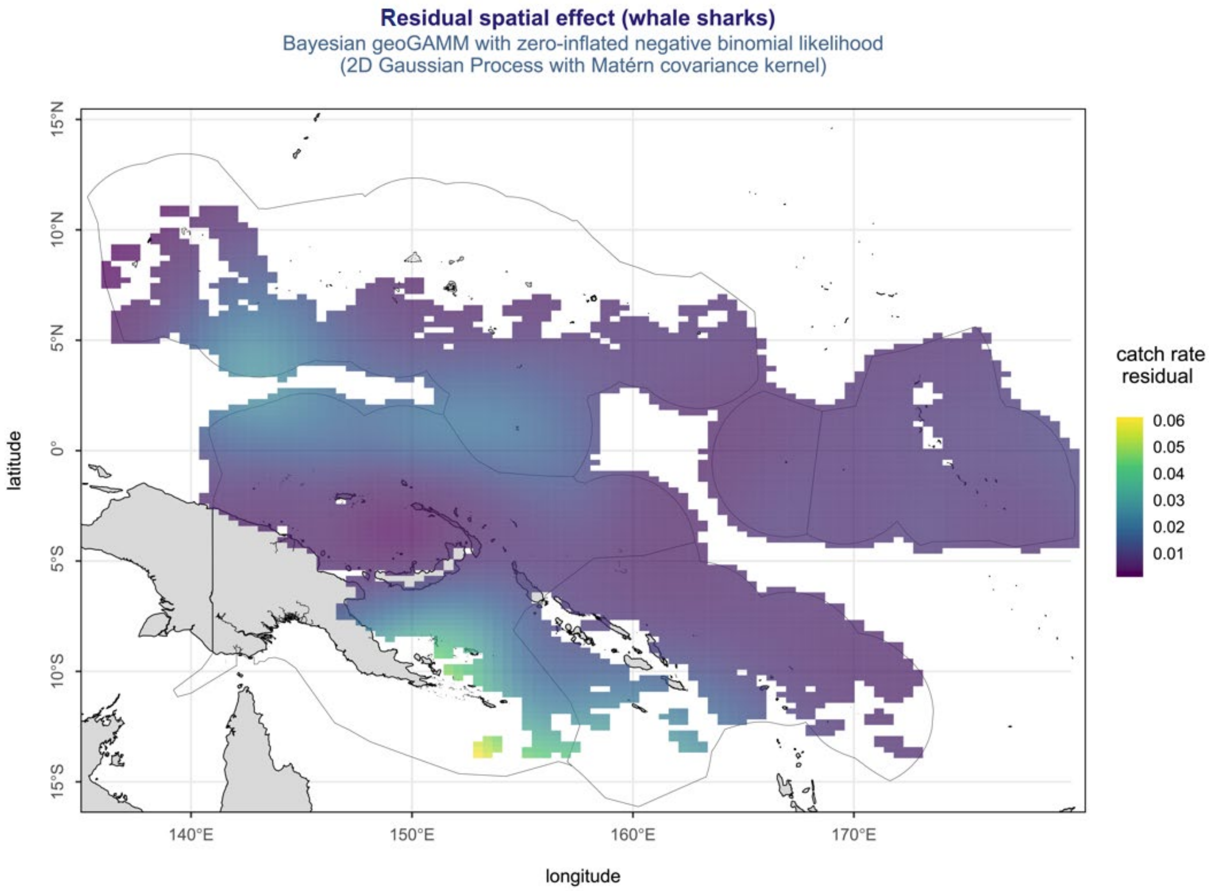
Residual spatial effect (whale sharks)
Bayesian geoGAMM with zero-inflated negative binomial likelihood
(2D Gaussian Process with Matérn covariance kernel)
15°N
10°N
5°N
0°
5°S
10°S
15°S
latitude
140°E
150°E
160°E
170°E
longitude
catch rate
residual
0.06
0.05
0.04
0.03
0.02
0.01

Figure 8