Received: 16 July 2023 | Revised: 29 September 2023 | Accepted: 26 October 2023

DOI: 10.1002/ecs2.4751

ECOSPHERE
AN ESA OPEN ACCESS JOURNAL

ARTICLE

Coastal and Marine Ecology

Evidence from interpretable machine learning to inform spatial management of Palau's tuna fisheries

Eric Gilman[1] | **Milani Chaloupka**[2]

[1]Fisheries Research Group, Honolulu, Hawaii, USA

[2]Ecological Modelling Services Pty Ltd and Marine Spatial Ecology Lab, University of Queensland, Brisbane, Queensland, Australia

Correspondence
Eric Gilman
Email: egilman@utas.edu.au

Funding information
Nature Conservancy, Grant/Award Number: A22-A-2023

Handling Editor: Sean D. Powers

Abstract

Static and dynamic area-based management tools hold substantial potential to balance socioeconomic benefits derived from fisheries and costs from bycatch mortality of at-risk species. Palau longline fisheries have high bycatch of at-risk species including the olive ridley marine turtle and silky and blue sharks. This study analyzed a two decades-long time series of observer and electronic monitoring datasets from the Palau distant-water and locally-based pelagic longline fisheries. An interpretable or explainable machine learning-based modeling approach was used to derive spatially resolved species-specific catch rate predictions. These models were conditioned on a suite of potentially informative environmental, bathymetric, ocean-climate metric, vessel, monitoring system, and set-specific operational predictors. Overall, there would be limited ecological tradeoffs from focusing fishing effort within primary catch rate hotspots for target bigeye and yellowfin tunas. Mean field prediction surfaces also defined catch rate hotspots for at-risk species of silky and blue sharks, olive ridley turtle, and pelagic stingray, which did not overlap the hotspots for target species. The predicted target species hotspots, however, overlap olive ridley and pelagic stingray warmspots. Results also identify opportunities for temporally dynamic spatial management to control catch rates of target and bycatch species. Management of fishery operational predictors of fishing depth and soak duration present additional opportunities to balance catch rates of at-risk bycatch and target species. A transition to employing 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 commercial catch. Our findings support evidence-informed evaluation of spatial management strategies and complementary measures to meet objectives for balancing socioeconomic benefits derived from target species catch with costs to threatened species.

KEYWORDS
area-based management, bycatch hotspots, dynamic spatial management

INTRODUCTION

Tuna resources supply the third most valuable globally traded aquatic products, worth about USD 14.6 billion (FAO, 2022). They also provide substantial economic revenue, employment, and food security to fishing and coastal states. Several Pacific island countries and territories obtain a large proportion of their gross domestic product from revenue from tuna fisheries, including fees from issuing licenses and effort and catch quota to foreign fishing vessels (Aqorau, 2009; Bell et al., 2015; FFA, 2015; Gillett, 2016). Capture and processing sectors generate additional revenue and substantial employment and contribute to local food security and tourism sectors in the Pacific islands region (Bell et al., 2015; FFA, 2015; Gillett, 2016).

However, fisheries targeting tunas and other highly productive species can have profound impacts on co-occurring species exposed to incidental capture, particularly when those species have low reproductive potential due to long generation lengths, low fecundity, and other life history traits that make them vulnerable to elevated mortality levels (Hall et al., 2017; Jorgensen et al., 2022; Musick, 1999). There has been increasing concern over the broad effects from selective fishery removals of pelagic apex and mesopredators such as altered population and size structure, cascading effects through top-down trophic links in some ecosystems, and reduced population fitness from fisheries-induced evolution (Cox et al., 2002; Hinke et al., 2004; Kitchell et al., 2002; Polovina & Woodworth-Jefcoats, 2013; Ward & Myers, 2005a). There has also been increasing attention to risks from bycatch to food, nutrition, and livelihood security (Jaiteh et al., 2017; Seidu et al., 2022).

Pelagic longlining has been the main commercial fishing sector of the Pacific Island nation of Palau (Dacks et al., 2020; Jaiteh et al., 2021; Republic of Palau, 2022). The Palau tuna longline fisheries have produced high value products including for the Japanese *sashimi* market and for the Palau domestic market (Dacks et al., 2020; Sisior, 2004). In 2020, the establishment of a no-take marine reserve within 80% of the Palau 594,000 km^2 exclusive economic zone (EEZ) came into effect through regulations promulgated under the Palau National Marine Sanctuary Act (Republic of Palau, 2019). Unintended consequences included displacement of effort by the locally based longline vessels to other areas of the western and central Pacific Ocean with less restrictive bycatch management frameworks (such as a Palau shark retention ban) and an abrupt, large reduction in supply of pelagic seafood to the Palau domestic market that exacerbated pressure on overstressed nearshore resources including coral reef fish communities (Gillett, 2016; Jaiteh et al., 2021; SPC & FFA, 2015; Wabnitz et al., 2018). The Palau government is now reevaluating spatial management strategies for commercial tuna fisheries (Palau MAFE, SPC, & U.S. Department of State, 2022; Palau Office of the President, 2022).

Ecological objectives of area-based management tools (ABMTs) for blue water fisheries include contributing to maintaining stocks of principal market species above limit and near target thresholds, reducing incidental bycatch including threatened species, protecting habitat critical for certain life stages of species exposed to fisheries, reducing trait-based selective fishing mortality and fisheries-induced evolution, and maintaining ecosystem structure and functions (Gilman, Kaiser, et al., 2019; Hilborn et al., 2022). A review of blue water protected areas concluded that they have relatively high promise to mitigate fisheries bycatch of threatened species, to protect habitats important for critical life history stages of some species, and to increase local abundance of target stocks (Gilman, Kaiser, et al., 2019). However, few studies have assessed ecological responses to blue water ABMTs, providing a limited basis for causal inferences (Gilman, Kaiser, et al., 2019).

Pelagic longline principal market species are highly migratory and fecund broadcast spawners with extensive spawning grounds, wide larval dispersal, and protracted spawning seasons (Collette et al., 2011; Dueri & Maury, 2013; Schaefer, 2001). Thus, protection by a no-take reserve of a very small proportion of their total distribution, of the individuals of a stock, of spawning stock biomass, and of spawning habitat, as is the case for the Palau sanctuary, is expected to have minimal effect on recruitment or absolute biomass (Essington, 2010; Gilman, Kaiser, et al., 2019; Hampton et al., 2023; Myers et al., 1999; Stefansson & Rosenberg, 2006). However, some longline-targeted species may have residency times ranging from months to years (Adam et al., 2003; Sibert & Hampton, 2003). No-take reserves could provide protection to individuals for a sufficient proportion of their lifetime during which a large proportion of their total growth occurs, augmenting their local biomass (number of individuals and body size) within the protected area and adjacent spillover areas (Boerder et al., 2017; Bucaram et al., 2018; Filous et al., 2022; Gilman, Kaiser, et al., 2019). Furthermore, if the recent proliferation of large blue water marine-protected areas (Gannon et al., 2017; Marine Conservation Institute, 2023) continues, then the cumulative area of the network of reserves could reach the substantial area required to affect absolute stock biomass (Stefansson & Rosenberg, 2006).

ABMTs are one of a suite of available approaches for fisheries management, where an ensemble of measures is often needed to achieve objectives (Selig et al., 2017).

The Palau longline fisheries have apparently high bycatch of at-risk species such as olive ridley turtles (*Lepidochelys olivacea*) and silky (*Carcharhinus falciformis*) and blue (*Prionace glauca*) sharks (Gilman et al., 2016; Jaiteh et al., 2021). There are now numerous methods available to mitigate at-risk species bycatch in pelagic longline fisheries that are also commercially viable and that support a range of approaches for effective compliance monitoring (Hall et al., 2017; Poisson et al., 2016). This includes both static and dynamic ABMTs, which hold substantial potential to balance fishery-dependent socioeconomic benefits and costs to threatened species exposed to bycatch fishing mortality, including in pelagic longline and other blue water fisheries (Gilman, Chaloupka, Fitchett, et al., 2020; Gilman, Kaiser, et al., 2019; Halpern, 2003; Mannocci et al., 2020; Slooten, 2013).

This study provides evidence to inform spatial management strategy evaluation for the Palau pelagic longline fisheries. The study objectives were to (1) identify any spatially and temporally predictable hot and cold spots for principal market species and at-risk bycatch species and (2) determine whether static and dynamic spatial fishery closures might provide practical options for separating hotspots for target and at-risk bycatch species catch rates. Findings are intended to help support evidence-informed policy for the Palau government to apply area-based fisheries management approaches to balance minimizing threatened species bycatch with maximizing target species catch.

METHODS

Data sources and study area

The study used monitoring data from two pelagic longline fleets that fish in the Palau EEZ: (1) a distant-water Japan-based fishery and (2) a locally based fishery. The study analyzed observer and electronic monitoring (EM) datasets for fishing conducted within and adjacent to the Palau EEZ, summarized in Appendix S1: Table S1 and displayed in Appendix S1: Figure S1. Of the 1,638 sets in the study sample, 26 were made during Palau locally based trips in areas adjacent to the Palau EEZ seaward margin, in a high seas pocket and in the Indonesia EEZ. Locally based vessels would periodically fish in adjacent areas when catch rates of commercial species within the Palau EEZ were poor (personal communication, 16 June, 2023, Terry Huang, former base manager, Pacific International Trading Inc.). The six vessel flag states of locally based vessels were China ($N = 88$ sets), Cook Islands ($N = 51$ sets), Kiribati ($N = 12$ sets), Palau ($N = 206$ sets), Taiwan ($N = 433$ sets), and Vanuatu ($N = 4$ sets). The distant-water sampled effort was conducted by Japanese-flagged vessels.

During the study period, logbook data indicate that the observer and EM-monitoring coverage rate was 1.1% of sets, and 0.7% and 11.2% of sets made by the locally based and distant-water fleets, respectively. The logbook dataset is missing records, and therefore, these monitoring coverage rates are overestimates.

The fleet-specific set intensity is summarized using a 2D kernel density estimator (Appendix S1: Figure S1) (Venables & Ripley, 2002). Set locations are not shown to reduce visual clutter, to prevent obscuring the density bands, and to comply with data confidentiality requirements. The distant-water pelagic longline fleet operated mainly in the western region of the Palau EEZ while the locally based fishery operated mainly in the eastern region (Appendix S1: Figure S1). The number of observed longline sets by the locally based fishery increased significantly during the 5-year period from 2006 to 2010 and then again during the 5-year period from 2016 to 2020.

There were 28 potentially informative continuous and nominal categorical predictors, summarized in Appendix S1: Table S2 (see also Appendix S1: Table S3 for a summary of SHAP value-based predictor importance). The section below, *Potentially informative environmental and pelagic habitat predictors*, provides details on the environmental and bathymetry predictors. Other potentially informative predictors were excluded due to data quality constraints such as use of "shark lines" and hook size (see Gilman et al., 2016).

Overview of statistical modeling workflow

We used recent advances in machine learning (ML) approaches coupled with Shapley additive feature explanations (SHAP) to derive interpretable species-specific and spatially resolved catch predictions for pelagic longline fishing fleets that fish in the Palau EEZ for bigeye tuna (*Thunnus obesus*), yellowfin tuna (*T. albacares*), combined billfishes (1621 swordfish *Xiphias gladius*, 1623 istiophorid billfishes—mainly blue marlin *Makaira nigricans* and Indo-Pacific sailfish *Istiophorus platypterus*), silky shark, blue shark, pelagic stingray (*Pteroplatytrygon violacea*), and olive ridley turtle. Our modeling workflow, outlined in detail below, can be summarized as follows: (1) identify and extract potentially informative environmental predictors; (2) impute missing values for key operational predictors such as hook type, bait type, and hooks per set using chained imputation procedures; (3) identify the ML algorithm appropriate for each of the species-specific catch data time series in terms of potential predictive performance; (4) fit the species-specific spatially resolved ML models with the set of 28 potentially informative predictors; (5) explore model fit using recent advances in interpretable ML tools using SHAP values for assessing the predictor marginal effects; and (6) derive spatially resolved catch (or bycatch) prediction surfaces or maps for each species to support evidence-informed marine spatial planning.

Potentially informative environmental and pelagic habitat predictors

We focused on using macro-scale ocean/climate indicators such as the Pacific Decadal Oscillation (PDO) index and Multivariate El Niño Southern Oscillation (ENSO) Index (MEI) as potential environmental drivers known to affect both pelagic fish and marine turtle productivity (Bjorndal et al., 2017; Free et al., 2019; Newman et al., 2016). 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 index and MEI were then matched with the month of each pelagic longline set—the PDO and MEI time series lagged by 1–3 months and 12 months were also included to potentially reflect any delay in ocean productivity response to ocean temperature effects (Bjorndal et al., 2017; Reisinger et al., 2022; Saba et al., 2007). Seascape features and depth are related predictors affecting pelagic biodiversity hotspots and tuna catch rates in the Pacific Ocean (Gilman et al., 2012; Morato et al., 2010), so 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). Lunar illumination has been shown to be informative of tuna catch in the Palau region (Gilman et al., 2016), so we sourced predicted moonlight intensity for the date: time and geolocation of each set using the moonlit package for R (Śmielak, 2023). The strength of correlation among all the continuous predictors (including spatial predictors: longitude and 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.

ML-based missing data imputation

Dealing with missing data in one or more predictors is a major challenge for principled statistical modeling (Kuhn & Johnson, 2013; 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). Around 60% of the 1683 sets were missing one of the following three predictors (hook type, leader type, and lightstick usage), while 48% of the sets were missing number of hooks deployed per set and 24% were missing bait type with 4% missing number of hooks between floats. Some sets were missing multiple predictors with 26% of sets missing all three predictors (hook type, leader type, and lightstick) while 8% of the sets were missing all five predictors (hook type, leader type, lightstick, bait type, and hooks per set). The missing data were not *missing completely at random* (MCAR) as determined with a test for MCAR (Little, 1988; χ^2 test $= 1561$, $\mathrm{df} = 52$, $p < 0.0001$) using the nanair package for R (Tierney & Cook, 2023)—so naively deleting missing cases or variables in our study is simply not appropriate but requires modeling the missingness instead to support robust statistical inference (Gelman & Hill, 2006; Murray, 2018). 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 a high-dimensional dataset considered here, this sort of Bayesian measurement-error modeling procedure (Goldstein et al., 2018; Richardson & Gilks, 1993) is not computationally feasible. Here we used a fast multivariate missing data imputation approach based on multiple chained random forests (RFs) (an ensemble ML algorithm) to impute all missing data for all continuous and categorical predictors using the missRanger package for R (Mayer, 2021) with the ranger package for R as the backend (Wright & Ziegler, 2017)—all missing data were simultaneously imputed multiple times until the minimum mean out-of-bag error was found (Mayer, 2021). The chained RF 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 comprises the original 1683 sets and 28 predictors but now without any missing values and so was the dataset then used in all our subsequent analyses. It is important to note that ML approaches like RF make minimal assumptions about data distributions or data dependence and require no data transformation.

Statistical modeling approach

We then used ML-based modeling approaches (Kuhn & Johnson, 2013), coupled with recent developments in explainable artificial intelligence (AI) tools (Lundberg et al., 2020; Qiu et al., 2022; Scholbeck et al., 2020), to derive interpretable species-specific and spatially resolved catch predictions for pelagic longline fishing fleets that operate in the Palau EEZ. ML approaches are increasingly used in a wide range of knowledge domains including medicine, finance, geoscience, ecology, paleobiology, climatology, fisheries, marine spatial planning, and economics to derive informed predictions from data that could include spatial–temporal structures, nonlinear predictor functional form, and complex predictor interactions (Bergen et al., 2023; Dedman et al., 2017; Effrosynidis et al., 2020; Foster et al., 2022; Gerassis et al., 2021; Sokhansanj & Rosen, 2022; Viquerat et al., 2022; Yang et al., 2022). ML-based approaches are powerful tools for applied predictive modeling and make few assumptions about data structures (Kuhn & Johnson, 2013). However, ML models are often considered difficult to understand, explain, and interpret—a common lament being that they might predict well but who knows why. A rapidly evolving area of ML/AI-based computer science research has been directed toward resolving that long-standing concern by developing both model-specific and model-agnostic interpretable ML or *explainable* AI tools (Lundberg et al., 2020; Wikle et al., 2023). So, our modeling workflow, outlined in more detail below, comprises spatial ML-based predictive modeling for each of the seven species-specific catch data series and then model-specific predictions explored using model-agnostic tools to derive insight into which predictors are driving the predictive performance of each model. Model-agnostic interpretable tools are general and can be applied to any predictive model based on any type of algorithm (ML, generalized linear model [GLM], generalized linear mixed effects model [GLMM], generalized additive mixed effects model [GAMM], etc.), whereas model-specific tools can only be applied to a specific ML algorithm (Wikle et al., 2023).

Selecting an appropriate ML algorithm

The first challenge in our modeling workflow was to determine which ML algorithm was the most applicable for the species-specific longline fishery catch data. Usually, ML-based applications apply a single prediction algorithm often with little if any specific knowledge domain justification. Here, we adopt an automatic ML or AutoML procedure (He et al., 2021; Steinruecke et al., 2019) in the first instance to explore which prediction algorithm might be best suited for each of the species-specific catch time series. We used the AutoML procedure on the H2O.ai platform (H2O.ai, 2022; LeDell & Poirier, 2020) via both the h2o (LeDell et al., 2023) and agua (Kuhn et al., 2023) interface packages for R to (1) explore, (2) hyperparameter tune, and (3) evaluate a large number of regression or classification models using six prediction algorithm classes (gradient boosting machine, xgboost, distributed RF, neural nets, GLM, and stacked ensemble) and four 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 (mean absolute error [MAE], root mean square error [RMSE], R^2, mean residual deviance) for the regression-based models and (area under the curve, accuracy, RMSE, logloss) for classification-based models (see Kuhn & Johnson, 2013). All ML modeling workflows were applied within the tidymodels meta-learning framework for R (Kuhn & Wickham, 2020).

Species-specific interpretable ML models

We then fitted the species-specific supervised ML algorithm determined using AutoML to each of the seven species-specific catch data series using all of the 28 predictors. The response variable (hence *supervised*) in the case of six species (yellowfin tuna, bigeye tuna, pelagic stingray, billfish, blue shark, and silky shark) was the recorded set-specific catch with hooks per set as a nonproportional effort proxy (Davies & Jonsen, 2011) being one of the potentially informative predictors. On the other hand, the olive ridley turtle bycatch was low with 94% of sets recording zero turtles, 4% of sets with one turtle, and 2% of sets with two or more turtles—so the set-specific response variable was recoded as a binary classification (0, ≥1) and then the ML model fitted with Bernoulli likelihood and again hooks per set being one of the potentially informative predictors. We did not adjust for response class-imbalance using for instance the commonly used synthetic minority over-sampling (SMOTE) or perhaps other data augmentation approaches because (1) olive ridley bycatch is in fact a rare event in these particular fisheries (Gilman et al., 2016) and (2) SMOTE-based class-imbalance adjustment is of questionable benefit for ML approaches (Blagus & Lusa, 2013). Again, all modeling workflows were applied within the tidymodels meta-learning framework for R (Kuhn & Wickham, 2020).

We used SHAP-based summary and SHAP-based dependence plots to help explain model performance and derive insight into the predictor functional form and any informative interactions with other predictors. SHAP is an acronym of sorts for Shapley additive feature values (Lundberg et al., 2020) where "feature" is an ML term synonymous with the term "predictor." A SHAP value is the average or expected marginal contribution of that predictor value to the predicted 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. So, in our context, higher SHAP values imply greater contribution of a specific predictor to the catch rate.

A SHAP-based 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 1683 set-specific values. SHAP values account for all predictive information in a specific feature that results from interactions and dependencies with other features or predictors in the model. A SHAP dependence plot is the ML equivalent of an average marginal effect summary in inferential-based modeling that shows the apparent functional form of the selected predictor and interaction with the most important conditioning variable found for that selected predictor. It provides insight into any complex nonlinear effect of that predictor on the pelagic longline catch for that species.

These two tools (SHAP summary and dependence) are both necessary and sufficient to help interpret and understand the main drivers of the predictive performance of each species-specific catch model and were derived using (1) the kernelshap R package (Mayer & Watson, 2023) to calculate model-agnostic SHAP values for each of the 1683 sets in each of the seven species-specific predictive models and then (2) SHAP summary and dependence visualization using the shapviz R package (Mayer, 2023).

Spatial ML models

All ML models fitted in the previous section included the georeferenced location of each set—so longitude and latitude were included as specific predictors. This approach is a common practice in ML-based species distribution models to identify for instance apparent regional hotspots for interactions between marine species of concern and fishing gears (Burns et al., 2023). However, this approach does not explicitly account for potential local neighborhood effects or covariance structure between the georeferenced locations. Nonetheless, it has been shown recently that SHAP-augmented ML approaches such as *xgboost* can indeed perform as well as more conventional spatially explicit statistical models to account for explicit spatial effects and provide robust spatial predictions (Li, 2022). Nevertheless, we conducted extensive spatial cross-validation using nearest neighbor distance matching-based resampling strategies (Milà et al., 2022) to determine whether predictive model performance would be improved by accounting for explicit spatial structure in all our ML models (see Appendix S1: Section S1, *Geospatial Model Evaluation Approach*, which shows that accounting more explicitly for spatial structure could be beneficial for predictive model performance).

There are several spatial regression type ML methods to explicitly account for spatial covariance (see Georganos & Kalogirou, 2022), including spatial RF with eigenvector spatial filtering (Liu, Jin, et al., 2022; Liu, Kounadi, et al., 2022; Reisinger et al., 2022)—an approach also used in a more conventional GLM(M)-based model of coral bleaching on the Great Barrier Reef (Hughes et al., 2021). We used the spatialRF R package (Benito, 2021) with eigenvector spatial filtering (Dray et al., 2006) and a matrix of the distance (in kilometers) between all sets to further explore species-specific spatial effects using the top 10 SHAP summary predictors determined previously using the species-specific ML models. The distance matrix was calculated using the geodist package for R (Padgham, 2021). This approach was used for the six species with a continuous catch response variable (yellowfin, bigeye, pelagic stingray, billfish, blue shark, and silky shark) since it turns out that all species are best fit using an RF algorithm. The distance thresholds for spatialRF model fits ranged from 0 to 1000 km to assess potential spatial autocorrelation using Moran's I metric (Pebesma & Bivand, 2023). We can also assess which of the predictors contribute more importantly to supporting model transferability (see Ludwig et al., 2023) using spatialRF with spatial cross-validation.

However, the response variable for the olive ridley turtle was binary and was best fit using a gradient boosting machine not RF. So, for the olive ridley, we used a mixed-effects spatial gradient boosting machine ML model (GPBoost) to explicitly account for spatial effects and nonlinear predictor functional form (Sigrist, 2023). We fitted this spatial ML model using the gpboost R package (Sigrist, 2023), which uses the LightGBM algorithm (Ke et al., 2017), and the structured spatial effects are modeled using Gaussian processes with a Matérn covariance kernel (Gelfand & Schliep, 2016). See Zhou et al. (2022) for a recent example of using GPBoost with SHAP-based explanations to predict and interpret manual car driver fatigue or Sokhansanj and Rosen (2022) for predicting COVID-19 disease severity.

The spatially explicit models for each of the seven species were then used to derive a species-specific spatial prediction for each of the 1683 sets. Then these set-specific predictions were used to derive spatially resolved species-specific prediction surfaces to support evidence-informed marine spatial planning. So, we rasterized the spatialRF- and gpboost-derived set-specific predictions for each species but limit the spatial surface predictions within close proximity of the set geolocations used in training the ML models in the first place (Meyer & Pebesma, 2022).

We do that spatial interpolation (Pebesma & Bivand, 2023) using a generalized additive model or geoGAM(M) (Kammann & Wand, 2003) with response-specific likelihood and georeferenced set locations modeled as a 2D Gaussian process surface with Matérn covariance kernel (Gelfand & Schliep, 2016). These models were fit using the Stan computation engine (Carpenter et al., 2017) via the brms R interface with the cmdstanr backend (Bürkner, 2017). A similar two-step ML-based modeling process for spatially explicit data to derive prediction surfaces can be found in modeling of wind speeds (Li, 2019) and bike-sharing activities (Schimohr et al., 2023).

Throughout the entire workflow, we used the tidyverse R meta-package (Wickham et al., 2019) for data pre- and post-processing, terra R package for spatial data processing (Hijmans, 2023), sf R package for vector-based mapping (Pebesma, 2018), and ggplot2 R package (Wickham, 2016) for visualizations with the *viridis* color palette from the colorspace R package (Zeileis et al., 2020) that was used for the SHAP summary and dependence plots and the mapped spatial prediction surfaces. The patchwork R package (Pedersen, 2022) was used for multi-panel plot layouts.

RESULTS

Appropriate ML algorithm for each species

The most appropriate ML algorithm to be applied to each species-specific dataset identified using AutoML was (1) distributed RF (Breiman, 2001) for six species (yellowfin tuna, bigeye tuna, pelagic stingray, billfish, blue shark, and silky shark) and (2) a gradient boosting machine such as XGBOOST (Chen et al., 2023) or LightGBM (Ke et al., 2017) for the olive ridley model with Bernoulli likelihood. The AutoML performance metric ranking plot for yellowfin tuna is shown as one species-specific example in Figure 1. RF predictive performance for all four metrics was ranked very close to that for stacked ensembles (comprising a complex mix of both best-in-each-algorithm-class and all algorithms) and far better ranking than for gradient boosting machines (including XGBOOST) and substantially better than a GLM or neural net. A similar pattern of comparative RF predictive performance was apparent for the other five species.

Species-specific interpretable ML models

ML models with RF-based regression using the ranger (Wright & Ziegler, 2017) engine were then applied to each data catch set for the six species (yellowfin tuna, bigeye tuna, pelagic stingray, billfish, blue shark, and silky shark) that were identified as best modeled using RF by AutoML. The olive ridley turtle model was fit using XGBOOST-based classification with Bernoulli likelihood using the H2O engine (LeDell et al., 2023). All workflows were applied within the tidymodels meta-learning framework for R (Kuhn & Wickham, 2020) to ensure consistent application of each algorithm and derive the output suitable for calculating Shapley values for the SHAP Summary and Dependence plots.

The mean absolute SHAP values for each of the 28 predictors for each of the seven species are summarized in Appendix S1: Table S3. We show the SHAP summary plots for two target species (yellowfin tuna and bigeye tuna) and two at-risk bycatch species (silky shark and olive ridley turtle) to help identify the most important marginal predictor effects of catch for those specific species. SHAP summary plots for billfishes, pelagic stingray, and blue shark are included in Appendix S1: Section S3. SHAP values indicate the species-specific relative effect (rank order) on catch rate (catch per set) conditioned on 28 potentially informative predictors. We refer to the top five predictors with the highest SHAP value for each species as having important marginal predictor effects of species-species catch rate, where the SHAP values indicate the species-specific rank order on catch per set conditioned on 28 potentially informative predictors.

Commercial species

The SHAP summary plot for the predicted yellowfin tuna catch is shown in Figure 2 where the top five predictors in descending order of importance were latitude, longitude, soak duration, fishing year, and month of fishing year. Higher yellowfin tuna catch was predicted at lower latitudes, more westward longitudes, at longer soak durations, later in the season (month) and in more recent years. The "fleet origin" predictor shows that predicted yellowfin catch was higher in the distant-water fleet than the local fleet.

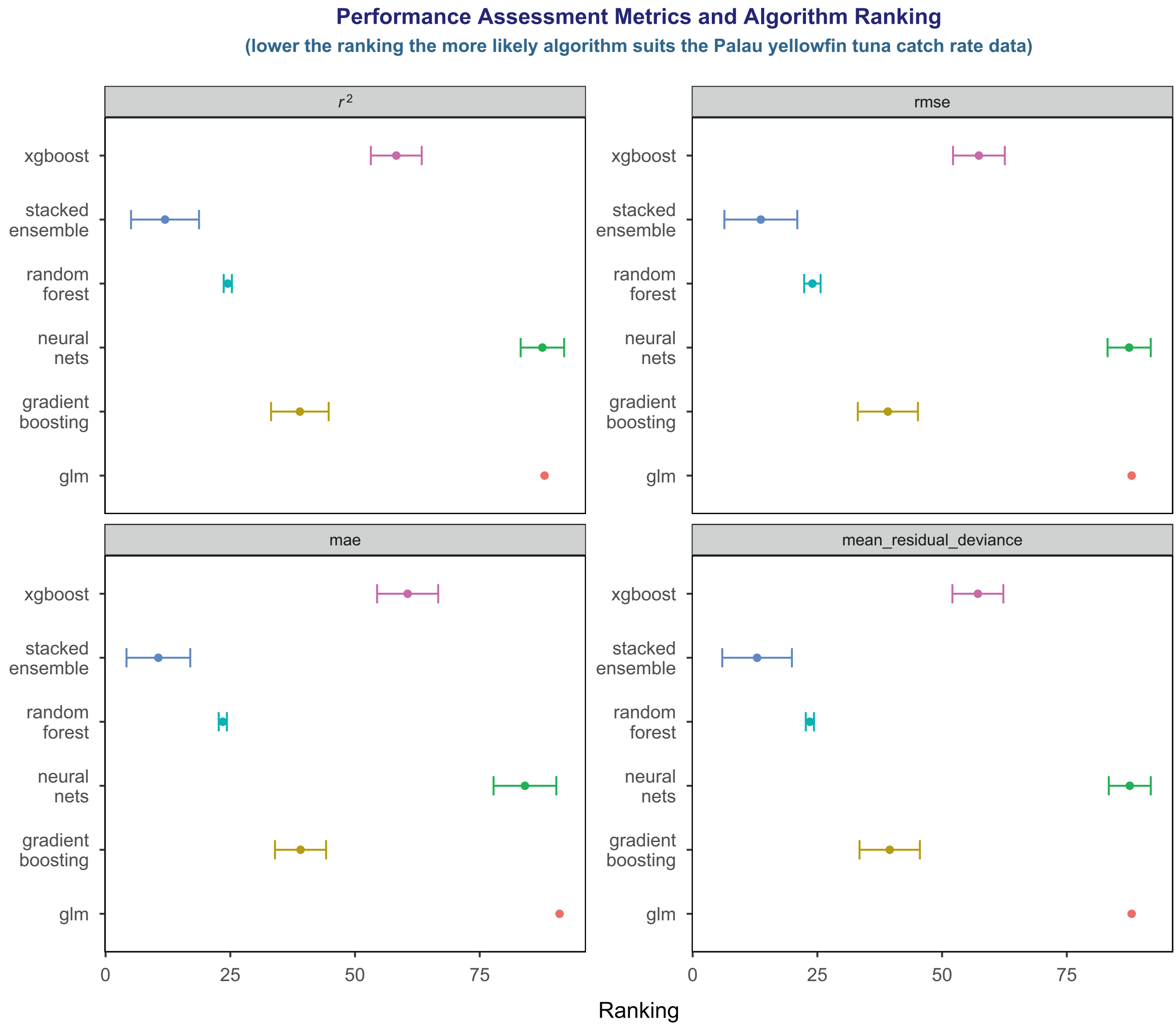

FIGURE 1 Machine learning algorithm selection based on four performance assessment metrics for the yellowfin tuna catch data series. The distributed random forest class has the best ranking relative to the stacked ensemble class and also shows little variability. GLM, generalized linear model; MAE, mean absolute error; RMSE, root mean square error.

The SHAP summary plot for the predicted bigeye tuna catch is shown in Figure 3 where the top five predictors in descending order of importance were soak duration, use of lightsticks, fleet origin, vessel flag state, and hooks between float. Higher bigeye tuna catch was predicted at longer soak durations, when lightsticks were used, in the distant-water Japanese-flagged fleet, and for the locally based Chinese-flagged vessels, and for higher number of hooks between floats. Spatial predictors (longitude and latitude) were in the top 10 but not as important predictors of bigeye catch compared with yellowfin tuna catch (Figure 2).

Appendix S1: Figure S8 shows the SHAP summary plot for billfishes. The top five predictors of the 28 predictors in descending order of importance were the fishing year, number of hooks between float, vessel flag, MEI in the most recent previous month of set deployment (no lag), and latitude. Billfish catch was lower (<0 SHAP value) in recent years, higher for sets with fewer hooks between floats (>0 SHAP value), and higher for Taiwanese-flagged vessels.

At-risk species

The SHAP summary plot for the predicted silky shark catch is shown in Figure 4. The main predictors were, in descending order, the vessel flag state (vessels),

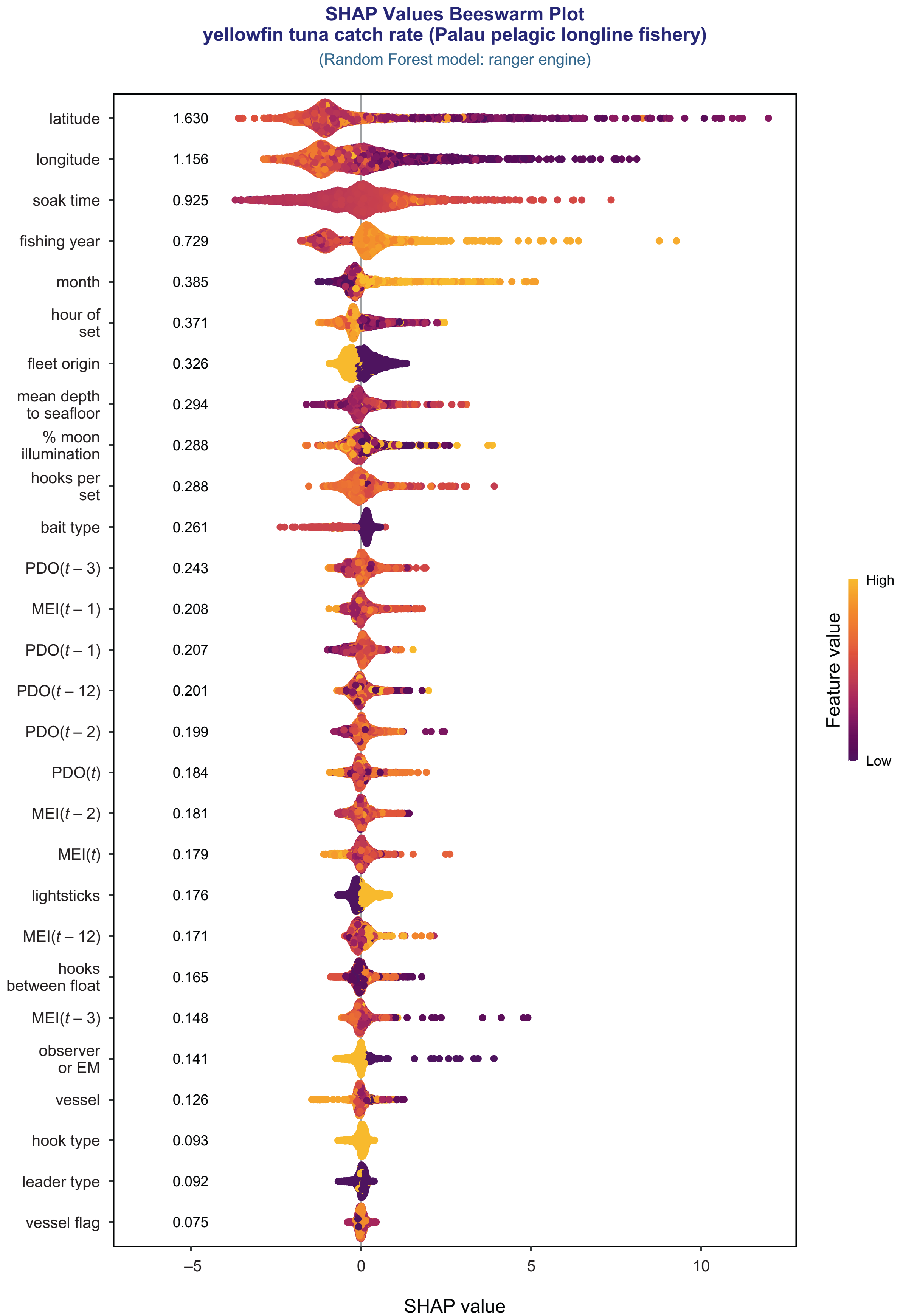

FIGURE 2 Legend on next page.

PDO in the recent month, bait type, and the two spatial predictors. Higher silky shark catch was predicted for the Taiwanese-flagged vessels, at negative PDO index values reflecting cooler regional sea surface temperatures (SST) (Houk et al., 2020), and more westward but for a range of latitudes. Lower silky shark catch was predicted for sets deployed with fish bait compared with sets using squid or a mix of squid and fish for bait.

The SHAP summary plot for the predicted olive ridley turtle bycatch is shown in Figure 5. The top five predictors in descending order of importance were latitude, bathymetric depth, intensity of lunar illumination, hooks per set, and longitude. Higher bycatch was predicted at lower latitudes and more westward, and higher moonlight intensity was predicted for the set-specific date:time and higher fishing effort (hooks per set). The bathymetric depth marginal effect is a more complex nonlinear effect and best revealed with a SHAP dependence plot (see below).

The SHAP summary plot for the predicted pelagic stingray catch is shown in Appendix S1: Figure S9. Only the top 10 of the 28 predictors are included in Appendix S1: Figure S9. The top five of the 28 predictors in descending order of importance were monitoring method (EM or observer), time of day of the start of the set, latitude, MEI 12 months prior, and season (month). Stingray catch was lower for observer recorded catch than for EM-based records (EM recorded higher catch). Catch was higher earlier in 24-h cycle, higher for those sets deployed at lower latitudes, and higher later in the season.

The SHAP summary plot for the predicted blue shark catch is shown in Appendix S1: Figure S10. The top five of the 28 predictors in descending order of importance were latitude, monitoring method, time of day of the start of the set, season, and number of hooks between floats. Blue shark catch was higher at higher latitudes, higher for observer program recorded catch than for EM system records, higher later in 24-h cycle, lower later in the season, and higher with more hooks between floats.

SHAP dependence plots

Now we consider SHAP dependence plots for the two target species and two selected at-risk bycatch species to further clarify marginal predictor functional form and predictor interaction effect on predicted catch or bycatch.

The SHAP dependence plot for the predicted yellowfin tuna catch is shown in Figure 6 where panels a–c show the top three SHAP-based predictors (latitude, longitude, and soak time) conditioned by the most important interaction predictor. Figure 6a shows the predicted nonlinear relationship between the predicted catch (SHAP value on the *y*-axis) and latitude and the predicted interaction with longitude: each dot in the plot is the predicted set-specific catch summarized as a SHAP value. It is evident here that yellowfin tuna catch was highest at low latitudes eastward of 132° E—other more nuanced trends are also apparent. Catch decreases westward (Figure 6b) and shows a stronger relationship with soak time for the distant-water fleet (Figure 6c). Figure 6d shows that while predicted catch for yellowfin tuna was not only higher for the distant-water fleet (see Figure 2) but the higher catch for this fleet occurred at lower latitudes (Figure 6d). Other effects are apparent in all panels of Figure 6 that reflect the discovery of nuanced interactions between the predictors.

The SHAP dependence plot for the predicted bigeye tuna catch is shown in Figure 7 where panels a–c show the top three SHAP-based predictors (soak time, lightsticks, and fleet origin) conditioned by the most important interaction predictor. Figure 7a shows a similar pattern for soak time effect on predicted bigeye catch as found for yellowfin tuna (Figure 6c)—a stronger soak time effect for the distant-water fleet. Catch was higher when lightsticks were used and lightstick catch itself was lower for sets that occurred at higher MEI values (warm ENSO phase) and perhaps similar to the effect for the distant-water fleet shown in Figure 7c. Figure 7d shows that predicted bigeye catch was higher for the vessels flagged to China, the Cook Islands, and Japan and that

FIGURE 2 SHAP summary plot for the yellowfin tuna random forest model. The beeswarm density polygon for each predictor (or feature) shows a dot for each of the 1683 set-specific Shapley values. The predictors, shown on the left-hand side of the plot panel, are arranged in descending order of relative importance based on the mean absolute Shapley value of each beeswarm density polygon. SHAP values to the left of the zero SHAP value centerline show predicted negative effect of that predictor on yellowfin tuna catch (catch decreases) and to the right show positive impact (catch increases). The color legend shows the direction of the predicted impact of that predictor or feature. For example, there was higher yellowfin tuna catch at lower latitudes (latitude), in more recent years (fishing year) and later in the season (month), and lower catch expected from the local longline fleet and higher catch for the distant-water fleet (fleet origin). For this latter predictor, fleet origin, with categorical and not numerical values, the alphabetical order of the first letters of the two predictor categories of locally based and distant water is used to assign which category is low and high on the color legend, where, in this case, distant water is low/purple and locally based is high/yellow. EM, electronic monitoring; MEI, Multivariate El Niño Southern Oscillation Index; PDO, Pacific Decadal Oscillation; SHAP, Shapley additive feature explanations.

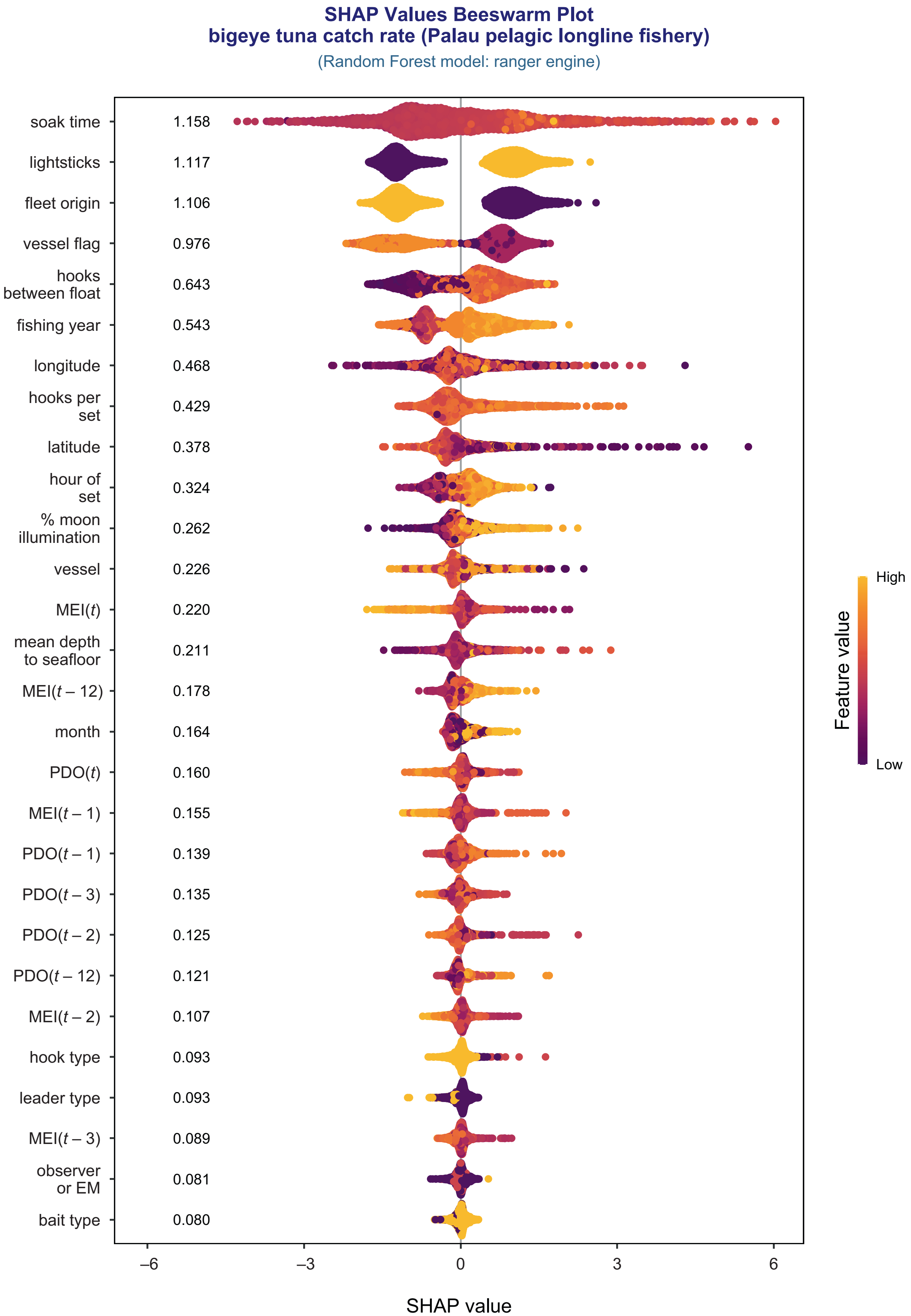

FIGURE 3 SHAP summary plot for the bigeye tuna random forest model. EM, electronic monitoring; MEI, Multivariate El Niño Southern Oscillation Index; PDO, Pacific Decadal Oscillation; SHAP, Shapley additive feature explanations.

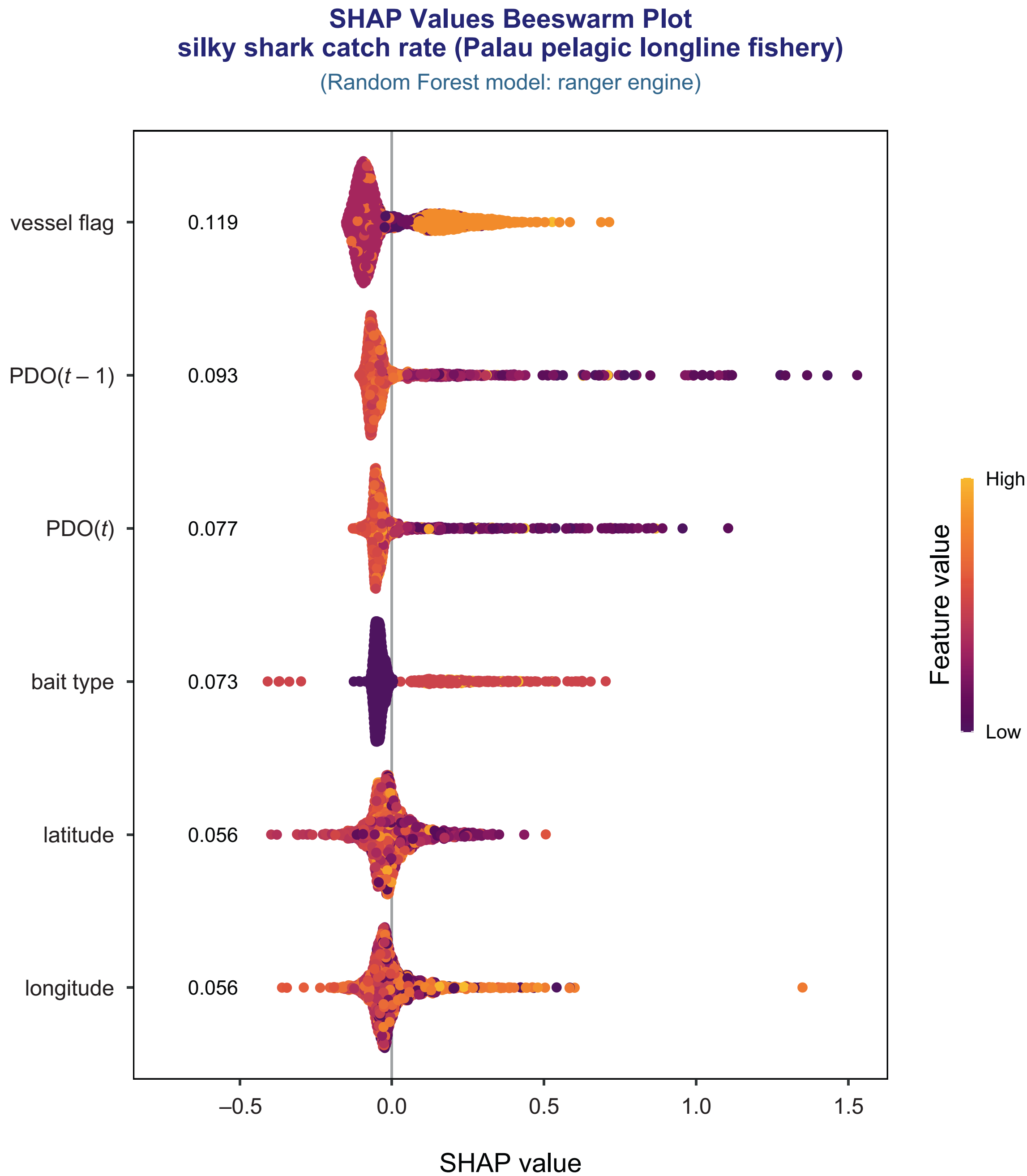

FIGURE 4 SHAP summary plot for the silky shark random forest model. PDO, Pacific Decadal Oscillation; SHAP, Shapley additive feature explanations.

the predicted catch for the Taiwan flag vessels shows some influence of recent PDO (higher predicted bigeye tuna catch with negative PDO index values, lower catch with positive values) that perhaps reflects nuanced vessel flag operational decisions in space and time. These nonlinear and complex interaction effects are what ML approaches are especially able to capture and SHAP-based diagnostic plots are able to reveal.

The SHAP dependence plot for the predicted silky shark catch is shown in Figure 8 where panels a–c show the top three SHAP-based predictors (vessel flag, recent PDO, and bait type) conditioned by the most important interaction predictor. Figure 8a shows that Taiwanese-flagged vessels not only had higher silky shark catch but that highest catches occurred in the most recent year or so while the lowest predicted catches were for Chinese-flagged vessels that operated in the earlier years prior to around 2010. The higher silky shark catches by the Taiwanese-flagged vessels occurred during negative PDO (cooler regional SST) and again perhaps reflective

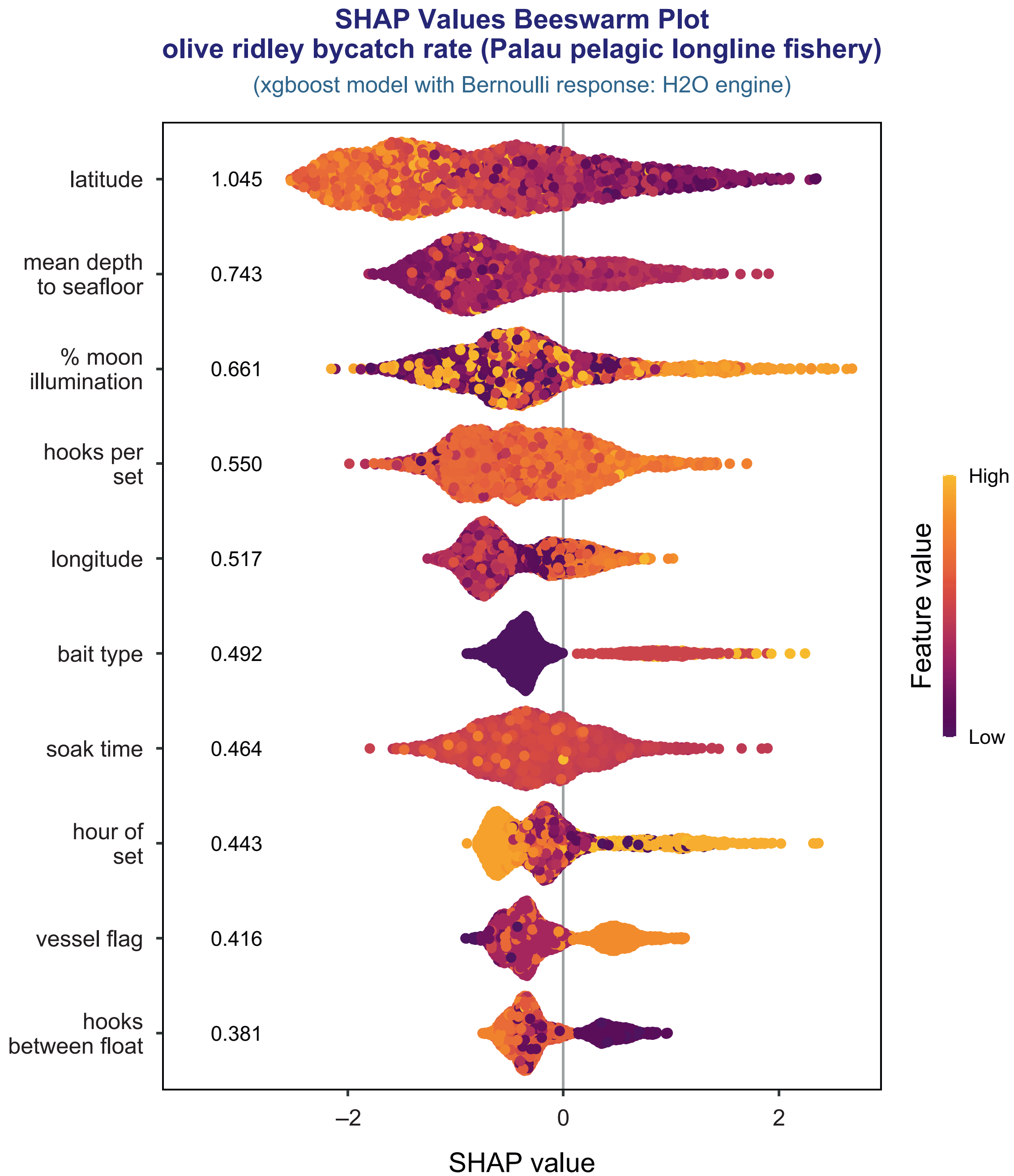

FIGURE 5 SHAP summary plot for the olive ridley turtle gradient boosting machine (XGBOOST) model. SHAP, Shapley additive feature explanations.

of flag-specific coordinated operational decisions in space and time.

The SHAP dependence plot for the predicted olive ridley turtle bycatch is shown in Figure 9 where panels a and b show SHAP-based predictors (latitude and bathymetric depth) conditioned by the most important interaction predictor. Figure 9a shows the decreasing catch with increasing latitude effect was most evident for the sets deployed with a higher number of hooks between floats. Figure 9b shows that the bathymetric depth effect identified in the SHAP summary plot (Figure 5) was highest around a depth of 4000 m and occurred later in the year.

Spatial prediction surfaces for marine spatial planning

Different predictor effects were apparent for all seven species revealed using SHAP summary and dependence plots. But marginal spatial effects (latitude and longitude)

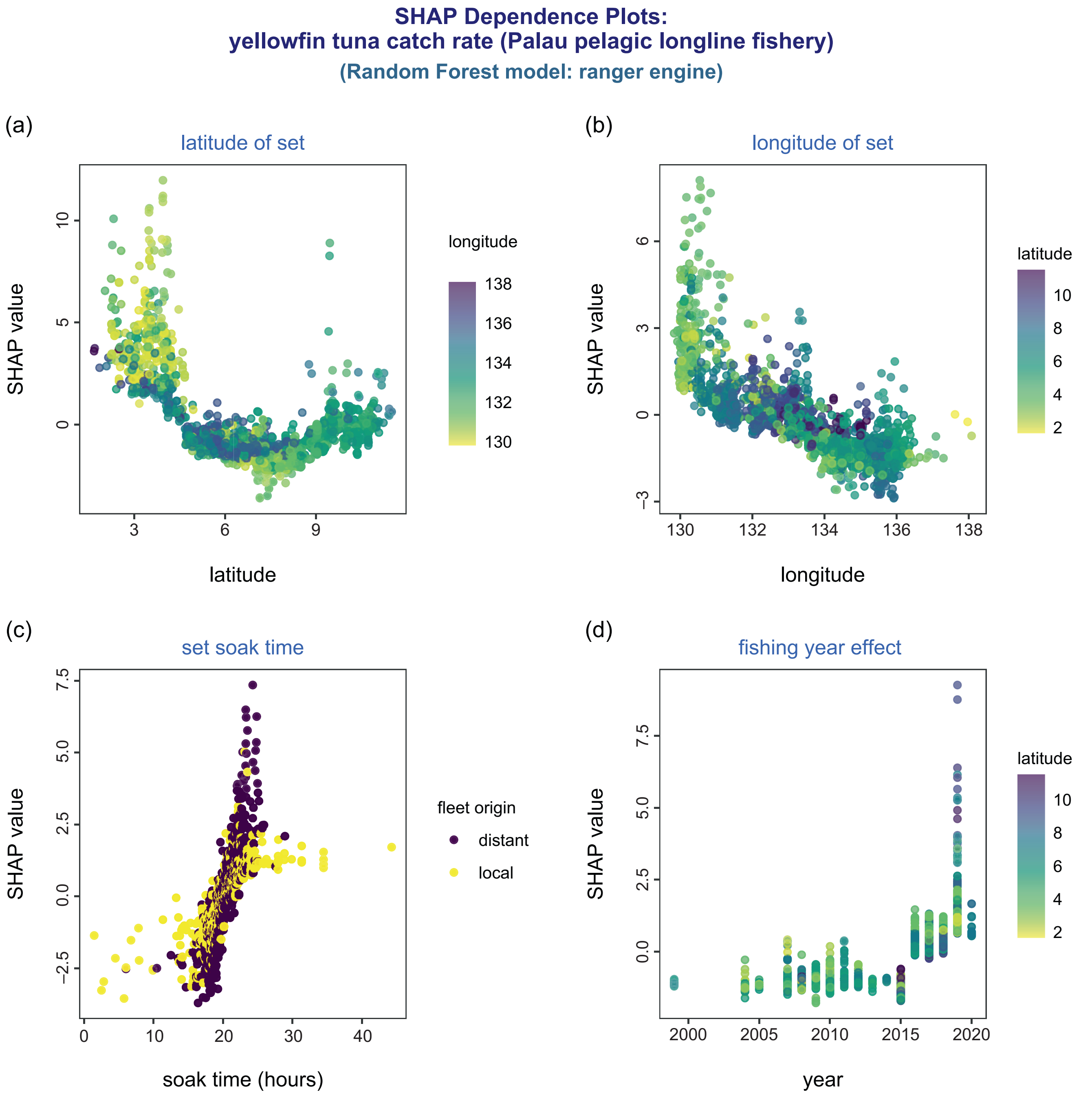

FIGURE 6 SHAP dependence plot for the yellowfin tuna random forest model. SHAP, Shapley additive feature explanations.

were important predictors (though not necessarily the most important) of species-specific catch or bycatch. Hence, spatially explicit RF (spatialRF) models for six species and a spatially explicit gradient boosting machine model (gpboost) for olive ridley turtles were fitted to the species-specific data sets to support spatially explicit prediction surfaces or maps. The set-specific predictions derived from these spatial ML models for each species are shown in Appendix S1: Figure S5 for six species (yellowfin bigeye, billfish, silky shark, and blue shark) and Appendix S1: Figure S6 for the olive ridley turtle—the catch is here converted for convenience to a catch-per-unit-effort prediction of catch per 1000 hooks. We also found using spatialRF that the predictors that contribute most to spatial model prediction transferability were (1) soak time for the yellowfin tuna set-specific predictions, (2) both soak time and number of hooks between set for bigeye tuna set-specific predictions, and (3) the PDO for silky shark set-specific predictions.

Figure 10a–d shows the mean field prediction surfaces for yellowfin tuna, bigeye tuna, pelagic stingray, and silky shark catch. Predicted catch was highest for

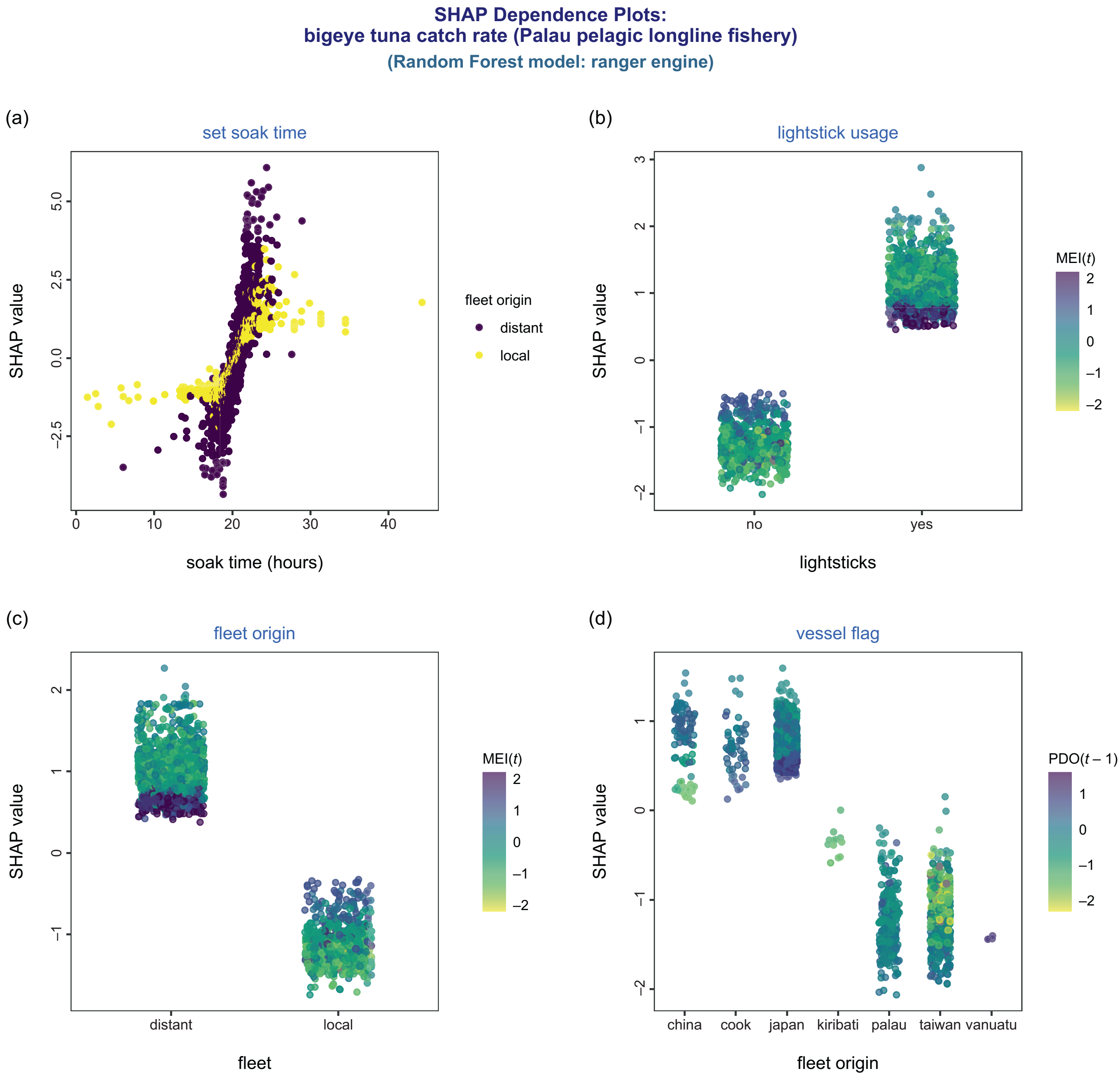

FIGURE 7 SHAP dependence plot for the bigeye tuna random forest model. MEI, Multivariate El Niño Southern Oscillation Index; PDO, Pacific Decadal Oscillation; SHAP, Shapley additive feature explanations.

both yellowfin and bigeye tuna in the southwestern region of the EEZ, where mainly the distant-water fleet operated between 1999 and 2020 (Appendix S1: Figure S1). On the other hand, predicted pelagic stingray and silky shark catch was highest in the eastern central region of the EEZ, where mainly the locally based fleet operated between 1999 and 2020 (Appendix S1: Figure S1). There is a predicted secondary hotspot (a warmspot) for pelagic stingray catch in the southwestern region.

Figure 11a,b shows the prediction surfaces for billfishes and blue shark catch. Predicted catch was highest for blue sharks in the northwestern region of the EEZ, where only the distant-water fleet operated between 1999 and 2020. On the other hand, predicted billfish catch was highest in the eastern central and southeastern regions of the EEZ, where mainly the locally based pelagic longline fleet operated between 1999 and 2020.

Figure 12 shows the prediction surface for olive ridley turtle bycatch. Predicted bycatch was highest in three areas: (1) in the southwestern region where mainly the distant-water fleet operated, and (2) central eastern and (3) southeastern regions, where only the locally based fleet

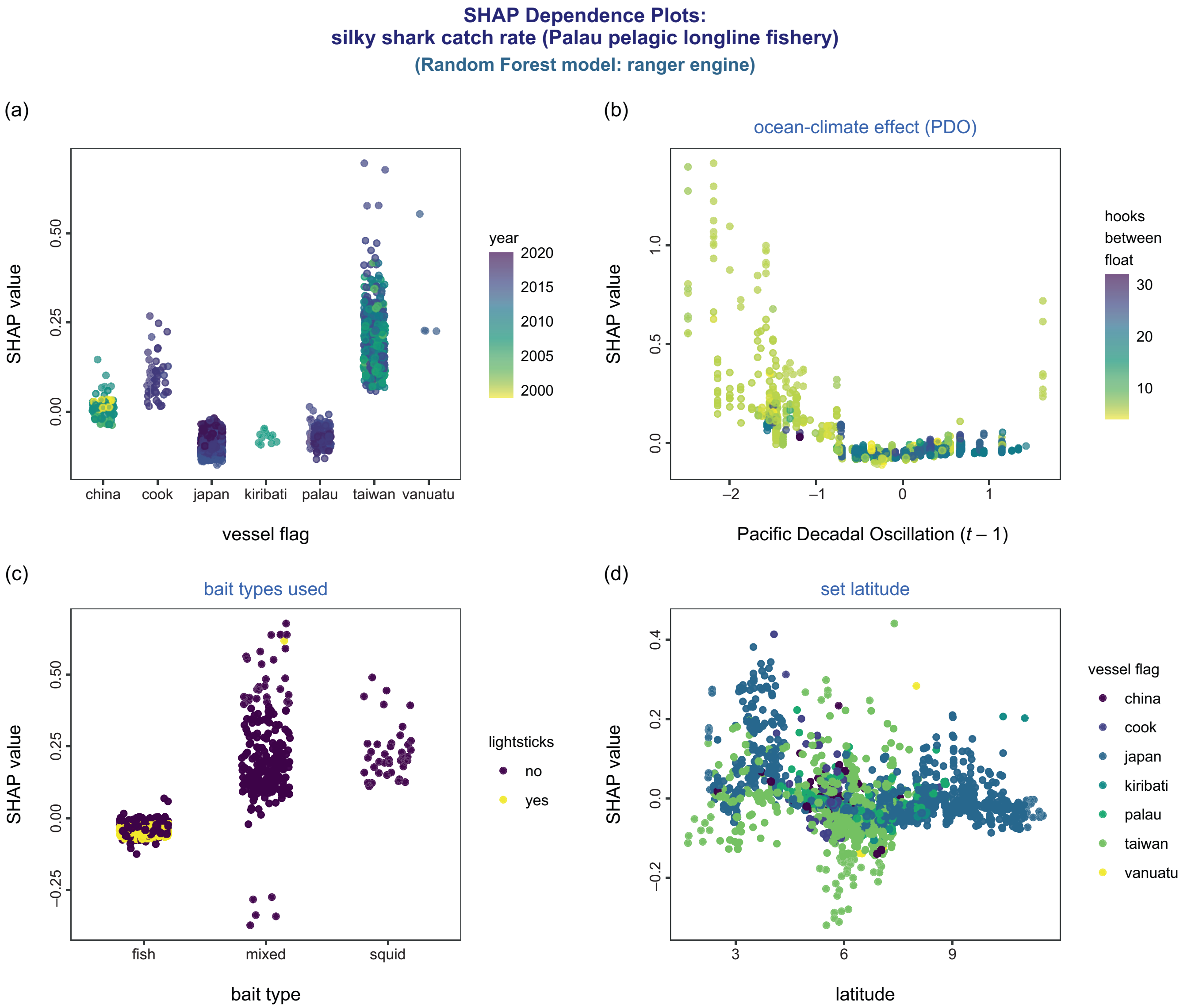

FIGURE 8 SHAP dependence plot for the silky shark random forest model. PDO, Pacific Decadal Oscillation; SHAP, Shapley additive feature explanations.

operated between 1999 and 2020. The southeastern region hotspot is attributable entirely to the local-based fleet operating during the 5-year period from 2006 to 2010. As a sanity check, we can fit a similar rasterizing or spatial interpolation model of the gpboost set-specific predictions (Appendix S1: Figure S7) using the sdmTMB package for R, which is an interface to template model builder (TMB) to fit spatial GLMMs with gradient boosting machine (SPDE)-based Gaussian Markov random fields (Anderson et al., 2022). This spatial GLMM regression modeling approach has been used recently for species distribution models of commercially exploited groundfish species (Commander et al., 2022). The sdmTMB-rasterised spatial map for olive ridley bycatch based on a GLMM with Beta likelihood is shown in Appendix S1: Figure S7. Both rasterised prediction maps (Figure 12; Appendix S1: Figure S7) are similar using either approach for the mean field predicted olive ridley bycatch spatial effect.

DISCUSSION

Evidence supporting static area-based management

The spatial prediction maps of expected catch rates identify options for spatial management approaches to separate static target bigeye tuna and yellowfin tuna catch rate hotspots (areas of highest catch per set conditioned on 28 potentially informative predictors) in the southwest portion of Palau's EEZ from at-risk species bycatch hotspots to the east (silky shark, olive ridley, and stingray),

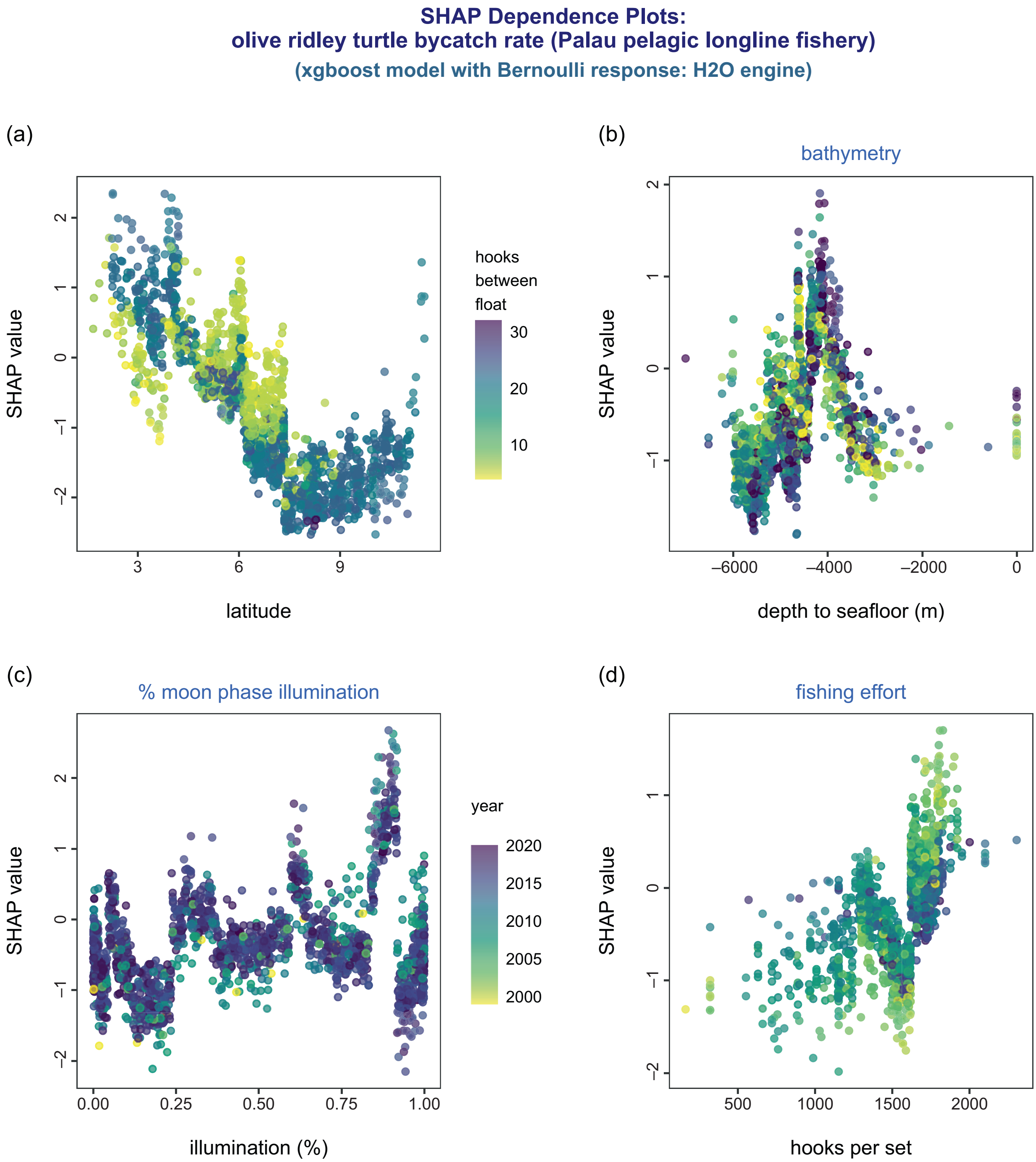

FIGURE 9 SHAP dependence plot for the olive ridley XGBOOST model. SHAP, Shapley additive feature explanations.

and northwest (blue shark). There were overlapping olive ridley and billfish hotspots to the southeast of the Palau EEZ (high seas pocket and Indonesia EEZ). One yellowfin hotspot overlaps with a warmspot or secondary, moderately high area of stingray catch rate, and the southern yellowfin and bigeye hotspots overlap with an olive ridley warmspot.

Overall, there would be limited ecological tradeoffs from zoning the Palau EEZ to focus fishing effort within the tuna hotspots. However, additional research on socio-economic effects of alternative area-based management strategies is a priority. For instance, research is needed to determine the economic viability of alternative fishing grounds, where ex-vessel revenue might be influenced by the seafood products being supplied, distance from port, and trip duration. For example, if a vessel makes only a few sets per trip to fill up the fish hold, and must land catch within a few days to meet product quality

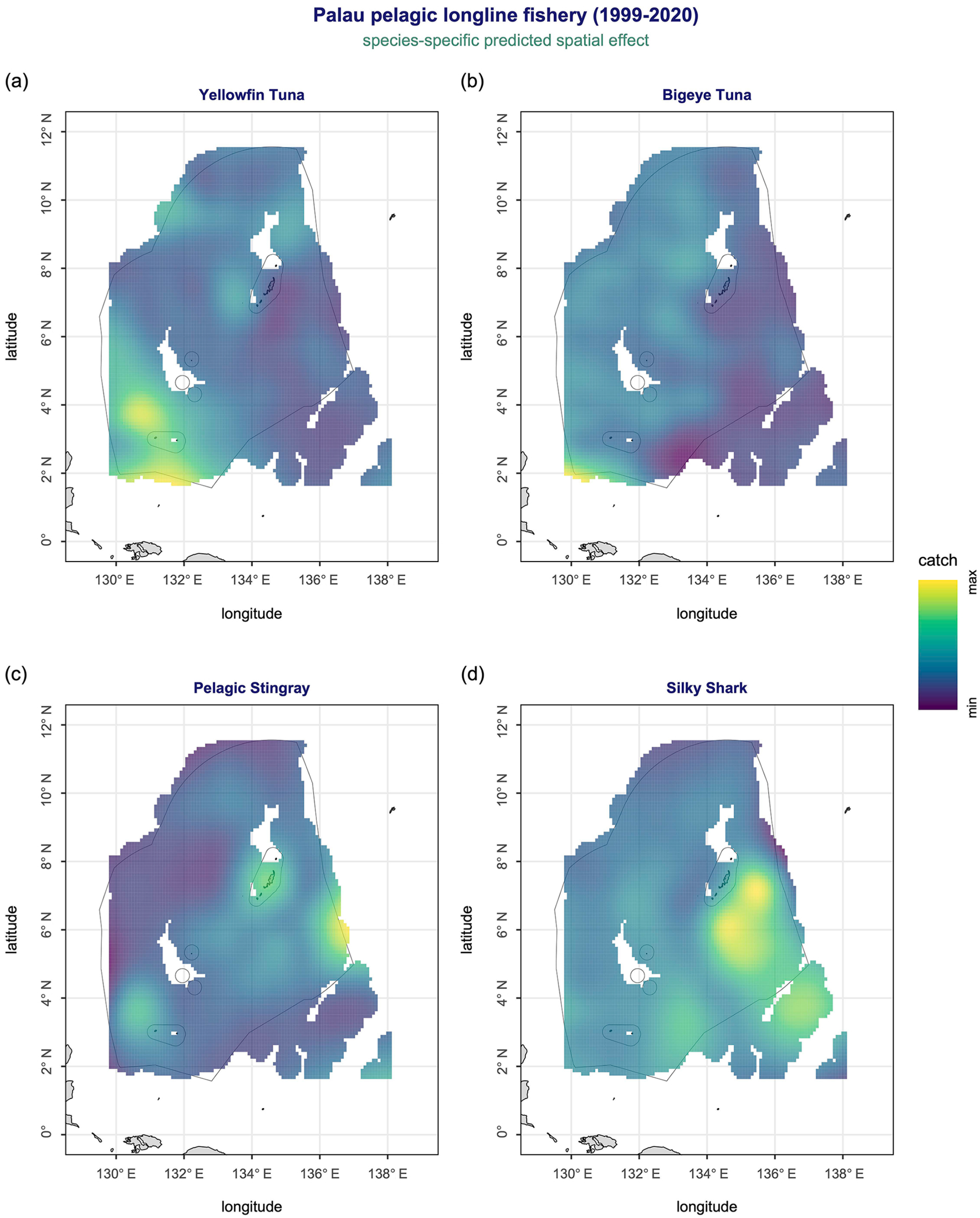

FIGURE 10 Rasterized spatial prediction maps over the 22-year period (1999–2020) highlighting the expected catch for (a) yellowfin tuna, (b) bigeye tuna, (c) pelagic stingray, and (d) silky shark, showing the seaward margin of the Palau exclusive economic zone.

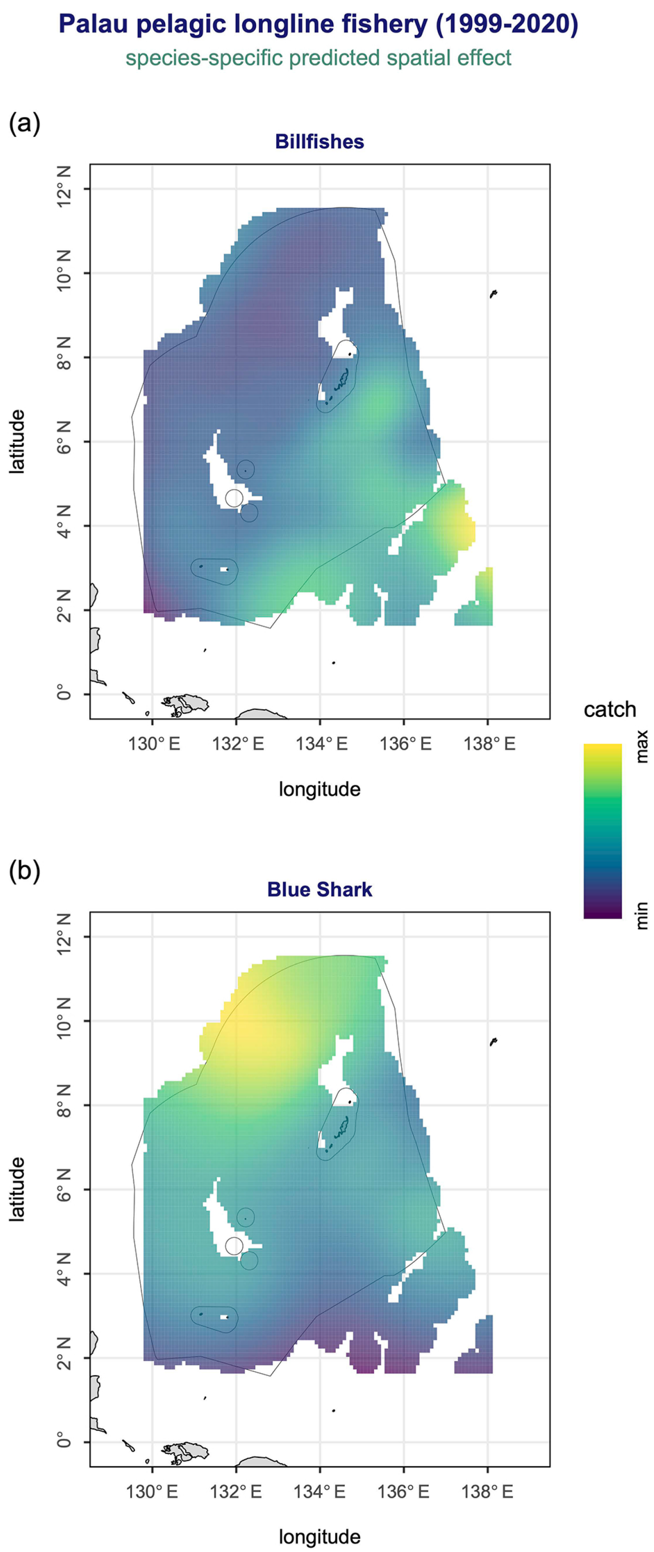

FIGURE 11 Rasterized spatial prediction maps over the 22-year period (1999–2020) highlighting the expected catch for (a) billfishes and (b) blue shark, showing the seaward margin of the Palau exclusive economic zone.

requirements for fresh chilled product for the Japan *sashimi* market, then fishing at grounds close to port, despite lower target species catch rates than would occur at more distant fishing grounds, might optimize revenue. Another priority is to investigate the potential economic cost that would be caused by introducing a condition in license agreements to restrict fishing in the olive ridley hotspot zone outside the Palau EEZ due to the exclusion of the overlapping billfish hotspot. The local fleet would target billfishes during seasons with relatively low tuna catch rates (Gilman et al., 2016); however, billfishes were a relatively small proportion of the local fleet's commercial catch (1.1 billfish per 1000 hooks compared with 4.0 yellowfin and 2.7 bigeye tuna per 1000 hooks).

Another priority is to explore differences in the fishing modes and technical capacities of the two fleet segments, which might inform the evaluation of alternative management strategies, including alternative area-based and bycatch management approaches. Might some informative predictors represent barriers for the locally based fleet to viably fish in the target tuna hotspot—where it might be necessary to fish deep to achieve high bigeye and yellowfin tuna catch rates? For example, referring to nominal catch rates shown in Appendix S1: Figure S5 (catch per set without conditioning on various information predictors that significantly explain species-specific catch rate), the local fleet had the highest bigeye catch rates in the core of their fishing grounds to the southeast of port (yellowfin tuna catch rates tended to be higher along the southern and western margins of their fishing grounds). The Okinawa fleet predominantly made nighttime deep sets with a mean of 22 hooks between floats, while the locally based fleet predominantly made shallow sets with a mean of 10 hooks between floats, both at night and during the day (Gilman et al., 2016). Discussed below, hooks between floats (an indicator for relative fishing depth) was an informative predictor of catch rates for bigeye tuna, blue shark, pelagic stingray, and billfishes. In the 1980s, the Okinawa-based fleet successfully converted from making shallow sets to target yellowfin tuna to a deep-set bigeye tuna targeting fishery (Palau Conservation Society, 1999). In 2016, The Nature Conservancy and Palau government initiated a similar effort for the Palau locally based fleet (Beverly, 2016; TNC, 2016). This technical assistance initiative could be resumed to enable shallow-setting vessels to develop the capacity to fish deeper like the Okinawa fleet so that fishing in the tuna hotspot, and avoiding threatened bycatch hotspots, is economically viable.

Jaiteh et al. (2021) used Palau longline observer data to compare catch rates of blue sharks, pelagic stingrays, and silky sharks within and outside of the area where the Palau National Marine Sanctuary allows pelagic longline fishing. Their findings on predicted spatial effects were similar to this study's findings, except that they predicted some catch rate hotspots that were not found in the

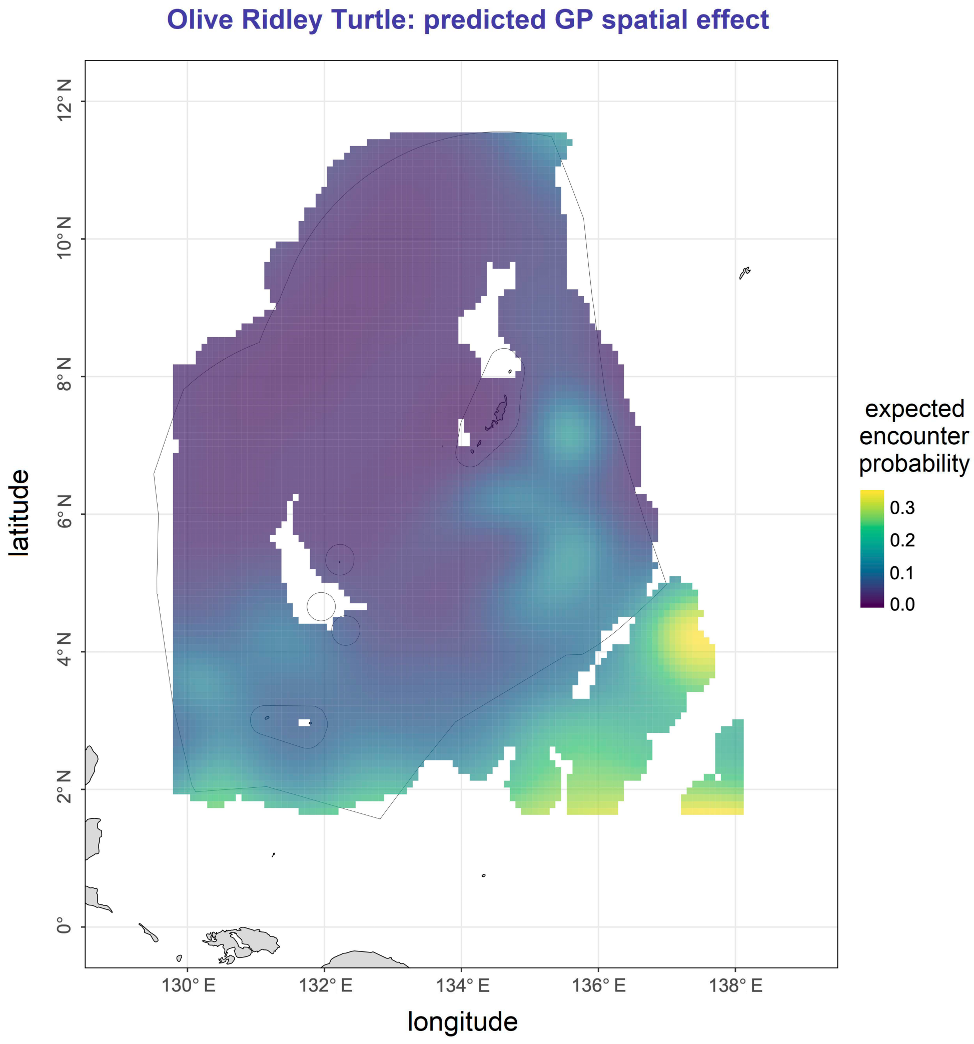

FIGURE 12 Rasterized spatial prediction map over the 22-year period (1999–2020) highlighting the expected (mean) encounter probability for the olive ridley marine turtle, showing the seaward margin of the Palau exclusive economic zone.

current study, located in the Indonesia EEZ and high seas outside of areas with observed effort. Using a shorter time series (beginning in 2010) and excluding the Palau EM datasets, Jaiteh et al. (2021) employed a regression-based modeling approach that included a small set of potentially informative predictors (year, month, and fleet) to condition catch rates. Jaiteh et al. (2021) made spatial predictions outside of actual fishing set geolocations for which no predictor estimates were available—an issue that was explicitly addressed in this study, discussed in Appendix S1: Section S1. Regression-based modeling evaluation and predictive spatial validation were not undertaken, and the model fits for the three species had low apparent predictive performance (Jaiteh et al., 2021).

Globally categorized as Vulnerable (IUCN, 2023), the most recent assessment of the western and central Pacific Ocean silky shark stock found the stock to not be overfished but is subject to extensive overfishing (Clarke et al., 2018). Recent fishing mortality was substantially higher than the fishing mortality rate (F) predicted to produce maximum sustainable yield (MSY) ($F_{\text{recent}}/F_{\text{MSY}} = 1.6$) such that if silky shark catches remain at recent levels, then there is a high probability that the stock will become overfished (Clarke et al., 2018). However, there was large uncertainty with the stock assessment, and findings are considered indicative and unreliable for management decisions (WCPFC, 2019).

Globally categorized as Vulnerable (IUCN, 2023), the Palau EEZ overlaps with a low risk and high threat olive ridley Regional Management Unit (Wallace et al., 2010, 2011). Despite removals being from a low-risk unit, the potentially high cumulative magnitude of mortalities of olive ridleys in regional longline fisheries might be a concern.

The most recent assessment of the north Pacific Ocean blue shark stock, which used an ensemble of modeling approaches, concluded that the stock is neither overfished nor is overfishing occurring (ISC, 2022). The species has a relatively low predicted probability of occurrence in the Pacific tropical equatorial waters (ISC, 2022; Kaschner et al., 2019). The global species is categorized as Near Threatened (IUCN, 2023) and is less vulnerable to over-exploitation compared with other pelagic shark species (Smith et al., 1998).

There have been no stock assessments of Pacific Ocean pelagic stingrays. The global species is categorized as Least Concern (IUCN, 2023). A regional assessment found that pelagic stingray relative abundance in the tropical Pacific Ocean increased between 1950 and 1990 (Ward & Myers, 2005a). Consistent with the regional assessment, a previous study of observer program data from the Palau locally based fleet found increasing relative abundance of pelagic stingrays (Gilman et al., 2016). The authors hypothesized that this might be due to mesopredator release, including from reductions in the abundance of some shark species that prey on pelagic stingrays and reduced local abundance of some sympatric competitors (Gilman et al., 2016).

Evidence supporting dynamic area-based management

Results identify opportunities for temporally dynamic area-based management of target and bycatch catch rates. First assessing diel-scale temporal dynamics, blue shark catch rates were highest with sets that were initiated later in the 24-h cycle, while pelagic stingray catch rates exhibited the opposite response. This predictor was marginally important (sixth highest predictor) for both billfishes and yellowfin tuna with the same effect as for pelagic stingray, with higher catch rates in sets that began earlier in the 24-h cycle. When combined with management of fishing depth, particularly relevant when fishing in the blue shark hotspot in the northwestern zone of the Palau EEZ, initiating setting earlier in the 24-h cycle would reduce blue shark catch risk and increase yellowfin tuna and billfishes catch rates, but with a trade-off of an increased pelagic stingray catch rate. The interacting effect of the time of day and depth of fishing on species-specific catch rates is discussed in the following section.

Considering temporal dynamics at a scale of within a month, olive ridley turtle catch rates were higher during periods of higher moonlight intensity. Reduced effort around the full moon would reduce the risk to olive ridley turtles, particularly in the olive ridley catch rate hotspot. Moonlight intensity is an informative predictor of catch rates of some species in pelagic longline fisheries (Bromhead et al., 2012; Hoyle et al., 2022; Kot et al., 2010; Poisson et al., 2010). This is inferred to be a result of the effect of moon phase on night-time ambient light levels, which affects the diel vertical migration of some species susceptible to capture in pelagic longline fisheries and their prey, occurring shallower at night around a new moon and deeper at night with increased lunar illumination around the full moon (Gilly et al., 2006; Hoyle et al., 2022; Prihartato et al., 2016). The effect of moonlight intensity on turtle catch risk might also be due to turtles being more capable of visually detecting baited hooks (Kot et al., 2010), which is also apparent for bycatch risk of some seabird species during longline night-time sets (Cherel et al., 1996; Jiminez et al., 2020).

At a seasonal scale, blue shark catch rates were higher earlier in the year, while yellowfin tuna and pelagic stingray catch rates were higher later in the year, and olive ridley catch rates were also higher later in the year when at locations with a depth of about 4000 m. Hence, reduced fishing effort earlier in the year, particularly in the blue shark catch hotspot in the northwest zone, would reduce blue shark catch with minimal effect on commercial species catch rates. Reduced effort later in the year in the pelagic stingray hotspot in the western zone and in the olive ridley bathymetrically defined hotspot could reduce the catch risk of these at-risk species but with a potential trade-off of reduced yellowfin tuna catch rates. Season can have a large effect on species-specific local abundance and catch rates due to monthly variability in environmental conditions, prey distributions, and other factors (Kot et al., 2010; Rodrigues et al., 2022).

At an interannual scale, billfish catch rates were higher with lower MEI values corresponding with cooler regional SST, and pelagic stingray catch rates showed the opposite effect with higher catch rates with higher MEI values with a one-year lag during warmer ocean temperatures. Positive MEI values represent El Niño phase-like conditions, and negative values represent La Niña phase-like conditions. In the western and central Pacific Ocean, ENSO phases are associated with large-scale east–west shifts in the warm pool and the highly productive convergence zone between the warm pool and cold tongue. This variability in the spatial occurrence and temporal occurrence of areas of high productivity causes variability in the distributions, recruitment, and biomass of pelagic predators (Bjorndal et al., 2017; Free et al., 2019; Lehodey et al., 1997, 2006; Newman et al., 2016).

At a decadal scale, silky shark catch rates were higher with negative PDO index values, both during the most recent month and with a one-month lag, reflecting cooler 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 (Houk et al., 2020; Newman et al., 2016). Lags in responses in species-specific catch rates to these climate cycles 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). These climate cycle phase effects on Palau billfishes, stingray, and silky shark longline catch rates might reflect changes in local abundance, changes in absolute abundance, or both. Additional research could assess whether locations of species-specific catch rate-defined hotspots and coldspots vary by climate cycle phase, which could inform the design of spatially mobile area-based management strategies where fishery-closed areas might vary in location during different climate cycle phases in order to best meet management objectives. Indirectly related, and not explored in this study, outcomes of climate change are causing shifts in the distribution, phenology, population dynamics, and biomass of pelagic marine species (Bjorndal et al., 2017; Free et al., 2019; Lehodey et al., 2015; Poloczanska et al., 2013). For example, distributions of Pacific Ocean tunas are shifting eastward, reducing their local abundance and hence catch rates in the Palau EEZ (Bell et al., 2021), which could be accounted for in the evaluation of alternative area-based management strategies.

Dynamic area-based fisheries management may be more effective and efficient at achieving bycatch management objectives compared with static ABMTs (Dunn et al., 2016; Hazen et al., 2018; Pons et al., 2022). However, compared with static ABMTs, dynamic fisheries management, including temporally dynamic measures that restrict fishing by the time of day or part of a month, and particularly quasi real-time approaches, requires relatively more robust enabling environment conditions for effective compliance monitoring (Gilman et al., 2006; Gilman, Hall, et al., 2022; Little et al., 2015).

EM versus observer monitoring

Monitoring method of observer or EM program was an important predictor of catch rate for two of the at-risk bycatch species, with a higher stingray catch rate for sets monitored with EM compared with sets with an onboard human observer, and the opposite effect for blue sharks. While not one of the top SHAP-based predictors of species-specific catch rate, catch rates were higher for sets with observers than sets with EM for silky shark, olive ridley turtles and billfishes, with the opposite effect for yellowfin tuna. It is unclear whether this was caused by a deficit with a monitoring system. It is a research priority to investigate the EM and observer programs of the distant-water and locally based fisheries to determine potential causes of poor data quality, such as by conducting trips with both monitoring methods to enable an assessment of precision.

Studies comparing the precision between observer and EM systems on pelagic longline fisheries, where both monitoring methods were employed simultaneously, found that causes of low precision were due to inadequate EM camera setups, where the camera fields of view did not include the outboard side of the rail near the hauling station, preventing the EM analyst from viewing the area where crew release non-retained catch in the water (Emery et al., 2018; Gilman, Castejon, et al., 2020; Piasente et al., 2012; Stahl & Carnes, 2020). Too fast EM playback review speeds and inadequate attentiveness of EM analysts to detect when crew discard catch in the water were additional causes of low precision between EM and observer data for discarded catch (Stahl & Carnes, 2020). Poor species identification skills have also been proposed as a cause for low precision between EM and observer estimated catch (Brown et al., 2021). Another identified cause was inattentive observers who did not consistently record discarded catch (Gilman, Castejon, et al., 2020). Statistical sampling bias faced by observer programs but not EM programs is also a potential cause of low precision between EM and observer data. This includes an observer effect, observer displacement effect, and observer coercion and corruption (Babcock et al., 2003; Benoit & Allard, 2009; Cahalan & Faunce, 2020). Other data quality issues that were encountered in the study are discussed in Appendix S1: Section S2.

Operational predictors

The bigeye tuna and blue shark SHAP values plots show higher catch rates with more hooks between floats, with the opposite effect for billfishes. Discussed above, time-of-day of fishing was also an important predictor of pelagic stingray and blue shark catch rates. The time-of-day of fishing operations and fishing depth can affect the vertical overlap (encounterability) and catch risk of some pelagic marine predators whose vertical distributions can vary temporally due to diel vertical migration cycles that mirror the movements of their prey, time of day of foraging and temporal variability in diving behavior (Gilman, Chaloupka, et al., 2019; Musyl et al., 2011; Rodrigues et al., 2022). These two variables also affect species-specific at-vessel mortality rates (whether catch are alive or dead when retrieved during the gear haulback before being handled by crew) (Ellis et al., 2017; Gilman, Chaloupka, et al., 2022; Orbesen et al., 2017). The number of pelagic longline hooks that are attached between two floats is an approximate index for *relative* but not *absolute* fishing depth. The more the hooks that are deployed between two floats, the deeper the depth range of the hooks along a catenary curve if all other variables are constant (Rice et al., 2007; Ward & Myers, 2005b). Variables other than number of hooks between floats that explain actual fishing depth include shoaling from ocean currents and wind, and various gear designs such as the length of mainline between floats, mainline diameter and material, distance between floats, distance between the point of attachment to the mainline of the first branch line and the point of attachment of the nearest float line, distance between branch lines, and length of branch lines and float lines (Rice et al., 2007; Ward & Myers, 2005b). Managing the depth and time-of-day of fishing can result in tradeoffs for threatened bycatch species. For instance, deeper fishing reduces the catch risk of epipelagic threatened species such as silky and oceanic whitetip sharks and hard-shelled marine turtles but increases the catch of mesopelagic species such as thresher sharks (Gilman, Chaloupka, et al., 2019). Fishing depth, as indicated by number of hooks between floats, very likely explains why the shallow-set Palau locally based fleet (with a mean of 10 hooks per float) had higher nominal catch rates of epipelagic species, including a ca. 6 times larger olive ridley turtle, 3.7 times larger silky shark, and 2.3 times larger pelagic stingray catch per 1000 hooks, than the deep-set distant-water fleet (with a mean of 22 hooks per float), and the distant-water fleet had a ca. 1.5 times larger blue shark catch per 1000 hooks, a mesopelagic species (Musyl et al., 2011).

Sets with longer soak durations had higher bigeye and yellowfin tuna catch rates. Sets with lightsticks had higher bigeye catch rates than sets without lightsticks, sets with squid or a mix of fish and squid used for bait had higher silky shark catch rates than sets with only fish bait, and sets with more hooks had higher olive ridley turtle catch rates than sets with fewer hooks. These latter three predictors were heavily imputed, creating uncertainty in these findings.

These four predictors are known to significantly explain species-specific catch rates in pelagic longline fisheries. Longer soaks might increase catch rates as organisms have a longer time period and hence risk of capture, with an increased probability that a school of pelagic predators will encounter a section of a pelagic longline (Capello et al., 2013; Ward et al., 2004). However, longer soak duration might also result in sections of the gear becoming saturated with catch, higher bait loss rates, higher depredation rates, falloff due to mechanical action, and higher escapement rates (for species that have a high probability of surviving the gear soak and in particular when monofilament nylon and not more durable materials are used for leaders), and thus beyond some threshold, longer gear soaks might result in lower catch rates for some species (Poisson et al., 2010; Ward et al., 2004; Ward & Myers, 2007).

The number of hooks deployed per set is frequently included in longline catch rate standardization models as a measure of relative fishing effort (Brodziak & Walsh, 2013; Hoyle et al., 2014). With increasing baited hooks per set, catchability might increase due to increased area fished, increasing the probability that a school will encounter the gear, and reduced probability of gear saturation, but this also might increase the competition for catch by adjacent hooks and thus reduce catch rates (Ward & Hindmarsh, 2007). Increasing hooks per set might result in increasing soak times, or might result in crew increasing setting and haulback speeds and reduced duration between the end of a haul and start of the next set (Ward & Hindmarsh, 2007). Because longline vessels typically retrieve gear in the reverse order that it was deployed, the number of hooks per set might affect the soak time of different sections of the gear.

Lightsticks (chemiluminescent and battery-powered light-emitting diode fishing lights), mainly used in shallow-set pelagic longline fisheries, can increase catch rates of pelagic predators susceptible to longline capture by directly attracting predators or attracting their prey and might increase predators' ability to visually detect prey (Hazin et al., 2005; Poisson et al., 2010; Witzell, 1999). Lightstick wavelength and flicker rate can affect species- and ontogenetic stage-specific catch rates of fishes and marine turtles (Afonso et al., 2021; Crognale et al., 2008; Wang et al., 2007). Battery-powered fishing lights can increase the sink rate of baited hooks, reducing seabird catch risk (Gianuca et al., 2016)—primarily problematic at higher latitudes, seabird bycatch is not documented to occur in the Palau fishery.

Different species and sizes of marine predators have different prey and hence preferences for different types of longline bait. This preference is a function of a bait's chemical, visual, acoustic and textural characteristics, and size (Gilman, Chaloupka, Bach, et al., 2020; Hall et al., 2017). Using only fish for bait, and banning the use of squid, would reduce silky shark catch rates and, from results from a global meta-analysis, would also reduce marine turtle and blue shark catch rates but might also reduce catch rates of tunas and istiophorid billfishes (Gilman, Chaloupka, Bach, et al., 2020).

Management strategy of input or output control and area-based management implications

The Palau longline fisheries are subject to an input control (an effort limit under the Parties to the Nauru

Agreement Longline Vessel Day Scheme, PNA, 2022). However, it is likely that the vessel day scheme, which started in 2015 in Palau, has not constrained longline effort in the Palau EEZ, especially since 2020 when most locally based vessels departed when the Palau National Marine Sanctuary Act came into effect (down to 1 locally based vessel in 2021, Republic of Palau, 2022). Therefore, the catch rate employed in this study (catch per set conditioned by all predictors) is appropriate for informing spatial management options. Given an objective of minimizing threatened bycatch, selecting commercial fishing zones with lowest threatened species captures per unit of effort would be a suitable area-based management approach under the current management framework. If output controls were used for either or both target species and threatened bycatch species, then the ratio of threatened to target species catch would be a more appropriate catch rate unit to identify commercial fishing zones (Dagorn et al., 2013; Gilman et al., 2018). With a bycatch threshold, zones with the lowest ratio of threatened 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.

CONCLUSIONS

Static and dynamic ABMTs hold substantial potential to balance socioeconomic benefits derived from fisheries and ecological costs to threatened species exposed to bycatch fishing mortality. The Palau longline fisheries have high bycatch of at-risk species such as the olive ridley marine turtle and silky and blue sharks (Gilman et al., 2016; Jaiteh et al., 2021). Area-based management of blue water fisheries has relatively high promise to mitigate bycatch of at-risk species (Gilman, Chaloupka, et al., 2019).

The study analyzed observer and EM datasets for 1638 sets by distant-water and locally based pelagic longline fishing vessels conducted within and adjacent to the Palau EEZ over two decades, between 1999 and 2020. The distant-water fleet predominantly made night-time deep sets while the locally based fleet predominantly made shallow sets both at night and during the day.

We used recent advances in interpretable or explainable ML-based modeling approaches (Scholbeck et al., 2020; Wikle et al., 2023) to derive robust spatial predictions of species-specific catch rates suitable for supporting informed marine spatial planning. These models were conditioned on a suite of potentially informative environmental, bathymetric, ocean-climate metric, vessel, and set-specific operational predictors of catch rate. ML algorithms can learn complex relationships between the response or outcome and the predictors including nonlinear and interaction and spatial effects. The interpretable ML methods that we used, including SHAP summary and SHAP dependence graphical tools (Lundberg et al., 2020), helped to derive a deeper understanding of predictor functional forms and the spatially resolved predicted species-specific catch rates. We contend that interpretable ML approaches hold great promise to improve both predictive modeling and understanding of pelagic longline fishing catch rates of target species and bycatch of threatened species.

Mean field prediction surfaces define primary catch rate hotspots for silky shark, olive ridley turtle, and pelagic stingray, which did not overlap hotspots for target species (bigeye and yellowfin tunas). A predicted target species catch rate hotspot was in the southwestern region of Palau's EEZ, overlapping secondary olive ridley and pelagic stingray hotspots. Overall, there would be limited ecological tradeoffs from zoning the Palau EEZ to focus fishing effort within the tuna hotspot. Additional research is needed on socioeconomic effects of alternative area-based management strategies.

Results also identify opportunities for temporally dynamic area-based management of target and bycatch catch rates. Particularly within the blue shark hotspot, initiating setting earlier in the 24-h cycle would reduce blue shark catch risk and increase yellowfin tuna and billfishes catch rates, but with a trade-off of increased pelagic stingray catch rate. Reduced fishing effort earlier in the year, particularly in the blue shark hotspot, would reduce blue shark catch with minimal effect on commercial species catch rates. Additional research could assess whether locations of species-specific catch rate hotspots and coldspots vary by interannual and decadal climate cycle phase, which could inform the design of spatially mobile, dynamic area-based management strategies.

EM and observer monitoring systems had low precision in estimated catch rates for two at-risk bycatch species (blue shark and pelagic stingray). It is a research priority to investigate the EM and observer programs to determine potential causes of poor data quality, such as deficits with species identification skills, the EM camera setup and fields of view, inattentiveness of observers or EM reviewers, and sources of statistical sampling bias (observer effect, observer displacement effect, and observer coercion and corruption) (Babcock et al., 2003; Stahl & Carnes, 2020). In addition to low precision between EM and observer program data, other data quality issues were encountered in the study (missing values, invalid records, and missing priority data fields), which if investigated and addressed could improve the certainty of future studies that employ analyses of these datasets.

ABMTs are one of an ensemble of available approaches for fisheries management. A suite of measures is often needed for fisheries management strategies to achieve objectives (Selig et al., 2017). This includes whether input controls on effort or fleetwide and vessel-based output controls on target or bycatch species are employed and are set at levels that effectively constrain the fishery. A transition to employing fleetwide or vessel-based catch rate output controls that effectively constrain the fishery would alter the spatial management strategy to focus on zones with the lowest ratio of threatened bycatch to commercial catch. In addition to ABMTs and input and output controls, other bycatch management approaches include reduced vertical overlap, gear designs, and fishing methods that increase selectivity, mitigation of ghost fishing, handling and release practices, offsets, trade restrictions and bans, and market-based mechanisms such as ecolabeling (Gilman, Chaloupka, et al., 2022; Hall et al., 2017; Selig et al., 2017). This includes fishing depth, which, when combined with the time-of-day of fishing, affects the vertical overlap and catch risk of some species. SHAP summary plots found hooks between floats, an index for relative fishing depth, was a main predictor of catch rate for bigeye tuna, blue shark, and billfishes. Fishing depth very likely explains why the shallow-set locally based fleet had higher catch rates of olive ridley turtle, silky shark, and pelagic stingray epipelagic species and lower catch rates of blue shark, a mesopelagic species, compared with the deep-set distant-water fishery. Palau could require deep-fishing to reduce costs to threatened epipelagic species but with trade-offs of increased catchability of at-risk mesopelagic species. Management of operational predictors soak duration and hooks per set, which affect effective fishing power (Poisson et al., 2010; Ward & Hindmarsh, 2007), and lightstick use and bait type, which affect species selectivity (Afonso et al., 2021; Gilman, Chaloupka, Bach, et al., 2020; Hall et al., 2017; Poisson et al., 2010), provide additional opportunities to balance threatened bycatch and target catch rates. Findings support evidence-informed policy for the Palau government to apply ABMTs and complementary management measures to meet objectives for balancing benefits from target species catch with costs to threatened species.

AUTHOR CONTRIBUTIONS

Eric Gilman and Milani Chaloupka conceived and designed the study, analyzed the data, and wrote the manuscript.

ACKNOWLEDGMENTS

We are grateful to Dr. Graham Pilling, Pacific Community (SPC), and Dr. Francois Poisson, Institut Français de Recherche pour L'exploitation de la Mer (IFREMER), for reviewing a draft manuscript. Dataset queries were kindly executed by Emmanuel Schneiter, Aurélien Panizza, and Eparama Loganimoce of the Pacific Community. We are grateful to the Palau government for authorization to access fisheries monitoring datasets. Eric Gilman and Milani Chaloupka received funding from The Nature Conservancy California Oceans Program.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The fisheries observer and electronic monitoring data used in this study are owned by and are available from the Ministry of Agriculture, Fisheries and the Environment of the Republic of Palau (palau.mafe@palaugov.org; https://www.palaugov.pw/executive-branch/ministries/agriculture-fisheries-and-environment/), and restrictions apply to their availability. Under the terms of a required nondisclosure agreement with the Palau government, the authors are prevented from making the Palau government data publicly available. As detailed in *Methods*, the query of the Palau national fisheries observer and electronic monitoring program database conducted for this study was for the period between April 1999 and January 2020 for pelagic longline fishing by Palau locally based vessels and by a distant-water Japan-based fishery within the Palau exclusive economic zone, for the 16 operational, spatial, temporal, vessel, and monitoring system predictors listed in Appendix S1: Table S1.

ORCID

Eric Gilman https://orcid.org/0000-0002-4216-2513
Milani Chaloupka https://orcid.org/0000-0001-8109-005X

REFERENCES

Adam, M., J. Sibert, D. Itano, and K. Holland. 2003. "Dynamics of Bigeye (*Thunnus obesus*) and Yellowfin (*T. albacares*) Tuna in Hawaii's Pelagic Fisheries: Analysis of Tagging Data with a Bulk Transfer Model Incorporating Size-Specific Attrition." *Fisheries Bulletin* 101: 215–228.

Afonso, A., B. Mourato, H. Hazin, and F. Hazin. 2021. "The Effect of Light Attractor Color in Pelagic Longline Fisheries." *Fisheries Research* 235: 105822.

Albers, S. 2022. "rsoi: Import Various Northern and Southern Hemisphere Climate Indices." R Package Version 0.5.5. https://CRAN.R-project.org/package=rsoi.

Anderson, S., E. Ward, P. English, and L. Barnett. 2022. "sdmTMB: An R Package for Fast, Flexible, and User-Friendly Generalized Linear Mixed Effects Models with Spatial and Spatiotemporal Random Fields." *bioRxiv* 2022.03.24.485545. https://doi.org/10.1101/2022.03.24.485545.

Aqorau, T. 2009. "Recent Developments in Pacific Tuna Fisheries: The Palau Arrangement and the Vessel Day Scheme." *The International Journal of Marine and Coastal Law* 24: 557–581.

Assis, J., L. Tyberghein, S. Bosh, H. Verbruggen, E. Serrão, and O. De Clerck. 2018. "Bio-ORACLE v2.0: Extending Marine Data Layers for Bioclimatic Modelling." *Global Ecology and Biogeography* 27: 277–284.

Babcock, E., E. Pikitch, and G. Hudson. 2003. *How Much Observer Coverage Is Enough to Adequately Estimate Bycatch?* Washington, DC: Pew Institute for Ocean Science, Miami, and Oceana.

Bell, J., V. Allain, E. Allison, S. Andrefouet, N. Andrew, M. Batty, M. Blanc, et al. 2015. "Diversifying the Use of Tuna to Improve Food Security and Public Health in Pacific Island Countries and Territories." *Marine Policy* 51: 584–591.

Bell, J. D., I. Senina, T. Adams, O. Aumont, B. Calmettes, S. Clark, M. Dessert, et al. 2021. "Pathways to Sustaining Tuna-Dependent Pacific Island Economies during Climate Change." *Nature Sustainability* 4: 900–910.

Benito, B. 2021. "R Package spatialRF: Easy Spatial Regression with Random Forest." R Package Version 1.1.4. https://doi.org/10.5281/zenodo.4745208.

Benoit, H., and J. Allard. 2009. "Can the Data from At-Sea Observer Surveys Be Used to Make General Inferences about Catch Composition and Discards?" *Canadian Journal of Fisheries and Aquatic Sciences* 66: 2025–39.

Bergen, S., M. Huso, A. Duerr, M. Braham, S. Schmuecker, T. Miller, and T. Katzner. 2023. "A Review of Supervised Learning Methods for Classifying Animal Behavioural States from Environmental Features." *Methods in Ecology and Evolution* 14: 189–202.

Beverly, S. 2016. *Setting Longlines Deep*. Koror: The Nature Conservancy.

Bjorndal, K., A. Bolten, M. Chaloupka, V. Saba, C. Bellini, M. Marcovaldi, A. Santos, et al. 2017. "Ecological Regime Shift Drives Declining Growth Rates of Sea Turtles throughout the West Atlantic." *Global Change Biology* 23: 4556–68.

Blagus, R., and L. Lusa. 2013. "SMOTE for High-Dimensional Class-Imbalanced Data." *BMC Bioinformatics* 14: 106.

Boerder, K., A. Bryndum-Buchholz, and B. Worm. 2017. "Interactions of Tuna Fisheries with the Galápagos Marine Reserve." *Marine Ecology Progress Series* 585: 1–15.

Bosch, S., and S. Fernandez. 2021. "sdmpredictors: Species Distribution Modelling Predictor Datasets." R Package Version 0.2.10. https://CRAN.R-project.org/package=sdmpredictors.

Breiman, L. 2001. "Random Forests." *Machine Learning* 45: 5–32.

Brodziak, J., and W. Walsh. 2013. "Model Selection and Multimodel Inference for Standardizing Catch Rates of Bycatch Species: A Case Study of Oceanic Whitetip Shark in the Hawaii-Based Longline Fishery." *Canadian Journal of Fisheries and Aquatic Sciences* 1740: 1723–40.

Bromhead, D., S. Clarke, S. Hoyle, B. Muller, P. Sharples, and S. Harley. 2012. "Identification of Factors Influencing Shark Catch and Mortality in The Marshall Islands Tuna Longline Fishery and Management Implications." *Journal of Fish Biology* 80: 1870–94.

Brown, C., A. Desbiens, M. Campbell, E. Game, E. Gilman, R. Hamilton, C. Heberer, D. Itano, and K. Pollock. 2021. "Electronic Monitoring for Improved Accountability in Western Pacific Tuna Long-Line Fisheries." *Marine Policy* 132: 104664.

Bucaram, S. J., A. Hearn, A. Trujillo, W. Rentería, R. Bustamante, G. Morán, G. Reck, and J. Garcia. 2018. "Assessing Fishing Effects Inside and Outside an MPA: The Impact of the Galapagos Marine Reserve on the Industrial Pelagic Tuna Fisheries during the First Decade of Operation." *Marine Policy* 87: 212–225.

Bürkner, P. 2017. "brms: An R Package for Bayesian Multilevel Models Using Stan." *Journal of Statistical Software* 81: 1–28.

Burns, E., D. Bradley, and L. Thomas. 2023. "Global Hotspots of Shark Interactions with Industrial Longline Fisheries." *Frontiers in Marine Science* 9: 1062447.

Cahalan, J., and C. Faunce. 2020. "Development and Implementation of a Fully Randomized Sampling Design for a Fishery Monitoring Program." *Fishery Bulletin* 118: 87–99.

Capello, M., P. Bach, and E. Romanov. 2013. "Fine-Scale Catch Data Reveal Clusters of Large Predators in the Pelagic Realm." *Canadian Journal of Fisheries and Aquatic Sciences* 70: 1785–91. https://doi.org/10.1139/cjfas-2013-0149.

Carpenter, B., A. Gelman, M. Hoffman, D. Lee, B. Goodrich, M. Betancourt, M. Brubaker, J. Guo, P. Li, and A. Riddell. 2017. "Stan: A Probabilistic Programming Language." *Journal of Statistical Software* 76(1): 1–32.

Chen, T., T. He, M. Benesty, V. Khotilovich, Y. Tang, H. Cho, K. Chen, et al. 2023. "xgboost: Extreme Gradient Boosting." R Package Version 1.7.5.1. https://CRAN.R-project.org/package=xgboost.

Cherel, Y., H. Weimerskirch, and G. Duhamel. 1996. "Interaction between Longline Vessels and Seabirds in Kerguelen Waters and a Method to Reduce Seabird Mortality." *Biological Conservation* 75: 63–70.

Clarke, S., A. Langley, C. Lennert-Cody, A. Aires-da-Silva, and M. Maunder. 2018. *Pacific-Wide Silky Shark (Carcharhinus falciformis) Stock Status Assessment and Addendum, SC14-SA-WP-08*. Kolonia: Western and Central Pacific Fisheries Commission.

Collette, B., K. Carpenter, B. Polidoro, M. Juan-Jorda, A. Boustany, D. Die, C. Elfes, et al. 2011. "High Value and Long Life – Double Jeopardy for Tunas and Billfishes." *Science* 333: 291–92.

Commander, C., L. Barnett, E. Ward, S. Anderson, and T. Essington. 2022. "The Shadow Model: How and Why Small Choices in Spatially Explicit Species Distribution Models Affect Predictions." *PeerJ* 10: e12783.

Cox, S., T. Essington, J. Kitchell, S. Martell, C. Walters, C. Boggs, and I. Kaplan. 2002. "Reconstructing Ecosystem Dynamics in the Central Pacific Ocean, 1952–1998. II. A Preliminary Assessment of the Trophic Impacts of Fishing and Effects on Tuna Dynamics." *Canadian Journal of Fisheries and Aquatic Sciences* 59: 1736–47.

Crognale, M., S. Eckert, D. Levenson, and C. Harms. 2008. "Leatherback Sea Turtle *Dermochelys coriacea* Visual Capacities and Potential Reduction of Bycatch by Pelagic Longline Fisheries." *Endangered Species Research* 5: 249–256.

Dacks, R., S. Lewis, P. James, L. Marino, and K. Oleson. 2020. "Documenting Baseline Value Chains of Palau's Nearshore and Offshore Fisheries Prior to Implementing a Large-Scale Marine Protected Area." *Marine Policy* 117: 103754.

Dagorn, L., K. N. Holland, V. Restrepo, and G. Moreno. 2013. "Is It Good or Bad to Fish with FADs? What Are the Real Impacts of the Use of Drifting FADs on Pelagic Marine Ecosystems?" *Fish and Fisheries* 14: 391–415.

Davies, T., and I. Jonsen. 2011. "Identifying Nonproportionality of Fishery-Independent Survey Data to Estimate Population Trends and Assess Recovery Potential for Cusk (*Brosme brosme*)." *Canadian Journal of Fisheries and Aquatic Sciences* 68: 413–425.

Dedman, S., R. Officer, M. Clarke, D. G. Reid, and D. Brophy. 2017. "Gbm.auto: A Software Tool to Simplify Spatial Modelling and Marine Protected Area Planning." *PLoS One* 12(12): e0188955.

Dray, S., P. Legendre, and P. Peres-Neto. 2006. "Spatial Modelling: A Comprehensive Framework for Principal Coordinate Analysis of Neighbour Matrices (PCNM)." *Ecological Modelling* 196: 483–493.

Dueri, S., and O. Maury. 2013. "Modelling the Effect of Marine Protected Areas on the Population of Skipjack Tuna in the Indian Ocean." *Aquatic Living Resources* 26: 171–78.

Dunn, D., S. Maxwell, A. Boustany, and P. Halpin. 2016. "Dynamic Ocean Management Increases the Efficiency and Efficacy of Fisheries Management." *Biological Sciences* 113: 668–673.

Effrosynidis, D., A. Tsikliras, A. Arampatzis, and G. Sylaios. 2020. "Species Distribution Modelling Via Feature Engineering and Machine Learning for Pelagic Fishes in the Mediterranean Sea." *Applied Sciences* 10: 8900.

Ellis, J., S. Phillips, and F. Poisson. 2017. "A Review of Capture and Post-Release Mortality of Elasmobranchs." *Journal of Fish Biology* 90: 653–722.

Emery, T., R. Noriega, A. Williams, J. Larcombe, S. Nicol, P. Williams, N. Smith, et al. 2018. "The Use of Electronic Monitoring within Tuna Longline Fisheries: Implications for International Data Collection, Analysis and Reporting." *Reviews in Fish Biology and Fisheries* 4: 887–907.

Essington, T. 2010. "Trophic Cascades in Open Ocean Ecosystems." In *Trophic Cascades. Predators, Prey and the Changing Dynamics of Nature*, edited by J. Terborgh and J. Estes, 91–106. Washington, DC: Island Press.

FAO. 2022. *The State of World Fisheries and Aquaculture 2022. Towards Blue Transformation*. Rome: Food and Agriculture Organization of the United Nations.

FFA. 2015. *Economic Indicators Report*. Honiara: Pacific Islands Forum Fisheries Agency.

Filous, A., A. M. Friedlander, M. Toribiong, R. J. Lennox, G. Mereb, and Y. Golbuu. 2022. "The Movements of Yellowfin Tuna, Blue Marlin, and Sailfish within the Palau National Marine Sanctuary and the Western Pacific Ocean." *ICES Journal of Marine Science* 79(2): 445–456.

Foster, W., G. Ayzel, J. Münchmeyer, T. Rettelbach, N. Kitzmann, T. Isson, M. Mutti, and M. Aberhan. 2022. "Machine Learning Identifies Ecological Selectivity Patterns across the End-Permian Mass Extinction." *Paleobiology* 48: 357–371.

Free, C., J. Thorson, M. Pinsky, K. Oken, J. Wiedenmann, and O. Jensen. 2019. "Impacts of Historical Warming on Marine Fisheries Production." *Science* 363: 979–983.

Gannon, P., E. Seyoum-Edjigu, D. Cooper, T. Sandwith, B. Dias, C. Palmer, B. Lang, J. Ervin, and S. Gidda. 2017. "Status and Prospects for Achieving Aichi Biodiversity Target 11: Implications of National Commitments and Priority Actions." *Parks* 23: 13–26.

Gelfand, A., and E. Schliep. 2016. "Spatial Statistics and Gaussian Processes: A Beautiful Marriage." *Spatial Statistics* 18 (Part A): 86–104.

Gelman, A., and J. Hill. 2006. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge: Cambridge University Press.

Georganos, S., and S. Kalogirou. 2022. "A Forest of Forests: A Spatially Weighted and Computationally Efficient Formulation of Geographical Random Forests." *ISPRS International Journal of Geo-Information* 11: 471.

Gerassis, S., E. Giráldez, M. Pazo-Rodríguez, Á. Saavedra, and J. Taboada. 2021. "AI Approaches to Environmental Impact Assessments (EIAs) in the Mining and Metals Sector Using AutoML and Bayesian Modeling." *Applied Sciences* 11: 7914.

Gianuca, D., R. Sant'ana, and T. Neves. 2016. "Influence of Electric Fishing Lights on Sink Rates of Baited Hooks in Brazilian Pelagic Longline Fisheries: Implications for Seabird Bycatch." *Brazilian Journal of Oceanography* 64: 95–100.

Gillett, R. 2016. *Fisheries in the Economies of Pacific Island Countries and Territories*. Noumea: Pacific Community.

Gilly, W., U. Markaida, C. Baxter, B. Block, A. Boustany, L. Zeidberg, K. Reisenbichler, B. Robison, G. Bazzino, and C. Salinas. 2006. "Vertical and Horizontal Migrations by the Jumbo Squid *Dosidicus gigas* Revealed by Electronic Tagging." *Marine Ecology Progress Series* 324: 1–17.

Gilman, E., V. D. R. Castejon, E. Loganimoce, and M. Chaloupka. 2020. "Capability of a Pilot Fisheries Electronic Monitoring System to Meet Scientific and Compliance Monitoring Objectives." *Marine Policy* 113: 103792.

Gilman, E., M. Chaloupka, P. Bach, H. Fennell, M. Hall, M. Musyl, S. Piovano, F. Poisson, and L. Song. 2020. "Effect of Pelagic Longline Bait Type on Species Selectivity: A Global Synthesis of Evidence." *Reviews in Fish Biology and Fisheries* 30: 535–551.

Gilman, E., M. Chaloupka, L. Benaka, H. Bowlby, M. Fitchett, M. Kaiser, and M. Musyl. 2022. "Phylogeny Explains Capture Mortality of Sharks and Rays in Pelagic Longline Fisheries: A Global Meta-Analytic Synthesis." *Scientific Reports* 12: 18164. https://doi.org/10.1038/s41598-022-21976-w.

Gilman, E., M. Chaloupka, L. Dagorn, M. Hall, A. Hobday, M. Musyl, T. Pitcher, F. Poisson, V. Restrepo, and P. Suuronen. 2019. "Robbing Peter to Pay Paul: Replacing Unintended Cross-Taxa Conflicts with Intentional Tradeoffs by Moving from Piecemeal to Integrated Fisheries Bycatch Management." *Reviews in Fish Biology and Fisheries* 29: 93–123.

Gilman, E., M. Chaloupka, M. Fitchett, D. Cantrell, and M. Merrifield. 2020. "Ecological Responses to Blue Water MPAs." *PLoS One* 15: e0235129.

Gilman, E., M. Chaloupka, M. Merrifield, N. Malsol, and C. Cook. 2016. "Standardized Catch and Survival Rates, and Effect of a Ban on Shark Retention, Palau Pelagic Longline Fishery." *Aquatic Conservation: Marine and Freshwater Ecosystems* 26: 1031–62.

Gilman, E., M. Chaloupka, and M. Musyl. 2018. "Effects of Pelagic Longline Hook Size on Species- and Size-Selectivity and Survival." *Reviews in Fish Biology and Fisheries* 28: 417–433.

Gilman, E., M. Chaloupka, A. Read, P. Dalzell, J. Holetschek, and C. Curtice. 2012. "Hawaii Longline Tuna Fishery Temporal Trends in Standardized Catch Rates and Length Distributions and Effects on Pelagic and Seamount Ecosystems." *Aquatic Conservation: Marine and Freshwater Ecosystems* 22: 446–488.

Gilman, E., P. Dalzell, and S. Martin. 2006. "Fleet Communication to Abate Fisheries Bycatch." *Marine Policy* 30: 360–66.

Gilman, E., M. Hall, H. Booth, T. Gupta, M. Chaloupka, H. Fennell, M. Kaiser, D. Karnad, and E. J. Milner-Gulland. 2022. "A Decision Support Tool for Integrated Fisheries Bycatch Management." *Reviews in Fish Biology and Fisheries* 32: 441–472.

Gilman, E., M. Kaiser, and M. Chaloupka. 2019. "Do Static and Dynamic Marine Protected Areas that Restrict Pelagic Fishing Achieve Ecological Objectives?" *Ecosphere* 10: e02968. https://doi.org/10.1002/ecs2.2968.

Goldstein, H., W. Browne, and C. Charlton. 2018. "A Bayesian Model for Measurement and Misclassification Errors alongside Missing Data, with an Application to Higher Education Participation in Australia." *Journal of Applied Statistics* 45: 918–993.

H2O.ai. 2022. "H2O: Scalable Machine Learning Platform. v3.38.0.2." https://github.com/h2oai/h2o-3.

Hall, M. A., E. Gilman, H. Minami, T. Mituhasi, and E. Carruthers. 2017. "Mitigating Bycatch in Tuna Fisheries." *Reviews in Fish Biology and Fisheries* 27: 881–908.

Halpern, B. S. 2003. "The Impact of Marine Reserves: Do Reserves Work and Does Reserve Size Matter?" *Ecological Applications* 13: S117–S137.

Hampton, J., P. Lehodey, I. Senina, S. Nicol, J. Scutt Phillips, and K. Tiamere. 2023. "Limited Conservation Efficacy of Large-Scale Marine Protected Areas for Pacific Skipjack and Bigeye Tunas." *Frontiers in Marine Science* 9: 2817. https://doi.org/10.3389/fmars.2022.1060943.

Hazen, E., K. Scales, S. Maxwell, D. Briscoe, H. Welch, S. Bograd, H. Bailey, et al. 2018. "A Dynamic Ocean Management Tool to Reduce Bycatch and Support Sustainable Fisheries." *Science Advances* 4: eaar3001. https://doi.org/10.1126/sciadv.aar3001.

Hazin, H., F. Hazin, P. Travassos, and K. Erzini. 2005. "Effect of Light-Sticks and Electralunie Attractors on Surface-Longline Catches of Swordfish (*Xiphias gladius*, Linnaeus, 1959) in the Southwest Equatorial Atlantic." *Fisheries Research* 72: 271–77.

He, X., K. Zhao, and C. X. Xiaowen. 2021. "AutoML: A Survey of the State-of-the-Art." *Knowledge-Based Systems* 212: 106622.

Hijmans, R. 2023. "terra: Spatial Data Analysis." R Package Version 1.7-39. https://CRAN.R-project.org/package=terra.

Hilborn, R., V. Agostini, M. Chaloupka, S. Garcia, L. Gerber, E. Gilman, Q. Hanich, et al. 2022. "Area-Based Management of Blue Water Fisheries: Current Knowledge and Research Needs." *Fish and Fisheries* 23: 492–518.

Hinke, J., I. Kaplan, K. Avdin, G. Watters, R. Olson, and J. Kitchell. 2004. "Visualizing the Food-Web Effects of Fishing for Tunas in the Pacific Ocean." *Ecology and Society* 9: 10.

Houk, P., A. Yalon, S. Maxin, C. Starsinic, A. McInnis, M. Gouezo, Y. Golbuu, and R. van Woesik. 2020. "Predicting Coral-Reef Futures from El Niño and Pacific Decadal Oscillation Events." *Scientific Reports* 10(1): 7735.

Hoyle, S., A. Langley, and R. Campbell. 2014. *Recommended Approaches for Standardizing CPUE Data from Pelagic Fisheries. WCPFC-SC10-2014/SA-IP-10*. Kolonia: Western and Central Pacific Fisheries Commission.

Hoyle, S., S. I. Lee, and D. Kim. 2022. "CPUE Standardization for Southern Bluefin Tuna (*Thunnus maccoyii*) in the Korean Tuna Longline Fishery, Accounting for Spatiotemporal Variation in Targeting through Data Exploration and Clustering." *PeerJ* 10: e13951. https://doi.org/10.7717/peerj.13951.

Hughes, T., J. Kerry, S. Connolly, J. Alvarez-Romero, C. Eakin, S. Heron, M. Gonzalez, and J. Moneghetti. 2021. "Emergent Properties in the Responses of Tropical Corals to Recurrent Climate Extremes." *Current Biology* 31: 5393–99.

ISC. 2022. *Stock Assessment and Future Projections of Blue Shark in the North Pacific Ocean Through 2020*. Yokohama: Shark Working Group, International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific Ocean.

IUCN. 2023. *Red List of Threatened Species Version 2022-2*. Gland: International Union for the Conservation of Nature.

Jaiteh, V., N. Loneragan, and C. Warren. 2017. "The End of Shark Finning? Impacts of Declining Catches and Fin Demand on Coastal Community Livelihoods." *Marine Policy* 82: 224–233.

Jaiteh, V., T. Peatman, S. Lindfield, E. Gilman, and S. Nicol. 2021. "Bycatch Estimates from a Pacific Tuna Longline Fishery Provide a Baseline for Understanding the Long-Term Benefits of a Large, Blue Water Marine Sanctuary." *Frontiers in Marine Science* 8: 720603. https://doi.org/10.3389/fmars.2021.720603.

Janitza, S., E. Celik, and A. Boulesteix. 2018. "A Computationally Fast Variable Importance Test for Random Forests for High-Dimensional Data." *Advances in Data Analysis and Classification* 12: 885–915.

Jiminez, S., A. Domingo, H. Winker, D. Parker, D. Gianuca, T. Neves, R. Coelho, and S. Kerwath. 2020. "Towards Mitigation of Seabird Bycatch: Large-Scale Effectiveness of Night Setting and Tori Lines across Multiple Pelagic Longline Fleets." *Biological Conservation* 247: 108642.

Jorgensen, S., F. Micheli, T. White, K. Van Houtan, J. Alfaro-Shigueto, S. Andrzejaczek, N. Arnoldi, et al. 2022. "Emergent Research and Priorities for Elasmobranch Conservation." *Endangered Species Research* 47: 171–203.

Kammann, E., and M. Wand. 2003. "Geoadditive models." *Applied Statistics* 52: 1–18.

Kaschner, K., K. Kesner-Reyes, C. Garilao, J. Segschneider, J. Rius-Barile, T. Rees, and R. Froese. 2019. "AquaMaps: Predicted Range Maps for Aquatic Species. Version 10/2019." www.aquamaps.org.

Ke, G., Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, and T.-Y. Liu. 2017. "LightGBM: A Highly Efficient Gradient Boosting Decision Tree." *Advances in Neural Information Processing Systems* 30: 3149–57.

Kitchell, J., T. Essington, C. Boggs, D. Schindler, and C. Walters. 2002. "The Role of Sharks and Longline Fisheries in a Pelagic Ecosystem of the Central Pacific." *Ecosystems* 5: 202–216.

Kot, C., A. Boustany, and P. Halpin. 2010. "Temporal Patterns of Target Catch and Sea Turtle Bycatch in the US Atlantic Pelagic Longline Fleet." *Canadian Journal of Fisheries and Aquatic Sciences* 67: 42–57.

Kuhn, M., and K. Johnson. 2013. *Applied Predictive Modeling* 600. New York: Springer.

Kuhn, M., and H. Wickham. 2020. "Tidymodels: A Collection of Packages for Modeling and Machine Learning Using Tidyverse Principles." https://www.tidymodels.org.

Kuhn, M., Q. Yan, and S. Pawley. 2023. "agua: 'tidymodels' Integration with 'h2o'." R Package Version 0.1.2. https://CRAN.R-project.org/package=agua.

LeDell, E., N. Gill, S. Aiello, A. Fu, A. Candel, C. Click, T. Kraljevic, et al. 2023. "h2o: R Interface for the 'H2O' Scalable Machine Learning Platform." R Package Version 3.40.0.1. https://CRAN.R-project.org/package=h2o.

LeDell, E., and S. Poirier. 2020. "H2O AutoML: Scalable Automatic Machine Learning." 7th ICML Workshop on Automated Machine Learning. https://www.automl.org/wp-content/uploads/2020/07/AutoML_2020_paper_61.pdf.

Lehodey, P., J. Alheit, M. Barange, T. Baumgartner, G. Beaugrand, K. Drinkwater, J. Fromentin, et al. 2006. "Climate Variability, Fish and Fisheries." *Journal of Climate* 19: 5009–30.

Lehodey, P., M. Bertignac, J. Hampton, A. Lewis, and J. Picaut. 1997. "El Niño Southern Oscillation and Tuna in the Western Pacific." *Nature* 389: 715–18.

Lehodey, P., I. Senina, S. Nicol, and J. Hampton. 2015. "Modelling the Impact of Climate Change on South Pacific Albacore Tuna." *Deep Sea Research Part II: Topical Studies in Oceanography* 113: 246–259.

Li, L. 2019. "Geographically Weighted Machine Learning and Downscaling for High-Resolution Spatiotemporal Estimations of Wind Speed." *Remote Sensing* 11: 1378.

Li, Z. 2022. "Extracting Spatial Effects from Machine Learning Model Using Local Interpretation Method: An Example of SHAP and XGBoost." *Computers, Environment and Urban Systems* 96: 101845.

Little, A., C. Needle, R. Hilborn, D. Holland, and C. Marshall. 2015. "Real-Time Spatial Management Approaches to Reduce Bycatch and Discards: Experiences from Europe and the United States." *Fish and Fisheries* 16: 576–602.

Little, R. 1988. "A Test of Missing Completely at Random for Multivariate Data with Missing Values." *Journal of the American Statistical Association* 83: 1198–1202.

Liu, X., O. Kounadi, and R. Zurita-Milla. 2022. "Incorporating Spatial Autocorrelation in Machine Learning Models Using Spatial Lag and Eigenvector Spatial Filtering Features." *ISPRS International Journal of Geo-Information* 11: 242.

Liu, Z., Y. Jin, L. Yang, L. Yan, Y. Zhang, M. Xu, J. Tang, Y. Zhou, F. Hu, and J. Cheng. 2022. "Incorporating Egg-Transporting Pathways into Conservation Plans of Spawning Areas: An Example of Small Yellow Croaker (*Larimichthys polyactis*) in the East China Sea Zone." *Frontiers Marine Science* 9: 941411.

Ludwig, M., A. Moreno-Martinez, N. Hölzel, E. Pebesma, and H. Meyer. 2023. "Assessing and Improving the Transferability of Current Global Spatial Prediction Models." *Global Ecology & Biogeography* 2: 356–368.

Lundberg, S., G. Erion, H. Chen, A. DeGrave, J. Prutkin, B. Nair, R. Katz, et al. 2020. "From Local Explanations to Global Understanding with Explainable AI for Trees." *Nature Machine Intelligence* 2: 2522–5839.

Mannocci, L., F. Faben Forget, M. Travassos Tolotti, P. Bach, N. Bez, H. Demarcq, D. Kaplan, et al. 2020. "Predicting Bycatch Hotspots in Tropical Tuna Purse Seine Fisheries at the Basin Scale." *Global Ecology and Conservation* 24: e01393.

Marine Conservation Institute. 2023. *Marine Protection Atlas*. Seattle: Marine Conservation Institute. https://mpatlas.org/.

Mayer, M. 2021. "missRanger: Fast Imputation of Missing Values." R Package Version 2.1.3. https://CRAN.R-project.org/package=missRanger.

Mayer, M. 2023. "shapviz: SHAP Visualizations." R Package Version 0.8.0. https://CRAN.R-project.org/package=shapviz.

Mayer, M., and D. Watson. 2023. "kernelshap: Kernel SHAP." R Package Version 0.3.7. https://CRAN.R-project.org/package=kernelshap.

Meyer, H., and E. Pebesma. 2022. "Machine Learning-Based Global Maps of Ecological Variables and the Challenge of Assessing them." *Nature Communications* 13: 2208.

Milà, C., J. Mateu, E. Pebesma, and H. Meyer. 2022. "Nearest Neighbour Distance Matching Leave-One-Out Cross-Validation for Map Validation." *Methods in Ecology and Evolution* 13: 1304–16.

Morato, T., S. Hoyle, V. Allain, J. Simon, and S. Nicol. 2010. "Seamounts Are Hotspots of Pelagic Biodiversity in the Open Ocean." *Proceedings of the National Academy of Sciences of the United States of America* 107: 9707–11.

Murray, J. 2018. "Multiple Imputation: A Review of Practical and Theoretical Findings." *Statistical Science* 33: 142–159.

Musick, J., ed. 1999. *Life in the Slow Lane: Ecology and Conservation of Long-Lived Marine Animals*. Symposium 23. Bethesda, MD: American Fisheries Society.

Musyl, M., R. Brill, D. Curran, N. Fragoso, L. McNaughton, A. Nielsen, B. Kikkawa, and C. Moyes. 2011. "Postrelease Survival, Vertical and Horizontal Movements, and Thermal Habitats of Five Species of Pelagic Sharks in the Central Pacific Ocean." *Fishery Bulletin* 109: 341–361.

Myers, R., K. Bowen, and N. Barrowman. 1999. "Maximum Reproductive Rate of Fish at Low Population Sizes." *Canadian Journal of Fisheries and Aquatic Sciences* 56: 2404–19.

Newman, M., M. Alexander, T. Ault, K. Cobb, C. Deser, E. Di Lorenzo, N. Mantua, et al. 2016. "The Pacific Decadal Oscillation, Revisited." *Journal of Climate* 29: 4399–4427.

Orbesen, E., D. Snodgrass, G. Shideler, C. Brown, and J. Walter. 2017. "Diurnal Patterns in Gulf of Mexico Epipelagic Predator Interactions with Pelagic Longline Gear: Implications for Target Species Catch Rates and Bycatch Mitigation." *Bulletin of Marine Science* 93: 573–589.

Padgham, M. 2021. "geodist: Fast, Dependency-Free Geodesic Distance Calculations." R Package Version 0.0.7. https://github.com/hypertidy/geodist.

Palau Conservation Society. 1999. *Palau's Locally Based Foreign Tuna Fishery: Benefits and Costs to Palau*. Koror: Palau Conservation Society.

Palau MAFE, SPC, and U.S. Department of State. 2022. *Republic of Palau Climate Resilient Marine Spatial Planning Project*. Koror; Noumea; Washington, DC: Palau Ministry of Agriculture, Fisheries and the Environment; Pacific Community; U.S. Department of State.

Palau Office of the President. 2022. *Executive Order No. 476 to Establish Coordinating Mechanisms for the Implementation of Marine Spatial Planning for the Blue Prosperity Plan*. Koror: Republic of Palau Office of the President.

Pebesma, E. 2018. "Simple Features for R: Standardized Support for Spatial Vector Data." *The R Journal* 10: 439–446.

Pebesma, E., and R. Bivand. 2023. *Spatial Data Science: With Applications in R*. New York: Chapman and Hall/CRC. https://doi.org/10.1201/9780429459016.

Pedersen, T. 2022. "patchwork: The Composer of Plots." R Package Version 1.1.2. https://CRAN.R-project.org/package=patchwork.

Piasente, M., B. Stanley, T. Timmiss, H. McElderry, M. Pria, and M. Dyas. 2012. *Electronic Onboard Monitoring Pilot Project for* *the Eastern Tuna and Billfish Fishery. FRDC Project 2009/048. ST-IP-05*. Kolonia: Western and Central Pacific Fisheries Commission.

PNA. 2022. *Palau Arrangement for the Management of the Western Pacific Tuna Fishery – Management Scheme Longline Vessel Day Scheme*. Majuro: Parties to the Nauru Agreement.

Poisson, F., F. Crespo, J. Ellis, P. Chavance, P. Bach, M. Santos, B. Seret, et al. 2016. "Technical Mitigation Measures for Sharks and Rays in Fisheries for Tuna and Tuna-like Species: Turning Possibility into Reality." *Aquatic Living Resources* 29: 402.

Poisson, F., J. Gaertner, M. Taquet, J. Durbec, and K. Bigelow. 2010. "Effects of Lunar Cycle and Fishing Operations on Longline-Caught Pelagic Fish: Fishing Performance, Capture Time, and Survival of Fish." *Fishery Bulletin* 108: 268–281.

Poloczanska, E., C. Brown, W. Sydeman, W. Kiessling, D. Schoeman, P. Moore, K. Brander, et al. 2013. "Global Imprint of Climate Change on Marine Life." *Nature Climate Change* 3: 919–925.

Polovina, J., and P. Woodworth-Jefcoats. 2013. "Fishery-Induced Changes in the Subtropical Pacific Pelagic Ecosystem Size Structure: Observations and Theory." *PLoS One* 8: e62341. https://doi.org/10.1371/journal.pone.0062341.

Pons, M., J. Watson, D. Ovando, S. Andraka, S. Brodie, A. Domingo, M. Fitchett, et al. 2022. "Trade-Offs between Bycatch and Target Catches in Static Versus Dynamic Fishery Closures." *Sustainability Science* 119: e2114508119.

Prihartato, P., X. Irigoien, M. Genton, and S. Kaartvedt. 2016. "Global Effects of Moon Phase on Nocturnal Acoustic Scattering Layers." *Marine Ecology Progress Series* 544: 65–75.

Qiu, W., H. Chen, A. Dincer, S. Lundberg, M. Kaeberlein, and S. Lee. 2022. "Interpretable Machine Learning Prediction of All-Cause Mortality." *Communications Medicine* 2: 125.

Reisinger, R., P. Trathan, C. Johnson, T. Joyce, J. Durban, R. Pitman, and A. Friedlaender. 2022. "Spatiotemporal Overlap of Baleen Whales and Krill Fisheries in the Western Antarctic Peninsula Region." *Frontiers in Marine Science* 9: 914726.

Republic of Palau. 2019. *Republic of Palau Public Law 10-157 (RPPL 10–157). Amendment to the Palau National Marine Sanctuary Act*. Koror: Palau National Congress.

Republic of Palau. 2022. *Annual Report to the Commission. Part 1: Information on Fisheries, Research and Statistics. Republic of Palau-2021. WCPFC-SC18-AR/CCM-18*. Kolonia: Western and Central Pacific Fisheries Commission.

Rice, P., C. Goodyear, E. Prince, D. Snodgrass, and J. Serafy. 2007. "Use of Catenary Geometry to Estimate Hook Depth during near-Surface Pelagic Longline Fishing: Theory Versus Practice." *North American Journal of Fisheries Management* 27: 1148–61.

Richardson, S., and W. Gilks. 1993. "A Bayesian Approach to Measurement Error Problems in Epidemiology Using Conditional Independence Models." *American Journal of Epidemiology* 138: 430–442.

Rodrigues, L., P. Kinas, and L. Cardoso. 2022. "Optimal Setting Time and Season Increase the Target and Reduce the Incidental Catch in Longline Fisheries: A Bayesian Beta Mixed Regression Approach." *ICES Journal of Marine Science* 79: 1245–58.

Saba, V., P. Santidrián-Tomillo, R. Reina, J. Spotila, J. Musick, D. Evans, and F. Paladino. 2007. "The Effect of the El Niño Southern Oscillation on the Reproductive Frequency of Eastern Pacific Leatherback Turtles." *Journal of Applied Ecology* 44: 395–404.

Schaefer, K. 2001. "Assessment of Skipjack Tuna (*Katsuwonus pelamis*) Spawning Activity in the Eastern Pacific Ocean." *Fishery Bulletin US* 99: 343–350.

Schimohr, K., P. Doeblr, and J. Scheiner. 2023. "Prediction of Bike-Sharing Trip Counts: Comparing Parametric Spatial Regression Models to a Geographically Weighted XGBoost Algorithm." *Geographical Analysis* 55: 651–684. https://doi.org/10.1111/gean.12354.

Scholbeck, C., C. Molnar, C. Heumann, B. Bischl, and G. Casalicchio. 2020. "Sampling, Intervention, Prediction, Aggregation: A Generalized Framework for Model-Agnostic Interpretations." In *Machine Learning and Knowledge Discovery in Databases: International Workshops of ECML PKDD 2019*, edited by P. Cellier and K. Driessens, 205–216. Würzburg, September 16–20, 2019, Proceedings, Part I: Springer International Publishing.

Seidu, I., L. Brobbey, E. Danquah, S. Oppong, D. van Beuningen, M. Seido, and N. Dulvy. 2022. "Fishing for Survival: Importance of Shark Fisheries for the Livelihoods of Coastal Communities in Western Ghana." *Fisheries Research* 246: 106157.

Selig, E., K. Kleisner, O. Ahoobim, F. Arocha, A. Cruz-Trinidad, R. Fujita, H. Mafaniso, et al. 2017. "A Typology of Fisheries Management Tools: Using Experience to Catalyse Greater Success." *Fish and Fisheries* 18: 543–570.

Sibert, J., and J. Hampton. 2003. "Mobility of Tropical Tunas and the Implications for Fisheries Management." *Marine Policy* 27: 87–95.

Sigrist, F. 2023. "Latent Gaussian Model Boosting." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 45: 1894–1905.

Sisior, K. 2004. "Tuna Fisheries in the Waters of the Republic of Palau." SCTB17 Working Paper NFA-20. 17th Meeting of the Standing Committee on Tuna and Billfish. Secretariat of the Pacific Community, Noumea, New Caledonia.

Slooten, E. 2013. "Effectiveness of Area-Based Management in Reducing Bycatch of the New Zealand Dolphin." *Endangered Species Research* 20: 121–130.

Śmielak, M. 2023. "Biologically Meaningful Moonlight Measures and Their Application in Ecological Research." *Behavioural Ecology and Sociobiology* 77: 21.

Smith, S., D. Au, and C. Snow. 1998. "Intrinsic Rebound Potentials of 26 Species of Pacific Sharks." *Marine and Freshwater Research* 49: 663–678.

Sokhansanj, B., and G. Rosen. 2022. "Predicting COVID-19 Disease Severity from SARS-CoV-2 Spike Protein Sequence by Mixed Effects Machine Learning." *Computers in Biology and Medicine* 149: 105969.

SPC and FFA. 2015. *Future of Fisheries. A Regional Roadmap for Sustainable Pacific Fisheries*. Noumea; Honiara: Secretariat of the Pacific Community and Pacific Islands Forum Fisheries Agency.

Stahl, J., and M. Carnes. 2020. *Detection Accuracy in the Hawai'i Longline Electronic Monitoring Program with Comparisons between Three Video Review Speeds*. PIFSC Data Report DR-20-012. Honolulu: Pacific Islands Fisheries Science Center, National Marine Fisheries Service.

Stefansson, G., and A. A. Rosenberg. 2006. "Designing Marine Protected Areas for Migrating Fish Stocks." *Journal of Fish Biology* 69: 66–78.

Steinruecke, C., E. Smith, D. Janz, J. Lloyd, and Z. Ghahramani. 2019. "The Automatic Statistician." In *Automated Machine Learning: Methods, Systems, Challenges. The Springer Series on Challenges in Machine Learning*, edited by F. Hutter, L. Kotthoff, and J. Vanschoren. Cham: Springer.

Tierney, N., and D. Cook. 2023. "Expanding Tidy Data Principles to Facilitate Missing Data Exploration, Visualization and Assessment of Imputations." *Journal of Statistical Software* 105(7): 1–31.

TNC. 2016. *Setting Gear Deep by Palau Locally-Based Pelagic Longline Vessels*. Koror: The Nature Conservancy.

Venables, W., and B. Ripley. 2002. *Modern Applied Statistics with S*, 4th ed. New York: Springer.

Viquerat, S., C. Waluda, A. Kennedy, J. Jackson, M. Hevia, E. Carroll, D. Buss, et al. 2022. "Identifying Seasonal Distribution Patterns of Fin Whales across the Scotia Sea and the Antarctic Peninsula Region Using a Novel Approach Combining Habitat Suitability Models and Ensemble Learning Methods." *Frontiers in Marine Science* 9: 1040512.

Wabnitz, C., A. Cisneros-Montemayor, Q. Hanich, and Y. Ota. 2018. "Ecotourism, Climate Change and Reef Fish Consumption in Palau: Benefits, Trade-Offs and Adaptation Strategies." *Marine Policy* 88: 323–332.

Wallace, B., A. DiMatteo, A. Bolten, M. Chaloupka, B. Hutchinson, F. Abreu-Grobois, J. Mortimer, et al. 2011. "Global Conservation Priorities for Marine Turtles." *PLoS One* 6: e24510.

Wallace, B., A. DiMatteo, B. Hurley, E. Finkbeiner, A. Bolten, M. Chaloupka, B. Hutchinson, et al. 2010. "Regional Management Units for Marine Turtles: A Novel Framework for Prioritizing Conservation and Research across Multiple Scales." *PLoS One* 5: e15465. https://doi.org/10.1371/journal.pone.0015465.

Wang, J., L. Boles, B. Higgins, and J. Lohmann. 2007. "Behavioral Responses of Sea Turtles to Lightsticks Used in Longline Fisheries." *Animal Conservation* 10: 176–182.

Ward, P., and S. Hindmarsh. 2007. "An Overview of Historical Changes in the Fishing Gear and Practices of Pelagic Longliners, with Particular Reference to Japan's Pacific Fleet." *Rev Fish Biol Fisheries* 17: 501–516.

Ward, P., and R. Myers. 2005a. "Shifts in Open-Ocean Fish Communities Coinciding with the Commencement of Commercial Fishing." *Ecology* 86: 835–847.

Ward, P., and R. Myers. 2005b. "Inferring the Depth Distribution of Catchability for Pelagic Fishes and Correcting for Variations in the Depth of Longline Fishing Gear." *Canadian Journal of Fisheries and Aquatic Sciences* 62: 1130–42.

Ward, P., and R. Myers. 2007. "Bait Loss and Its Potential Effects on Fishing Power in Pelagic Longline Fisheries." *Fisheries Research* 86: 69–76.

Ward, P., R. Myers, and W. Blanchard. 2004. "Fish Lost at Sea: The Effect of Soak Time on Pelagic Longline Catches." *Fisheries Bulletin* 102: 179–195.

WCPFC. 2019. *Silky Shark (Carcharhinus falciformis) Stock Status and Management Advice*. Kolonia: Western and Central Pacific Fisheries Commission.

Wei, T., and V. Simko. 2021. "R Package 'corrplot': Visualization of a Correlation Matrix (Version 0.92)." https://github.com/taiyun/corrplot.

Wickham, H. 2016. *ggplot2: Elegant Graphics for Data Analysis*, 2nd ed. New York: Springer-Verlag.

Wickham, H., M. Averick, J. Bryan, W. Chang, L. McGowan, R. François, G. Grolemund, et al. 2019. "Welcome to the Tidyverse." *Journal of Open Source Software* 4: 1686.

Wikle, C., A. Datta, B. Hari, E. Boone, I. Sahoo, I. Kavila, S. Castruccio, S. Simmons, W. Burr, and W. Chang. 2023. "An Illustration of Model Agnostic Explainability Methods Applied to Environmental Data." *Environmetrics* 34: e2772.

Witzell, W. 1999. "Distribution and Relative Abundance of Sea Turtles Caught Incidentally by the U.S. Pelagic Longline Fleet in the Western North Atlantic Ocean, 1992–1995." *Fisheries Bulletin* 97: 200–211.

Wright, M., and A. Ziegler. 2017. "Ranger: A Fast Implementation of Random Forests for High Dimensional Data in C++ and R." *Journal of Statistical Software* 77: 1–17.

Yang, S., H. Zhang, W. Fan, H. Shi, Y. Fei, and S. Yuan. 2022. "Behaviour Impact Analysis of Tuna Purse Seiners in the Western and Central Pacific Based on the BRT and GAM Models." *Frontiers in Marine Science* 9: 881036.

Zeileis, A., J. Fisher, K. Hornik, R. Ihaka, C. McWhite, P. Murrell, R. Stauffer, and C. Wilke. 2020. "Colorspace: A Toolbox for Manipulating and Assessing Colors and Palettes." *Journal of Statistical Software* 96: 1–4.

Zhang, T., A. Andrew Hoell, J. Perlwitz, J. Eischeid, D. Murray, M. Hoerling, and T. Hamill. 2019. "Towards Probabilistic Multivariate ENSO Monitoring." *Geophysical Research Letters* 46: 10532–40.

Zhou, F., A. Alsaid, M. Blommer, R. Curry, R. Swaminathan, D. Kochhar, W. Talamonti, and L. Tijerina. 2022. "Predicting Driver Fatigue in Monotonous Automated Driving with Explanation Using GPBoost and SHAP." *International Journal of Human–Computer Interaction* 38: 719–729.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Gilman, Eric, and Milani Chaloupka. 2024. "Evidence from Interpretable Machine Learning to Inform Spatial Management of Palau's Tuna Fisheries." *Ecosphere* 15(2): e4751. https://doi.org/10.1002/ecs2.4751