INTER-AMERICAN TROPICAL TUNA COMMISSION

SCIENTIFIC ADVISORY COMMITTEE

TENTH MEETING

San Diego, California (USA)
13-17 May 2019

DOCUMENT SAC-10 INF-D

DEVELOPING ALTERNATIVE CONSERVATION MEASURES FOR BIGEYE TUNA IN THE EASTERN PACIFIC OCEAN: A DYNAMIC OCEAN MANAGEMENT APPROACH

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CONTENTS

1. INTRODUCTION

The tropical tuna purse-seine fishery in the Eastern Pacific Ocean (EPO) is one of the biggest in the world, with recent annual catches exceeding 600,000 tons (SAC-10-03). Although management measures to maintain exploitation rates at sustainable levels are in place (e.g., Resolution C-17-02), some populations may have started to experience notable declines. This is the case for bigeye tuna (*Thunnus obesus*), for which the last assessment showed considerable uncertainty with respect to stock status, and that a decreasing trend in spawning stock biomass is projected to continue into the near future (SAC-09-05). Unfortunately, this is not only a local issue and similar declines may be occurring in other regions (e.g. ICCAT).

Because of this, the IUCN has classified bigeye tuna as a vulnerable species with a decreasing population trend (Collette et al. 2011). To meet management objectives, the Inter-American Tropical Tuna Commission (IATTC) has implemented a 2018-2020 conservation plan, which includes a 72-day fishery closure, as well as an additional 30-day closure of an area known as the “corralito”. These measures are vessel class-specific but the relationship between capacity and fishing mortality is unclear. Moreover, most of the bigeye purse-seine catch is produced by the fishery on floating-objects which targets skipjack tuna (*Katsuwonus pelamis*).

Considering the continuing increase in fishing effort in the purse-seine fishery, in terms of the number of sets, despite restrictions on adding capacity to the fleet since 2002 (Resolution C-02-03), in 2018 the staff proposed limiting the number of floating-object and unassociated sets. However, this proposal was not adopted, due in part to anticipated difficulties with implementation and monitoring. Thus, alternative and adaptive management measures that decrease bigeye catches while minimizing the impact on skipjack catches need to be developed. Toward this end, the commission funded project J.2.a, which has to, among other tasks, evaluate alternative management measures, such as closed areas and gear restrictions.

This study, which is part of the J.2.a project, investigates the relationship between bigeye catch and a suite of variables, including spatio-temporal, operational and environmental factors, to understand bigeye tuna distribution and dynamics in the EPO. This document explores the utility of these habitat models to provide decision-makers and resource-users with near real-time maps of high probability of bigeye catches. The application of our approach for forecasting on a seasonal timescale and how our outputs can assist end-users in the development of effective catch-based conservation measures are also discussed.

2. METHODS

All data processing and analytical work was carried out in the Microsoft R Open environment (MRO 3.4.3; https://mran.microsoft.com/rro). Microsoft R Open is the enhanced distribution of R from Microsoft Corporation and includes additional capabilities for improved performance, parallelization, and reproducibility.

2.1. Fisheries observer data

We used 23 years (1995–2017) of fisheries’ observer data[2] from the EPO tropical tuna purse-seine fishery (IATTC vessel class 6; > 363 t of capacity). The data include set-level information on total tuna catch by weight category and species along with location, date and time of fishing, and other operational characteristics (details on the onboard observer program can be found in here). The data set contained information on more than 450,000 sets, ~75,000 (16.5%) of which caught bigeye tuna. The distribution of purse seine fishing effort was reasonably constant over the IATTC convention area[3] through this time period, with most effort concentrated between 20N and 20S. However, almost the totality of bigeye tuna is caught on floating-object sets (FOB sets) (i.e. bigeye tuna is rarely caught by purse seiners when fishing on tunas associated with dolphins or on unassociated schools), which principally occur between 10N and 20S (IATTC 2018). Because of this, the working dataset was constrained to 10N-20S and FOB sets only. Since the late 1990s, most FOB sets of Class-6 vessels are estimated to have been sets on drifting fish aggregating devices (FADs) (FSR 4, FSR 16). The final dataset contained 145,877 sets, ~73,000 (~50%) of which had positive bigeye tuna catch (Table 1). During this period, the observer coverage rate was 98.07% on purse seine vessels of class 6. The proportion of zeros varied between size class: 25, 43, 46 and 23% for small (=<2.5 kg.), medium (>2.5 and =<15 kg.), juveniles (=<15 kg.) and large tuna (>15 kg.), respectively (Table 2). The

[2] Data collected by AIDCP onboard observer program.

[3] The eastern Pacific Ocean from 50°S to 50°N and from the coast to 150°W.

"juveniles" category approximates immature bigeye and was created as the sum of small and medium size bigeye tuna.

2.2. Predictive variables

A total of 23 variables were available for inclusion in species distribution models (SDMs), which included 3 spatio-temporal variables, 12 surface variables, 4 subsurface variables, and 4 operational variables (Table 3). The three spatio-temporal variables included location of set and day of the year, as seasonality may affect catches. Spatio-temporal variables can be confounded with environmental factors and reflect certain natural processes not captured by the surface and subsurface variables. The majority of environmental data was sourced from daily/weekly fields of global data assimilative models (i.e. assimilate available data from satellites and *in situ* platforms) that include the IATTC convention area at 0.25° ($\sim$25 km) resolution (available at http://marine.copernicus.eu/ and https://www.aviso.altimetry.fr/). The 0.25° spatial resolution, combined with a fine temporal scale, is considered sufficient for habitat modeling (Scales et al. 2016).

The twelve surface variables chosen included sea surface temperature (SST) and its gradient (SST_grad; calculated as the change in temperature at the same pixel over a period of 7 days), salinity (Sal), sea surface height (SSH), current vorticity (Vol), current speed (Speed), current direction (Dir), eddy kinetic energy (EkE), finite size Lyapunov exponents (FSLE), front index (FrontIndex; estimated as a count of the front pixels in the grid cell for the 7 day window), Chlorophyll a (CHL), and Chlorophyll a gradient (CHL_grad; computed as the difference in Chlorophyll a concentration in the same pixel over a 7-day period).

The four subsurface variables included temperature at 100 m depth (sst_100), mixed layer depth (MLD), isothermal layer depth (ILD) and bulk buoyancy frequency (BF, also known as Brunt-Väisälä frequency). Whereas the use of temperature at 100 m depth and mixed layer depth is well known by the scientific community, ILD and BF are reasonably new (Brodie et al. 2018). ILD and BF provide indices of water column structure, respectively, the depth of surface mixing and degree of stratification in the upper water column. ILD was calculated as the depth corresponding to a 0.5$\circ$C temperature difference relative to sea surface temperature (Monterey and Levitus 1997). BF offers a measure of the upper water column stability and was averaged over the upper 200 m of the water column to produce a daily field, where higher BF values indicate a more stable water column. Both variables provide a daily field of 0.25$\circ$ resolution comparable to surface variables. The two-dimensional (i.e. vertical and horizontal space) structure of ILD and BF described water column properties and have proven to be helpful to improve SDMs for large pelagic species (Brodie et al. 2018).

The four operational variables included net depth (NetDepth; the hanging depth of the purse-seine net), object depth (OBJDepth; the observer's estimate of the length of the material hanging below the floating object), set time (SetTime), and the percentage of the object covered with epibiota (OBJEpibiotaPcnt). All operational variables were taken from observer data for each fishing set. These operational variables were chosen as they are known to affect catches of tuna (Lennert-Cody et al. 2008; Orue et al. 2019).

2.3. Model specification

In the interest of robustness and to inform comparisons, we took a multi-model approach, building 7 size-specific presence–absence (catch vs. zero catch per set, binary response) models with each set of variables, from simplest to most complex models. The following models were established for each tuna size category: i) spatio-temporal, ii) surface, iii) subsurface, iv) environmental (surface + subsurface), v) spatio-temporal and environmental, vi) operational, and vii) operational and environmental (Table 4).

2.3.1. Spedies distribution models: Boosted Regresstion Trees

Model building – Boosted Regression Trees (BRTs) are a flexible classification algorithm based on machine learning principles (De'ath 2007; Elith et al. 2008). Because of that, some of the caveats of more commonly used techniques (e.g. generalized linear or generalized additive mixed models - GLMM/GAMM) are not applicable. BRTs present a series of advantages, such as being tolerant to missing values, outliers, collinearity, and non-independence, and the inclusion of irrelevant predictors (Leathwick et al. 2006). While GLMM/GAMM methods seek to fit the most parsimonious model to a data set, BRTs combine predictions of many simple models (i.e. many shallow classification trees) to maximize robustness and predictive performance and reduce associated error (Scales et al. 2017). Accordingly, we fitted size category-specific BRTs with all available sets of covariates. Nonetheless, GAM and Random Forest (RF) models were also fitted to the tuna presence-absence data in a preliminary stage of the modeling to better understand consistency and help interpretation between algorithms. BRTs performed better than their equivalent GAMMs and had very similar performance to the RFs. As such, we decided to use BRTs to build all the models in this study. All algorithms were implanted in R (BRTs: *dismo* package (Hijmans et al. 2017); RF: *randomForest* package (Liaw and Wiener 2002); GAM: *mgcv* package (Wood 2001)).

In fitting BRTs, we adapted the protocols outlined by Brodie et al. 2018, Elith et al. 2008, and Scales et al. 2017, and the *dismo* package developed by. Presence–absence models were built with a binomial (Bernoulli) distribution. We used a tree complexity of 3, a bag fraction of 0.7, and conducted sensitivity analyses on learning rate (“shrinkage”) for each model set, aiming for at least 1,000 trees in final model configurations. The sensitivity runs determined 0.1 as the learning rate to be used in all the models, except for subsurface models for small and large tuna, where a value of 0.075 was used. Tree complexity refers to the number of nodes in a tree, which constrains the maximum size of each of the regression trees that together make up a boosted regression tree model. By controlling the number of nodes/branches, tree complexity also sets the maximum number of interactions between predictor variables that are possible (i.e. 3 in this case as two/three-way interactions among variables might be important). Bag fraction refers to the percentage of the data that is randomly used for model building at each step, which usually ranges between 0.6-0.75 (Elith et al. 2008). The stochasticity that this step provides to the model building process improves model performance (Soykan et al. 2014).

The potential for model simplification was evaluated with the function *gbm.simplify*. Simplified models were fitted by re-running models without those variables that gave no evidence of improving predictive performance. Deviance explained, variable importance, as well as interactions between variables were also estimated for all the models using the function *gbm.interactions*. Final size-specific models (i-vii) were run 10 times to investigate consistency and robustness and estimate standard deviations. Each of these configuration settings and the performance procedure are described in detail by Elith and Leathwick 2017; Elith et al. 2008; Hazen et al. 2018; Scales et al. 2017; and Soykan et al. 2014.

Model validation – A k-fold cross-validation method was used to evaluate the reliability and the predictive performance of final models. This method consists of using independent data sets for model building (i.e. the training data) and model validation (i.e. the test data), where data is partitioned into k equally sized segments or folds through random resampling. Model performance is assessed by successively removing each subset, re-building the model on the retained data, and predicting on the omitted data (Elith and Leathwick 2009). In this study, a k = 4 partitioning method was used, meaning that 75% of the observations were used for model building, and the other 25% for model validation in an iterative procedure that was repeated 10 times. Hold-out validation avoids the overlap between training data and test data, yielding a more accurate estimate of the generalization performance of the algorithm (Villarino et al. 2015).

The predictive power of the model was assessed by computing a set of diagnostic metrics. The mean Area Under the receiver-operating Curve (AUC) (Hanley and McNeil 1982) and the mean True Skill Statistic (TSS)

(Allouche et al. 2006) were calculated for each iteration from each confusion matrix. The AUC provides a single measure of overall model accuracy that is threshold independent, with an AUC value of 0.5 indicating the prediction is as good as random, whereas 1 indicates perfect prediction (Fielding and Bell 1997). AUC has been extensively used in SDMs and measures the ability of the model to correctly predict where a species is present or absent (Elith et al. 2006). An AUC value of >0.75 is considered to have a good predictive power and is acceptable for conservation planning (Pearce and Ferrier 2000). TSS is an alternative measure of model accuracy that is threshold dependent and not affected by the size of the validation set (Allouche et al. 2006). It is an appropriate evaluative tool in cases where model predictions are formulated as presence–absence maps (Allouche et al. 2006). TSS is on a scale from -1 to +1, with 0 representing no predictive skill and is calculated from the confusion matrix outputs as sensitivity plus specificity minus 1 (i.e. TSS = sensitivity + specificity - 1). Threshold independent and dependent statistics, such as AUC and TSS, respectively, should be used in combination when evaluating the predictive power of a SDM (Pearson et al. 2006).

Making predictions – For illustration purposes, we generated a series of daily predictions of the probability of occurrence of bigeye tuna per size-class over the IATTC convention area for 10 days randomly selected between 2002-2017. A series of time-matched environmental data fields (both surface and subsurface variables) and the median values of the operational parameters were used to generate daily predictions based on final models and their best number of trees using function *predict* in the package *raster* (Hijmans et al. 2015). Two sets of predictions were independently generated using model iv (environmental) and model vii (environmental + operational) and the difference between them estimated to inform consistency and interpretation, and to visualize the effect of accounting for operational variables on the predictions. The spatial resolution of predictive surface was set at the lowest common resolution of environmental data fields (0.25°).

3. RESULTS

3.1. Model performance

Models including environmental and operational variables (i.e. model vii) demonstrated better performance under the diagnostic measures we used (deviance explained, AUC and TSS) (Table 4). In general, complex models (i.e. models v, vii) had better performance than simpler models including sets of variables individually (i.e. models i, ii, iii). Models explained between 7.51% and 31.19% (mean 21.89%) of the deviance in the data, had AUC values between 0.68 and 0.85 (mean 0.79), and had TSS values that ranged between 0.25 and 0.55 (mean 0.45) (Table 4). The comparison in model performance lead us to recommend the use of models that include environmental and operational data (model vii) for dynamic ocean management.

3.2. Drivers of Bigeye tuna presence

An examination of the relationships between environmental and operational variables (best model, model vii) and species presence showed a range of patterns for each bigeye tuna size category, based on variable importance analysis (Fig. 1) and partial dependence plots (Fig 2, 3, 4, 5, 6).

3.2.1. Small bigeye

17 variables were included in the final model, for which relative variable importance was 2.5%-14.6%. EkE, CHL_grad and FSLE were dropped from the final model as they did not improve predictive capability. Only 7 variables contributed more than 5%: SST_{100} (14.6%), SSH (11.5%), OBJDepth (10.7%), NetDepth (8.6%), FrontIndex (7.8%), Sal (6.5%) and CHL (6.5%) (Fig. 1).

In predicting the relative probability of small bigeye, the model identified elevated probabilities of small tuna catch in the 20-28^{o}C SST_{100} range. SSH showed an evident positive relationship with small bigeye catch, and so did with two operational variables (OBJDepth and NetDepth). Deeper floating objects (up to 100 m depth) and nets (>120 fathoms) were associated with higher probabilities of catching small bigeye. Similarly, the model showed higher probabilities of small tuna catch with moderate FrontIndex values, salinity values around 33-35 PSU, and low CHL values. The effect of the remaining environmental and operational variables on small bigeye included in model vii are detailed in the partial dependence plots of Fig. 2.

3.2.2. Medium bigeye

20 variables were included in the final model, for which relative variable importance was 0.1%-27.6%. No variables were dropped from the final model based on the gbm.simplify test. Only 7 variables contributed more than 5%: SST_{100} (27.6%), Sal (10.1%), NetDepth (9.3%), ILD (6.9%), FrontIndex (6.5%), Vel (6.5%) and SSH (6.5%) (Fig. 1).

The model identified elevated probabilities of medium size bigeye catch in the 20-28^{o}C SST_{100} range and salinity values around 35 PSU. NetDepth showed a positive relationship with medium size bigeye catch, and so did low and moderate values of ILD. Similarly, the model showed higher probabilities of medium size bigeye catch with moderate-high FrontIndex values, current speed values > 1 knot, and high values of SSH. The effect of the remaining environmental and operational variables on medium size bigeye included in model vii are detailed in the partial dependence plots of Fig. 3.

3.2.3. Juvenile bigeye

The category “juveniles” was artificially created as the presence of either small and/or medium size bigeye, as observers do not use this category when reporting catches. From the ~68,000 occurrences used to build the juvenile model, ~63,000 corresponded to medium size tuna. Thus, similarities should be expected between the medium and juvenile categories, although differences also exist.

19 variables were included in the final model, for which relative variable importance was 1%-27.5% (i.e. EkE was dropped from the final model based on the gbm.simplify test). Only 8 variables had contributions above 5%: SST_{100} (27.5%), Sal (10%), NetDepth (9.4%), ILD (7.1%), Vel (6.3%), FrontIndex (6%), SSH (5.7%) and CHL (5.2%) (Fig. 1).

Once again, the model identified elevated probabilities of juvenile bigeye catch in the 20-28^{o}C SST_{100} range and salinity values peaking around 35 PSU. NetDepth showed a positive relationship with juvenile bigeye catch, and so did with low and moderate values of ILD. Similarly, the model showed higher probabilities of juvenile bigeye catch with current speed values > 1 knot, moderate-high FrontIndex values, high values of SSH, and low values of CHL (< 1 mg m^{-3}). The effect of the remaining environmental and operational variables on juvenile bigeye included in model vii are detailed in the partial dependence plots of Fig. 4.

3.2.4. Large bigeye

17 variables were included in the final model, for which relative variable importance was 2.2%-15.9%. EkE, CHL_grad and FSLE were dropped from the final model as they did not improve performance capability. Only 7 variables contributed more than 5%: Sal (15.9%), SST_{100} (13%), FrontIndex (11.3%), SST (8.6%), Vel (5.9%), CHL (5.6%), and ILD (5.5%) (Fig. 1). It is worth noting that no operational variables contributed more than 5% for this size category.

The model identified higher probabilities of large tuna catch around salinity values of 35 PSU. For SST_{100}, higher probabilities of large bigeye were found in 15-28^{o}C range, whereas a positive relationship was observed for FrontIndex. SST showed an evident negative relationship with large bigeye catch, with a peak around 21^{o}C, while the opposite relationship was observed for Vel (higher probabilities at higher current speeds). Similarly, the model showed higher probabilities of large bigeye catch at low CHL (<1 mg.m^{-3}) and

ILD (< 50 m) values. The effect of the remaining environmental and operational variables on large bigeye included in model vii are detailed in the partial dependence plots of Fig. 5.

3.2.5. Total bigeye

Like for the category "juveniles", from the ~73,000 presences used to build the total model, ~63,000 corresponded to medium size tuna. Thus, similarities should be expected between these two categories, although differences also exist due to the relationships associated with small and large bigeye tuna.

19 variables were included in the final model, for which relative variable importance was 1.1%-26.1% (i.e. EkE was dropped from the final model based on the gbm.simplify test). Only 7 variables had contributions above 5%: SST_{100} (26.1%), Sal (10.4%), NetDepth (8.7%), ILD (7.5%), FrontIndex (7%), Vel (6.6%), and CHL (5.2%) (Fig. 1).

Once again, the model identified elevated probabilities of total bigeye catch in the 20-28^{o}C SST_{100} range and salinity values peaking around 35 PSU. NetDepth showed a positive relationship with total bigeye catch, and so did at low and moderate values of ILD. Similarly, the model showed higher probabilities of total bigeye catch at moderate-high FrontIndex values, with current speed values > 1 knot, and low values of CHL (< 1 mg m-3). The effect of the remaining environmental and operational variables on total bigeye catch included in model vii are detailed in the partial dependence plots of Fig. 6.

3.3. Predictions

Models iv and vii were used to predict species habitat suitability in the convention area for 10 days randomly selected between 2000 and 2017. The difference between predictions established using each model were computed to inform the effect of fixing operational parameters in the predictions.

Predictions for those 10 days revealed spatial differences among sizes, with, in general, higher probabilities of large bigeye predicted in latitudes of 20S and >20N, higher probabilities of small bigeye predicted around 20N and 20S bands, and the other three size categories (i.e. medium, juveniles and total) predicted more intensively offshore of -80E and in all the equatorial band (20N-20S) (Fig. 7).

The effect of including operational variables into species distribution models was apparent for all size-category predictions (Fig. 8). Differences in the predicted probability between models iv and vii indicated that operational variables can affect predictions at different levels according to the size category. For example, adding operational variables increased, in general, the probability for small bigeye but decreased it for juveniles and total. In the case of medium and large size categories, differences are area specific with higher probabilities in the equatorial band and negative poleward.

4. DISCUSSION

Dynamic ocean management (DOM) tools are emerging as practical management solutions to accommodate the different biological, environmental, economic, and social needs in a dynamic world. Many fisheries are taking advantage of this novel approach to adaptively manage both target and non-target species. Some good examples of implementation are the ECOCAST program off the US west coast (https://coastwatch.pfeg.noaa.gov/ecocast/) (Hazen *et al*. 2018), and the bluefin tuna seasonal forecasting program in Australia (Hobday et al. 2011a). Usually, the implementation of DOM tools is facilitated by a four-stage operationalization[4] framework: acquisition, prediction, dissemination, and automation (Welch et al. 2018). This study has conducted the acquisition and prediction stages, is disseminating, as a first step, results in different scientific events, including the SAC and international conferences (e.g. CLIOTOP), and is planning for automation with the assistance of external collaborators. However, this is a

[4] A stepwise process by which a DOM tool is implemented and applied

workflow that must be continuously repeated to integrate data requirements and management needs.

Ideally, our DOM tool should operate in near real-time (e.g. weekly) and be designed to maximize target species catch while minimizing bycatch. Because of that, the staff is working on similar models for skipjack and yellowfin tuna, which are expected to be ready in the short-medium term. Figure 9 shows, as an example, partial dependence plots of model vii (i.e. environmental + operational) for juvenile yellowfin tuna. Although similarities exist, both bigeye and yellowfin tuna models show differences that could be translated into different spatio-temporal distributions. Thus, the inclusion of weighting parameters in model assembling, based on management and decision makers needs, seems an additional aspect to consider for the effective implementation of the DOM tool in the EPO.

The DOM tool can be used as a forecast tool that produces spatial management recommendations for near-real time or future environmental conditions. However, its use can be very different depending on the approach chosen for the implementation and the additional management measures that are in force (e.g. catch-based limits). For example, high probability bigeye tuna maps (or ratios when other species are integrated) can be produced to inform fleets on the areas to be ideally avoided by either ethic principles or because catch-limits exist. The latter requires well-defined catch limits that are usually derived from reliable stock assessment outputs as well as clear allocation systems. Because of these requirements, the implementation of this DOM option would not be straightforward. A third possibility would be to use DOM outputs to shape adaptive seasonal closures. Current management measures include a 72 days closure and an additional 30 days closure in the area known as the “corralito”, which is static. Although the effectiveness of the closure has not been evaluated in detail yet, it could be expected that dynamic and adaptive closures present benefits over static closures, especially for highly migratory species like tunas. This has proven to be true in other ocean regions for several large pelagic species, including tuna, swordfish, or sharks (Hazen et al. 2018; Hobday et al. 2011a; Hobday et al. 2016; Hobday et al. 2011b; Little et al. 2015; Siedlecki et al. 2016; Tommasi et al. 2017).

The present work has also identified the potential effect of some gear characteristics on the catch of bigeye tuna. Floating-object depth and net depth seem to be significant variables when considering bigeye tuna catch probabilities, with higher probabilities found, in general, at both deeper floating objects and nets. Unlike floating object depth, however, which seemed to be more similar throughout the study area, net depth is negatively correlated with longitude (Fig. 10); i.e. vessels operating in the western area of the EPO often used deeper nets. Because catches could also be explained by inherent spatio-temporal dynamics, it is hard to attribute such an effect uniquely to gear characteristics. Thus, future analyses should consider this and other additional factors (e.g. FAD densities, Vessel ID, number of sets in an area) to better understand which changes in capture probability are due to catchability or abundance, particularly in a highly dynamic fishing system like the EPO.

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Table 1. Number of sets by set type with and without bigeye tuna catch and proportion of sets with occurrences.

Set Type	*Sets with absences*	*Sets with presence*	*Total number of Sets*	*Proportion of sets with occurrences*
DOL	200151	51	200202	0.02
UNA	102234	1413	103647	1.36
FOB	75994	73372	149366	49.12
Total	378379	74836	453215	16.51

Table 2. Number of sets by set type and size-category with and without bigeye tuna catch and proportion of sets with occurrences.

Size class	*Sets with absences*	*Sets with presence*	*Proportion of sets with occurrences*
Small	108563	37314	25.58
Medium	82448	63429	43.48
Juveniles	77680	68197	46.75
Large	112289	33588	23.02
Total	72771	73106	50.11

Table 3. Comparing variables' data sources for species distribution models.

Variable	*Acronym and unit*	*Spatial resolution*	*Temporal Frequency*	*Temporal coverage*	*Product*	*Source*
Spatio-temporal						
Latitude	Lat (°)	Exact location	Set by set	1995-2017	-	Fisheries observer data
Longitude	Lon (°)	Exact location	Set by set	1995-2017	-	Fisheries observer data
Day of year	DoY (day)	-	Set by set	1995-2017	-	Fisheries observer data
Surface						
Sea surface temperature	SST (°C)	0.25°	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	http://marine.copernicus.eu/services-portfolio/access-to-products/?option=com_csw&view=details&product_id=GLOBAL_REANALYSIS_PHY_001_025
Δ Sea surface temperature	SST grad (°C)	0.25°	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	Derived from models
Salinity	Sal (PSU)	0.25°	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	http://marine.copernicus.eu/services-portfolio/access-to-products/?option=com_csw&view=details&product_id=GLOBAL_REANALYSIS_PHY_001_025
Sea surface height	SSH (m)	0.25°	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	http://marine.copernicus.eu/services-portfolio/access-to-products/?option=com_csw&view=details&product_id=GLOBAL_REANALYSIS_PHY_001_025
Current vorticity	Vol (m/s)	0.25°	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	http://marine.copernicus.eu/services-portfolio/access-to-products/?option=com_csw&view=details&product_id=GLOBAL_REANALYSIS_PHY_001_025
Current speed	Speed (m/s)	0.25°	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	http://marine.copernicus.eu/services-portfolio/access-to-products/?option=com_csw&view=details&product_id=GLOBAL_REANALYSIS_PHY_001_025
Current direction	Dir (degrees)	0.25°	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	http://marine.copernicus.eu/services-portfolio/access-to-products/?option=com_csw&view=details&product_id=GLOBAL_REANALYSIS_PHY_001_025

Eddie Kinetic Energy	EkE (m/s)	0.25º	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	Derived from models
Finite Size Lyapunov Exponents	FSLE (days^{-1})	0.04º	daily	1995-2017	Lyapunov Exponents and Orientations	https://www.aviso.altimetry.fr/en/data/products/value-added-products/fsle-finite-size-lyapunov-exponents.html
Front Index	FrontIndex (count)	0.25º	weekly	2002-2017		Derived from models
Chlorophyll a	CHL (mg/l)	0.25º	weekly	1998-2017	GLOBAL_REANALYSIS_BIO_001_029	http://marine.copernicus.eu/services-portfolio/access-to-products/?option=com_csw&view=details&product_id=GLOBAL_REANALYSIS_BIO_001_029
Δ Chlorophyll a	CHL grad (mg/l)	0.25º	weekly	1998-2017	GLOBAL_REANALYSIS_BIO_001_029	Derived from models
Subsurface						
Temperature at 100 m	sst_100 (ºC)	0.25º	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	http://marine.copernicus.eu/services-portfolio/access-to-products/?option=com_csw&view=details&product_id=GLOBAL_REANALYSIS_PHY_001_025
Isothermal layer depth	ILD (m)	0.25º	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	Derived from models
Bulk Brunt-Väisälä frequency	BF (s^{-1})	0.25º	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	Derived from models
Mixed layer depth	MLD (m)	0.25º	daily	1995-2017	GLOBAL_REANALYSIS_PHY_001_025	http://marine.copernicus.eu/services-portfolio/access-to-products/?option=com_csw&view=details&product_id=GLOBAL_REANALYSIS_PHY_001_025
Operational						
Net depth	NetDepth (fathoms)	Exact location	Set by set	1995-2017	-	Fisheries observer data
Object depth	OBJDepth (m)	Exact location	Set by set	1995-2017	-	Fisheries observer data
Set time	SetTime (h)	Exact location	Set by set	1995-2017	-	Fisheries observer data
Percent coverage epibiota	OBJEpibioPcnt (%)	Exact location	Set by set	1995-2017	-	Fisheries observer data

Table 4. Performance of models i) spatio-temporal, ii) surface, iii) subsurface, iv) environmental (surface + subsurface), v) spatio-temporal and environmental, vi) operational, and vii) operational and environmental for each size category of bigeye tuna.

Model			Lr	n.trees	Dev	Dev.SD	AUC	AUC.SD	TSS	TSS.SD	Dropped variables
Small	1	fit	0.1	1050	14.38	0.07	0.79	0.00	0.44	0.00	
		simp	-	-	-	-	-	-	-	-	
	2	fit	0.1	1650	15.37	-	-	-	-	-	
		simp	0.1	1600	15.15	0.15	0.76	0.00	0.38	0.01	EkE, chl_grad, FSLE
	3	fit	0.075	1150	9.74	0.14	0.71	0.00	0.32	0.01	
		simp	-	-	-	-	-	-	-	-	
	4	fit	0.1	1900	17.00	-	-	-	-	-	
		simp	0.1	1850	16.79	0.12	0.77	0.00	0.40	0.00	EkE, chl_grad, FSLE
	5	fit	0.1	1900	19.84	-	-	-	-	-	
		simp	0.1	2000	19.51	0.18	0.79	0.00	0.43	0.00	EkE, FSLE, BF, Dir, Chl_grad, Vel, MLP
	6	fit	0.1	3400	11.24	0.11	0.72		0.31		
		simp	-	-	-	-	-	-	-	-	
	7	fit	0.1	4400	25.50	0.17	0.82		0.48		EkE, chl_grad, FSLE
		simp	-	-	-	-	-	-	-	-	
Medium	1	fit	0.1	1350	25.28	0.06	0.82	0.00	0.50	0.00	
		simp	-	-	-	-	-	-	-	-	
	2	fit	0.1	2050	23.20	-	-	-	-	-	
		simp	0.1	2000	23.28	0.12	0.81	0.00	0.47	0.01	EkE
	3	fit	0.1	1550	16.27	0.09	0.76	0.00	0.39	0.01	
		simp	-	-	-	-	-	-	-	-	
	4	fit	0.1	2250	25.62	0.15	0.82	0.00	0.50	0.00	
		simp	-	-	-	-	-	-	-	-	
	5	fit	0.1	1700	29.48	-	-	-	-	-	
		simp	0.1	1750	29.12	0.06	0.84	0.00	0.54	0.00	sst_grad, chl_grad, vel, MLP, BF, EkE, Dir_cor, FSLE, SSH, Vol
	6	fit	0.1	2650	11.92	0.14	0.73	0.00	0.33	0.00	
		simp	-	-	-	-	-	-	-	-	
	7	fit	0.1	3400	30.22	0.16	0.85		0.54	0.00	
		simp	-	-	-	-	-	-	-	-	
Juveniles	1	fit	0.1	1300	24.79	0.06	0.82	0.00	0.49	0.00	
		simp	-	-	-	-	-	-	-	-	
	2	fit	0.1	2000	22.99	-	-	-	-	-	
		simp	0.1	2200	23.13	0.08	0.81	0.00	0.47	0.00	EkE
	3	fit	0.1	1300	16.22	0.11	0.76	0.00	0.39	0.00	
		simp	-	-	-	-	-	-	-	-	
	4	fit	0.1	2200	25.08	-	-	-	-	-	
		simp	0.1	2300	25.19	0.13	0.82	0.00	0.49	0.00	EkE
	5	fit	0.1	1800	29.11	-	-	-	-	-	
		simp	0.1	2100	29.10	0.10	0.84	0.00	0.53	0.00	EkE, FSLE, Chl grad, Vel, Dir, BF, Vol, SST grad
	6	fit	0.1	2600	12.18	0.09	0.72	0.00	0.33	0.00	
		simp	-	-	-	-	-	-	-	-	
	7	fit	0.1	3150	29.74	0.18	0.84	0.00	0.52	0.00	EkE
		simp	-	-	-	-	-	-	-	-	
Large	1	fit	0.1	1900	22.74	0.03	0.81	0.00	0.49	0.01	
		simp	-	-	-	-	-	-	-	-	
	2	fit	0.1	2200	20.17	-	-	-	-	-	
		simp	0.1	2150	20.29	0.19	0.80	0.00	0.44	0.00	EkE
	3	fit	0.075	1350	11.75	0.13	0.73	0.00	0.34	0.00	
		simp	-	-	-	-	-	-	-	-	
	4	fit	0.1	2700	23.70	-	-	-	-	-	
		simp	0.1	2650	23.35	0.20	0.82	0.00	0.48	0.01	EkE, FSLE, Chl grad
	5	fit	0.1	2100	28.60	-	-	-	-	-	
		simp	0.1	2350	28.38	0.16	0.84	0.00	0.54	0.00	EkE, FSLE, Chl grad, SSH, Dir_cor, Vel, Mlp, SST grad, Vol, BF
	6	fit	0.1	2150	7.51	0.08	0.68	0.00	0.25	0.00	
		simp	-	-	-	-	-	-	-	-	
	7	fit	0.1	3650	27.58	0.14	0.83	0.00	0.50	0.00	EkE, FSLE, Chl grad
		simp	-	-	-	-	-	-	-	-	
Total	1	fit	0.1	1450	26.46	0.07	0.83	0.00	0.51	0.00	
		simp	0.1	-	-	-	-	-	-	-	
	2	fit	0.1	2150	22.19	-	-	-	-	-	
		simp	0.1	2100	22.09	0.10	0.80	0.00	0.46	0.01	EkE
	3	fit	0.1	1100	16.16	0.09	0.76	0.00	0.39	0.00	
		simp	0.1	-	-	-	-	-	-	-	
	4	fit	0.1	2550	25.63	-	-	-	-	-	
		simp	0.1	2650	25.76	0.10	0.82	0.00	0.49	0.01	EkE
	5	fit	0.1	2050	30.67	-	-	-	-	-	
		simp	0.1	1800	30.17	0.11	0.84	0.00	0.55	0.00	EkE, FSLE, chl_grad, Vel, Dir, sst_grad, SSH, Vol
	6	fit	0.1	2400	11.83	0.09	0.72	0.00	0.31	0.01	
		simp	-	-	-	-	-	-	-	-	
	7	fit	0.1	3450	31.19	0.17	0.85	0.00	0.54	0.01	EkE
		simp	-	-	-	-	-	-	-	-	

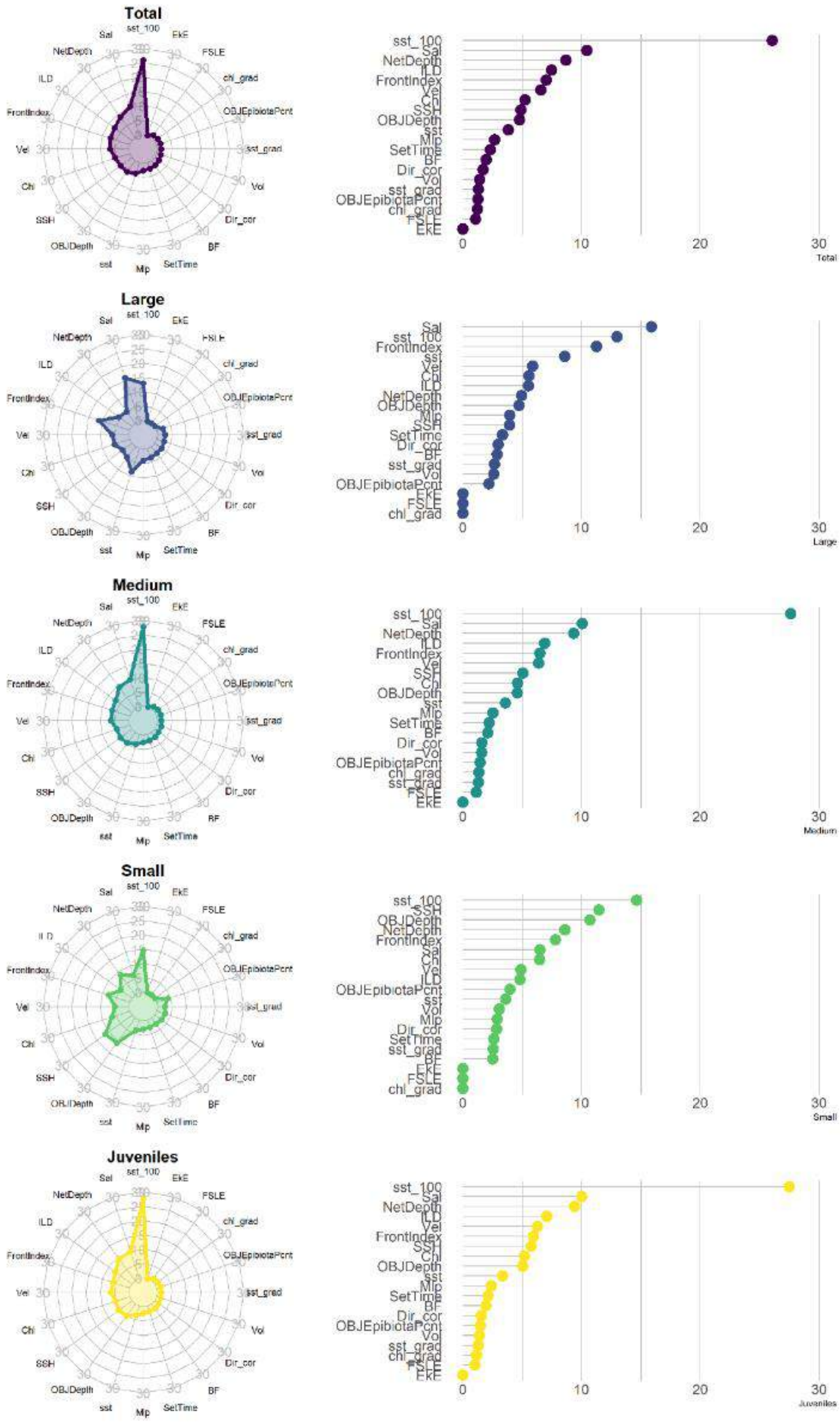

Figure 1. Spider plots and bar plots of the relative influence (%) of each environmental and operational variable within species distribution models for bigeye tuna: total (purple); large (dark blue); medium (turquoise); small (green); juveniles (yellow). Variable acronyms are described in Table 3.

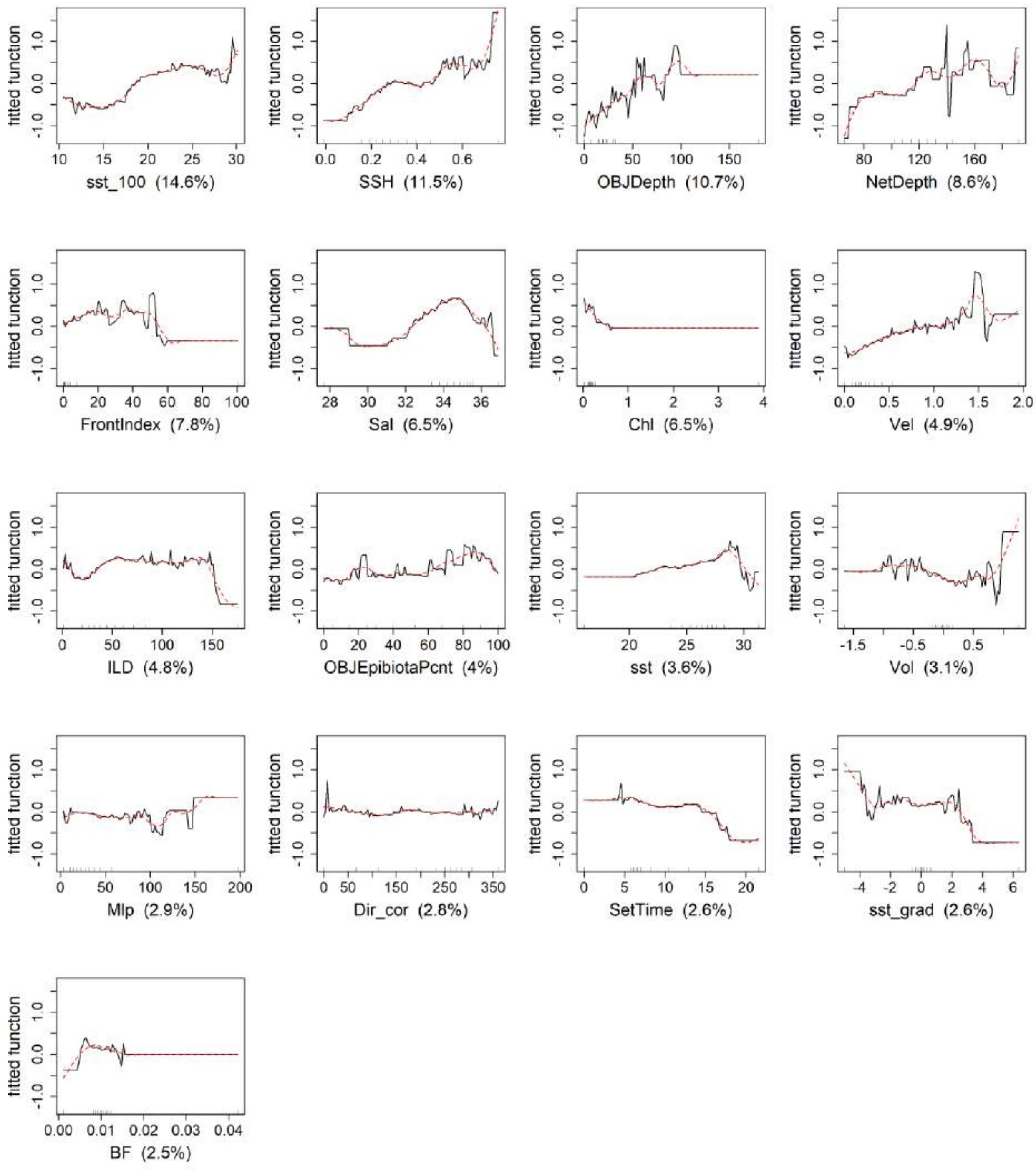

Figure 2. Partial dependence plots of presence–absence boosted regression trees (BRTs), showing relative probability of the presence of small bigeye tuna as a response to environmental and operational variables. Variable importance scores are listed for each variable in parenthesis.

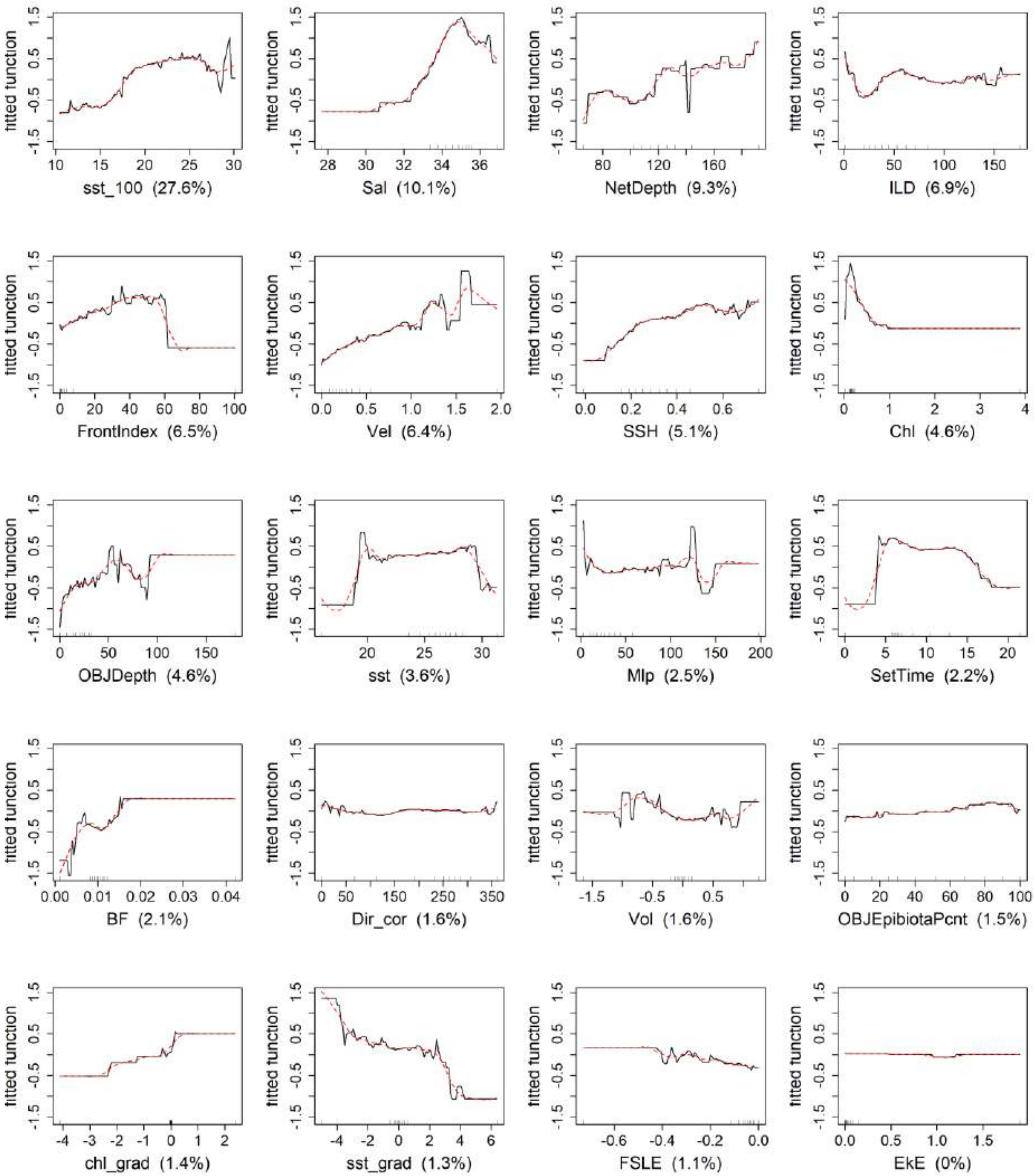

Figure 3. Partial dependence plots of presence–absence boosted regression trees (BRTs), showing relative probability of the presence of medium size bigeye tuna as a response to environmental and operational variables. Variable importance scores are listed for each variable in parenthesis.

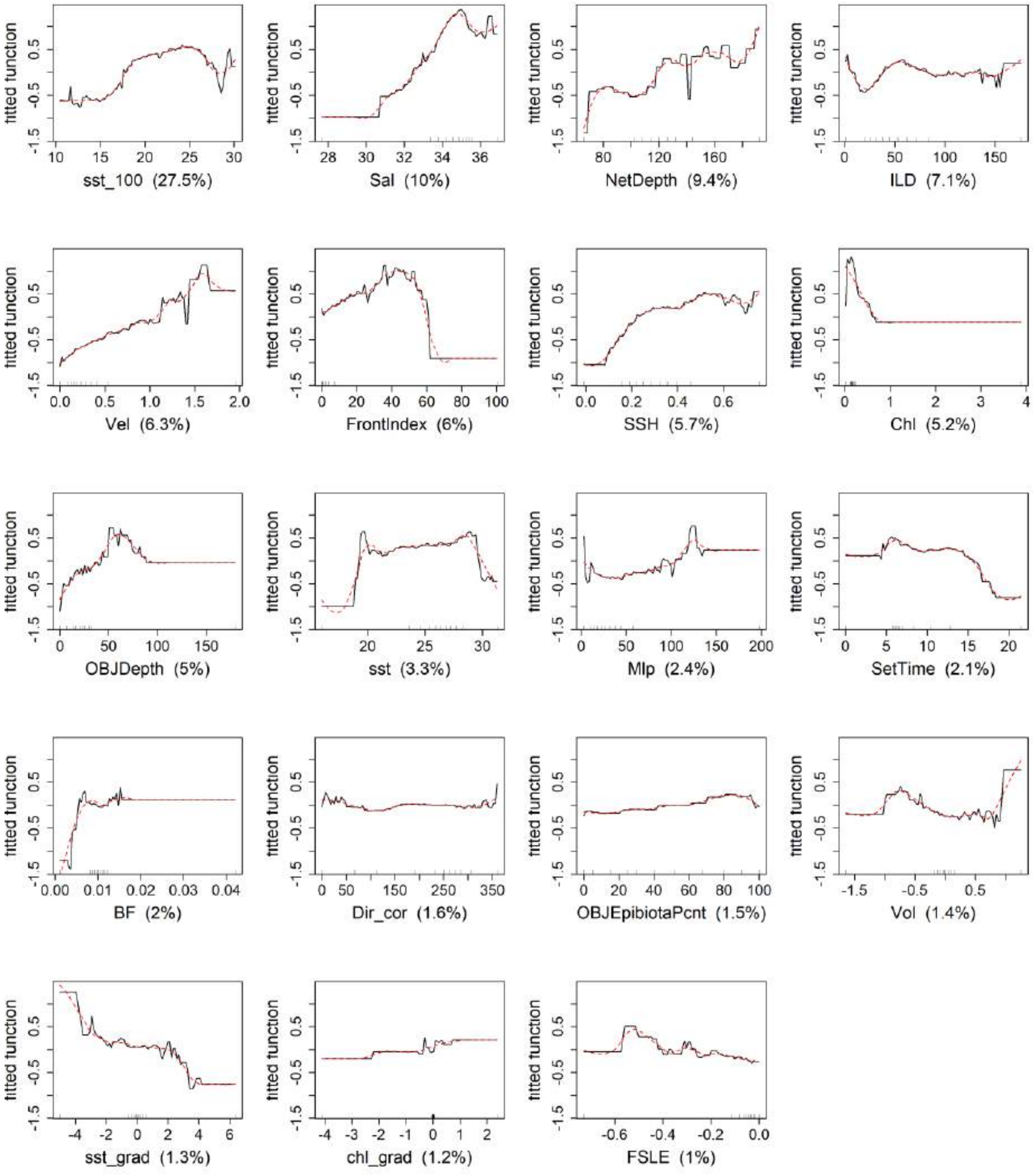

Figure 4. Partial dependence plots of presence–absence boosted regression trees (BRTs), showing relative probability of the presence of juvenile bigeye as a response to environmental and operational variables. Variable importance scores are listed for each variable in parenthesis.

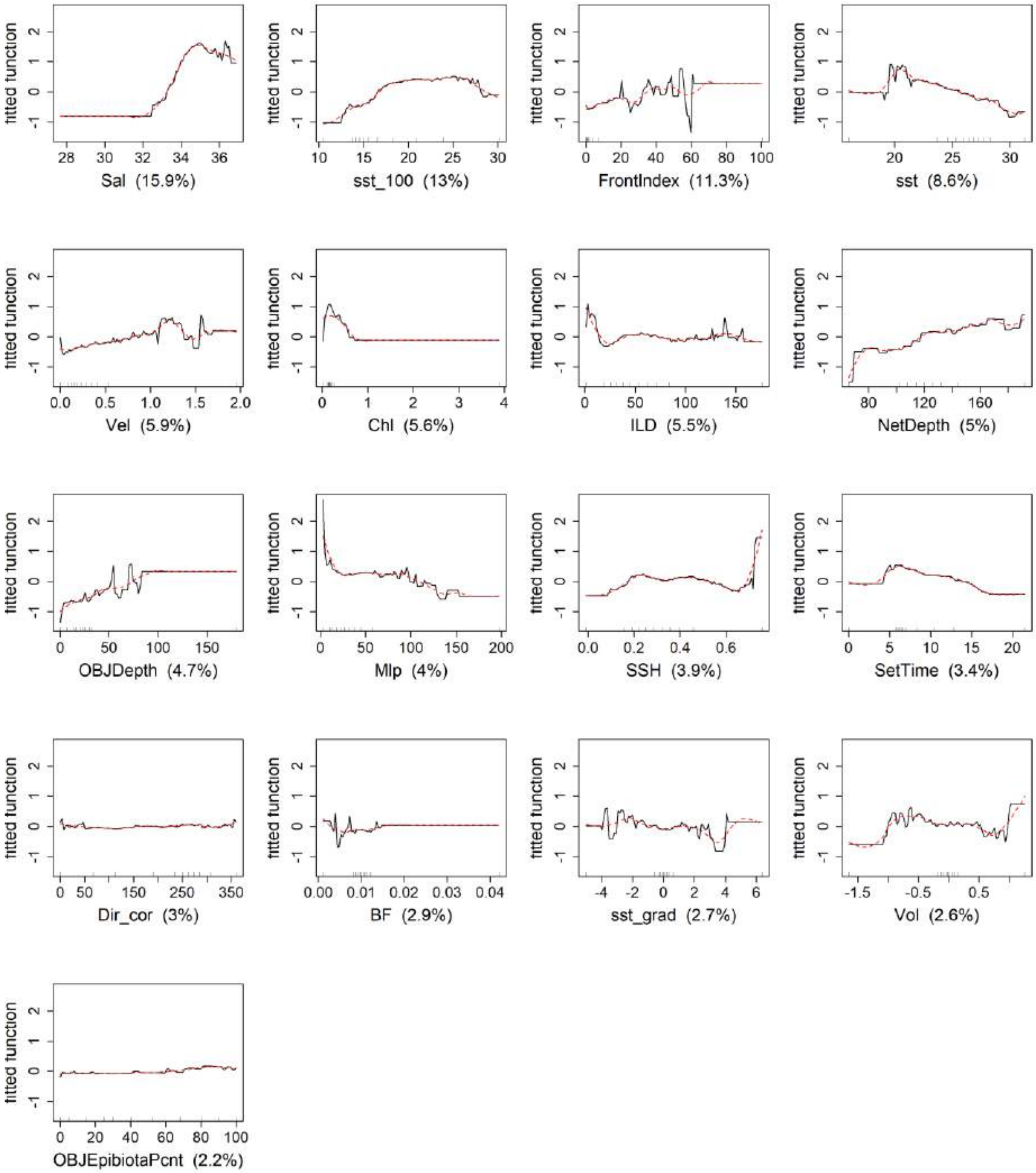

Figure 5. Partial dependence plots of presence–absence boosted regression trees (BRTs), showing relative probability of the presence of large bigeye as a response to environmental and operational variables. Variable importance scores are listed for each variable in parenthesis.

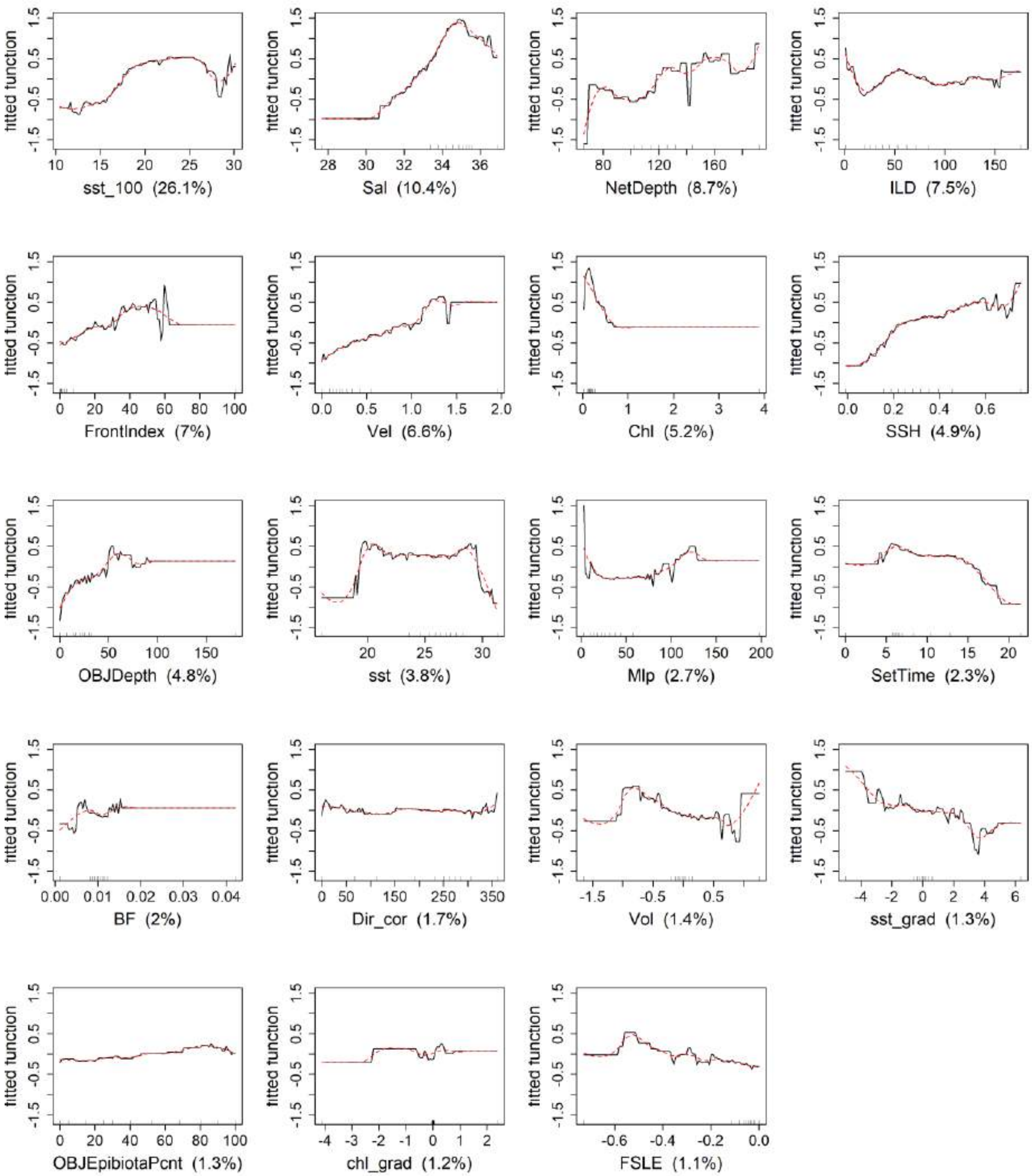

Figure 6. Partial dependence plots of presence–absence boosted regression trees (BRTs), showing relative probability of the presence of total bigeye as a response to environmental and operational variables. Variable importance scores are listed for each variable in parenthesis.

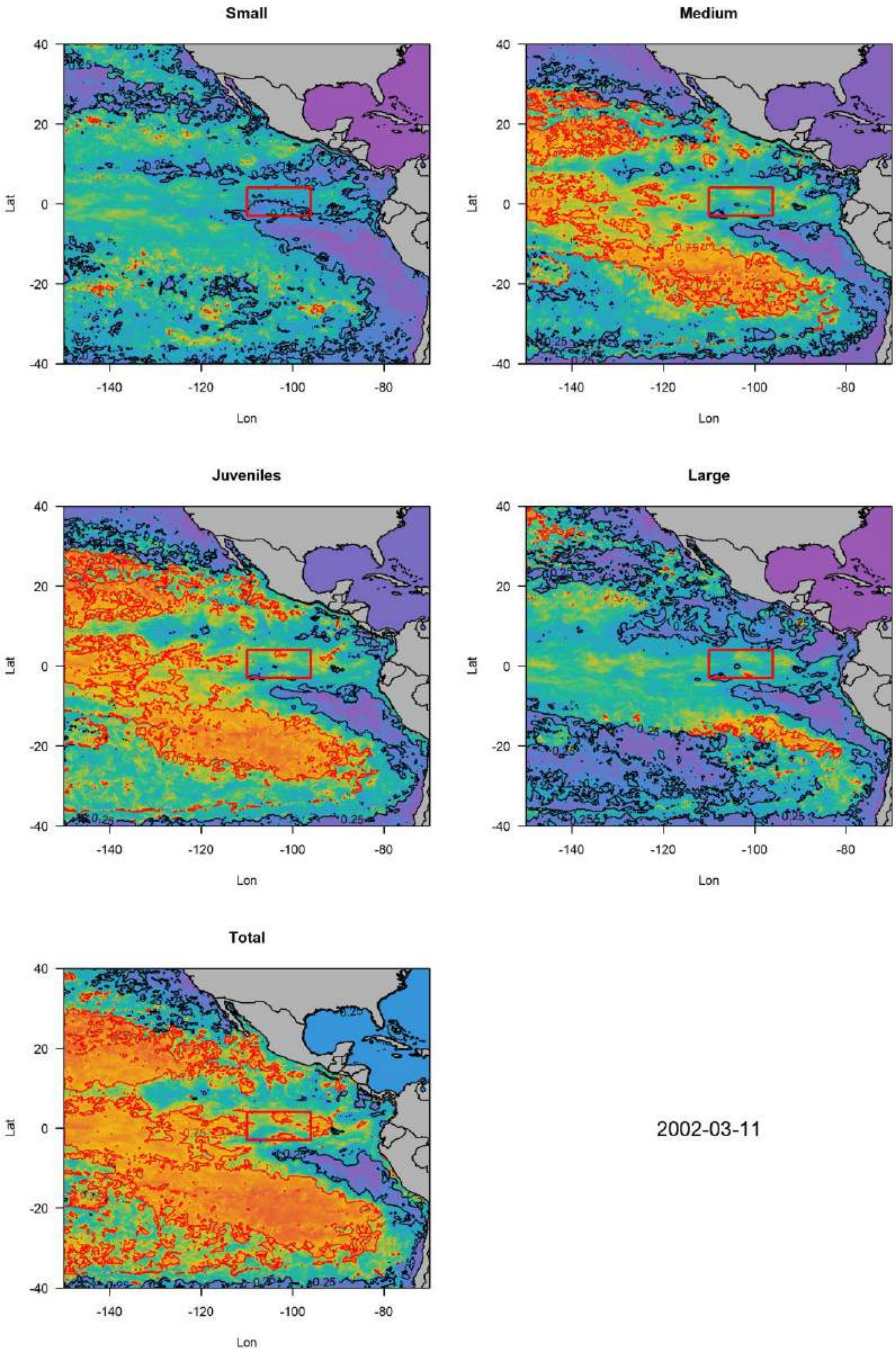

Figure 7. Prediction by size category using model vii (i.e. environmental and operational variables) for a day randomly selected between 2002 and 2017 (i.e. 2002-03-11).

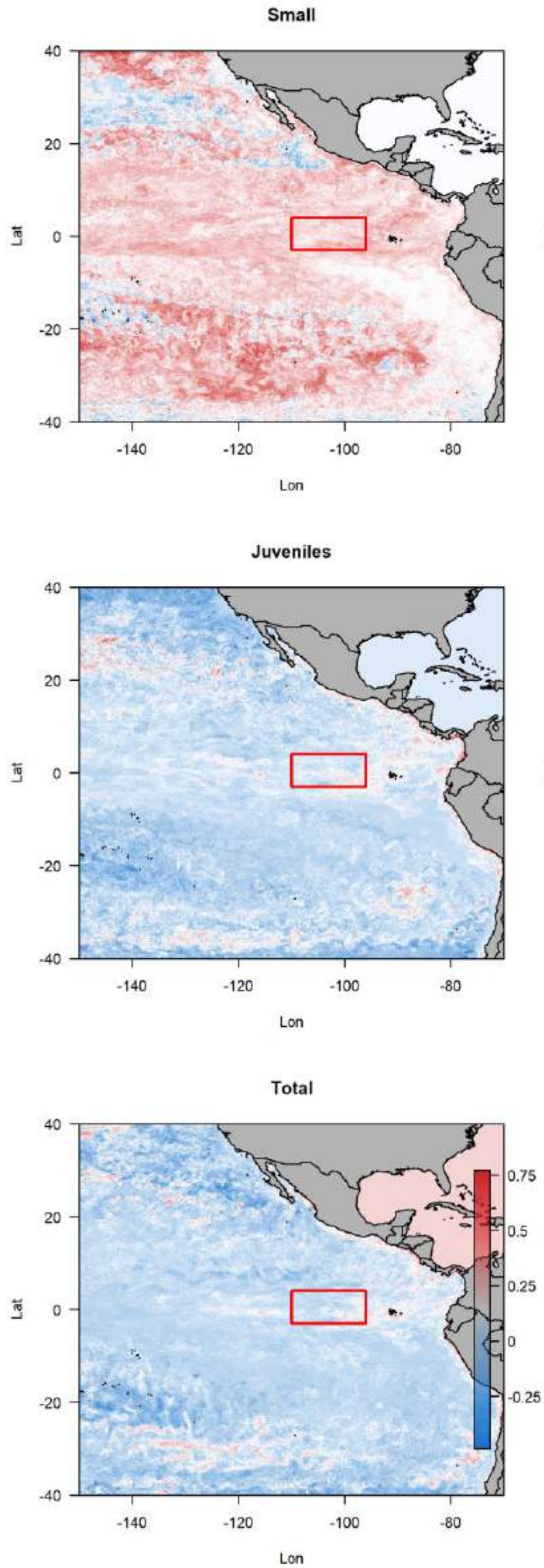

Figure 8. Differences by size category for predictions considering operational variables (i.e. model vii) and those predictions without operational variables (i.e. model iv) for a day randomly selected between 2002 and 2017 (i.e. 2002-03-11).

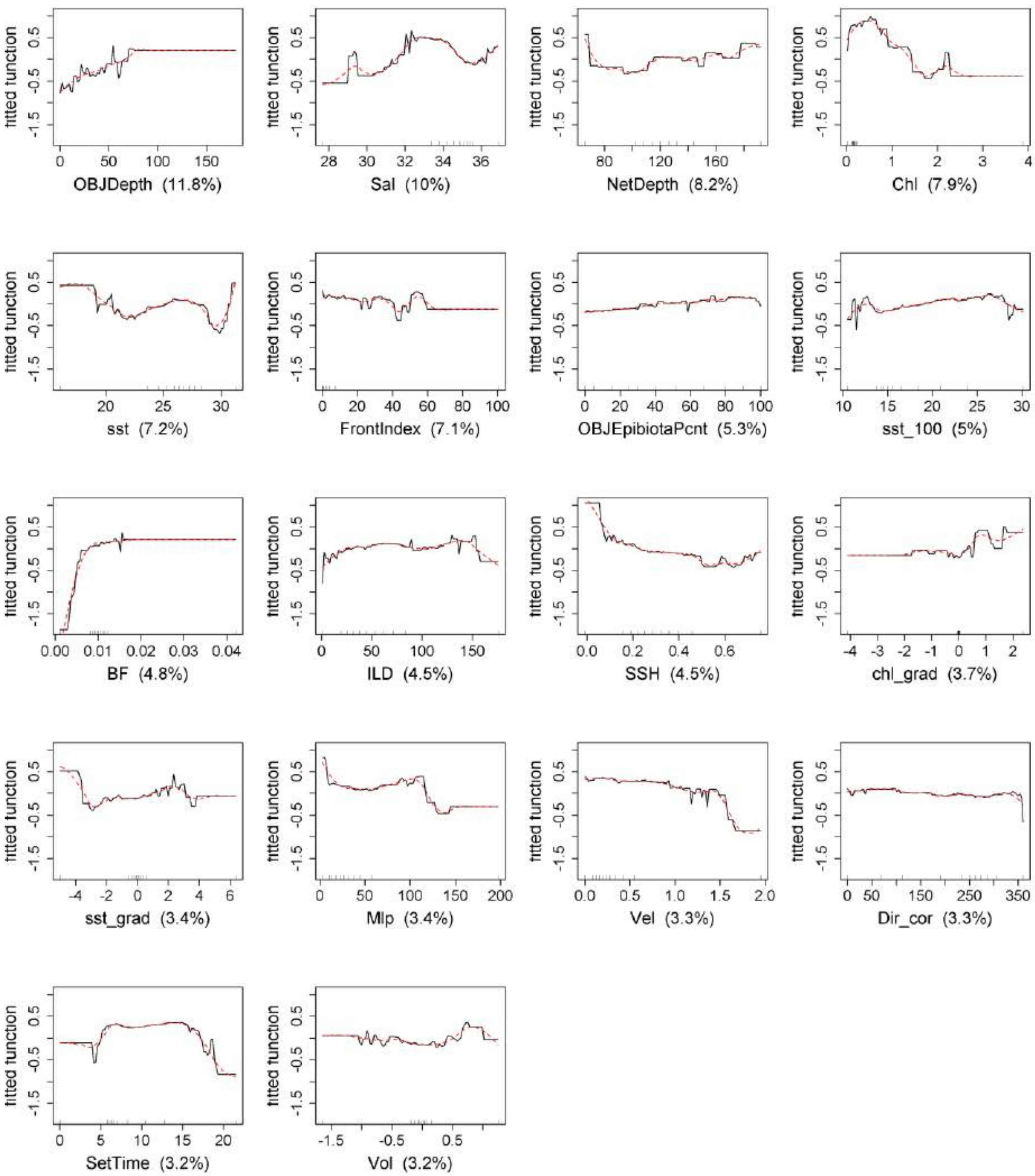

Figure 9. Partial dependence plots of presence–absence boosted regression trees (BRTs), showing relative probability of the presence of juvenile yellowfin tuna as a response to environmental and operational variables. Variable importance scores are listed for each variable in parenthesis.

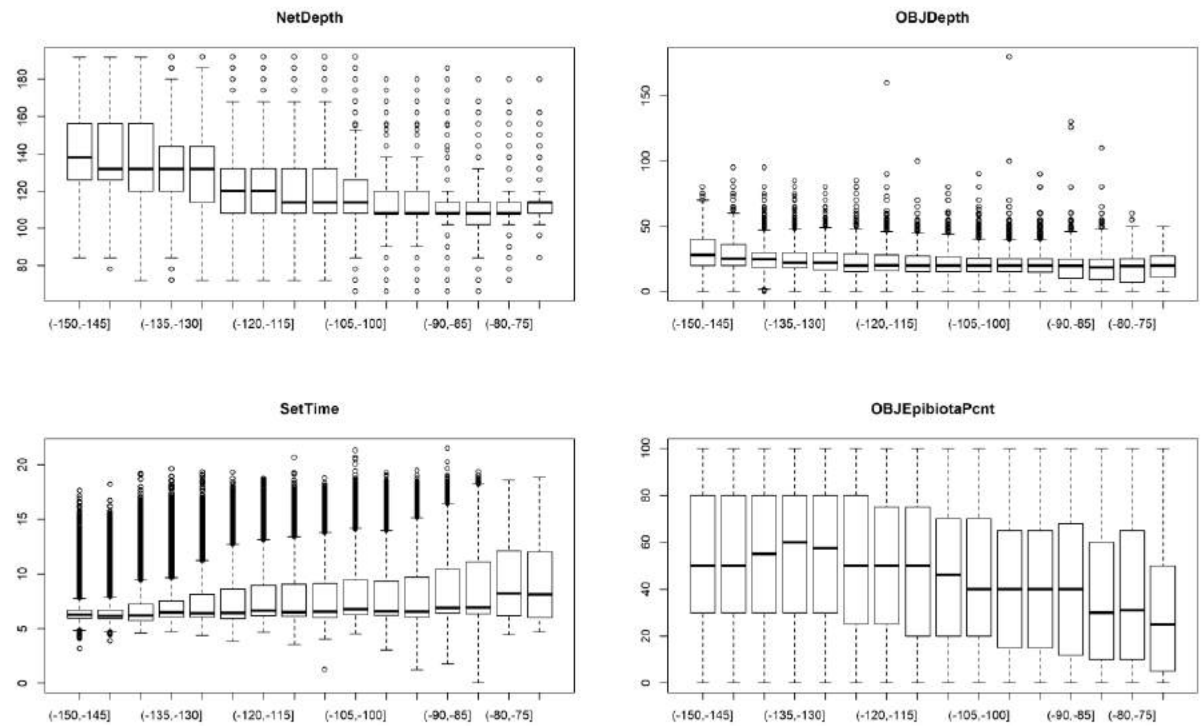

Figure 10. Boxplots of operational variables in relation to Longitude in the eastern Pacific Ocean.