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Competing interest statement

The authors have no competing interest to declare.

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Abstract

The advent of big data and machine learning offers great promise for addressing conservation and management questions in the oceans. Yet, few applications of machine learning exist to mitigate the overexploitation of marine resources. Tropical tuna purse seine fisheries (TTPSF) are distributed worldwide and account for two thirds of the global tuna catch. In these fisheries, the use of Drifting Fish Aggregating Devices (DFADs)—man-made floating objects massively deployed by fishers to increase their tuna catches—results in the incidental catch of non-target species, termed bycatch. We explored the possibility of applying machine learning on echosounder buoys attached to DFADs — representing an unprecedented source of big data – for identifying high bycatch risk at DFADs. We trained random forests algorithms to differentiate between high and low bycatch occurrence based on matched echosounder and onboard observer data for the same DFADs (representing sample sizes of 838 and 2144 in the Atlantic and the Indian Ocean, respectively). Algorithms showed a better performance in the Atlantic Ocean (accuracy of 0.66 *versus* 0.58 in the Indian Ocean) and were best at detecting the "high bycatch" occurrence class. These results unravel the potential of machine learning applied to fishers' buoys data for bycatch reduction and improved selectivity in one of the largest fisheries worldwide.

Keywords: **Atlantic Ocean; drifting fish aggregating devices; echosounder buoys; Indian Ocean; random forests; tropical tuna purse seine fisheries**

Introduction

The past decade has seen an unprecedented rise in data collections on aquatic ecosystems (Durden et al 2017). In the oceans, emerging sources of datasets include automatic vessel tracking systems (Kroodsma et al. 2018) and autonomous underwater vehicles (Sahoo et al. 2019). To accelerate the processing of these massive and complex datasets often referred to as “big data”, machine learning algorithms have emerged as powerful tools, with promising applications in marine sciences (Beyan & Browman 2020). Together, big data and machine learning have a huge potential for addressing conservation and management issues in the oceans.

With over half of the world's oceans subject to industrial fishing (Kroodsma et al. 2018), the overexploitation of marine resources is a pervasive threat to marine biodiversity. Pursuant to the Sustainable Development Goal 14 of the United Nations, achieving sustainable use of ocean resources is a major societal challenge. Machine learning tools provide new opportunities for improving the management of fisheries by allowing the automated monitoring of catches for both target and non-target species (Bradley et al. 2019; Malde et al. 2020). There is a growing need for pragmatic and illustrative cases for how these tools can be used to promote sustainable fishing practices at sea.

The global catch of tropical tuna is close to 5 million tons per year and tropical tuna purse seine fisheries (TTPSF) account for two thirds of this global catch (ISSF 2019). In these fisheries, the use of Drifting Fish Aggregating Devices (DFADs)—man-made floating objects deployed by fishers to increase their tuna catches—results in the incidental catch of other fish species, termed bycatch (Dagorn et al. 2013). Though bycatch in TTPSF is relatively lower than in some other fisheries (with a reported discards rate of 3.9% in TTPSF *versus* 12.3% in pelagic longlines fisheries, for example) (Roda et al. 2019), the sheer magnitude of TTPSF means that the induced mortality on non-target species is not negligible. Moreover, the strong associations of some species with DFADs make them particularly vulnerable to bycatch (Forget et al. 2015). Decreasing overall bycatch volumes in TTPSF is central to the application of an ecosystem approach to fisheries management (Pikitch et al. 2004).

Between 81,000 and 121,000 DFADs are deployed every year by fishers across the globe, and this number is likely to have increased since this estimate was made (Gershman et al. 2015). Most DFADs are equipped with satellite-linked echosounder buoys that automatically provide remote information on their geolocation and fish presence. These buoys represent an unprecedented source of big data for scientists who can use this constellation across the oceans as a scientific platform for observing pelagic biodiversity (Moreno et al. 2016). While echosounder buoys have been designed to provide fishers with information on tuna presence, we postulate that data from these buoys can also inform on the presence of bycatch. In this study, we explored the potential of processing echosounder buoy data with machine learning to assess bycatch risk at DFADs prior to fishing sets. Our novel approach opens the door to the development of new machine learning tools to aid fishers in reducing bycatch, thereby improving selectivity in TTPSF.

Methods

Database description

We obtained echosounder data from Marine Instruments "M3I" buoys attached to DFADs deployed by French purse seiners in the Atlantic and Indian oceans for the 2013-2018 period. Each buoy is equipped with a GPS and an echosounder operating at 50 Khz. Simplified acoustic profiles are stored every 2 h and transmitted by satellite every 12 h (by default) in the form of 50 integer acoustic scores (ranging from 0 to 7) indicating the acoustic energy recorded within 3-m depth layers over a total detection range of 150 m (Figure S1) (Baidai et al. 2020). We obtained bycatch data from scientific observer programs onboard French purse seiners in the Atlantic and Indian oceans implemented under the EU Data Collection Framework (DCF) and the French OCUP program (Observateur Commun Unique et Permanent). Bycatch data were used to associate acoustic profiles with the actual bycatch biomass, based on the assumption that the entire aggregation is encircled and captured. For each DFAD fishing set, dedicated observers recorded species-specific bycatch in numbers of individuals, or in weight when the number of individuals was too high to be reliably counted. Numbers were converted to weight based on the mean recorded individual length and published length-weight relationships. Total bycatch biomass was then calculated by summing species-specific biomasses. Observers also recorded the date, time, GPS location and the buoy unique identifier associated with each set.

Acoustic data pre-processing

We pre-processed acoustic data for standardization and reduction of dimensionality as illustrated in Figure S1 (detailed in Baidai et al. 2020). We excluded the two layers corresponding to the transducer blanking zone (from 0 to 6 m depth). Acoustic scores were first aggregated temporally by averaging them over 4-h slots. Next, acoustic scores were aggregated vertically based on a cluster analysis (Murtagh & Legendre 2014), which identified 6 homogeneous groups of depth layers in each ocean (Baidai et al. 2020). For each homogeneous depth group, acoustic scores recorded for each of the layers constituting the group were summed and rescaled to obtain a single score per depth group and time interval (Baidai et al. 2020). This pre-processing led to daily acoustic matrices of 6 x 6 dimension providing synthetic acoustic profiles.

Machine learning

The originality of our approach lies in the ability of machine learning to detect bycatch occurrence at DFADs based on patterns on echosounder buoy outputs when bycatch species were present, with no required a priori knowledge on these patterns, nor on species-specific acoustic responses. We considered as bycatch species all non-tuna teleosts (Table S2). Because these species have swim bladders and usually form dense schools, they are highly detectable by echosounder buoys. In contrast, sharks generally occur in low numbers around DFADs (between 2 and 6 individuals on average in the Atlantic and Indian oceans, respectively), have no swim bladder and do not usually form dense schools. Hence, owing to their relatively insignificant biomass, they were less likely to be detected by the echosounders and were excluded from our analyses.

We obtained learning datasets by matching bycatch biomasses reported by observers with daily acoustic matrices in each ocean, based on buoy identifiers, and dates and times of the sets. We discarded aberrant buoy identifiers for which positions reported by observers were inconsistent with GPS positions. We used daily acoustic matrices corresponding to the day preceding the set in order to avoid potential disturbances to fish aggregations induced by the fishing operation. Because very few sets contained no bycatch (only 5.4% in the Atlantic Ocean and 6.2% in the Indian Ocean), we used a cutoff for categorizing sets into “high” and “low” bycatch, and performed a binary classification. We defined the best cutoff among values ranging from 0.1 to 1 t in each ocean as the one leading to the highest classification accuracy (see below).

In each ocean, we applied a random forest (RF) classification algorithm (Breiman 2001) to discriminate between high and low bycatch occurrence using the R package “randomForest” (Liaw & Wiener 2002). A random forest consists of an ensemble of independent decision trees leading to a more accurate prediction than that of any individual tree (Breiman 2001). Candidate predictor variables were the elements of the 6 x 6 daily acoustic matrices. To deal with the imbalanced number of observations in high and low bycatch classes, we resampled the dominant size class to make its frequency closer to the rarest class (Kuhn & Johnson 2013). We grew three thousand trees in each ocean. We assessed the number of predictor variables randomly sampled at each split (denoted as “*mtry*”) through a grid-search strategy implemented with the R package “caret” (Kuhn et al. 2019). We selected the best "*mtry*" as the value generating the lowest classification error rate. The importance of predictors was assessed using the mean decrease accuracy (i.e., the increase of prediction error after permuting each predictor, leaving all other predictors unchanged) (Breiman 2001).

We performed model training and evaluation through a hold-out validation (corresponding to setting a portion of the data aside to evaluate model performance) repeated 10 times. In each replica, we divided the original dataset into training and validation datasets, representing 75% and 25% of the data, respectively. We then derived the model accuracy (proportion of correct predictions) and the kappa coefficient (a reliability index) (Cohen 1968) on the validation dataset. Finally, sensitivity (true positive rate), specificity (true negative rate), and precision (positive predictive value) were derived from the confusion matrix.

Results

In both oceans, we obtained the best RF accuracy with a cutoff of 0.2 t between low and high bycatch classes (Figure S3-1 and S3-2). Learning datasets represented 838 and 2144 data points in the Atlantic and Indian Ocean, respectively (Figure 1, Table S4-1). In the Atlantic Ocean (AO), the high bycatch class corresponded to acoustic scores that were higher in intermediate depth layers (from 21 to 45 m), but slightly lower in shallow layers during the day (Figure S4-1). In the Indian Ocean (IO), differences were less clear, with a high bycatch class associated with slightly higher acoustic scores in shallow layers (from 6 to 18m) during the day.

The RF algorithm was better at discriminating high and low bycatch classes in the AO than in the IO, with respective accuracies of 0.66 and 0.58, and a kappa coefficient twice higher in the AO (Table 1). In both oceans, the sensitivity was higher than the specificity, indicating a better ability at detecting the high bycatch class (Table 1, Figure 2).

In the IO, the most important predictors corresponded to shallow layers (6-15 m) during the day (Figure 3). Conversely, in the AO, deep layers (27-150 m) during the day, and shallow layers (9-21 m) around dawn, appeared most important.

Discussion

Fishing on DFADs accounts for more than half of the tuna landings of TTPSF (Restrepo et al. 2017), but also leads to large overall bycatch volumes (Roda et al. 2019). We capitalized on the massive data available from fishers’ buoys analyzed through machine learning to assess whether they could inform potential bycatch risks at DFADs. RF algorithms showed promise to discriminate between high and low levels of teleost bycatch, particularly in the AO, and better detected the high bycatch class. Implemented in real time, these algorithms could help fishers to avoid fishing sets on DFADs associated with high risks of non-target species catch, thereby improving selectivity in TTPSF. Though additional research is needed to increase the algorithms’ accuracy, our approach shows great potential for progressing towards an ecosystem approach to fisheries (Pikitch et al. 2004). Indeed, our approach focuses on non-tuna teleost species impacted by fisheries and could help design spatio-temporal management measures that could lead to a reduction in overall bycatch volume, thereby complementing mitigation measures already in place for vulnerable species (e.g., Poisson et al. 2014). Regardless of the management strategy, knowledge on bycatch risk prior to fishing is key to support best fishing practices.

As bycatch species are generally known to occur shallower than tuna species (Forget et al. 2015; Macusi et al. 2017), we expected acoustic scores to be higher in shallower layers in the high bycatch class. In the AO, acoustic scores in shallower layers were instead higher in the low bycatch class. We also found a pronounced geographical structure, with 65% of our low teleost bycatch class originating from coastal Angola and Gabon (Appendix S5) (an area that is nevertheless characterized by high shark bycatch (Lopez et al. 2020)). In this region, the higher acoustic scores detected near the surface despite low teleost bycatch could be explained by an increased abundance of tuna in shallow layers usually occupied by bycatch species. RF algorithms further implemented at the regional scale had lower performances than the Atlantic-scale algorithm (Appendix S5). These results suggest that the higher performance in the AO compared to the IO could be related to the stronger geographical/environmental structure in the AO. Remarkably, these contrasted patterns between oceans and the importance of deep layers as predictor variables stress the need to reconsider the fixed 25 m depth layer previously assumed as adequate for discriminating bycatch and tuna species at DFADs (Orue et al. 2019).

Discrepancies between bycatch detection on echosounder profiles and in the catches may negatively affect the performance of algorithms by introducing noise. For example, small schooling fish like *Decapterus spp* and the blue runner *Caranx crysos* are characterized by a strong acoustic back-scatter, but are not always retained by the net. The buoy's blanking zone and its smaller acoustic cone in shallow layers also prevent the detection of bycatch species that occupy these positions in the water column during the night (Forget et al. 2015), leading to an overall underestimation of bycatch biomass from echosounders. Observer-derived bycatch estimates may be prone to estimation errors, especially in such large volume fisheries, but remain the most reliable data source of bycatch. In the future, observer data could be combined with complementary data sources, such as electronic monitoring, in an attempt to improve bycatch estimates (Ruiz et al. 2015). Finally, echosounder buoys cannot be used to detect sharks despite their vulnerability to bycatch and DFAD entanglement (Dagorn et al. 2013; Filmalter et al. 2013). A different machine learning approach applied to video data obtained from autonomous cameras attached to DFADs could be more appropriate for detecting shark species.

Echosounder buoys initially developed as fishing tools represent an unprecedented and massive source of information for characterizing patterns in pelagic fish occurrence (Moreno et al. 2016), but challenges remain for their utilization in direct fisheries management applications. Despite the large amounts of echosounder buoy data, matches with actual catches are limited (as shown by our modest learning datasets). Expanded coverage of observer programs and better reporting of buoy identifiers would help increase the size of learning datasets in the future. The potential for deriving accurate estimates of fish biomass from the current echosounder buoys is also limited, as illustrated by the poor performance of RFs for quantifying tuna biomass (Baidai et al. 2020). Finally, the unique sampling frequency of the echosounder buoys does not appear as the best technological approach to differentiate species. Nevertheless, our machine learning approach is applicable to any echosounder buoy type, including multi-frequency buoys that have revealed helpful for refining species differentiation (Moreno et al. 2019).

In conclusion, machine learning applied to massive data collected through fishers' buoys offers promise for assessing bycatch risk at DFADs and could help designing spatio-temporal measures for the reduction of bycatch in TTPSF. Implemented in real-time, such algorithms have the potential to help fishers avoid bycatch at DFADs by providing them with information prior to the fishing sets, paving the way for more sustainable fishing practices. Given the magnitude and extensive distribution of TTPSF worldwide, this novel approach could contribute to reduce the impact of fishing on pelagic marine ecosystems.

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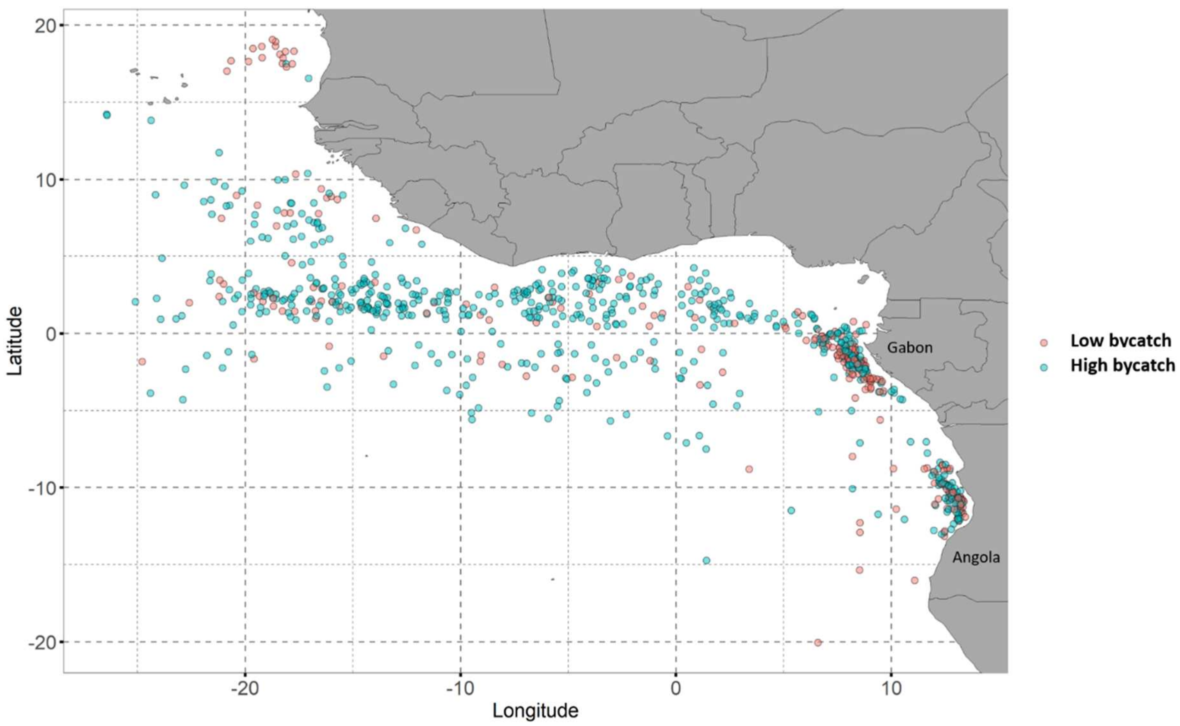
Tables

Table 1: Performances of the random forest classifications derived from a hold-out validation in each ocean. Mean and standard deviation values (in brackets) of evaluation metrics are provided.

Evaluation Metrics	Atlantic Ocean	Indian Ocean
Accuracy	0.66 (0.04)	0.58 (0.02)
Kappa	0.32 (0.07)	0.16 (0.03)
Sensitivity	0.74 (0.05)	0.63 (0.03)
Specificity	0.59 (0.05)	0.53 (0.03)
Precision	0.64 (0.03)	0.57 (0.02)

Figures



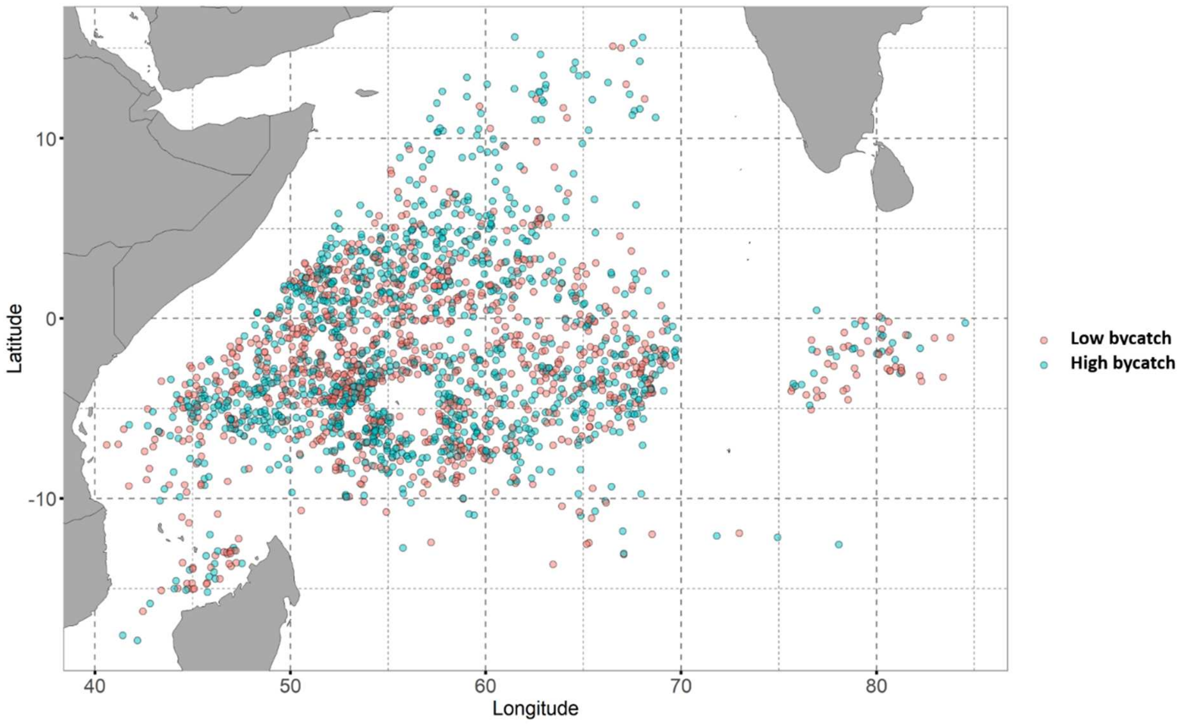


Figure 1: Geographical span of the learning datasets in the Atlantic (n=838 sets) and Indian oceans (n=2144 sets). Each point corresponds to a fishing set on DFAD and the colors represent high and low bycatch classes.

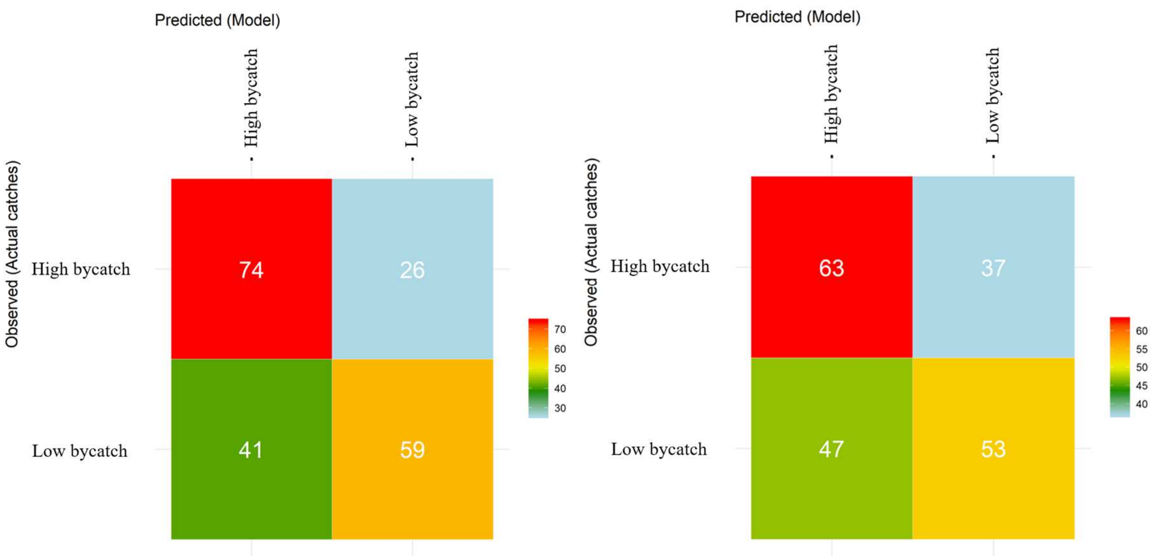


Figure 2: Confusion matrices standardized per row (i.e., with respect to observations) for random forest classifications in the Atlantic Ocean (left) and the Indian Ocean (right). The diagonal elements

represent the percentage of data points for which the predicted class is equal to the observed class, while off-diagonal elements are those that are misclassifed by the random forest. The color scale represent the percentage of data points.

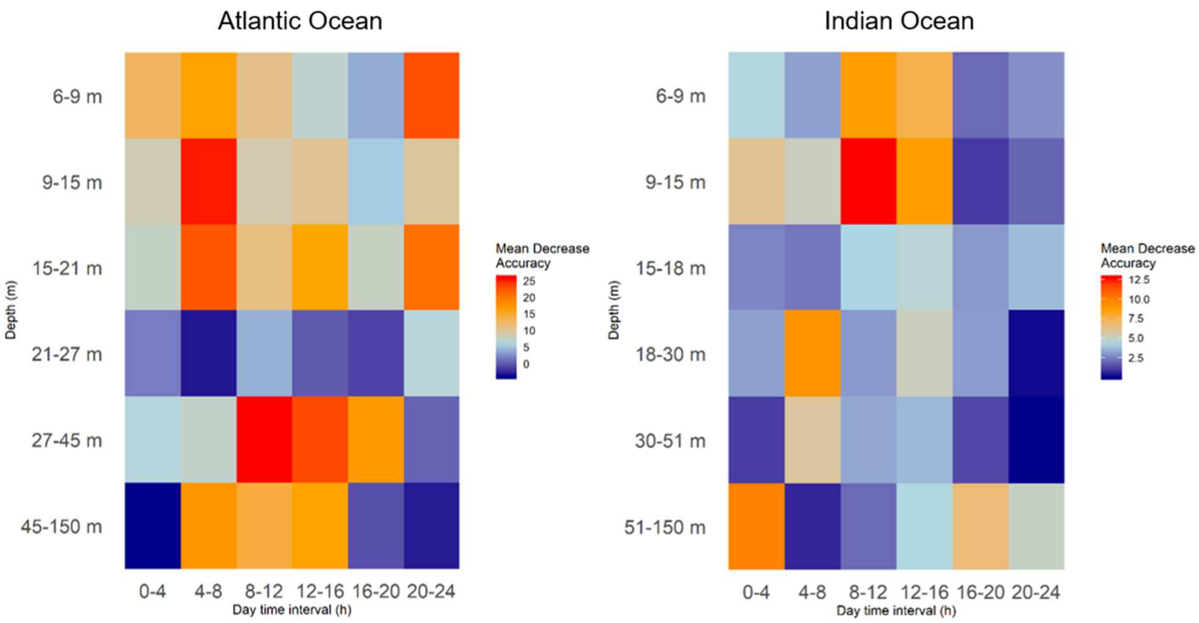


Figure 3: Importance of random forests predictors in the bycatch classification in both oceans assessed through the mean decrease accuracy (the mean decrease accuracy corresponds to the increase of prediction error after permuting each predictor, leaving all other predictors unchanged).