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Machine learning to detect bycatch risk: novel application to echosounder buoys data in tuna purse seine fisheries Laura Mannocci<sup>1\*</sup>, Yannick Baidai<sup>1,2</sup>, Fabien Forget<sup>1</sup>, Mariana Travassos Tolotti<sup>1</sup>, Laurent Dagorn<sup>1</sup>, Manuela Capello<sup>1</sup>

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## Competing interest statement

The authors have no competing interest to declare.

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## 3 Abstract

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

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

## 21 Introduction

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

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

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

45 vulnerable to bycatch (Forget et al. 2015). Decreasing overall bycatch volumes in TTPSF is central to  
46 the application of an ecosystem approach to fisheries management (Pikitch et al. 2004).

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

## 58 [Methods](#)

### 59 [Database description](#)

60 We obtained echosounder data from Marine Instruments “M3I” buoys attached to DFADs deployed  
61 by French purse seiners in the Atlantic and Indian oceans for the 2013-2018 period. Each buoy is  
62 equipped with a GPS and an echosounder operating at 50 Khz. Simplified acoustic profiles are stored  
63 every 2 h and transmitted by satellite every 12 h (by default) in the form of 50 integer acoustic scores  
64 (ranging from 0 to 7) indicating the acoustic energy recorded within 3-m depth layers over a total  
65 detection range of 150 m (Figure S1) (Baidai et al. 2020). We obtained bycatch data from scientific  
66 observer programs onboard French purse seiners in the Atlantic and Indian oceans implemented  
67 under the EU Data Collection Framework (DCF) and the French OCUP program (Observateur  
68 Commun Unique et Permanent). Bycatch data were used to associate acoustic profiles with the  
69 actual bycatch biomass, based on the assumption that the entire aggregation is encircled and

70 captured. For each DFAD fishing set, dedicated observers recorded species-specific bycatch in  
71 numbers of individuals, or in weight when the number of individuals was too high to be reliably  
72 counted. Numbers were converted to weight based on the mean recorded individual length and  
73 published length-weight relationships. Total bycatch biomass was then calculated by summing  
74 species-specific biomasses. Observers also recorded the date, time, GPS location and the buoy  
75 unique identifier associated with each set.

#### 76 [Acoustic data pre-processing](#)

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

#### 86 [Machine learning](#)

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

94 form dense schools. Hence, owing to their relatively insignificant biomass, they were less likely to be  
95 detected by the echosounders and were excluded from our analyses.

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

105 In each ocean, we applied a random forest (RF) classification algorithm (Breiman 2001) to  
106 discriminate between high and low bycatch occurrence using the R package “randomForest” (Liaw &  
107 Wiener 2002). A random forest consists of an ensemble of independent decision trees leading to a  
108 more accurate prediction than that of any individual tree (Breiman 2001). Candidate predictor  
109 variables were the elements of the 6 x 6 daily acoustic matrices. To deal with the imbalanced number  
110 of observations in high and low bycatch classes, we resampled the dominant size class to make its  
111 frequency closer to the rarest class (Kuhn & Johnson 2013). We grew three thousand trees in each  
112 ocean. We assessed the number of predictor variables randomly sampled at each split (denoted as  
113 “*mtry*”) through a grid-search strategy implemented with the R package “caret” (Kuhn et al. 2019).  
114 We selected the best “*mtry*” as the value generating the lowest classification error rate. The  
115 importance of predictors was assessed using the mean decrease accuracy (i.e., the increase of  
116 prediction error after permuting each predictor, leaving all other predictors unchanged) (Breiman  
117 2001).

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

## 125 Results

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

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

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

## 140 Discussion

141 Fishing on DFADs accounts for more than half of the tuna landings of TTPSF (Restrepo et al. 2017),  
142 but also leads to large overall bycatch volumes (Roda et al. 2019). We capitalized on the massive data



143 available from fishers' buoys analyzed through machine learning to assess whether they could inform  
144 potential bycatch risks at DFADs. RF algorithms showed promise to discriminate between high and  
145 low levels of teleost bycatch, particularly in the AO, and better detected the high bycatch class.  
146 Implemented in real time, these algorithms could help fishers to avoid fishing sets on DFADs  
147 associated with high risks of non-target species catch, thereby improving selectivity in TTPSF. Though  
148 additional research is needed to increase the algorithms' accuracy, our approach shows great  
149 potential for progressing towards an ecosystem approach to fisheries (Pikitch et al. 2004). Indeed,  
150 our approach focuses on non-tuna teleost species impacted by fisheries and could help design spatio-  
151 temporal management measures that could lead to a reduction in overall bycatch volume, thereby  
152 complementing mitigation measures already in place for vulnerable species (e.g., Poisson et al.  
153 2014). Regardless of the management strategy, knowledge on bycatch risk prior to fishing is key to  
154 support best fishing practices.

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

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

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

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

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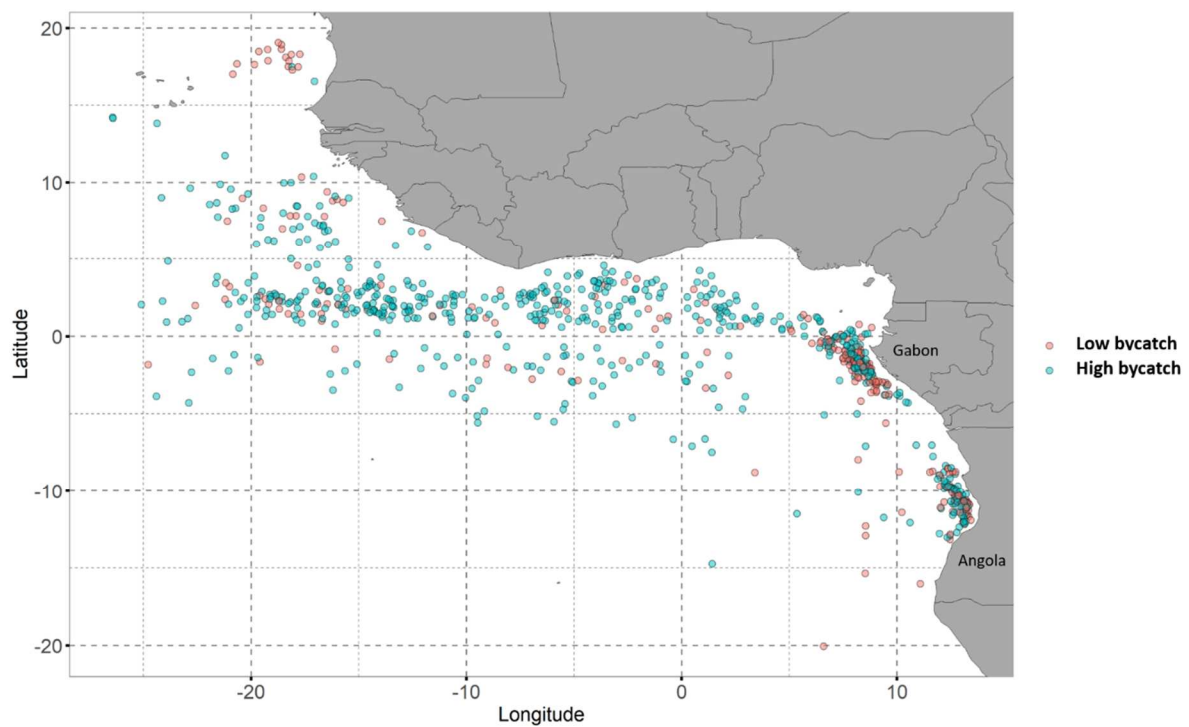
276

## 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



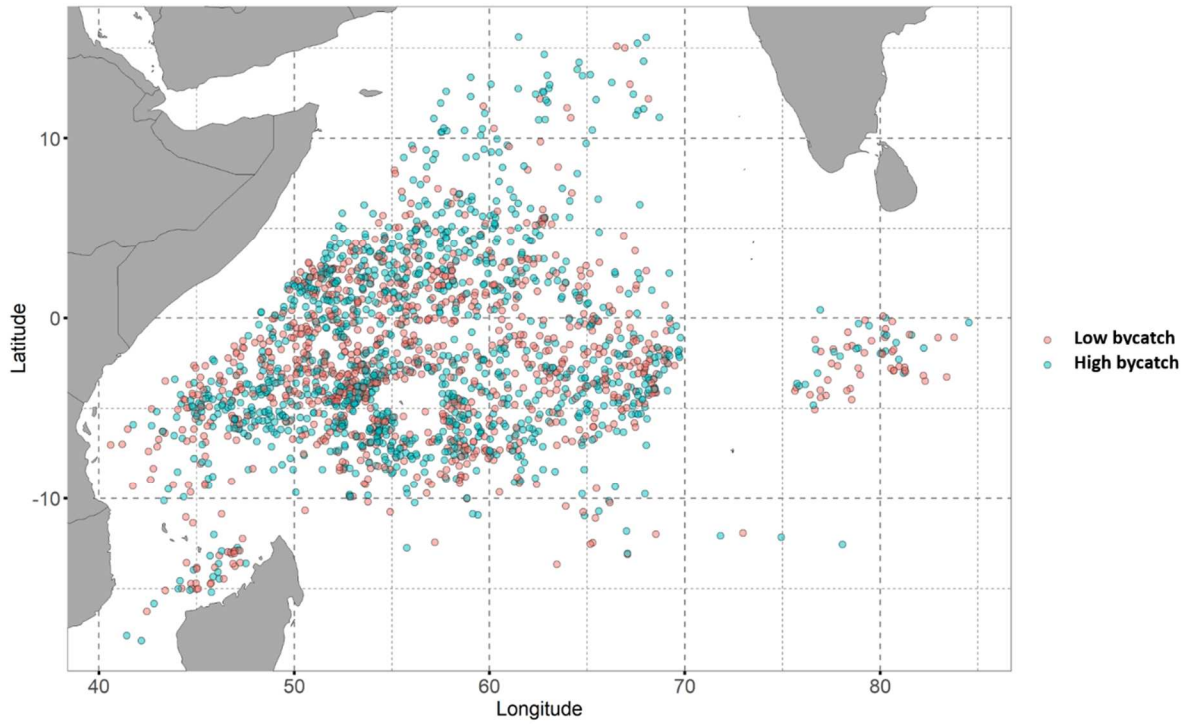


Figure 1: Geographical span of the learning datasets in the Atlantic (n=838 sets) and Indian oceans (n=2144 sets). Each point corresponds to a fishing set on DFAD and the colors represent high and low bycatch classes.

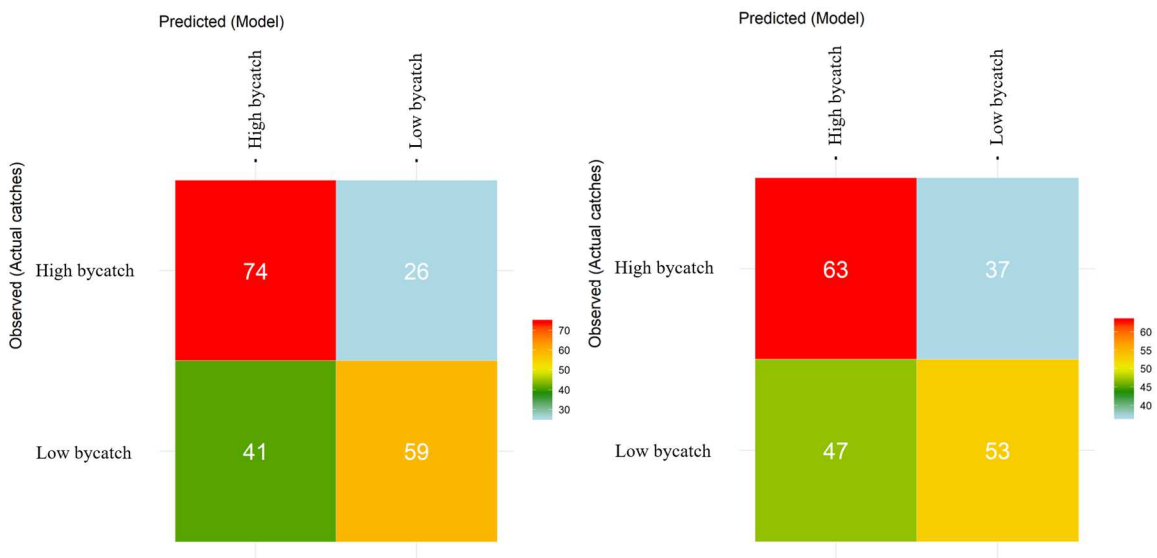


Figure 2: Confusion matrices standardized per row (i.e., with respect to observations) for random forest classifications in the Atlantic Ocean (left) and the Indian Ocean (right). The diagonal elements

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 misclassified by the random forest. The color scale represent the percentage of data points.

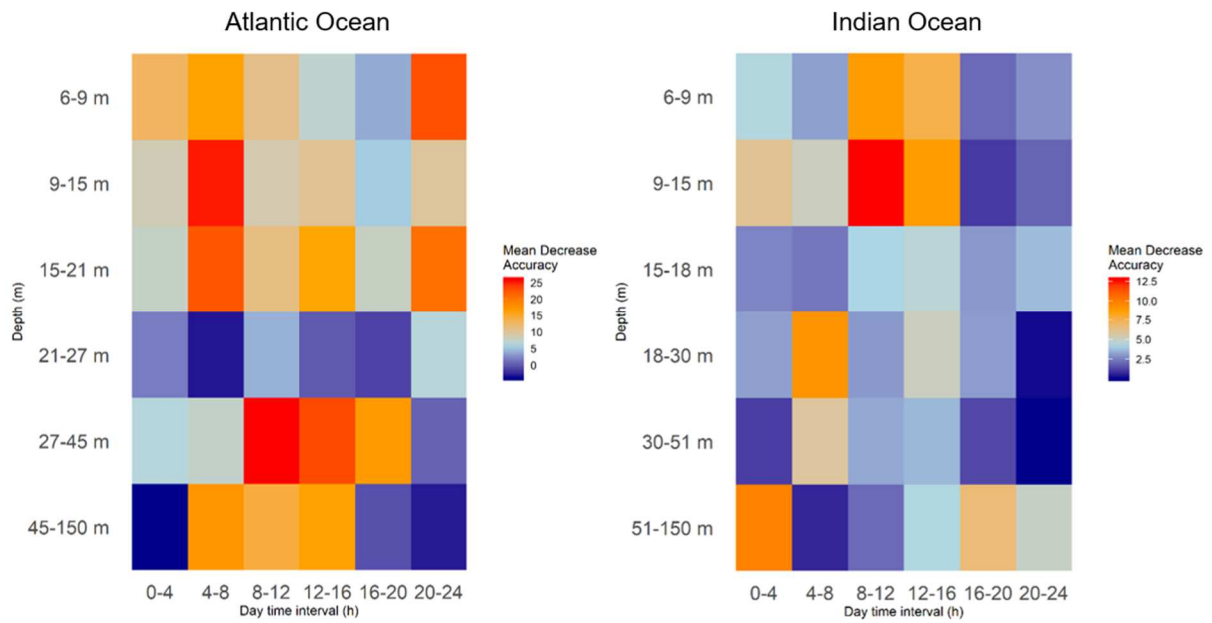


Figure 3: Importance of random forests predictors in the bycatch classification in both oceans assessed through the mean decrease accuracy (the mean decrease accuracy corresponds to the increase of prediction error after permuting each predictor, leaving all other predictors unchanged).