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AN ANALYSIS OF GEAR EFFECTS ON THE PRESENCE OF BIGEYE TUNA (*THUNNUS OBESUS*) IN THE CATCHES OF THE PURSE-SEINE FISHERY IN THE EASTERN PACIFIC OCEAN

Cleridy E. Lennert-Cody, Jason J. Roberts, Richard J. Stephenson

ABSTRACT

In this manuscript we develop a classification algorithm for the presence/absence of bigeye tuna catch in floating object sets to explore the effects of gear characteristics on occurrence of bigeye catch. Among the gear characteristics studied, it was found that the maximum depth of the object below the water's surface and the hanging depth of the purse-seine net had the most affect on whether bigeye tuna were caught, with catch more likely on 'deeper' objects and in 'deeper' nets (actual fishing depths are not know). These gear effects were found to vary spatially, with the greatest increases in the probability of catching bigeye tuna on deeper objects and in deeper nets in the southern area of the fishery. Nonetheless, the location of the set (latitude, longitude) was the strongest determinant with this data set for the presence of bigeye tuna catch. Sets in which bigeye tuna was caught, but none was predicted, were found to be concentrated within certain vessels suggesting that some vessels may also catch bigeye tuna in ways different from most of the fleet, *i.e.*, in ways poorly described by the predictors included in this analysis. This represents a form of a 'vessel effect' that could be amenable to further study. Results of this study indicate that fishermen have several options available to them to try to avoid catching bigeye tuna, including changing the in-water depth of the floating object and the actual fishing depth of the net, especially in certain areas of the fishery, and changing their overall fishing location. However, we believe that the characteristics of the floating object fishery for bigeye tuna identified in this and previous studies, and the complex nature of the gear and environmental interactions that determine the gear's actual fishing depth, argue against fishery-wide gear restrictions as a reasonable means of reducing bigeye catch.

1. INTRODUCTION

Despite recent efforts to improve the status of bigeye tuna (*Thunnus obesus*) in the eastern Pacific Ocean (EPO) using seasonal fishery closures (Maunder and Harley, 2006), the most recent stock assessment (Maunder and Hoyle, 2006) indicates that fishing mortality remains too high to be sustainable. Tunas are caught in the EPO by several different fishing gears, including longlines and purse-seines (FSR, 2006). The purse-seine fishery catches tunas in association with dolphins, in association with floating objects, and as free-swimming schools (Bayliff, 2001). The three most commercially-importance species taken in the purse-seine fishery are bigeye tuna, yellowfin tuna (*Thunnus albacares*) and skipjack tuna (*Katsuwonus pelamis*), with bigeye tuna caught predominantly in sets on floating objects (FSR, 2006). For the largest class of purse-seine vessels (greater than 363 mt fish-carrying capacity), the majority of floating object sets made in recent years are estimated to have been on fish aggregating devices (FADs; FSR, 2006). Operationally-feasible time-area closures have been estimated to reduced bigeye catches by less than that necessary for a sustainable fishery (Harley and Suter, 2007). Other options for reducing bigeye catches are currently being explored, including gear modifications (Maunder, 2006).

Floating object sets on bigeye tuna appear to be concentrated within certain vessels. Based on data collected by Inter-American Tropical Tuna Commission (IATTC) observers during the 2001-2005 period, approximately 54% of floating object sets of large vessels yielded catches of bigeye tuna, compared to 81% for yellowfin tuna and 93% for skipjack tuna. Yet total catches of bigeye tuna on floating objects are greater than catches of yellowfin tuna on floating objects. Over this five year period, complete IATTC observer data were available on floating object sets of 158 large purse-seine vessels. Of these vessels, 29% did not catch any bigeye tuna (Figure 1). Floating object sets, regardless of the tuna species caught, tended to be concentrated within vessels (Figure 1). However, even accounting for this, the relationship between numbers of sets on floating objects and numbers of sets on floating objects that caught bigeye, by vessel, is not linear (Figure 2), contrary to what would be expected if sets per vessels that caught bigeye tuna were proportional to total sets. Previous studies have also shown catch amounts of bigeye tuna to be concentrated within vessels (Harley et al., 2004). One possible explanation for this pattern is that some vessels improve their chances of catching bigeye tuna by way of where and when they fish, the gear they use and/or combinations of these options.

Separating gear effects on tuna catches from environmental effects has proved difficult with opportunistically collected data from this fishery because of the strong environmental gradients in the EPO (*e.g.*, Kessler, 2006). Some gear characteristics have been suggested to affect tuna catch (Lennert-Cody and Hall, 2000) during the 1993-1998 period of this fishery. However, this was a time when the fishery on floating objects was in transition from a fishery on flotsam (*e.g.*, tree limbs) in nearshore areas to a largely FAD-associated fishery further offshore (Lennert-Cody and Hall, 2000; FSR, 2006). Although partial confounding of gear and environmental factors is to be expected with fishery-dependent data, the need to find operationally-feasible means of reducing fishing mortality of bigeye tuna in the current FAD-dominated fishery, the availability of improved environmental data (*e.g.*, ocean color), and the availability of improved descriptive statistical techniques for large data sets (Berk, 2006) suggests gear effects warrant further study.

In this manuscript we present an analysis of the presence/absence of bigeye tuna catch in purse-seine sets on floating objects for the period 2001-2005. Given the results of the most recent stock assessment for bigeye tuna (Maunder and Hoyle, 2006), and that almost one half of floating object sets caught no bigeye, we focus on understanding processes that led to any amount of bigeye catch. The tree-based method random forests (Breiman, 2001) was used to build a classification algorithm for sets with and without bigeye tuna catch, placing more emphasis on correctly predicting the presence of catch. With this analysis, we attempt to determine: how well the presence of bigeye catch can be described by characteristics of the environment, and the fishing operation and gear; whether there is spatial structure in any gear effects on the presence of bigeye catch; and, the extent to which there may exist additional ‘vessel effects’ on the presence of bigeye catch beyond the explanatory ability of the predictors included in this analysis.

2. DATA

Data used in this analysis are from purse-seine sets on floating objects collected by IATTC observers aboard large vessels (> 363 mt fish-carrying capacity) between 2001 and 2005. Data were limited to sets that caught some amount of at least one of the three target species to avoid observations for which the fish escaped capture. Repeat sets on the same floating object, where they could be identified, were excluded. Data collected prior to 2001 were not included in this analysis to avoid potential trends in biases in tuna species identification. In particular, in 2000 the IATTC implemented a system for tracking tuna catch as part of the AIDCP ‘dolphin safe’ certification. As part of this process, the observer may discuss catch composition with the vessel’s fishing captain. In addition, in 2000 the IATTC passed a resolution encouraging vessels to retain all tuna catch (IATTC, 2000). This resolution has been renewed annually, although the degree of compliance is unclear (IATTC, 2004). Because tunas found in association with floating objects can be of small size, and hence less marketable, strict compliance with the resolution might affect a vessel’s decision as to whether to initiate a set. After data processing, a total of 10,425 floating object sets were available for analysis.

Over 85% of floating objects set upon during this five-year period were estimated to have been FADs (FSR, 2006). FADs may be constructed of a variety of materials, however, the most typical construction is a raft (often of bamboo) with old purse-seine netting hanging underneath. FADs often carry some form of locating device (*e.g.*, radio transmitter, satellite transmitter).

To describe variability in the occurrence of bigeye tuna catch, 21 predictors were considered in this analysis (Table 1). These predictors can be divided roughly into three groups: those describing aspects of fishing operations and gear, those describing the environment, and a miscellaneous collection. There were seven predictors included to describe aspects of the fishing operations and gear: vessel fish-carrying capacity, hanging depth of the purse-seine net, purse-seine mesh size, dolphin safety panel use, maximum floating object depth below the water's surface, percent of the object covered with fouling organisms, and start time of the set. Vertical stratification of species around floating objects has been noted by fishermen, fisheries observers and identified through research (Schaefer and Fuller, 2002). Aspects of the fishing operation and/or gear that interact with vertical structure of the object-associated community may affect catch composition. For a given combination of wind and current conditions, the fishing depth of the purse-seine net is affected by its hanging depth, mesh size and the presence of a dolphin safety panel, as well as its 'hang-in' (number of meshes per unit length along the cork line), and the amount of purse cable and chain. Although no data were available on hang-in or purse cable and chain weight, vessel capacity may be useful in this regard because larger boats can carry larger nets which typically require more robust purse cables and chain. The percentage of the object covered with fouling organisms was used as a proxy for time the object spent in the water (i.e., soak time), although the relationship between fouling and actual soak time may be compromised by the fact that vessels may set upon/use objects belonging to other vessels, and it is not possible to track individual objects across vessel trips. The start time of the set was included as a predictor because bigeye tuna have been shown to exhibit diel variability in their depth distribution when associated with floating objects (Schaefer and Fuller, 2002).

Environmental predictors included in this analysis relate to measures of upper-ocean circulation, stratification and productivity (Table 1). Three predictors were used to try to capture some of the characteristics of the larger-scale circulation in the EPO (e.g., major currents, eddies): sea surface height anomaly, the slope of the sea surface height anomaly, and a subjective estimate by the observer as to the presence of strong currents. Four predictors were used to describe stratification and productivity: *in-situ* sea surface temperature, the average probability of the occurrence of sea surface fronts, the average mixed layer depth, and the average chlorophyll-a density. In addition, water depth, location (latitude, longitude, plus higher order terms) and date (year, month) were also included as proxies for local environmental conditions not captured by the other environmental predictors. Two miscellaneous predictors included in the analysis were a proxy for the non-tuna community size at the object, and a proxy for the local object density (Table 1).

As anticipated, given the opportunistic nature of the data collection process, the inshore-offshore orientation of the fishery (Figure 3), and the gradients in the oceanographic environment (*e.g.*, Kessler, 2006), a number of these predictors are partially correlated (Table 2). For example, correlation between environmental predictors and predictors such as percent fouling likely result because floating objects will have a tendency drift offshore in many areas of the EPO, particularly south of the equator. The oceanography and bathymetry of the EPO result in correlations between latitude and longitude, and many environmental predictors such as sea surface temperature, chlorophyll-a density, and mixed layer depth. In addition, some gear and operational predictors are inherently correlated. For example, larger vessels (greater vessel capacity) can carry larger nets which may have greater hanging depth than smaller nets. Larger vessels can fish further offshore due to their greater fish- and fuel-carrying capacities. Examples of the spatial dependence of several gear predictors are shown in Figure 4.

The classification of each set as to the presence/absence of bigeye tuna catch was based on the catch weights. Both catch weights and loaded weights (metric tons) are estimated by observers. We use catch weights because they may more closely reflect the ecological relationship between the object-associated community and the environment and fishing gear.

3. METHODS OF ANALYSIS

With this analysis, we want to determine: how well the presence of bigeye tuna catch can be described by characteristics of the environment, fishing operations and gear; whether there is spatial structure in any gear effects; and, whether there may exist additional 'vessel effects'. Towards this end, the ensemble method 'random forests' (Breiman, 2001; Berk, 2006) was used to build a classification algorithm for the presence/absence of bigeye tuna catch. Random forests has been demonstrated to build better classification algorithms than other methods (Breiman, 2001). In addition, the estimates of misclassification errors provided by the random forest method are forecasting errors, and the relative costs of the two types of mistakes that can be made (predicting bigeye catch when none occurred – 'false positive'; predicting no bigeye catch when in fact there was catch – 'false negative') can be easily specified.

Random forests is a tree-based algorithm that builds on the classical Classification and Regression Tree approach (CART; Breiman et al., 1984). It can be described in three conceptual steps. First, a large number of CART-like trees ('forest') are constructed, each on a different randomly selected sample from the original data. (Observations not included in a particular random sample are referred to as 'out-of-bag' or 'OOB.') Second, each tree in the forest is built in a manner that is similar to a CART tree, but with two important differences: the candidate predictors that are available to define each node in the tree are a randomly selected subset of all predictors, drawn anew for each node; and, the resulting tree is not pruned. Finally, the predicted class of an observation by the forest is determined by majority vote among the individual trees for which the observation was OOB. (The predicted class of an observation from an individual tree in the forest is the dominant class on the relevant terminal node.) Details of the random forest algorithm can be found in Breiman (2001) and Berk (2006).

We use the **R** statistical computing (R Core Development Team, 2005) package *randomForest* (Liaw, 2002) to build a random forest classification algorithm for these data. The data set was randomly divided (by year) into two parts: a training data set with 5,212 sets (2,827 sets with bigeye, 2,385 without) and a test data set with 5,213 sets (2,847 sets with bigeye, 2,366 without). All classification algorithms were built on the training data set. The test data set was used to explore 'vessel effects' as described below. In the context of the current problem, it seems reasonable to place equal, if not added, emphasis on correctly predicting the presence of bigeye tuna catch when it occurred. Thus, we consider two different relative costs: equal relative costs of false negatives and false positives, and the relative cost of false negatives three times that of false positives. The different relative costs were achieved by building forests on data sets with different proportions of presence and absence observations ('sampsize' option in the *randomForest* package). Each classification algorithm was based on 5,000 trees.

Within the combinations of environmental conditions, locations, and fishing dates in the data set, we summarize the affects of gear characteristics on the presence of bigeye catch in several ways. The relative importance of each predictor was computed as the average decrease in prediction accuracy on the OOB data when the predictor's values were scrambled (Liaw and Wiener, 2002; Berk, 2006). In addition, the relationship of each of the most influential gear predictors to the occurrence of bigeye catch were summarized by plotting the inverse of the average log odds for the presence of bigeye tuna versus the predictor (a form of 'partial dependence;' e.g., Hastie et al., 2001). This provides an estimate of the effect of a particular predictor on the approximate probability of catching bigeye tuna, taking into account the average effects of the other predictors. To look for spatial structure in these relationships, we computed the inverse of the average log odds within each of 20 areas, where areas were selected according to the large-scale circulation patterns of the EPO (Kessler, 2006) and the spatial distribution of the fishery (Figure 3).

To explore 'vessel effects,' beyond what can be described by the available predictors, we compared observed and reported classes on the test data set. We focus on false negatives, bigeye tuna caught but none predicted, because this type of error may indicate alternative fishing strategies that were successful with respect to bigeye tuna. Because there are different numbers of sets per vessel in the data set (Figure 2), we compare the number of misclassifications of sets that caught bigeye to that which would be predicted from a binomial distribution. The binomial parameter was taken to be the false negative rate. That is, for each vessel we computed the probability that out of *n* sets that caught bigeye tuna there would have been *r* or more sets for which no bigeye tuna were predicted. We refer to these probabilities as 'per-vessel' probabilities. There is no convincing way to assess the extent that observations within vessels are independent, and thus, we use the per-vessel probabilities as a relative measure of 'vessels effects;' the smaller the probability, the more unusual the data of that vessel with respect to the data of other vessels.

4. RESULTS

The random forest classifier was reasonably successful at predicting the occurrence of sets with bigeye tuna catch (Table 3). Misclassification errors at equal relative costs for false negatives and false positives were 15.2% for sets that caught bigeye tuna and 18.2% for sets that did not (Table 3a). When emphasis was placed on the correct classification of sets with bigeye tuna (relative costs of false negatives three times that of false positives), the false negative rate decreased from 15% to 7.5%, while the false positive rate increased from 18.2% to 26.8% (Table 3b). (Achieving a false negative error rate of less than 7.5% would require higher relative costs, which may not be acceptable.) When location and date predictors were not included in the classifier, but the three to one relative cost was maintained, the false negative rate increased by 2%, while the false positive rate increased by about 7% (Table 3c).

Predictor importance shows indication of strengths among some gear and environmental predictors, even though the location of the set appeared to be the most influential in determining whether a set caught bigeye (Table 4). Of the gear and environmental predictors included in this analysis, object depth, chlorophyll, bathymetry, sea surface temperature and mixed layer depth appeared to be the most useful for predicting the presence of bigeye tuna catch with this data set. The importance of all variables increased when location and date predictors were not included in the classification algorithm, however, the relative dominance of gear and environmental predictors remained the same (Table 5). The overall weak levels of variable importance would be anticipated given the correlations between predictors (Table 2); when a specific predictor is not selected to define a node of a given tree, some of its predictive ability may be captured by other predictors with which it is correlated.

Based on the classification algorithm with a relative cost of false negatives to false positives of three to one (Tables 3(b), 4), the approximate probability of catching bigeye tuna increased the greater the object depth, the greater the net depth and the greater the percent fouling, however, increases were relatively small (0.10 or less; Figure 5). By area, slightly greater effects were seen. The greatest increases in approximate probability of catching bigeye tuna with object depth, 0.14 – 0.18, were found along the equator and in the southern area of the fishery between 100°-120°W (Figure 6). Similarly, the effect of net depth on the approximate probability of catching bigeye tuna was greatest along the equator and in the southern offshore area of the fishery, with maximum increases of 0.10 – 0.12 (Figure 7). Less spatial structure was evident in the effect of fouling, however, the greatest effect was found offshore south of the equator (not shown). To note is that in some areas the approximate probability of catching bigeye tuna decreased somewhat on the deepest objects and with the deepest nets (Figures 6-7).

In the test data set, there were 99 vessels over the five-year period that made at least one set catching bigeye tuna. The frequency distribution of per-vessel probabilities computed for these vessels using a binomial parameter of 0.075 (Table 3b) is show in Figure 8. Per-vessel probabilities at or close to 1.0 correspond to vessels with relatively few sets for which bigeye tuna was caught but none was predicted. That is, these are vessels for which the relationships captured by the random forest classifier adequately describe the occurrence of bigeye tuna. Per-vessel probabilities close to 0.0 correspond to vessels with a relatively large number of false negatives, relative to the number of sets in which these vessels caught bigeye tuna. That is, the random forest classifier failed to capture some of the important aspects of the data of these vessels. Within this group, the data of those vessels making the most sets on bigeye tuna might prove useful for exploring the possibility of other fishing strategies.

5. DISCUSSION

In this manuscript we have developed a classification algorithm for the presence/absence of bigeye tuna catch in floating object sets to explore the effects of gear characteristics on occurrence of bigeye catch. Among the gear characteristics studied (object depth, net depth, mesh size, safety panel use, and percent fouling of the object), it was found that object depth and net depth had the most affect on whether bigeye tuna were caught, with catches of bigeye tuna more likely on deeper objects and in deeper nets. However, these effects were found to vary spatially, with greater increases in the approximate probability of catching bigeye tuna on deeper objects and in deeper nets near the equator and in the southern area of the fishery. Nonetheless, the location of the set (latitude, longitude) was the strongest determinant with this data set for the presence of bigeye tuna catch. False negatives (bigeye tuna caught but none predicted) were found to be concentrated to some extent within certain vessels suggesting that some vessels may also catch bigeye tuna in ways different from most of the fleet, *i.e.*, in ways poorly described by the predictors included in this analysis. This represents a form of a 'vessel effect' that could be amenable to further study.

Although results of this analysis are consistent with fishermen's experience that deeper objects and deeper nets may be more likely to lead to catch of bigeye tuna in some areas, the actual magnitude of the gear effects must be viewed cautiously. The data used in this analysis were collected opportunistically during fishing trips rather than from a designed study. As a result, many of the environmental predictors (including latitude and longitude) are correlated with gear characteristics, making it impossible to estimate gear effects independent of environmental conditions. In addition, the actual fishing depth of the object and the actual fishing depth of the purse-seine net were not known. The in-water depth of both will vary depending on a number of factors. For example, the fishing depth of the net is determined by its hanging depth, and the rate at which it descends. Descent rate is a function of mesh size, dolphin safety panel use, the 'hang-in,' the weight of the purse cable and chain, and local wind and current conditions. This analysis may not have adequately captured the effect of descent rate on the presence of bigeye catch because no data were available on purse cable and chain weight, the 'hang-in,' or local wind and current conditions. Finally, the measure of object depth we have used is an estimate made by the observer, not an actual measurement, and is therefore subject to variability between observers.

The sometimes parabolic shape of the change in the approximate probability of catching bigeye tuna with object depth and net depth by area may indicate that the gear effects identified in this analysis reflect multiple processes. One possible explanation of the decrease in the probability of catching bigeye tuna on the deepest FADs or in deeper nets is simply that the decreases are the result of small sample sizes. In this data sets, about 90% of object depths were between 0.5 - 30.0 m and about 90% of net depths were between 96 - 168 fathoms. Another possibility is that this decrease may represent a different fishing strategy by some of the largest vessels. Larger vessels will have greater fish-carrying capacity, greater fishing range, and can carry a greater number of FADs (or material for constructing FADs). Instead of waiting for the optimal conditions to make a set so as to maximize catch on a particular FAD, these vessels may set on objects as they are encountered, a strategy made economically viable by the number and size of the FADs that can be placed and handled, the period of time for which the vessels can remain at sea, and the distance from port over which these larger vessels can afford to pursue their FADs as they drift in the prevailing currents.

The results presented in this manuscript add to results of previous studies (Harley et al., 2004; Harley and Suter, 2007), suggesting that the presence of bigeye tuna catch in floating object sets exhibits characteristics consistent with some level of fishermen control: almost half the floating object sets of large vessels, and almost one third of the large vessels making floating object sets, caught no bigeye tuna; the presence of bigeye tuna catch could be reasonably predicted with information on the set location, the environment and the gear characteristics; and, to some extent, the failure to predict the presence of bigeye tuna catch appeared to be concentrated within certain vessels, possibly indicating additional 'vessel effects.' Results of this study indicate that fishermen have several options available to them to try to avoid catching bigeye tuna, including changing the in-water depth of the object and the fishing depth of the net, especially in certain areas of the fishery, and changing their overall fishing location.

Given the current status of bigeye tuna populations (Maunder and Harley, 2006; Maunder and Hoyle, 2006) and the current operational infeasibility of spatial-temporal closures (Harley and Suter, 2007), gear restrictions might seem a reasonable option for reducing fishing mortality of bigeye tuna. However, gear restrictions would affect all vessels and all areas of the fishery, perhaps reducing catches of other target species. For example, skipjack tuna has been the dominant catch in floating object sets (FSR, 2006). Analyses of data from the 1993-1998 floating object fishery (Lennert-Cody and Hall, 2000) found some indication that catch per set of skipjack tuna increased with the hanging depth of the net. Fishery-wide restrictions on the hanging depth of the net might therefore reduce catches of skipjack tuna across a broad segment of the fishery, a seemingly unnecessary outcome given the focused nature of the fishery for bigeye tuna. Many factors combine to determine the actual fishing depth of a net in any given set of environmental conditions. For this reason, decisions on the set-up of fishing gear are best left to fishermen.

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TABLE 1. Description of predictors.

Predictor	**Additional details, and range of values (minimum, median, maximum), if applicable.**
Vessel fish-carrying capacity (‘vessel capacity’)	Metric tons. (397; 1,089; 2,833)
Hanging depth of the purse-seine (‘net depth’)	Counted in strips and converted to fathoms (1 strip = 6 fathoms). Actual fishing depth not measured. (72; 120; 180)
Size of the mesh in the net (‘mesh size’)	Stretch measurement in inches. (3.5; 4.25; 12.0)
Dolphin safety panel	Presence/absence.
Maximum depth of floating object below water’s surface (‘object depth’)	Estimated in meters by the observer. Actual depth not measured. (0.01; 18.1; 130)
Percent of the object covered with fouling organisms (‘percent fouling’)	(0; 40; 100)
Start time of the set (‘set time’)	Local time (decimal hours) of the release of the net skiff from the purse-seine vessel. (4.75; 6.68; 19.0)
Sea surface temperature (‘SST’)	Measured by the observer in °C. (13.0; 26.1; 31.4)

Predictor	**Additional details, and range of values (minimum, median, maximum), if applicable.**
Probability of a sea surface temperature front ('SST front')	Estimated at set locations using Advanced Very High Resolution Radiometer (AVHRR) SST data (Cayula and Cornillon, 1992; Roberts, 2005). The location of SST fronts were identified in the daytime AVHRR images from 1985-2005 by the presence of bimodal distributions in local SST. For each month, the proportion of days that a pixel contained a front and was cloud free is the estimate of the probability of a front. (0; 0.008; 0.07)
Mixed layer depth ('MLD')	Meters. Monthly average by 1° square area. The MLD was defined as depth at which the temperature falls to 0.5°C below the surface temperature (data from the World Ocean Database 1998; estimates courtesy of Pacific Fisheries Environmental Laboratory, N.M.F.S., Pacific Grove, California, as outlined in Monterey and Levitus (1997)). (0.7; 35.1; 414.0)
Depth of the sea floor below the surface ('bathymetry')	Meters. Sampled from a 1-minute global bathymetry data base (Smith, 2004) at the set location. See also Marks and Smith (2006). (-6,265; -3,395; -114)
Strong currents	Presence/absence (estimated by the observer).
Sea surface height anomaly ('SSH')	Anomaly from the 1993-1999 mean surface (Rio and Hernandez, 2004), at the set location (1/3° x 1/3° cell) for the week of the set (in centimeters). The altimeter products were produced by SSalto/Duacs and distributed by Aviso, with support from Cnes. (-21.25; 0.95; 34.12)
Slope of the sea surface height anomaly ('SSH slope')	Unitless (see SSH above for more details). ($3.8x10^{-7}$; $2.3x10^{-5}$;$1.5x10^{-4}$)
Chlorophyll-a density ('chlorophyll')	mg/m^3 . Average of 1998-2005 SeaWiFS measurements at the set location and month of the set. (0.06; 0.17; 2.63)
Latitude (and latitude^2)	Decimal degrees.
Longitude (and longitude^2, longitude·latitude)	Decimal degrees (negative).
Month	Categorical (1-12).
Year	Categorical (2001-2005).
Proxy for floating object density ('object density')	The number of unique object numbers within a 5° square area around the set location and one month prior to the set date. Ideally, the number of unique objects in a given area and time window would be computed. However, this was not possible because the data do not allow objects to be tracked across vessel trips, nor do the data identify objects shared with /stolen by other vessels. (0; 29; 584)
Proxy for size of the non-tuna object ('non-tuna bycatch')	Natural logarithm of the observer's count of the number of animals (other than tuna) that were brought onto the vessel's deck dead. (0; 4.29; 11.06)

TABLE 2. Correlation (Spearman) between continuous predictors. Predictors are described in Table 1.

	Vessel capacity	Net depth	Mesh size	Object depth	Fouling	Set time	Latitude	Longitude	SST	SST fronts	MLD	Bathy-metry	SSH	SSH slope	Chloro-phyll	Non-tuna bycatch
Vessel capacity																
Net depth	0.53															
Mesh size	0.42	0.47														
Object depth	-0.02	0.09	0.01													
Fouling	0.19	0.18	0.12	0.12												
Set time	-0.06	-0.11	-0.01	-0.12	-0.11											
Latitude	0.10	-0.03	0.05	-0.06	-0.11	-0.02										
Longitude	-0.44	-0.33	-0.19	-0.18	-0.25	0.20	-0.39									
SST	0.22	0.12	0.14	-0.11	-0.01	0.02	0.45	-0.21								
SST fronts	-0.06	-0.06	-0.03	-0.02	-0.08	0.04	-0.07	0.03	-0.24							
MLD	0.28	0.27	0.13	0.23	0.29	-0.21	0.09	-0.68	0.04	-0.14						
Bathymetry	-0.31	-0.22	-0.14	0.01	-0.13	0.02	0.29	0.23	-0.11	-0.03	-0.16					
SSH	0.11	0.07	0.06	0.06	0.08	-0.07	0.16	-0.25	0.18	<|.01|	0.25	-0.13				
SSH slope	0.08	<|.01|	0.01	-0.05	-0.03	0.04	0.25	-0.10	0.19	-0.02	<|.01|	-0.07	0.02			
Chlorophyll	-0.33	-0.30	-0.16	-0.19	-0.32	0.16	0.05	0.63	-0.06	0.20	-0.65	0.18	-0.06	-0.05		
Non-tuna bycatch	0.04	-0.01	-0.01	0.04	<|.01|	<|.01|	0.41	-0.15	0.15	-0.07	0.12	0.14	0.13	0.08	0.02	
Object density	-0.23	-0.16	-0.11	-0.02	-0.18	0.11	-0.28	0.59	-0.15	0.04	-0.37	0.04	-0.09	-0.08	0.43	-0.06

TABLE 3. Confusion tables for: (a) the classification algorithm with approximately equal relative costs of false negatives and false positives (430/433 = 0.993); (b) the classification algorithm with the relative costs of false negatives set at approximately three times that of false positives (213/640 = 0.333); and (c) the classification algorithm *without* location and date predictors at approximately three to one relative cost of false negatives to false positives. The initial classification algorithm fit to the data (i.e., without setting the relative costs of the two types of errors) yielded misclassification errors of approximately 9% for sets that caught bigeye and 22% for sets that did not.

	Observed class	Predicted class		Misclassification error
		0 (no bigeye)	1 (bigeye)	
(a)	0 (no bigeye)	1952	433	0.182
	1 (bigeye)	430	2397	0.152
(b)	0 (no bigeye)	1745	640	0.268
	1 (bigeye)	213	2614	0.075
(c)	0 (no bigeye)	1580	805	0.338
	1 (bigeye)	268	2559	0.095

TABLE 4. Variable importance (average percent increase in misclassifications when variable values were scrambled) for the classification algorithm with approximately three to one relative costs (misclassification errors are given in Table 3b). 'Latitude-longitude' indicates the interaction term between latitude and longitude constructed by taking the product of the two variables.

Predictor	**Importance**	
	No bigeye	**Bigeye**
Vessel capacity	0.53	0.83
Net depth	0.51	0.44
Mesh size	0.15	0.10
Object depth	0.24	1.30
Safety panel	0.18	0.10
Fouling	0.02	0.64
Set time	0.08	0.45
SST	0.66	1.50
SST fronts	0.20	0.38
MLD	2.36	1.39
Bathymetry	1.00	1.81
SSH anomaly	0.39	0.38

Predictor	**Importance**	
	No bigeye	**Bigeye**
SSH anomaly slope	0.14	0.33
Currents	<0.01	<0.01
Chlorophyll	2.43	3.95
Month	1.78	0.22
Year	0.29	0.48
Latitude	4.36	5.61
Longitude	6.34	8.84
Latitude^2	1.41	4.46
Longitude^2	6.28	8.92
Latitude-longitude	2.89	4.43
Object density	0.51	2.71
Non-tuna bycatch	-0.05	0.07

TABLE 5. Variable importance for the classification algorithm with approximately three to one relative costs but *without* location and date predictors. Misclassification errors are given in Table 3c.

Predictor	**Importance**	
	No bigeye	**Bigeye**
Vessel capacity	1.07	2.04
Net depth	1.06	1.13
Mesh size	0.19	0.23
Object depth	1.04	2.25
Safety panel	0.10	0.18
Fouling	0.19	1.02
Set time	0.21	0.68
SST	1.81	3.60
SST fronts	0.78	0.80

Predictor	**Importance**	
	No bigeye	**Bigeye**
MLD	5.34	4.07
Bathymetry	1.44	3.63
SSH anomaly	1.01	0.47
SSH anomaly slope	0.53	0.52
Currents	0.08	0.10
Chlorophyll	4.32	5.38
Object density	2.35	3.85
Non-tuna bycatch	0.44	0.54

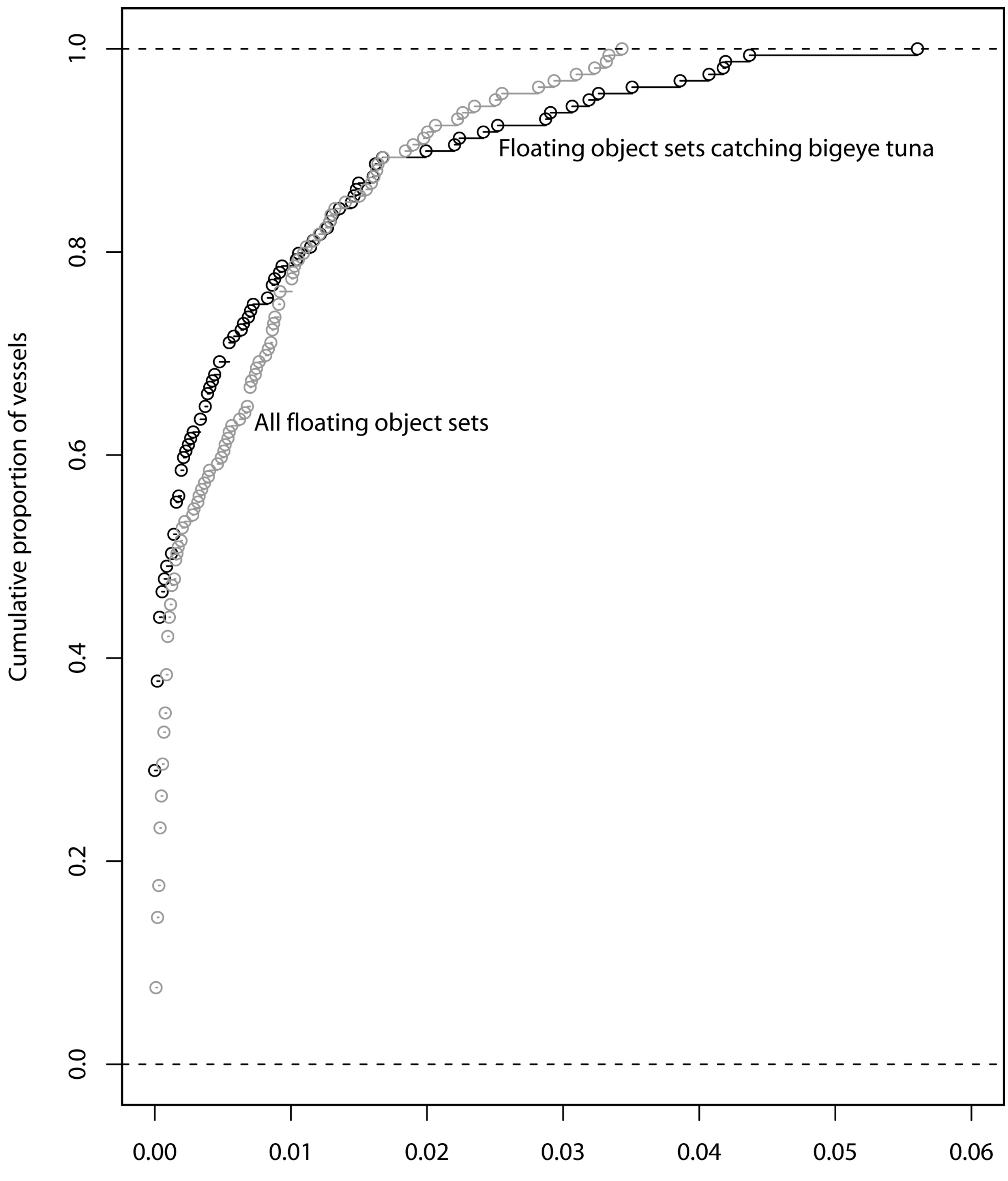


FIGURE 1. Cumulative proportion of vessels in the data set *versus* proportion of sets by vessel (gray) and proportion of sets that caught bigeye tuna by vessel (black).

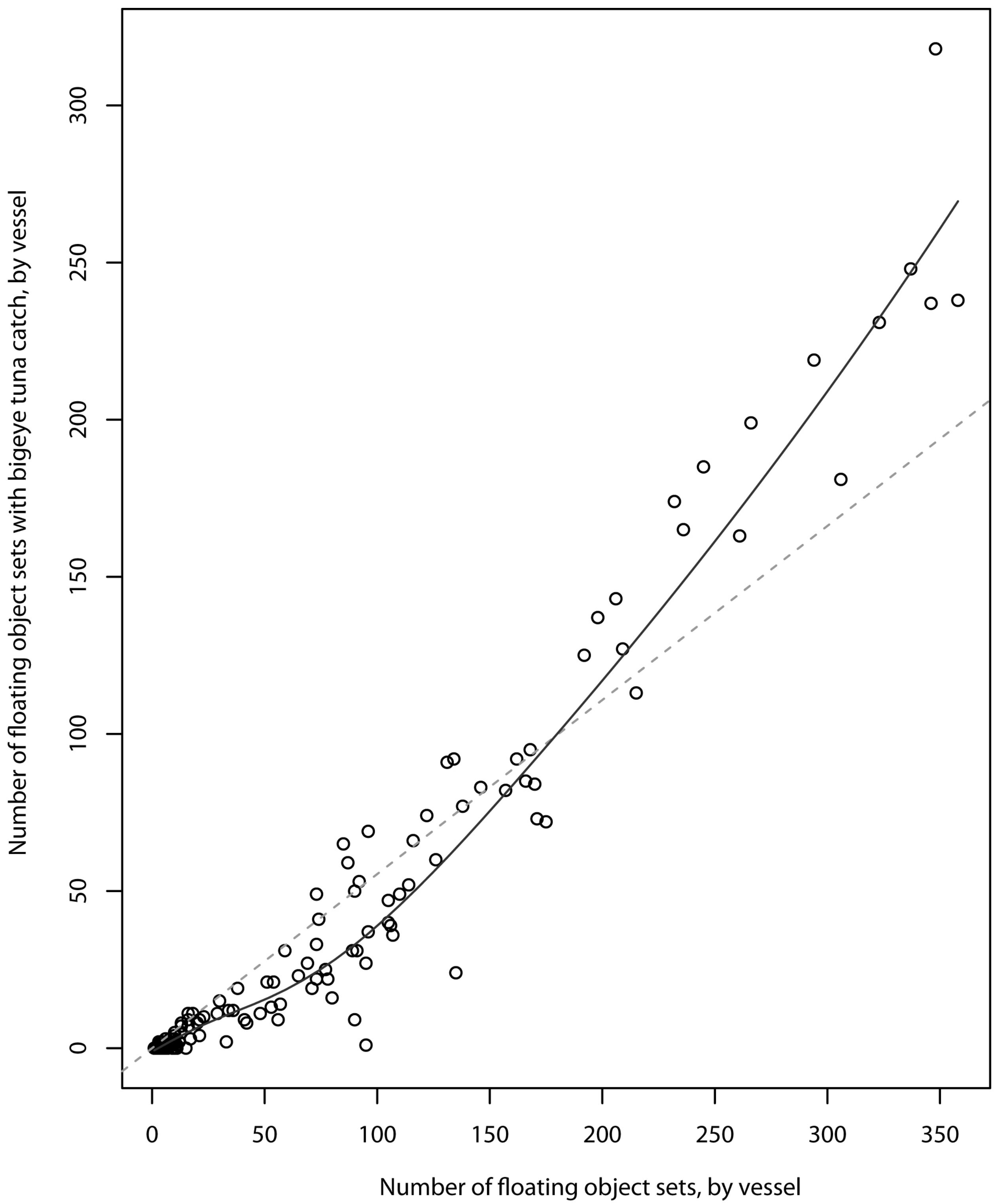


FIGURE 2. Number of sets *versus* number of sets that caught bigeye tuna, by vessel. The dashed gray line is the overall proportion of sets that caught bigeye tuna (0.54) multiplied by the number of sets per vessel. The solid black line is a locally-weighted regression smooth of the data points.

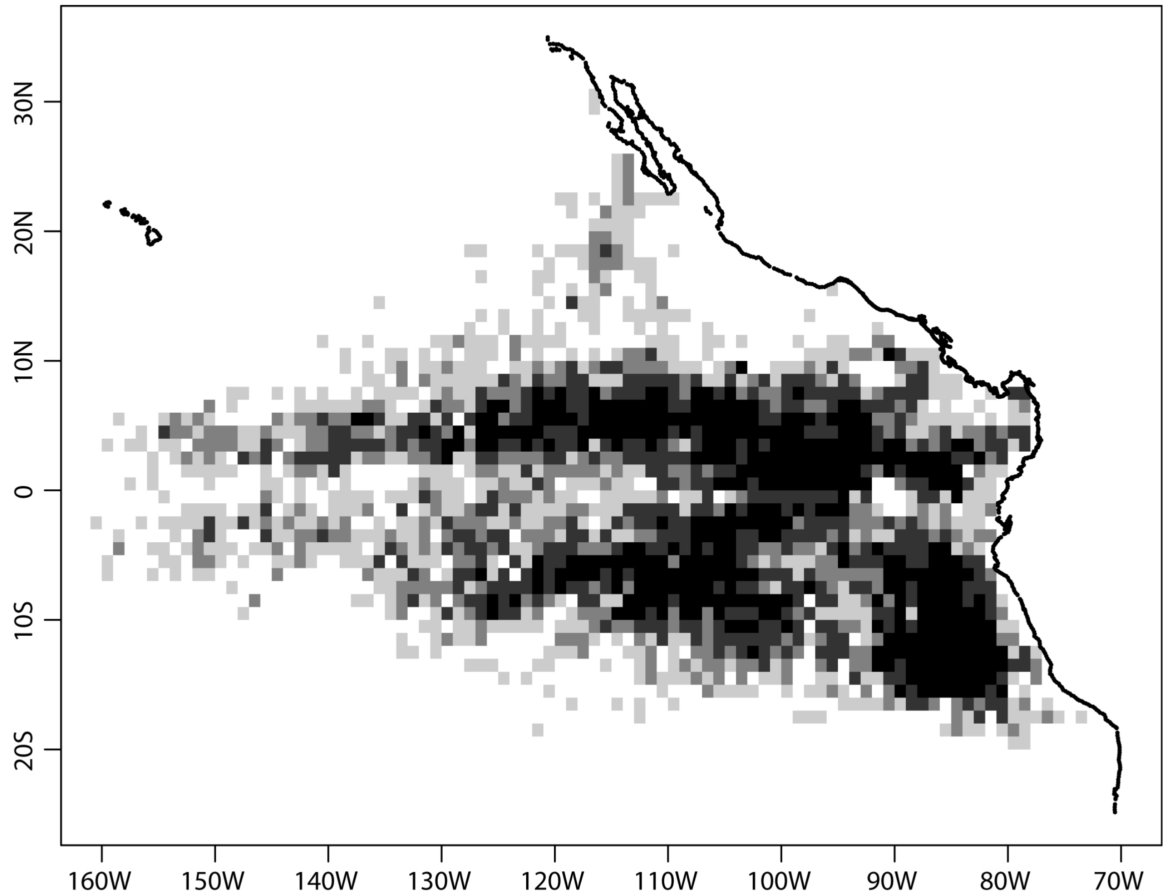
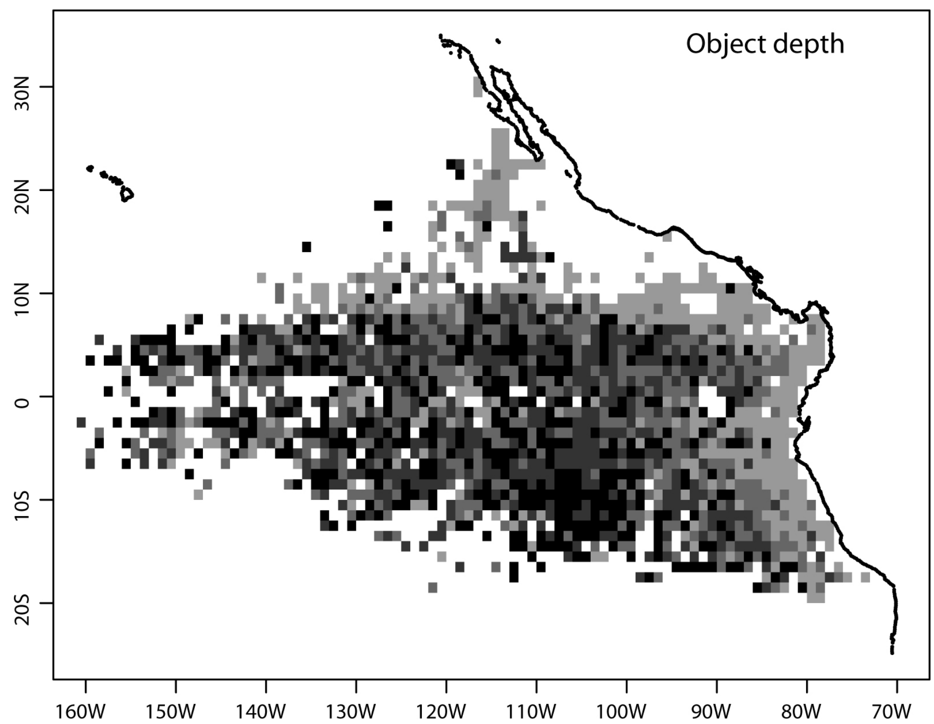


FIGURE 3. Number of floating object sets by 1° square area, 2001-2005. The darker the square, the more sets (lightest gray: 1-2; medium gray: 3-4; dark gray: 5-9; black: ≥ 10).



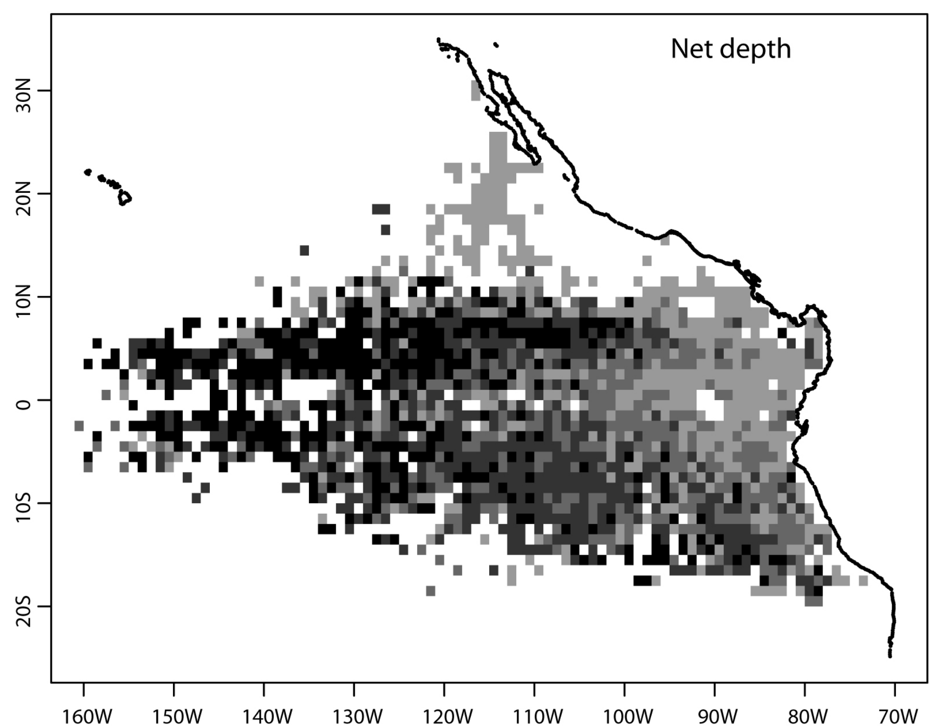


FIGURE 4. Average floating object depth (top) and net depth (bottom) by 1° square area. The darker the square, the deeper the object/net. The following are the approximate grayscale ranges for the two predictors. Object depth: ≤ 13.5m (lightest gray); 13.5-18m (medium gray); 18-20.5m (dark gray); >20.5m (black). Net depth: ≤ 114f (lightest gray); 114-122f (medium gray); 122-132f (dark gray); > 132f (black).

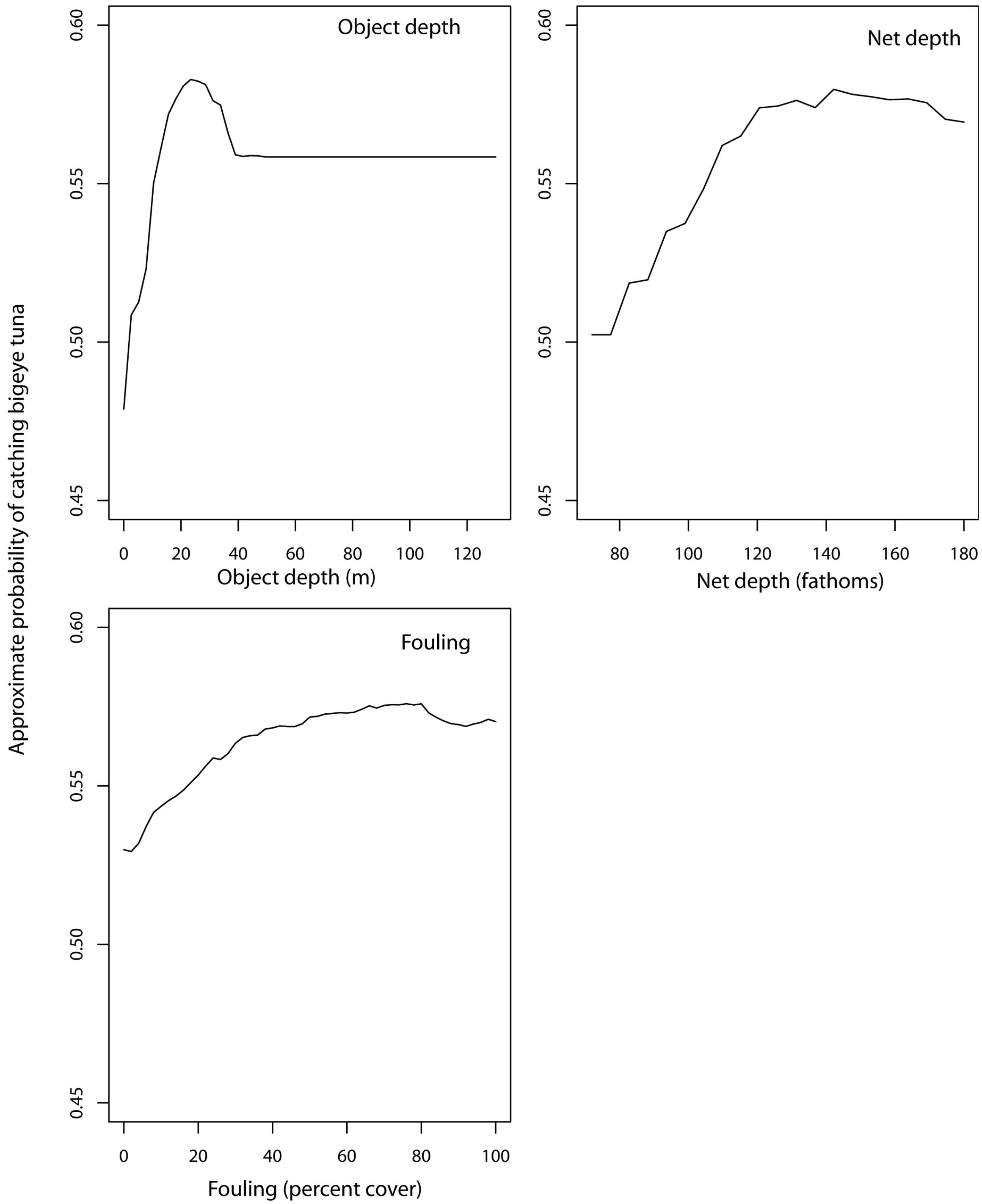


FIGURE 5. Approximate probability of catching bigeye tuna *versus* object depth (upper left), net depth (upper right) and percent fouling (lower left).

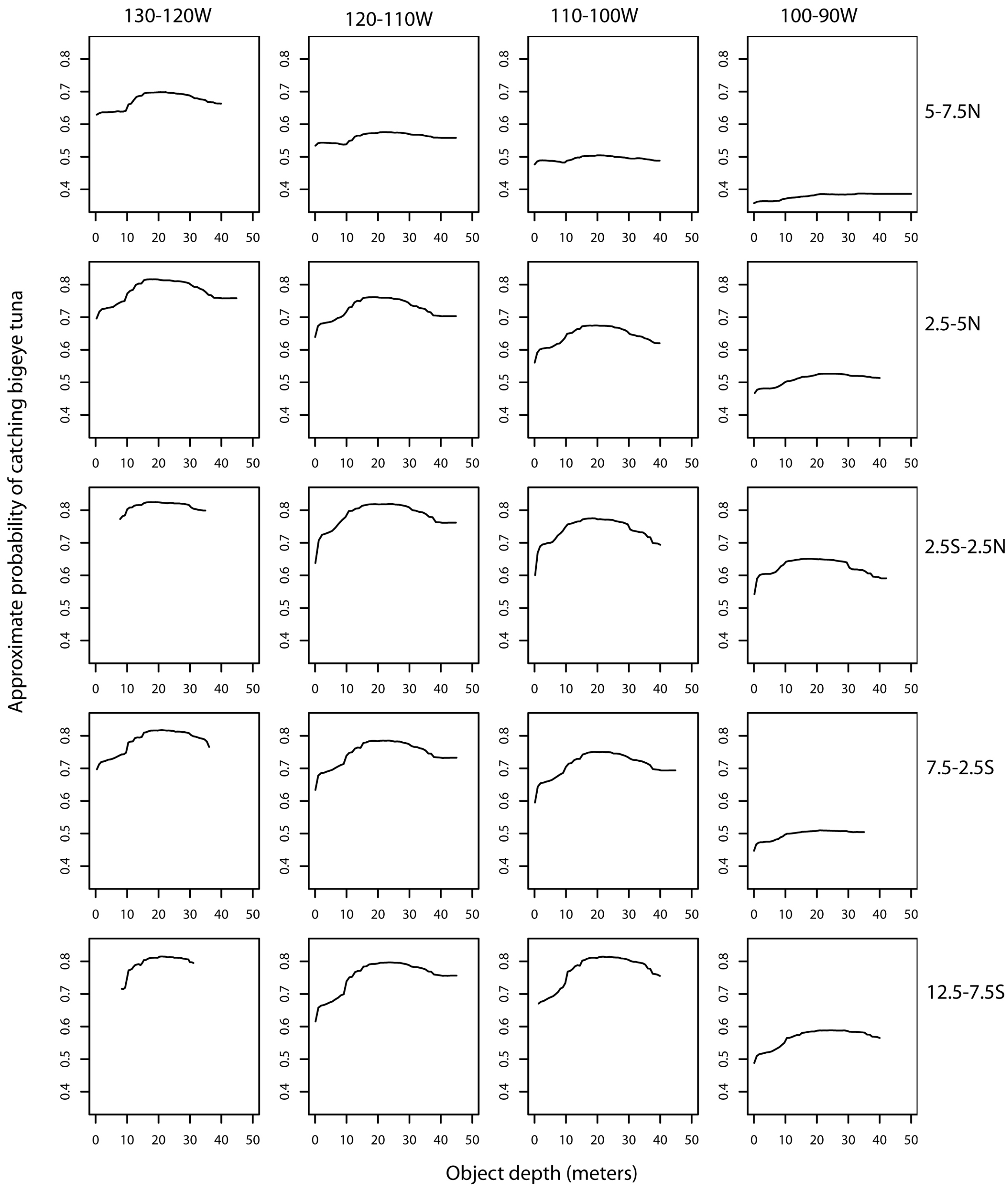


FIGURE 6. Approximate probability of catching bigeye tuna *versus* object depth, by area.

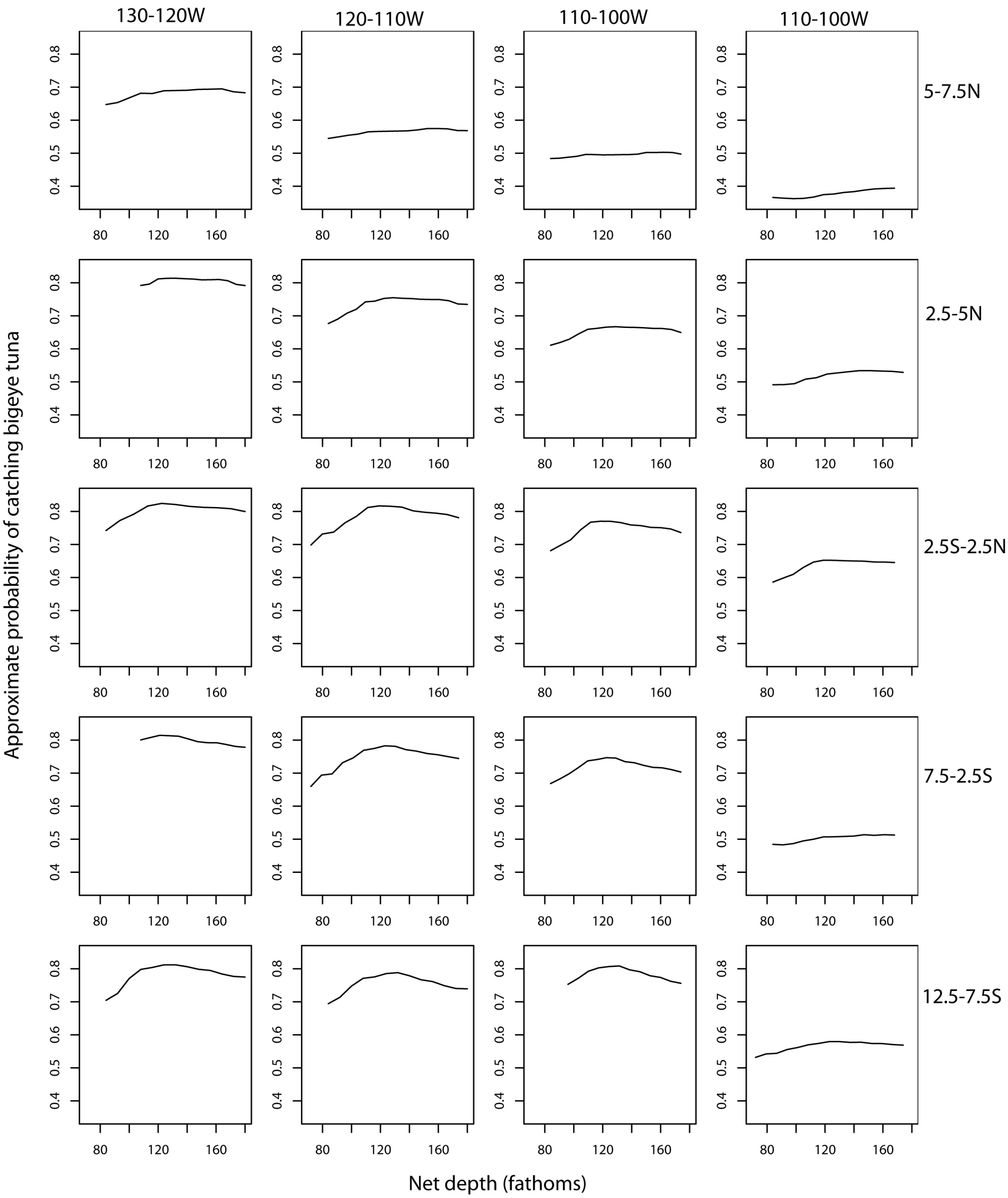


FIGURE 7. Approximate probability of catching bigeye tuna *versus* net depth, by area.

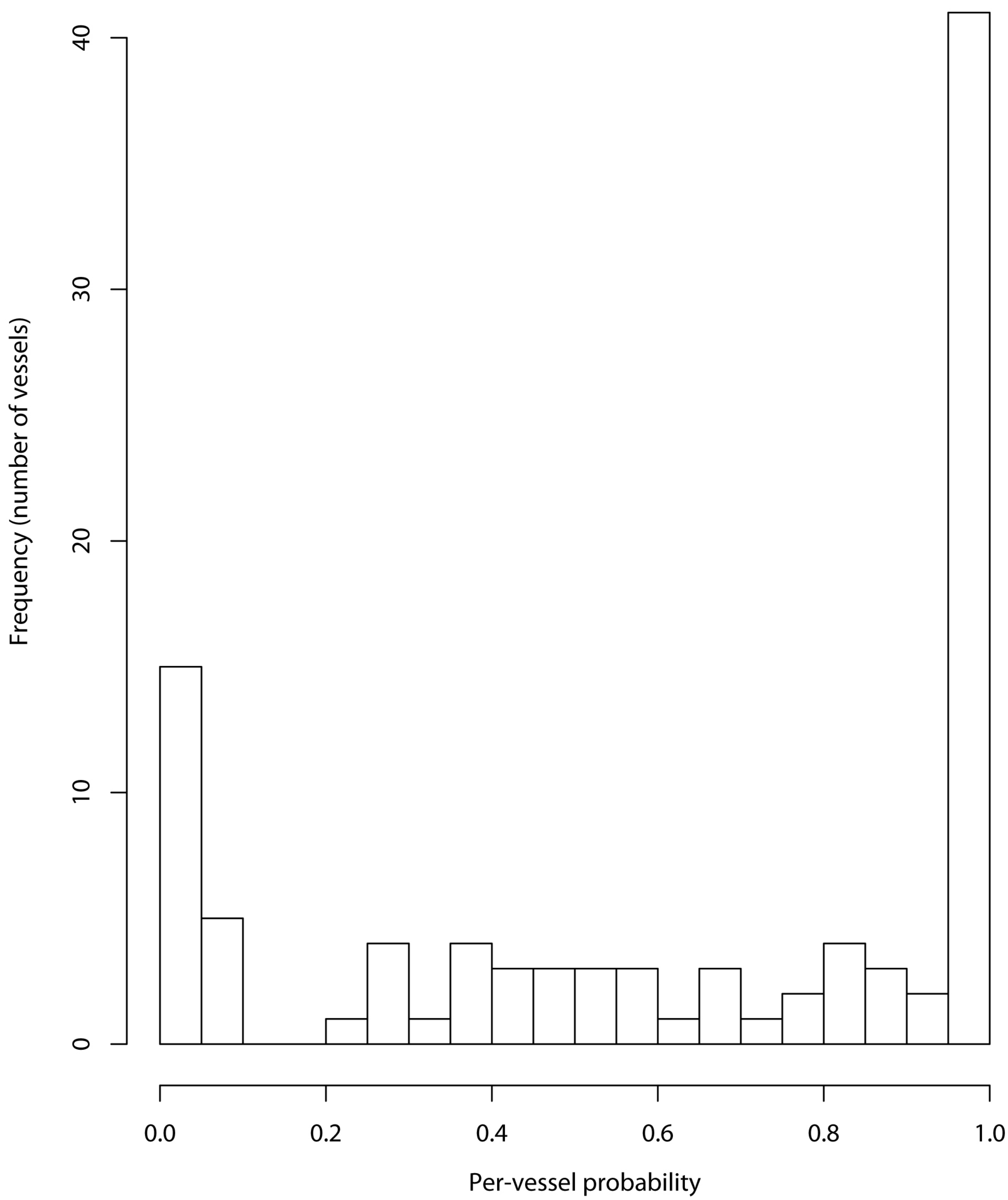


FIGURE 8. Frequency distribution of per-vessel probabilities.