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Generalized additive model and regression tree analyses of blue shark (*Prionace glauca*) catch rates by the Hawaii-based commercial longline fishery

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Abstract

Generalized additive model (GAM) and regression tree analyses were conducted with blue shark, *Prionace glauca*, catch rates (catch per set) as reported by National Marine Fisheries Service observers serving aboard Hawaii-based commercial longline vessels from March 1994 through December 1997 ($N = 2010$ longline sets). The objective was to use GAM and regression tree methodology to relate catch rates to a tractable suite of readily measured or computed variables. Because the predictor variables are also either provided in or easily computed from the logbooks that commercial vessels submit upon landing fish for sale, it is likely that a model or models fitted to accurate observer data could then be applied on a fleet-wide basis to serve as a standard of comparison for the logbooks. The GAM included nine spatio-temporal, environmental, and operational variables and explained 72.1% of the deviance of blue shark catch rates. Latitude exerted the strongest effects of any individual variable; longitude was the most influential variable when adjusted for the effects of all other factors. Relatively cold sea surface temperatures were associated with high catch rates. The initial regression tree included 68 terminal nodes and 11 predictors. It was refined to a final tree with 42 terminal nodes, which reduced the root mean deviance by 65.3%. The tree was partitioned first on latitude 26.6°N, and then branched out to reach terminal nodes after 2–8 additional partitionings. Sets south of this latitude were characterized by lower catch rates and partitionings on a greater number and variety of predictors. Northerly sets were characterized by higher and more variable blue shark catch rates. Predictions from the two analyses were highly correlated ($r = 0.903$, $P \ll 0.001$). Moreover, use of these methods in combination aided greatly in the interpretation of results. We conclude that GAM and regression tree analyses can be usefully employed in the assessment of blue shark catch rates in this fishery. We suggest that either or both of these models could serve as comparison standards for commercial logbooks. Published by Elsevier Science B.V.

Keywords: Blue shark; Catch rates; Generalized additive model; Regression tree

1. Introduction

Modern (i.e., computationally intensive) statistical methods currently used in fisheries biology to identify, characterize, and estimate the relationships between extrinsic factors and catch rates include generalized additive models (GAMs) and regression trees. A GAM

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is a nonparametric generalization of multiple linear regression, in which a link function is related to predictor variables by scatterplot smoothers in lieu of least-squares fits, and which is subject to less restrictive distributional assumptions than multiple linear regression (Hastie, 1992; Swartzmann et al., 1992). Regression trees are models that can serve as an alternative to linear or additive models, in which numeric response variables are split into increasingly homogeneous subsets by recursive binary partitioning on a set of categorical or numerical predictor variables, with results displayed as a dendrogram (Clark and Pregibon, 1992).

This paper presents the results of GAM and regression tree analyses of blue shark, *Prionace glauca*, catch rates as reported by National Marine Fisheries Service (NMFS) observers stationed aboard vessels of the Hawaii-based commercial longline fleet from March 1994 through December 1997. Several spatio-temporal, environmental, and operational variables provided in the observer data were tested to assess their influences on blue shark catch rates. The objective was to use GAM and regression tree methodology to relate catch rates to a tractable suite of readily measured or computed variables. Our purpose in defining this objective was to create the possibility of a fishery-wide application. Because all of the predictor variables are either provided in or easily computed from the logbooks that commercial vessels submit upon landing fish for sale, it seems likely that the coefficients from a model fitted to accurate observer data could be applied to the logbooks from unobserved trips. Therefore, the predicted catch rates could then serve as a standard of comparison for the logbooks. A standard of this sort could be considered potentially valuable because blue shark has been the most numerous species in the catch of this fishery throughout the decade (Ito and Machado, 1999), despite the fact that it is taken as incidental catch.

2. Materials and methods

The Hawaii-based commercial longline fishery primarily targets bigeye tuna, *Thunnus obesus*, and swordfish, *Xiphias gladius* (He and Laurs, 1998); the geographic distributions of fishing directed at these species are depicted in Fig. 1. The highest blue shark incidental catch rates are usually associated with swordfish-directed activity (He and Laurs, 1998; Ito and Machado, 1999). Detailed descriptions and maps of the seasonality, distribution, and catch patterns in this fishery are presented in He et al. (1997) and Ito and Machado (1999).

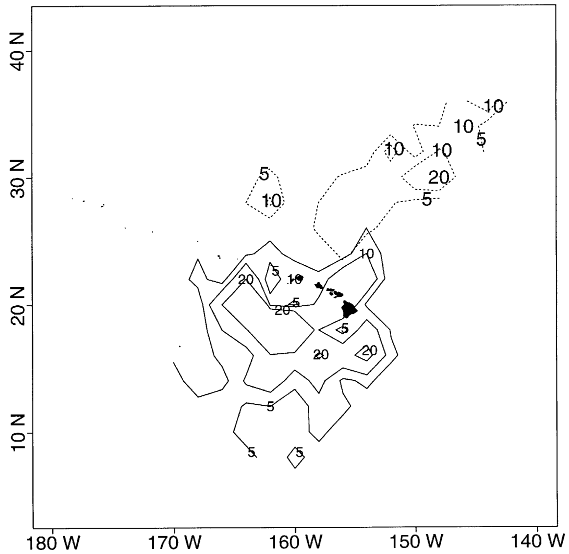

Fig. 1. Contour plot of longline sets with NMFS observers deployed from March 1999 through December 1997. Swordfish-directed sets are denoted by the dotted line; tuna-directed sets are denoted by the solid line. The labels represent the numbers of observed sets within 2° × 2° squares.

Statistical analyses were conducted with data derived from records kept by NMFS observers stationed aboard Hawaii-based commercial longline vessels from March 1994 through December 1997. Observers were present on 190 trips, performing duties that included gathering data concerning fishing effort and obtaining species-specific tallies of catches and discards. These trips deployed a total of 2198 longline gear sets, but sets with incomplete records were excluded from analyses. Consequently, analytical procedures were initiated with 2010 longline sets deployed on 176 trips, an average of 11.4 sets per trip.

Each individual record (i.e., summary of one gear set) employed in analyses included the catch of blue shark and 11 candidate predictor variables. These included three spatio-temporal variables (the date, and latitude and longitude), three environmental variables (sea surface temperature, the angle of the sun to the horizon, and the visible proportion of the moon), and five operational characteristics (the number of hooks per set, light sticks per hook,[1] hooks per float, time at the initiation of the set, and vessel length). All variables were obtained directly by the observers except the solar and lunar indices, which were calculated from the date and geographic position.

GAM development followed methods similar to those described by Bigelow et al. (1999), who recently presented GAMs for both swordfish, *X. gladius*, and blue shark within the Hawaii-based fishery from 1991 through 1995, with the following specifics. Analyses were conducted in S-PLUS (MathSoft, 1996) according to fitting, testing and plotting procedures described by Hastie (1992). The response variable was blue shark per set, so it was assumed that the underlying probability distribution was the Poisson (Swartzmann et al., 1992; Bigelow et al., 1999). As such, logarithms were the appropriate link function. All predictor variables were numeric except the set time, which was expressed as a four-level factor variable to accommodate its circularity. The factor levels ($1 = 0300-0859$ h, $2 = 0900-1459$ h, $3 = 1500-2059$ h, $4 = 2100-0259$ h) were defined after preliminary examination of frequency distributions. Variable selection proceeded by forward entry. This procedure was chosen because preliminary attempts to fit a model by backward elimination yielded results that were regarded as biologically meaningless (e.g., the effect of longitude superseded that of latitude).

At each stage of forward entry, the Akaike information criterion (AIC) was computed for every candidate predictor not yet entered. The variable with the highest AIC was tested as the next entry; the decision was predicated upon a forward entry F-test with a significance criterion of $P < 0.05$. Forward entry continued until additional variables no longer yielded significant reductions in the residual deviance. The effects of the various predictors were depicted in *loess* plots with the ordinate set to a uniform scale. Adequacy of model fit was assessed in terms of the pseudocoefficient of determination (pseudo-$R^2 = 1 -$ residual deviance/null deviance; Swartzmann et al., 1992) and from partial residuals plots. The relative effectiveness of the different types of predictors was then assessed by computing reduced models (e.g., a GAM with only environmental variables as predictors) and evaluating the significance tests, residual deviance, and pseudo-R^2.

Regression trees were developed with natural log-transformed catch rates data from all sets that yielded at least one blue shark ($N = 1911$ sets). Zeroes were deleted from this analysis, but not GAM development, because the Poisson structure underlying the latter accommodates zeroes. The suite of candidate predictors was identical to the GAM except for years and months, which were regarded as categorical rather than as a single numeric variable. The tree was initially "grown" from the entire set of possible predictors, and then examined in terms of its constituent predictors, residual mean deviance, residuals, and normal probability plot of residuals. It was "pruned" to reduce overfitting after performing cross-validation procedures adapted from Clark and Pregibon (1992). The tree size corresponding to the average minimum deviance estimated by cross-validation was chosen as the starting point for further investigation of tree size. This involved examination of the tree structure (i.e., "topology") in an effort to identify partitionings that were not biologically meaningful (e.g., back-transformed predictions that differed by less than one blue shark). Agglomeration of nodes was considered appropriate if the resulting increase in the residual mean deviance was small and the distribution of the residuals was thereby improved. Tree structure was then altered to its final form. The plot of the final tree depicts sequences of as many as five partitionings, while the lower levels and terminal nodes are described in the text.

The results of GAM and regression tree analyses were compared in terms of the significance and relative importance of predictor variables, as well as their predictions. The first involved comparison of the order of entry into the GAM to the identities and positions of variables within the regression tree. The second involved computation of the correlation between the back-transformed predictions obtained from the two methods.

3. Results

Longline sets monitored by NMFS observers were distributed seasonally across 40° of latitude

[1] Light sticks are phosphorescent plastic tubes about 10–15 cm in length that are attached to the leader above the hook, used primarily in swordfish-targeted fishing.

Table 1
Summary of effort and catches on trips of Hawaii-based commercial longline vessels that carried NMFS observers. Total catch refers to all species of fishes; other entries refer to blue shark

Year	Trips	Gear sets	Total catch	Blue shark	Percentage	Blue shark catch per set
Data used in analysis						
1994–1997	176	2010	70 143	23872	34.0	11.9
1994	41	411	12 658	4313	34.1	10.5
1995	45	514	17 805	5739	32.2	11.2
1996	52	628	18 665	6777	36.3	10.8
1997	38	457	21 015	7043	33.5	15.4
All data						
1994–1997	190	2198	75 924	25474	33.6	11.6

(5°N–45°N) and 50° of longitude (140°W–170°E). Sets in winter were concentrated west of the main Hawaiian Islands, and from northeast to northwest across a broad longitudinal band ca. 30°N. The area fished was roughly triangular in shape and centered about the main islands in spring, followed by movement toward the northwest in summer, and concentration north and northeast of the islands in autumn. Swordfish-directed sets were generally located to the north and northeast of the tuna-directed activity (Fig. 1). Detailed descriptions and maps of the seasonality, distribution, and catch patterns in this fishery are presented in He et al. (1997) and Ito and Machado (1999).

Blue shark comprised approximately one-third of the catches throughout the study period (Table 1). The mean blue shark catch rate was 11.9 per set; the median and maximum were 6 and 359 blue sharks per set. The annual mean blue shark catch rate increased by 43% in 1997 relative to 1996. This reflected high catch rates in the first 2 months of the year, which yielded two of the four highest monthly mean values during the study period, and 15.5% of the blue sharks. All of these statistics were calculated without any standardization.

3.1. GAM of blue shark catch rates

Two predictor variable characteristics required consideration during development and interpretation of a GAM of blue shark catch rates. Several correlations, primarily but not exclusively among the operational factors, were significant. Numbers of hooks were positively correlated with hooks per float ($r = 0.86$, $P \ll 0.001$), but negatively correlated with light sticks per hook ($r = -0.64$, $P \ll 0.001$) and vessel length ($r = -0.47$, $P \ll 0.001$). Hooks per float were also negatively correlated with light sticks per hook ($r = -0.71, P \ll 0.001$). This variable was also markedly bimodal and kurtotic. For these reasons, hooks per float were not used in the GAM. Sea surface temperature was negatively correlated with latitude ($r = -0.79$, $P \ll 0.001$), equivalent to a mean decrease of −0.4°C per degree of latitude.

GAM development proceeded until nine variables had been entered (Table 2). Set time did not affect blue shark catch rates significantly ($P = 0.383$), but all other candidate predictors yielded significant reductions in the residual deviance (nine F-tests: all $P \leq 0.005$). However, the decrements in the residual deviance and increments in the pseudo-R^2 decreased rapidly as the number of predictors increased, particularly beyond 6 (Fig. 2). It was noteworthy that the total number of hooks yielded a larger reduction in the residual deviance as the sixth entry than when tested as the fifth. This indicated that its effect was contingent upon the presence of light sticks per hook in the model. All relationships between the predictor variables and blue shark catch rates were significantly non-linear (nine χ^2-tests: all $P < 5.0 \times 10^{-11}$). There were 8.4–8.8, 6.8–9.0, and 8.2–8.4 non-linear degrees of freedom for the spatial, environmental, and operational factors, respectively.

Geographic location was the predominant influence on blue shark catch rates. Latitude provided the largest reduction in the residual deviance. The loess plot (i.e., the GAM result for this variable) (Fig. 3) revealed a non-linear response pattern from low latitudes to ca. 32°N. There was a local maximum ca. 25–30°N, and a

Table 2
Analysis of deviance of a nine-variable GAM of blue shark catch rates. The reductions in the AIC and residual deviance, degrees of freedom, and the F-test and associated significance, are presented for each term[a]

Predictor variable	ΔAIC	ΔResidual deviance	d.f.	F_{enter}	P
Latitude	−13702.44	−13719.990	8.78	127.793	⩽0.001
Longitude	−5029.78	−5046.555	8.39	76.631	⩽0.001
Temperature	−1559.01	−1573.947	7.47	29.850	⩽0.001
Date	−1211.95	−1227.168	7.61	25.591	⩽0.001
Light sticks	−613.10	−629.565	8.23	12.989	⩽0.001
Hooks	−627.81	−644.591	8.39	13.881	⩽0.001
Vessel length	−294.96	−311.620	8.33	7.048	1.7×10^{-9}
Solar index	−129.22	−147.132	8.95	3.147	0.0009
Lunar index	−89.87	−103.395	6.76	2.947	0.005

[a] Loess smoothing was applied to all variables; null deviance = 32473.45, d.f. = 2009; residual deviance = 9069.488, d.f. = 1936.094; pseudo-R^2 = 0.721.

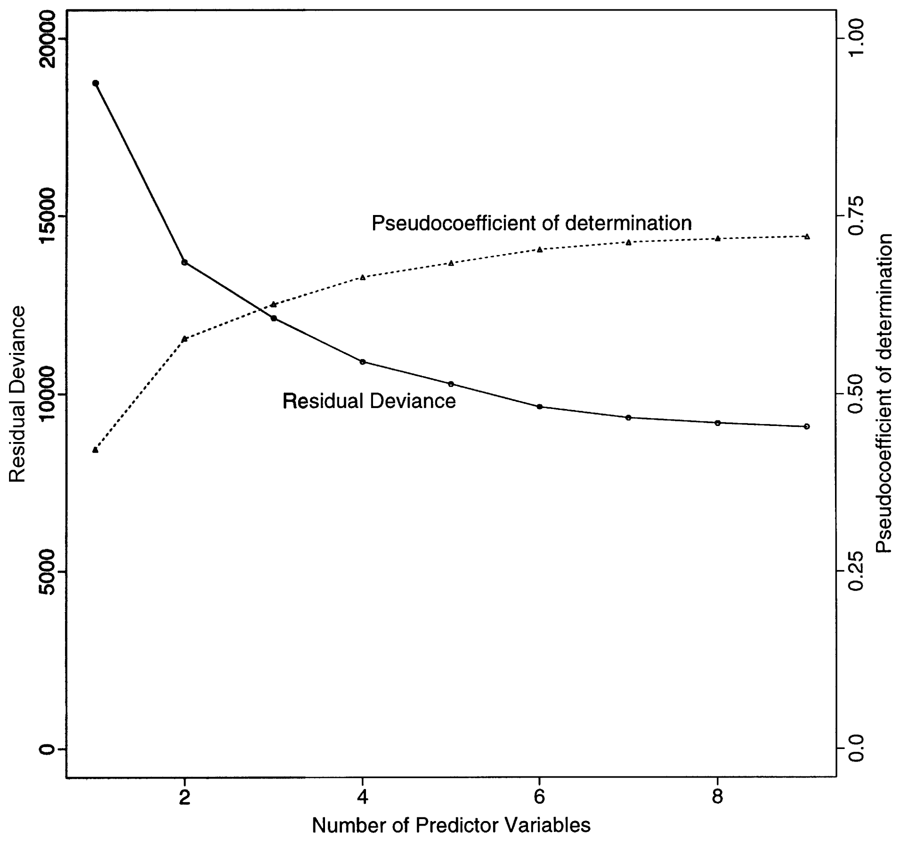

Fig. 2. Relationships between the residual deviance and the pseudocoefficient of determination and the number of predictor variables in a GAM of blue shark catch per set.

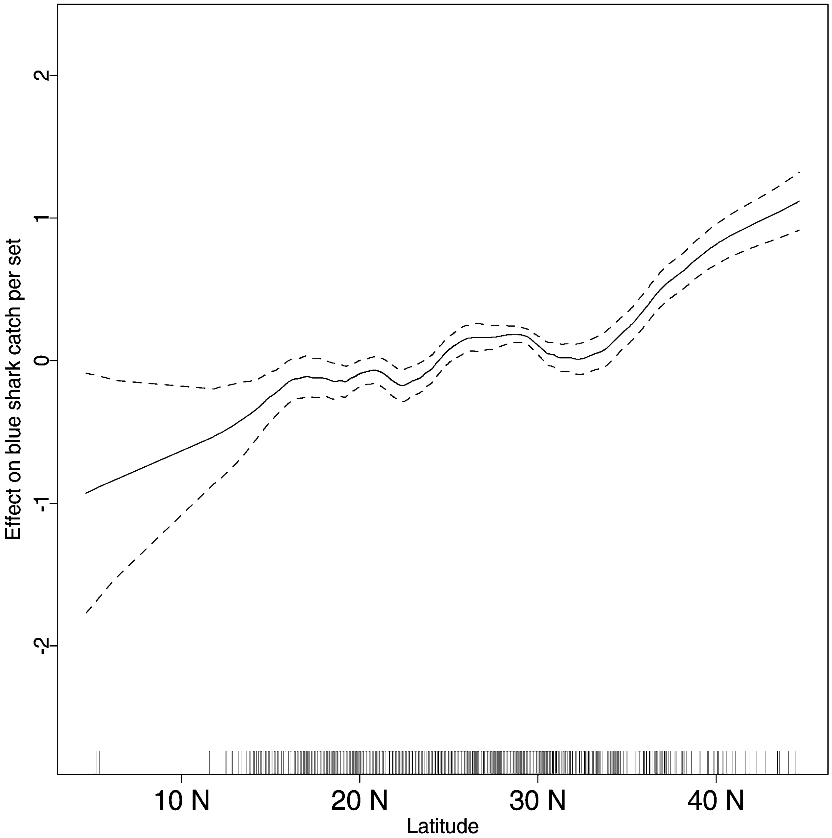

Fig. 3. The effect of latitude on blue shark catch per set as estimated by a nine-variable GAM. The response scale reflects natural log-transformation.

strong positive relationship between latitude and catch rates beyond 32°N. The loess plot of longitude (Fig. 4) exhibited a sharp break between 165°W and 170°W, and a strong negative effect on blue shark catch rates from ca. 155°W eastward. This plot exhibited the greatest response range, which indicated that longitude exerted the greatest effect on blue shark catch rates when adjusted for all other factors.

Sea surface temperature was the most influential environmental factor for blue shark catch rates (Fig. 5). The most prominent feature of its loess plot was a steady decline from ca. 18°C to lower levels of ca. 25°C. There was a trend of increase at 27–30°C, but this region included only 10.6% of all sets. The other environmental factors (not shown), the lunar and solar indices, were the final model entries. These yielded significant but minor reductions in the deviance, and increased the pseudo-R^2 by 0.008.

The operational factors entered the model in sequence as its fifth to seventh variables. The loess plot of light sticks per hook (Fig. 6) revealed relatively low blue shark catch rates among sets conducted without light sticks (44%). There was pronounced curvature at 0.2–0.5 light sticks per hook, with the maximum positive effect within this region ca. 0.45. Numbers of hooks (Fig. 7) exhibited the greatest response range in its loess plot within this class of predictors. As expected, blue shark catch rates generally increased with hook numbers throughout the range employed. The relationship between blue shark catch rates and vessel length (Fig. 8) exhibited marked, irregular curvature throughout the size range. This differed from both light sticks and hooks, which were approximately linear and smoothly curved in the upper halves of their respective ranges.

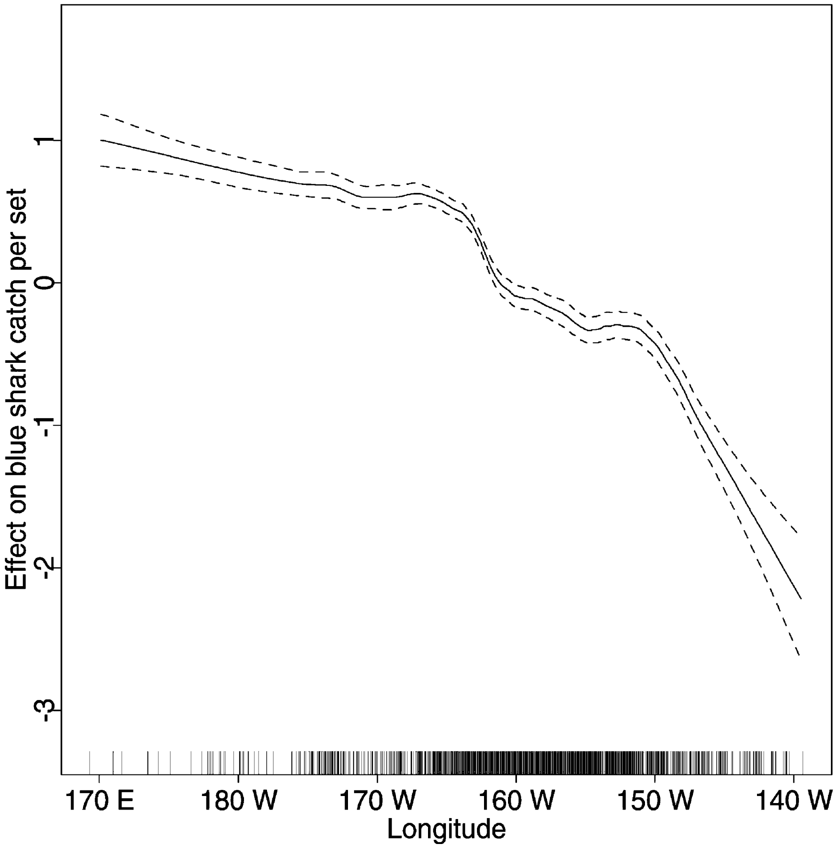

Fig. 4. The effect of longitude on blue shark catch per set as estimated by a nine-variable GAM. The response scale reflects natural log-transformation.

The loess plot depicting blue shark catch rates over time (Fig. 9), adjusted for the other predictors, exhibited steady increase from its minimum throughout 1994. This was the only year that temporal patterns exerted strong effects on catch rates. The back-transformed predictions from the GAM (Fig. 10) generally tracked the measured values closely. The exceptions were January and December 1997, when the measured catch rates were considerably greater than those predicted by the GAM.

Computation of reduced models (Table 3) demonstrated that a six-variable GAM comprised of latitude, longitude, temperature, the date, the number of light sticks per hook, and the total number of hooks yielded explanation close to that of the full model (pseudo-$R^2 = 0.703$). Geographic location described blue shark catch rates more effectively than the other types of predictors. Operational factors, in turn, described blue shark catch rates more effectively than environmental variables. Date of fishing explained only a small proportion of the deviance of blue shark catch rates (pseudo-$R^2 = 0.058$).

3.2. Regression tree analysis of blue shark catch rates

The distribution of blue shark catch rates after natural log-transformation appeared roughly normal (Fig. 11), and heteroscedasticity was greatly reduced. Regression tree analysis then revealed many relationships between catch rates and the predictor variables (Table 4).

The initial tree structure included 68 terminal nodes and 11 of 12 candidate predictors. Set time was not

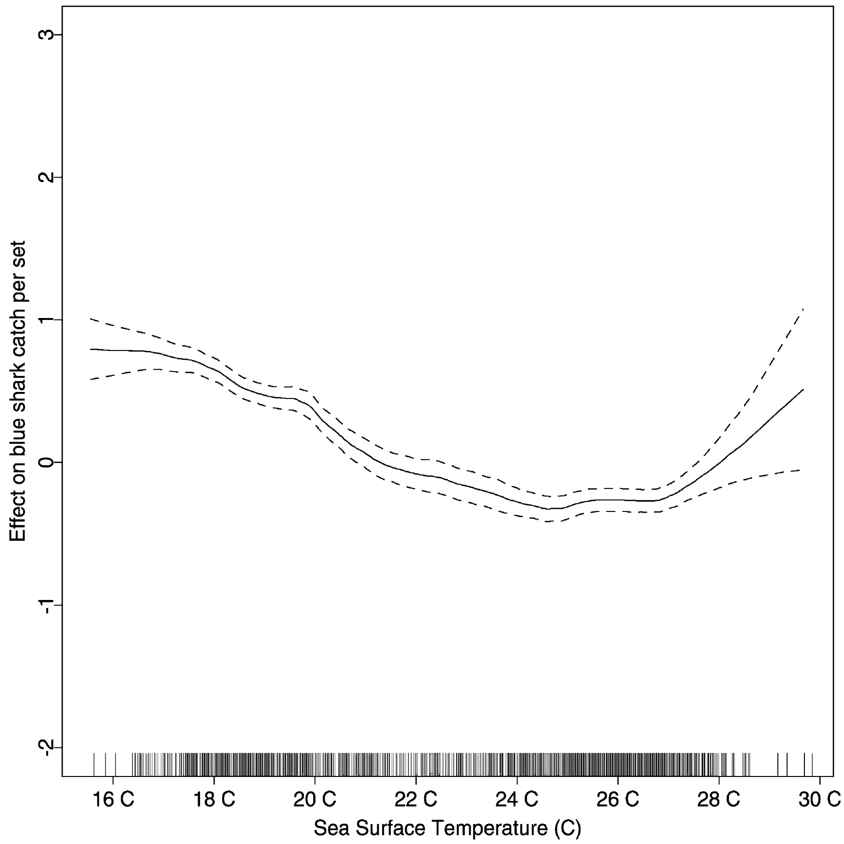

Fig. 5. The effect of sea surface temperature on blue shark catch per set as estimated by a nine-variable GAM. The response scale reflects natural log-transformation.

''chosen'' by the fitting algorithm. A series of five cross-validation procedures generated minimum deviance estimates at 46.4–47.1 terminal node. The tree that was refitted on the basis of cross-validation included 48 terminal nodes and retained all of the 11 predictor variables within its structure. Agglomeration of three pairs of nodes with catch rate estimates that differed by less than one blue shark yielded the final tree with 42 terminal nodes. The mean terminal node size was 45.5 sets, but four nodes included 104–151

Table 3
Results obtained by fitting reduced GAMs of blue shark catch rates. The fit of each model is summarized in terms of its AIC, residual deviance, and pseudocoefficient of determination[a]

Predictor variables	AIC	Residual deviance	d.f.	Pseudo-R^2
Date	30613.93	30596.67	2001.37	0.058
Latitude, longitude	13743.23	13706.91	1991.84	0.578
Temperature, lunar index, solar index	21674.15	21625.74	1985.80	0.334
Light sticks, hooks, vessel length	20217.42	20165.59	1984.08	0.379
Latitude, longitude, temperature, date, light sticks, hooks	9731.36	9631.64	1960.14	0.703

[a] The null deviance for each model is 32473.45, d.f. = 2009; loess smoothing was applied to all variables.

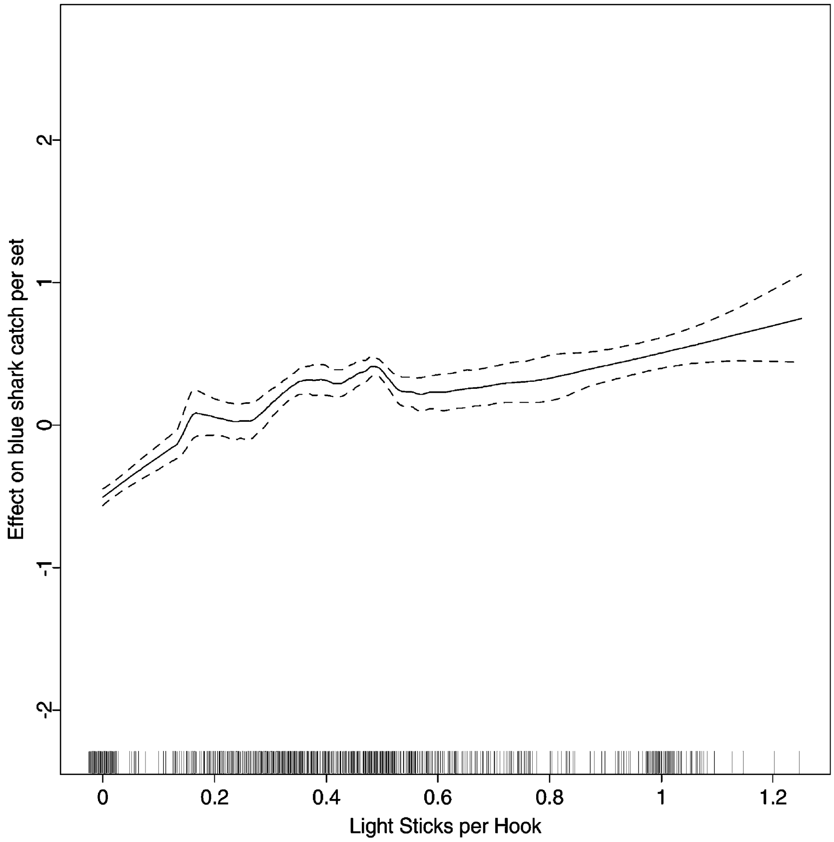

Fig. 6. The effect of the number of light sticks per hook on blue shark catch per set as estimated by a nine-variable GAM. The response scale reflects natural log-transformation.

sets, which together comprised 26.1% of the tree. The residual mean deviance (0.368) was 14% greater than that of the initial tree, but was attained with 26 fewer terminal nodes. These refinements are summarized in Table 4.

The regression tree (Fig. 12) was examined in terms of the dimensions of its structure because the vertical position of a node pair is a function of the importance of the parent split (Clark and Pregibon, 1992), the identities and values of the partitioning variables, the levels within the tree at which the partitionings were located and the various catch rate estimates generated by the partitionings. The tree split first at latitude 26.6°N, and then branched out to reach terminal nodes

Table 4

Summary of a regression tree analysis of natural log-transformed blue shark catch rates. The number of predictors within the tree, terminal nodes, deviance, residual mean deviance, percent reduction in the root mean deviance, and mean and median residuals are presented for each stage of the analysis. See text for listing and description of predictors

Stage	Predictors	Terminal nodes	Deviance	Residual mean deviance	Reduction of root mean deviance	Mean residual	Median residual
Initial tree	11	68	596.9	0.324	69.9	4.6×10^{-18}	0.031
Pruned tree	11	48	659.3	0.354	66.8	3.3×10^{-17}	0.017
Final tree	11	42	688.6	0.368	65.3	-1.6×10^{-16}	−0.002

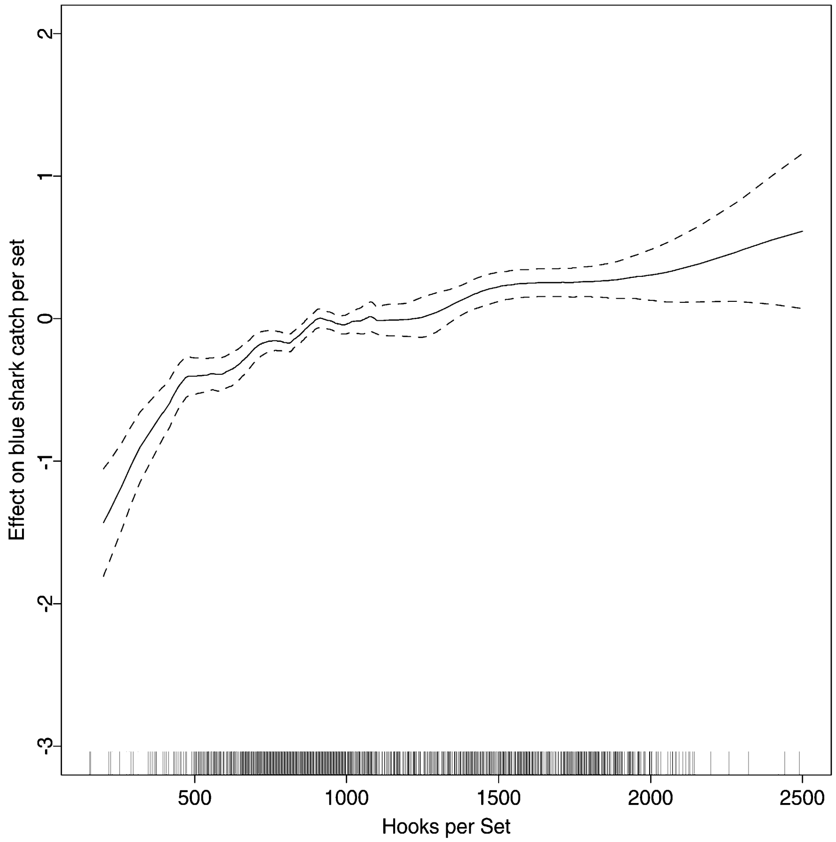

Fig. 7. The effect of the number of hooks per set on blue shark catch per set as estimated by a nine-variable GAM. The response scale reflects natural log-transformation.

after 2–8 additional partitionings. The two subtrees (i.e., left and right sides) each contained 21 terminal nodes, with 58.2 and 41.8% of the sets in the left and right sides, respectively. The most obvious topological feature was the difference in the depth of the partitionings in the two subtrees, which reflected greater differences between nodes. For example, the initial split on longitude in the right subtree corresponded to means of 9.2 and 25.0 blue shark per set, where the corresponding split on vessel length in the left subtree corresponded to 5.6 and 3.3 blue shark per set. The left subtree, which corresponded to sets deployed south of 26.6°N, was also characterized by partitionings on a greater number of predictors than northerly sets, along with lower catch rates. Northerly sets were characterized by higher and more variable blue shark catch rates, depicted by much deeper splits within the tree topology.

Blue shark catch rates south of 26.6°N were first partitioned on a vessel length of 65.85 ft. Smaller vessels had lower catch rates. These sets were then partitioned on light sticks per hook; approximately 90% of these sets employed 0–0.26 light sticks per hook. These sets were categorized further according to longitude, latitude, months, and the solar index. Sets deployed by larger vessels split first on longitude, with higher blue shark catch rates west of l61.3°W. Longitude was also the basis of partitionings at deeper hierarchical levels within this subtree. Additional splits were predicated upon months, hooks per float, longitude, latitude, hooks, vessel length, and the lunar index. Year was the basis of a single partitioning, which reflected higher catch rates in 1994 and 1995 than in 1996 and 1997, among vessels larger than 65.85 ft and west of 161.3°W.

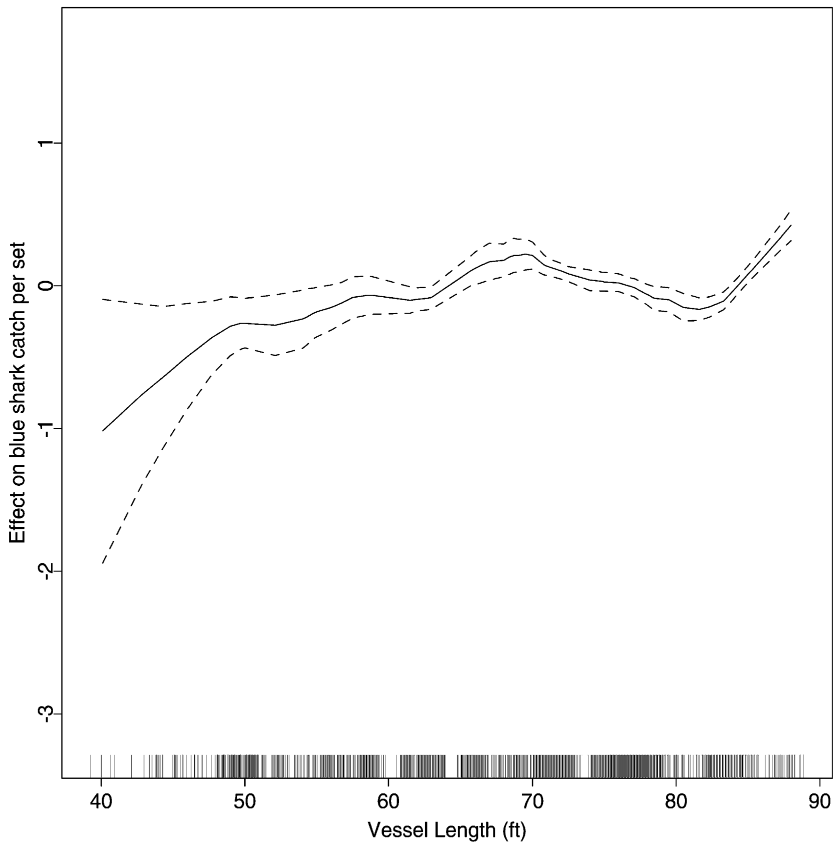

Fig. 8. The effect of vessel length (ft) on blue shark catch per set as estimated by a nine-variable GAM. The response scale reflects natural log-transformation.

Blue shark catch rates north of 26.6°N were primarily affected by geography and seasonal variation. The 20 partitionings of these sets included three on longitude, two on latitude, three on months, and five on temperature. The eight terminal nodes from west of 162.7°W were characterized by a 17.1-fold range in predicted catch rates. This large range resulted from a partitioning on years caused by relatively low catch rates in 1994. These nodes, which were defined by additional partitionings on longitude, latitude, and months, comprised 14.0% of the tree, but yielded 42.7% of all blue sharks. The other main branch of the northern subtree underwent a second partitioning on longitude at 153.9°W. Terminal nodes categorized by temperature, months, years and latitude (left section) contained 13.3% of the sets and yielded 17.5% of the blue sharks, with an average catch rates of 16.4 blue sharks per set. Terminal nodes categorized by months, hooks per float, the lunar index, longitude, and years (right section) included 14.4% of the sets, and yielded 11.1% of the blue sharks, for an average catch rate of 9.6 per set.

3.3. Comparison of GAM and regression tree analyses

Results of the analyses were comparable in three major respects. First, the two types of models included the same suite of significant predictors, although temporal effects were expressed as a continuous variable in the GAM but as categorical variables in the regression tree. Second, their two sets of predictions agreed closely. Third, several prominent features of the loess plots apparently corresponded to partitionings within the regression tree.

Back-transformed predictions from the GAM and the regression tree (Fig. 13) were compared after

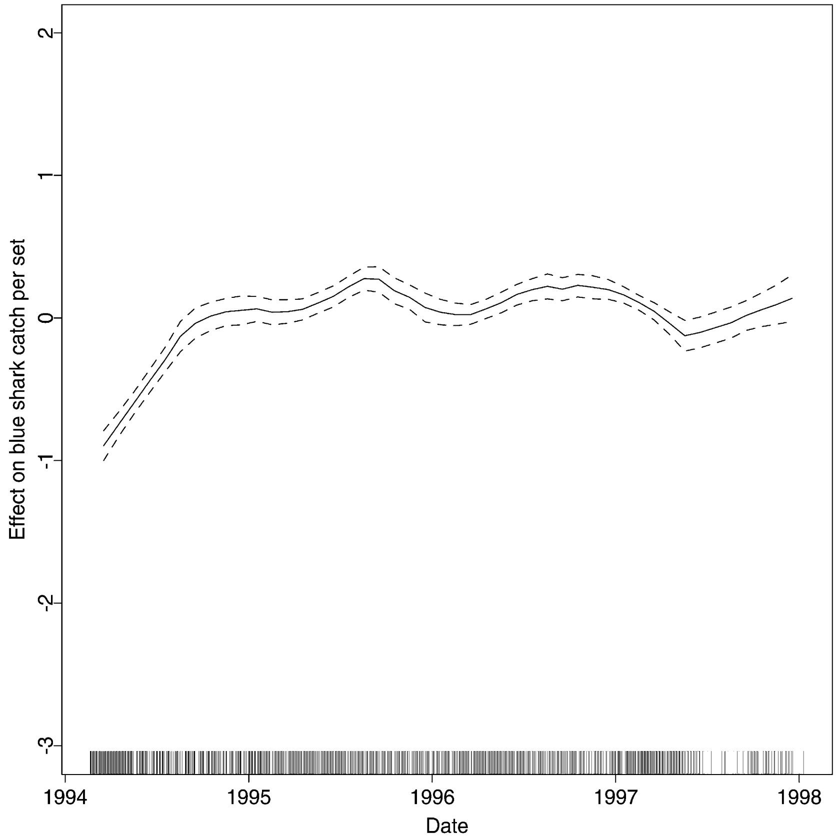

Fig. 9. The effect of temporal variation on blue shark catch per set as estimated by a nine-variable GAM. The response scale reflects natural log-transformation.

trimming 1% of the observations, to reduce the influence of high catches on eight sets. The two sets of predictions were highly correlated ($r = 0.903$, $P \ll 0.001$). Inclusion of the eight sets reduced the correlation coefficient by 0.099 ($r = 0.804$, $P \ll 0.001$).

Both analyses demonstrated that geography was the predominant influence on blue shark catch rates. Latitude was the first entry into the GAM and the basis for the first partitioning in the regression tree. Its loess plot exhibited a local maximum coincident with the first partitioning in the tree. Longitude was second into the GAM, and the basis for the first partitioning among the northerly sets with relatively high blue shark catch rates. Its loess plot exhibited the greatest response range among the predictors, while the tree topology also depicted strong longitudinal effects.

The two analyses also appeared compatible with respect to the environmental factors. Temperature was third into the GAM, and the basis of one-fourth of the partitionings in the northern subtree with its relatively high blue shark catch rates. In contrast, the lunar and solar indices were the final entries into the GAM, and only present at the lowest hierarchical levels in the regression tree.

The use of months and years as categorical variables in the regression tree facilitated interpretation of the effect of time in the GAM. The regression tree contained seven partitionings on months, but only four on years, three of which reflected lower catch rates in 1994 than in all other years. Analogously, the response range in the loess plot was greater within than between years since 1994. Thus, temporal factors were influential regarding blue shark catch rates, but primarily in terms of intra- rather than interannual variation, in the last 3 years of the study.

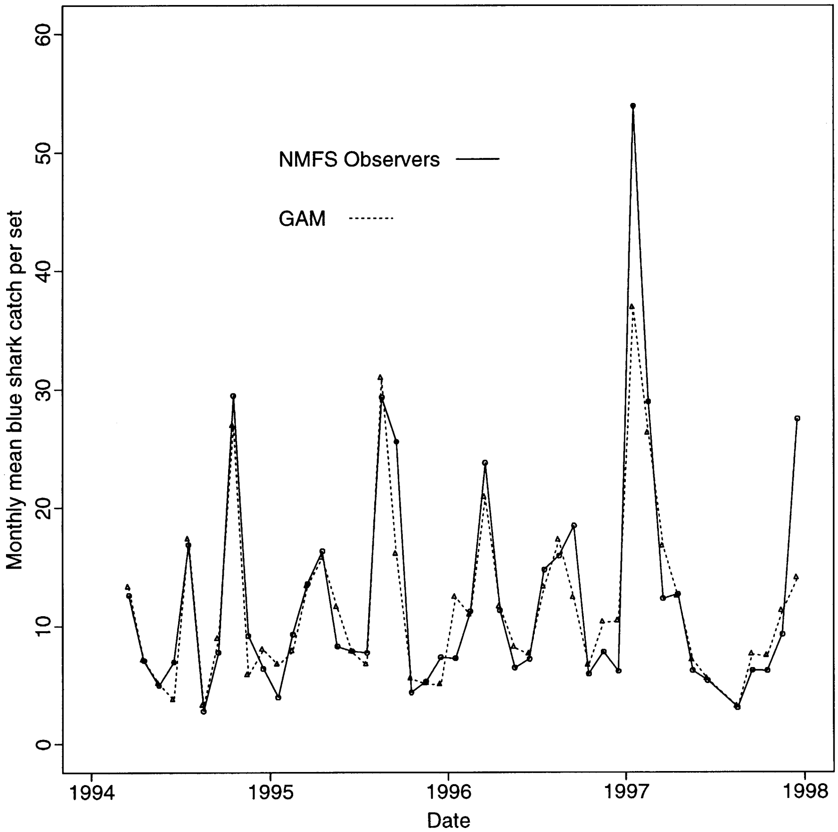

Fig. 10. Back-transformed monthly mean GAM predictions of blue shark catch per set (dashed line with triangles) in relation to measured mean blue shark catch per set (solid line with open circles) from March 1994 to December 1997.

The results from the two analyses regarding the operational factors were comparable in one respect: concentration of these partitionings within the mid- and lower hierarchical levels and the topology of the regression tree appeared to be consistent with sequential and relatively late entry into the GAM. Beyond this, however, these factors represented the principal disparities between analyses. Vessel length provided the initial partitioning among southerly sets in the regression tree, but was the last of the operational factors to enter the GAM. Light sticks, in contrast, was the first of these factors into the GAM, but was the basis of the next partitioning beneath vessel length in the southern subtree. The loess plot of the number of hooks exhibited a large response range, but this variable was absent from the northern subtree and present only as the basis of one partitioning in the southern subtree.

4. Discussion

A significant characteristic of this study was its utilization of data gathered by fishery observers. Because the responsibilities of these individuals do not include participation in the deployment or retrieval of longline gear, it is reasonable to expect that they would be less likely to overlook or miscount any of the catch than actively fishing crew members. Thus, the results presented herein are presumably founded upon highly accurate data.

A second significant characteristic of this study was its application of two modern statistical methods to blue shark catch rates, and generation of closely comparable results. The latter, in particular, was reassuring, although not surprising. Venables and Ripley (1994) likened the process of developing a regression tree to forward variable selection in regression. Both

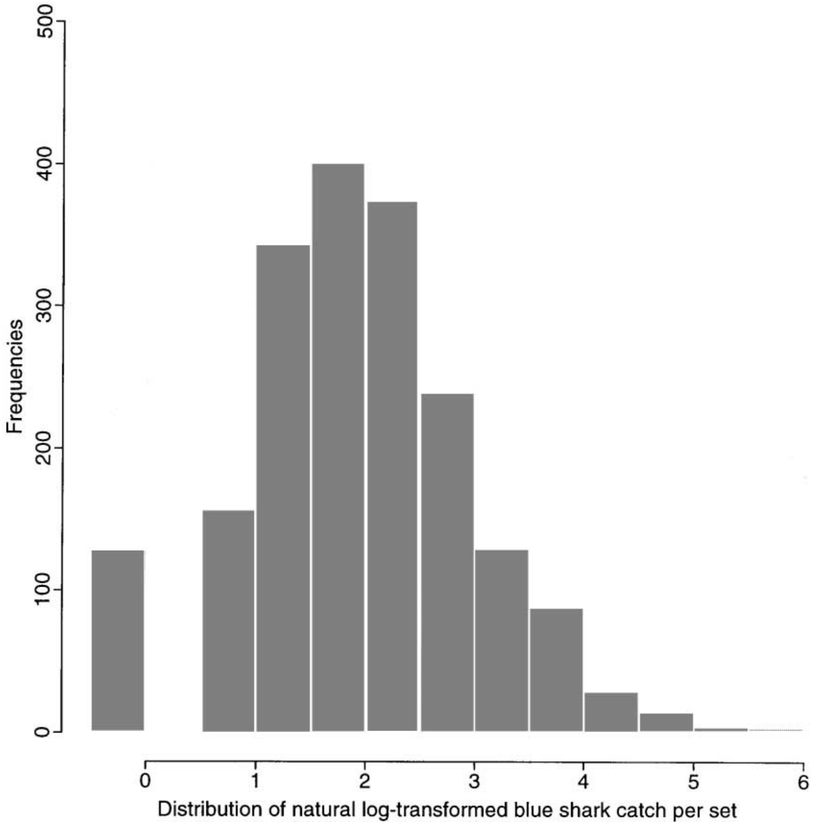

Fig. 11. Distribution of natural log-transformed blue shark catch per set.

methods represent hierarchical refinement of probability models. It was noteworthy that this study provided examples of how these methods could be employed in a mutually complementary manner. Interpretation of the GAM was facilitated by examination of the topology and hierarchical structure of the regression tree, even as the partitionings within the latter were examined in relation to non-linear features of the loess plots.

Both the GAM and regression tree were regarded as parsimonious models. Its pseudocoefficient of determination (pseudo-$R^2 = 0.721$) indicated that the GAM explained a large proportion of the deviance of blue shark catch rates, and nine forward entry F-tests were highly significant (all $P \leq 0.005$), which demonstrated that inclusion of these predictors was appropriate. In contrast, the test of set time ($P = 0.383$) did not reveal a need for a larger model, at least with this suite of candidate predictors. The final regression tree was also considered to be of an appropriate form because it included the same predictors as the GAM, and was pruned on the basis of consistent results from a series of cross-validation procedures as well as the biological criterion that terminal nodes must differ by at least a whole organism. In other words, terminal nodes defined by differences of less than one shark were combined in the final regression tree because such differences were considered biologically meaningless.

The principal complexity encountered in this study was the fact that the observed longline sets did not form a homogeneous or standardized set of measurements. The Hawaii-based longline fishery primarily targets tuna or swordfish, but in different locations and by different methods. Tuna-directed fishing operations are generally conducted in daytime by small vessels near the main Hawaiian Islands, with many hooks per set but few light sticks, whereas swordfish are targeted

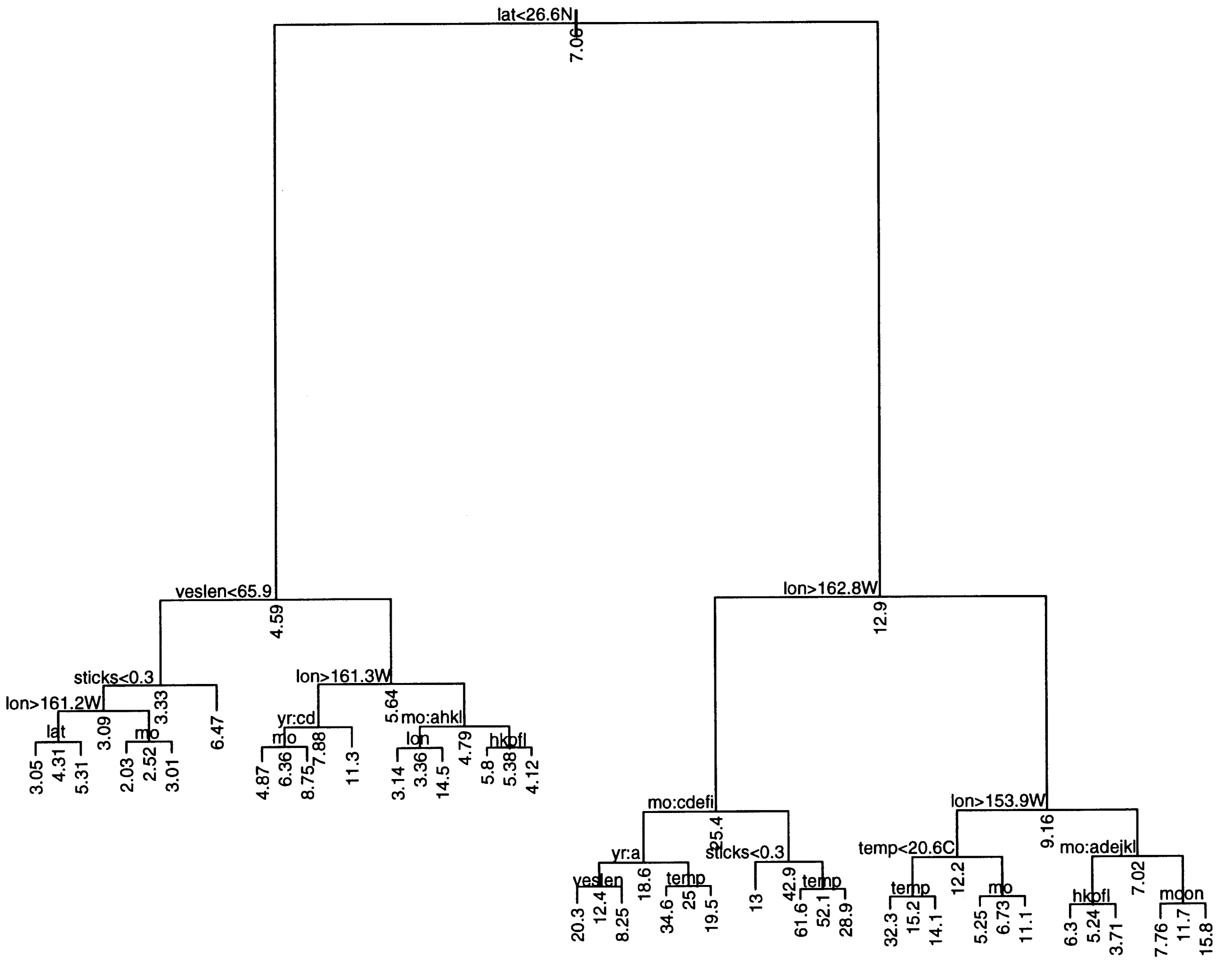

Fig. 12. Regression tree of blue shark catch per set. The partitioning variable and its value are presented adjacent to, and the prediction is presented beneath each split. Abbreviations are: lat (latitude), lon (longitude), temp (sea surface temperature), mo (month), yr (year), sticks (light sticks), hkpfl (hooks per float), veslen (vessel length), and moon (visible proportion of the moon). Values for months and years are letters, e.g., "a" denotes January or 1994, respectively. The lowest level shown (see text for explanation) has the partitioning variable centered, with predictions beneath.

from the Hawaiian Archipelago to 45°N, with gear deployed at night, including greater numbers of light sticks, but fewer hooks per set than tuna fishing (He et al., 1997). Despite these differences, it proved possible to develop models that were amenable to clear biological or operational interpretation. Moreover, this does not preclude further investigation of model performance within specific regions of the distributions of the independent variables, which could represent types of fishing, or assessment of the practical utility of reduced models, which might entail some sacrifice of accuracy in exchange for simplified interpretation or reduction of data collection requirements.

These analyses were expected to reveal strong geographic effects on blue shark catch rates, with latitude predominant. These expectations were fulfilled, although the relationship between latitude and catch rates is largely indirect. A substantial proportion of the incidental blue shark catch by the Hawaii-based longline fishery since 1990 has been associated with swordfish-directed effort (He et al., 1997). From 1991 to 1995, the latter was centered within the subtropical frontal zone ca. 30°N, a region

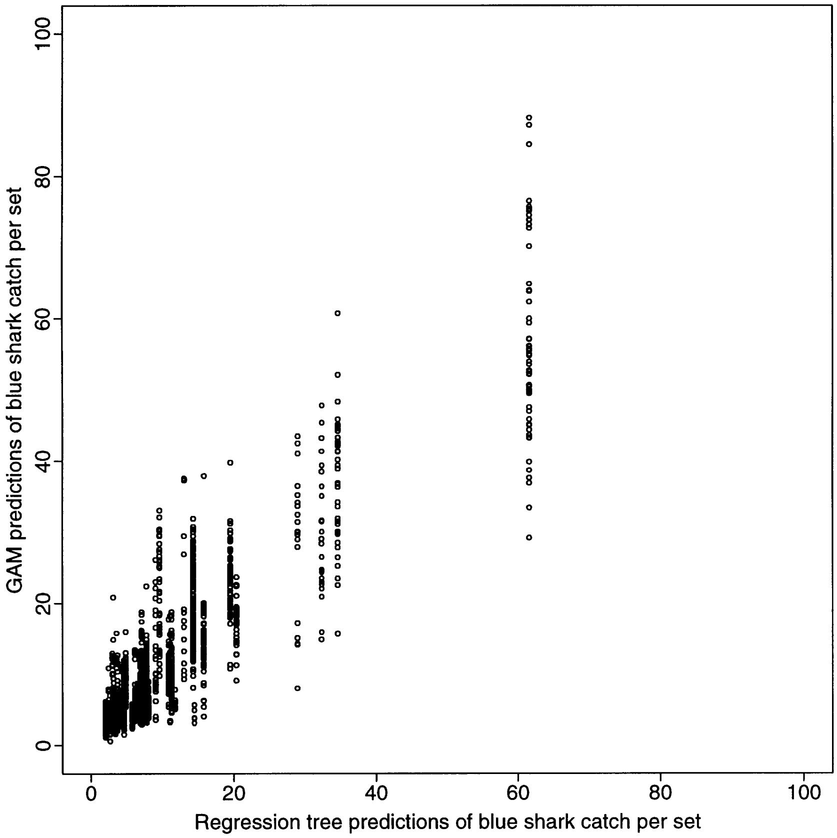

Fig. 13. Scatter plot of back-transformed predicted values obtained from the GAM and regression tree analyses.

characterized by latitude-related oceanographic factors (e.g., an abundance of food organisms caused by intersections of currents or water masses) that favor concentration of swordfish (Bigelow et al., 1999). Such known oceanographic phenomena, in turn, presumably affect the distribution of fishermen by influencing their expectations of success. In addition to the indirect effect, the life history of blue shark includes latitudinal reproductive migrations (Nakano et al., 1985; Pearcy, 1991) that could affect catch rates by altering availability to this fishery. The seemingly strong effect of longitude, depicted by the wide response range in the loess plot, was probably more closely related to the type of fishing effort than blue shark abundance per se. Over 90% of all blue sharks from south of 26.6°N were caught east of 165°W. This proximity to the main Hawaiian Islands suggests that these were primarily tuna sets. Given the differences in gear configuration between swordfish and tuna sets, relatively low blue shark catch rates are not surprising. The operational factors in general appeared comparable to the distribution of fishing in the sense that both reflect expectations of catch, and exert their effects accordingly. Although these were not the most important variables, the presence of these factors in the models is useful because it allows estimation of the effects of manipulations that might affect efficiency or serve as preventive or ameliorative measures.

The relative importance of the environmental factors was consistent with physiological and ecological considerations. It was predictable that temperature would exert strong effects because it acts directly on a fish in at least two ways. Temperature is first and foremost a controlling factor, governing metabolism (Fry, 1971). As such, it exerts strong effects on energetic demands, even in a eurythermal species such as blue shark, and thereby influences distribution because a species would presumably evolve preferences for habitat with predictably sufficient food resources. High blue shark catch rates associated with swordfish-directed effort in the transition zone probably reflect their co-occurrence in a food-rich region. Temperature also functions as a directive factor (Fry, 1971), eliciting behavioral responses (e.g., movement along gradients). Since responses of this type would presumably exert more subtle effects on catch rates, it is not surprising that, in addition to those higher up, there were three partitionings on temperature at the lowest hierarchical level in the northern subtree, defining terminal nodes. Thus, the regression tree captured the statistical essence of processes occurring at different levels of biological organization. Similarly, the solar and lunar indices, representing influences on visual predatory behavior, were expressed as partitionings at terminal nodes in the regression tree and as the final entries into the GAM.

The results presented herein were consistent with those of Bigelow et al. (1999). These authors developed a GAM of blue shark catch rates from logbook data gathered on swordfish-directed trips from 1991 to 1995, and determined that latitude, longitude, and sea surface temperature were the most important predictor variables, in that order. Because the present study generated similar results from observations of all types of effort, it suggests that the validity of these authors' work was not necessarily limited to swordfish-directed effort.

It would appear that either GAM, regression tree, or both types of analyses developed from fishery observer data could be usefully employed as a comparison standard for logbooks. Specifically, the quality of the underlying data, the indications of relatively broad validity, and the consistency of results between methods, all indicate that a statistical model fitted to fishery observer data could serve as a useful standard against which to compare captains' logbooks. This would be useful, because these are the principal monitoring tool in this fishery. This possibility will be explored in a subsequent report.

5. Conclusions

We conclude from our development, comparison, and interpretation of GAM and regression tree analyses of fishery observer data that these models can be usefully employed in assessment of blue shark catch rates. We suggest that these models represent appropriate comparison standards for the logbooks submitted by commercial vessels.

Acknowledgements

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