Fisheries Research 247 (2022) 106178

Contents lists available at ScienceDirect

Fisheries Research

journal homepage: www.elsevier.com/locate/fishres

A novel habitat-based approach for combining indices of abundance from multiple fishery-independent video surveys

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A R T I C L E I N F O

Keywords:
Index of abundance
Fishery-independent monitoring
Habitat models
Assessment
Time series

A B S T R A C T

Three surveys in the eastern Gulf of Mexico use baited remote underwater video systems to assess changes in abundance of reef fishes: the National Marine Fisheries Service (NMFS) Southeast Area and Monitoring and Assessment Program Reef Fish Video Survey, the NMFS Panama City (Florida) survey, and the Fish and Wildlife Research Institute of the Florida Fish and Wildlife Conservation Commission survey. These surveys use similar sampling gear and video-processing protocols, but they vary in spatial extent and habitats sampled. Each survey has been used individually to produce indices of relative abundance to assess various reef fish, but species trends may vary across surveys, possibly making subsequent assessment models more complex. A combined index could yield a more representative and statistically powerful characterization of the relative abundances of commercially important species. We developed a method for combining video count data from these surveys for managed reef-fish species into a combined index for the eastern Gulf using habitat data in classification and regression trees (CART) and general linear models (GLMs). CART results indicated that several site-specific and landscape-level habitat variables could be used to predict site occupancy of target species. We then used the CART-derived habitat groups as a variable shared among surveys in fitting a GLM to catch data to derive estimated annual abundances. We evaluated models' potential and utility for a single estimated relative-abundance index for key managed reef species in the region compared to a suite of alternative GLMs of less complexity. Models that incorporated habitat covariates across the surveys showed better fits than models that did not incorporate habitat information. We also developed model-weighting methods that allowed us to account for the variation in spatial footprint in the surveys when combining data, allowing for what is likely a more representative index of regional relative abundance trends. Our results indicated that the data can be reliably combined into a single index. These methods should be evaluated for similar instances of combining survey data in other species, ecosystems, and management frameworks.

1. Introduction

Accurately modeling biomass using age-structured stock-assessment models in support of fishery management requires multiple data inputs, including both life-history and fishery-dependent (landings) data. Time series of fishery-dependent data, however, are often affected by regulatory changes, market prices, and other socioeconomic factors (Rotherham et al., 2007; de Mutsert et al., 2008), which can confound the relationship between trends observed in fishery-dependent data and trends in the true population. Instead, therefore, randomly sampled fishery-independent data are vital in characterizing and assessing population trends in fish and are critical inputs to stock-assessment models (Walters and Martell, 2004). Best practices for regional stock assessments demand that, when possible, assessments should not use fishery-dependent data if reliable fishery-independent data are available for the same portion of the population (SEDAR, 2015a). Fishery-independent data are also significant sources of information on life history, length and age composition, and spatial structure for

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https://doi.org/10.1016/j.fishres.2021.106178
Received 10 August 2021; Received in revised form 10 November 2021; Accepted 11 November 2021
Available online 24 November 2021

Table 1
Summary of sample sizes (sites for which videos were read), by year, for the Florida Fish and Wildlife Research Institute (FWRI), SEAMAP Reef Fish Video (SRFV), and NMFS Panama City (PC) video surveys. No data were available or used (due to low sample sizes) from any survey from 1998 to 2001 or 2003.

Year	FWRI	SRFV	PC	Total
1993		115		115
1994		90		90
1995		61		61
1996		133		133
1997		162		162
2002		152		152
2004		148		148
2005		274		274
2006		276	70	346
2007		318	44	362
2008		206	85	291
2009		262	99	361
2010	145	221	143	509
2011	221	335	156	712
2012	237	281	150	668
2013	184	164	94	442
2014	286	230	153	669
2015	224	152	143	519
2016	194	206	168	568
Total	1491	3786	1305	6582

managed species.

Especially valuable is a time series of independently measured abundances for species of interest that are used in fitting assessment model–generated trends. Annual abundance is often estimated using generalized linear models (GLMs) that standardize catch and effort data over time to explain variation in catch rates that reflect changes in catchability rather than changes in population size. Explanatory variables that reduce variability in catchability include environmental-habitat factors (Maunder and Punt, 2004; Xiao et al., 2004).

Fishery-independent surveys frequently use random-stratified sampling to reflect variability more accurately in abundance by accounting for known sources of that variability (Walters and Martell, 2004). Variation that cannot be accounted for through stratification can often be explained using important habitat, spatial, environmental, and biotic covariates in a GLM used to predict annual abundances. These covariates can reduce an index's coefficient of variation (CV), increasing in revealed trends the index's precision and confidence. The value of fishery-independent indices to a stock-assessment model is a function of the length of the time series they are based on, the size selectivity of the survey or sampling gear used in gathering the data, the degree to which a survey has covered the spatial extent of the population, and the ability to reduce the CV around estimates by including important explanatory variables in a fitted model (Helser et al., 2004; Maunder and Punt, 2004). If more than one survey examines the same species and ranges, combining them into one index rather than treating them independently stands to increase their value to stock assessment by better representing the overall population and by reducing the variation around annual abundance estimates (Gwinn et al., 2019).

Three such surveys were considered in the present study, broadly targeting the reef-fish assemblage in the eastern Gulf of Mexico (east of 87.5° W and north of 24.3° N, and herein referred to as eastern Gulf), and operating under three separate designs. As a result, the estimated index for a given species across these studies often had a large CV and assessment reviews questioned the appropriateness of combining the datasets. To improve our ability to assess these reef-fish species in the eastern Gulf, we developed a modeling and habitat-weighting scheme that allows the survey data to be combined and treated as representing a single survey, which potentially improves precision and confidence in assessments of managed reef-fish species.

1.1. Background

The eastern Gulf supports a diverse reef-fish assemblage, whose species have very different life histories and support different fishery user groups (de Mutsert et al., 2008; Geers et al., 2016; Karnauskas et al., 2017). For this reason, the Gulf of Mexico Fishery Management Council (gulfcouncil.org) manages more than 30 reef species found throughout the expansive Gulf shelf. In support of resource management in the eastern Gulf, federal and state agencies developed surveys for tracking the abundance of those species (Grüss et al., 2018; Switzer et al., 2015). For example, the Southeast Area and Monitoring and Assessment Program (SEAMAP) developed its groundfish trawl survey to assess fish populations on sand, mud, and other low-relief habitat in the region and provide critical data on the subadult, pre-fishery life stage of many of the managed reef species (Pollack and Ingram, 2014; Switzer et al., 2015). However, assessing the adult, reef-associated stages of critical species requires sampling methods—such as visual methods—that can be used primarily in rugose, untrawlable habitats.

For such habitats, stereo-baited remote underwater video (S-BRUV) arrays are highly effective in identifying and enumerating fish species associated with reef and rocky marine habitats (Whitmarsh et al., 2017). Because fish are not captured or retained, S-BRUV surveys exhibit generally less species and size-selectivity than do other capture gears typically used in the region (Christiansen et al., 2020). In addition, S-BRUVs can be deployed in waters deeper than those that can be visually surveyed by scuba divers (Willis and Babcock, 2000; Watson et al., 2005; Harvey et al., 2012; Keenan et al., 2018).

Three research groups have established S-BRUV surveys in the eastern Gulf, but their survey domains vary spatially and they started in different years: 1) the National Marine Fisheries Service (NMFS) Southeast Fisheries Science Center SEAMAP Reef Fish Video Survey (SRFV), which began in 1992; 2) the NMFS Panama City (PC) video survey, which began in 2005; and 3) the Florida Fish and Wildlife Conservation Commission's Fish and Wildlife Research Institute (FWRI) survey, which began in 2008. Despite their differences, the S-BRUV sampling gear, protocols, and derived abundance metrics can be directly compared because the groups have been careful to use identical standardized deployment and video-annotation methods (Table 1, Fig. 1; Campbell et al., 2014, 2015; Devries et al., 2014; Gunther et al., 2014).

Each of these surveys has submitted an independent index for the assessment of managed reef fishes through SEDAR (the SouthEast Data, Assessment, and Review program), usually beginning after 5 years of annual survey data have become available (sedarweb.org). At panel discussions at SEDAR stock-assessment workshops, participants noted that a combined index representing the eastern Gulf would provide a more accurate picture of reef-fish population trends and the greatest statistical power. Furthermore, a single index would reduce complications when incorporating individual indices in stock-assessment models, which sometimes showed conflicting trends in similar segments of the population due to differing spatial coverage, particularly when the models could not account for spatial heterogeneity. Data from these surveys were first combined for the 2015 stock assessment of red grouper (*Epinephelus morio*). However, these efforts did not account for variability in the quality of habitat sampled by each survey and instead modeled only fixed-effect factors for space (three levels) and depth (two levels) (SEDAR, 2015b).

Our objectives, therefore, were to improve upon initial efforts by developing a statistical approach to combining data from the three surveys that would account for variation among surveys, including differences in spatial footprint, habitats sampled, and site-selection protocols. We aimed to incorporate important covariates into a GLM framework that would be familiar to most assessors and fishery managers and to weight the contribution of each data source into final abundance estimates as a function of the representative area sampled and of the habitat quality encountered in each survey. Final model-estimated relative-abundance trends would therefore better represent

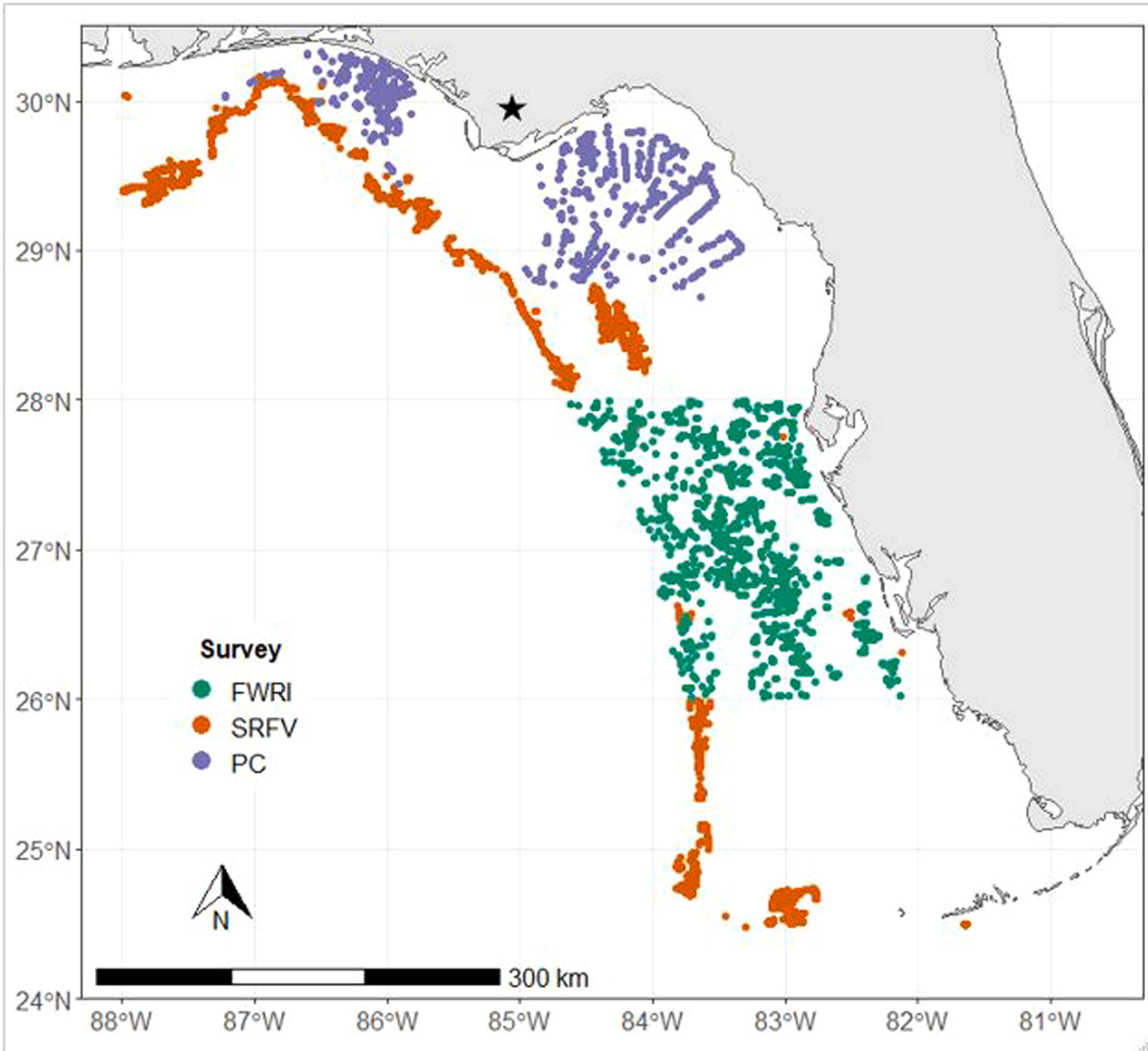

Fig. 1. Map of all video sites included in the index for each survey (by laboratory) across all years, 1993–2016. Cape San Blas, the geographic feature used in stratifying the PC survey is noted with a star.

overall regional population trends, simplify inputs in the assessment model, and carry less error than if each index were incorporated separately.

2. Methods

2.1. Description of the three surveys

2.1.1. SEAMAP reef fish video

The SRFV survey has been conducted on hard-bottom habitats of the U.S. Gulf since 1992 (Fig. 1). The annual survey is conducted between April and May and samples ~300 sites associated with high-relief reef habitat throughout the Gulf (1244 km^2, eastern Gulf; 527 km^2, western Gulf), primarily around the shelf break (target depth, 50–150 m). Sites are selected using a stratified random design; strata are determined by region (east and west of the Mississippi delta) and total proportion of reef area in a sampling block (10′ × 10′ latitude/longitude blocks). The SRFV survey was developed using habitat-mapping data (initially course data on bathymetry, but subsequently refined through the use of multibeam sonar with ancillary use of side-scan sonar) to target reef habitat in each sampling block, but the research design does not explicitly apportion sampling across different reef types by using habitat-specific metrics (Campbell et al., 2014, 2015). Although this survey began in 1992, data from 1992 were excluded because different video-annotation protocols were used. In addition, data from 1998 to 2001 and from 2003 were excluded, as in earlier calculations of reef-fish indices because of various events in those years that limited sample sizes (Campbell et al., 2014). For these analyses only the data from the eastern Gulf were used.

2.1.2. Panama city

The PC survey targets inner-shelf (in waters 7–60 m deep) reef habitats in the northeastern Gulf, from Pensacola, FL, to Cedar Key, FL. Survey design has changed since the survey began in 2005, but since 2010 a stratified-random, unequal-probability design has been used. Blocks measure 5′ × 5′, and sites are randomly and proportionally allocated by region (east or west of Cape San Blas; Fig. 1) and depth (<20 m, 20–30 m, and 30–60 m). Sites are described using side-scan sonar before the S-BRUV gear is deployed, and reef habitats are classified according to the Coastal and Marine Ecological Classification Standard (CMECS; Devries et al., 2014; Gardner and Overly, 2018).

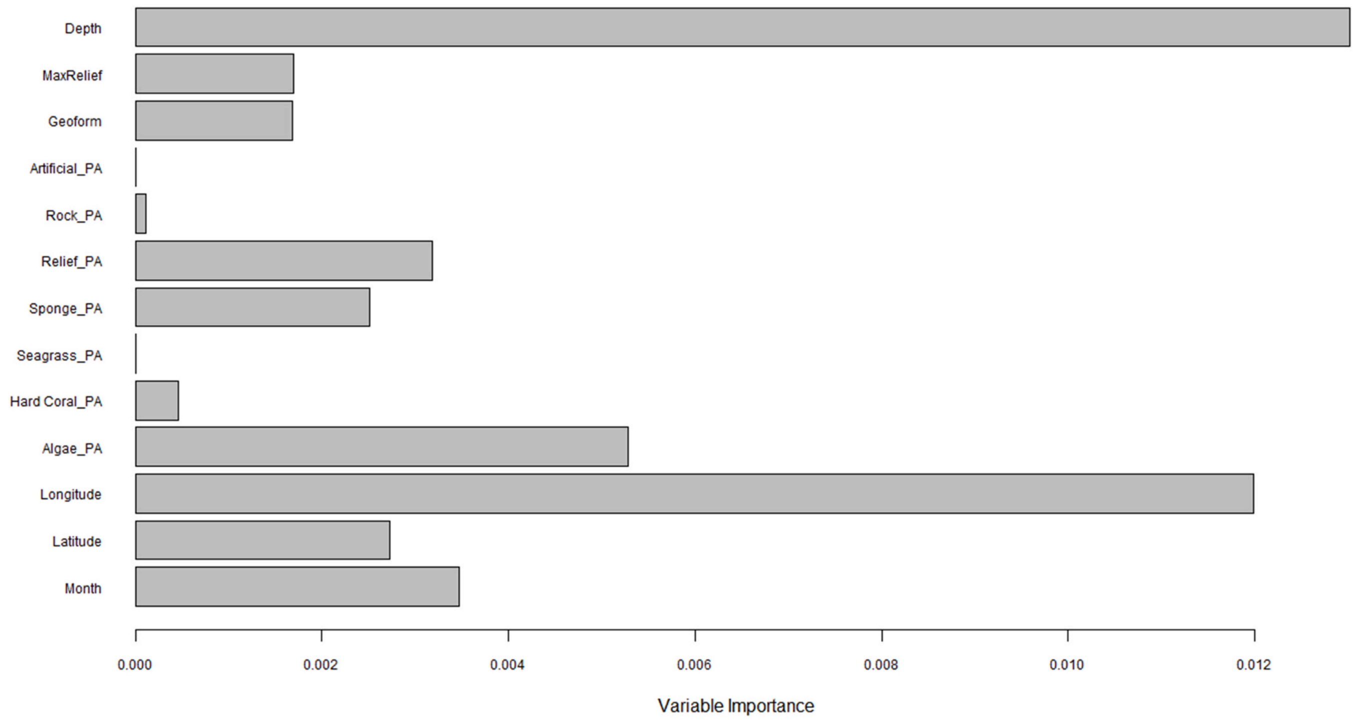

Fig. 2. Example of variable importance ranking before fitting the final CART habitat model for red snapper with the FWRI data.

Before field sampling, a scaled, composite score is calculated based on physical attributes of identified reefs (using relief, reef area, and rugosity) and the range of values is parsed into quantiles. The lower quantile is entered into the selection model once, the mid values three times, and the upper quantile five times. This allows the video site selection to process a greater chance of selecting higher-relief reefs without excluding any habitats from selection. Within each block, two sites are randomly selected with the minimum distance separating them being 250 m (Devries et al., 2014).

Alternate sites are also selected for use when another boat is fishing the primary site or when sonar reveals no hard bottom there. Two hundred sites are selected for sampling each year, with the number of samples varying in a year because of a variety of environmental and personnel factors (Table 1).

2.1.3. Fish and Wildlife Research Institute, Florida Fish and Wildlife Conservation Commission

The FWRI survey targets shelf and shelf-break reef habitats on the central West Florida Shelf off Tampa Bay and Charlotte Harbor. It uses a stratified-random survey design for mapping where 200 sites of annual effort are proportionally allocated among spatial strata for NMFS statistical zones 4 and 5 (offshore of Tampa Bay and Charlotte Harbor areas) with 100 side-scan mapping sites in each (Fig. 1). Sites are further stratified by depth with a nearshore (10–36 m) and an offshore (37–110 m) stratum. Before the S-BRUV gear is deployed, sites are mapped using side-scan sonar (Keenan et al., 2018), and geoforms are delineated and classified using the CMECS standard. Video deployment sites are then randomly selected from sites shown by side-scan sonar to include reef habitat (Keenan et al., 2018; Thompson et al., 2018).

2.2. Video annotation protocols

For all three surveys, abundance of all managed reef fishes identified is estimated as the maximum number of individuals observed in a single video frame (recorded as MaxN) during 20 min of video (Campbell et al., 2015). Procedures for identifying, counting, and describing habitat in the videos are the same in all three surveys. Various habitat metrics, including composition of substrate, biota, and vertical relief, are also quantified for each video processed. These variables include the presence and percent cover of rock, sand, sponges, soft coral, hard coral, algae, and unidentifiable sessile organisms, as well as the estimated maximum vertical relief. Videos were excluded from subsequent analyses if the water at a site was highly turbid or if deployment errors were noted (e.g., the camera pod fell on its side; the video recording time was short).

2.3. Test species

We explored the utility of various approaches to combining data from all three surveys for four species of management interest that had been assessed as being overfished or as having been overfished during the previous decade (SEDAR, 2013, 2014, 2015b, 2015c) and that vary with respect to life history, center of distribution, and recent population trajectories. Red snapper (*Lutjanus campechanus*) is a schooling species that has undergone significant changes in regulation in recent decades and may be recovering in the eastern Gulf (SEDAR, 2018). Red grouper is a protogynous hermaphroditic species that is widely distributed and generally abundant but that has been declining in recent years (SEDAR, 2015b). Gray triggerfish (*Balistes capriscus*) is widely distributed throughout the Gulf, especially in inner-shelf habitats (SEDAR, 2015c). Gag (*Mycteroperca microlepis*) is a protogynous hermaphroditic species that is much less abundant than the other test species throughout the eastern Gulf (Lindberg et al., 2013; SEDAR, 2014).

2.4. Survey-specific habitat models

Populations are often hyperstable at locations with high-quality habitat, such that population trends at sites of low to moderate habitat quality may be better indicators of overall population status (MacCall, 1990; Lindberg et al., 2013). Therefore, survey-generated indices of abundance for assessments should, when possible, account for habitat variability and quality. We developed combined-index models to account for random interannual variability in the quality of habitat sampled by each survey and to more fully capture the variation in

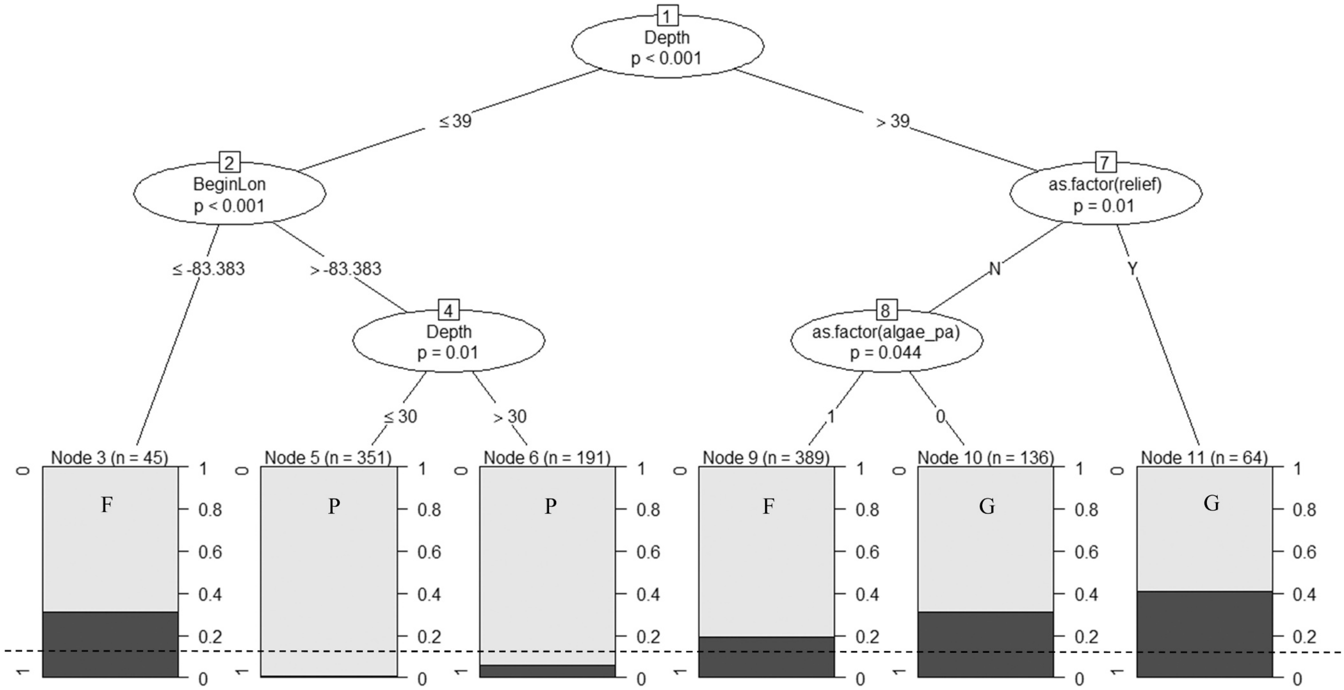

Fig. 3. Example of a final CART model for red snapper for FWRI data. Nodes indicate the proportion of sites given by criteria that had at least one red snapper present. Sample size of video sites that met the criteria are shown above the bar graph. Overall presence of red snapper for this survey was 0.15, indicated by the dashed line. Habitat distinctions (fair, F; good, G; poor, P) are indicated for each node based on proportion present.

population trends across the eastern Gulf. Factors that define habitat quality vary widely among species, and, among the three surveys, habitat variables available to define habitat quality differ due to mapping methodology. Therefore, as a first step, we conducted a series of analyses to define a common habitat quality metric that ranked habitat as fair, good, or poor (herein, FGP habitat classes) for each species and each survey that will be used in index models. To accomplish this, we used a classification and regression tree (CART), a tool that has proved useful in fisheries ecology and in describing fish–habitat associations (De'ath and Fabricius, 2000; Yates et al., 2016). The CART was especially useful in the present study because it can include both continuous and categorical data while still being able to account for collinearity among variables (De'ath and Fabricius, 2000). The CART models described here were applied independently for each species–survey combination for a total of 12 habitat models.

For each CART analysis, the response variable was the presence or absence of the species of interest (present defined as MaxN > 0); spatial predictor variables were the latitude, longitude, and water depth at each sampling location. Month was included as a possible temporal variable. We also used presence of different habitat categories (e.g., rock, hard coral, sponge; see video methods, above). For analyses of FWRI and PC survey data, habitat type, as determined from side-scan sonar (geoform; see Keenan et al., 2018), was also included as a landscape-scale habitat variable; no comparable metric was available for SRFV survey data.

Because multiple combinations of physical and habitat variables are possible, we first performed a random-forest analysis to reduce the number of candidate variables included in the final CART fitting used to define index variables. Random-forest analyses were conducted separately for each survey, using its full data set. They involved fitting 2000 CART models using randomly selected subsets of five variables. A measure of the importance of a variable in predicting that a species would be present was calculated as a scaleless number based on the number of final models that contained the variable after selection (Fig. 2; Appendices A1–A11; Hothorn et al., 2006).

Based on these results, for each survey, the top 50% of the variables were retained for possible inclusion in a final CART model based on variable importance. These variables were used to differentiate habitat quality in each survey and allowed for more efficient model fitting without excluding those variables likely to contribute to a final model. The final models that predicted presence for each species and survey were created using training data sets consisting of a randomly selected 80% of the data. The remaining 20% of the data were used to test the final model and determine misclassification rates. The proportion of sites with positive catches (MaxN > 0) at each terminal node given by the variable criteria was then evaluated to determine whether the described habitat could be characterized as *good* (occupancy at more than twice the overall proportion positive of the full data set), *fair* (one-half to twice the overall proportion positive for the full data set), or *poor* habitat (less than half the overall proportion positive of the full data set; see example in Fig. 3).

Conducting analyses for each survey and species resulted in 12 final habitat models. An example with the FWRI red snapper data is shown in Fig. 3. All analyses were conducted using R version 3.0.2 (R Core Team, 2008) and the Party package (Hothorn et al., 2006).

2.5. *Combined index models*

Because relative abundance (MaxN) does not conform to assumptions of normality, we used a negative-binomial GLM and confirmed that a zero-inflated version of the model was not appropriate given the lack of overdispersion (dispersion estimates ranged from 1.01 to 1.06 across species). We then explored a series of models to test the improvement in model fit gained by including survey and newly defined habitat variables. The first model represented a nominal, or year-only, index (*MaxN = Y*). This model is frequently included when presenting indices for assessment to illustrate how annual trends compare with trends generated from model-based estimates that account for habitat, spatial, or other important variables (SEDAR, 2015b). The second model included survey in addition to year (*MaxN = Y*Survey*) and accounts for variability in survey-specific sampling effects from year to year. The third model dropped the survey effect but included the site-specific habitat quality variable (Hab; FGP) defined from the CARTs (*MaxN = Y*Hab*) to

Table 2
Area weighting values for each survey by area and proportion of mapped grids with reef habitat. Final area weighting values are shown for the three time periods.

Survey	Total universe area (km^2)	Total mapped area (km^2)	Proportion of grids with habitat	Total universe area × proportion grids with habitat (km^2)	Area weighting values (1993–2005)	Area weighting values (2006–2009)	Area weighting values (2010–2017)
SRFV	34,490	11,194	0.81	27,936.9	1.0	0.65	0.52
PC	22,104	356	0.67	14,860.9	0.0	0.35	0.28
FWRI	37,290	1379	0.29	10,814.1	0.0	0.00	0.20

Table 3
Proportion of sites, by survey, where each species was observed (MaxN>0).

	Overall proportion present		
Species	SRFV	PC	FWRI
Red snapper	0.16	0.42	0.15
Red grouper	0.27	0.38	0.40
Gray triggerfish	0.15	0.45	0.13
Gag	0.07	0.23	0.03

determine whether these habitat classes improved model performance beyond just the year effect. The fourth and most complex model included the habitat quality variable in addition to year and survey (*MaxN* = *Y*Survey*Hab*).

We hypothesized that the model accounting for both survey and habitat variability would represent the best model of population trends for the eastern Gulf. Therefore, for this model we also tested a method for generating combined annual estimates of relative abundance that weighted survey-level estimates by the estimated quantity of habitat contained within each habitat class for each survey area. To define these weights, we first determined for each survey the proportion of sampling units mapped over its duration that contained reef habitat. This proportion was then multiplied by the spatial extent of each survey to estimate the total area of reef habitat contained within each survey area. It is these proportions that were used to weight each survey's contribution to final model annual abundance estimates. At the survey level, the FWRI survey covered the greatest aerial extent, followed by the SRFV and PC surveys (Table 2). In terms of the proportion of mapped sampling units with reef habitat, however, a markedly greater number of sampling units contained reef habitat in the SRFV (81%) and PC (67%) surveys than in the FWRI survey (29%). Based on these values, we estimated that 52% of sampling units containing reef fell within the SRFV survey domain, 28% fell within the PC survey domain, and 20% fell within the FWRI survey domain. Accordingly, these percentages were used to define survey-specific weighting factors (Table 2). These differences in percentage of reef sampling units are the result of differing mapping methods and levels of randomization and how they are included or excluded in research design.

Survey-specific weighting factors were then apportioned among habitat categories based on the proportion of samples that fell within each habitat category; because habitat-quality designations varied with species, proportioning the survey weights among habitat categories was also species-specific. This yielded a data set of weighting values for each combination of survey, habitat category, and year for each species modeled. These values were multiplied to adjust the model-estimated means and confidence intervals generating a weighted index model estimate of abundance.

Ultimately, we fit five GLM formulations for each of the four species for a total of 20 index models. All models were fit using the PROC GLIMMIX procedure in the SAS Enterprise Guide (version 7.1, © 2017), and the weighting was achieved using its LS MEANS statement.

Results from the five models were compared using standard model-selection metrics, including AIC and BIC. We also evaluated model CVs, calculated as the standard error divided by the estimated mean, which are often used to weight the contribution of index models to stock assessment (Campbell, 2004; Walsh and Brodziak, 2015). Population trends derived from the four model formulations were also plotted to elucidate how different model-generation and weighting protocols might influence interannual trends in relative abundance. While modeling of independent survey data is conducted to account for variation in sampling that would be missed if using nominal, or year only

Table 5
Proportion of sites in each habitat category for each species and laboratory, as determined by CART models.

	SRFV		
Species	F	G	P
Red snapper	0.498	0.334	0.168
Red grouper	0.405	0.287	0.307
Gray triggerfish	0.303	0.111	0.586
Gag	0.427	0.184	0.389
	PC		
	F	G	P
Red snapper	0.331	0.467	0.202
Red grouper	0.783	0.014	0.203
Gray triggerfish	0.821	0.000	0.179
Gag	0.648	0.116	0.236
	FWRI		
	F	G	P
Red snapper	0.264	0.290	0.447
Red grouper	0.537	0.051	0.412
Gray triggerfish	0.936	0.064	0.000
Gag	0.000	0.176	0.824

Table 4
Variables chosen in CART model that predicted the presence of reef fish at a site. Variables are spatial, landscape habitat (geoform), or video-coded habitats. These variables and their associated thresholds were then used to determine FGP (i.e., fair, good, or poor) habitats for subsequent index fitting. Final CART model misclassification rates using a 20% subset of retained data are shown for each species.

	Variables in final habitat CART model		
Species	SRFV	PC	FWRI
Red snapper	Soft coral, longitude, hard coral, shell, latitude	Longitude, depth, algae	Depth, longitude, algae, relief
Red grouper	Hard coral, depth, relief, longitude, sessile organisms	Rock, geoform, depth, latitude	Sponge, relief, rock
Gray triggerfish	Seagrass, hard coral, latitude, longitude, relief	Relief, latitude, longitude, geoform, depth	Geoform, relief
Gag	Soft coral, latitude, longitude, relief, hard coral	Geoform, depth, rock	Relief, depth
	Misclassification rate		
Species	SRFV	PC	FWRI
Red snapper	0.14	0.27	0.16
Red grouper	0.24	0.34	0.33
Gray triggerfish	0.17	0.33	0.11
Gag	0.09	0.20	0.04

Table 6
Akaike's information criterion (AIC), Bayesian information criterion (BIC) and overall coefficient of variation (CV) comparison of naïve models (year only and year*survey only) to a model with habitat class included when all three data sets were aggregated. Both AIC and BIC are the same for the full model whether weighted or unweighted, but CV varies. Weighted indices were not calculated for the null models, so there are no weighted CVs.

Species		Year	Y * Survey	Y*Hab	Y*Survey*Hab
Red Snapper	AIC	13,442.91	12,985.37	12,576.81	12,022.3
	BIC	13,578.75	13,243.47	12,970.75	12,783.01
	CV(unweighted)	0.278	0.279	0.278	0.281
	CV(weighted)	–	–	–	0.269
Red Grouper	AIC	11,173.28	10,917.39	10,504.36	9984.76
	BIC	11,301.99	11,168.04	10,898.31	10,696.08
	CV(unweighted)	0.111	0.114	0.121	0.161
	CV(weighted)	–	–	–	0.103
Gray Triggerfish	AIC	10,281.28	9592.83	9507.71	8918.44
	BIC	10,417.12	9850.93	9901.65	9556.89
	CV(unweighted)	0.165	0.166	0.232	0.189
	CV(weighted)	–	–	–	0.164
Gag	AIC	5812.28	5426.17	5294.45	4962.93
	BIC	5948.13	5684.27	5688.39	5662.52
	CV(unweighted)	0.308	0.309	0.365	0.372
	CV(weighted)	–	–	–	0.312

averages of abundance, fitted models are often evaluated against nominal annual trends to identify large, unexplained deviations that may be indicative of potential model fit issues. When comparing final population trends among models for each species, they were first adjusted to the overall model mean to standardize the values to 1 (i.e., estimated MaxN was converted to relative MaxN, as such results are typically presented) and then used in fitting assessment models.

3. Results

3.1. Species presence in each survey

The proportion of videos in which species of interest were observed varied markedly between species and surveys (Table 3). Red grouper were commonly observed in all surveys, with a proportion positive ranging from 20% to 40%, whereas gag was the least commonly observed species in all surveys (<10% for SRFV and FWRI, <25% for PC). For all species other than red grouper, the Panama City (PC) survey led to the highest positive observations of all three surveys (Table 3).

3.2. Survey-specific habitat models

Twelve CART models were fitted, and the resultant nodes were used to define habitat quality (FGP) for index development. Two to 6 variables were retained in the final CART models; overall, variables retained varied by species and survey, although some consistencies were observed (Table 4; individual CARTs can be seen in B.1–B.11). Within each survey, at least one variable was retained across all species-specific analyses, suggesting a consistent cofactor in the survey. For the SRFV survey it was the presence of hard coral and longitude, for the PC survey it was depth, and for the FWRI survey it was the presence of relief taller than 0.1 m. Similarly, certain variables were consistently retained across surveys for a species; for red snapper, longitude was retained for all three surveys, whereas for gray triggerfish, it was the presence of relief taller than 0.1 m. No similar consistencies were evident for either red grouper or gag. Other variables retained for species- and survey-specific analyses included latitude, side-scan-derived geoform, and the presence of soft corals, shell, rock, algae, sponge, and sessile organisms (Table 4). Overall, CART models performed well in predicting the presence of each species; misclassification rates ranged from 4% to 34%. Misclassification rates were generally highest for species and survey combinations with the highest proportion present, notably red grouper (PC and FWRI) and gray triggerfish (PC); in contrast, misclassification rates were lowest for gag, the rarest of the species (Table 4). But these values were calculated at the level of individual node assignments rather than at the defined FGP habitat class, so misclassification values at the functional scale for this index were even lower.

Results from CART-derived proportions of habitat quality were integrated with estimates of reef coverage for each respective survey to define species-specific weighting factors. The distribution of FGP habitat classes varied markedly among surveys and species (Table 5). Overall, the fair habitat class accounted for the greatest proportion of habitat-quality classes for most species and survey combinations, especially for the PC survey. In contrast, the poor habitat class was the most often sampled habitat class for gray triggerfish in the SRFV survey and for red snapper and gag in the FWRI survey. Aside from gray triggerfish in the PC survey (for which no habitats were characterized as good) and gray triggerfish (for which no habitats were characterized as poor) and gag (for which no habitats were characterized as fair) in the FWRI survey, all other species and survey combinations contained all three habitats.

3.3. Combined index models

All five index models (*Year, Year*Survey, Year*Hab, Unweighted Year*Survey*Hab*, and *Weighted Year*Survey*Hab*) were fit successfully for all four species examined (Table 6). Although CV increased slightly, AIC and BIC values declined with the addition of explanatory variables beyond just the nominal or year only model. Of the two factor models, the *Year*Hab* model performed better than the *Year*Survey* model in terms of AIC and BIC. However, the lowest CVs of the two models varied by species (Table 6). Across all species, the lowest AIC and BIC values were for the full *Year*Survey*Hab* model. The application of survey- and habitat-specific weighting factors resulted in lower CVs than in the unweighted habitat model, and generally the lowest CVs of all models fit across species, except in gag. Accordingly, it appears that in general the best-fitting model was the one that included year, survey, and habitat, whereby annual estimates were the weighted averages of the survey and habitat means (Table 6).

Indices produced by the five model formulations captured similar trends in relative abundance for all four species, but models differed somewhat in patterns through time (Fig. 4). In general, the weighted full model followed the pattern of the nominal, year-only model, with deviations resulting from how additional factors account for sampling variation resulting in an overall improved fit to the data. The *Year*Survey* and *Year*Survey*Hab* unweighted models deviated in annual trends more strongly from the other two models (Fig. 4). Further, a comparison of the unweighted models to the weighted models shows that including the weighting factors is important. This might imply that the surveys are not consistent enough over time with the sampling of the habitats due to site selection, randomness, or some unmeasured properties.

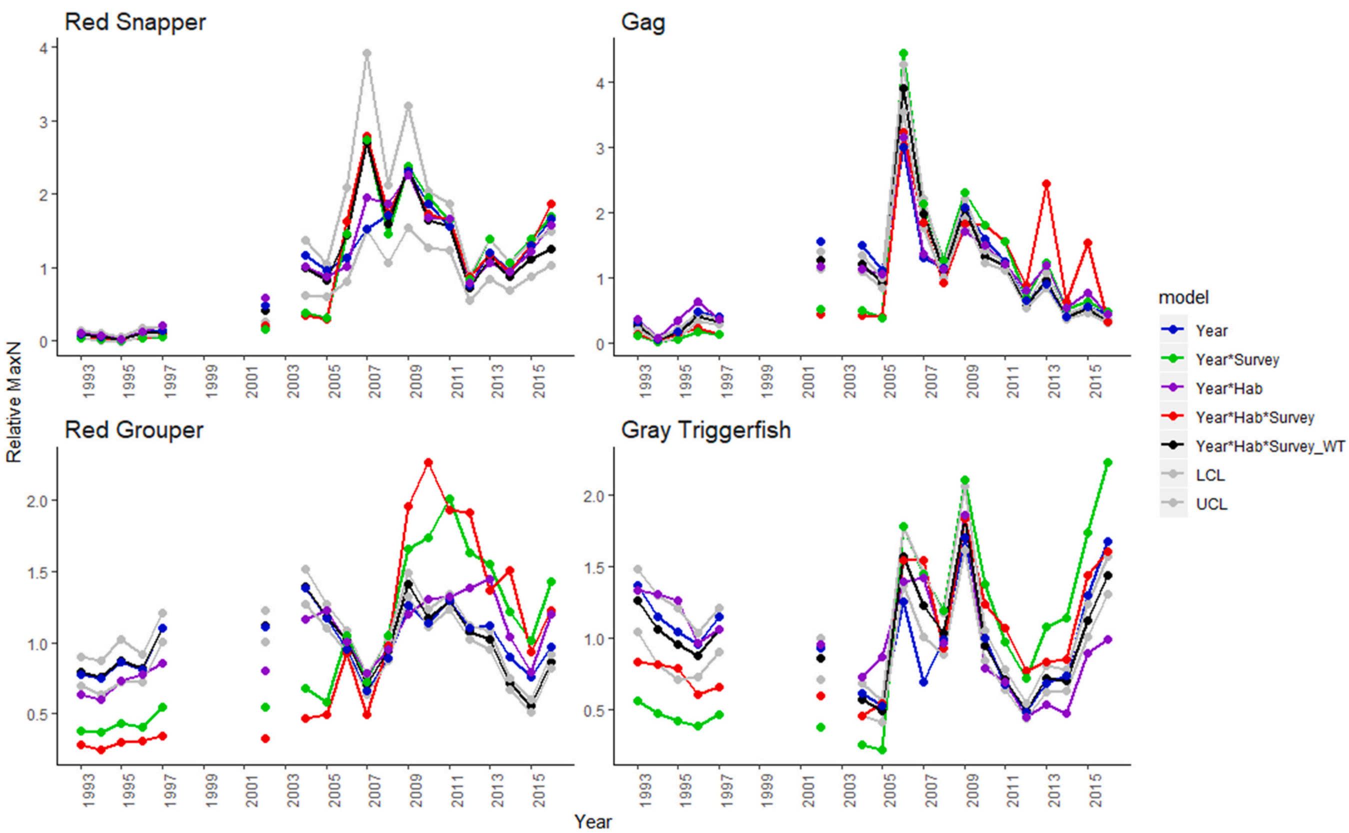

Fig. 4. Abundance trends generated for all species and models. Confidence limit (LCL, UCL) are shown for the final, weighted index. Note that the y-axes differ between top and bottom plots.

4. Discussion

In this paper, we demonstrated a new method of integrating into one index abundance data obtained from multiple surveys that varied in space, habitat, and time frame. By including habitat type and quality, we were able to account for important sources of variation in reef-fish abundance estimates for each survey. We devised a weighting scheme that balanced differences among the surveys stemming from the sampling of different areas that nevertheless overlapped ecologically to some degree. Overall, trends in the indices generated did not differ markedly from those observed in the nominal count data. The combined-habitat weighted model, however, improved overall index performance and more appropriately accounted for interannual variation in the habitat sampled in each survey (e.g., reduced CVs). To our knowledge, this is the first attempt 1) to integrate results from CART and GLM models as a means of combining data from multiple surveys using the same type of gear and 2) to explicitly account for variability in habitats sampled through time. Applying these methods will improve the quality of fishery-independent data used in reef-fish stock assessments for the eastern Gulf of Mexico; will simplify subsequent assessment models; and could offer still broader application to surveys or systems for which the quality of sampled habitats varies with site selection or survey design.

Hierarchical analysis and dynamic factor analysis have proved useful in combining separately modeled trends using regional fisheries data (Conn, 2010; Peterson et al., 2017). Yet those methods do not allow for survey-specific weighting using a priori information, such as habitat quality, which we incorporated into our analyses. Furthermore, the data sets we used overlapped in region and were collected using the same type of gear, so they do not require that individual index models be evaluated. Rather, incorporating habitat as a standard metric in a single weighted model allows consideration of variability among surveys while fitting a single population trend for assessments. This is straightforward and is familiar to assessment reviewers because it is similar to the use of standard index methods. Our results also showed that fit is improved when habitat is incorporated as an explanatory factor in addition to survey and year, as compared to a suite of simpler models (Table 6).

Results from CART analyses indicate that, for managed reef fishes in the eastern Gulf, both site-level habitat and landscape-level metrics were important predictors of species-specific occupancy rates. Given that these key variables are both categorical and continuous and may be colinear, the CART methodology offers a straightforward method for predicting the presence of reef fish at a site (De'ath and Fabricius, 2000). Furthermore, this method detected thresholds or breaks in the habitat variables used, providing a straightforward way of interpreting the critical habitat interactions for these species. Earlier research regarding fishery-independent indices and general fish ecology has demonstrated the importance of habitat to population dynamics (Maunder and Punt, 2004). For reef fish, the influence of complex bathymetry and biogenic habitats has been noted in several ecosystems, because they indicate both structure and forage base (Lindberg et al., 2013; Campbell et al., 2015; Keenan et al., 2018; Switzer et al., 2020). We saw a similar pattern, with the presence of the reef fish studied being predicted by both landscape-level variables (i.e., geoform) as well as site-specific features such as rock, sponge, extent of relief, and sediment type (Table 4). Geoform data were available only for the PC and FWRI surveys; as such, the CART method developed in the present study allowed for the inclusion of this highly-informative metric. Landscape-scale effects of habitat are likely evident in the SRFV data; however, these effects largely remain unknown. Ultimately, analyses would be greatly improved through efforts to cross-validate multibeam sonar data against the FWRI and PC geoforms generated from side scan sonar data, but this has been difficult to achieve because the habitat-mapping methods have differed in resolution. Future standardization among surveys will require efforts towards integration of side-scan- and multibeam-determined habitat types.

The results of our analyses and the subsequent ability to appropriately combine and weight the three data sets illustrate a reliable method that solves data concerns regarding the assessment and management of reef fish in the eastern Gulf (e.g., lack of complete shelf spatial coverage in the individual surveys). While the three data sets have been available for at least several years, regional assessments have often incorporated only the SRFV survey because it is the longest time series and due to uncertainty as to the best practices for combining the data. Furthermore, the use of three individual indices, which may detect different trends, risked diluting the ability of the assessment model to fit to fishery-independent data. This was a point of discussion in earlier assessments by the science and statistical committee of the Gulf of Mexico Fisheries Management Council. Our method allows us to provide the largest possible data set for these key species at the broadest geographical scale possible, collected using a type of gear that offers selectivity not matched in breadth by the other available independent data sets for the region (Christiansen et al., 2020). These methods have been presented, reviewed by fishery-assessment panels, and, for several reef species, incorporated into SEDAR models (Thompson et al., 2017, 2018, 2019).

Although the analytical approach developed in the current study proved effective in combining data from multiple surveys into a single population index, the utility of and confidence in these methods could be improved upon through several future considerations. Overall, the CART method performed well in handling the complex habitat data available, and the shared habitat variables generated through CART analyses universally improved model fits. However, there were several instances where, for a particular combination of survey and species, the model was unable to differentiate all three habitat levels. It is unclear whether these instances resulted from inherent properties of the design of specific surveys, or perhaps habitat preferences or general sparseness of available data for a particular species. As this time series matures and additional data become available it is possible that species-habitat relationships will become better defined and these issues will resolve themselves. Regardless, we suggest that results from future analyses for these species be critically reviewed to ensure that any changes evident in CART results to not have unexpected consequences to final index results. Another important consideration when combining data among surveys is how to appropriately account for variability in size composition. Often, size composition from multiple data sources is accomplished through the fitting of multinomial models (Walter et al., 2020), although survey weighting approaches have also been used (Thompson et al., 2020). Future efforts should focus on evaluating whether the survey and habitat weighting protocols developed in the present study can be extended to combine size-composition data, and how these results compare to more traditional methods.

While our primary objective in developing this method was to streamline fishery-independent data inputs for reef-fish stock assessments, the resultant indices of abundance have applicability that extends well beyond stock assessment. The eastern Gulf supports a range of species with unique life histories that support diverse commercial and recreational fisheries in several states. Furthermore, environmental phenomena, such as red tides, hurricanes, emergences of invasive species such as lionfish (*Pterois* spp.), and population responses to habitat changes should be considered in evaluations of fishery dynamics and management. Given this faunal and environmental diversity, data sets combining geographic and habitat data for all the eastern Gulf can provide greater insight into population-level status and distribution than can individual, smaller-scale surveys, which can exhibit localized trends that can differ markedly from those evident at the regional level (Nye et al., 2010).

Our methodology can also be applied to other regions, systems, and ecological questions. Compared with many fishery surveys, we are data rich, given our large sample sizes, extensive mapping, and detailed video descriptions of habitat for several key managed species. Given the importance of evaluating habitat metrics, these methods are most appropriately applied to surveys that can characterize sites beyond location and depth. Also, this method is limited to variation in survey spatial footprint and time series and does not consider differences in selectivity among gear types. Future work with this method will include linking survey sites between artificial and natural reefs, as artificial reefs have recently begun to be sampled in these surveys and are of regional interest because they may be key to the abundance of fishery species, but because these habitats have existed in the region for only a relatively short time, they have not been addressed here.

Though helpful, the indices developed here and their value to stock assessments and ecological insight can be improved further with a truly singular, appropriately stratified-random design. Work has begun to integrate such dimensions into survey designs, thereby more thoroughly and more consistently sampling the eastern Gulf. These efforts will contribute to our goal of using fishery-independent data to determine population trends in the region and to address newly emerging ecological questions regarding reef-fish species.

CRediT authorship contribution statement

Kevin Thompson: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Theodore Switzer:** Conceptualization, Data curation, Supervision, Writing – review & editing. **Mary Christman:** Methodology, Software, Formal analysis, Writing – review & editing. **Sean Keenan:** Investigation, Data curation. **Christopher Gardner:** Investigation, Data curation, Writing – review & editing. **Katherine Overly**: Investigation, Data curation, Writing – review & editing. **Matt Campbell:** Investigation, Data curation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work required significant field and video analyses by a large team of researchers from multiple institutions. At FWRI, they include many staff who generated data, with significant thanks to the video leadership team of Sheri Parks, Amanda Tyler-Jedlund, Brett Pittinger, Noelle Roman, and Jen Herting. At Panama City, they include Reef Fish Survey team members Isabella Masarik and Amanda Ravas and former team leader Doug DeVries. SRFV work includes contributions from Brandi Noble, Joseph Salisbury, Paul Felts and Kevin Rademacher. This work was completed using a variety of vessels and captains with significant support from R/V *Gulf Mariner* (captains: B. Heagey, B. Cassels, and A. Farmer), NMFS vessels R/Vs *Crosswinds* (captain: M. Raffield), *Pisces, Caretta,* and *Southern Journey*. We thank FWC scientists Doug Adams and Shanae Allen and two anonymous reviewers for thoughtful insight and comments on this manuscript.

Funding for this project was from National Fish and Wildlife Foundation (grant numbers FL 40624, FL 45766, FL 50347, FL and 58101), the U.S. Department of Commerce, National Oceanic and Atmospheric Administration (NOAA), National Marine Fisheries Service (grant number NA09NMF4330152), NOAA's Restore Science Program (grant number NA19NOS4510192), NOAA's SEAMAP (NA11, NA16), U.S. Department of the Interior, U.S. Fish and Wildlife Service, Federal Aid for Sportfish Restoration (grant numbers F14AF00328, F15AF01222, F16AF00898, F17AF00932, and F18AF00665) and proceeds from State of Florida saltwater fishing license sales. The statements, findings, views, conclusions, and recommendations contained in this document are those of the authors, do not necessarily reflect the views of the U.S. Department of Commerce, and should not be interpreted as representing

the opinions or policies of the U.S. government. The mention of trade names or commercial products does not constitute their endorsement by the U.S. government. There is no conflict of interest declared in this article.

Appendix A

See Appendix Fig. A1. – A11.

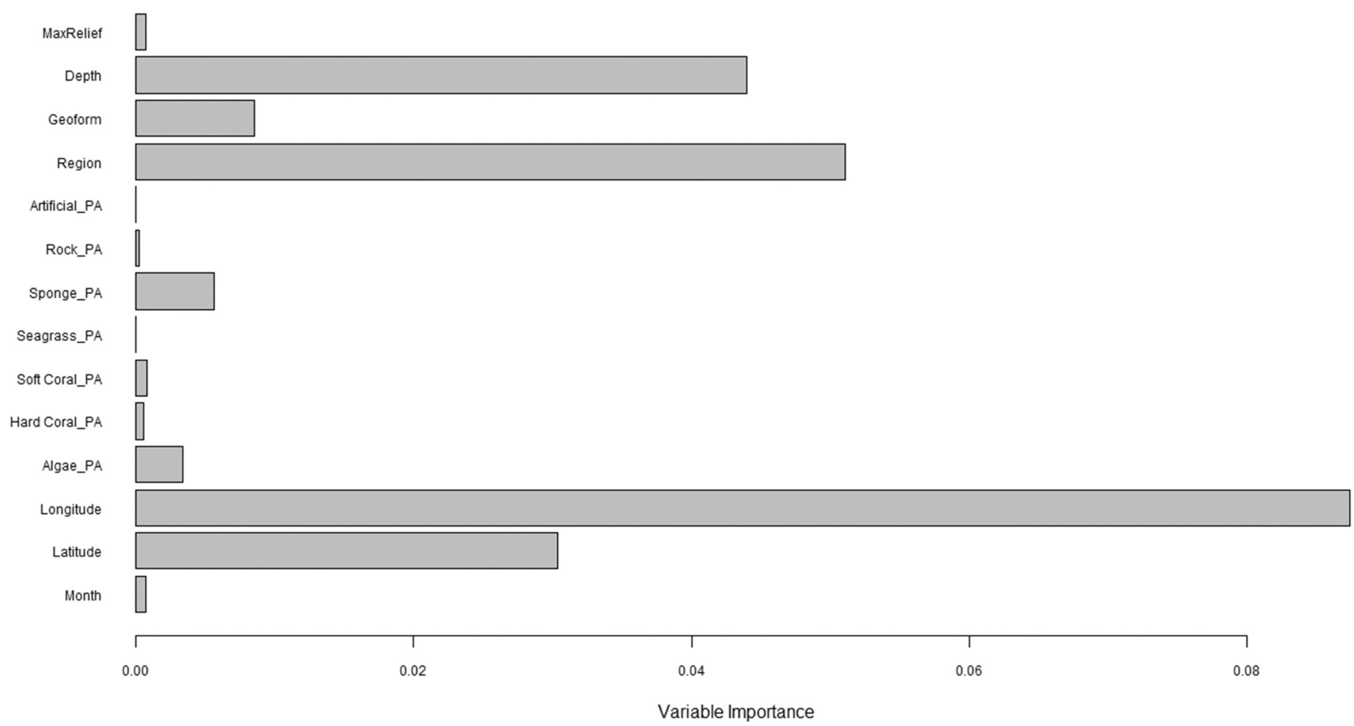

Fig. A1. Variable-importance ranking from random forest analysis before fitting the final CART habitat model for red snapper with PC data.

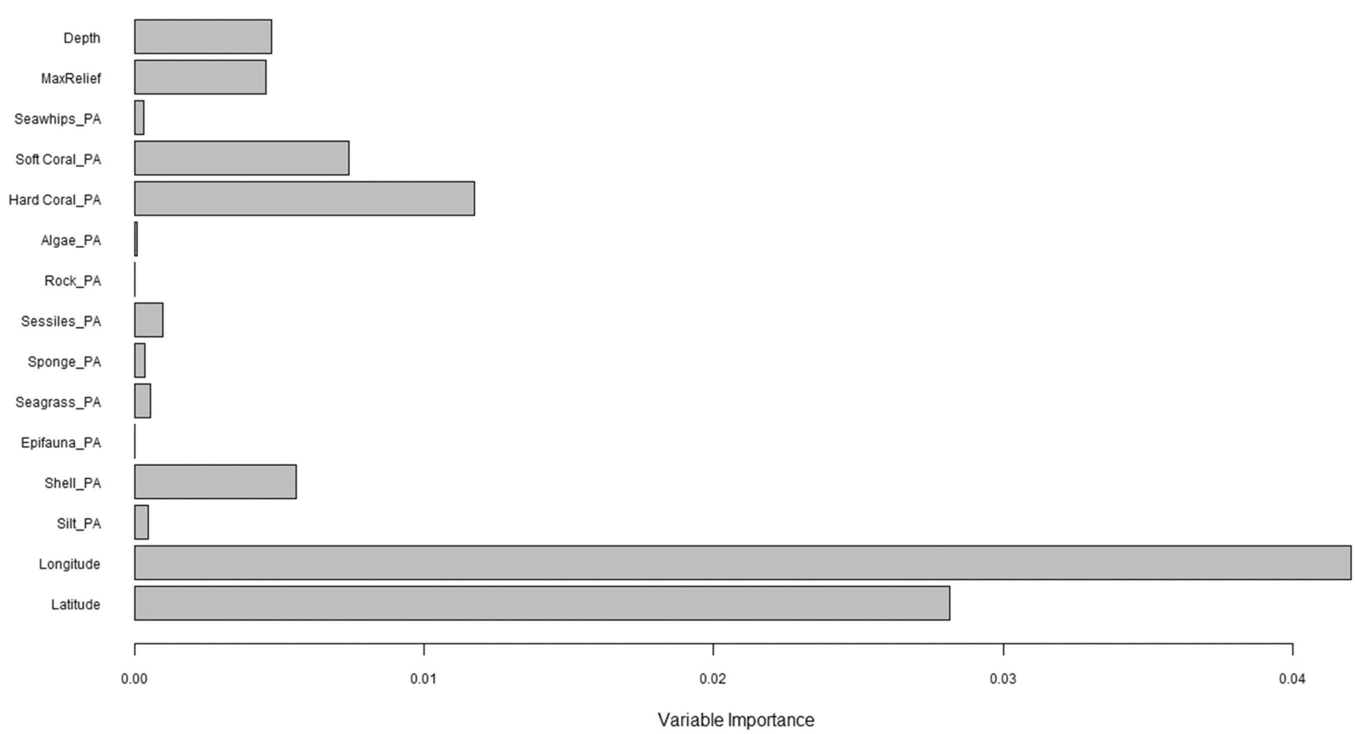

Fig. A2. Variable-importance ranking from random forest analysis before fitting the final CART habitat model for red snapper with SRFV data.

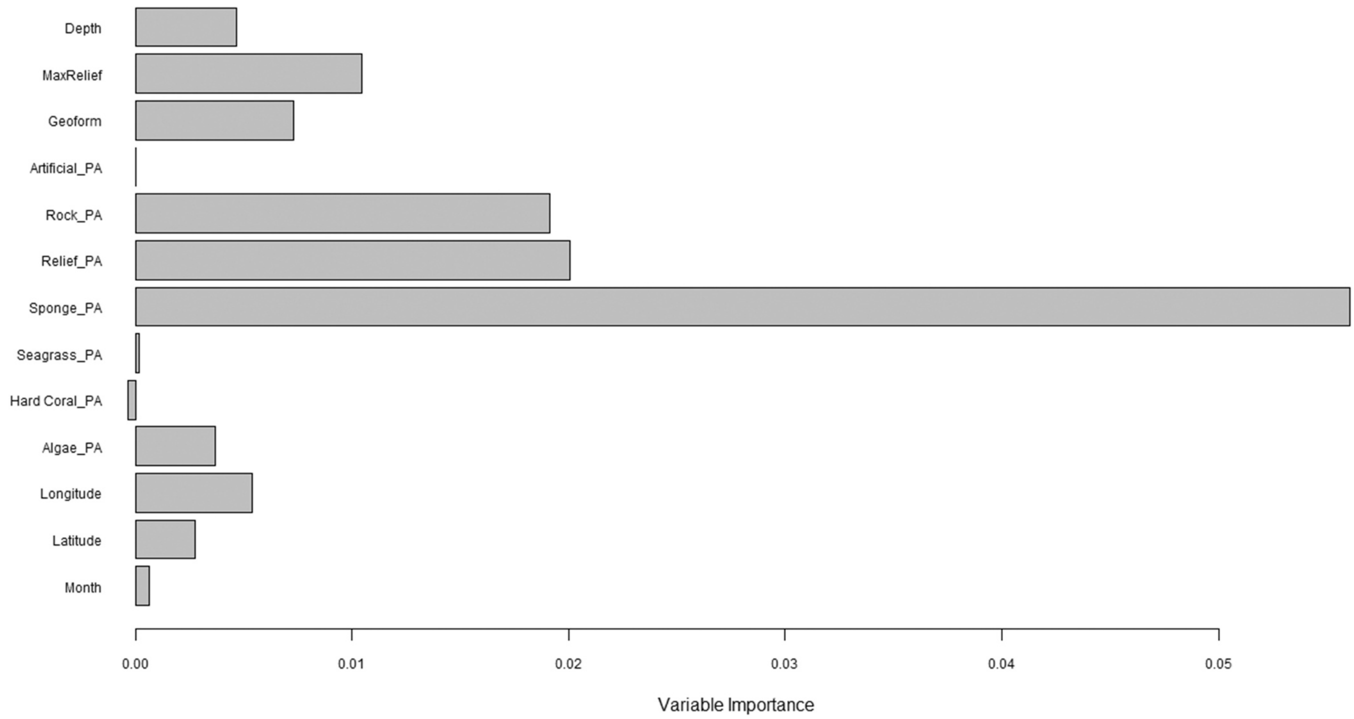

Fig. A3. Variable-importance ranking from random forest analysis before fitting the final CART habitat model for red grouper with FWRI data.

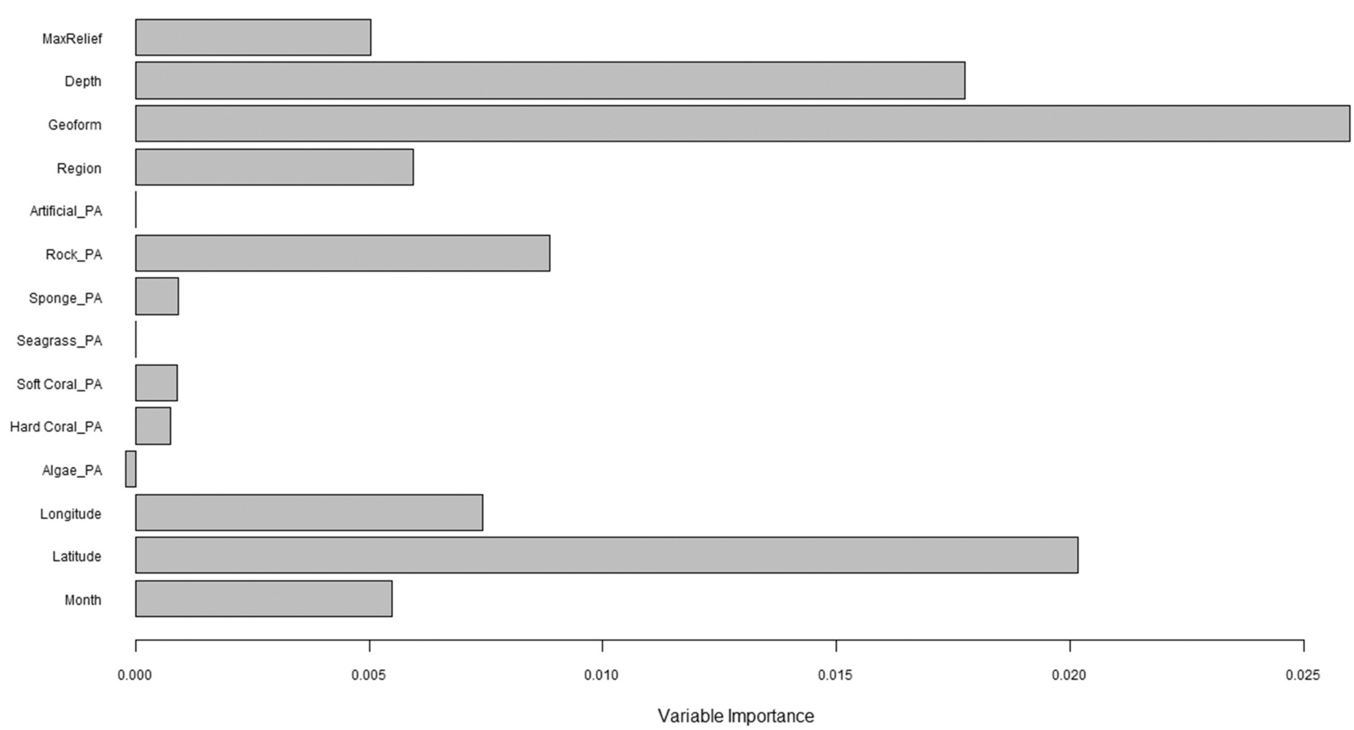

Fig. A4. Variable-importance ranking from random forest analysis before fitting the final CART habitat model for red grouper with PC data.

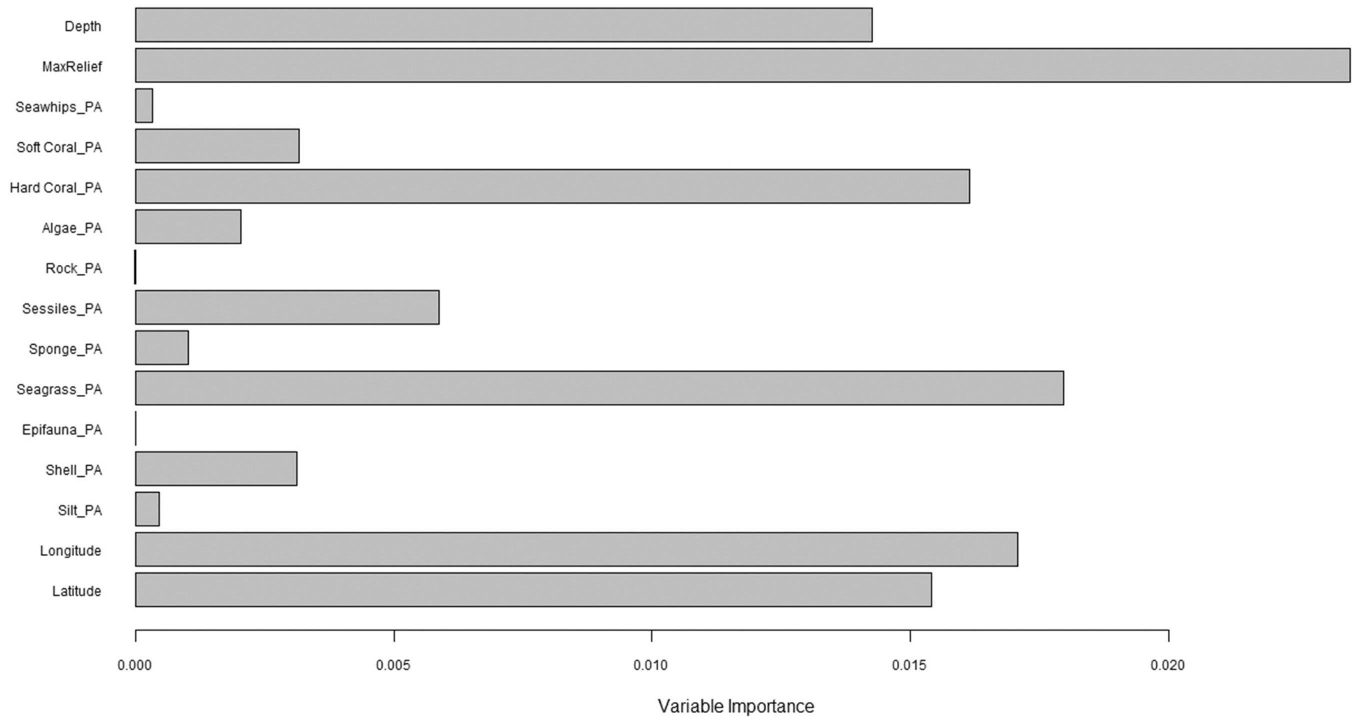

Fig. A5. Variable-importance ranking from random forest analysis before fitting the final CART habitat model for red grouper with SRFV data.

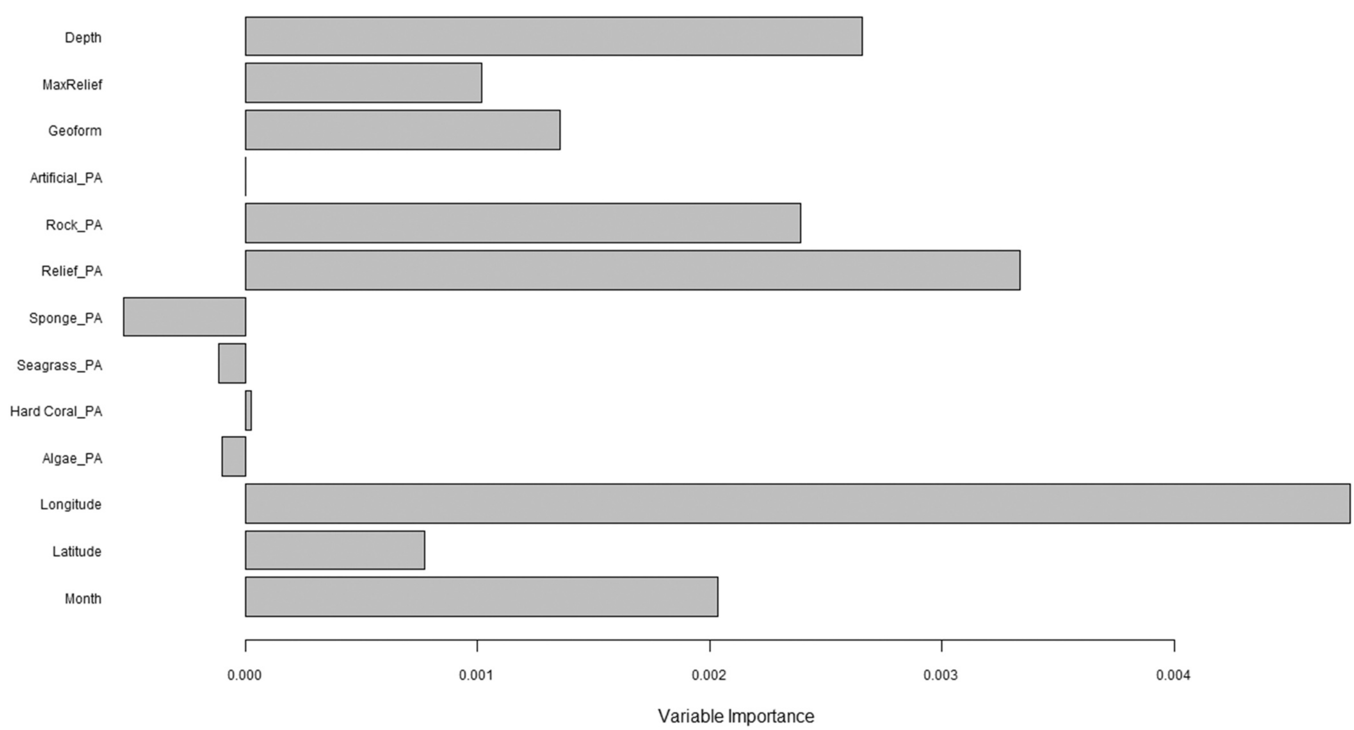

Fig. A6. Variable-importance ranking from random forest analysis before fitting the final CART habitat model for gray triggerfish with FWRI data.

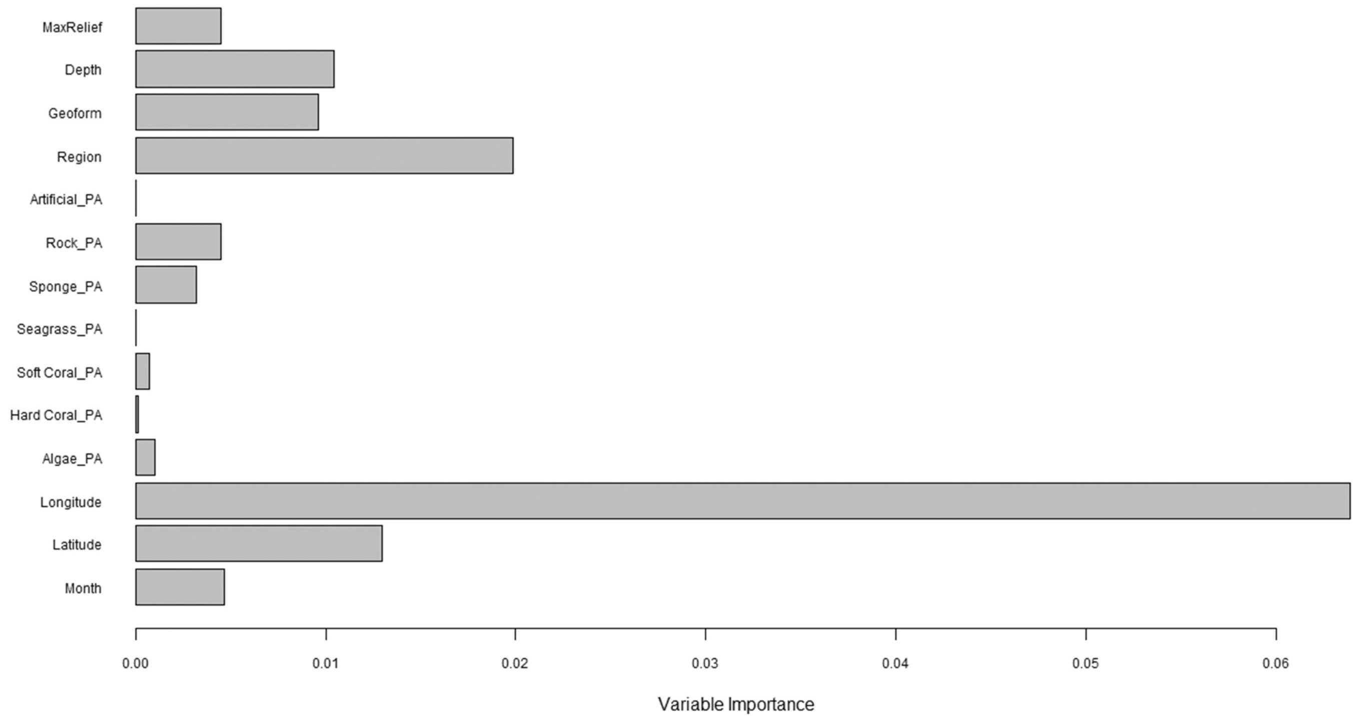

Fig. A7. Variable-importance ranking from random forest analysis before fitting the final CART habitat model for gray triggerfish with PC data.

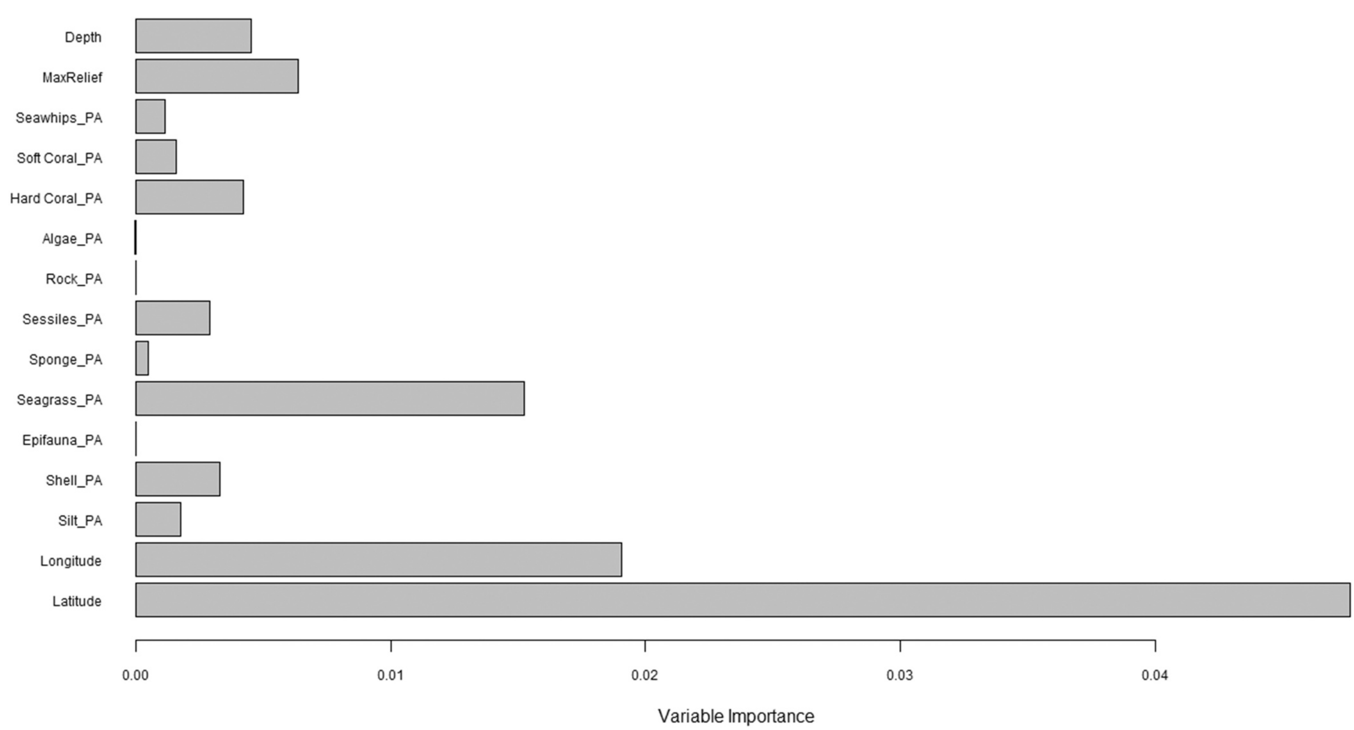

Fig. A8. Variable-importance ranking from random forest analysis before fitting the final CART habitat model for gray triggerfish with SRFV data.

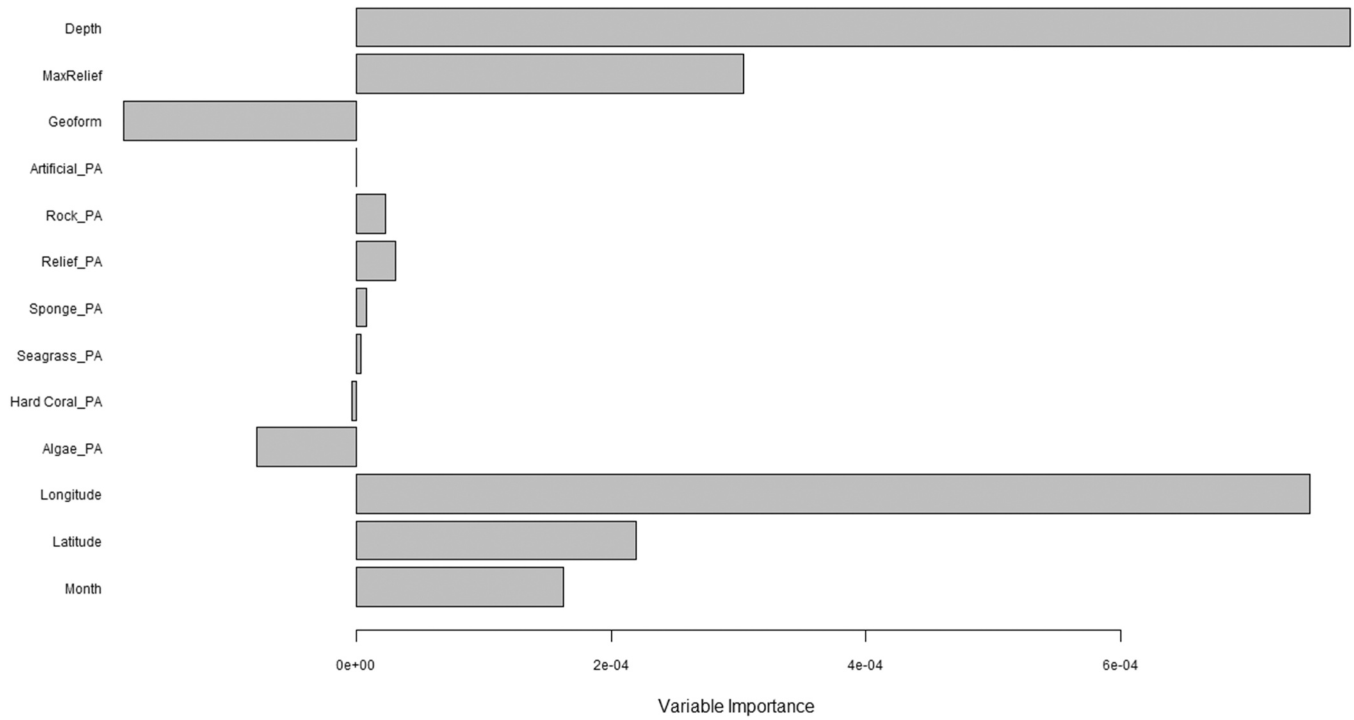

Fig. A9. Variable-importance ranking from random forest analysis before fitting the final CART habitat model for gag with FWRI data.

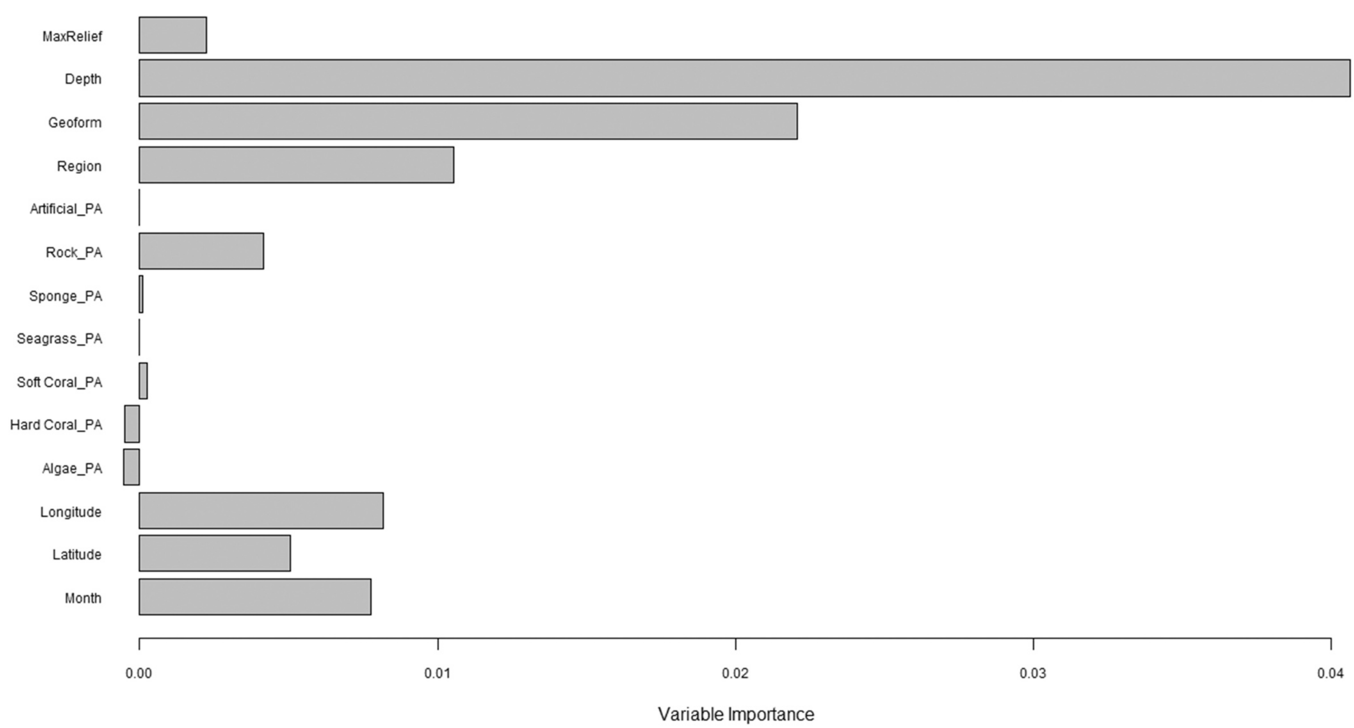

Fig. A10. Variable-importance ranking from random forest analysis before fitting the final CART habitat model for gag with PC data.

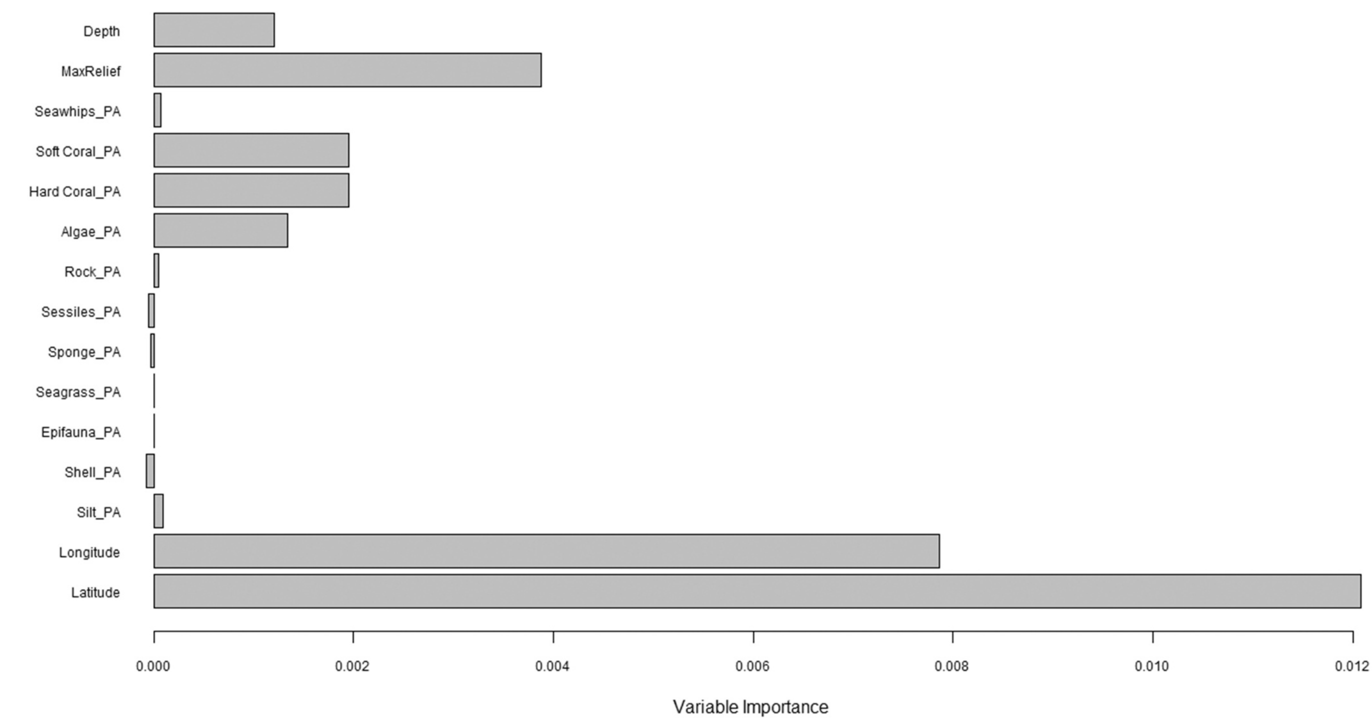

Fig. A11. Variable-importance ranking from random forest analysis before fitting the final CART habitat model for gag with SRFV data.

Appendix B

See Appendix Fig. B1. – B11.

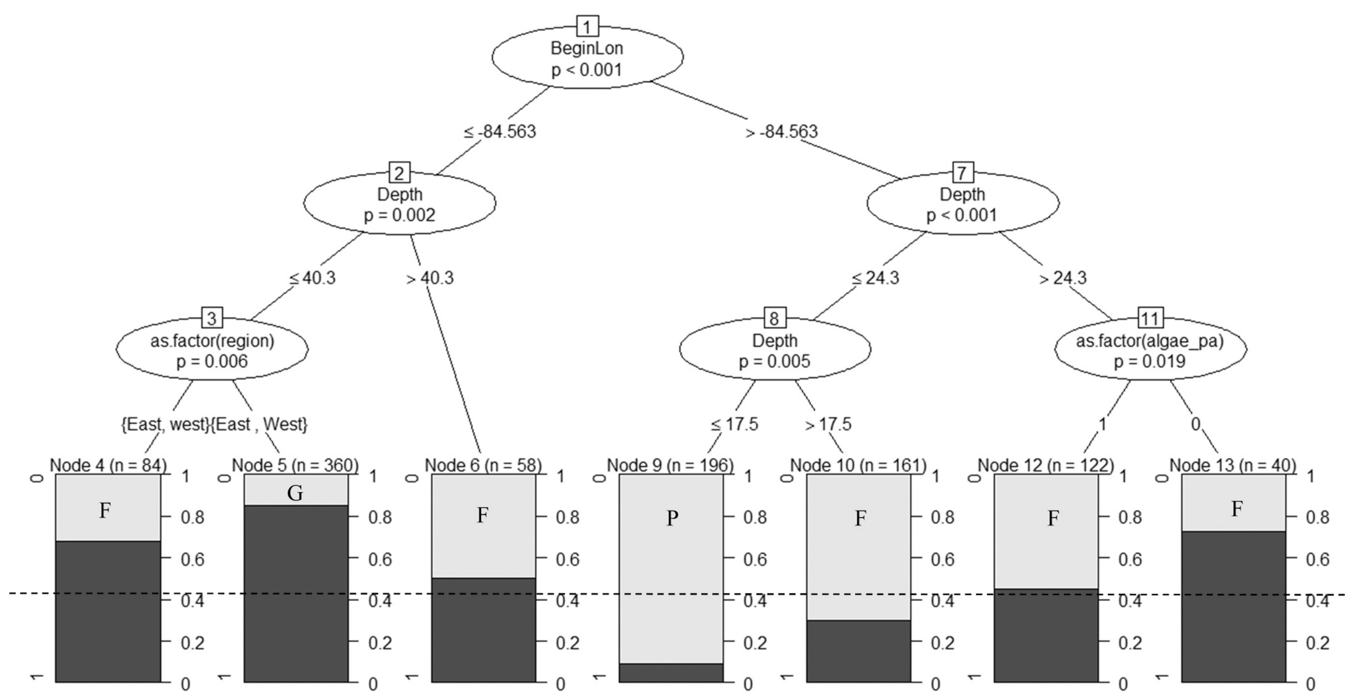

Fig. B1. Final CART model for red snapper for PC data. Nodes indicate the proportion of sites given by criteria that had at least one red snapper present. Sample size of video sites that met the criteria are shown above the bar graph.

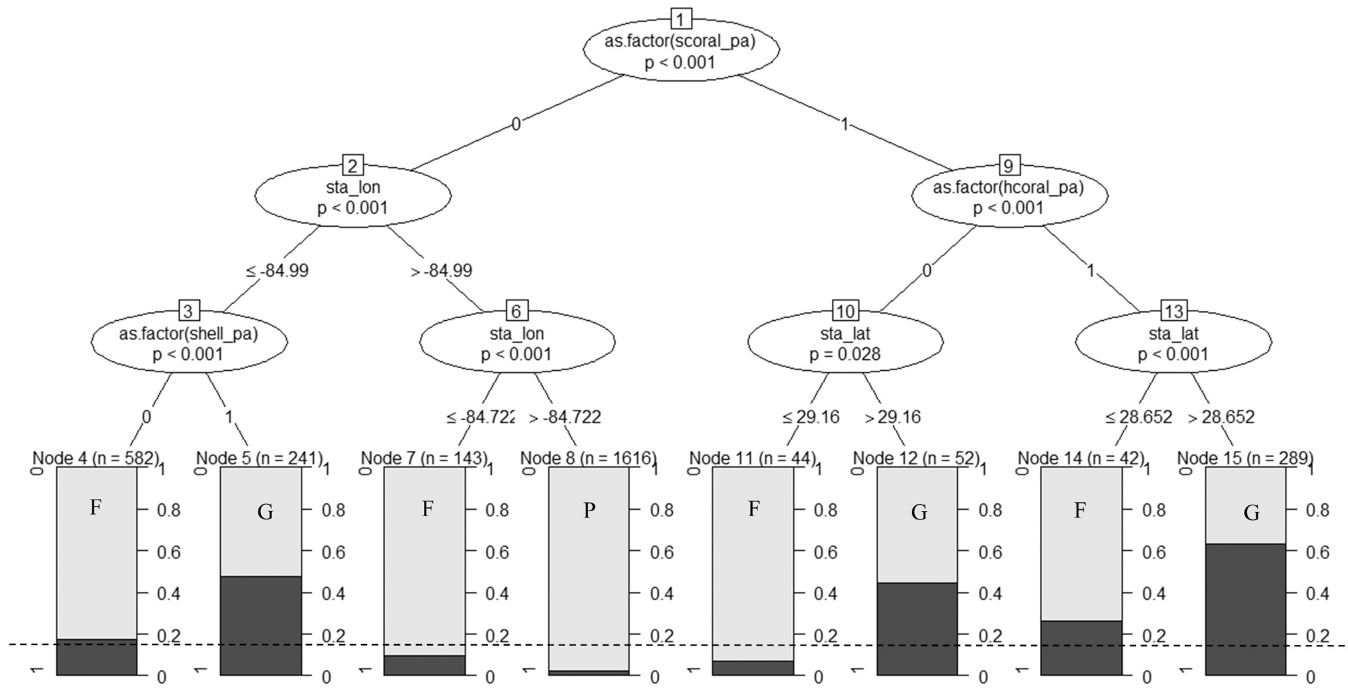

Fig. B2. Final CART model for red snapper for SRFV data. Nodes indicate the proportion of sites given by criteria that had at least one red snapper present. Sample size of video sites that met the criteria are shown above the bar graph.

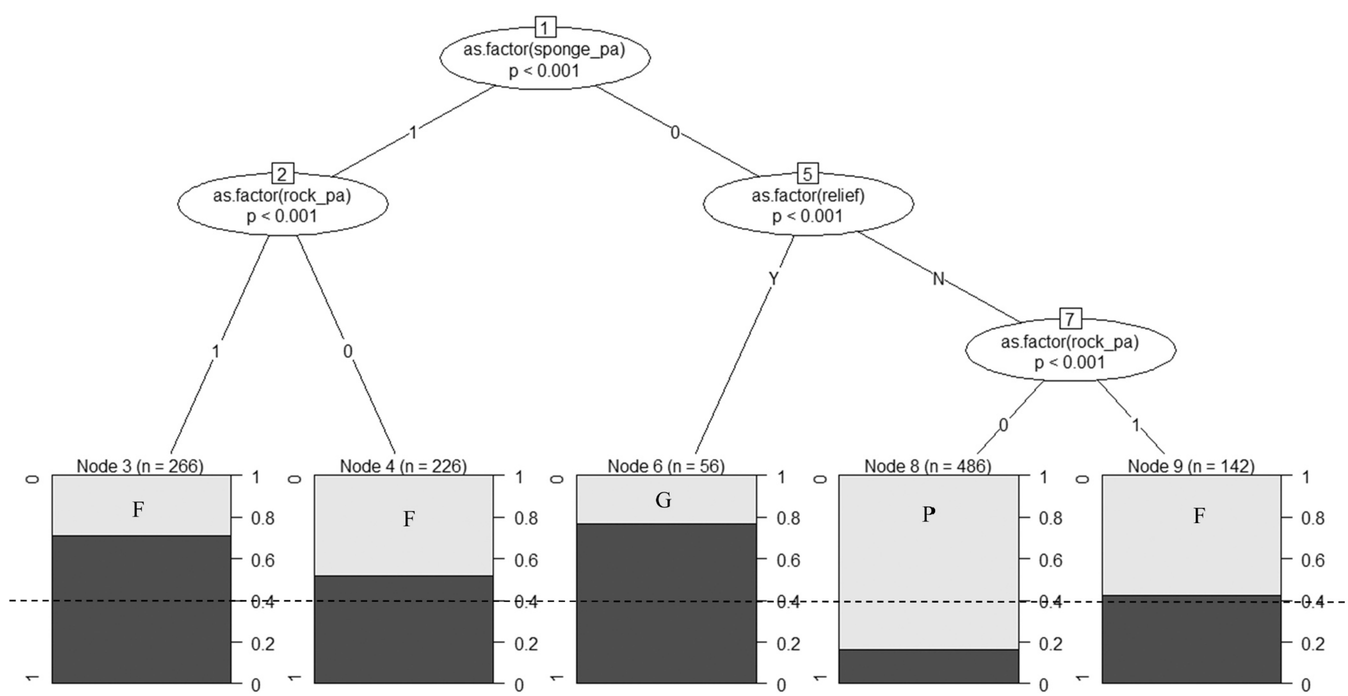

Fig. B3. Final CART model for red grouper for FWRI data. Nodes indicate the proportion of sites given by criteria that had at least one red grouper present. Sample size of video sites that met the criteria are shown above the bar graph.

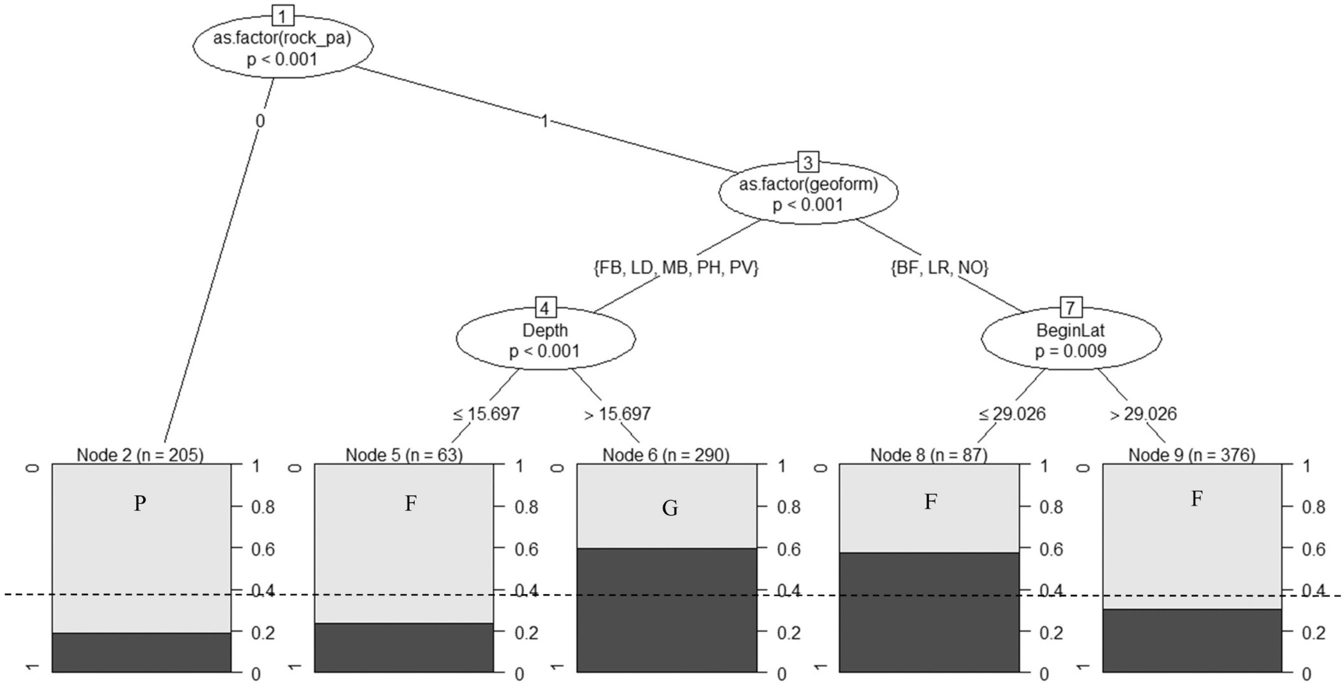

Fig. B4. Final CART model for red grouper for PC data. Nodes indicate the proportion of sites given by criteria that had at least one red grouper present. Sample size of video sites that met the criteria are shown above the bar graph.

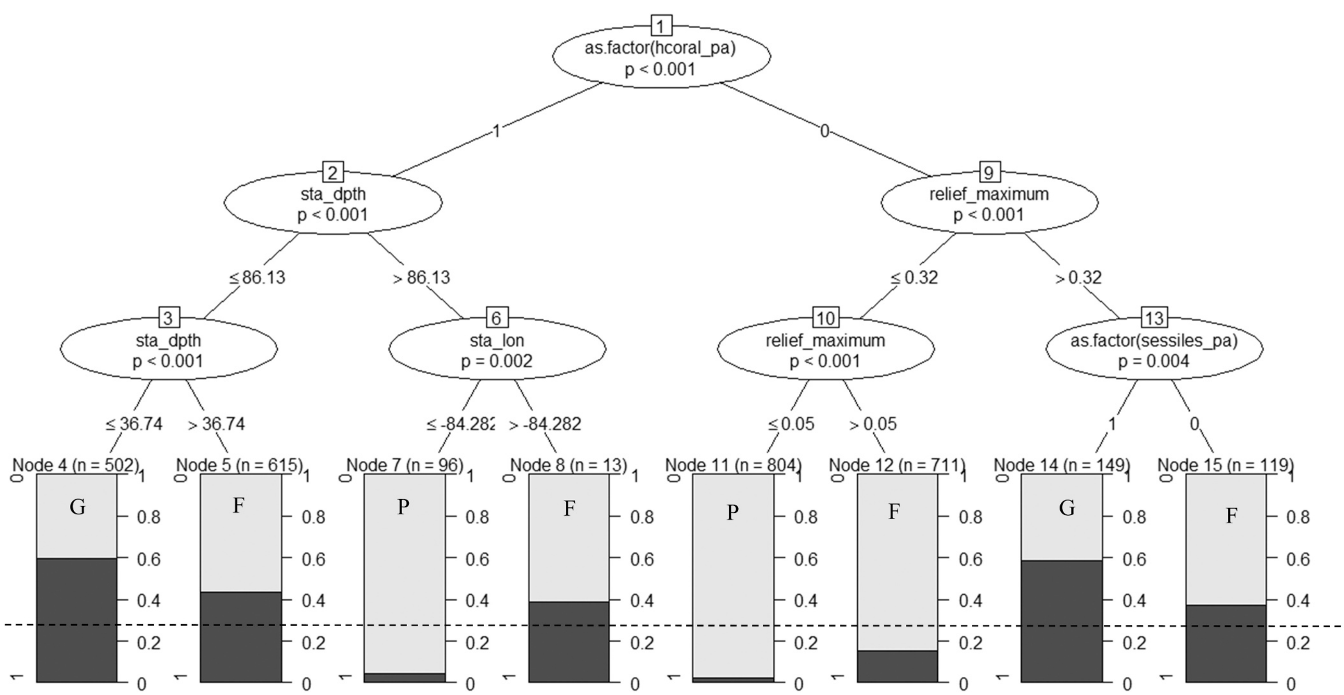

Fig. B5. Final CART model for red grouper for SRFV data. Nodes indicate the proportion of sites given by criteria that had at least one red grouper present. Sample size of video sites that met the criteria are shown above the bar graph.

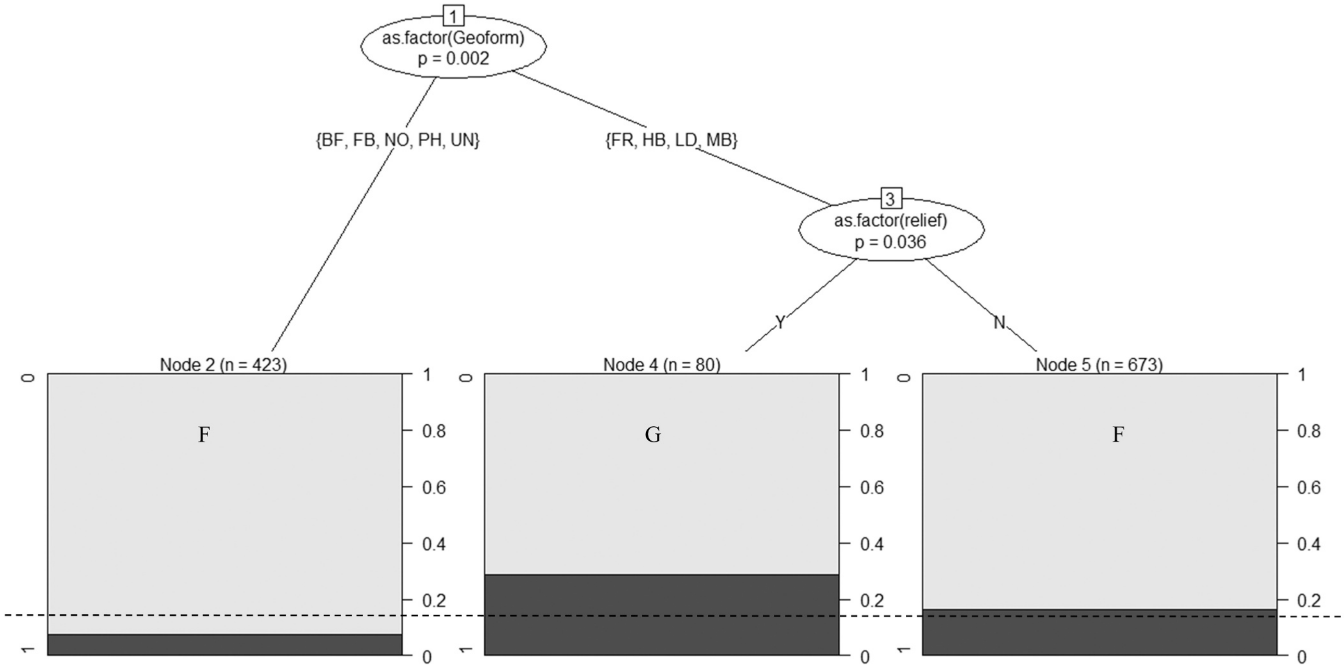

Fig. B6. Final CART model for gray triggerfish for FWRI data. Nodes indicate the proportion of sites given by criteria that had at least one gray triggerfish present. Sample size of video sites that met the criteria are shown above the bar graph.

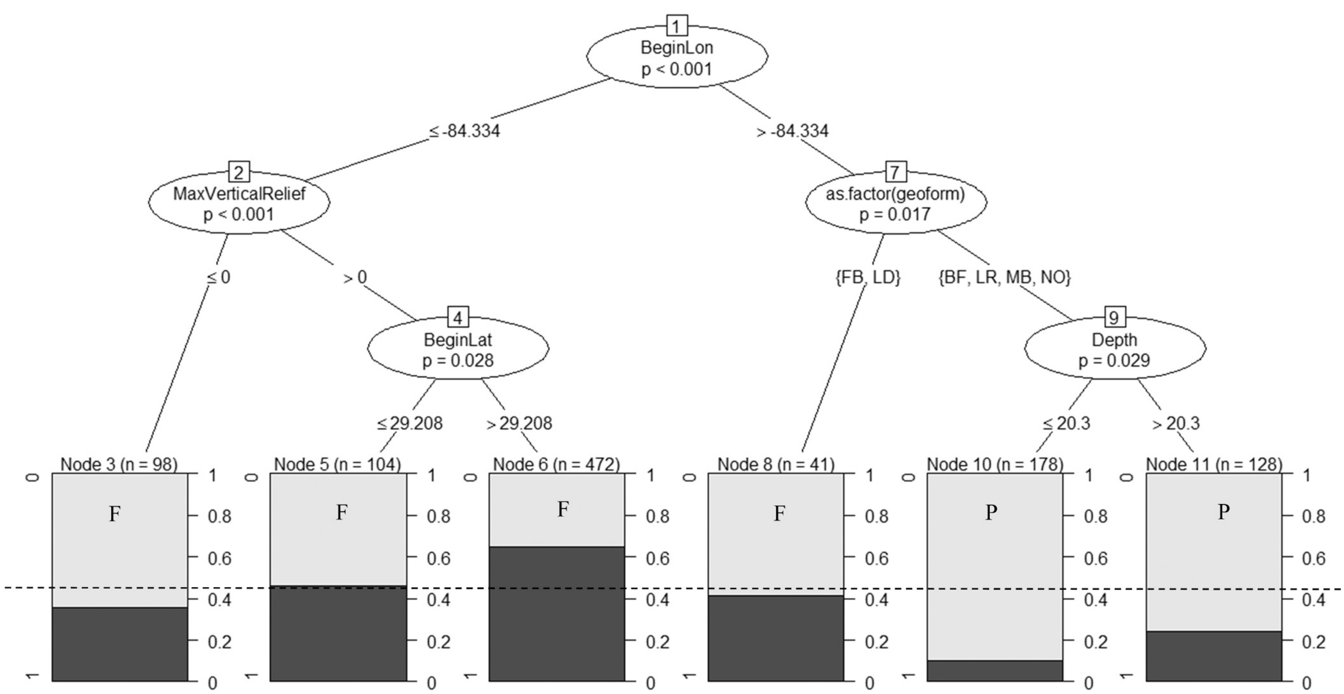

Fig. B7. Final CART model for gray triggerfish for PC data. Nodes indicate the proportion of sites given by criteria that had at least one gray triggerfish present. Sample size of video sites that met the criteria are shown above the bar graph.

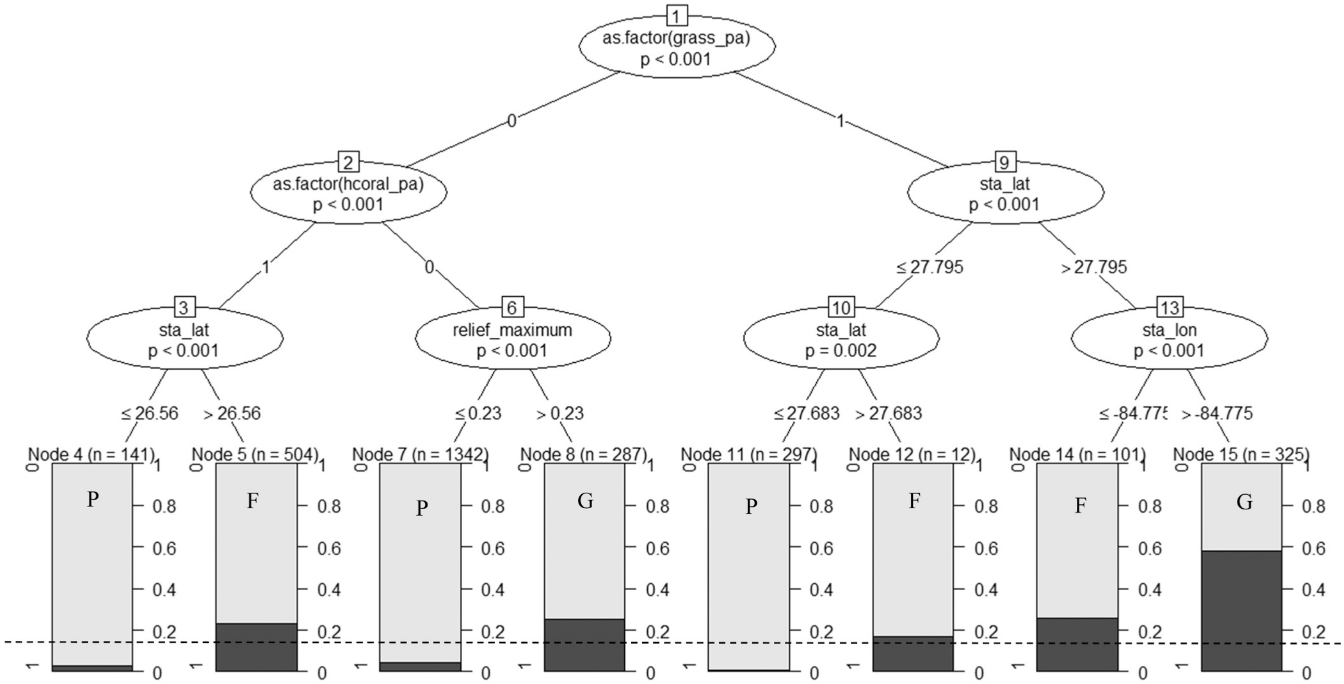

Fig. B8. Final CART model for gray triggerfish for SRFV data. Nodes indicate the proportion of sites given by criteria that had at least one gray triggerfish present. Sample size of video sites that met the criteria are shown above the bar graph.

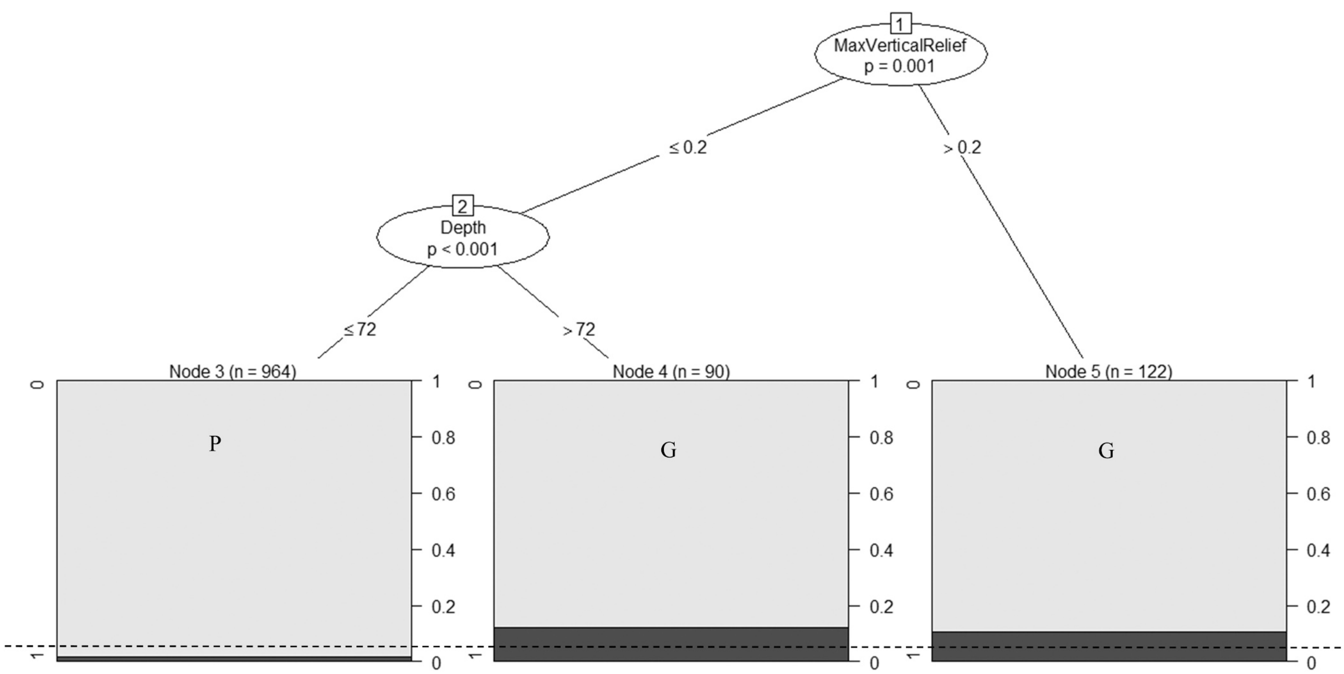

Fig. B9. Final CART model for gag for FWRI data. Nodes indicate the proportion of sites given by criteria that had at least one gag present. Sample size of video sites that met the criteria are shown above the bar graph.

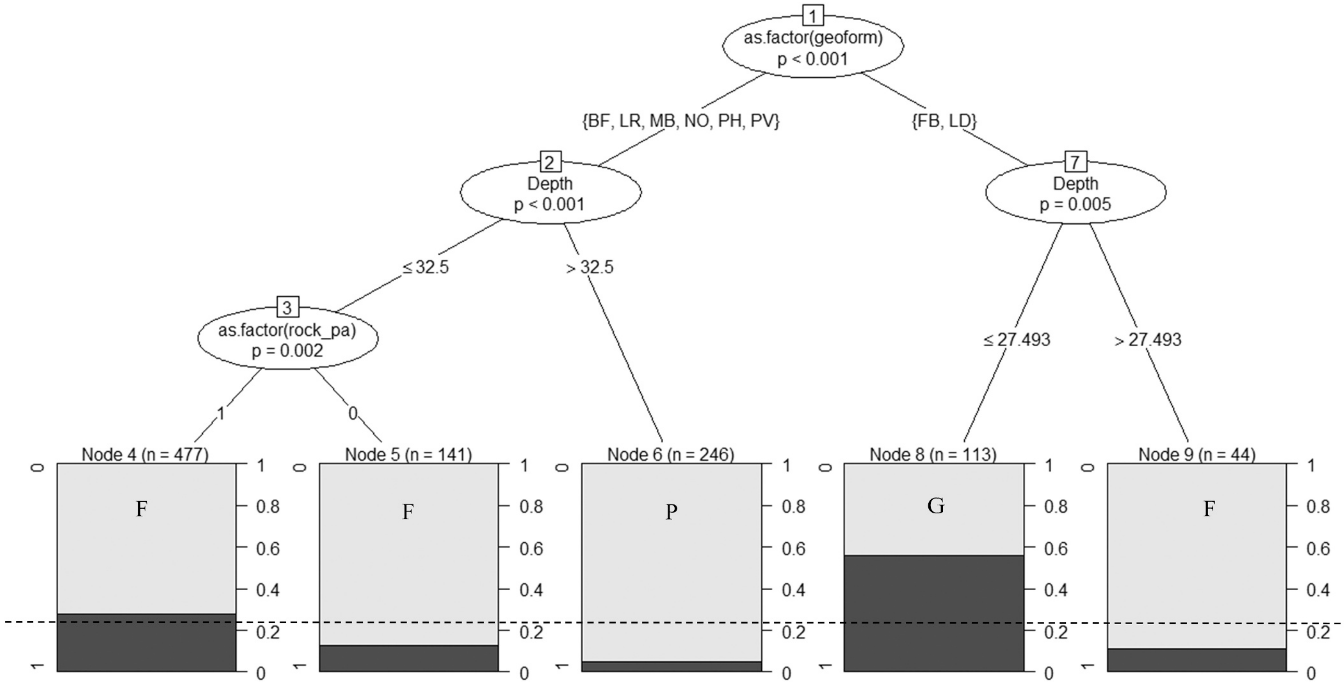

Fig. B10. Final CART model for gag for PC data. Nodes indicate the proportion of sites given by criteria that had at least one gag present. Sample size of video sites that met the criteria are shown above the bar graph.

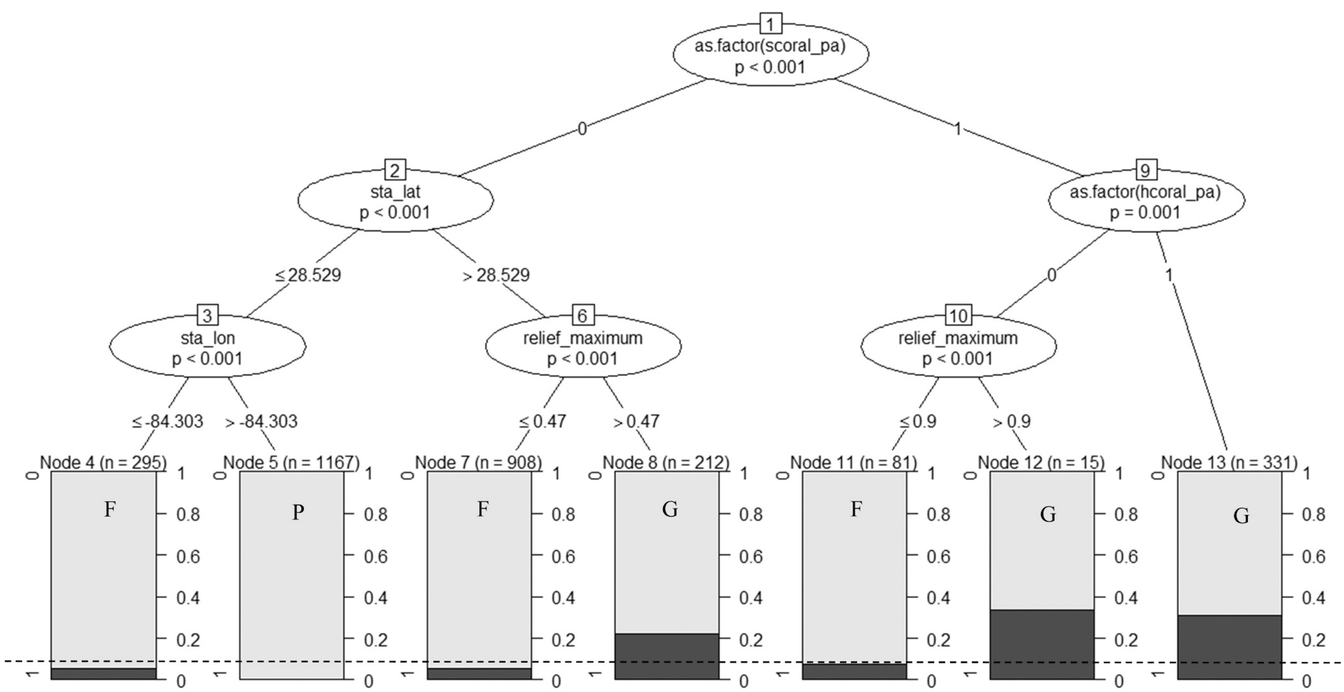

Fig. B11. Final CART model for gag for SRFV data. Nodes indicate the proportion of sites given by criteria that had at least one gag present. Sample size of video sites that met the criteria are shown above the bar graph.

References

Campbell, M.D., Pollack, A.G., Gledhill, C.T., Switzer, T.S., DeVries, D.A., 2015. Comparison of relative abundance indices calculated from two methods of generating video count data. Fish. Res. 170, 125–133. https://doi.org/10.1016/j.fishres.2015.05.011.

Campbell, R.A., 2004. CPUE standardisation and the construction of indices of stock abundance in a spatially varying fishery using general linear models. Fish. Res. 70, 209–227. https://doi.org/10.1016/j.fishres.2004.08.026.

Campbell, M.D., Rademacher, K.R., Hendon, M., Felts, P., Noble, B., Felts, M., Salisbury, Moser, J., 2014. SEAMAP reef fish video survey: relative indices of abundance of Red Grouper. SEDAR 42. North Charleston, SC. http://sedarweb.org/docs/wpapers/S42_DW_11_SEAMAP_video_index.pdf.

Christiansen, H.M., Switzer, T.S., Keenan, S.F., Tyler-Jedlund, A.J., Winner, B.L., 2020. Assessing the relative selectivity of multiple sampling gears for managed reef fishes in the eastern Gulf of Mexico. Mar. Coast. Fish. 12, 322–338. https://doi.org/10.1002/mcf2.10129.

Conn, P.B., 2010. Hierarchical analysis of multiple noisy abundance indices. Can. J. Fish. Aquat. Sci. 67, 108–120. https://doi.org/10.1139/F09-175.

R. Core Team. 2008. R: a language and environment for statistical computing. Vienna, Austria.

De'ath, G., Fabricius, K.E., 2000. Classification and regression trees: a powerful yet simple technique for ecological data analysis. Ecology 81 (11), 3178–3192.

Devries, A., Gardner, L., Raley, P., Ingram, W., 2014. Red grouper Epinephelus morio findings from the NMFS Panama City laboratory trap & camera fishery-independent survey 2004–2014. SEDAR 42. North Charlston, SC. http://sedarweb.org/docs/wpapers/S42_DW_15_PC_%20trap_video.pdf.

Gardner, C.L., Overly, K.E., 2018. Red grouper Epinephelus morio findings from the NMFS Panama City laboratory trap & camera fishery independent survey 2004–2017. SEDAR 61. North Charlston, SC. http://sedarweb.org/docs/wpapers/S61_WP_01_PC%20Reef%20camera%20survey.pdf.

Geers, T.M., Pikitch, E.K., Frisk, M.G., 2016. An original model of the northern Gulf of Mexico using Ecopath with Ecosim and its implications for the effects of fishing on ecosystem structure and maturity. Deep. Res. Part II Top. Stud. Oceano 129, 319–331. https://doi.org/10.1016/j.dsr2.2014.01.009.

Grüss, A., Perryman, H.A., Babcock, E.A., Sagarese, S.R., Thorson, J.T., Ainsworth, C.H., Anderson, E.J., Brennan, K., Campbell, M.D., Christman, M.C., Cross, S., Drexler, M. D., Drymon J., M., Gardner, C.L., Hanisko, D.S., Hendon, J., Koenig, C.C., Love, M., Martinez-Andrade, F., Morris, J., Noble, B.T., Nuttall, M.A., Osborne, J., Pattengill-Semmens, C., Pollack, A.G., Sutton, T.T., Switzer, T.S., 2018. Monitoring programs of the U.S. Gulf of Mexico: inventory, development and use of a large monitoring database to map fish and invertebrate spatial distributions. Rev. Fish. Biol. Fish. 28, 667–691. https://doi.org/10.1007/s11160-018-9525-2.

Gunther, C.B., Switzer, T.S., Keenan, S.F., McMichael, R.H. J., 2014. Indices of abundance for red grouper (Epenephelus morio) from the Florida Fish and Wildlife Research Institute (FWRI) video survey on the West Florida Shelf. SEDAR 42. North Charlston, SC. http://sedarweb.org/docs/wpapers/S42_DW_08_FWRI_viedo_index.pdf.

Gwinn, D.C., Bacheler, N.M., Shertzer, K.W., 2019. Integrating underwater video into traditional fisheries indices using a hierarchical formulation of a state–space model. Fish. Res. 219, 105309 https://doi.org/10.1016/j.fishres.2019.105309.

Harvey, E.S., Newman, S.J., McLean, D.L., Cappo, M., Meeuwig, J.J., Skepper, C.L., 2012. Comparison of the relative efficiencies of stereo-BRUVs and traps for sampling tropical continental shelf demersal fishes. Fish. Res. 125–126, 108–120. https://doi.org/10.1016/j.fishres.2012.01.026.

Helser, T.E., Punt, A.E., Methot, R.D., 2004. A generalized linear mixed model analysis of a multi-vessel fishery resource survey. Fish. Res. 70, 251–264. https://doi.org/10.1016/j.fishres.2004.08.007.

Hothorn, T., Hornik, K., Zeileis, A., 2006. Unbiased recursive partitioning: a conditional inference framework. Research Report Series 8, Department of Statistics and Mathematics, WU Wien, 2004. J. Comput. Graph. Stat. 15, 651–674. https://doi.org/10.1198/106186006×133933.

Karnauskas, M., Kelble, C.R., Regan, S., Quenée, C., Allee, R., Jepson, M., Freitag, A., Craig, J.K., Carollo, C., Barbero, L., 2017. 2017 Ecosystem Status Report Update for the Gulf of Mexico. NOAA Technical Memorandum NMFS-SEFSC-706. U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Marine Fisheries Service Southeast Fisheries Science Center, Miami, FL.

Keenan, S.F., Switzer, T.S., Thompson, K.A., Tyler-Jedlund, A.J., Knapp, A.R., 2018. Comparison of reef-fish assemblages between artificial and geologic habitats in the northeastern Gulf of Mexico: implications for fishery-independent surveys. Am. Fish. Soc. Symp. 86, 141–163.

Lindberg, W.J., Christman, M.C., Marcinek, D.M., 2013. Fishery-independent indices of abundance for gag (Mycteroperca microlepis) in the northeastern Gulf of Mexico, with intrinsic habitat quality controlled and contrasted. SEDAR33. North Charleston, SC.

MacCall, A.D., 1990. Dynamic geography of marine fish populations. Books in recruitment fishery oceanography. Univ. Washington Press, Seattle, U.S., p. 163

Maunder, M.N., Punt, A.E., 2004. Standardizing catch and effort data: a review of recent approaches. Fish. Res. 70, 141–159. https://doi.org/10.1016/j.fishres.2004.08.002.

de Mutsert, K., Cowan, J.H., Essington, T.E., Hilborn, R., 2008. Reanalyses of Gulf of Mexico fisheries data: landings can be misleading in assessments of fisheries and fisheries ecosystems. Proc. Natl. Acad. Sci. 105, 2740–2744. https://doi.org/10.1073/pnas.0704354105.

Nye, J.A., Bundy, A., Shackell, N., Friedland, K.D., Link, J.S., 2010. Coherent trends in contiguous survey time-series of major ecological and commercial fish species in the Gulf of Maine ecosystem. ICES J. Mar. Sci. 67, 26–40. https://doi.org/10.1093/icesjms/fsp216.

Peterson, C.D., Belcher, C.N., Bethea, D.M., Driggers, W.B., Frazier, B.S., Latour, R.J., 2017. Preliminary recovery of coastal sharks in the south-east United States. Fish 18, 845–859. https://doi.org/10.1111/faf.12210.

Pollack, A.G., Ingram, G.W., 2014. Red grouper abundance indices from SEAMAP groundfish surveys in the northern Gulf of Mexico. SEDAR 42. North Charleston, SC.

Rotherham, D., Underwood, A.J., Chapman, M.G., Gray, C.A., 2007. A strategy for developing scientific sampling tools for fishery-independent surveys of estuarine fish in New South Wales, Australia. ICES J. Mar. Sci. 64, 1512–1516. https://doi.org/10.1093/icesjms/fsm096.

SEDAR. 2015c. SEDAR 43 Gulf of Mexico Gray Triggerfish Stock Assessment Report. North Charleston, SC. ⟨http://sedarweb.org/sedar-43-final-stock-assessment-report-gulf-mexico-gray-triggerfish⟩.

SEDAR. 2015b. SEDAR 42 Stock Assessment Report Gulf of Mexico Red Grouper. North Charleston, SC. ⟨http://sedarweb.org/sedar-42-final-stock-assessment-report-gulf-mexico-red-grouper⟩.

SEDAR, 2013. SEDAR 31 – Gulf of Mexico red snapper stock assessment report. North Charleston, SC. ⟨http://sedarweb.org/sedar-31-stock-assessment-report-gulf-mexico-red-snapper⟩.

SEDAR, 2014. SEDAR 33 Gulf of Mexico Gag Stock Assessment Report. North Charleston, SC. ⟨http://sedarweb.org/sedar-33-stock-assessment-report-gulf-mexico-gag-grouper⟩.

SEDAR. 2018. SEDAR 52 Gulf of Mexico Red Snapper Assessment Report. North Charleston, SC. ⟨http://sedarweb.org/sedar-52-gulf-mexico-red-snapper-final-stock-assessment-report⟩.

SEDAR. 2015a. PW7: Data Best Practices. SEDAR Procedural Workshop. North Charleston, SC. http://sedarweb.org/sedar-pw-07-data-best-practices-final-report-sept-2015.

Switzer, T.S., Chesney, E.J., Baltz, D.M., 2015. Habitat use by juvenile red snapper in the northern Gulf of Mexico: ontogeny, seasonality, and the effects of hypoxia. Trans. Am. Fish. Soc. 144, 300–314. https://doi.org/10.1080/00028487.2014.991447.

Switzer, T.S., Tyler-Jedlund, A.J., Keenan, S.F., Weather, E.J., 2020. Benthic habitats, as derived from classification of side-scan-sonar mapping data, are important determinants of reef-fish assemblage structure in the eastern Gulf of Mexico. Mar. Coast. Fish. 12 (1), 21–32.

Thompson, K.A., Switzer, T.S., Christman, M.C., Keenan, S.F., Gardner, C.L., Campbell, M.D., Pollack, A., 2017. Indices of abundance for gray snapper (Lutjanus griseus) using combined data from three independent video surveys SEDAR51. SEDAR. North Charleston, SC. ⟨http://sedarweb.org/docs/wpapers/S51_DW_15_Combined%20video%20survey%20index%20.pdf⟩.

Thompson, K.A., Switzer, T.S., Christman, M.C., Keenan, S.F., Gardner, C.L., Campbell, M.D., 2018. Indices of abundance for red grouper (Epinephelus morio) using combined data from three independent video surveys SEDAR61. SEDAR. North Charleston, SC. http://sedarweb.org/docs/wpapers/S61_WP_03_Combined%20Video%20surveys_v2.pdf.

Thompson, K.A., Switzer, T.S., Christman, M.C., Keenan, S.F., Gardner, C.L., Overly, K.E., Campbell, M.D., 2019. Indices of abundance for gray triggerfish (Balistes capriscus) using combined data from three independent video surveys. SEDAR62. SEDAR. North Charleston, SC. http://sedarweb.org/docs/wpapers/S62_WP_01_combined_video_index.pdf.

Walsh, W.A., Brodziak, J., 2015. Billfish CPUE standardization in the Hawaii longline fishery: model selection and multimodel inference. Fish. Res. 166, 151–162. https://doi.org/10.1016/j.fishres.2014.07.015.

Walter, J.F., Thompson, K.A., Switzer, T.S. 2020. Model-based size composition of vermilion snapper obtained from three visual surveys. SEDAR67. SEDAR. North Charleston, SC.

Walters, C., Martell, S.J.D., 2004. Fisheries Ecology and Management. Princeton University Press, Princeton, NJ.

Watson, D.L., Harvey, E.S., Anderson, M.J., Kendrick, G.A., 2005. A comparison of temperate reef fish assemblages recorded by three underwater stereo-video techniques. Mar. Biol. 148, 415–425. https://doi.org/10.1007/s00227-005-0090-6.

Whitmarsh, S.K., Fairweather, P.G., Huveneers, C., 2017. What is Big BRUVver up to? Methods and uses of baited underwater video. Rev. Fish. Biol. Fish. 27, 53–73. https://doi.org/10.1007/s11160-016-9450-1.

Willis, T.J., Babcock, R.C., 2000. A baited underwater video system for the determination of relative density of carnivorous reef fish. Mar. Freshw. Res. 51, 755–763.

Xiao, Y., Punt, A.E., Millar, R.B., Quinn, T.J., 2004. Models in fisheries research: GLMs, GAMS and GLMMs. Fish. Res. 70, 137–139. https://doi.org/10.1016/j.fishres.2004.08.001.

Yates, K.L., Mellin, C., Caley, M.J., Radford, B.T., Meeuwig, J.J., 2016. Models of marine fish biodiversity: assessing predictors from three habitat classification schemes. PLoS One 11, 1–16. https://doi.org/10.1371/journal.pone.0155634.