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Indices of abundance for Gag (*Mycteroperca microlepis*) using combined data from three independent video surveys

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Introduction

Currently there are three different stationary video surveys for reef fish conducted in the northern Gulf of Mexico (GOM). The NMFS SEAMAP reef fish video survey, carried out by NMFS Mississippi Laboratory (Pascagoula), has the longest running time series (1992-1997, 2002, and 2004+), followed by the NMFS Panama City lab survey (2005+), with the most recent survey being the Florida Fish and Wildlife Research Institute SEAMAP survey (FWRI, starting year 2008). While the surveys use standardized deployment, camera field of view, and fish abundance methods to assess fish abundancies on reef or structured habitat, there are variations in survey design and habitat characteristics collected in addition to the time period and area sampled. Traditionally the surveys have submitted independent indices for each survey, however, combining indices across datasets likely increases predictive capabilities by allowing for the largest possible sample sizes in model fitting. Previous research has indicated that combining data across changing spatial areas and surveys and using a year only model, can yield spurious conclusions regarding stock abundance (Campbell 2004; Ye et al. 2004). As such, we used a habitat-based approach to combine relative abundance data for generating annual trends for Gag (*Mycteroperca microlepis*) throughout the eastern GOM.

Survey Comparisons

Survey design

The MS Labs survey primarily targets high-relief topographic features along the continental shelf from south Texas to south Florida. Sites are selected using a stratified, random design with strata determined by region and total proportion of reef area in a sampling block (10 minute latitude X 10 minute longitude blocks). Sites are selected at random from known reef areas identified through habitat mapping (multi-beam and side-scan sonar). This survey uses the Mississippi river delta as a geographic feature separating the west and east regions of the GOM (Campbell et al. 2017). This index was limited to the eastern portion of the survey due to low to absent catches of Gag in the western region.

The Panama City video survey targets the inner shelf of the northeast GOM. Survey design has changed through time, but since 2010 a two-stage unequal probability design has been used. Blocks are

5 minutes x 5 minutes in size with sites randomly, proportionally allocated by region, sub-region and depth. This survey is broken up into eastern and western regions by Cape San Blas in the Florida Panhandle. Sites are described using side-scanning before video deployment (Gardner et al. 2017).

The FWRI survey initially focused on the regions offshore of Tampa Bay and Charlotte Harbor, FL (NMFS statistical zones 4 and 5) with habitats either inshore (10-36 m depth) or offshore (37-110 m depth). The survey has since expanded to include statistical zones 9 and 10 off the Florida Panhandle in 2014 with additional sites added in 2016 to cover the entirety of the West Florida Shelf from statistical zones 2-10, although only data from statistical zones 4 and 5 are included in these analyses. Sites are initially mapped using side scan sonar over a 0.1 nm x 0.3 nm area. Video deployment sites are then randomly assigned proportionally across region and depth zones (Thompson et al. 2017).

Video reads

All three surveys use paired stereo-imaging cameras at each site. All videos are read to identify the maximum number of individuals of each species viewed in a single frame within a 20 minute time frame (i.e. MaxN, MinCount). Habitat characteristics on video are also noted with the percentage or presence/absence of abiotic and biotic habitat types that may contribute to fish biomass (e.g. sponge, algae, and corals), although some categories are not shared among all labs (Campbell et al. 2017; Gardner et al. 2017; Thompson et al. 2017).

Data reduction

For all surveys, video reads were excluded if they were unreadable due to turbidity or deployment errors. For the MS Labs, data included in this index are from 1993 and on, due to different counting methods in 1992. Furthermore, MS Labs data was only included from the region east of the Mississippi delta due to different potential populations of Gag in the western GOM. The entire spatial extent of the Panama City data was used from 2006 on with 2005 excluded because of an incomplete survey. The FWRI data was limited to 2010 and on due to the previous year's not including side-scan geoform as a variable which was determined to be potentially important. FWRI data were spatially limited to zones 4 and 5 due to the other areas of the WFS not having enough years of sampling. Final sample sizes by lab and year can be found in Table 1 and spatial coverage is shown in Figure 1.

Index Construction

Habitat models

To combine the data from all three surveys into one model predicting Gag relative CPUE throughout the time series, we created a habitat variable that included each lab's individual variables that could be applied to all the data. This was done so final index models can account for changing effort and habitat allocation through time rather than limiting the model to be predicted only by year and lab. We first determined the percentage of sites that occurred on good, fair, or poor (G, F, P) habitats for each survey independently. For this we used a categorical regression tree approach (CART) because it can account for correlations among variables and can include both continuous and categorical data. It has been previously demonstrated to be a useful tool in fisheries ecology and specifically in describing fish-habitat associations (De'Ath and Fabricus 2000; Yates et al. 2016).

For these initial analyses, MaxN for each site was reduced to a presence and absence variable and was used as the response variable for habitat designations. Predictor variables included the habitat metrics coded on the video reads (reduced to presence/absence), the latitude and longitude of each site and depth for all three labs. For FWRI and Panama City's data, side-scan geoform was also included as a landscape-level habitat variable, with values derived using a modified version of the Coastal and Marine Ecological Classification Standard (CMECS) classification approach (habitats used in these analyses are in Table 2). Geoform was not included as a predictor variable for the analysis of MS Lab's data because their habitat mapping has primarily been conducted utilizing multibeam sonar, and at present, comparable habitat classification is not possible using the MS Lab's multibeam data. We first used a random forest approach to reduce the number of potential variables to be selected from in the final model for each lab's dataset to reduce redundant or correlated variables used in the final indexing model. For the random forest, each lab was modeled separately with the entirety of that lab's dataset. The random forest runs fit 2000 CARTS to the data and then determined each variables importance, a scale-less number used to indicate the number of final models each variable occurred in and its significance therein. An example of output is given in Fig. 2 for the FWRI dataset.

We retained approximately 50% of the potential variables for each lab given by the random forest importance values for a final CART model. The final model was created by fitting the presence of Gag at site to the independent variables for a training dataset of 80% of the data. The remaining 20% of the data were retained in a test dataset to determine misclassification rates for each of the three models. The proportion of sites with positive Gag catches at each terminal node were then evaluated to determine the habitat characteristics defining good, fair or poor habitat. Terminal nodes with double the overall proportion of positive catches for a dataset were assigned a good habitat code. Poor sites were determined by proportion positives that were at least half of the overall proportion positive and were generally approaching zero. The remaining sites were deemed fair and included the range of the overall proportion positive. All analyses were carried out using R version 3.0.2 (R Core Team 2014) and the Party package for CART (Hothorn et al. 2006).

CART results varied by lab with respect to the final variables chosen, but all three labs had depth in the final model. Gag were generally associated with higher relief habitats for FWRI and Pascagoula's data, and while not explicitly selected in the PC model, side-scan Geoform habitat type was and represents relief as well (Figs. 3-5). This species has divergent proportions present across the surveys, with Pascagoula (7.3%) and FWRI (3.1%) having low occurrence rates but PC has significantly higher occupancy at sites surveyed at 20.8%.

The site characteristics that define each node and habitat code were then used to create a habitat variable (hab: G, F, P) that was then back-applied to each site for each lab's dataset. The datasets were then combined for the index model. The final proportion of sites in the three habitat categories for each lab and year are shown in Table 3.

Index model fitting and diagnostics

Like the individual survey indices, the combined dataset remained didn't conform to assumptions of normality (Fig. 6). We initially evaluated zero-inflated and standard negative binomial models, but given the low dispersion parameter (1.04), we determined the negative binomial model to be most appropriate. The final index model was then:

*MaxN = Y*Hab *Lab*

Where Hab is the CART derived habitat code and Lab represents the survey that collected the data for each site. Backwards variable selection was used and indicated that the full model performed best, given by AIC, compared to models with only one or two of the potential variables.

Model diagnostics showed no discernible patterns of association between Pearson residuals and fitted values or the fitted values and the original data (Fig. 7), indicating correspondence to underlying model assumptions (Zuur et al. 2009).

The index was fit in SAS using the Proc GLIMMX procedure. To account for the variation in survey area, differences in area mapped with known habitat, and the distribution of Fair, Good, and Poor habitats by survey by year, the estimated MaxN means provided by the glm were adjusted. The known potential survey universe for each of the three was first multiplied by the proportion of habitat mapping grids that had reef habitat to provide an area weight. This was then multiplied by each year x lab X hab combination (up to 9 for the final years with three surveys and three habitat levels), providing a weighting factor for each of the mean estimates. Area weighting factors are provided in Table 4. Weighted index values were then standardized to the grand mean following standard SEDAR protocols.

Length compositions

Length compositions for this species by survey varied, most notably with Gag being smaller in general for the PC survey (Fig. 8). As such, additional adjustments were made to the raw annual length compositions for inclusion in the assessment. Previous assessments have used a multinomial weighting approach for this (see Vermilion Snapper, SEDAR67-WP-16, Walter et al. 2020), however given the number of lengths recorded for this species across the surveys and length bins used for the assessment, there were too many zero observations to allow for a successful, converged model. As such, a more straightforward weighting approach was used. Proportional frequencies for each year across the length bins were created by combining individual survey observations after they had been multiplied by the area weighting factor used in the index development depending on survey and time (Table 3). Annual length compositions provided can be seen in Fig. 9.

Results and Discussion:

Annual standardized index values for Gag in the Eastern Gulf of Mexico, including coefficients of variation, are presented in Table 4. The model are high in early, low proportion present, Pascagoula only year (~50-100%), but steadily decreasing CV's as additional surveys are added and continue with CV's in the range of ~15-20%% in the final years. Biomass trends for Gag in the eastern GOM show relatively stable population in early years followed by large increases in recruitment in 2006 followed by another, smaller peak in 2009. Following the 2009 peak the abundance is generally decreasing with a slight increase in the terminal year of 2019 (Table 5; Fig. 10).

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Table 1. Summary of sample sizes by year for each of the three included video surveys, Florida Fish and Wildlife Research Institute (FWRI), NMFS Pascagoula (PASC), and NMFS Panama City (PC). No data were available or used from any survey from 1998-2003.

Year	FWRI	PC	Pascagoula	total
1993			115	115
1994			90	90
1995			61	61
1996			133	133
1997			162	162
2002			152	152
2004			149	149
2005			274	274
2006		91	276	367
2007		54	319	373
2008		84	206	290
2009		107	262	369
2010	158	136	221	515
2011	222	158	337	717
2012	237	150	281	668
2013	185	87	164	436
2014	287	168	230	685
2015	224	170	152	546
2016	195	181	206	582
2017	154	150	221	525
2018	127	100	213	440
2019	183	90	310	583
Total	1972	1726	4534	8232

Table 2. Proportion of sites for each habitat level (**F**air**, G**ood**, P**oor) as determined by individual lab categorical regression trees (CARTs) for Gag presence. Note the gap in sampling for the Pascagoula lab (1998-2002 and 2003).

Pascagoula

Year	F	G	P
1993	0.38	0.16	0.46
1994	0.46	0.16	0.39
1995	0.28	0.21	0.51
1996	0.17	0.26	0.56
1997	0.23	0.22	0.56
2002	0.11	0.41	0.48
2004	0.11	0.35	0.54
2005	0.15	0.22	0.64
2006	0.15	0.20	0.65
2007	0.12	0.21	0.67
2008	0.09	0.14	0.77
2009	0.13	0.23	0.65
2010	0.18	0.19	0.63
2011	0.15	0.26	0.60
2012	0.09	0.18	0.73
2013	0.12	0.26	0.63
2014	0.10	0.23	0.68
2015	0.07	0.20	0.72
2016	0.11	0.17	0.71
2017	0.12	0.11	0.76
2018	0.09	0.15	0.76
2019	0.15	0.14	0.71

PC

Year	F	G	P
2006	0.34	0.30	0.36
2007	0.50	0.19	0.31
2008	0.13	0.80	0.07
2009	0.43	0.46	0.11
2010	0.64	0.18	0.18
2011	0.72	0.13	0.15
2012	0.71	0.09	0.19
2013	0.61	0.30	0.09
2014	0.61	0.15	0.24
2015	0.53	0.05	0.42
2016	0.46	0.04	0.50
2017	0.67	0.21	0.12
2018	0.35	0.29	0.36
2019	0.39	0.16	0.46

FWRI

Year	F	G	P
2010	0.33	0.03	0.64
2011	0.38	0.00	0.62
2012	0.35	0.03	0.62
2013	0.40	0.03	0.57
2014	0.33	0.02	0.65
2015	0.40	0.02	0.58
2016	0.32	0.01	0.67
2017	0.38	0.01	0.61
2018	0.35	0.03	0.62
2019	0.43	0.04	0.54

Table 3. The habitat weighting used with the annual distribution of Fair, Good, Poor habitats to adjust estimated model means to account for variation across surveys

Survey	Total Universe Area (km^2)	Total mapped area (km^2)	Proportion of grids with habitat	Total Universe Area X Prop transects	Area Weighting values (1993-2005)	Area Weighting values (2006-2009)	Area Weighting values (2010-2017)
SRFV	34490	11194	0.81	27936.9	1.0	0.65	0.52
PC	22104	356	0.67	14860.9	0	0.35	0.28
FWRI	37290	1379	0.29	10814.09	0	0	0.20

Table 4. Number of stations sampled (N) by survey and year, proportion of positive sets, standardized index, and CV for the annual FWRI Gag video index of the West Florida Shelf.

year	N	Prop present	Std. Index	LCL	UCL	CV
1993	115	0.052	0.292	0.230	0.354	0.520
1994	90	0.011	0.053	0.031	0.076	1.037
1995	61	0.016	0.157	0.102	0.213	0.858
1996	133	0.075	0.433	0.365	0.501	0.385
1997	162	0.068	0.356	0.308	0.403	0.327
1998						
1999						
2000						
2001						
2002	152	0.184	1.390	1.258	1.522	0.233
2003						
2004	149	0.188	1.354	1.222	1.485	0.238
2005	274	0.109	0.999	0.912	1.087	0.215
2006	367	0.150	3.272	2.969	3.575	0.227
2007	373	0.137	2.061	1.836	2.286	0.268
2008	290	0.103	1.261	1.144	1.378	0.228
2009	369	0.171	2.226	2.067	2.385	0.175
2010	515	0.130	1.255	1.171	1.340	0.164
2011	717	0.126	1.288	1.217	1.358	0.134
2012	668	0.079	0.636	0.593	0.678	0.164
2013	436	0.064	1.062	0.956	1.168	0.245
2014	685	0.060	0.471	0.435	0.507	0.186

2015	546	0.053	0.551	0.509	0.593	0.188
2016	582	0.053	0.372	0.343	0.401	0.190
2017	525	0.065	0.653	0.596	0.709	0.212
2018	440	0.052	0.491	0.447	0.535	0.220
2019	583	0.079	1.366	1.243	1.490	0.222

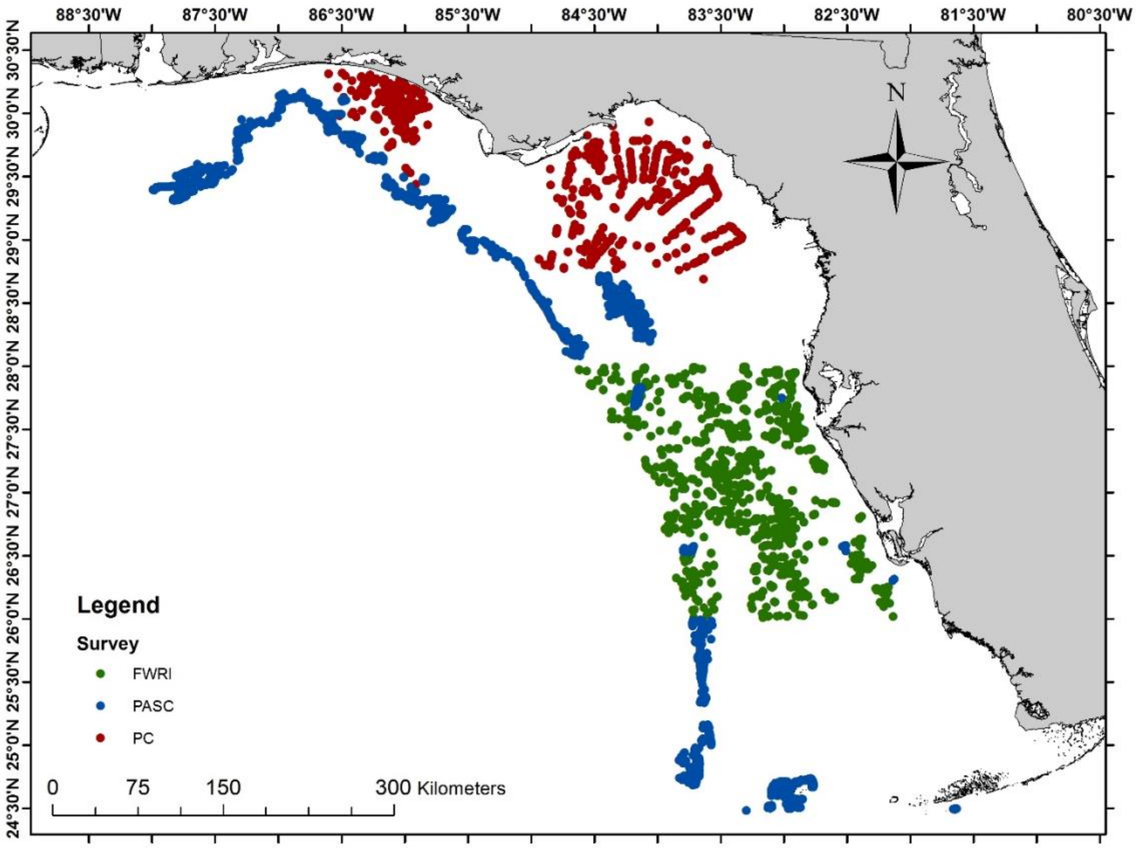

Figure 1. Map of the total video sites included in the index for each survey (by lab) across all years 1993-2019.

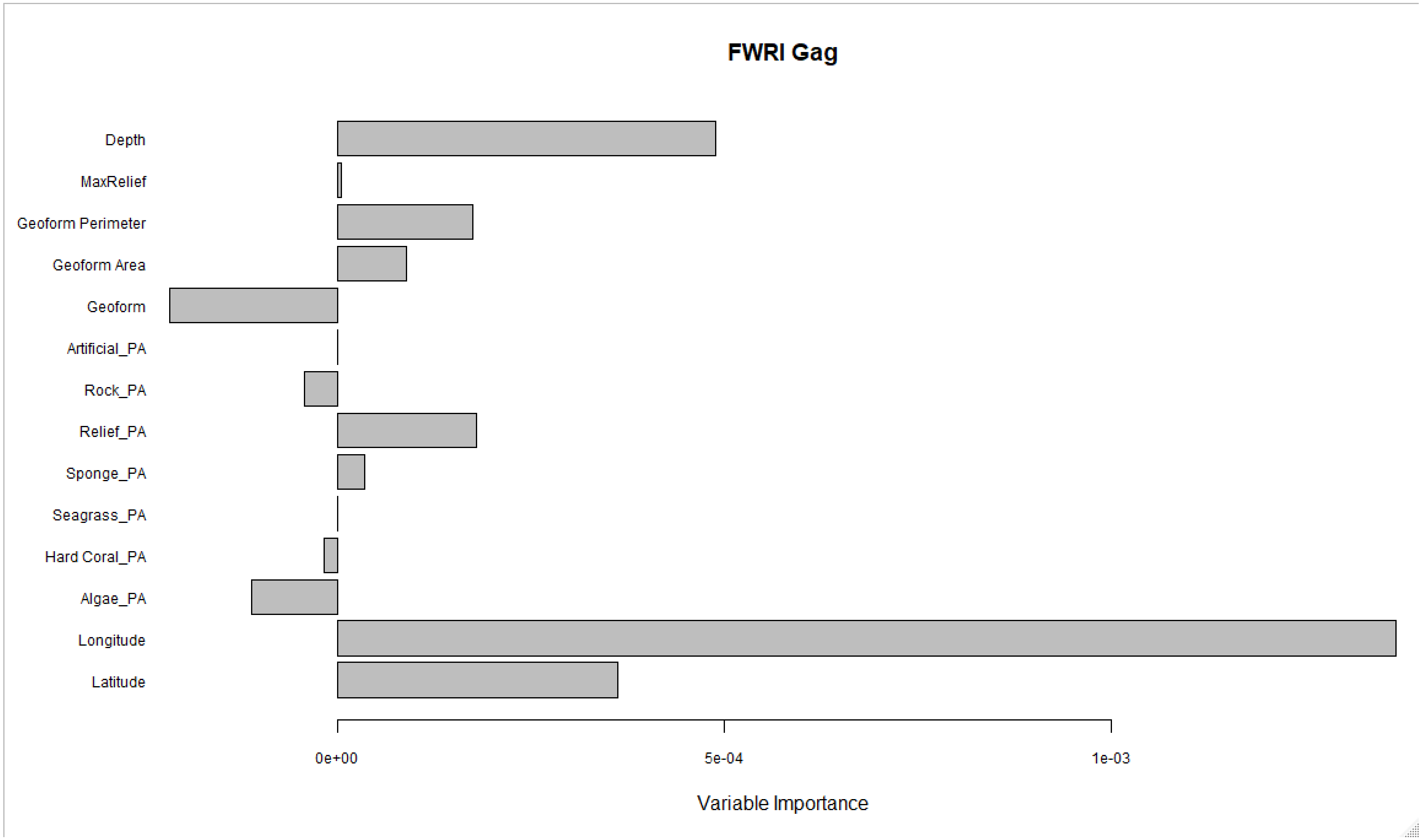

Figure 2. Random Forest generated variable importance for Gag presence using FWRI survey data.

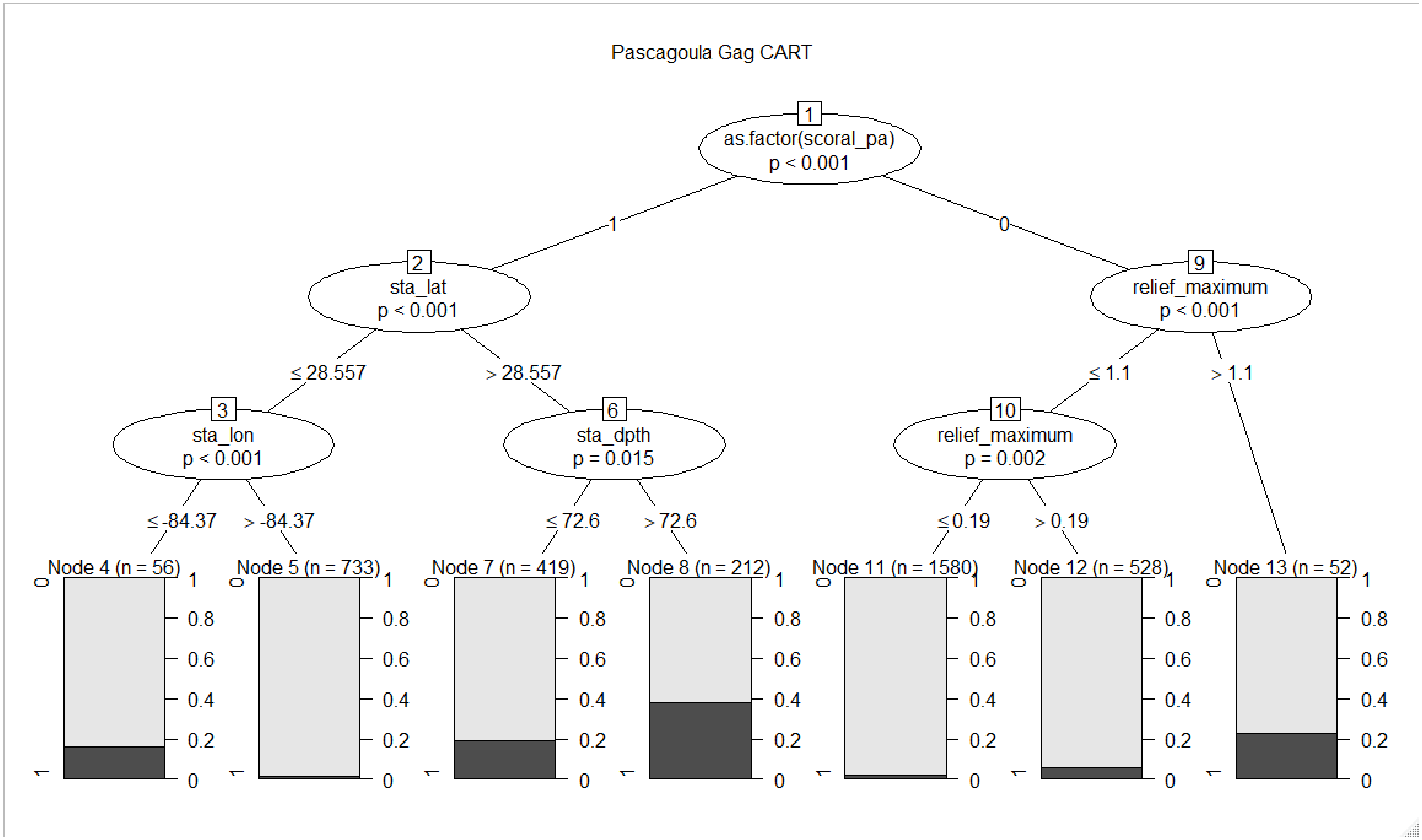

Figure 3. CART results for Gag for Pascagoula's video survey. Shaded portion of the plots indicate proportion of sites given by a node where Gag were observed (7.3% of sites had Gag present overall).

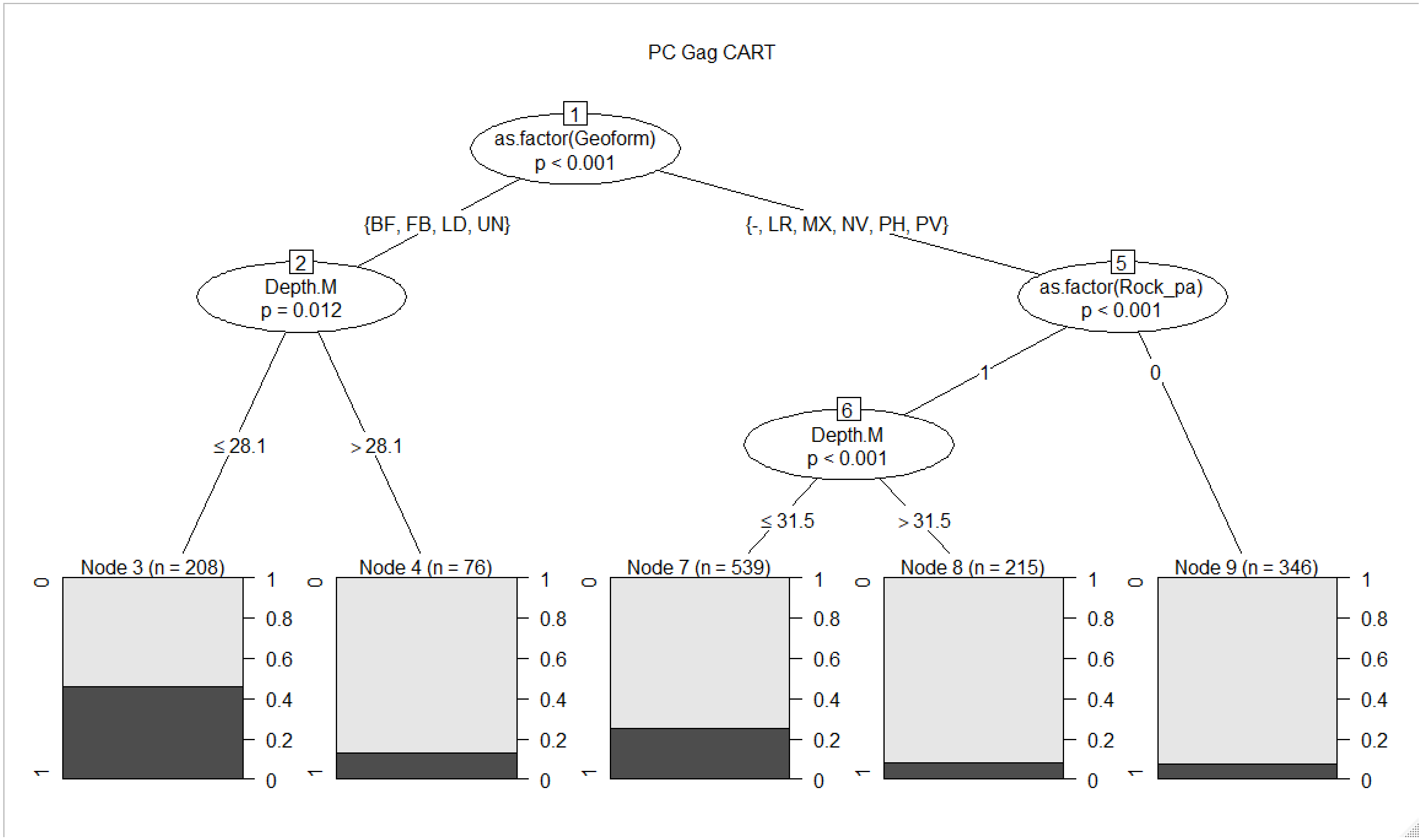

Figure 4. CART results for Gag for Panama City's video survey. Shaded portion of the plots indicate proportion of sites given by a node where Gag were observed (20.8% of sites had Gag present overall)

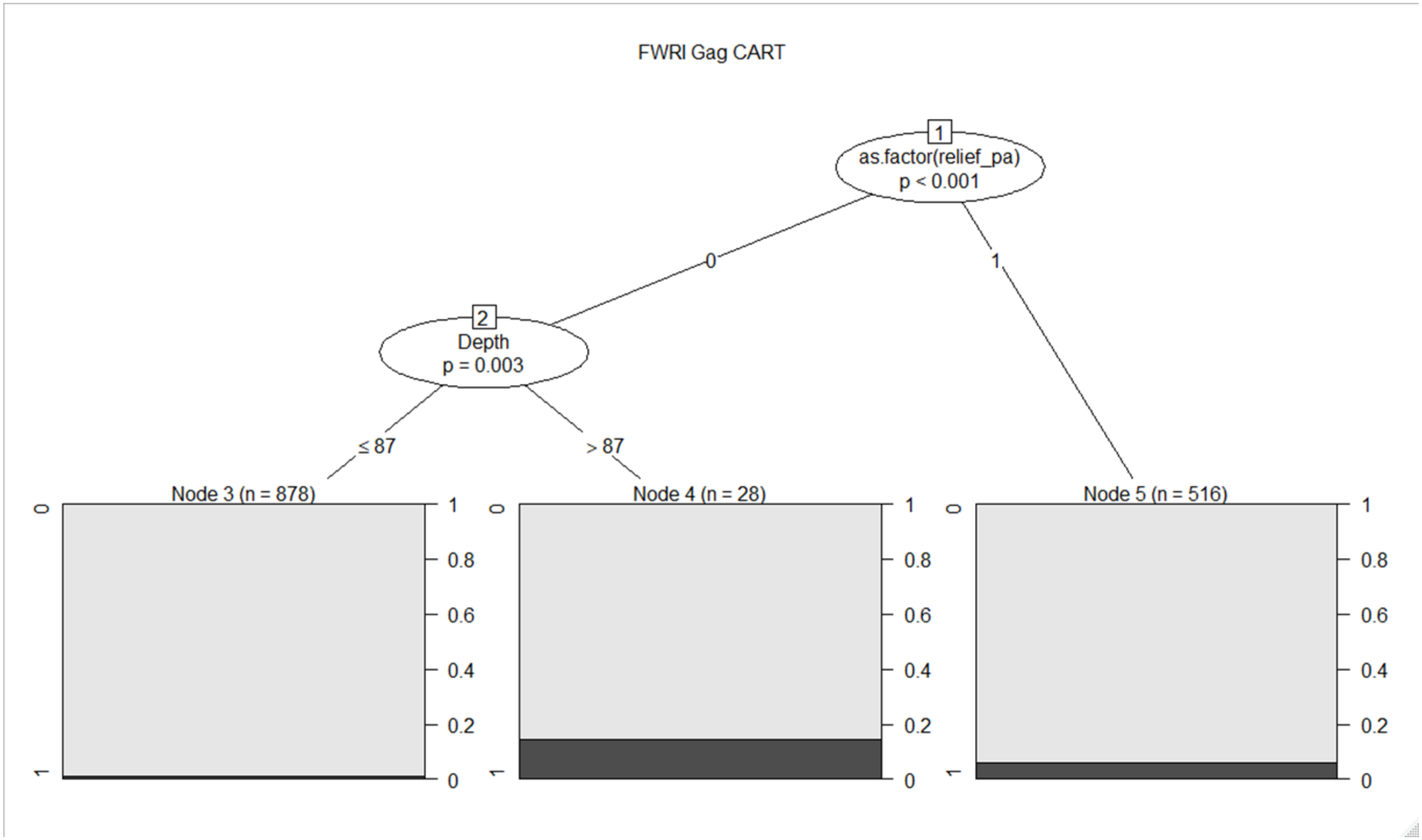

Figure 5. CART results for Gag for FWRI's video survey. Shaded portion of the plots indicate proportion of sites given by a node where Gag were observed (3.1% of sites had Gag present overall).

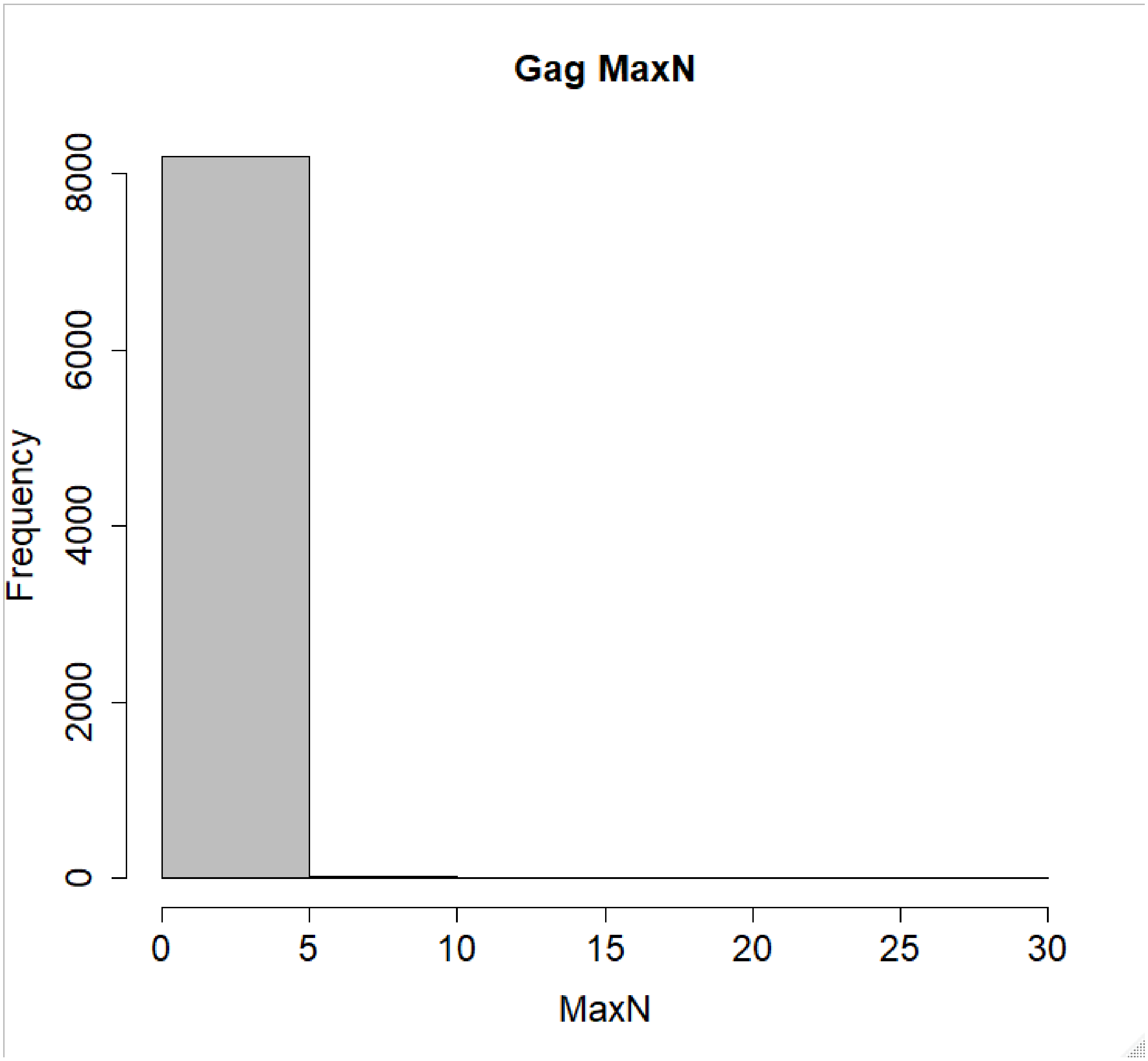

Figure 6. MaxN count distribution for Gag observed in all three video surveys on the West Florida Shelf used for the combined index.

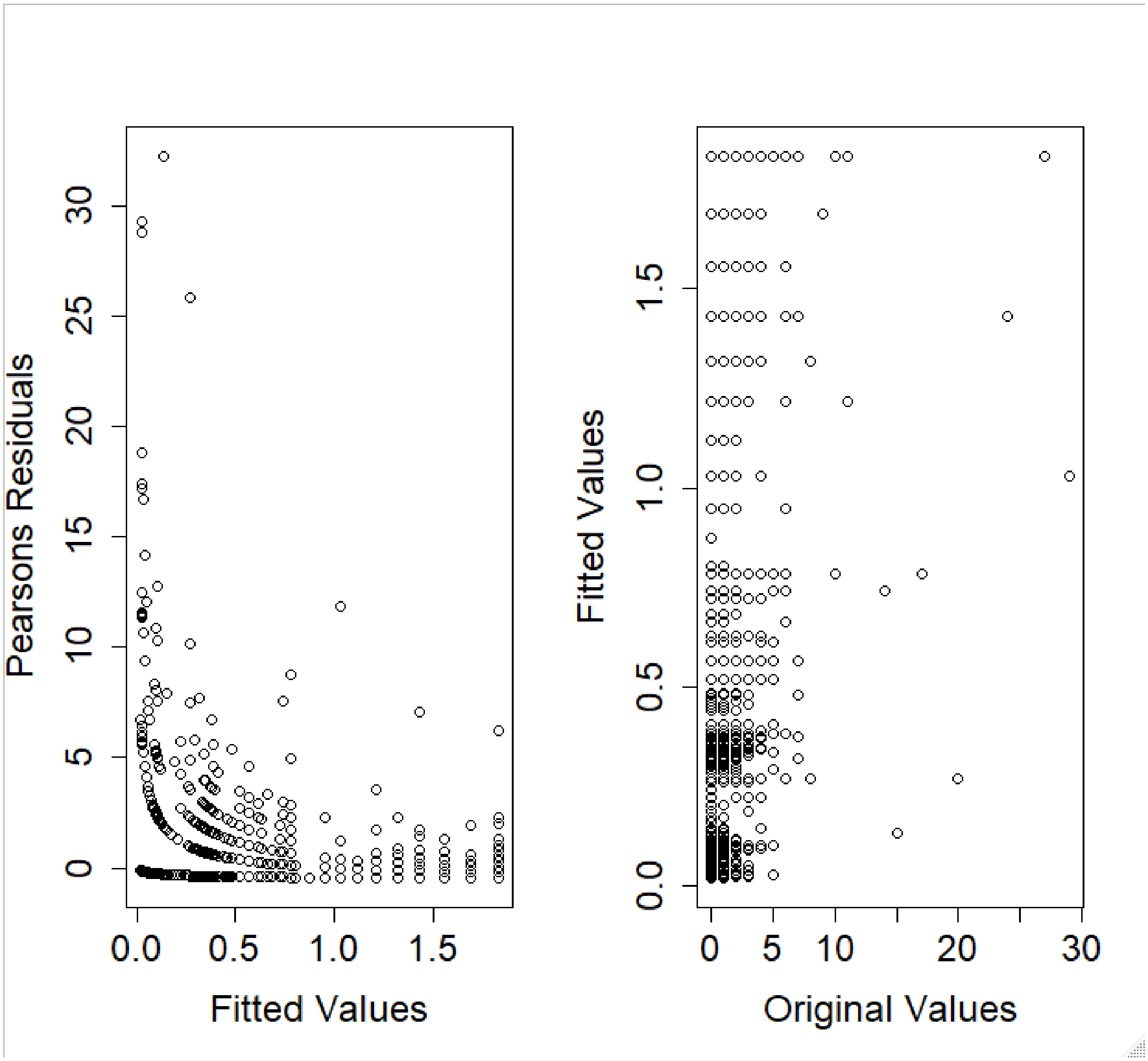

Figure 7. Model diagnostic plots showing fitted best model values against Pearson residuals (left panel) and fitted values plotted against original data values (right panel).

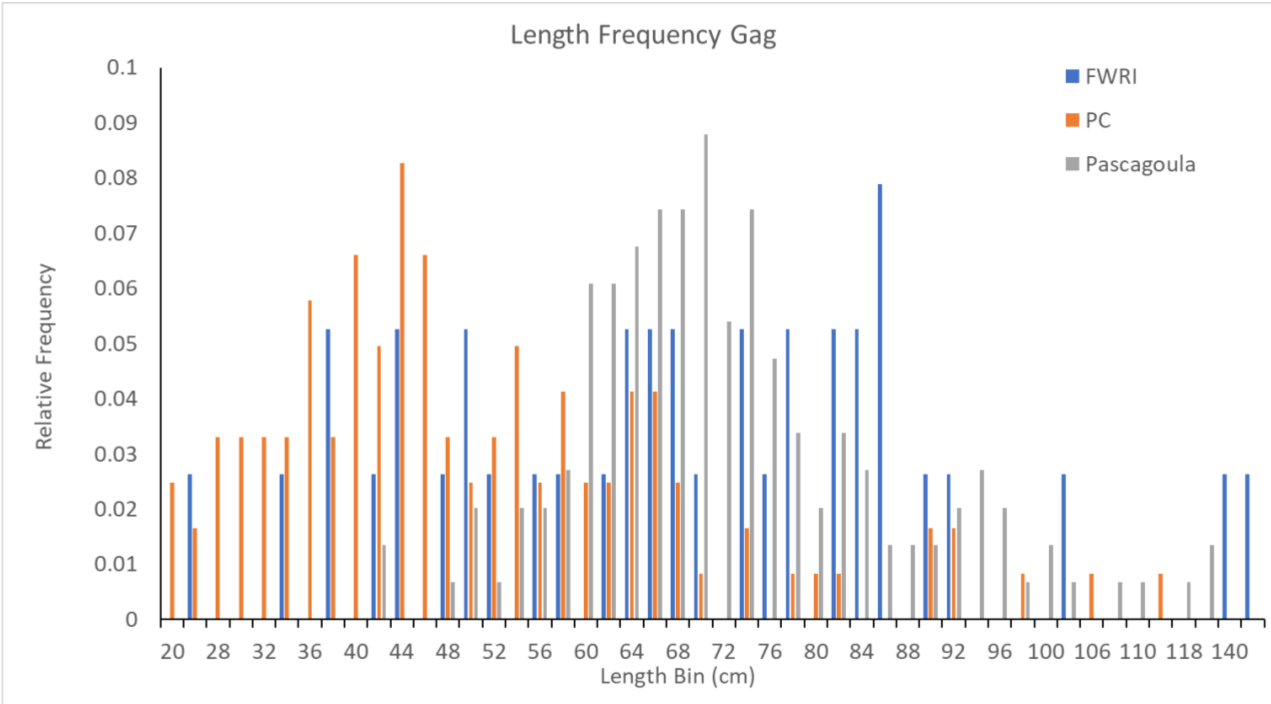

Figure 8. Length frequency by survey used in the combined video index.

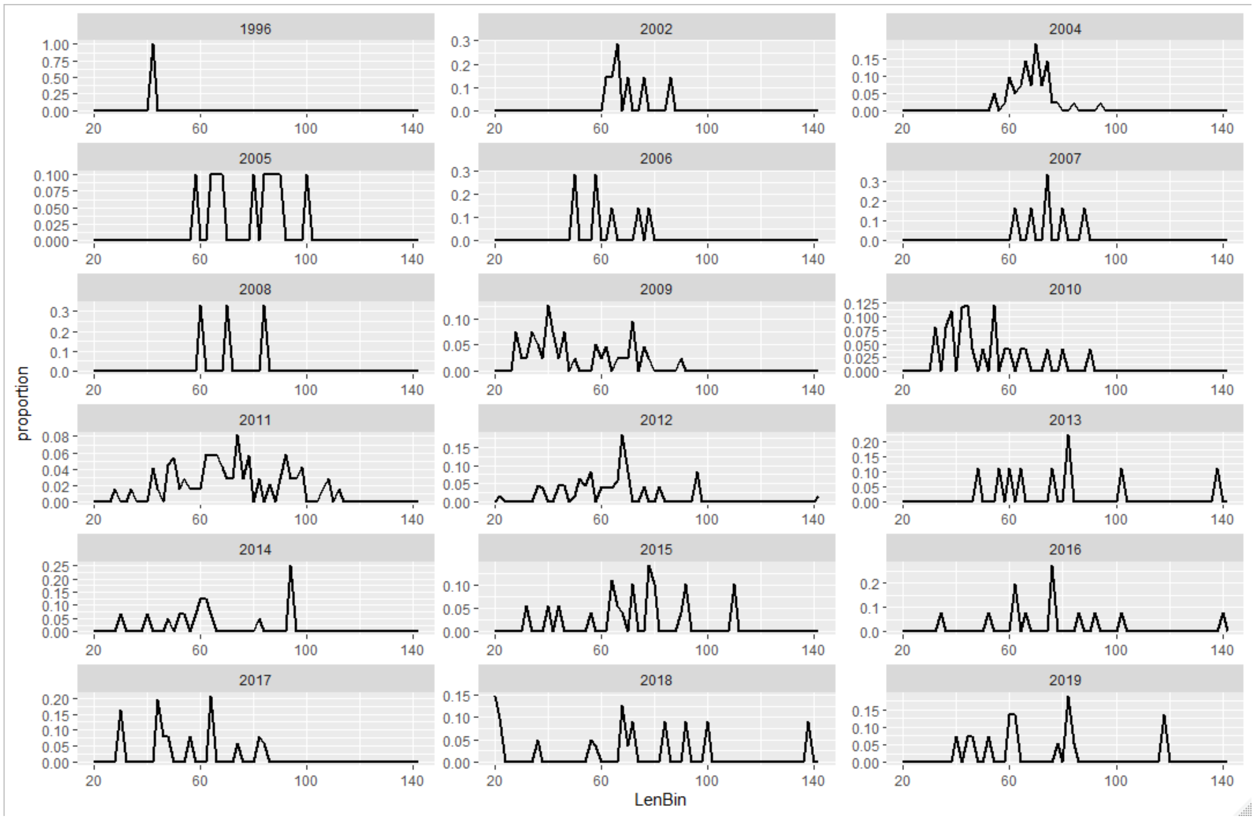

Figure 9. Survey area weighted proportional length composition for Gag in the video index by year.

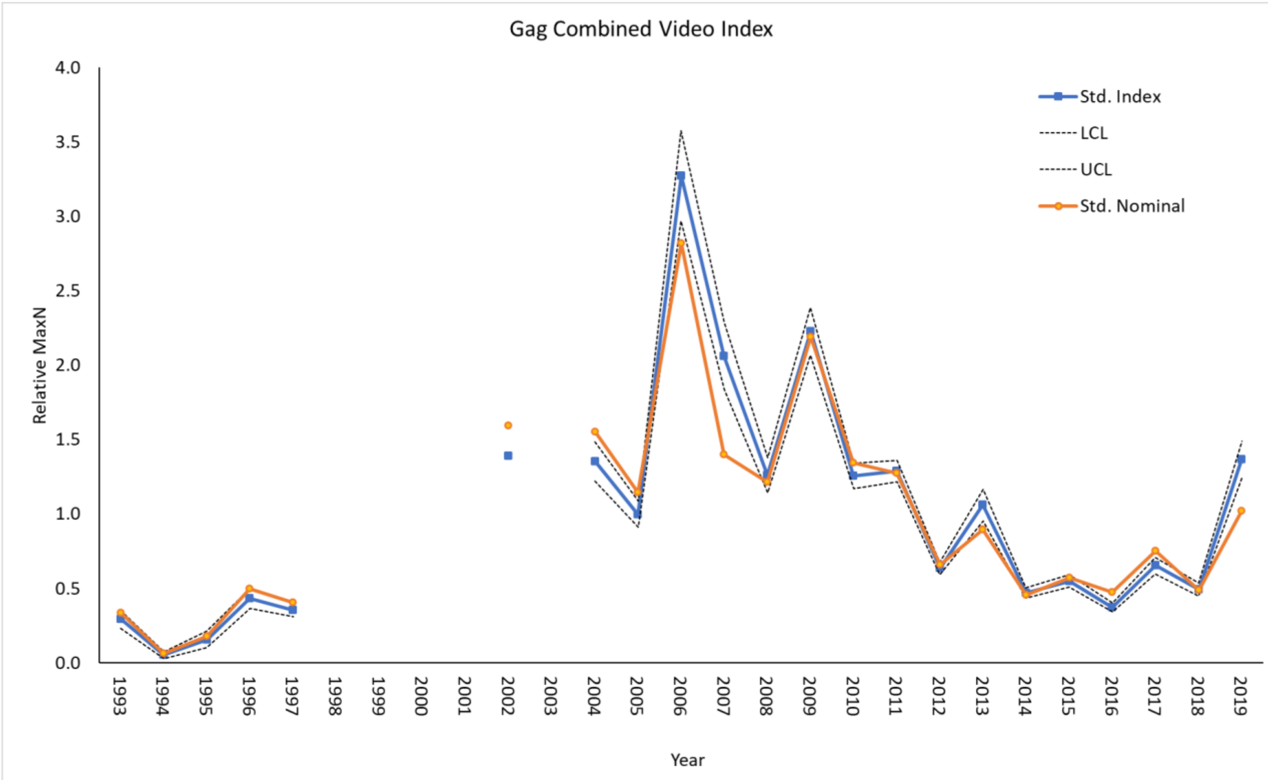

Figure 10. Relative standardized index (solid red line) with 2.5% and 97.5% confidence intervals (black dotted lines) and relative nominal index (solid blue line) for Gag CPUE (MaxN) using the integrated West Florida Shelf video data.