Standardized video counts of southeast US Atlantic mutton snapper (*Lutjanus analis*) from the Southeast Reef Fish Survey

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Standardized video counts of southeast US Atlantic mutton snapper (*Lutjanus analis*) from the Southeast Reef Fish Survey

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Abstract
Standardized video counts of mutton snapper (*Lutjanus analis*) were generated from video cameras deployed by the Southeast Reef Fish Survey during 2011–2022 (note that no sampling occurred in 2020 due to covid-19). The analysis included samples taken between Cape Hatteras, North Carolina and St. Lucie Inlet, Florida, from 14 to 115 m deep. The index is meant to describe the population abundance trend of mutton snapper in the region using a variety of predictor variables that could influence their abundance and video detection. We compared multiple model structures using AIC and ultimately applied a zero-inflated negative binomial model to standardize the video count data with eight predictor variables; the final model fit well based on various model diagnostics. The 2011–2022 index values and uncertainty included a calibration factor to account for a change in camera type after 2014.

Background

The Marine Resources Monitoring, Assessment, and Prediction (MARMAP) program has conducted most of the historical fishery-independent sampling in the U.S. South Atlantic (North Carolina to Florida). MARMAP has used a variety of gears over time, but chevron traps are one of the primary gears used to monitor reef fish species and have been deployed since the late 1980s. In 2009, MARMAP began receiving additional funding to monitor reef fish through the SEAMAP-SA program. In 2010, the SouthEast Fishery-Independent Survey (SEFIS) was initiated by NMFS to work collaboratively with MARMAP/SEAMAP-SA using identical methods to collect additional fishery-independent samples in the region. Together, these three programs are now called the Southeast Reef Fish Survey (SERFS). In 2010, video cameras were attached to some traps deployed by SERFS, and beginning in 2011 all traps included video cameras (Figure 1).

The SERFS currently samples between Cape Hatteras, North Carolina, and St. Lucie Inlet, Florida. This survey targets hardbottom habitats between approximately 15 and 115 meters deep. SERFS began affixing high-definition video cameras to chevron traps on a limited basis in 2010 (Georgia and Florida only), but, since 2011, has attached cameras to all chevron traps as part of their normal monitoring efforts. In 2015, the video cameras were changed from Canon to GoPro to implement a wider field of view and thus observe more fish. A calibration study (detailed below) with both camera types used simultaneously was undertaken to account for differences in fish counts.

Hard-bottom sampling stations were selected for sampling in one of three ways. First, most sites (74.4%) were randomly selected from the SERFS sampling frame that consisted of approximately 4,300 sampling stations on or very near hard bottom habitat. Second, some stations (15.1%) in the sampling frame were sampled opportunistically even though they were not randomly selected for sampling in a given year. Third, new hard-bottom stations were added during the study period through the use of information from various sources including fishermen, charts, and historical surveys (10.5%). These new locations were investigated using a vessel echosounder or drop cameras and sampled if hard bottom was detected. Only those new stations landing on or near hardbottom habitat were included in the analyses. All sampling for this study occurred during daylight hours between April and October on the R/V *Savannah*, R/V *Palmetto*, R/V *Sand Tiger*, or the NOAA Ship *Pisces* using identical methodologies as described below. Samples were intentionally spread out spatially on each cruise (see Figure 2 in Bacheler and Carmichael 2014).

Chevron traps were constructed from plastic-coated, galvanized 2-mm diameter wire (mesh size = 3.4 cm^2) and measured 1.7 m × 1.5 m × 0.6 m, with a total volume of 0.91 m^3. Trap mouth openings were shaped like a teardrop and measured approximately 18 cm wide and 45 cm high. Each trap was baited with 24 menhaden (*Brevoortia* spp.). Traps were typically deployed in groups of six, and each trap in a set was deployed at least 200 m from all other traps to provide some measure of independence between traps. A soak time of 90 minutes was targeted for each trap deployed.

Canon Vixia HFS-200 high-definition video cameras in Gates underwater housings were attached to chevron traps in 2011–2014, facing outward over the mouth. In 2015, Canon cameras were replaced with GoPro Hero 4 cameras over the trap mouth. Fish were counted exclusively using cameras over the trap mouth. A second high-definition GoPro Hero, Hero 3+, or Hero 4 video or Nikon Coolpix S210/S220 still camera was attached over the nose of most traps in an underwater housing, and was used to quantify microhabitat features in the opposite direction. Cameras were turned on and set to record before traps were deployed, and were turned off after trap retrieval. Trap-video samples were excluded from our analysis if videos were unreadable for any reason (e.g., too dark, camera out of focus, files corrupt) or the traps did not fish properly (e.g., bouncing or dragging due to waves or current, trap mouth was obstructed).

In advance of the switch to GoPro cameras exclusively in 2015, we conducted a calibration study in the summer of 2014 where Canon and GoPro cameras were attached to traps side-by-side and fish were counted at the same time. A total of 54 side-by-side comparisons were recorded. Mutton snapper were observed in only 6 calibration videos, so we used a more general calibration for all closely-related lutjanids that included 101 paired calibration samples, as recommended by Bacheler et al. (2023). This allowed us to use a robust calibration factor that expanded Canon counts to make them comparable to GoPro counts.

Relative abundance of reef fish on video has been estimated using the *MeanCount* approach (Conn 2011; Schobernd et al. 2014). *MeanCount* was calculated as the mean number of individuals of each species over a number of video frames in the video sample. Video reading time was limited to an interval of 20 total minutes, commencing 10 minutes after the trap landed on the bottom to allow time for the trap to settle. One-second snapshots were read every 30 seconds for the 20-minute time interval, totaling 41 snapshots read for each video. The mean number of individuals for each target species in the 41 snapshots is the *MeanCount* for that species in each video sample. Zero-inflated modeling approaches described below require count data instead of continuous data like *MeanCount*. Therefore, these analyses used a response variable called *SumCount*, which was simply the sum of all individuals seen across all video frames. *SumCount* and *MeanCount* track exactly linearly with one another when the same numbers of video frames are used in their calculation (Bacheler and Carmichael 2014). Therefore, *SumCount* values were only used from videos where 41 frames were read (94.4% of all samples).

SERFS employed video readers to count fish on videos. There was an extensive training period for each video reader, and all videos from new readers were re-read by fish video reading experts until they were very high quality. After that point, 10% or 15 videos (whichever was larger) were re-read annually by fish video reading experts as part of quality control. Video readers also quantified microhabitat features (biotic density and substrate composition), in order to standardize for habitat types sampled over time. Water clarity was also scored for each sample as poor, fair, or good. If bottom substrate could not be seen, then water clarity was considered poor, and if bottom habitat could be seen but the horizon was not visible, water clarity was considered fair. If the horizon could be seen in the distance, water clarity was considered to be good. Including water clarity in index models allowed for a standardization of fish counts based on variable water clarities over time and across the study area. A CTD cast was also taken for each simultaneously deployed group of traps, within 2 m of the bottom, and water temperature from these CTD casts was available for standardization models.

Data and Treatment

Overall, there were 16,370 survey videos with data available covering a period of 13 years (2011–2022; note no sampling occurred in 2020 due to covid-19). Although data were available from 2010, they were not considered here due to limitations in spatial coverage and a different camera used in that year. For the years considered, several data filters were applied. We removed any data points in which the survey video was considered unreadable by an analyst (e.g., too dark, corrupt video file), or if the trapping event was flagged for any irregularity that could have affected catch rates (e.g., trap dragged or bounced). Additionally, any survey video for which fewer than 41 video frames were read was removed from the full data set. Standardizing the number or readable frames for any data point was essential due to our use of *SumCount* as a response variable (see above). We also identified any video sample in which corresponding predictor variables were missing and removed them from the final data set.

Of the 16,370 video samples considered for inclusion, 2,566 were removed based on the data filtering process described above, leaving 13,804 videos included in the analysis, of which 611 were positive for mutton snapper (4.4%). The spatial distribution of the videos included in the analysis cover the area from Cape Hatteras, North Carolina, to St. Lucie Inlet, Florida (Figure 2).

Standardization

Response Variable

We modeled *SumCount* as the response variable. *SumCount* measured the total number of mutton snapper observed across all 41 frames of each video.

Explanatory Variables

We considered eight explanatory variables: year, season, depth, latitude, water temperature, turbidity, current direction, and substrate composition. Although all of these explanatory variables were considered, we included in the final formulation only those that improved model performance based on AIC (as long as models converged).

YEAR (y) – Year was included because standardized video counts by year are the objective of this analysis. We modeled data from 2011–2022 (excluding 2020 when no sampling occurred). Annual summaries of data points considered are outlined in Table 1.

SEASON (t) – Season is a temporal parameter based on the day of the year of sampling (Figure 3). The season parameter is treated as a factor with days distributed among quartiles.

DEPTH (*d*) – Water depth was treated as a factor with four levels based on quartiles (Figure 3). Annual depth distribution for survey data are outlined in Table 1.

LATITUDE (*lat*) – The latitude of video samples (Figure 3) was divided into 4 levels based on quartiles.

TEMPERATURE (*temp*) – The bottom water temperature was collected from cluster of stations and incorporated as a predictor variable. Bottom temperatures ranged from 12.4 to 32.6 degrees Celsius (Figure 3). For the model, temperature was treated as a factor with 4 levels based on quartiles.

TURBIDITY (*wc*) – Turbidity can affect both species distribution and the ability of an analyst to observe and identify species on videos. Turbidity information is recorded during video analysis based on the ability of an analyst to perceive the horizon and surrounding habitat, and it was scored at three levels: poor, fair, and good. Given that poor water clarity occurred rarely and was associated with very few mutton snapper observations, it was removed from all analyses, leaving only fair and good levels.

CURRENT DIRECTION (*cd*) – This categorical variable describes current direction based on the video point of view. Current direction was included to better account for variability in detection due to the current moving fish away or towards the camera. This variable is assigned one of three levels during video processing: away, sideways, or towards.

SUBSTRATE COMPOSITION (*sc*) – Substrate composition is an estimate of the proportion of the visible substrate that is hardbottom and is assigned during video processing. This variable was treated as a categorical variable with 4 levels: none (0%), low (1–9%), moderate (10–39%), and high (≥40%).

Zero-Inflated Model

The recommendation of the video index workshop (Bacheler and Carmichael 2014) was to apply a zero-inflated modeling approach to the development of fishery-independent video indices. Zero-inflated models are valuable tools for modeling distributions that do not fit standard error distributions due to an excessive number of zeroes. These data distributions are often referred to as “zero-inflated” and are a common condition of count based ecological data. Zero inflation is considered a special case of over-dispersion that is not readily addressed using traditional transformation procedures (Hall 2000, Zeileis et al. 2008). Due to the high proportion of zero counts found in our data set, we used a zero-inflated mixed model approach that accounts for the high occurrence of zero values, as well as the positive counts. The model does so by combining binomial and count processes (Zuur et al. 2009, Zeileis et al. 2008).

The modeling approached used here was similar to that used in many previous SEDARs. We initially considered a full null model (1) using both a zero-inflated Poisson (ZIP) and a zero-inflated negative binomial (ZINB) formulation as:

$$SumCount = y + wc + cd + sc + d + t + lat + temp \,|\, y + wc + cd + sc + d + t + lat + temp \quad (1)$$

In this formulation, variables to the left of the "|" apply to the count sub-model, and variables to the right (or below) apply to the binomial sub-model. We compared the variance structure of each model formulation using AIC and likelihood ratio tests (Zuur et al 2009) to determine the most appropriate model error structure for the development of a mutton snapper video index. The results of these tests showed clear support for the ZINB formulation (Table 2). These results concur with our expectations based on the over dispersion of video survey data and with the recommendations of the video index development panel (Bacheler and Carmichael 2014).

We used a step-wise backwards model selection procedure based on AIC to systematically exclude unnecessary parameters from our full model formulation. We first conducted model selection on the left (count) sub-model, with the best model being one that included year (y), substrate composition (sc), and season (t). Further reduced count sub-models resulted in convergence issues, so we retained this 3-parameter count sub-model. We then performed model selection on the right (binomial) sub-model, and all combinations of reduced models also displayed convergence issues. Thus, our final ZINB model formulation, based on the results of AIC and likelihood ratio tests (Zuur et al. 2009), included three predictors on the negative binomial side (y, sc, and t) and all eight predictors on the binomial side. The data were fit well using the final (best) model (Figure 4). All data manipulations and analyses were conducted using R version 4.1.1 (R Core Team 2021). Modeling was executed using the zeroinfl function in the countreg package (Zeileis and Kleiber 2017) available from the Comprehensive R Archive Network (CRAN).

Calibration of gear

Because camera gear changed in 2015 (from Canon to GoPro), index values in 2011–2014 were adjusted to make them comparable to values in 2015–2022. Mutton snapper were only observed on 6 videos during the calibration study, so we instead used calibrations from all lutjanid species (N = 101 available calibration videos). *MeanCounts* from GoPros cameras were regressed on *MeanCounts* from Canon cameras to estimate a slope of 1.683 and a standard error of 0.029 (Figure 5). The slope (i.e., calibration factor) was used to adjust the 2011–2014 index values to make them comparable to data from later years.

Uncertainty

Uncertainty in the index was computed using a bootstrap procedure with n = 1,000 replicates. In each replicate, a data set of the original size was created by drawing observations (rows) at random with replacement. This was done by year, to maintain the same annual sample size as in the original data. The model (Equation 1) was fitted to each data set, and uncertainty (CVs) was computed. All of the 1,000 runs converged.

Uncertainty in the calibration factor was included in the bootstrap procedure by drawing a random value from a normal distribution with a mean of 1.683 and a standard error of 0.029 (estimates from the regression). These values, one for each bootstrap replicate, were used to scale up the 2011–2014 index estimates. Thus, this method accounts for the adjustment in the 2011–2014 estimates, as well as the corresponding CVs.

Results and discussion

The final ZINB model included three predictors (*y*, *sc*, and *t*) on the negative binomial side and eight predictors (*y, wc, cd, sc, d, t, lat,* and *temp*) on the binomial side. This final model fit well (Figure 4) and model residuals were reasonable (Figure 6). The convergence issues that prevented full exploration of reduced sub-models was most likely due to low proportion positives among levels of variables. For most species, full and reduced models are very similar. Generally, the proportion positive, nominal index, and standardized index all increased over the time series, while CVs tended to decline (Table 3). The proportion positive was highest in 2021 (7.5%) and lowest in 2011 (0.9%), while CVs ranged from 0.15 to 0.58 (Table 3). The standardized and nominal indices tracked each other very closely, with the nominal index falling within the 95% confidence intervals of the standardized index in all years (Figure 7).

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Table 1. Number of videos, depth range, latitude range, and day of the year range of samples included in the analyses.

Year	Number of video samples	Depth (m) range	Latitude (ºN) range	Day of the year range
2011	543	15-94	27.23-34.54	140-299
2012	1017	15-105	27.23-35.01	115-284
2013	1114	15-98	27.33-35.01	115-278
2014	1364	16-109	27.23-35.01	114-295
2015	1374	15-110	27.26-35.02	112-296
2016	1409	16-115	27.23-35.01	125-300
2017	1409	15-111	27.23-35.02	117-273
2018	1647	16-114	27.23-35.00	116-278
2019	1538	14-110	27.23-35.01	121-269
2020	0	-	-	-
2021	1373	16-109	27.23-35.01	119-274
2022	1016	16-113	27.23-35.01	117-271

Table 2. Comparison of zero-inflated Poisson and zero-inflated negative binomial models using preliminary model error structure comparison.

Model	df	Likelihood	AIC	χ^2	df	*p*-value
ZIP	58	-3459	7034.8			
ZINB	59	-3043	6204.9	831.9	1	<0.0001

Table 3. The relative nominal *SumCount*, number of videos included (*N*), proportion of videos in which mutton snapper were observed (i.e., proportion positive), standardized index, and CVs for the SERFS mutton snapper video index, 2011–2022.

Year	Relative nominal *SumCount*	*N*	Proportion positive	Standardized index	CV
2011	0.136	543	0.009	0.083	0.46
2012	0.182	1017	0.005	0.235	0.58
2013	0.344	1114	0.009	0.263	0.50
2014	0.860	1364	0.026	0.769	0.26
2015	1.350	1374	0.057	1.188	0.19
2016	0.557	1409	0.026	0.581	0.26
2017	0.968	1409	0.044	1.007	0.24
2018	1.340	1647	0.060	1.501	0.16
2019	2.065	1538	0.070	2.248	0.15
2021	1.501	1373	0.075	1.394	0.16
2022	1.696	1016	0.069	1.731	0.20

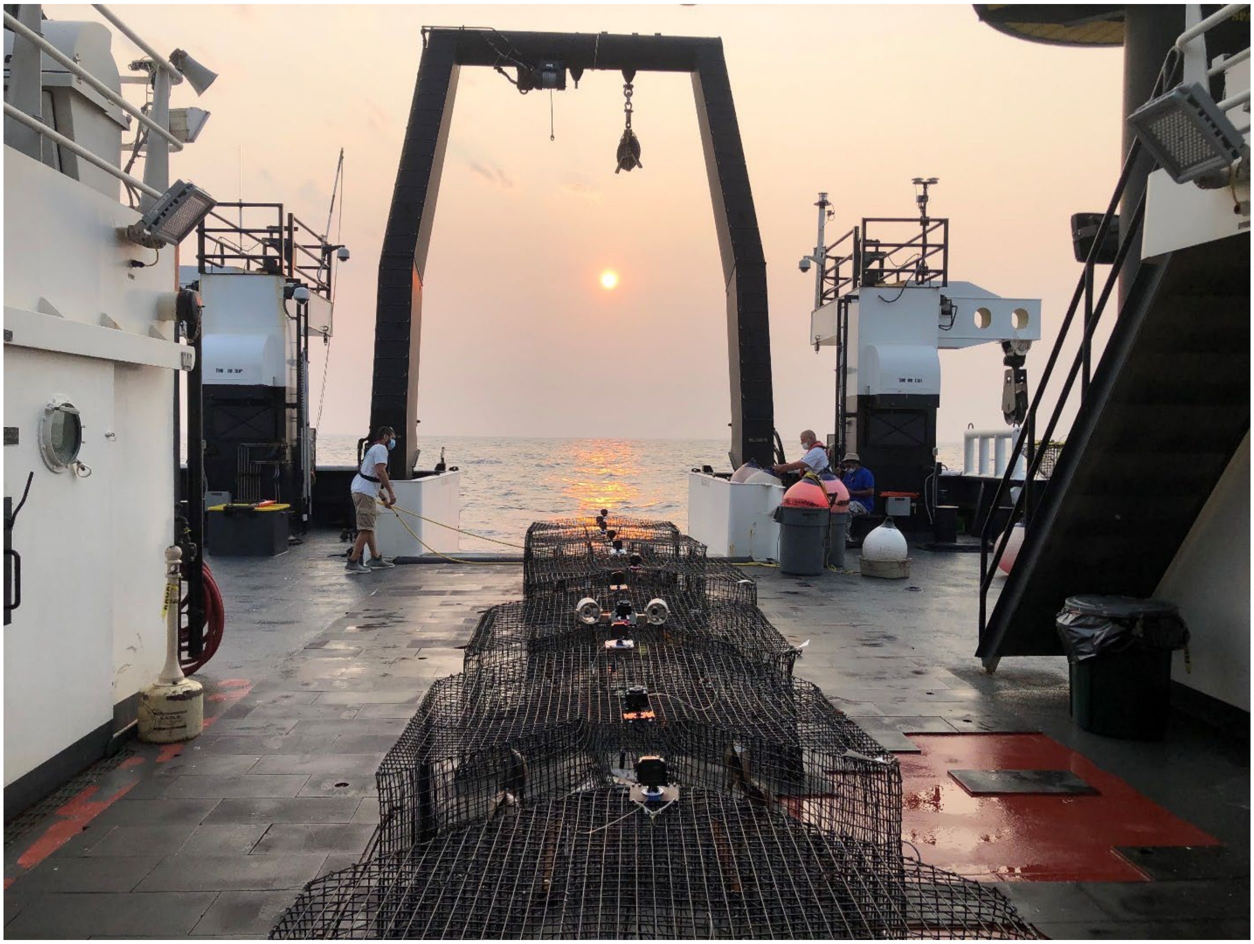

Figure 1. Chevron traps used by SERFS showing the GoPro cameras over the trap mouth and nose.

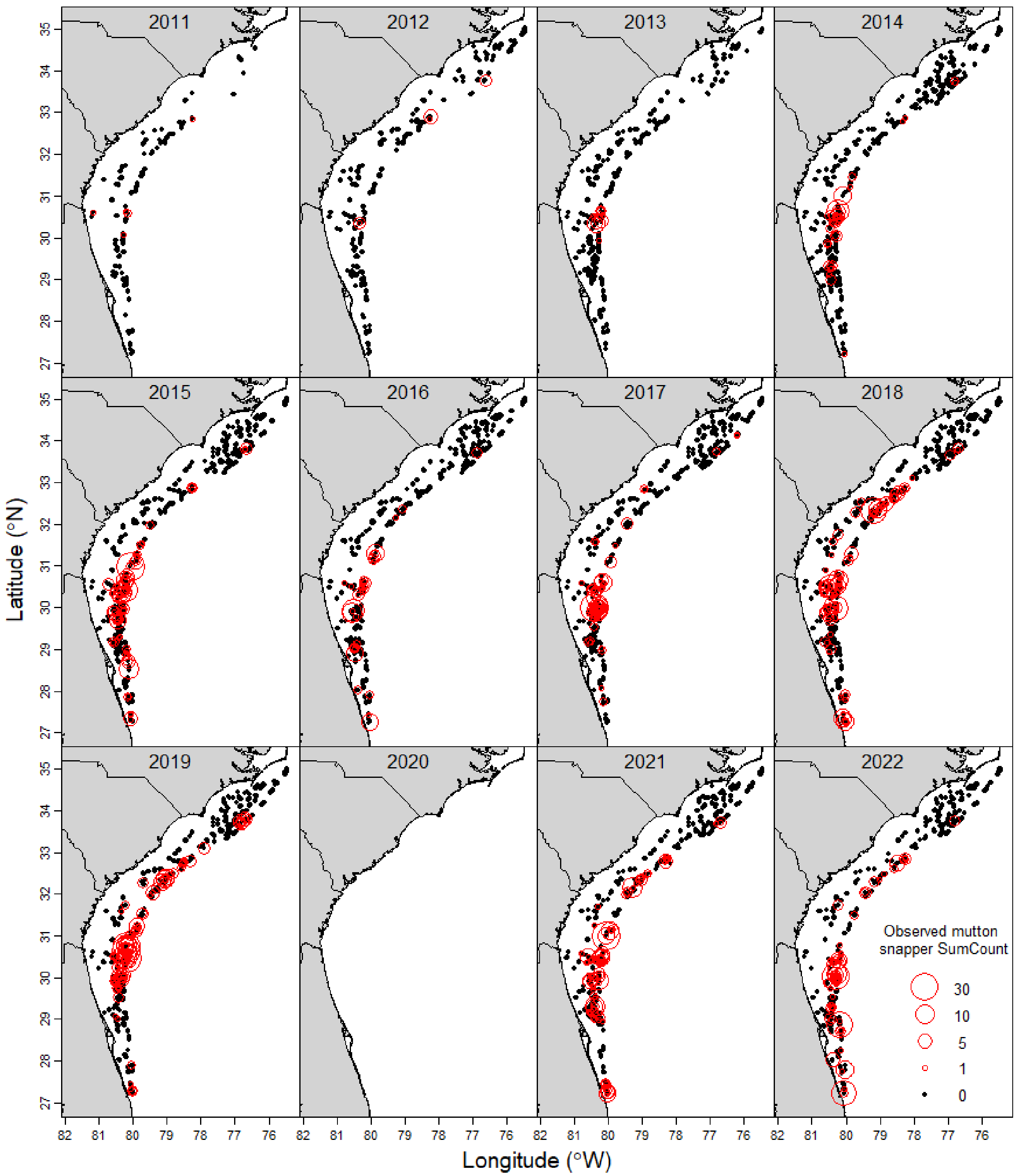

Figure 2. Bubble plots of mutton snapper *SumCounts* from videos collected by the Southeast Reef Fish Survey, 2011–2022. Black points show locations where mutton snapper were not observed on video and red bubbles show where mutton snapper were observed on video, with the size of the bubbles scaled to their video *SumCount*. Note that points overlap often. No sampling occurred in 2020 due to the covid-19 pandemic.

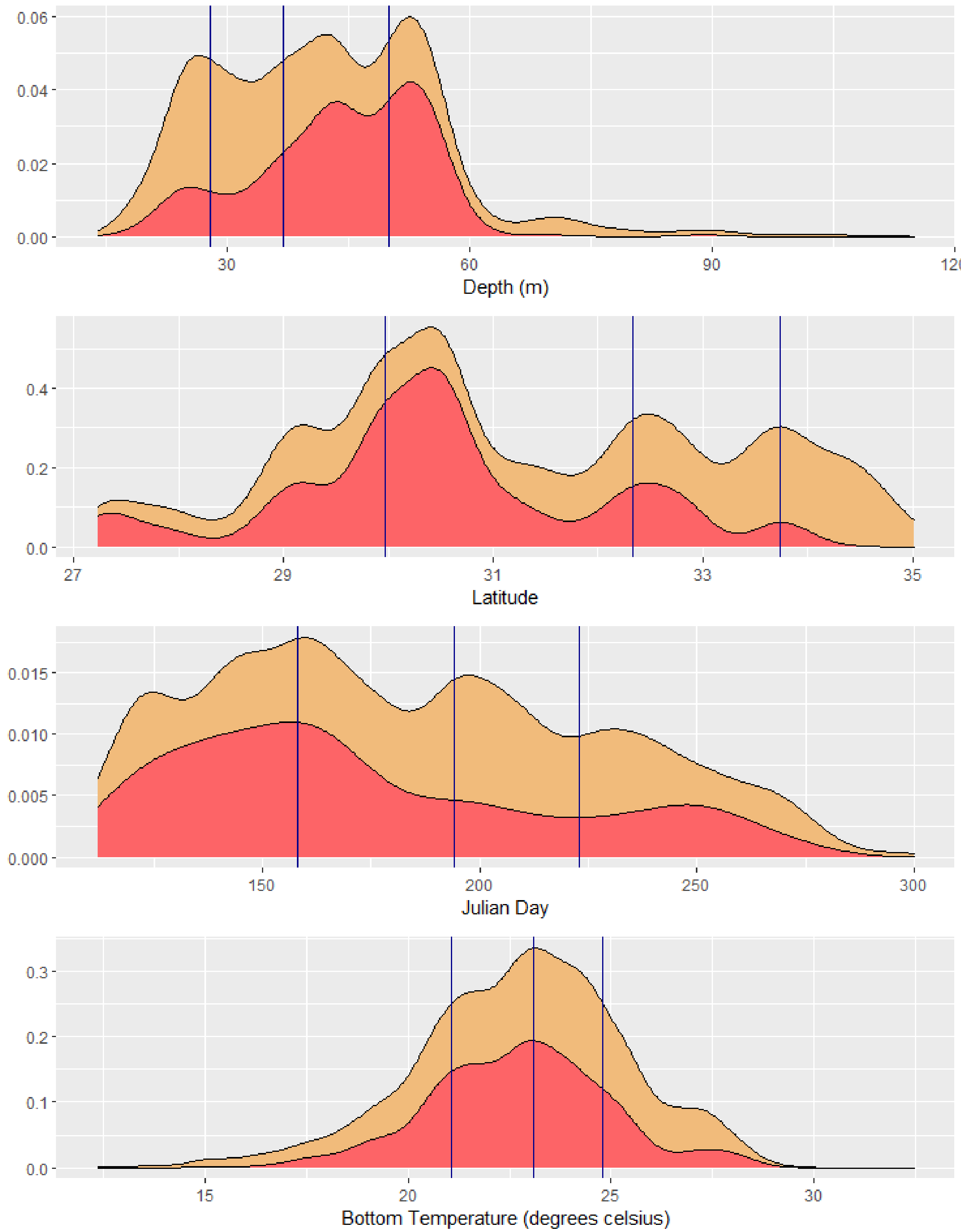

Figure 3. Distribution of data collected as continuous variables for positive (red) and zero (orange) counts. Vertical lines represent break points for factor definitions.

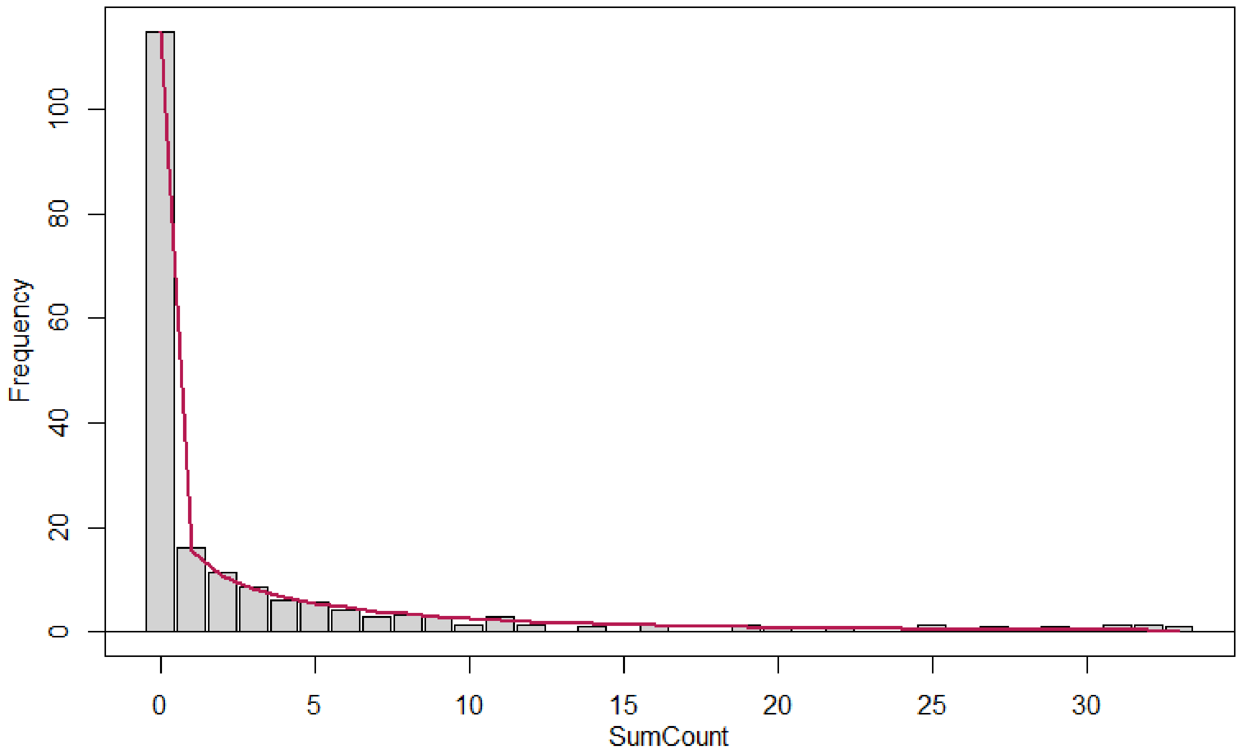

Figure 4. Model diagnostic plots of fitted model values (red line) against the original data distribution for the preferred model for mutton snapper.

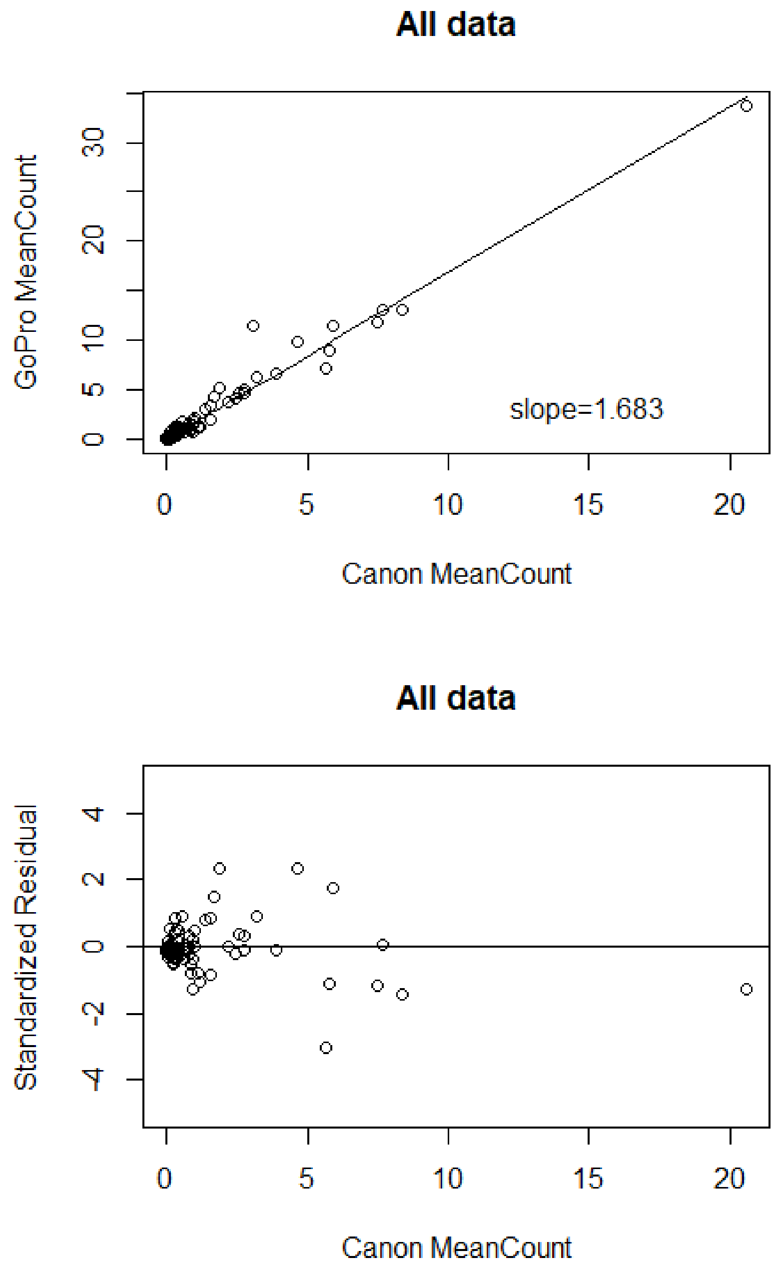

Figure 5. Top row: relationship between mutton snapper *MeanCounts* using GoPro and Canon cameras from the 2014 camera calibration study using all data. Bottom row: standardized residuals from all data.

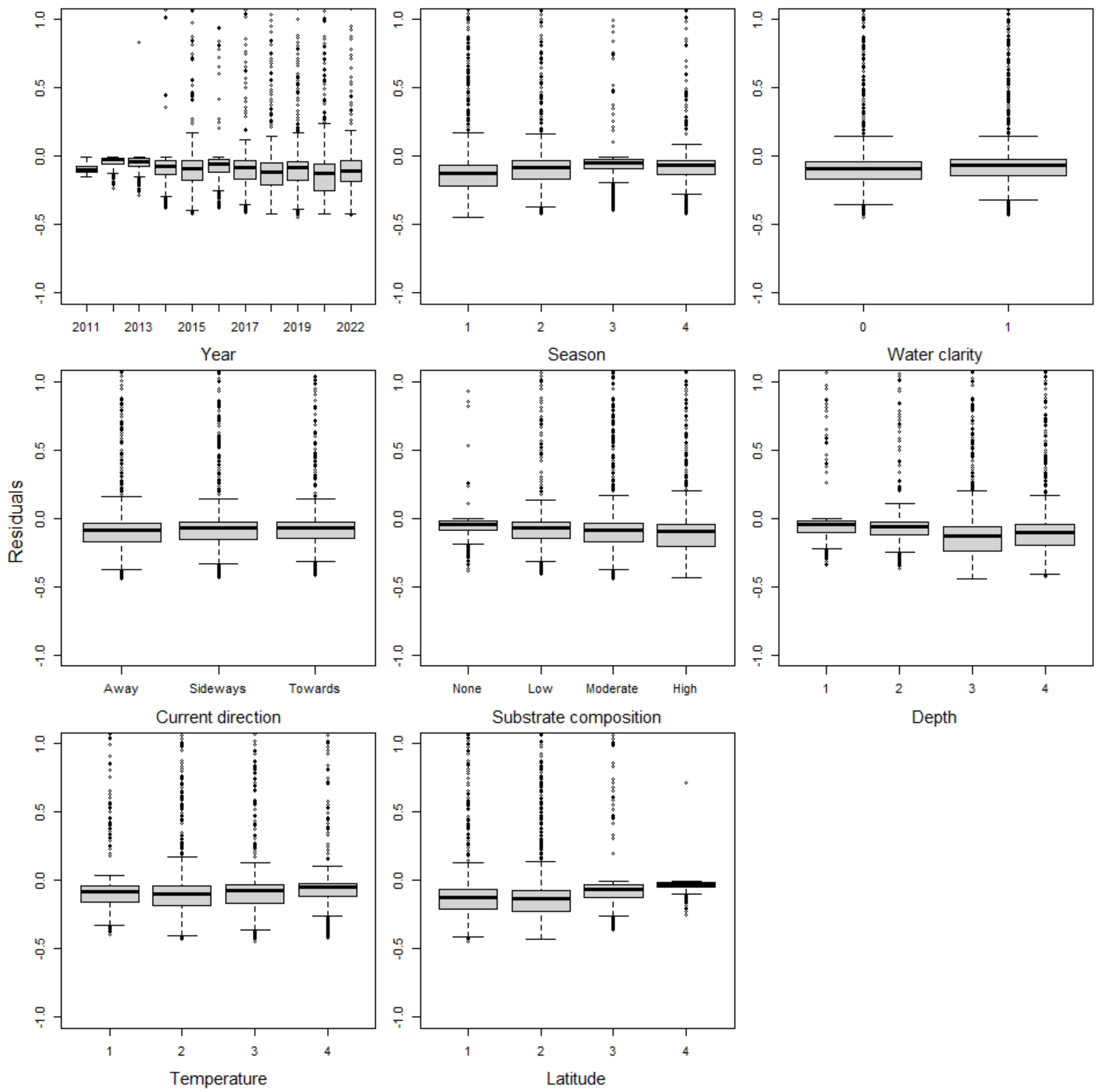

Figure 6. Residuals for all levels of each categorical predictor variable included in the zero-inflated negative binomial model.

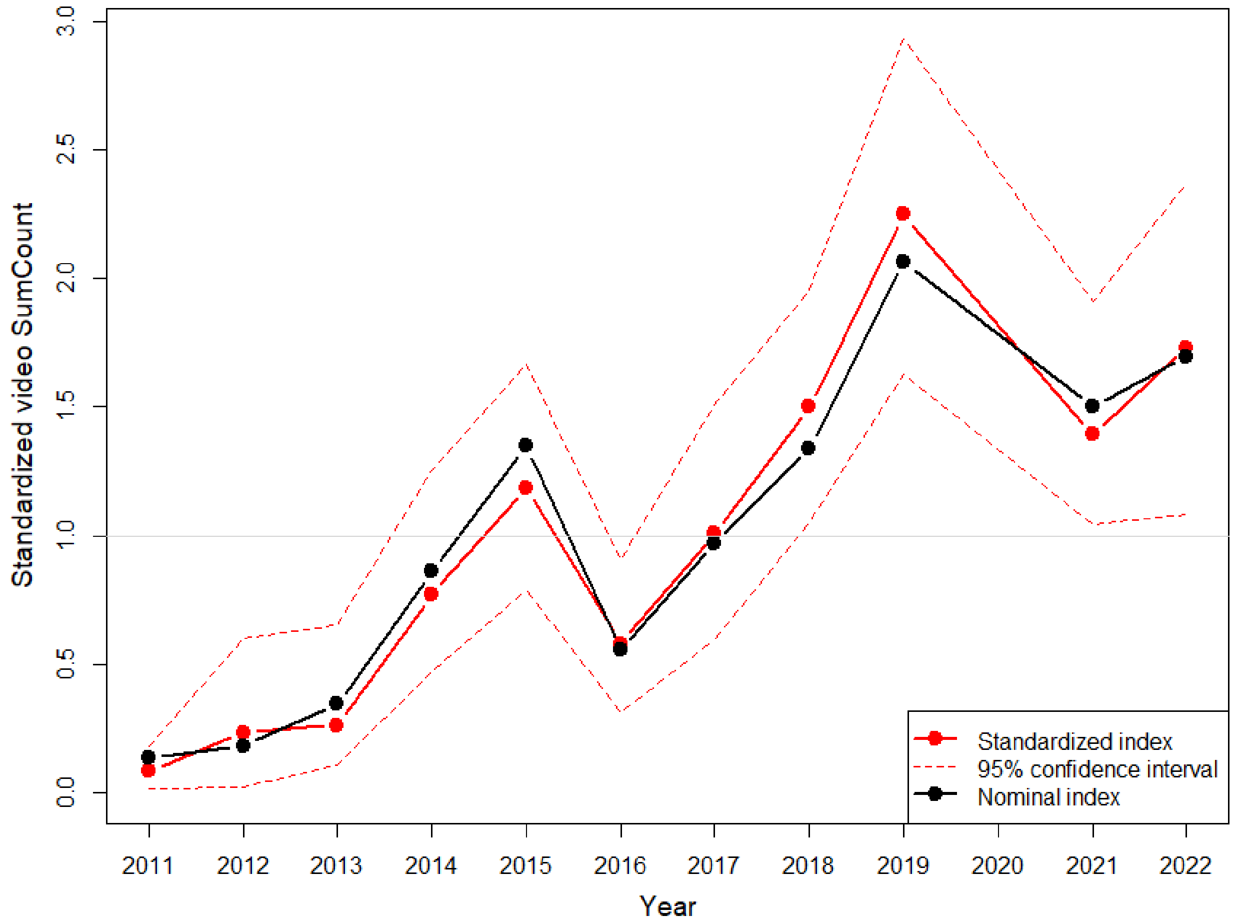

Figure 7. Mutton snapper relative standardized index (red line and points) with 2.5% and 97.5% confidence intervals (red dashed lines) and the relative nominal index (black line with points) from SERFS video data using a zero-inflated negative binomial model.