National Marine
Fisheries Service
NOAA

Fishery Bulletin
established in 1881

Spencer F. Baird
First U.S. Commissioner
of Fisheries and founder
of *Fishery Bulletin*

Effects of incomplete sampling and standardization on indices of abundance from a fishery-independent trawl survey off the Atlantic coast of the southeastern United States

Amy Zimney
Tracey Smart (contact author)

Email address for contact author: smartt@dnr.sc.gov

Marine Resources Research Institute
South Carolina Department of Natural Resources
217 Fort Johnson Road
Charleston, South Carolina 29412

Abstract—Abundance indices from fishery-independent surveys are preferred in stock assessments for their robust scientific designs that minimize uncertainty and bias. When sampling does not adhere to the design, researchers employ techniques such as imputation or standardization to improve accuracy and reduce bias. We examined 2 methods for adjusting for incomplete sampling within the Coastal Trawl Survey (CTS) of the Southeast Area Monitoring and Assessment Program—South Atlantic for 3 species commonly encountered in survey sampling, the Atlantic croaker (*Micropogonias undulatus*), bluefish (*Pomatomus saltatrix*), and white shrimp (*Litopenaeus setiferus*): design-based imputation of missing data and standardization through the delta-generalized-linear-model approach. Additionally, we determined the effect of modifying the seasonal component of the survey design through retrospective simulation. For all 3 species, standardization improved precision in annual abundance estimates relative to values estimated with the design-based method. When a stratum missed in sampling overlapped with an area or time of high variability for a species (e.g., 2019), standardization did not improve precision over the design-based method. Results from examination of the effects of dropping entire seasons, because of funding or logistical challenges, indicate that rotating which season is dropped was the best approach to balancing characteristics of each species. Overall, we recommend the standardization approach for accounting for missing data within the CTS time series.

Manuscript submitted 12 April 2022.
Manuscript accepted 2 September 2022.
Fish. Bull. 120:252–267 (2022).
Online publication date: 28 September 2022.
doi: 10.7755/FB.120.3-4.6

Generally, the purpose of fishery-independent surveys is to provide population data to stock assessments to reduce uncertainty in stock statuses and management measures informed by the stock assessments (Walters and Pearse, 1996). Reduction in uncertainty relies on fishery-independent surveys having robust scientific designs that are not influenced by management or fishing practices (Cochran, 1977; Williams and Carmichael[1]). To reduce assessment uncertainty, considerable effort has been applied to developing best practices for minimizing error in abundance indices derived from survey data (Walters, 2003; Maunder and Punt, 2004; Shelton et al., 2014). Additionally, much work has been done to address bias in index calculation due to spatial variability in sampling or fishing and to ensure that effort is defined appropriately (Campbell, 2004, 2015). Precision can be gained in fishery-independent surveys either by increasing sampling effort or by using a stratified-random sampling design to optimize effort allocation (Xu et al., 2015). However, the realities of funding, weather, and vessel reliability and availability more often than not result in decreased or incomplete sampling effort decreasing precision of a survey. In particular, changing environmental conditions and funding concerns that affect completion of surveys are highly pervasive issues among surveys, and many survey programs are facing hard decisions regarding reducing effort while still providing comparable time series. In the absence of increased precision from a priori design, researchers may turn to analytical tools.

Stock assessment models often rely on the inclusion of catch rate time series (either fishery-independent or fishery-dependent) that are proportional to population abundance (generally referred to as indices of abundance) (Francis, 2011). Often it is assumed that these time series are proportional to stock size (Hilborn and Walters, 1992; Arreguín-Sánchez, 1996; Quinn and Deriso, 1999), on the basis of the sampling design, stability of catchability, and consistency in trends among

[1] Williams, E. H., and J. Carmichael (eds.). 2009. South Atlantic fishery independent monitoring program workshop final report, 85 p. South Atl. Fish. Manag. Counc. and Natl. Mar. Fish. Serv., Southeast Fish. Sci. Cent., Beaufort, NC. [Available from Southeast Fish. Sci. Cent., Natl. Mar. Fish. Serv., 101 Pivers Island Rd., Beaufort, NC 28516.]

indices of abundance (Quinn and Deriso, 1999). For an index of abundance to reflect stock size trends, the data must be collected according to a robust scientific design consistently through time. When deviations from the design occur, those deviations should be accounted for in some way. Standardizing catch data increases the accuracy of estimates (Walters, 2003; Maunder and Punt, 2004) and allows accounting for incomplete sampling during the time series. Typical statistical standardization techniques (e.g., generalized linear models or generalized additive models) provide the opportunity to quantify the effects of either sampling or environmental characteristics on estimates of abundance and to essentially correct those estimates for deviations in sampling or environmental conditions (Wilberg et al., 2009).

Off the Atlantic coast of the southeastern United States, fish, elasmobranch, and invertebrate species in nearshore, coastal waters are surveyed through fishery-independent sampling of the Southeast Area Monitoring and Assessment Program—South Atlantic's Coastal Trawl Survey (SEAMAP-SA CTS). Sampling of trawlable habitats through the CTS began in this region (Fig. 1) in

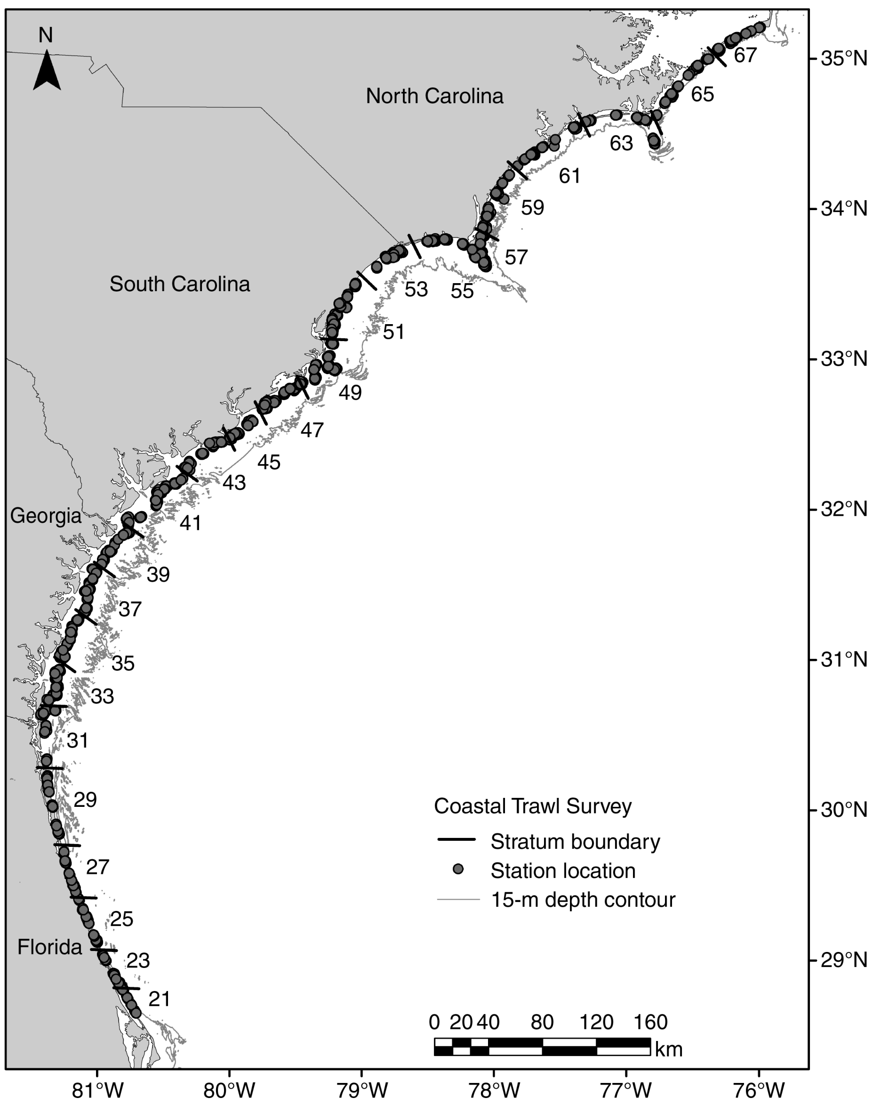

Figure 1

Map of study area showing the stratum boundaries and locations of stations of the Coastal Trawl Survey of the Southeast Area Monitoring and Assessment Program—South Atlantic where Atlantic croaker (*Micropogonias undulatus*), bluefish (*Pomatomus saltatrix*), and white shrimp (*Litopenaeus setiferus*) were sampled from 1990 through 2019. Numbers are those assigned to strata. Stations are located in trawlable habitat from 4.6 to 9.1 m off the Atlantic coast of the southeastern United States.

1986, and since 1990 the CTS has monitored abundance trends in shallow depths (<9.1 m) using a standardized stratified-random sampling design. Each year, the number of stations allocated for sampling is determined by available funding, but the spatial and temporal portions of the survey design have remained consistent over time. This consistency makes it possible for estimates based on catch rate time series from this survey to serve as indices of abundance for stock assessments.

Historically, the rates at which stations were missed were low, and the missed stations were generally spread out among strata instead of entire strata being missed. More recently, however, the CTS has experienced challenges to sampling all of the stations allocated for sampling as a result of the increased frequency of weather conditions unsuitable for sampling (including prolonged periods of winds and sea states above sampling cut-offs and major hurricanes), damaged gear (caused by debris from river run-off following hurricanes and major rain events), logistical challenges (including low tidal amplitude preventing departures), and mechanical failures making the aging vessel unavailable for sampling. In some seasons during 2018 and 2019, these challenges meant that entire strata were not sampled. Given these challenges, it has become more likely that annual abundance estimates based on survey data from years with completely unsampled strata or high numbers of unsampled stations will not be proportional to true abundance or will not index the same portion of the population as estimates based on data from other years with more complete sampling of strata.

Herein, we present catch and effort time series for 3 species of management interest commonly encountered in CTS sampling: the Atlantic croaker (*Micropogonias undulatus*), bluefish (*Pomatomus saltatrix*), and white shrimp (*Litopenaeus setiferus*). These species have a variety of distributions (spatially and temporally) (senior author, unpubl. data), and incomplete sampling may affect abundance estimates in different ways. In light of recent difficulties completing CTS sampling, we present annual abundance for these species in 2 ways, a nominal, design-based estimate and a standardized estimate, to assess if these time series need correcting through standardization because of incomplete sampling. In addition, we provide results of our examination of the effects of sampling and environmental covariates on the standardized estimate of abundance to identify potential drivers of abundance and the need for correction for each species. Because the challenges for completing survey sampling as designed are expected to continue, changes to the survey design, such as dropping a sampling season, are under consideration. To determine the effects of these potential design modifications on abundance estimates, we also conducted retrospective simulations on the standardized indices of abundance for all 3 species. On the basis of these analyses, we provide a recommendation on which estimate is most appropriate for use as an index of abundance and on whether there is a preferred design modification strategy.

Materials and methods

Study design and gear

Sampling for the CTS, a fishery-independent research program, was conducted by the South Carolina Department of Natural Resources (SCDNR) in coastal Atlantic waters off the southeastern United States between Cape Hatteras, North Carolina, and Cape Canaveral, Florida (Fig. 1). Consistent sampling methods were in place from 1990 through 2019 and were used to target the full spatial range in each of 3 seasons: spring (April and May), summer (July and August), and fall (September and November). Trawl surveys were conducted at randomly selected stations from a pool of stations within 24 strata based on latitude and depth (Fig. 1) between the inshore 4.6-m depth contour and the offshore 9.1-m depth contour. To reduce variability of the data, the method of allocating stations was changed in 2001 from proportional allocation (based on the total surface area of each stratum) to optimal allocation (Thompson, 1992), with higher effort allocated to strata with historically higher variability and with the number of stations allocated within each stratum determined anew each year. The total number of allocated stations per season has ranged between 78 and 112, depending on funding and other survey priorities, but the spatial footprint of the survey has remained consistent.

Sampling was conducted during daylight hours (between 1 h after sunrise to 1 h before sunset) on board the R/V *Lady Lisa*, a 22.9-m wooden-hulled, double-rigged St. Augustine shrimp trawler owned and operated by the SCDNR Marine Resources Division, by using a pair of 22.9-m mongoose-type Falcon trawl nets (Beaufort Marine Supply Inc.[2], Beaufort, SC) without turtle excluder devices (Willis et al., 2015; Zimney[3]). The body of the trawl net was constructed of #15 net twine with 47-mm stretch mesh, and the codend was constructed of #30 net twine with 41-mm stretch mesh. At each station, the pair of nets were towed for 20 min, excluding wire-out and haul-back times, with a target speed of 1.3 m/s, relative to the bottom.

The catch from each net was processed independently and assigned a unique collection number. The contents of each net were sorted to species (with limited exceptions sorted to genus or family only), and the total biomass and number of individuals were recorded. When trawl nets contained high volume catches, selected species were removed (e.g., endangered species and species that posed a risk to staff during handling), the remaining net contents were placed into shrimp baskets and weighed, and a randomly selected basket was sorted and processed as described above. Abundance and biomass data for each

[2] Mention of trade names or commercial companies is for identification purposes only and does not imply endorsement by the National Marine Fisheries Service, NOAA.

[3] Zimney, A. 2021. SEAMAP-SA Coastal Trawl Survey data and sample collection methods. Southeast Data, Assessment, and Review SEDAR78-WP01, 4 p. [Available from website.]

species were then used to estimate the total abundance and biomass of each species in the full catch by using the ratio of the weight of subsampled catch placed in baskets to the total weight of the full catch. When large numbers of an individual species occurred in the processed catch, all individuals of that species were weighed, and then a haphazardly selected subsample was counted (subsamples were approximately 30–60 individuals). The total number of individuals of a species in the catch was then estimated by using the ratio of the weight of the processed species subsample to the total species weight.

Hydrographic data, measurements of surface and bottom temperature and salinity, were logged at each station, with a Van Dorn water sampler (Eijkelkamp North America Inc., Wilmington, NC) in 1990–1992, an SBE 19 SeaCAT Profiler CTD in 1993–2005 and 2017 (Sea-Bird Scientific, Bellevue, WA), or an SBE 19plus SeaCAT Profiler CTD in 2006–2019 (V1 or V2, Sea-Bird Scientific). From these CTD casts, we extracted the deepest measurement of temperature and salinity, as long as it was within 1 m of the bottom, to use in analyses (hereafter, these measurements are referred to as *bottom temperature* and *bottom salinity*).

Data and nominal abundance estimation

The data available for use in abundance estimation included a unique collection number, date of deployment, season, tow duration (in minutes), stratum, station, latitude, longitude, depth, bottom temperature, bottom salinity, and the number of individuals and aggregate weight of each species captured. Data from the paired nets were pooled for analysis to form a standard unit of effort at each station sampled (a trawl tow). Estimates of abundance were expressed as the number of individuals per hectare. Estimated area swept by a net was calculated by multiplying the expected average width of the net opening (13.5 m), based on Stender and Barans (1994), by the distance in meters trawled and dividing the product by 10,000 m^2/ha. Then, the estimated area swept for each of the paired nets was combined. If area swept could not be accurately estimated (e.g., if a U-turn was executed to avoid entanglement with a gill net), data for that tow were omitted from analyses.

From 1990 through 2019, sampling was conducted at 8403 of the 8568 allocated stations, and 24 strata were fully missed (Table 1, Fig. 1): 1 stratum (21) in fall 1990, 2 strata (65 and 67) in spring 2013, 4 strata (37, 39, 65, and 67) in spring 2018, 7 strata (29, 57, 59, 61, 63, 65, and 67) in fall 2018, 3 strata (63, 65, and 67) in spring 2019, and 7 strata (21, 23, 25, 27, 63, 65, and 67) in fall 2019. Where entire strata were missed, the average long-term nominal abundance was calculated for each species in each stratum and season and imputed for the missing value as the nominal abundance. In total, 58 trawl tows were excluded from analyses (Table 1). Nine tows were excluded because the area swept could not be accurately estimated, and 14 tows were eliminated because the tow duration was not equal to 20 min, indicating deviation from normal operations. Additionally, 35 tows were excluded from standardization because covariate information was missing.

Annual nominal abundance (A) was calculated by determining the sum of the number of individuals (*individuals*) caught per hectare (*area swept*) and dividing it by the total number of tows (t) for a given combination of stratum (st), season (se), and year (y):

$$A_{\mathrm{y}} = \sum\nolimits_{\mathrm{t=1}}^{\mathrm{t}} \frac{individuals_{\mathrm{t,st,se,y}}}{area\,swept_{\mathrm{t,st,se,y}}} \Big/ t_{\mathrm{st,se,y}}. \tag{1}$$

The nominal index of abundance was then normalized by dividing the annual nominal abundance by the overall mean abundance for the full time series, producing a value of relative abundance for each year. These values provide reference points for individual years in relation to the time series, with a value of 1 being the long-term mean.

In recent years (2015–2019), sampling for the CTS has not been completed at all of the allocated stations for the reasons described in the "Introduction." Consequently, entire strata have been missed in some seasons primarily in the outer ranges of the study area where longer windows of suitable weather conditions are needed for travel and sampling (Table 1). Where an entire stratum was missed during a season, the long-term average nominal abundance was calculated for each stratum and season and imputed as a proxy for the nominal abundance of the missed stratum for use in Equation 1 (Little and Rubin, 1987; Walters, 2003). The long-term average was used rather than the average for the most recent years because using only data from recent years could have introduced bias if a stratum was sampled unusually early or late in a season (timing can vary by up to 6 weeks) or was missed in several of the recent years, as occurred for strata 65 and 67, for example.

Standardization with delta-generalized linear models

Because of incomplete seasonal and regional sampling coverage, annual abundance was standardized among years through the "delta-GLM" method (Lo et al., 1992; Dick, 2004; Ballenger et al.[4]), in which the standardized abundance is produced by using the product of predicted values from 2 generalized linear models (GLMs). In the first GLM, species presence and absence is the response variable, sampling or environmental covariates are included, and the binomial error distribution is used. In the second GLM, only data from the tows for which the species of interest were present are used, and the number per hectare is the response variable. Sampling and environmental covariates are also included in this second model, and this positive GLM is fitted with either the gamma or lognormal error distribution. Both gamma and lognormal error distributions were considered for the positive GLM because preliminary analyses found that both error distributions

[4] Ballenger, J., T. Smart, K. Kolmos, and M. Reichert. 2013. Trends in relative abundance of gray triggerfish in waters off the SE US based on fishery-independent surveys. Southeast Data, Assessment, and Review SEDAR32-DW04, 77 p. [Available from website.]

Table 1

The number of stations allocated for sampling each year, the number of stations at which survey tows were completed, the survey strata with missed stations, and the number of stations with available data that were included in analysis for standardization of indices of abundance for Atlantic croaker (*Micropogonias undulatus*), bluefish (*Pomatomus saltatrix*), and white shrimp (*Litopenaeus setiferus*) sampled during the Coastal Trawl Survey of the Southeast Area Monitoring and Assessment Program—South Atlantic off the Atlantic coast of the southeastern United States from 1990 through 2019. Percent positive rates, the percentage of tows with species present, are given for each species in each year. An asterisk (*) indicates that a stratum was missed in at least one season in the given year.

Year	No. of stations allocated	No. of stations with complete sampling	Strata with missed stations	No. of stations with data used	Percent positive rate (%)		
					Atlantic croaker	Bluefish	White shrimp
1990	234	231	21*, 61	227	65.2	43.2	50.2
1991	234	233	61	231	64.5	36.8	47.6
1992	234	234	–	232	56.0	40.1	37.5
1993	234	234	–	233	50.2	30.0	39.9
1994	234	234	–	233	53.2	32.6	43.8
1995	234	234	–	232	59.1	47.8	51.7
1996	234	234	–	229	58.5	45.3	48.3
1997	234	234	–	232	43.8	30.5	47.2
1998	234	234	–	232	64.4	33.5	57.9
1999	234	234	–	233	44.6	35.6	55.8
2000	234	234	–	234	44.9	37.2	54.7
2001	306	306	–	295	63.0	46.9	44.6
2002	306	306	–	301	45.9	23.9	49.2
2003	306	306	–	304	63.1	46.1	43.5
2004	306	306	–	304	54.9	36.9	46.7
2005	306	306	–	301	58.5	28.8	39.5
2006	306	306	–	303	54.8	20.7	45.6
2007	306	306	–	305	54.2	27.8	55.6
2008	306	306	–	304	53.3	36.3	62.1
2009	336	336	–	335	60.9	40.9	51.6
2010	336	336	–	335	50.1	40.0	40.3
2011	336	336	–	336	59.8	38.1	44.9
2012	336	336	–	336	69.9	33.3	64.0
2013	306	295	63, 65*, 67*	294	83.1	39.7	62.4
2014	306	306	–	306	70.9	38.9	43.8
2015	336	329	35, 63, 65	329	71.4	35.0	50.2
2016	336	331	29, 33, 35, 39	330	70.0	31.5	64.2
2017	306	294	21, 31, 35, 59, 61, 63, 67	293	71.8	22.1	65.6
2018	306	228	21, 23, 25, 27, 29*, 31, 33, 35, 37*, 39*, 41, 51, 53, 55, 57*, 59*, 61*, 63*, 65*, 67*	228	78.9	23.2	60.5
2019	306	258	21*, 23*, 25*, 27*, 29, 31, 61, 63*, 65*, 67*	258	84.9	24.0	69.0
Total	8568	8403		8345	61.1	34.8	51.3

fit data from the CTS for several species relatively well. Additionally, although other zero-inflated models have been used for standardization, the design of the CTS works well with the delta-GLM framework, and other models do not provide large improvements in variability for common species such as those examined here (Smart and Zimney[5]).

[5] Smart, T., and A. Zimney. 2021. Spanish mackerel indices of abundance in U.S. South Atlantic waters based on the SEAMAP-SA fishery-independent Coastal Trawl Survey. Southeast Data, Assessment, and Review SEDAR78-WP02, 22 p. [Available from website.]

Both error distributions were compared with the Akaike information criterion (AIC) in identical base models, and the one with the lowest AIC value was chosen as the model to use for analysis (Akaike, 1973).

Year, *season*, *stratum*, *bottom temperature*, and *bottom salinity* were included as model covariates. *Season* was defined as spring, summer, and fall as described earlier. *Stratum* was previously defined in the first paragraph of the "Materials and methods" section and in Figure 1 and served as a proxy for location (latitude and longitude). Observed values of bottom temperature and bottom salinity were binned by using quantiles, with 5 bins for bottom temperature (<20.2°C, 20.2–23.0°C, 23.1–26.5°C, and ≥26.6°C) and 2 bins for bottom salinity (<34.9 and ≥34.9). The data for these covariates were binned rather than left continuous for consistency with accepted index formulations for the CTS in recent stock assessments (Smart and Boylan[6]). The addition of these covariates also is consistent with recent standardization techniques used in many recent assessments in the region. The delta-GLM for all species started with the same base model:

$$A_y = Pr(y, se, st, temp, sal) \times A_p(y, se, st, temp, sal), \quad (2)$$

where Pr = the likelihood of a species being present in year y, season se, stratum st, bottom temperature $temp$, and bottom salinity sal; and

A_p = the abundance of a species when it is present in year y, season se, stratum st, bottom temperature $temp$, and bottom salinity sal.

No interaction terms were included in the delta-GLM formula for consistency with recent accepted index formulations (Smart and Boylan[6]; Smart and Zimney[5]). Results of preliminary data analysis indicate no obvious interactive trends for any individual species examined in this study, and no multicollinearity was found for covariates included in the equation.

The covariates included in the final delta-GLM models (both the binomial GLM and positive GLM) were chosen by using AIC with backward selection, with the exception that *year* was always included in each model to allow an annual abundance value to be produced. The effect of covariates on standardized abundance estimates for each species was determined by using separate analyses of variance (ANOVA) for both the presence of a given species and the abundance of that same species estimated with model covariates as fixed factors. The final delta-GLM standardized abundance index for each species is the product of the mean responses from the linear predictors of *year* and any selected covariates from the 2 GLMs. Jackknifing was used to determine coefficients of variation, standard error, and standard deviations for each delta-GLM analysis. Residual and quantile-quantile (Q-Q) plots were used as diagnostic tools to determine the fit of the models. All analyses were performed in R, vers. 4.1.1 (R Core Team, 2021).

The delta-GLM used in this study was based primarily on code adapted from Dick (2004). As with the nominal index, the delta-GLM standardized index was normalized by dividing the annual standardized abundance by the overall mean standardized abundance for the time series, with a value of 1 being the mean for the time series. Nominal abundance calculations and delta-GLM analysis were performed for 3 species of management interest: the Atlantic croaker, bluefish, and white shrimp. Because these species also have generally been commonly caught in tows over the full length (1990–2019) of the CTS time series, their distributions and abundances lend themselves to the analyses outlined herein. Over the period of the CTS time series, the Atlantic croaker was often the most abundant species caught during CTS sampling annually, having widespread spatial and temporal distributions. Bluefish primarily were caught in northern strata in spring and fall. Given the recent sampling challenges during these seasons, estimates of the abundance of bluefish have the potential to be heavily affected by incomplete sampling. The white shrimp was another widely distributed species, largely occurring from northern Florida to central North Carolina.

In addition to comparison of design-based and standardized indices, the effects of several potential survey design modifications were investigated for each species. Design modifications under consideration are primarily focused on dropping a season from sampling in any given year. Potential scenarios for this design change are permanently dropping a season (3 scenarios: spring, summer, or fall), rotating the season that is dropped each year, or randomly selecting a season to drop each year. We retrospectively applied these 5 scenarios to the raw data for the 3 species during the period 2014–2019 to investigate the effect of the design for years when sampling coverage was severely incomplete (i.e., in 2018 and 2019) or was complete or mostly complete (i.e., in 2014–2017). Once these scenarios were applied to the raw data, we ran the delta-GLM analysis again for the full time series and examined the standardized abundance estimates and variability for all 5 scenarios and for the current survey design that includes all seasons.

Results

All covariates (*year*, *season*, *stratum*, *bottom temperature*, and *bottom salinity*) were selected for inclusion by using the AIC for both the binomial and positive delta-GLMs for the Atlantic croaker, bluefish, and white shrimp. For all 3 species the lognormal error structure had the lowest AIC value, indicating that it was the most appropriate error distribution to be used for the positive model.

Atlantic croaker

The Atlantic croaker was the most abundant species caught in CTS sampling, of the 3 species examined in this study. It was also the most common, occurring in 61% of all tows between 1990 and 2019 (Table 1). Atlantic croaker were distributed relatively evenly, both spatially and temporally, throughout the study area with specimens caught in all seasons and strata (Fig. 2, A and B). Atlantic croaker generally were more abundant in summer than in spring and least abundant in fall. Although this species occurred in all strata, abundance of Atlantic croaker increased from the southern portion of the study area to the northern portion. Atlantic croaker were abundant in a range of bottom temperatures but were more

[6] Smart, T. I., and J. Boylan. 2013. King mackerel index of abundance in coastal US South Atlantic waters based on a fishery-independent trawl survey. Southeast Data, Assessment, and Review SEDAR38-DW-11, 39 p. [Available from website.]

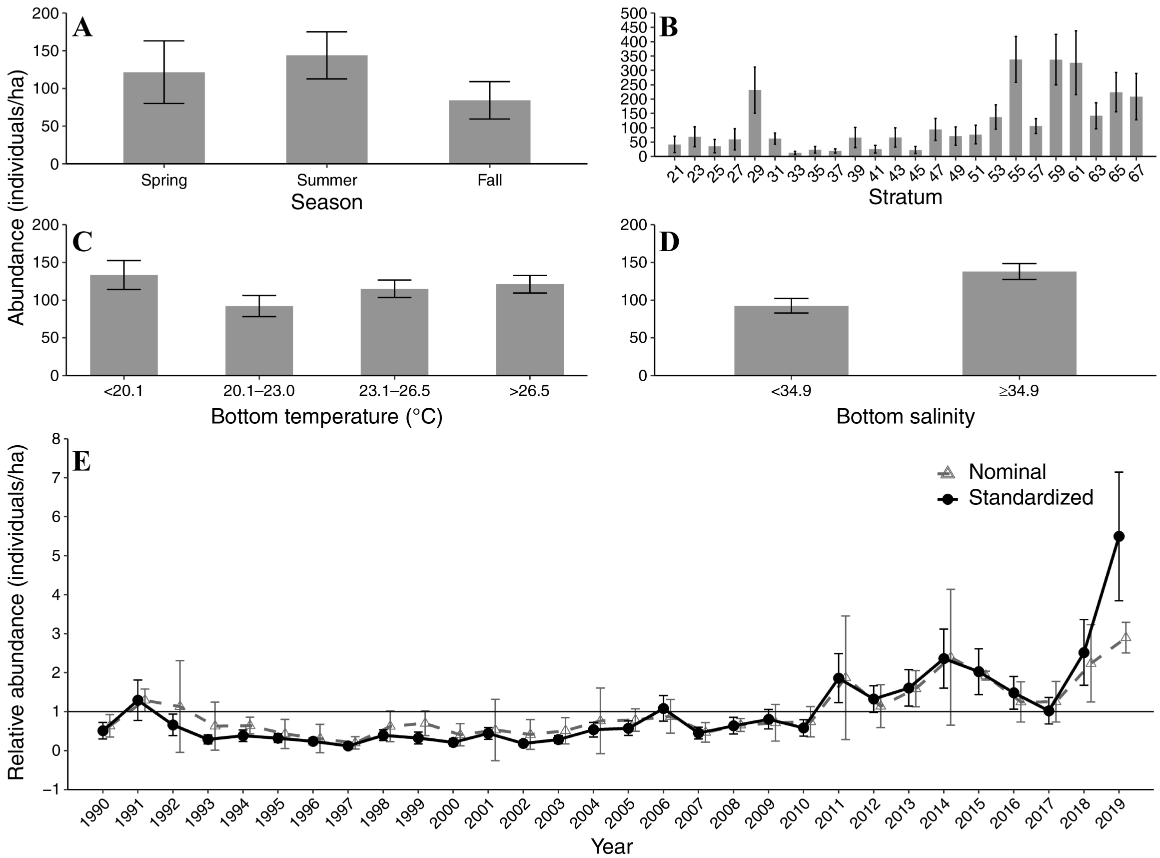

Figure 2

Nominal abundance of Atlantic croaker (*Micropogonias undulatus*), by (**A**) season, (**B**) stratum, (**C**) bottom temperature, and (**D**) bottom salinity, based on data from sampling off the Atlantic coast of the southeastern United States from 1990 through 2019, with design-based imputation of missing values. (**E**) Nominal and standardized relative abundances of Atlantic croaker estimated by using the design-based method and delta-generalized linear models, respectively, are provided by year. Error bars indicate the standard errors of the means. The horizontal gray line indicates the long-term mean of 1 for relative abundance over the full period of the time series.

abundant in waters with bottom salinities greater than 34.9 than in waters with other salinities (Fig. 2, C and D).

From 1990 through 2010, nominal abundance of Atlantic croaker remained relatively low compared with the mean nominal abundance for the time series, with the normalized nominal abundance below the time series mean for most years (Fig. 2E). After 2010, nominal abundance was more variable and had a general trend of values increasing to levels above the time series mean (Fig. 2E).

The trend in delta-GLM standardized abundance of Atlantic croaker was similar to that in nominal abundance, although the trend in standardized estimates was less variable (Fig. 2E, Suppl. Table). The exception to this similarity is that, for 2019, the predicted abundance of Atlantic croaker in the standardized index was almost twice the abundance predicted in the nominal index. This large difference between the nominal and standardized abundance values in 2019 coincides with the only occasion when the variability in the standardized estimate was higher than that of the nominal estimate for this species, indicating that variability drove the disagreement between the estimates produced with the 2 methods. In 2018 and 2019, limited sampling occurred in the northernmost strata where Atlantic croaker were generally more abundant than in other strata. The raw average nominal abundance in 2019 (excluding the imputed values for missed strata) was the highest in the history of the CTS (359.8 individuals/ha) (senior author, unpubl. data), possibly contributing to the standardized estimate being higher than the nominal estimate. In contrast, the data imputed for missed strata for nominal abundance were from years with lower abundance. All covariates were significant in the binomial and positive delta-GLMs for predicting the presence and abundance of Atlantic croaker (Table 2). Results from the use of diagnostics, such as residual and Q-Q plots, indicate reasonable fits for both models (Suppl. Fig. 1).

Table 2

Results from analysis of variance for presence and abundance of Atlantic croaker (*Micropogonias undulatus*), bluefish (*Pomatomus saltatrix*), and white shrimp (*Litopenaeus setiferus*) from standardization with binomial and positive delta-generalized linear models. Data used in models are from sampling of the Coastal Trawl Survey of the Southeast Area Monitoring and Assessment Program—South Atlantic conducted during 1990–2019 off the Atlantic coast of the southeastern United States. The significance level is 0.05.

Covariate	df	Deviance	Residual df	Residual deviance	*F*	*P*
Atlantic croaker						
Binomial model						
Null			8344	11,159.10		
Year	29	413.00	8315	10,746.10		<0.01
Season	2	498.71	8313	10,247.40		<0.01
Stratum	23	1188.01	8290	9059.40		<0.01
Temperature	3	11.06	8287	9048.30		0.01
Salinity	1	63.89	8286	8984.40		<0.01
Positive model						
Null			5092	31,609.00		
Year	29	2590.40	5063	29,019.00	19.61	<0.01
Season	2	1293.70	5061	27,725.00	142.02	<0.01
Stratum	23	4554.10	5038	23,171.00	43.47	<0.01
Temperature	3	140.80	5035	23,030.00	10.31	<0.01
Salinity	1	103.00	5034	22,927.00	22.62	<0.01
Bluefish						
Binomial model						
Null			8344	10,788.80		
Year	29	202.78	8315	10,586.00		<0.01
Season	2	242.50	8313	10,343.50		<0.01
Stratum	23	547.31	8290	9796.20		<0.01
Temperature	3	166.85	8287	9629.30		<0.01
Salinity	1	25.37	8286	9604.00		<0.01
Positive model						
Null			2906	6282.10		
Year	29	330.53	2877	5951.50	7.22	<0.01
Season	2	157.77	2875	5793.70	49.95	<0.01
Stratum	23	1093.65	2852	4700.10	30.11	<0.01
Temperature	3	197.89	2849	4502.20	41.77	<0.01
Salinity	1	4.43	2848	4497.80	2.80	0.09
White shrimp						
Binomial model						
Null			8344	11,562.80		
Year	29	251.60	8315	11,311.20		<0.01
Season	2	385.29	8313	10,925.90		<0.01
Stratum	23	1217.70	8290	9708.20		<0.01
Temperature	3	90.63	8287	9617.60		<0.01
Salinity	1	65.95	8286	9551.60		<0.01
Positive model						
Null			4282	17,992.00		
Year	29	1244.47	4253	16,748.00	13.29	<0.01
Season	2	1436.22	4251	15,312.00	222.40	<0.01
Stratum	23	1545.00	4228	13,767.00	20.80	<0.01
Temperature	3	46.54	4225	13,720.00	4.81	<0.01
Salinity	1	81.40	4224	13,639.00	25.21	<0.01

Bluefish

Bluefish were collected in 35% of all CTS tows from 1990 through 2019 (Table 1). Temporally, bluefish were more abundant in spring and fall (Fig. 3A). The spatial distribution of bluefish was primarily in the northern portion of the study area (strata ≥55), with the highest abundances occurring off North Carolina (Fig. 3B). Bluefish were more abundant in waters with bottom temperatures below 20.1°C and in waters with bottom salinities less than 34.9 (Fig. 3, C and D).

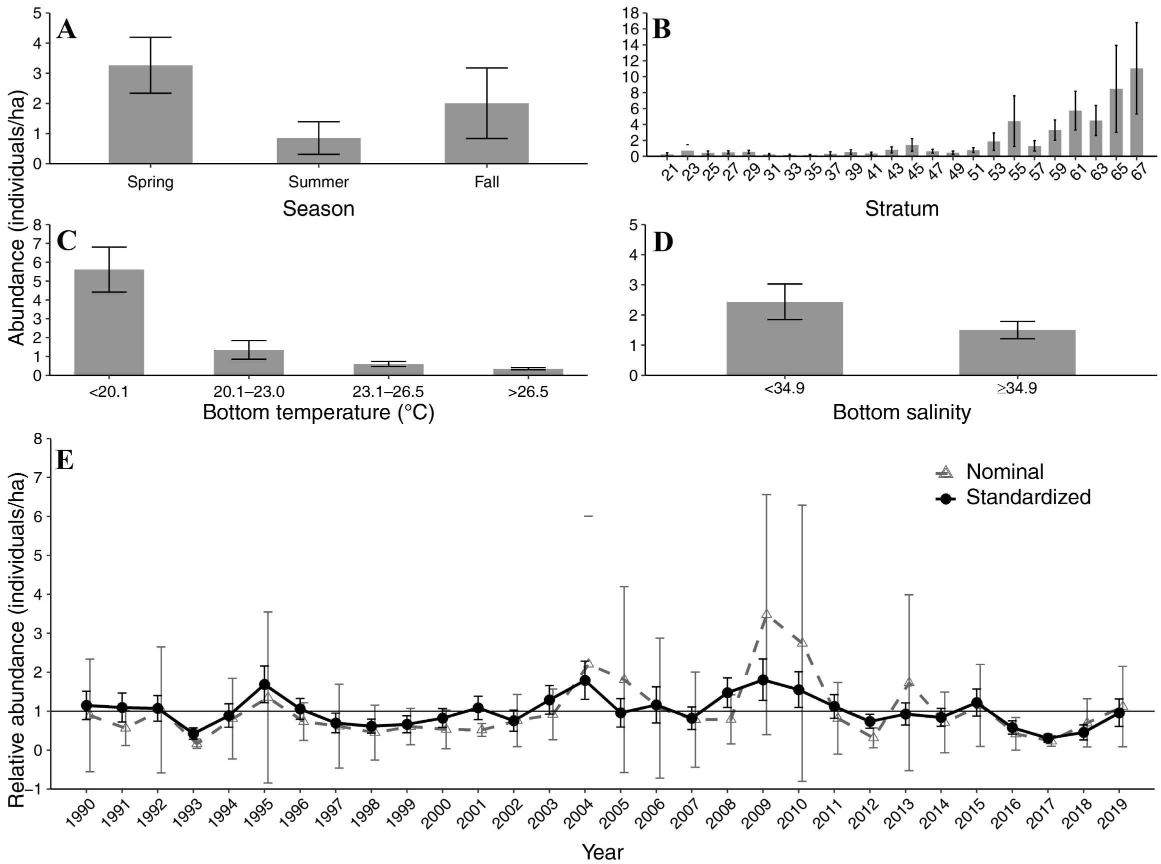

Figure 3

Nominal abundance of bluefish (*Pomatomus saltatrix*), by (**A**) season, (**B**) stratum, (**C**) bottom temperature, and (**D**) bottom salinity, based on data from sampling off the Atlantic coast of the southeastern United States from 1990 through 2019, with design-based imputation of missing values. (**E**) Nominal and standardized relative abundances of bluefish estimated by using the design-based method and delta-generalized linear models, respectively, are provided by year. Error bars indicate the standard errors of the means. The horizontal gray line indicates the long-term mean of 1 for relative abundance over the full period of the time series.

Nominal abundance of bluefish was generally stable near the time series mean without large positive or negative swings. Additionally, variability in nominal abundance of bluefish tended to be low when abundance was below the mean and high when abundance was above the mean (2004–2013) (Fig. 3E). Nominal abundance was similar to or below the time series mean from 2014 through 2019.

The trend in delta-GLM standardized abundance of bluefish was similar to that in nominal abundance, although with less variability, particularly when compared with trends for the years of peak nominal abundance: 1995, 2004, 2005, 2009, 2010, and 2013 (Fig. 3E, Suppl. Table). One exception is the estimate for 2001, which is almost twice as high with higher variability than that of the nominal estimate for that year. Although the error bars overlap, standardization also reduced the abundance estimates in 2009 and 2010 relative to the nominal estimates for those years. All covariates were significant in both the binomial and positive GLMs, except for bottom salinity, which was not significant in the positive model (Table 2). Examination of residual and Q-Q plots reveals reasonable fits for both the binomial and positive models (Suppl. Fig. 2).

White shrimp

White shrimp occurred in 51% of tows (Table 1) and were the most abundant penaeid shrimp species caught in CTS sampling. White shrimp were most abundant during the fall, relative to the other seasons (Fig. 4A). White shrimp were spatially distributed throughout the region but were most abundant in waters of northern Florida, with smaller peaks in abundance off South Carolina and New River, North Carolina (Fig. 4B). White shrimp were most abundant in bottom temperatures ranging between 20.1°C and 26.5°C (Fig. 4C) and in waters with bottom salinities less than 34.9 (Fig. 4D).

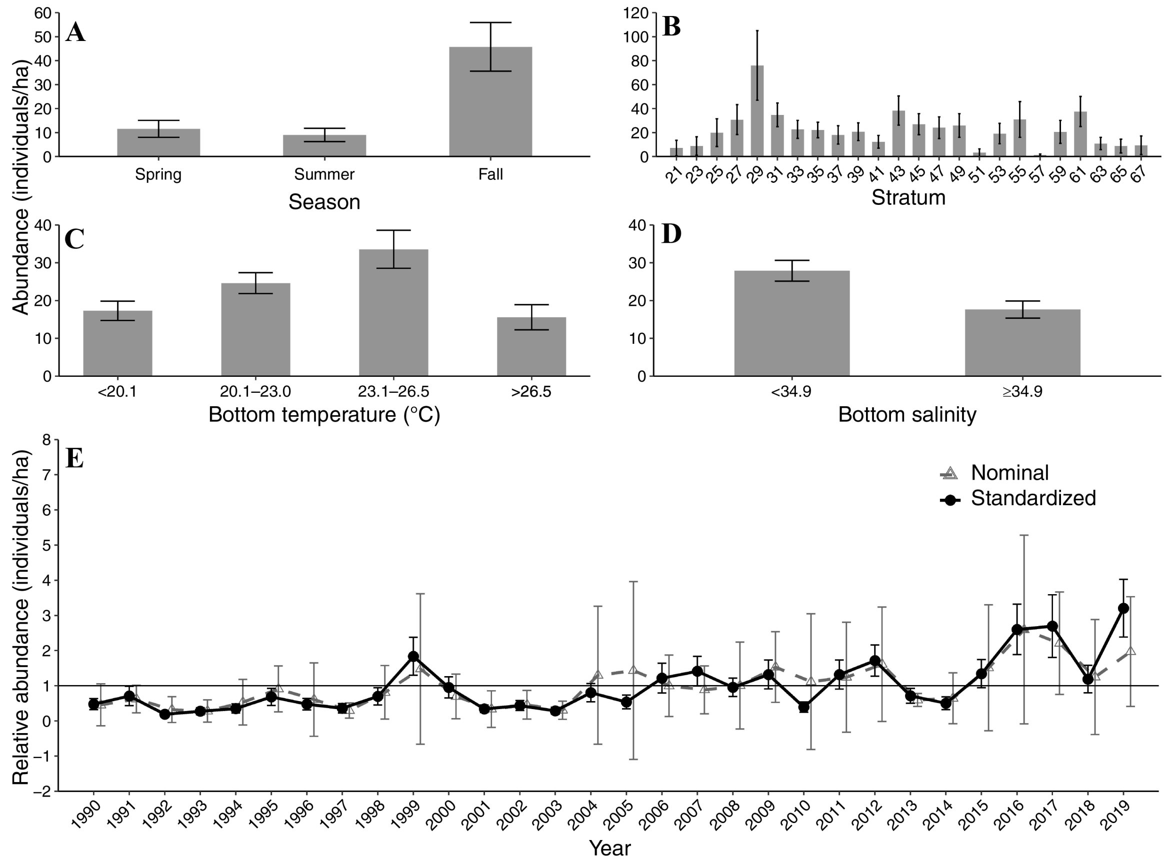

Figure 4

Nominal abundance of white shrimp (*Litopenaeus setiferus*), by (**A**) season, (**B**) stratum, (**C**) bottom temperature, and (**D**) bottom salinity, based on data from sampling off the Atlantic coast of the southeastern United States from 1990 through 2019, with design-based imputation of missing values. (**E**) Nominal and standardized relative abundances of white shrimp estimated by using the design-based method and delta-generalized linear models, respectively, are provided by year. Error bars indicate the standard errors of the means. The horizontal gray line indicates the long-term mean of 1 for relative abundance over the full period of the time series.

Nominal abundance of white shrimp was generally below, or relatively similar to, the mean for the time series from 1990 through 2003 (Fig. 4E). From 2004 through 2019, nominal abundance of white shrimp was variable but with a generally increasing trend compared with the trend of the time series mean. Variability in nominal abundance generally increased as abundance increased.

The trend in delta-GLM standardized abundance of white shrimp was similar to that in nominal abundance but with lower variability (Fig. 4E, Suppl. Table). Although the error bars overlap, the only notable difference between nominal and standardized estimates was in the abundance estimate for 2019, when the standardized abundance of white shrimp was higher than the nominal abundance. All covariates were statistically significant in predicting the presence (binomial model) and abundance (positive model) of white shrimp (Table 2). Examination of residual and Q-Q plots reveals reasonable fits for both delta-GLMs (Suppl. Fig. 3).

All species

For the 3 species examined in this study, the standardization of abundance through the use of delta-GLMs primarily affected the variability in annual estimates, reducing the average variability in nominal values for Atlantic croaker by 3%, for bluefish by 90%, and for white shrimp by 75% (Figs. 2E, 3E, and 4E). The magnitude of the variability of abundance estimates generally changed with the extent of spatial and temporal distribution and percent positive rate (i.e., the percentage calculated as the number of tows in which a given species was collected divided by the total number of tows conducted per year) among the 3 species examined. The Atlantic croaker had the widest distribution and highest occurrence of the 3 species, with the smallest annual nominal errors. The bluefish had the narrowest distribution and lowest occurrence of the 3 species and had an average normalized nominal standard error over 2 times higher than that for the Atlantic croaker (0.60 for bluefish and 0.26 for Atlantic croaker) and just slightly higher than that for the white shrimp (0.55). Standardization had little effect on annual abundance estimates, with the exception of increasing abundance estimates in 2019 for Atlantic croaker and in 2001 for bluefish (based on error bars that do not overlap; Figs. 2E and 3E). The years with strata that were missed in sampling (1990, 2013, 2018, and 2019) did not have noticeable differences between nominal and standardized abundance estimates, with the exception of 2019 for Atlantic croaker and white shrimp (although the latter had overlapping error bars) (Table 1, Figs. 2E and 4E).

The effect of scenarios of potential survey modifications on standardized abundance was not consistent among the 3 species examined in this study (Fig. 5, A–C). The Atlantic croaker had the most variable change to index values of the 3 species, with the scenario in which the dropped season was systematically rotated generally tracking most closely with the abundance index from the delta-GLM analysis that used the current survey design, which includes all seasons (Fig. 5A). The effect of each of the 3 scenarios in which a particular season was consistently dropped on the abundance of Atlantic croaker depended on the year examined, likely because the annual abundance is informed by the mean response to the other seasons, which itself is inconsistent among years, seasons, and strata. The effect of randomly selecting a season to be dropped was also relatively variable for Atlantic croaker and resulted in noticeable deviations from the values in the abundance index produced in the model analysis that included all seasons.

All 5 scenarios had minimal effects on the standardized abundance index for both bluefish and white shrimp relative to the model for all seasons (Fig. 5, B and C), and this outcome is most likely related to the more restricted (and predictable) spatiotemporal distribution of abundance for these 2 species relative to that of the Atlantic croaker. The few examples of noticeable deviations from the full index occurred for bluefish and white shrimp under the scenarios in which a single season was consistently not sampled and for white shrimp under the scenario in which the dropped season was rotated. The variability in the scenarios for survey design modifications differed among species and years, but not in a consistent way (Table 3).

Discussion

As a long-term fishery-independent survey, the CTS provides abundance and life history data for a variety of species of management interest. A stratified-random sampling design is used to conduct the CTS, with survey stations allocated to minimize variability in catch abundance estimates. Historically, annual sampling at the vast majority of allocated stations was completed and sampling occurred in all strata. However, in recent years (i.e., 2018 and 2019), allocated stations and full strata were left unsampled because of the use of an aging vessel, mechanical failures, stagnant funding and increased costs, and prolonged periods of weather conditions above levels deemed safe for sampling. In particular, strata at the northernmost and southernmost portions of the survey area were those most likely to remain unsampled.

In this study, we investigated whether or not our inability to complete the full spatial scope of the survey in each season affected the accuracy of abundance estimates by comparing nominal (design-based) and standardized (delta-GLM) estimates of abundance for Atlantic croaker, bluefish, and white shrimp. Surprisingly, only one major difference between estimates produced with these 2 methods was observed: one for Atlantic croaker for a year with incomplete sampling. Other than this instance, there were almost no discernible differences in estimates of abundance for the years with incomplete sampling relative to estimates for years with complete sampling. One reason for the lack of differences in estimates may be the use of average long-term values for nominal abundances for years with incomplete sampling versus the use of the standardization technique in which average values are applied within each model cell to account for missing data. Although standardization may involve the use of an improved average estimate because of the inclusion of more covariates than the relatively simple imputation method used to produce the nominal estimate (Walters, 2003), any loss of precision in an index resulting from decreased or lost effort can be balanced if stratification is incorporated into the design of a given survey and because of the similarity of using averages as empirical information (Xu et al., 2015).

In the case of the CTS, the stratified-random sampling design has been consistent over time, allowing minimization of loss of information when sampling was incomplete. This assumption that the design will balance incomplete sampling, however, may not remain true if completion of sampling continues to be eroded. It is currently unknown what the effect of incomplete sampling may be for species that are less common or less ubiquitous than the 3 species examined in this study.

The relationships between environmental covariates included in the standardization models and species abundance varied among the species examined in this study. The association between abundance and bottom temperature varied among species. There was little difference in abundance among temperatures for Atlantic croaker (Fig. 2C), but bluefish were most associated with temperatures <20.1°C, likely related to their presence in the northern strata of the study area in the spring and fall (Fig. 3, B and C). Abundance of white shrimp was less influenced by temperature than estimates for bluefish, but abundances generally increased with increasing temperatures for white shrimp, most likely reflecting the warmer waters in southern strata where white shrimp were abundant (Fig. 4, B and C). Salinity was less influential on species-specific abundance: there was no significant difference in abundance of bluefish among salinity levels, Atlantic croaker were significantly more abundant in waters with higher salinities (≥34.9) than in those with lower salinities (<34.9), and abundance of white shrimp followed the opposite trend.

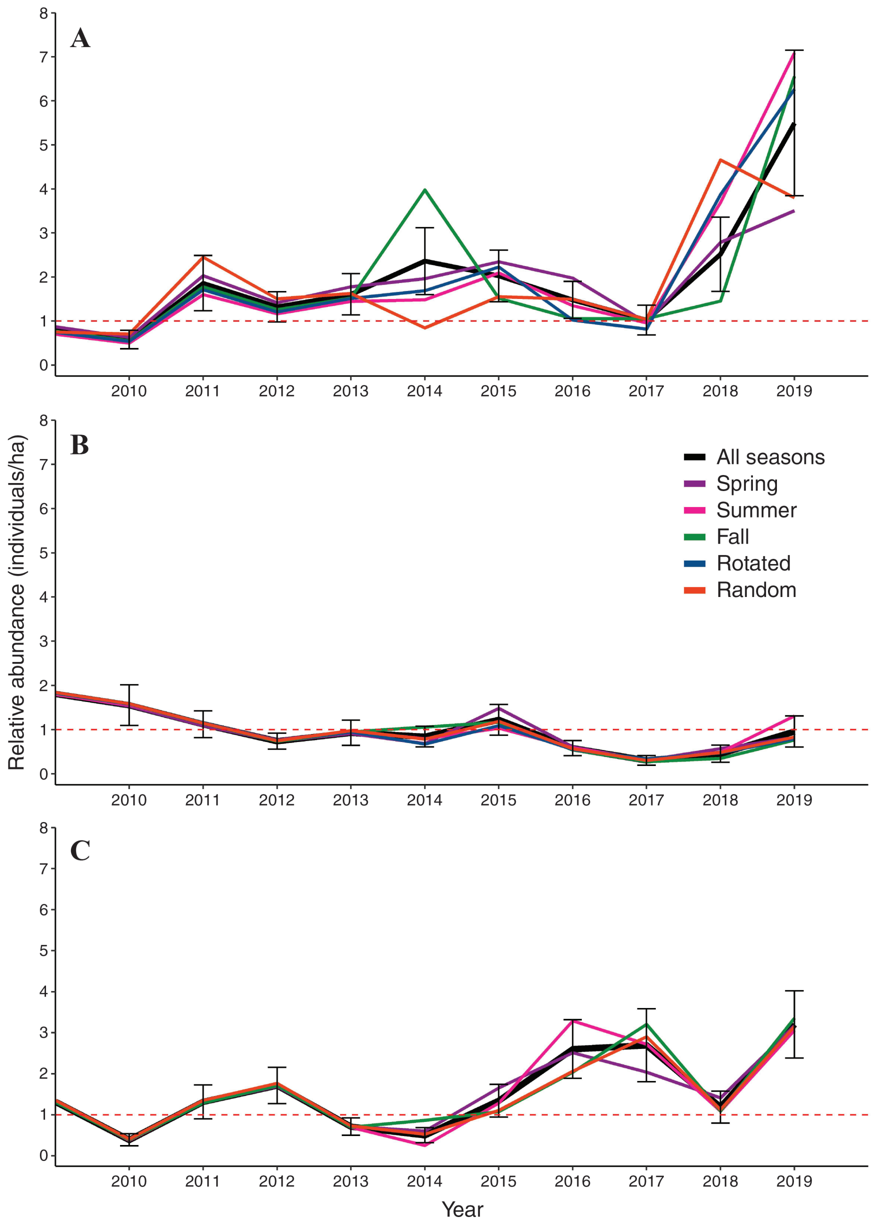

Figure 5

Abundance estimates for (**A**) Atlantic croaker (*Micropogonias undulatus*), (**B**) bluefish (*Pomatomus saltatrix*), and (**C**) white shrimp (*Litopenaeus setiferus*) standardized with generalized linear models for the 5 scenarios of potential design modifications of the Coastal Trawl Survey of the Southeast Area Monitoring and Assessment Program—South Atlantic: dropping spring (April and May), summer (July and August), or fall (September through November), rotating which season is dropped, or randomly dropping a season. The full time series was used in models with the survey design modifications applied to sampling conducted between 2014 and 2019 off the Atlantic coast of the southeastern United States. The black line in each panel indicates the standardized estimates of relative abundance produced under the current survey design, in which no season is dropped, with error bars for standard errors of the annual means. The dashed orange line in each panel indicates the long-term mean of 1 for relative abundance over the full period of the time series (1990–2019).

Table 3

Standard errors of standardized abundance estimates for (**A**) Atlantic croaker (*Micropogonias undulatus*), (**B**) bluefish (*Pomatomus saltatrix*), and (**C**) white shrimp (*Litopenaeus setiferus*) off the Atlantic coast of the southeastern United States between 2014 and 2019 for the 5 scenarios of potential design modifications of the Coastal Trawl Survey of the Southeast Area Monitoring and Assessment Program—South Atlantic: dropping spring (April and May), summer (July and August), or fall (September–November), randomly dropping a season, and rotating which season is dropped. For comparison, standard errors of abundance estimates produced under the current survey design, with no season dropped, are provided.

Year	All seasons	Spring	Summer	Fall	Random	Rotated
Atlantic croaker						
2014	57.08	47.03	58.54	109.40	27.66	47.23
2015	44.14	50.90	63.67	46.00	39.89	62.46
2016	31.67	43.37	40.72	29.07	34.23	27.66
2017	25.50	23.93	34.36	34.77	27.46	23.49
2018	63.52	68.38	127.71	50.56	129.87	125.47
2019	124.35	82.39	242.09	176.95	82.46	168.03
Bluefish						
2014	0.09	0.09	0.11	0.14	0.11	0.09
2015	0.14	0.18	0.15	0.18	0.19	0.14
2016	0.07	0.09	0.09	0.08	0.08	0.08
2017	0.04	0.06	0.05	0.05	0.04	0.06
2018	0.08	0.09	0.12	0.07	0.12	0.11
2019	0.14	0.17	0.22	0.14	0.18	0.14
White shrimp						
2014	1.73	2.61	1.11	2.98	1.78	2.66
2015	3.81	5.19	4.54	4.00	4.23	4.56
2016	6.83	7.54	10.74	6.80	7.08	7.16
2017	8.48	8.06	11.58	10.82	11.42	8.38
2018	3.71	5.11	4.95	3.62	4.76	4.69
2019	7.81	9.11	10.19	9.30	9.10	9.66

Population levels for Atlantic croaker are driven by the combination of temperature and salinity, with winter temperatures being primarily influential on survivorship and salinities above 10 potentially mitigating the effects of extremely low temperatures on survivorship (Lankford and Targett, 2001; Hare and Able, 2007). Bluefish are known to overwinter between North Carolina and Florida, and they generally migrate northward in the spring as water temperatures increase and then migrate southward in the fall as water temperatures decrease (Wilk[7]; Fahay et al., 1999). In previous studies, the low temperature tolerance of juvenile bluefish was found to be 13–15°C (Hare and Cowen, 1996), and their growth slowed at water temperatures greater than 24°C (Hartman and Brandt, 1995). It is possible that the binary binning of bottom salinity meant the relationship could not be resolved for bluefish or that bluefish were present at times with more variable salinities (e.g., variable run-off in fall due to seasonal rains and tropical systems). The reduced abundance of white shrimp above a salinity of 34.9 likely reflects their high abundances around large estuarine systems with relatively high freshwater or estuarine outflow. Results from previous studies support the notions that abundance of adult white shrimp is positively correlated with water temperature and negatively correlated with salinity and that mortality occurs at temperatures below 10°C (Joyce, 1965; SAFMC, 1981; Diop et al., 2007; Fowler et al., 2018).

In general, standardization decreased variability relative to design-based estimation of abundance in 18 of 30 survey years (60%) for Atlantic croaker, in 12 survey years (40%) for bluefish, and in 16 survey years (53%) for white shrimp (Figs. 2E, 3E, and 4E). For all 3 species examined in this study, the primary variables of *season* and *stratum* in the design-based GLMs accounted for more of the deviance explained by GLMs than either *bottom temperature* or *salinity* and often explained levels of deviance similar to those explained by *year* (Table 2). Both the spatial and temporal elements of the survey design enabled us to find that those species with more restricted distributions have greater variability in estimates of abundance. This pattern of small distribution and larger variability may be partially accounted

[7] Wilk, S. J. 1977. Biological and fisheries data on bluefish, *Pomatomus saltatrix* (Linnaeus). Natl. Mar. Fish. Serv., Northeast Fish. Sci. Cent., Sandy Hook Lab. Tech. Ser. Rep. 11, 44 p. [Available from website.]

for through the nominal estimation used in this study but is likely more adequately addressed by using the standardization method that can incorporate other drivers such as environmental conditions (Figs. 2E, 3E, and 4E).

The bluefish had the most uneven spatial distribution of the 3 species examined and had some of the highest annual standard error estimates, but the white shrimp was the species most unevenly distributed among seasons and had moderate standard error estimates (Figs. 3B, 3E, 4B, and 4E). Carruthers et al. (2011) suggested that the choice to impute missing data rather than to standardize by using conventional GLM techniques should be dependent on the spatial dynamics of a population and the spatial grain of the missing data. This choice between methods is especially important if there are area and time interactions and the unobserved areas do not adhere to the mean abundance trend. Use of imputation tends to lead to greater bias than use of a GLM, unless the spatial scale of imputation is relatively fine and the imputed data are representative of the overall population.

In our study, we chose to impute a mean based on the full time series, although imputing a mean based on data from only recent years may have been more representative of more recent trends for each species. However, for bluefish, using *stratum* in the imputation method is more appropriate than using larger latitudinal bins because *stratum* has the finest spatial scale consistent with the survey design (*station* cannot be used as a variable because not every station is sampled each year). Because of the uneven spatial distribution of bluefish, future work should determine if the use of *station* for imputation is more appropriate than the use of *stratum*. One caveat to using *station* is that, because not every station is selected for sampling each year, the use of *station* may result in a decrease in sample sizes that inform calculations.

There were only 2 observed differences in abundance estimates between the nominal and standardization methods as revealed by error bars not overlapping for Atlantic croaker in 2019 and for bluefish in 2001. The year 2019 was the only year of incomplete sampling during which the 3 northernmost strata were not sampled in both spring and fall. In general, these strata are also the ones that typically have moderate to high abundances of Atlantic croaker (Fig. 2B). Not surprisingly, for 2019, the nominal abundance estimate was markedly lower than the standardized value. The difference between the nominal and standardized abundance estimates is likely a result of the standardization method better accounting for the effects of covariates on abundance, for the general increasing trend in 2019, and for the typically higher catches in these strata than the design-based approach, even with the average nominal abundance imputed as a proxy for the missing data. By comparison, there was no change in the estimates for either bluefish or white shrimp in 2019. Catches of white shrimp in survey tows in the northernmost strata were generally low (Fig. 4B); therefore, missing data for these strata likely did not have a great effect on the annual abundance estimate from either calculation. Generally, the highest abundances observed for bluefish occurred in the 3 northernmost strata and in spring and fall (Fig. 2, A and B). This consistent positive relationship between *stratum* (latitude) and abundance likely allowed those consistently high catches to be captured in the calculations of both the nominal and standardized methods, resulting in very similar estimates for 2019. In contrast to survey effort in 2019, all allocated stations were sampled in 2001.

Two of the few exceptions to improvement in accuracy (i.e., reduced error) of the standardized abundance estimates were for Atlantic croaker in 2019 and for bluefish in 2001. For Atlantic croaker in 2019, the estimate of abundance increased significantly following standardization, and the error rate increased almost 3-fold. Strata were missed in sampling or not sampled completely in both spring and fall in 2019, the most variable and least abundant seasons in the full time series for Atlantic croaker, respectively. Abundance of Atlantic croaker in fall 2019 was higher than in any other previous fall but also was more variable, likely a result of not sampling in the northernmost strata where this species is abundant but the abundance is variable and of not sampling in the southernmost strata where this species is least abundant, reducing the number of strata in which there were zero or near zero encounters. In addition, the use of imputation in the design-based calculation did not account for uncertainty in the imputed estimates for multiple seasons and strata and, therefore, reduced variability for 2019 by default (Carruthers et al., 2010). In contrast, errors for all seasons and strata in 2019 continued to be incorporated when the standardization technique was used, potentially leading to the higher variability in estimates for that year. Further comparisons should examine variability of estimates based on imputed data.

Regarding bluefish in 2001, there is no record of unusual circumstances in CTS historic data for that year; therefore, there may have been unusual conditions that were not accounted for in the current analyses. If so, these conditions were likely specific to bluefish because the estimates for the other 2 species in 2001 were similar and had decreased standardized variability as expected.

Results of the exercise of retrospectively dropping seasons for the years 2014–2019 indicate that the likely effects of major modifications to the survey would be species-specific (i.e., not all species abundance estimates remained consistent among all modification scenarios). Removing whole seasons did not change the pattern of increased abundance of Atlantic croaker in 2019 for most scenarios: dropping fall, dropping summer, and systematically rotating which season was dropped from analysis (Fig. 5A). By comparison, removing spring or randomly dropping seasons between 2014 and 2019, decreased the standardized abundance estimate for Atlantic croaker in 2019 compared with the standardized estimate produced with data for all seasons. Interestingly, dropping seasons did not change the pattern of abundance for bluefish or white shrimp (Fig. 5, B and C). Both species had lower abundance estimates and more variability compared with estimates for Atlantic croaker, but with standardization we were able to successfully predict abundances for these species even with the loss of full seasons. Therefore, there may be an interaction between annual abundance of each species, species distributions or predictability, strata or seasons that are sampled, and effects of standardization on variability and estimates of abundance that need to be considered before making changes to the survey design.

Fishery-independent indices of abundance generally are essential for most stock assessment models currently in use, are preferred over fishery-dependent indices, and are often upweighted relative to other indices because of their adherence to standardized designs and resistance to temporal changes in catchability or sampling systems (Wilberg et al., 2009). For the CTS, delta-GLM indices of abundance indicate that standardization decreased variability in annual abundance estimates for all species examined and potentially "corrected" data from the year in which sampling was most incomplete for one of the species most commonly encountered in the survey, the Atlantic croaker. On the basis of the improvements in variability alone, we recommend moving forward with standardization for species for which long-term time series are available. Because of the advanced age of the vessel used for surveys and the trend of more extreme weather events, standardization may become even more important in future years (and for more species) as completion of CTS sampling is likely to continue to be challenging.

Given that the survey design needs to be modified to account for these potential constraints on sampling completion, that the effect on variability among modification scenarios was not informative, and that the best performing model varied among species and years (Table 3), we also recommend rotating the season that is not sampled, rather than any of the other modification scenarios examined in this study, if modifications become necessary. The effect of a given season on the abundance index is species specific, and results of this study indicate that rotation of the dropped season is the best approach for a multispecies survey if sampling effort needs to be reduced.

Conclusions

In this study, as expected, a common standardization technique (the delta-GLM method) improved estimation of variability in abundance time series from a fishery-independent survey over that of the simpler approach of imputation of average abundance values for Atlantic croaker, bluefish, and white shrimp. These improvements in uncertainty become increasingly important as costs of conducting surveys increase and funding for long-term surveys stagnates, as has been experienced for the CTS. The results of this study indicate that survey programs that cannot complete sampling as designed in a given year could deal with that incompletion through techniques that involve a delta-GLM. We also found that, when funding is severely limited, rotating the season that is not sampled may be the most appropriate approach for multispecies surveys. For surveys without a seasonal structure, incorporating a time element, such as month, a posteriori and rotating which months are prioritized may be a way to cope with limited funding and sampling effort as well, although it would need to be examined on a case-by-case basis.

In addition, for the CTS, over 24 species currently are of management interest and are sampled sufficiently to produce indices of abundance. For this high variety of species, more work needs to be done to examine the effects of survey design modifications because the results of this study were not consistent among species. The delta-GLM method is just one of many standardization techniques that can be employed. Other types of models, such as those that use continuous covariates or other error structures, may be more appropriate or better at improving variability estimation than the analyses for which results are presented herein.

Resumen

Los índices de abundancia procedentes de estudios independientes de la pesca son los preferidos en las evaluaciones de poblaciones debido a sus sólidos diseños científicos que minimizan la incertidumbre y el sesgo. Cuando el muestreo no se ajusta al diseño, los investigadores emplean técnicas como la imputación o la estandarización para mejorar la precisión y reducir el sesgo. Examinamos 2 métodos para ajustar el muestreo incompleto en la Prospección de Arrastre Costero (CTS) del Programa de Monitoreo y Evaluación del Área sureste del Atlántico Sur para 3 especies comúnmente encontradas en el muestreo de la prospección, la corvina del Atlántico (*Micropogonias undulatus*), la anjova (*Pomatomus saltatrix*) y el camarón blanco (*Litopenaeus setiferus*): la imputación de datos faltantes con base en el diseño y la estandarización a través del enfoque del modelo lineal generalizado delta. Además, determinamos el efecto de modificar el componente estacional del diseño de la prospección mediante una simulación retrospectiva. Para las 3 especies, la estandarización mejoró la precisión de las estimaciones de abundancia anual con relación a los valores estimados con el método basado en el diseño. Cuando un estrato omitido en el muestreo coincidía con un área o época de alta variabilidad para una especie (p. ej., 2019), la estandarización no mejoró la precisión con respecto al método basado en el diseño. Los resultados del análisis de los efectos de la exclusión de temporadas enteras, debido a problemas de financiación o logísticos, indican que la rotación de la temporada a excluirse fue el mejor enfoque para equilibrar las características de cada especie. En general, recomendamos el enfoque de estandarización para contabilizar los datos faltantes en las series temporales de la CTS.

Acknowledgments

We would like to thank the numerous field biologists involved with the SEAMAP-SA CTS and the vessel crews for their collection of the data included in our study. In addition, we appreciate the suggestions and feedback from 3 anonymous reviewers that greatly improved the manuscript. This paper is contribution no. 852 for the SCDNR Marine Resources Research Institute. Funding was provided by NOAA through the SEAMAP-SA grant (NA21NMF4350372) to SCDNR.

Literature cited

Akaike, H.
1973. Information theory and an extension of the maximum likelihood principle. *In* Second international symposium on information theory; Tsaghkadzor, 2–8 September 1971 (B. N. Petran and F. Csaki, eds.), p. 267–281. Akadémiai Kiadó, Budapest, Hungary.

Arreguín-Sánchez, F.
1996. Catchability: a key parameter for fish stock assessment. Rev. Fish Biol. Fish. 6:221–242. Crossref

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. Crossref
2015. Constructing stock abundance indices from catch and effort data: some nuts and bolts. Fish. Res. 161:109–130. Crossref

Carruthers, T. R., M. K. McAllister, and R. N. M. Ahrens.
2010. Simulating spatial dynamics to evaluate methods of deriving abundance indices for tropical tunas. Can. J. Fish. Aquat. Sci. 67:1409–1427. Crossref

Carruthers, T. R., R. N. M. Ahrens, M. K. McAllister, and C. J. Walters.
2011. Integrating imputation and standardization of catch rate data in the calculation of relative abundance indices. Fish. Res. 109:157–167. Crossref

Cochran, W. G.
1977. Sampling techniques, 3rd ed., 448 p. John Wiley and Sons, New York.

Dick, E. J.
2004. Beyond 'lognormal versus gamma': discrimination among error distributions for generalized linear models. Fish. Res. 70:351–366. Crossref

Diop, H., W. R. Keithly Jr., R. F. Kazmierczak Jr., and R. F. Shaw.
2007. Predicting the abundance of white shrimp (*Litopenaeus setiferus*) from environmental parameters and previous life stages. Fish. Res. 86:31–41. Crossref

Fahay, M. P., P. L. Berrien, D. L. Johnson, and W. W. Morse.
1999. Essential fish habitat source document: bluefish, *Pomatomus saltatrix*, life history and habitat characteristics. NOAA Tech. Memo NMFS-NE-144, 64 p.

Francis, R. I. C. C.
2011. Data weighting in statistical fisheries stock assessment models. Can. J. Fish. Aquat. Sci. 68:1124–1138. Crossref

Fowler, A. E., J. W. Leffler, S. P. Johnson, L. B. DeLancey, and D. M. Sanger.
2018. Relationships between meteorological and water quality variables and fisheries-independent white shrimp (*Litopenaeus setiferus*) catch in the ACE Basin NERR, South Carolina. Estuar. Coasts 41:79–88. Crossref

Hare, J. A., and R. K. Cowen.
1996. Transport mechanisms of larval and pelagic juvenile bluefish (*Pomatomus saltatrix*) from South Atlantic Bight spawning grounds to Middle Atlantic Bight nursery habitats. Limnol. Oceanogr. 41:1264–1280. Crossref

Hare, J. A., and K. W. Able.
2007. Mechanistic links between climate and fisheries along the east coast of the United States: explaining population outbursts of Atlantic croaker (*Micropogonias undulatus*). Fish. Oceanogr. 16:31–45. Crossref

Hartman, K. J., and S. B. Brandt.
1995. Comparative energetics and the development of bioenergetics models for sympatric estuarine piscivores. Can. J. Fish. Aquat. Sci. 52:1647–1666. Crossref

Hilborn, R., and C. J. Walters.
1992. Quantitative fisheries stock assessment: choice, dynamics and uncertainty, 570 p. Chapman and Hall, London.

Joyce, E. A., Jr.
1965. The commercial shrimps of the northeast coast of Florida. Fla. Board Conserv. Mar. Lab., Prof. Pap. Ser. 6, 224 p.

Lankford, T. E., Jr., and T. E. Targett.
2001. Low-temperature tolerance of age-0 Atlantic croakers: recruitment implications for U.S. Mid-Atlantic estuaries. Trans. Am. Fish. Soc. 130:236–249. Crossref

Little, R. J. A., and D. B. Rubin.
1987. Statistical analysis with missing data, 304 p. John Wiley and Sons, New York.

Lo, N. C.-h., L. D. Jacobson, and J. L. Squire.
1992. Indices of relative abundance from fish spotter data based on delta-lognormal models. Can. J. Fish. Aquat. Sci. 49:2515–2526. Crossref

Maunder, M. N., and A. E. Punt.
2004. Standardizing catch and effort data: a review of recent approaches. Fish. Res. 70:141–159. Crossref

Quinn, T. J., II, and R. B. Deriso.
1999. Quantitative fish dynamics, 542 p. Oxford Univ. Press, New York.

R Core Team.
2021. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. [Available from website, accessed September 2021.]

SAFMC (South Atlantic Fishery Management Council).
1981. Profile of the penaeid shrimp fishery in the South Atlantic, 286 p. SAFMC, Charleston, SC. [Available from website.]

Shelton, A. O., J. T. Thorson, E. J. Ward, and B. E. Feist.
2014. Spatial semiparametric models improve estimates of species abundance and distribution. Can. J. Fish. Aquat. Sci. 71:1655–1666. Crossref

Stender, B. W., and C. A. Barans.
1994. Comparison of the catch from tongue and two-seam shrimp nets off South Carolina. North Am. J. Fish. Manag. 14:178–195. Crossref

Thompson, S. K.
1992. Sampling, 343 p. John Wiley and Sons, New York.

Walters, C.
2003. Folly and fantasy in the analysis of spatial catch rate data. Can. J. Fish. Aquat. Sci. 60:1433–1436. Crossref

Walters, C., and P. H. Pearse.
1996. Stock information requirements for quota management systems in commercial fisheries. Rev. Fish Biol. Fish. 6:21–42. Crossref

Wilberg, M. J., J. T. Thorson, B. C. Linton, and J. Berkson.
2009. Incorporating time-varying catchability into population dynamic stock assessment models. Rev. Fish. Sci. 18:7–24. Crossref

Willis, C. M., J. Richardson, T. Smart, J. Cowan, and P. Biondo.
2015. Diet composition, feeding strategy, and diet overlap of 3 sciaenids along the southeastern United States. Fish. Bull. 113:290–301. Crossref

Xu, B., Y. Ren, Y. Chen, Y. Xue, C. Zhang, and R. Wan.
2015. Optimization of stratification scheme for a fishery-independent survey with multiple objectives. Acta Oceanol. Sin. 34:154–169. Crossref