Eastern Gulf of Maine Sentinel Survey 2010-2020 Report*

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* Part of this report repeats the contexts of the final report for 2010-2018 by John Carlucci because this report is an update of the report for 2010-2018 with the addition of 2019 and 2020 data.

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I. Introduction:

Since their collapse in the 1990s, Atlantic cod stocks in The Gulf of Maine have struggled to recover and spawning stock densities remain at historic lows. This is particularly true in The Eastern Gulf of Maine (EGOM) which, despite virtually no directed fishing effort in this area, remains at lower densities relative to the rest of the Gulf of Maine (Pershing *et al*., 2013). Active state and federal fisheries-independent bottom trawl survey programs in the GOM have sampling stations within the EGOM, but their spatial and temporal coverage is limited because of restricted gear use in areas with complex bathymetry and a high density of fixed gear (i.e. lobster traps). Consequently, trawl survey monitoring effort for groundfish that reside in complex benthic habitats tends to be low and estimations of abundance derived from that survey data may be misrepresentative of the local population. Therefore, there is a great need to understand the population dynamics of cod as well as other groundfish species, such as Atlantic halibut, cusk and white hake, in this area in order to produce more informed abundance estimates. Because of the lack of success of the 2004 rebuilding program for cod, and the ongoing failure to reach 2014 rebuilding projections, it seems unlikely that the directionality of bias in the stock assessment is leading to under-exploitation, as this would inherently accelerate the rebuilding process. Subsequently, it seems more likely that these biases may be leading to scenarios of further stock overexploitation and inadequate management (Pershing *et. al.* 2013).

In order to understand the spatial variability in fish populations, which may skew estimations of fish abundance, fine-scale surveys such as the EGOM Sentinel Survey are essential for providing spatially explicit data that uses a different methodology in an area that is not well covered by existing monitoring programs. Additionally, fine-scale surveys can provide the necessary data for stock assessments to account for this spatial variability in abundance. The EGOM Sentinel Survey provides a platform to test some of the implicit assumptions in a scientific survey. In addition, it can provide data for a sparsely sampled area to augment survey coverage and, consequently, the stock assessment that is derived from these survey datasets. However, because fine-scale surveys are subject to the finite list of environmental conditions and habitat structures that occur within their spatially restricted survey area, they can suffer from a high level of spatial variability in comparison with coast-wide surveys, which sample a more representative suite of habitats and environmental conditions, given that they are not limited by sampling density or gear restrictions resulting from complex habitat. Consequently, and depending on the bounds of the survey area, fine-scale surveys can be more susceptible to abundance estimates associated with high uncertainty, making it challenging to incorporate the data into the stock assessment process.

This report focuses on the analysis of catch data from nine seasons of the EGOM Sentinel Survey to develop a modeling framework for estimating groundfish abundance. Statistical models were used to evaluate which environmental variables might influence groundfish abundance indices and to understand habitat preferences of cod, cusk, white hake, and halibut for the stratified random stations. High frequencies of zero catch observations for species such as halibut and cusk, in combination with possible patchy distributions of fish populations, makes modeling catch data difficult. As data collection continues, it is likely that future models will provide a better fit with a more robust dataset. Thus, the methods described in this study can be used in future Sentinel Survey data analysis.

II. General Methods

II-1. Sentinel Survey Sampling Methods

The Eastern Gulf of Maine Sentinel Survey operates in the inshore eastern Gulf of Maine, from the southern end of Penobscot Bay to the Canadian border, and targets four species of groundfish including Atlantic cod (*Gadus morhua*), Atlantic halibut (*Hippoglossus hippoglossus*), white hake (*Urophycis tenuis*), and cusk (*Brosme brosme*) from June through October. The survey utilizes two types of passive gear, baited longline and jigs, which are deployed at stations chosen based on a random design stratified by four depth strata.

Strata 0: 0-50m
Strata 1: 50-80m
Strata 2: 80-150m
Strata 3: 150m+

II-1-a. Jigging

Two unbaited jigs with three hooks each are deployed for five minutes, at five sites within each station. Fishermen may search for suitable habitat over which to drop gear within 1.5 minutes in each direction from the station coordinates. During each five minute drop, if a fish is caught, that jig is not re-dropped for the remaining time. Jigging is conducted at all 78 random sites, including those which have a longline component. Current survey design includes 36 inshore jigging stations in strata 0, 12 offshore jigging stations (4 in each strata 1-3), and at all 30 stations which longline is also utilized (Figure 1). The jigging component of the Sentinel Survey is intended to target Atlantic cod, being visual predators and occupying generally shallower habitats than the other three target species.

II-1-b. Longline

200 hook longlines are set for one hour at 30 stations, 10 in each strata 1-3 (Figure 1). As with jigging sites, fishermen may choose suitable habitat within 1.5 minutes of the station coordinates. Longlines are baited with squid and/or herring and are intended to target white hake, Atlantic halibut and cusk, due to their perceived greater catchability on the longline as compared to jig, and greater use of offshore habitats as compared to Atlantic cod.

In 2016, no longline data was collected due to budgetary constraints resulting in a jig-only survey year. Prior to 2017 a 2,000 hook longline, soaking for two hours had been used but due to an increasing level of gear congestion and logistical difficulties for sampling in the survey area, an analysis was conducted to evaluate the effects of fishing with a shortened, 200-hook longline for one hour. The results of the analysis showed that there was minimal temporal variation between sizes of longline sets and there was no statistical significance between abundance trends calculated for the 2000-hook set versus the 200-hook set. As a result, it was feasible to use a shortened set to alleviate logistical issues without adversely affecting the design-based abundance index that is derived from the stratified random stations.

*The full justification for the shortened longline set can be found in the section I-1-E. of the Appendix

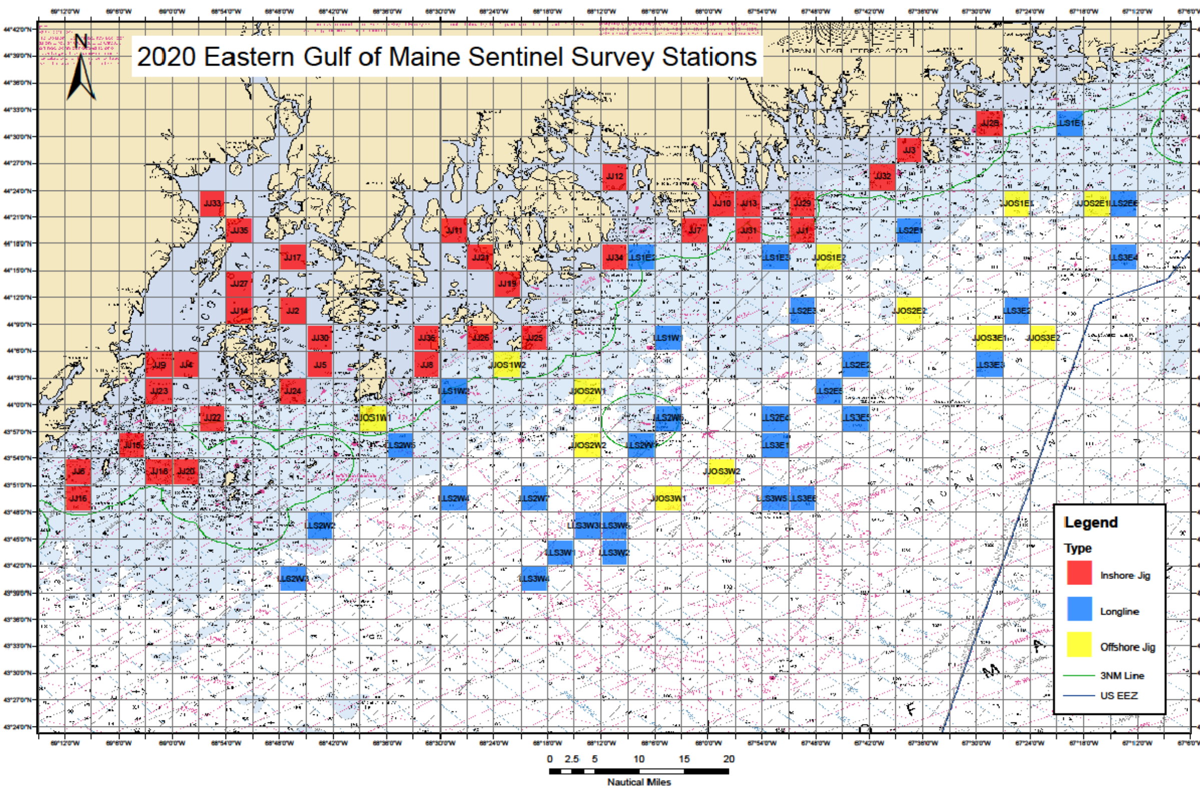


Figure 1. 2020 Eastern Gulf of Maine Sentinel Survey Stations.

II-1-c. Fisherman's Choice

In addition to the stratified random stations, there are a limited number of stations at which fishermen may choose to set both longline and jigs anywhere within the survey area to target species of interest using their expertise and historical knowledge. Catch of target species at these stations are not used in abundance index calculations, but are an important component of the Sentinel Survey used for Catch Per Unit Effort (CPUE) analysis and to ensure that depth remains the most significant variable influencing catch. This is important to test after every season, as the survey's stratified design is based upon the assumption that depth is the greatest driver of abundance for the four target species. Because Fishermen's Choice (FC) station catch data is not used in developing abundance indices, fishermen may bait longlines with items other than squid and herring if they so choose.

*For more information about survey design, including pilot years, changes over the course of the survey and yearly allocation of fishing effort, see Appendix I-1

II-2. Sentinel Survey Modeling Methods

II-2-a. Abundance Indices

One of the main outputs of this study is the estimation of an abundance index for each species, which is then compared to previous year's indices in order to identify potential trends in abundance. Random stations are stratified by depth so that the influence of depth is accounted for and therefore a stratified mean abundance and variance can be used for an abundance index that still includes depth as a variable. Because of the large number of zeroes in the dataset, the delta mean method described in Pennington (1983) was adopted to estimate abundance at stratified random stations. By this method, the stratified mean abundance and standard deviation for each species of interest is calculated using weighted area data, then summed per strata such that:

$$\bar{x} = \sum_{s=1}^{3} \bar{x}_s * w$$

and:

$$\sigma_{\bar{x}} = \sqrt{\sum_{s=1}^{3} w^2 * \left(1 - \frac{n_{sampled}}{area}\right) * s^2}$$

where the stratified mean ($\bar{x}$) is equal to the sum of the mean number of fish within each of three strata ($\bar{x}_s$) multiplied by the weight (w). Stratified standard deviation is equal to the square root of the summation of one minus the number of stations sampled in each of three strata ($n_{sampled}$) divided by the number of possible stations in a given strata multiplied by the weight squared and the variance squared (s^2). Mean abundance and variance were calculated for both the longline and jig data with the delta mean approach (Pennington, 1983) using the '*fishmethods*' package (Nelson, 2013) in R. Estimates of abundance were calculated separately for fish caught at stratified random longline (LL) stations, inshore random jigging (JJ) stations, offshore jigging (JJO & JL) stations, and a combination of all jigging data (JJ & JJO & JL) for each year. Abundance indices were calculated for cod, halibut, cusk, and white hake inside the survey region.

II-2.b. Modeling Approaches

Two models, a Generalized Additive Model (GAM) and a Boosted Regression Tree (BRT) are also used to develop abundance indices with the intention of alleviating sampling bias and the effect of the high frequency of zeroes in Sentinel Survey data. The GAM used in this analysis utilizes a Tweedie distribution which considers both Poisson and gamma distributions, and allows for flexible parameterization of error distribution. Despite the flexibility of the Tweedie GAM, it remains subject to statistical assumptions that can limit model performance.

As is consistent with developing GAMs, terms that were not statistically significant ($p > 0.05$) were dropped sequentially beginning with the highest *p*-value and then compared to the full model containing all variables using Akaike Information Criterion (AIC) (Burnham and Anderson, 2004). A combination of AIC and the cross-validation scheme described by Tanaka and Chen (2016) were used to compare similar models. Based on AIC values, the model with the lowest AIC score was selected as the better model. However, AIC values tend to penalize models that contain more covariates. In this analysis, AIC values selected the simplest models with the fewest number of covariates, even though simpler models explain less of the deviance in the data. In every instance, the full model outperformed the reduced model and therefore all variables were included in GAMs run for Abundance Index analysis.

In 2018, boosted regression trees (BRT) were incorporated as an additional and robust model to ensure the use of models most appropriate for the Sentinel Survey dataset. Boosted regression tree models utilize a machine learning process that is not subject to the same statistical assumptions as the Tweedie GAM, in which insignificant variables must be removed to better explain relationships between explanatory variables and the response. Instead of determining a quantitative relationship between variables and the response, BRT's define each variable's relative influence/contribution to the model relative to the others, allowing for a fully-informed model containing all explanatory variables regardless of their significance in the model. As a result, the BRT can utilize more data to better explain the relationships between explanatory variables and the response variable (Elith and Leathwick, 2016).

*Additional information on model selection and cross-validation can be found in Appendix I-2

III. Results & Discussion

III-1. Stratified Random Jigging Stations

III-1-a. Abundance Indices

The first of three abundance indices developed for Atlantic cod using jigging gear considers only fish caught at the inshore jigging stations (strata 0: 0-50m). For all years, the BRT trends match the design-based abundance, but the GAM deviates from the design-based index trend in two years, 2013 when an increase was predicted, and 2015 when no change was predicted. While the data suggests slight fluctuations in cod abundance in nearshore areas over the time series, no overall increases or decreases have been identified, although a steady increase over the past two survey seasons may suggest a current upward trend (Figure 2). Standard error and coefficient of variation (CV) were low for both design and model based indices for all years

(0.05 or lower), and although model error and CV were slightly lower than that of design, the differences were very slight (Table 1).

The analysis for cod caught at offshore jigging stations consider jigging stations from strata 1-3, and also includes fish caught jigging at longline stations. The BRT model could not converge due to the limited number of cod caught at offshore jigging stations each year, and therefore the only model-based abundance index for offshore cod is using a GAM. The offshore jig component was not added until 2013, and therefore 2012 is omitted from this dataset. The predicted trends in abundance indices for the GAM model differ from that of the design-based model for 2013 to 2015, when the GAM predicts an increase in 2014 and a decrease in 2015. With those exceptions, the model and design-based indices show similar trends over the survey time series. Abundance indices for offshore jig have remained fairly low, generally less than 0.2, with the exception of particularly high catch in 2016 which resulted in an index around 0.5, more than double typical indices (Figure 3). Despite the uncharacteristic catch in 2016, the confidence intervals remained fairly low for the design-based index, although they are greater than the inshore jig CVs (Table 2).

Finally, all stations types (inshore jig, offshore jig and jig at longline) and depth strata (0-3) were combined to determine relative abundance of cod over the entire survey area. The BRT model matches the design-based abundance index in almost every year with the exception of predicting an increase in 2014, but there are several more deviations between the GAM model and observed catch. Like the BRT, the GAM predicted an increase in 2014, but also predicted dissimilar trends such as an increase in 2017 and a decrease in the most recent 2020 season. The highest predicted indices occurred in the first year of the study in 2012, with a sharp decrease in 2013 to levels around 0.2, around which yearly indices have fluctuated since. The lowest estimated index around 0.1 occurred in 2018, however 2019 indices rebounded to more typical values around 0.2, which stayed consistent into 2020 (Figure 4). The abundance indices for cod at all jigging stations had fairly low CVs, with the highest of 0.19 occurring in 2019 for the design-based index (Table 3).

Overall, error and CVs for abundance indices remained low for cod caught on jigs on the Sentinel Survey, although model indices generally outperformed design indices with comparatively smaller values. Due to lower and more sporadic cod catch at offshore areas, those abundance indices are likely the least informed of the three, with the most informed being inshore jig showing almost unperceivable differences between design and model based error and CV.

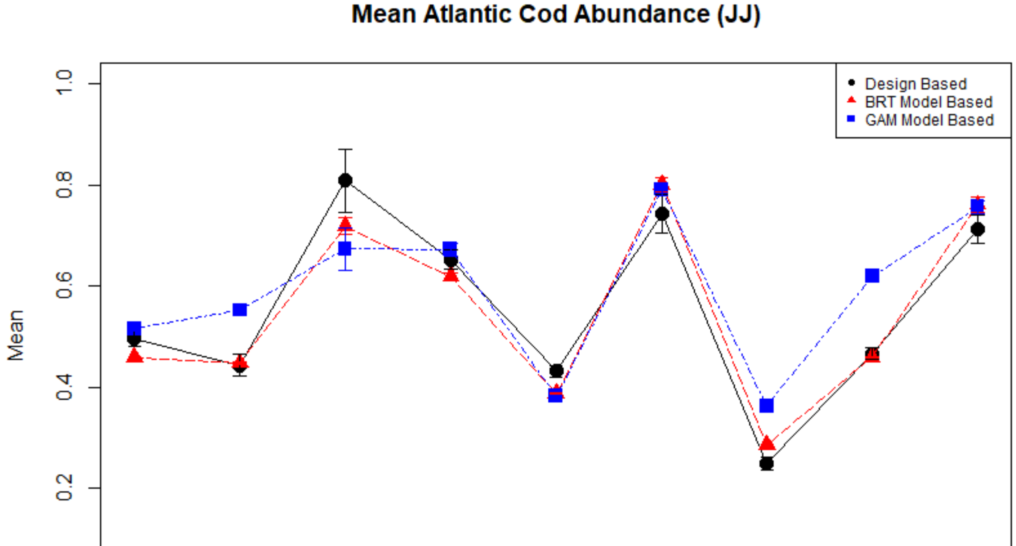


Figure 2: Relative Abundance of Atlantic cod at inshore jig (JJ, Strata 0) stations from 2012-2020.

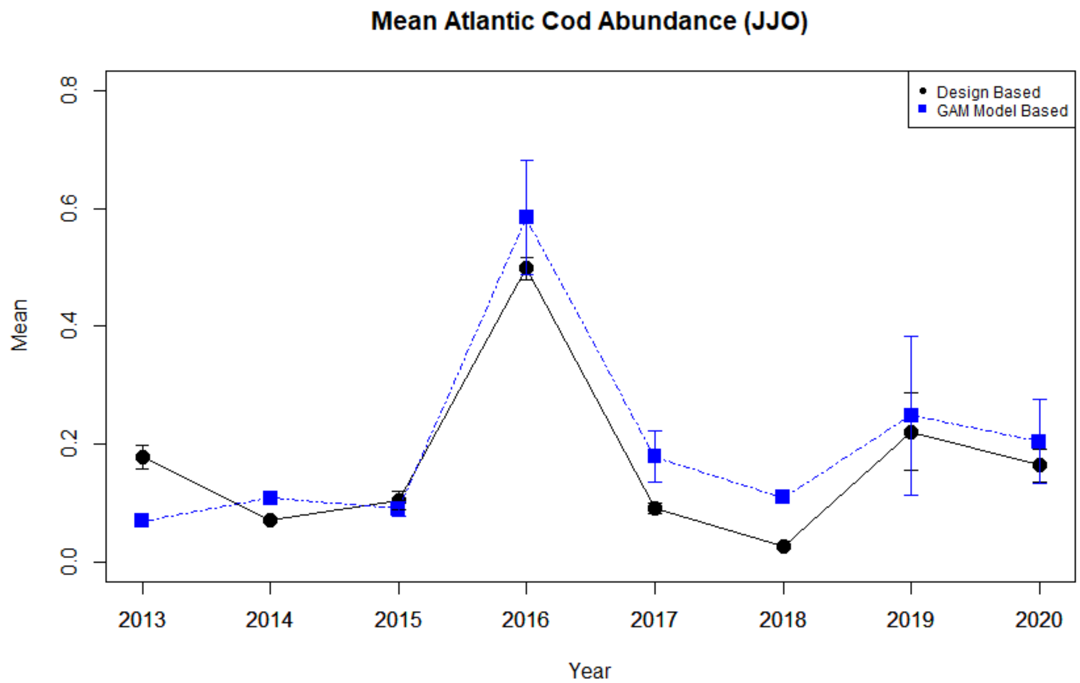


Figure 3: Relative Abundance of Atlantic cod at offshore jig (JJO & JL, Strata 1-3) stations from 2012-2020.

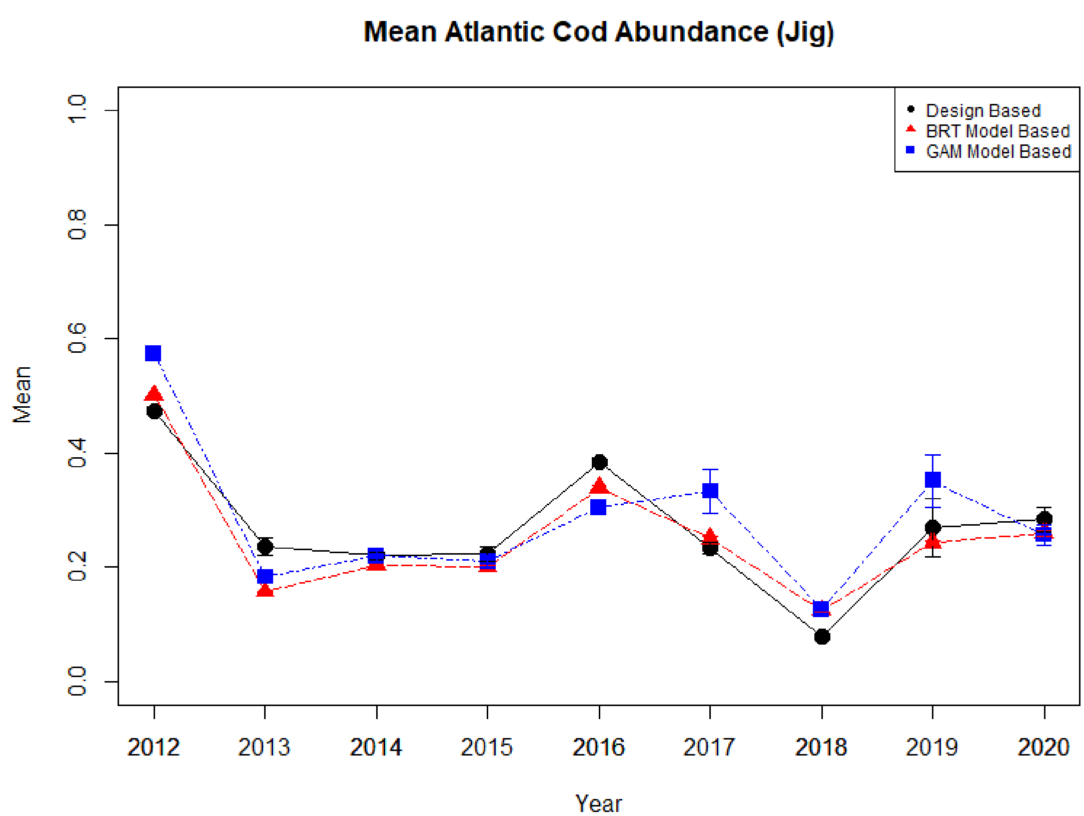


Figure 4: Relative Abundance of Atlantic cod at all jig (JJ, JJO & JL, Strata 0-3) stations from 2012-2020.

Table 1. Design and model-based delta-mean estimated abundance, standard error ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for Atlantic cod calculated based on inshore jig data from 2012-2020.

Species	**Cod**								
Index Type	**Design**			**GAM**			**BRT**		
Year	**Abundance**	$\sigma_{\bar{x}}$	**CV**	**Abundance**	$\sigma_{\bar{x}}$	**CV**	**Abundance**	$\sigma_{\bar{x}}$	**CV**
2012	0.47	0.01	0.02	0.52	<0.01	0.01	0.48	<0.01	0.01
2013	0.44	0.02	0.05	0.55	0.01	0.02	0.45	<0.01	0.01
2014	0.75	0.03	0.04	0.67	0.04	0.06	0.75	0.04	0.05
2015	0.65	0.02	0.03	0.67	0.01	0.02	0.64	0.01	0.01
2016	0.44	0.01	0.02	0.38	<0.01	0.01	0.37	<0.01	0.01
2017	0.74	0.04	0.05	0.79	0.01	0.02	0.79	0.02	0.02
2018	0.26	0.01	0.04	0.36	0.01	0.03	0.26	<0.01	0.01
2019	0.44	0.01	0.02	0.62	0.01	0.01	0.47	<0.01	<0.01
2020	0.71	0.03	0.04	0.76	0.01	0.02	0.76	0.02	0.03

Table 2. Design and model-based delta-mean estimated abundance, standard error ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for Atlantic cod calculated based on offshore jig data from 2013-2020.

Species	**Cod**					
Index Type	**Design**			**GAM**		
Year	**Abundance**	$\sigma_{\bar{x}}$	**CV**	**Abundance**	$\sigma_{\bar{x}}$	**CV**
2013	0.18	0.02	0.11	0.07	<0.01	0.03
2014	0.07	<0.01	0.04	0.11	<0.01	0.03
2015	0.10	0.02	0.15	0.09	0.01	0.13
2016	0.50	0.02	0.04	0.58	0.10	0.17
2017	0.09	0.01	0.10	0.18	0.04	0.24
2018	0.03	<0.01	0.13	0.11	0.01	0.10
2019	0.22	0.07	0.30	0.25	0.13	0.54
2020	0.16	0.03	0.16	0.20	0.07	0.35

Table 3. Design and model-based delta-mean estimated abundance, standard error ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for Atlantic cod calculated based on all jig data from 2012-2020.

Species	**Cod**								
Index Type	**Design**			**GAM**			**BRT**		
Year	**Abundance**	$\sigma_{\bar{x}}$	**CV**	**Abundance**	$\sigma_{\bar{x}}$	**CV**	**Abundance**	$\sigma_{\bar{x}}$	**CV**
2012	0.47	0.01	0.01	0.57	<0.01	0.01	0.50	<0.01	<0.01
2013	0.24	0.02	0.07	0.18	<0.01	0.02	0.14	<0.01	0.01
2014	0.22	0.01	0.03	0.22	0.01	0.04	0.21	<0.01	0.02
2015	0.22	0.01	0.06	0.21	0.01	0.05	0.20	<0.01	0.01
2016	0.38	0.01	0.02	0.30	<0.01	0.01	0.34	0.01	0.02
2017	0.23	0.01	0.05	0.33	0.04	0.12	0.25	0.01	0.02
2018	0.08	<0.01	0.05	0.13	<0.01	0.02	0.11	<0.01	0.01
2019	0.27	0.05	0.19	0.35	0.05	0.13	0.23	0.01	0.03
2020	0.28	0.02	0.08	0.26	0.02	0.07	0.27	0.01	0.04

*For Jig model fit and output see Appendix II-1.

III-1-b. Habitat Preference

Habitat preferences for cod were evaluated based on a GAM run on the entire jig dataset (JJ, JJO & JL) for the years 2012-2020. The variables considered and used in both BRT and GAM models include month, year, sediment class (soft, mixed, or hard as classified by Poppe, 2005), depth (meters), presence and absence of mackerel and pollock, bottom temperature (degrees C) and sea surface temperature (degrees C).

The Atlantic cod caught on the Sentinel Survey displayed highly significant relationships ($p<0.001$) with sediment type, depth and sea surface temperature (Table 4). Our results indicate that cod prefer hard, rocky bottom to mixed and soft sediments, and are most frequently caught in shallow water, less than 50 meters, at the inshore jigging sites. These results are consistent with several other studies of habitat use by juvenile Atlantic cod, which suggest that the preference for harder sediment acts as protective cover from predators (Gregory & Anderson, 1997; Gotceitas & Brown, 1992; Guan, Chen & Wilson, 2016). These shallow, rocky areas are precisely where state and federal trawl surveys are not able to sample, highlighting the need for fine-scale surveys, such as the Sentinel Survey, to help piece together a more informed idea of cod abundance and habitat preferences in the eastern Gulf of Maine.

Water in these shallow areas can warm up to temperatures around 25 degrees C in the summer time, but cod are more likely to be caught when surface temperatures are below 10. Bottom temperature was also found to be significant ($p<0.05$) and follows a similar pattern to surface temperature, preferring cooler water around the same temperature range (Table 4). Additionally, mackerel and pollock are frequently caught as bycatch on jigs, and there was some concern over whether catching these species was negatively impacting the survey's ability to catch cod, and therefore cod abundance was modeled against the presence (1) and absence (0) of these species. The presence of mackerel does not appear to impact the survey's ability to catch cod, but cod do display a significant relationship with pollock presence ($p<0.01$). Additionally, cod prefer cooler bottom temperatures, around 6 degrees Celsius, as well as sea surface temperatures less than 10 degrees Celsius (Figure 5). These preferences in temperature may be related to temporal shifts in abundance, as our analysis shows high cod catch later in the season in September ($p<0.001$), although July and August are also significant when looking at catch in the entire survey region (Table 4).

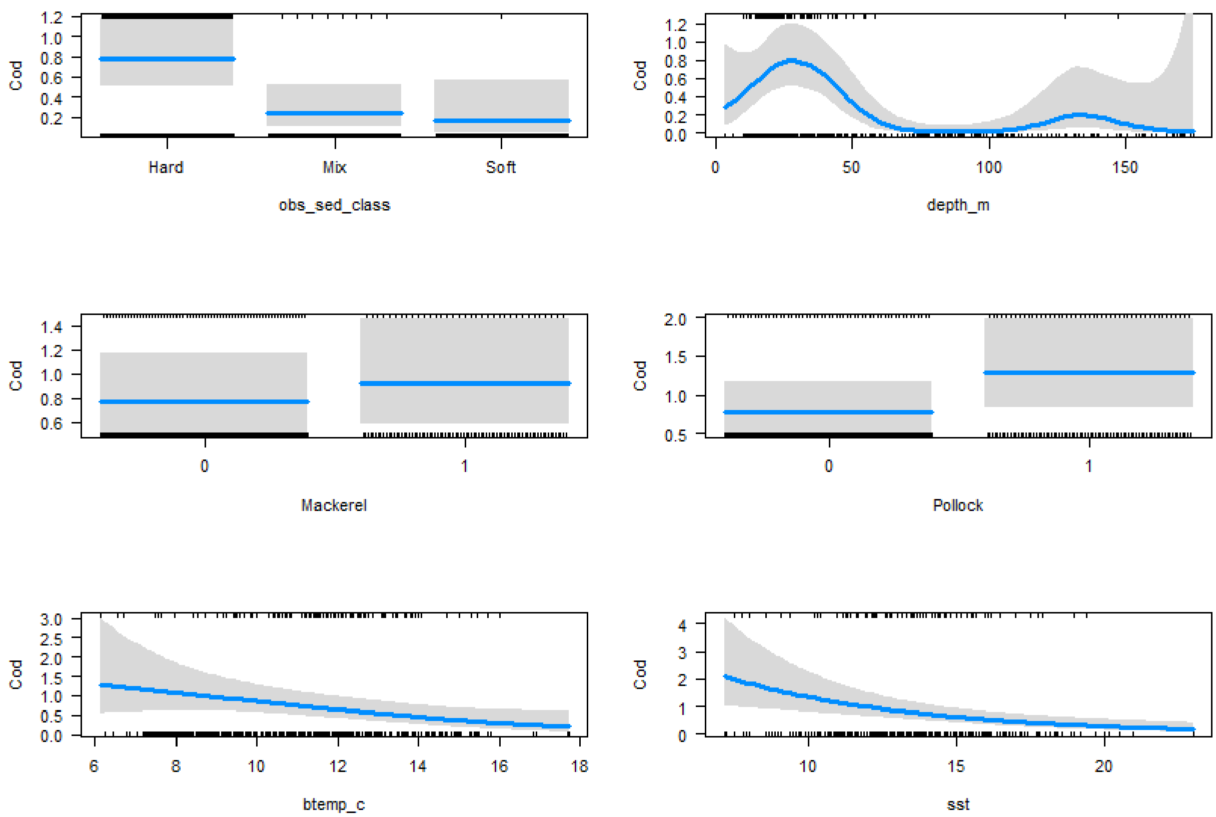


Figure 5: Jigging Model-derived relationships between cod abundance and sediment type, depth, presence/absence of mackerel, presence/absence of pollock, bottom temperature, and sea surface temperature for Atlantic cod in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.

Table 4. Results of the Tweedie GAM for cod in the jig data. Asterisks (*) denote levels of significance for each variable (no asterisk means the variable is not statistically significant (p>0.05). (***) represents most significant variable(s) (p<0.001, ** represents p<0.01 and * represents p<0.05).

Station Type	Inshore Jig	Offshore Jig	Combined Jig
	P-Value	P-Value	P-Value
Intercept	***	**	***
Mix Sediment	**	0.46	***
Soft Sediment	1.0	0.36	*
Pollock	*	0.06	**
Mackerel	0.34	0.66	0.29
July	*	0.51	**
August	**	0.71	**
September	**	0.99	***
October	0.10	1.0	0.09
Year	0.19	0.31	0.49
SST	**	**	***
BT	**	0.42	*
Depth	0.31	0.60	***
Deviance Explained	33.2%	63.9%	41%

III-2. Stratified Random Longline Stations

III-2-a. Abundance Indices

The model-based abundance index trends for white hake follow the design-based trends during all years with the exception of 2015 when the GAM predicted an increase, and in 2018 when the BRT predicted a decrease. Of the four target species, white hake are caught in the highest and most consistent numbers, with abundance indices remaining mostly unchanged over the course of the time series. 2013 saw the highest catch of white hake, at almost two times the abundance index of other years, but the confidence intervals suggest that it is uncertain whether the increase in index for that year is representative of an upwards trend in abundance for that year. Although there is an appreciable sample size of white hake, they have a very patchy distribution as white hake are an aggregating species (Bigelow and Schroeder, 1953). As a result, there is the potential for high variability in white hake catches, such as 2013, leading to higher CV values. Despite remaining fairly constant since 2015, the results of the Sentinel Survey seem to indicate a slight but steady increase in abundance index values, possibly indicating an upward trend in white hake abundance in this study area (Figure 6). The standard error and coefficient of variation for the design-based abundance indices were more variable, and generally higher than that of the model-based indices (Table 5).

Atlantic halibut are caught infrequently on the survey (generally 1-3 individuals since the reduction of hooks in 2017), and therefore have comparatively lower and more variable abundance indices as compared to white hake. Despite large differences in the magnitude between design-based and model-based abundance indices for halibut, they identify similar trends with the exception of the BRT estimating an increase in 2018 (Figure 7). Overall, halibut abundance indices have remained fairly unchanged since 2015 (note the magnitude of the mean index), with a possible slight increase in 2020. However some years show fairly high CVs and these abundance indices should be evaluated with care due to low samples sizes and seasonal trends in halibut abundance (discussed in the next section), which may bias results.

Similar to halibut, cusk are caught fairly infrequently on the survey, generally only one or two individuals per year at random stations. High catches in 2018 and 2019 followed by a year of zero catch in 2020 with high CVs is likely indicative of sampling error and not of trends in cusk abundance, and therefore the model-based abundance indices may be more reliable for this particular species, which suggests little change in cusk abundance over the survey time series (Table 5). Despite the sharp increase in design-based index for 2018, the GAM estimated only a marginal increase and the BRT actually predicted a slight decrease (Figure 8). Magnitude aside, general trends of model indices remained consistent with design indices for other years.

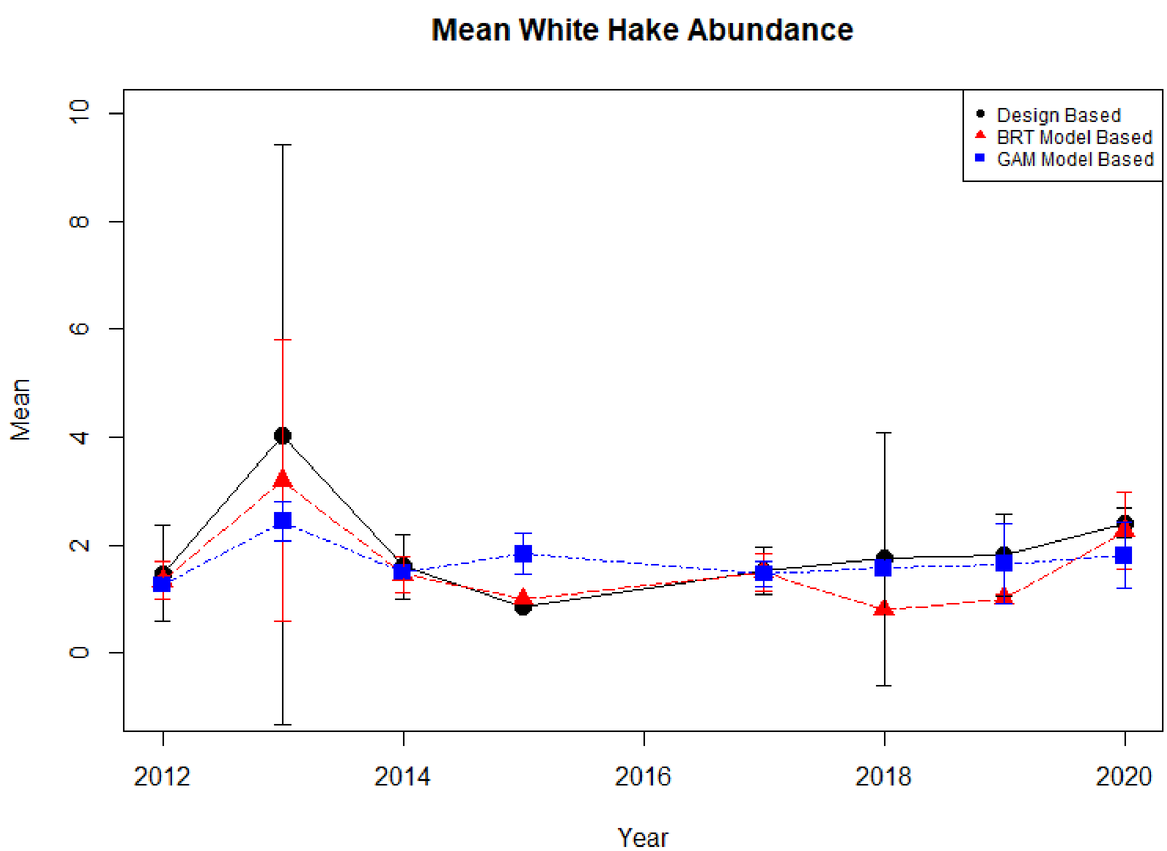


Figure 6. Delta mean estimated mean abundance and associated standard deviation for white hake caught at stratified random longline stations from 2012-2020.

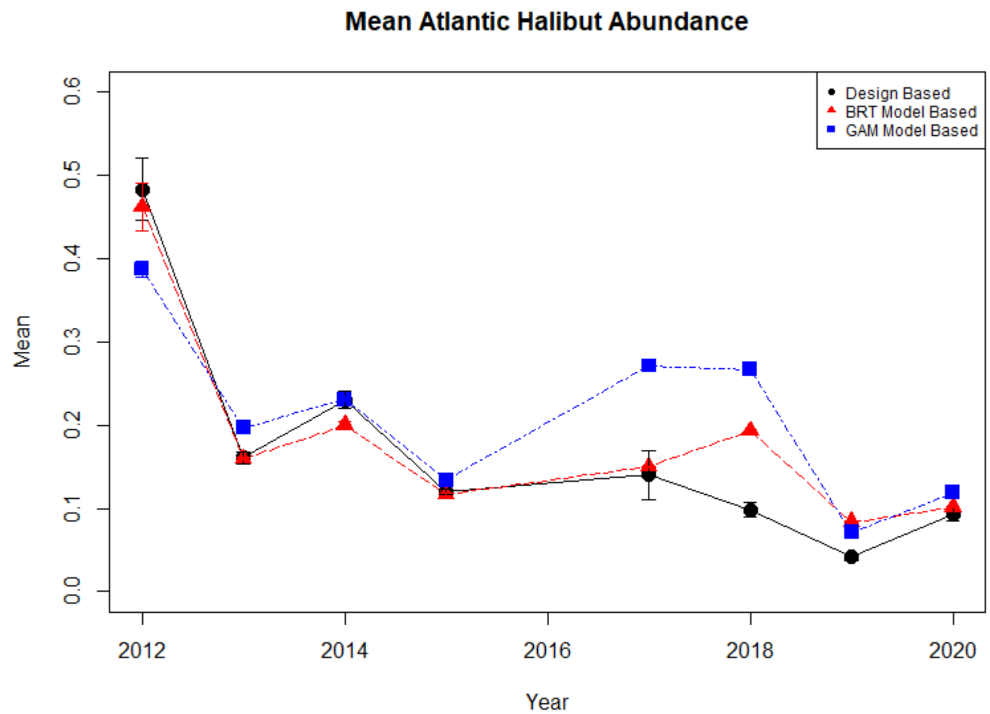


Figure 7. Delta mean estimated mean abundance and associated standard deviation for Atlantic halibut caught at stratified random longline stations from 2012-2020.

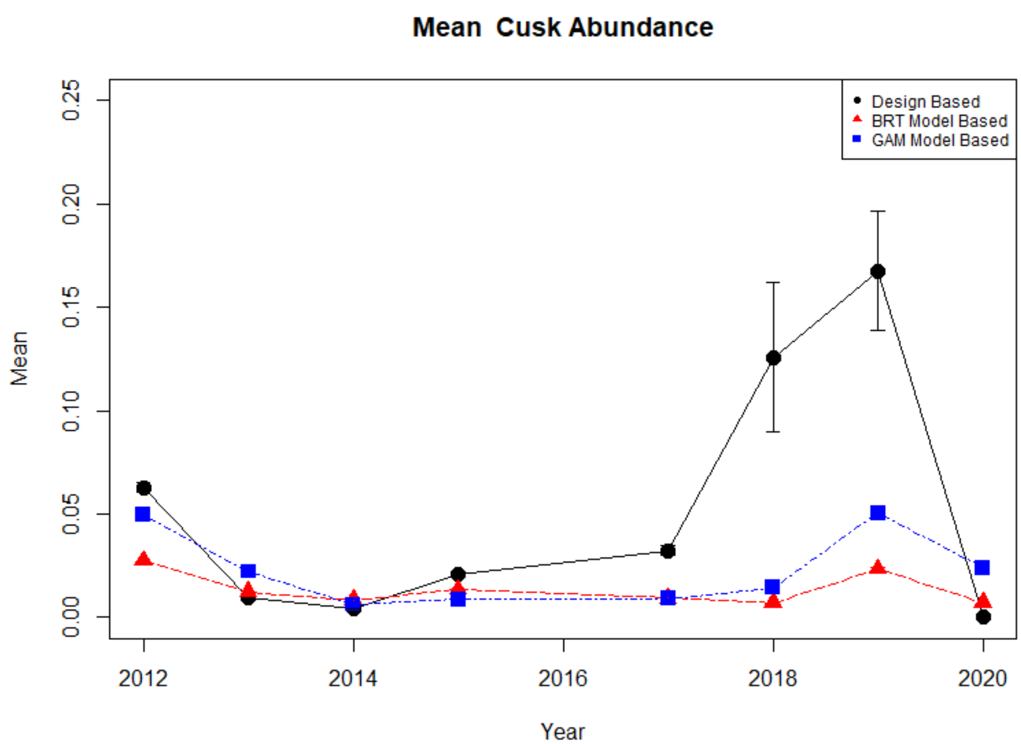


Figure 8. Delta mean estimated mean abundance and associated standard deviation for cusk caught at stratified random longline stations from 2012-2020.

Table 5. Design and model-based delta-mean estimated abundance, standard error ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for white hake calculated based on longline data from 2012-2020.

Species	**White hake**								
Index Type	**Design**			**GAM**			**BRT**		
Year	**Abundance**	$\sigma_{\bar{x}}$	**CV**	**Abundance**	$\sigma_{\bar{x}}$	**CV**	**Abundance**	$\sigma_{\bar{x}}$	**CV**
2012	1.47	0.89	0.60	1.26	0.12	0.10	1.33	0.35	0.26
2013	4.04	5.38	1.33	2.43	0.37	0.15	3.20	2.61	0.82
2014	1.60	0.60	0.37	1.50	0.09	0.06	1.45	0.34	0.24
2015	0.86	0.03	0.03	1.84	0.39	0.21	0.99	0.03	0.03
2017	1.51	0.44	0.29	1.46	0.22	0.15	1.50	0.35	0.23
2018	1.75	2.35	1.35	1.57	0.14	0.09	0.78	0.04	0.05
2019	1.82	0.77	0.42	1.65	0.74	0.45	1.00	0.09	0.09
2020	2.40	0.27	0.11	1.81	0.62	0.34	2.26	0.71	0.32

Table 6. Design and model-based delta-mean estimated abundance, standard error ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for halibut calculated based on longline data from 2012-2020.

Species	**Halibut**								
Index Type	**Design**			**GAM**			**BRT**		
Year	**Abundance**	$\sigma_{\bar{x}}$	**CV**	**Abundance**	$\sigma_{\bar{x}}$	**CV**	**Abundance**	$\sigma_{\bar{x}}$	**CV**
2012	0.48	0.04	0.08	0.39	0.01	0.03	0.46	0.03	0.06
2013	0.16	0.01	0.04	0.20	<0.01	0.02	0.16	<0.01	0.01
2014	0.23	0.01	0.05	0.23	<0.01	0.02	0.20	<0.01	0.02
2015	0.12	<0.01	0.03	0.13	<0.01	0.01	0.12	<0.01	0.01
2017	0.14	0.03	0.21	0.27	<0.01	0.01	0.15	<0.01	0.01
2018	0.10	0.01	0.09	0.27	<0.01	0.01	0.19	<0.01	<0.01
2019	0.04	<0.01	0.10	0.07	<0.01	<0.01	0.08	<0.01	0.01
2020	0.09	0.01	0.09	0.12	<0.01	<0.01	0.10	<0.01	<0.01

Table 7. Design and model-based delta-mean estimated abundance, standard error ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cusk calculated based on longline data from 2012-2020.

Species	**Cusk**								
Index Type	**Design**			**GAM**			**BRT**		
Year	**Abundance**	$\sigma_{\bar{x}}$	**CV**	**Abundance**	$\sigma_{\bar{x}}$	**CV**	**Abundance**	$\sigma_{\bar{x}}$	**CV**
2012	0.063	<0.01	0.03	0.050	<0.01	0.02	0.027	<0.01	0.01
2013	0.010	<0.01	0.01	0.022	<0.01	0.01	0.012	<0.01	<0.01
2014	0.004	<0.01	0.01	0.006	<0.01	<0.01	0.009	<0.01	<0.01
2015	0.021	<0.01	0.02	0.009	<0.01	<0.01	0.014	<0.01	<0.01
2017	0.032	<0.01	0.07	0.009	<0.01	<0.01	0.009	<0.01	<0.01
2018	0.126	0.04	0.29	0.014	<0.01	<0.01	0.007	<0.01	<0.01
2019	0.168	0.03	0.17	0.051	<0.01	0.03	0.024	<0.01	0.04
2020	0	0	NA	0.024	<0.01	<0.01	0.007	<0.01	<0.01

*For Longline model fit and output see Appendix II-2

III-2-b. Bait and Habitat Preference

For each variable considered; bait type, sediment type, depth, month, bottom temperature and sea surface temperature, only species for which the GAM identified relationships will be discussed. Cusk will be omitted from much of the habitat discussion as they are caught so infrequently on the Sentinel Survey that our analysis was only able to identify a relationship between cusk and sediment type (Table 8).

Both halibut and white hake displayed significant relationships with bait type, and although they are caught using both types of bait used on the longline, Atlantic halibut are more frequently caught using herring and white hake appear to prefer squid (Figure 9). These are curious results which are contrary to the literature which suggests that white hake are commonly found preying on herring, with only few occurrences of cephalopods, while halibut generally show the opposite trend, with cephalopods making up almost 20% of halibut stomach biomass (Davis, 2004; Garrison, 2000; and Powles, 1958; Bigelow and Schroeder, 2002). Unfortunately, changes in bait price and availability has prevented the Sentinel Survey from consistently baiting longlines with both squid and herring. In 2017 and 2018 squid prices were high and therefore only herring was used. In 2019 and 2020, with concerns over low herring stocks in the Gulf of Maine, the quota was reduced from 75,000 to 15,000 metric tons, increasing the price of herring enough that it was not economically feasible to use in the survey (Whittle, 2019). The polarity of bait in the past four years presents a problem with evaluating bait preferences, since our models assume that the hooked species had a choice between both herring and squid and made the decision to go for one over the other. Future study is needed to better understand how these inconsistencies combined with significant preferences in bait for our target species may be impacting not only bait preference data, but also potentially catch and abundance index calculations.

Cusk and white hake displayed significant relationships with sediment type, but halibut did not (Table 8). White hake prefer mixed and soft sediments over hard, rocky ones, but cusk show the opposite trend, with higher catch occurring over hard sediments which is corroborated by the literature (Bigelow and Schroeder, 2002). The high uncertainty around cusk abundance over hard bottom suggests that more data is needed in order to draw informed conclusions about cusk habitat use (Figure 10).

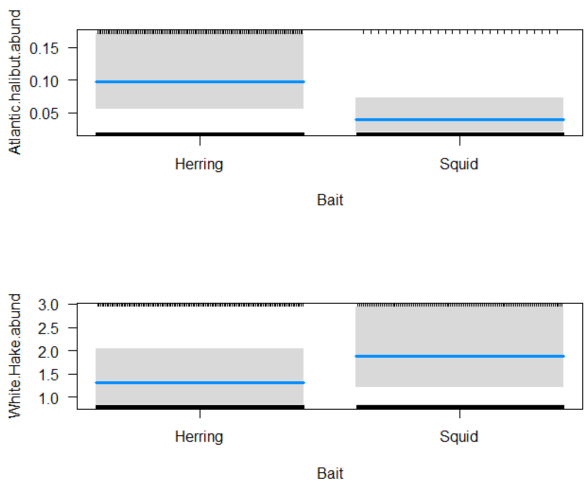
Atlantic halibut and white hake have highly significant relationships with depth ($p<0.001$) (Table 8). Halibut caught on the Sentinel Survey are most often caught at depths between 50 and 200 meters, although uncertainty becomes high for the deeper regions (Figure 7). There are two peaks in depth preference for halibut, the highest occurring around 70 meters, and the second around 140 meters. It has been documented that halibut have been found over mixed sediments in waters up to 750 to 900 meters depth, but these depths exceed the limits of the Sentinel Survey study area, suggesting that true halibut depth preferences may not be accurately represented in this survey analysis (Bigelow and Schroeder, 2002). White hake were observed predominantly in waters greater than 200 meters depth, with some occurrence in waters less than 40 and between 150 to 200 meters depth over mixed and soft sediments. The model shows a lower average abundance of white hake in waters 40 to 100 meters deep, consistent with findings by Davis *et. al.* (2004) (Figure 11).

Catch of halibut is highest in June and continues to decrease month after month, with the exception of a slight increase in September, before showing the lowest catch in October. Halibut are described as "boreal fish" in which catch is most abundant when water temperature is the coolest (Bigelow and Schroeder, 2002). Results here agree with the literature regarding halibut habits because highest catch frequencies are observed in the earliest part of the survey season, June, which is when waters are coolest over the course of the sampling season. This seasonal trend in halibut catch may contribute to higher CV values for abundance indices for halibut, as variation in catch in the early months could greatly impact the number of fish caught over the entire season.

White hake displays a less linear pattern from month to month, beginning with moderate catch in June and lowest catch in July followed by an increase to the highest catch in September before decreasing slightly at the end of the survey season (Figure 12). Like halibut, the catch of these mature, ripe hake is abundant in the earlier part of the survey season, despite the literature suggesting that they spawn at random throughout the year. As a result, white hake spawning behaviors and timing may have implications on Sentinel Survey catch trends for the species, but the data to support this hypothesis is currently unavailable. The increase in white hake abundance during the autumn months may be the result of food availability or increased sampling of stations over suitable habitat, but there are no clear conclusions as to why white hake catch increases in the fall. A more thorough analysis is required before any conclusions are made about temporal trends in white hake catch.

Bottom temperature was found to be highly significant for both halibut and white hake, but surface temperature was only highly significant for white hake (Table 8). White hake prefer bottom temperatures between 7 and 9 degrees Celsius, and surface temperatures between 12 and

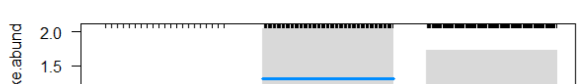
19 degrees Celsius (Figure 13 & 14). The preferred sea surface temperatures may appear high, but are likely more indicative of a seasonal trend (highest catch being in the hottest summer months) in catch rather than a true relationship with surface temperature. Despite the clear relationship between month and sea surface temperature, both variables passed a variance



inflation test prior to being incorporated into any model. It is possible that the variance inflation test did not find month and sea surface temperature to be colinear because month is defined as a factor rather than a numerical variable. However, removing month or sea surface temperature from any model resulted in a model with a poorer performance and a lower deviance explained. Halibut appear to show preferences towards higher bottom and surface temperatures, which is contrary to their preference for the cooler months of the survey. Looking at the box plots in Figures 9 and 10, we see few observations of fish caught at those temperatures, but also high uncertainty due to those high temperature ranges being infrequently sampled. The low catch of halibut and high uncertainty at higher temperatures, calls into question the validity of the relationship between halibut and temperature.

Figure 9: Longline model-derived relationships between catch abundance and bait for Atlantic halibut and white hake in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.

Figure 10: Longline model-derived relationships between catch abundance and sediment type for Atlantic halibut, white hake and cusk in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed



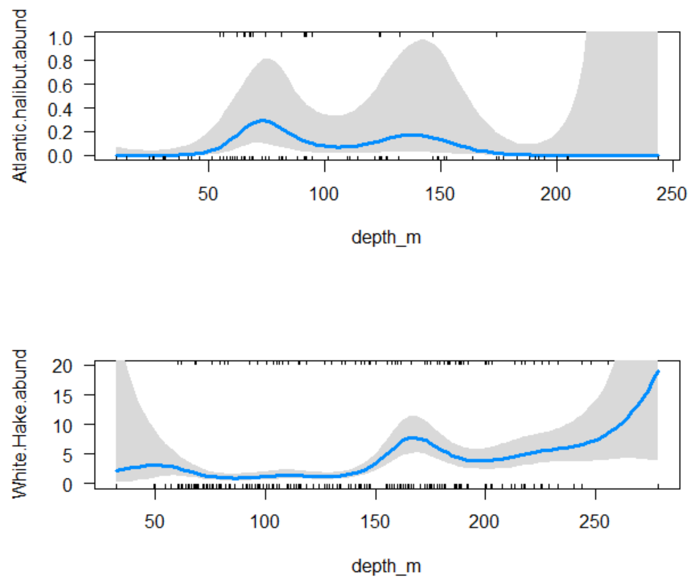
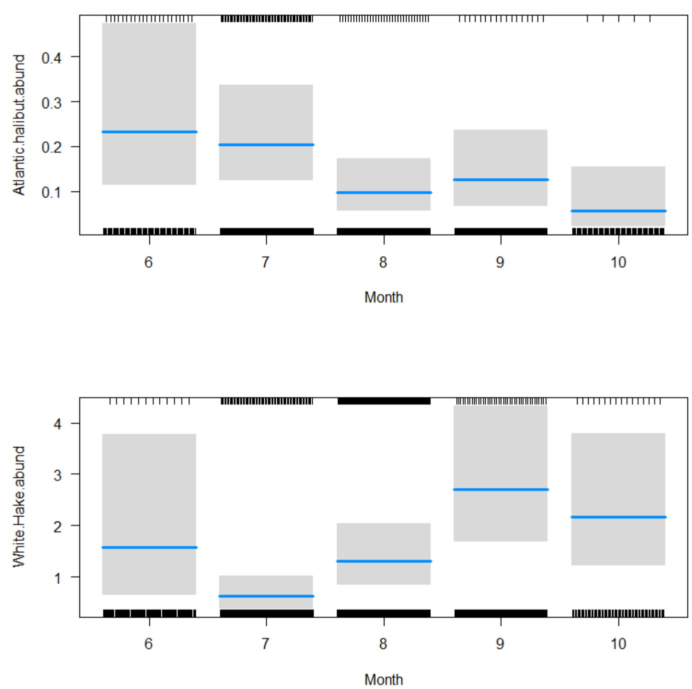
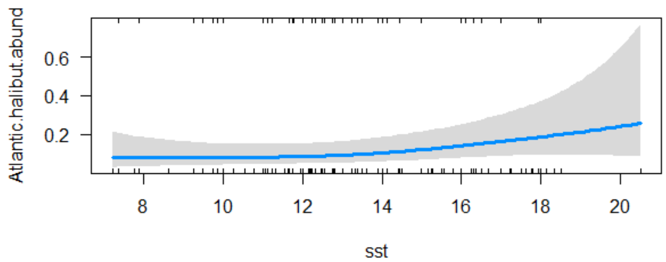
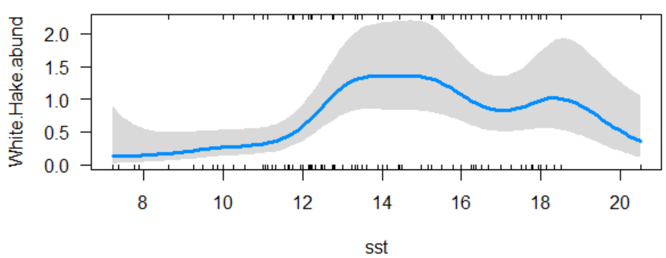


Figure 11: Longline model-derived relationships between catch abundance and depth for Atlantic halibut and white hake in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.

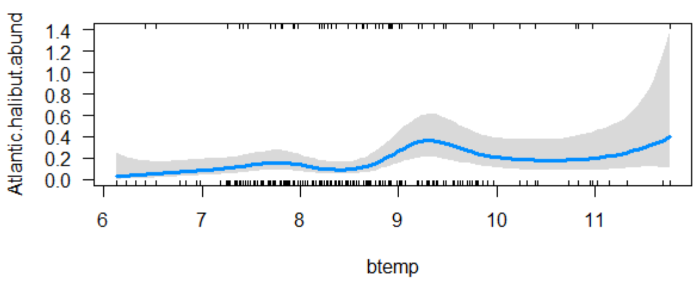


.**Figure 12:** Longline model-derived relationships between catch abundance and month for Atlantic halibut and white hake in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed





.**Figure 13:** Longline model-derived relationships between catch abundance and sea surface temperature (degrees Celsius) for white hake in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.



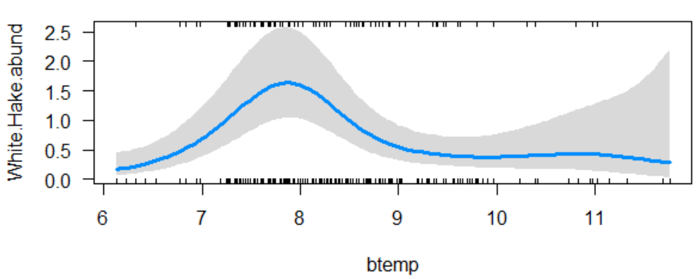


Figure 14: Longline model-derived relationships between catch abundance and bottom temperature (degrees Celsius) for white hake in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.

Table 8. Results of the Tweedie GAM for white hake, halibut and cusk on longline data. Asterisks (*) denote levels of significance for each variable (no asterisk means the variable is not statistically significant (p>0.05), (***) represents most significant variable(s) (P<0.001).

Species	**White hake**	**Halibut**	**Cusk**
	P-Value	**P-Value**	**P-Value**
Intercept	*	***	1.0
Mix Sediment	***	0.15	*
Soft Sediment	**	0.14	**
Squid	**	***	0.91
July	*	0.65	1.0
August	0.65	**	1.0
September	0.20	0.10	1.0
October	0.49	*	1.0
SST	***	*	0.56
BT	***	***	0.78
Depth	***	***	0.39
Deviance Explained	42.8%	28.6%	31.3%

III-3. Catch Per Unit Effort

Catch per unit effort (CPUE) for halibut, cusk and white hake were calculated using longline catch from Fisherman's Choice stations, while cod CPUE was derived from jig catch at FC stations. At this time, only 2014-2020 data is included for cod analysis because bottom temperatures were not collected on the Sentinel Survey before 2014, and GAMs cannot operate with incomplete fields. For random stations, estimated bottom temperature was extracted from FVCOM for 2012-2013, but has not yet been completed for fisherman's choice jig stations. In the future, FVCOM should be used to determine bottom temperatures for those stations in order to get a more complete view of cod CPUE over time.

Due to the fact that the number of Fisherman's Choice (FC) stations has not remained consistent over the time series, the CPUE is standardized by taking the mean of fish caught at all stations sampled that year. It is important to note that the number and types of vessels used for the Sentinel Survey have varied and changed over time, resulting in a range of fisherman experience and curiosity that can have an impact on catch at these stations, which may not be reflective of actual changes in CPUE. For example, prior to 2019 only two fishermen (which often changed year to year) employed by the survey completed FC stations, but a shift to a volunteer structure brought in a greater number of fishermen, who's willingness to volunteer my speak to a greater curiosity in the study. Regardless, the 2019 season showed a spike in CPUE for all longline species except halibut, zero of which were caught that year.

Overall, mean white hake design and model-based CPUE has declined over the time series, with the obvious exception of extremely high catch in 2019. This is not consistent with our abundance indices for this species, which suggests a slight increase over the time series (Figures 6 & 15).

Catch of halibut at Fisherman's Choice stations has fluctuated since the beginning of the survey, but the most recent 2020 season is the highest mean catch since 2012. The 2020 design-based mean around 0.35 also followed two years of zero halibut catch, suggesting an increase in CPUE, although the model based means identified different patterns in 2018 and 2019, and therefore the zero catch in these years is likely not indicative of true trends. The rising and falling trends of halibut CPUE match the abundance indices almost exactly, although the magnitude of change suggested by CPUE is much higher (Figures 7 & 16).

Cusk CPUE has also fluctuated greatly, and saw two years of zero catch, one of which being 2018, before seeing record high catch in the past two seasons. The BRT model-based means for cusk CPUE matched design trends fairly well until 2017, when it estimated a mean around 0.05, which it has also predicted for all of the following years. The GAM model matched trends well until the past two survey seasons, when it estimated only a slight increase from 2018 to 2019 and actually predicted a decrease in the most recent season. The trend in cusk CPUE for the last few years does not reflect the abundance indices calculated. Since no cusk were caught at random longline stations in 2020, abundance indices identified a sharp decline for cusk, while CPUE suggests much higher values than typically seen on the survey (Figures 8 & 17).

The extreme high and low CPUE values seen for longline species in recent years may be indicative of the fact that less Fisherman's choice stations were completed in those years. Typically, before 2019, 12 FC stations would be completed each year, but in 2019 only 10 were completed and in 2020 only 6 FC stations were done. Less stations means fewer chances to catch fish, but also makes any catch more influential on CPUE results since the mean is taken. This is not as much of an issue for jigging CPUE as the capacity to catch fish is much lower using jigging gear than longline.

For Atlantic cod, mean catch at each station followed design based CPUE trends every year, with the exception of the BRT estimating no change between 2015 and 2016 instead of a decrease. CPUE for cod on the jig has generally stayed around or below 1, except in 2017 when mean catch was around 2.25 (Figure 18). Fisherman's Choice stations generally occur outside of strata 0 (inshore jig), however there have been several FC stations in less than 50m of water and therefore the combined jig index will be compared to CPUE instead of offshore only. CPUE estimates for cod do not match abundance indices for the first portion of the time series, although they do follow the same trends for 2017 to present. CPUE identified a decrease in 2016 and a sharp increase in 2017 which is opposite of what design-based abundance indices predicted. It is interesting to note however, that while the combined jig index did not identify a sharp increase in 2017, the inshore jigging index did (Figure 2 & 4).

*For nominal CPUE, GAM and BRT values see Appendix II-3

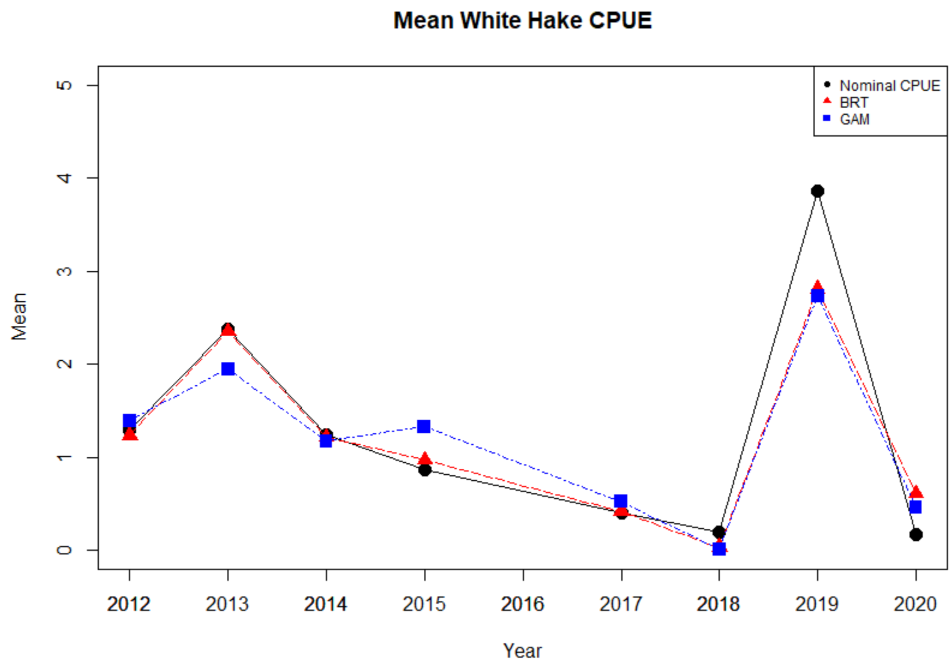


Figure 15. Predicted nominal, GAM, and BRT standardized CPUEs for white hake derived from Fisherman's Choice stations from 2012 to 2020.

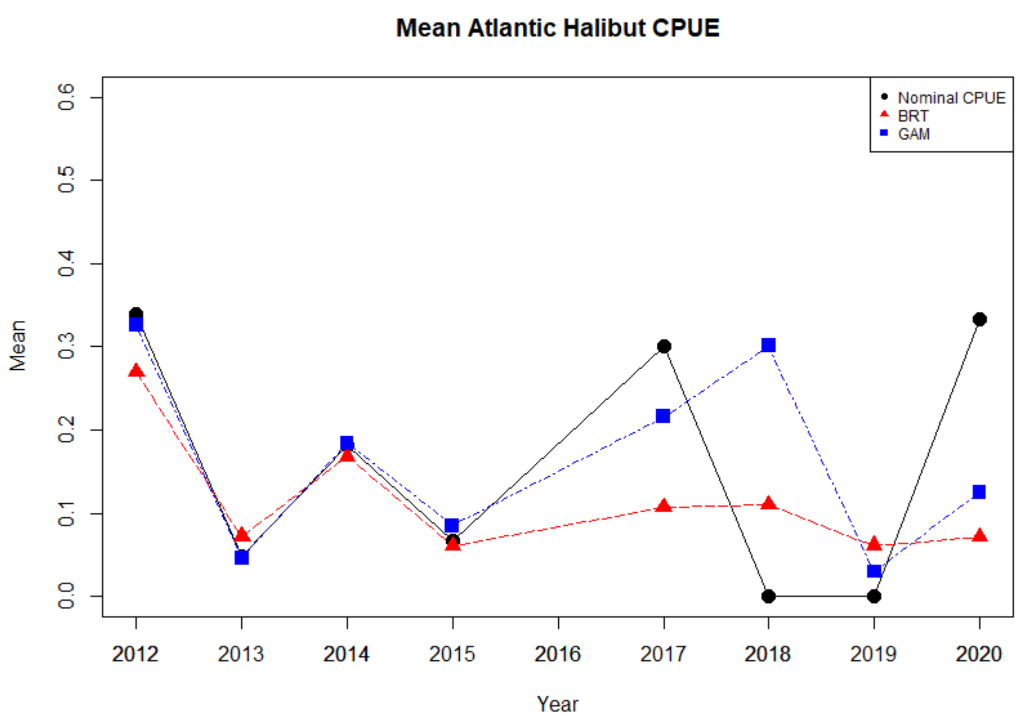


Figure 16. Predicted nominal, GAM, and BRT standardized CPUEs for Atlantic halibut derived from Fisherman's Choice stations from 2012 to 2020.

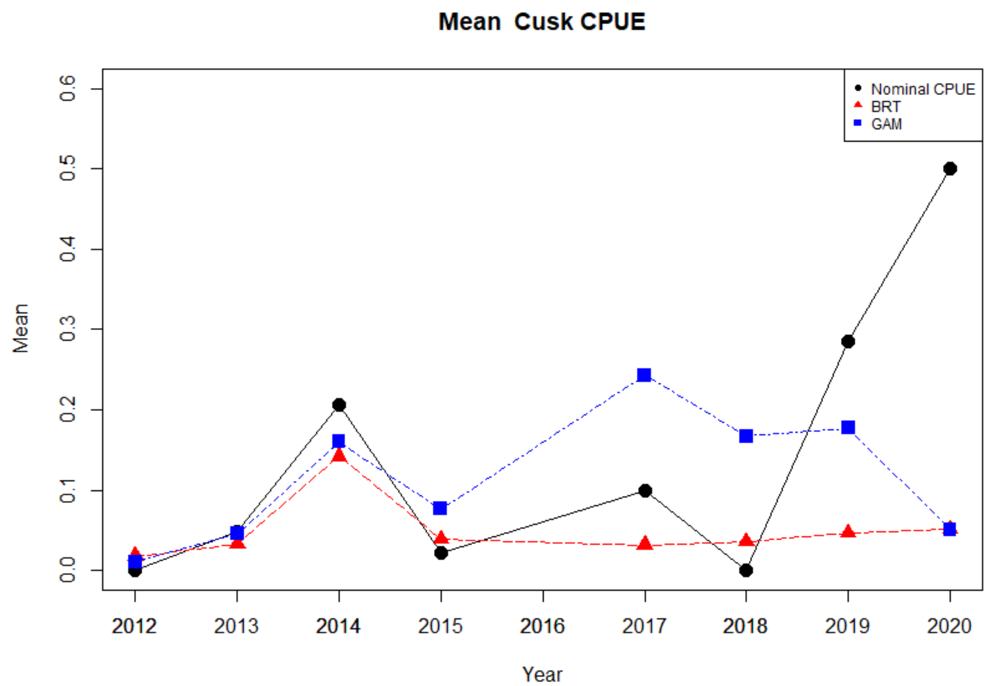


Figure 17. Predicted nominal, GAM, and BRT standardized CPUEs for cusk derived from Fisherman's Choice stations from 2012 to 2020.

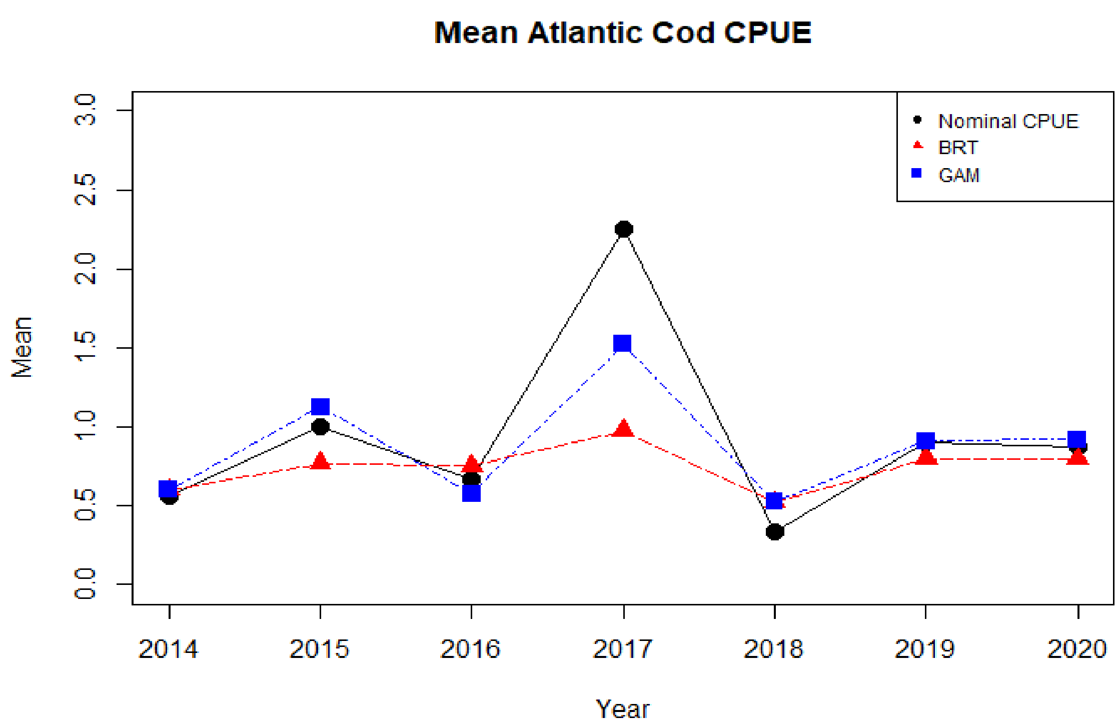


Figure 18. Predicted nominal, GAM, and BRT standardized CPUEs for cod derived from Fisherman's Choice stations from 2014 to 2020.

IV. Data Gaps and Limitations

IV-1. Inconsistencies and Potential Bias

Due to changes in design and the personnel responsible for collecting field data, data collection has varied over the duration of the survey time series. During the pilot years (2010-2011) observed sediment type was not collected. For these years, USGS data (Poppe et al., 2005) were used to determine sediment type. However, the distance between the sample sites of this data is much greater than that of the Sentinel Survey. In a comparison between the USGS data and observed data in the survey, the USGS sediment data are not reliable on the scale relevant to this survey program. Thus, it was decided in 2012 to use sediment data observed on board during the survey. Additionally, bottom temperature was not recorded or only partially recorded for 2010-2013. As previously mentioned, bait on the longlines has not remained consistent and for the past four seasons only one bait type could be used, potentially biasing results if target species have either preferences or disfavor for a particular type of bait. Also, the number of stations at which we are able to complete sampling varies each year, although the number of stations selected for potential sampling per station type (inshore jig, offshore jig only, random longline, or fisherman's choice) remained proportional across years.

Modeling data with a high proportion of zero catch observations is complex because there are more zeros in the response variable than is assumed under a Poisson or negative binomial distribution. To prevent zeros from biasing the results, any model would have to consider the number and proportion of zeros and alleviate the effect they would have on the whole data set. It is important to include zeros in count or catch data because it provides resolution to the data set and reduces the chance to create bias in parameter estimates and standard deviations. Therefore, the model must also be able to distinguish between true and false zeros. "True" zeros occur when the survey observes zero fish in an area in which fish abundance is truly zero, while "false" zeros occur when zero fish are observed in an area that does contain fish. False zeroes misrepresent the spatial distribution and abundance of the local fish population. Consequently, there is a constant need for continuous testing of statistical models used by the survey to evaluate their fit to the dataset and ensure that the model appropriately explains the findings in this study.

IV-2. Catchability Study

Even though this study shows that catching non-target species does not inhibit the ability to catch cod, results of the study showed that the gear used in the jigging methodology had a very low and relatively fixed catchability for cod. Evidence to support these results was provided in the 2018 sampling season by qualitative video and image data collected by an on-board observer which showed a high density of cod present, but only one cod was foul-hooked on the jigging gear during sampling. Additionally, no cod were observed on a nearby longline. This evidence is subject to being circumstantial as video gear was only deployed at a single fishermen's choice station. It is possible that this one station could have been a nursery ground for juvenile cod. Nonetheless, implications of the video footage confirm a need to quantify and account for gear catchability in order to limit bias in abundance estimates which is introduced by the gear type.

With the intention of exploring the questions of catchability and false zeros in the Sentinel Survey dataset, a catchability study was run from 2019 to 2020. This catchability study utilized a 50 fathom gillnet with three different panels including mesh sizes of 3.5”, 5” and 6.5”, which soak for a total of one hour (the same duration as survey longline gear). These mesh sizes were informed by a study conducted by Methven and Schneider (1998), which suggested that this design should return a good distribution of size classes for age zero to adult cod. The goal of this catchability study is to compare presence/ absence of the four target species between gillnet and survey gear (longline and jig) in order to attempt to quantify the prevalence of false zeros.

Preliminary findings from the 16 stations involved in the 2019/2020 gillnet catchability study were surprising in that they suggested that the longline and jigging gear appeared to be more successful at capturing target species than the gillnet. In 2 out of 14 sampled stations in which at least one target species was caught, there was 100% consistency in the presence or absence of target species across both gillnet and survey gear. There were 11 out of 14 stations at which the survey gear identified the presence of at least one target species that was not captured in the gillnet. There was only one site at which the gillnet captured a target species that was not also captured on the survey gear. While there is arguably a small sample size for this study, these results run contrary to the anticipated outcome that gillnets will outperform survey gear (longline and jigs) in their ability to capture target species. These results have surprised both fishermen and scientists alike, and it has been noted that gillnets are generally set for more than the single hour at which they are soaking for this study, and that they may not be able to perform as anticipated if they are set for such a short period of time. Regardless, the gillnets are not currently operating in a way in which this data can be used to quantify false zeros, and may actually validate the use of current gear as the best option for catching target species in this under sampled area with current time and budget constraints.

*For more information about design and preliminary results for the Gillnet Catchability Study see Appendix III.

V. Conclusions

Current design-based abundance estimates for cod, halibut, and cusk are highly precise in most years of the time series, however indices for Atlantic cod caught on the jig are the most precise and the most consistent with model-based indices in both trend and magnitude. The comparatively higher precision for jig species as compared to longline species is likely due, in part, to inconsistencies and changes to longline design and implementation over the course of the survey. Changes such as bait and hook number as well as a survey year in which no longline stations could be completed may bias results, but jigging station design has remained consistent since the addition of offshore stations in 2013. Additionally, jigging gear specifically targets cod, while the longline targets three species which may require different bait, hook size and habitat ranges to efficiently capture all of them. Also longline generally only operates at greater than 50m depth, while the jig covers the entire survey area, potentially gaining better insight to cod preferences for habitat since all ranges are considered, and resulting in more informed model-based abundance indices.

While design-based indices are very close to model-based for all cod jigging stations, overall model-based abundance indices generally resulted in lower error and variability than design-based indices for all species, particularly for cusk and white hake which are prone to outliers and may need to include greater consideration of model-based abundance indices which generally don't predict such outliers.

Of the four target species, all but cusk saw their abundance indices increase slightly from the 2019 season. 2018 was a historic low for cod catch, and therefore increased catch at random jig stations as well as at fishermen's choice stations in 2019 and 2020 is a promising trend in cod abundance. Two halibut were caught on the Sentinel Survey this year, as compared to a single one in 2019, so while there appears to be an increase in halibut abundance from the previous year, this may just represent sampling bias that generally accompanies species with low sample sizes. White hake indices show a slight increase and comparatively higher precision to the last several years of the Sentinel Survey. There also appears to be a slight but steady increase in abundance indices for white hake since 2015. The shockingly high abundance indices of cusk in 2018 and 2019 followed by zero catch in 2020 appear to be outliers, especially when compared to predicted model indices, and therefore current trends in cusk abundance remain unclear.

The EGOM Sentinel Survey should continue to collect data without changing the survey design and should try to keep methods and analyses as consistent as possible from year to year to prevent any additional bias from being introduced. Preliminary catchability study results suggest that survey gear is in fact able to effectively capture target species, but there remains a tremendous need to continue sampling in such a data-poor region, particularly for Atlantic cod, whose preferred habitat directly overlaps with areas that cannot be sampled by state and federal surveys.

VI. Acknowledgements

I would like to thank our partners at The Maine Center for Coastal Fisheries, Pat Shepard, Carla Guenther, Paul Anderson and Mike Thalhauser for providing the means to conduct this survey through their collaboration, support, and invaluable connection to the fishermen of Maine. An especially big thank you to all the fishermen who volunteered their time and vessels for our 2020 survey season and made the trips so enjoyable: Matt Trundy, Josh and Tom Duym, Mike Sargent, Abraham Beal, Dominick Zanke, Matt Shepard and Josiah Rhys. To the continued support of The NOAA Northeast Fisheries Science Center Cooperative Research program and to Jocelyn Runnebaum and Geoffrey Smith at The Nature Conservancy for their input and continued financial support of the Eastern Gulf of Maine Sentinel Survey. We would like to acknowledge Drs. John Hoey, Fred Serchuk, and Russell Brown for providing advice on the design and implementation of the Sentinel Survey. Thanks to our 2020 UMaine volunteer sea samplers, Jay Kim and Jamie Beehan, as well as my predecessor John Carlucci and all prior observers for their willingness to help collect data. Finally, I would like to thank my advisors, Yong Chen and Dave Townsend, for their continued support of this survey and my studies.

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