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Original research article

Developing a longline/jig sentinel survey program for an area with limited monitoring and fishing efforts

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ABSTRACT

Areas, such as coastal eastern Gulf of Maine (GOM), perceived to have low density of target fish species and having high density fixed gear, are often subject to low fishing pressure and not well monitored. This can lead to a shortage of information regarding the fine scale dynamics of groundfish populations. Sentinel surveys are commonly developed for such areas with little monitoring and commercial fishing activity as a cost effective way to collect relevant data for monitoring the dynamics of fish stocks. In this study, we outline an approach that utilizes information from other survey programs and pilot study for designing a survey that satisfies both the wish of fishermen participants to contribute their knowledge and experience in determining groundfish abundance and distribution and the statistical rigor required for stock assessments. Through an analysis of spatial and density distribution of groundfish populations based on data from pilot seasons of the sentinel survey and other monitoring programs, we designed a survey that has good spatial and temporal coverage and captures the spatial variability in species composition and size structure of key species. The spatially explicit data collected in the program can contribute to a better understanding of groundfish stock status in the eastern GOM. The approach, although developed for the coastal eastern GOM, is also applicable to other areas with similar issues.

1. Introduction

Effective monitoring of fish populations is essential in assessing the dynamics of fish populations and developing effective fishery management strategies. Such monitoring programs usually include the collection of data from both commercial fisheries and fishery independent surveys (Hilborn & Walters, 1992). When fish stocks decline to a low level, the fishery dependent information is often lost; either through management induced moratoriums or through decreases in fishing effort and effectively no catch in areas where the density of fish stocks is perceived to be too low to be profitable (Gillis, 2002; NRC, 2000; Powers, 2004).

Fisheries-independent survey programs, such as bottom trawl surveys by state and federal agencies, exist in many fisheries ecosystems to monitor spatio-temporal dynamics of fish communities (Sherman, Stepanek, & Sowles, 2005; Sosebee & Cadrin, 2006). However, the spatial and temporal coverage of these surveys is often limited because of financial and/or logistic constraints (ICES, 2013; NOAA, 1988). Trawl gears are not suitable for surveying areas with complex bottom, and their sampling catchability for some species tends to be low. For example, cusk (*Brosme brosme*) in the Gulf of Maine (GOM) tend to inhabit complex bottom, they are rarely caught in trawls (Hareide, 1995; Runnebaum, Guan, Cao, O'Brien, & Chen, 2018). The existence of a large number of fixed gear such as lobster traps in the coastal GOM can also prevent the use of bottom trawl survey. Lack of fishing activity and limited survey efforts over a large spatial area thus reduce our ability to monitor the evolution of commercially important fisheries resources, and can subsequently reduce our ability to quickly develop an appropriate management response to possible changes in the status of fisheries resources possibly induced by changes in environments and management regulations.

Our study is focused on the GOM, which supports some of the most important fisheries in the Northeastern USA, such as American lobster (*Homarus americanus*) and multispecies groundfish fisheries. Although not closed to groundfish fisheries, the eastern GOM (EGOM) has been perceived to have a low density of groundfish stocks, and there is virtually no directed fishing effort for groundfish species in the EGOM. However, lobstermen have reported catching groundfish as bycatch in their traps (Zhang and Chen, 2015; Boenish & Chen, 2018; Runnebaum et al., 2018). Currently, most groundfish stock assessment and the development of management strategies encompass the whole GOM, although the majority of fishing effort and catch occurs in the western

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Gulf of Maine (WGOM). Sparse fishery-independent and fishery-dependent data in the EGOM and skewed distribution of the groundfish fisheries in the WGOM may complicate the determination of the status of groundfish stocks in the GOM potentially leading to scenarios of local stock overexploitation or inadequate management (Guan, Chen, & Wilson, 2017). The low stock abundance, little fishing activity, and low monitoring efforts with limited spatial coverage call for the development of a new program for close monitoring of groundfish populations in the EGOM.

We develop the Eastern Gulf of Maine Sentinel Survey/Fishery to perform this monitoring of groundfish populations in the EGOM. Sentinel surveys/fisheries have commonly been employed to collect relevant data for monitoring the dynamics of fish stocks in areas with little or no commercial fishing activity (e.g., Florida spiny lobster, Canadian groundfish, Celtic sea herring, American shad, and Atlantic shark; Gillis, 2002; Hilton, Latour, Watkins, & Rhea, 2010; Henry, 2013). Sentinel programs are often implemented as some combination of commercial fisheries and scientifically designed surveys; however, specific methods used in survey design are seldom described in detail (e.g., Gillis, 2002).

In this study we provided a framework to design a sentinel survey/fishery that satisfies both the wish of fishermen participants to contribute their knowledge and experience in determining groundfish abundance and distribution; and the statistical rigor required for stock assessments. We refer to our program as a sentinel survey/fishery because it is comprised of both stratified random stations (the survey) as well as fishermen's choice stations (the fishery). Although this study is focused on the EGOM, many fisheries suffer similar problems as groundfish in the EGOM with limited monitoring efforts and low population levels (Gillis, 2002; Hilton et al., 2010; NOAA, 2012; Powers, 2004). The framework developed in this study can be readily modified for use in other fisheries.

2. Methods

As a result of low fishing efforts and lack of commercial fishery data in the study area, the design of the sentinel survey/fishery is divided into the two phases. For the first phase, fishermen used their local knowledge to select fishing sites. The second phase is a stratified random survey program, which is designed using the data collected from the first phase, together with information from other sources. Such a two-phase approach uses fishermen's local knowledge and existing information to identify an optimal design of a fishery-independent survey program for an area with low groundfish abundance, complex bottom types, large quantity of fixed gears (i.e., lobster traps) which prevent conventional bottom trawl survey and maintain a limited scope of sampling to reduce sampling mortality.

The survey area was established to maximize total area that can feasibly be covered by two boats based on information from fishermen and the area of the sentinel survey/fishery in 2010 and 2011 (Fig. 1). This area was then divided (approximately evenly) into separate eastern and western sections. A grid of 3 nautical miles by 3 nautical miles was overlaid on the survey area to divide possible survey locations (Fig. 2). There are a total of 352 grids in the study area. Grid size was selected to maximize total number of sites without creating gear overlap (the longline gear stretches 2 nautical miles in length). Each square of the grid is a possible survey site and fishermen are allowed to select which side of the grid to set gear based on current, tide and weather conditions.

2.1. Phase one: pilot seasons

We completed pilot seasons of the sentinel fishery in 2010 and 2011 to collect background information on fish stocks in the area. In 2010, one boat sampled 30 stations and in 2011, two boats sampled 60 stations (30 per boat). Fishing locations in the pilot seasons were determined by boat captains based on focus group meetings with other fishermen, identified historical fishing grounds and discussions with sentinel fishery participants. To maximize the spatial coverage of the sampling, the study area was divided into two areas of similar sizes in 2011. In the second year, the fishing stations were evenly divided between the two survey areas (30 sites each). Stations were fished using a 2 nautical mile demersal longline that consisted of 8 totes with 250 #12 mustad, semi-circle, easy-baiter hooks per tote (2000 total). Hooks were attached to a white, #7 groundline every fathom with a 15 inch, #550 green gangion that was spliced into the groundline. Hooks were baited with a combination of squid and herring. Longline gear was selected in order to target habitat and species that are not covered by existing trawl surveys. Gear specifications and setup were determined through consultation with current hook and line fishermen who have been successful recently elsewhere in New England. Data collected during this phase were used to inform survey design and begin development of a commercial abundance index.

2.2. Phase two: stratified random survey

The second phase of the EGOM sentinel survey/fishery continues to sample some of the stations selected by fishermen, but also incorporates a stratified random survey design (Cochran, 1953) for a majority of the stations. Design is an important aspect of any fisheries survey as the quality of estimates derived from survey data can be greatly improved through proper design (Jolly & Hampton, 1990). We employed a stratified random sampling design because it allows for more precise estimates of the population mean particularly when surveying variables that are spatially autocorrelated as is often the case with fish populations (ICES, 2004). In order to increase this precision the sampling area must be stratified in a way such that the sample population within a stratum is more homogeneous than a random sample from the overall area (Hilborn & Walters, 1992). Analysis of existing data including those from the first phase and other sampling programs in the study area to determine parameters that affect species distribution can help inform this stratification process.

Although survey design was modified during this phase, longline gear remained unchanged throughout the survey. We continued to utilize two boats sampling 30 stations each from June through October. In 2012 a target soak time of 2 h was added to the survey protocol, although actual soak time varied due to tide strength and logistical constraints. Analysis not included in this paper shows no significant relationship between soak time and catch, suggesting this target is sufficient (Henry, 2013).

2.3. Survey design

Many groundfish surveys follow a stratified random sampling design (Halliday & Koeller, 1981; ICES, 1992; Sherman et al., 2005); however little explanation is given for how these strata are selected. We analyzed catch information from the two pilot seasons of the sentinel survey and multiple sampling regimes conducted by the Maine DMR (Table 1) to determine potential environmental variables that might influence the distribution of Atlantic cod (*Gadus morhua*), cusk, white hake (*Urophycis tenuis*) and Atlantic halibut (*Hippoglossus hippoglossus*). We selected these four species based on: 1) their importance (i.e., cusk and halibut in the GOM are species of concern under the Endangered Species Act and Atlantic cod is a depleted species in the GOM); 2) spatial structure (studies indicated potential eastern GOM subpopulations for white hake (Ames, 2012) and cod (Ames, 1998); and 3) lack of coverage by the existing state and federal bottom trawl survey programs (few cusk and halibut are caught in bottom trawl surveys (Blaylock & Legault, 2012; COSEWIC, 2003; Hareide, 1995)).

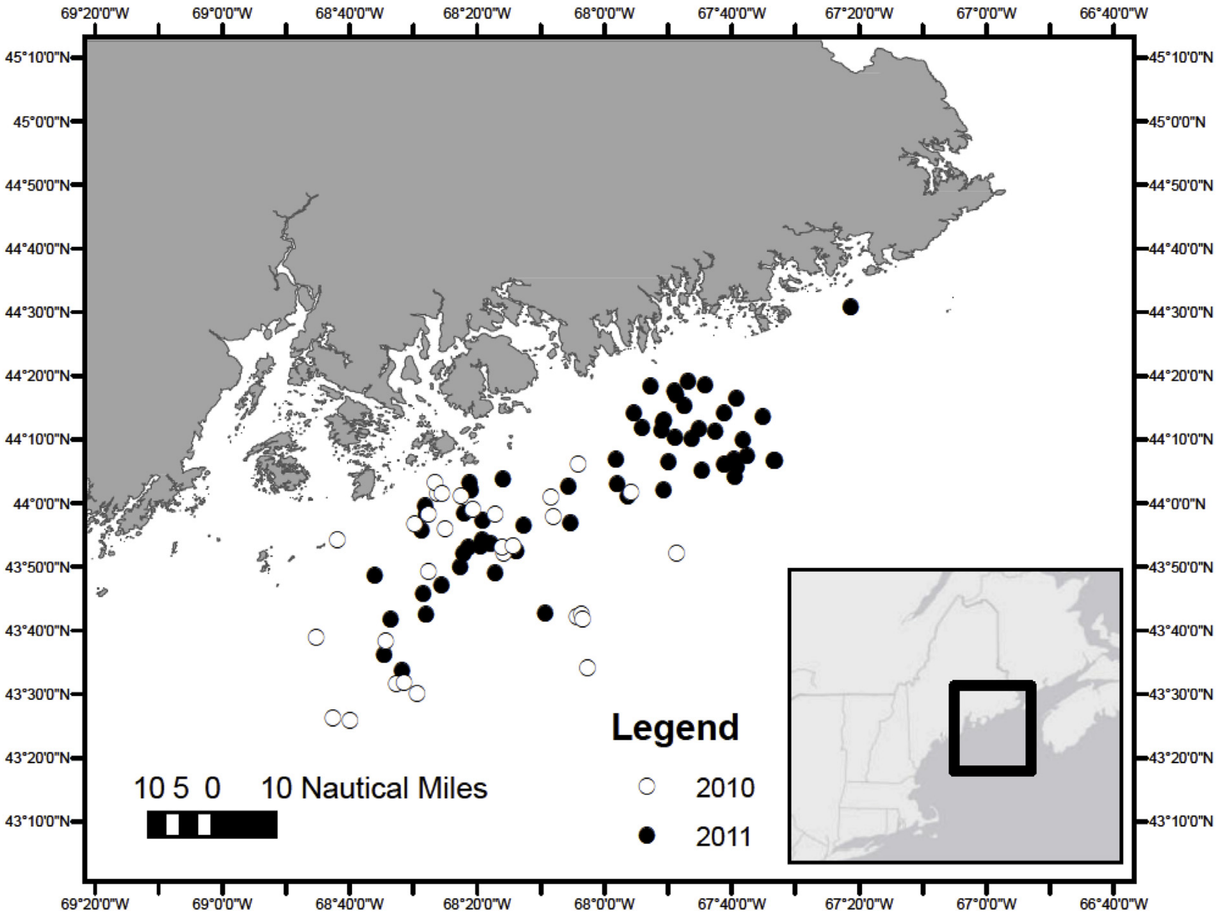

Fig. 1. Map of survey station locations in 2010 and 2011.

2.4. Data sets in the analysis

Information on distribution of Atlantic cod, cusk, white hake and Atlantic halibut in the EGOM is limited. However, we were able to use multiple datasets from existing sampling regimes collected by the Maine DMR to inform our survey design. Since 2000 the DMR has operated a trawl survey in the inshore waters of Maine and New Hampshire (Sherman et al., 2005). This is a random stratified survey operated in the spring and fall and collects biological information on species composition as well as environmental observations. In our analysis, we used catch abundance of white hake and cod from the 2000 through 2010 surveys as well as tow duration, depth, sea surface temperature, latitude and longitude, which are considered important in influencing the spatial distribution of groundfish species (Guan et al., 2017). Results from spring and fall surveys were analyzed separately. Cusk and halibut catch in this survey is limited so other data sets were used for these species.

Data from the Maine DMR lobster sea-sampling program were used for analysis of cusk distribution. Since 1985 the Maine DMR has placed trained sea samplers on commercial lobster boats throughout the Maine coastline to collect biological data on lobster catch (Zhang and Chen 2015). Bycatch composition and abundance data are also collected opportunistically. While trips throughout the year are observed, cusk observations were most frequent in the spring (the months of April through June). Data from 2006 to 2011 were analyzed both as a whole dataset including all observations and for spring observations alone.

Data used in the analysis of Atlantic halibut distribution came from the Maine DMR's halibut database. These data come from multiple sources: an experimental longline fishery conducted by three to six fishermen in federal waters from 2000 to 2004 (Kanwit, 2007) , DMR's longline survey which used a stratified random design to select stations fished in 2007–2008 (Kanwit, DeGraaf, & Bartlett, 2008), and the Maine state commercial fishery. These datasets were combined and common variables including catch abundance, fishing location and depth were used in our analysis.

We also analyzed catch observations from the first two years of the sentinel survey (2010 and 2011 described in section 2.1).

2.5. Stratification selection

We used generalized linear models (GLMs) with the number of individuals caught as our response to determine which parameters influence the distribution of species abundance. Possible explanatory variables included in models were: year, depth, effort (soak time or tow duration) sea surface temperature, sediment type, longitude and latitude. These variables were selected because previous studies have demonstrated their influence on the spatio-temporal distribution of groundfish species in the GOM (Bigelow & Schroeder, 1953; Scott, 1982a,b; Cargnelli, Griesbach, & Morse, 1999; Chang, Morse, & Berrien, 1999; COSEWIC, 2003). All data were observed and collected during the respective sampling program with the exception of sediment type which we assigned to survey locations using sediment maps developed for the GOM by Poppe, Williams, and Paskevich (2005).

Due to the high frequency of zero observations and overdispersion in the response we used zero inflated models to avoid violating assumptions implicit when using standard distributions (Martin, Wintle, Rhodes, Field, & Low-choy, 2005). Often these violations are addressed by log transforming the response variable; however, this is not ideal for data with many zeroes for two reasons: 1) in order to log transform the zeroes an arbitrary number must first be added to the data, 2) the data

Fig. 2. Survey Area in the eastern Gulf of Maine.

Table 1
Data used in designing the survey.

Data Source	Species	Gear Type	Season(s)	Years
Pilot sentinel survey	Atlantic cod Atlantic halibut Cusk white hake	Longline	Summer	2010–2011
Maine (DMR) Inshore Trawl Survey	Atlantic cod white hake	Trawl	Fall/Spring	2000–2010
Maine DMR Lobster sea sampling	Cusk	Lobster Trap	Spring	2006–2011
Maine DMR Halibut Database	Atlantic halibut	Longline	Spring	2000–2011

are then dominated by the new value of the transformed zero observations (Hinton & Maunder, 2003). Zero-inflated models are an alternative way to address this issue and are becoming an increasingly popular choice for modeling abundance in many ecological fields (Martin et al., 2005) as well as fisheries data (Ichinokawa, Oshima, & Takeuchi, 2012; Minami, Lennert-Cody, Gao, & Roman-Verdesoto, 2007; Walsh, Chang, & Lee, 2013).

There are two approaches to modeling data with a high frequency of zeros. The first is a zero altered or hurdle model. Zero altered models consist of two parts. The first part is a binomial model that models the probability of a positive response. The second part of the model is a count process that models the non-zero responses. This count process is zero truncated, thus there is some threshold or "hurdle" that must be reached (as modeled in the binomial portion) in order to have a positive response. Once this hurdle is reached the count process is modeled (Zuur, Ieno, Walker, Saveliev, & Smith, 2009). Zero inflated, or mixture models are similar to zero altered models in that they have two components, however they differ in the way that they treat zero observations. The binomial process models the probability of observing a "false zero" (no fish were detected but the conditions are suitable for fish to be caught) versus the probability of a positive count or true zero (no fish were detected because the conditions are such that they will never occur). Thus, the count process includes both zero and non-zero values and is modeled with a negative binomial or Poisson distribution. The binomial process and the count process are modeled with the following probabilities:

$$P(Y_i = 0) = \pi_i + (1 - \pi_i)\cdot\left(\frac{k}{\mu_i + k}\right)^k$$

$$P(Y_i = n) = (1 - \pi_i)\cdot\frac{\Gamma(Y_i + k)}{\Gamma(k)\Gamma(Y_i + 1)}\cdot\left(\frac{k}{\mu_i + k}\right)^k\cdot\left(1 - \frac{k}{\mu_i + k}\right)^{Y_i}$$

We use zero-inflated models to model catch data from the sentinel survey because they include zero observations in the count process of the model. Zero inflated models were produced using the pscl package (Zeileis, Kleiber, & Jackman, 2008). All models were produced in the statistical program R (R Core Development Team, 2012).

Initial models were fit for each dataset that included all the explanatory variables that may influence the fish distribution and abundance: year, effort (such as tow duration or soak time) depth, sea surface temperature, sediment type, longitude and latitude. These covariates are incorporated into the above probabilities through the following link functions:

$$\mu_i = e^{\alpha+\beta_1\times X_{i1}+\beta_2\times X_{i2}...+\beta_n\times X_{in}} \quad and \quad \pi_i = \frac{e^{\nu+\gamma_1\times X_{i1}+\gamma_2\times X_2...+\gamma_n\times X_{in}}}{1+e^{\nu+\gamma_1\times X_{i1}+\gamma_2\times X_2...+\gamma_n\times X_{in}}}$$

Limited tempo-spatial coverage of some datasets resulted in limited contrast in the data. As a result, some explanatory variables were not suitable for every model. Final models were selected based on Akaike Information Criterion (AIC).

Once the variable(s) that have significant impacts on the distributions of these four target species were identified in the GLM analyses, overall average coefficient of variation (CV) was calculated for length and abundance of each species in each dataset at constant intervals of the stratification variable(s). Trend analysis of average CVs was conducted to identify values of each stratification variable that divide the population into the most homogeneous strata. Due to the physical limitations of longline gear and in order to minimize gear conflict with other inshore fisheries in the survey area (i.e., lobster traps), depths of 0–50 m were removed (it is clear from the first two pilot seasons of the sentinel fishery that this area is not operable because of fixed gear). In 2012 we added 36 stations in the 0–50 m depth strata that were surveyed with rod and reel jigging gear to increase our spatial coverage to include these shallow areas.

2.6. Fishermen selected stations

We allocate 8 stations per survey area (16 stations in total) to let fishermen decide where they want to fish. Fishermen were instructed to select these stations based upon historic fishing areas or optimal groundfish habitat structure based on their knowledge and experience. There is no limitation on the locations within each survey area for this type of station. If fishermen prefer, they can fish in a grid selected for a random station. Each fisherman needs to fish their 8 sites within a given area (east or west) to make certain that there are 8 stations in each area. This ensures good spatial coverage. Thus, essentially this is an area-specific fishery.

Abundance per station was modeled with GLMs using data from all fishermen's choice stations to develop a standard abundance index. Data from 2010 was the reference year. Year is included as a categorical variable in the count part of the model (even when not statistically significant) in order to account for annual variation (Maunder & Punt, 2004). Standardized CPUE is calculated as the year coefficient of the count portion of the model (Maunder & Punt, 2004). This number describes the relative change in annual abundance.

3. Results

3.1. Survey design models

Models developed from DMR survey data for Atlantic cod showed latitude and longitude as significant in the binomial portion of the model. Additional variables including depth, sediment types and season were significant in the count portion of the model. When data were modeled separately by season, depth was the only significant variable in the binomial portion of the model for fall data. Depth, temperature and sand were also significant in the count portion of the fall model. The spring model was similar although in addition to depth, temperature was significant in the binomial portion of the model while the count portion also included multiple sediment types, temperature and tow duration as significant while depth was not a significant variable. Atlantic cod catch data from the pilot seasons of the sentinel survey were limited (cod was only caught at 12 of the 90 stations surveyed in 2010 and 2011). The model developed from these data show sand/silt/clay (the coarser and firmer sediment type) as the only significant variable, indicating that higher cod abundance is related to relatively coarse bottom type. Relative importance of each variable in individual models of all datasets is shown in Table 2.

Table 2
Relative importance of variables used in the cod ZINB model for survey design (1 = most significant, 2 = second most significant, and 3 = third most significant, – = not significant, NA = not available or not included in the best fitting model (based on AIC).

"Count"	Soak Time	Sediment	Depth	Water Temp	Latitude	Longitude
DMR Total	–	1	1	NA	1	1
DMR Spring	2	1		3	NA	NA
DMR Fall	–	2	1	1	NA	NA
Sentinel	–	–	–	NA	NA	NA
"Binomial"						
DMR Total	–	–	–	NA	1	1
DMR Spring	–	–	1	2	NA	NA
DMR Fall	–	–	1	–	NA	NA
Sentinel	–	–	–	NA	NA	NA

The model selected for survey development using all seasons of cusk bycatch data from the DMR lobster sea sampling program included soak time, depth, sediment of sand-clay/silt and summer season as significant variables in the count portion of the model and sediment type of sand-clay/silt and spring and summer season as significant in the binomial portion of the model. This indicates that more cusk are generally found at deeper stations with mid-sized grain sediment and are less likely to be encountered in spring and summer months. Separate analysis of spring data showed that abundance of cusk was highly positively correlated with depth. In both models depth was the most significant variable (indicated by the smallest p-value). Models from sentinel pilot data show sediment types as the only variables correlated with cusk abundance. Variables in each model, ranked by importance, are shown in Table 3.

White hake catch abundance from DMR bottom trawl surveys across all seasons show depth, temperature and fine sediment significant in the binomial portion of the models. These variables and other sediment types, latitude and longitude are also significant in the count portion of the model. Models of spring and fall data separately show similar results with depth significant in the binomial portion of the fall data and depth and temperature in the spring data. Depth, temperature and multiple sediment types are also significant in the count portion of the fall and spring models with latitude and longitude also being significant in the fall. Sentinel data show depth, soak duration and medium grained sediment as significant in the binomial portion of the model however only depth is significant in the count portion with higher abundance positively correlated with deeper stations (Table 4).

Models of Atlantic halibut abundance from DMR data included only

Table 3
Relative importance of variables used in cusk ZINB models for survey design (1 = most significant, 2 = second most significant, – = not significant, NA = not available or not included in the best fitting model (based on AIC).

"Count"	Soak Time	Sediment	Depth	Latitude	Longitude
DMR Total	2	2	1	–	–
DMR Spring	–	2	1	–	–
Sentinel	–	1	–	NA	NA
"Binomial"					
DMR Total	–	1	–	–	–
DMR Spring	–	–	–	–	–
Sentinel	–	–	–	NA	NA

Table 4
Relative importance of variables used in white hake ZINB models for survey design (1 = most significant, 2 = second most significant, – = not significant, NA = not available or not included in the best fitting model (based on AIC).

"Count"	Soak Time	Sediment	Depth	Water Temp	Latitude	Longitude
DMR Total	NA	2	1	1	1	1
DMR Spring	NA	2	1	2	NA	NA
DMR Fall	NA	2	1	2	1	2
Sentinel	–	–	1	NA	NA	NA
"Binomial"						
DMR Total	NA	–	1	1	–	–
DMR Spring	NA	–	1	1	NA	NA
DMR Fall	NA	–	1	–	–	–
Sentinel	2	2	1	NA	NA	NA

Table 5
Relative importance of variables used in halibut ZINB models for survey design (1 = most significant, 2 = second most significant, – = not significant, NA = not available or not included in the best fitting model (based on AIC).

"Count"	Soak Time	Sediment	Depth	Water Temp	Latitude	Longitude
DMR Total	NA	1	1	NA	NA	NA
DMR Spring	NA	1	1	NA	NA	NA
Sentinel	2	–	1	NA	NA	NA
"Binomial"						
DMR Total	NA	–	–	NA	NA	NA
DMR Spring	NA	–	–	NA	NA	NA
Sentinel	–	–	1	NA	NA	NA

depth and sediment, both of which were significant in the count portion of the model. When spring data were modeled separately, depth became more significant while other sediment types remained significant. Modeling of sentinel halibut data showed depth as significant in both the binomial and count portion of the models and the sand-silt/clay sediment type as correlated with higher catch abundance although with less significance than depth. Table 5 shows the overall significance of each variable across models.

3.2. Defining strata

According to these analyses, depth was the most consistently highly significant variable determining species abundance across all datasets (Tables 2–5). Other environmental variables were also significant in numerous models, however, when designing a survey for multiple species it is impossible to include specific results from all species models in the design. Rather, the relative significance of variables overall, across all species must be assessed. Therefore, depth was deemed the most appropriate variable for stratifying the survey. Average coefficient of variation (CV) of abundance of each species in each dataset at 10 m increments shows that CVs decrease as depth increases (Fig. 3). Average CV of length at 10 m increments show smaller CVs at shallow and deep depths, with slightly higher CVs at medium depth ranges (Fig. 4). Based on trend analysis of these graphs, depth strata of 50–80 m, 80–150 m and > 150 m minimize variance within and maximize variance between each stratum. Average CVs of length and abundance calculated across species for each depth strata support these strata definitions (Figs. 5-6).

Abundance data show that catch by species is distributed across depth strata (Figs. 7-8) so effort was allocated in proportion to total area in each stratum with a minimum of two stations per stratum in order to calculate variance. Stations were selected randomly for each stratum as well as alternate stations to be used in the case of unforeseen circumstances that do not allow for fishing to occur at the original station.

3.3. Results of 2012 survey

3.3.1. Random stations

The 2012 survey included 29 stratified random stations. Catch data from these stations are considered fishery independent because the locations were selected randomly and fishing methods and effort were standardized. We used GLMs to model abundance and remove variability that was not due to changes in abundance, but rather a function of other independent variables. This method is the same as the approach used to standardize CPUE discussed earlier (section 2.6).

We modeled cod abundance from random longline stations and jigging stations in 2012 using a categorical variable for gear type. This model showed fewer cod captured with longline gear type versus jigging gear. Additionally, cod abundance was positively related to depth. Cusk were caught at 8 of the random longline stations in 2012. The count portion of the model shows an inverse relationship between depth and catch abundance. Catch rate of white hake at random stations was greater than 50% so a traditional GLM with a negative binomial distribution was fit to the data. The best fitting model included only depth which was positively related to abundance. Halibut were caught at 15 of the random stations in 2012. The model shows halibut abundance is inversely related with depth and soft sediment. Largest abundance is associated with shallow areas of mixed sediment type. All GLMs demonstrate quantitatively that depth is consistently the most significant variable in determining abundance. Therefore the depth stratification of the survey design is appropriate for these species.

3.3.2. Standardized CPUE from fishermen's choice stations

Cod were caught at 16% of all fishermen's choice stations. Cod abundance per station was low with the most productive station yielding 4 fish. GLM results show depth significant in the count portion of the model, having a positive impact on cod abundance, i.e. cod were more likely to be captured at deeper stations. Standardized CPUE shows an increasing trend to 0.81 in 2011 and 1.81 in 2012 (Fig. 9).

Cusk were caught at 17% of the fishermen's choice stations. The largest encounter rate was in 2010 when 17 cusk were captured at one station; however in 2012 no cusk were encountered at any station. Depth was significant in the binomial portion of the model, with a higher probability of zero catch occurring at shallow depths. Sand/silt/clay (the coarser, firmer sediment type) was significant in the count portion of the model, and associated with larger abundances. Given the fact that no cusk were caught at fishermen's choice stations in 2012, CPUE standardization did not work well, making the interpretation of standardized CPUE derived for the fishermen's choice stations difficult (Fig. 10). This suggests that fishermen's choice stations do not provide reliable information on the temporal trend of cusk in the survey area.

White hake were caught at 45% of the fishermen's choice stations. White hake was the most abundant of our target species with over 100 captured at multiple stations. Model results show depth had a positive impact on abundance with an increase in catch abundance at deeper stations. Sediment was also significant in the count portion of the model; sd-st/cl (finer sediment) was positively related with abundance. Standardized CPUE shows an increase to 1.95 in 2011, then decreasing to 1.28 in 2012 (Fig. 11).

Halibut were caught at 44% of the fishermen's choice stations. Halibut were the second most abundant of our target species with nine or more captured at one or more stations each year. Models show a negative relationship between depth and abundance with a decrease in catch abundance at deeper stations. Although not significant, sediment was included in the binomial portion of the model because it provided the best overall fit and the most significant count portion of the model. Standardized CPUE shows an increasing trend to 0.12 in 2011 and 0.27

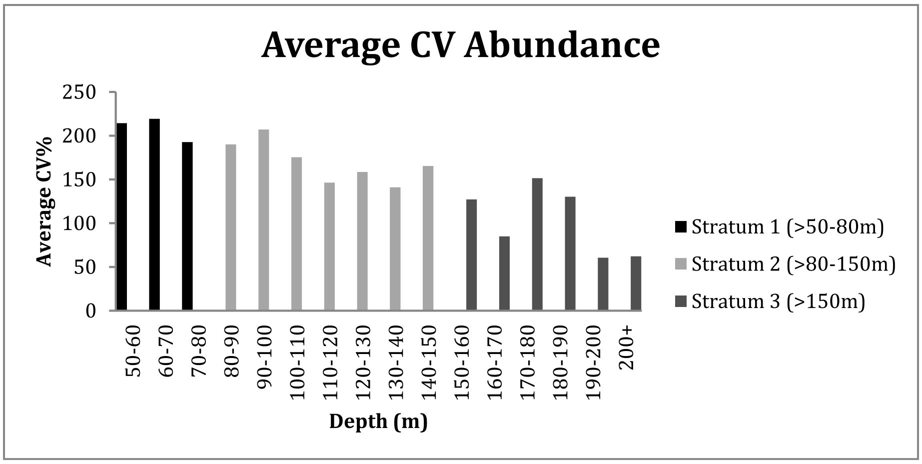

Fig. 3. Average CV abundance by 10 m depth increments for sentinel pilot seasons from 2010 to 2011.

in 2012, but large uncertainties are associated with the estimates (Fig. 12).

4. Discussion

Many groundfish surveys are stratified by depth (ICES, 2004); however few describe the process used to identify this stratification variable. Depth is a convenient choice for stratification because it is a static variable and its value is often readily available, but it is also important because it is correlated with groundfish abundance (Grosslein, 1969). Ideally, stratification would be determined by the frequency distribution of the variable of interest (Cochran, 1953) in this case. If this information were known for groundfish in this study, there would be no need for the survey. Therefore the best alternative is to stratify based upon a variable that is highly correlated with the variable of interest (Cochran, 1953). Relationships between groundfish species and depth are well documented (e.g. Bigelow & Schroeder, 1953), and our analysis demonstrates this correlation for the species of interest in the location of interest, supporting the use of depth stratification in the survey design. Other variables were significant in determining species distributions for some datasets, but because the survey targets multiple species, a simple approach to stratification is preferred (ICES, 2004). Incorporating other covariates into the design may improve the precision of estimates of some species; however these gains may be offset by a loss of precision of estimates of other target species (ICES, 2004).

The GLM method was used in this study for identifying the key variables that might significantly influence fish abundance distribution.

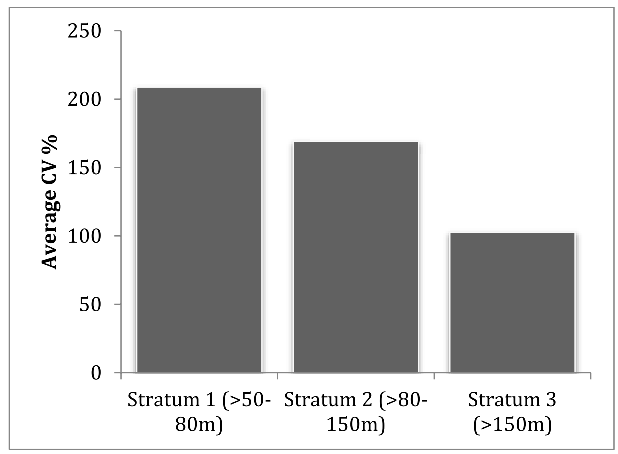

Fig. 5. Average CV abundance by stratum for sentinel pilot seasons from 2010 to 2011.

Although other methods such as GAM and some machine learning methods can also be used for such a purpose, the GLM is sufficient to serve the objectives of identifying key variables in this study. A comparison of multiple methods in the analysis of fish distribution and environmental variables is beyond the scope of this study. Partial dependency plots can be used to display marginal relationships between the response and each preditor variable. Although we did generate such plots, they are not included in this paper because of page limitation.

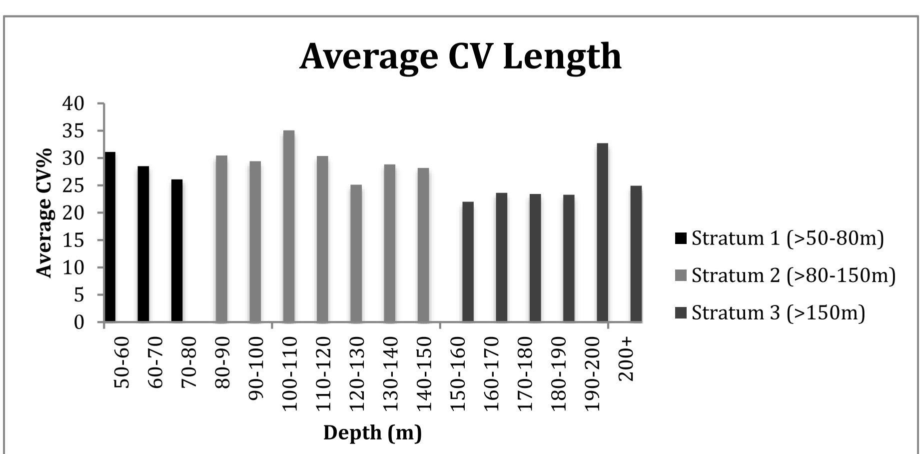

Fig. 4. Average CV length by 10 m depth increments for sentinel pilot seasons from 2010 to 2011.

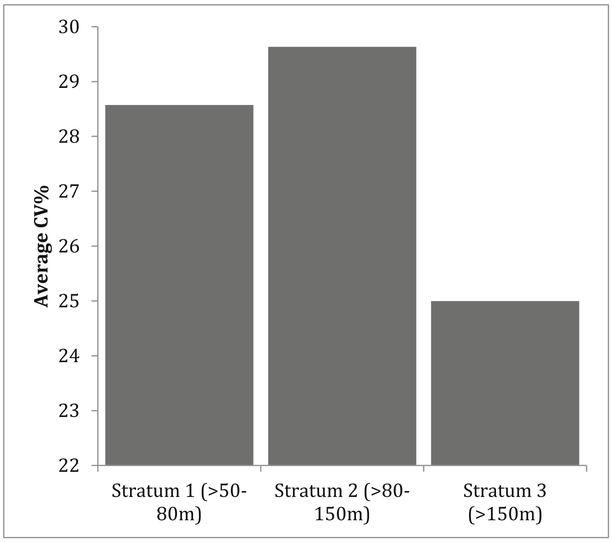

Fig. 6. Average CV length by stratum for sentinel pilot seasons from 2010 to 2011.

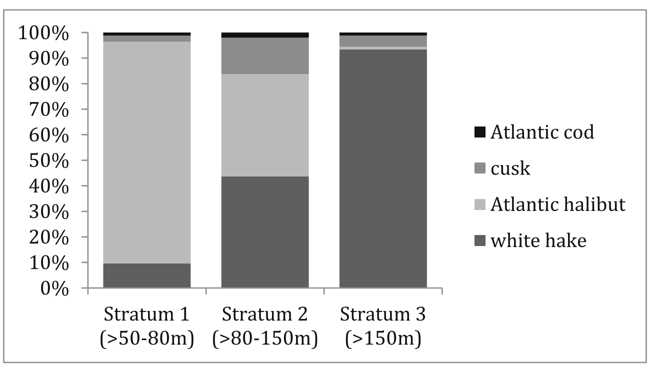

Fig. 7. Proportion of total average catch per station by species for sentinel pilot seasons from 2010 to 2011.

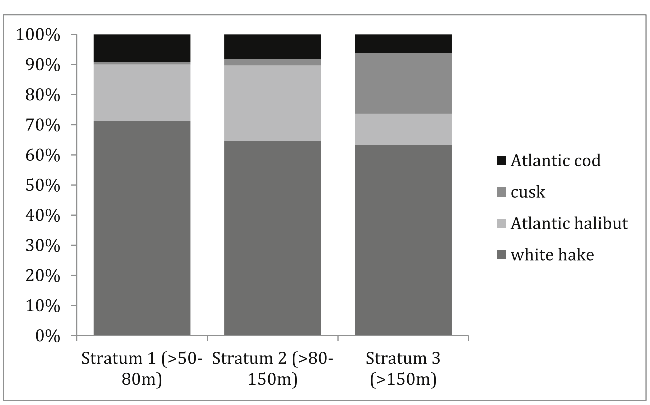

Fig. 8. Proportion of total average catch per station by species for the Maine Department of Marine Resources bottom trawl survey data.

These plots can be found in Henry (2013).

Once the stratification variable(s) is determined, proper division of strata is necessary to utilize the gains in precision of estimates available through stratification. If strata are divided in such a way that they are not more homogeneous than the entire survey area, stratification is ineffective (Hilborn & Walters, 1992). Through analysis of coefficients of variation across depth increments, we increased the probability that we were improving the precision of our estimates by dividing strata to

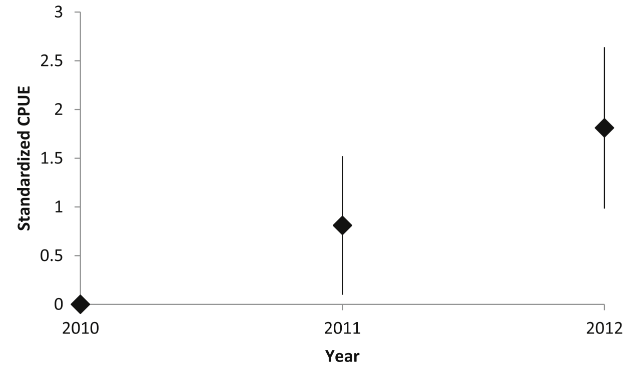

Fig. 9. Cod Standardized CPUE and standard error.

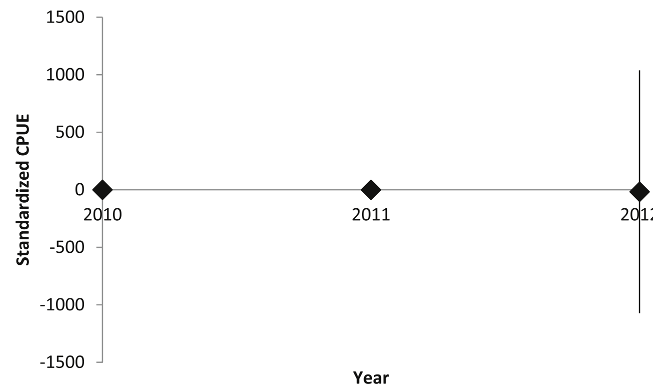

Fig. 10. Cusk Standardized CPUE and standard error.

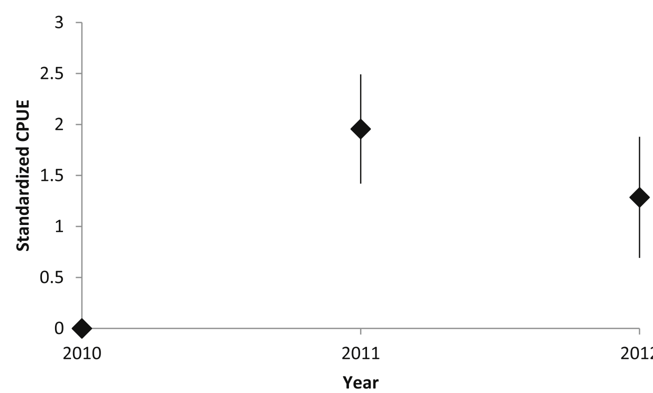

Fig. 11. White Hake Standardized CPUE and standard error.

decrease variance within strata and increase the variance between strata.

The final piece of survey design is the allocation of stations per strata. Optimal survey design allocates the number of stations in each stratum in proportion to the variability within the stratum (Smith & Gavaris, 1993). Because this information is often unknown prior to the start of the survey, stations are usually allocated in proportion to abundance as this is often directly related to variance (Taylor, 1961). In a multispecies survey, different strata are likely to have different levels of abundance and variability for each species as our analysis demonstrates (Figs. 6-7). Therefore many multispecies surveys allocate sampling in proportion to stratum area (e.g. Maine DMR inshore trawl, NMFS bottom trawl survey).

The eastern Gulf of Maine Sentinel survey/fishery also allocates a portion of stations where fishing locations are selected by fishermen based on historic groundfishing sites or habitat conditions. These stations are not random and care must be taken to account for this during data analysis; however they provide important information to establish

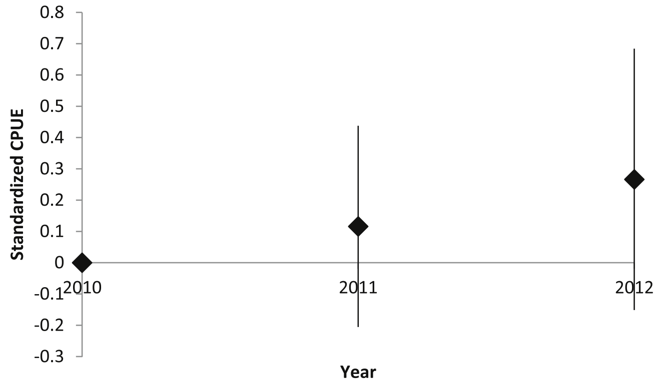

Fig. 12. Halibut Standardized CPUE and standard error.

a commercial abundance index. Additionally these fishermen's choice stations incorporate fishermen's knowledge and emphasize the important role of fishermen in data collection.

The choice of longline and jig for this survey resulted from the fact that this area in the GOM is saturated by the faxed gear (i.e., lobster traps) and a lot of inshore area has rocky bottom, making the employment of trawl in this area out of the question. Longline and jig have been used in fishing groundfish species such as Atlantic cod, Atlantic halibut and cusk in the Gulf of Maine. These methods are not as efficient as trawl in capturing groundfish. However, because this is a fishery-independent survey and we were interested in comparing relative difference in survey abundance over time, the consistency of the gear and design used over time in the survey makes the data collected over the time comparable. This addresses the objective of developing this survey program.

5. Conclusions

This paper provides a blueprint for survey design in areas with little commercial fishing effort and limited sampling effort but where background data exist either from fishery independent surveys or historic catch records. Analysis of existing data should be used to optimize survey design and increase precision of estimates derived from survey data. This is particularly important in areas with little commercial fishing effort and limited temporal and spatial coverage of existing fishery independent surveys.

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