

**Combining bottom trawl and acoustic data to improve survey
derived abundance estimates of semipelagic species.**

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy

University of Washington

2014

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Abstract

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Abundances of semipelagic fishes are often estimated using acoustic or bottom trawl (BT) surveys, both of which sample a fraction of the water column. Acoustic instruments are effective at sampling the water column, but they have a near-bottom acoustic dead zone (ADZ), where fish near the seafloor cannot be detected. Bottom trawl surveys cannot account for fish that are located above the effective fishing height (EFH) of the trawl. In this dissertation I develop methods for combining BT and acoustic data to improve abundance estimates of semipelagic species. Semipelagic walleye pollock (*Gadus chalcogrammus*) was chosen as a case study because they are a dominant species with important commercial and ecological roles in the North Pacific.

A model combining a subset of acoustic and BT data was developed to estimate ADZ correction and BT efficiency parameters. Fitting this model to the data provided estimates of the catchability ratio between BT and acoustics, the EFH of the BT, and the density dependent efficiency of the BT. Estimates of experimentally-derived ADZ correction and BT efficiency parameters were then used to develop a model predicting BT efficiency as a function of BT catch rate. It was found that BT efficiency decreased with increasing bottom trawl catches resulting in hyperstability of the abundance index derived from BT survey. Density-dependent BT efficiency resulted in spatially and temporarily variable bias in survey CPUE and biased population age structure derived from survey data. Logistic regression models were developed to predict the availability (q_a) of pollock to both acoustic and BT gears using environmental predictors and fish length. Findings indicated that on average, availability of pollock in the EBS to the BT was larger than to the acoustics. Availability to both gears depended mostly on bottom depth, light conditions, and fish length, and to a lesser extent on sediment size. Availability to the acoustic gear also depended on surface temperature. A method was developed for combining pollock abundance estimates from BT and acoustic surveys using estimates of efficiency and availability to the BT and acoustic gears. Coefficients of variation (CV) obtained for combined estimates were generally lower than those obtained from either BT, or acoustic surveys.

Although this work specifically addresses the assessment of walleye pollock in the EBS it has general applicability in the assessment of other semipelagic species. Methods presented in this dissertation can be applied to other semipelagic species to obtain estimates of ADZ correction or BT efficiency parameters. Similarly, methods for estimating density dependence of the BT, availability to the BT and acoustic gears, and combining BT and acoustic abundance estimates can be applied to other species.

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ACKNOWLEDGEMENTS

First, I thank my wife Beata Dymowska for her support throughout this project. Without her support, help, and patience in picking up slack in the house and parental duties I would never be able to start or finish this work. I also thank my wife's parents (Kazimierz Dymowski and Malgorzata Dymowska) for being there when we needed help. I thank my daughters Sara and Gabi for being joyful and happy despite my busy schedule. You are the real inspiration behind everything I do.

I wish to thank my advisors, three of whom chaired my supervisory committee. I thank André Punt for helping me build confidence in the quantitative field of fishery science and for always getting back to me with reviews and answers to my questions remarkably quickly regardless of time of day or night. I thank John Horne for keeping me on track and help in shaping each chapter and a final product. I thank Nate Mantua for helping me to navigate through the PhD program and for help in understanding oceanography of the Bering Sea. Finally, I thank Jim Ianelli for his work on pollock stock assessment, which inspired most of my work in this dissertation. Most of all I thank Jim for being open to the new ideas and for taking his time to explore them in pollock stock assessment.

This work would not be possible without help of many colleagues from AFSC. First, I'd like to thank Alex De Robertis and Patrick Ressler, who put lots of work into preparing acoustic data used in this research and who spend long time discussing with me ideas developed in this dissertation. I thank all the people who took part in the AFSC acoustic and bottom trawl surveys in the eastern Bering Sea. Special thanks to my present coworkers who helped collect data for this project: J. Conner, C. Yeung, T. Buckley, A. Vijgen, D. Nichol, K. Sawyer, L. Britt, J. Hoff,

B. Lauth, P. Jensen, D. Stevenson, J. Brogan, V. White, D. Drumm, M. Dawson, D. Benjamin, C. Long, J. Murawski, P. Jensen, P. Cumiskey, D. Urban, E. Munk, J. Webb, B. Daly, K. Johnson, and many others. What a great privilege it is to work with you all!

This work would not possible without help of my present and former supervisors. Without Gary Walters I would probably still be working in the R&D of apple processing. It was also his support and ideas that make me interested in pollock in the EBS. I thank Dave Somerton for introducing me to the many issues of fishery-independent surveys and for convincing me to pursue PhD work. I also thank Bob Lauth for many discussions and the best support a PhD student can get from the supervisor to complete PhD in six years.

I also need to thank UW teachers and students, who through their work and discussions helped me to form and develop ideas for this study. Thanks to: T. Essington, R. Hilborn, J. Horne, A. Punt, I. Stewart, B. Burke, S. Barbeaux, I. Spies, K. Ono, J. Thorson, C. Wenzel, K. Williams and many others.

I'd like to thank all who provided editorial support: B. Burke, B Dymowska, J. Horne, B. Lauth, J. Lee, C. Long, N. Mantua, P. Ressler, C. Rooper, D. Somerton, J. Thorson, M. Wiggins A. Punt, J. Webb, P. von Szalay, O. R. Godø, R. O'Driscoll, C. Wilson, and 4 anonymous reviewers.

Financial support was provided by NOAA advanced studies program and AFSC.

CHAPTER 1. INTRODUCTION

Fishery-independent surveys are important tools for estimating the abundance of fish populations in marine ecosystems (Hilborn and Walters 1992). Abundance estimates for demersal fish species are best assessed using bottom trawl (BT) surveys while the abundance of pelagic fish species is best assessed using acoustic surveys. It is prudent to perform both BT and acoustic surveys to assess the abundance of species that may occupy both habitats (hereafter referred to as semipelagic species) to ensure that sampling encompasses the entire vertical distribution of the population (e.g., Karp and Walters, 1994). Semipelagic fish are known to alter their horizontal and vertical distributions in response to changes in environmental variables such as light intensity (e.g. Beamish, 1966; Abe et al., 1999; Gauthier and Rose, 2002), temperature (e.g. Swartzman et al., 2002), food distribution (e.g. Onsrud et al., 2004), and water currents (e.g. Stensholt et al. 2002). These responses influence the fraction of fish that will be enumerated in a BT survey (e.g. Petrakis et al., 2001) and an acoustic survey (Lawson and Rose, 1999), and may impact uncertainty in abundance estimates from both surveys.

It has been proposed to combine estimates from each of the surveys to provide more accurate and precise abundance indices for stock assessments and other studies (Godø and Wespestad, 1993; Hjellvik et al., 2007). However, combining estimates from the two survey types is difficult because of different biases associated with the abundance estimation from data collected by each survey. The existence of the acoustic dead zone (ADZ) is a key concern when acoustic surveys (e.g. McQuinn et al., 2005) are used to estimate abundance of semi-pelagic species because animals close to the bottom are inaccessible to, or undersampled by acoustic instruments (Ona and Mitson, 1996). Although small when compared to the entire water column, the ADZ can contain a substantial fraction of the biomass of a semipelagic species. Constraints of the BT

survey include the inability to sample above the effective fishing height (EFH; Aglen, 1996; Hjellvik et al., 2003) of the net, the unknown impact of fish responses to the vessel (Handegard and Tjøstheim, 2009), the unknown catchability of the bottom trawl (Somerton et al., 1999), and possible density dependent effects on the efficiency of the bottom trawl (O'Driscoll et al., 2002, Hoffman et al., 2009). Studies are needed to assess relationships between biases of each survey method to improve our ability to directly compare or combine estimates derived from both surveys.

Analyses in this dissertation have been performed using densities of walleye pollock (*Gadus chalcogrammus*; hereafter referred to as pollock). Pollock was chosen for this investigation because they are a dominant species with important commercial and ecological roles in the North Pacific. Pollock account for ~5% of global fish harvest, with annual harvests ranging from 4-7 million metric tons (Bailey et al., 1999), and were ranked second in the world among marine species in capture production in 2008 (FAO 2010). Pollock are also considered a semipelagic species, with a fraction of the population in midwater, and the remainder associated with the bottom (Karp and Walters, 1994). Pollock are enumerated by BT and acoustic surveys in the Eastern Bering Sea (EBS; Ianelli et al., 2009).

Although it has been recognized that environmental stimuli may affect walleye pollock vertical distribution (e.g. Kotwicki et al. 2009), the vertical distribution of near-bottom pollock remains an important unresolved issue for both types of surveys, which are used in the stock assessment of EBS pollock (Karp and Walters, 1994; Godø, 2003). Changes in vertical distribution that occur between sunrise and sunset are of particular interest, as the BT and acoustic surveys used for pollock stock assessment are conducted during this time. Trends in abundance estimates

derived from these two surveys can differ (Godø and Wespestad, 1993), which can decrease the confidence in population abundance estimates. Consequently, the two surveys are currently treated as independent indices of abundance in stock assessment models (Ianelli et al., 2009). Both surveys assume that all fish in the survey area are equally likely to be sampled (Gunderson, 1993). This assumption implies that a constant proportion of pollock are above and below the height sampled by the BT (0 - 3m above the bottom). The relative proportion of fish detected by the two surveys will vary if pollock alter their vertical distribution when surveys are conducted or within the spatial extent of the survey. Variation in this proportion implies that catchability of each survey may vary in space and time. Variable survey catchability of pollock in the EBS is a concern because it could affect the accuracy of methods used to estimate the abundance and distribution of pollock stocks. A review of pollock assessment methodology has identified research on pollock vertical distribution a priority because it has great potential to improve stock assessments (Godø, 2003).

The goal of this study was to quantify biases, explain relationships between abundance estimates, and to combine abundance estimates from BT and acoustic survey methods. This goal was accomplished by completing the following objectives:

1. Combine a subset of acoustic and BT data to estimate efficiency parameters of BT and ADZ correction (chapter 2).
2. Correct BT survey catch per unit effort (CPUE) estimates for density dependent efficiency of the BT trawl (chapter 3).
3. Estimate environmentally-dependent availability of pollock to the BT and acoustic surveys (chapter 4).

4. Combine data from bottom trawl and acoustic surveys to improve reliability of abundance estimates (chapter 5).

To achieve the first objective a set of simultaneously collected abundance data was obtained using BT and acoustic gear and fit to four models that combined BT and acoustic data. The best model provided parameters estimates needed to achieve the remaining objectives: BT performance parameters, the catchability ratio between BT and acoustics, and an ADZ correction.

To achieve the second objective, a posterior distribution of the BT efficiency, derived from best model obtained in chapter 2, was used to obtain a function that predicted BT efficiency in relation to the BT catch. This function was then used to adjust the time series of BT survey abundance estimates from 1982 through 2012. The adjusted abundance time series was included in the pollock stock assessment to assess the impact of density-dependent BT efficiency on stock assessment model outcomes.

To achieve the third objective, posterior distributions of availabilities for BT and acoustics, derived from best model obtained in chapter 2, were used to obtain functions that predicted the availability of pollock to the BT and acoustic surveys in relation to environmental factors and fish length.

Finally, a method was developed to combine BT and acoustic survey data using functions developed in the previous chapters. A function which predicted BT efficiency in relation to the BT catch, the catchability ratio between the BT and acoustic gear, and estimates of the vertical overlap between BT and acoustic gears were used to derive whole water column estimates of pollock abundance from combined BT and acoustic surveys data. Coefficients of variation (CV)

were used to compare whole water column combined abundance estimates to estimates obtained from each survey separately.

CHAPTER 2. COMBINING BOTTOM TRAWL AND ACOUSTIC DATA TO MODEL ACOUSTIC DEAD ZONE CORRECTION AND BOTTOM TRAWL EFFICIENCY PARAMETERS FOR SEMIPELAGIC SPECIES

2.1. Introduction

Species that occupy demersal and pelagic habitats (hereafter referred to as semipelagic) are often surveyed using bottom trawl (BT) and acoustic trawl (AT) surveys (Karp and Walters, 1994). Combining the abundance estimates from these two sampling methods is problematic because the biases associated with each method are unknown and inherently different (McQuinn et al., 2005). Consequently, abundance indices from both surveys are often treated as independent data sources in stock assessment, as is the case for walleye pollock (*Gadus chalcogrammus*; hereafter referred to as pollock) in the Eastern Bering Sea (EBS; Ianelli et al., 2009). Combined estimates from AT and BT surveys are desirable because they could provide a more accurate and precise abundance index for stock assessment and other studies (Godø and Wespestad, 1993; Hjellvik et al., 2007). Combined estimates would also provide more accurate estimates of local density for spatial dynamics studies, spatial ecological models and other studies that use abundance estimates or spatial density data (e.g. Spencer, 2008, Ressler et al., 2012). However, combining estimates from the two survey types is difficult because of shortcomings of each survey method, and the unknown catchability ratio between the two methods. The existence of the acoustic dead zone (ADZ) is a key concern when AT surveys (e.g. McQuinn et al., 2005) are used to estimate abundance of semi-pelagic species because the part of the population that is close to the bottom is inaccessible to or undersampled by acoustic instruments (Ona and Mitson, 1996). Although small when compared to the entire water column, the ADZ can contain a substantial fraction of

the biomass of a semi-pelagic species. A BT survey is conducted for pollock to sample a part of the fish population that is present in the ADZ to mitigate the ADZ problem (Godø and Wespestad, 1993). However, the BT survey has its own constraints that make the two data sets hard to directly compare or combine. This includes the inability to sample above the effective fishing height (Aglén, 1996; Hjellvik et al., 2003), the unknown impact of fish responses to the vessel (Handegard and Tjøstheim, 2009), the unknown catchability of the bottom trawl (Somerton et al., 1999), and possible density-dependence of the efficiency of the bottom trawl (O’Driscoll et al., 2002, Hoffman et al., 2009).

In this study, I propose a modeling approach that combines simultaneously collected bottom trawl and acoustic data and environmental data to estimate the ADZ correction, bottom trawl efficiency parameters (effective fishing height, density-dependence), and the catchability ratio between acoustic and BT abundance estimates. This approach builds on present understanding of the processes associated with the collection of fish abundance data from acoustics and bottom trawl given in Figure 2.1. Acoustics detects fish in the water column between near-surface and near-bottom dead zones, while the bottom trawl detects fish that are near the bottom up to the effective fishing height (Hjellvik et al., 2003). The near-surface acoustic dead zone is not a concern for a majority of semi-pelagic species because they are rarely in this zone, and the term “ADZ” is consequently used to refer to the near-bottom acoustic dead zone. Direct measurement of fish density in the ADZ is difficult. However, bottom trawl sampling can be used to estimate the density of fish near the seafloor. The information about unknown processes (e.g. ADZ, trawl efficiency) associated with data collection by both methods can be obtained by combining acoustic and bottom trawl data in one model. A semi-pelagic pollock from the EBS has been chosen as a test case because it has been assessed using both BT and AT surveys since the 1980s

(Ianelli et al., 2009). Both of these surveys detect substantial parts of the pollock population, indicating that pollock resides in both pelagic and near-bottom habitat (Kotwicki et al., 2005). Although the data used in this study are for EBS pollock, the method is broadly applicable to AT and BT surveys of other semipelagic or semidemersal species.

2.2. Methods

Acoustic and bottom trawl catch data were collected during the annual EBS BT surveys conducted between 2005 and 2009 by the Alaska Fisheries Science Center (AFSC). The surveys were conducted using chartered fishing vessels (F/V *Aldebaran*, F/V *Arcturus*, and F/V *Northwest Explorer*) over the EBS, at the centers of a 20×20 nautical mile (nmi) grid (Figure 2.2). The corners of the grids were also sampled in areas surrounding St. Matthew Island and the Pribilof Islands. The surveys were conducted in June and July and used the same standard trawl (83-112 eastern otter trawl; Stauffer, 2004) during all years (Lauth, 2010). Surveys started in the southeastern corner of the survey area and proceeded westward. Tow duration was approximately 30 min at 1.54 m s⁻¹ (3 knots).

2.2.1. Acoustic data

All survey vessels were equipped with 38 kHz Simrad ES60 split beam echosounders and 7 degree (between half power points) ES 38B transducers which were calibrated twice during each survey using the standard sphere technique (Foote et al., 1987; Honkalehto et al., 2011). Echosounders used a 1 ms pulse length, and a 0.5 m backstep above the sounder-detected bottom. Acoustic backscatter while vessel was trawling was processed using a semi-automated procedure (Kotwicki et al., 2009) to produce the nautical area scattering coefficient, s_A (a linear measure of backscatter per unit area: see MacLennan et al., 2002) in bottom-referenced vertical

layers. Layers between the echosounder-detected bottom and 5 m off bottom were integrated in 0.25 m increments, while layers above 5 m were integrated in 1 m intervals. A periodic and systematic error which can result in a maximum 1 dB (23%) difference in acoustic measurements made on individual transmissions with the ES60 (Ryan and Kloser, 2004; Keith et al., 2005) was removed by fitting the error to the otherwise constant transmit pulse and correcting the data. Acoustic data were recorded from the area directly below the vessel, while the BT was located approximately 100 – 300 m behind the boat. Additionally, the net may drift to one side of the boat during setting and towing resulting in an additional offset (Engås et al., 2000). This approach resulted in a small offset between the location of the BT and the location of acoustic data collection as compared to the distance covered by the trawl (~2,800 m) during a deployment.

To ensure that recorded backscatter was attributed to walleye pollock, the 1,934 candidate bottom trawl tows were examined for consistency. First, only catches where pollock made up at least 75% by weight of all pelagic fish in the catch (i.e., excluding flatfishes and skates) and the pollock catch was > 50 kg were further considered. Second, the backscatter data from 483 hauls meeting these criteria were examined to ensure that bottom integrations and artefacts such as noise spikes were excluded. In addition, a diffuse layer of surface-associated backscatter that did not contain adult pollock (De Robertis et al., 2008), was excluded from further processing by visually identifying the lower boundary of this layer. This depth ranged from 10 to 100 m and averaged 37 m below the surface. Third, 128 hauls with bottom integrations or a high degree of demersal backscatter that were not characteristic of pollock aggregations (i.e. attributed to aggregations of jellyfish or macrozooplankton) were also excluded from the analysis. This was done to minimize possibility of bias associated with the bycatch species that could have different

trawl and acoustic vulnerability (e.g., O’Driscoll 2003). This left 355 tows with backscatter predominantly attributed to pollock to be used in further analyses.

2.2.2. Bottom trawl catches

The areal density of pollock from bottom trawls was estimated using the area-swept method (e.g. Alverson and Pereyra, 1969). Area swept was estimated by multiplying distance fished, as indicated by bottom contact sensor (Somerton and Weinberg, 2001), by the average distance between wing tips measured using Netmind¹ spread sensors (see Weinberg and Kotwicki, 2008 for details). After each tow, fork lengths for 150 – 200 pollock were measured to the nearest centimeter. The length frequency sample was then extrapolated to the entire pollock trawl catch. The catch per unit effort (CPUE) estimate at length ($CPUE_L$) was obtained using

$$CPUE_{Li} = \frac{N_{Li}}{A_i} \quad [2.1]$$

where N_L is a number of fish at length L in the catch and A is the area-swept in nmi^2 , and i indicates an individual tow. $CPUE_L$ was then transformed into equivalent s_A ($s_{A,BT}$) using the formula (e.g. Doray et al., 2010):

$$s_{A,BT_i} = 4\pi \sum_L CPUE_{Li} \times 10^{TS_L/10} \quad [2.2]$$

¹ Reference to the trade names does not imply endorsement by the National Marine Fishery Service, NOAA.

where

$$TS_L = 20 \log L - 66 \quad [2.3]$$

is the experimentally-derived target strength of pollock (Traynor, 1996).

2.2.3. Predictor variables

Depth and temperature were measured during each trawl using a micro-bathymograph (MBT) attached to the headrope of the trawl. Average bottom depth values were obtained by averaging MBT-detected headrope depth and Netmind-detected headrope height above the bottom over the duration of a tow. Near-bottom light levels were collected during each trawl using Wildlife Computers MK-9 archival tags (see Kotwicki et al., 2009 for details) mounted on the headrope of the bottom trawl. These tags provided relative values of near-bottom light levels every second that were then averaged over the duration of the trawl haul. Sediment size was estimated at each station using historical data from grabs and dredges (Smith and McConnaughey, 1999) interpolated by ordinary kriging (Paul Spencer, AFSC, unpubl. data). Sediment data were expressed in units of “phi” (Φ , negative \log_2 of the diameter in mm), where higher values correspond to smaller particle sizes (Wentworth, 1922). Tidal current speed, to be used as a proxy of bottom current, was predicted for each tow using Oregon State University’s Tidal Inversion Software (<http://www.oce.orst.edu/research/po/research/tide/region.html>; Egbert et al., 1994; Egbert and Erofeeva, 2002). Mean fish length was calculated from length frequency samples using the formula:

$$\bar{L}_i = \frac{\sum_{L_i} N_{L_i} L}{N_i} \quad [2.4]$$

where N_{Li} is total number of fish of length L in sample i and N_i is total number of fish in sample i .

2.2.4. Model construction

It is assumed that a functional relationship exists between density estimates that are obtained from the acoustics and bottom trawl given that data collection took place simultaneously. This relationship can be specified as: $s_{A,BT} \sim f(s_A)$. The form of this functional relationship can be constructed using knowledge of the processes involved in acoustic data collection and bottom trawl catch. From figure 2.1 it can be deduced that bottom trawl equivalent s_A ($s_{A,BT}$) can be predicted using acoustic backscatter that was detected above the ADZ up to the effective fishing height plus unknown equivalent s_A in ADZ, which results in equation:

$$s_{A,BT_i} = r_q \left(\sum_b^{h_l} s_{Ai} + D_i \right) e^{\varepsilon_i} \quad [2.5]$$

where r_q is the catchability ratio between the bottom trawl, and acoustics, that accounts for differences in catchability between both methods, h_l is the effective fishing height of the trawl, D_i is the unobserved fish backscatter in the ADZ in s_A units (thereafter referred to as the ADZ correction), b is the backstep in meters used in processing acoustic data, i is a tow subscript, and e^{ε} is log-normally distributed error. A log-normal error was assumed following Walters and Martell (2004), who argue that a log-normal distribution is appropriate because most quantitative observations in fish dynamics arise as a product of a model component and a proportional observation (r_q in this case), and the sum of logs of such proportions is likely to be normally distributed because of the Central Limit Theorem.

To determine the most appropriate model for relating acoustic and bottom trawl data, a set of alternative models was developed and compared using AICc (Akaike's Information Criterion corrected for finite sample size; Burnham and Anderson, 2010). The first term in all models is of the same form as in equation [2.5] and represents acoustic backscatter up to the effective fishing height. The second term, which represents the ADZ correction, differs among models.

Model A:

$$s_{A,BT_i} = r_q \left(\sum_{0.5}^{h_1} s_{Ai} + D_{const} \right) e^{\epsilon_i} \quad [2.6]$$

is the simplest with the ADZ term (D_{const}) independent of all covariates and constants. This type of model has been used in past attempts to estimate the effective fishing height of the BT (e.g. Aglen, 1996, Rose and Nunnallee, 1998, von Szalay et al., 2007).

Model B:

$$s_{A,BT_i} = r_q \left(\sum_{0.5}^{h_1} s_{Ai} + D_{ui}(h_2) \right) e^{\epsilon_i} \quad [2.7]$$

has the ADZ term ($D_{ui}(h_2)$) is independent of all environmental covariates, however, the ADZ term is not constant but rather determined by the backscatter observed immediately above the ADZ. This term represents the ADZ correction based on geometric approach of Ona and Mitson (1996). This correction is appropriate for flat bottom areas (Patel et al., 2009) such as in the EBS, and assumes that fish density in the ADZ is uniform from an acoustically visible layer just above the ADZ to the bottom. One improvement to the method incorporated here is use of the

observations to estimate the parameter h_2 , which determines height of the acoustic layer that is used for ADZ correction, and which is usually chosen arbitrarily.

To apply the Ona and Mitson (1996) ADZ correction a theoretical height of the ADZ (h_{ADZ}) was estimated using formula:

$$h_{ADZ} = h_{eq} + h_{\tau} + h_b, \quad [2.8]$$

where h_{eq} is equivalent lost height, h_{τ} is partial integration zone height, and h_b is the height of the backstep. h_{eq} is the height of the near-bottom layer that is lost due to the curved nature of the leading edge of the acoustic beam and equals $2.83 \times 10^{-3} \times BD$ for a 7 degree beam, where BD is the bottom depth. h_{τ} is the height that is lost due to the inability to resolve backscatter associated with the bottom from backscatter associated with fish that are in close proximity to the bottom. This value depends on the length of transmitted pulse and equals $c\tau/4$ where c is the speed of sound, and τ is the pulse duration. h_b is the height of the zone above the echosounder-detected bottom that is used to avoid echo integration of the seafloor. This height has been set at 0.5 m to equal the value used in pollock AT surveys in the EBS.

Model C:

$$S_{A,BT_i} = r_q \left(\sum_{0.5}^{h_1} S_{Ai} + e^{b|X_i|} \sum_{0.5}^{h_2} S_{Ai} + e^{c|X_i|} \right) e^{\epsilon_i} \quad [2.9]$$

has the ADZ correction term specified as $e^{b|X_i|} \sum_{0.5}^{h_2} S_{Ai} + e^{c|X_i|}$ which represents an ADZ correction based on acoustic backscatter data up to height h_2 (similar to model B) as well as a constant parameter c (intercept in $\mathbf{c}[X_i]$; similar to model A). Inclusion of c was necessary because at

times all fish caught by the BT were located in the ADZ, making it impossible to predict their density using s_A data exclusively. This model does not assume that fish density in the ADZ is the same as in the layer above. Instead, it assumes that fish density in the ADZ can be a function of s_A observed above the ADZ and environmental variables. This assumption seems reasonable in light of recent findings that density of pollock in the layers close to the bottom can be predicted using environmental variables (Kotwicki et al., 2009). Environmental variables and mean fish length are included in model C as the linear covariates $\mathbf{b}[\mathbf{X}_i]$ and $\mathbf{c}[\mathbf{X}_i]$, where \mathbf{b} and \mathbf{c} are vectors of parameters and $[\mathbf{X}_i]$ is a matrix of the predictor variables including: bottom depth, bottom temperature, surface temperature, sediment size, current speed, bottom light level, and mean fish length.

Model D:

$$s_{A,BT_i} = \left(\frac{1}{r_q \left(\sum_{0.5}^{h_1} s_{Ai} + e^{b[\mathbf{X}_i]} \sum_{0.5}^{h_2} s_{Ai} + e^{c[\mathbf{X}_i]} \right)} + \frac{1}{a} \right)^{-1} e^{\varepsilon_i} \quad [2.10]$$

is the same as Model C, but allows for density dependence in bottom trawl efficiency. The parameter a represents density dependence of the efficiency of the bottom trawl within the bottom trawl effective fishing zone, defined as the layer from the sea floor to the effective fishing height. When fish densities are much lower than a , the term $1/a$ is negligible, and model D converges to model C. However, with increased fish density, a becomes more influential, resulting in reduced BT efficiency. For example, at fish density equal to the value of a , BT efficiency will be approximately half of the efficiency at lowest densities.

2.2.5. Model fitting

Model fitting was performed using maximum likelihood, assuming log-normal error with negative log-likelihood (*NLL*) function:

$$NLL = 0.5N_T \log(2\pi\sigma^2) + \frac{\sum_{i=1}^{N_T} (\log(s_{A,BT_i}) - \log(\hat{s}_{A,BT_i}))^2}{2\sigma^2}, \quad [2.11]$$

where N_T is the number of tows, σ^2 is the error variance, and \hat{s}_{A,BT_i} is the model prediction.

Model fitting was performed using Automatic Differentiation Model Builder (ADMB Project, 2009). It was necessary to fit the model for all possible combinations of h_1 and h_2 , and create a likelihood surface in relation to these parameters because h_1 and h_2 are not continuous (i.e. h_1 and h_2 represent heights of the discrete layers of integrated backscatter). Initial fitting indicated that this surface could be limited to the first 60 layers above the ADZ. Thus, 3,600 model fits were required to obtain one likelihood surface. All four models were initially fitted to the acoustic and bottom trawl data ignoring environmental predictors to compare the general performance of the models without performing variable selection in models C and D at the same time. Backward variable selection was then undertaken for the linear predictors in the model that proved to be best among all models based on AICc.

2.2.6. Model diagnostics

Model diagnostics were performed using residual analyses that included: scatter plots of the observed values and standardized residuals versus predicted values, histograms of standardized residuals, normal Q-Q plots, standardized residuals versus predicted values and predictors, and ANOVA analyses of standardized residuals over time (with year as factor) and across vessels.

Variance inflation factors (VIF) were also calculated for all linear terms in the final model to quantify the effects of possible multicollinearity in linear predictors (Kutner et al., 2004).

Sensitivity analyses was also performed for possible bias in TS – fish length relationship. The 95% confidence bounds around the slope and intercept of this relationship (equation [2.3]) are 16.85 to 22.0, and -68.43 to -60.68 respectively (computed from the data in Traynor, 1996). An error in this equation could affect abundance estimates derived from acoustic data (Godø et al., 1998) and values of $s_{A,BT}$, which could affect results in two ways. First, if either the intercept or the slope of this equation are biased the estimate of parameter r_q would change. This effect would be of minor concern, because abundance estimates from both data sources are treated as relative indices of abundance, and the parameter r_q would still provide a means to combine or compare data from both surveys. Second, if the slope of the equation [2.3] is biased, the relationship between fish density in the ADZ and mean fish length could be affected, which could be problematic in estimation of the ADZ correction. Therefore, sensitivity analyses were performed at the limits of the slope confidence bounds to assess to what degree this relationship could be affected by error in the slope of equation [2.3].

2.2.7. Estimation of predictor effects

The relative impact of the linear predictors was determined using parameter estimates from the final model and mean values of all linear and non-linear predictors estimated from the data. For example, the ADZ correction was calculated from the best model for all observed values of bottom depth, while all other predictors were fixed at their means to estimate relative effect of the bottom depth on the ADZ correction. All calculated ADZ values were then divided by their

mean to show a change in ADZ correction relative to its mean value. These analyses were conducted for the ADZ correction factor and the BT predicted catch.

2.3. Results

2.3.1. Model selection

Model D, which used both acoustic data as well as the intercept for the ADZ correction, had lowest AICc score even without using environmental predictors (Table 1), indicating that model D fit the data best among models examined. Since all four models have the same structure for the prediction of bottom trawl catches from the acoustic data, and they differ only in the form of the ADZ correction and density-dependence, it can be concluded that the ADZ correction used in model D performed best at predicting fish density in ADZ. Selection of model D also indicated that inclusion of the parameter a , that accounts for density-dependence in the efficiency of the bottom trawl, was appropriate.

Including environmental predictors in model D improved the fit of the model to the data significantly by reducing the AICc by 51.72 (negative log likelihood 329.16). Bottom depth, mean fork length, surface temperature, sediment size, bottom light, and current speed proved to be important predictors of fish density in the ADZ (detailed parameter values are presented in Table 2). Bottom temperature did not improve model fit and it was eliminated from final model in variable selection process.

2.3.2. Model diagnostics

Diagnostic plots (Figure 2.3) indicated that the assumption of log normal error was appropriate. Visual examination of plots of standardized residuals against all predicted values and predictors

(not shown) indicated that no apparent trends occurred in the residuals. ANOVA analyses of standardized residuals over time (with year as factor; Figure 2.4) did not reject the null hypothesis that there were no temporal trends in residuals ($p = 0.818$). ANOVA analyses of standardized residuals between vessels indicated no vessel effect ($p = 0.64$). These results confirm that the form of the final model was appropriate. Estimates of VIFs were in the range of 1-2 (Table 3), indicating that multicollinearity of predictor variables had a small impact on inflating variance around predictor parameters (Kutner et al., 2004).

2.3.3. Bottom trawl efficiency parameters

The parameters r_q , h_l , and a can be used to describe BT efficiency relative to observed acoustic backscatter in the effective fishing zone and predicted fish density in the ADZ because they provide information necessary to relate the two types of data. The estimate of h_l indicates that the effective fishing height of the BT is on average ~ 16 m. The estimate of r_q was 0.96 and not significantly different from 1, indicating that the catchabilities of the two surveys are effectively the same. However, the catchabilities are comparable only at low densities because the estimate of $a = 4133$ implies that bottom trawl efficiency is reduced at higher densities (Figure 2.5). For example, the BT will be only half maximum efficiency, at fish densities equivalent to the value of a (or $\sim 778,911.40$ cm fish /nmi²). Such a density will result in an estimated pollock catch of approximately 3 metric tons (t) during 30 min tow; catches of this size (and greater) occurred on average in 2.5% of tows in EBS BT surveys.

2.3.4. Acoustic dead zone correction parameters

Estimates of pollock densities in the ADZ confirmed expectations that a large proportion of EBS pollock may be located in the ADZ. ADZ corrections for the stations used in this analysis ranged

between 8-97% (mean 60%, median 63%) of all the fish in the entire water column (Figure 2.6). The estimate of h_2 indicates that fish density in the ADZ is predicted best using acoustic backscatter data from the first layer above it. Results also indicate that predictors such as environmental variables and fish length can be used to predict fish density in the ADZ. Assessment of these predictors over the range of observed environmental variability is presented in Figure 2.7. Low estimates of VIFs indicated that possible correlations between predictor variables are not of a concern. Bottom depth was by far the most influential environmental predictor for fish density in the ADZ, and its effect ranged from ~ 0.6 of the mean prediction in the shallowest depths of 40-60 m to 2 at the depths of 160 m (Figure 2.7a). The surface temperature effect increased from 0.8 to 1.5 over 2 to 10°C (Figure 2.7b). Pollock densities in the ADZ increased from 0.9 to 1.2 relative to the mean as sediment size was decreased from 1 to 7 phi (Figure 2.7c). Increasing light levels decreased pollock densities in the ADZ (Figure 2.7d). Inclusion of current speed in the model was supported by AICc, but this variable had a minor effect on pollock densities in the ADZ (Figure 2.7e). On the other hand, an increase in mean pollock length led to large increases in the density of pollock in the ADZ (0.6 for the smallest pollock (~ 20 cm fork length) to 1.60 for the largest pollock (>60 cm fork length; Figure 2.7f)).

2.3.5. Environmental effects on bottom trawl catch

Predictions of bottom trawl catch at a given s_A in the effective fishing zone indicated that environmental variables and fish size had a substantial effect on predicted BT catches (Figure 2.7). Bottom depth was the most influential environmental predictor for BT catches and its effect ranged from ~ 0.75 of the mean in the shallow depths to the 1.5 in the deep areas covered by the survey (Figure 2.7a). The effect of surface temperature effect varied from 0.9 to 1.2 over the range of observed temperatures (Figure 2.7b). Decreasing sediment size had an increasing effect

on bottom trawl catches from 0.9 to 1.1 of the mean (Figure 2.7c). Increasing light levels decreased pollock catch from 1.05 to 0.95 (Figure 2.7d). The effect of current speed on BT catch was minimal (Figure 2.7e). Standardized pollock catch in the BT increased from 0.75 for the smallest pollock (~20 cm length) to 1.30 for > 60 cm pollock (Figure 2.7f). The sensitivity analysis for inaccuracies in the TS ~fish length (equation [2.3]) indicated that for any value of the slope within confidence bounds the relationship between ADZ fish density and fish length remains monotonically increasing (data not shown).

2.4. Discussion

2.4.1. Interpretation of model selection

Best fit to the data by model D indicated that the catchability of either BT or AT survey for pollock is variable in space and time because it depends on environmental variables, and is density-dependent in the case of the BT survey. However, it is likely that environmental variables are affecting catchability indirectly by impacting fish distribution patterns and behavior. Similar conclusions have been reported by Godø and Wespestad (1993), where they state that the “survey conditions”, or environmental impacts on distribution patterns impact catchability differently from year to year. Additionally, Aglen et al. (1999) found environmentally driven variable availability and efficiency of the bottom trawl and variable availability to an echosounder for Atlantic cod, haddock and redfish. These studies indicate that achieving constant survey catchability across time and space for semi-pelagic species may be impossible regardless of survey standardization efforts (Stauffer, 2004). Catchability is unknown for most fishery-independent surveys, but it is assumed to be stationary in time and space (Kimura and Somerton, 2006) because survey data are often perceived to be of better quality than fishery data

(Harley et al., 2001). Findings of this study indicate that problems associated with non-stationary catchability in the fishery-dependent data (i.e. commercial fishery data; e.g. Godø and Engås, 1989; Hilborn and Walters, 1992; Wilberg et al., 2010) may also arise with survey data. This can be problematic for example, in geostatistical estimates of fish abundance because they require that underlying local CPUE data are proportional to abundance (Rivoirard et al. 2000). The fact that local CPUE data from either the AT or the BT survey may not be proportional to fish density can introduce errors in these estimates. The same assumption is often made in spatial dynamics studies, which use CPUE data to investigate relationships between fish distributions and environmental factors (e.g. Bartolino et al. 2011). In the case of these studies, the presence of non-stationary, environmentally-dependent catchability makes it impossible to distinguish environmental effects on fish spatial distribution from environmental effects on catchability. This conundrum can be resolved by combining results from two surveys, conducted simultaneously, in a model that accounts for factors influencing both surveys as was presented here. In the EBS pollock example, the models predicted an ADZ correction and BT efficiency parameters. The next logical step will be to use these results to estimate environmental effects on catchability and correct local density estimates for environmental effects, thereby providing spatial distribution data that is reflective of actual species distributions.

2.4.2. Bottom trawl efficiency parameters

One of the main goals of this study was to estimate BT efficiency parameters. These parameters are needed when combining acoustic and BT survey data, but they should be especially useful in years when only a BT survey was conducted. In the case of pollock in the EBS, BT surveys are conducted annually, while AT surveys occur on a biennial schedule (Ianelli et al. 2009).

Efficiency of a bottom trawl - Selection of Model D indicates that the BT does not capture fish in proportion to their abundance in the effective fishing zone. Declining survey BT efficiency with increasing fish density has also been observed by Hoffman et al. (2009) for Atlantic croakers and white perch in Chesapeake Bay and earlier by O'Driscoll et al. (2002) for capelin off Newfoundland. These findings contradict those reported by Godø et al. (1999), who deduced, from observations of Atlantic cod and haddock, that BT efficiency should increase with increased density. However, Godø et al. (1999) acknowledged that their study was limited to observations of fish behavior in close proximity to the opening of the trawl, and did not account for fish behavior over the entire area between the vessel and the trawl.

Density-dependence of bottom trawl efficiency can be troublesome to stock assessment because it suggests that pollock CPUE from the BT survey may be hyperstable (Hilborn and Walters, 1992). Hyperstability implies that detected changes in fish abundance are smaller than actual changes and it occurs commonly in fishery-dependent data (e.g. Harley et al., 2001). In certain cases it could, if not accounted for, contribute to management decisions that lead to stock collapse as it did for the northern cod stock (Hutchings, 1996; Walters and Maguire, 1996). Fishery-independent surveys have been thought to avoid hyperstability problems (e.g. Harley et al., 2001); however, findings of this study suggest that this assumption may not always be accurate. The effect of hyperstability on CPUE could be dampened by accounting for corrections based on simultaneously collected acoustic data since these data are likely not hyperstable because of the linearity principle of echo integration (Foote, 1983) and negligible acoustic shadowing effect (Zhao and Ona, 2003) at the backscatter levels observed for pollock in the EBS.

Effective fishing height (vertical herding) - Effective fishing height of bottom trawls has been a topic of recent research (Aglen, 1996; Hjellvik et al., 2003; Handegard and Tjøstheim, 2009). This study indicated that average effective fishing height for pollock in the EBS was about 16 m. This result differs from that reported by von Szalay et al. (2007), who concluded, from a model similar to Model A, that the effective net height was equal to the measured net height. Their conclusion is not supported by data used in this study, as model A performed significantly worse than Models C and D. An effective fishing height of 16 m compared to a 2.4 m mean headrope height (von Szalay and Somerton, 2009) implies that pollock dive in response to the passing boat and/or trawl warps. This conclusion confirms the findings of Rose and Nunnallee (1998) where correlations between BT and acoustic data indicated a pollock diving response to the bottom trawl. A diving response to an approaching trawl was also observed for other semi-pelagic species including haddock (Ona and Godø 1990), and Atlantic cod (Handegard et al. 2003, Handegard and Tjøstheim 2005).

Catchability ratio - The catchability ratio parameter r_q is important when data from the AT or BT survey need to be provided on the same scale. For example, estimating spatial distribution using both AT and BT survey data is possible only if the ratio of catchability for the two gears is known. Without this information, distributions from combined surveys would be positively biased to the survey with higher catchability. Similarly to the effective fishing height, which is regarded as the extent of pollock vertical herding, r_q can be thought of as quantifying horizontal herding by bottom trawls. Bottom trawl doors and bridles create mud clouds that can herd fish into the path of the trawl (Engås and Godø, 1989; Dickson, 1993). The r_q estimate in best model was not significantly different from 1, which indicated that horizontal herding of pollock by the EBS survey bottom trawl is not strong, and densities that are detected by a BT survey are similar

to those detected by an AT survey (assuming that pollock TS-fish length relationship is not biased). This conclusion is consistent with the findings of Somerton (2004), who did not observe horizontal herding of pollock or Pacific cod in response to a bottom trawl in the Gulf of Alaska.

The inclusion of the effective fishing height parameter together with the catchability ratio in one model could create a potential for confounding (i.e. an increase in the one of the parameters would cause a decrease in the other) when acoustic densities exhibit similar vertical distributions. However variability in vertical distribution (in the data) provided enough information to prevent confounding between these parameters, because the effective fishing height is affected by vertical distribution in different way than the catchability ratio. The relatively tight confidence bounds around each of the two parameters indicate that they are not strongly confounded.

Specific parameter values obtained in this study could be different if acoustic data from a free-running survey vessel (speed ~10 knots) instead of trawling vessel (speed ~3 knots) was used. To date two studies have been performed to compare pollock s_A from free-running versus trawling vessels. De Robertis and Wilson (2006) found that s_A from a free-running vessel was significantly higher than from a trawling vessel by approximately 20%. On the other hand von Szalay and Somerton (2009) found that s_A from the free-running vessel was significantly lower than from trawling vessel by approximately 30%. These contrasting results indicate that the relationship between trawling and free-running s_A could be specific to the vessel-trawl combination (von Szalay and Somerton, 2009). In such case it would be prudent to perform experiments collecting data from a free running AT survey vessel and a trawling BT survey vessel (e.g. paired comparisons) to obtain specific vessel-to-vessel parameter estimates. Moreover, De Robertis and Wilson (2011) showed that changes in fish behavior in time and

space could also result in different backscatter readings from the same vessel. Although this spatio-temporal variability in how pollock behave when they encounter a survey vessel may have contributed to the unexplained deviance seen in models, given that model residuals are similar among years (Figure 2.4), there do not appear to be any major interannual changes in pollock behavior.

2.4.3. Acoustic dead zone correction

Results of this study indicate that acoustic backscatter combined with other predictors, such as environmental variables and fish size can be used to predict fish density in the ADZ. The value for the parameter h_2 indicates that fish density in the ADZ is best predicted using acoustic backscatter data from the first sampled layer above ADZ. This is similar to the method proposed by Ona and Mitson (1996), but does not assume that fish density in the ADZ is equal to that in the first layer. Experimentally-derived here ADZ correction assumes that fish density in the ADZ is a linear function of s_A in the layer just above the ADZ and both the slope and the intercept of this function can be determined using other variables that may affect actual fish density in the ADZ.

Since Ona and Mitson (1996) showed how to theoretically estimate the lost sampling volume associated with the ADZ, their correction has been widely used to correct acoustic density estimates (e.g. Rose, 2003; McQuinn et al., 2005; Kotwicki et al., 2009). However, the method makes two assumptions. The first assumption is that the ADZ height is based on a flat seafloor over the footprint of the acoustic beam. In reality, the theoretical ADZ can differ from the dead zone height because of seabed slope and topography (e.g. Kloser et al., 2001, Patel et al., 2009), the angle of incidence of the beam on the seafloor (which is influenced by transducer motion;

Mello and Rose, 2009), or inaccurate bottom detections (MacLennan, 2004). The second assumption is that fish density in the ADZ is equivalent to the density immediately above the ADZ. This assumption may be violated in the case of semi-pelagic species (e.g. Lawson and Rose, 1999, Rooper et al., 2010), due to greater affinity of these species to the sea floor. Lastly, there is an ambiguity in choosing the height of the layer just above the ADZ to correct the ADZ. All of these assumptions were not necessary in model D, which estimated ADZ correction empirically based on the data collected from bottom trawl.

Comparison of models B and D indicated that an empirically-estimated ADZ correction is preferable to a theoretical value. Moreover, better performance of model A compared to model B indicated that, using a simple constant for an ADZ correction may be more appropriate than using one based on sampling geometry alone. This finding suggests that the density of pollock in the ADZ is rarely the same as in the layer just above it. It also indicates that models for ADZ correction should be tested empirically.

2.4.4. Environmental effects

This investigation provides evidence that the density of pollock in the ADZ depends on many environmental factors and shows that s_A alone is a rather poor predictor of fish density in the ADZ. Semi-pelagic fish behavior in the water column can be affected by the fish size as well as environmental factors (e.g. Michalsen et al., 1996; Aglen et al., 1999; Kotwicki et al., 2009). Changes in behavior may influence fish vertical distribution close to the bottom and hence abundance in the ADZ. Therefore it is preferable to use the experimentally-derived ADZ correction, that accounts for environmental effects, over one that uses geometric approach exclusively.

Higher fish abundance in the ADZ with depth is expected because the volume of the ADZ increases with depth (Ona and Mitson, 1996). The surface temperature effect detected in the model (Figure 2.7a) may be explained by pollock avoidance of warmer temperatures that would result in increased need for oxygen and food consumption (Clarke and Johnston, 1999). In the EBS, areas with high surface temperatures have a greater vertical temperature gradient than areas with colder surface temperatures. Pollock, therefore, may have more incentive to be near bottom (in colder water) in areas with a higher surface temperature to conserve energy. Additionally, zooplankton availability in the water column generally decreases in the EBS by the end of summer (Springer et al., 1989; Chuchukalo et al., 1996; Coyle et al., 1996), indicating that this energy saving behavior may be reasonable when surface temperatures are highest. The model predicted higher fish densities in the ADZ with decreasing sediment size ranging from sand to mud. A possible explanation may be that pollock prefer to be closer to the sandy-mud bottom, prevalent on the middle EBS shelf (Smith and McConnaughey, 1999), due to higher food availability on the inner shelf with 10-fold larger infaunal biomass than on the outer shelf (Walsh and McRoy, 1986). This study also predicted that pollock density in the ADZ is lower with increased near-bottom light levels. This finding seemingly contradicts a previous study on the effect of light on pollock vertical distribution, which indicated that pollock tend to be higher off bottom in low near-bottom light conditions (Kotwicki et al. 2009). However this study did not look explicitly at the ADZ, but only at pollock observed by the AT. Lastly, although current speed was selected (based on AICc), the magnitude of the current speed effect proved to be very small and at this point it can be considered negligible. Future research, using presented here methodology, could explore additional environmental factors which are likely to influence pollock densities in the ADZ.

This study also found a size-dependent effect with pollock abundance in the ADZ, with larger pollock more likely to be present in the ADZ. This result was expected because larger pollock are more demersal (Karp and Walters, 1994). Also, survey selectivity curves derived in pollock stock assessments show that the selectivity of the AT survey is lower for larger pollock (Ianelli et al., 2009), suggesting that larger pollock are more likely to be present in the ADZ.

2.4.5. Implications for stock assessment

Looking forward I advocate that combined acoustic-bottom trawl survey to be considered in place of the separate AT and BT surveys to minimize possible biases associated with environmental variability (Godø and Wespestad, 1993). If the surveys are performed on separate vessels, it is important to schedule them at approximately the same time and location.. Both AT and BT surveys have shortcomings that can complicate interpretation of survey abundance data. In the AT survey the ADZ causes bias (e.g. McQuinn et al., 2005), and can lead to spatial and temporal changes in the AT survey catchability (Kotwicki et al., 2009) because of the dependence of the fish density in the ADZ on environmental variables. In the case of the BT survey, the existence of a bottom trawl blind zone (Figure 2.1) and density-dependence of BT catches indicate similar bias and catchability problems. However, performing both surveys on one platform and using models such as the one presented here could mitigate these problems. Further research on the models that quantify the ADZ correction incorporating environmental factors and BT efficiency parameters could concentrate on two aspects that have been shown here but remain still unresolved. First, variability in catchability of both AT and BT surveys needs to be better understood. Parameters estimated in models that combine bottom trawl and acoustic data could provide the means to estimate changes in catchability of either survey in relation to environmental factors, allowing estimation of the magnitude of these effects on survey

abundance indices. Second, this knowledge would also be useful for deriving one abundance index by combining results from both BT and AT surveys and testing these new indices in stock assessment models.

Ecosystem monitoring to better understanding ecosystem patterns and processes is a dominant theme of the ecosystem-based approach to management (Grumbine, 1994; Christensen et al., 1996, Mangel et al., 1996). However, understanding of the abundance of key organisms in the ecosystem can be negatively impacted by the environmental variability that affects monitoring tools (BT and AT surveys in this case; Godø and Wespestad, 1993; Godø, 1994). To account for this impact one needs to understand how the monitoring is affected by the environment and integrate environmental data into stock assessment process. I perceive this study as a step toward this goal. This topic requires further research that could concentrate on either including environmental variables in the process of estimating abundance indices, or by integrating environmental variability into catchability estimates within stock assessment models. Regardless of the avenues that are pursued in the future, collection of environmental data during stock assessment surveys is essential.

2.5. Tables

Table 2.1. AICc and Negative log-likelihood values for the four competing models.

	Number of parameters	Negative log-likelihood	AICc
Model A	4	419.26	844.59
Model B	4	442.60	893.27
Model C	6	370.65	751.46
Model D	7	361.36	734.96

Table 2.2. Estimates of the parameters of the final model with 95% confidence limits. Parameters b are from the linear function $\mathbf{b}[\mathbf{X}]$, and parameters c are from the function $\mathbf{c}[\mathbf{X}]$. Predictors are indicated by subscripts: BD – bottom depth, FL – mean fork length, ST – surface temperature, BL – near bottom light, SS – sediment size, and CS – current speed. The confidence limits for the parameters h_1 and h_2 were obtained from a likelihood profile over h_1 and h_2 ; the confidence limits for remaining parameters are asymptotic approximations conditioned on the best estimates for h_1 and h_2 .

Parameter	Estimate	St. Dev	Lower 95%	Upper 95%
r_q	0.9567	0.2385	0.4892	1.4242
a	4133.1000	1193.3000	1794.2320	6471.9680
σ	0.6116	0.0230	0.5665	0.6567
b_{BD}	0.0151	0.0031	0.0090	0.0212
b_{FL}	0.0023	0.0007	0.0009	0.0037
c_{BD}	-0.0138	0.0050	-0.0236	-0.0040
c_{ST}	0.3684	0.0629	0.2451	0.4917
c_{SS}	0.2656	0.0946	0.0802	0.4510
c_{BL}	-0.0073	0.0047d	-0.0165	0.0019
c_{FL}	0.0013	0.0010	-0.0007	0.0033
c_{CS}	0.0020	0.0008	0.0004	0.0036
c	2.3322	0.9990	0.3742	4.2902
h_1	16 m		12 m	20 m
h_2	0.75 m		0.75m	<1 m

Table 2.3. Variance inflation factors (VIF) for the linear predictors included in the final model.

Linear predictor	VIF
Bottom depth	1.80
Surface temperature	1.46
Sediment size	1.73
Bottom light	1.14
Fork length	1.28
Current speed	1.19

2.6. Figures

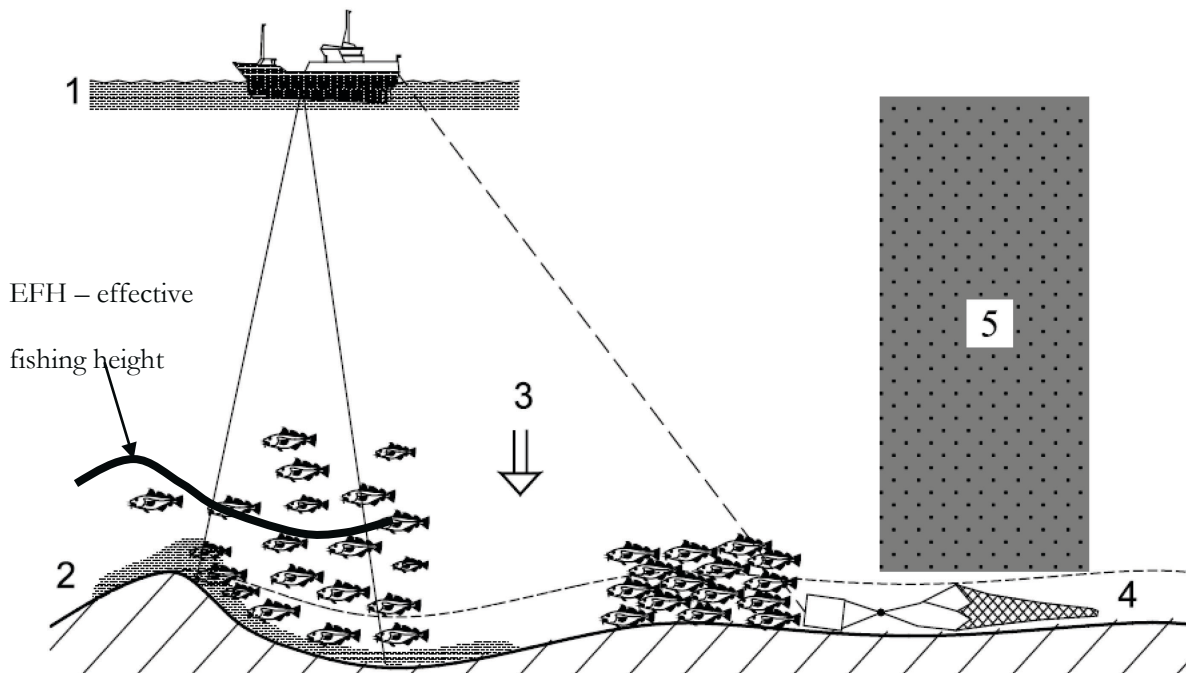


Figure 2.1. Illustration of the water column area sampled by the acoustic beam and in the volume swept of the bottom trawl (modified from Hjellvik et al., 2003). (1) The upper acoustic dead zone, (2) the acoustic bottom dead zone (ADZ), (3) vertical herding when fish are pelagically distributed above the bottom trawl, (4) the height of the trawl opening and (5) the blind zone of the bottom trawl. The effective acoustic sampling is conducted in the area between (1) and (2). Note that the BT samples all the fish in the ADZ and some fish above it, while the AT samples all the fish above the ADZ.

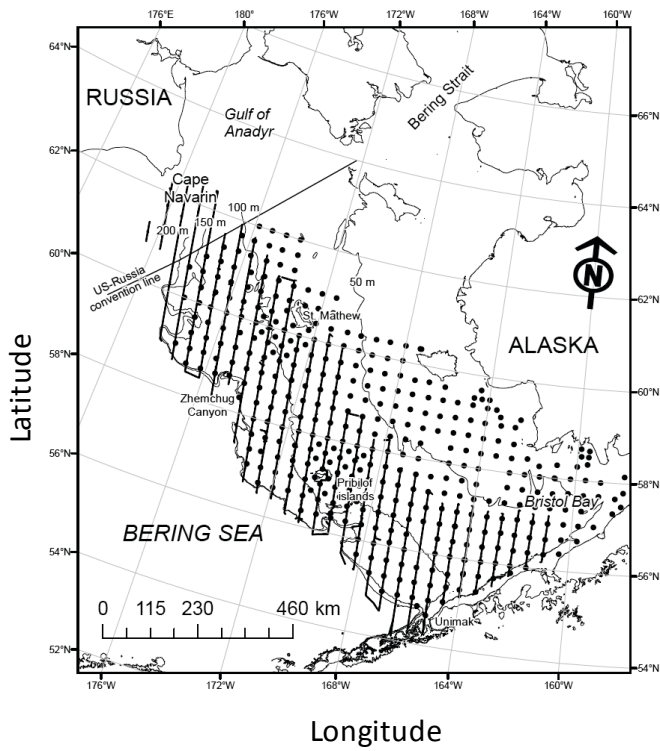


Figure 2.2. Bottom trawl (points) and acoustic (parallel lines) survey locations.

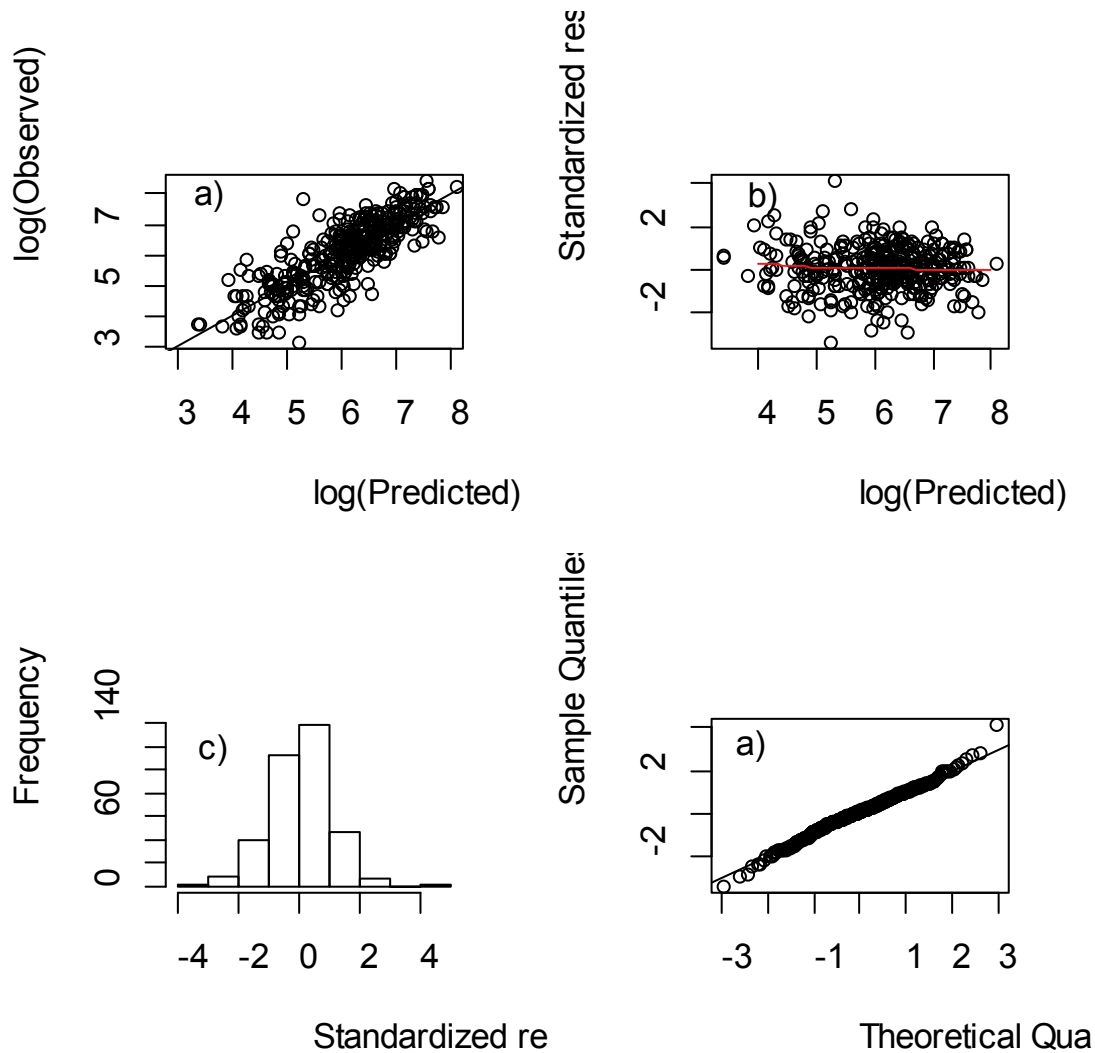


Figure 2.3. Diagnostics plots for the final model: a - scatter plot of $\log(\text{observed})$ vs. $\log(\text{predicted})$, line represents a $y=x$ relationship, b – scatter plot of standardized residuals vs. $\log(\text{predicted})$, line represents a loess smooth going through the data, c - histogram of standardized residuals, d – a QQ plot showing sample quantiles (obtained from standardized residuals) vs. theoretical quantiles of normal distribution.

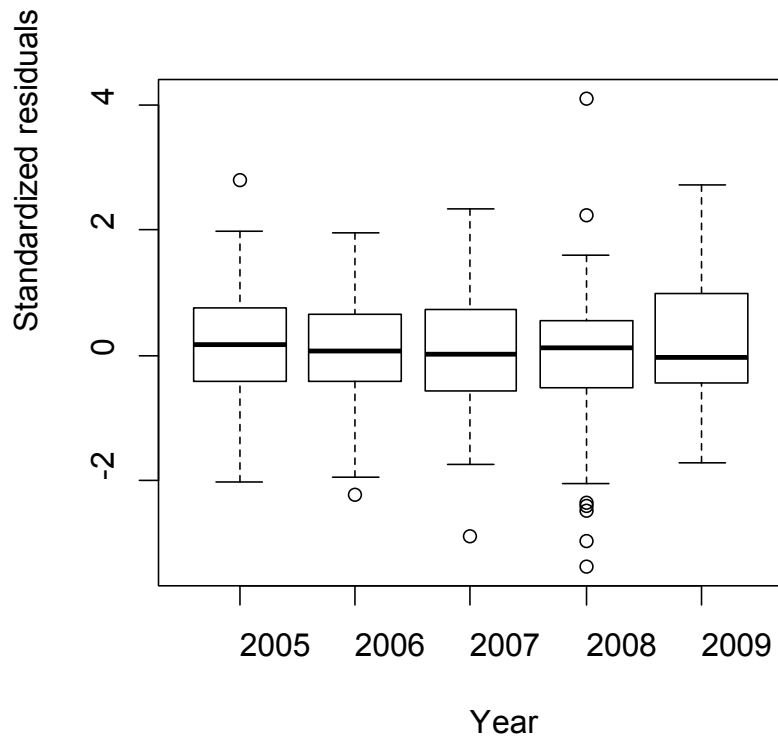


Figure 2.4. Standardized residuals from Model D by year. Box upper and lower boundaries represent upper and lower quartiles. Whiskers represent maximum and minimum values except outliers (circles), which are defined as points with values greater than 1.5 times the lower and upper quartiles.

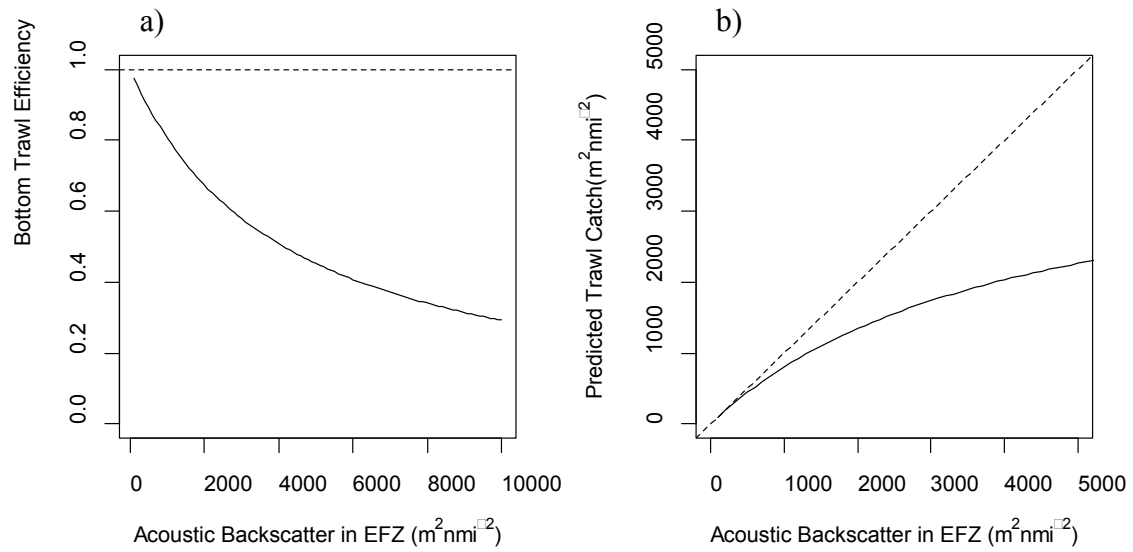


Figure 2.5. Predicted bottom trawl efficiency (a) and predicted bottom trawl catches (b) as a function of acoustic backscatter in the effective fishing zone (EFZ; solid lines). Dashed lines on both panels indicate density independent efficiency.

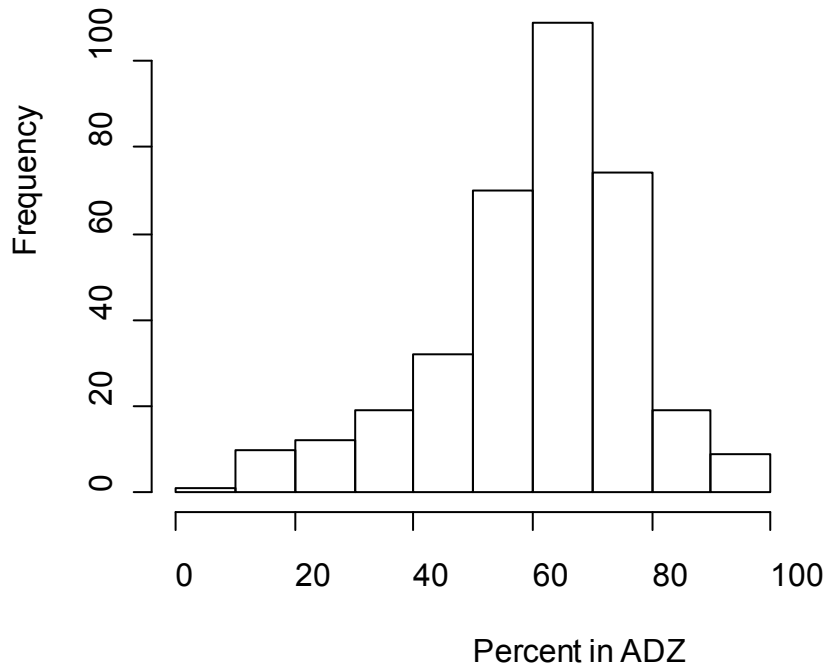


Figure 2.6. Histogram of the model-predicted biomass in the acoustic dead zone as a proportion of the entire water column for all trawl stations (n=355) used in analysis.

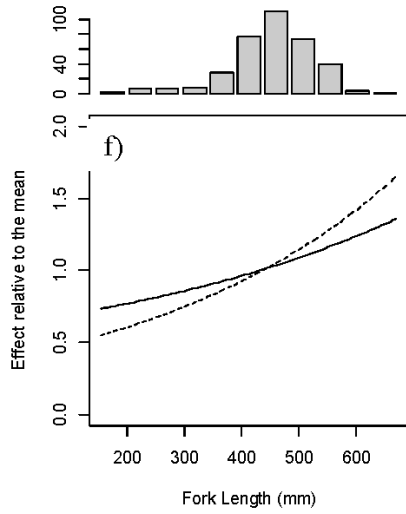
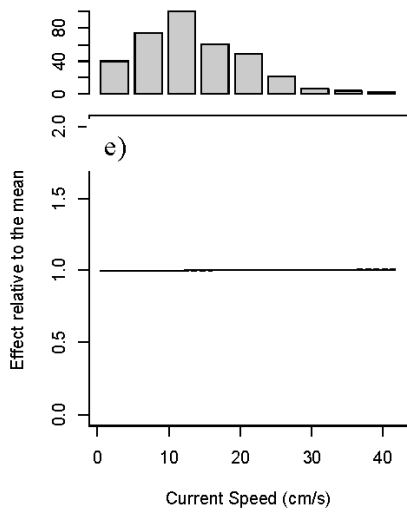
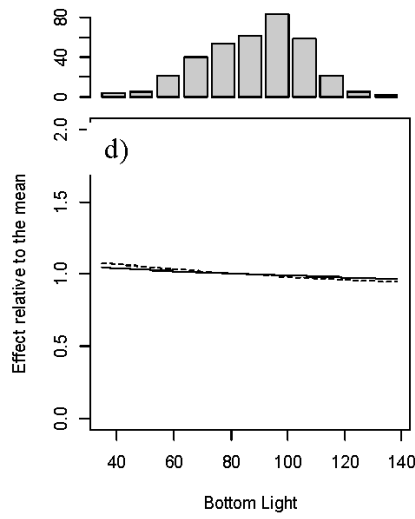
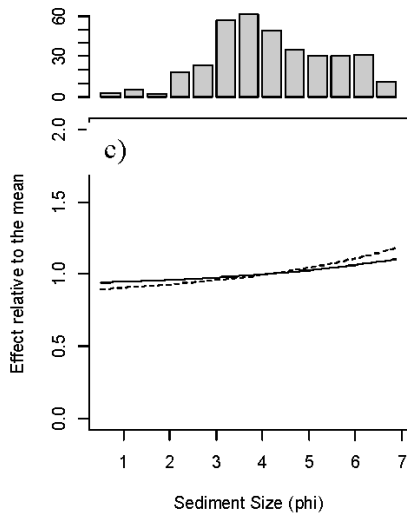
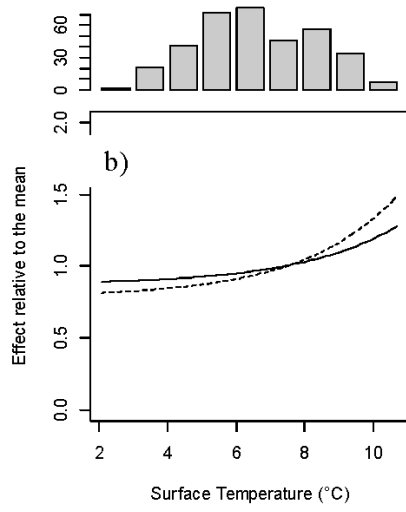
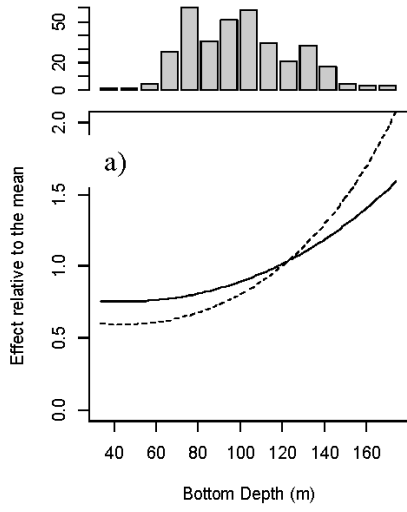


Figure 2.7. Relative effects of environmental variables and mean pollock length on predicted areal densities in the acoustic dead zone (dashed line) and bottom trawl catches (solid line). Effects were estimated relative to the mean predictions in the range of observed environmental variability presented in the histograms.

CHAPTER 3. CORRECTING DENSITY-DEPENDENT EFFECTS IN ABUNDANCE ESTIMATES FROM BOTTOM TRAWL SURVEYS

3.1. Introduction

Indices of abundance are important for estimating population trends in stock assessment and hence fishery management. Ideally, abundance indices should be based on fishery-independent data collection methods such as design-based surveys (Maunder and Punt, 2004). Indices based on commercial fishery catch per unit effort (cpue) should be avoided since they are unlikely to be proportional to actual abundance (Beverton and Holt, 1957; Peterman and Steer, 1981; Swain and Sinclair, 1994; Harley *et al.*, 2001; Maunder and Punt, 2004) and may fail to reflect changes in abundance due to “hyperstability” or “hyperdepletion” (Hilborn and Walters, 1992).

Hyperstability represents situation when cpue stays high as abundance drops, while in case of hyperdepletion, cpue drops much faster than abundance. Stock assessments relying on such data may fail to track population changes and could potentially lead to fishery collapse or underutilization (Hutchings, 1996; Walters and Maguire, 1996; Erisman *et al.*, 2011). Fishery-independent bottom-trawl (BT) surveys, which are assumed to be proportional to abundance, have been widely used to provide indices of abundance to avoid problems associated with the hyperstability or hyperdepletion of the commercial cpue data (Godø, 1994; Ianelli *et al.*, 2012). However, density-dependent effects in survey bottom-trawl operations may also result in hyperstable indices of abundance (Kotwicki *et al.*, 2013) similar to those observed with commercial cpue data.

Density-dependent effects of the BT have been identified as factors that may affect reliability of abundance estimates from BT surveys (Godø *et al.*, 1990; Godø and Weststad, 1993; Godø,

1994; Aglen *et al.*, 1997; Kotwicki *et al.*, 2013). For example, survey trawl capture efficiency for Atlantic cod (*Gadus morhua*) and haddock (*Melanogrammus aeglefinis*) increases with fish density (Godø *et al.*, 1999). The opposite effect was observed for capelin (*Mallotus villosus*; O'Driscoll *et al.*, 2002), Atlantic croakers (*Micropogonias undulates*) and white perch (*Morone americana*; Hoffman *et al.*, 2009), and walleye pollock (*Gadus chalcogrammus*; Kotwicki *et al.*, 2013). Despite these findings, evaluations of the spatial and temporal variability in density-dependent BT survey efficiency are lacking, and methods which correct time-series of survey abundance indices are unavailable.

The derivation of a relative index of abundance from a fishery-independent survey is based on the relationship $u = qD$, where u is the catch rate (fish density) detected by the BT, D is the true density, and q is a proportionality constant, usually referred to as catchability (Punt and Hilborn, 1997). Catchability is often decomposed into two components $q = q_a q_e$, (Godø, 1994), where q_a is availability to the BT [i.e. the proportion of fish in the water column present between the bottom and effective fishing height (EFH) of the BT; hereafter it is referred to as bottom trawl zone (BTZ)] and q_e is BT efficiency (the proportion of fish in the BTZ caught by the trawl). Catchability is unknown for most fishery-independent surveys, but it is often assumed to be stationary in time and space (Kimura and Somerton, 2006). This assumption can be critical for stock assessments, spatial dynamics studies, and ecological modelling (Kotwicki *et al.*, 2013). Estimates of abundance trends may be misleading if either q_e or q_a of the BT is affected by density (Godo, 1994). Consequently, methods for estimating q_e and correcting survey-derived indices of abundance for density-dependence are needed.

Developing an estimator for q_e is difficult because this requires independent measures of fish density in the BTZ (Somerton *et al.*, 1999). Past studies estimating q_e for semi-pelagic species have used independent estimates of abundance in front of the bottom trawl derived from acoustic backscatter data within the BTZ (O’Driscoll *et al.*, 2002; Hoffman *et al.*, 2009; Doray *et al.*, 2010). To avoid biases, these data need to be relatively free from contamination by other species and need to have an estimate of the acoustic dead-zone correction (Ona and Mitson, 1996; Kotwicki *et al.*, 2013). The methods are difficult to apply because most time-series of the BT survey data lack acoustic measurements. In addition, backscatter data from many survey tows are often contaminated by other organisms even if acoustic data are available. Consequently, BT efficiency is usually estimated in an experimental manner outside of standard survey operations (O’Driscoll *et al.*, 2002) or alternatively for a subset of tows where contamination (in the backscatter) from other species can be assumed negligible (Hoffman *et al.*, 2009). If estimates of q_e were provided for all tows within the survey time-series, a more reliable index of abundance could be available for stock assessments and ultimately fishery management.

The purpose of this investigation is to produce a more reliable BT survey index for walleye pollock (hereafter referred to as “pollock”) in the eastern Bering Sea (EBS) by extending on Hoffman *et al.* (2009) and O’Driscoll *et al.* (2002) to incorporate experimentally-derived acoustic dead-zone corrections and BT efficiency parameters derived from combining acoustic and BT survey data (Kotwicki *et al.*, 2013). My method incorporates uncertainty associated with the estimation of the acoustic dead-zone correction and BT efficiency parameters. Estimates of q_e are also obtained for all tows in the survey time-series by modelling the relationship between survey cpue and q_e . I postulate that $q_{e,i} = f(u_i)$, where i indicates a survey tow when q_e is density-dependent. From this relationship $q_{e,i}$ was estimated for all tows in a survey time-series

and hence new estimates of total BT survey abundance. The secondary goal of this paper is to assess if density-dependent q_e for pollock in the EBS leads to a hyperstable index of abundance by assessing the relationship between mean survey catching efficiency and corrected index of abundance. Pollock was chosen for this investigation because it is a key species in subarctic Pacific ecosystems and supports a substantial fishery that accounts for ~5% of global fish harvest, with annual harvests ranging from 4 to 7 million tonnes (Bailey *et al.*, 1999). It ranked second in the world among marine species in capture production in 2008 (FAO, 2010).

3.2. Methods

3.2.1. Data

The EBS BT survey has been conducted annually over a standard grid of stations since 1982 (Lauth and Nichol, 2013). Most of the 376 survey stations were located at the centres of a 20×20 nautical mile grid (Figure 3.1). Stations at the corners of the grids were also sampled in two regions (near St. Matthew Island and the Pribilof Islands). The surveys are conducted annually in June and July using a standardized sampling gear (the 83-112 Eastern otter trawl). The survey stations are visited beginning with those in the northeastern corner (Bristol Bay) of the area and then proceeding westward. The standard tow duration is 30 min on bottom, and the tow speed is 1.54 m s^{-1} (3 knots; see Lauth and Nichol, 2013 for details). During 2005–2009, acoustic backscatter data were collected annually for all BT hauls. A detailed description of acoustic data processing is given in Kotwicki *et al.* (2013).

3.2.2. Abundance indices

Total population estimates from the EBS BT survey (hereafter referred to as the *status quo* index of abundance) were derived using methods detailed in Wakabayashi *et al.* (1985). In brief, the catch rates are calculated as $u_i = n_i/E_i$, where n_i is the number of pollock caught in tow i and E_i is the corresponding fishing effort. Haul effort was based on area-swept estimates (Godø and Engås, 1989), defined as the product of tow distance and average net width measured with acoustic sensors (Kotwicki *et al.*, 2011). Mean stratum catch rates (in no. hectare⁻¹) weighted by stratum area were combined to estimate the total abundance. Variances and coefficients of variation (*CVs*) around abundance estimates were calculated assuming stratified random sampling to assure consistency with the presently used methods for variance estimation in pollock EBS surveys (for details, see Wakabayashi *et al.*, 1985).

Population-at-age estimates were derived using methods described by Wakabayashi *et al.* (1985) and Kimura (1989). In brief, length frequencies were weighted by cpue for each tow and combined across tows to estimate population at length. Yearly age–length keys (combined over entire survey area) were then applied to compute numbers by age and length class by strata. Finally, these data were summed over strata to estimate total survey area population at age.

3.2.3. Estimating bottom-trawl efficiency using acoustic data

Catch rates are corrected for density-dependence using:

$$\hat{u}_i = \frac{u_i}{q_{e,i}} \quad [3.1]$$

where \hat{u}_i is a BT survey catch rate for tow i corrected for density-dependence. An estimate of $q_{e,i}$ is needed for each tow to apply equation [3.1] to the u_i data. It has been shown previously that

estimates of q_e can be obtained using acoustic backscatter data within the BTZ (O’Driscoll *et al.*, 2002; Hoffman *et al.*, 2009; Doray *et al.*, 2010). However, there were only 355 out of approximately 11 000 survey tows with reliable acoustic backscatter data that could be attributed mostly to pollock (see Kotwicki *et al.*, 2013 for details). These 355 tows are representative of typical survey tows as they came from a 5-year period (2005–2009) and were spread out over the entire survey area. The function $q_{e,i} = f(u_i)$ is needed because the only available density estimate for each BT survey tow was u_i . The acoustic backscatter data was used to estimate Bayesian posterior distributions of $q_{e,i}$ for the 355 tows and used those to extrapolate $q_{e,i}$ to tows without acoustic data, as explained later.

Estimates of pollock density in the BTZ were obtained from acoustic data collected during trawls coupled with a model which combines BT and acoustic data:

$$\begin{aligned}
 s_{A,BT_i} &= \left(\frac{1}{r_q(\delta_{1_i} + \delta_{2_i})} + \frac{1}{a} \right)^{-1} e^\varepsilon \\
 \delta_{1_i} &= \sum_{0.5}^{EFH} s_{A_i} \\
 \delta_{2_i} &= e^{\mathbf{b}X_i} \sum_{0.5}^h s_{A_i} + e^{\mathbf{c}X_i}
 \end{aligned}
 \tag{3.2}$$

(Model D of Kotwicki *et al.*, 2013), where s_{A,BT_i} is an equivalent of u_i in units (m^2 nautical mile $^{-2}$; for details, see Kotwicki *et al.*, 2013) of acoustic backscatter s_A , r_q is the catchability ratio between the BT and acoustics which accounts for differences in catchability between the two methods, EFH is the effective fishing height of the trawl, e^ε is log-normally distributed error, $(\delta_{1_i} + \delta_{2_i})$ is the fish density in backscatter units in the BTZ, where δ_{1_i} is the acoustic

backscatter in the BTZ above the acoustic dead zone, and δ_{2_i} is the estimate of acoustic backscatter in the acoustic dead zone (hereafter referred to as the ADZ correction). The parameter h determines the height of the near-bottom acoustic layer, which is used to estimate the ADZ correction. Environmental variables, that have been shown to affect pollock density in ADZ (bottom depth, surface temperature, sediment size, current speed, bottom light level; Kotwicki *et al.*, 2013) and mean fish length were included in the model as the linear covariates \mathbf{bX}_i and \mathbf{cX}_i , where \mathbf{b} and \mathbf{c} are vectors of parameters and \mathbf{X}_i is a matrix of the predictor variables. The parameter a quantified the extent of density dependence of q_e within the BTZ.

To estimate q_e , equation (3.2) needs to be transformed to the following form:

$$s_{A,BT_i} = q_{e,i} s_{A,BTZ_i} \quad [3.3]$$

where s_{A_i,BT_i} is the BT cpue expressed in units of s_A , and s_{A_i,BTZ_i} is an estimate of actual fish abundance in the BTZ. From equation (3.2), note that $s_{A,BTZ_i} = \delta_1 + \delta_2$ and after algebraic transformation, equation (3.2) becomes:

$$s_{A,BT_i} = \frac{ar_q s_{A,BTZ_i}}{a+r_q s_{A,BTZ_i}} \quad [3.4]$$

so that

$$q_{e,i} = \frac{ar_q}{a+r_q s_{A,BTZ_i}}. \quad [3.5]$$

The highest posterior density estimate (HPD) of the vector \mathbf{q}_e was found by minimizing the negative log-likelihood (NLL) function:

$$NLL = 0.5N_T \log(2\pi\sigma^2) \frac{\sum_{i=1}^{N_T} (\log(s_{A,BT_i}) - \log(\widehat{s_{A,BT_i}}))^2}{2\pi\sigma^2} \quad [3.6]$$

over the parameters from equation (3.2) using ADMB (Fournier *et al.*, 2012). N_T is the number of tows, σ is the error variance, and $\widehat{s_{A,BT_i}}$ is the model prediction. Markov Chain Monte Carlo (MCMC) sampling was used to develop a posterior distribution of vector \mathbf{q}_e , resulting in a thinned set of 1000 vectors. Priors for all parameters for the MCMC analysis were chosen to be uniform in the plausible parameter range.

A preliminary analysis of the HPD estimates of \mathbf{q}_e suggested that the relationship between $q_{e,i}$ and $cpue_i$ had an exponential form because the rate of decline in q_e decreased exponentially with an increase in $cpue$. The following three models were fitted to the posterior means for $q_{e,i}$:

$$q_{e,i} = \exp(-\beta_1 s_{A,BT_i}) \quad [3.7a]$$

$$q_{e,i} = \exp(-(\beta_1 s_{A,BT_i} + \beta_2)) \quad [3.7b]$$

$$q_{e,i} = \beta_0 + \exp(-(\beta_1 s_{A,BT_i} + \beta_2)) \quad [3.7c]$$

where $\boldsymbol{\beta}$ is a vector of parameters to be estimated. Model [3.7a] represents a function where q_e decreases exponentially with increasing fish density starting from 1 at very low densities and asymptotically declining to 0 at extremely high densities. Model [3.7b] includes parameter β_2 , which allows the BT efficiency to differ from 1 at zero abundance, and model [3.7c] is an extension of model [3.7b], which allows the BT efficiency at extremely high abundance to differ from 0. The parameters of models 3.7a-c were estimated using the non-linear least squares (nls) function in R (R Core Team, 2012), and the fits were evaluated using residual analysis. The fits of the three models were compared using the likelihood ratio test ($\alpha = 0.05$; Hilborn and Mangel, 1997). The best of models 3.7a-c was then fitted to each sample from the posterior of \mathbf{q}_e and used to estimate 1000 vectors of parameters ($\boldsymbol{\beta}$). Each parameter vector was then used to estimate a vector of BT efficiency for each tow of the entire time series of BT survey data ($\mathbf{q}_e, \text{survey}$). These

estimates were then used in subsequent analyses to estimate new abundance indices and spatial and temporal variability in the BT efficiency.

3.2.4. New abundance estimates

The posterior draws for $\mathbf{q}_{e,survey}$ were each used to recompute the individual tow-specific catch rates (u_i). Each set was then used to recompute abundance estimates resulting in a set of 1000 population abundance (total and by age) estimates. There are two sources of uncertainty associated with new abundance indices: within-stratum sampling variability in cpue and the “additional variability” associated with q_e . The need to account for this additional variability in the indices of abundance has been recognized by other researchers (Punt and Butterworth, 2003; Maunder and Punt, 2004). The variance of the new abundance estimates was estimated using a two-stage resampling process. First, a sample was drawn from the MCMC-derived \mathbf{q}_e survey vectors, which was used to derive the vector of \hat{u}_i values. A stratified (by year and survey stratum) bootstrap resample was then drawn with replacement from \hat{u}_i , and the total abundance was estimated as outlined above. This procedure was repeated 1000 times. Because the abundance estimates are not independent, an among-years variance-covariance matrix (Σ_u) was estimated using:

$$\Sigma_u = (\mathbf{y}_j - \mu_y)(\mathbf{y}_j - \mu_y)^T \quad [3.8]$$

where \mathbf{y}_j is year-specific abundance for bootstrap replicate j and μ_y is the year-specific mean abundance across all bootstrap replicates.

Since mean abundance replicates represent a corrected distribution of the survey process, the mean and variance provide an alternative index of abundance (hereafter referred to as the new

index of abundance) to use within the stock assessment model (Ianelli *et al.*, 2012). To determine if the *status quo* index was hyperstable, the new index was contrasted with the *status quo* BT survey index. The hyperstable index detects changes in the population abundance that are smaller than actual changes in the population abundance (Hilborn and Walters, 1992). To determine if the *status quo* index was hyperstable, mean BT survey catching efficiency (i.e. the ratio of the *status quo* index over the new index) was plotted against the *status quo* index because the negative slope of this relationship would indicate hyperstability of the *status quo* index.

3.2.5. Estimation of the population age structure of new index of abundance

The impact of the variability in q_e among tows and the tendency of pollock to form dense schools by age class on the estimated survey proportions-at-age by year was explored. This was done by sampling \hat{u}_i vectors, and applying the methodology described above to estimate mean q_e by age for each survey year and the means of the distributions of the proportions-at-age.

3.2.6. Effect of the new BT index on stock assessment model output

The effect of replacing the *status quo* BT index of abundance with the new BT index in the stock assessment was investigated for the three BT survey data inputs: abundance, age structure, and the variance–covariance matrix. The assessment was run three times, replacing model inputs to explore the impact of each component. In the first run, only the total abundance estimates were replaced; in the second run, total abundance estimates and age structure were replaced; and in the third, all three inputs were replaced. The outputs from the runs of the assessment were compared in terms of the estimates of spawning–stock biomass (SSB) and the *CVs* of three estimates.

3.3. Results

3.3.1. Bottom-trawl efficiency

Likelihood ratio tests (p -value = 0.0031) and a lack of trends in the residuals (Figure 3.2) indicated that the three-parameter model [3.7c] was the best of the models considered (see Table 3.1 for mean parameter β values and their standard deviations for model [3.7c]). The q_e , which is close to 1 for very low catches decreases exponentially with catch (Figure 3.3) and asymptotically approaches 0.44 at extremely large catches. The parameter q_e varied spatially within the range of 0.50–0.98 (Figure 3.4) and temporally within similar range (results not shown). Examples presented on Figure 3.4 show that q_e in 1999 and 2012 varied spatially; however, spatial distribution of q_e was different between years, indicating temporal variability in q_e across years. Furthermore, q_e varied with pollock age and was generally lowest for ages between 3 and 8, with large interannual variability (Figure 3.5).

3.3.2. New abundance estimates

The new index of total abundance was consistently larger in absolute terms than the *status quo* index (Figure 3.6a), but the trends in relative abundance were very similar (Figure 3.6b). With the respect to the mean, the new index tended to be higher than the *status quo* index when the latter was high and lower when it was low, indicating evidence of hyperstability in the *status quo* index (Figure 3.6b). The hyperstability was confirmed by a negative trend in the relationship between mean survey efficiency and population abundance (Figure 3.7). Year-specific CV 's for the *status quo* index and from the diagonal of the Σ_u matrix indicated that the uncertainty around the new index increased by 55% on average (Figure 3.6c). This increase was highly variable and ranged from 30% in 2009 to 102% in 1997.

The population age structure, represented by proportions-at-age, differed markedly between the *status quo* and new series (Figure 3.8). Abundance at age for ages 3–8 for the new index was generally larger, while the abundance at age for the other ages was generally smaller.

3.3.3. Effect of the new index on stock assessment model output

As expected, the replacement of the *status quo* index with the new index of abundance indicates that the BT index is hyperstable. However, the consequences of the extent of hyperstability appear to be small in the pollock stock assessment because the differences in SSB estimates were less than 3% (Figure 3.9a). The replacement of the *status quo* abundance estimates with the new index resulted in increased SSB estimates during the early part of the time-series (when abundance was highest) and decreased estimates of SSB for the years after 1990 (Figure 3.9a; line 1). The addition of the new proportions-at-age had little effect on the SSB (Figure 3.9a; line 2). Finally, replacement of all three new components of the index (abundance, age structure, and variance–covariance matrix) resulted in changes similar to those observed in line 1 up to year 2004, but estimates of SSB after 2004 were higher. The *CV* for SSB decreased for almost all years when the abundance and proportion-at-age time-series were replaced (Figure 3.9b; lines 1 and 2). However, inclusion of a variance–covariance matrix led to higher *CV*s for both the early and most recent years and lower *CV*s between 1992 and 2000 (Figure 3.9b; line 3).

3.4. Discussion

Density-dependence of the BT survey catchability is a potential source of concern because it causes a systematic bias in bottom trawl cpue that could lead to bias in the assessment results and subsequent management advice. This bias increases with increasing fish density for pollock in the EBS resulting in a non-linear negative relationship between q_e and fish density. This

relationship violates a major assumption that BT survey cpue is proportional to fish density and that q does not change in space or in time (Wilberg *et al.*, 2010). The consequences of this could be serious for a wide range of products derived from BT survey data because the effect of variable q_e impacts cpue estimates at an individual station level. These include, but are not limited to, stock assessments that use abundance estimates at age and their variances (Godo *et al.*, 1999, Ianelli *et al.*, 2012), studies of density-dependent effects on distribution (Spencer, 2008; Kotwicki and Lauth, 2013), density-dependent mortality (Myers and Cadigan, 1993), recruitment (Myers, 2001), and ecological studies on density-dependent interactions between species (Ressler *et al.*, 2012). Below, I will review some major implications of findings of this study for two types of users: those who use the BT survey data as an index of abundance over the entire survey area and those who use spatially-explicit cpue data as a measure of fish density at particular sampling locations.

3.4.1. Survey-wide index of abundance

Survey-wide indices of abundance are used for management purposes in stock assessments. Results of this study indicate that density-dependence in q_e can impact stock assessments in three ways by (i) causing an index of abundance to become hyperstable, (ii) providing biased estimates of the age structure of the population, and (iii) causing (spatial and) temporal variability in survey catchability. Fishery-independent surveys have been thought not to be hyperstable (Harley *et al.*, 2001). However, results of this study suggest that this assumption may not always be valid. Relative to the mean, changes in abundance between years detected by the new index were larger than those detected by the *status quo* index (Figure 3.6b), indicating hyperstability (Hilborn and Walters, 1992). Besides problems with detecting the correct magnitude of the change in abundance from year to year, a hyperstable BT survey-based index of abundance could

also infer false trends. For example, a hyperstable index would increase if mean fish densities were the same between two years, but fish were more aggregated in the first year and more dispersed in the second because mean trawl efficiency would be higher during the more dispersed year. The changes in the SSB estimates that were observed in the pollock assessment suggest that the *status quo* BT index is hyperstable, even though the magnitude of the effect seems to be relatively minor (<3%). Nevertheless, ignoring density-dependence of the survey BT q_e would be imprudent. Abundance indices corrected for density-dependence in the presence of a negative correlation between q_e and fish density provide a better chance for detecting changes in stock size, and hence provide better advice for management.

High variability in the mean BT survey efficiency evident in Figure 3.7 indicates that density-dependence in q_e may lead to situations other than hyperstability. For example, the population estimate for 1983 was twice that for 1999, but mean survey efficiency for both years was similar. This was possible because of temporal variability in q_e (Figure 3.4). Moreover, temporal variability in survey q_e can lead to detection of false trends in population size among years. For example, corrected population estimates for 1985 and 1995 were approximately equal at 15 billion fish, but the uncorrected estimates were 11.2 and 9.5 billion fish, respectively. This temporal variability in q_e implies additional uncertainty about the index of abundance that is unaccounted for by sampling variability. Therefore, the estimates of uncertainty should include two sources: that from sampling variability and that from uncertainty associated with the estimate of survey efficiency. The increase in the *CV* of the new index ranged between 30 and 102%. This indicates that ignoring the contribution of uncertainty in q_e may also lead to bias in the stock assessment models, particularly the estimates of uncertainty. The need to account for the other sources of variability in the assessment models has been shown previously by Punt *et*

al. (2005), where they attribute this additional variation to fluctuations in catchability and estimate it as an additional parameter in the assessment. Here, two main sources of variation were accounted for, but it needs to be acknowledged that other sources may exist. For example, uncertainty may also arise from the second component of q : q_a . For semipelagic species such as pollock, q_a depends on variability in the proportion of fish from the entire water column that are present in the BTZ, which depends on factors such as light level and fish length (Kotwicki *et al.*, 2009). Lastly, the fact that different proportions of the resource may be present from year to year in the area surveyed can also result in an overly-optimistic impression of the precision of the survey index of abundance (Geromont and Butterworth, 2001). For pollock, this additional variability is likely since the BT survey area likely misses an unknown but variable fraction of the pollock population distribution each year (Ianelli *et al.*, 2012).

Results of this study provide evidence that a density-dependent q_e can also result in biased estimates of the age structure of the index of abundance when different ages are encountered at different densities. Although q_e does not directly depend on age, but on density, large changes in the index for ages 3–8 can be attributed to the tendency of pollock of this age range to aggregate in dense schools, resulting in lower q_e according to model 3.7c. Younger and older pollock tend to be more spread out, so q_e is higher for these ages. This is of a concern because most stock assessments that are used for management purposes are based on age-structured population models (Punt and Hilborn, 1997). Biases in the estimates of abundance-at-age for pollock vary substantially within and across years and can be as large as 45% (Figure 3.5). Although the effects on estimates of pollock SSB observed here were small, biases in age structure have been shown to affect population estimates in age-structured assessments (Coggins and Quinn, 1998), recruitment, and total allowable catch (Reeves, 2003) and need to be avoided or estimated (Punt

et al., 2008). It is reasonable to conclude that similar biases were present in length frequency data reported from the survey because the age-structure estimates are determined directly from length frequency data. This indicates that density-dependent q_e should be added to other causes of error in survey length frequency data, such as gear selectivity, or problems associated with subsampling of a catch (Hilborn and Walters, 1992). While discussing possible biases in population age and length structure that can be caused by density-dependent q_e , method presented here failed to account for the low selectivity of the gear for pollock smaller than 20 cm (1-year-old pollock) that can escape through the trawl meshes (Somerton *et al.*, 2011). This may cause estimates of u_i for these size classes to be biased. However, the selectivity parameters estimated within assessment (Ianelli *et al.*, 2012) likely minimize the impact of this source of bias for management purposes. Nevertheless, the interaction between BT survey gear selectivity (and interannual variability) and abundance indices as used in assessment models should be evaluated.

The *CVs* about the new BT abundance index on average were over 50% larger than *CVs* around the *status quo* BT index because of the uncertainty associated with the estimates of q_e .

Surprisingly, this increase did not cause much of the increase in uncertainty around SSB estimates from the assessment. In fact, the *CV* of the estimates of SSB for 8 of the 31 years was slightly lower. I attribute this result to the fact that the new index, despite the higher *CVs*, is actually more consistent with other data used when fitting the assessment model (i.e. the acoustic-trawl survey and fishery data).

3.4.2. Spatially explicit CPUE data

Survey-derived fish distribution data are extensively used in spatial dynamics studies because of their widely-recognized advantages over commercial fishery data. However, little attention has been given to the reliability of the cpue data as derived from BT survey catches or other types of fish detection equipment. Generally, researchers assume that cpue data represent actual fish density or that it is proportional to fish density. This study indicates that density dependence in q_e can cause the catching efficiency of the BT to vary spatially (Figure 3.4), which can lead to large errors in estimates of spatial distribution, because estimated variability in spatial distribution may be driven by BT catching efficiency rather than actual differences in fish density. For example, Swartzman (1997) has shown that the degree of fish aggregation can be affected by environmental variables such as temperature and bottom depth. In this case, a systematic change in any environmental variable affecting fish density in aggregations could introduce a false trend in abundance time-series or spatial patterns because of the changes in density-dependent q_e . This adds to the existing evidence that spatially-varying catchability can be environmentally driven (Godo *et al.*, 1999; Kotwicky *et al.*, 2009, 2013). This is a concern because Thorson *et al.* (2013) showed that relative indices of abundance will generally be biased measures of changes in population abundance in presence of spatially-varying catchability.

Findings of this study indicate that, similar to the index of abundance, local (at station) cpue estimates are also hyperstable because detected differences between cpue at different stations (or at the same station, but at different times) are smaller than differences in actual fish density. In other words, density-dependence of q_e indicates that the BT does not capture fish in proportion to their abundance in the BTZ. Hyperstable cpue leads to the perception that spatial distribution is less variable than in reality. This is of concern especially in the studies of density-dependent

effects on spatial distribution (e.g. Pettigas, 1998; Spencer, 2008; Ressler *et al.*, 2012; Kotwicki and Lauth, 2013). Some density-dependent effects can be underestimated or even missed as higher densities can be grossly underestimated. For example, the tendency of certain ages of pollock to form dense aggregations would be underestimated in the areas where q_e is low (Figure 3.4). On the other hand, other effects may be overestimated. For example, if predator abundance was assessed using the BT (therefore underestimated due to density-dependent q_e) and prey density was assessed by the acoustics, per capita prey consumption at high densities of predators may be overestimated because it would be attributed to the lower abundance of predators. Similar errors could be expected in estimating effects of environmental variables on fish distribution when these variables affect fish density.

This study shows how BT efficiency estimates from a subset of survey tows can be incorporated into stock assessments to improve model-derived estimates of fish abundance. It, therefore, seems essential that methods be developed to incorporate survey q_e information into spatial dynamics and ecological modelling studies that use local cpue data. This is important because density-dependent processes are thought to be one of the major drivers in population dynamics (Guckenheimer *et al.*, 1977) as well as spatial dynamics (Ciannelli *et al.*, 2008). Without correct density information, it may be impossible to identify which processes are density-dependent and which are density-independent. Although this study did not attempt to investigate spatial dynamics of pollock in the EBS, estimates of \dot{u}_i , together with their posteriors (derived from the MCMC analysis), could provide a way to test the findings from previous studies of pollock distribution and predator-prey interactions (Pola, 1985; Kotwicki *et al.*, 2005; Ressler *et al.*, 2012; Kotwicki and Lauth, 2013).

The causes of the density-dependent q_e are poorly understood and warrant further investigation. Godo *et al.* (1999) indicated that BT q_e for Atlantic cod and haddock may be affected by schooling behaviour, which could cause fish at higher densities to be herded more easily into path of the trawl. Johnsen and Harbitz (2013) speculated that the synchronized behaviour of sandeel (*Ammodytes marinus*) triggers a density-dependent cascading reaction amongst neighbouring individuals and causes increase in q_e of the survey dredge. On the other hand, Hoffman *et al.* (2009) and O'Driscoll *et al.* (2002) indicated that q_e for Atlantic croakers, white perch, and capelin may be affected by gear avoidance behaviour or trawl saturation. In the case of EBS pollock, results of this study indicate that these latter effects are important. However, more research is needed to understand the causes of density-dependence in the q_e of the survey BT.

3.4.3. Implications for stock assessment and studies that rely on survey data

The precautionary approach to fishery management requires that the preventive measures are taken first and, subsequently, relaxed if research demonstrates convincingly that they are not necessary (Garcia, 1994). This means that the consequences of density-dependent q_e in BT surveys should be considered for a given stock assessment. To date, only a handful of studies have undertaken either estimation of density-dependent q_e or discussed the problems that it can cause for stock assessment or other studies (Godø *et al.*, 1999; O'Driscoll *et al.*, 2002; Hoffman *et al.*, 2009). This study shows that the biases caused by density-dependent q_e are important because they can lead to errors in stock assessment and population and spatial dynamics studies, which may lead to poor quality management advice. Although the problems with density-dependent q_e have been identified for only few species so far, evidence is lacking on the extent of the problem. Two basic approaches to investigate potential effects of density-dependent q_e can

be pursued. First, as presented here, it requires an independent measure of fish density in the BTZ that can be used to estimate the relationship between fish density and q_e . A second approach could involve sensitivity analyses to explore possible effects of density-dependent q_e on stock assessment outputs and management advice. This approach will allow an evaluation of the appropriate level of precaution, given some plausibility that q_e is density-dependent.

3.5. Tables

Table 3.1. Posterior mean parameter values and posterior standard deviations for parameters in model (7c).

Parameter	β_0	β_1	β_2
Mean	0.447	0.00046	0.645
Standard deviation	0.035	0.00014	0.059

3.6. Figures

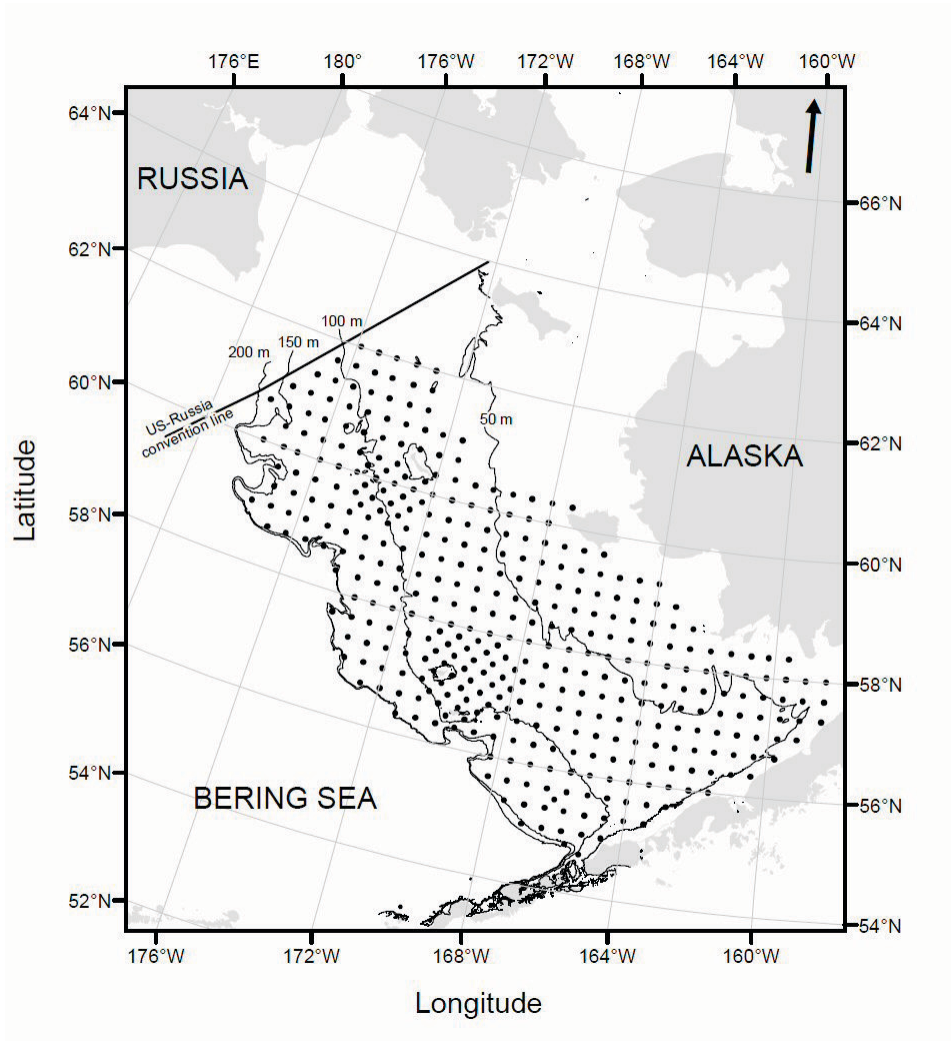


Figure 3.1. Location of the EBS bottom-trawl survey stations.



Figure 3.2. Standardized residuals against fitted values for models (7a), (7b), and (7c).

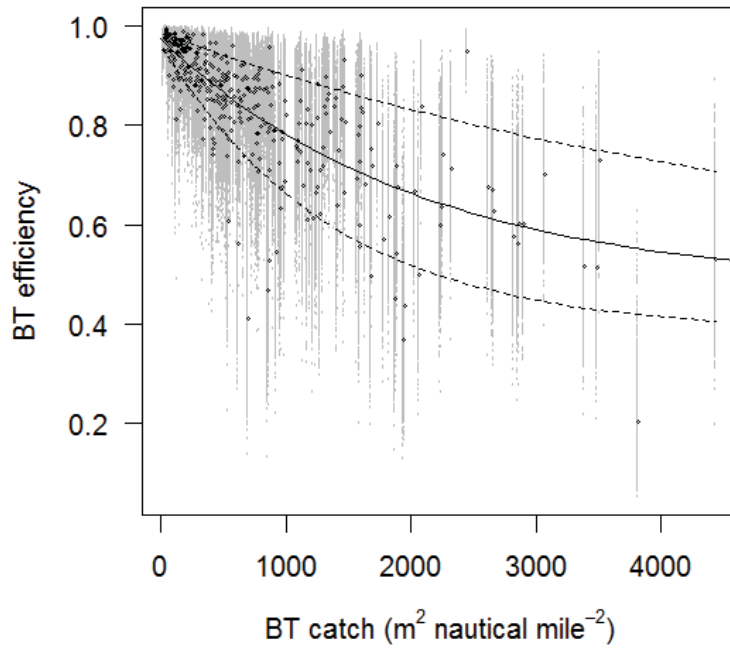


Figure 3.3. MCMC-derived vectors of BT efficiency vs. bottom-trawl (BT) catch. Black and gray points, respectively, represent the mean and all estimates of BT efficiency (q_e) from the MCMC samples. The black line represents the fit of model (7c) to the means, and dashed lines represent 95% confidence bounds around model predictions of q_e .

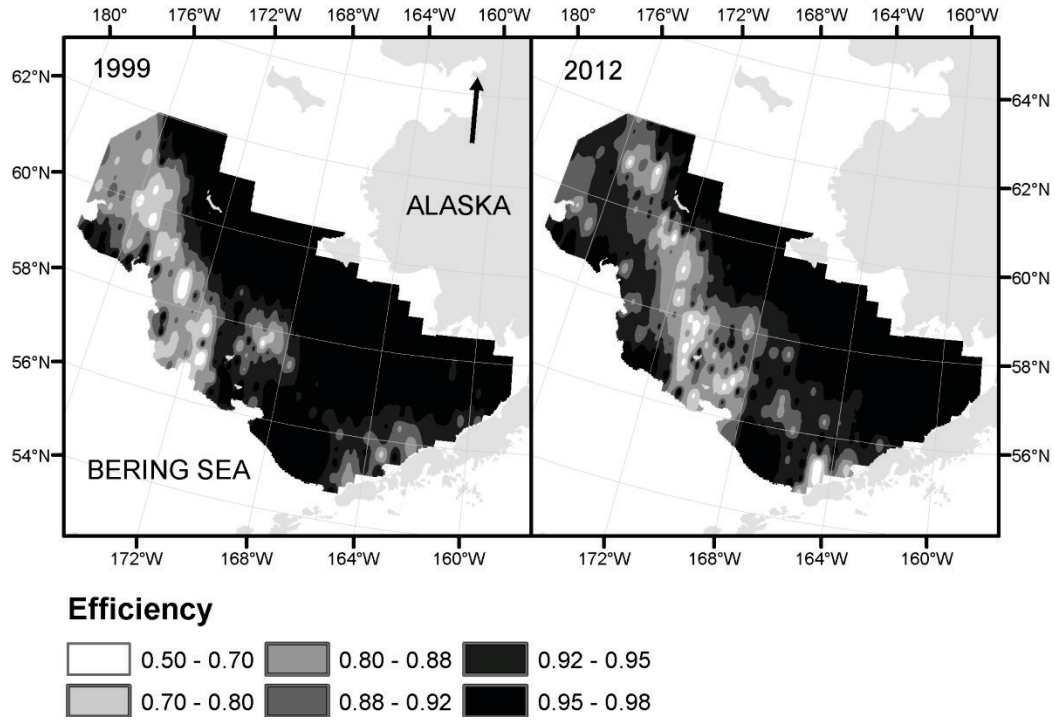


Figure 3.4. Examples of distribution of EBS survey bottom-trawl efficiency (q_e) from years 1999 and 2012.

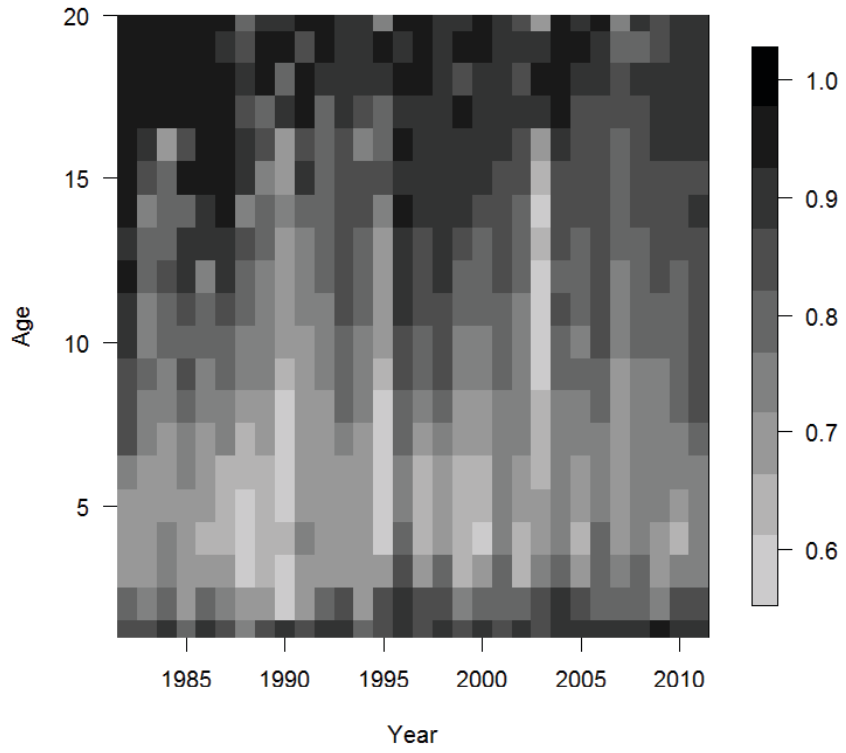


Figure 3.5. Bottom-trawl survey efficiency by year and age.

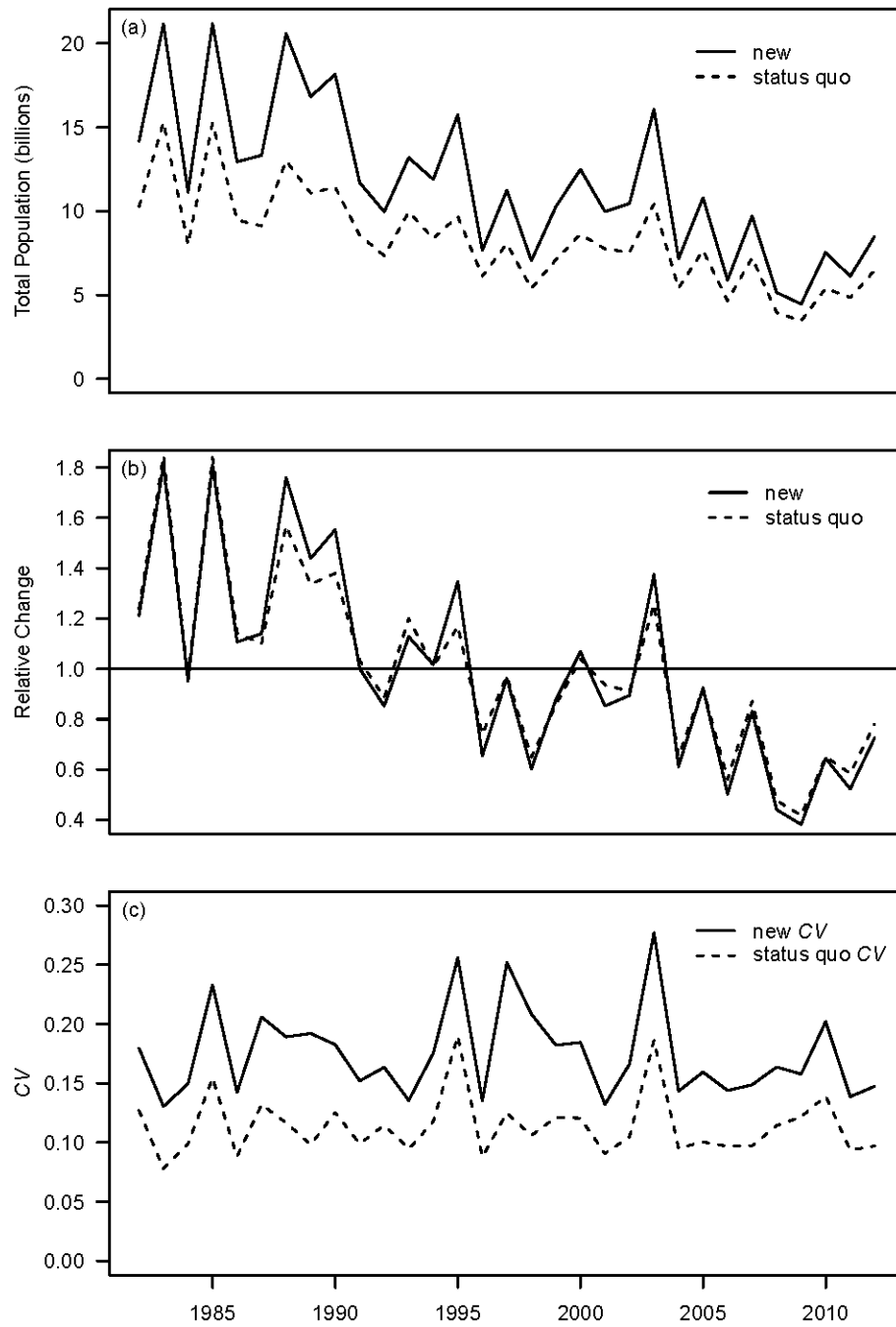


Figure 3.6. (a) Time-series of new vs. *status quo* total abundance estimates, (b) change relative to the mean abundance across the time-series, and (c) new vs. *status quo* coefficient of variation (*CV*) and relative increase in the *CV*.

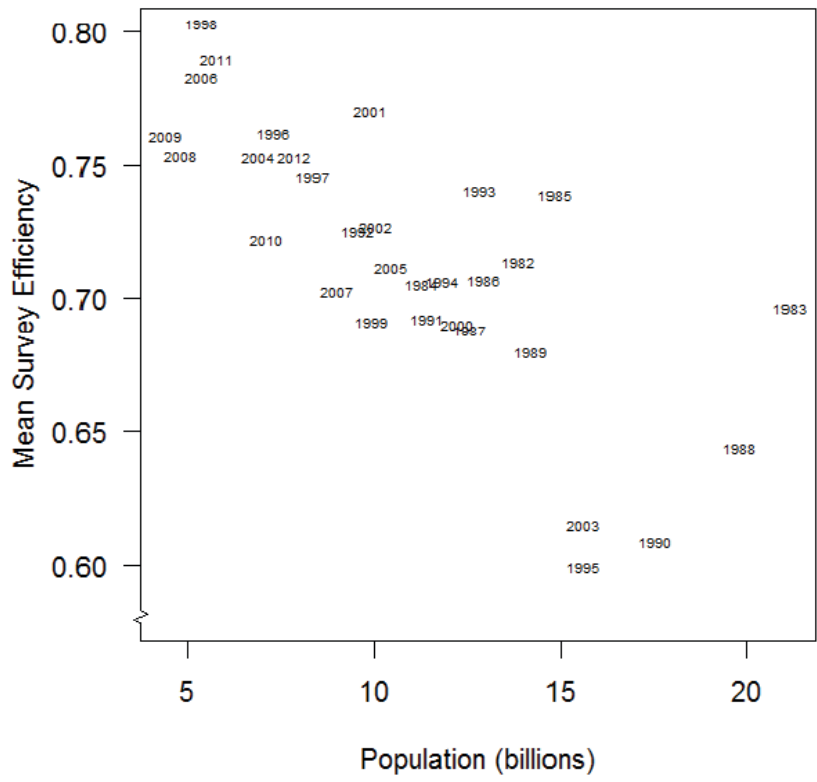


Figure 3.7. Mean survey efficiency vs. total abundance.

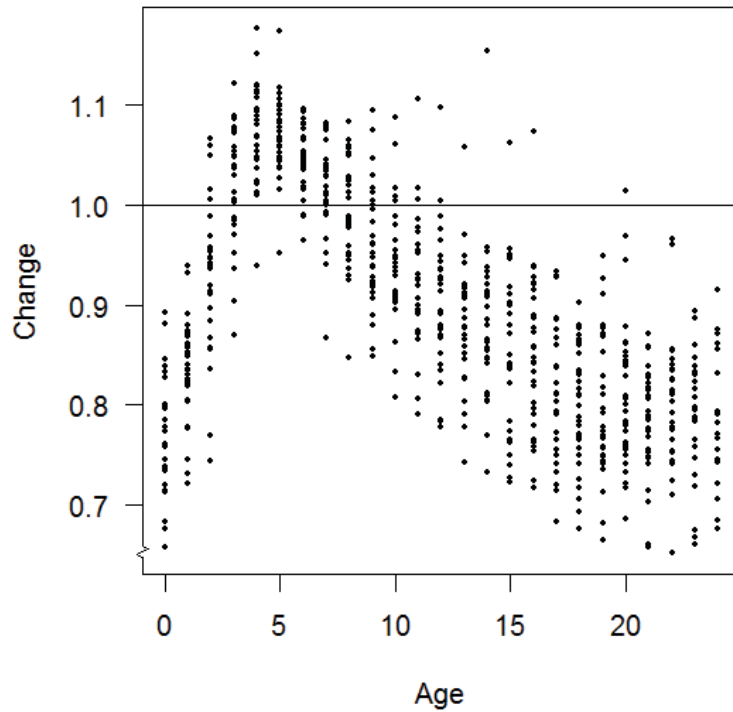


Figure 3.8. Relative change in the proportion of abundance at age (new divided by *status quo*) for EBS survey time-series. Each dot represents a survey year. Horizontal line represents no change.

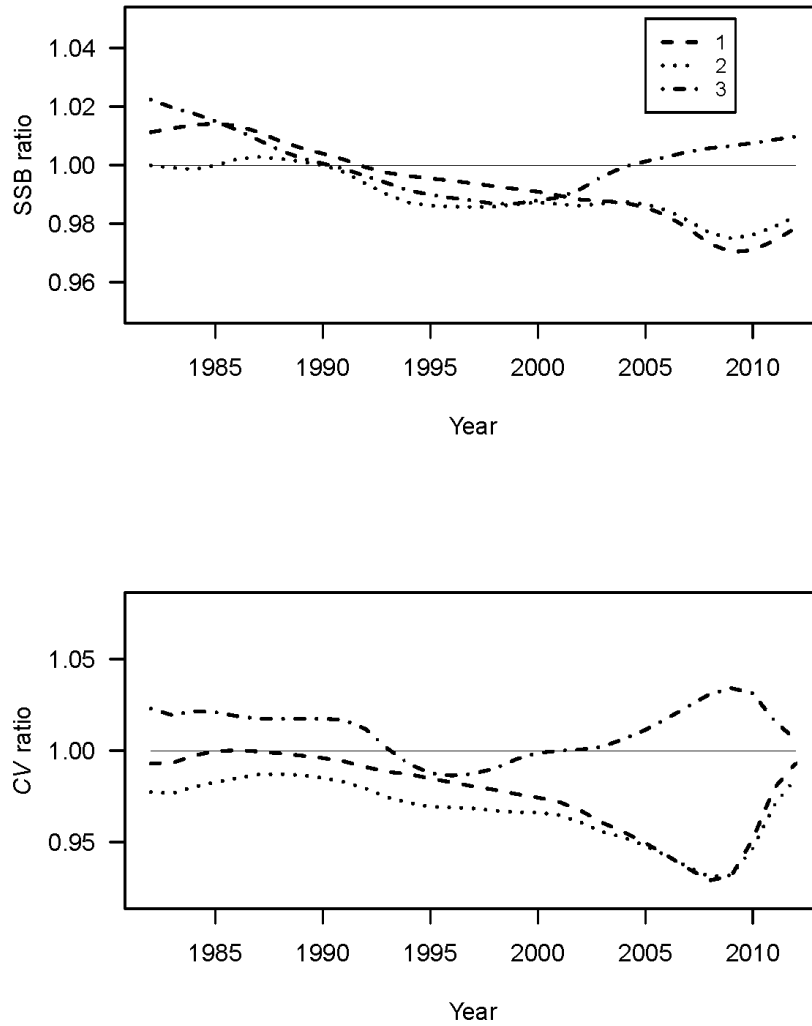


Figure 3.9. Ratio of spawning–stock biomass (SSB) (upper panel) and CV of SSB (lower panel) estimated from the the stock assessment using the new index of abundance relative to that estimated from *status quo*. Line 1 represents a ratio when only abundance estimates were replaced. Line 2 represents a ratio when abundance estimates and age structure were replaced. Line 3 represents a ratio when abundance estimates, age structure, and variance structure were replaced.

CHAPTER 4. FACTORS AFFECTING THE AVAILABILITY OF WALLEYE POLLOCK TO ACOUSTIC AND BOTTOM TRAWL SURVEY GEAR

4.1. Introduction

Semipelagic fish species occupy both demersal and pelagic habitats. The semipelagic gadoid walleye pollock (*Gadus chalcogrammus*) in the eastern Bering Sea is surveyed using both bottom trawl (BT) and acoustic sampling gears (Karp and Walters 1994). This is necessary because neither gear type can detect all of the fish within the water column. Bottom trawls catch fish from near bottom up to the effective fishing height (EFH) of the trawl. Acoustic instruments detect fish through the majority of the water column except near boundaries that include near-bottom and near-surface acoustic dead zones (ADZs, Hjellvik et al. 2003). The near surface ADZ is not a concern for pollock because they are rarely found in surface waters (Honkalehto et al., 2011). Therefore in this paper, “ADZ” refers to the near-bottom acoustic dead zone. Pollock BT and acoustic surveys have been performed in the EBS for decades (Honkalehto et al. 2011, Lauth and Nichol 2013). However, understanding of the relationship between abundance indices from these two surveys is lacking, and consequently two separate indices of abundance are currently used in the pollock stock assessment (Ianelli et al., 2012).

To understand how BT and acoustic abundance indices are related, it is necessary to understand catchability of each survey. Catchability is defined as the product of availability (q_a) to the sampling gear and the efficiency (q_e) of that gear (e.g., Godø 1994). The availability of pollock to the BT gear ($q_{a,BT}$) is defined as the proportion of fish in the water column that are present in

the bottom trawl zone (BTZ, i.e. between the substrate and the EFH) and availability to the acoustic gear ($q_{a,A}$) as the proportion of pollock present above the ADZ. The efficiency of the BT ($q_{e,BT}$) is defined as a proportion of fish within BTZ that are caught by the BT. The efficiency of the acoustic gear ($q_{e,A}$) can be assumed to be 1, because negligible acoustic shadowing effect (Zhao and Ona 2003) at the backscatter levels observed for pollock in the EBS (Kotwicki et al. 2013). Catchability is unknown for most fishery-independent surveys, and is often assumed stationary in time and space, resulting in constant bias in survey abundance estimates (Kimura and Somerton, 2006). Surveys with constant bias are often useful as relative indices of abundance, especially if undertaken over long time periods (Rose et al., 2000). However, changes in fish vertical distribution in response to environmental factors can result in variable q_a , and thus lead to temporal variability in the bias in abundance estimates (Lawson and Rose, 1999; Petrakis et al., 2001), which can result in misleading abundance trends over time and space and could cause biases in stock assessments (Walsh, 1996, Thorson et al., 2013) or affect interpretation from process studies on ecological and spatial dynamics (e.g., Kotwicki et al., 2013).

Despite the consequences of variable catchability, only a handful of studies addressed problems of spatially- and temporarily-variable q_a of fish to BT and acoustic survey gears. The presence of target specie(s) in the ADZ (e.g., McQuinn et al., 2005) or in the zone above the EFH (Hjellvik et al., 2003) impacted the ability of the survey gear to detect or capture all fish present in the water column (Lawson and Rose 1999) leading to biases in abundance estimates from either survey. Michalsen et al. (1996) showed that q_a for the bottom trawl for Atlantic cod (*Gadus morhua*), and haddock (*Melanogrammus aeglefinus*) varied over the diel cycle in response to light and tidal currents. Availability of Atlantic cod to acoustic and bottom trawl surveys also

changes between day and night (Lawson and Rose 1999, McQuinn et al. 2005). Pollock BT and acoustic surveys are conducted exclusively during daylight hours to avoid a diel bias in catchability; however, Kotwicki et al. (2009) showed that variations in daytime light were large enough to affect q_a of pollock to the BT and acoustic surveys, leading to non-stationarity in survey catchability. In addition to light effects, studies have also found that the vertical distribution of semipelagic species can be affected by other factors such as depth (e.g., Beamish, 1966; Abe et al., 1999; Gauthier and Rose, 2002), water temperature, currents, fish length (e.g., Godo and Wespestad, 1993, Michalsen et al., 1996, Kotwicki et al., 2013), and predator-prey interactions (e.g., Giske et al., 1990).

In summary, because q_a is a function of environmental conditions, achieving constant survey catchability across time and space for semipelagic species may be impossible regardless of survey standardization efforts. It is therefore important to determine the relationship between q_a and the environment, and develop methods to incorporate this knowledge into stock assessments and other studies that use survey data. Modelling the relationship between q_a and environmental variability should improve the accuracy of abundance estimates and lead to a better understanding of ecosystem processes (e.g., Hjellvik et al., 2002, Kotwicki et al., 2013).

The derivation of q_a for either BT or acoustic surveys is difficult because it requires knowledge of the total amount of fish available to either survey. To obtain q_a estimates for the BT, it is necessary to know the density of fish above the EFH, which can be obtained from acoustic data collected simultaneously with each BT tow. To obtain q_a estimates for acoustics, it is necessary to know the density of fish in the ADZ. In this study, synchronously-collected BT and acoustic data was used to extend previous studies of q_a (Anglen et al., 1999; Hjellvik et al. 2003; Kotwicki

et al., 2009), using ADZ correction estimates and BT EFH parameter estimates from acoustic and BT data (Kotwicki et al. 2013). The evaluation of the relationship between q_a and environmental covariates improved understanding of pollock vertical availability to both the BT and acoustic surveys. This has the potential to improve how survey results inform pollock stock assessment model, and also contribute to general understanding of their vertical behavior. Although the data used in this study are for EBS pollock, the method is broadly applicable to acoustic and BT surveys of other semipelagic or semidemersal species.

4.2. Methods

The acoustic backscatter and bottom trawl catch data used in this investigation were collected during the annual EBS Alaska Fisheries Science Center (AFSC) BT surveys conducted in June and July between 2005 and 2009 (Lauth and Nichol, 2013). Note that the acoustic data analyzed here do not come from the biennial acoustic-trawl survey of walleye pollock (Honkalehto et al. 2011). BT surveys were conducted using the chartered fishing vessels FV *Aldebaran*, FV *Arcturus*, and FV *Northwest Explorer* to sample fixed stations at the centers of a 20×20 nautical mile (nmi) grid cells (Figure 4.1) using a standard 83-112 eastern otter trawl (Stauffer, 2004). The corners of the grid cells were also sampled in areas surrounding St. Matthew Island and the Pribilof Islands. Surveys started in the southeastern corner of Bristol Bay and proceeded westward. The standard tow duration and speed was 30 min at 1.54 m s⁻¹ (3 knots).

Processing of acoustic data is described in Kotwicki et al. (2013). In summary, acoustic backscatter at 38 kHz collected while the vessel was trawling was processed using a semi-automated procedure (Kotwicki et al., 2009) to produce the nautical area scattering coefficient, s_A (m²·nmi⁻²; a linear measure of backscatter per unit area; MacLennan et al., 2002). Bottom-

referenced vertical layers between the echosounder-detected bottom and 5 m off bottom were integrated in 0.25 m intervals, while layers above 5 m from bottom were integrated in 1 m intervals. To ensure that recorded backscatter was correctly attributed to walleye pollock, candidate bottom trawl tows were restricted to tows with catches where pollock made up at least 75% by weight of all pelagic fish in the catch. Tows with smaller percentages were excluded (i.e. attributed to aggregations of jellyfish or macrozooplankton). This procedure resulted in 355 tows over the five year period. Catch per unit effort (CPUE) estimates at length from BT catch samples were estimated using the area-swept method (Alverson and Pereyra, 1969) and length frequency subsamples from the BT. These estimates were transformed into equivalent s_A ($s_{A,BT}$) units using method of Doray et al. (2010) and an empirical target strength-length relationship for pollock (Traynor, 1996). Hereafter, for consistency and comparability between data from BT and acoustics, all measures of pollock density are presented in units of s_A .

4.2.1. Predictor variables

Depth and temperature were measured during each trawl using a micro-bathymograph (MBT) attached to the headrope of the BT. Average bottom depth was obtained by averaging a sum of MBT-detected headrope depth and acoustically-detected headrope height above the bottom over the duration of a tow. Near-bottom light levels were collected during each trawl using Wildlife Computers MK-9 archival tags (see Kotwicki et al., 2009 for details) also attached to the headrope of the BT. These tags provided relative values (between 0 and 256) of near-bottom light levels sampled at 1 Hz that were then averaged over the duration of the trawl haul. Sediment size was estimated at each station using historical data from grabs and dredges (Smith and McConnaughey, 1999), interpolated (Paul Spencer, AFSC, unpubl. data) using ordinary kriging (Oliver and Webster, 1990). Sediment data were expressed in units of “phi” (negative

\log_2 of the diameter in mm), where higher values correspond to smaller particle sizes (Wentworth, 1922). Tidal current speed, used as a proxy for bottom current, was predicted for each tow using Oregon State University's Tidal Inversion Software (<http://www.oce.orst.edu/research/po/research/tide/region.html>; Egbert et al., 1994; Egbert and Erofeeva, 2002). Mean fish length was calculated from length frequency data obtained from BT catch samples.

4.2.2. Availability calculations

By definition, availability is the proportion of fish that are present in the water column available to the survey gear. Specifically, availability of pollock to the BT is defined as:

$$q_{a,BT_i} = \frac{s_{A,BTZ_i}}{s_{A,t_i}} \quad [4.1],$$

where q_{a,BT_i} is the proportion of fish available to the BT at location i , s_{A,BTZ_i} is fish density in the BTZ, and s_{A,t_i} is total fish density in the water column. Availability of pollock to acoustic measurement is defined as:

$$q_{a,A_i} = \frac{s_{A_i}}{s_{A,t_i}} \quad [4.2]$$

where q_{a,A_i} is the proportion of fish available to acoustic measurement, and s_{A_i} is fish density above ADZ. Estimates of s_{A,BTZ_i} and s_{A,t_i} were obtained from acoustic data collected during trawls, coupled with a model that combines bottom trawl and acoustic data (Model D of Kotwicki et al., 2013). :

$$s_{A,BTZ_i} = \left(\frac{1}{r_q(s_{A,BTZ_i})} + \frac{1}{a} \right)^{-1} e^\varepsilon \quad [4.3a]$$

$$s_{A,BTZ_i} = \sum_{0.5}^{EFH} s_{A_i} + e^{\mathbf{b}\mathbf{X}_i} \sum_{0.5}^h s_{A_i} + e^{\mathbf{c}\mathbf{X}_i} \quad [4.3b]$$

where s_{A,BT_i} is fish density detected by the BT, r_q is the catchability ratio between the bottom trawl and acoustics (which accounts for differences in catchability between the two methods), EFH is the effective fishing height of the trawl, and e^ε is log-normally distributed error. Acoustic backscatter in the BTZ from 0.5 m to the EFH is represented by the term $\sum_{0.5}^{EFH} s_{A_i}$, and the term $e^{\mathbf{b}\mathbf{X}_i} \sum_{0.5}^h s_{A_i} + e^{\mathbf{c}\mathbf{X}_i}$ is an estimate of the ADZ correction. The parameter h determines the height of the near-bottom acoustic layer, which is used to estimate the ADZ correction. Environmental variables (bottom depth, surface temperature, sediment size, current speed, bottom light level) and mean fish length were included in the model as linear covariates \mathbf{X}_i , where \mathbf{b} and \mathbf{c} in Equation 4.3b are vectors of parameters. The parameter a represents density dependence of BT efficiency within the BTZ (Kotwicki et al. 2013).

Equation [4.3a] was fitted to the data using Automatic Differentiation Model Builder (ADMB; Fournier et al., 2012) to obtain maximum likelihood estimates (MLEs) of the vectors $\mathbf{q}_{a,BT}$ and $\mathbf{q}_{a,A}$ (each element of these vectors represents an estimate of q_a at location i) under the assumption of log-normality:

$$NLL = 0.5N_T \log(2\pi\sigma^2) + \frac{\sum_{i=1}^{N_T} (\log(s_{A,BT_i}) - \log(\widehat{s_{A,BT_i}}))^2}{2\sigma^2} \quad [4.4]$$

where N_T is the number of tows, σ is the error variance, and $\widehat{s_{A,BT_i}}$ is the model prediction from Equation 4.3a. Between-tow variability in $\mathbf{q}_{a,BT}$, and $\mathbf{q}_{a,A}$, was assessed by estimating their corresponding means and standard deviations, and constructing histograms.

Posterior distributions for $\mathbf{q}_{a,BT}$ and $\mathbf{q}_{a,A}$ were obtained using Markov Chain Monte Carlo (MCMC) sampling, based on the Metropolis-Hasting algorithm (Plummer et al., 2006), and

obtaining a sample of 1,000 vectors from the posterior distribution of \mathbf{q}_a . Priors for all parameters for the MCMC analysis were chosen to be uniform over ranges exceeding possible values for the parameters. The MCMC chain was thinned by choosing every 10,000th sample to avoid autocorrelation between subsequent samples. MCMC diagnostics were performed by visual examination of traces and density plots for all parameters, estimating autocorrelation between samples, and calculating Geweke statistics for all parameters (Cowles and Carlin, 1996). None of these diagnostics indicated a lack of convergence of the MCMC algorithm.

4.2.3. Estimating relationship between availability and predictor variables

Data used to estimate catchability and availability from fisheries surveys have been commonly fitted using logistic regression (Harley and Myers, 2001; Somerton et al., 2007), with the assumption that data comes from a binomial distribution. Preliminary analysis of the MLE estimates of \mathbf{q}_a suggested that the assumption of a binomial distribution was inappropriate due to overdispersion (i.e. additional variance in the response data; Hinde and Demétrio, 1998). Sources of overdispersion have been attributed to sampling methods and fish behavior (Coggins and Quinn, 1998; Crone and Sampson, 1998), and to spatial heterogeneity (Lindén and Mäntyniemi, 2011).

The highest posterior density estimates of the \mathbf{q}_a vectors were fitted to the logistic function:

$$q_{a,E_i} = \frac{1}{1+e^{-(\alpha+\beta\mathbf{X}_i+\varepsilon_i)}} \quad [4.5]$$

where E denotes equipment type (BT, acoustics), α is an offset parameter, β is a vector of parameters, \mathbf{X}_i is a matrix of the predictor variables, and ε is a normal error. Three alternative approaches were taken to fit equation [4.5] to the $\mathbf{q}_{a,BT}$ data to account for overdispersion. The

first method used generalized linear modeling (glm function in R; Faraway, 2005) assuming a quasi-binomial likelihood. In quasi-likelihood, overdispersion is modeled by the addition of a constant overdispersion parameter that scales the variance around the mean, allowing the variance in the response variable to differ from the variance assumed for the binomial distribution (Hinde and Demétrio, 1998). The second method used generalized linear mixed modeling (lme4 package in R; Bates, 2012), where overdispersion is modeled as a random effect in the linear predictor (Hinde and Demétrio, 1998). The third method involved beta regression models (Ferrari and Cribari-Neto, 2004) extended by Simas et al. (2010), who suggested linking the overdispersion parameter to an additional set of predictors allowing the variance of the response variable to depend on predictors. The “logit” link function was used for the response variable in all three models. The “identity” link was used to model the variance component in the beta regression models.

Model selection was performed by removing model terms one by one and using AICc (Akaike’s Information Criterion corrected for finite sample size; Burnham and Anderson, 2010). First, the full model was run, and AICc was calculated. Second, all possible reduced models were run by removing one predictor variable at a time. The variable was permanently removed if the AICc of the reduced model was lower than the AICc of all other reduced models as well as the full model. Term removal continued until no reduction in the AICc was achieved. The three methods for handling overdispersion were compared by inspecting residuals and performing leave-one-out cross validation (Kohavi, 1995) based on the root mean square error (RMSE) for the response variable. The best method was then applied to each of 1,000 samples from the posterior distributions of \mathbf{q}_a and used to estimate 1,000 vectors of parameters α and β and the

overdispersion parameters for both the BT and acoustic data. Estimated means of these parameters were then used to assess the effect of predictors on q_a .

The effect of each predictor was assessed by predicting q_a in the range of predictor values (i.e. range between observed minimum and maximum values of each predictor) while all other predictors were set at their weighted (by density) means estimated from the data. For example, q_a was predicted using the best model for all observed values of bottom depth, while all other predictor variables were fixed at their means to estimate relative effect of the bottom depth on q_a . The interpretation of interaction terms was examined using bivariate contour plots of predicted q_a in the observed range of both predictors, while all other predictors were set to their weighted means.

The effect of each predictor on variance (V_a) for the beta regression was assessed by estimating 95% confidence bounds around q_a predictions in the range of observed predictor values, while all other predictors were set to their means. Confidence bounds were determined using the mean prediction of a precision parameter (ϕ) obtained from 1,000 samples from the posterior of \mathbf{q}_a . Variance was then estimated using Ferrari and Cribari-Neto, 2004:

$$V_{a,i} = \frac{q_{a,i}(1-q_{a,i})}{1+\phi} \quad [4.6].$$

Estimates of $q_{a,i}$ and $V_{a,i}$ were then used in the $qbeta$ function (R Core Team, 2012) to obtain 95% confidence limits for the q_a predictions.

4.3. Results

4.3.1. Availability estimates

MCMC trace and density plots indicated good convergence for all parameters used in estimation of $\mathbf{q}_{a,BT}$ and $\mathbf{q}_{a,A}$. No autocorrelation was detected between MCMC samples for any of the parameters. Geweke statistics showed no significant differences between the beginning (first 10%) and second half of the MCMC chains. Most of the pollock in the water column were available to the BT during most of the hauls (Figure 4.2a; mean $q_{a,BT} = 0.915$), while availability to the acoustics was much lower (Figure 4.2b; mean $q_{a,A} = 0.287$). Between location variability of the $q_{a,BT}$ (standard deviation = 0.147) was lower than $q_{a,A}$ (standard deviation = 0.197).

4.3.2. Model selection

The RMSE from the cross validation procedure for $\mathbf{q}_{a,BT}$ was lowest for the model based on a beta distribution (RMSE = 0.124; the RMSEs for both other methods were 0.153) which also had a better residual pattern relative to fitted values (Figure 4.3). Using beta regression approach with the extension of Simas et al. (2010) also enabled the overdispersion parameter (\emptyset) to be linked to predictors. This linkage was important because it also provided a way to address heteroscedasticity (i.e. non-stationary variance) within the regression framework (Simas et al., 2010). For example, scatterplots of quasi-binomial and mixed effect model standardized residuals (from BT model) against fitted values (Figure 4.3a and 4.3b), and plots of beta regression residuals (non-standardized) vs. bottom light and bottom depth (Figure 4.4a and 4.4c) exhibited heteroscedastic patterns. Variance among predicted values was larger at lower light levels and in deeper waters. In beta regression heteroscedasticity was avoided (by modelling \emptyset as

a dependent variable) as shown in plots of standardized residuals against fitted values (Figure 4.3c) and against bottom light and bottom depth (Figure 4.4b and 4.4d).

Predictor effects on q_a are based on the beta regression method. The final beta regression models indicated that:

$$q_{a,BT_i} \sim BL * BD + PP + FL * \log(\text{total}) + \text{factor}(\text{year}) \quad [4.7]$$

$$\phi_{a,BT_i} \sim BL + BD + PP + FL * \log(\text{total}) + \text{factor}(\text{year}) \quad [4.8]$$

and

$$q_{a,A_i} \sim BL + BD + ST + PP + FL * \log(\text{total}) + \text{factor}(\text{year}) \quad [4.9]$$

$$\phi_{a,A_i} \sim BL + BD + PP + TC + \text{factor}(\text{year}) \quad [4.10]$$

where BL is near-bottom light, BD is bottom depth, FL is the mean fork length of pollock, PP is sediment size, TC is tidal current speed, and “total” stands for total density of pollock in the water column.

4.3.3. Availability of pollock to the BT and acoustic gear

The predicted proportion of pollock available to the BT was lowest (0.65) at the darkest conditions and increased with increasing light levels to nearly 1 (Figure 4.5a). The confidence bounds around $q_{a,BT}$ indicated predictions of $q_{a,BT}$ are highly uncertain in dark conditions and that precision increases with light intensity. Fork length was the second most influential predictor of $q_{a,BT}$, which increased from 0.8 to 0.97 across the range from the hauls with the small to largest mean fish lengths (Figure 4.5b). Fork length also affected the uncertainty of the $q_{a,BT}$ estimate, because confidence bounds indicated low precision in $q_{a,BT}$ in tows with smaller fish and

increased precision with increasing fish length. The third most important variable was bottom depth; $q_{a,BT}$ was highest at the shallowest depths and decreased slightly with depth (Figure 4.5c). The confidence bounds were narrowest in shallow waters and widened with depth. A decrease in sediment size led to a slight increase in $q_{a,BT}$ and its precision (Figure 4.5d). Increase in total pollock density had only slight decreasing effect on $q_{a,BT}$ and its precision (Figure 4.5e).

The interactions $BL \times BD$ and $FL \times \log(\text{total})$ in the $q_{a,BT}$ model indicate a non-linear relationship between these variables and $q_{a,BT}$. The $BL \times BD$ interaction indicated that $q_{a,BT}$ is >0.9 at near bottom light conditions above 80 relative units regardless of depth (Figure 4.6a). Similarly, $q_{a,BT}$ is > 0.9 at depths below 60 m regardless of light conditions. However, predicted $q_{a,BT}$ decreased rapidly with decreasing light levels and increasing depth (Figure 4.6a). A similar pattern was observed for the interaction between FL and $\log(\text{total})$, where tows with both high and low pollock density had high and relatively constant predicted $q_{a,BT}$. However, simultaneously increasing density and decreasing pollock length rapidly reduced predicted $q_{a,BT}$ (Figure 4.6b).

Predicted proportions of pollock available to acoustic equipment were generally lower than predictions for the BT in comparable conditions (Figure 4.7). Confidence bounds around the predictions of $q_{a,A}$ were much wider than confidence bounds around $q_{a,BT}$, indicating higher uncertainty in the $q_{a,A}$ predictions (Figure 4.7). Relatively strong effects on $q_{a,A}$ were observed for surface temperature and fork length, with $q_{a,A}$ decreasing from about 0.6 to 0.2 with increasing values of these two variables (Figure 4.7a, and 4.7b). Uncertainty of $q_{a,A}$ was independent of the values of these two variables. $q_{a,A}$ but its uncertainty decreased with decreasing sediment size (Figure 4.7c). Increasing depth tended to increase $q_{a,A}$ and its

uncertainty (Figure 4.7d). Increasing near-bottom light levels led $q_{a,A}$ to decrease slightly, but the uncertainty in the $q_{a,A}$ estimate decreased with increased light levels (Figure 4.7e). Total fish density affected $q_{a,A}$, but only at low densities (Figure 4.7f). Increasing tidal current speed did not affect $q_{a,A}$, but it led uncertainty to decrease slightly (Figure 4.7g).

4.4. DISCUSSION

4.4.1. Variation in the availability of pollock

Factors affecting the vertical distribution of fish in the water column determine the proportion of the population available to survey gear (e.g., Aglen et al., 1999; Lawson and Rose, 1999). In the case of pollock in the EBS, $q_{a,BT}$ varied between 0.1 and 1 and $q_{a,A}$ varied between 0 and 1. This range of variability is a concern because it indicates that each survey methodology is prone to large errors in abundance estimates. The availability of pollock to the BT and acoustic surveys appears to depend on several factors; the spatial and temporal variability in availability can be partially explained by environmental variability, fish demographics and spatial distribution. Knowledge of these effects on catchability can increase the accuracy and precision of abundance estimates from both types of surveys.

Assuming that the BT and acoustics sample different parts of the water column, one would predict that the effects of variables influencing q_a for one gear type may have the opposite effect on the other (i.e. $q_{a,BT}=1- q_{a,A}$; Kotwicki et al., 2009). Results of this study indicate that this linkage exists to a certain degree as indicated by the opposite slopes of the relationships between predictor variables and $q_{a,BT}$ and $q_{a,A}$ (i.e. when fish become less available to one survey, they become more available to the other.). However it is apparent that this relationship is not as

simple as it was presumed previously by Kotwicki et al. (2009). Differences in the relationship between predictor effects on $q_{a,BT}$ and $q_{a,A}$ arise from the vertical distribution of pollock in the water column and the fact that the BTZ and the ADZ represent different regions in the water column, i.e., $q_{a,BT}$ is determined by the proportion of fish in the BTZ, while $q_{a,A}$ is determined by the proportion of fish above the ADZ. In this study, the BTZ extended to 16 m off bottom and the approximate height of the ADZ ranged between 1 – 1.5 m (Kotwicki et al., 2013) resulting in approximately 15 m of the water column being measured by both gear types. Vertical migration between the ADZ and the rest of water column, and between the BTZ and the rest of the water column are likely to differ because of the large difference between the top of the ADZ and the BTZ, which accounts for differences in predictor effects between $q_{a,BT}$ and $q_{a,A}$ (e.g. surface temperature significantly affected $q_{a,A}$, without affecting $q_{a,BT}$).

Results of this study confirm that near-bottom light levels and depth are among the most important factors affecting pollock availability to BT and acoustic surveys. Trends in the effects of near-bottom light intensity and depth on pollock q_a for both the BT and acoustic gear were similar to earlier findings (Kotwicki et al., 2009): increasing light levels and decreasing depth increased $q_{a,BT}$ and decreased $q_{a,A}$. However, the magnitudes of the effects estimated in this study were smaller than those reported previously. This difference is attributed to differences in methodology of estimating the ADZ corrections and the EFH. In this study, I used empirically-derived ADZ corrections and EFHs estimated from equation [4.3] using synchronously collected BT and acoustic data. In contrast, Kotwicki et al. (2009) used theoretical ADZ correction estimates derived from the ADZ volume assuming that fish density in the ADZ is equal to fish density above the ADZ (Ona and Mitson, 1996). Empirically-derived ADZ corrections and EFHs

are preferable to theoretical estimates because of better performance of the models that combine BT and acoustic data (Kotwicki et al. 2013).

Mean fork length of fish from the BT was also an important predictor for both $q_{a,BT}$ and $q_{a,A}$, indicating that smaller fish are more likely to be distributed above the bottom while larger fish tend to be closer to bottom. This is consistent with previously reported findings that larger pollock are more demersal (Shuntov, 1992; Karp and Walters, 1994). Miyashita et al. (2004) noted that most of the aggregations of large pollock stay near the bottom, while smaller pollock often ascend to the mid-water to follow zooplankton. Findings of this study are also consistent with the estimates of acoustic and BT survey selectivity curves derived in the pollock stock assessment (Ianelli et al., 2009), that show low selectivity for larger pollock in the acoustic survey, suggesting that larger pollock are more likely to be present in the ADZ.

The effect of sediment size for both $q_{a,BT}$ and $q_{a,A}$ suggests that it plays a role in pollock vertical distribution. Decreasing sediment particle size was associated with lower pollock availability to acoustic gear indicating higher proportions of pollock in the ADZ (Figure 4.7c). A possible explanation may be that pollock prefer to be closer to the sandy mud bottom, prevalent on the middle EBS shelf (Smith and McConnaughey 1999). Such bottom types are typical of the outer shelf and part of the middle shelf and may have higher food availability (Walsh and McRoy 1986) than sandy bottom types more typical in the inner EBS shelf. Increased pollock density also appeared to affect both $q_{a,BT}$ and $q_{a,A}$ (Figure 4.5e, and 4.7f). I speculate that these effects may indicate a spillover effect from both the ADZ and BTZ. Both the ADZ and BTZ have finite volumes and at high densities limited space in the preferred zone could cause fish to move to a less preferable depth.

Surface temperature affected $q_{a,A}$, indicating that pollock tended to be closer to the bottom when near surface water temperature increased. This effect was not detected for $q_{a,BT}$ indicating that the changes in vertical distribution occurred in the water column above the ADZ. Surface temperatures in the EBS vary seasonally with the maximum surface temperature occurring in the late summer and early autumn (August, September; Stabeno et al., 2012), when the abundance of zooplankton decreases in the EBS (Springer et al., 1989; Chuchukalo et al., 1996; Coyle et al., 1996) and the diets of 30–49 cm pollock shift from zooplankton to fish and decapods (Dwyer et al., 1987) possibly because of the low abundance of zooplankton prey (Willette et al., 1999). It is plausible that pollock vertical distribution shifts downwards as the season progresses in response to changes in zooplankton abundance and shifts in their diet. Although data from the EBS is lacking, seasonal changes in vertical distribution of pollock consistent with my hypothesis have been found in the Sea of Japan (Kooka et al., 1998), where pollock are distributed deeper during autumn than during spring.

The percent of the variance explained by the predictors in the BT and acoustic beta regression analyses were approximately 32% and 29%, respectively. Large residual variances suggest that other potentially important variables could account for this variability. For example, juvenile pollock (< 22 cm), may shift their vertical distribution to colder (deeper) waters to conserve energy when food is scarce (Sogard and Olla, 1996). Juvenile pollock have been observed to alter their vertical distribution to avoid predators (Sogard and Olla, 1993). Olla and Davis (1990) reported that juvenile pollock also move vertically within water column in response to prey density. Vertical distribution of copepods and euphausiids may affect pollock q_a because they are major food sources for pollock smaller than 50 cm (Dwyer et al., 1987). Pollock larger than 50 cm feed mainly on small pollock, other fish, and benthos (Dwyer et al., 1987; Yoshida, 1994;

Shuntov et al., 2000). Prey density has been found to influence vertical distributions of other species such as herring (*Clupea harengus*), whiting (*Merlangius merlangus*), and Norway pout (*Trisopterus esmarkii*; Onsrud et al., 2004). Weather conditions affect vertical distribution and BT catch rates of scad (*Trachurus trachurus*) and mackerel (*Scomber scombrus*; Ehrich and Stransky, 1999); where changes were attributed to higher turbidity and bottom oscillation currents during increased wave-action. Although not studied, predator avoidance, prey fields, and weather conditions are all plausible variables that may affect pollock vertical distribution, and thus availability to BT and acoustic surveys. I did not include these additional variables in this investigation because data has been scarce in the EBS, however new data sources and new methods of estimation of the pollock prey distribution are being developed (Ressler et al. 2013). These developments will provide new data that could be used to improve predictions of q_a in the future.

Results of this study indicate that availability and associated uncertainty depend on environmental conditions. Using the beta distribution regression approach with the extension of Simas et al. (2010) enabled the inclusion of a precision parameter (ϕ) that was dependent on the predictors. Accounting for this dependence was important because it addressed heteroscedasticity within the regression (Simas et al., 2010) and also provided insight into relationship between variability in q_a and predictor variables. It was found that uncertainty among predicted values of $q_{a,BT}$ is larger at low light levels (40-60 relative units) and in deep waters (140 – 160 m; Figure 4.5c) than at higher light levels and shallower water. This pattern is not surprising as pollock in shallow water and in high light conditions are almost always near the bottom (Kotwicki et al., 2009) resulting in highly precise predictions of $q_{a,BT}$ close to 1. At low light levels and in deep water pollock, can be found anywhere in the water column, resulting in

higher uncertainty in $q_{a,BT}$. Similarly, the expected decrease in uncertainty in $q_{a,BT}$ with increased size was also expected because large pollock tend to be distributed consistently close to the bottom, while small pollock are often present higher in the water column (Shuntov et al. 1993).

4.4.2. Implications to the BT and acoustic surveys

Results of this study underscore the importance of using both BT and acoustics when estimating the abundance of a semipelagic species, due to the uncertainties associated with each gear type. The BT may be better suited to estimate pollock abundance in the EBS because the majority of pollock in the water column are generally available to the BT, and variability in $q_{a,BT}$ was lower than in $q_{a,A}$. However, despite higher availability, Kotwicki et al. (2014) showed that pollock BT catch efficiency (i.e. $q_{e,BT}$) is density-dependent and variable (values ranging between 0.5-1). The effect of highly variable $q_{e,BT}$ will increase variability in catchability of the BT because it is one of two components of total catchability (i.e. $q_{BT}=q_{a,BT}*q_{e,BT}$). In contrast, acoustic efficiency (i.e. $q_{e,A}$) for pollock can be assumed to be 1 (Kotwicki et al., 2009), with variability in catchability of acoustic surveys dependent only on vertical availability of pollock in the water column above the ADZ (i.e., $q_A=q_{a,A}$). Further studies that incorporate uncertainty estimates associated with catchability are necessary to assess suitability of each sampling method.

Although the samples used in analyses resulted in average $q_{a,BT}$ values much higher than average $q_{a,A}$ values, there are areas and conditions for which an acoustic survey would be more appropriate than a bottom trawl survey. To illustrate this point the effects of the interaction term $BL \times BD$ were estimated for conditions that would likely cause pollock to migrate vertically up in the water column; $FL = 30$ cm, total density = $5,000 \text{ m}^2\text{nm}^{-2}$, and $BT = 3^\circ\text{C}$. These conditions were uncommon in the BT samples, but are common in the areas where pollock are detected

using the acoustic surveys (Honkalehto et al., 2011; Ianelli et al., 2009). Most pollock 30 cm in length are predicted to be above the EFH of the BT (hence unavailable to the BT) in waters deeper than 80 m and light levels lower than 80 relative units (Figure 4.8a). Under the same conditions, the majority of 30 cm pollock is available to the acoustic gear. These results are corroborated by BT survey selectivity curves derived in pollock stock assessments that show selectivity of the BT survey to be low for ages 1-4 (length ~ 10 – 40 cm), while selectivity for the acoustic survey at these ages is much higher (Ianelli et al., 2009).

The overall effect of variable catchability on abundance estimates and age-specific population trends derived from BT and acoustic surveys has not been quantified. Results of this study demonstrate the large variability in q_a for BT and acoustic surveys, which underscores a need for a retrospective analysis of BT and acoustic survey data to assess effects of variability in survey q on total population abundance estimates from both gear types. This can be achieved by estimating availability and efficiency (i.e. $q_{a,BT}$, $q_{a,A}$, $q_{e,BT}$) for the EBS time series of BT and acoustic survey data using models derived here and in Kotwicki et al. (2014). Such a study would provide information on the times and areas that are best suited to sampling by either BT or acoustic gear types and areas that should be sampled using both gear types due to high variability in q_a values. Calculation and comparison of population abundance estimates would also provide insight into survey-wide variability in catchability from both gear types.

4.5. Figures

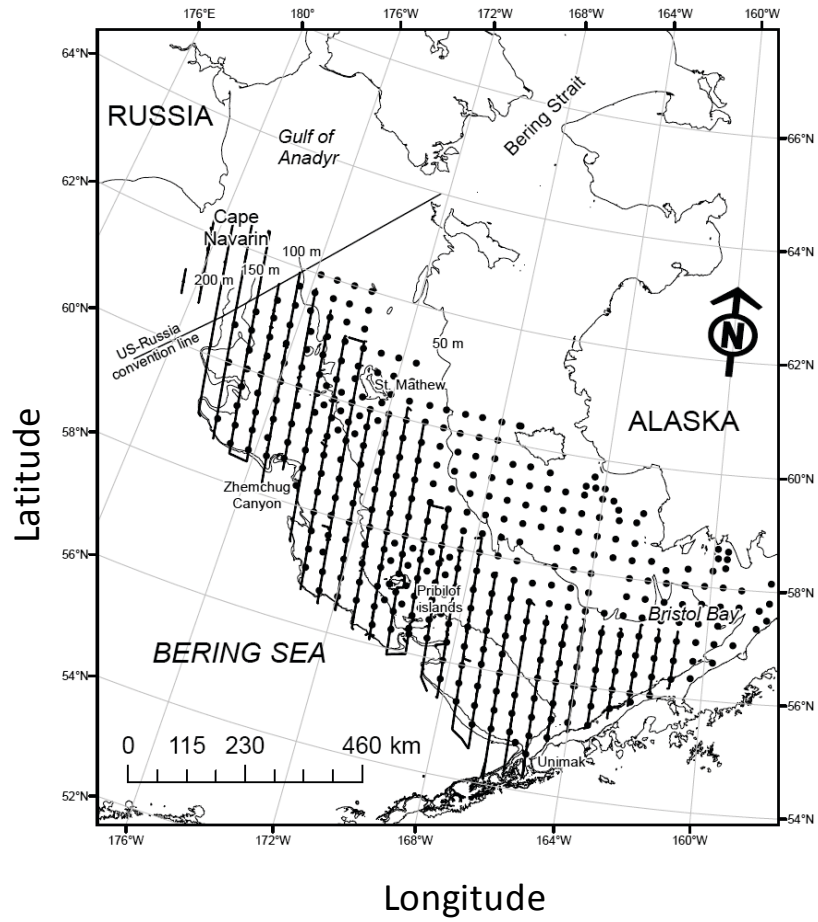


Figure 4.1. Bottom trawl (points) and acoustic (lines) survey locations.

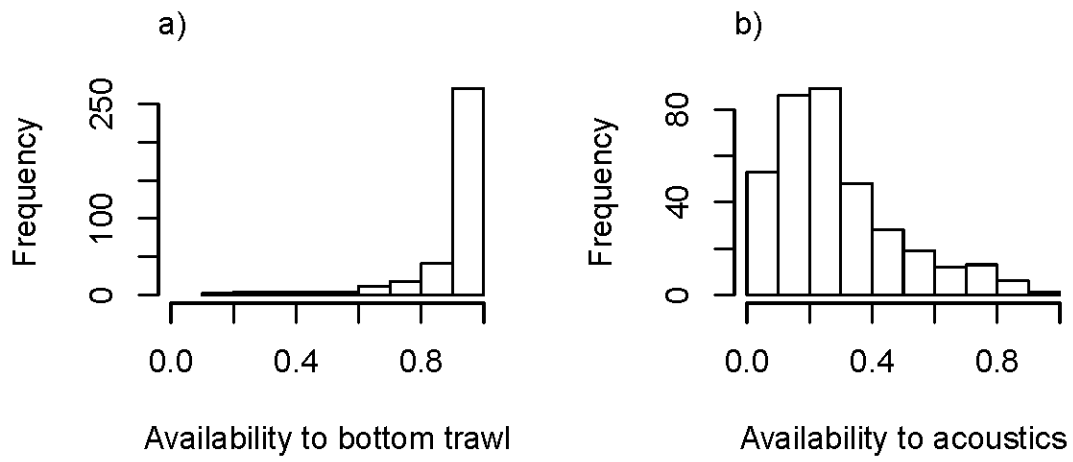


Figure 4.2. Histograms of availability of pollock to the bottom trawl (a) and acoustics gear (b).

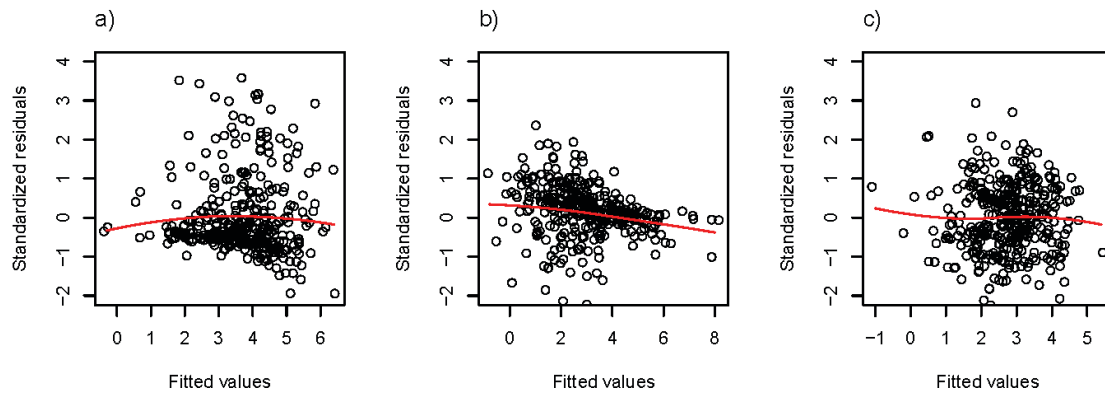


Figure 4.3 Standardized residuals (from models of BT availability) plotted against fitted values from three methods: a) mixed effects, b) quasi-binomial, and c) beta regression. Solid lines represent smooth spline fitted to the residuals.

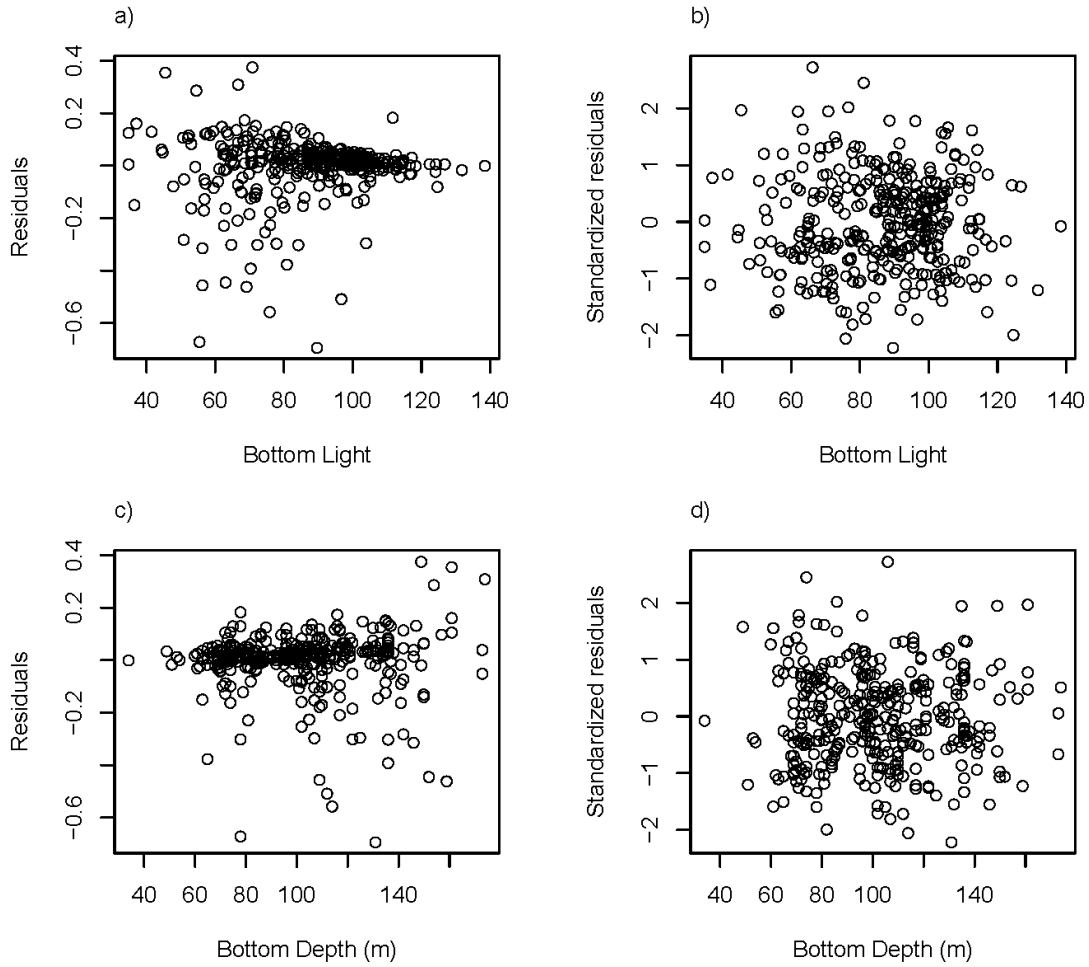


Figure 4. 4. Examples of scatterplots of residuals (a,c) and standardized residuals (b,d) vs. bottom light and bottom depth for bottom trawl availability beta regression models.

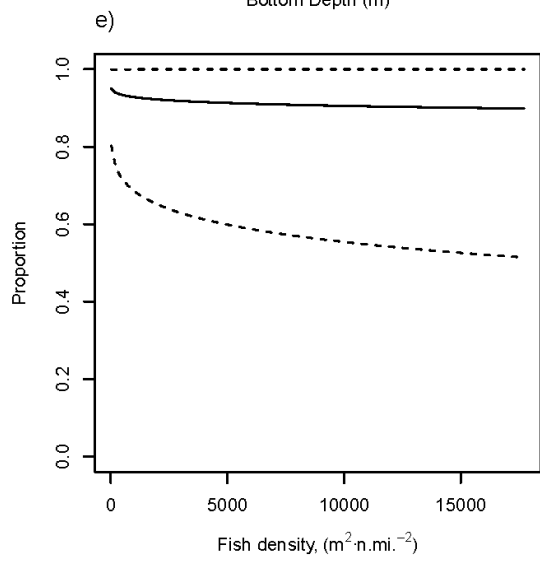
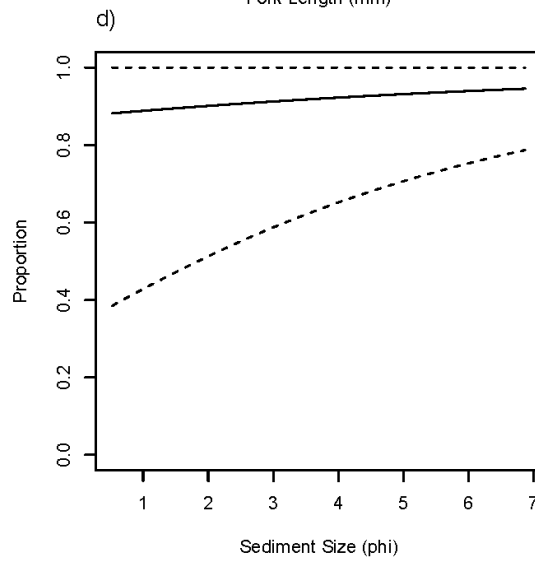
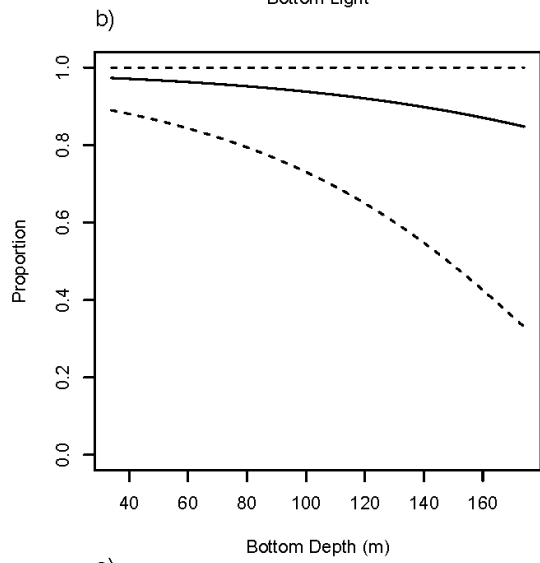
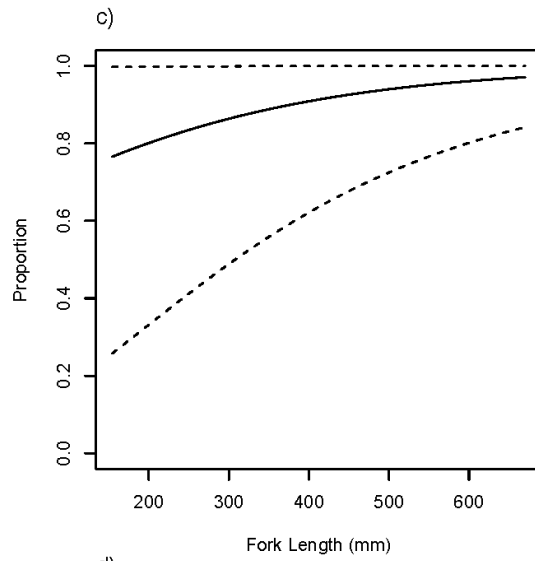
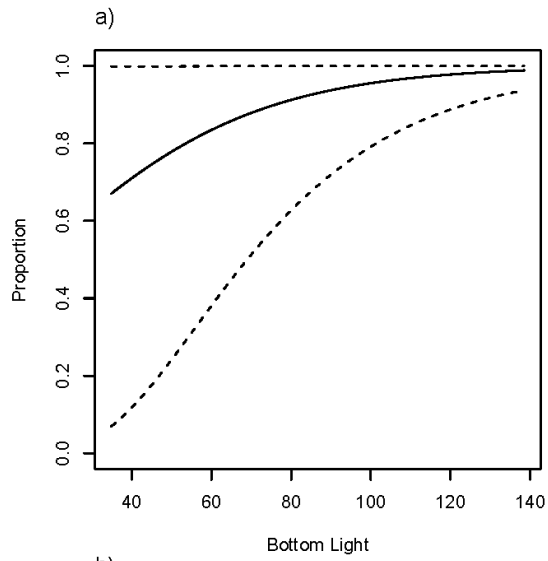


Figure 4.5. Predictor effects on pollock availability to the bottom trawl (solid lines) with 95% confidence bounds (dashed lines).

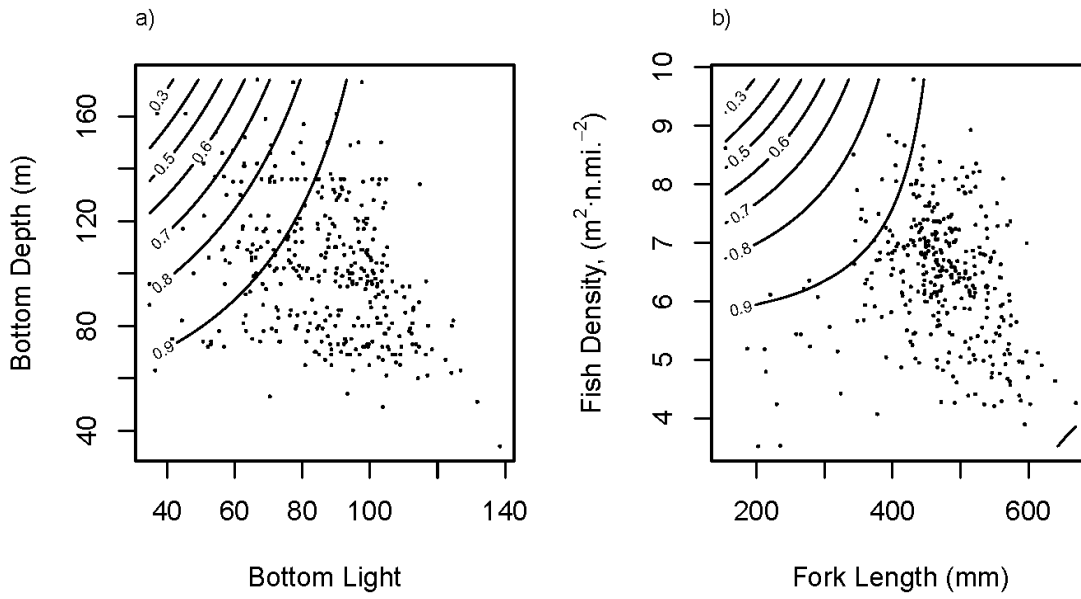


Figure 4.6. Contours of pollock availability to the bottom trawl for interaction effects: Bottom Light and Bottom Depth (a) and Fork Length and Fish density (b). Points represent data used in analysis.

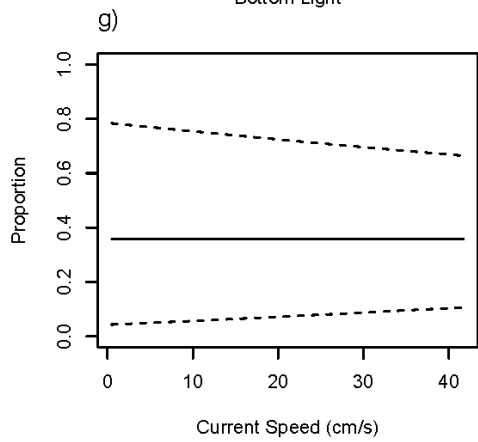
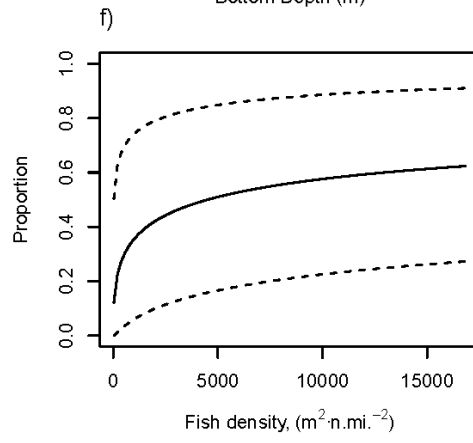
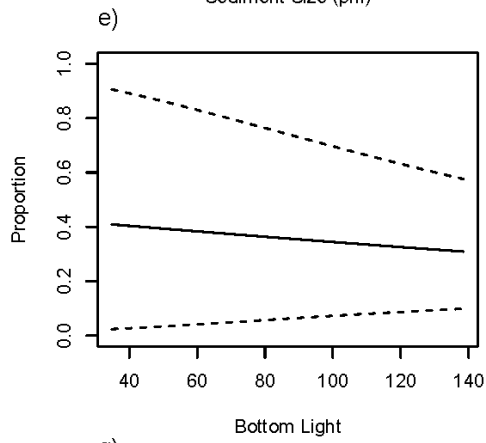
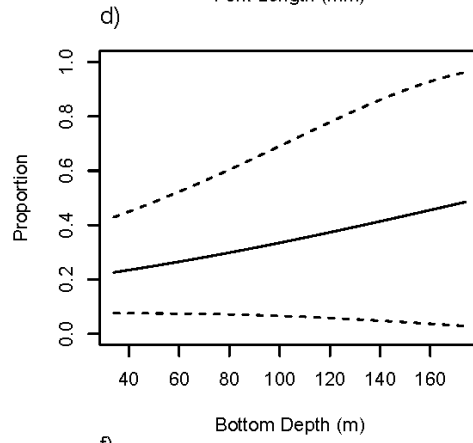
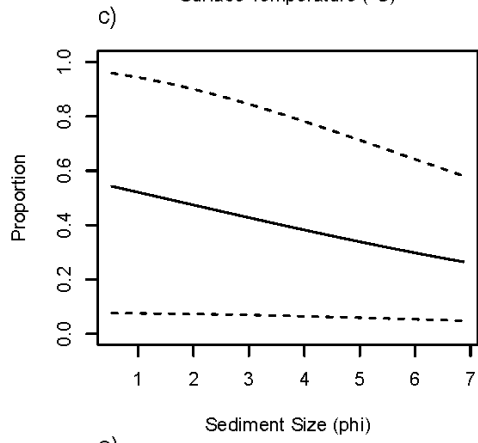
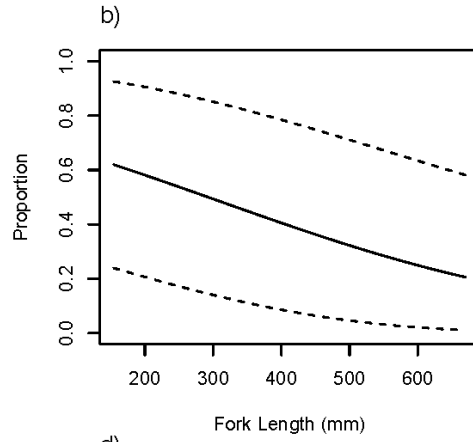
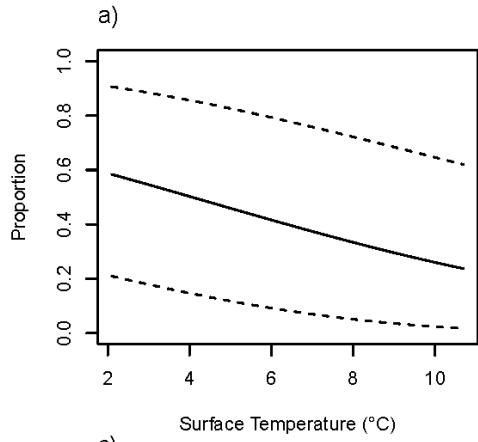


Figure 4.7. Predictor effects on pollock availability to the acoustics (solid lines) with 95% confidence bounds (dashed lines).

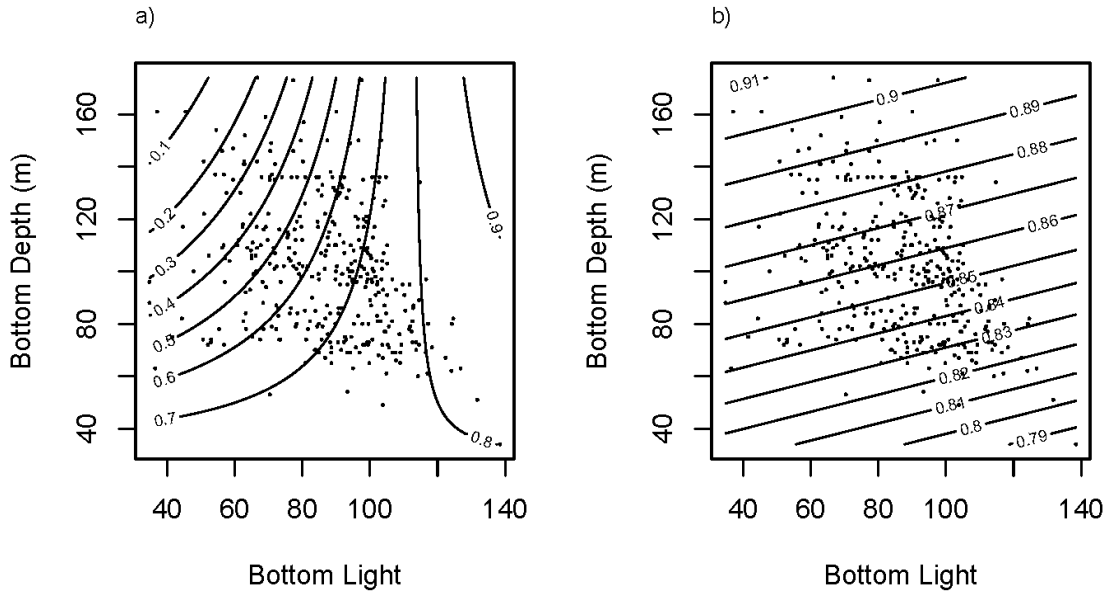


Figure 4.8. Bottom light and dept effect on the pollock availability to the bottom trawl (left) and acoustics (right) in following conditions: FL = 30 cm, total density = $5000 \text{ m}^2\text{nm}^{-2}$, and BT = 3°C . Points represent data used in analysis.

CHAPTER 5. COMBINING DATA FROM BOTTOM TRAWL AND ACOUSTIC SURVEYS TO IMPROVE RELIABILITY OF THE ABUNDANCE ESTIMATES

5.1. INTRODUCTION

Fishery-independent surveys can be useful for estimating total abundance of a fish population and describing their spatial distribution providing the survey results are reliably accurate and precise (Hilborn and Walters 1992). Abundance indices from fishery-independent surveys are generally considered more reliable compared to fishery-dependent indices (Maunder and Punt, 2004). However, quantitative assessments of the reliability of survey abundance estimates are often lacking or are limited to the estimation of sampling error, which often leads to an underestimation of uncertainty (Punt and Butterworth, 2003). The “additional variation” in abundance estimates can be caused by variation in catchability of the survey gear (Kotwicki et al. 2014), and can lead to bias in population abundance estimates (Hjellvik et al. 2002, Kotwicki et al. 2014), stock assessment outcomes (Thorson et al. 2013), and spatial dynamics and ecological modeling studies (Kotwicki et al. 2013).

In stock assessments, the reliability of survey abundance estimates is often evaluated by measures of their precision (e.g. Ianelli et al. 2013), assuming their accuracy (or bias) remains constant. Bias in survey abundance estimates arises when survey gear catchability (i.e. the ratio of the survey estimate of abundance to the true abundance; e.g. Godo 1994) doesn't equal 1. When catchability is freely estimated but constant, the survey estimates inform the stock assessment as an index (constant bias) and will still track spatial and temporal trends in

abundance (Pennington and Strømme 1998). Such relative indices can be particularly informative if they cover long periods (Rose et al., 2000). In these cases, estimates of precision obtained from observation error may be sufficient to assess reliability of the abundance estimate. However, when catchability changes, it can cause additional variation in the observed abundance trends (Kotwicki et al. 2014). In such cases, both observation error and variability in catchability must be accounted for to fully evaluate the reliability of an abundance estimate (e.g., Pennington and Godø 1995; Punt and Butterworth 2003; Maunder and Punt 2004).

Walleye pollock (*Gadus chalcogrammus*; hereafter referred to as pollock) in the eastern Bering Sea (EBS) are surveyed using bottom trawl (BT) and acoustic surveys (Ianelli et al. 2013; Lauth and Nichol 2013; Honkalehto et al. 2013). Kotwicki et al (2014) quantified BT efficiency ($q_{e,BT}$) in survey estimates of pollock abundance, and showed that the additional variability associated with $q_{e,BT}$ can represent a substantial source of uncertainty in abundance estimates, and can lead to a bias in the pollock stock assessments if it is ignored. Variable availability (i.e. the proportion of fish from the whole water column available to the survey gear; q_a) may also be an important source of the variability in catchability for the BT and acoustic survey abundance indices. Kotwicki et al. (in review) reported that achieving constant survey catchability across time and space for pollock in the EBS may be impossible regardless of efforts to standardize survey operations because q_a is a function of environmental conditions. It is therefore important to quantify the effect of variability in q_a on the uncertainty associated with abundance indices from the BT and acoustic surveys.

Uncertainty related to abundance estimates must be assessed at the scale of spatial sampling (i.e. among survey stations or “grid cells”) and at the scale of a survey (i.e. the population abundance

estimate). Understanding spatial variability in catchability among stations, and how it affects the uncertainty of abundance estimates can help optimize survey effort allocation and improve inferences in ecological and spatial dynamics studies. Uncertainty in survey-wide abundance estimates is needed for stock assessments so that the abundance indices are assigned appropriate statistical weights (Simmonds 2003). Abundance indices derived from BT and acoustic surveys have been used in EBS pollock stock assessments for decades (Ianelli et al. 2013; Lauth and Nichol 2013; Honkalehto et al. 2013), but formal assessment of their reliability has been limited. Recently, Ianelli et al. (2013) used a BT survey abundance index that had been corrected for variable $q_{e,BT}$ (Kotwicki et al. 2014) within the assessment. The uncertainty of this new index (as measured by its coefficient of variation, or CV) was ~55% larger than that of the old index, where uncertainty had been estimated using just sampling error. The influence of the larger CV of the new BT survey index reduced its weight in the stock assessment model and implicitly increased the weights of other survey indices with lower CVs (such as the acoustic survey). Including a more accurate CV estimate for a single index thus needs to include a re-evaluation of the relative weights of other indices, especially if some component weights are based on subjective judgments.

It is important to provide accurate uncertainty estimates for both the BT and acoustic survey indices of abundance for pollock in the EBS, accounting for variation in the catchability of both surveys. Combining estimates from the BT and acoustic surveys should provide a more accurate and precise abundance index than either survey could provide alone (Godø and Wespestad, 1993; Hjellvik et al., 2007). In practice, combining these estimates is challenging because the catchabilities of the two surveys likely differ (Hovgard and Riget, 1992; Engås and Soldal, 1993), and the vertical overlap in fish distribution (hereafter referred to as “overlap”) is unknown

(Aglen, 1996; Hjellvik et al., 2003). I propose a method for combining data from BT and acoustic surveys using estimates of the catchability ratio (r_q) and overlap (as in Kotwicki et al. 2013). Various sources of uncertainty associated with combined abundance estimates as well as those associated with abundance estimates from each survey are analyzed. This was done using estimates of catchability and their variances at each survey grid cell using previously developed models (Kotwicki et al. 2013, 2014, in review), and new models developed for combined survey catchability. For the BT survey, two sources of uncertainty are accounted for: $q_{e,BT}$ and pollock availability to the BT ($q_{a,BT}$; Kotwicki et al. in review). For the acoustic survey, it was assumed that efficiency was constant (Kotwicki et al. in review) but that variable availability ($q_{a,A}$) was incorporated in the abundance estimates. For the combined estimate three sources of uncertainty were accounted for: $q_{e,BT}$, r_q (Kotwicki et al. 2013) as well as overlap.

5.2. METHODS

5.2.1. Pollock density data

Acoustic and BT catch data were collected during BT and acoustic surveys of the EBS shelf conducted by the Alaska Fisheries Science Center (AFSC) during summers in years 2004, and 2006-2010. During these years both surveys were conducted on different vessels, but at approximately the same time (i.e., each survey grid cell was sampled by both survey methods within the same two week period). Also, as environmental data were only available from the BT survey I assumed that these data reasonably represented environmental conditions for both surveys. The EBS BT survey has been conducted annually over a standard grid of stations since 1982 (Lauth and Nichol 2013). Most of the 376 survey stations were located at the centers of a 37 x 37 km (20×20 nautical mile) grid (Figure 5.1). Stations at the corners of the grids were

also sampled in two regions (near St. Matthew Island and the Pribilof Islands). The BT surveys were conducted using a standardized bottom trawl gear (the 83-112 Eastern otter trawl), and started in the north eastern corner of the area (Bristol Bay) with the survey vessels proceeding westward. Standard BT tow duration was 30 minutes on bottom at a tow speed approximately 1.54 m s^{-1} (i.e. 3 knots; see Lauth and Nichol 2013 for details). Acoustic survey transects were designed to coincide with the north-south lines of BT survey stations (Figure 5.1). Acoustic data were collected using a Simrad 38 kHz EK60 scientific echosounder. Trawling was conducted to confirm species identities and to determine fish length distributions. These samples were collected primarily using a midwater trawl (Aleutian Wing Trawl) and occasionally with a bottom (83-112) or Methot trawl (see Honkalehto et al., 2013, for details). Approximately 100 midwater trawls were conducted during each acoustic survey, and approximately 95% of the catch weight was pollock. Pollock length data from midwater trawls were aggregated in strata based on acoustic backscatter, geographic proximity of hauls, and similarity in pollock length composition from the hauls (Honkalehto et al., 2013). The acoustic equipment was calibrated 2 to 4 times during each cruise using the standard sphere method (Foote et al., 1987).

For the purposes of this study, pollock density was estimated within each survey grid cell using acoustic units of nautical area scattering coefficient (s_A , a linear measure of backscatter per unit area, $\text{m}^2 \text{ nmi}^{-2}$; MacLennan et al., 2002) from both BT and acoustic surveys. For the bottom trawl stations, an area-swept method (e.g. Alverson and Pereyra, 1969) was used to estimate pollock density, accounting for distance fished (as indicated by a bottom contact sensor; Somerton and

Weinberg, 2001) and average distance between wing tips (measured using Netmind² spread sensors; Weinberg and Kotwicki, 2008). BT survey density estimates in kg ha⁻¹ were then transformed into equivalent s_A (m²nmi⁻²) using the Doray et al. (2010). For acoustic surveys, pollock density was estimated using s_A at 38 kHz, fish lengths, and species composition from midwater trawl catches (Honkalehto et al. 2013), and pollock-specific target strength-length relationship (Traynor, 1996). s_A data collected in 0.5 nm intervals were averaged (within each grid cell), resulting in a single acoustic density estimate for each BT survey grid cell.

5.2.2. Predictor variables

Near-bottom, and surface water temperature were measured during each BT survey tow using a micro-bathymograph (MBT, Seabird SBE-39) attached to the headrope of the BT. Average bottom depth was obtained by averaging a sum of MBT-detected headrope depth and acoustically-detected headrope height above the bottom over the duration of a tow. Near-bottom light levels were collected during each trawl using Wildlife Computers MK-9 archival tags (see Kotwicki et al., 2009 for details) also attached to the headrope of the BT. These tags provided relative values (between 0 and 256) of near-bottom light levels sampled at 1 Hz and were then averaged over the duration of the trawl. Sediment size was estimated at each station using historical data from grabs and dredges (Smith and McConnaughey, 1999), interpolated (Paul Spencer, AFSC, unpubl. data) using ordinary Kriging (Oliver and Webster, 1990). Sediment data

² Reference to the trade names does not imply endorsement by the National Marine Fishery Service, NOAA.

were expressed in units of “phi” (negative \log_2 of the diameter in mm), where higher values correspond to smaller particle sizes (Wentworth, 1922). Tidal current speed, used as a proxy for bottom current, was predicted for each tow using Oregon State University’s Tidal Inversion Software (<http://www.oce.orst.edu/research/po/research/tide/region.html>; Egbert et al., 1994; Egbert and Erofeeva, 2002). Mean fish length was calculated from length frequency data obtained from BT catch samples.

5.2.3. Water column abundance estimates

Estimates of the whole water column pollock abundance at each survey grid cell (hereafter referred to as grid cell abundance) in any survey was obtained using:

$$\hat{A}_i = A_i/q_i \quad [5.1]$$

where \hat{A}_i and A_i are expected and observed water column abundance at location i , and q_i is the “catchability”. The parameter q_i for each method was estimated at each grid cell using the experimental models developed in Kotwicki et al. (2014, in review). This approach resulted in three options for estimating \hat{A}_i :

Option 1. From [5.1], the expected grid cell abundance was estimated from BT survey data using:

$$\hat{A}_{BT_i} = A_{BT_i}/q_{BT_i} \quad [5.2]$$

where \hat{A}_{BT_i} is expected abundance in the water column at grid cell i , A_{BT_i} is the observed abundance from the BT survey at grid cell i and q_{BT_i} is the BT catchability at grid cell i ,

$$q_{BT_i} = q_{e,BT_i}q_{a,BT_i} \quad [5.3]$$

(e.g. Godø 1994), where q_{e,BT_i} is the density-dependent BT efficiency at grid cell i , and q_{a,BT_i} is the availability to the BT at grid cell i . The density-dependent BT efficiency is estimated using:

$$q_{e,BT_i} = \beta_0 + \exp(-(\beta_1 s_{A,BT_i} + \beta_2)) \quad [5.4]$$

where s_{A,BT_i} is the BT CPUE at grid cell i transformed into equivalent s_A (Kotwicki et al. 2013), β_0 , β_1 , and β_2 are parameters of the BT density-dependent efficiency function estimated in Kotwicki et al. (2014). The availability to the BT is estimated using:

$$q_{a,BT_i} = \frac{1}{1+e^{-(\alpha_{BT}+\boldsymbol{\gamma}_{BT}\mathbf{X}_i)}} \quad [5.5]$$

where α_{BT} is an offset parameter, $\boldsymbol{\gamma}_{BT}$ is a vector of parameters of the BT availability function estimated in Kotwicki et al. (*in review*), and \mathbf{X}_i is a matrix of the predictor variables.

q_{a,BT_i} is assumed to be beta distributed, with variance:

$$V_{a,BT_i} = \frac{q_{a,BT_i}(1-q_{a,BT_i})}{1+\Phi_{BT}} \quad [5.6]$$

(Ferrari and Cribari-Neto, 2004), where Φ_{BT} is a precision parameter linked to \mathbf{X}_i (using “identity” link; Simas et al. 2010), which allows the variance of the response variable to depend on predictors. The “logit” link function was used for the q_{a,BT_i} .

Option 2. From [5.1], the expected grid cell abundance was estimated from acoustic survey data using:

$$\hat{A}_{A_i} = A_{A_i}/q_{A_i} \quad [5.7]$$

Where \hat{A}_{A_i} is expected abundance in the water column at grid cell i , A_{A_i} is the observed abundance in the acoustic survey at grid cell i , and q_{A_i} is the acoustic gear catchability at grid cell i equal to q_{a,A_i} , the availability to the acoustic gear:

$$q_{a,A_i} = \frac{1}{1+e^{-(\alpha_A+\gamma_A \mathbf{X}_i)}} \quad [5.8]$$

where α_A is an offset parameter, γ_A is a vector of parameters, \mathbf{X}_i is a matrix of the predictors. As for q_{a,BT_i} , q_{a,A_i} is assumed to be beta-distributed with precision parameter Φ_A .

In contrast to equation [5.5], the parameters of equation [5.8] are not available from Kotwicki et al. (in review). Even though Kotwicki et al. (in review) used data from 0.5 to 3 m above the bottom, the current practice in the EBS pollock assessment is to use an acoustic estimate of the mid-water (above 3 m off bottom) component of the population (Honkalehto et al. 2013), while the BT survey is used for an estimate of the near-bottom component (i.e. below 3 m off bottom). The practice of using acoustic survey data above 3 m off bottom was established because the survey BT headrope height is approximately 3 m (Lauth 2010) and it was believed that the effective fishing height corresponded to the headrope height (von Szalay et al. 2007). Recently Kotwicki et al. (2013) showed that the effective fishing height of the EBS survey BT is on average 16 m. To evaluate consistency with indices presently used in the pollock stock assessment only acoustic data above 3 m off bottom were used. New estimates of the parameters in the relationship between q_{a,A_i} and the predictor variables (\mathbf{X}_i) were calculated assuming that all pollock above 3 m off bottom are available to the acoustic survey, using BT and acoustic data collected simultaneously during a subset (n=355) of the BT tows during 2005-2009 (see Kotwicki et al. 2013, Kotwicki et al. in review, for details). Availability data from these tows was defined as:

$$q_{a,A_i} = \frac{s_{A_i}}{s_{A,t_i}} \quad [5.9]$$

where s_{A,t_i} is the water column fish density (obtained from Kotwicky et al. 2013), and s_{A_i} is fish density above 3m off bottom. These data were then fitted to the function [5.8] using beta regression (Simas et al. 2010), and estimates of parameters α and γ were used to estimate q_{a,A_i} for each survey location.

Option 3. From equation [5.1], the expected grid cell abundance was estimated using combined data from both BT and acoustic surveys:

$$\hat{A}_{C_i} = A_{C_i}/q_{C_i} \quad [5.10]$$

where:

$$A_{C_i} = A_{BT_i}/q_{e,BT_i} + r_q A_{A_i} \quad [5.11]$$

$A_{BT_i}/q_{e,BT_i}$ represents fish abundance at grid cell i in the zone between the bottom and effective fishing height after correcting A_{BT_i} for the density-dependent efficiency (q_{e,BT_i}) of the bottom trawl (Kotwicky et al. 2014). The second term on the RHS of Eq 5.11, $r_q A_{A_i}$, represents fish abundance between 3 m off bottom and the surface as observed in the acoustic survey. By definition, it is assumed that all fish that are present are observed by one or both of the surveys. The term r_q is the catchability ratio between the bottom trawl and acoustics based on the differences in bias associated with each method (Kotwicky et al. 2013),

$$q_{C_i} = 1 + o_{C_i} \quad [5.12]$$

q_{C_i} is the catchability of the combined survey, and o_{C_i} is the overlap between the two survey methods. The minimum value of q_{C_i} is 1, when no fish were present in the zone between 3 m and

the effective fishing height (i.e. in the overlap zone). In other words, each survey detects a separate, additive portion of the total water column pollock abundance. The maximum value of q_{C_i} is 2, where all fish in the water column were within the overlap zone.

The o_{C_i} was modelled using Kotwicki et al. (in review) and defined as:

$$o_{C_i} = \frac{1}{1+e^{-(\alpha_C+\gamma_C X_i)}} \quad [5.13]$$

where α_C is an offset parameter, γ_C is a vector of parameters, X_i is a matrix of the predictor variables. o_{C_i} was assumed to be beta-distributed with precision parameter Φ_C .

Predictions of o_{C_i} were obtained using the same methods as predictions of q_{a,A_i} from the BT and acoustic data collected simultaneously during a subset of the BT survey tows in years 2005-2009 (see Kotwicki et al. in review, for details). Parameter values were obtained by fitting equation [5.13]. Estimated parameters α , and γ were then used to predict o_{C_i} for all of the survey grid cells used in the analysis.

Not all predictor values were available for each grid cell. In these cases simplified models, with fewer predictors were refitted to the data and used for predictions of q_{a,BT_i} , q_{a,A_i} , and o_{C_i} . In all, <1% (out of ~ 20,000) of the survey grid cells had missing predictor data such as light, temperature, or mean fish length measurements.

5.2.4. Variance estimates

It was necessary to account for multiple sources of uncertainty to estimate variances of pollock abundance estimates (see Table 5.1). Uncertainty in estimates for Option 1 are associated with the estimation of q_{e,BT_i} and q_{a,BT_i} . To account for these sources of uncertainty, the variance of

the \hat{A}_{BT_i} at each BT tow location was estimated using a two-stage re-sampling process. First, a sample was drawn from the MCMC-derived $\mathbf{q}_{e,BT}$ survey vectors obtained in Kotwicki et al. (2014), and then a set of values for q_{a,BT_i} were drawn from a beta distribution, whose mean and variance were calculated using equations [5.5] and [5.6]. This procedure was repeated 1,000 times and the replicates were used to obtain estimates of variance and CV of mean \hat{A}_{BT_i} .

Uncertainty for Option 2 is associated with the estimation of q_{a,A_i} . The variance of \hat{A}_{A_i} at each acoustically sampled survey grid cell was estimated by drawing 1,000 replicate values for q_{a,A_i} from the associated beta distribution, and these values were used to obtain the variance and CV for \hat{A}_{A_i} . Finally, uncertainty for Option 3 (the combined estimate) is associated with the estimation of q_{e,BT_i} , r_q , and o_{C_i} . The variance of \hat{A}_{C_i} at each grid cell sampled by both BT and acoustic surveys was estimated using a two-stage re-sampling process. First, a sample was drawn from the MCMC-derived $\mathbf{q}_{e,BT}$ and \mathbf{r}_q vectors obtained in Kotwicki et al. (2014) then 1,000 replicate values for o_{C_i} were drawn, and these values were used to estimate the variance and CV of \hat{A}_{C_i} .

5.2.5. Assessment of the reliability of abundance estimates

The mean and variance of \hat{A}_{BT_i} , \hat{A}_{A_i} , and \hat{A}_{C_i} represent a corrected distribution for the survey process error across time and space, providing a way to assess the reliability of each survey method at each survey grid-cell. The goal is to provide corrections to the abundance estimates to account for variable catchability (equations 5.2, 5.7, and 5.10) and obtain unbiased abundance estimates. Therefore, the estimated CV at each grid cell was used as a reliability statistic, where a lower CV indicated a more reliable method of estimating abundance. CVs were plotted on the

survey grid maps to identify areas best suited for sampling pollock using BT, acoustics, or combined surveys.

Region-wide indices of abundance were also examined for areas covered by both surveys using options 1, 2, and 3. As with the station-specific values, overall CVs for each index were compared to judge reliability. The region-wide estimates of CVs (for each year) were obtained using a parametric bootstrap approach (Efron and Tibshirani 1993) based on 1,000 samples (with replacement) from the distributions for \hat{A}_{BT_i} , \hat{A}_{A_i} , and \hat{A}_{C_i} .

Preliminary analyses indicated that the CV of the abundance estimates depended on the mean and the variance of predicted catchability. A simulation was performed to illustrate the effect of the beta-distributed catchability on the CVs of the abundance estimates. The simulation resampled 1,000 times from each combination of mean and variance of plausible values of catchability. Catchability values between 0 and 1 are plausible for the BT and acoustic surveys. Values between 1 and 2 are plausible for the combined survey. Observed values of variance in catchability varied between 0 and 0.2. Plausible catchability distributions were therefore defined as mean values of catchability between 0 and 2 and variance between 0 and 0.2.

5.3. Results

5.3.1. Water column catchability and abundance estimates

Estimates of q_{BT_i} varied between 0.2 and 1 (mean = 0.87; standard deviation = 0.10; Fig 5.2).

The q_{BT_i} estimates varied spatially and temporarily, and were generally large (>0.8) in locations with bottom depths shallower than 100 m (Figure 5.3). The q_{BT_i} values were often lower than 0.8 in deeper locations, dropping to less than 0.5 in locations with the highest pollock densities. The

CV estimates for \hat{A}_{BT_i} ranged between 0.01 and 32, but the majority of CVs were < 1 . The spatial distribution of the CV estimates were inverse to the values of q_{BT_i} (Figure 5.3), with high CVs generally in waters deeper than 100m and low CVs in shallower waters. Spatial patterns in CV estimates indicated that the reliability of the BT survey was generally high in waters shallower than 100 m, but deteriorated quickly at deeper depths. At depths greater than 150 m, BT survey abundance estimates were generally highly uncertain with CVs > 1 .

Estimates of q_{A_i} varied between 0 and 0.7 (mean = 0.22; standard deviation = 0.16; Fig 5.2). The q_{A_i} estimates varied spatially and temporarily, and were generally low (< 0.3) in locations shallower than 100 m (Figure 5.4). In locations deeper than 100 m, q_{A_i} was often higher and increased with depth. The CVs for \hat{A}_{A_i} , were approximately two orders of magnitude higher than the CVs for \hat{A}_{BT_i} with values ranging between 3 and 32. Unlike the bottom trawl results, the spatial distribution of the acoustic CVs appeared more random and less related to depth (Figure 5.4). The CVs indicated that the reliability of grid cell abundance estimates from the acoustic survey were lower than those from the BT survey for the majority of the surveyed area of the EBS. These results indicate that abundance estimates in the deepest survey locations (> 150 m) were unreliable (CV >1) for both survey methods.

Estimates of q_{C_i} varied between 1 and 1.35 (mean = 1.21; standard deviation = 0.05; Fig 5.2). The q_{C_i} estimates varied spatially and temporarily, and were relatively lower in locations shallower than 100 m (Figure 5.5). Higher q_{C_i} values in the deeper waters indicated a tendency for the overlap between the BT and acoustic data to be higher in deeper areas. Unsurprisingly, the CVs for the \hat{A}_{C_i} were lower than those for the \hat{A}_{BT_i} and \hat{A}_{A_i} and ranged between 0.05 and 0.31.

The spatial distribution of the CV estimates followed patterns similar to q_{C_i} (Figure 5.5), with high CVs generally in waters deeper than 100 m and low CVs in shallower waters. The reliability of grid cell abundance estimates from the combined survey was higher than that from estimates derived from either survey in most areas deeper than 100 m. Estimates from the BT survey were often more reliable in areas shallower than 100 m. Note that the acoustic survey does not usually extend into areas with bottom depths shallower than 50-75 m (Figure 5.1).

CV sensitivity simulations indicated that the reliability of a grid cell abundance estimate depended on the value of the estimate of catchability and its variance. Abundance estimates become less reliable as catchability decreases and variance in catchability increases. For example, catchability must be > 0.4 to obtain an abundance estimate with the $CV < 1$ (Figure 5.6a), and its variance must be lower than 0.04, which was the case for the majority of BT survey samples. Higher precision in catchability is required to produce abundance estimates with $CVs < 1$ when mean catchability is < 0.4 . The level of precision in the acoustic survey catchability estimates was poorer. For combined abundance estimates, the survey catchability estimates were always > 1 , because of the overlap zone that is sampled by both survey methods. Simulation for the values of catchability > 1 (representative of combined surveys; Fig. 6b) indicated that CVs of abundance estimates were less dependent on the precision in catchability compared to the CVs from either survey. Combined abundance estimates generally had lower CVs than estimates from either survey regardless of the degree of overlap and the uncertainty associated with the estimate of the overlap.

5.3.2. Survey-wide abundance estimates

The most reliable survey-wide abundance estimates were obtained from combined BT and acoustic surveys. CVs of mean abundance estimates from combined surveys ranged from 0.16 to 0.19 (Table 5.2). CVs for the BT survey were low (<1) in 2004, and 2008, but were high in other years (>1). CVs for the acoustic survey were high (>1) in all years indicating unreliable point estimates of abundance.

5.4. Discussion

5.4.1. Estimates from combining different survey methods

The main purpose of this study was to evaluate alternative methods for estimating total pollock abundance. Estimates from combining BT and acoustic survey data (Option 3) were found to be more reliable than estimates derived from either survey data set separately. The uncertainty of pollock abundance estimates was highly dependent on the mean and the variance of stations-specific catchability estimates. Catchability was highest and had the smallest variance for q_{C_i} , which resulted in corrected estimates of abundance that had higher reliability than BT and acoustic abundance estimates at both survey grid cell resolution and for region-wide scales. Combined estimates are corrected for spatial and temporal changes in survey catchability. These estimates can be used in studies that require unbiased abundance data on both survey resolution and region-wide scales. In contrast to estimates based on the BT and acoustic surveys alone, the combined estimates meet the two main objectives of fishery-independent surveys, producing reliable estimates of both total abundance and distribution (Hilborn and Walters 1992).

There are some caveats to the approach presented here. Combining survey information to develop abundance estimates were based on data collected during two summer surveys

conducted on different vessels sampling at different times. The approach here assumed that the differences due to sample collection timing are negligible. It was assumed that pollock vertical and horizontal distribution remained the same (on average) between the time each survey method sampled each grid cell. It was also assumed that environmental conditions were constant during the two surveys. Abundance estimates would be biased and their uncertainty underestimated if these assumptions were violated. Nonetheless, the magnitudes of these potential biases were considered small since environmental conditions in the EBS during summer change relatively slowly (Stabeno et al. 2001). These assumptions and sources of uncertainty could be avoided by conducting a combined BT-acoustic survey using a single vessel.

The spatial extent of the combined-data method was limited since significant areas with pollock were omitted due to only one source of survey information being available. Generally, acoustic surveys are conducted in areas deeper than 75 m, and only data from the BT survey are available in shallower waters. It would be necessary to use all three analytic methods to estimate abundance in the entire survey domain, with the combined estimates taking precedence wherever possible, and using single survey estimates in other areas to estimate summer pollock abundance.

5.4.2. Variation in catchability

Fishery-independent surveys are conducted to provide a time series of abundance, length (or age) composition, and distribution of fish species (e.g. Benoît and Swain 2003). It is essential for catchability to remain stationary across time and space to maintain comparability among survey observations (e.g. Stauffer 2004), or alternatively, to have precise estimates of catchability.

Fishery-independent surveys are standardized by maintaining survey operations to assure stationary catchability (Benoît and Swain 2003, Stauffer 2004). Standardizing survey methods is

an important step towards achieving stationarity in catchability. However, variability in catchability over time and space can remain due to the fish distribution and the inherent properties of the sampling gear relative to environmental conditions. This study indicates that although both BT and acoustic pollock surveys in the EBS have been operationally standardized, catchability in both methods varies, which can lead to biases in abundance estimates (Lawson and Rose, 1999; Petrakis et al., 2001). Recognizing the potential for these biases would be critical for fisheries stock assessments (Walsh, 1996, Thorson et al., 2013), ecological studies (Ressler et al., 2012), and spatial dynamics studies (Kotwicki and Lauth 2013).

Survey-derived abundance estimates can be corrected to mitigate effects of variable catchability. Catchability estimates can be used to correct abundance estimates by using equation [5.1] (e.g. Lawson and Rose 1999, Ward and Myers 2005) or other functions (e.g. Hjellvik et al. 2002) to correct bias associated with variable catchability. For example, Lawson and Rose (1999) found that mean daytime densities for Atlantic cod detected using acoustics were an order of magnitude higher than at night. They concluded that diel changes in acoustic density resulted from variations in detectability caused by cod vertical movements, and advocated the use of a time-dependent detectability coefficient to obtain acoustic-based abundance estimates of semi-demersal fish. Ward and Myers (2005) noticed catchability variations due to longline depth, and obtained abundance indices corrected for variable catchability to resolve inconsistencies in the time series of abundance estimates. Fraser et al. (2007) derived size-dependent catchability coefficients for many groundfish species, for which abundance is assessed using a BT survey, and applied these coefficients to survey data to obtain absolute estimates of abundance.

Although the studies cited above succeeded in reducing biases from abundance estimates, they did not account for the variability associated with the estimation of catchability. The uncertainty in estimating the bias likely increases the variance of an abundance estimate. Hjellvik et al. (2002) noted that using an uncertain bias correction factor improved the accuracy of the survey abundance estimates, but decreased the precision. The adjustment removed bias, but increased uncertainty. The cost of increased uncertainty in the corrected abundance estimates may be too high when survey catchability is constant between years and only varies between day and night, but may be justified if there are substantial year-to-year differences (Hjelvik et al. 2002). Results of this study indicate that pollock catchability in the EBS depends on factors that can vary significantly among years. The most important factors affecting pollock catchability among those studied were bottom depth, near-bottom light levels, and fish length. Bottom depth remains the same over time for a given location, but pollock spatial distribution changes from year to year, resulting in changes in the bottom depths where pollock are found. Near-bottom light levels vary spatially and temporally over the EBS shelf (Kotwicki et al. 2009). The demographic structure of pollock (age distribution) also changes from one year to the next (Ianelli et al. 2012). The between-year variability in these factors suggests that survey catchability would also vary from year to year. Therefore, it seems advisable to use revised pollock abundance indices from the EBS BT and acoustic surveys which account for this variability. The challenge remains to account for the high levels of uncertainty in catchability estimates at some survey locations. Kotwicki et al. (in review) showed that 95% confidence limits around catchability estimates can sometimes encompass nearly all possible values of catchability. In such cases, corrected replicates of local abundance estimates can vary between the detected density and infinity, which inflates CV estimates and results in unreliable grid cell abundance estimates. The high station-

specific CVs simply mean that when one survey method observes part of the water column, it provides very little insight on the total abundance within the unobserved part of the water column. One unreliable grid cell abundance estimate can detrimentally influence the survey-wide estimate. This influence was observed in all survey-wide abundance estimates derived from the acoustic surveys and five of the BT survey estimates (years: 2006, 2007, 2009, 2010, and 2012). These results indicate that approaches to correct one survey method to obtain total abundance estimates were unreliable.

There are two possible ways to reduce high CVs of corrected abundance estimates caused by large uncertainty in catchability estimates. First, grid cell abundance estimates can be corrected using mean estimate of catchability. This would ignore uncertainty in catchability but would likely eliminate the bias associated with variable catchability (e.g. Lawson and Rose 1999, Ward and Myers 2005) and lead to an under-estimate of the variance. Second, improving predictions of catchability estimates would reduce uncertainty in abundance estimates. Catchability models with few predictor variables only explained approximately 30% of the variability in catchability (Kotwicki et al. in review). Other predictors such as oxygen concentration, pH, salinity, turbidity could be tested to see if they can reduce the remaining residual variation. These variables can be measured by adding sensors to the sampling equipment of the survey vessels. Estimates of prey and predator density distribution could also be tested to determine if they improve precision of catchability estimates (e.g. Ressler et al. 2012). Another option to improve the precision in catchability estimates would be to use acoustic data collected simultaneously with the BT (Kotwicki et al. 2013) to further refine estimates of BT survey catchability and total water column abundance. This approach is difficult because of the time and resources required for processing acoustic data. Development of automated techniques to process acoustic data and

development of methods to partition acoustic data in areas of mixed species is needed to streamline processing of simultaneously collected BT and acoustic data. Similarly, it would be useful to conduct a large numbers of bottom trawls during the acoustic survey, and use the methodology of Kotwicki et al. (2013) to estimate abundance of pollock in the acoustic dead zone. Increase in the number of bottom trawls during acoustic surveys would enable estimation of total water column abundance and acoustic survey catchability. The best way to produce reliable estimates of pollock abundance would be the development of a combined BT-acoustic survey, because results indicate that greater precision in pollock abundance estimates in the EBS could be achieved by combining concurrent BT and acoustic survey estimates.

5.4.3. Sources of variation in abundance estimates

Results of this study indicate that combined abundance estimates are generally more reliable than estimates derived from either the BT or the acoustic survey. In some survey grid cells combined estimates resulted in poorer precision than BT survey abundance estimates. For example, BT survey estimates were often more precise than the combined estimates in waters shallower than 100m. This was especially true when low densities of large fish were present and near-bottom light levels were high. In such conditions, the precision of the BT catchability estimate is high and the BT survey provides abundance estimates that are less uncertain than a combined estimate. In contrast, the BT survey abundance estimates were imprecise in deep areas where high densities of pollock were present and at low near-bottom light levels.

The reliability assessment of abundance estimates from different surveys should not be limited to the sampling error, but need to account for sources of uncertainty in catchability. Not including uncertainty in catchability can lead to underestimation of the uncertainty in the abundance

estimates. Kotwicki et al. (2014) showed that the CVs of abundance indices from pollock BT surveys increased on average 55% when uncertainty in $q_{e,BT}$ was included in the variance estimates, but that study did not account for the uncertainty in availability. Walline (2007) used a geostatistical approach to estimate variance in pollock abundance estimates using acoustic data and concluded that the CV ranged between 0.05 to 0.09. Variance estimation was limited to the fish available to each survey in both of these studies. This approach is reasonable when the objective is to estimate abundance of fish available to the survey gear. When the objective is to estimate abundance in the whole water column, variance estimates may be underestimated if they ignore variation in availability to the survey gear. The need to account for this additional variability in abundance indices has been recognized in stock assessments (Punt and Butterworth, 2003; Maunder and Punt, 2004). Kotwicki et al. (2014) showed that failing to account for variability in the pollock $q_{e,BT}$ leads to biased outcomes in pollock stock assessment. It is likely that not accounting for variability in the availability could lead to similar biases.

5.4.4. Reliable abundance indices and stock assessment

For the pollock stock assessment in the EBS, acoustic and bottom trawl survey data are currently used as separate abundance indices. Catchability of each survey is estimated by age groups and is allowed to vary slightly over time (Ianelli et al. 2013). The observation error assumed for the acoustic abundance index is specified to have an average CV of 20%, weighted by year-specific sampling error. The BT index variability is derived solely from the sampling error (Ianelli et al. 2013). This approach acknowledges additional variability associated with variable catchability, but this assumption requires some subjectivity (through specified prior variance) in how much variability is allowed (Ianelli et al. 2013). Variance around abundance indices that accounts for uncertainty associated with varying catchability of pollock for each survey would assure that an

objective statistical weight is apportioned to each abundance index and yearly estimate. A step in this direction was made in Ianelli et al. (2013) by correcting BT abundance index for variable $q_{e,BT}$, using a covariance matrix (derived from corrected index of abundance), and assuming a multivariate log-normal distribution for abundance estimates derived from the BT survey. This likely represents the first example of formally including independently derived estimates of survey process error in a fishery stock assessment.

In this study estimation of variation associated with pollock availability to either the BT or acoustic survey led to highly uncertain survey-wide indices of total abundance (CVs > 1). Nevertheless, the combined estimates accounted for major sources of variation in catchability and were reasonably precise (CVs < 0.2). Combined abundance estimate CVs were generally lower than those used currently for either survey in the pollock stock assessment (Ianelli et al. 2013).

This study demonstrates that combined abundance estimates are preferable at the sample resolution (grid cell) and region-wide when the total water column abundance of pollock in the EBS is needed. Results of this study suggest that in the EBS pollock may be more demersal than pelagic, so the BT survey data appeared more reliable in many areas than the acoustic survey for assessing total water column abundance of pollock, particularly in shallow bottom depths. This conclusion is valid for pollock in the EBS, but extending to other pollock stocks or other semi-pelagic species would require area-specific study. For example, pollock apparently exhibits more pelagic behavior in other regions such as the Sea of Japan (Kooka et al. 1998), the Pacific coast of Hokkaido (Miyashita et al. 2004), or in the Aleutian Basin (Bailey 2011). Other semipelagic species can also exhibit various degrees of pelagic vs. demersal behavior and need to be sampled

appropriately. The techniques presented here can be used to determine which sampling method results in most reliable abundance estimates for specific areas and species.

5.5. Tables

Table 5.1. Summary of the methods for estimating uncertainty of grid cell abundance estimates.

	Catchability (q)			Observation error
	Gear efficiency (q_e)	Catchability ratio (r_q)	Availability (q_a)	
Option 1	MCMC		Beta distribution	Bootstrap
Option 2			Beta distribution	Bootstrap
Option 3	MCMC	MCMC	Beta distribution	Bootstrap

Table 5.2. Estimates of survey-wide means and CVs of s_A [$\text{m}^2\text{nmi}^{-2}$] estimated for the BT and acoustic and combined surveys. Mean s_A values were omitted when the CV exceeded 1.

year	Mean BT	Mean acoustic	Mean combined	CV BT	CV acoustic	CV combined
2004	391.44		662.01	0.16	21.7	0.17
2006			470.41	23.1	27.4	0.16
2007			683.32	24.0	17.1	0.18
2008	274.36		456.95	0.24	20.1	0.16
2009			362.64	16.3	24.6	0.18
2010			635.29	30.7	14.8	0.19
2012			618.23	24.4	31.3	0.16

5.6. Figures

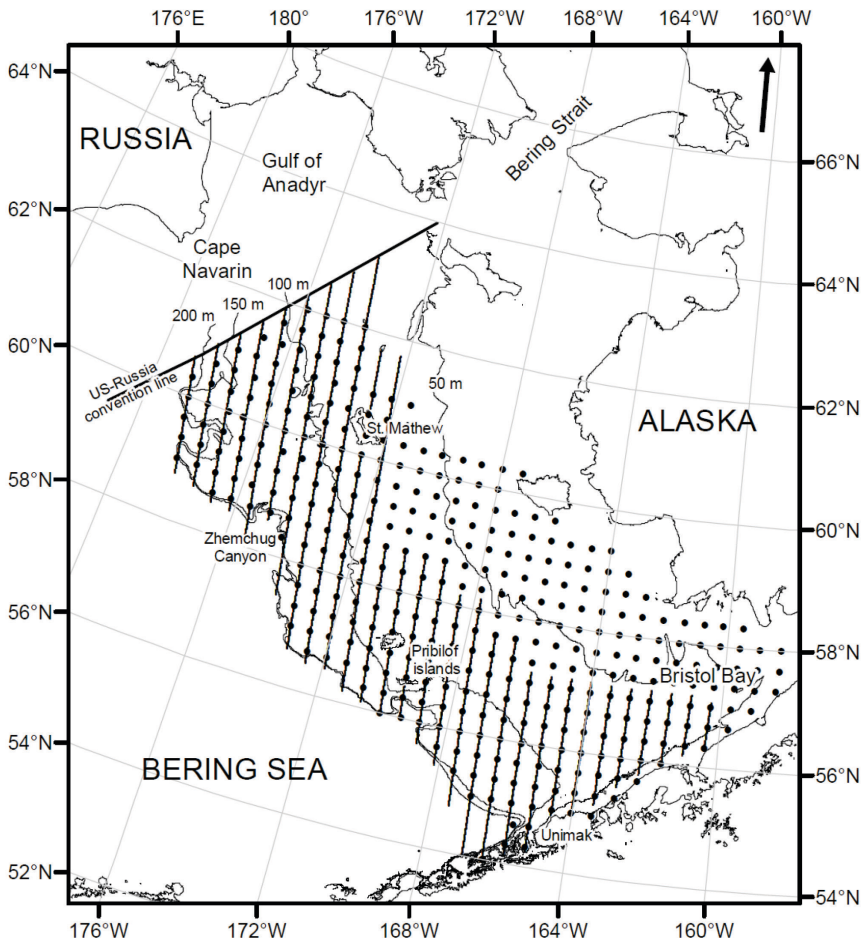


Figure 5.1. BT (points) and acoustic (lines) survey locations.

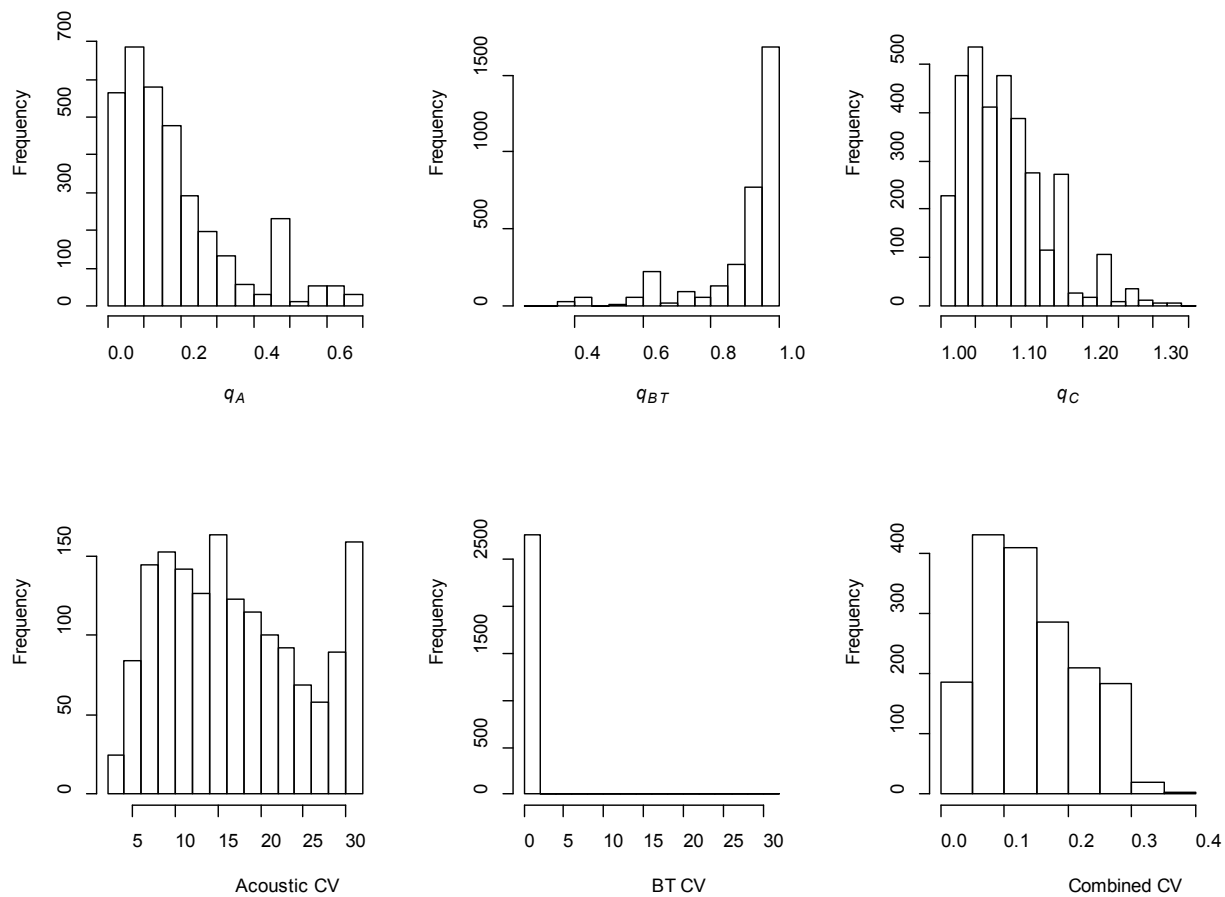


Figure 5.2. Histograms of catchability (top panels) and abundance estimate CVs (bottom panels) for pollock acoustic (first column), bottom trawl (BT; second column) and combined (third column) surveys.

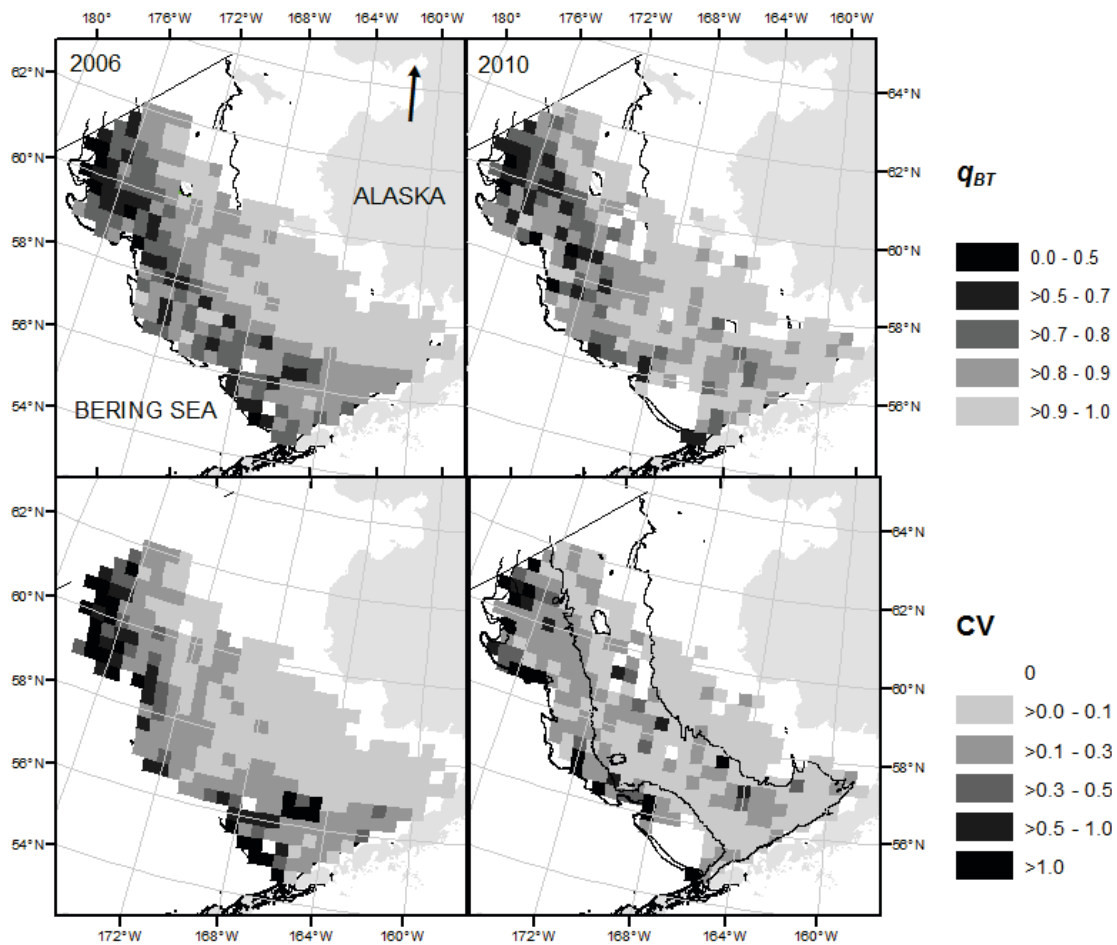


Figure 5.3. Examples of the spatial distribution of bottom trawl catchability (q_{BT} ; top panel) and the CV of abundance (bottom panel) in years 2006 and 2010.

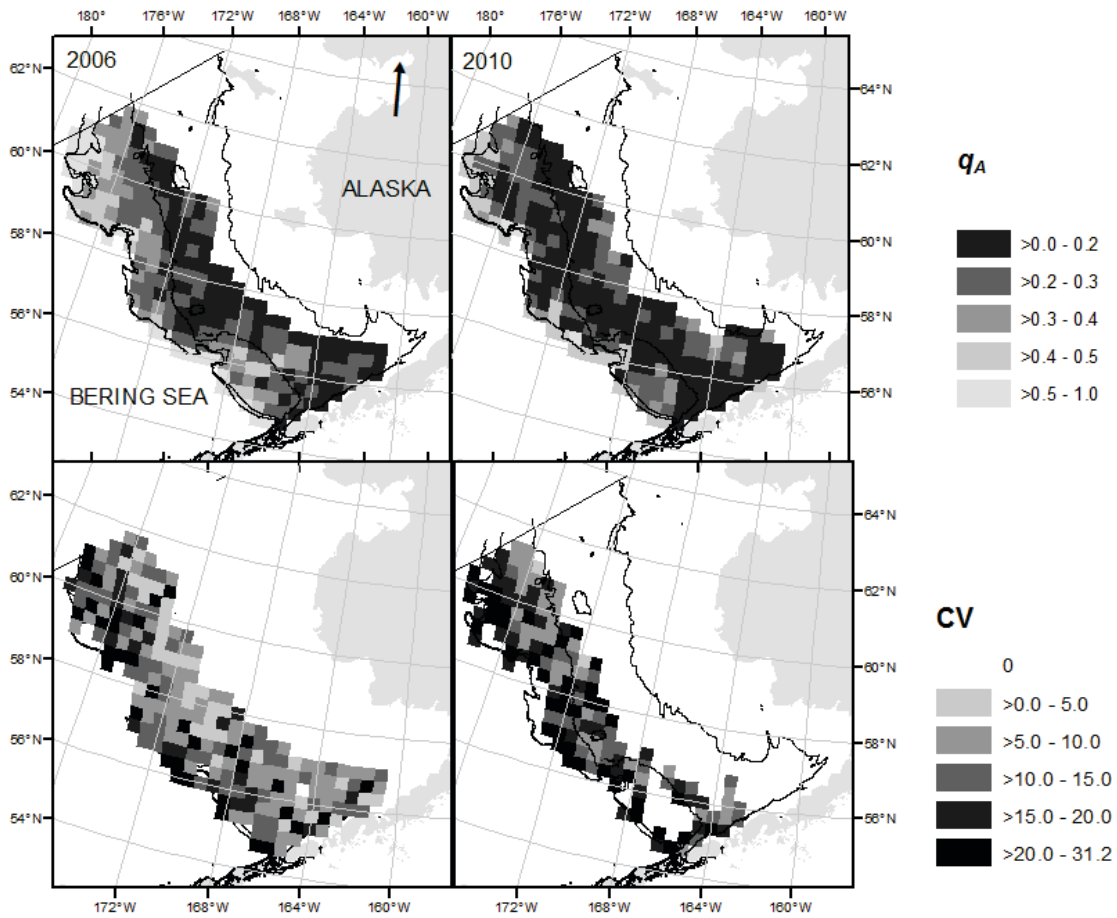


Figure 5.4. Examples of the spatial distribution of the acoustic survey catchability (q_A ; top panel) and the CV of abundance (bottom panel) in years 2006 and 2010.

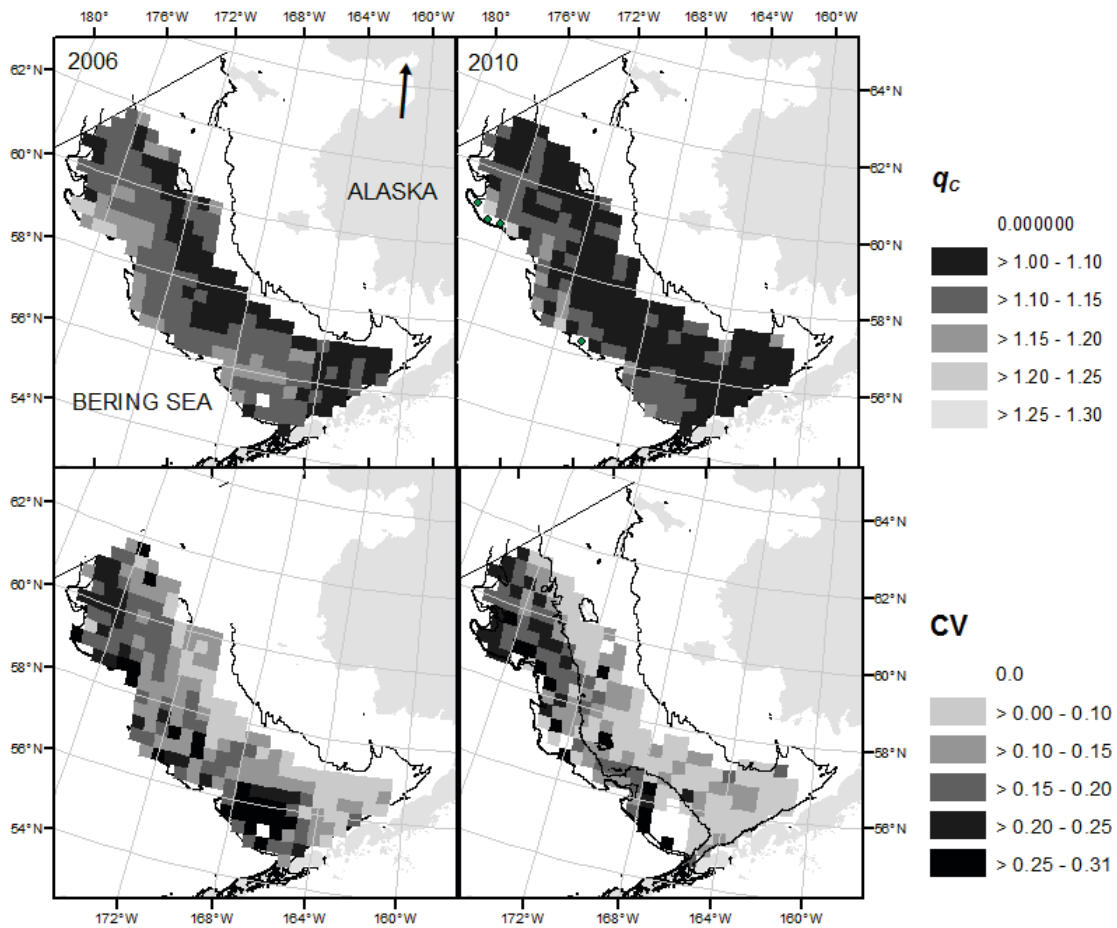


Figure 5.5. Examples of the spatial distribution of the combined surveys catchability (q_C ; top panel) and the CV of abundance (bottom panel) in years 2006 and 2010.

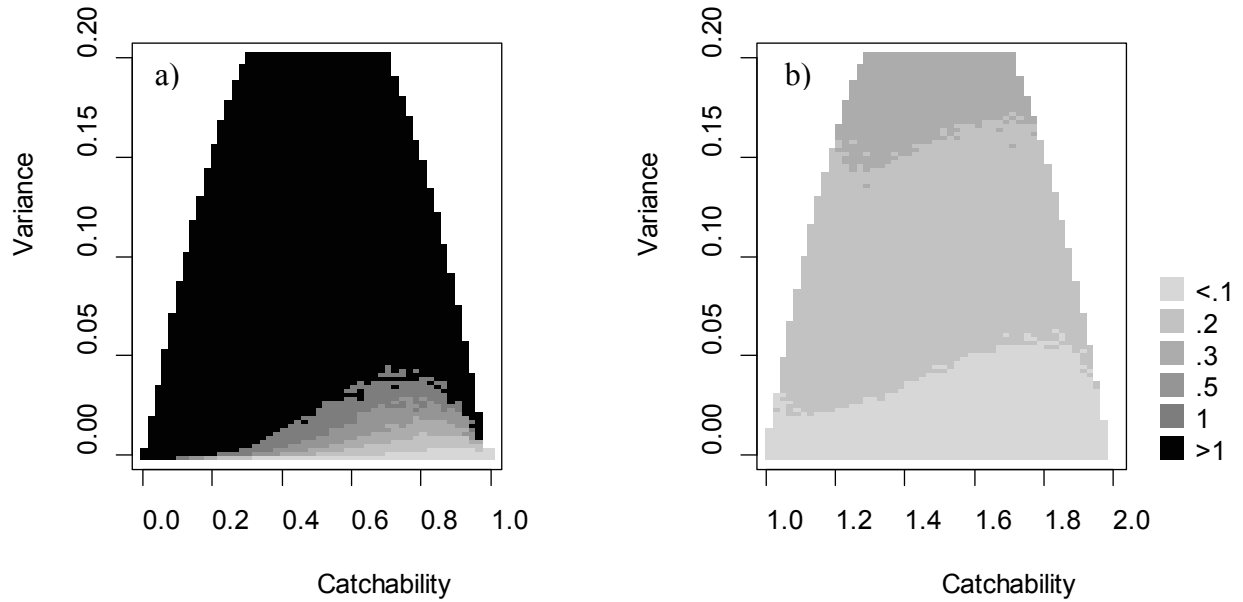


Figure 5.6. Simulated values of abundance estimate coefficient of variation in relation to catchability and variance in catchability. Note that catchabilities between 0 and 1 are representative of the BT and acoustic surveys (left) and catchabilities between 1 and 2 are representative of the combined survey (right).

CHAPTER 6. SUMMARY

6.1. Findings.

The main purpose of this dissertation was to evaluate if combining bottom trawl and acoustic data improves survey-derived abundance estimates of a semipelagic species. In the case of pollock in the EBS, improvements in abundance estimates were achieved in two ways. First, abundance estimates from the BT surveys were corrected for density-dependent BT efficiency using a function derived from acoustic data. Second, whole water column abundance estimates were improved by combining BT and acoustic survey data. Methodology for combining data from the BT and acoustics has been developed in chapters 2-5, and specific findings of each chapter are summarized below.

Chapter 2. Predictions of effective fishing height (EFH), density-dependent trawl efficiency, and the catchability ratio between acoustic and BT gears were obtained by modeling bottom trawl catches as a function of acoustic measurements and an environmentally-dependent, acoustic dead zone (ADZ) correction. The EFH of the BT used in the survey was approximately 16 m, indicating that pollock dive in response to the approaching BT. The estimate of catchability ratio between BT and acoustic gears was 0.96 and not significantly different from 1, indicating that catchabilities of the two surveys are the same. However, catchabilities were comparable only at low densities. Estimates of the density-dependence parameter implied that bottom trawl efficiency decreased with increased pollock densities. It was also found that the commonly used ADZ correction of Ona and Mitson (1996) could lead to large biases in whole water column abundance estimates of pollock in the EBS. Developed here, an experimentally-

derived ADZ correction can improve spatial dynamic studies and ecological modeling by reducing biases in acoustic data.

Chapter 2 confirmed that the detectability of pollock using acoustic surveys and the catchability of pollock by bottom trawl surveys are spatially and temporarily variable. This is an important result because it implies that the assumption of stationary catchability in time and space (Kimura and Somerton 2006) is not appropriate for both types of pollock surveys in the EBS. The violation of this assumption could lead to misleading estimates of abundance trends (Godo 1994), and bias in stock assessment outcomes (Thorson et al. 2013), spatial dynamics studies, and ecological modeling (Kotwicki et al. 2013). Consequently, the findings led to the recommendation: to develop methods for estimating BT and acoustic gear efficiency, and availability to correct survey-derived indices of abundance for variable catchability.

Chapter 3. A method for estimating density-dependent BT efficiency (q_e) as a function of the BT catch rate (u) was developed. A function $q_e \sim f(u)$, was derived using experimentally-derived ADZ correction and bottom trawl efficiency parameters (see chapter 2) obtained by combining a subset of bottom trawl catch data with synchronously collected acoustic data. It was found that q_e decreased with increasing bottom trawl catches, resulting in hyperstability of the abundance index. Density-dependent q_e resulted in spatially and temporarily variable bias in survey CPUE, and biased population age structure derived from the BT survey data. The relationship $q_e \sim f(u)$ was used to correct the EBS BT survey abundance index for density dependence. A variance-covariance matrix was generated for a new abundance index accounting for sampling error, and the uncertainty associated with the estimation of q_e . Incorporating estimates of the new abundance index impacted outputs from the EBS pollock stock assessment model. Although

changes were minor, the result supported incorporating estimates of q_e into the walleye pollock stock assessment to avoid negative consequences of the density-dependent efficiency of the BT.

Chapter 4. Logistic regression models were developed to predict the availability (q_a) of pollock to both acoustic and BT gears in relation to bottom depth, light intensity, fish length, tidal currents, surface and bottom temperature, and sediment size. Results built on previous chapters and quantified uncertainty associated with the estimation of the ADZ correction using Bayesian methods. On average, availability of walleye pollock to the bottom trawl was larger than to the acoustic gear. Availability and variability in availability to both gears depended on bottom depth, light conditions, fish length and, to a lesser degree, sediment size. These findings indicate that pollock catchability of the BT and acoustic surveys in the EBS can vary spatially and temporally, which violates assumption of stationary survey catchability.

Chapter 5. Findings outlined in chapters 2, 3, and 4, were used to obtain combined whole water column abundance estimates from BT and acoustic surveys. The means and coefficients of variation (CV) of the abundance estimates were obtained for all survey 20 x 20 mile grid cells in the EBS where samples from both surveys were taken. Combined estimates accounted for uncertainty in the catchability ratio of both surveys, as well as uncertainty associated with the vertical overlap sampled by both gears. CVs of combined abundance estimates were compared to those obtained for the abundance estimates predicted from BT or acoustic data independently. Lower CV values indicated that combined estimates were more reliable than acoustic survey estimates over the spatial extent of the acoustic survey. Abundance estimates derived from the BT survey were more reliable than combined estimates only in shallow (less than 75m depth)

areas. For pollock in the EBS, combined BT and acoustic abundance estimates were preferable to estimates derived from either survey independently.

6.2. Applications of findings for pollock research in the EBS

Combining BT and acoustic surveys. Combining BT and acoustic survey data produces the most reliable estimates of pollock abundance in the EBS. This finding confirms that both BT and acoustic surveys are needed to assess abundance of pollock in the EBS. Combined estimates incorporate survey process error associated with spatial and temporal changes in catchability. In contrast to a single survey, combined estimates provide abundance estimates of total fish population, and local (i.e. grid cell) abundance estimates corrected for the biases associated with variable catchability. Combined estimates can be improved further by a combined BT-acoustic survey for pollock in the EBS, where BT and acoustic data are collected simultaneously. A combined survey will provide better accuracy and precision in abundance estimates compared to either survey separately, or by combining data from separate surveys. Combined surveys will also provide researchers, who use pollock abundance data, with abundance estimates corrected for spatially and temporally variable catchability in each survey. Corrected data would result in more accurate estimates of spatial and temporal changes in pollock abundance and distribution, and ensure more accurate estimates of uncertainty.

Since 2004, AFSC has been collecting acoustic data during BT surveys. These data have been used to estimate an acoustic vessel of opportunity (AVO) abundance index (Honkalehto et al. 2011; Ianelli et al. 2013). The AVO index represents an alternative to the acoustic survey index in years when the acoustic survey is not conducted. The AVO index is highly correlated with the total abundance index from pollock acoustic surveys (Honkalehto et al. 2011), but lacks length

frequency and age-length data that are used when modeling the demographic structure of the acoustic survey abundance index. To obtain these data during the BT survey fish must be captured above the effective fishing height of the BT, which is difficult to achieve since BT survey vessels are not equipped with the midwater trawls. AFSC is currently carrying out studies to determine the feasibility of capturing midwater fish using the BT, or using camera devices to determine lengths of pollock above the EFH (Williams et al. 2010).

Correcting BT index of abundance for density dependent efficiency. Density-dependent efficiency of the bottom trawl resulted in a hyperstable abundance index when derived using the pollock BT survey data. Stock assessments based on a hyperstable index may fail to track population changes, which could potentially lead to overfishing (e.g., Hutchings 1996; Walters and Maguire 1996; Erisman et al. 2011). To date, it was assumed that the pollock abundance index from the BT survey is proportional to abundance (i.e. not hyperstable; Ianelli et al. 2012). The discovery of hyperstability in this dissertation led to development of a new abundance index that was corrected for the density-dependent efficiency of the BT. This new abundance index was used in the EBS pollock stock assessment in 2013 (Ianelli et al. 2013). The resulting pollock stock assessment model indicated that although the bias caused by hyperstability of the former abundance index was minor (~ 3%), incorporating estimates of density dependent q_e into the walleye pollock stock assessment will avoid biases associated with density-dependent BT efficiency.

Spatial and temporal variation in catchability. Results presented in Chapters 3 and 4 demonstrated that catchabilities of both the BT and the acoustic pollock surveys in the EBS are variable in time and space and depend on fish demographics, environmental variables, and in the

case of the BT survey, density of pollock. It can be inferred from this result that achieving constant catchability in either survey is impossible, regardless of standardization efforts of survey methods (Stauffer 2004). This is a cause of concern, since violation of the constant catchability assumption can lead to errors in stock assessment predictions, estimates of spatial distribution, and ecological modeling. To mitigate problems associated with variable catchability, abundance estimates can be corrected using the three options presented in Chapter 5. For Pollock, the best option is to use combined abundance estimates from BT and acoustic surveys, as they proved to be reliable over the entire survey area. Corrected estimates can be used in future studies of pollock spatial distribution and in the stock assessment. To date only seven years of data are available due to the difficulty in accessing AFSC acoustic data records before 2004.

Additional variance in abundance index. Variance estimates for abundance estimates are needed for stock assessment models so that abundance indices are assigned appropriate statistical weights (Simmonds 2003). This is especially important when multiple abundance indices are used. This dissertation demonstrates that variation in BT efficiency and pollock availability to the BT and acoustic surveys add variability to the abundance index derived from both surveys. Because underestimation of the variability can bias stock assessment outcomes (Thorson et al. 2013), it is important to include this additional variability in pollock abundance estimates. Coefficients of variation (CVs) for the BT abundance estimates obtained in chapter 3 accounted for uncertainty in BT efficiency. These CVs were on average 55% larger than CVs obtained from observation error alone. Including these new CV estimates in the pollock stock assessment model changed its outcome, indicating that not including the contribution of uncertainty in BT efficiency may lead to bias in the stock assessment. Further increase in uncertainty in abundance

indices from both the BT and acoustic surveys can be expected due to variation in availability of pollock to survey gears. As shown in Chapter 5, estimation of variation associated with pollock availability to either the BT or the acoustic survey increases uncertainty in survey-wide abundance indices, due to the uncertainty in availability estimates. In combined estimates, sources of variation in catchability were included and estimates of abundance had high precision, with CVs generally lower than those currently used in the pollock stock assessment (cf. Ianelli et al. 2013). Therefore, it is recommended that combined survey abundance estimates should be used instead of abundance estimates from a single survey. In the future, a combined BT and acoustic pollock survey conducted on the same vessel has the potential to provide the most reliable abundance estimates.

Pollock vertical distribution in the EBS. Near-bottom light levels, depth, and fish length are the most important factors affecting pollock availability to BT and acoustic sampling gears. The average availability of pollock was found to be 0.87 for the BT and 0.22 for the acoustics survey, indicating that pollock in the EBS are more demersal than pelagic. However, pollock tend to behave more like pelagic than demersal species in waters deeper than 150 m, or areas with low light levels (Kotwicki et al. 2009). Young pollock (1-3 years old) also tend to behave more like a pelagic than a demersal species.

The variance explained by predictors in the beta regression availability analyses were approximately 32% and 29% for BT and acoustic gears. Large residual variances suggest that other variables could reduce this residual variability. For example, juvenile pollock (smaller than 22 cm), may shift their vertical distribution to colder waters to conserve energy when food is scarce (Sogard and Olla, 1996). Juvenile pollock have been observed to alter their vertical

distribution to avoid predators (Sogard and Olla, 1993). Olla and Davis (1990) reported that juvenile pollock also move up and down within the water column in response to prey density. Vertical distribution of copepods and euphausiids, major food sources for pollock smaller than 50 cm (Dwyer et al., 1987), may affect pollock q_a . Predator avoidance, prey fields, and weather conditions are also plausible variables that may affect pollock vertical distribution, and consequently their availability to BT and acoustic surveys. These additional variables were not included in this study because no data were available. New data sources and new methods of estimating pollock prey distribution are being developed (e.g. Ressler et al. 2012). These developments will provide data needed to possibly improve predictions of q_a in the future.

6.3 General application to other semipelagic species

This dissertation focused on methods used to assess abundance of pollock in the EBS, but the same methods can be applied to pollock in other areas, or to any other semipelagic species sampled using BT or acoustic surveys. Findings of this dissertation should not be automatically extended to other areas or species because results may differ between species and areas, as specific results will depend on the distribution and behavior of the species under consideration. For instance, this study suggests that pollock may be more demersal than pelagic in the EBS, therefore the BT survey appeared to sample more pollock than the acoustic survey in the majority of the EBS area. This conclusion is valid for pollock in the shallow EBS, but pollock are known to exhibit more pelagic behavior in other regions such as the Sea of Japan (Kooka et al. 1998), the Pacific coast of Hokkaido (Miyashita et al. 2004), or in the Aleutian Basin (Bailey 2011). Applying methods presented in this dissertation can help answer the question which sampling method is most appropriate for a particular area or species.

Methods presented in this dissertation can be also applied to other semipelagic species around the world. Varying availability to BT and acoustic survey gears have caused increased uncertainty in abundance estimates of Atlantic cod and haddock in Norway (Godø and Wespestad 1993; Michalsen 1996). Problems with declining survey BT efficiency with increasing fish density were observed for Atlantic croaker and white perch in Chesapeake Bay (Hoffman et al. 2009), and for capelin off Newfoundland (O’Driscoll et al. 2002). Methodology presented in this dissertation can be used to estimate the magnitude of catchability variation and density-dependence, to correct abundance estimates, and to estimate additional variation caused by these factors.

6.4 Variation in catchability

This dissertation underscores the importance of accounting for survey process error in stock assessments of fish populations. There are two sources of uncertainty associated with abundance indices derived from fishery-independent surveys: within-stratum sampling variability and “additional variability” associated with variation in catchability. The need to account for additional variability in abundance indices has been recognized by other researchers (Punt and Butterworth, 2003; Maunder and Punt, 2004). The results presented in Chapter 3 illustrate that not accounting for variability associated with variation in BT efficiency can bias stock assessment outcomes. One way to account for the additional variability associated with catchability in stock assessment models is to estimate this variability as an additional parameter (Punt et al. 2005). Another option, presented in this dissertation, is to estimate additional variability using posterior distributions of parameters used in catchability estimates. Models

developed in Chapters 2-5 enabled estimation of catchability and its variance for BT, acoustic, and combined methods of estimating abundance.

Catchability is unknown for most fishery-independent surveys, but assumed to be stationary in time and space (Kimura and Somerton, 2006) as survey data are often perceived to be of better quality than fishery data (Harley et al., 2001). Results presented in this dissertation indicate that problems associated with non-stationary catchability in fishery-dependent data (i.e. commercial fishery data) may also occur in survey data (Godø and Engås, 1989; Hilborn and Walters, 1992; Wilberg et al., 2010). Consequently, the assumption of stationary catchability needs to be tested, and the potential for bias associated with variable catchability should be acknowledged in studies using survey- derived abundance estimates. Negative effects of varying survey catchability are not limited to stock assessments, but can also affect results of spatial dynamic studies and ecological modeling. If catchability is dependent on spatially-varying demographic or environmental factors then catchability is confounded with abundance estimates causing bias in spatial dynamic studies, and makes it impossible to resolve species distribution from the distribution of catchability. In such cases, estimates of relationships between environmental variables and fish abundance will be biased. To avoid these biases it is necessary to use estimates of abundance that are corrected for biases associated with catchability such as those derived in Chapter 5.

6.5. Conclusion

Results of this dissertation show that BT and acoustic surveys for semipelagic species can be complementary not only because they sample different parts of the water column but also because they can provide information about biases associated with other sampling gear. For

example, BT data can be used to obtain estimates of fish density and potential abundance estimate bias associated with the ADZ (McQuinn et al., 2005). On the other hand biases in the BT survey can be estimated using acoustic data. It was shown that acoustic data can be used to estimate EFH of the BT and density-dependent efficiency of the BT. Data from the BT can be used to estimate variation in availability of fish to the acoustic gear and vice versa. Combining bottom trawl and acoustic abundance estimates can lead to improved abundance estimates of semipelagic species.

The main conclusion of this study is that combining BT and acoustic survey data can produce the most reliable survey index of abundance, especially when both BT and acoustic data are collected simultaneously. This can be achieved by development of a combined BT-acoustic survey for semipelagic species, where BT and acoustic data are collected throughout the range of the species. A combined survey can provide better accuracy and precision in abundance estimates than can be provided by either survey separately. A combined survey can also provide researchers with abundance estimates corrected for spatially- and temporally-variable catchability of each sampling method. These estimates would improve estimates of spatial and temporal changes in species distribution abundance, and provide more accurate estimates of uncertainty in abundance indices.

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APPENDIX: SUPPLEMENTARY MATERIALS FOR CHAPTER 5.

Parameters for equations [5.8] and [5.13] were obtained by fitting equations to the acoustic survey availability and overlap data (q_{a,A_i} and o_{C_i}) using beta regression (Simas et al. 2010) as described in Kotwicki et al. (*in review*). The final models indicated that:

$$q_{a,A_i} \sim \text{BL} + \text{BD} + \text{PP} + \text{FL} + \text{factor}(\text{year}) \quad [\text{A1}]$$

$$\emptyset_{a,A_i} \sim \text{BL} + \text{BD} + \text{PP} + \text{FL} + \text{factor}(\text{year}) \quad [\text{A2}]$$

and

$$o_{C_i} \sim \text{BL} * \text{BD} + \text{BT} + \text{FL} + \text{factor}(\text{year}) \quad [\text{A3}]$$

$$\emptyset_{C_i} \sim \text{BL} * \text{BD} + \text{PP} + \text{FL} + \text{factor}(\text{year}) \quad [\text{A4}]$$

where BL is near-bottom light, BD is bottom depth, FL is the mean fork length of pollock, PP is sediment size, and BT is bottom temperature.

To validate appropriateness of models assumptions diagnostics were performed using residual analyses that included: scatter plots of standardized residuals versus predicted values, histograms of standardized residuals, normal Q-Q plots, and standardized residuals versus predictors.

Variance inflation factors (VIF) were calculated for all linear terms in the final models to quantify the effects of possible multicollinearity in linear predictors (Kutner et al., 2004).

Diagnostic plots (Figure A1) indicated that the assumption of beta distributed error was appropriate. There were no apparent trends in residuals based on visual examination of plots of standardized residuals against all predictors (Figures A2 and A3). Estimates of VIFs were in the

range of 1-2 (Table A1), indicating that multicollinearity of predictor variables had a small impact on inflating variance around predictor parameters (Kutner et al., 2004).

Table A1. Variance inflation factors for models [A1] and [A3].

Model	BL	BD	FL	PP	BT
A1	1.14	1.50	1.21	1.67	NA
A3	1.13	1.19	1.06	NA	1.05

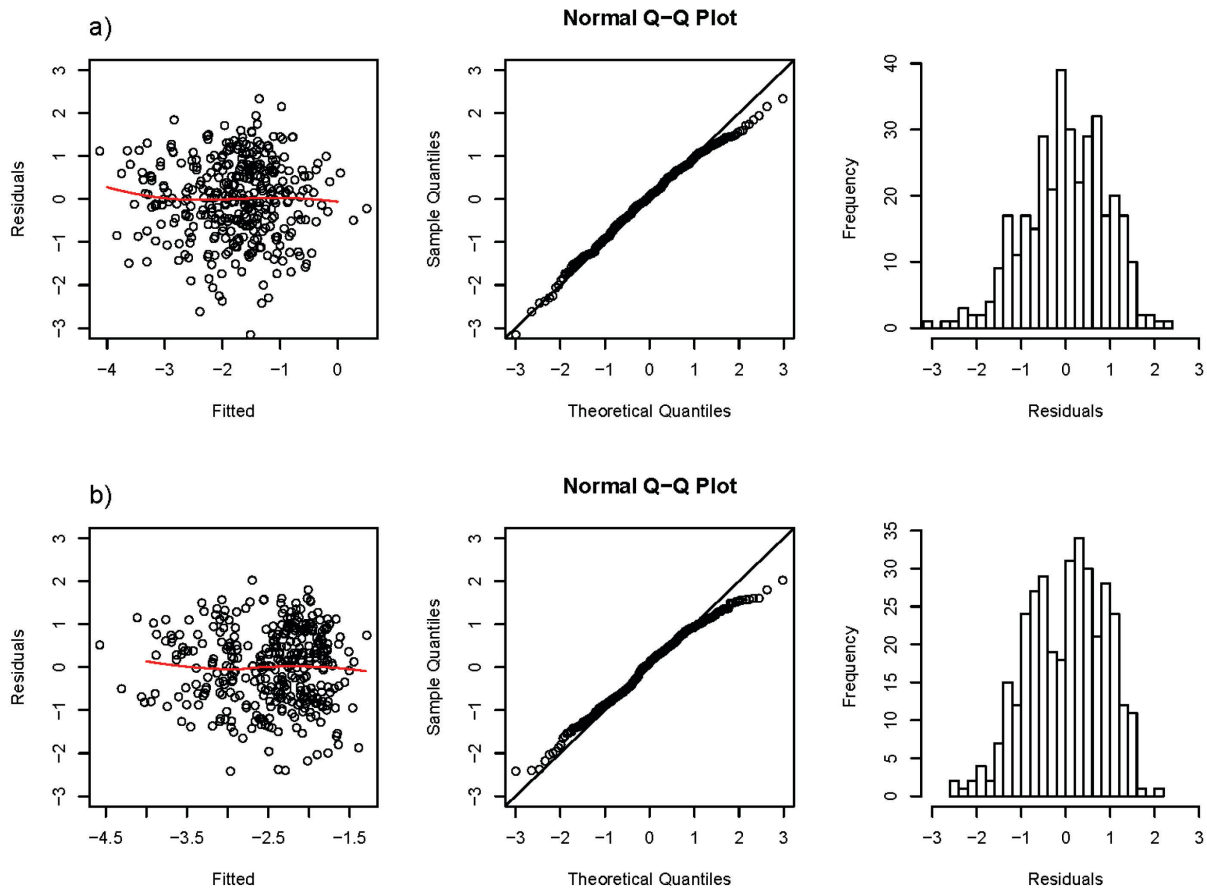


Figure A1. Plots of residuals vs. fitted values, normal Q-Q plots, and histograms of residuals for models A1 (a) and A3 (b).

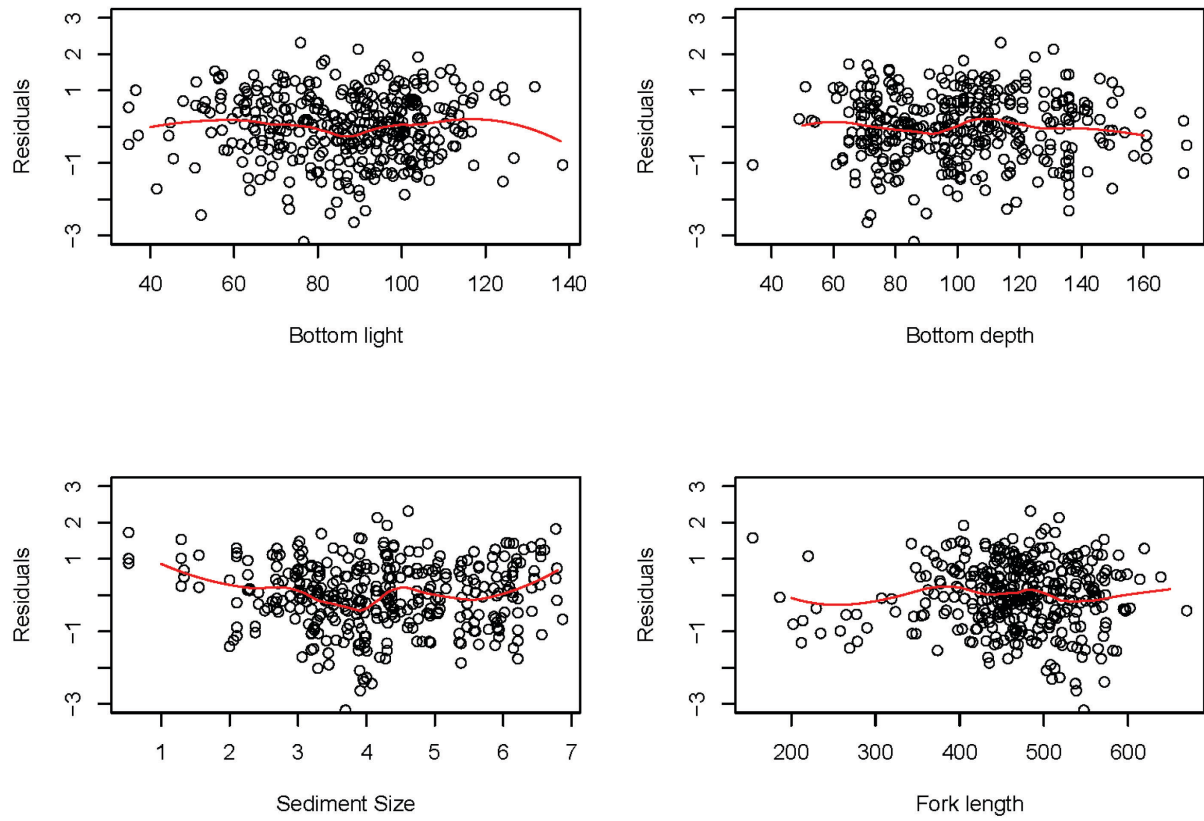


Figure A2. Plots of the residuals against linear predictors for model A1.

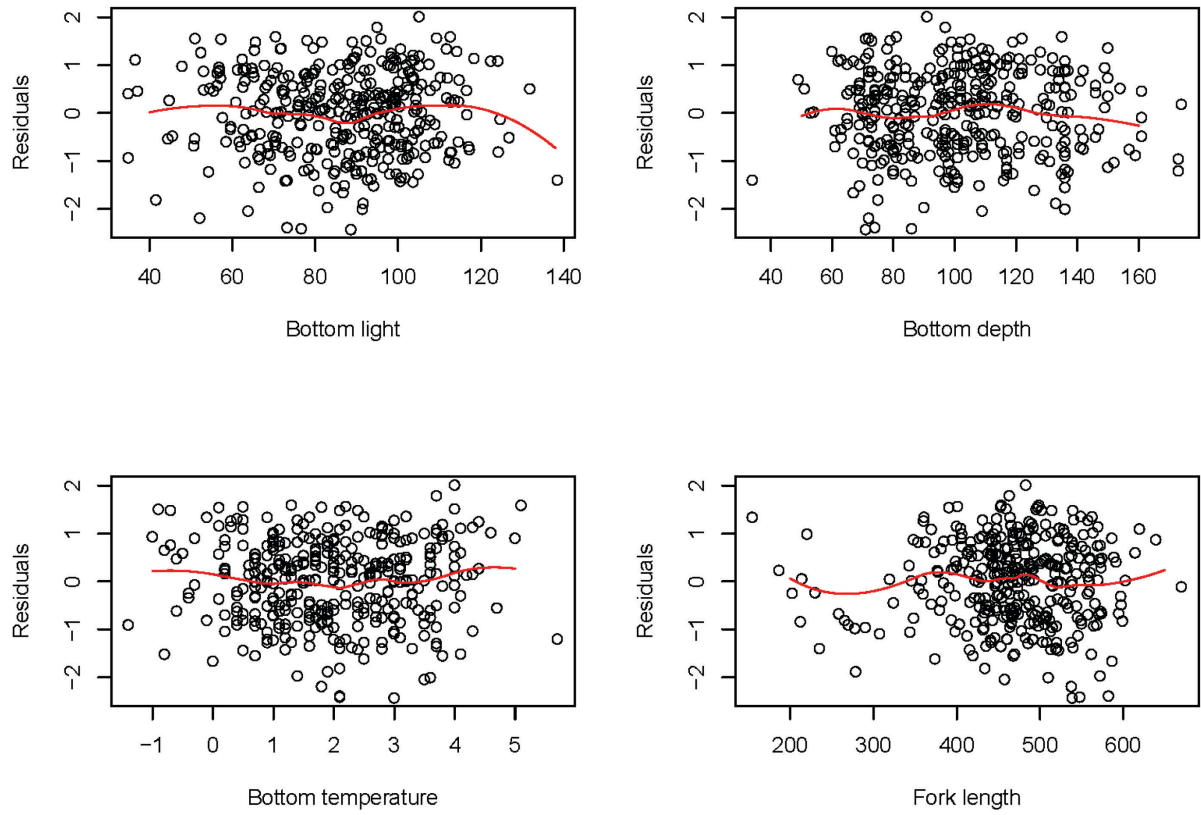


Figure A3. Plots of the residuals against linear predictors for model A3.