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<table>
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<tr>
<th>Journal:</th>
<th>Canadian Journal of Fisheries and Aquatic Sciences</th>
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<tr>
<td>Manuscript ID</td>
<td>cjfas-2016-0362.R2</td>
</tr>
<tr>
<td>Manuscript Type:</td>
<td>Article</td>
</tr>
<tr>
<td>Date Submitted by the Author:</td>
<td>31-Jan-2017</td>
</tr>
<tr>
<td>Complete List of Authors:</td>
<td>Kotwicki, Stan; National Marine Fisheries Service - NOAA, Ressler, Patrick; National Marine Fisheries Service - NOAA Ianelli, James; Alaska Fisheries Science Center, Punt, André; University of Washington, School of Aquatic and Fishery Sciences Horne, John K.; University of Washington,</td>
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<tr>
<td>Keyword:</td>
<td>fishery survey, abundance estimates, bottom trawl, acoustic-trawl survey, Walleye pollock</td>
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Title:

Combining data from bottom trawl and acoustic surveys to estimate an index of abundance for semipelagic species.

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Abstract

Fishery-independent surveys are useful for estimating abundance of fish populations and their spatial distribution. It is necessary in the case of semipelagic species to perform acoustic-trawl (AT) and bottom-trawl (BT) surveys to assure that sampling encompasses both midwater and demersal components of the population. Abundance estimates from both survey types are negatively biased because of the blind zones associated with fish vertical distribution. These biases can vary spatially and temporally, resulting in confounded trends and additional variation in abundance estimates. To improve abundance estimates for semipelagic species we propose a new method for combining BT and AT survey data using environmental variables to predict the vertical overlap. On an example of pollock AT and BT surveys in the eastern Bering Sea we show that combined estimates provide more reliable whole water column and spatial distribution estimates than either survey can by itself. Although the combined estimates are still relative they account for the uncertainty in the bias ratio between two survey methods and uncertainty associated with the extent of the water column sampled by both surveys. Our method of combining BT and AT data can be extended to other semipelagic species.

INTRODUCTION

Fishery-independent surveys can be useful for estimating the abundance of fish populations and describing their spatial distribution, if the survey results are reliable (both accurate and precise in detecting changes in fish abundance; Hilborn and Walters 1992). Abundance indices from fishery-independent surveys are generally considered more reliable than fishery-dependent indices (Maunder and Punt 2004). However, reliability is difficult to assess when the survey does not cover entire extent of the stock. This is often the case with surveys of semipelagic species,
which occupy both benthic and pelagic habitats. It is prudent to perform both bottom trawl (BT) and acoustic-trawl (AT) surveys to assess the abundance of such species so that sampling encompasses both the midwater and demersal components of the population (e.g., Karp and Walters 1994). However, since 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), water currents (e.g. Stensholt et al. 2002), and predator distribution (Massé 1996; Rose 1993), the relative proportion of fish detected by the two surveys will vary in space and over time (e.g. Lawson and Rose 1999; Petrakis et al. 2001; Kotwicki et al. 2015), resulting in additional uncertainty in the indices of abundance derived from both BT and AT surveys.

Trends in abundance estimates derived from BT and AT surveys of a stock can differ (Godø and Wespestad 1993), and they are usually treated as independent indices of abundance in stock assessment models (Ianelli et al. 2012). It has been proposed that combining estimates from BT and AT surveys would provide more reliable abundance indices for stock assessments and other studies (Godø and Wespestad 1993; Hjellvik et al. 2007). In practice, combining such estimates is challenging because the availability (i.e. a proportion of fish from the whole water column available the survey gear) to both surveys is variable in time and space (Hovgård and Riget 1992; Engås and Soldal 1992; Hjellvik et al. 2003; Aglen 1996; Kotwicki et al. 2015). Availability to the AT and BT surveys depends on the proportion of fish present in the acoustic dead zone (McQuinn et al. 2005) and the inability of the BT to sample above the effective fishing height (EFH; Fig. 1; Aglen 1996; Hjellvik et al. 2003). Additionally abundance estimates from AT and BT surveys have different sources of uncertainty. For example, AT survey abundance estimates
can be affected by errors associated with the estimation of the fish target strength (Traynor 1996). BT survey abundance estimates can be affected by varying sampling efficiency (Somerton et al. 1999) and possible density-dependent effects on the efficiency (efficiency is defined as the ratio of the number of fish caught by the BT to the number of fish present in path of the trawl prior to the capture; O’Driscoll et al. 2002; Hoffman et al. 2009; Kotwicki et al. 2014) of the BT gear.

We propose a new conceptual approach to combining BT and AT survey data to obtain relative distribution and abundance estimates for walleye pollock (*Gadus chalcogrammus*; hereafter referred to as pollock) in the eastern Bering Sea (EBS). Combined abundance estimates that take account of the variable availability of each survey have great potential to improve the accuracy and precision of the fishery-independent information used in stock assessments for pollock (Godø 2003; Kotwicki et al. 2015). Our method uses previously reported estimates of the bias ratio between AT and BT data (*r*ₚ) and EFH (Kotwicki et al. 2013), as well as a new method to estimate vertical overlap in pollock distribution between AT and BT data (hereafter referred to as “overlap”), thereby allowing estimation of the reliability of the combined survey index.

**METHODS**

*Conceptual model*

Survey estimates of the whole water column abundance of pollock at each survey grid cell (hereafter referred to as “grid cell abundance”; see subsection “Pollock density data” for details on these estimates) can be modeled as:

\[
\hat{A}_{C_l} = \frac{A_{C_l}}{q_{C_l}},
\]  

[1]
where $\hat{A}_{C_i}$ is predicted whole water column abundance at location $i$, $q_{C_i}$ is the “availability” or proportion of fish from the whole water column available to the combined survey, and $A_{C_i}$ is the observed water column abundance derived from BT and AT surveys as follows:

\[
A_{C_i} = A_{BT_i} + r_q A_{AT_i}, \tag{2}
\]

where $A_{BT_i}$ and $A_{AT_i}$ represent observed pollock abundance at grid cell $i$ from the BT and AT surveys respectively and $r_q$ is the bias ratio between the BT and AT survey abundance data (formerly referred to as the “catchability ratio” and estimated in Kotwicki et al. (2013) based on the differences in biases associated with each survey method). $A_{BT_i}$ and $A_{AT_i}$ were estimated in acoustic backscatter units and averaged over survey grid cells (see Kotwicki et al. 2013; Honkalehto et al. 2013 for details). According to the conceptual depiction of sampling processes (Fig. 1), all fish present in the water column are assumed to be observed by either one or both of the surveys resulting in the proportion of fish observed equal to 1 or above because the combined sum of surveys is a sum of partly overlapping observations.

Availability of the combined estimate is defined as:

\[
q_{C_i} = 1 + o_{C_i} \tag{3},
\]

where $o_{C_i}$ is the vertical overlap between the two survey methods (the proportion of fish present in the vertical layer between 3 m above the seafloor and an EFH of 16 m above the seafloor; Kotwicki et al. 2013). The 3 m above the seafloor cut off was used because standard AT survey procedures restricted scrutinizing of pollock backscatter data to 3 m above the detected seabed (Honkalehto et al. 2011; Lauffenburger et al. 2016). To estimate the $o_{C_i}$ (and thus $q_{C_i}$) for each survey grid cell we developed a model predicting $o_{C_i}$ as a function of environmental predictor...
variables (e.g. light intensity, temperature) and pollock mean length. The minimum value of $q_{ci}$ is 1, when no fish were present in the zone between 3 m and the effective fishing height (i.e. in the overlap zone) and each survey detects a separate, additive portion of the whole water column pollock abundance. The maximum value of $q_{ci}$ is 2, where all fish in the water column were within the overlap zone and were fully detected by both surveys.

*Pollock density data*

Acoustic and BT abundance data were collected during BT and AT surveys of the EBS shelf conducted by researchers at the Alaska Fisheries Science Center (AFSC) during summers 2004 and 2006-2012 using standard methods. The surveys were conducted on different vessels during these years, but at approximately the same time (i.e., each survey grid cell was sampled by both surveys within the same two-week period). Both surveys were conducted exclusively during daylight hours to avoid a diel bias in catchability. The EBS BT survey was conducted over a standard grid of stations located at the centers of a $37 \times 37$ km ($20 \times 20$ nautical mile) grid (Fig. 2; Lauth and Nichol 2013). The BT surveys were conducted using a standardized trawl gear (the 83-112 Eastern otter trawl), beginning in the eastern edge of the area (Bristol Bay) and proceeding westward. Standard BT tow duration was 30 minutes on bottom at a tow speed of approximately 1.54 m s$^{-1}$ (i.e. 3 knots; see Lauth and Nichol 2013 for details). During the AT survey (see Honkalehto et al. 2013 for details), acoustic data were collected at 38 kHz using a Simrad EK60 scientific echosounder to estimate pollock abundance along transects designed to approximately coincide with the north-south lines of BT survey stations. The exact location of these transects was changed by a small, random distance each year per recommended acoustic survey practice (Simmonds and MacLennan 2005). Trawling was conducted to confirm species identities, determine fish length distributions, and collect other biological information to convert
the acoustic data to estimates of fish abundance. Trawl samples were collected primarily using a
midwater trawl (Aleutian Wing Trawl) and occasionally the 83-112 Eastern otter bottom trawl.
Approximately 100 midwater trawls were conducted during each AT survey, and approximately
95% of the catch weight was pollock. The acoustic equipment was calibrated two to four times
during each cruise using the standard sphere method (Foote et al. 1987).

For the purposes of this study, pollock density $A_{BT,i}$ and $A_{AT,i}$ 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, $m^2 \text{ nmi}^{-2}$; MacLennan et al. 2002) from both BT and AT surveys. For
the BT stations, a swept-area method (e.g. Alverson and Pereyra 1969) was used to estimate
pollock density from the BT catch, accounting for distance fished (as indicated by a bottom
contact sensor; Somerton and Weinberg 2001) and average distance between wing tips
(measured using Netmind (Reference to the trade names does not imply endorsement by the
survey density estimates in kg ha$^{-1}$ were then transformed into equivalent $s_A$ ($m^2\text{ nmi}^{-2}$; measure
of abundance proportional to biomass) by multiplying the number of pollock at each length by
the expected backscatter per fish obtained from a target strength-length model (Traynor 1996)
and then summing the results over all lengths (see Mackinson et al. 2005; Doray et al. 2010;
Kotwicki et al. 2013). Equivalent $s_A$ estimates per length were needed because the relationship
between $s_A$ and biomass changes as a function fish length. BT density data were corrected for
density-dependent efficiency ($q_{e,BT,i}$; described in Kotwicki et al. 2014), resulting in the BT
survey density estimates ($A_{BT,i}$). For AT surveys, pollock $s_A$ measured between 3m off bottom
up to 16 m below the surface in 0.5 nmi (926 m) along-transect intervals were averaged within
each BT survey grid cell, resulting in a single acoustic density estimate for each survey grid cell 
\((A_{AT_l})\).

**Predictor variables for overlap**

Modeling of BT and AT survey overlap \(o_{C_l}\) as a function of environmental conditions and 
pollock mean length was conducted in a manner similar to the modeling of the availability to BT 
and AT surveys by Kotwicki et al. (2015). The \(o_{C_l}\) can be expressed as:

\[
o_{C_l} = \frac{1}{1 + e^{-(\alpha_C + \gamma_C X_i)}}[4]
\]

where \(\alpha_C\) is an offset parameter, \(\gamma_C\) is a vector of parameters, \(X_i\) is a matrix of the predictor 
variables. \(o_{C_l}\) was assumed to be beta-distributed with variance:

\[
V_{o_{C_l}} = \frac{o_{C_l}(1-o_{C_l})}{1+\varnothing}[5]
\]

where \(\varnothing\) is a precision parameter linked to \(X_i\) (using “identity” link; 
Simas et al. 2010), allowing the variance of the response variable to depend on predictors.

Parameter values were obtained by fitting equations [4 and 5] to \(o_{C_l}\) data (i.e. proportion of \(s_A\) 
between 3m and EFH to the sum of total water column \(s_A\) and acoustic dead zone correction) and 
predictor variables obtained during a subset of the BT survey tows in years 2005-2009 (see 
Kotwicki et al. 2013 for details). Environmental data from the BT survey were used in modelling 
overlap for both surveys, as we assumed that these data reasonably represented environmental 
conditions. Environmental data included: near-bottom and surface water temperatures, average 
bottom depth, near-bottom light levels, sediment size, and tidal current speeds (see Kotwicki et
al. 2015 for details on environmental data collection). Mean fish length was calculated from length frequency data obtained from BT catch samples.

Backward model selection for equations [4] and [5] was performed by removing model terms one by one using Akaike’s information criterion corrected for finite sample size (AICc; Burnham and Anderson 2010). Since both $o_{C_{i}}$ and $\emptyset$ were linked to predictor variables in the beta regression models, the term with the greatest reduction in AICc was removed from one of the linkages at a time. Estimated parameters $a,$ and $\gamma$ and predictor data 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, so simplified models with fewer predictors were refitted to the data and used for predictions of $o_{C_{i}}$ in these rare (< 1% of 20,000) cases.

Residual analysis was used to evaluate the appropriateness of model assumptions (see supplemental materials). Correlations and 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).

Indices of abundance

Survey wide indices of abundance for AT and BT surveys were limited to the area common to both surveys and were estimated over all grid cells using formulas:

$$\bar{A}_S = \frac{\sum_i A_{S_i}}{n},$$  \hspace{1cm} [7]

$$\sigma_S^2 = \frac{\sum_i (A_{S_i} - \bar{A}_S)^2}{n-1},$$  \hspace{1cm} [8]

where index $S$ indicates either $AT$ or $BT$. 

9
Likewise, the survey wide combined index of abundance ($\bar{A}_C$) and its variance $\sigma^2_C$ from all grid cells were computed using the formulae:

$$\bar{A}_C = \frac{\sum_i \hat{A}_{Ci}}{n},$$  \hspace{1cm} [5]$

$$\sigma^2_C = \frac{\sum_i (\hat{A}_{Ci} - \bar{A}_C)^2}{n-1}. \hspace{1cm} [6]$$

$\bar{A}_C$ and $\sigma^2_C$ were calculated 1,000 times using samples from posterior distribution (see following section for details) for $\hat{A}_{Ci}$ and means from these 1,000 replicates used as the basis for the mean estimate of the combined index of abundance and its variance. All three indices of abundance were compared relative to the long term mean of each index. Proportions of abundance detected by each index were also compared.

Propagating uncertainty

Uncertainty in the combined pollock abundance index $\hat{A}_{Ci}$ is associated with the estimation of $A_{BTi}$, $A_{ATi}$, $r_q$, and $q_{Ci}$. Markov chain Monte Carlo (MCMC) derived posterior distributions for $A_{BTi}$ and $r_q$ for each station were available from Kotwicki et al. (2014). The sample of the posterior distribution for $\hat{A}_{Ci}$ at each grid cell was obtained using a two-stage re-sampling process. First, a sample was drawn from the MCMC-derived $A_{BTi}$ and $r_q$ vectors, then 1,000 replicate values were drawn from beta distributed $o_{Ci}$, resulting in 1,000 samples from the posterior distribution for $\hat{A}_{Ci}$. The results were then used to calculate means and coefficients of variation (CV) for each $\hat{A}_{Ci}$ according to Equations [5] and [6].

Because the CV of the index of abundance is likely to depend on the mean and the variance of predicted availability, a simulation study was performed to illustrate the effect of the beta-
distributed availability on the CVs of the grid cell abundance estimates. The simulation resampled 1,000 times from each combination of mean and variance of plausible values of availability. Values between 0 and 1 are plausible for the BT and AT surveys. Values between 1 and 2 are plausible for the combined survey. Expected values for availability and its variance for the AT and BT surveys were obtained from Kotwicki et al. (2015). Plausible availability distributions were defined as mean values of availability between 0 and 2 and variance between 0 and 0.2. Contour plots of simulated CV values were overlaid with scatter plots of predicted values of availability vs. variance for AT, BT, and combined abundance estimate. This overlay allowed for comparison of expected CVs of the grid cell abundance estimates between these three methods.

Results

Model diagnostics

The diagnostic plots (supplemental materials; Fig. S1) indicated that the assumption of beta distributed error was not inappropriate. There were no apparent trends in residuals based on visual examination of plots of standardized residuals against all predictors. All correlations between predictors were relatively low (between 0.02 and 0.54). Estimates of VIFs were in the range of 1-2, indicating that multicollinearity of predictor variables had a small impact on inflating variance around predictor parameters.

Predictions of combined AT and BT availability

Variable selection resulted in the following final beta regression models for \( o_{ct} \):

\[
o_{ct} \sim BL \times BD + BTemp + FL + \text{factor(year)}
\]  

[7]
\[ \Phi_{C_i} \sim BL \times BD + PP + FL + \text{factor(year)} \]  

where BL is near-bottom light, BD is bottom depth, FL is the mean fork length of pollock, PP is sediment size, and BTemp is bottom temperature (Table 1). The interaction of BL × BD in the \( \sigma_{C_i} \) model implied a non-linear relationship between these variables and \( \sigma_{C_i} \). In general this interaction indicated higher values of \( \sigma_{C_i} \) in the bright and deep conditions and lower values of \( \sigma_{C_i} \) in shallow waters (Fig. 3a). Modeling also detected a significant BL × BD interaction on \( \Phi_{C_i} \), indicating an increase in variance in the predictions of \( \sigma_{C_i} \) in the bright and deep conditions (Fig. 3b). The predicted \( \sigma_{C_i} \) and variance in \( \sigma_{C_i} \) increased with increase in bottom temperature (Fig. 3c) and with decreased pollock size (Fig. 3d). Sediment size did not have significant effect on the prediction on \( \sigma_{C_i} \) but it affected its variance (Fig. 3e).

Modeled \( \sigma_{C_i} \) led to estimates of \( q_{C_i} \) between 1 and 1.35 (mean = 1.094; among-cell standard deviation = 0.051). The \( q_{C_i} \) estimates varied spatially and temporarily, and were relatively lower in locations shallower than 100 m (Fig. 4, upper panels). 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. The CVs for the \( \hat{A}_{C_i} \) ranged between 0.05 and 0.31 (Fig. 4, lower panels). The spatial distribution of the CVs indicated that uncertainty in the \( \hat{A}_{C_i} \) estimates was generally higher in waters deeper than 100 m and lower in shallower waters. There was inter-annual variation in CVs due to the year effect and predictor conditions such as bottom light, temperature, and fish length varying among years.

CV sensitivity simulations indicated that the reliability of a grid cell abundance estimate depends on availability and its variance. Water column abundance estimates become less reliable as
availability decreases and variance in availability increases. For example, availability must be > 0.4 and the variance of availability must be lower than 0.04 to obtain an abundance estimate for a cell with a CV < 1 (Fig. 5a). High precision in availability is required to produce abundance estimates with CVs < 1 when mean availability is < 0.4. The level of precision in the AT survey availability estimates was poorer in general than for BT survey availability. For combined abundance estimates, the survey availability estimates were always ≥1, because of the overlap zone, which is sampled by both survey methods. Simulation for the values of availability > 1 (representative of combined estimate; Fig. 5b) indicated that CVs of abundance estimates were less dependent on the precision in availability compared to the CVs expected from either survey. Hence, the simulations indicated that we can expect generally lower CVs with combined abundance estimates than with estimates from either survey regardless of the degree of overlap and the uncertainty associated with the estimate of the overlap.

Pollock distribution

Estimates of $A_{BT_i}$, $A_{AT_i}$ and $A_{C_i}$ were plotted on maps to compare spatial distribution of pollock in the EBS as detected by BT, AT, and combined methods (Fig. 6). Comparison of distribution maps between combined and single survey estimates often (but not always) indicated large differences in pollock distribution as detected by the BT and AT methods, demonstrating that neither survey by itself is able to provide distribution information on entire extent of the pollock population in the EBS. For example, the AT survey consistently missed pollock in the shallow areas of the EBS, while the BT survey often missed pollock in the deeper areas, and the AT survey generally detected more pollock in the northern areas, while the BT survey detected more pollock in the south. There was also large interannual variability in the areas where most pollock was detected by each survey. For example, the BT survey detected more pollock in the middle...
part of the surveyed area in 2006, while AT survey detected higher pollock densities in the north in 2008.

Survey-wide indices of abundance

Interannual variation in the combined index of abundance was similar to that detected by both AT and BT indices, in most years falling between the AT and BT indices of abundance (Fig. 7). The CVs of mean abundance index from combined surveys ranged from 0.16 to 0.19. The proportion of pollock detected by either single survey varied from 26-47% for AT and 61-83% for BT surveys (Fig. 8). The proportion of pollock in the overlap zone varied from 4 to 11%.

Discussion

Pollock distribution and survey grid cell abundance

Our study represents a first attempt to estimate whole water column relative abundance from combined BT and AT survey data to obtain distribution and abundance of pollock in the EBS. The maps of $A_{BT_i}$, $A_{AT_i}$, and $A_{C_i}$ (Fig. 6) indicated that BT and AT survey methods failed to correctly detect the entire extent of pollock spatial distribution in the EBS, due to large gaps in areas where pollock was not available to one of the surveys. It is impossible to distinguish between true and false zeros in the case of a single survey (either AT or BT). Combined estimates at the survey grid cell resolution provide a more comprehensive picture of pollock distribution in the EBS because they include all the areas where pollock were present, assuring that all pollock in the water column are accounted for by at least one of the surveys (Fig. 1). In other words, combining BT and AT survey methods results in the elimination (or substantial reduction) of blind zones and it assures sampling the entire spatial extent of pollock distribution.
CV sensitivity simulations indicated that the reliability of a grid cell abundance estimate depended on the value of the availability and its variance. Water column abundance estimates obtained from either AT or BT are likely to be less reliable than combined estimates because availability of each survey is <1, while $q_{C_l}$ is always >1 (Fig. 5). Moreover, from the simulations it is apparent that even highly uncertain estimates of $q_{C_l}$ will likely lead to acceptable abundance estimates with CV <0.3. In the case of either single survey, CVs <0.3 are very difficult to obtain as they require both high values of availability as well as high precision in the estimate of availability. Estimates of availability from Kotwicki et al. (2015) indicate that obtaining CVs <0.3 for the water column abundance estimates is likely to be impossible for the AT survey, due to low availability in many parts of the surveyed area. It may be possible for the BT survey, but only at a limited number of survey grid cells where availability is high (e.g. for large fish in shallow and bright areas; Fig.5 in Kotwicki et al. 2015).

It is necessary to have some form of the estimate of the $o_{C_l}$ [equation 3] to obtain estimates of $\hat{A}_{C_l}$ [equation 1]. However our simulation results indicate that the high precision of the $o_{C_l}$ is not necessary, supporting the conclusion that the existence of the vertical overlap zone between coverage of the two surveys is a smaller problem than existence of blind zones for AT and BT surveys. In this study we obtained $o_{C_l}$ predictions from a beta regression model using a large set (355 hauls) of highly scrutinized acoustic data collected synchronously with the BT data (from Kotwicki et al. 2013) and a set of predictor variables collected at the same time. This procedure required a large amount of effort, which may appear as prohibitive in applying this method to other semipelagic species. However, our results indicate that regardless of the precision in estimation of $o_{C_l}$, combining BT and AT data is likely to produce more precise water column...
abundance estimates than a single survey. Even a small set of simultaneously collected AT and BT data could be used to obtain some rough estimates of $\alpha_{C_l}$. The same appears to be true for the estimates of EFH of the BT gear, which is necessary to estimate $\alpha_{C_l}$. In this study we used the estimate of EFH = 16m from Kotwicki et al. (2013). They reported 95% confidence intervals obtained from a likelihood profile to be between 12 and 20m, but in the present analyses we ignored this variability because it had small impact on overall estimates of $\alpha_{C_l}$ (i.e. at 12 m average overlap was approximately 8.2 %, while at 20 m average overlap was 10.3% of the whole water column abundance).

The most important parameter needed to obtain $\hat{A}_{C_l}$ is the bias ratio ($r_q$) used in equation [2]. Formerly this parameter was referred to as catchability ratio (Kotwicki et al. 2013). However we find the term “bias ratio” to be preferable because $r_q$ accounts for biases associated with differences in sampling efficiency between the AT and BT survey methods within the vertical layer sampled by each method. Sampling efficiency of the AT survey depends on multiple factors such as: the target strength ~ length relationship (Traynor 1996), calibration error (Foote 1987), fish behavior in response to approaching vessel (e.g. change in tilt; Jech and Horne 2002), or vessel avoidance (De Robertis et al. 2008). Sampling efficiency of the BT survey depends on horizontal and vertical herding by the BT (Somerton et al. 1999) and escapement: through the meshes (Williams et al. 2010), under the footrope (Kotwicki et al. 2005), or by out swimming the net (Weinberg et al. 2002). These effects result in biases in abundance estimates, which are specific to each survey. The biases of each survey index, as long as they remain constant, are considered irrelevant in the stock assessment models because they do not affect trends in the abundance measured by each. However, $r_q$ is required when the abundance estimates from BT
and AT surveys are added (equation 2). The expected value of $r_q$ for EBS pollock surveys estimated in Kotwicki et al. (2013) is 0.96 indicating that the magnitude of biases associated with each survey type are similar. However, uncertainty associated with the estimation of $r_q$ is high with standard deviation of 0.24. This high uncertainty in the estimate of $r_q$ was accounted for by using samples from the posterior distribution of $r_q$ when estimating the CV of the combined index.

**Factors affecting overlap**

Similarly to previous studies of factors affecting availability of pollock to single survey gear (Kotwicki et al. 2015), we found that BD and BL had the most significant effects on overlap (Table 1, Fig. 3) indicating that pollock density in the overlap zone is dependent on interaction between these two variables. The lowest values of overlap were predicted for waters shallower than 100 m and were likely associated with the majority of pollock being present in the acoustic dead zone (Fig. 6 in Kotwicki et al. 2015). At the low light conditions in these depths, pollock seem to move up from the acoustic dead zone toward the sea surface, increasing overlap. In the depths deeper than 120 m our model predicted highest overlap in high light conditions. At low light conditions in these bottom depths, pollock also move up toward the sea surface, but to an extent that they move up out of the overlap zone where they are detected only by the AT survey. We need to emphasize that BD and BL effects described here apply to daytime pollock vertical distribution, as all the data used in modelling overlap as well as the survey data used for combined estimates were collected exclusively during daylight. Secondly, there was a very low correlation between BD and BL (-0.32) indicating that BD is very poor predictor of daytime BL levels during summer in the EBS. This finding underscores the necessity of collecting light data.
when studying the vertical distribution of semipelagic species (see discussion in Kotwicki et al. 2009 for discussion of factors affecting near bottom light levels).

The effect of FL on overlap was consistent with Kotwicki et al. (2015) who found that large pollock tended to have a more demersal distribution than small pollock. There was also a slight increase in overlap with increased BT, which we attribute to pollock moving up from the acoustic dead zone; however, this effect was weak and it was not detected in any previous study of pollock vertical distribution.

Beta regression models provide ability to link model variance estimates (equation 5) to predictors. This linkage was important in our study because it not only provided a way to address heteroscedasticity within the regression framework (Simas et al. 2010), but it also provided the ability to identify factors affecting variability in the overlap. We expected this variability to be dependent on certain factors. For example, in shallow water fish have limited ability to distribute themselves in the different parts of the water column because of limited space, leading to low variability in overlap (Fig. 3b). In the deep water, more space becomes available and fish have more ability to move within the water column resulting in more variability in overlap. The estimates of relationships between overlap variance and predictors also enabled us to propagate uncertainty from the predicted overlap to the combined index of abundance by resampling from beta-distributed overlap predictions at each survey grid. This assured that the appropriate mean and variance were used to correct for sample specific availability (equation 1) when availability was not constant across time and space (Fig. 4).

Survey-wide indices of abundance
The survey-wide combined index of abundance displayed interannual trends similar to both AT and BT survey-wide indices, though the magnitude of interannual changes detected by the combined index appeared smaller (Fig. 7). Our results indicate that combining BT and AT data will likely produce more reliable index of pollock abundance in the EBS, because combined sampling encompasses the entire water column. Combined estimates are corrected for spatial and temporal changes in the overlap and are likely to be more useful for ecological studies that require abundance data on both survey resolution and region-wide scales. In contrast to estimates based on the BT and AT surveys alone, the combined estimates meet both main objectives of fishery-independent surveys, producing reliable estimates of both index of abundance and distribution (Hilborn and Walters 1992). Year-to-year differences in the proportion of abundance detected by each survey indicate high variability in pollock availability to both surveys. This is of concern because this variation reduces proficiency in detecting annual changes in population size, a critical function of an index of abundance in stock assessment models (Hilborn and Walters 1992). The majority of pollock were detected by BT surveys in all years, indicating that pollock in the EBS is more benthic than pelagic during daytime. The proportions detected by AT surveys were particularly small (<30%) in years when low abundance of young pollock (ages 1-3) was observed (Ianelli et al. 2014). These results are not surprising because young pollock tend to have a more pelagic distribution then older pollock (Kotwicki et al. 2015). In conclusion, our findings confirm that both BT and AT surveys are needed to assess abundance of pollock in the EBS. Incorporation of the model predicting overlap in relation to environmental factors allowed us to incorporate survey process error associated with spatial and temporal changes in availability into combined estimates.
Variance of the abundance indices

In contrast to the CVs estimated for the single survey indices, CVs for the combined indices estimated in this study account for large part of the variability in availability associated with the vertical availability of pollock to the survey gear. Therefore, we conclude that they provide a more accurate estimate of uncertainty than CVs from a single survey. CV estimates for the combined indices of abundance ranged from 0.16 - 0.19, which is in line with currently-used CV estimates for the BT survey, which range from 0.13 – 0.27 (Kotwicki et al. 2014), and the AT survey which are set to average 0.2, due to the currently unknown impact of variable availability on AT survey variance estimates (Ianelli et al. 2014). However CVs for indices from single surveys do not account for variation in availability to the survey gear. The uncertainty assessment of abundance indices from different surveys should not be limited to the sampling error, but needs to account also for sources of uncertainty in catchability (e.g. Løland et al. 2007). Not including uncertainty in catchability can lead to underestimation of the uncertainty in the abundance index. Kotwicki et al. (2014) showed that the CVs of abundance indices from pollock BT surveys increased on average 55% when uncertainty in sampling efficiency was included in the variance estimates, but that study did not account for the uncertainty in availability. Walline (2007) used a geostatistical simulation approach to estimate variance in AT pollock abundance estimates using spatially-explicit acoustic backscatter data and size composition from midwater trawling and concluded that the CV ranged between 0.05 to 0.09, but he acknowledged that additional sources of uncertainty were not included in his estimate. Lauffenburger et al. (2016) reported recently that the proportion of pollock in the near-bottom layer not assessed by the AT survey varies from 20% to 60% depending on the year, and this...
variation is not accounted for in the variance estimates from index of abundance. Presently variance estimation for indices of abundance from the AT and BT surveys are limited to the fish available to the respective surveys. This approach is reasonable when the objective is to estimate abundance indices of fish available to the survey gear. When the objective is to estimate index of abundance for 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 sampling efficiency leads to biased outcomes in pollock stock assessment.

Caveats

There are some caveats to the approach presented here. Combining survey information to develop abundance estimates were based on data collected during BT and AT summer surveys conducted over several years on different vessels sampling at slightly different times. The approach here assumed that the differences due to sample collection timing were negligible. It was also assumed that pollock vertical and horizontal distribution remained the same (on average) between the times each survey method sampled each grid cell. It was also assumed that environmental conditions were constant during the two surveys. Potentially additional uncertainty in combined abundance estimates could result from violation of these assumptions are unknown. However, we believe that this additional uncertainty is likely to be small for several reasons. First, collection of data used to model overlap as well as the surveys were performed exclusively during daylight hours. Second, starting in 2006, daytime pollock abundance has been estimated acoustically during both AT and BT surveys (Honkalehto et al.
Between 2006 and 2013 the observed correlation between these two acoustic abundance estimates was very high ($r = 0.95$, $n = 6$ surveys; Honkalehto et al. 2014) suggesting that the average daytime vertical distribution of pollock (and by implication, the overlap) does not change much in time between these 2 surveys. Third, environmental conditions which affect pollock vertical distribution in the EBS during summer change relatively slowly, over months rather than weeks (Stabeno et al. 2001). Fourth, a significant portion of the variability in overlap has been accounted for in our estimates of combined index CV thanks to the resampling process applied in estimation of these CVs. Nevertheless, these assumptions and sources of uncertainty could be avoided by conducting a combined BT-acoustic survey using a single vessel. A combined survey will likely provide better precision in abundance indices compared to either survey separately or a combined index, because all data will be collected at the same time (Godø 2003). Combined surveys will also provide researchers, who use pollock abundance data, with abundance estimates corrected for spatially- and temporally-variable availability 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.

**Implications for assessments**

For the pollock stock assessment in the EBS, AT and BT survey data are currently used as separate relative indices of abundance (Ianelli et al. 2014). Information on trends in relative abundance indices is critical in long-term stock assessment (Walters 2003). However, these trends may be biased from year to year as both AT and BT surveys detect different proportion of stock every year (Fig. 8). Because combined estimates use both data sources they result in more complete estimates of spatial and temporal changes in pollock abundance and distribution, and
ensure more accurate estimates of uncertainty. However, only seven years of AT survey data
were available at time of our analyses. In contrast, the BT survey data have been collected since
1982. Ideally, future AT surveys will be performed on the yearly basis and on the same boats as
the BT surveys, which would allow for the incorporation of the new time series into the EBS
pollock stock assessment.

This paper focused on a method to combine BT and AT survey abundance estimates for EBS
pollock, but the same method can be applied to pollock in other areas, or to any other species
with semipelagic behavior sampled using BT or AT surveys. For example, varying availability to
BT and AT survey gears have caused increased uncertainty in abundance estimates of Atlantic
cod and haddock in Norway (Godø and Wespestad 1993; Michalsen 1996). Similar approaches
could also be developed for other species where two observation methods cover different parts of
the target species such as species that often reside close to the surface, where sonar and
echosounder (e.g. Misund et al. 1996), or lidar and echosounder (e.g. Churnside et al. 2003) can
be used to estimate their abundance.

Acknowledgements

Foremost, we would like to thank everyone who participated or helped with the organization of
the EBS AT and BT surveys. We also thank Paul Conn, Alex De Robertis, Taina Honkalehto,
Knut Korsbrekke, Bob Lauth, Jeff Napp, Dave Somerton, Paul Spencer, Chris Wilson and 2
anonymous reviewers for reviews and discussions that greatly improved the quality of this paper.

The findings and conclusions in the paper are those of the authors and do not necessarily
represent the views of the National Marine Fisheries Service.
REFERENCES


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Table 1. Predictor effects on pollock vertical overlap ($o_{C_i}$) and on precision parameter ($\varphi_{C_i}$) from the beta regression model.

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Figures captions

Figure 1. Illustration of conceptual model of walleye pollock sampling by an echosounder and a bottom trawl. Note that acoustic data are collected directly under the survey vessel, while the bottom trawl catches pollock some distance behind the vessel. Diving occurs in the time between vessel passing over the school of pollock and trawl caching the same school.

Figure 2. BT (points) and AT (lines) survey locations.

Figure 3. Effects of predictors on the vertical overlap between bottom trawl and acoustic data as predicted by the beta regression: contours of overlap with respect to interaction effect of bottom light and bottom depth (a), contours of variance in overlap with respect to interaction effect of bottom light and bottom depth (b), points represent actual observations. Linear effects of bottom temperature (c), fork length (d), and sediment (e) on overlap, with 95% confidence bounds (dashed lines).

Figure 4. Examples of the spatial distribution of the combined survey’s catchability ($q_C$; top panels) and the CV of survey grid cell water column abundance (bottom panel) in years 2006 and 2010 (lower panels). The CVs were obtained from the samples from the posterior distribution for $\tilde{A}_{Ci}$ at each survey grid cell.

Figure 5. Simulated values of abundance estimate coefficient of variation in relation to catchability and variance in catchability overlaid with the predicted scatterplots of catchability vs. variance for AT (+), BT (×), and combined (.) surveys. Note that catchabilities between 0 and 1 are representative of the BT or AT surveys (left) and catchabilities between 1 and 2 are representative of the combined survey (right).

Figure 6. Examples of the spatial distribution of pollock as detected by AT (top panel) BT (middle panel), and combined survey (bottom panel) data in years 2006, 2008, and 2010.

Figure 7. Comparison of the scaled abundance indices derived from AT, BT, and combined survey methods.

Figure 8. Year specific proportions of fish abundance detected in survey-wide area by BT survey (Lower 3m + Overlap) and AT survey (Above 16m + Overlap).
a) Bottom Depth (m) vs. Bottom Light

b) Bottom Depth (m) vs. Bottom Light

c) Overlap vs. Bottom Temperature (°C)

d) Overlap vs. Fork Length (mm)

e) Overlap vs. Sediment Size (phi)
Acoustic backscatter ($s_A; \ m^2 \ nmi^{-2}$)

- 0 - 100
- 100 - 200
- 200 - 500
- 500 - 1000
- 1000 - 2000
- 2000 - 11560