Application of an acoustic–trawl survey design to improve estimates of rockfish biomass

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Abstract—Biomass estimates of several species of Alaskan rockfishes exhibit large interannual variations. Because rockfishes are long lived and relatively slow growing, large, short-term shifts in population abundance are not likely. We attribute the variations in biomass estimates to the high variability in the spatial distribution of rockfishes that is not well accounted for by the survey design currently used. We evaluated the performance of an experimental survey design, the Trawl and Acoustic Presence/Absence Survey (TAPAS), to reduce the variability in estimated biomass for Pacific ocean perch (*Sebastes alutus*). Analysis of archived acoustic backscatter data produced an acoustic threshold for delineating potential areas of high ("patch") and low ("background") catch per unit of effort (CPUE) in real time. In 2009, we conducted a 12-day TAPAS near Yakutat, Alaska. We completed 59 trawls at 19 patch stations and 40 background stations. The design performed well logistically, and Pacific ocean perch (POP) accounted for 55% of the 31 metric tons (t) of the catch from this survey. The resulting estimates of rockfish biomass were slightly less precise than estimates from simple random sampling. This difference in precision was due to the weak relationship of CPUE to mean volume backscattering and the relatively low variability of POP CPUE encountered. When the data were re-analyzed with a higher acoustic threshold than the one used in the field study, performance was slightly better with this revised design than with the original field design. The TAPAS design could be made more effective by establishing a stronger link between acoustic backscatter and CPUE and by deriving an acoustic threshold that allows better identification of backscatter as that from the target species.

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Typically, surveys of resource biomass are designed around simple random sampling (SRS), stratified simple random sampling (SSRS), or systematic sampling (Thompson, 2002). One of these standard designs will perform adequately when the resource is relatively uniformly distributed or when the areas where variability in biomass is highest are static and well known. In practice, many resources, such as fish populations, exhibit highly variable and complex spatial structure, and standard survey methods lead to extremely imprecise estimates of biomass (Hanselman and Quinn, 2004). Novel sampling designs have been developed to improve abundance estimation under these circumstances. One example is adaptive cluster sampling (ACS; Thompson, 1990; Thompson and Seber, 1996), which has been explored both in the field (e.g., Lo et al., 1997; Woodby, 1998; Conners and Schwager, 2002; Hanselman et al., 2003) and in simulation studies (Christman, 1997; Brown, 1999; Christman and Pontius, 2000; Christman and Lan, 2001; Brown, 2003; Su and Quinn, 2003). Other methods have been used: double sampling, ratio, and regression estimator approaches to improve precision (Eberhardt and Simmons, 1987; Hanselman and Quinn, 2004; Fujioka et al., 2007). These approaches improve precision by relating a variable that is expensive or difficult to collect (e.g., trawl catches) to a correlated auxiliary variable of which many samples can be collected quickly or inexpensively (e.g., acoustic data).

A resource for which standard survey methods have proven inadequate, Alaskan rockfishes (*Sebastes* spp.) are abundant and supported a valuable commercial trawl fishery with an average exvessel value of US$ 15 million between 2008 and 2010. Survey estimates of biomass for many Alaskan rockfish species exhibit large interannual variations that are not consistent with the longevity (>80 years) and relatively low productivity of these species (Hanselman et al., 2003; Fig. 1). One of the causes of imprecision in survey estimates of biomass is the high variability in the spatial distributions of rockfish populations. For example, the biomass estimate of Pacific ocean perch (*Sebastes alutus*) from the survey conducted in 1999 was driven by several very large catches, out of >800 trawls, that resulted in extremely imprecise estimates (Fig. 1). In addition to having variable spatial distributions, some rockfish species have an affinity for rocky habitat, school semipelagically, and use different habitat types by size class (Stanley et al., 2000; Zimmermann, 2003; Rooper et al., 2010). These factors contribute to high sampling variability and demonstrate the need for examining alternative sampling designs or other technologies to improve survey estimates of biomass (Godø, 2009).

The difficulty of surveying rockfish populations has been studied by using traditional survey designs like SSRS for some time (e.g., Lenarz and Adams, 1980). More recently, several attempts to improve survey precision for Alaskan rockfish species have been made by using alternative sampling designs. The utility of ACS has been examined in several studies (Hanselman et al., 2001; 2003). Many recent attempts have been made to use concurrently collected acoustic data to improve abundance estimation for demersal species (Ona et al.[1]; Hanselman and Quinn, 2004; McQuinn et al., 2005; Fujioka et al., 2007). This subject also was the focus of a European-Union–funded project (combining acoustic and trawl surveys to estimate fish abundance, CATEFA; Hjellvik et al., 2007). These studies showed improvements in survey precision with the use of various measures, including accuracy and travel costs, but none of the survey designs were much more precise than that of a design that was stratified optimally for a particular species. For Pacific ocean perch (POP) in the Gulf of Alaska (GOA), Krieger et al. (2001) showed a relatively strong relationship between catch rates and raw acoustic backscatter in a small study area. Acoustic data were collected sporadically during the NMFS GOA trawl surveys between 2001 and 2004 (Hanselman and Quinn, 2004) and have been collected consistently from 2005 to the current study (2012). Several studies have correlated these acoustic data with trawl catch for rockfishes (Hanselman and Quinn, 2004; Fujioka et al., 2007) and walleye pollock (*Theragra chalcogramma*) (von Szalay et al., 2007). Although much of the previous research has focused on combining results from trawl surveys and acoustic surveys into a single biomass estimate by assessing their relative catchabilities, the focus of our study was to attempt to use acoustic data to improve a traditional trawl survey design.

Our objective was to test the hypothesis that the use of acoustic data in real time in the field to delineate areas with higher trawl-survey catch per unit effort (CPUE) of POP, relative to other survey areas, could increase precision of biomass estimates from trawl surveys. To test this hypothesis, we employed an experimental sampling design, the Trawl and Acoustic Presence/Absence Survey (TAPAS) (Everson et al., 1996). This design is a variant of the double sampling design (Thompson, 2002) and acoustic backscatter data are used to estimate the presence and size of areas, or "patches," where CPUE may be high, compared with other survey areas, and to estimate the proportion of the total area classified as patches. Trawls are conducted at stations randomly selected before a cruise (planned stations) and in the acoustically detected high-CPUE patches identified during a cruise. The rationale of this design is to reduce sampling variability by allocating more sampling effort in the areas of higher CPUE. If high-CPUE areas can be correctly identified with acoustic backscatter, it should be possible to estimate biomass more efficiently. As with other double sampling designs, a critical assumption is that the auxiliary variable (e.g., acoustic backscatter) shows a strong correlation with the primary variable (e.g., trawl CPUE). We believe our study describes the first field application of this TAPAS design.

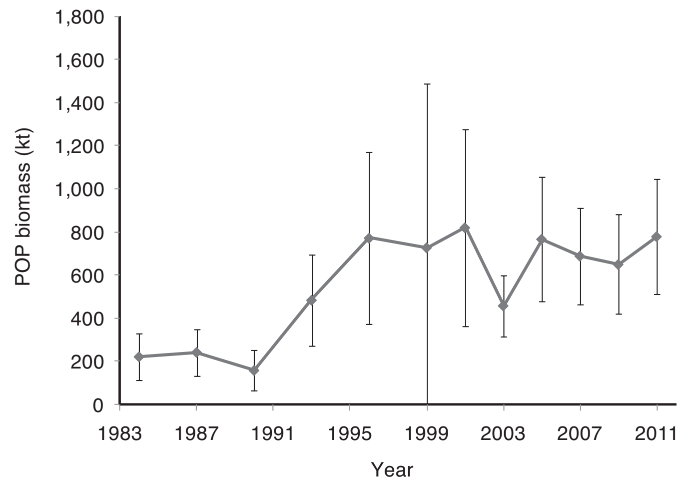

Figure 1

Biomass estimates, shown in kilotons (kt), for Pacific ocean perch (*Sebastes alutus*, POP) determined from National Marine Fisheries Service groundfish trawl surveys conducted in the Gulf of Alaska. Error bars are approximate 95% confidence intervals.

Materials and methods

Field methods

The study area for our 2009 field experiment was chosen because we had prior CPUE and acoustic data from the NMFS GOA trawl surveys and CPUE data from a prior ACS experiment (Hanselman et al., 2003). We confined

[1] Ona, E., M. Pennington, and J. H. Vølstad. 1991. Using acoustics to improve the precision of bottom-trawl indices of abundance. ICES Council Meeting (CM) document, 1991/D:13, 11 p.

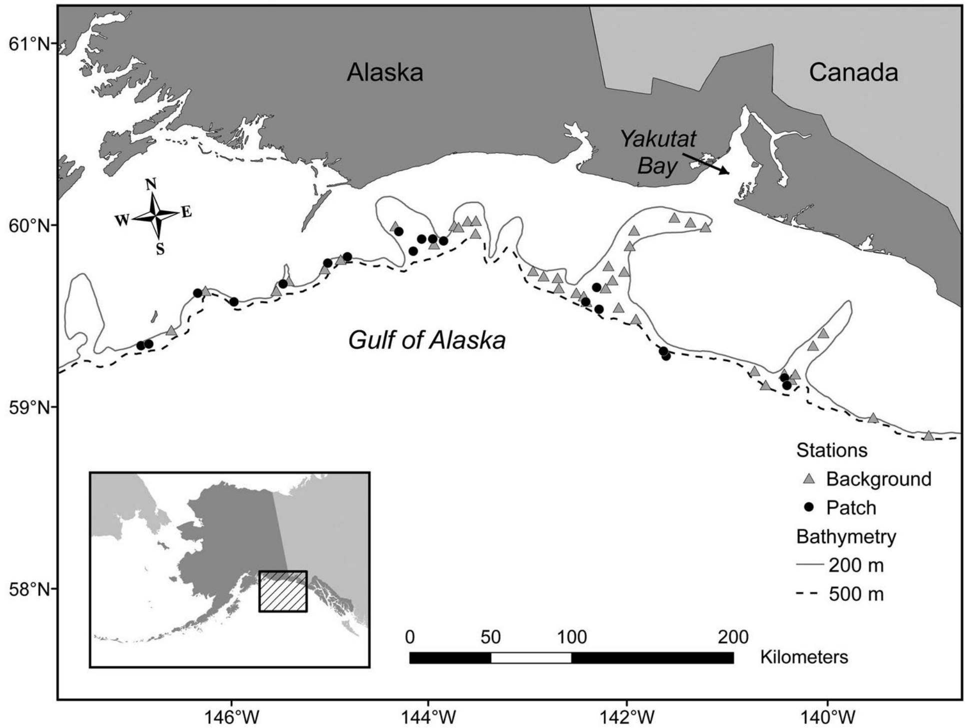

Figure 2

Stations sampled during an experimental rockfish acoustic–trawl survey conducted in 2009 near Yakutat, Alaska, at depths of 200–500 m. Gray triangles indicate "background" stations, which were areas of low-density catch per unit of effort (CPUE) identified in the field through the use of acoustic data. Black circles indicate "patch" stations, which were areas of high CPUE identified in the field.

our study area to the NMFS-delineated strata on the continental shelf break at depths of 200–500 m in the Yakutat area of the GOA (Fig. 2) because these depths contain the bulk of POP biomass. The sampling area was 7800 km^2.

The vessel used for our 2009 study was the FV *Sea Storm*, a 38-m stern ramp trawler with 1710 continuous horsepower. Stations were sampled with a standardized Poly-Nor'eastern high-opening bottom trawl rigged with roller gear and a 27.2-m headrope. All gear was the standard gear used for the NMFS GOA trawl surveys. For further details on the vessel and gear used for our 2009 study, see the report by von Szalay et al. (2010). Acoustic backscatter was measured continuously during the day and during trawling, with a calibrated Simrad[2] (Kongsberg Maritime AS, Horten, Norway) ES60 echosounder and a hull-mounted 38-kHz transducer. A total of 48 stations were preselected randomly from among stations that were successfully trawled during previous NMFS GOA trawl surveys (Fig. 2). The use of previously trawled locations eliminated search time for new locations suitable for random trawls. Once random stations were selected, we constructed the most efficient path, or trackline, to connect these planned stations. Depending on the acoustic backscatter encountered during a survey, these planned stations were later classified as either "background stations" (with low CPUE) or "patch stations" (with high CPUE).

The identification of patch stations required a simple and consistent definition for the spatial variability in acoustic backscatter along the trackline so that we could determine areas of intense backscatter that were large enough for bottom trawling. Acoustic backscatter data were examined in real time by using the Echoview live viewing module (Myriax Pty., Ltd., Hobart, Australia), and Echoview scripts were used to integrate the acoustic backscatter in cells along the seafloor. The conformal cells in this analysis had a height of 10 m (from 1.5 m to 11.5 m off the seafloor) and a length of 100 m. The lower boundary of each cell was situated 1.5 m off the seafloor to avoid errors in Echoview-derived bottom detection and to account for the "acoustic dead zone" (Simmonds and MacLennan, 2005)—the area where fishes are difficult to detect acoustically because the echo from the seafloor masks their acoustic signals. The value of 1.5 m was estimated with the equations in Ona and Mitson (1996) and a peak POP depth of ~225 m (Hanselman et al., 2001). The 10-m height of the cells examined in our study was considerably larger than the mean height (~6 m) of the nets used in NMFS

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

bottom trawl surveys, but this difference accounts for POP swimming above a trawl net that may dive down into the net path in response to the pressure wave of the trawl. This potential for "herding" may increase the effective height of the net. In addition, Aglen (1996) found that the correlation between catch and acoustic backscatter off the seafloor was greatest for Atlantic species of *Sebastes* and suggested that a taller acoustic layer should be more robust for identification of areas of intense backscatter. The actual size of the acoustic layer, however, does not contribute directly to biomass estimates, which are based on CPUE data from trawls.

Patch definition was determined with the use of 2 metrics: 1) the value of mean volume backscattering, S_v (log decibels re 1 m^{-1}; MacLennan et al., 2002) that defines high acoustic intensity (S_v threshold) and 2) the proportion of cells where the S_v threshold was exceeded. A proportion criterion was used to smooth the S_v values across cells to avoid defining small areas with high acoustic backscatter as discrete patches. Analysis of archived data indicated that a proportion was preferable to a moving average that was sensitive to intermittent large increases in S_v. The distance for evaluating the proportion of cells was a sampling window that spanned 31 cells for a total of 3.1 km, which is comparable to the distance needed to prepare for and conduct a bottom trawl. For our study, an area became designated as a patch when the proportion of cells in the sampling window that exceeded an S_v of –65.6 dB was 0.39 or higher. The criteria for patch definition were determined by using the 80^{th} percentile of values from acoustic backscatter data measured aboard the FV *Sea Storm* during a NMFS GOA trawl survey in 2005 in the same Yakutat area. The acoustic backscatter data were echo-integrated in Echoview, and the S_v values were exported and analyzed with R software scripts, vers. 2.9.0 (R Development Core Team, 2009), which generated graphs showing values of S_v that defined the start and end of patches meeting the threshold criteria (Fig. 3). In each identified patch, a location for a patch station that was at least 1 km (a single trawl length) from the edge of that patch was randomly selected, and a 10-min trawl was conducted from that random location as the starting point.

The CPUE data collected from these trawls were assigned to patch stations (random trawls conducted within identified patches) or background stations (trawls conducted within planned stations at which the acoustic threshold was not exceeded). It is important to note that if a planned station was found to be located within an acoustically identified patch, a trawl was conducted at a patch station that was randomly selected within that patch rather than at the preselected location.

Data analysis

The acoustic backscatter data were processed and then categorized according to vessel activity. Echoview software was used to correct the backscatter data for noise and erroneous seafloor tracking. Partitioning backscatter by vessel activity was necessary to accurately estimate the size of patches and the total length of the path traveled by the FV *Sea Storm* inside patches. Hence, to eliminate double counting, we avoided trackline segments where the boat circled around to set up trawls or searched for ground suitable for trawls. Seven vessel-activity categories were assigned to each 100-m cell: 1) transiting between stations, 2) returning to set up a trawl, 3) searching for ground suitable for trawls, 4) trawl deployment, 5) trawling (with offset for trawl distance behind the vessel), 6) trawl recovery, and 7) other transit that was not part of our study. Categories 1 and 4–6 were included in this study. Overlap, defined as anywhere the vessel path was within 50 m of the haul or earlier vessel path, was measured with ArcGIS software (ESRI, Redlands, CA, vers. 9.2).

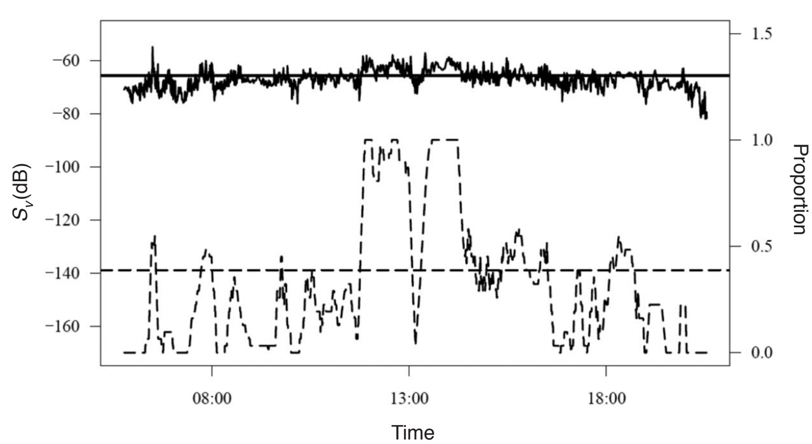

Figure 3

Example of script outputs for real-time monitoring of patches during a 2009 acoustic–trawl survey. The time series (solid wavy line) and solid horizontal line represent mean volume backscattering (S_v) per 100 m and S_v threshold, respectively. The dashed time series and horizontal lines represent the proportion of 100-m cells exceeding the S_v threshold over a 3.1-km window and the threshold for the proportion, respectively. Time is given in Alaska Daylight Time.

CPUE was an estimate of fish density (kg/km^2) at each station and was calculated as the catch of a species in kilograms divided by the area sampled (i.e., the product of the net width in kilometers and the trawl trackline in kilometers). Patch length was computed with the haversine formula to calculate great-circle distances (as implemented in the R package argosfilter; R Development Core Team. 2009) between GPS coordinates for every 100-m interval. These calculations were compared with results from summing the number of cells to verify that all cells were very close to 100 m in length and that the GPS systems functioned correctly. For example, using the GPS coordinates, we checked that a 10-cell window in Echoview was ~1 km in length.

We computed biomass estimates with 2 types of methods to compare magnitude and precision. With the first method, we omitted the patch stations, except when a patch station was originally a planned station, and calculated the abundance with an SRS estimator with the sample size used as if the full number of trawls had been sampled by simple random sampling (Thompson, 2002). For the second method, we used the estimator derived for the TAPAS design. The TAPAS estimator is functionally similar to an SSRS estimator, with an important exception: in the TAPAS estimator, CPUE values from patch stations are treated as multiple strata weighted by their associated patch size, but, in an SSRS estimator, only the total area estimated to be in the patch stratum is used. An SSRS estimator was not used in our study for 2 reasons: 1) each patch is a separate stratum with a sample size of one, and therefore within-strata variances cannot be computed and 2) the sampling design introduces patch length as an additional random variable that may or may not correlate with CPUE. If there is no correlation with patch length and CPUE, and the relationship between S_v and CPUE is weak, then using the TAPAS design is similar to suboptimally allocating samples in an SSRS design. This suboptimal allocation would cause the TAPAS estimator to perform slightly worse than an SSRS estimator because of the extra random variable introduced, and the SSRS estimator would in turn be no better than an SRS estimator.

The focus of the TAPAS design is to reduce the sampling variance in estimating biomass based upon the degree to which acoustic backscatter corresponds with trawl CPUE. Each of these measures shows a relationship with true fish density, and systematic biases relative to true density may exist in either measure because of processes such as fishes herding to trawl nets or responding to vessel noise. For Alaskan groundfishes, it is commonly assumed that trawl CPUE is less variable than acoustic backscatter as a measure of fish density (over the path of the trawl), although scenarios could occur where this assumption was not realistic (Fréon and Misund, 1999). Information that addresses systematic biases, such as catchability and availability of fish to a sampling method, could be incorporated into the TAPAS design, although this approach would not address the central issue of the imprecision of survey estimates that result from variable spatial distributions of rockfish. For stocks with quantitative stock assessment models, the degree of systematic biases potentially can be addressed by estimating catchability and gear selectivity parameters.

The stratum-wide TAPAS and SRS estimates of biomass were calculated with the following formulae based on Everson et al. (1996):

$$\hat{D}_0 = \frac{\sum_1^{n-I} \hat{d}_i}{n-I}, \tag{1}$$

$$\hat{D}_1 = \frac{\sum_I l_i \hat{d}_i}{l'}, \tag{2}$$

$$\hat{B}_0 = A\hat{D}_0\left(1-\frac{l'}{L}\right), \tag{3}$$

$$\hat{B}_1 = A\hat{D}_1\frac{l'}{L}, \tag{4}$$

$$\hat{B} = \hat{B}_0 + \hat{B}_1, \tag{5}$$

$$\Rightarrow \hat{B} = A\left(\hat{D}_0\left(1-\frac{l'}{L}\right)+\hat{D}_1\frac{l'}{L}\right), \tag{6}$$

$$\hat{B}_{SRS} = A\frac{\sum_1^{n-I^*} \hat{d}_i}{n-I^*}, \tag{7}$$

where $\hat{D}_0$ = the mean CPUE (kg/km^2) of the background trawls;
n = the total sample size;
I = the total number of patches encountered;
$\hat{d}_i$ = the CPUE (kg/km^2) of trawl i;
$\hat{D}_1$ = the mean CPUE of the patch trawls;
l' = the total track length within patches;
$\hat{B}_0$ = the estimated biomass for swept areas at background stations (kg);
A = the total sampling area (km^2);
L = the total length (km) of the trackline traveled by the vessel throughout this study;
$\hat{B}_1$ = the estimated biomass for swept areas at patch stations (kg);
$\hat{B}$ = the TAPAS estimate of total biomass in the sampling area;
$\hat{B}_{SRS}$ = the SRS estimate of total biomass in the sampling area; and
I^* = the number of patches that were not planned stations.

The variance derived in Equation 7 of Everson et al. (1996) left out covariance and area terms. We derived an improved estimator of the variance (Table 1) using the delta method (Quinn and Deriso 1999); this derivation is presented in the Appendix. We computed confidence intervals with the “log-Bayes” method suggested by Everson et al. (1996). Finally, we computed SRS and TAPAS confidence intervals with the bootstrap method (Efron and Tibshirani, 1993). In complex sampling designs, there are alternative ways to bootstrap confidence intervals (Rao and Wu, 1988; Smith, 1997; Christman and Pontius, 2000). For our study, we examined several bootstrap methods and found that the results among them were similar. Thus, for comparison with analytical results, bootstrapping was conducted as suggested

Table 1

Biomass and variance estimators for 2 sampling designs, simple random sampling (SRS) and Trawl and Acoustic Presence/Absence Survey (TAPAS), the latter of which was evaluated as a way to reduce the variability in estimated biomass for Pacific ocean perch (*Sebastes alutus*). $\hat{B}$=estimated biomass (kg), $\hat{d}_i$=estimated catch per unit of effort (CPUE, kg/km^2) in trawl i, $\bar{d}$=the mean CPUE, A=total sampling area (km^2), a=the amount of A sampled (km^2), n=total sample size, $\hat{p}$=the estimated proportion of the trackline in patches, l_i=the estimated length (km) of trackline in patch i, l'=the estimate of length (km) of total trackline in patches, $\bar{l}$=the mean patch length, and L=the length of the entire trackline, I=the number of patches, I^*=the number of patches excluding those originally in the background, and $\hat{n}_L$=an estimate of the effective number of independent samples on the trackline; the denominator of 12 was derived from the range parameter of the acoustic variogram.

Estimator	Biomass	Variance
SRS	$\hat{B}_{SRS}=A\frac{\sum_1^{n-I^*}\hat{d}_i}{n-I^*}$	$\hat{V}\left[\hat{B}\right]=\left(1-\frac{a}{A}\right)A^2\left(\begin{array}{l}(1-\hat{p})^2\hat{V}\left[\hat{D}_0\right]+\hat{p}^2\hat{V}\left[\hat{D}_1\right]\\+\left(\hat{D}_0-\hat{D}_1\right)^2\hat{V}[\hat{p}]\\+2\hat{p}\left(\hat{D}_1-\hat{D}_0\right)C\hat{o}v\left[\hat{D}_1,\hat{p}\right]\end{array}\right)$
TAPAS	$\hat{B}=A\left(\begin{array}{l}\frac{\sum_1^{n-I}\hat{d}_i}{n-I}\frac{L-l'}{L}\\+\frac{\sum_{n-I+1}^{n}l_i\hat{d}_i}{l'}\frac{l'}{L}\end{array}\right)$	$\hat{p}=\frac{l'}{L}$ $\hat{V}\left[\hat{D}_0\right]=\frac{1}{n}\frac{\sum_1^{n-I}(\hat{d}_i-\bar{d})^2}{n-I-1}$ $\hat{V}\left[\hat{D}_1\right]=\frac{1}{L^2}\left(\frac{\sum_{n-I+1}^{n}\hat{p}_i^2(\hat{d}_i-\bar{d})^2}{(n-I-1)\hat{p}^2}+\bar{d}^2\sum_{n-I+1}^{n}\frac{\hat{p}_i-\frac{\hat{p}_i}{\hat{p}}}{\hat{p}^2\hat{n}_L}\right)$ $\hat{V}[\hat{p}]=\frac{\hat{p}(1-\hat{p})}{\hat{n}_L}$ $\hat{n}_L=L/12$ $C\hat{o}v\left[\hat{D}_1,\hat{p}\right]=\left(\begin{array}{c}\sum_{i=1}^{I}C\hat{o}v\left(\hat{d}_i,\hat{p}_i\right)\frac{\hat{p}_i}{\hat{p}}+\\\sum_{i=1}^{I}\sum_{j=1}^{I}\left(C\hat{o}v\left(\hat{p}_i,\hat{p}_j\right)\frac{\hat{d}_i\hat{p}-\sum_{k=1}^{I}\hat{p}_k\hat{d}_k}{(\hat{p})^2}\right)\end{array}\right)$

by Everson et al. (1996): pairs of patch lengths and associated values of patch CPUE were resampled to preserve any correlation between patch length and CPUE. The number of patches selected was parametrically bootstrapped by drawing from a Poisson distribution with the realized number of patches as the mean of the distribution. An additional Poisson random variable was drawn to determine whether a patch station was included in the SRS estimator. The mean of this second Poisson distribution was the number of planned stations that occurred in a patch during the survey. This source of variability reflects the probability that any of the observed patch stations could have been located at one of our planned stations. Bootstrapping was conducted 10,000 times with the R statistical package (R Development Core Team, 2009). For the TAPAS estimators, both the CPUE values and the patch lengths were resampled with replacement, but, for the SRS estimator, only the CPUE values were resampled. Percentile confidence intervals were constructed with the bias-corrected method of Efron and Tibshirani (1993) that was used in Everson et al. (1996). This method centers intervals on the analytically estimated mean.

To improve the precision of the biomass estimates obtained with our planned design, we re-analyzed the data with alternative patch definitions. First, we examined the relationships of trawl CPUE to other variables, such as the maximum S_v, variance or standard deviation of S_v, median S_v, depth, products and ratios of these quantities, and multiple regressions. These examinations were done to see if focusing on different quantitative characteristics of the acoustic backscatter could result in an improved threshold. We then chose a number of alternative patch definitions and, with the

Table 2

Catch (kg), number of individuals, and mean fork length (cm) of fish and associated coefficient of variation (CV) for the top species caught during our experimental rockfish acoustic–trawl survey conducted in 2009 near Yakutat, Alaska.

Common name	Scientific name	Weight (kg)	Number of individuals	Mean fork length (cm)	Length CV (%)
Pacific ocean perch	*Sebastes alutus*	16,603	27,276	32.3	19
Walleye pollock	*Theragra chalcogramma*	3110	3988	45.8	12
Shortraker rockfish	*Sebastes borealis*	2173	426	65.3	15
Arrowtooth flounder	*Atheresthes stomias*	1738	1506	37.6	32
Shortsp ine thornyhead	*Sebastolobus alascanus*	1020	5131	24.0	27
Dover sole	*Microstomus pacificus*	789	963	40.2	15
Sablefish	*Anoplopoma fimbria*	775	292	61.0	20
Dusky rockfish	*Sebastes variabilis*	426	262	46.1	5
Silvergray rockfish	*Sebastes brevispinis*	381	167	54.8	13
Jellyfish	*Chrysaora melanaster*	320	187	—	—
Other		2836	8444	—	—

best alternative, estimated biomass and precision for comparison with our original field results.

We examined the spatial structure of the S_v along the entire trackline and fish densities from trawls using classical method of moments sample variograms (Cressie, 1993). We also re-examined the densities of POP in trawls from an ACS experiment conducted in 1998 (Hanselman et al., 2001), during which trawls were conducted at a higher spatial resolution (i.e., closer together) than they were in our 2009 study. We coarsened the spatial resolution (upscaled the support) of the acoustic data by aggregating the S_v values so that the distance between S_v values was 1 km, which was the sampling resolution (support) of the trawl data (Atkinson and Tate, 2000). We varied the maximum distance of spatial correlation until a clear range was identified. We then fitted different variogram models (spherical, circular, exponential, and linear) to determine the best shape of the variogram model.

Results

Field sampling occurred during daylight hours over 12 days in August 2009. A total of 59 trawls were completed, with 40 background trawls and 19 patch trawls (Fig. 2). The total weight of all species caught was 30.1 metric tons (t). POP made up 55% of the overall catch from our study, followed by walleye pollock and shortraker rockfish (*S. borealis*) (Table 2). Mean CPUE of POP was 42,450 kg/km^2 in patch trawls and 7,475 kg/km^2 in background trawls. The total trackline covered was 1250 km; 112 km of this total was in patches where we trawled. Overall, about 20% of the trackline (230 km) was above the threshold S_v but was either not long enough to invoke our patch definition or deemed untrawlable by the captain of the FV *Sea Storm*. A return to trawl inside patch stations added an additional travel cost of about 2% beyond the cost of trawling only at planned stations. The last 2 of the 59 trawls were conducted after our planned trackline was completed, and the stations of these 2 trawls were identified with an alternative patch definition (see discussion later in this section); therefore, we did not use them in our main analysis.

Before comparing S_v measurements with trawl densities, we checked for normality of the data. The distribution of S_v along the trackline was reasonably normal (Fig. 4), but trawl densities of POP were left-skewed and required transformation to approach normality. Hanselman and Quinn (2004) showed that power transformations were superior to the logarithm for POP survey data. Applying the Box-Cox power transformation showed that the likelihood surface at different powers was relatively flat between 0.1 and 0.3. We chose to use the fourth-root of trawl CPUE because it showed a better residual pattern and had higher correlation with S_v than did the logarithm and lower power transformations. The relationship between S_v and POP CPUE was relatively weak, particularly below –70 dB (Fig. 5). The relationship between POP CPUE and patch length was tenuous, with a low correlation coefficient (r=0.08). In some cases when our patch algorithm detected a patch, schools of POP appeared to dissipate or move off the seafloor in the time it took to return to the same location and set up a trawl (Fig. 6).

The resulting biomass estimates were very similar among the different types of estimators (Table 3, Fig. 7). All estimates of biomass from our study were much more precise, in terms of the coefficient of variation (CV), than estimates of biomass based on data for the same area from the NMFS GOA trawl survey conducted in 2009 (Fig. 7). The bootstrap procedure yielded similar estimates of biomass and precision between the TAPAS and SRS estimators. If we included the 2 trawls conducted opportunistically off the planned trackline, on the basis of our alternative patch definition, the TAPAS design, with much higher biomass estimates, performed better than the SRS design (CV=27% vs. CV=34%).

We examined our results with respect to the variables that would have produced a better correlation with trawl CPUE. The weak relationship between S_v and POP CPUE was obtained when comparing only for the length of the trawl trackline (offset for trawl distance behind the vessel). Higher correlations between acoustic backscatter and trawl CPUE resulted when acoustic backscatter was calculated from segments that were centered at the trawl track and 3–5 times the length of the trawl trackline than from segments that were only the length of the trawl trackline. We derived 4 new patch definitions, using a 3-trawl-length sampling window (~3 km), in addition to the patch definitions we used in the field (Table 4). We show results as if we had used the patch definition with the best relationship between S_v and POP density in the field.

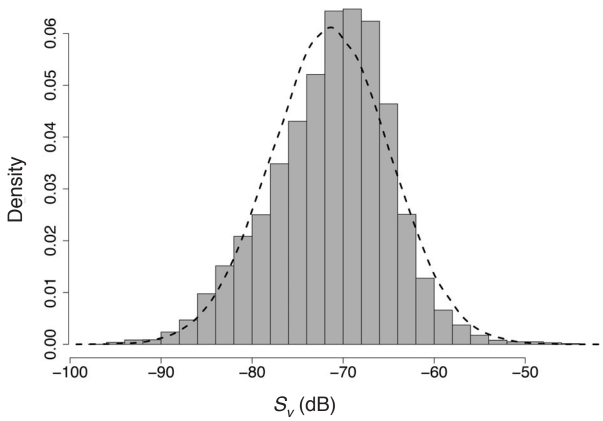

Figure 4

Distribution of values of mean volume backscattering (S_v) for 100-m segments over the trackline (n=12,998 segments) surveyed during our 2009 acoustic–trawl survey. The dashed line is a density plot of a normal distribution with the same mean and standard deviation.

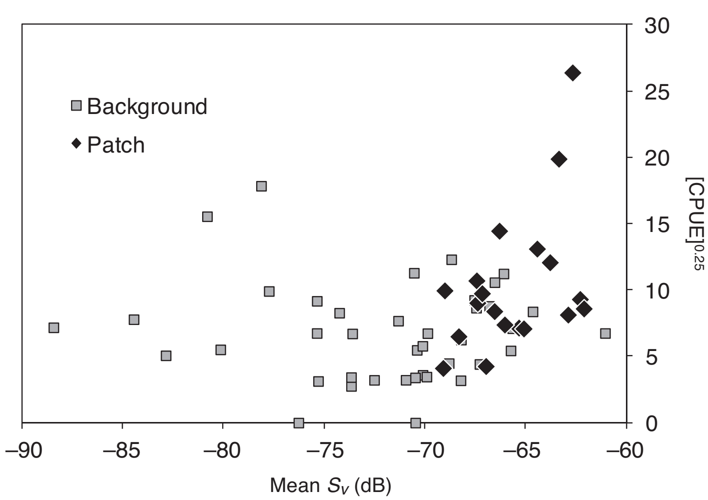

Figure 5

Fourth-root transformed Pacific ocean perch (*Sebastes alutus*) catch per unit of effort (CPUE) versus mean volume backscattering (S_v) per trawl from our 2009 acoustic–trawl survey. Light gray squares indicate background stations, and black diamonds indicate patch stations.

Comparing these patch definitions, we found that the strongest predictor of POP CPUE was the one that used the 90th percentile of maximum S_v in a 3-trawl-length sampling window, which approximated the window we used for our 2009 survey (Fig. 8). This sampling window also gave the lowest error rate in identifying areas of below-average CPUE as a patch station when they should not be (Table 5). The standard deviation of the 3-trawl-length sampling window also performed reasonably well. Alternative 5, one of the alternative patch definitions (Table 4), was attempted to combine backscatter variability and maximum S_v, but it did not perform better than maximum S_v alone. The addition of depth as a variable to any of these alternatives in a multiple regression yielded minor, insignificant improvements to the model.

As a basis for a modified patch definition, we re-analyzed the acoustic data using an S_v criterion of –58.11 dB derived from the 90th percentile of the maximum S_v from the original 2005 FV *Sea Storm* data in our 31-cell window. Only 8 of the previous 19 patch stations were located in patches under this new definition.

Because of this smaller sample size, SRS estimates were less precise with this new patch definition than with the original patch definition. However, despite the smaller sample size, the new threshold for TAPAS did yield a slightly improved CV than the CV obtained with the original threshold (Table 3). Overall biomass estimates were slightly higher, and all measures of precision yielded similar results (Table 3).

Variogram analysis of the S_v measurements showed strong spatial correlation at the spatial resolution of the trawl data (Fig. 9A). Variogram analysis of the values of trawl CPUE collected during our study revealed no appreciable spatial structure, likely because the trawls were relatively far apart (146 km on average). Alternatively, we compared the S_v measurements from our 2009 study with the values of CPUE collected during an ACS experiment conducted in 1998 (Hanselman et al. 2001); CPUE data were collected at a finer scale (27 km on average) in the ACS experiment than in our study (Fig. 9B). We fitted a spherical model to the S_v measurements and a linear model to the trawl CPUE on the basis of visual fit

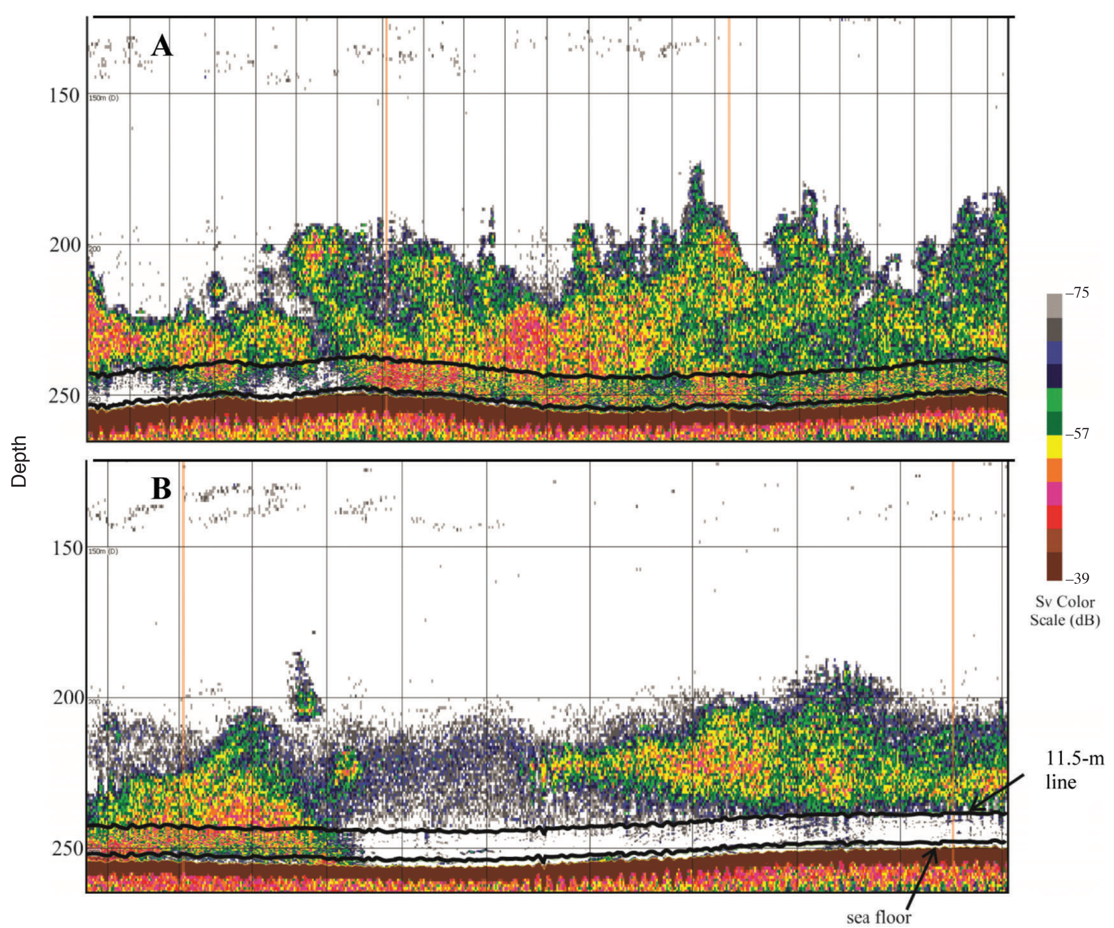

Figure 6

Acoustic backscatter observed (**A**) during patch detection and (**B**) after returning to a trawl location. The black vertical lines mark 100-m distance intervals, the orange vertical lines mark the distance sampled with the trawl, the thick black horizontal lines show the 10-m conformal integration window.

and goodness of fit (coefficient of determination, r^2). The range of correlation for the S_v measurements was larger (~13 km) than the range of correlation for the trawl densities (~8 km). The variogram for the trawl CPUE data had a relatively larger nugget, or unexplained microscale variance, than the variogram for the S_v data.

Discussion

The study area, Yakutat, and target species, POP, for our field study were chosen to increase the likelihood of obtaining a strong relationship between acoustic backscatter and trawl CPUE. Several previous studies had observed relatively strong relationships for rockfishes between S_v and trawl CPUE in the GOA (Krieger et al., 2001; Hanselman and Quinn, 2004; Fujioka et al., 2007), and the Yakutat area was known to have high rockfish abundance. Additionally, Hanselman and Quinn (2004) and Fujioka et al. (2007) showed that stratifying by acoustic backscatter or double sampling could improve precision of biomass estimates on the basis of data collected during previous ACS surveys for rockfishes and biennial NMFS GOA trawl surveys. The use of real-time processing of acoustic backscatter to determine patches was efficient, and POP were the most commonly caught species and were found in higher densities than other fishes at patch stations. However, the conditions that make the TAPAS design more efficient than random sampling, as shown in simulation studies (Spencer et al., 2012), did not materialize in the fieldwork described here.

For the TAPAS design to be more effective than SRS, the categorization of patch and background areas must show a correspondence with trawl CPUE (i.e., CPUE values consistently should be higher at the patch stations than at the background stations). When this correspondence does not occur, the use of these categories does not improve the precision of biomass estimates and increases variability because the sizes of the patch

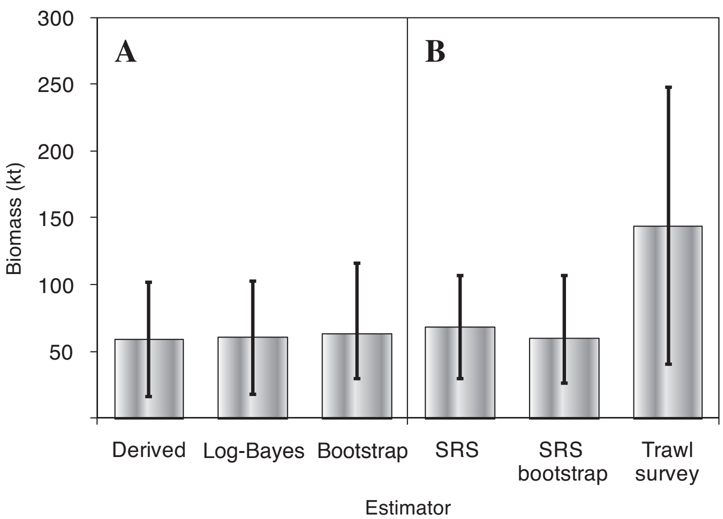

Figure 7

Comparison of bootstrap versus derived analytical results for the estimators for the Trawl and Acoustic Presence/Absence Survey (TAPAS) sampling design, with (**A**) a proportion of the 80th percentile of the mean volume backscattering (S_v) in a 31-cell window and (**B**) simple random sampling (SRS) and the 2009 NMFS trawl survey in the same area. Analytical confidence intervals are approximately 95% (±2 standard deviation). Bootstrap confidence intervals are bias-corrected 95% percentile intervals.

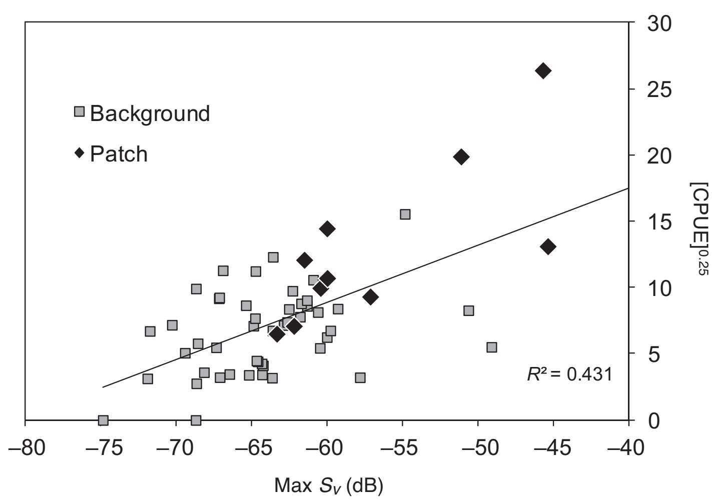

Figure 8

Relationship of maximum mean volume backscattering (S_v) to the fourth root of Pacific ocean perch (*Sebastes alutus*) catch per unit of effort (CPUE), from our 2009 acoustic–trawl survey, in an acoustic sampling window with a length of 3 trawls (~ 3.0 km). Light gray squares indicate background stations, and black diamonds indicate patch stations.

and background areas are estimated. Despite the minimal requirement of classifying the acoustic data into only 2 categories, the results of our study indicate that the effectiveness of the TAPAS design remains dependent upon the strength of the relationship between S_v and trawl CPUE. Patch size and CPUE were only weakly correlated, and the variance of the planned stations was not as high as expected. Variogram analysis of ACS data showed that the spatial correlation range for trawl CPUE may be smaller than the range for S_v data. Previous variograms estimated for the NMFS GOA trawl surveys had indicated a range of ~4.5 km (Hanselman et al. 2001), which was also smaller than the range of the acoustic backscatter collected in our study. The larger range of the S_v data may indicate that some of the intensity of S_v is a result of ambient variables other than POP density. The nugget (unexplained variance) of the trawl CPUE is large, relative to the total variance for the trawl CPUE, an indication that the trawl CPUE data likely have more measurement error than the acoustic data and that the data were sparser. The trawl CPUE variogram in our study had a larger range than did the individual areas analyzed in Hanselman et al. (2001). This difference in range could have occurred because the aggregated data in our study had more pairs of trawl densities at larger lag distances than did the spatially explicit variograms with smaller sample sizes in that earlier study.

One source of discrepancy between the acoustic and trawl data is that multiple species contribute to the acoustic backscatter. Von Szalay et al. (2007) had success relating acoustic backscatter of walleye pollock with CPUE in the Bering Sea. However, walleye pollock make up the majority of the biomass in the Bering Sea; in contrast, POP is one of a number of abundant species in the GOA. Krieger et al. (2001) had more success relating acoustic backscatter with rockfishes using a Simrad EK500 quantitative echosounder. In their study, which was conducted in the more rugged habitat off Southeast Alaska, the catch was primarily rockfishes and contained species that were smaller in size than the larger rockfish species and walleye pollock that made up the non-POP catch in our study. Although we restricted our study area to depths where POP would be the dominant species and, indeed, where POP was the largest component of our catch, our original sampling algorithm revealed patches of acoustic backscatter that were not characteristic of rockfishes. Steadier and less intense than backscatter associated with rockfishes, these patches may have been caused by squid (*Berryteuthis* spp.) or eulachon (*Thaleichthys pacificus*). In addition, a substantial amount of walleye pollock was caught coincident with POP catches. The TAPAS design may perform better in multispecies situations because of the relatively relaxed requirement of categorizing data into 2 groups, as opposed to the more involved effort of a statistical regression required for double sampling in a regression design.

Differences in the portions of the water column surveyed by the 2 sampling methods also can lead to low correspondence between acoustic and trawl data. Rockfishes can be closely associated with the seafloor and, perhaps, in the acoustic dead zone, but walleye pollock and other species are typically observed higher in the water column. We also noted the ephemeral nature of fish schools (Fig. 6), which may be attributed to responses to vessel noise or to changes in the position of fishes in the water column for foraging. Diurnal and seasonal changes in the level of aggregation clearly could hinder the effectiveness of our acoustic algorithm in relation to fish CPUE. Changes of the vertical orientation of POP to the seafloor also could influence backscatter and may have affected our acoustic algorithm (Fréon and Misund 1999).

When the field data from our study were re-analyzed with different patch definitions, we found that CPUE was more strongly related to acoustic backscatter in a window longer than the typical trawl distance—likely a result of the extremely fine spatial structure of schools or to the behavioral reactions of fishes to the initial pass of the FV *Sea Storm* over the patch (Mitson and Knudsen, 2003). If the spatial structure of schools was relatively narrow, then the trawl net may not have passed through the same school that was identified by the echosounder because of currents and imperfect tracking of the original vessel path (Ona and Godø, 1990; Engas et al., 2000). Re-analysis revealed that the use of the 90th percentile of maximum S_v was more successful in identifying stations where rockfish CPUE was high and resulted in slightly more precise biomass estimates, compared with results from the original patch definition, despite a lower sample size. As with the analysis of Hanselman and Quinn (2004) with their ACS simulations, our re-analysis of the acoustic data showed that the TAPAS estimator can be improved when a high criterion of acoustic backscatter is used for the patch definition (i.e., additional sampling is invoked only in a few, high fish-density instances) and essentially outliers are removed from the random sampling portion of the ACS and TAPAS estimators.

The TAPAS design incorporates aspects of both adaptive sampling, which usually consists of a single sampling gear applied to a highly variable spatial distribution, and double sampling designs that rely on sampling primary and auxiliary variables (Thompson, 2002). The TAPAS design provides one operational method for implementing a double sampling for stratification design. The use of acoustics to stratify a survey area was generally recommended by Fujioka et al. (2007) and Hjellvik et al. (2007), with the difference that acoustic backscatter is continuously monitored rather than sampled in discrete units.

Table 3

Parameter estimates from 2 sampling designs, Trawl and Acoustic Presence/Absence Survey (TAPAS), and simple random sampling (SRS), with the use of 2 different patch definitions. Patch definitions are based on percentiles of mean or maximum volume backscattering (S_v) from acoustic data collected during our 2009 acoustic–trawl survey. Rockfish densities and biomass estimates are given in metric tons per square kilometers (t/km^{2}) and metric tons (t), respectively. n=total sample size, I=the number of patches, l'= the estimate of length (km) of total trackline in patches, L=the length of the entire trackline, D_0=the mean background CPUE, D_1=the mean patch CPUE, B_0=the background biomass, B_1=the patch biomass, B=the TAPAS estimate of total biomass (kg), B_{SRS}= the SRS estimate of total biomass. SRS coefficients of variation (CVs) were calculated by using the full sample size (n).

Parameter	80th percentile of mean S_v	90th percentile of max S_v
N–I	40	41
n	57	49
I	17	8
l'	93.6	43.5
L	1251	1251
D_0	7.48	7.43
D_1	9.74	24.82
B_0	53,928	55,898
B_1	5684	6734
B	59,612	62,632
CV_B (analytical)	34.6	34.0
CV_B (bootstrap)	34.5	33.6
B_{SRS}	68,517	68,517
CV_{SRS} (analytical)	27.8	30.0
CV_{SRS} (bootstrap)	30.2	31.9

Results from our study and the ACS design attempted by Hanselman et al. (2003) highlight that even when focusing specifically on the abundance of rockfishes, it is difficult to survey stocks with high spatial variability that exist on both trawlable and untrawlable grounds. In the ACS surveys of Hanselman et al. (2003) specialized tire gear was used, which made trawling on each cluster station possible, but made comparisons of CPUE impractical between those ACS surveys and surveys that used typical NMFS trawl gear. In our study, we used standard NMFS trawl gear; however, it could not be used in all observed patch stations. If POP were more abundant in some of these untrawlable patches and we had used different gear that would have allowed us to survey those patches, we may have had higher

Table 4

The original method used in our 2009 acoustic–trawl survey and proposed alternative methods for selection of "patches," or areas where catch per unit of effort may have been high, compared with other survey areas, on the basis of acoustic backscatter over a sampling window of 3 trawl lengths. Patch definitions were based on a threshold of mean volume backscattering (S_v). Alternatives were created to maximize the strength of the relationship of S_v to CPUE and improve survey precision.

Original patch definition
The S_v was computed for each 100-m cell within a moving window of 31 cells or 3.1 km. A patch was defined when the proportion of these cells exceeding an S_v value of –65.6 dB was greater than 0.39 (the 80th percentile of the backscatter data collected in the Yakutat, Alaska, area in 2005 aboard the FV *Sea Storm*).
Alternative 1
Higher field threshold definition To account for the uniform and weak nonrockfish backscatter encountered in the field, the S_v threshold was increased to –61.4 dB from the value used in the original method. The threshold for the moving proportion was lowered to 0.13. These values were computed from the 90th and 50th percentiles of our field data, respectively. The rationale for this definition was to detect patches when the acoustic backscatter was more variable but stronger than the backscatter detected as patches with the original patch definition.
Alternative 2
Standard deviation of S_v To capture the tight intermittent clustering of rockfish schools, we used the following threshold: the standard deviation of S_v was above the 80th percentile. The rationale of this definition was to capture some distributional properties associated with rockfish acoustic backscatter.
Alternative 3
Variance to mean ratio of S_v To remove uniform, diffuse acoustic backscatter and account for tight intermittent clustering of rockfish schools, we used the following threshold: the variance-to-mean ratio was above the 80th percentile. The rationale of this definition was to identify a patch when the variance-to-mean ratio moved far above 1 (e.g., departing from a Poisson distribution toward a hypergeometric distribution).
Alternative 4
Maximum S_v If the survey was conducted in a depth stratum and area where the target species was abundant, it was assumed that pulses in maximum S_v should reflect the dominant species. For this alternative, the 90th percentile of maximum S_v was used.
Alternative 5
Maximum S_v and standard deviation of S_v This method refined Alternative 4 by adding variability into the criterion in a multiple regression. The rationale of this definition was similar to the rationale of Alternative 2.

POP densities in our patch trawls. When comparing our estimates with assessments of Hanselman et al. (2003), we found that the CV on mean CPUE was lower at the planned stations in our study than in the SRS portion of the ACS study. Unlike the bimodal bootstrap distribution of the SRS estimates in Hanselman et al. (2003), a relatively Gaussian distribution resulted when bootstrapping the TAPAS and SRS estimators. Both designs have the disadvantage of having a variable sample size, but both have the advantage of completing a survey in a single pass through a study area. The TAPAS design imposed a small additional cost for travel time because our vessel had to return to trawl a random location in a patch, but the daily number of trawls conducted was not affected. The ACS and TAPAS designs are both more efficient than some of other two-stage designs that require the completion of an initial random sample before the second stage can begin. Another challenge with field studies of spatially variable species is that performance of survey designs depends highly on the fish densities encountered in a given survey.

Previous attempts to improve the correspondence between acoustic backscatter and trawl CPUE have focused on partitioning the acoustic backscatter to species (Mackinson et al., 2005) and quantifying relative catchability of these 2 sampling methods (McQuinn et

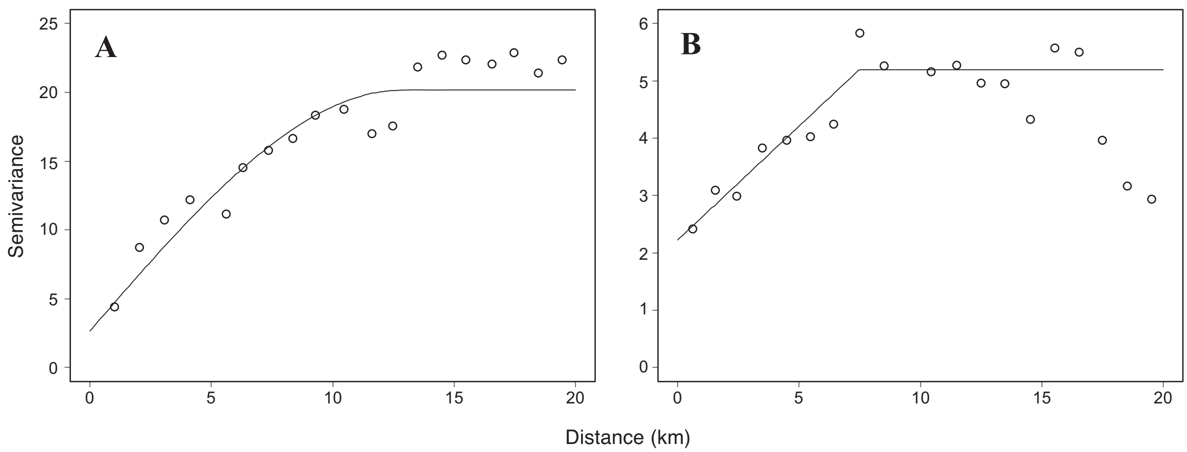

Figure 9

(**A**) Variogram of mean volume backscattering (S_v) from the vessel path (n=669 mean values) sampled during our 2009 acoustic–trawl survey. Line is spherical model fit: range (where spatial correlation ends)=12.9 km, partial sill (explained variance)=17.5 km, nugget (unexplained microscale variance)=2.6 (**B**) Variogram of [CPUE]$^{0.25}$ during the 1998 adaptive-cluster-sampling experiment (n=147 trawls). The line is the linear model fit: range=7.5 km, partial sill=3.0 km, nugget=2.2.

Table 5

Comparison of 5 alternative methods of patch selection to the original design for a 3-trawl-length (~3.0 km) acoustic sampling window.

Patch definition	Description	Selects above average CPUE	Selects below average CPUE	Error rate (%)
Original	80th percentile, 0.38 of the time	14	4	22
1	90th percentile, 0.12 of the time	7	2	22
2	80th percentile of the standard deviation of S_v	4	1	20
3	80th percentile of variance to mean ratio	4	1	20
4	90th percentile of max S_v	6	1	14
5	80th percentile of 1/max S_v×SD (S_v)	4	1	20

al., 2005). Beare et al.[3] found that using the length and species composition information from trawls to partition acoustic backscatter to species improved correlations. Mackinson et al. (2005) used a fuzzy logic approach to examine the relationship between acoustic backscatter and trawl CPUE, and they found that depth was a better predictor of trawl CPUE than was acoustic backscatter. For Alaskan groundfishes, species composition can be inferred relatively accurately by depth (Hanselman and Quinn 2004). Further work should focus on identifying specific characteristics of acoustic backscatter, such as school shape, target strength, and school density that would contrast rockfishes from co-occurring species. However, multivariate analyses have shown that distinguishing POP backscatter from walleye pollock backscatter is challenging (Spencer et al.[4]).

Increased precision for future applications of the TAPAS design could be attained in several ways. Improved correspondence between acoustic backscatter and trawl CPUE, for example, could be obtained from better partitioning of acoustic backscatter to species and quantifying the availability and vulnerability of a fish to these 2 sampling methods. Spencer et al. (2012) showed

[3] Beare, D. J., D. G. Reid, T. Greig, N. Bez, V. Hjellvik, O. R. Godø, M. Bouleau, J. van der Kooij, S. Neville, and S. Mackinson. 2004. Positive relationships between bottom trawl and acoustic data. ICES CM (council meeting) document 2004/R:24, 15 p.

[4] Spencer, P. D., D. H. Hanselman, and D. R. McKelvey. 2011. Evaluation of echosign data in improving trawl survey biomass estimates for patchily-distributed rockfish. North Pacific Research Board Final Report 809, 110 p. [Available from http://doc.nprb.org/web/08_prjs/809_final%20report_revised%20_2_.pdf, accessed September 2011.]

that the highest gains in efficiency for the TAPAS design, compared with SRS in simulations, were achieved when the spatial correlation of fish density was low and there was a large number of patches of small size. Such circumstances resulted in the TAPAS design sampling a high proportion of the total area of patches in the population. In addition, Spencer et al. (2012) showed that a modified TAPAS design, in which every third patch was sampled, resulted in higher efficiency than did an SRS design. However, the situations in Spencer et al. (2012) where there were significant gains in performance relative to SRS occurred only when there was a strong relationship between S_v and CPUE. Everson et al. (1996) showed that precision could be most improved when patches were smallest and they were a low proportion of the total survey area such that the probability of sampling high-CPUE areas during a random survey was low. These results indicate that the TAPAS design may show greater gains in precision for biomass estimates of a stock that is even more concentrated into small areas than is POP.

For these rockfish stocks, the greatest improvement in precision of trawl-survey indices of biomass can be achieved by increasing the overall sample size in the narrow depth band where they are most abundant. The ACS and TAPAS designs are useful frameworks for efficiently adding samples in abundant areas, and they also can serve to improve the NMFS trawl index in specific high-variability strata. Clearly, these designs should be applied only in depths and areas of known high abundance and variability of a species of interest, and the design should use a high threshold for invoking additional sampling.

For the TAPAS design to be applied efficiently, the specific acoustic backscatter characteristics of a target species need to be well known so that the relationships between patch definition, patch length, and CPUE are strong. Under these conditions (e.g., a patch station reliably has high CPUE), it might be beneficial to obtain an additional commercial vessel to follow the primary survey vessel, sample patch stations, and retain the catch, while the primary survey vessel continues to sample planned stations. These cost-recovery surveys (e.g., Hanselman et al. 2003) have been useful in Alaska as zero- or low-cost alternatives to the normal practice of discarding catch on purely random surveys.

Even if a design that combines acoustic surveys and trawl surveys could provide superior estimates of biomass, in practice, such a design would have to be modified to a context of a multispecies groundfish survey in most situations. Such adaptation is an additional complication in the use of novel sampling designs, given the competing sampling goals and limited resources of fisheries monitoring. In a multispecies context, the TAPAS design may be a way to add more sampling effort for major species groups that occupy a similar depth or area when differentiation of backscatter is difficult (as it is for rockfishes and walleye pollock). An avenue of future research would be to examine the precision of biomass estimates determined with the TAPAS design for multiple species that produce significant acoustic backscatter.

Conclusions

Our work shows that sampling fish populations with high spatial variability remains a challenge. To more accurately understand acoustic and spatial patterns for POP and other rockfishes, it may be necessary to consider more quantitative acoustic or geostatistical methods and to move away from the traditional paradigm of bottom trawl surveys (Godø, 2009). However, in areas that are fortunate enough to have a long time series of standardized fishery-independent surveys, it is rare and, perhaps, unwise to make changes to the sampling design or the sampling method. TAPAS and analogous designs could be used to increase sampling intensity for specific stocks, without necessarily creating a break in a biomass time series. The potential improvement in the precision of biomass estimates through the use of the TAPAS design when a strong relationship exists between S_v and CPUE (Spencer et al., 2012) offers motivation for continuing to refine our understanding of acoustic and spatial patterns and the methods used to define high-CPUE patches.

Acknowledgments

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Appendix

This appendix outlines the method with which we derived TAPAS variance estimators. Capital letters denote random variables; lower case letters denote realized values of random variables. This formulation redefines l'/L as an estimate of p, which is the proportion of the survey area in the patches, so that the properties of the binomial distribution can be used to capture the variability of track lengths of patches. Overbar notation refers to the mean, and hat notation refers to a sample estimate.

Definitions

p–Proportion of survey area in patches,

$$\frac{l'}{t},$$

a–Total area swept by bottom trawl, A–Total area of sampling area, D_0–Mean background CPUE, B_0–Background biomass, $AD_0(1–p)$, t–Total track length, l'–Total track length within patches,

$$l'=\sum_I l_i,$$

l_i–Length of track in patch i, I–Total number of patches encountered, L–Sum of length in patches, L_i–Length of patch i, $\bar{D}_i$–Mean CPUE within patch i, D_1–Mean patch CPUE in all patches,

$$D_1=\frac{\sum_I L_i\bar{D}_i}{L},$$

B_1–Patch biomass,

$$A\frac{\sum_I L_i\bar{D}_i}{t}=AD_1p,$$

$B– B_0 + B_1$, B–Total biomass

$$\Rightarrow B=AD_0(1-p)+AD_1p=A\left(D_0(1-p)+D_1p\right).$$

Biomass variance

After defining the variables, we derived the variance of the overall biomass estimate ($V[B]$):

$$V[B]=A^2V\left[D_0(1-p)+D_1p\right].$$

We used the definition of the variance of a sum:

$$V[B]=A^2\left(V\left[D_0(1-p)\right]+V\left[D_1p\right]+2Cov\left[D_0(1-p),D_1p\right]\right).$$

We applied the definition of the variance of a sum again:

$$V[B]=A^2\left(V\left[D_0-D_0p\right]+V\left[D_1p\right]+2Cov\left[D_0(1-p),D_1p\right]\right),$$
$$V[B]=A^2\begin{pmatrix}V\left[D_0\right]+V\left[D_0p\right]+2Cov\left[D_0,-D_0p\right]+V\left[D_1p\right]\\+2Cov\left[D_0(1-p),D_1p\right]\end{pmatrix}.$$

We removed constants and re-arranged the equation so that covariance terms were at the end:

$$V[B]=A^2\begin{pmatrix}V\left[D_0\right]+V\left[D_0p\right]+V\left[D_1p\right]-2Cov\left[D_0,D_0p\right]\\+2Cov\left[D_0(1-p),D_1p\right]\end{pmatrix}.$$

We defined parts to simplify the derivation with the delta method:

$$P=V\left[D_0p\right],$$
$$Q=V\left[D_1p\right],$$
$$R=Cov\left[D_0,D_0p\right],$$
$$S=Cov\left[D_0(1-p),D_1p\right],$$
$$V[B]=A^2\left(V\left[D_0\right]+P+Q-2R+2S\right).$$

Part P:

$$P=E\left[\frac{\partial D_0 p}{\partial D_0}\right]^2 V\left[D_0\right]+E\left[\frac{\partial D_0 p}{\partial p}\right]^2 V\left[p\right]+$$
$$2E\left[\frac{\partial D_0 p}{\partial D_0}\right]E\left[\frac{\partial D_0 p}{\partial p}\right]Cov\left[D_0,p\right]$$

$$P=E\left[\hat{p}\right]^2 V\left[D_0\right]+E\left[D_0\right]^2 V\left[\hat{p}\right]$$
$$+2E\left[D_0\right]E\left[\hat{p}\right]Cov\left[D_0,\hat{p}\right].$$

Part Q:

$$Q=E\left[\frac{\partial D_1 p}{\partial D_1}\right]^2 V\left[D_1\right]+E\left[\frac{\partial D_1 p}{\partial p}\right]^2 V\left[p\right]$$
$$+2E\left[\frac{\partial D_1 p}{\partial D_1}\right]E\left[\frac{\partial D_1 p}{\partial p}\right]Cov\left[D_1,p\right]$$

$$Q=E\left[p\right]^2 V\left[D_1\right]+E\left[D_1\right]^2 V\left[p\right]$$
$$+2E\left[D_1\right]E\left[p\right]Cov\left[D_1,p\right].$$

Part R:

$$R=E\left[\frac{\partial D_0}{\partial D_0}\right]E\left[\frac{\partial (D_0 p)}{\partial D_0}\right]V\left[D_0\right]$$
$$+E\left[\frac{\partial D_0}{\partial \hat{p}}\right]E\left[\frac{\partial (D_0 p)}{\partial p}\right]V\left[p\right]$$

$$+E\left[\frac{\partial D_0}{\partial D_0}\right]E\left[\frac{\partial (D_0 p)}{\partial p}\right]Cov\left[D_0,p\right]$$
$$+E\left[\frac{\partial D_0}{\partial p}\right]E\left[\frac{\partial (D_0 p)}{\partial D_0}\right]Cov\left[p,D_0\right]$$

$$R=E\left[p\right]V\left[D_0\right]+E\left[D_0\right]Cov\left[D_0,p\right].$$

We aggregated the parts:

$$V\left[B\right]=A^2\left(V\left[D_0\right]+P+Q-2R+2S\right),$$

$$V\left[B\right]=A^2\begin{pmatrix} V\left[D_0\right]+E\left[p\right]^2 V\left[D_0\right]+E\left[D_0\right]^2 V\left[p\right] \\ +2E\left[D_0\right]E\left[p\right]Cov\left[D_0,p\right]+ \\ E\left[p\right]^2 V\left[D_1\right]+E\left[D_1\right]^2 V\left[p\right] \\ +2E\left[D_1\right]E\left[p\right]Cov\left[D_1,p\right]+ \\ -2\left(E\left[p\right]V\left[D_0\right]+E\left[D_0\right]Cov\left[D_0,p\right]\right)+ \\ +2\begin{pmatrix} E\left[1-p\right]E\left[D_1\right]Cov\left[D_0,p\right] \\ -E\left[D_0\right]E\left[D_1\right]V\left[p\right] \\ -E\left[D_0\right]E\left[p\right]Cov\left[D_1,p\right] \end{pmatrix} \end{pmatrix}.$$

We rearranged the terms (covariance between D_0 and $\hat{p}$ was assumed to be zero):

$$V\left[B\right]=A^2\begin{pmatrix} \left(1-E\left[p\right]\right)^2 V\left[D_0\right]+E\left[p\right]^2 V\left[D_1\right]+ \\ \left(E\left[D_0\right]-E\left[D_1\right]\right)^2 V\left[p\right] \\ +2E\left[p\right]\left(E\left[D_1\right]-E\left[D_0\right]\right)Cov\left[D_1,p\right] \end{pmatrix}.$$

We estimated the biomass variance by replacing expected values with sample statistics:

$$\hat{V}\left[\hat{B}\right]=\left(1-\frac{a}{A}\right)A^2\begin{pmatrix} \left(1-\hat{p}\right)^2 \hat{V}\left[\hat{D}_0\right]+\hat{p}^2\hat{V}\left[\hat{D}_1\right] \\ +\left(\hat{D}_0-\hat{D}_1\right)^2 \hat{V}\left[\hat{p}\right] \\ +2\hat{p}\left(\hat{D}_1-\hat{D}_0\right)C\hat{o}v\left[\hat{D}_1,\hat{p}\right] \end{pmatrix},$$

whereas $\left(1-\frac{a}{A}\right)$ was the finite population correction.

Derivation of the variance of the estimates of *p*, D_0, and D_1

Variance of the estimate of *p*:

Each patch accounted for some proportion of the total length of the trackline so that $p_i=L_i/t$. We were interested in the overall proportion of the trackline that was in the patches, or p. The parameter p was considered to be a parameter of a binomial distribution. In a binomial distribution, an estimate of p is X/n, where X was the number of successes in n discrete observations. In our TAPAS application, the total of the discrete observations was $\hat{n}_L$ (the number of 100-m segments along the survey trackline) and X was the number of these observations that were in a patch. Our sample estimate of X/n was $\hat{p}$ with the binomial estimated variance:

$$\hat{V}\left[\hat{p}\right]=\frac{\hat{p}(1-\hat{p})}{\hat{n}_L}.$$

These $\hat{n}_L$ observations could have been assumed to be independent, but there was likely some spatial correlation. For our application, variogram analysis of acoustic backscatter data indicated that the range parameter was ~12 km. This range resulted in an effective sample size that was much smaller than the total number of discrete sampling units, and variance was underestimated. The value of $\hat{n}_L$ used in the variance equation should reflect this autocorrelation. In our application, we divided our total trackline length (~1200 km) by the variogram range parameter (~12 km), a calculation that yielded an $\hat{n}_L$ ~100.

Variance of the estimate of D_0:

The variance in D_0 was the straightforward random sampling estimator shown as the variance of $\hat{D}_0$ in Table 1.

Variance of the estimate of D_1:

Recall that D_1 was estimated as

$$D_1 = \frac{\sum_{i=1}^{I} L_i \bar{D}_i}{L}.$$

We expressed the L_i in terms of p and made substitutions to obtain

$$D_1 = \frac{\sum_{i=1}^{I} p_i \bar{D}_i}{\sum_{i=1}^{I} p_i} = \frac{\sum_{i=1}^{I} p_i \bar{D}_i}{p} = \sum_{i=1}^{I} z_i \bar{D}_i,$$

where $z_i = p_i/p$.

This expression rescaled the values of p_i so that they summed to one. In this case, we observed a given number of "samples" of trackline from the patches, and z_i was the proportion of all the patch trackline that was in patch i. This calculation was still a binomial distribution, except, in this case, we ignored the background category and were concerned only with the patches.

We applied the delta method to this sum of products of random variables:

$$V\left[\sum_{i=1}^{I} z_i \bar{D}_i\right] = \sum_i \left(V\left[z_i\right] E\left[\bar{D}_i\right]^2 + V\left[\bar{D}_i\right] E\left[z_i\right]^2 \right) + 2\sum_{i \neq j} E\left[\bar{D}_i\right] E\left[z_j\right] Cov(\bar{D}_i, z_j).$$

The variance of z_i could be obtained with the same method as that for the variance of p, with an adjusted n_L. We substituted sample statistics for expected values to obtain the estimated variance of D_1:

$$\hat{V}\left[\hat{D}_1\right] = \frac{1}{L^2} \left(\frac{\sum_{n-I+1}^{n} \hat{p}_i^2 (\hat{d}_i - \bar{d})^2}{(n-I-1)\hat{p}^2} + \bar{d}^2 \sum_{n-I+1}^{n} \frac{\hat{p}_i - \frac{\hat{p}_i}{\hat{p}}}{\hat{p}^2 \hat{n}_L} \right).$$

In theory, the term for Cov($\bar{D}_i$, z_j) should be a nonzero value. For example, consider a case with 2 patches. If the proportion in one patch is large, the proportion in the other patch is small, and CPUE and patch length (the proportion) are correlated, then the CPUE would be small in the patch with the small proportion. However, as the number of patches becomes much greater than 2, the covariance between patches and density decreases as $z_j \to 0$. We assumed this covariance was negligible:

$$V\left[\sum_{i=1}^{I} z_i \bar{D}_i\right] = \sum_i \left(V\left[z_i\right] E\left[\bar{D}_i\right]^2 + V\left[\bar{D}_i\right] E\left[z_i\right]^2 \right).$$

Covariance of [D_1, p]:

Recall

$$D_1 = \frac{\sum_{i=1}^{I} p_i \bar{D}_i}{\sum_{i=1}^{I} p_i} = \frac{\sum_{i=1}^{I} p_i \bar{D}_i}{p},$$

$$p = \sum_{i=1}^{I} p_i.$$

Here, we did not substitute z_i for p_i/p because the set of p_i was common to both functions. Recall that the covariance of 2 functions of random variables was

$$\mathrm{Cov}\left(g(x), h(x)\right) \cong 2\sum_{i>j} \mathrm{Cov}\left(x_i, x_j\right) \frac{\partial g}{\partial x_i} \frac{\partial h}{\partial x_j}.$$

In our application, $g(x) = D_1$ and $h(x) = p$.

We applied the delta method:

$$\mathrm{Cov}\left(D_1, \hat{p}\right) = \sum_{i=1}^{I} \sum_{j=1}^{I} \left(\mathrm{Cov}\left(\bar{D}_i, p_i\right) \frac{p_i}{p} + \mathrm{Cov}\left(p_i, p_j\right) \frac{\bar{D}_i p - \sum_{k=1}^{I} p_k \bar{D}_k}{(p)^2} \right).$$

We used the argument above that Cov ($\bar{D}_i$, p_j) , where $i \neq j$, can be ignored. This argument leaves only the Cov ($\bar{D}_i$, p_i), which, in the sampling design of the TAPAS, was expected to be a nonzero value (i.e., the length of a given patch is correlated with the CPUE of that patch):

$$\mathrm{Cov}\left(D_1, p\right) = \sum_{i=1}^{I} \mathrm{Cov}\left(\bar{D}_i, p_i\right) \frac{p_i}{p} + \sum_{i=1}^{I} \sum_{j=1}^{I} \left(\mathrm{Cov}\left(p_i, p_j\right) \frac{\bar{D}_i p - \sum_{k=1}^{I} p_k \bar{D}_k}{(p)^2} \right).$$

We substituted sample statistics to obtain the covariance of [D_1, p] :

$$\hat{Cov}\left[\hat{D}_1, \hat{p}\right] = \left(\begin{array}{c} \sum_{i=1}^{I} \hat{Cov}\left(\hat{d}_i, \hat{p}_i\right) \frac{\hat{p}_i}{\hat{p}} + \\ \sum_{i=1}^{I} \sum_{j=1}^{I} \left(\hat{Cov}\left(\hat{p}_i, \hat{p}_j\right) \frac{\hat{d}_i \hat{p} - \sum_{k=1}^{I} \hat{p}_k \hat{d}_k}{(\hat{p})^2} \right) \end{array} \right).$$