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The use of adaptive cluster sampling for hydroacoustic surveys

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Resource managers are often required to estimate the size of a wildlife population based on sampling surveys. This problem is especially critical in fisheries, where stock-size estimation forms the basis for key policy decisions. This study looks at design-based methods for a hydroacoustic fisheries survey, with the goal of improving estimation when the target stock has a patchy spatial distribution. In particular, we examine the efficiency and feasibility of a relatively new design-based method known as adaptive cluster sampling (ACS). A simulation experiment looks at the relative efficiency of ACS and traditional sampling designs in a hydroacoustic survey setting. Fish densities with known spatial covariance are generated and subjected to repeated sampling. The distributions of the different estimators are compared.

Hydroacoustic data frequently display strong serial correlation along transects and so traditional designs based on one-stage cluster sampling are appropriate. Estimates of total stock size for these designs had a markedly skewed distribution. ACS designs performed better than traditional designs for all stocks with small-scale spatial correlation in fish density, yielding estimates with lower variance. ACS estimators were not skewed and had a lower frequency of large errors. For the most variable stock the use of ACS reduced the coefficient of variation (CV) of the stock size estimate from over 0.9 to around 0.5. Differences between traditional and ACS designs were consistent over multiple realizations of each spatial covariance model.

A survey of rainbow smelt (*Osmerus mordax*) in the eastern basin of Lake Erie was used as a case study for development of a survey design. A field trial showed that use of ACS for the survey is feasible but pointed out some areas for further research. The biggest drawback to use of ACS is uncertainty in the final sample size. This can be partially controlled by applying ACS within a stratified design. ACS retains the unbiased and non-parametric properties of design-based estimation but allows increased sampling in high-density areas that are of greater biological interest. For stocks with an aggregated or patchy spatial distribution ACS can provide a more precise estimate of stock size than traditional survey methods.

Keywords: adaptive cluster sampling, survey design, spatial sampling, stock assessment, patchy distributions.

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Introduction

A persistent problem in the management of natural resources is estimating the size of a population or stock from a limited sample. Determining the population size is particularly important in fisheries management where key policy decisions are based on the estimated size of a stock. Historically, fish stocks were often assessed with methods yielding only a relative index of abundance (Gunderson, 1995). Recently, there has been an increased effort not only to estimate stock sizes absolutely but also to quantify the uncertainty in the estimate. Hydroacoustic methods provide both absolute abundance estimates and a much larger sample size than traditional fishing gears, thus allowing wider application of statistical sampling theory to stock assessment surveys.

Statistical theory provides a number of design-based methods for estimating the mean density or total population size. These methods are primarily designed for situations where sample units are independent and the underlying distribution is fairly normal, conditions rarely met by fisheries data. More usually fish density data show strong skewness, high kurtosis, and local correlation, resulting in a very large variance of estimation (Gilbert, 1987; Foote and Stefansson, 1993; Patil and Rao, 1994). These problems are particularly acute when the target stock has an aggregated or "patchy" spatial distribution (Appenzeller and Leggett, 1996; Barrange and Hampton, 1997). This study looks at design-based methods for a hydroacoustic survey, with the goal of improving estimation when the target stock has a patchy spatial distribution. In particular, we examine the efficiency and feasibility of a relatively new (Thompson, 1990; Thompson and Seber, 1996) design-based method known as adaptive cluster sampling (ACS). While this study is based on fisheries applications the results are also applicable to spatial surveys in many other fields, including forestry (Roesch, 1993), wildlife ecology (Smith *et al.*, 1995), and epidemiology (Thompson, 1996).

Design-based methods for hydroacoustic surveys

Hydroacoustic data processing provides a direct estimate of the area- or volume-normalized fish density over a sampling unit. If densities in adjacent sampling units are independent, the variance of the stock-size estimate can be estimated simply with the sample variance. When adjacent sampling units are strongly correlated, however, the observed sample variance will grossly underestimate the true variance of estimation (Williamson, 1982). The correct design-based approach in this situation is to use cluster sampling formulas, with the transect being the primary unit and the integrated segments of cruise track (referred to as EDSUs in some literature) as secondary units. Key works on the design of hydroacoustic surveys include Francis (1984), Gavaris and Smith (1987), Jurvelius and Auvinen (1989), and Jolly and Hampton (1990). A special ICES workshop held in 1992 (ICES, 1993) reviewed design- and model-based approaches for hydroacoustic stock assessment. Current hydroacoustic survey designs are primarily based on cluster sampling with parallel transects across the study area, placed by either systematic or stratified random designs (Brandt *et al.*, 1991; Hampton, 1996; Simmonds and Fryer, 1996).

There has been considerable interest also in model-based methods of estimation (Sullivan, 1991; Swartzman, 1992; Stolyarenko, 1992; Steffanson, 1996). Geostatistical methods have become popular for modeling data with spatial correlation (Guillard *et al.*, 1992; Petitgas, 1993a,b; Pelletier and Parma, 1994; Williamson and Traynor, 1996). Model-based approaches forecast the total stock size by predicting fish density in unsampled regions of the study area, and allow calculation of the uncertainty of the total based on estimated variance of the error terms in the model (Ripley, 1981; Foote and Steffanson, 1993). In some situations an appropriate model-based estimate can greatly improve precision over random sampling designs (Sullivan, 1991). For stocks with very patchy distributions, however, a smoothed surface-trend model may be a very poor fit to the data (Foote and Steffanson, 1993; Murray, 1996). Comparison of ACS estimation with model-based methods is not included in this paper but will be the subject of future work.

Adaptive cluster sampling (ACS)

Adaptive cluster sampling (ACS) is a design-based method that can be used when data are strongly correlated. The basic theory was put forth by Thompson (1990, 1991a,b, 1992, 1996), Seber and Thompson (1994), and Thompson and Seber (1996). ACS was designed especially for situations where standard cluster sampling is ineffective; when the target stock tends to concentrate in a few dense clusters rather than being evenly distributed over the study area. Theoretical analysis shows that ACS reaches its greatest efficiency, relative to simple random sampling, when the target organisms are highly clustered, rare, or both (Thompson, 1990; Thompson and Seber, 1996; Christman, 1997). Monte-Carlo simulations (Conners, 1999) show that high relative efficiency of ACS is associated with frequency distributions of fish density that are strongly skewed, have high kurtosis and have a large proportion of units with zero or very low densities. These types of distributions are frequently observed in fisheries data, especially with species that exhibit schooling behaviour or strong microhabitat associations (Hampton, 1996; Simmonds and Fryer, 1996).

The Lake Erie smelt survey

As a framework and motivation for this study we use data from a hydroacoustic survey of rainbow smelt (*Osmerus mordax*) in the eastern basin of Lake Erie (42°30′N, 80°W). Estimates of the total number of yearling and older (YAO+) smelt are used in formulating catch limits and stocking policies for smelt and their predators (Einhouse *et al.*, 1997). The New York Department of Environmental Conservation (NYSDEC) Lake Erie Fisheries Unit in Dunkirk, New York provided assistance, data, and ship-time for testing adaptive sampling techniques. The Lake Erie Fisheries Unit would like to optimize a survey design for estimating the total stock size of smelt, with an accurate estimate of the associated variance. Data from preliminary surveys suggest a "patchy" distribution of smelt density with small-scale "hot-spots" of high fish density and a large-scale pattern of higher densities associated with particular depth contours. Frequency distributions of the existing survey data are strongly skewed and

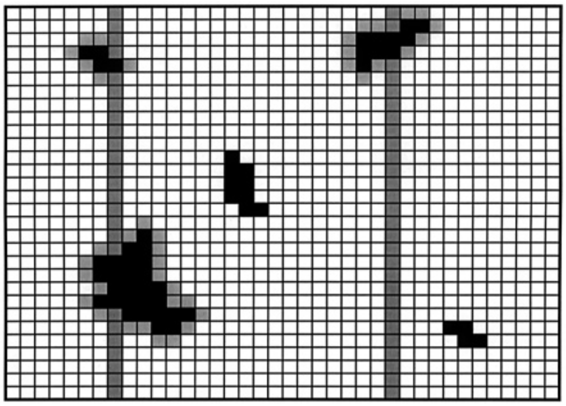

Figure 1. An example of strip adaptive cluster sampling for a patchy population. Black squares represent fish densities above the critical value. The initial sample consists of two transects which detect three patches. Units adjacent to high densities are added adaptively until densities drop below the critical value. The final sample size includes the initial transects plus adaptively added units.

correlation coefficients between adjacent sampling units are 0.6–0.8, indicating strong local correlation. These features suggested that ACS may be particularly efficient for estimating the total size of this stock.

Methods

ACS with primary and secondary units

In a typical hydroacoustic survey transect locations are selected according to some sample design; each transect then includes a set of secondary sampling units in which the fish density is measured by integrating the acoustic signal over a fixed distance. The type of ACS sampling that applicable to such exercises is, therefore, ACS with primary and secondary units (Thompson, 1991b; Thompson and Seber, 1996; Pontius, 1997). The transects are the primary units and the integrated sampling units are the secondary units in this form of "Strip ACS" (Figure 1). The initial sampling design consists of one or more randomly, or systematically placed, transects. All of the sampling units in the initial design are measured and units that meet a pre-specified *criterion* are identified. The criterion is determined by the researcher but is often the presence of a rare species or a density higher than some set value. For the adaptive stage of sampling *secondary units* are added in the neighbourhood of any *secondary* unit meeting the ACS criterion. The final sample includes all of the initial transects plus, where any transect intersects a high-density cluster, a "cloud" of adaptively added secondary units. The number of units added to the sample depends on the ACS criterion and neighbourhood definition used, as well as on the scale of the secondary units and the spatial distribution of the target fish.

ACS provides two methods for estimating the overall mean density (or total) and variance of the estimator (Table 1). Both estimators balance the total number of fish in a cluster or network (y_k^*) against the probability of detecting that network, based on its "width" (x_k) relative to the initial sampling design. Estimation of the mean over the study area is based on the means within the sampled networks, including a large number of networks of size one and the few larger networks. The first estimator, referred to as the Hansen–Hurwitz-type (HH) estimator, is based on sampling with replacement and draw-by-draw selection probability for each transect. Variance estimation for the HH estimator is based on variance between density estimated by each transect. The second estimator, the Horvitz–Thompson-type (HT) estimator, may be used when sampling with or without replacement. The HT estimator uses a combinatoric argument to estimate individual and pair-wise inclusion probabilities (α_k, α_{kr}) for each network (Table 1). This calculation is conceptually simple, but can be complex to implement (Conners, 1999).

When the total number of transects in the study area (N) is large the two estimation procedures yield nearly identical results [$\alpha_k \rightarrow (x_k/N)$]. For both estimators the estimated probability of detecting a network is a function of the number of transects that intersect it, and the probability of selecting those transects with the initial survey design. Thus, large clusters have a higher probability of being detected, and are down-weighted in the estimation of the overall mean. Small clusters and units that do not meet the criterion have smaller inclusion probabilities and contribute more to the overall mean. This weighting counteracts the positive bias in the estimated mean that would normally result from including a large number of high-density units in the sample.

Simulation study

A simulation study was conducted to test the efficiency of ACS for a fish stock similar to Lake Erie smelt. Simulated test stocks were created with known true total size and different levels of spatial aggregation. Selected stocks were sampled repeatedly using both traditional and ACS designs. The study included four, one-stage, cluster sampling (traditional) designs and two ACS designs with different initial transect layouts. For each sampling replicate the estimated total stock size and variance of the estimator were calculated. The experiment tabulated relative estimation errors – the difference between the estimated and true total, $[(\hat{T} - T)/T]$ – over 5000 random samples of each design. These were compared based on the distribution of the estimated total $\hat{T}$ and the variance of the estimator over the

Table 1. Notations and formulae for Adaptive Cluster Sampling with primary and secondary units, based on Thompson and Seber 1996 (Chapter 4.7).

A. "Hansen-Hurwitz-Type" Estimation

$$w_j = \frac{1}{m_j}\sum_{k=1}^{K}\frac{y_k^*}{x_k}I_{jk} \quad \tilde{\mu}_{HH} = \frac{1}{n}\sum_{j=1}^{n} w_j \quad \hat{V}(\tilde{\mu}_{HH}) = \frac{N-n}{Nn}\frac{1}{(n-1)}\sum_{j=1}^{n}(w_j - \tilde{\mu}_{HH})^2$$

N	Number of possible primary units (transects) in the study area
n	Number of primary units in the initial sample, j=1,2, . . . n
m_j	Number of secondary units in primary unit (transect) j
k	Index of unique ACS network, k=1,2, . . . K
y_{kJ}	Measured fish density for a secondary unit (EDSU or sampling unit)
y_k^*	Sum of measured fish densities over all secondary units in network k
x_k	Number of primary units (transects) that intersect network k
I_{jk}	Indicator variable: =1 if transect j intersects network k
w_j	Mean fish density over all networks detected by transect j
μ_{HH}	"Hansen-Hurwitz Type" estimator of mean fish density
$\hat{V}(\mu_{HH})$	Estimated variance of estimator for mean fish density

B. "Horvitz-Thompson-Type" Estimation

$$\tilde{\mu}_{HT} = \frac{1}{M}\sum_{k=1}^{K}\frac{y_k^*}{\alpha_k}J_k \quad \hat{V}(\hat{\mu}_{HH}) = \frac{1}{M^2}\sum_{k=1}^{K}\sum_{r=1}^{K}\frac{y_k^* y_r^*}{\alpha_{kr}}\left(\frac{\alpha_{kr}}{\alpha_k\alpha_r} - 1\right)$$

$$\alpha_k = 1 - \binom{N-x_k}{n}\Big/\binom{N}{n} \quad \alpha_{kr} = 1 - \left[\binom{N-x_k}{n} + \binom{N-x_r}{n} - \binom{N-x_k-x_r+x_{kr}}{n}\right]\Big/\binom{N}{n}$$

N, n, k, y_k^*, x_k	Defined as above
M	Total number of secondary units in the study area
J_k	Indicator varible: =1 if initial sample intersects network k
α_k	Estimated inclusion probability for network k
α_{kr}	Estimated joint inclusion probability for networks k and r
x_{kr}	Number of primary units that intersect **both** networks k and r

sampling replicates. The programming was conducted in MATLAB 4.1.

An isotropic spherical variogram model was used to calculate the variance-covariance matrix for points on a 100×50 grid. This covariance matrix was then combined with randomly generated, standard normal variables to produce a bivariate normal surface with the modeled covariance structure. In order to give the simulated data the strong skewness observed in the Lake Erie data the generated densities were exponentiated. This ensured that the points on the final simulated grid had a lognormal distribution. After experimentation with several sets of variogram parameters four model specifications were selected for sampling. The selected models (Table 2) represent stocks with no local correlation ("Random"), with strong local correlation over a large range ("Big Patches"), and with strong local correlation over a smaller range ("Small Patches"). A fourth stock ("Rare Patches") represents strong local correlation with relatively high background noise or "nugget", which is most similar to the Lake Erie smelt data. All of the test stocks were generated with a constant mean, which implies no large-scale spatial pattern. A number of realizations were generated for each of the spatial models; grids "typical" of each spatial model are shown in Figure 2. The four grids in Figure 2 were standardized to have an equal "true population" total fish. For ease of interpretation the conclusions were based largely on comparison of these four standardized test stocks. These conclusions were, however, verified over 20 realizations of the stochastic spatial surface for each model.

Table 2. Spatial models and simulated test stocks

	Generation model (spherical variogram)				
Stock	Mean	Sill	Range	Nugget	(% of sill)
Random	5.0	6.0	4	6.0	(100%)
Big patches	5.0	6.0	20	0.6	(10%)
Small patches	5.0	6.0	4	0.6	(10%)
Rare patches	4.2	8.0	4	2.4	(30%)

Sampling and estimation for the traditional designs were performed using one-stage cluster sampling formulas (Cochran, 1977; Thompson, 1992). Equal allocation of transects to strata was used in stratified designs.

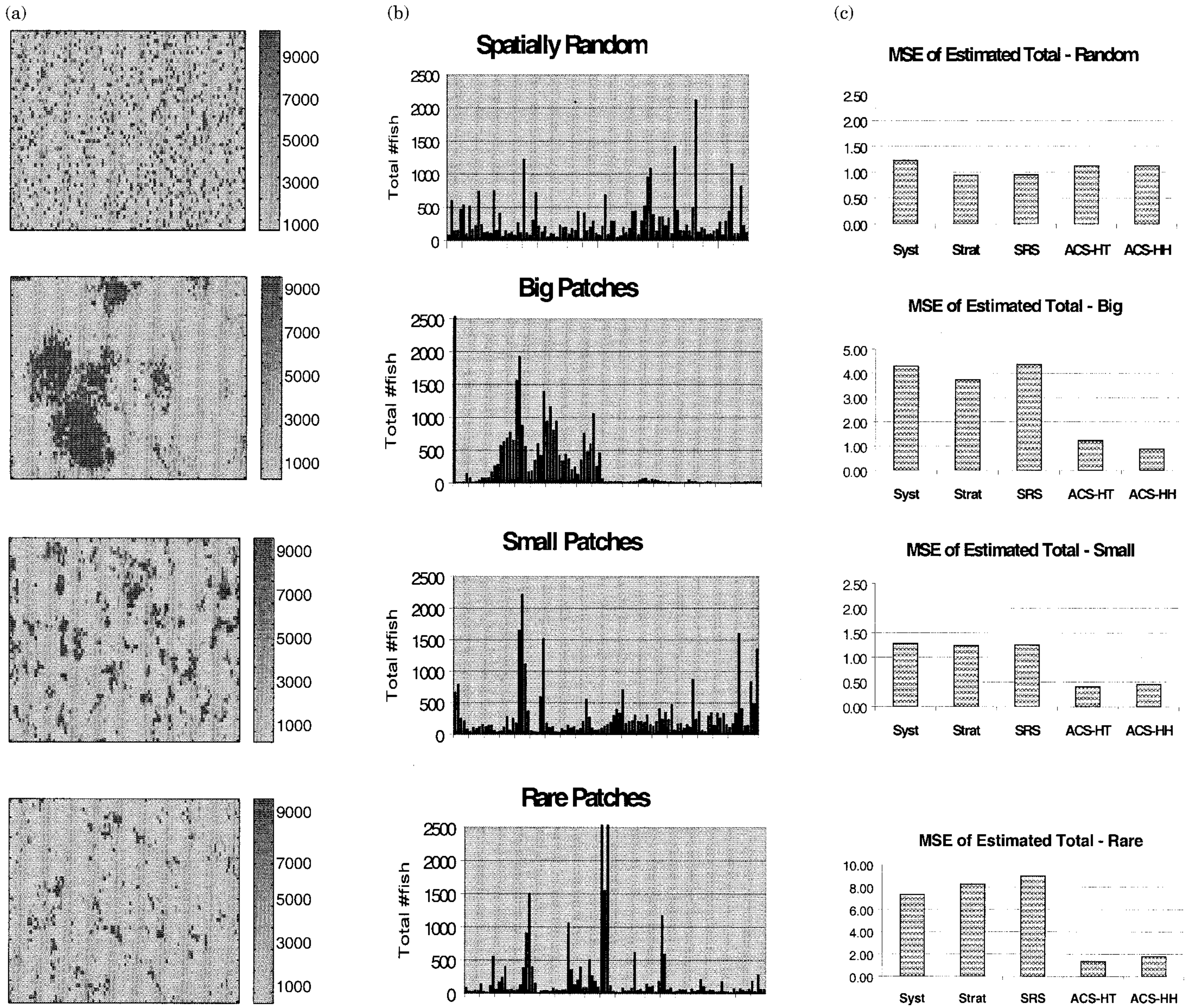

Figure 2. Simulated target stocks for sampling comparison: (a) greyscale map of "true" density grid; (b) transect totals for each stock (sum of densities from each column); (c) variance of estimation (MSE) for total stock size for different sampling designs.

Traditional designs included random selection of 10 transects, systematic selection of 10 transects with a random start and three stratified, random sampling designs. Stratified designs divided the study grid along the long axis into two strata with five transects/stratum, into five strata with two transects per stratum and along both axes of the study grid to form 10 strata, with two (half-length) transects in each stratum. Results were similar for the three types of stratification and so only the two-stratum design is presented here.

ACS sampling was performed according to Thompson and Seber (1996, Section 4.7) with the transects as primary units and the individual grid cells as secondary units (Figure 1). A "neighbourhood" definition of four adjacent cells – the four cells sharing a common boundary with the target cell – was used as in other work on ACS. For both ACS designs the critical value defining networks was set at the 80th percentile of the true distribution of the grid points. Other studies (Conners, 1999) have shown that this is near the optimal critical value for a skewed population and that final estimates are not sensitive to small differences in critical value. In order to minimize the computations network statistics (t_k, w_k, α_k) were tabulated for the entire grid and so each sampling simulation simply looked up values for the networks intersected by the sample. Calculation of two-way inclusion probabilities for the HT estimator proved to be complex; for a detailed algorithm and computer code, see Conners (1999). Output from the sampling simulations for ACS designs included the final sample size after addition of adaptive units. Initial sample sizes for ACS designs were selected to give expected final sample sizes as close as possible, in total number of secondary units sampled, to the fixed size of the traditional designs.

Field trial of ACS for hydroacoustic surveys

In addition to the simulation study, we used one night of the 1998 Lake Erie survey to test the practicality of a field implementation of an ACS design. Ship time was provided by the NYSDEC. The ACS trial consisted of one initial transect followed by the addition of adaptive sampling units. As a definition of the ACS "neighbourhood" we added units along transect segments parallel to the initial transect at a spacing of 1.5 km, collecting hydroacoustic data over the range of latitude where units above the critical value had been observed.

Results

Simulation study

The simulation study showed clear differences in the behaviour of the estimators between traditional and ACS methods (Table 3). The estimators from traditional cluster sampling, based on the sample mean, were unbiased but did *not* have a symmetric distribution. Figure 3 shows the relative errors of estimation [$(\hat{T} - T)/T$] from cluster sampling with stratified, random transect selection. The distribution of the estimator is markedly right-skewed with a large fraction of estimates lower than the true stock size but a few estimates much higher than the true total. While most of the sampling replicates produced estimates close to the true total, relative errors close to -1 ($\hat{T}$ near 0) and above $+1$ ($\hat{T}$ more than twice T) were not uncommon. This skewness was evident in estimators from all traditional cluster sampling designs.

The positive skewness in the traditional estimators was a result of a small effective sample size from a strongly skewed underlying distribution. Traditional one-stage, cluster-sampling designs are, in effect, a random sample of transect totals. The effective sample size is equal only to the number of transects in the survey. Depending on the presence and number of high-density "patches" intersected by a transect, transect totals can vary widely (Figure 2). The presence of spatial correlation tends to create a strongly skewed distribution of transect totals. Smaller patch size and the increased rarity of patches increases the variance and skewness of the transect totals (Figure 2). For the simulations a sample of 10 transects (10% of the total study area) was selected and so estimation of the stock size is based on ten transect totals. This effective sample size is too small to give the sample mean a Normal distribution or anything even approximating one. In many field surveys this pattern would be compounded by large-scale trends in density and variation in the length of transects. While skewness in the estimator can be reduced by increasing the number of transects, for many surveys a larger number of transects would not be feasible.

Adaptive cluster sampling both increased the efficiency of estimation over traditional sampling designs and produced estimators with a more symmetric distribution (Figure 3). Simulated ACS designs included both systematic and stratified random designs for initial transect selection. Both initial designs produced estimators with symmetric distributions and reduced error frequency relative to traditional designs. The reduced frequency of estimates in the "upper tail" could be an important consideration for a resource manager using estimated stock size to set fishery regulations.

Table 3 summarizes the features of the distribution of the estimated stock size over the 5000 replicates of each sampling design. This table compares the results for fixed-size traditional designs with ACS designs that have an average final sample size closest to the same number of secondary units. The relative variance of estimation for the different sampling designs is most easily seen by looking at the coefficient of variation or CV. For the stock (random) with no spatial correlation both

Table 3. Results of simulation study: distributions of the estimate of total stock size (T) over 5000 random samples. Each of the four standardized test stocks were sampled by traditional one-stage cluster sampling designs (Tr) and Adaptive Cluster Sampling (ACS) designs. The two different estimators for ACS designs (see text) are denoted by HH and HT as in Table 1.

Standardized test stock	Sampling design	Average final sample size	T $\times 10^{-7}$	Estimated total stock size T: Distribution of estimator over 5000 random samples: Var (T) $\times 10^{-14}$	Bias $\times 10^{-7}$	MSE $\times 10^{-14}$	Skewness	Kurtosis	C.V.	Relative error of T Frequency: "Good" <10%	"Poor" >50%	Relative efficiency (to SRS*)
Random	Tr-Systematic	500	3.015	0.98	0.015	1.23	1.09	1.73	0.37	0.21	0.10	0.96
Random	Tr-Stratified	500	3.011	0.94	0.011	0.94	0.89	1.92	0.32	0.23	0.10	1.00
Random	Tr-SimpleRS	500	3.010	0.97	0.010	0.95	0.88	1.92	0.32	0.23	0.10	0.97
Random	ACS-Stratifed-HT	449	3.022	1.14	0.022	1.12	1.10	2.08	0.35	0.22	0.12	0.93
Random	ACS-Stratifed-HH	449	3.021	1.12	0.021	1.12	1.10	2.08	0.35	0.22	0.12	0.95
Small patches	Tr-Systematic	500	2.988	1.34	−0.012	1.28	0.24	1.28	0.38	0.11	0.29	0.51
Small patches	Tr-Stratified	500	2.997	1.25	−0.003	1.25	0.81	1.80	0.37	0.19	0.15	0.54
Small patches	Tr-SimpleRS	500	3.000	1.27	0.000	1.25	0.84	1.85	0.37	0.18	0.15	0.53
Small patches	ACS-Stratifed-HT	674	3.005	0.39	0.005	0.41	0.25	1.64	0.21	0.34	0.02	1.23
Small patches	ACS-Stratifed-HH	674	3.000	0.47	0.000	0.46	0.37	1.67	0.23	0.33	0.02	1.03
Big patches	Tr-Systematic	500	2.990	2.69	−0.010	4.30	1.77	2.67	0.69	0.10	0.10	1.47
Big patches	Tr-Stratified	500	2.970	3.82	−0.030	3.74	1.57	2.53	0.65	0.17	0.23	1.04
Big patches	Tr-SimpleRS	500	2.998	4.44	−0.002	4.37	1.43	2.38	0.70	0.14	0.34	0.89
Big patches	ACS-Systematic-HT	684	3.506	4.68	0.506	1.24	2.04	3.33	0.32	0.50	0.12	0.59
Big patches	ACS-Systematic-HH	684	3.002	8.26	0.002	0.89	1.03	2.25	0.31	0.00	0.12	0.34
Rare patches	Tr-Systematic	500	3.000	10.02	0.000	7.35	1.29	1.88	0.90	0.10	0.69	0.80
Rare patches	Tr-Stratified	500	2.982	8.54	−0.018	8.29	1.43	2.25	0.97	0.06	0.59	0.95
Rare patches	Tr-SimpleRS	500	3.034	9.22	0.034	9.02	1.49	2.34	0.99	0.07	0.59	0.88
Rare patches	ACS-Stratifed-HT	602	3.024	1.43	0.024	1.38	0.62	1.33	0.39	0.06	0.21	4.59
Rare patches	ACS-Stratifed-HH	602	3.026	1.82	0.026	1.80	0.41	1.52	0.44	0.22	0.33	3.59

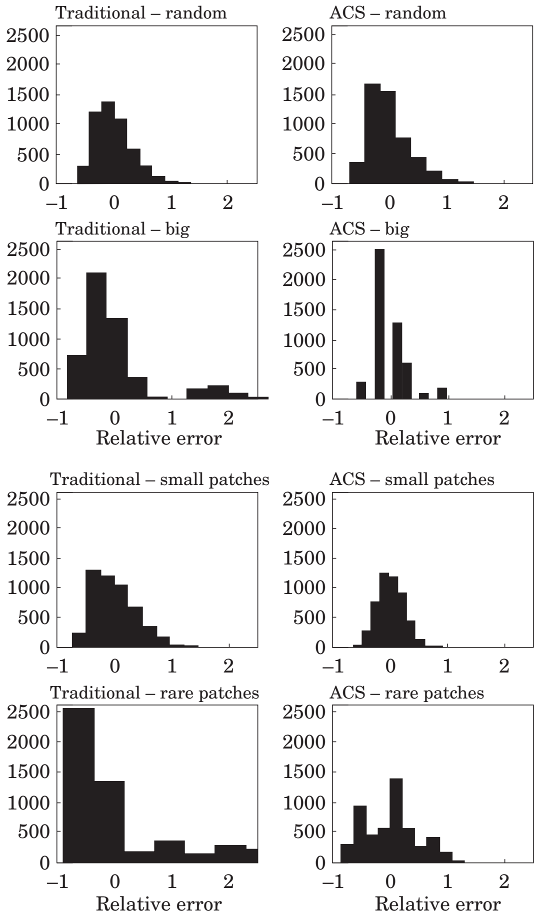

Figure 3. Distribution of the Relative Errors $(\hat{T} - T)/T$ over 5000 sampling replicates. The results are shown for the four standardized test stocks. "Traditional" is stratified random sampling and "ACS" is ACS sampling from a stratified random design. Note the high skewness of the traditional estimator.

traditional designs and the stratified ACS design produced CVs in the range of 0.32–0.37. For the stocks with positive spatial correlation, however, use of ACS reduced the CV compared to all three traditional designs. The stock with small patches had a CV of 0.37–0.38 for traditional sampling designs but 0.21–0.23 for the ACS designs. For the stock with big patches ACS reduced the CV from 0.65–0.70 for traditional designs to 0.31–0.32. The stock with rare patches showed a reduction in CV from 0.90–0.99 to 0.39–0.44. For a particular stock ACS with the initial systematic design performed less efficiently than ACS from a stratified random design, as a result of stronger limitation on final sample size. This point will be discussed later in the text.

In order to be sure that the results were not an artifact of particular test stocks the simulations were repeated over stocks from 20 realizations of each of the four spatial models. A check of variance components showed that uncertainty in estimation due to sampling was greater than that due to the stochastic variation in the underlying model. The greater efficiency of ACS over traditional designs was consistent over the repeated realizations of the correlated spatial models. For each model the stratified ACS estimator was the statistical "best" estimator, in that it minimized the mean squared error over both the spatial super-population model and random sample selection (Hedayat and Sinha, 1991, Chapter 10; Bellhouse, 1977).

Table 3 shows the "Relative Efficiency" for each sampling design. This measure compares the variance of the sampling estimator to the theoretical variance of a simple random sample of "equivalent" size:

$$RE = \frac{Var_{SRS}(n_{eq})}{Var(\hat{T})} \quad \hat{V}_{SRS}(n_{eq}) = \frac{(N - n_{eq})}{N} * \frac{\sigma^2}{n_{eq}}$$

where σ^2 is the true variance of the simulated test stock and n_{eq} is the size of the "equivalent" sample. Following Seber and Thompson (1994, Table 4.4), the "equivalent" sample size is 500 units for the fixed-size designs and the average final sample size for ACS designs. A Relative Efficiency greater than one indicates that the sampling estimator has a smaller variance than is expected from simple random sampling, or that it is more efficient than simple random sampling. Fixed-size cluster designs were more efficient than SRS only when systematic and stratified cluster designs were applied to the stock with big patches. These two designs are known to be efficient for situations where the local covariance, in this case covariance between the transect totals, is monotonically decreasing (Ripley, 1981, page 25). ACS designs were more efficient than "equivalent" SRS for both the small and the rare target stocks. This is consistent with the results of previous authors (Thompson, 1991b; Christman, 1997), who have demonstrated that ACS is more efficient than SRS when the target stock is rare or highly aggregated or both. For the "rare patches" stock the relative efficiency of ACS designs is over three times that of SRS. The ACS designs were not efficient for the "big patches" stock because the large final sample size made the equivalent SRS variance small.

Thompson and Seber (1996, page 129) and Christman (1997) compared the relative efficiencies of the two ACS estimation procedures (the HH and HT estimators). These authors also found that both estimators had a relative efficiency >1 for target stocks that were rare or highly aggregated or both but lower efficiency for more dispersed stocks. Both authors also note that the HT estimator has better efficiency – lower variance – than the HH estimator, with the difference becoming more pronounced as the initial sample size is increased. In our simulations the initial sample size never exceeded 10%, and the two estimators gave very similar results. Both

Table 4. Distribution of final sample size over 5000 random samples for ACS designs. Sample size in terms of secondary units, including adaptively added units.

Standardized test stock	Initial sample design	Initial sample size	Average final size	Standard deviation	90th percentile	Final/ initial	90%/ initial
Random	Stratified	400	449	10.0	462	1.12	1.16
	Systematic	400	455	5.9	461	1.14	1.15
Small	Stratified	400	674	50.4	736	1.68	1.84
	Systematic	250	521	42.0	572	2.09	2.29
Rare	Stratified	400	602	38.4	651	1.50	1.63
	Systematic	250	473	48.3	550	1.89	2.20
Big	Stratified	400	1087	89.2	1158	2.72	2.90
	Systematic	100	684	276.7	863	6.84	8.63

estimation procedures also gave reasonable estimates of the variance of T.

One of the greatest concerns about the implementation of ACS is the random nature of the final sample size and the possibility that the final sample might grow too large to be feasible. Distributions of final sample size, in secondary units, for some of the simulated ACS samples are shown in Table 4. The difference between initial and final sample size was strongly related to the spatial distribution of the stock. For the stock with no spatial correlation the average final sample sizes were only 11–13% larger than the initial sample regardless of the initial sample size or design. For this stock none of the final sample sizes exceeded 1.25 times the initial sample size. The ‘‘small’’ and ‘‘rare’’ stocks, which both have strong correlation over a short range, had a greater increase in average final sample size over initial size. Final sample size for these stocks was 1.5–1.7 times the initial sample size using stratified random ACS and 1.7–2.1 times the initial sample size when starting from a systematic sample. The stock with a few ‘‘big’’ clusters showed the greatest increase in final sample size with the average final sample sizes for this stock being 2–4 times the size of the initial sample.

For all of the test stocks the increase from initial to final sample size was larger when the initial design was systematic that when a stratified random initial design was used. In the case of the ‘‘small’’ and ‘‘rare’’ stocks, this effect produced substantial differences. These differences occur because our algorithm for stratified ACS treated each stratum as a separate entity. This meant that adaptive sampling for clusters located near the edge of the stratum was stopped at the stratum boundary and not allowed to expand into adjacent strata. Thompson and Seber (1996, p. 134) state that terminating a network at the stratum boundary is slightly less efficient than using complete networks but ACS estimators will still be design-unbiased for the stratum totals and may be combined into an overall estimate assuming independence of the strata. Defining networks in this way makes the strata into ‘‘partition boundaries’’ that limit the potential size of any network and this is one of the strategies suggested by Thompson and Seber (1996, p. 161) as a means of controlling the final sample size. In our simulations this stratified design clearly acted to reduce the final sample sizes and gave slightly higher efficiencies than the systematic design.

Results of the field trial

One night of the 1998 Lake Erie smelt survey was used to test the practicality of the field implementation of ACS. The trial showed that use of an ACS design is feasible but identified some potential problems. Real-time data analysis capability and differentially corrected GPS are needed to identify units meeting the ACS criterion during the survey and accurately position adaptive units. The capabilities of the survey vessel are important, especially the relative travel speeds with and without data collection.

The simulation experiment and theoretical work use an ACS ‘‘neighbourhood’’ definition of four-adjacent-cells but this definition is not practical for an actual hydroacoustic survey. We followed a ‘‘neighbourhood’’ definition of parallel transect segments by using Loran navigation lines as approximate parallels. Adaptive units for ACS were identified as segments of parallel transects over the same latitude as units above the critical density. Four of the 24 sampling units in the initial segment met an ACS criterion of density greater than 5000 smelt/ha; three of these were near the southern shoreline and one was further north (Figure 4). Adaptive transect segments were surveyed on either side of the initial transect over the latitude range of both ‘‘patches’’. This meant that data were collected on some extra units not strictly needed for ACS. These extra units may be useful for other purposes (e.g. mapping of the high-density patches), but they increase the final sample size and

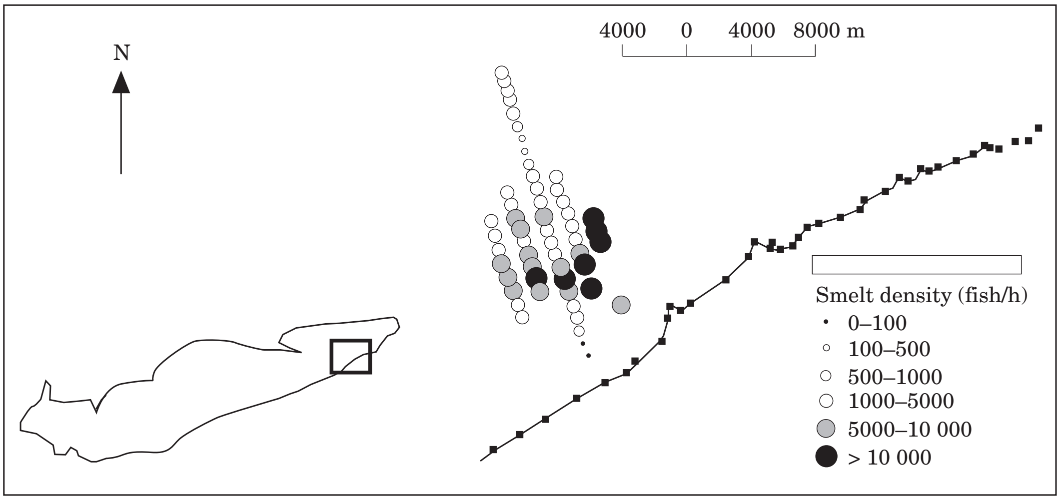

Figure 4. Data from a field trial of ACS on Lake Erie. Each circle represents a five-minute integrated sampling unit; shaded units meet ACS criterion of $y_{ij}>5000$ fish/hectare. The long centre transect is the initial transect.

decrease the efficiency of ACS. A survey vessel with a high travelling speed when not sampling would increase the efficiency of ACS by reducing the travel time between sampled units and facilitating the collection of data at the right points only. The addition of adaptive segments was halted to the west at the boundary of the sampling stratum and to the east by approaching daylight.

The field trial illustrated the greatest concern with the application of ACS viz. the detection of a large patch that results in a large final sample size. With only one night of sampling we were unable to complete all of the adaptive sampling of the detected network. Using greater spacing between adaptive segments could decrease the amount of adaptive sampling but too great a distance may affect the accurate estimation of the patch total. More research is needed on the best "neighbourhood" definition, given patches of an expected size and shape, for use with ACS.

Conclusions

The advent of hydroacoustic stock assessment has resulted in dramatic increases in the amount of data that can be collected but lack of independence between adjacent sampling units can restrict the applicability of design-based theory in this setting. Cluster sampling designs are effective for a spatially dispersed stock when transect totals are reasonably consistent over the study area. A target stock with a spatially patchy distribution, however, will have a strongly skewed distribution of transect totals. This will lead to high variance and poor performance of traditional estimators. Patchy spatial distributions can be caused by irregular distributions of microhabitat, by behavioural traits such as schooling or by a combination of factors. Strong local correlation is common in fisheries and many other environmental applications.

Adaptive cluster sampling (ACS) was designed for spatially patchy or rare events or both scenarios together. In simulations ACS performed better than traditional cluster sampling designs whenever local correlation was present. ACS estimators exhibited an unbiased, symmetric distribution with a consistently lower variance than traditional designs. The coefficient of variation for the most variable of the test stocks was reduced from 0.9 for traditional cluster sampling to 0.4 using ACS (Table 3). ACS also provided greater protection against gross mis-estimatation of total stock size. Figure 5 summarizes the frequency with which the estimated totals fall within a fixed percentage of the true total. For the stock with small patches, ACS designs reduced the frequency of "poor" estimates (relative error more than 50%) to less than three percent, and substantially increased the percentage of "good" estimates (within 10% of the true total). For the simulated stock with rare patches that most closely resembled the Lake Erie smelt data more than half the estimates from traditional designs were "poor". Using ACS designs to survey this stock both decreased the frequency of "poor" estimates and increased the frequency of "good" estimates. This difference in tail behaviour of the estimators may not seem significant in a statistical sense but when estimated stock size is the basis for management policy a reduced frequency of large overestimates may be very important.

The greatest limitation to practical use of ACS is the uncertainty in the final sample size: there is always a possibility that the final sample will outgrow either the

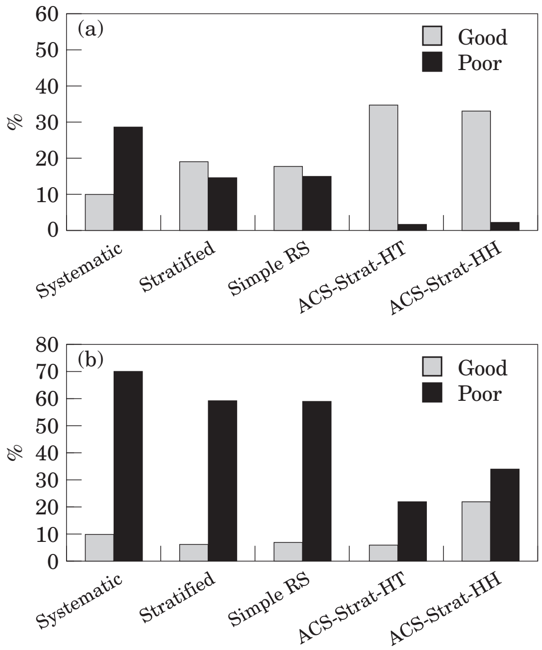

Figure 5. Comparison of the frequency of "Good" estimates (within 10% of the true total) and "Poor" estimates (more than 50% off of the true total) from traditional and adaptive cluster sampling designs.

available budget or the schedule. Some recent research has addressed methods to limit the final size of an ACS sample (Salehi and Seber 1997a,b; Brown and Manly 1998). Thompson and Seber (1996) discuss general ways to limit the final sample size. One practical approach is to implement ACS within a stratified initial design, with the adaptive sample ending at stratum boundaries. This adds both operational and design flexibility to the survey; ACS parameters and sampling intensity can be adjusted as the survey progresses as long as the parameters are consistent over each stratum. A large sample in one stratum could be partially offset by using greater transect spacing or a higher critical value in subsequent strata. It may also be possible to use a form of post-stratification to analyse portions of the survey that are interrupted by weather or equipment problems. A field trial on Lake Erie demonstrated that ACS is feasible for hydroacoustic surveys. More research is needed on the optimal definition of the ACS "neighbourhood" in a line-transect setting and on tradeoff effects between the number and length of the transects used.

ACS retains the unbiased and non-parametric properties of design-based estimation but allows increased sampling in high-density areas that are of greater biological interest. For many fish stocks most of the population is located in a few high-density areas and so increasing the sampling effort in them makes both statistical and biological sense. In these circumstances ACS provides improved precision of stock estimation and is less sensitive to errors caused by the highly skewed distribution of density data. The greater the degree of spatial aggregation exhibited by the stock, the greater is the potential efficiency gain from using ACS. Strong skewness or kurtosis in density data is a good indication that ACS designs may be effective for a particular stock and worth the extra effort in survey design and field execution.

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