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Performance comparison of traditional sampling designs and adaptive sampling designs for fishery-independent surveys: A simulation study

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ABSTRACT

We compared the performance of two traditional sampling designs with three adaptive sampling designs using simulated data based on fishery-independent surveys for yellow perch in Lake Erie. Traditionally, the fishery-independent survey has been conducted with a stratified random sampling design based on basin and depth strata; however, adaptive sampling designs are thought to be more suitable for surveying heterogeneous populations. A simulation study was conducted to compare these designs by examining the accuracy and precision of the estimators. Initially in the simulation study, we used bias, variance of the mean, and mean squared error (MSE) of the estimators to compare simple random sampling (SRS), stratified random sampling (StRS), and adaptive two-phase sampling (ATS). ATS was the best design according to these measurements. We then compared ATS, adaptive cluster sampling (ACS), adaptive two-stage sequential sampling (ATSS), and the currently used stratified random sampling design. ATS performed better than the other two approaches and the current stratified random sampling design. We concluded that ATS is preferable for yellow perch fishery-independent surveys in Lake Erie. Simulation study is a preferred approach when we seek an appropriate sampling design or evaluate the current sampling design.

1. Introduction

Fishery independent surveys provide valuable information on fish population characteristics and play important roles in fisheries stock assessment (Gunderson, 1993; Rago, 2005). The importance of fishery independent surveys has been well recognized, but the important role of sampling design for these surveys is less appreciated. Often, traditional survey methods are used without considering survey designs that maximize the precision and accuracy of the estimator (Mier and Picquelle, 2008). Fishery independent surveys are usually expensive and time-consuming, and an efficient sampling design is key to the success of these surveys. Recently, investigators have begun to pay more attention to the importance of survey sampling and are exploring a variety of aspects of designs (Bez, 2002; Brown, 2003; Kimura and Somerton, 2006). Based on the previous studies, we compared the performance of traditional and adaptive sampling designs with emphasis on simulation application for performance comparison.

Simple random sampling (SRS) and stratified random sampling (StRS) are commonly used sampling methods for fishery independent surveys. SRS is the simplest sampling method and other complex sampling methods usually include SRS to some degree (Cadima et al., 2005). StRS is used for heterogeneously distributed populations to increase the precision of estimates (Cadima et al., 2005). In StRS, the survey area is divided into strata that are internally more homogeneous based on habitat characteristics, such as basins, bathymetry, or other important hydrographic variables. Stratum construction and sample allocation are critical for a successful StRS (Rago, 2005). The best allocation of the sample in each stratum is usually determined by three factors: (1) the total number of elements in each stratum; (2) the variability of observations within each stratum; (3) the cost of obtaining an observation from each stratum (Scheaffer et al., 2006). If variance and cost information are not available, proportional allocation or any other allocation method can be used to allocate the total sample size among the strata.

For patchy or rare populations, these traditional sampling designs can be inefficient because they may fail to detect the aggregation patterns. In recent literature, adaptive sampling designs have been used to improve the precision of the estimates (Hanselman et al., 2003; Su and Quinn, 2003; Brown et al., 2008).

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A sampling design is defined as "adaptive" when the sample selection procedure depends on previous observations in the sample (Salehi and Smith, 2005). Such "adaptive" sampling designs appearing in the literature include the adaptive two-phase sampling design (ATS) (Francis, 1984), the adaptive cluster sampling design (ACS) (Thompson, 1990, 1992; Thompson and Seber, 1996), and the adaptive two-stage sequential sampling design (ATSS) (Brown et al., 2008). Adaptive sampling designs are more suitable for single species surveys because a gain of precision for one species will often be at the expense of other species.

ACS has been reported to be more efficient than SRS for aggregated or rare populations (Thompson, 1990; Thompson and Seber, 1996). ACS can also be combined with some other traditional sampling methods, such as stratified sampling and systematic sampling to get better estimation (Thompson and Seber, 1996). Several researchers have applied this method to fishery surveys and have obtained satisfactory results (Hanselman et al., 2003; Smith and Lundy, 2006; Sullivan et al., 2008). In ACS, a set of sampling units are randomly selected in the survey area. If the density of a sampled unit is larger than a pre-defined critical value, then its neighborhood will be sampled in the next round. Similar to the previous step, if the density of each newly sampled unit is larger than the critical value, its neighborhood will be sampled; otherwise the sampling is finished. Thus, this sampling process will not stop until all units that satisfy the critical value are sampled (Thompson and Seber, 1996). The outermost units are called "edge" units and are not used in estimation. However, there are difficulties for applying ACS in practice, such as how to determine appropriate critical values, how to schedule survey times in practice when vessel days are fixed, the indefinite sampling problem due to a low critical value, and the costly "edge" unit issue (Hanselman et al., 2003; Su and Quinn, 2003). ATSS may solve some of these issues (Salehi and Smith, 2005; Brown et al., 2008). The process of ATSS is similar to stratified ACS. Both are two stage samplings with primary samples and critical values. The difference is that ATSS is not strictly required to sample neighbor units of the randomly sampled units in the first round but sampling the units nearby in each stratum. The use of a stopping rule and the counting of edge units are not necessary for ATSS. ATS is another two-stage sampling technique in which the sample allocation at the second stage is determined by the variability of samples at the first stage. Compared to ACS and ATSS, ATS is more practical and flexible because the critical value is not needed for ATS, there is no "edge" unit issue, and adding or deleting a small number of sites in the second phase does not influence the estimates dramatically (Francis, 1984; Brown, 1999).

Yellow perch is one of the most important commercial and sport fish species in Lake Erie (Baldwin and Saalfeld, 1962; Regier and Harman, 1973; Jiao et al., 2006). Previous studies (Yellow Perch Task Group, 2008) found that the distribution of yellow perch in the lake is heterogeneous and that the western area has a higher density than the eastern area. Based on our preliminary study, there are a few small areas that have much higher densities than their surrounding area in the lake. Therefore we wanted to evaluate if adaptive sampling designs would provide more efficient estimates than the design currently used in the Lake Erie fishery-independent survey, which is a partnership survey between the Ontario Commercial Fisheries' Association (OCFA) and the Ontario Ministry of Natural Resources (OMNR) Lake Erie Fisheries Management Unit (LEMU). Additionally, there are some problems associated with the current stratified survey design that may be remedied by using an adaptive sampling design. For instance, fish density in each stratum is not homogeneous and the heterogeneity varies among years, which may adversely affect the efficiency of the stratified design relative to SRS. To address these problems, we conducted a simulation study to compare SRS, StRS, ACS, ATSS, and ATS based on the example data of yellow perch fishery-independent surveys. Our objectives were to explore the efficiency of the current method (StRS) and to find out the most efficient sampling designs in order to improve the fishery-independent surveys in the Great Lakes. This is the first study that compares the efficiencies of ACS, ATSS and ATS together through a simulation study.

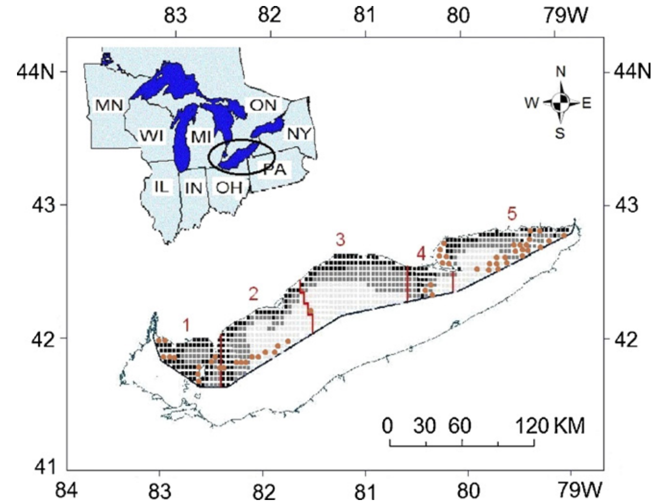

Fig. 1. Basins and strata partitions of the study area of current fishery-independent sampling survey in Lake Erie (modified based on Ontario Ministry of Natural Resources, unpublished. Contact: Andy Cook, andy.cook@mnr.gov.on.ca). Number 1, 2, 3, 4 and 5 represent West Basin, West-Central Basin, East-Central Basin, Pennsylvania Ridge and Eastern Basin, respectively. The unit size is 2.5 min × 2.5 min and the number of strata in each basin is 2 or 3 based on water depth. The darker area denotes shallow water and lighter area denotes deep water. The dots denote the locations that were not sampled.

2. Materials and methods

2.1. Study area and current survey design

Lake Erie is nearly evenly divided by Canada and the United States, and the current fishery-independent survey is only conducted within the Canadian side of the lake. The Canadian side is partitioned into five basins for this survey; Western Basin, West-Central Basin, East-Central Basin, Pennsylvania Ridge, and Eastern Basin. The Lake Erie fishery-independent survey has been conducted within the Canadian side of Lake Erie annually since 1989. In this survey, standard gangs of gillnets consisting of 14 different mesh sizes are fished in two distinct manners: canned and bottomed sets. The canned sets are suspended in the water and the bottom sets are fished near the bottom of the lake. The bottomed sets are mainly used for collecting yellow perch, so in this study only the bottomed sets design were analyzed. In this design, each basin was divided into 2 or 3 strata based on water depth, and each stratum contains many sampling units, each of which is 2.5 min × 2.5 min (Fig. 1). Some of these units are not included in the sampling frame (unsampled) because they are located on shipping routes or other obstacles. The number of units varies from stratum to stratum. In total there are 14 strata and 119 units (Table 1).

In order to compare the efficiency of StRS and ATS in the simulations, we divided the study area into 2, 3 and 4 strata, respectively, based on water depth, and the unit size was set to 2 min × 2 min (Fig. 2). Due to the change of unit size and sample sizes, the efficiency of the currently used sampling method may be different from StRS. Therefore, we compared StRS versus ATS based

Table 1
Current spatial stratification of fishery-independent survey for each basin in the Canadian side of Lake Erie. The strata stratification was based on basins and water depth. The West Basin was divided into two strata, and each of the other 4 basins was divided into 3 strata resulting in 14 total strata. The total number of units was 690.

Basin	Stratification by surface area	Number of sampling units
West Basin (WB)	Water depth from 0 to 10 m	16
	Water depth > 10 m	6
West-Central (WC) & East-Central Basin (EC)	Water depth from 0 to 15 m	11 (WC)/8 (EC)
	Water depth from 15 to 20 m	15 (WC)/11 (EC)
	Water depth > 20 m	10 (WC)/17 (EC)
Pennsylvania Ridge (PR) & Eastern Basin (EB)	Water depth from 0 to 15 m	1 (PR)/6 (EB)
	Water depth from 15 to 30 m	1 (PR)/8 (EB)
	Water depth > 30 m	2 (PR)/7 (EB)

on not only the currently used 14 strata but also fewer strata (2–4).

2.2. "True" density used in the simulation study

Ordinary kriging was used to interpolate the survey data over all basins. The goal of this study was to determine a lake-wide estimate. Ordinary kriging is one of the most commonly used spatial interpolation methods (Schabenberger and Gotway, 2005). The idea is to estimate the value at an unknown location by using the combination of weights and values at known locations. The weights are estimated according to semivariance among known values. We used the interpolated survey data in 1993 and 2003, respectively, as our "true" density. We chose these 2 years because the fish densities and distributions are quite different, and this is helpful in comparing the efficiency of different sampling designs. The number of fish caught (individuals/lift) at each site was interpolated to a density surface using the ArcGIS software package (version 9.2, 2007, ESPI, Inc., USA) (Fig. 3). The unit size of the interpolated density maps was 2 min × 2 min. The lake was divided into 1, 2, 3, and 4 strata based on the water depth as well as 5 strata based on basins. For each stratum, we calculated the mean, standard deviation (SD) and coefficient of variation (CV) of the survey data in 1993 and 2003, respectively (Table 2).

2.3. Sampling design

2.3.1. Stratified random sampling (StRS)

The current Lake Erie fishery-independent survey is based on a stratified random sampling design (StRS). The survey area was divided into 2–3 strata for each basin based on the water depth (Table 1). The formula for the estimator of the mean for StRS is

$$\hat{\mu} = \frac{1}{N}\sum_{i=1}^{L} N_i \bar{y}_i \tag{1}$$

where N is the total number of the population units, L is the number of strata, N_i is the number of population units in the ith stratum, and $\bar{y}_i$ is the mean of the samples from the ith stratum.

2.3.2. Adaptive cluster sampling (ACS)

Thompson and Seber (1996) described ACS in detail and provided two unbiased estimators of the mean: the Hansen–Hurwitz estimator (HH) and the Horvitz–Thompson estimator (HT). An ACS design usually includes the following two steps: (i) n_1 units are first randomly selected from the study area; and (ii) the neighborhoods (i.e., top, bottom, left, right for each initial sampling unit) are sampled if their values are larger than a predefined critical value, and the neighborhoods of the newly sampled units are also selected based on the same rule until all the desirable neighborhoods are sampled. The group of adjacent units whose values are all at least as great as the critical value is known as a network. The adjacent units that have been sampled form many networks. The formula for the Hansen–Hurwitz (HH) estimator is

$$\hat{\mu}_{\mathrm{HH}} = \frac{1}{n_1}\sum_{i=1}^{n_1} \frac{1}{m_i}\sum_{j \in T_i} y_j = \frac{1}{n_1}\sum_{i=1}^{n_1} w_i \tag{2}$$

where y_j is the density of unit j, T_i is the ith network, m_i is the number of units in T_i, n_1 is the number of networks (not necessarily distinct), and w_i is the mean of the m_i observations in T_i.

The formula for the Horvitz–Thompson (HT) estimator is

$$\hat{\mu}_{\mathrm{HT}} = \frac{1}{N}\sum_{k=1}^{K} \frac{y_k}{\alpha_k} \tag{3}$$

$$\alpha_k = 1 - \left[\binom{N - x_k}{n} \Big/ \binom{N}{n}\right] \tag{4}$$

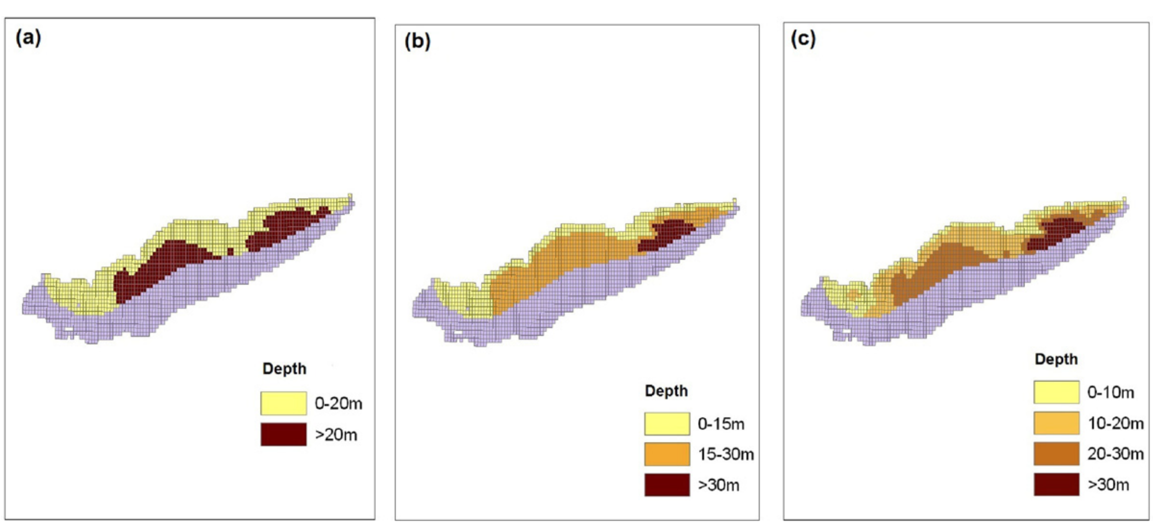

Fig. 2. Strata partitions of the study area used in the simulation study: comparison among stratified random sampling (StRS) and adaptive two-phase sampling (ATS). The study area was divided into (a) 2 strata, (b) 3 strata and (c) 4 strata based on water depth, respectively.

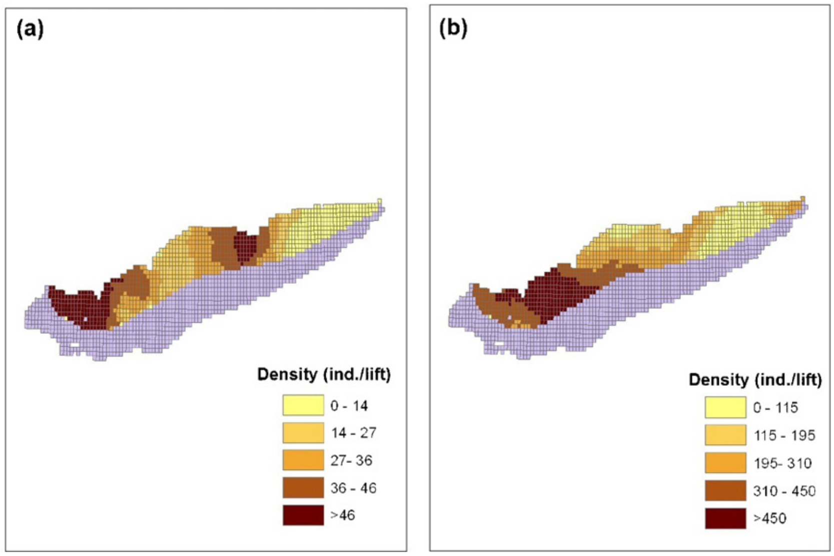

Fig. 3. Density interpolation maps of yellow perch based on survey data of (a) 1993 with mean density 43.6 individuals/lift, and standard deviation of 47.5; (b) 2003 with mean density 275.5 individuals/lift, and standard deviation of 168.3.

where y_k is the sum of the y-values for the kth distinct network, K is the total number of distinct networks in the population, N is the number of population units, α_k is the probability that a unit in network k, which contains x_k units, and n is the number of distinct networks.

To evaluate the properties of the HH and HT estimators, we sampled repeatedly from the interpolated survey data (the "true" density) for 1993 and 2003 with n_1 set as 30 units and the critical value set as the sample mean of these 30 units. A stopping rule of level 2 (the searching neighbor procedure was only conducted twice) was used to limit the total sampling effort to a practical level. When a stopping rule is used, both HH and HT estimators are biased (Su and Quinn, 2003).

2.3.3. Adaptive two-stage sequential sampling (ATSS)

Brown et al. (2008) described the procedure for ATSS and the formula to calculate an unbiased estimate of the mean. ATSS is performed in two stages. Suppose a total population of N units was divided into M primary areas (clusters) based on the preliminary knowledge of the population distribution, which can be uniformly selected or selected based on geographical characteristics or management convenience. In the first stage, m strata from each of the M primary areas are selected randomly without replacement. In the second stage, initially n_{i1} units were selected from each area m_i using simple random sampling. If the mean value of the random sample is larger than a pre-defined critical value and g_i is the number of samples whose values were larger than the critical value in the m_i area, then $g_i \times \lambda$ number of additional units would be selected at random from the remaining units in the m_i strata. Here, λ is a predetermined value to quantify the extra sampling intensity. In the present study, n_{i1} = 15 units were randomly sampled in each primary unit at stage 2, and the mean value of the initial samples across the m area was used as the critical value. In the present study, we let $m = M = 5$ and $\lambda = 2$. The formula to calculate the ATSS estimator of the mean density is

$$\hat{\mu} = \frac{1}{N}\sum_{i=1}^{m}\left(\frac{g_i}{n_{l1}}\bar{y}_{\text{ic}} + \frac{n_{i1}-g_i}{n_{i1}}\bar{y}_{\overline{\text{ic}}}\right)N_i \quad (5)$$

where $\bar{y}_{\text{ic}}$ and $\bar{y}_{\overline{\text{ic}}}$ are the mean of units satisfying and not satisfying the condition C in the final sample set from area m_i. Here, condition C is true when the sample value is larger than the critical value. N is

Table 2
Mean, standard deviation (SD) and coefficient of variation (CV) of the survey data in 1993 and 2003. The unit for the mean value was individuals/lift.

Number of strata	Stratum index	Mean		SD		CV	
		1993	2003	1993	2003	1993	2003
1	1	43.61	275.51	47.50	168.26	1.09	0.61
2	1	58.13	282.07	55.98	153.51	0.96	0.54
	2	21.77	265.64	12.10	188.06	0.56	0.71
3	1	73.85	291.97	67.27	150.60	0.91	0.52
	2	29.93	302.82	12.09	164.28	0.40	0.54
	3	7.27	47.14	5.92	29.59	0.81	0.63
4	1	85.43	291.76	74.55	145.10	0.87	0.50
	2	39.03	275.29	23.65	159.00	0.61	0.58
	3	26.09	330.65	9.91	164.85	0.38	0.50
	4	7.27	47.14	5.92	29.59	0.81	0.63
5	1	149.79	406.26	56.17	64.68	0.37	0.16
	2	34.60	485.57	9.90	94.37	0.29	0.19
	3	33.46	214.40	10.15	76.35	0.30	0.36
	4	37.50	177.97	10.92	41.77	0.29	0.23
	5	11.87	101.12	8.45	59.14	0.71	0.58

the total number of units in the survey area, and N_i is the number of units in stratum i.

2.3.4. Adaptive two-phase sampling (ATS)

Francis (1984) described the procedure of ATS and discussed its advantages. An ATS survey is carried out in two phases. The first phase is designed in the same way as a traditional stratified random sampling. Based on catches obtained from the first phase, more stations are allocated to some strata for the second phase of the survey. Let A_i be the area of the stratum i, n_i be the sample sizes for stratum i in Phase 1, L is the number of strata, and V_i be the variance of the samples from the Phase 1 survey in stratum i. Let n be the total sample size allocated for sampling for the survey and $n_1 = \sum_{i=1}^{L} n_i$ be the initial (Phase 1) station allocation. Here n_1 is set as a fraction of n. Phase 2 stations should be allocated according to the following procedure:

Step 1. Calculate the estimated relative gain (reduction in variance) G_i from adding 1 station to stratum i by

$$G_i = \frac{A_i^2 V_i}{n_i(n_i + 1)} \tag{6}$$

where A_i is the size of the ith stratum, V_i is the variance of the first round samples, and n_i is the sample size in the ith stratum.
Step 2. Allocate 1 station to the stratum with the highest value of G_i.
Step 3. Add 1 to n_i and recalculate G_i for the stratum just chosen.
Step 4. Repeat steps 2 and 3 as many times as necessary until $n_1 = n$.

In this study, we set $n_1 = 0.8n$ in Phase 1. In estimating fish density and its variance, 2-phase data are treated as if they came from a traditional stratified sampling design. Thus, the estimator of the mean in ATS is

$$\hat{\mu} = \frac{1}{N}\sum_{i=1}^{L} N_i \bar{y}_i \tag{7}$$

where $\bar{y}_i$ is the mean of the samples from the ith stratum calculated based on the final sample units allocated to stratum i in Phase 2. Since the high density area usually has high variation in fisheries, the ATS tends to give biased estimates (the bias is usually negative) because the mean from Phase 2 sampled strata is usually less than the mean from Phase 1 samples only. The latter mean is unbiased, which suggests that the mean of total samples underestimates the population mean (Francis, 1984).

2.4. Simulation study

The currently used yellow perch survey stratification scheme (14 strata) is based on the basins, water depth, and management units. It is still an arbitrary stratification. In addition, the shape of the lake and the depth distribution are irregular in Lake Erie. ACS and ATSS are not suitable for the stratification scheme based on water depth because the strata may be separated while having the same depth. Additionally, it is difficult to compare the five sampling designs directly because the final sample size of the two adaptive sampling designs is unknown at the design stage and is difficult to control. Therefore, we divided these designs into two groups where they can be easily compared: (1) SRS, StRS and ATS; (2) ACS, ATS and ATSS. In the third comparison, we examined the performance of ATS and the currently used StRS design based on the current survey settings.

In the first simulation situation (Scenario 1), we compared two traditional sampling designs, SRS and StRS with one adaptive sampling design, ATS. We stratified the study area into 1, 2, 3 or 4 strata, and varied the total sample sizes (defined as n, which is the total

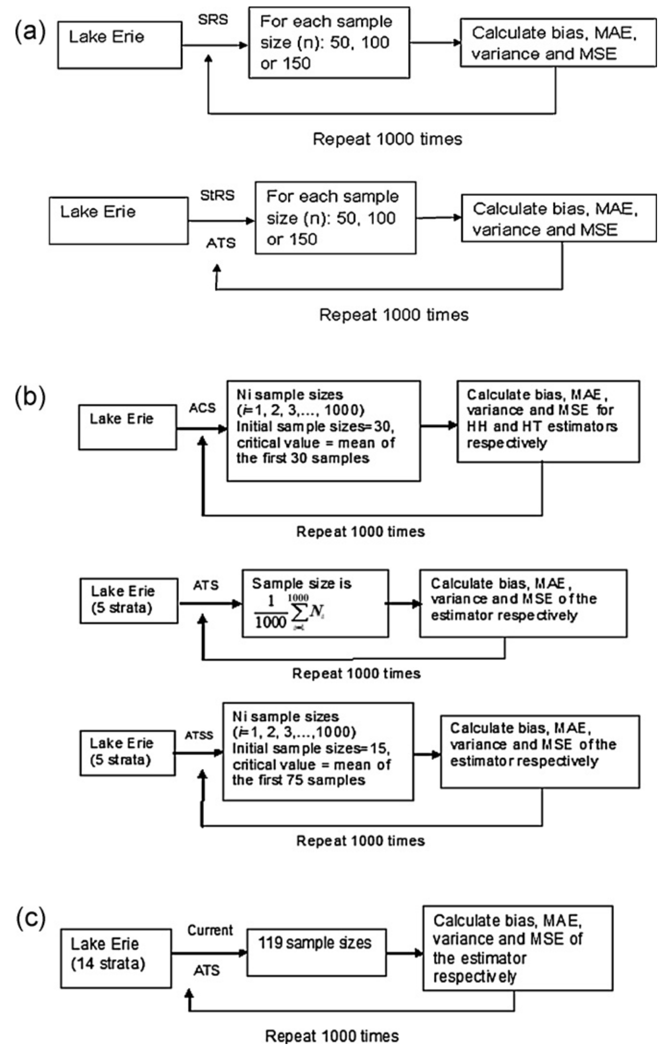

Fig. 4. Simulation procedure used to compare the different sampling designs: (a) comparison among SRS, StRS and ATS; (b) comparison among ACS, ATSS and ATS; (c) comparison between the current sampling design and ATS. The same procedure was used for simulations when the 1993 and 2003 were assumed as the true population.

number of element units drawn from the surveyed area) from 50 to 150 with step size of 50. For StRS, stratum sample size n_i was allocated based on proportional allocation (Fig. 4a).

Secondly, we compared the adaptive sampling designs ACS with ATS, and ATSS with ATS. When comparing ATSS and ATS, we used 5 strata because the lake was divided into 5 basins when doing the fishery-independent surveys. Water depth was not used for stratification because the same strata could be separated in parts while having the same water depth (Fig. 2). We did not consider stratification in ACS because Brown (1999) found that the stratified ACS was not more efficient than ACS. For ACS, we first randomly sampled $n_1 = 30$ sites in the lake and then used the mean value of these 30 samples as the critical value. For ATSS, we first randomly sampled $n_{1i} = 15$ sites at each stratum, respectively, and then used the mean catch of these 75 samples as the critical value. When comparing ATS with ACS or ATS with ATSS, it is not possible to know the exact final total sample size n for ACS and ATSS before the survey. To overcome this difficulty, we used the average final sample sizes ($\bar{n} = \sum_{r=1}^{R} n_r$) from $R = 1000$ simulation replications of ACS or ATSS as the total sample size n used in ATS in the comparisons of ATS with ACS and ATS with ATSS, respectively (Fig. 4b).

Finally we compared the best adaptive sampling design with the currently used sampling method. In this scenario, 14 strata and $n = 119$ were used, which is the current sampling approach (Fig. 4c).

2.5. Performance measurements

We used five performance measures to compare the statistical properties and relative performance of the different designs. They were bias (B), variance of the mean (V), the mean squared error (MSE), the relative efficiency (RE), and coefficient of variance (CV) of each estimator. The formulas are as follows:

$$B = \frac{1}{R}\sum_{i=1}^{R}(\hat{\mu}_i - \mu) \tag{8}$$

$$V = \frac{1}{R}\sum_{i=1}^{R}(\hat{\mu}_i - \bar{\mu})^2 \tag{9}$$

$$\mathrm{MSE} = B^2 + V \tag{10}$$

$$\mathrm{RE} = \frac{\mathrm{MSE}_1}{\mathrm{MSE}_2} \tag{11}$$

$$\mathrm{CV} = \frac{\sqrt{V}}{\bar{\mu}} \tag{12}$$

where $\hat{\mu}_i$ is the estimated mean value, μ is the "true" mean, $\bar{\mu}$ is the mean of $\hat{\mu}_i$, R is the number of runs of simulation for each scenario. For SRS, StRS, and ATSS, the estimates are unbiased, so MSE = V theoretically. In this study because the stopping rule is applied, the estimators from ACS are biased, so for ACS and ATS, we used MSE = $B^2 + V$.

3. Results

3.1. Comparison of simple random sampling (SRS), stratified random sampling (StRS), and adaptive two-phase sampling (ATS)

Since the estimators of μ from SRS and StRS are unbiased, only the biases of $\hat{\mu}_{\mathrm{ATS}}$ are shown for the interpolated survey data in 1993 and 2003, respectively (Table 3). The biases from all these sampling designs were very small compared with the mean values (Table 2). For the 1993 data, MSE decreased with increasing number of strata (L) and sample size (n) for all the three sampling designs (Table 4): ATS always resulted in the smallest MSE at each combination of L and n for all the designs, and SRS resulted in the largest MSE. For the 2003 data, the ranking of the designs based on MSE was not as uniform as in 1993, especially at $L = 2$ (Table 4). At $n = 50$, SRS resulted in the largest MSE, and the MSE from StRS was the smallest among the three designs. When $n \geq 100$ and $L \geq 3$, StRS and ATS performed very similarly (Fig. 5).

Table 3
Biases from ATS as a function of sample size and number of strata when the interpolated data in 1993 and 2003 were treated as "true" populations. The number of simulations of ATS was 1000.

Strata	Sample sizes					
	1993			2003		
	50	100	150	50	100	150
2	0.10	0.01	0.10	−1.37	0.40	−0.04
3	0.01	0.20	0.03	−0.39	0.47	−0.40
4	−0.20	−0.20	−0.09	−0.25	−0.22	0.30

3.2. Comparison of ATS with adaptive cluster sampling (ACS) and ATS with adaptive two-stage sequential sampling (ATSS)

In Scenario 2, first we compared ACS with ATS using the interpolated data in 1993 and 2003. The final average sample sizes $\bar{n}_{\mathrm{acs}}$ obtained from ACS were 99.1 and 139.9 for 1993 and 2003, respectively. Then we ran simulations for ATS with $L = 5$ strata, and $n = 100$ or 140 for 1993 and 2003 separately. Bias, variance of the mean, and MSE were compared in Table 5. For ACS, both HH and HT estimators were calculated; the HT estimator had lower bias and lower MSE than the HH estimator. ATS performed better than ACS in terms of bias and MSE (Table 5).

Similarly, to compare ATSS with ATS, we first ran simulations for ATSS in 1993 and 2003. The final average sample sizes $\bar{n}_{\mathrm{atss}}$ were 109.2 and 140.7 for 1993 and 2003, respectively. Then, we ran a simulation for ATS with sample sizes set to 110 and 140 for 1993 and 2003, respectively. ATS resulted in smaller MSE and CV than those from ATSS, whereas their bias was negligible (Table 5).

3.3. Comparison of ATS with the current survey design

ATS performed best in the last two scenarios. In Scenario 3, we compared the best adaptive sampling approach (ATS) with the design currently used (StRS). Bias, V, MSE, and CV were compared in Table 6. StRS can provide unbiased estimators if all units in each stratum have the same probability to be chosen. Since some locations cannot be sampled (Fig. 1), the estimators from StRS were biased (Table 6). ATS resulted in smaller MSE and CV than those from the current sampling design in 1993 and 2003. The current sampling design also resulted in larger biases than ATS in both 1993 and 2003 (Table 6).

4. Discussion

This study showed that adaptive two-phase sampling (ATS) performed better than the traditional simple random sampling (SRS) and stratified random sampling (StRS) in most situations using the simulated data based on fishery-independent surveys for yellow

Table 4
Estimated MSEs in the simulation when Scenarios 1 was used, i.e., comparison among SRS, StRS, and ATS. The 1993 and 2003 years' interpolation densities were treated as the "true" densities.

Strata	SRS			StRS			ATS		
	50	100	150	50	100	150	50	100	150
1993									
1	43.54	20.99	12.57						
2				37.09	18.20	12.24	31.55	15.88	9.80
3				35.36	16.12	9.44	25.55	11.54	7.10
4				31.05	14.65	8.52	21.40	10.96	6.34
2003									
1	536.95	234.09	160.85						
2				579.79	237.71	161.49	559.56	262.6	166.22
3				489.04	218.89	127.41	448.53	216.85	126.19
4				451.43	203.33	126.73	441.83	205.54	138.81

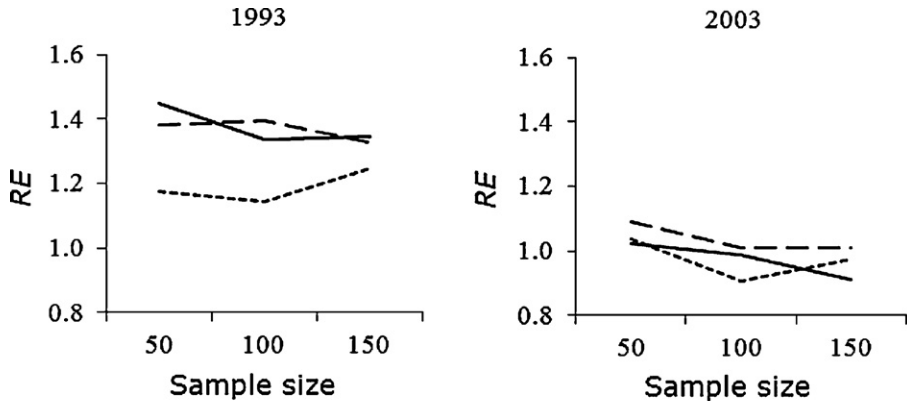

Fig. 5. Relative efficiencies (RE) of StRS over ATS when the interpolated catch data in 1993 (a) and 2003 (b) were assumed as "true" data. The sample sizes are 50, 100, and 150; the strata are 2 (dotted line), 3 (dash line), and 4 (solid line).

Table 5
Estimated bias, variance of the mean (*V*), MSE and CV when Scenario 2 was used, i.e., comparison between ATS and ACS; ATS and ATSS. The interpolated density data were treated as "true" densities.

Performance measures	1993			2003		
	ATS	ACS		ATS	ACS	
		HH	HT		HH	HT
Bias	−0.05	−4.14	−0.43	0.29	−23.18	5.97
V	2.33	43.96	48.96	31.77	688.28	862.18
MSE	2.33	61.10	49.14	31.86	1225.59	897.82
CV	0.04	0.17	0.17	0.02	0.10	0.10

Performance measures	1993		2003	
	ATS	ATSS	ATS	ATSS
Bias	0.03	0	0.29	0
V	1.92	2.13	31.77	60.05
MSE	1.92	2.13	31.86	60.05
CV	0.03	0.03	0.02	0.03

perch in Lake Erie. It also performed better than the adaptive sampling designs of adaptive cluster sampling (ACS) and adaptive two-stage sequential sampling (ATSS) based on the simulated data in 1993 and 2003. The reason that ATS had better precision than StRS was the more effective sample allocation in each stratum. In theory, StRS had better precision than SRS because the variable of interest in each stratum was almost homogeneous (Scheaffer et al., 2006). However, in Lake Erie, yellow perch density varied temporally and spatially, and it was difficult to find an appropriate strata division for each year. When the density in each stratum was heterogeneous and sample size was small, StRS performed even worse than SRS. Under these circumstances, ACS and ATSS did not perform as well as Hanselman et al. (2003) and Brown et al. (2008) described. The causes for poor performance of ACS may include (1) the studied population is not sufficiently clustered, (2) the critical value is too small, and (3) the neighborhood definition is too large (Brown, 1999). In this study, the first reason is most likely. For ACS, we calculated both HH and HT estimators. The HT estimator was reported to be preferable in a stopping rule case (Su and Quinn, 2003). In this study, the HT estimator was less biased and had smaller MSE but larger variance of the mean.

Besides efficiency, ATS is more flexible and practical in reality than StRS in relatively small areas, such as lakes and reservoirs. The formula used to calculate variance reduction (Eq. (6)) could include a cost factor that is of interest. A subjective weighting factor derived from prior knowledge may be added to it. For example, if we know the cost for each trip before the second phase, we can include this information in this formula, which can be revised as $G_i = A_i^2 V_i / (n_i(n_i+1)\sqrt{c_i})$, where c_i is the cost for each trip in stratum *i*. This is one of the tradeoffs that fisheries managers often face, i.e., better estimation versus lower cost. It also provides alternative options for making decisions on survey plans.

In a conventional sampling design, it is possible that some strata will be under-sampled or not sampled due to bad weather and vessel or gear problems (Francis, 1984). Traditional sampling designs lack the ability to deal with this situation because the sample plan is determined before sampling, and it is likely that some strata will be under-sampled or not sampled. In contrast, ATS is able to decrease the negative effect of under-sampling. This is because once the first phase sampling finished, there is no theoretical problem if the samples in Phase 2 are not totally allocated. In addition, the procedure for allocating stations in Phase 2 can be applied with a smaller sample size if not all will be sampled (Francis, 1984).

ATS performed better than SRS and StRS for the data with a larger range of relative variation, based on the coefficient of variation among strata. When the interpolated density in 1993 was

Table 6
Comparison of bias, *V*, MSE and CV from ATS and current sampling approach (i.e., Scenario 3). The interpolated density data were treated as "true" densities.

Year	1993		2003	
	Current	ATS	Current	ATS
Bias	−0.49	0.01	−2.16	0.93
MAE	1.20	1.06	4.72	4.21
V	1.42	1.32	29.38	27.92
MSE	1.66	1.32	34.05	28.78
CV	0.03	0.03	0.02	0.02

treated as the "true" data, the ranges of CVs were 0.40, 0.51 and 0.49 for 2, 3 and 4 strata, respectively. When the interpolated density in 2003 was treated as the "true" data, the ranges were only 0.17, 0.11 and 0.13. ATS resulted in much smaller MSE than SRS and StRS when 1993 data were used in the simulation. But MSE from SRS, StRS and ATS were close to each other when 2003 data were used in the simulation. The reason for the large range of CVs is that the strata division is not totally consistent with the density distribution. In some strata, density distribution is more heterogeneous than the others. Traditional sampling methods often lead to low accuracy, but ATS is more suitable for this situation. When each stratum shows similar relative variation, the efficiency of ATS will decrease.

Adaptive sampling designs have showed advantages compared with traditional methods in some cases, but they also have their practical limitations. For ACS, if the prior knowledge about the population distribution before survey is limited, selecting an appropriate critical value can be difficult (Su and Quinn, 2003). Hanselman et al. (2003) recommended three methods that can be used to determine a fixed critical value, and they were 80th quantile of the past survey data, the mean of the past survey data, and the mean of initial samples. In this study, the mean of initial samples was used as a critical value, because yellow perch density changed substantially over time, past survey data would not be representative for the current data. A high critical value may lead to a smaller sample size, and a low critical value may make sampling continue indefinitely. Su and Quinn (2003) suggested using order statistics in ACS to replace an arbitrary critical value, but this method still has its limitations (Hanselman et al., 2003). Furthermore, "edge units" do not involve later statistical estimation because they do not satisfy the condition of selection, but require much effort. To avoid these problems, we used a relatively large initial sample size (30) and a stopping rule to terminate the sampling process (Lo et al., 1997). We applied ACS instead of stratified ACS (SACS) in this study because Brown (1999) found the differences between ACS and SACS were small and statistically insignificant based on sample sizes and variances. ATSS avoided "edge units" and neighborhood sampling, but it still has to face problems of selecting a critical value and an initial sample size as in ACS. Both ACS and ATSS cannot give the exact total sample size before sampling. The problems mentioned above do not exist in ATS. The only difficulty of using ATS may be the sample size in Phase 1. Francis (1984) recommended allocating about 75% of total sample size into Phase 1, and 80% of total sample size was used in this study. The results showed that it was a reasonable proportion to apply.

Systematic sampling (SYS) was reported to be more efficient than random sampling and adaptive sampling in some simulated populations (Pooler and Smith, 2005; Mier and Picquelle, 2008). However, in this study, the interpolated survey data were used as "true" density instead of simulated populations. In this case SYS has very limited choices of sample allocation. For example, if we have 1000 fixed cells, and the sample size is 100, the number of sample allocations is 10 at most for SYS. We did a preliminary study on comparing SYS with other sampling designs. The results indicated that SYS was not as accurate as other sampling designs in this case. In addition, the Canadian side of Lake Erie was used as study area, which has an irregular shape and a variety of hydrologic conditions. Some locations were not suitable to be sampled due to multiple practical reasons such as shallow water and obstacles in the water. Therefore SYS cannot work well in reality for fishery-independent surveys in Lake Erie. We excluded SYS from the traditional sampling designs for the final comparison.

Two methods of inference are commonly used in sampling surveys: design-based and model-based (Thompson, 1992). In the design-based inference, the population y-values are regarded as unknown constants, but model-based inference considers y as one single realization of stochastic processes. Therefore, choosing an appropriate sampling design will improve the accuracy and precision of estimators for design-based inference. However, design-based sampling usually requires a large sample size and small observation errors. The difficulties of model-based inference include building a reliable model and finding correct explanatory variables. Since the observation error is not avoidable and the sample size is limited in many fishery-independent surveys, we suggest that model-based inference ought to be applied when the survey is not based on a well-designed survey. Nevertheless, an efficient sampling design is also necessary for saving cost and reducing biases. Therefore the model-assisted optimal survey design was suggested for fishery surveys (Chen et al., 2004). In this study, we only considered the randomness induced by sampling designs in the simulations. However, this does not mean that the randomness caused by survey process is not important. Combining design-based inference and model-based inference efficiently is the goal of future studies.

For fishery-independent surveys in Lake Erie, another important target species is walleye. The canned gillnets are mainly designed for the walleye survey. However, yellow perch and walleye show different distribution patterns over time. If we survey these two species separately, it would increase the budget considerably. ATS has the potential for sampling design tradeoffs in multi-species survey. In the first phase, yellow perch and walleye may be sampled in the same locations based on StRS. Then the rest of the samples would be allocated, respectively, for yellow perch and walleye. The final sampling design would be made considering budget, cost, and all the other related factors.

Our simulation study also suggested that in different fisheries, the best sampling design can be different. Previous simulation studies have found that ACS (Hanselman et al., 2003; Sullivan et al., 2008) and ATSS (Salehi and Smith, 2005; Brown et al., 2008) performed better in Pacific ocean perch, sea lampreys, freshwater mussels, and blue-winged teal surveys. Simulation studies are suggested to search for most appropriate fisheries survey designs in general. Through simulation studies, ATS was found to be more suitable for yellow perch fishery-independent surveys in Lake Erie. The appropriate sampling method must consider the spatial and temporal distribution pattern of the target species as well as the requirements for accuracy and the cost.

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