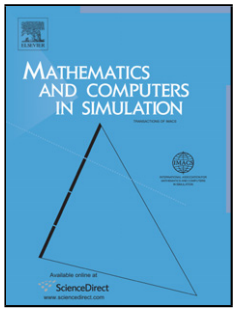


Title: Adaptive survey designs for sampling rare and clustered populations

Authors: Jennifer A. Brown, Mohammad Salehi M., Mohammad Moradi, Bardia Panahbehagh, David R. Smith

PII: S0378-4754(12)00217-0
DOI: doi:10.1016/j.matcom.2012.09.008
Reference: MATCOM 3865

To appear in: *Mathematics and Computers in Simulation*

Received date: 22-5-2012
Revised date: 17-8-2012
Accepted date: 25-9-2012

Please cite this article as: J.A. Brown, M.S. M., M. Moradi, B. Panahbehagh, D.R. Smith, Adaptive survey designs for sampling rare and clustered populations, *Mathematics and Computers in Simulation* (2010), doi:10.1016/j.matcom.2012.09.008

# Adaptive survey designs for sampling rare and clustered populations

Jennifer A Brown[a], Mohammad Salehi M.[b], Mohammad Moradi[c], Bardia Panahbehagh[d] and David R Smith[e]

[a] *Department of Mathematics and Statistics, University of Canterbury, Christchurch, New Zealand, Email: jennifer.brown@canterbury.ac.nz, Telephone +64 3 364 2600, Fax +64 3 364 2587, Corresponding author*

[b] *Department of Mathematics, Statistics and Physics, Qatar University, Doha, Qatar*

[c] *Department of Statistics, Razi University, Bagh Abrisham, Kermanshah6714967346, Iran.*

[d] *Department of Mathematics, Department of Mathematical Sciences, Isfahan University of Technology, Isfahan 81746-73441, Iran*

[e] *U.S. Geological Survey, 1700 Leetown Rd, Kearneysville, WV 25430 USA*

Abstract: Designing an efficient large-area survey is a challenge, especially in environmental science when many populations are rare and clustered. Adaptive and unequal probability sampling designs are appealing when populations are rare and clustered because survey effort can be targeted to subareas of high interest. For example, higher density subareas are usually of more interest than lower density areas. Adaptive and unequal probability sampling offer flexibility for designing a long term survey because they can accommodate changes in survey objectives, changes in underlying environmental habitat, and changes in species-habitat models. There are many different adaptive sampling designs including adaptive cluster sampling, two-phase stratified sampling, two-stage sequential sampling, and complete allocation stratified sampling. Sample efficiency of these designs can be very high compared with simple random sampling. Large gains in efficiency can be made when survey effort is targeted to the subareas of the study site where there are clusters of individuals from the underlying population. These survey methods work by partitioning the study area in some way, into strata, or primary sample units, or in the case of adaptive cluster sampling, into networks. Survey effort is then adaptively allocated to the strata or primary unit where there is some indication of higher species counts. Having smaller, and more numerous, strata improves efficiency because it allows more effective targeting of the adaptive, second-phase survey effort.

**Keywords:** *Adaptive cluster sampling: Two-phase sampling: Stratified sampling: Adaptive two-stage sequential sampling: Complete allocation stratified sampling*

## 1 Introduction

The need for information for successful environmental management has led to an interest in developing new designs for statistical surveys. Environmental managers require information for monitoring current status and long term trends in environmental quality, and for assessing the impacts of changes in management practice. Examples include monitoring of protected areas such as national parks [11], monitoring for biodiversity [22], and designs to detect contamination [24]

Some of the principle features of survey designs that provide good support for environmental management are designs that are robust for large areas, flexible and adaptable for heterogeneity, and responsive to change. Surveys must be capable of providing summary information on species occurrence, abundance, and structure collected from large areas of land or water. Large area surveys require a degree of spatial spread, or distribution of sample sites over the landscape, and this spread must be achieved in a statistical valid way to allow estimation of the population parameters of interest [15]. Environmental systems are complex with a high degree of spatial and temporal heterogeneity in the underlying ecosystems. Surveys need to be flexible and adaptable to ensure they provide targeted information from such complex systems. Another important feature of environmental surveys is that because information needs and priorities change, surveys must be capable of responding to shifts in survey objectives.

Adaptive and unequal probability survey designs offer many attractive features for environmental surveys. Adaptive and unequal probability surveys can be designed for surveys of large areas providing the desired spatial spread and flexibility for responding to heterogeneity and changing priorities, while maintaining the key elements of probability-based statistical surveys. Adaptive sampling refers to sampling designs where the protocol for data-collection changes, evolves or adapts during the course of the survey. Unequal probability sampling is where the sample units (e.g., sample sites) have different probabilities of appearing in the sample [39].

There are many examples of adaptive sampling in environmental science. Here we review some of the designs that can be useful for sampling populations that are rare and clustered. A text on adaptive sampling was published in 1996 by Thompson and Seber [39], which presents much of the theoretical background and development of estimators. The emphasis is on rare and clustered populations is simply because these are often the most challenging to survey and are also very common in environmental science [17]. There is no one definition for rare and clustered populations that all statisticians and ecologists agree on, but generally these are populations that are difficult to detect (so in fact may not be rare, but sightings are rare), or the population that are sparse in some sense. Sparseness can be because there are few individuals in the population or because the population covers a very large area. McDonald [17] has an excellent discussion of the variety of rare and clustered populations ranging from snakes, and freshwater mussels to polar bears and walruses.

## 2 Adaptive cluster sampling

Adaptive cluster sampling was introduced by Thompson [38] and was one of the early suggested designs for surveying clustered populations. The design typically starts with a random sample, although it can also be applied to systematic sampling [36, 1], stratified sampling [37, 6] and two-stage sampling [28].

Prior to sampling, a threshold value is chosen, $C$, and if any of the units in the initial sample meet or exceed this threshold, $y_i \geq C$, then neighboring units are sampled. If any of these neighboring units meet this condition, their neighboring units are selected and so on. As sampling continues for any cluster that is detected in the initial sample, the shape and size of the cluster can be described.

The final sample is the collection of clusters that were detected in the initial sample, including any of the sample units that were in the initial sample but below the threshold. Survey effort is targeted to searching in the neighborhood of the location of where any plant (or animal) that is found in the initial sample. This feature of the design is very appealing. The design uses the intuitive behavior of a field biologist that once a rare plant is found they want to search in the immediate neighborhood, and puts this behavior in the framework of (unequal) probability sampling.

Horvitz–Thompson estimators are used for the population parameters in adaptive cluster sampling [39]. Two terms need to be defined to help understand the terminology to distinguish “networks” and “clusters”. A network is the collection of units around the unit in the initial sample that triggered neighborhood searching. All these units will have met the condition.

Neighborhood searching is an adaptive process, and for neighborhood searching to stop, units must have been measured and their value found to be below the threshold. These units are called “edge units”. Together, networks and edge units make up a cluster. Any unit in the initial sample that does not meet the condition is considered a network of size one.

In the example in figure 1 of blue-winged teal [31] an initial sample of 10 quadrants is taken (left side of figure). The survey was designed with the threshold condition, $y_i \geq 1$ and the definition of the neighborhood as the four surrounding quadrants. Only one quadrant in the initial sample triggered adaptive selection of the surrounding quadrants.

The final sample size is 16 (right side of figure), but in total, many more than 16 units had to be visited: the four neighboring units are always visited or checked if ducks are present, but only those in the initial sample or in a network are used in calculating the sample estimators. These other units are the edge units, and are visited and checked so that the “edge” of the networks can be defined. With a simple condition like $y_i \geq 1$, these units only needed to be checked to see if ducks are present or absent. However, when the condition is that the sample unit has a value that is larger than a count then the unit would need to be enumerated to check if the condition were met.

Software packages can be used to assist with these calculations, e.g. SAMPLE at http://www.lsc.usgs.gov/aeb/davids/acs/ [21].

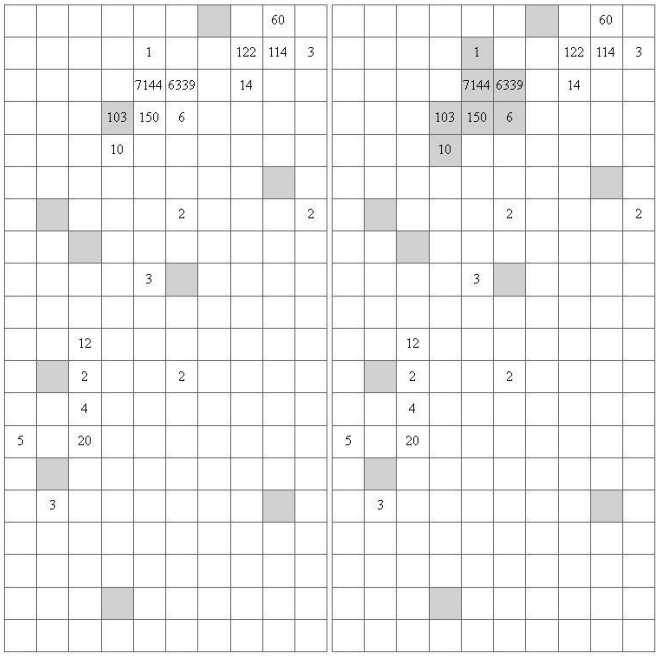


**Fig. 1.** Adaptive cluster sampling of blue-winged teal (from Smith et al., 1995).

The efficiency of adaptive cluster sampling depends firstly on how clustered the population is and, secondly, on the survey design. As a general principle, the more clustered the population is, the more efficient adaptive cluster sampling is compared with simple random sampling. The design choices in adaptive cluster sampling are the sample unit size and shape, the size of the initial sample, the criteria for adaptive selection, and the neighborhood definition (e.g. the surrounding 2, 4 or 8 neighboring units). There is considerable literature on how to design an efficient survey and much of this is reviewed in [30, 40]. A general principle is that efficient designs will be where the final sample size is not excessively larger than the initial sample size, and which has small networks. This can be achieved by using large criteria for adapting and small neighborhood definitions [5].

An issue often raised with adaptive cluster sampling is that the size of the final sample is not known prior to sampling and this can make planning the field work difficult. Restricting the final sample size by a stopping rule has been suggested [7, 27, 16]. Another approach is an inverse sampling design, where surveying stops once a set number of nonzero units have been selected [9, 29].

Adaptive cluster sampling has been used in a range of environmental situations. Some recent examples are the use of adaptive cluster sampling for surveys of plants [25], waterfowl [31], seaweed [13]), shellfish [33], marsupials [30], forests [35, 18], herpetofauna [23], larval sea lampreys [34]), sediment load in rivers [2]), in hydroacoustic surveys [10] and fish eggs [16].

## 3 Stratified and two-stage sampling

Adaptive sampling can also be used with conventional stratified and two-stage sampling. Two-stage sampling and stratified sampling are related in that in both designs the study area is sectioned into strata or primary units. In stratified sampling all strata are selected while in two-stage sampling a selection of primary units is chosen. Sampling (in the second phase) is done by taking a sample of secondary units from the chosen primary units, noting that in stratified sampling all primary units are chosen.

Both stratified and two-stage sampling can be very useful for sampling rare and clustered populations in the same way that adaptive cluster sampling is. Even if the location and size of the species-clusters are not known, as long as their location can be approximated by some auxiliary information and species-cluster size can be approximated by existing biological knowledge, survey effort can be targeted. One useful measure for approximating species-cluster location is a habitat suitability score estimated from environmental resource selection functions [3] or from habitat modeling. This suitability score can be used to delineate primary units with differing levels of propensity for species occupancy. Survey effort can then be allocated among primary units targeting effort to the primary units or strata that are thought to be most likely to contain the clusters of interest. Even in situations where habitat maps and habitat prediction models for species distribution have some uncertainty, sectioning the study area into strata and primary units should be based on the idea of minimizing the within-primary unit or the within-stratum variance so that the units within the primary units are as similar as possible.

### 3.1 Two-phase stratified sampling

One of the early adaptive stratified designs was proposed by Francis [12]. In the two-phase stratified design the survey area is sectioned into strata and initial survey effort allocated based on the best available information using the standard approach of putting more effort in the more variable strata. After this initial phase of sampling, the preliminary information can be used to improve the estimate of the strata variability, and the remaining survey effort can be allocated to the strata that will be most effective in reducing the overall sample variance.

Using the first phase sample results to estimate within-stratum variance, the remaining sample units are added one by one to an individual stratum. At each step of this sequential allocation of sample units, the stratum that is allocated the unit is chosen on the basis of where the greatest reduction in variance will be. For some populations, rather than using within stratum variance of the criteria for adaptive allocation, the square of the stratum mean is preferred [12]. The final estimates are based on the pooled information from the first and second phases. This does result in a small bias, and bootstrapping has been proposed for bias correction and variance estimation [19].

This adaptive allocation in the second phase is done to adjust or to make up for any shortcomings in the initial allocation of effort. As information is gained during the course of the survey, the design for data-collection evolves and adapts.

A similar scheme was proposed by Jolly and Hampton [14]. The design has been extended to surveying multiple populations [20]. Smith and Lundy [32] used a modified design to conduct a stratified sample of sea scallops. Based on the within-stratum mean from the first phase, a fixed amount of effort was allocated to each stratum where the mean was above a threshold value. They used the Rao–Blackwell method [39] to derive an unbiased estimate for the population.

### 3.2 Adaptive two-stage sequential sampling

Another example of adaptive allocation with two-stage sampling is adaptive two-stage sequential sampling [8]. An initial sample is taken from selected primary units. Then, in the second phase, additional units are allocated to the primary units proportional to the number of observed units in that primary unit that exceed a threshold value $g_i \cdot \lambda$, where $g_i$ is the number of sampled units in the $i^{th}$ primary unit that exceed the threshold value and $\lambda$ is a multiplier.

### 3.3 Complete allocation stratified sampling

Adaptive sampling has been applied to conventional stratified in a design called complete allocation stratified design [26]. This is a simplified design for adaptive stratified sampling. If any unit in a stratum has a value that exceeds a threshold, the stratum is completely surveyed. It is simplified in two ways: the rule to decide on whether a stratum is to be allocated additional survey effort does not require the first-phase survey in the stratum to be completed. Secondly, the instruction to the field crew on how much additional effort is required is simply to survey the entire stratum.

The complete allocation stratified design merges the best features of some of the previous adaptive designs. In adaptive cluster sampling, the appeal is that it allows the field biologist to target survey effort to neighborhoods where individuals from a rare species were observed in the initial (first-phase) sample. This

adaptive searching of the neighborhood in adaptive cluster sampling is similar to conducting a complete search in the vicinity of the found individual. In complete allocation, once an individual is observed, the neighborhood is completely searched. The difference is that in adaptive cluster sampling, the neighborhood is not defined prior to sampling and, for some populations, can be excessively large [5]. In complete stratified allocation, the searched neighborhood is defined and restrained by the stratum boundary.

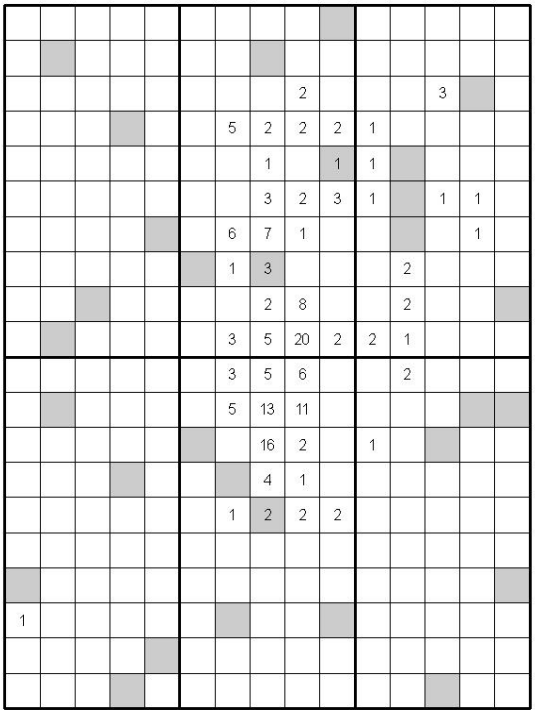

**Fig. 2.** Complete allocation stratified sampling of buttercups (from Brown 2010).

In the example in figure 2 of Castle Hill buttercups [4] the study site was divided into 12 strata. In the first phase, a simple random sample of size 3 was taken from each of the stratum. Three strata had first-phase samples containing buttercups. In the second phase, these three strata were surveyed completely. The total final sample size is therefore (3 x 25) + 9 x 3) = 102.

In the simulation study of Salehi and Brown [26] gains in efficiency over non-adaptive stratified sampling were for some designs, very large.

### 3.4 Comparison of adaptive designs

We extend the buttercup dataset study and compare three adaptive designs with simple random sampling. In this analysis the Castle Hill buttercup site data [4] is revisited. The site was divided into smaller, and larger, strata than shown in figure 2, and buttercups were sampled with conventional stratified sampling and two-stage sampling, complete allocation stratified sampling, and, for comparison, simple random sampling. In such comparative studies it is important to match the total survey effort so that survey efficiency (sample variance) can be evaluated fairly. In our analysis we conducted complete allocation sampling, and then, based on the number of selected strata for stratified and two-stage sampling, set the within-stratum sample size so that the three designs had approximately the same total sample size. Simple random sampling was the total final sample size from complete allocation sampling.

The terminology of strata being applied to two-stage sampling is to for the reader's clarity only. The term primary sample unit is more usual for two-stage sampling, but as discussed in the introduction to this section, the difference between the two when undertaking the sampling process is that in stratified sampling all strata are selected and in two-stage sampling a selection of strata (primary sample units) are selected.

We divided the study area for each simulation, into equal sized strata. We used a range for the number of strata, from $H$ = 6, 10, 12 to 25 strata. Strata need not be equal sized for these designs, but we used this strategy for convenience and to allow comparison among designs with large and small strata. Initial sample sizes within the strata, $n_h$, for complete allocation sampling ranged from 1 to 10 (Figure 3). In figure 3 the relative efficiency of each design (sample variance compared with sample variance from simple random sampling) is shown, along with the expected final sample size for complete allocation sampling. The expected final sample size from complete allocation sampling includes the count of sample units from strata that were completely enumerated ($N_h$) and units that were in strata that were not completely enumerated,

$$E(n) = \sum_{k=1}^{H}\left(N_k \pi_k + n_k\left((1-\pi_k)\right)\right),$$

where $\pi_k$ is the selection probability that the entire stratum $h$ is selected. See Salehi and Brown [26] for description of the sample estimators. In this discussion we have directly accounted for the survey effort in strata that were not completely enumerated and have assumed there is some cost associated with surveying these strata.

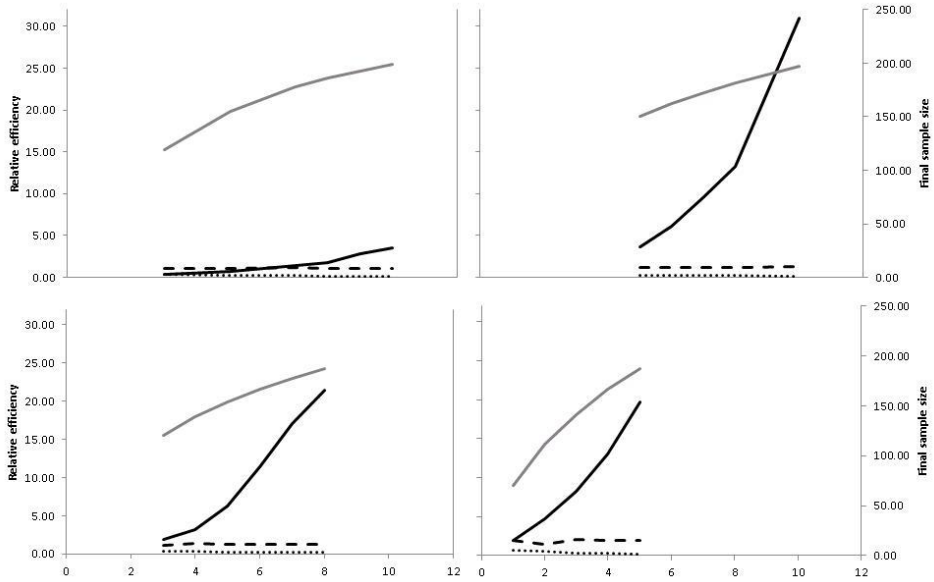


**Fig. 3.** The relative efficiency of three survey designs compared with simple random sampling. The grey line in each graph is the final sample size, the solid black line is the relative efficiency for complete allocation sampling, the dashed line for stratified sampling and the dotted line for two-stage sampling. On the horizontal axis is the within-strata initial sample size for complete allocation sampling.. The top left graph is for 6 strata, the top right 10 strata, the bottom left 12 strata, and the bottom right 25 strata.

The within stratum sample size for complete allocation is shown on the horizontal axis in figure 3. For conventional stratified sampling the within stratum sample size can be calculated from the final sample size. For example, the design with 6 strata the final sample size is 120. Therefore the conventional stratified sampling within stratum sample size will be 20.

For two-stage sampling the number of strata (primary sample units) selected in the first stage was $m$ = 4 with the design where the study area was divided into 6 strata, $m$ = 7 for 10 strata, $m$ = 8 for 12 strata, and $m$ = 17 for 25 strata.

Conventional stratified sampling was more efficient than simple random sampling (with the same sample size) for all survey options. Relative efficiency was higher for the designs with more strata; sampling with 25 strata had relative efficiencies of about 2 over simple random sampling.

Any gain in efficiency from conventional stratified sampling was well exceeded by complete allocation stratified sampling. For this design efficiencies were as high as 20 times over simple random sampling. There were two options where the design was less efficient (6 strata with the two smallest initial within-strata sample size), but in general complete allocation stratified sampling exceeded conventional stratified sampling

in relative efficiency. Gains in efficiency increased with larger initial within strata sample sizes, as noted by Salehi and Brown [26]. They suggest that having a larger sample size in the initial search has the effect of reducing any first-phase error by correctly identifying whether the stratum should be a completely enumerated.

## 4 Discussion

Adaptive and unequal probability sampling designs offer a wide range of flexible and useful survey techniques. These designs are especially useful for environmental sampling and for surveys of rare and clustered populations because they allow survey effort to be targeted to where any plant or animal of interest has been found. Changes to survey objectives can be readily accommodated by altering primary unit, or strata, boundaries, shifting first-phase allocation to effort among primary units, and changing the threshold condition used for second-phase adaptive allocation. Similarly, as the underlying environmental habitat changes, or as habitat models improve, the sample design can be modified. The flexibility in adaptive and unequal probability sampling is that population estimates derived from surveys where design features have changed (e.g., relative survey effort allocation and threshold condition) are still comparable. In long term environmental monitoring these two features of design flexibility and estimates that are comparable among-years are important considerations.

Adaptive and unequal probability sampling can be applied to any sampling situation. Our discussion has focused on rare and clustered populations in environmental application, but there are numerous other fields where these designs could be useful including surveys of infectious disease outbreaks, poverty mapping, rare events in financial markets, and many other applications where an event has a contagious pattern (in space, time or any other dimension). We have discussed adaptive selection as a complement to simple random sampling, two-stage and stratified sampling. We use the terminology suggested by Salehi and Brown [39] with the use of the terms “adaptive searching” and “adaptive allocation” to distinguish two categories. Adaptive searching refers to designs such as adaptive cluster sampling where the neighborhood is searched. In contrast, in adaptive allocation, extra effort is initiated once a collection of units are sampled (e.g. the stratum or the primary unit). The distinction between the two classes is based on where and when the decision to allocate extra effort can be made: immediately after an individual sample unit is measured or once a collection of units has been completely sampled.

In adaptive cluster sampling, extra effort is allocated for adaptive searching in the neighborhood of any unit in the initial sample that meets the threshold condition. Complete allocation stratified sampling [26] is another example of adaptive searching where as soon as a unit in the stratum is found that has a value that exceeds the threshold, second phase effort to enumerate the entire stratum begins. With stratified or two-stage designs such as two-phase stratified sampling [12] and adaptive two-stage sequential sampling [8] adaptive allocation of additional effort is triggered on the basis of a measure of the whole stratum (or primary unit).

All the designs discussed are remarkably efficient, giving estimates of populations that have lower variance than the conventional design without the adaptive selection. However, as with conventional sampling, the survey must be carefully designed to achieve these efficiencies. Design features include choice of the size and number of stratum, allocation of effort to the first phase (i.e. the initial sample before the additional effort is allocated) relative to second-phase effort, the threshold used to trigger adaptive allocation, and, for adaptive cluster sampling, the neighborhood definition.

It is important to ensure adequate effort is available for the adaptive allocation that occurs in the second phase of sampling if large gains in efficiency are to be realized. For the same amount of effort, Brown et al. [8] recommend putting less effort into the initial sample of the selected primary sample units to ensure more effort is available for the sequential allocation of additional units, compared with the reverse. However, as Salehi and Brown [26] caution, there needs to be sufficient first phase effort in complete allocation stratified sampling to reduce the error in failing to detect a unit that would trigger complete enumeration. Another recommendation is that the threshold value that is used to “trigger” adaptive allocation of additional units should be relatively high. These recommendations are consistent with what is recommended for adaptive cluster sampling [5, 30].

For adaptive stratified and two-stage designs sample efficiency improves when the strata, or primary units, create boundaries that encompass aggregates or clusters. This is because the adaptive allocation of effort to primary units is a very effective way of targeting effort to where the species of interest is located. Similarly

when stratification intensity increases with more, and smaller, strata or primary units the survey efficiency improves as the strata or primary units become closer to matching the size of the aggregates in the underlying population.

**ACKNOWLEDGEMENTS**

Thank you to Miriam Hodge and Blair Robertson for ongoing collaborative work in this field, and to two anonymous reviewers for their review and very helpful suggestions on the manuscript. This paper was presented at the 19th International Congress on Modelling and Simulation (MODSIM2011) at the Perth Convention and Exhibition Centre in Perth, Western Australia, from 12 to 16 December 2011.

**REFERENCES**

[1] B. Acharya, G. Bhattarai, A. de Gier, and A. Stein, Systematic adaptive cluster sampling for the assessment of rare tree species in Nepal, For. Ecol. Manage. 137 (2000) 65–73.
[2] M. Arabkhedri, F.S. Lai, I.Noor-Akma, M.K. Mohamad-Roslan, An application of adaptive cluster sampling for estimating total suspended sediment load, Hydrol. Res. 41 (2010) 63–73.
[3] M.S. Boyce, P.R. Vernier, S.E. Nielson, F.A.K. Schmiegelow, Evaluating resource selection functions, Ecol. Modell. 157 (2002) 281-300.
[4] J.A. Brown, in: Yue Rong (Ed.), Environmental Statistics and Data Analysis, ILM Publications, Hertfordshire, UK, 2010, pp. 81-96.
[5] J.A. Brown, Designing an efficient adaptive cluster sample, Environ. Ecol. Stat. 10 (2003) 95–105.
[6] J.A. Brown, A comparison of two stratified sampling designs: adaptive cluster sampling and a two-phase sampling design, Aust. N. Z. J. Stat. 41 (1999) 395–404.
[7] J.A. Brown, B.F.J. Manly, Restricted adaptive cluster sampling, Environ. Ecol. Stat .5 (1998) 47–62.
[8] J.A. Brown, M.M. Salehi, M. Moradi, G. Bell, D.R. Smith, An adaptive two-stage sequential design for sampling rare and clustered populations, Pop. Ecol. 50 (2008) 239–245.
[9] M.C. Christman, F. Lan, Inverse adaptive cluster sampling, Biometrics 57 (2001) 1096–1105.
[10] M.E. Conners, S.J.Schwager, The use of adaptive cluster sampling for hydroacoustic surveys, ICES J. Mar. Sci. 59 (2002) 1314–1325.
[11] S.G. Fancy, J.E. Gross, S.L. Carter, Monitoring the condition of natural resources in US national parks, Environ. Monit. Assess. 151 (2009) 161–174.
[12] R.I.C.C. Francis, An adaptive strategy for stratified random trawl surveys, N. Z. J. Mar. Fresh. Res. 18 (1984) 59–71.
[13] N.A. Goldberg, J.N. Heine, J.A. Brown, The application of adaptive cluster sampling for rare subtidal macroalgae, Mar. Biol. 151 (2006) 1343–1348.
[14] G.M. Jolly, I. Hampton, A stratified random transect design for acoustic surveys of fish stocks, C. J. Fish Aquat. Sci. 4 (1990) 1282–1291.
[15] A.J. Lister, C.T. Scott, and C.T Scott Use of space-filling curves to select sample locations in natural resource monitoring studies, Environ. Monit. Assess. 149 (2009) 71–80.
[16] N.C.H. Lo, D. Griffith, J.R. Hunter, Using restricted adaptive cluster sampling to estimate Pacific hake larval abundance, California Cooperative Oceanic Fisheries Investigations Report 37 (1997) 160–174.
[17] L.L. McDonald, in: W.L Thompson, W.L. (Ed), Sampling Rare and Elusive Species. Island Press, Washington DC, 2004, pp. 11–42.
[18] S.Magnussen, W.Kurz, D.G. Leckie, D.Paradine, Adaptive cluster sampling for estimation of deforestation rates, Europ. J. For. Res. 124 (2005) 207–220.
[19] B.F.J. Manly, Using the bootstrap with two-phase adaptive stratified samples from multiple populations at multiple locations, Environ. Ecol. Stat. 11 (2004) 367–383.
[20] B.F.J. Manly, J.M. Akroyd, K.A.R. Walshe, Two-phase stratified random surveys on multiple populations at multiple locations, N. Z. J. Mar. Fresh. Res. 36 (2002) 581–591.
[21] L.W. Morrison, D.R. Smith, D.W. Nichols, and C.C. Young, Using computer simulations to evaluate sample design: an example with the Missouri bladderpod, Pop. Ecol. 50 (2008) 417–425.
[22] S.E. Nielsen, D.L. Haughland, E Bayne, J Schieck,. Capacity of large-scale, long-term biodiversity monitoring programmes to detect trends in species prevalence, Biodivers. Conserv. 18 (2009) 2961–2978.
[23] B.R. Noon, N.M. Ishwar, K. Vasudevan, Efficiency of adaptive cluster and random sampling in detecting terrestrial herpetofauna in a tropical rainforest, Wildl. Soc. Bull. 34 (2006) 59-68.

[24] A.R. Olsen, B.D. Snyder, L.L. Stahl, J.L. Pitt, Survey design for lakes and reservoirs in the United States to assess contaminants in fish tissue, Environ. Monit. Assess. 150 (2009) 91–100.
[25] T. Philippi, Adaptive cluster sampling for estimation of abundances within local populations of low-abundance plants, Ecology 86 (2005) 1091–1100.
[26] M.M. Salehi and Brown, J.A. Complete allocation sampling: An efficient and easily implemented adaptive sampling design, Pop. Ecol. 52 (2010) 451-456.
[27] M.M. Salehi, G.A.F. Seber, Unbiased estimators for restricted adaptive cluster sampling, Aust. N. Z. J. Stat. 44 (2002) 63–74.
[28] M.M. Salehi, G.A.F. Seber, Two-stage adaptive cluster sampling, Biometrics 53 (1997) 959–970.
[29] G.A.F. Seber, and M.M. Salehi, in: Armitage, P. Colton, T. (Eds.) Encyclopedia of Biostatistics Volume 1, second ed. Wiley and Sons, Chichester, 2004, pp.59–65.
[30] D.R. Smith, J.A. Brown, N.C.H. Lo, in: Thompson WL (Ed.), Sampling Rare and Elusive Species, Island Press, Washington DC, 2004, pp. 75–122.
[31] D.R. Smith, M.J. Conroy, D.H. Brakhage, Efficiency of adaptive cluster sampling for estimating density of wintering waterfowl, Biometrics 51(1995) 777–788.
[32] S.J. Smith, Lundy, M.J. Improving the precision of design-based scallop drag surveys using adaptive allocation methods, C. J. Fish. Aquat. Sci. 63 (2006) 1639–1646.
[33] D.R. Smith, R.F. Villella, D.P. Lemarié, Application of adaptive cluster sampling to low-density populations of freshwater mussels, Environ. Ecol. Stat. 10 (2003) 7–15.
[34] W.P. Sullivan, B.J. Morrison, F.W.H. Beamish, Adaptive cluster sampling: estimating density of spatially autocorrelated larvae of the sea lamprey with improved precision, J. Great Lakes Res. 34 (2008) 86–97.
[35] M. Talvitie, O. Leino, M. Holopainen,. Inventory of sparse forest populations using adaptive cluster sampling, Silva Fennica 40 (2006) 101–108.
[36] S.K. Thompson, Adaptive cluster sampling: Designs with primary and secondary units, Biometrics 47 (1991) 1103–1115.
[37] S.K. Thompson, Stratified adaptive cluster sampling, Biometrika 78 (1991) 389–397.
[38] S.K. Thompson, Adaptive cluster sampling, J. Am. Stat. Assoc. 85 (1990) 1050–1059.
[39] S.K. Thompson, G.A.F. Seber, Adaptive Sampling, Wiley, New York, 1996.
[40] P. Turk, J.J. Borkowski, A review of adaptive cluster sampling: 1990–2003, Environ Ecol Stat 12 (2005) 55–94.