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Inventory of Sparse Forest Populations Using Adaptive Cluster Sampling

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In many studies, adaptive cluster sampling (ACS) proved to be a powerful tool for assessing rare clustered populations that are difficult to estimate by means of conventional sampling methods. During 2002 and 2003, severe drought-caused damage was observed in the park forests of the City of Helsinki, Finland, especially in barren site pine and spruce stands. The aim of the present study was to examine sampling and measurement methods for assessing drought damage by analysing the effectiveness of ACS compared with simple random sampling (SRS). Horvitz-Thompson and Hansen-Hurwitz estimators of the ACS method were used for estimating the population mean and variance of the variable of interest. ACS was considerably more effective than SRS in assessing rare clustered populations such as those resulting from drought damage. The variances in the ACS methods were significantly smaller and the inventory efficiency in the field better than in SRS.

Keywords adaptive cluster sampling, simple random sampling, drought damage, coarse woody debris, efficiency
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1 Introduction

Since the late 1980s in Finland, increasing concern has been shown for how forest planning and management influence the amount of dead tree (coarse woody debris, CWD) volume and number of species (Mielikäinen and Hynynen 2003). The significance of global carbon dynamics and preserving biodiversity has led to growing interest in the quantity and quality of deadwood (e.g. Huston and Marland 2003). CWD has many functions in the ecological processes of forests; e.g. it is the source of organic material and carbon dioxide in the atmosphere and the habitat for a wide variety of organisms (Siitonen 1998). In southern Finland, the amount of CWD per hectare in fresh mineral soils of old spruce-dominant forests can be as much as 90–120 $m^3 ha^{-1}$ (Siitonen et al.

2000). In managed forests, however, the amount of CWD is only about 10 $m^3 ha^{-1}$, due to the management methods used in the forests. Dead trees are important indicators of biodiversity in forests, and therefore methods for assessing CWD are becoming more significant.

Traditionally, forest inventories have been carried out with the aim of collecting data related to timber production planning. If preserving biodiversity is an additional objective, forest management planning becomes more complex than when timber production is the only purpose (Ringvall 2000). The natural distribution of ecosystems is fragmented, mainly due to human intervention. Ecological distributions are very rarely randomly distributed (Levin 1992). With conventional forest inventory methods, large areas must be covered to achieve acceptable precision of biodiversity objects (Green and Young 1993).

It is possible to detect valuable biodiversity objects with methods different from those used in conventional forest planning. For example, line transect sampling (Buckland et al. 1993), transect relascope sampling (e.g. Ståhl et al. 2001) and line intersect sampling (Warren and Olsen 1964) are methods that are based on an intersect network developed in the study area. Line inventory methods can be more effective in estimating CWD than plot-based methods (e.g. Warren and Olsen 1964, Bailey 1970, Ringvall and Ståhl 1999). In a two-stage guided transect sampling design, subsampling within strips is guided by prior information in the second stage after selecting wide strips in the first stage (Ståhl et al. 2000).

Adaptive cluster sampling (ACS) has been suggested as a method for estimating rare and clustered populations that are difficult to estimate precisely using conventional sampling methods (e.g. Thompson 1990, 1991, Roesch 1993). When the object of interest is found, further measurements are carried out in the vicinity of the initial plot. New plots are measured until no more objects of interest are found. In this way, sampling is allocated to local areas with large amounts of the variable. However, the efficiency of the ACS method is dependent on the density and clustering degree that are not known before the initial sampling. In addition, the total sample size is not known beforehand, which increases the uncertainty in deciding which study method to use.

One main positive aspect in cluster sampling is the cost-efficiency. With the same costs, it is possible to measure additional plots (Cochran 1977). On the other hand, if the sampling size is not larger than that of simple random sampling (SRS) the reliability is lower, due to increased numbers of similar units in the clusters (Kangas and Päivinen 2003).

Few studies have addressed the problem of sampling forest phenomena using ACS. Roesch (1993) was the first to combine the probability-proportional-to-size sampling schemes that are commonly used in forestry with an ACS scheme to develop a system that could be applied to many inventory systems. Acharya et al. (2000) sampled rare tree species using systematic ACS and determined that for a clustered species the efficiency for density estimation increased by as much as 500%; however, for an unclustered species it decreased by 40%. They also suggested that an optimal group size would relate to design efficiency, because when groups become too large ACS becomes comparable to complete enumeration.

The aim of the present study was to examine sampling and measurement methods for assessing CWD by analysing the effectiveness of ACS compared with SRS. SRS offers a basis for comparison with the adaptive and nonadaptive sample designs because it is an unbiased estimator of the population mean. In the ACS method, the Horvitz-Thompson (HT) and Hansen-Hurwitz (HH) estimators were used for estimating the population mean and variance of CWD.

2 Methods: Adaptive Cluster Sampling

In sampling rare clustered phenomena, ACS has the advantage compared with other, more conventional, sampling methods (e.g. Thompson 1990, Roesch 1993). The initial set of units is selected using a probability sampling procedure and additional units are added to the sample from the neighbourhood of unit i in case the variable of interest (y_i) satisfies a given criterion, i.e. if $y_i \in C$, $C = \{x : x \geq c\}$ prior to sampling. The procedure is repeated until no new additional plots can be found whose variable exceeds the given value.

Table 1. Simple random sampling, modified Horvitz-Thompson and Hansen-Hurwitz estimators according to Salehi (2003) used in the study.

Estimator	Mean	Variance
Simple random sampling (SRS)	$\hat{\mu}_{SRS} = \frac{1}{n}\sum_{i=1}^{n} y_i$	$\mathrm{var}(\hat{\mu}_{SRS}) = \frac{\sum_{i=1}^{n}(y_i - \hat{\mu}_{SRS})^2}{n-1}$
Horvitz-Thompson (HT)	$\hat{\mu}_{HT} = \frac{1}{N}\sum_{k=1}^{\kappa} \frac{y_k^*}{\alpha_k}$	$\hat{\mathrm{var}}(\hat{\mu}_{HT}) = \frac{1}{N^2}\left[\sum_{j=1}^{K}\sum_{k=1}^{K} \frac{y_j^* y_k^*}{\alpha_{jk}}\left(\frac{\alpha_{jk}}{\alpha_j \alpha_k} - 1\right)\right]$
Hansen-Hurwitz (HH)	$\hat{\mu}_{HH} = \frac{1}{n_1}\sum_{i=1}^{n_1} w_i$	$\hat{\mathrm{var}}(\hat{\mu}_{HH}) = \frac{N - n_1}{Nn_1(n_1 - 1)}\sum_{i=1}^{n_1}(w_i - \hat{\mu}_{HH})^2$

N = number of units in the population, n_1 = number of units in the initial sample, κ = number of distinct networks represented in the initial sample, y_i = observation in unit i, y^*_k = sum of observations in network k, w_i = mean of the observations in the network that includes the ith unit of the initial sample, α_k = the probability of the initial sample intersect network A_k, α_{jk} = the probability that the initial sample includes at least one unit in each of networks j and k.

Thus, sampling effort is focused on local areas with large amounts of the variable.

The population consists of N units $\{1, 2, \ldots, N\}$ and has variables of interest $y = \{y_1, y_2, \ldots, y_N\}$. In forest applications, a tree or sample plot is normally taken as a basic unit. For every unit i in the population, a physical neighbourhood A_i will be defined that consists of a collection of units that includes unit i. If unit j is in the neighbourhood of unit i, then unit i is also in the neighbourhood of unit j (Thompson 1990).

A *network* is defined as a group of units whose values are all at least as large as the critical value C. A unit that does not satisfy this condition, but is in the neighbourhood of the unit that does, is referred to as an *edge unit* (Thompson 1990). The difference from conventional sampling designs is that the procedure for selecting an adaptive sample is dependent on the population values observed in the field. It is a characteristic of ACS that the sample size is not known beforehand.

Two ACS estimators, HT (Horvitz and Thompson 1952) and HH (Hansen and Hurwitz 1943) estimators, have been widely examined. Thompson (1990) presented modified HT and HH type estimators that are designed for unbiased use in the ACS method (Table 1). The difference between the HT and HH estimators is that the HT estimator is based on the inclusion probability of each unit i in the population (Thompson 1990), while the HH estimator is calculated by taking an SRS of size n_1 from a population of w_i values (Salehi 2003). In general, the modified HT estimator usually has smaller variance estimates (s^2), but is more difficult to calculate than the HH estimator. However, Salehi (2003) advised ecologists to use the HT estimator in calculations.

The probability (α_k) that the initial sample intersects network A_k is defined in Table 1 as

$$\alpha_k = 1 - \binom{N - m_k}{n_1} \bigg/ \binom{N}{n_1} \qquad (1)$$

where N = total sample size, n_1 = initial sample size and m_k = the number of units in the network that includes unit k. The probability (α_{jk}) that the initial sample includes at least one unit in each of the networks j and k is defined as

$$\alpha_{jk} = 1 - \left[\binom{N - m_j}{n_1} + \binom{N - m_k}{n_1} - \binom{N - m_j - m_k}{n_1}\right] \bigg/ \binom{N}{n_1} \qquad (2)$$

where m_j is the number of units in the network that includes unit j. In comparison, the mean value of the SRS estimator is dependent only on the units in the initial sample and does not take into account the units added in the second phase.

The efficiency of the method is dependent on the number of plots that are adaptively added to the sample. An adaptive sampling design is effective when the final size is similar to the initial sample size, which is the case in rare populations (Smith et al. 2003). If the critical value is too low, the final sample size will be excessively large. Similarly, if the critical value is too large there may be no or only a very small adaptive sample in cases where there is no unit in the initial sample with a value that exceeds the critical value (Brown 2003). Brown (2003) pointed out that the HH estimator of ACS is more efficient than the SRS estimator when

$$\mathrm{var}(\bar{y}\,|v) > \mathrm{var}(\hat{\mu}\,|n)$$
$$\Rightarrow \frac{\sum_{k=1}^{K}\sum_{i\in\Psi_k}(y_i-w_i)^2}{N-1}\left(\frac{1-\frac{n}{N}}{1-\frac{n}{v}}\right) > \sigma^2 \qquad (3)$$

where $\bar{y}$ = the sample mean, v = the final sample size, $\hat{\mu}$ = the estimate of the population mean and n = the initial sample size. In other words, ACS is more efficient if the within network variance σ^2_{wn} of the population is larger than the variance σ^2 of the total population.

Furthermore, comparison between ACS and SRS can be based on the cost-efficiency of the method. The costs of an inventory method can be described as the time taken in a plot (including the time spent on moving to the next plot). It is often cheaper to sample plots within a cluster than to select a new cluster. When healthy forest areas are inventoried, most of the time is spent on moving from one plot to another and measurements in a plot can be done quickly. If more plots near each other are inventoried the inventory efficiency grows significantly.

3 Material

3.1 Study Data

The study area included the park forests of the Helsinki City area in southern Finland, consisting of 3700 ha. Park forests are recreational areas of Helsinki, whose forests are managed to preserve biodiversity despite the presence of environmental stress and heavy recreational use. The forest of the area is predominantly old-growth stands dominated mostly by Norway spruce (*Picea abies* (L.) Karst.), Scots pine (*Pinus sylvestris* L.) or silver birch (*Betula pendula* Roth).

During 2002 and 2003, severe drought-caused damage was observed in the park forests of the City of Helsinki. In the park forests, CWD diverts people's opinions from the positive aspects of biodiversity to the negative aspects of unattractive appearance and the danger of falling trees. Thus, the need for inventorying drought damage is high. The damaged areas were situated especially in barren site pine and spruce stands. However, there were large healthy areas that showed little or no drought damage. Damage was located within clusters in certain forest types and the damage proportion from the total area was rather small. As a result, the ACS method seemed an ideal alternative for sampling the damage.

3.2 Fieldwork

Only forest areas ≥5 ha were selected for the study. All dead trees were counted from a circular sample plot with a 19.95-m radius located in the centre of a 0.25-ha square cell defined from aerial photographs. The circular sample plots were situated 50 m from each other in the north-south and east-west directions. A total of $n_1 = 61$ initial sample plots, representing 0.5% of the total area, were selected randomly from the systematic grid for field measurements.

The diameters of dead standing trees that were situated in the circular sample plots were measured in 2-cm diameter classes. Information on the basal area per hectare of the sample plots was taken from a compartmentwise inventory. The basal area per hectare correlates strongly with the volume per hectare and can therefore be used in estimating the proportion of dead volume per hectare (e.g. Nyyssönen 1954). Moreover, basal area per hectare is easier to measure than volume per hectare in the field and was used here. Tree species distribution was not determined, since only the amount of dead tree volume was studied.

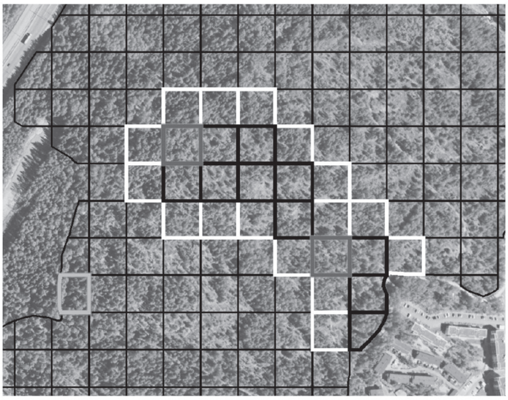

Fig. 1. Arrangement of the sample. Initial random sample plots are seen in grey. Additional neighbouring units (black) are added to the network until all the cells that include damage in the neighbourhood are found. Additional units, called edge units, that do not have damage are marked with white.

The degree of damage was described on a scale of 0 to 9. The damage classes were defined according to the proportion of dead tree volume compared with total volume. The critical value *C* was defined as damage class 1, i.e. 10–19% of the basal area consisted of dead trees. If the damage class of a sample plot was larger than zero, 4 additional sample plots were measured north, south, west and east of the plot (Fig. 1). The plots were added repeatedly until all additional plots were classified as damage class zero.

In comparison, the estimators were calculated with damage class 2 as the critical value. We examined how the effect of smaller sample and cluster size due to larger critical value would influence the estimates of population mean and variance and the efficiency of an ACS method in the case of drought damage.

4 Results

4.1 Critical Value $C = 1$

The number of initial sample plots was 61. Most of the initial units fell into damage class zero and no adaptive units were taken in their neighbourhood; however, a total of 96 units were added to the sample. The mean size of adaptively sampled networks was 11 units, of which the largest network was a total of 35 units.

Table 2. Distribution of initial sample plots into damage classes.

Class	Simple random sampling		Adaptive cluster sampling	
	Frequency	%	Frequency	%
0	51	84	116	73
1	6	10	26	16
2	2	3	9	6
3	2	3	4	3
4	0	0	1	1
5	0	0	1	1
6	0	0	1	1
7	0	0	1	1
Total	61	100	159	100

The damage class distribution differed between SRS and ACS (Table 2). Larger proportions of damaged units were detected with the ACS than the SRS methods and the damage class distribution was wider in the ACS method, since plots in damage classes 4–7 were not found in the initial sample (Table 2). Moreover, proportionally increased numbers of plots in damage classes 2 and 3 were observed with the ACS than with the SRS methods, while 84% and 73% of the plots were classified as damage class zero using SRS and ACS, respectively. In comparison to SRS, ACS had an over 2.5 times larger sample size; however, Smith et al. (2003) and Brown (2003) suggested that an adaptive method would be more efficient if the final sample size were not much larger than the initial sample size.

The SRS, HT and HH estimators for the population mean and variance were calculated. The sample means and variances of the 3 sample designs are shown in Table 3. The mean values for all the estimators were very similar. The HH estimator showed the smallest variance, while that of the HT estimator was slightly larger. The largest variance estimate was obtained with SRS (initial sample).

In the present study, the inventory efficiency was calculated and compared with the data obtained during working days, thus making it

Table 3. Number of units in the initial sample (n_1), number of units in the final sample (v), estimates ($\hat{\mu}$), variance estimates (s^2) and coefficients of variation (CV) of simple random sampling (SRS), Horvitz-Thompson (HT) and Hansen-Hurwitz (HH) estimators.

	SRS	HT, C=1	HH, C=1	HT, C=2	HH, C=2
n_1	61	61	61	61	61
v	61	159	159	81	81
$\hat{\mu}$	0.2623	0.2550	0.2525	0.2542	0.2541
s^2	0.4558	0.0074	0.0052	0.0073	0.0069
CV	2.5739	0.3368	0.2857	0.3370	0.3265

possible to include travelling times between plots that were specific for each area. The daily measuring times were divided by the number of sample plots inventoried that day. As seen in Fig. 2, the inventory efficiency was doubled when a separate plot inventory was compared with the clustered plot inventory. The mean time spent in a single sample plot was 40 min, corresponding to the inventory efficiency obtained with SRS; with ACS the mean time spent in clustered sample plots was 18 min.

If the size of SRS were the same as that of ACS with critical value 1, the time spent on measuring the cells in SRS would be twice as much as in ACS. The variance of SRS would decrease to 0.2443 which, however, is still considerably larger than the HT and HH variances.

Table 4. Efficiency of HH estimator with critical values 1 and 2. Comparison value is calculated from the left-hand side of Eq. 3. σ^2_{wn} = within-network variance.

	σ^2_{wn}	Comparison value
$C=1$	0.00616	0.0099
$C=2$	0.00004	0.0002

4.2 Critical Value $C=2$ Compared with $C=1$

When damage class 2 was taken as the critical value, the total sample size was 81 units. The sample means of the different estimators did not differ from the mean values achieved with a critical value of 1. However, there was considerable difference in the HH variance, indicating the superiority of damage class 1 as a critical value. The estimates of the HT estimator differed from those of the HH estimator by having slightly smaller variance estimates when the larger critical value was used. It is also worth noting that, using damage class 2, both ACS estimators had smaller variance estimates than the HT estimator with damage class 1 as the critical value.

In the present study, σ^2 was unknown and Eq. 3 could not be solved. Thus, only the left-hand side of the equation was used to compare critical values 1 and 2 (comparison value). Damage class 1 proved to be more effective than damage

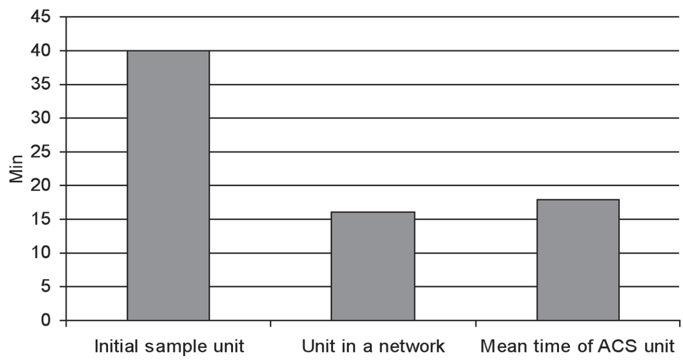

Fig. 2. Inventory efficiency. The mean time used in an initial sample unit (single plot), in a unit belonging to a network and in an average ACS plot.

class 2 as the critical value when the HH estimator was used (Table 4). The equation could not be solved with the HT estimator.

5 Discussion

When clustered forest phenomena are inventoried, e.g. CWD in managed forests, there is more uncertainty than in inventorying conventional forest variables. In the present study, ACS was more effective than SRS in cases of drought damage, which occurred in clustered populations (see also Thompson 1990, Roesch 1993, Acharya et al. 2000).

If population groups are larger than sample plots, it is more efficient to measure and estimate the variables of interest using the ACS method (Acharya et al. 2000). In many situations, the costs of a unit that do not satisfy the critical value *C* are lower than those of a plot that do. Furthermore, moving from one sample plot to another takes time; if the plots are situated near each other the time spent on walking is decreased rapidly (Table 4).

Brown (2003) suggested that the final sample size in ACS should not be excessively larger than the initial sample size. The sample size can be reduced by increasing the critical value. On the other hand, if the networks are very small the disadvantage of the relatively small σ^2_{wn} compared with σ^2 will become more important than the advantage of having the final sample size near the initial sample size. Moreover, Brown (2003) pointed out that the size of a network should be large enough such that σ^2_{wn} is similar to σ^2. In the present study, comparison between alternative critical values showed that a smaller critical value resulted in a smaller variance estimate with the HH estimator, but made no difference with the HT estimator.

Possible sources of error in the fieldwork included measurement and positioning errors in locating the centre of a circular sample plot. However, the effects of these errors could not be analytically observed in the results. The diameters were measured as 2-cm diameter classes, which can cause random error in calculating the damage class value of a sample plot. The highest probability of having a false damage classification was with those plots in which the dead tree proportion was at the border between 2 damage classes; this influence was greater if only a few trees were measured.

Furthermore, one source of error is the smaller circular plot size (0.125 ha) compared with the cell size (0.25 ha). If the damaged trees were not situated at regular intervals in the 0.25-ha area but rather in the corner of it, the damage class value detected from a circular sample plot could differ from that of a square plot. However, the error resulting from a smaller-sized circular plot would be random error.

Both the above-mentioned sources of error can lead to the risk of misidentifying the variable of interest. Misidentifications in conventional sampling may compensate for each other, but this is not the case in adaptive sampling. Therefore, an adaptive sampling method should be employed only for variables that can be identified with full confidence. In the present study, the misidentifications of dead trees could cause erroneous results, i.e. either over- or underestimations.

The data used in the study were obtained from the city forests; most of the time was spent moving by car in the city traffic rather than in the forests. With the data obtained, it was not possible to make a total survey cost budget, which would have given more information on the efficiency of ACS and how the inventory scheme can be designed to be most effective.

By tradition, biodiversity conservation has focused on protecting individual threatened species, but this species-by-species approach is expensive and inefficient. Due to the complex relationships between species and their biotopes, a biotope approach to biodiversity conservation is often preferable. There are many means of describing vegetation diversity, the most common of which include the extent, structure, composition, biomass or production and condition of the vegetation or species. Each aspect can be assessed on the ground, but may be assessed more effectively from various forms of remote-sensing data. In future research on drought damage, a method based on two-phase sampling will be developed. In the first phase, auxiliary data derived from digital aerial photographs or laser scanning will be used to locate potential drought damage. In the second phase, ACS will be utilized in field measurements and accuracy assessment.

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References

Acharya, B., Bhattarai, G., de Gier, A. & Stein, A. 2000. Systematic adaptive cluster sampling for the assessment of rare tree species in Nepal. Forest Ecology and Management 137: 65–73.

Bailey, G.R. 1970. A simplified method of sampling logging residue. Forestry Chronicle 46: 288–294.

Brown, J.A. 2003. Designing an efficient adaptive cluster sample. Environmental and Ecological Statistics 10: 95–105.

Buckland, S.T., Anderson, D.R., Burnham, K.P. & Laake, J.L. 1993. Distance sampling. Estimating abundance of biological populations. Chapman & Hall, London UK. 466 p.

Cochran, W.G. 1977. Sampling techniques. 3rd edition. Wiley, New York. 448 p.

Green, R.H. & Young, R.C. 1993. Sampling to detect rare species. Ecological Applications 3: 351–356.

Hansen, M.M. & Hurwitz, W.N. 1943. On the theory of sampling from finite populations. Annals of Mathematical Statistics 14: 333–362.

Horvitz, D.G. & Thompson, D.J. 1952. A generalization of sampling without replacement from a finite universe. Journal of the American Statistical Association 47: 663–685.

Huston, M.A. & Marland, G. 2003. Carbon management and biodiversity. Journal of Environmental Management 67: 77–86.

Kangas, A. & Päivinen, R. 2003. Metsän mittaus. Silva Carelica 27. University of Joensuu. 172 p. (In Finnish).

Levin, S.A. 1992. The problem of pattern and scale in ecology. Ecology 73: 1943–1967.

Mielikäinen, K. & Hynynen, J. 2003. Silvicultural management in maintaining biodiversity and resistance of forests in Europe – boreal zone: case Finland. Journal of Environmental Management 67(1): 47–54.

Nyyssönen, A. 1954. Estimation of stand volume by means of the relascope. Communicationes Instituti Forestalis Fenniae 44(6). 31 p. (In Finnish with English summary).

Ringvall, A. 2000. Assessment of sparse populations in forest inventory. Development and evaluation of probability sampling methods. Ph.D. thesis. Acta Universitatis Agriculturae Sueciae Silvestria 151.

— & Ståhl, G. 1999. Field aspects of line intersect sampling for assessing coarse woody debris. Forest Ecology and Management 119: 163–170.

Roesch, F.A. Jr. 1993. Adaptive cluster sampling for forest inventories. Forest Science 39(4): 655–669.

Salehi, M.M. 2003. Comparison between Hansen-Hurwitz and Horvitz-Thompson estimators for adaptive cluster sampling. Environmental and Ecological Statistics 10: 115–127.

Siitonen, J. 1998. Lahopuun merkitys metsäluonnon monimuotoisuudelle – kirjallisuuskatsaus. In: Annila, E. (ed.). Monimuotoinen metsä. Metsäluonnon monimuotoisuuden tutkimusohjelman väliraportti. Metsäntutkimuslaitoksen tiedonantoja 705: 132–161. (In Finnish).

— , Martikainen, P., Punttila, P. & Rauh, J. 2000. Coarse woody debris and stand characteristics in mature managed and old-growth boreal forests in southern Finland. Forest Ecology and Management 128(3): 211–225.

Smith, D.R., Villella, R.F. & Lemarie, D.P. 2003. Application of adaptive cluster sampling to low-density populations of freshwater mussels. Environmental and Ecological Statistics 10 (1): 7–15.

Ståhl, G., Ringvall, A & Lämås, T. 2000. Guided transect sampling for assessing sparse populations. Forest Science 46(1): 108–115.

— , Ringvall, A. & Fridman, J. 2001. Assessment of coarse woody debris – a methodological overview. Ecological Bulletins 49: 57–70.

Thompson, S.K. 1990. Adaptive cluster sampling. Journal of the American Statistical Association 85(412): 1050–1059.

— 1991. Stratified adaptive cluster sampling. Biometrika 78(2): 389–397.

Warren, W.G. & Olsen, P.F. 1964. A line intersect technique for assessing logging waste. Forest Science 10: 267–276.

Total of 25 references