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Efficiency of adaptive cluster sampling and traditional sampling for coastal mangrove in Hainan of China

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ABSTRACT: Based on two species of Coastal Mangrove in Hainan of China, *Sonneratia Apetala Buch-Ham* and *Sonneratia caseoli*, we estimated the density of the two species to evaluate the efficiency of adaptive cluster sampling (ACS), simple random sampling (SRS) and traditional systematic sampling (SYS). Our initial experimental designs for ACS consisted of 5 unit areas, 6 initial sampling proportions, 4 initial sample sizes and 5 criterion values in 1,000 repetitions. From the aspect of factors influencing efficiency, we analysed the efficiency of ACS in various designs. We also compared the efficiencies of the three methods on the indexes of the relative error, the variance of density estimator and the relative sampling efficiencies. We found that ACS yielded smaller variance than the traditional sampling methods. ACS was a powerful sampling method when a population was spatially aggregated. We also determined the optimum unit area for the two species studied using the two estimators (*HT* and *HH*) of adaptive cluster sampling. They were 20 m^2 (2 × 10 m), 15 m^2 (3 × 5 m) for *S. Apetala Buch-Ham* and 25 m^2 (5 × 5 m), 15 m^2 (3 × 5 m) for *S. caseolari*, respectively.

Keywords: adaptive cluster sampling; Horvitz-Thompson estimator; Hansen-Hurwitz estimator; simple random sampling; systematic sampling

The mangroves, known as a long-term adaptation to tidal and flood impacts and the tropical, subtropical coastal shelterbelt, have a huge role in disaster reduction. Studies of mangroves, including tall trees and low shrubs, face significant sampling challenges for sustainable resource management, monitoring and assessments. Previous attempts to estimate the distribution and abundance of mangroves have used a variety of techniques, each with its own underlying assumptions, biases, and limitations. Sampling mangroves may often produce estimation problems because of the rarity and patchy distribution of many species of mangroves. The problems are that many sampling units contain zero plant detections, and some sampling designs become highly inefficient because little information is provided on the species.

Adaptive cluster sampling (ACS) first proposed by Thompson (1990) can provide more efficient estimates and higher rates of encountering rare and clustered distribution species than comparable traditional sampling designs (Brown, Manly 1998; Smith et al. 2004). ACS allows the inclusion of additional sampling units (e.g. quadrats) in the immediate neighbourhood of any quadrat in which the target species is found. Thompson (1990) also

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proposed the modified unbiased estimators such as Horvitz-Thompson (*HT*) and Hansen-Hurwitz (*HH*) for ACS. The advantages of ACS over traditional sampling designs such as simple random sampling (SRS) and systematic sampling (SYS) are believed to be twofold: (1) an increase in sampling efficiency resulting in more precise estimates of population parameters, and (2) an increase in the number of observations of the target species may result in more reliable estimates of other population parameters such as species richness and composition, and relative abundance. These advantages should be pronounced especially for rare and clustered populations such as mangroves.

ACS is often used in some research areas in which the number of targets is of natural distribution but is difficult to determine. The research on the application of ACS develops rapidly, and has been used increasingly in many fields such as biological environment, forestry and fishery survey. Brown (1994) surveyed some biological species by ACS, mainly including the patchy distribution of rare plants and the number of tree species. Philippi (2005) used the ACS to estimate the abundance of low density plant population within a local area. He compared the ACS sampling efficiency in 1 m^2 and 4 m^2 of the different area of sampling unit, and compared the estimation precision of *HH* and *HT*. The conclusion was that the variance of *HT* estimation was less than *HH*; the estimation results in 1 m^2 and 4 m^2 of the initial sampling units were both reasonable. Many scholars believe that the ACS yields good results in the surveying of forest resources, particularly in the cluster and patchy distribution of the population (Roesch 1993; Smith et al. 1995). Magnussen et al. (2005) simulated the sampling efficiency of eighteen artificial spatial populations of deforestation polygons with each 200 × 200 km^2 using ACS and SRS designs, and the result was that the sampling error of ACS was 30% lower than that of SRS.

Although many scholars carried out relevant researches on the ACS method, and made some case studies, their researches were usually a comparison between the results of ACS technology and traditional sampling only under certain conditions (such as one or two fixed unit areas) (Roesch 1993; Smith et al. 1995; Magnussen et al. 2005; Philippi 2005). For ACS, different initial sample sizes, unit areas and criterion values (C) will all affect the results of estimation. Therefore it is necessary to further conduct the estimation effects in a variety of sampling designs, and then to obtain more efficient ACS designs and summarize the evolution of sampling results. The content of the research presented here is to take the coastal mangroves for the study area from Hainan Province of southern China, simulate the sampling of two mangrove coastal species *Sonneratia Apetala Buch-Ham* and *Sonneratia caseolari* based on the real distribution data in the investigated area, and to estimate the density for evaluating the efficiency of ACS, SYS and SRS designs.

MATERIAL AND METHODS

Study area

The Dongzhaigang Mangrove Natural Reserve is located in the northeast of Hainan Province, 32 km from Haikou (Fig. 1). The geographic coordinates are 19°38'–20°01'N and 110°34'–110°38'E. The altitude is about 10–80 m a.s.l., with gradient 3–7°. The terrain is high in the north and low in the south. The reserved areas are located in the northern fringe of a tropical monsoon climate. The

Fig. 1. The location of the Dongzhaigang Mangrove Natural Reserve in Hainan Province of Southern China

average annual temperature is 17.1°C, the highest temperature is 37.51°C and the lowest temperature is 3°C. The average annual sunshine is 2,200 h; the average annual rainfall 1,700–1,933 mm, more than 80% concentrated in May–October. All these climatic and geographic factors undoubtedly had a significant effect on the types of species composition of the mangrove family.

The reserved areas, with a lot of rare plants, are the mangrove provenance base, where there are *S. Buch-Ham*, *S. caseolari*, *Bruguiera sexangula*, *B. gymnorrhiza*, *B. s.* var. *rhynochopetala*, *Rhizophora stylosa*, *Ceriops tagal*, *Kandelia candel* and so on.

Six plots of different sizes were established using typical sampling because the mangrove species are distributed at the Hegang village in Haikou Dongzhaigang Mangrove Natural Reserve on the coast of the Qiongzhou channel, where *S. Apetala Buch-Ham*, *S. caseolaris* and *Kandelia candel* communities are present. Finally one of the plots was selected for simulation sampling designs considering its size is the largest one out of the six plots and its study area is 60 m × 100 m where is mostly *S. Apetala Buch-Ham* and *S. casolaris*. The two tree species are good species of mangrove forest and are naturally distributed in low salinity and muddy tidal flats. The height of *S. Apetala Buch-Ham* is generally about 10–15 m, diameter at breast height (DBH) is about 10–25 cm. *S. casolaris* height is about 5–8 m and DBH 4–15 cm.

Survey in the field

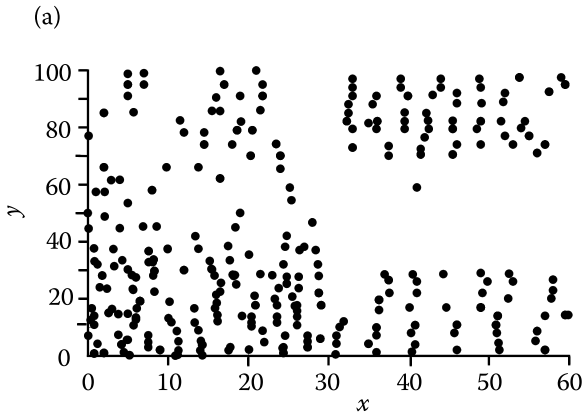
The trees were examined in the plot consisting of 60 quadrats (each 10 m × 10 m in size) distributed as adjacent grid in the mangrove community.

In order to measure the quadrat accurately, the ropes were pulled out along one side of the tidal flat, a pole was inserted at every 10-m interval, and taking the straight line of direction toward the mangrove forest by a compass where poles were set. Finally the borders of the plot were enclosed through benchmarking and by plastic ropes.

The origin was at the corner of each quadrat, through which two straight lines were perpendicular to the axes (*x*-axis, *y*-axis). The trees were measured, including locations, species name, height, DBH (by calliper), crown diameter (by tape), clear length (by a measuring rod) in each quadrat. Data on locations of *S. Apetala Buch-Ham* and *S. caseolaris* were extracted to use for a simulation study in the experiment. The spatial distributions of investigated trees are described in Fig. 2. The dots represent plants as Fig. 2 shows the actual coordinates *x* and *y* (in m) of *S. Apetala Buch-Ham* and *S. caseolaris* which appear rare and in spatial clustered distribution within the plot.

Adaptive cluster sampling

With an adaptive sampling scheme the procedure of selecting units to be included in the sample may depend on values of the variable of interest observed during the survey, i.e. the sampling is "adapted" to the data (Thompson 1990). ACS then operates under the rule that when the observed value of an initially sampled unit satisfies criterion conditions of interest (C), additional units in some pre-defined neighbourhoods will be added to the sample. Then, if any of these additional units satisfy C, the units in their neighbourhoods are added to the sample as well, and so on (Fig. 3). This process is iterated



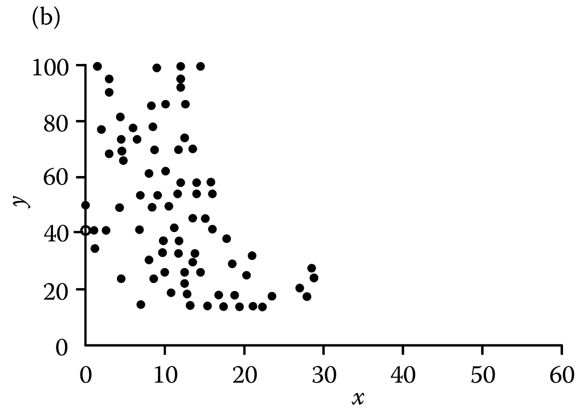


Fig. 2. The two species distributions: (a) the distribution of *Sonneratia Apetala Buch-Ham* and (b) the distribution of *Sonneratia caseolari* (x and y axes are the coordinate of the plot and the unit in m)

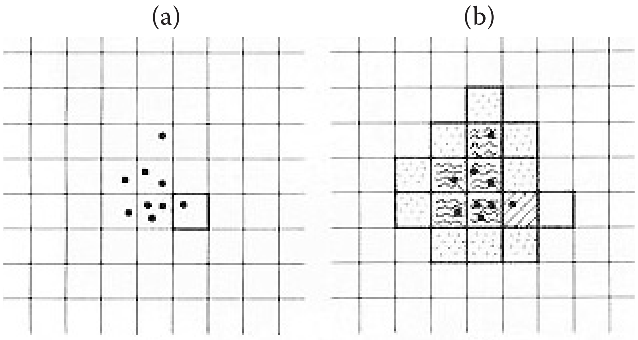


Fig. 3. ACS sampling procedure example with one cluster: (a) an initial sample unit and (b) cluster obtained by adding adaptively. The one initial quadrat is squared and indicated with diagonal stripes, additional quadrats within intersected network are indicated with wavy lines, and edge quadrats are stippled if the criterion condition (e.g. $y > 0$ tree in a quadrat)

until no units satisfying C are encountered (Turk, Borkowski 2005).

All neighbouring quadrats that collectively meet the criterion (e.g. $y > 0$) are called a network. The quadrats bordering each network that fail to meet the criterion are called edge quadrats. Network plus edge quadrats constitute the ACS cluster. Note that if any of the quadrats in a network is included in the initial random sample, the entire cluster will ultimately be included. In addition, it is important to note that any quadrat selected in the original sample that does not meet the criterion (i.e., $y = 0$) is considered a network of size 1. The grouping of quadrats into networks constitutes a partitioning of the initial population based on the size of the initial random sample.

Estimators

To estimate means and variances of interest, the modified Hansen-Hurwitz and Horvitz-Thompson estimators for ACS are described as follows.

A modified Hansen-Hurwitz type of estimator (HH)

According to Thompson (1990, 2002), an unbiased estimator of the population mean ($\hat{y}_{HH}$) formed by modifying the Hansen-Hurwitz estimate:

$$\hat{y}_{HH} = \frac{1}{n}\sum_{i=1}^{n} w_i \tag{1}$$

The variance of $\hat{y}_{HH}$ is:

$$\mathrm{Var}\,(\hat{y}_{HH}) = \frac{N-n}{Nn\,(N-1)}\sum_{i=1}^{n}(w_i - \hat{y}_{HH})^2 \tag{2}$$

where:

N – total number of sample units (quadrats) in the population,

n – quadrats sampled,

w_i – represents the average of the observations in the i-th network, define $w_i = y_i/x_i$, x_i – number of units in the i-th network, y_i – observation values of the i-th network.

A modified Horvitz-Thompson type of estimator (HT)

Thompson (1990) presented the modified Horvitz-Thompson estimator, taking full advantage of probability of three kinds of units' network inclusion in the sample (initial sample units, initial sample units' neighbourhood units which satisfy C, and edge units).

$$\hat{y}_{HT} = \frac{1}{N}\sum_{k=1}^{v}\frac{y_k}{a_k} \tag{3}$$

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

$$\alpha_{ik} = 1 - \left[\frac{\binom{N-x_j}{n} + \binom{N-x_k}{n} - \binom{N-x_j-x_k}{n}}{\binom{N}{n}}\right] \tag{5}$$

$$\mathrm{Var}\,(\hat{y}_{HT}) = \frac{1}{N^2}\left[\sum_{j=1}^{v}\sum_{k\neq j}^{v}\frac{y_j y_k}{\alpha_{jk}}\left(\frac{\alpha_{jk}}{\alpha_j\alpha_k} - 1\right)\right] \tag{6}$$

where:

$\hat{y}_{HT}$ – an unbiased estimator of the population mean using the modified Horvitz-Thompson estimate,

v – number of distinct networks in the sample,

N – total number of sample units (quadrats) in the population,

n – quadrats sampled,

y_k – observation values of the network that includes unit k,

y_j – observation values of the network that includes unit j,

α_k – probability of the K-th network inclusion in the sample, i.e. partial inclusion probability,

α_{jk} – probability that the initial sample contains at least one unit in each of the networks j and k.

Simulation

Simulation can be useful for evaluating sampling designs because it permits experimental comparison across populations and designs (Brown 2003; Morrison et al. 2008). In practice, it is often infeasible to analytically derive the sampling distribution for estimators across a range of populations and designs. Simulation study makes it possible to evaluate the sampling distribution of estimators based on a lot of repeated samplings. Comparisons across multiple populations and a broad range of designs can result in robust recommendations (Morrison et al. 2008).

Sampling designs

According to the characteristic of the rare, aggregate population, and the result of the smallest relative error of density estimator in many repetitions, the least initial sampling fraction was 0.06. The smallest initial unit area was 2 × 5 m.

The quantity of units that could be selected in different unit sizes was 600, 400, 300, 240 and 200. The network did not expand mainly when C increased to 4 or 5. As the C continued to increase, the initial population was close to that of SRS. So the largest criterion value was no more than 5. Thus, criterion values (Ca) were set to be 1, 2, 3, 4 and 5, respectively. When the value of a selected unit was equal to or higher than the criterion value (C > Ca), additional unit cross-shaped neighbourhood would be added to the sample.

Selecting the amount of units consisted of samples from a population. The results reckoned by different samples were different and also differed from the true value. Thus, the simulated results obtained by the sample only once cannot confirm whether the sampling method is good or not. We should compare various sampling methods and as many repetitions as possible.

The relative errors of the mean density estimated by *HH* and *HT* were respectively smaller than 5% in different repetitions and unit areas designs. The mean density estimated was to be invariable as repetitions increased to 1,000. Sampling designs were as follows:

– The conditions that the initial sampling fraction and C were invariant: various unit areas impacting on efficiency were analysed and compared, and a regular pattern was obtained. Sampling was simulated using ACS in five types of unit area designs [10 m^2 (2 × 5 m), 15 m^2 (3 × 5 m), 20 m^2 (2 × 10 m), 25 m^2 (5 × 5 m), 30 m^2 (3 × 10 m)] and six initial sampling fractions (6, 8, 10, 12, 14 and 16%).
– Provided that the initial sample size and C were invariant: sampling was also simulated using ACS in five types of unit area design [10 m^2 (2 × 5 m), 15 m^2 (3 × 5 m), 20 m^2 (2 × 10 m), 25 m^2 (5 × 5 m), 30 m^2 (3 × 10 m)]. According to previous survey experience and considering that the final sample size has enlarged, the lowest limit of the initial sample size was 15 and four kinds of initial sample sizes were 15, 25, 35 and 45. The optimal unit area was obtained in which the sampling was the most efficient.

Evaluated indicators

The survey data were imported into the software SAMPLE (it can be downloaded at http://www.lsc.usgs.gov/aeb/davids/acs/) to simulate sampling. The sampling without replacement was replicated 1,000 times in the process. The shape of sample unit was square or rectangle, and neighbourhood was cross-shaped. To evaluate the performance of sampling designs, we used measures of design efficiency such as the variance of density estimator, relative error of density estimator and the relative sampling efficiencies. The relative sampling efficiencies (RE) are the ratio of variance from a traditional sampling design to variance from the candidate design with the final sample size equal among the two designs. The final sample size is fixed for conventional designs, but is random in adaptive designs. Thus, for adaptive designs the expected sample size was the average of final sample sizes over 1,000 simulations. The variance of density estimator (E(v)) and the relative error of density estimator are other measures of efficiency and precision. The relevant formulas are as follows:

Density estimator and variance in the *i* times sampling are u_i and v_i (i =1, 2, ..., n), respectively:

$$\mu_i = \frac{N}{A}\hat{y}_{HT,\,HH} \tag{7}$$

where:

$\hat{y}_{HT,\,HH}$ – estimated values of the population mean using *HT* and *HH* estimate method, respectively,
N – total number of sample units in the population,
A – total study area.

$$\mathrm{E}(\hat{\mu}_i) = \frac{\sum_{i=1}^{n}\mu_i}{n} \tag{8}$$

$\mathrm{E}(\hat{\mu}_i)$ expresses the mean density estimated in certain repetitions and n represents the number of repetitions.

The variance of estimator is:

$$\mathrm{Var}\,(\hat{\mu}_i) = \frac{A^2}{N^2}\,\mathrm{Var}_i\,(\hat{y}_{HT,\,HH}) \tag{9}$$

Then the variance of estimator in m times repetitions is:

$$E(v) = \frac{\sum_{i=1}^{n} \mathrm{var}\,(\hat{\mu})}{n} \qquad (10)$$

The relative sampling efficiencies:

$$\text{Efficency}\ (\hat{\mu}) = E_{\bar{y}}(v_i)/E_{\hat{\mu}_i}\ (v_i) \qquad (11)$$

where:

$\hat{\mu}$ – estimated population mean using ACS,

$E_{\bar{y}}(v_i)$ – variance of density estimated using the traditional methods in the same final sample size of ACS,

$E_{\hat{\mu}_i}(v_i)$ – ACS variance of density estimated. An efficiency > 1 indicates that ACS would be more precise than SRS or SYS and an efficiency < 1 indicates that the reverse is true – that SRS or SYS would be more precise than ACS.

The formula of the relative error of density estimator:

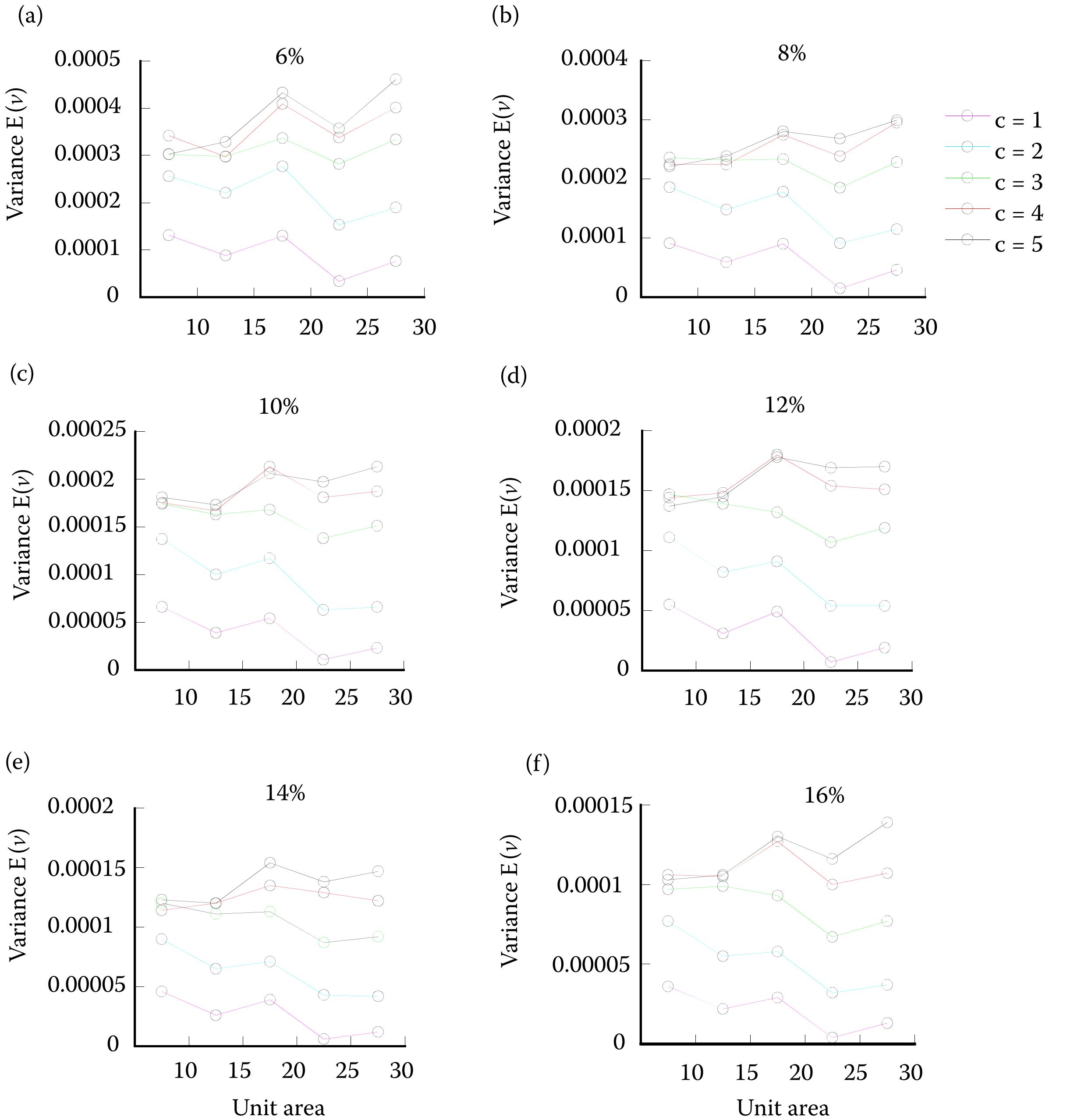


Fig. 4. The ACS variance in various unit areas, criterion values and initial sampling fractions for *S. Apetala Buch-Ham* (a–f) represent different initial sampling fractions at unit areas and criterion values, respectively

$$\text{Relative error of density estimator} = \frac{\text{Mean of density estimated} - \text{Real total density}}{\text{Real total densiy}} \tag{12}$$

RESULTS AND DISCUSSION

Unit areas, initial sampling proportions and criterion values impacting on the variance

We would know that the *HT* and *HH* estimators of ACS for the mean relative errors of density estimated were 1.313 and 1.235% for *S. Apetala Buch-Ham* and 2.082 and 1.95% for *S. caseolari* in 6 initial sampling proportions and 5 unit areas when C were 1 to 5, which were all smaller than 5%. The difference between the density estimated and the real density was small, and the biggest relative errors were 4.425% for *S. Apetala Buch-Ham* and 4.446% for *S. caseolari*. The relative errors were much smaller for various unit areas. The *HT* and *HH* estimators for the density variances were similar in various simulation sampling designs. The *HT* estimator of *S. Apetala Buch-Ham*, for instance, increased with the increase of C in a certain unit area and initial sampling fraction. The estimator variance decreased as the unit area increased when C was 1. If C were 2 and 3, the estimator variances in various unit areas differed, while the trends were to decrease. When C was 4 or 5, the trends of variance were rising (Fig. 4).

For the results in Fig. 4, generally speaking, the smaller the C, the more units added to the sample. Thus the variances were smaller and the estimations were more accurate. Because of less units sampled, the variances increased as we increased C.

From general structures for further analysis, since the population is divided into different unit areas, the larger the unit area, the larger the unit value and the more easily a huge network could be formed. Besides, the numbers of networks formed in both different unit areas and different C are different. The larger the C, the more networks will be formed. Thus, for a certain unit area, when C is small, there are more units being included in the network and the larger networks are easily formed, while the size of a network would be smaller with the increase of C and the number of networks. The total variances of the population consist of the variances within networks and the variances between networks. The variance within networks decreased as a result of the decrease of network size. This was to result in a smaller variance proportion of the total variance in the network. The proportion of population variance comprised of within network variance might be the most important factor affecting sampling efficiency (Smith et al. 1995). For ACS, the greater the proportion of population variance comprised of within network variance was, the more efficient the sampling design was (Christman 1997, 2000; Brown 2003).

In a certain unit area, the proportion of population variance comprised of within network variance decreased as the C values increased, which increased the sample variance too. In a certain C, with the increase of unit area, the proportion of population variance increased, but the variance decreased.

The above factors influencing the sampling effect interacted and correlated. When C increased, the factors such as network size, proportion of population variance comprised of within network variance and the amount of effective information in the sample, affecting ACS sampling effect were getting smaller and smaller, because the factor influenced

Table 1. Estimates and relative efficiency (RE) when C = 1 and the initial proportion and unit size were 6% and 10 m^2 for the two species

Species	SRS			SYS			ACS		
	density (trees·ha^{-1})	variance (trees·ha^{-1})	RE^a	density (trees·ha^{-1})	variance (trees·ha^{-1})	RE^a	density (trees·ha^{-1})	variance (trees·ha^{-1})	number of units
S.ABH (*HH*)	0.0621	0.0012	5.88	0.0622	0.000722	3.54	0.06227	0.000204	292
S.ABH (*HT*)	0.06145	0.0011	8.73	0.0621	0.0011	5.52	0.06208	0.000126	292
S.C (*HH*)	0.0143	0.000110	2.62	0.0145	0.0000669	1.59	0.014632	0.000042	111
S.C (*HT*)	0.01445	0.000106	3.57	0.01447	0.000106	2.17	0.014102	0.0000297	111

SRS – simple random sampling, SYS – systematic sampling, ACS – adaptive cluster sampling, SABH (*HH*) or (*HT*) – estimates for *Sonneratia Apetala Buch-Ham* species using the *HH* or *HT* method, SC (*HH*) or (*HT*) – estimates for *Sonneratia caseolari* species using the *HH* or *HT* method, RE^a = $\text{Var}_{(SRS)}/\text{Var}_{(ACS)}$, RE^b = $\text{Var}_{(SYS)}/\text{Var}_{(ACS)}$

by unit area was becoming lesser. As C was 4 or 5, the range of factor variation and the effect on ACS sampling efficiency were reduced, and then the superiority of ACS was not notable. The overall survey for ACS was close to the traditional SRS. In a certain initial sampling proportion, the variance increased as the unit area increased. This was because the initial sampling size decreased with the unit area increasing and the final efficiency information was getting less. According to each factor, its change rule and sampling results, we could conclude that when C was 1, the sampling efficiency was best based on the results (Fig. 3). So it was optimum for C = 1.

From simulation at a certain unit area, the mean *HH* and *HT* estimators were both close to the real density in each initial sampling proportion, and there were no significant changes as initial sampling proportions increased, while the variances of density estimated by *HH* and *HT* decreased. The real density of *S. Apetala Buch-Ham* and *S. caseolari* was 0.0623 trees·ha^{-1} and 0.0145 trees·ha^{-1}, respectively. Relative to *HT*, the amplitude of fluctuation for the results obtained by *HH* was smaller than *HT* and the density of *HH* was closer to the true value (Table 1). This result was similar to that of Talvitie et al. (2005).

For the two estimators (*HT* and *HH*), the variance decreased as the initial sampling proportion increased in a certain unit area and C (Fig. 4). But since *HH* estimator does not consider the probability of the units included in the network, the influence of network change on sampling result was weaker for *HH* than *HT* owing to different unit areas and C. Comparing *HT* with *HH*, the variance of *HT* estimator was smaller when the unit area was large in a certain initial proportion and C. Table 1 shows the result of one design for the condition C = 1, the initial proportion and unit size were 6% and 10 m^2. The variance of *HT* (0.000126) was smaller that of *HH* (0.000204) for S.ABH (*S. Apetala Buch-Ham*).

Unit areas, initial sampling proportions and criterion values impacting on relative efficiencies (RE)

Generally, ACS was compared with traditional sampling techniques by the relative efficiency presented by Thompson and Seber (1996), the ratio of variance from traditional sampling method and ACS (e.g. variance of SRS divided by variance from ACS design). When the ratio was greater than 1, the efficiency of ACS was higher in the same final sample size. The relative efficiencies of ACS (*HT* or *HH*) and the traditional methods were usually greater than 1 in various initial sampling propor-

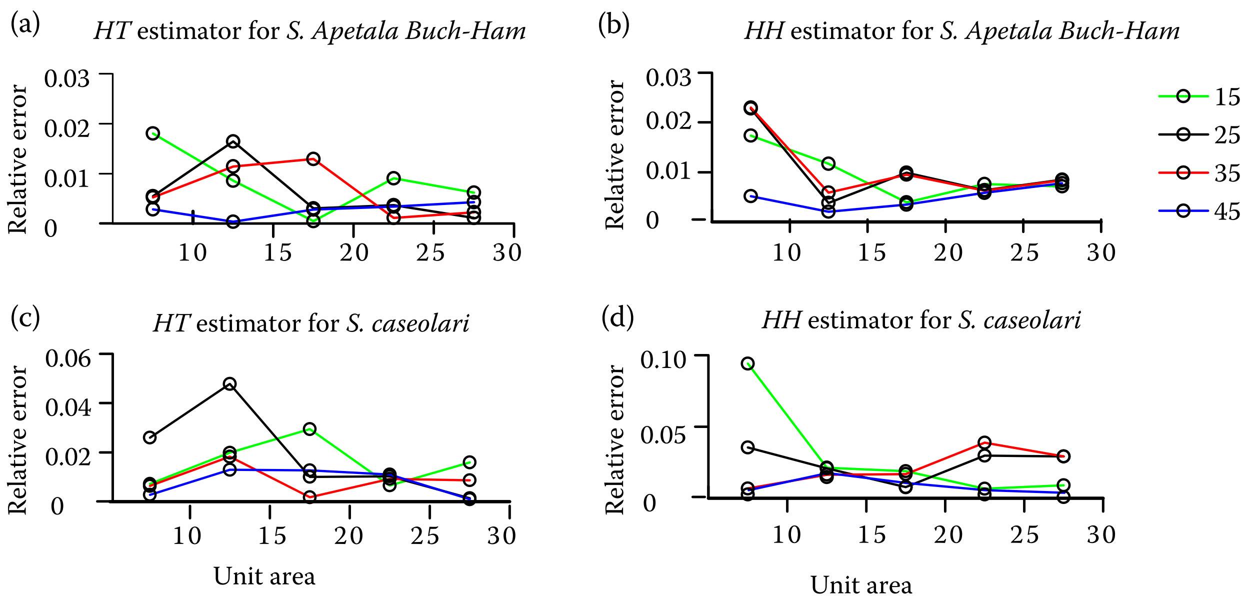


Fig. 5. The ACS relative errors of mean of density estimator at different initial sample sizes by *HH* and *HT* estimated methods in various unit areas. (a) ACS relative error of *HT* estimator for *S. Apetala Buch-Ham* at different initial sample sizes and various unit areas, (b) ACS relative error of *HH* estimator for *S. Apetala Buch-Ham* at different initial sample sizes and various unit areas, (c) ACS relative error of *HT* estimator for *Sonneratia caseolari* at different initial sample sizes and various unit areas, (d) ACS relative error of *HH* estimator for *Sonneratia caseolari* at different initial sample sizes and various unit areas

tions, unit areas and C. For example, $RE^a > 1$ and $RE^b > 1$ in Table 1. These indicated the efficiency of ACS was higher than SRS and SYS in the same final sample size of 292 and 111.

The efficiency of the traditional methods increased more quickly as the initial sampling proportions increased, while the superiority of ACS contributed more and more weakly. So it was excellent to sample 6% initially from the population when ACS made full use of advantages relative to the traditional methods.

As for SYS and SRS in the same sample size, the efficiency of the former was higher when the sample size was large. In a certain sample size, with the increase of unit area, the relative efficiency of SYS increased. In a certain unit area, along with the sample size reduced the relative efficiency of SYS was reduced. Therefore, SYS reached a higher relative efficiency based on the larger sample size.

Reasonable unit areas in the same initial sample size

The design was conducted in the same initial sample size and repeated sampling 1,000 times when C was 1. The mean relative errors of *HT* and *HH* were about 1% in four kinds of initial sample sizes (15, 15, 35 and 45).

We simulated several sampling efficiencies in different unit areas and initial sampling sizes based on the relative errors of density estimation in four unit areas.

Fig. 5 shows that as the unit area increased, the relative errors of *HH* and *HT* presented roughly the same change rule. From the visual point of view, the unit area changed from 10 m^2 to 15 m^2 with greater relative error and variation of density. The relative errors and variations of density decreased with four initial sample sizes as the unit area increased.

As for *HT* estimation for *S. Apetala Buch-Ham*, the simulation sampling was perfect when the unit area was 20 m^2 (Fig. 5a). As for *HH* estimation, when the unit area was 15 m^2, the relative error was reduced quickly (Fig. 5b). So the sampling effect was best when the unit area was 15 m^2. That meant the relative error of density was larger when the unit area was smaller than 15 m^2. While the unit area was larger than 15 m^2, though the relative error was reduced, the range of the relative error decreased too. And at the same time, with unit area increasing, the final sample size would increase significantly as well. That would lead to a higher sampling cost. Similarly, for *S. caseolaris*, sampling was perfect when the unit area was 25 m^2 for *HT* estimation (Fig. 5c), while 15 m^2 for *HH* estimation (Fig. 5d).

CONCLUSIONS AND SUGGESTIONS

The above analyses show that in a certain unit area, the initial sampling proportion and C, the variance of *HT* estimator is lower than that of the *HH* estimator, and the variance of ACS is generally lower than that of SRS and SYS.

Density estimators using ACS are very close to the real values. The final sample sizes of SRS and SYS are the same as those of adaptive sampling (*HH* and *HT* estimators). We know from the above analyses that:

(i) ACS is more efficient than the traditional SRS and SYS and SYS is more efficient than SRS,

(ii) for the two estimators, the sampling efficiency based on the modified *HT* is greater than that based on the modified *HH* estimator.

In ACS designs, the variance estimated by the modified *HT* estimator is smaller usually than that estimated by the modified *HH* estimator. However, the modified *HT* estimator usually deviates from the real density more than the modified *HH* estimator and this might be related to the network structure of population. For a population with different network structure, the efficiency of each estimator should be studied further. At the same time, the modified *HT* estimator is usually more complex than the modified *HH* estimator. So in sampling designs or practical investigation applications, we should choose a reasonable sampling estimator, not blindly pursuing minimum variance. With varied forms of neighbourhood, the neighbourhood's form affects both the network size and the final sample size for ACS designs. And only the cross-shaped neighbourhood is used here. The neighbourhood of ACS impacting on the sampling efficiency can be further studied.

The uncertainty of the final sample size is one of the main existing problems for ACS. Although there has been some related research, the final sample size cannot be accurately predicted. Therefore, further research on controlling the final sample size of ACS is to be carried out. And how to cooperate the ground sampling technology and 3S techniques more closely with each other is also continued to be explored.

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