EVALUATING DESIGN UNBIASEDNESS OF THE PRE-FELLING INVENTORY IN PENINSULAR MALAYSIA

TY Lam¹, K Abdul Rahman², I Shamsudin² & MD Potts¹

¹Department of Environmental Science, Policy and Management University of California, Berkeley, California 94720,USA ²Forest Research Institute Malaysia, 52109 Kepong, Selangor Darul Ehsan, Malaysia

Received July 2012

LAM TY, ABDUL RAHMAN K, SHAMSUDIN I & POTTS MD. 2013. Evaluating design unbiasedness of the pre-felling inventory in Peninsular Malaysia. The forests in Peninsular Malaysia are sustainably managed under the Selective Management System, which requires completing a pre-felling (Pre-F) inventory prior to harvest. The goal of this study was to investigate design unbiasedness of the Pre-F inventory using theory and simulation models. Simulations were carried out with an artificial and an actual forest, the former representing a cyclic forest of mature and young trees and the latter being the 50-ha Pasoh census plot. Theoretically, the Pre-F inventory is biased in mean estimates because it consistently undersamples portions of a population. Simulation with the cyclic forest showed that the Pre-F inventory was biased in estimating mean stand density, basal area and volume when the inventory was set up aligned with the cyclic pattern. Results from the Pasoh plot showed that the Pre-F inventory was unbiased in mean stand variables. The contrast was likely due to seemingly random tree distribution in Pasoh. However, using a design unbiased sampling method is more desirable because underlying tree distribution pattern in a forest is normally unknown. We recommend the Random Point Start method, which is unbiased in all simulation trials in addition to retaining all the advantages of the current Pre-F protocol.

Keywords: Probability sampling, randomness, accuracy, systematic sampling, simulation, tropical forest

LAM TY, ABDUL RAHMAN K, SHAMSUDIN I & POTTS MD. 2013. Penilaian ketidakpincangan reka bentuk inventori sebelum tebangan di Semenanjung Malaysia. Hutan di Semenanjung Malaysia diurus dengan mampan di bawah sistem pengurusan memilih yang memerlukan inventori sebelum tebangan dijalankan sebelum penebangan pokok dilaksanakan. Tujuan kajian adalah untuk menentukan ketidakpincangan reka bentuk inventori sebelum tebangan menggunakan teori dan model simulasi. Simulasi dijalankan ke atas hutan tiruan dan hutan sebenar. Hutan tiruan mewakili pusingan hutan yang terdiri daripada pokok matang dan muda. Hutan sebenar pula terdiri daripada pokok di plot 50 hektar di Pasoh. Secara teori, inventori sebelum tebangan pincang dalam penganggaran purata kerana secara konsisten persampelan sebahagian daripada populasinya rendah. Simulasi hutan tiruan menggambarkan kepincangan dalam penganggaran purata kepadatan dirian, luas pangkal serta isi padu apabila inventori dilaksanakan bersesuaian dengan hutan pusingan. Simulasi plot di Pasoh menunjukkan yang inventori sebelum tebangan tidak pincang dalam purata pemboleh ubah dirian. Perbezaan ini mungkin disebabkan oleh taburan pokok secara rawak di Pasoh. Namun, kaedah persampelan tak pincang memberi keputusan yang lebih baik kerana taburan pokok di dalam hutan biasanya tidak diketahui. Kami mencadangkan agar penggunaan kaedah titik mula rawak yang tidak pincang dalam semua simulasi di samping dapat mengekalkan kesemua kelebihan penggunaan inventori sebelum tebangan.

INTRODUCTION

The need for improved management of tropical forests has received much attention since the early 1990s because of concern over rapid degradation and loss of forest areas as well as increased recognition of their role in delivering global ecosystem services related to biodiversity, carbon and water (ITTO 2002). This attention is reflected

in international efforts such as developing criteria and indictors as a tool for monitoring, assessing and reporting changes and trends in tropical forest conditions and management systems (ITTO 2005), setting up certification scheme as marketbased mechanisms that support sustainable tropical forest management (Forest Stewardship

tylam.forest@gmail.com

Council 2010), and establishing international programmes such as Reducing Emissions from Deforestation and Degradation (REDD+) that offer financial incentives for developing tropical countries to reduce emission due to landuse change (Parker et al. 2008). On a national and subnational scale, practising reduced impact logging, establishing conservation and protection area and implementing intensive reforestation projects are also ways to increase the sustainability of forestry. Thus, tropical countries are presented with many opportunities to sustain their forest resources with policies and practices that best suit their circumstances.

In Peninsular Malaysia, the Selective Management System (SMS) has been practised since the late 1970s to sustainably manage remaining virgin forests on steep hills (Thang 1987). The goal of the SMS is to maintain diversity of flora and timber species, to conserve soil and water as well as to be flexible in response to future changes in the socio-economic environment (Thang 1987). The SMS consists of a sequence of operations: (1) pre-felling (Pre-F) forest inventory to determine minimum cutting limits, (2) tree marking to select harvestable trees with diameter above the limit, (3) felling of the selected trees and (4) post-felling inventory to determine appropriate silvicultural treatments (Thang 1987). Hence, the system relies heavily on the Pre-F forest inventory to provide the necessary information to decide on the felling regime. The Pre-F inventory design needs to have desirable statistical properties such as unbiasedness and acceptable level of precision in population estimates. To define the two statistical properties, one imagines that samples are taken under a specific inventory design repeatedly for a large number of times and population estimates then calculated every time for each repeated sample. The inventory design is unbiased if the average of all the population estimates from repeated samples is equal to the true population value and it is highly precise if all population estimates are highly similar (Husch et al. 2003).

The Pre-F inventory is based on systematic sampling with nested fixed area plots, which are either square or rectangular and have target trees of different size classes (Anonymous 1997). The inventory design has previously been evaluated for timber aspects such as basal area and tree volume by Wan Razali and Wan Mohd Shukri (1999) as well as Wan Mohd Shukri and Wan Razali (2002) and for biodiversity by Potts et al. (2005). Wan Razali and Wan Mohd Shukri (1999) evaluated statistical reliability of the Pre-F inventory, i.e. estimation of achievable confidence interval and per cent error based on the different sampling intensities of the nested plots. Wan Mohd Shukri and Wan Razali (2002) expanded the reliability study to look at tree density, basal area and volume by three tree species groups (i.e. dipterocarp, non-dipterocarp and all tree species). Both studies found that the estimates of tree density, basal area and volume from the Pre-F inventory should produce reliable results with 90–95% confidence and $\pm 10-20\%$ error (Wan Razali & Wan Mohd Shukri 1999, Wan Mohd Shukri & Wan Razali 2002).

The above two studies focused on design precision rather than design unbiasedness of the Pre-F inventory. Design unbiasedness of a specific sampling design occurs when the expected value of a variable calculated from all possible samples of a population under the design equals the true population value of the variable (Thompson 2002). Thus, if a sampling design is unbiased, then, the average of the estimates from all the repeated samples (all possible estimates of total number of trees with selection probabilities introduced by the design taken into account) should be equal to the true population value (true total number of trees). An unbiased design produces an accurate estimate of a variable. On the other hand, design precision is the variability in the estimates from all the repeated samples. A design with high precision will result in estimates that are very similar, whereas a design with low precision will produce estimates that are highly variable. Finally, an unbiased design may not necessarily be precise and vice versa.

The purpose of the Pre-F inventory is to estimate stand and stock variables to determine minimum cutting limits for a forest area. Hence, design unbiasedness, which leads to accurate estimates of stand density and volume, is considerably more important than the precision of the two stand parameters. Biased or inaccurate estimates of stand density and volume would negatively affect calculation of minimum cutting limit, and in turn affect management decisionmaking, which could have long-term effects on sustainability. The goal of this study was to determine whether the design of the current Pre-F inventory was unbiased from both theoretical and empirical standpoints. The unbiasedness of Pre-F inventory was theoretically examined using sampling principles. Furthermore, the Pre-F inventory design was empirically tested using two datasets—an artificial and an actual dataset—to study the design properties.

MATERIALS AND METHODS

Pre-F inventory design

When a forest compartment is selected for harvesting with SMS, the Pre-F inventory is carried out one or two years before harvesting operation to estimate stand density and stand volume of the compartment (Thang 1987). As mentioned, the inventory is based on a systematic sampling with nested plots of various sizes (Figure 1), and the standard protocol is summarised as follows (Anonymous 1997):

Establishment of base line

A base line was placed across the compartment perpendicular to the geographical contour lines that would divide the compartment approximately in half.



Figure 1 Pre-felling inventory design under the Selective Management System

Selection of start and end points

Start and end points were selected along the base line, which defined the area to be sampled (Figure 1). The standard protocol stressed that the inventory should cover as much area as possible (Anonymous 1997). The start point was generally chosen to be on the boundary of the compartment and in reference to a topographic feature such as a river (Figure 1). The standard protocol does not specify the choice of end point but it is most often located at the boundary of a compartment.

Establishment of inventory lines

Inventory lines were placed perpendicular to the base line (Figure 1). The first inventory line was 50 m away from the start point and subsequent inventory lines were placed 100 m apart.

Establishment of nested plots

Nested plots were established on both sides of the base line and on the inventory lines with the latter crossing the plot centres (Figure 1). On each inventory line, the centre of the nested plot closest to the base line was 50 m away. Nonetheless, all nested plots were placed 100 m apart. Five plots of different sizes were nested into a single plot with the largest measuring $50 \text{ m} \times 20 \text{ m} (0.1 \text{ ha})$ and the smallest measuring $2 \text{ m} \times 2 \text{ m} (0.0004 \text{ ha})$ (Table 1). Each plot targeted trees of different sizes (Table 1).

Overall, when implemented, the Pre-F inventory design produces a systematic grid of $100 \text{ m} \times 100 \text{ m}$ plots with specific requirement that the grid should start 50 m away from the start point.

Simulated cyclic forest population

A cyclic forest population was simulated to draw inference on the unbiasedness of the Pre-F inventory design under these types of forest condition. A cyclic forest population is where some features of the population occur repeatedly over a spatio-temporal interval, e.g. a plantation forest. Simulated populations have the advantage of the true parameters being known, which is desirable for bias analysis. A cyclic forest population was simulated in a rectangular forest compartment measuring 2000 m × 1000 m (200 ha). The 200-ha forest compartment was divided into 10 contiguous blocks of 20 ha each measuring 2000 m × 100 m. Each 20-ha block was then subdivided into a 6-ha area (2000 m \times 30 m) located at the lower part of the block and a 14-ha area (2000 m \times 70 m) located at the upper part of the block. In the 6-ha area, the forest population (generated from random number) was simulated with stand density of 1000 trees ha⁻¹, mean diameter at breast height (dbh) 10 cm and standard deviation 2 cm. In the 14-ha area, where the forest population was generated from random number, the stand density was 250 trees ha⁻¹ with mean dbh 70 cm and standard deviation 14 cm. The dbh was simulated assuming a normal distribution. The mean and standard deviation values were chosen so as to maintain 20% coefficient of variation in the dbh distribution making the two populations comparable. For ease of simulation, all trees were randomly placed. The simulated 6-ha area had stand characteristics resembling a young regenerated forest whereas the 14-ha area had stand characteristics that resembled a mature forest; thus, creating a cyclic forest with a mature area and a regenerated clearcut strip (Figure 2).

Plot type	Dimension (m)	Plot area (ha)	Tree size
1	50×20	0.1000	$\geq 30 \text{ cm dbh}$
2	25×20	0.0500	≥ 15 and < 30 cm dbh
3	10×10	0.0100	\geq 5 and < 15 cm dbh
4	5×5	0.0025	\geq 1.5 m height; < 5 cm dbh
5	2×2	0.0004	0.15 to 1.5 m height

 Table 1
 Nested plot design of Pre-F inventory

dbh = diameter at breast height



Figure 2 Distribution of trees for the simulated cyclic population of 200 ha; each dot depicts a tree

Pasoh forest population

The actual forest data came from the Pasoh forest dynamics plot, which is a long-term and large-scale ecological study site. The plot is located within the Pasoh Forest Reserve in Peninsular Malaysia and is coordinated by the Forest Research Institute Malaysia and the Center for Tropical Forest Science, Harvard University (Potts et al. 2005). The Pasoh plot is located in lowland mixed dipterocarp forest with aseasonal climate of high and evenly distributed rainfall (Potts et al. 2005). The soil condition and topography in the study site were relatively uniform with elevation spanning only 24 m (Manokaran & LaFrankie 1990). The plot measured 1000 m × 500 m (50 ha) and was established according to a standardised protocol (Condit 1998). All plants with ≥ 1 cm dbh were tagged and their locations mapped to the nearest 0.1 m. Each individual was identified to species level and measured for dbh. The first census was completed in 1989. The plot has been subsequently remeasured every five years. A total of 335,352 individuals and 814 plant species were identified by the end of the first census (Manokaran et al. 2004).

Simulation of Pre-F

The simulations consisted of three approaches to randomly laying down a 100 m × 100 m systematic grid over the cyclic and Pasoh forest populations: (1) PreF-v: Pre-F inventory with vertical base line, (2) PreF-h: Pre-F inventory with horizontal base line and (3) RPS: random point start method. For the first two approaches, the base line, inventory lines and plots were laid out according to the aforementioned Pre-F protocol except that the base line was placed in one of the two directions with start and end points falling on the boundaries of the actual or simulated forest area. For the PreF-v, the base line was placed vertically by randomly choosing an x-coordinate, whereas for the PreF-h the base line was placed horizontally by randomly choosing a y-coordinate (Figure 2). While for some trials the base line did divide the forest area in half, this deviation from the Pre-F protocol did not affect the validity of our results. For RPS, random x- and y-coordinates were chosen to be the coordinates of the start point, and a 100 m × 100 m grid was extended horizontally and vertically from this point forward. The RPS method was first proposed by Iles (2003) to ensure unbiased mean estimate but similar idea had been mentioned elsewhere (Valentine et al. 2009)

Thus, there were six combinations studied, i.e. two forest populations by three approaches. For simplicity, only the 50 m \times 20 m plot size (0.1 ha) was used to sample trees in the simulation for cyclic population, which was sufficient to illustrate the unbiasedness in a simulated population. For the Pasoh population, the nested plot was used to sample trees in the simulation. However, it was limited to the three larger plot sizes, i.e. plot types 1 to 3 (50 m \times 20 m, 25 m \times 20 m and 10 m \times 10 m) because tree height had not been measured.

A potential sampling problem arose when sampling near the boundaries of the two forest populations, i.e. a portion of a plot might fall outside the boundaries. There are many proposed methodologies in dealing with boundary issues (Husch et al. 2003). To simplify computation in this study, a torus forest area was constructed. A torus is constructed from a square or rectangular by connecting both pairs of opposite edges together without twists, which represents a doughnut-shaped object in three dimensions (Gray et al. 2006). Essentially, a torus is the infinite replications of the same square or rectangle joined together. Thus, the main assumption was that the actual forest population was surrounded by population having the same structures and composition.

The stand variables of interest were stand density (trees ha⁻¹), stand basal area (m² ha⁻¹) and stand volume (m³ ha⁻¹). Stand volume was calculated as the sum of individual tree volume scaled to per unit area. The individual tree volume function for standing trees \geq 5 cm dbh was calculated using the formula in Wan Mohd Shukri and Wan Razali (2002),

$$\operatorname{Vol}_{\operatorname{tree}} = \left(\pi \times \operatorname{dbh}^2 \times \operatorname{L} \times 0.75 \right) / 40000 \qquad (1)$$

where L = merchantable height (m), 0.75 = assumed tree form factor and 40,000 = unit conversion. The merchantable height was assumed to be 5 m for trees with dbh \geq 5 cm and < 15 cm, 10 m for trees with dbh \geq 15 cm and < 60 cm, 15 m for trees with dbh \geq 60 cm and < 75 cm and 20 m for trees with dbh \geq 75 cm.

Monte Carlo simulations with 2000 iterations were carried out for each of the six combinations, which resulted in 2000 estimates for each stand variable. Additionally for Pasoh, the three stand variables were calculated for each plot type. For each estimate of stand variable, bias (BIAS = estimate – true) and per cent bias (%BIAS = $100\% \times [\text{estimate} - \text{true}] / \text{true})$ were calculated. Finally, BIAS and %BIAS were summarised by 0.025 and 0.975 sample quantiles. Empirical 95% confidence interval (95% CI) was defined as the range between 0.025 and 0.975 sample quantiles. The simulation study was performed with R open source statistical software.

RESULTS AND DISCUSSION

Systematic sampling is often carried out in many forest surveys of large areas with the expressed goals of obtaining representative samples of the area, cost effectiveness in travelling and ease of explaining and understanding the basic sampling design. Systematic sampling in principle selects one starting plot at random and the other plots are placed at a predetermined angle and distance apart. Hence, the design is often associated with cluster sampling in that only one cluster of plots is selected for each starting plot. In other words, the plots are not independent of each other, which in turn, imply that observations are not independent. In many field operations, it is a usual practice to only place one grid and assume that the plots are selected at random even though they are systematically placed. In short, there is only a sample size of one in most field operations. From a sample size of one, it is possible to obtain unbiased estimator of population mean or total but not an unbiased estimator of its variance (Thompson 2002). Thus, the goal of designing a systematic sampling is to have a design that ensures unbiased estimate of population mean or total such as stand density, stand basal area and stand volume as in this study.

Theoretical evaluation

Inherently, from a theoretical standpoint, the current Pre-F inventory produces biased mean estimates of the variables of interest (e.g. total number of trees) due to its design, i.e. the design induces a systematic error in the calculation of estimated mean. The error is caused by restricting the number of choices in placing the base line as well as the non-random selection of the start point. For the base line to divide a forest compartment in half, there are only a few ways to do so depending on the configuration of the forest compartment. In addition, the start point along the base line is restricted to be on the boundary of a forest compartment, which in turn, constrains the first inventory line to be always 50 m away from the boundary. Taken together, these two constraints resulted in a limited total number of possible choices in laying out the Pre-F inventory grid over a forest compartment.

To support this argument, we consider a rectangular forest population depicted in Figure 3a. There are a total of eight possible choices of arranging the Pre-F inventory grid over the forest population, i.e. combination of four choices of placing the base line and two choices of placing the start point (Figure 3a). The base line may be placed vertically (parallel to y-axis), horizontally (parallel to x-axis) and the two diagonals to effectively divide the rectangular forest population in half. For each base line, the start point may be placed on either side of the two boundaries. The white rectangles represent $50 \text{ m} \times 20 \text{ m}$ plots. Thus, the white area represents the total coverage of the eight possible choices of placing the Pre-F inventory grid (Figure 3a). As depicted, there are remaining grey areas that are not covered by the white $50 \text{ m} \times 20 \text{ m}$ plots. These are forest populations that are systematically left out from sampling due to the constraints in the current protocols. Hence, a systematic error is introduced into calculation of the estimated mean by leaving certain portion of the forest area unsampled.

If the Pre-F inventory protocol does not restrict the need to divide the forest compartment in half, constraining the start point to forest compartment boundaries still creates a similar issue. To illustrate this point, consider a vertical base line that may be placed anywhere along the x-axis (Figure 3b), all possible ways of placing the Pre-F inventory grid will result in horizontal white strips and will leave a large portion of the forest area unsampled. A similar conclusion is reached by extending for other orientations of the base line. Furthermore, this undersampling of the forest area issue persists even for irregularlyshaped forest compartment, which may be worse if the shape further restricts the number of choices in orienting the base line to divide the forest population in half. In contrast, the RPS method, as proposed in this study, effectively insures that the whole forest area has a chance to be sampled because the start point can be anywhere within the forest compartment.

As argued above, Pre-F inventory design would likely produce biased estimates of population mean or total because portions of the population are excluded from sampling due to the established protocols. From another perspective, the produced estimates are unbiased for the subpopulation where the samples are covering (e.g. white area in Figure 3a) but are biased for the whole population. Thus, the Pre-F inventory is adequate when making inference on this subpopulation but not over the whole population.



Figure 3 Theoretical evaluation of the SMS Pre-F inventory design: (a) a hypothetical rectangular forest compartment whereby all possible ways of laying down the Pre-F inventory grid is depicted according to the protocols, (b) three possible ways of laying down the Pre-F inventory grid with vertical base line excluding the protocol requiring division of forest compartment in half by the base line; white area depicts coverage of the 50 m × 20 m plots over the grey area of the forest compartment

Simulation of the cyclic population

Simulations on the cyclic forest showed that PreF-v design resulted in significant bias for the three stand variables, whereas Pre-h and RPS designs were unbiased (Figure 4, Table 2). On average, the PreF-v underestimated the true stand density by 47.1% (Figure 4a) with average estimated stand density of 251.1 trees ha-1 (95%CI = 247.2-255.0 trees ha⁻¹; Table 2). On the other hand, the PreF-v overestimated the true stand basal area by an average of 37.5% (Figure 4b) with average estimated stand basal area of $99.4 \text{ m}^2 \text{ ha}^{-1} (95\% \text{ CI} = 97.4 - 101.5 \text{ m}^2 \text{ ha}^{-1}; \text{ Table 2}).$ Similarly for stand volume, PreF-v overestimated the true value on average by 66.1% (Figure 4c) with average estimated stand volume to be $1088.8 \text{ m}^3 \text{ ha}^{-1}$ (95%CI = 1065.1–1113.6 m³ ha⁻¹; Table 2).

The PreF-h and RPS designs were unbiased for the cyclic population with the simulations producing an average percent bias of 0% (Figure 4) or average estimated stand variables similar to the true values (Table 2). However, the 95% CI of PreF-h was narrower than those of RPS designs for all three stand variables (Table 2), indicating a higher precision with the PreF-h design. For example, the 95% CI of stand density for PreF-h was 225.3–703.5 trees ha⁻¹, whereas it was 246.9–1014.4 trees ha⁻¹ for the RPS method. The wide 95% CI under RPS design was particularly apparent for stand basal area and stand volume (Table 2).

The cyclic population was purposely set up to represent a population with repeated characteristics, i.e. a recurrence of regenerated and mature forest areas. Furthermore, the population was set up in such that the sample



- **Figure 4** Per cent bias of three sampling designs (PreF-v, PreF-h and RPS) for the simulated cyclic forest population for (a) stand density, (b) stand basal area and (c) stand volume; symbols depict average per cent bias for each of the sampling designs and vertical bars depict empirical 95% confidence interval
 - Table 2Mean estimated stand density, stand basal area and stand volume and its 0.025 and
0.975 sample quantiles in parentheses from simulations of cyclic forest populations

	Stand density (trees ha-1)	Stand basal area (m ² ha ⁻¹)	Stand volume (m ³ ha ⁻¹)
True	475.0	72.3	774.8
PreF-v	251.1	99.4	1088.8
	(247.2, 255.0)	(97.4, 101.5)	(1065.1, 1113.6)
PreF-h	481.3	72.6	777.8
	(255.3, 703.5)	(42.8, 102.8)	(431.3, 1130.0)
RPS	480.8	72.2	773.6
	(246.9, 1014.4)	(8.2, 103.4)	(27.1, 1136.4)

Pre F-v = pre-felling inventory with vertical base line, PreF-h = pre-felling inventory with horizontal base line, RPS = random point start method; true population values of stand variables are presented for comparison

plots would consistently fall on the mature forests when using vertical base line for all iterations in the simulation. As expected, Pre-F inventory with vertical base line consistently underestimated stand density and overestimated stand basal area and stand volume of the whole cyclic population because the mature forest had larger trees that were sparsely distributed. When looking at the results more carefully, the simulation of Pre-F inventory with vertical base line resulted in an estimated stand density of 251.1 trees ha⁻¹ (95%CI = 247.2-255.0 trees ha⁻¹; Table 2), which closely matched the true stand density of mature forest (250 trees ha⁻¹). In other words, Pre-F inventory with vertical base line unbiasedly estimated the subpopulation of the cyclic forest population (mature forest).

On the other hand, the Pre-F inventory with horizontal base line did not result in any biased estimates of population mean. The contradictory results between Pre-F inventory with vertical and horizontal base lines were due to the way the population was sampled. The sample plots when laid out with horizontal base line, sampled a mixture of regenerated and mature forest populations to different degrees. Depending on the location of the horizontal base line, the sample plots covered 40 to 100% of the mature forest. Thus, on average, the Pre-F inventory with horizontal base line would capture the whole population. In short, the appeared unbiasedness is by chance that horizontal base line allows the Pre-F inventory to capture two subpopulations of the cyclic population adequately. However, in reality, it is close to impossible to know conditions of a forest prior to inventory, unless remotely sensed data are available. Thus, the theoretical arguments presented above that Pre-F inventory design has design bias are supported by the simulation study on the cyclic forest population.

Simulation of the Pasoh population

Results from simulations of the Pre-F inventory using the Pasoh plot data suggested that the PreF-v, PreF-h and RPS designs were unbiased in estimating the three stand variables. However, the degree of unbiasedness depended on the three plot types (Figure 5, Table 3). For stand density, PreF-v overestimated it by an average of 2.1% with an average estimate of 81.9 trees ha⁻¹. However, the 95%CI of 79.6-84.2 trees ha⁻¹, covering the true value of 80.3 trees ha⁻¹ suggested that the potential bias was marginally insignificant. For plot types 2 and 3, PreF-v slightly underestimated and overestimated stand density respectively but 95%CI suggested that the biases were insignificant. On the other hand, PreF-h and RPS designs did not result in any significant bias across plot types.

For stand basal area, PreF-v resulted in a slight average bias of -3.6% with a lower average estimate of $15.9 \text{ m}^2 \text{ ha}^{-1}$ for plot type 1. However, the 95%CI suggested this bias to be insignificant



Figure 5 Per cent bias for three different plot types (Ptype 1, Ptype 2, Ptype 3) for Pasoh forest population for (a) stand density, (b) stand basal area and (c) stand volume; refer to Table 1 for specification of plot types; symbols depict average per cent bias for PreF-v (●), PreF-h (□) and RPS (▲); vertical bars depict empirical 95% confidence interval

	Stand density (trees ha ⁻¹)			Stand basal area (m ² ha ⁻¹)			Stand volume (m ³ ha ⁻¹)		
	Ptype1	Ptype2	Ptype3	Ptype1	Ptype2	Ptype3	Ptype1	Ptype2	Ptype3
True	80.3	223.5	1182.4	16.5	7.5	6.7	150.8	48.5	21.8
PreF-v	81.9	220.8	1197.0	15.9	7.4	6.7	140.4	48.1	21.9
	(79.6,	(209.6,	(1092.0,	(14.8,	(7.0,	(6.1,	(127.3,	(45.2,	(19.9,
	84.2)	234.8)	1294.0)	17.1)	8.0)	7.6)	153.2)	51.7)	24.7)
PreF-h	80.2	224.0	1191.3	16.5	7.4	6.8	150.3	48.1	21.9
	(74.6,	(210.0,	(1124.0,	(15.3,	(6.7,	(6.3,	(133.0,	(43.8,	(20.4,
	85.6)	234.8)	1296.0)	17.8)	7.8)	7.4)	168.3)	50.8)	24.0)
RPS	80.8	225.0	1200.6	16.7	7.5	6.8	152.0	48.8	22.1
	(74.2,	(208.8,	(1104.0,	(14.5,	(6.9,	(6.2,	(126.2,	(44.8,	(20.0,
	88.2)	240.4)	1296.1)	18.7)	8.1)	7.5)	177.7)	52.9)	24.4)

Table 3Mean estimated stand density, stand basal area and stand volume and 0.025 and 0.975 sample
quantiles in parentheses from simulations of the Pasoh forest population

Pre F-v = pre-felling inventory with vertical base line, PreF-h = pre-felling inventory with horizontal base line, RPS = random point start method; true population values of stand variables are presented for comparison

(Figure 5b, Table 3). For plot types 2 and 3, the average bias from PreF-v was very slight and insignificant. Similar to stand density, PreF-h and RPS designs did not produce any significant bias across all plot types. The results of stand volume resembled those of stand basal area (Figure 5c, Table 3). Similarly, the PreF-v resulted in an average of -6.9% bias with an average estimated stand volume of 140.4 m³ ha⁻¹ for plot type 1, but the 95%CI suggested this to be insignificant (Figure 5c, Table 3).

Lastly, when comparing 95% CI, RPS consistently had the widest range compared with PreF-v and PreF-h for all three stand variables for plot type 1. For plot type 2, the 95% CI was comparable between the three sampling designs. On the contrary, PreF-v had the widest 95% CI for all three stand variables for plot type 3.

For the Pasoh population, the results suggested that the Pre-F inventory design with either vertical or horizontal base line produced unbiased or marginally unbiased estimates of population mean, despite arguments from the theoretical point of view. Thompson (2002) suggested that mean and variance estimators were good only if the units of the population could reasonably be conceived as being in random order or homogenous. Thus, while individual species are spatially aggregated in the Pasoh plot, the trees as a whole are close to being randomly distributed, which contribute to the perceived unbiasedness of Pre-F inventory when simulated using this forest population. Interestingly, the average per cent bias of Pre-F inventory with vertical base line reduced from plot type 1 to plot type 3 with plot type 1 having the largest marginally absolute bias. This suggests that trees with dbh \geq 30 cm are more aggregated than smaller trees and are more heterogeneous in terms of tree sizes possibly due to dispersal limitation. For trees with dbh between 15 and 30 cm and with dbh between 5 and 15 cm, tree densities of the two subpopulations are significantly higher and visual depiction of their tree locations shows less clustering. Furthermore, the two subpopulations are bounded by dbh limits, which would relatively homogenise the tree sizes within each subpopulation. Nonetheless, we argue that the design issue of Pre-F inventory still persists and the degree of aggregation of trees in an actual forest area is unknown, which likely depends on tree species and their life histories. Thus, the design unbiasedness property of RPS method is more desirable without the need to make any underlying assumption about a population.

Random point start method

As expected, the RPS resulted in unbiased estimates of population stand variables because of the design itself. There is no base line restriction, i.e. either horizontal or vertical because the xand y-coordinates of start point are randomly chosen at each iteration. In short, the RPS would cover the full range of forest conditions. When inspected closely, the 95% CI of RPS method was wider than the Pre-F inventory designs. This was to be expected because due to random placement of grid, a simulated grid could either be fully inside the mature forest and could be fully inside the regenerated forest. Thus, the RPS method would cover the two extremes of the cyclic population during simulation, which in turn generated a wider 95%CI or larger variance. Due to the design issue of Pre-F inventory, the variance estimates and 95%CI from RPS method were more accurate in reflecting sampling error of systematic sampling in the cyclic population.

Management implications

The Pre-F inventory design produces biased mean estimates of population stand density, stand basal area and stand volume. This is supported by the cyclic forest population and has significant implication on inventory design and forest management. As argued, the biased mean estimates would have an impact on management decision such as determining accurate minimum cutting limits for dipterocarp and non-dipterocarp tree species, which in turn would affect sustainability in SMS practice. Since systematic sampling does not have an unbiased estimator for variance, one should ensure that the design strives for unbiasedness in mean estimate. The current Pre-F inventory design results in both biased estimators for population mean and variance, which is undesirable in a sampling design. Although the simulation shows that unbiasedness could be marginally achieved with Pasoh forest, this is a unique finding that has not been replicated for other areas. In field operation, characteristics of the population of a forest compartment approximately 250 ha are unknown; hence, the purpose of carrying out a sampling. Thus, without knowing whether the true distribution of the population, estimates from Pre-F inventory run the risk of being biased. Therefore, it is recommended that a sampling design should strive for design unbiasedness, i.e. unbiasedness achieved without assumption of the underlying population (Thompson 2002). In this case, the RPS method is design-unbiased.

The RPS method can be easily explained and understood by practitioners. It can be easily implemented using a map, either paper or digital and a means to produce random number from either computer software or calculator. Most importantly, it does not require substantial changes to the current Pre-F inventory protocol except one procedure during the inventory planning stage prior to field work. During this stage, the planner generates a random coordinate for a start point based on available map and extends the grid to four perpendicular directions with one direction perpendicular to the contour lines. Any grid line that follows this direction can be designated as the base line and the other line as the inventory line. Thus, the RPS method retains all the advantages of the current Pre-F inventory protocol such as capturing as much variability as possible in the compartment.

ACKNOWLEDGEMENTS

This study was funded by the Global Environment Facility through UNDP Malaysia (MAL/04/ G31) and the International Tropical Timber Organization [PD 16502 Rev.3 (F)] with inkind financial assistance and support from the Government of Malaysia through the Ministry of Natural Resources and Environment as well as the Forest Research Institute Malaysia.

REFERENCES

- ANONYMOUS. 1997. Manual Kerja Luar: Sistem Pengurusan Memilih (Selective Management System). Jabatan Perhutanan Semananjung Malaysia, Kuala Lumpur.
- CONDIT RG. 1998. Tropical Forest Census Plots: Methods and Results From Barro Colorado Island, Panama and a Comparison With Other Plots. Springer-Verlag, Heidelberg.
- FOREST STEWARDSHIP COUNCIL. 2010. FSC Forest Stewardship Standards: Structure, Content and Suggested Indicators. Forest Stewardship Council, Bonn.
- GRAY A, ABBENA E & SALAMON S. 2006. Modern Differential Geometry of Curves and Surfaces with Mathematics. Third edition. CRC Press, Boca Raton.
- HUSCH B, BEERS TW & KERSHAW JR JA. 2003. *Forest Mensuration*. John Wiley and Sons, New York.
- ILES K. 2003. A Sampler of Inventory Topics: A Practical Discussion For Resource Samplers, Concentrating on Forest Inventory Techniques. Friesens Corporation, Altona.
- ITTO. 2002. *ITTO Guidelines for the Restoration, Management* and Rehabilitation of Degraded and Secondary Tropical Forests. ITTO Policy Development Series No. 13. International Tropical Timber Organization, Yokohama.
- ITTO. 2005. Revised ITTO Criteria and Indicators for Sustainable Management of Tropical Forests Including Reporting Format. ITTO Policy Development Series No. 15. International Tropical Timber Organization, Yokohama.
- MANOKARAN N & LAFRANKIE JV. 1990. Stand structure of Pasoh Forest Reserve, a lowland rain forest in Peninsular Malaysia. *Journal of Tropical Forest Science* 3: 14–24.

- MANOKARAN N, QUAH ES, ASHTON PS, LAFRANKIE JV, NOOR NSM, AHMAD WMSW & OKUDA T. 2004. Pasoh forest dynamics plot, Peninsular Malaysia. Pp 585–598 in Losos EC & Leigh Jr EG (eds) *Tropical Forest Diversity and Dynamism: Findings from a Large-Scale Plot Network*. Chicago University Press, Chicago.
- PARKER C, MITCHELL A, TRIVEDI M & MARDAS N. 2008. The Little REDD Book: A Guide to Governmental and Non-governmental Proposals to Reducing Emissions From Deforestation and Degradation. Global Canopy Programme, Oxford.
- POTTS MD, KASSIM AR, NUR SUPARDI MN, TAN S & BOSSERT WH. 2005. Sampling tree diversity in Malaysian tropical forests: an evaluation of a pre-felling inventory. *Forest Ecology and Management* 205: 385–395.
- THANG HC. 1987. Forest management systems for tropical high forest, with special reference to Peninsular Malaysia. *Forest Ecology and Management* 21: 2–30.

- THOMPSON SK. 2002. Sampling. John Wiley and Sons, New York.
- VALENTINE HT, AFFLECK DLR & GREGOIRE TG. 2009. Systematic sampling of discrete and continuous populations: sample selection and the choice of estimator. *Canadian Journal of Forest Research* 39: 1061–1068.
- WAN MOHD SHUKRI WA & WAN RAZALI WM. 2002. Statistical reliability in SMS's pre-felling inventory: inferences and implications for sampling tree density, basal area and volume. *Journal of Tropical Forest Science* 14: 1–15.
- WAN RAZALI WM & WAN MOHD SHUKRI WA. 1999. An evaluation of statistical reliability in SMS's pre-felling inventory: the case for confidence and error levels. *Journal of Tropical Forest Science* 11: 11–25.