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RESEARCH PAPER

Effect of permanent plots on the relative efficiency of spatially balanced sampling in a national forest inventory

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Abstract

• ***Key message*** **Using spatially balanced sampling utilizing auxiliary information in the design phase can enhance the design efficiency of national forest inventory. These gains decreased with increasing proportion of permanent plots in the sample. Using semi-permanent plots, changing every** ***n*****th inventory round, instead of permanent plots, reduced this phenomenon. Further studies for accounting the permanent sample when selecting temporary sample are needed.**
• ***Context*** National forest inventories (NFIs) produce national- and regional-level statistics for sustainability assessment and decision-making. Using an interpreted satellite image as auxiliary information in the design phase improved the relative efficiency (RE). Spatially balanced sampling through local pivotal method (LPM) used for selection of clusters of sample plots is designed for temporary sample; thus, the method was tested in a NFI design with both permanent and temporary clusters.
• ***Aims*** We estimated LPM method and stratified sampling for a NFI designed for successive occasions, where the clusters are permanent, semi-permanent, or temporary being replaced: never, every *n*th, and every inventory round, respectively.
• ***Methods*** REs of sampling designs against systematic sampling were studied with simulations of inventory sampling.
• ***Results*** The larger the proportion of permanent clusters the smaller benefits gained with LPM. REs of stratified sampling were not depending on the proportion of permanent clusters. The semi-permanent sampling with LPM removed the previously described decrease and resulted in the largest REs.
• ***Conclusion*** Sampling strategies with semi-permanent clusters were the most efficient, yet not necessarily optimal for all inventory variables. Further development of method to simultaneously take into account the distribution of permanent sample when selecting temporary or semi-temporary sample is desired since it could increase the design efficiency.

Keywords Auxiliary information · Local pivotal method · Permanent cluster · Relative efficiency · Sampling design · Semi-permanent cluster

1 Introduction

National forest inventories (NFIs) are the main source of information for characterizing the state of the forest resources (Vidal et al. 2016, p. 8). The most common inventory variables are forest area, mean growing stock volume, and distribution of growing stock volume into tree species and timber assortments (Tomppo et al. 2010; Vidal et al. 2016). In addition to the current growing stock, estimating the changes in the forests over time is important. The plots can be permanent, meaning they are remeasured in all consecutive inventory rounds, or temporary, meaning they are discarded after the first measurements. Temporary plots are mainly intended to capture the current state of the forest, whereas permanent plots in addition to the current state aim at capturing the changes (Scott 1998; Tomppo et al. 2010). Even though the increments of growing stock can be accurately measured via increment cores from temporary plots, estimating the changes such as natural mortality and harvests is much more precise from permanent than from temporary plots (e.g., Päivinen and Yli-Kojola 1989). NFIs can be solely on temporary plots (e.g.,

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Poland, Portugal, France, and Spain), solely on permanent plots (e.g., Austria, Iceland, China, and Canada), or a combination of these two plot types (e.g., Finland, Sweden, Netherlands, Estonia, New Zealand; see Tomppo et al. 2010). The designs also change constantly in time, for instance in France, plans to introduce permanent plots have been reported (Vidal et al. 2016).

An inventory with purely permanent plots is called continuous forest inventory (CFI). Sometimes, the permanent plots established may lose their importance as an indicator for change. For example, treatment bias can be imparted when permanent plots are managed differently than the surrounding forests and affect CFI estimates (Köhl et al. 2015). In such occasion, the possibility to redistribute also the permanent plots would be beneficial.

Another option is a sampling design where the permanent plots are only used for a limited time, i.e., they are semi-permanent. Such designs are flexible since the priorities in survey may be changed from a round to another by allocation of different numbers of temporary plots (Scott and Köhl 1994). A semi-permanent plot is surveyed in at least two consecutive inventory rounds but then relocated like a temporary plot. Therefore, it is capable of capturing change and, in addition, with an efficient reallocation, is not susceptible to the treatment bias in the same way as permanent plots. An example of this is sampling with partial replacement (e.g., Patterson 1950; Matis et al. 1984; Köhl et al. 1995).

The measurement costs of permanent plots have been higher than those of temporary plots, due to necessity of making sure the plot is found for remeasurements. However, with modern GPS, the trees in temporary plots may be located as accurately as the trees in permanent plots, and therefore, the measurement costs do not differ markedly any more (e.g., Tomppo et al. 2014). This makes it possible to introduce new permanent plots without additional costs.

In Sweden, the temporary clusters in the current NFI round, which began in summer 2018, were chosen with spatially balanced sampling using local pivotal method (LPM) in the sample selection (Grafström et al. 2017b). This has motivated us to test the same method in the Finnish NFI setting. In a spatially balanced sampling, the distribution of the auxiliary variables in the sample is matched as closely as possible to the distribution in the entire population (Grafström et al. 2012). Auxiliary data may be any data available for all units of the population with no upper limit for the number of auxiliary variables used. Typically, auxiliary variables are spatial location, other geographic data such as altitude, and remotely sensed data (e.g., Grafström and Ringvall 2013; Grafström et al. 2014). The underlying assumption is that auxiliary information and inventory variables should be correlated (Grafström et al. 2012). LPM is a sample selection method resulting in approximately spatially balanced sample (Grafström and Lundström 2013). The LPM was assessed in a simulation study with independent auxiliary information and real NFI field data, where all sampling units belonged to one and the same population available for sampling (Räty et al. 2018). In other words, the setting in the study corresponded to an inventory with temporary inventory plots solely. The LPM can also be connected with other sampling methods such as stratification: in such a case, the LPM would be carried out separately within each stratum.

So far, there is no approach accounting for the distribution of existing permanent sample when selecting a temporary sample with the LPM. Such an approach should not compromise the requirement that each unit in the population has larger than zero probability to be included in the sample. To date with LPM, it has been only possible to match the distribution of the temporary sample irrespective of the existing permanent sample. Therefore, in the case of permanent sample, stratification with systematic or random sample selection may be more efficient than stratification with LPM or pure LPM. In stratified sampling, the sample within a stratum is populated first with the permanent sample belonging to that stratum. Then, the remaining sample within a given stratum is filled using systematic or random selection. Thus, while stratified sampling (with or without LPM) was shown to be less robust than pure LPM in our previous study (Räty et al. 2018), it may be more robust than LPM in a design involving permanent plots.

The main survey principles in the NFIs in these two countries, Finland and Sweden, are alike (Tomppo et al. 2010). The sample plots are arranged in clusters, the location of which refers to a corner point (Fig. 1). The temporary clusters comprise one third ≈ 33% of the clusters in Sweden and 60% in Finland (Kangas et al. 2018). One inventory round lasts for 5 years, and each year, the sample of the systematically positioned clusters covers the entire country. The exceptions in Finland are the most northern part and southwestern archipelago which both are surveyed in one summer. The number of sample plots measured annually is approximately 10,000 and 15,000 in Sweden and Finland, respectively (Kangas et al. 2018). Thus, improving the cost efficiency is important.

We assess in this study the efficiency of sampling designs by simulating the second phase of inventory sampling with different proportions of permanent clusters in the sample. Our first hypothesis is that as the proportion of permanent clusters in the sample increases, the relative efficiency (RE) of sampling design using LPM for temporary plot selection decreases, because a larger proportion of sample is chosen without utilizing the auxiliary information. In other words, with a larger proportion of permanent clusters, it is more difficult to match the distribution of a total sample including both temporary and permanent clusters to the distribution of auxiliary variables over the study region. As our second hypothesis, we assume that as the proportion of permanent clusters in the sample increases, the performance of stratified sampling designs with systematic plot selection compared with that of

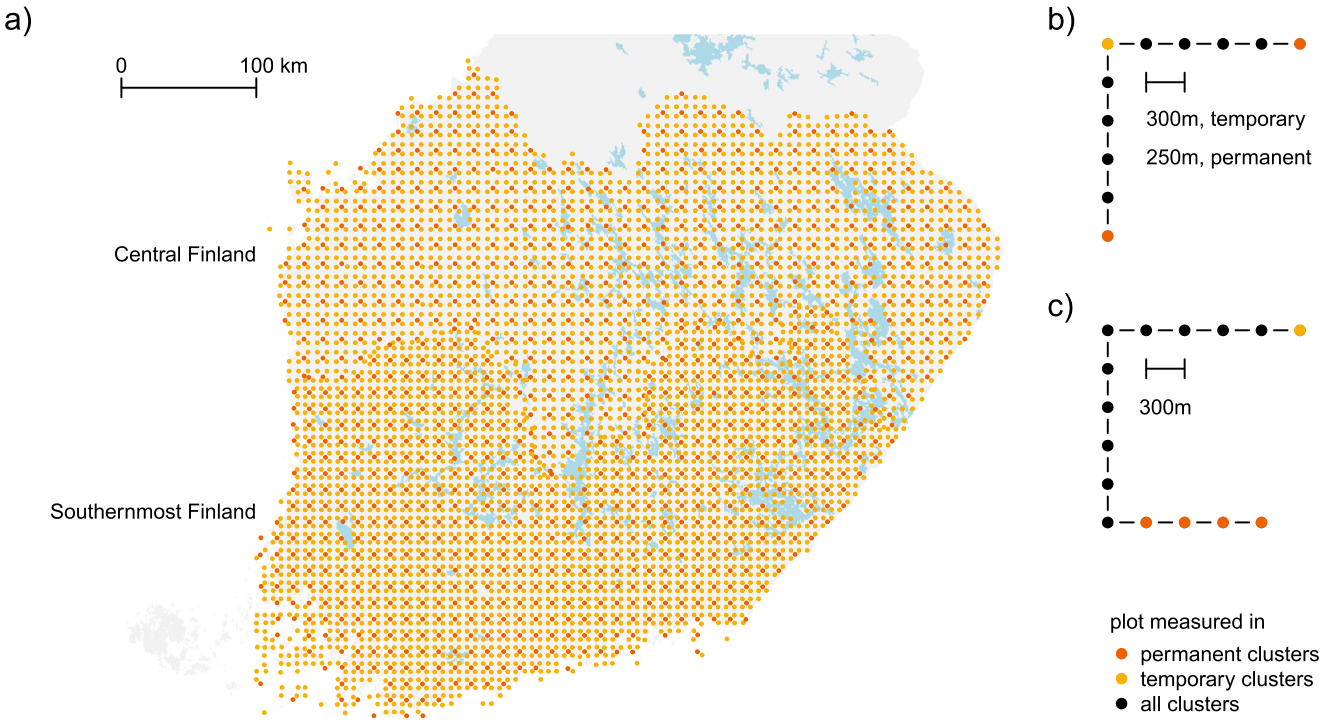

Fig. 1 **a** Locations of NFI11 sample plot clusters within the study region (red: permanent clusters, orange: temporary clusters). **b**, **c** Cluster design in Central Finland and Southernmost Finland (digital map data: © National Land Survey of Finland MML/VIR/MYY/328/08)

the LPM sampling improves. This is because the sampling units in the stratified sampling are selected independently of each other, without any need to account for the distribution of the permanent clusters in the same way as in LPM. In the last assessment, the permanent clusters are treated as semi-permanent, meaning all the semi-permanent clusters are resampled and allowed to change their position at the same time. In that case, both the entire temporary cluster population and semi-permanent cluster population are sampled with LPM using auxiliary variables. The setup could be thought as a maximal potential achievable with semi-permanent clusters. We assume that this semi-permanent/temporary sampling design would be more efficient than the design with permanent and temporary plots but not as efficient as the design where all clusters are temporary.

2 Material and methods

2.1 Study region and primary data

The study region is the southern part of Finland excluding the southwestern archipelago that covers about 153,000 km^2 land area and two sampling regions (Fig. 1a). Primary data in this study are the field data from the 11th Finnish NFI (NFI11) which was carried out in years 2009–2013. The sample plots are arranged in the clusters with slightly different cluster designs for the sampling regions (Fig. 1b, c). Data comprise altogether 46,914 field sample plots in $N = 5408$ clusters of which 1082 clusters were permanent and the rest 4326 were temporary.

Primary data in our study represents the population P from which the samples are chosen and population parameters are estimated. Our study is based on the main results of the Finnish NFI: total growing stock volume on the forested land (m^3), forested land area proportion, and mean growing stock volumes by tree species groups (m^3/ha) (Table 1). The forested land in this study is defined to include the two national forestry land classes: "forest land" and "poorly productive forest land" (Tomppo et al. 2011), resulting in an estimate close to the forest land as defined by the United Nations Food and Agriculture Organization (FAO 2012). The tree species–specific groups comprising all the growing stock volume are as follows: pine (*Pinus sylvestris* L.) including all conifers except spruce, spruce (*Picea abies* L.), and broadleaves, which mostly are birches (*Betula pendula* L. and *Betula pubescens* L.) (Korhonen et al. 2017).

2.2 Auxiliary information

Auxiliary information in this study was from the tenth multi-source NFI (MS-NFI10) (Tomppo et al. 2008), which was available as georeferenced raster layers of 20 × 20 m pixel size. These forest resource maps were based on the field measurements (NFI10 in years 2003–2008) and Landsat 5 TM images from year 2007 (Tomppo et al. 2012).

Table 1 Reference levels in the study: the population-level values for chosen population parameters (first row) and the mean squared errors (MSEs) for local pivotal method with spatial coordinates (=geospatial spread) by increasing proportion of permanent clusters (p) with the sample size of $n = 400$. Unit of MSE is the squared unit of that variable

	Proportion of forested land (%)	Total volume (Mill. m^3)	Mean volume (m^3/ha)			
			Coniferous		Broadleaf	All tree species
			Pine	Spruce		
Population	74.8	1553	59.6	48.1	28.3	136.0
MSE, $p = 0.1$	1.28	1.20E+15	2.80	3.76	1.24	5.80
MSE, $p = 0.2$	1.29	1.16E+15	2.73	3.71	1.15	5.78
MSE, $p = 0.3$	1.35	1.18E+15	2.78	3.54	1.13	5.59
MSE, $p = 0.4$	1.35	1.19E+15	2.86	3.62	1.13	5.57
MSE, $p = 0.5$	1.30	1.14E+15	2.84	3.64	1.08	5.48
MSE, $p = 0.6$	1.34	1.13E+15	2.71	3.46	1.07	5.39
MSE, $p = 0.7$	1.32	1.14E+15	2.70	3.60	1.06	5.39

To calculate the auxiliary variables for sampling units, i.e., clusters, a five-pixel window for each sample plot in a cluster was extracted from the forest resource map rasters: a center pixel where the plot center located and one adjacent pixel to all main cardinal directions, i.e., the so called Rook's case contiguity (e.g., Lloyd 2009). The cluster-level auxiliary variables were estimated as sums, means, or variances using equal weight for all extracted pixels belonging to any sample plot in the cluster. For the forested land proportion, for all pixels classified as land, and for growing stock volume–based mean and variance estimates, the pixels classified as forested land were utilized. Six forest resource thematic maps were utilized to produce the following six auxiliary variables for the clusters: (1) mean growing stock volume of all tree species, (2) mean growing stock volume of pine including other conifers than spruce, (3) mean growing stock volume of spruce, (4) mean growing stock volume of broadleaves, (5) variance of growing stock volume of all tree species within the cluster, and (6) forested land proportion (Table 2).

2.3 LPM

LPM utilizes auxiliary information in sample selection. In this study, the used combinations of cluster-level auxiliary variables are the ones that proved to be efficient in the previous study (Räty et al. 2018). LPM aims at selecting a sample from a population whose distribution in auxiliary space is as close as possible to its distribution in population (Grafström et al. 2012). Consequently, the sample is irregular if auxiliary variables include other variables besides spatial coordinates. Each sampling unit i in the population P of size N receives an (equal or unequal) initial inclusion probability, π_i, which sum up to the sample size, n:

$$n = \sum_{i=1}^{N} \pi_i \text{ and } 0 < \pi_i < 1 \tag{1}$$

In the selection process, the initial inclusion probabilities are turned into inclusion indicators, which are updated with an algorithm. However, while these indicators change during the process, the actual inclusion probabilities remain at the initial level. The updating is carried out using pairwise comparisons. Further, while the LPM algorithm is selecting a sample, the population divides into two: available and decided population. In the beginning, the entire population is available, i.e., all inclusion indicators differ from values 1 and 0. If the updated indicator value is 0, that unit will not be included in the sample and it is moved from the available population to the decided population. Similarly, a unit chosen to the sample and having an inclusion indicator value of 1 will also be moved to the decided population. As the selection proceeds, in every algorithm round, at least one unit is either chosen to the sample or loses its possibility to be included in the sample and thus is moved to the decided population. So, when LPM algorithm is running, the available population is diminishing and decided population consisting of included and excluded units is increasing. For more details of LPM, see, e.g., Grafström et al. (2012) and Fig. 2 in Räty et al. (2018).

The distance between the clusters is a Euclidian distance in the space of the auxiliary variables:

$$d(i,j) = \sqrt{\sum_{k=1}^{q} \left(x'_{ik} - x'_{jk}\right)^2} \tag{2}$$

where $\left(x'_{i1}, x'_{i2}, \ldots, x'_{iq}\right)$ are the standardized values of auxiliary variables associated to all pairs (i, j) of sampled clusters. Standardization of auxiliary variables guarantees an equal importance in distance calculation (Grafström and Ringvall 2013).

Table 2 Thematic maps utilized in the study, cluster-level auxiliary variable description, and correlation between the auxiliary and primary data

Variable	Thematic map (s)	Description	Correlation[4]
x_1	Mean volume of all tree species[1] (m^3/ha)	Mean	0.56
x_2	Mean pine volume[1] (m^3/ha)	Mean	0.54
x_3	Mean spruce volume[1] (m^3/ha)	Mean	0.64
x_4	Mean broadleaf volume[1,2] (m^3/ha)	Mean	0.49
x_5	Mean volume of all tree species[1] (m^3/ha)	Variance	0.37
x_6	Land class[2]	Proportion of forested land	0.67

[1] Defined only for pixels classified as forested land

[2] Utilized thematic maps "mean volume of birch" and "mean volume of other broadleaf species"

[3] The theme was aggregated to two classes: forested land and other lands. Pixels classified as water were discarded

[4] Correlation between the auxiliary and corresponding primary data in the national forest inventory field measurement data

2.4 Stratified sampling

In stratified sampling, the population is divided into as homogenous strata as possible using the auxiliary variables. We used equal-distanced limits along the cumulative distribution of the square root of the density function of auxiliary variable to define the strata (see Cochran 1977; section 5A.7). The sample size within each stratum was defined with optimal allocation where the within-stratum variance of auxiliary variable was weighted with the size of the stratum (Cochran 1977). In this study, we utilized the stratifications that proved to be most efficient and robust in our previous study (Räty et al. 2018).

The stratum for clusters was defined prior to the sampling simulation (Table 3). No separation was made between the permanent and temporary clusters in the population when it was stratified, but in the sample selection, the permanent clusters were chosen first using LPM with spatial coordinates with equal inclusion probability, called geospatial spread from this point onwards in this paper. Then, the temporary clusters were selected with LPM with geospatial spread based on the situation after the allocation of chosen permanent clusters into strata to fulfill the sample sizes in each of them (Table 4). If the number of sample clusters in any stratum exceeded the predefined sample size(s) already after allocation of permanent clusters, strata were combined.

As a result was a sample where the permanent plots were spatially as spread as possible in the whole test area and the temporary plots within each stratum. Standard stratified estimators were used to compute the estimates for population parameters from each stratified sample.

2.5 Design efficiency and sampling simulations

The hypotheses were tested in sampling simulations with the real NFI field clusters. In the simulations, the permanent and temporary NFI field clusters were put in one and the same population, i.e., the sampling population was $N = 5408$ clusters and sample size $n = 400$. Further, the clusters chosen for either set were not excluded from the selection of the other set. This corresponds to the situation where the two different cluster sets are spread independently from each other.

The sample selection method was LPM with geospatial spread for permanent clusters. For temporary and semi-permanent clusters, LPM with auxiliary data was used. In the case of stratification, first permanent and then temporary clusters were selected using geospatial spread. Further, proportion of permanent clusters in the sample was changed to show its impact on the performance of the sampling design. Thus, the changing elements in the sampling simulation were the sample selection method, auxiliary variables (Tables 3, 4, and 5) in the selection method, and proportion of permanent clusters resulting in several sampling designs. Performance of each sampling design was measured by the mean squared error (MSE):

$$MSE^2 = \frac{1}{T}\sum_{t=1}^{T}(\hat{y}_t - y)^2 \qquad (3)$$

where y is the true value of the target parameter (from Table 1), $\hat{y}_t$ the estimate obtained from the tth replication of the design, and $T = 5000$ is the number of replications.

Comparison of sampling designs was based on RE which is a ratio between the MSEs of reference and method (m = LPM or stratification):

$$RE_{m,p} = \frac{MSE_{ref,p}}{MSE_{m,p}} \qquad (4)$$

where p is the proportion of permanent clusters of the sample size, $p = 0.1$–0.7. The reference is a design where both permanent and temporary clusters are chosen with LPM with geospatial spread. It can be interpreted as a systematic sampling design which is close to the current sampling design of Finnish NFI. The reference was estimated separately for each level of proportion p. Values RE > 1 mean that the method under investigation is more effective than the reference.

Table 3 Limits of strata in stratifications based on cluster-level auxiliary variables (see Table 2 for definitions)

Name	Stratum/limits					
	1	2	3	4	5	6
Vol4	$x_1 < 87.4$	$87.4 \leq x_1 < 120.8$	$120.8 \leq x_1 < 159.4$	$x_1 \geq 159.4$	–	–
Vol5	$x_1 < 79.6$	$79.6 \leq x_1 < 107.7$	$107.7 \leq x_1 < 135.2$	$135.2 \leq x_1 < 169.8$	$x_1 \geq 169.8$	–
SPVol2	$x_4 < x_2 + x_3$ (conifer-dominated)				$x_4 \geq x_2 + x_3$ (others)	
	$x_1 < 89.1$	$89.1 \leq x_1 < 122.2$	$122.2 \leq x_1 < 160.5$	$x_1 \geq 160.5$	$x_1 < 78.5$	$x_1 \geq 78.5$
SPVol1	$x_4 < x_2 + x_3$ (conifer-dominated)				$x_4 \geq x_2 + x_3$ (others)	–
	$x_1 < 89.1$	$89.1 \leq x_1 < 122.2$	$122.2 \leq x_1 < 160.5$	$x_1 \geq 160.5$		
	$x_5 < 3952.2$	$x_5 \geq 3952.2$	$x_5 < 6001.8$	$x_5 \geq 6001.8$		
VolSpr	$x_1 < 99.2$		$99.2 \leq x_1 < 145.0$		$x_1 \geq 145.0$	
	$x_3 < 19.7$	$x_3 \geq 19.7$	$x_3 < 42.7$	$x_3 \geq 42.7$	$x_3 < 271.4$	$x_3 \geq 271.4$
FL%Vol	$x_6 < 0.36$	$0.36 \leq x_6 < 0.64$	$0.64 \leq x_6 < 0.86$		$0.86 \leq x_6 \leq 1.00$	
			$x_1 < 121.0$	$x_1 \geq 121.0$	$x_1 < 119.5$	$x_1 \geq 119.5$
FL%Pi	$x_6 < 0.36$	$0.36 \leq x_6 < 0.64$	$0.64 \leq x_6 < 0.86$		$0.86 \leq x_6 < 1.00$	
			$x_3 < 53.1$	$x_3 \geq 53.1$	$x_3 < 56.1$	$x_3 \geq 56.1$
Con5	$x_2 + x_3 < 59.3$	$59.3 \leq x_2 + x_3 < 85.3$	$85.3 \leq x_2 + x_3 < 110.6$	$110.6 \leq x_2 + x_3 < 144.9$	$x_2 + x_3 \geq 144.9$	–
Con6	$x_2 + x_3 < 53.3$	$53.3 \leq x_2 + x_3 < 77.4$	$77.4 \leq x_2 + x_3 < 97.3$	$97.3 \leq x_2 + x_3 < 120.2$	$120.2 \leq x_2 + x_3 < 152.2$	$x_2 + x_3 \geq 152.2$
Con3BL2	$x_2 + x_3 < 77.4$		$77.4 \leq x_2 + x_3 < 120.2$		$x_2 + x_3 \geq 120.2$	
	$x_4 < 25.8$	$x_4 \geq 25.8$	$x_4 < 25.3$	$x_4 \geq 25.3$	$x_4 < 25.5$	$x_4 \geq 25.5$
Con3FL%2	$x_2 + x_3 < 77.4$		$77.4 \leq x_2 + x_3 < 120.2$		$x_2 + x_3 \geq 120.2$	
	$x_6 < 0.61$	$x_6 \geq 0.61$	$x_6 < 0.68$	$x_6 \geq 0.68$FLC2	$x_6 < 0.59$	$x_6 \geq 0.59$
Pi3Spr2	$x_2 < 40.6$		$40.6 \leq x_2 < 66.2$		$x_2 \geq 66.2$	
	$x_3 < 53.5$	$x_3 \geq 53.5$	$x_3 < 51.7$	$x_3 \geq 51.7$	$x_3 < 49.6$	$x_3 \geq 49.6$
Spr3Pi2	$x_3 < 32.4$		$32.4 \leq x_3 < 71.2$		$x_3 \geq 71.2$	
	$x_2 < 54.6$	$x_2 \geq 54.6$	$x_2 < 54.3$	$x_2 \geq 54.3$	$x_2 < 53.1$	$x_2 \geq 53.1$

All simulations, analyses, and visualizations were made with R (R Core Team 2018). The LPM was performed with lpm1 function available in R package BalancedSampling (Grafström and Lisic 2018).

3 Results

In the reference method, no other auxiliary information was utilized besides spatial coordinates in sample selection. Further, the population from which the sample was chosen was always the same for both sets of clusters comprising all NFI clusters. The reference MSEs of target variables derived with simulation as well as the real values of population parameters are shown in Table 1. The simulation was replicated $T = 5000$ times which was a sufficient large number to let the estimates of mean to settle (Fig. 2).

When the proportion of permanent clusters in the sample increased, the RE of LPM decreases as expected (Fig. 3). Particularly, the RE of the forested land proportion decreased. It changed from the level of 1.80 to 1.16 as the proportion of temporary clusters changed from 90 to 30%. In the REs of mean growing stock volume and total growing stock volume, the decreases were 0.20 and 0.34 units, respectively (Table 5).

For the tree species–specific mean growing stock volumes, we were able to observe three phenomena: First, the decreasing trend as a function of increasing proportion of permanent clusters was not as obvious as for the other parameters. Second, for all tree species–specific mean growing stock volumes, the RE was larger if the auxiliary information included the tree-specific variables. Third, the clear differences in the REs between the cases using different auxiliary variables with small proportions of permanent clusters vanished as the proportion of permanent clusters increased. In the end, the REs were the same despite the auxiliary variables included in the sample selection.

For the stratified sampling, the changes depended both on the stratification and on estimated population parameter. For example, in broadleaf mean growing stock volume estimation, the REs had somewhat decreasing trend whereas in total growing stock volume estimation, the REs of most of the stratifications were fluctuating at the same level (Fig. 4). When stratification included forested land proportion, its estimation was efficient, otherwise not (Fig. 4, top left). The same applied for the tree species–specific growing stock volumes. If the stratification included information on a given tree species, the RE of that species was larger than that for the other stratifications.

When sampling with LPM utilizing the same set of auxiliary information in both temporary and permanent cluster

Table 4 The stratifications performed and both the sizes, N_s, and sample sizes, n_s, of strata. For a more detailed definition of auxiliary variables, see Table 3

Name	Stratifying variable(s)	Number of strata	N_1 n_1	N_2 n_2	N_3 n_3	N_4 n_4	N_5 n_5	N_6 n_6
Vol4	Volume x_1	4	1027	1888	1718	775	–	–
			93	103	108	96		
Vol5	Volume x_1	5	680	1458	1566	1192	512	–
			71	82	88	83	76	
SPVol2	Species group dominance[1]/volume x_1	6 (2/4,2)[2]	990	1869	1660	740	98	51
			83	101	104	92	11	9
SPVol1	Species group dominance/volume x_1	5 (2/4,1)[3]	990	1869	1660	740	149	–
			80	98	100	89	33	
VolSpr	Volume x_1/spruce volume x_3	6 (3/2)	978	671	1364	1125	746	524
			95	34	82	67	52	70
FL%Vol	% forested x_6/volume x_1	6 (4/1,1,2,2)[4]	813	1431	1183	825	733	423
			121	120	39	40	40	40
FL%Pi	% forested x_6/pine volume x_2	6 (4/1,1,2,2)	881	1258	864	726	894	785
			115	124	39	41	40	41
Con5	Volume of conifers x_2+x_3	5	754	1437	1577	1164	476	–
			72	93	102	80	53	
Con6	Volume of conifers x_2+x_3	6	558	1118	1323	1221	843	345
			56	78	88	78	58	42
Con3BL2	Volume of conifers x_2+x_3/volume of broadleaves x_4	6 (3/2)	1061	615	1569	975	691	497
			81	47	92	62	72	46
Con3FL%2	Volume of conifers x_2+x_3/% forested x_6	6 (3/2)	721	955	931	1613	532	656
			71	57	66	99	58	49
Pi3Spr2	Pine volume x_2/spruce volume x_3	6 (3/2)	842	840	1625	833	940	328
			62	80	102	66	66	24
Spr3Pi2	Spruce volume x_3/pine volume x_2	6 (3/2)	448	570	2375	1108	705	202
			32	60	157	86	51	14

[1] Clusters were divided into conifer-dominated forests, $x_2+x_3>x_4$, and others

[2] Four strata for conifer-dominated forests, two for the others

[3] As above, but "others" stratum was not further divided

[4] The two strata with largest proportion of forested land were further divided according to the volume of all tree species

populations, the effect of increasing proportion of these semi-permanent clusters was not anymore evident for all population parameter estimations (Fig. 5). The RE of forested land proportion and mean growing stock volume of pine did not have any detectable trend. For the other parameters, there was a slight decrease which seemed to turn to increase before the last simulated proportion, 70%. On the variable level, the RE of tree species–specific mean growing stock volumes depended on the chosen set of auxiliary variables similarly to the previous LPM case (Fig. 3).

4 Discussion

The aim of this study was to estimate the efficiency of spatially balanced and stratified sampling designs in a realistic NFI situation. Spatially balanced sampling used LPM in sample selection, and it was applied in two different setups: In the first setup, the field clusters were divided into permanent clusters being surveyed in the consecutive inventories and temporary clusters, which were measured only once. The location of permanent clusters was fixed and arranged spatially systematically in consecutive inventories, but the temporary clusters were reallocated inside the study region each simulation round with LPM utilizing remote sensing data from previous inventory. In the second setup, the cluster groups were semi-permanent and temporary; thus, both cluster populations were reallocated each simulation round with LPM utilizing similar auxiliary remote sensing data. In the first setup above, also the stratified sampling method was assessed. In all simulations, the sample size was fixed but different proportions of samples were allocated into the two cluster populations.

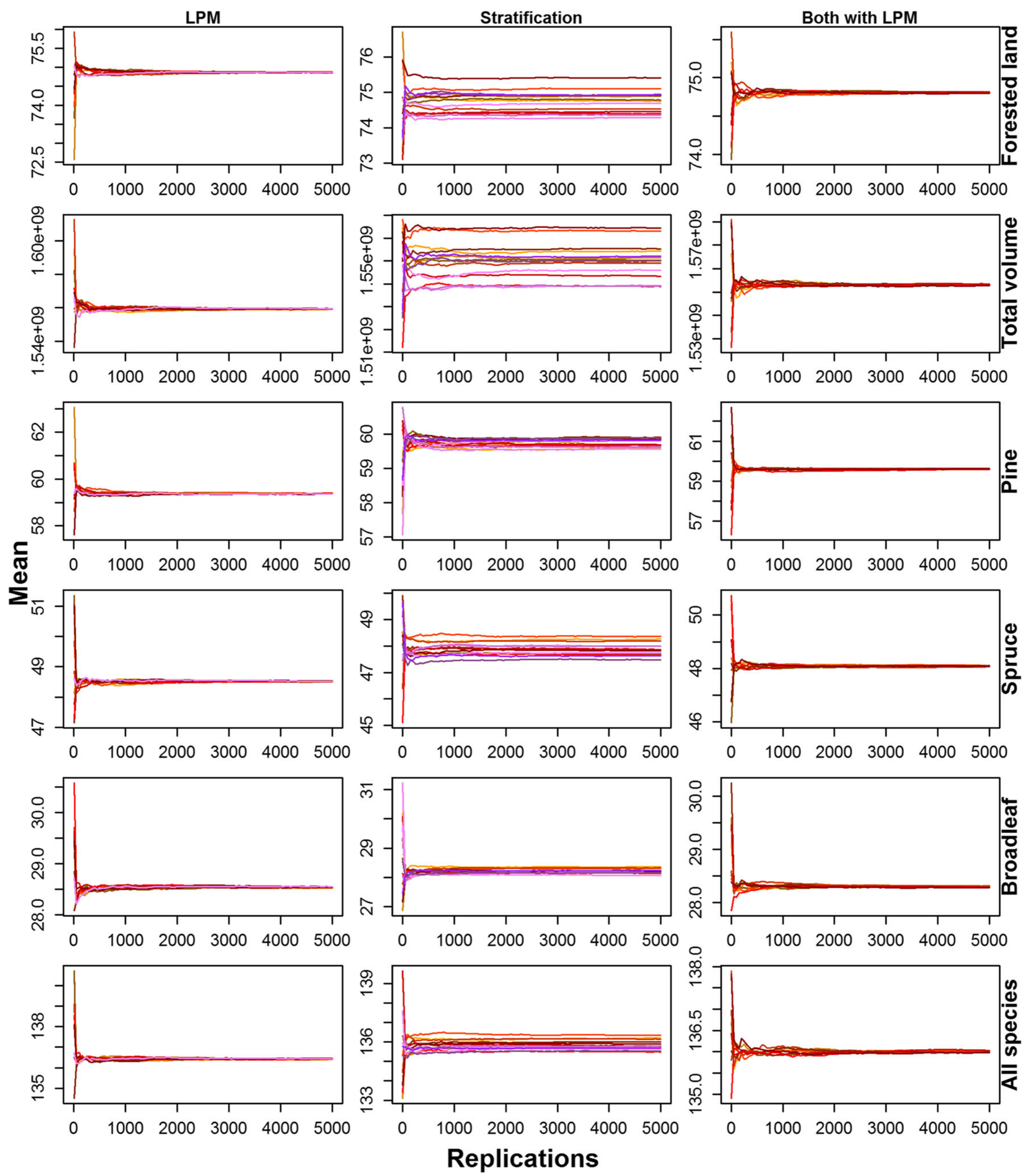

Fig. 2 Illustration of sample means for different population parameters in different sampling designs as a function of sample size

We estimated the sampling efficiencies using the fixed positions and designs of sample clusters from the previous inventories with total sampling intensity of 400/5408 ≈ 7.4%. A sampling design that is systematically placed should capture all the variation in the population, and the small sampling intensity guarantees that differences in design efficiency result from actual performance of the methods. Efficiencies of different sampling designs were studied in respect to the design where both cluster sub-populations were geospatially spread with LPM, which means that samples in sub-populations were close to a current systematic sampling design.

Our first hypothesis concerning the RE of LPM held. The RE of sampling designs decreased as the proportion of permanent clusters in the sample increased the sampling simulations (Fig. 3). In a previous study (Räty et al. 2018), where all the clusters were chosen with LPM from one population, the largest REs were 1.77 and 2.15 for total growing stock volume and forested land proportion estimation, respectively (Table 5). As the proportion of permanent clusters increased to 60% of the sample, the REs decreased even as much as 40% (Table 5). Nevertheless, as in the previous study (Räty et al. 2018), LPM was producing similar results irrespective of the

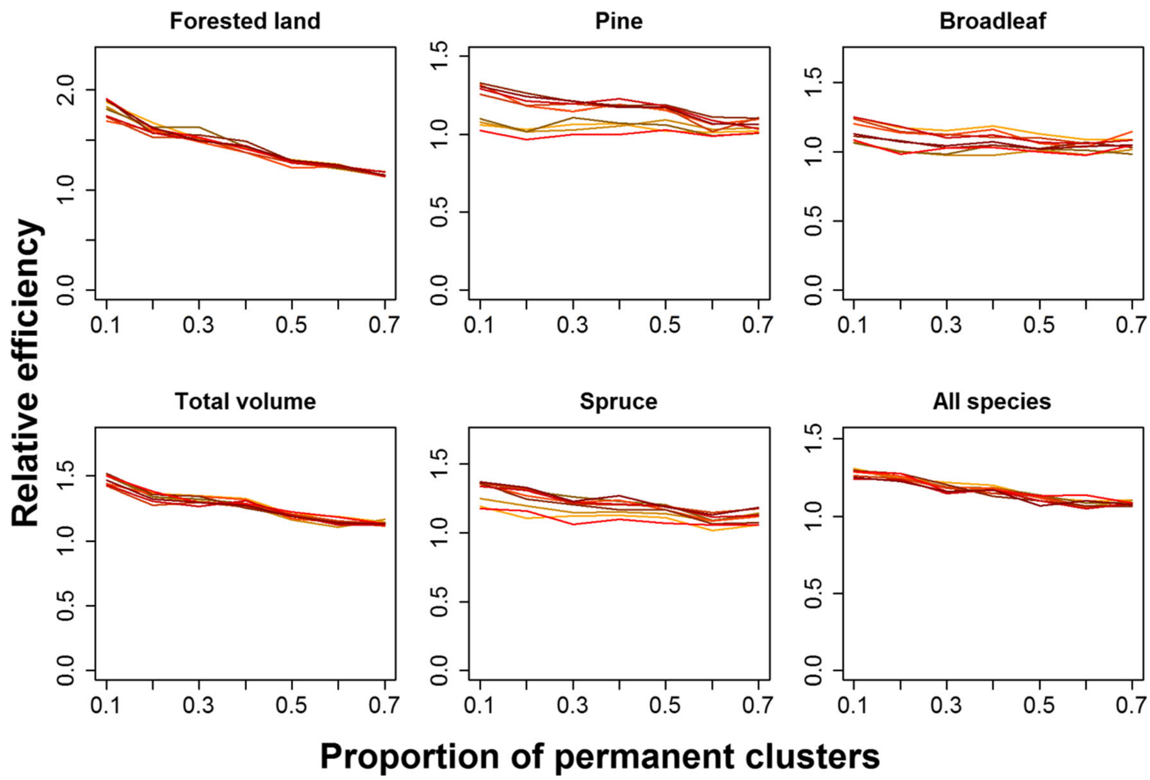

Fig. 3 Relative efficiency of sampling designs when proportion of permanent clusters in a sample of $n = 400$ varied from 10 up to 70%. The permanent clusters were chosen with local pivotal method (LPM) using spatial spread and temporary clusters with LPM utilizing also other auxiliary information besides spatial location

auxiliary variables chosen, but in stratification, the result depended heavily on the chosen stratification strategy (Figs. 3 and 4, Table 5). Thus, with LPM, the estimation of a given tree species–specific mean growing stock volume was enhanced if the growing stock volume for that species was included in the auxiliary information given to LPM (Table 5).

Also, the second hypothesis, that the stratified sampling would become more efficient in respect to LPM as the proportion of permanent clusters increases in the sample, held for some stratifications (Fig. 6). In fact, the stratified sampling was invariant in respect to the proportions (Table 5). However, the variation in performance between the different stratifications was large, and enhancement of RE of one or few population parameters meant often inefficiency in the other population parameter estimations. Contrarily, spatially balanced sampling was reaching about the same level of RE regardless of the set of auxiliary variables chosen. This means that the stratification should always be based on experience, consideration, and knowledge whereas with LPM, the RE is at least on the same level with systematic sampling (Fig. 3) (Grafström et al. 2017b).

The proportion of permanent clusters in the Finnish NFI is 60% (Kangas et al. 2018). Based on this study, sampling with LPM would enhance the estimation in respect to the current systematic sampling design, but the expected improvements are smaller than the previous studies (Grafström et al. 2017b; Räty et al. 2018) anticipated, being at 5–25% for different population parameters when the proportion of permanent plots in the sample is 60%. The question is whether the improvements gained at design phase with LPM would contribute enough in contrast to the other existing methods like post-stratification or model-assisted estimation methods (Haakana et al. accepted; Särndal et al. 1992; Kangas et al. 2016; Myllymäki et al. 2017) applied in the estimation phase to the results from systematic sampling design. Possibly, the most efficient approach would then be a combination of cluster-level LPM and plot-level post-stratification.

One possible way to mitigate the decrease in efficiency as the proportion of permanent plots in sample increases would be selecting both the permanent and temporary plots with LPM utilizing auxiliary information. Even though changes happening in the permanent plots during the years would impact also on their distribution, it would still probably match the distribution of auxiliary variables better than systematically chosen permanent clusters. If the permanent plots are mainly used for estimating short-range changes, semi-permanent plots that are measured, say two to three times, could be a useful compromise that would improve the design efficiency (Table 6). However, the strategies of using permanent and semi-permanent sample plots in NFI need to be studied further, because permanent plots produce time series data that are valuable. Naturally, taking into account the distribution of

Table 5 Relative efficiencies of sampling designs with local pivotal method and stratified sampling when the proportion of permanent clusters out of $n = 400$ sample clusters is 0%, 10%, 30%, and 60% and permanent clusters were distributed systematically. Result for $p = 0$ is from a previous study (Räty et al. 2018)

LPM design						Relative efficiency						Stratification	Relative efficiency					
Auxiliary variables																		
All tree species, x_1	Pine, x_2	Spruce, x_3	Broadleaf, x_4	Variance, x_5	Forested land, x_6	Forested land	Total volume	Mean volume					Forested land	Total volume	Mean volume			
								Pine	Spruce	Broadleaf	All tree species				Pine	Spruce	Broadleaf	All tree species
$p = 0$																		
X					X	2.15	1.77	1.03	1.21	1.00	1.48	Con3BL2	2.77	1.22	0.71	0.75	0.76	0.9
X		X			X	2.07	1.66	1.19	1.55	0.99	1.45	Con3FL%2	2.00	1.50	0.96	1.06	0.92	1.15
	X	X			X	2.07	1.59	1.49	1.56	1.05	1.36	Con5	1.03	1.33	1.02	1.10	0.90	1.25
X			X		X	2.04	1.67	1.14	1.16	1.26	1.40	Con6	1.02	1.32	1.03	1.08	0.95	1.24
X	X				X	2.02	1.64	1.40	1.43	1.10	1.37	Vol5	0.96	1.24	1.03	1.12	1.03	1.22
X				X	X	2.00	1.67	1.12	1.26	0.99	1.41	SPVol2	0.95	1.23	0.87	1.07	0.85	1.21
	X	X	X		X	2.00	1.58	1.42	1.46	1.29	1.34	FL%Vol	0.94	1.27	0.93	1.11	0.85	1.24
X	X	X	X		X	1.88	1.60	1.40	1.51	1.29	1.40	Vol4	0.92	1.23	0.87	1.05	0.82	1.20
X	X	X	X	X	X	1.81	1.58	1.42	1.51	1.28	1.40	Pi3Spr2	0.91	1.26	0.91	1.06	0.85	1.21
$p = 0.1$																		
X					X	1.90	1.49	1.03	1.17	1.09	1.28	Con3FL%2	1.90	1.68	1.10	1.26	1.29	1.40
X	X				X	1.89	1.48	1.32	1.35	1.14	1.25	FL%Vol	1.59	1.13	0.96	1.12	1.16	1.18
X				X	X	1.89	1.51	1.06	1.25	1.06	1.29	FL%Pi	1.49	0.87	1.19	0.94	1.14	0.93
X			X		X	1.81	1.48	1.06	1.19	1.25	1.29	Con6	1.11	1.55	1.13	1.29	1.18	1.38
	X	X			X	1.79	1.47	1.31	1.42	1.14	1.31	Spr3Pi2	1.05	1.28	1.29	1.44	1.20	1.27
X		X			X	1.76	1.50	1.07	1.36	1.09	1.31	Con5	1.03	1.51	1.11	1.26	1.22	1.44
X	X	X	X		X	1.75	1.45	1.25	1.34	1.23	1.25	Vol6	1.03	1.54	1.11	1.28	1.21	1.47
	X	X	X		X	1.71	1.45	1.29	1.38	1.26	1.28	Vol5	1.01	1.51	1.00	1.17	1.21	1.42
X	X	X	X	X	X	1.71	1.46	1.29	1.34	1.20	1.30	Pi3Spr2	0.97	1.32	1.38	1.39	1.30	1.30
$p = 0.3$																		
X		X			X	1.59	1.34	1.08	1.25	0.99	1.19	Con3FL%2	1.99	1.68	1.07	1.17	1.16	1.36
X	X				X	1.59	1.37	1.19	1.21	1.06	1.23	FL%Vol	1.65	1.09	0.92	0.99	1.06	1.10
X					X	1.58	1.37	1.05	1.10	1.15	1.22	FL%Pi	1.60	0.91	1.17	0.89	1.06	0.91
	X	X			X	1.57	1.34	1.21	1.24	1.04	1.17	Spr3Pi2	1.11	1.31	1.25	1.33	1.13	1.16
	X	X	X		X	1.56	1.33	1.20	1.23	1.11	1.17	Con5	1.09	1.45	1.09	1.19	1.13	1.34
X					X	1.56	1.31	0.99	1.06	1.03	1.16	Vol6	1.08	1.47	1.07	1.14	1.18	1.42
X	X	X	X		X	1.52	1.33	1.17	1.21	1.12	1.21	Con6	1.07	1.48	1.05	1.12	1.11	1.34
X				X	X	1.50	1.35	1.05	1.12	0.98	1.17	Vol5	1.07	1.50	0.99	1.11	1.08	1.34
X	X	X	X	X	X	1.50	1.34	1.17	1.22	1.13	1.17	SPVol1	1.02	1.32	0.99	1.14	1.00	1.30
$p = 0.6$																		
X			X		X	1.29	1.21	1.02	1.08	1.09	1.13	FL%Vol	2.21	1.22	0.88	0.89	0.90	1.09
	X	X			X	1.28	1.15	1.07	1.11	1.05	1.09	FL%Pi	2.15	1.05	1.18	0.76	0.93	0.87
X					X	1.27	1.20	0.99	1.07	0.97	1.15	Con3FL%2	1.91	1.54	1.01	1.14	1.06	1.25
X	X	X	X		X	1.25	1.16	1.05	1.16	1.09	1.10	Con6	1.09	1.44	1.06	1.17	1.04	1.27
X	X	X	X	X	X	1.24	1.16	1.06	1.12	1.06	1.07	Con5	1.05	1.36	1.04	1.10	1.05	1.26
X	X				X	1.23	1.13	1.14	1.08	1.09	1.08	SPVol1	1.04	1.27	0.94	1.06	0.96	1.24
X				X	X	1.23	1.13	1.03	1.10	1.01	1.10	Vol5	1.04	1.41	0.97	1.04	1.03	1.31
X		X			X	1.23	1.13	1.00	1.08	1.02	1.09	Spr3Pi2	1.03	1.21	1.22	1.31	1.04	1.13
	X	X	X		X	1.22	1.13	1.14	1.13	1.08	1.09	Pi3Spr2	1.03	1.23	1.33	1.29	1.07	1.19

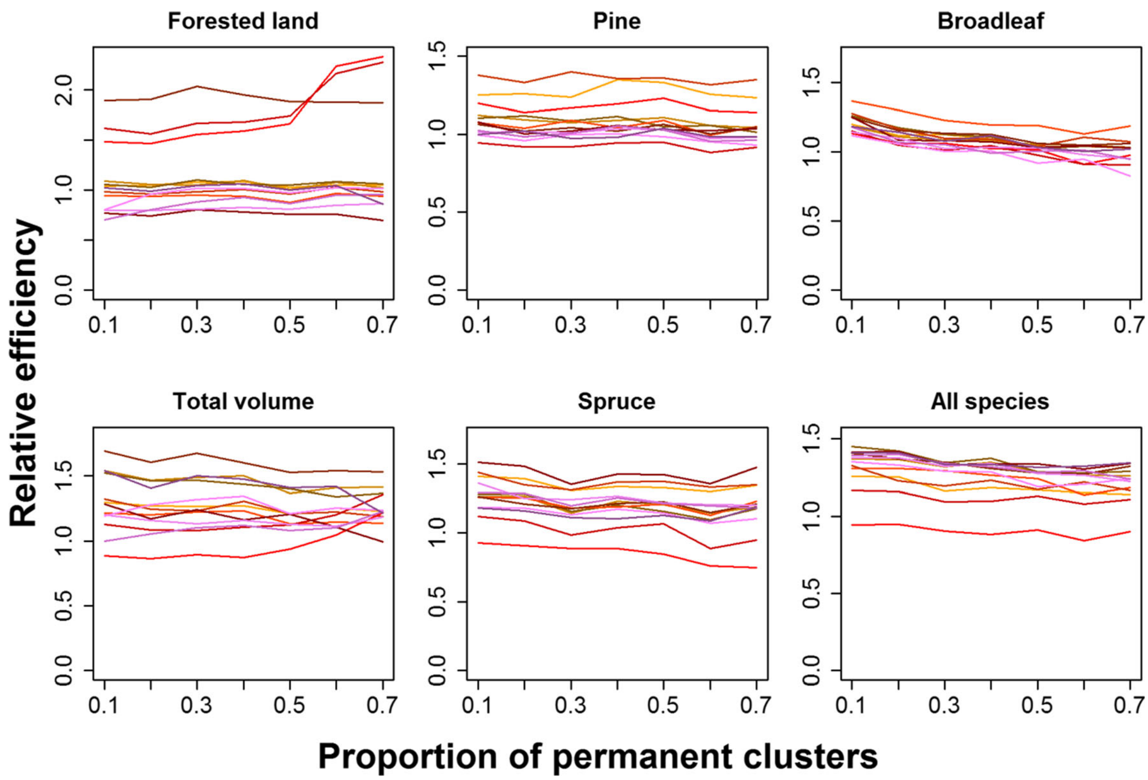

Fig. 4 Relative efficiency of stratified sampling designs when proportion of permanent clusters in a sample of $n = 400$ varied from 10 to 70%. Both the permanent and temporary clusters were chosen with local pivotal method (LPM) with geospatial spread within the strata

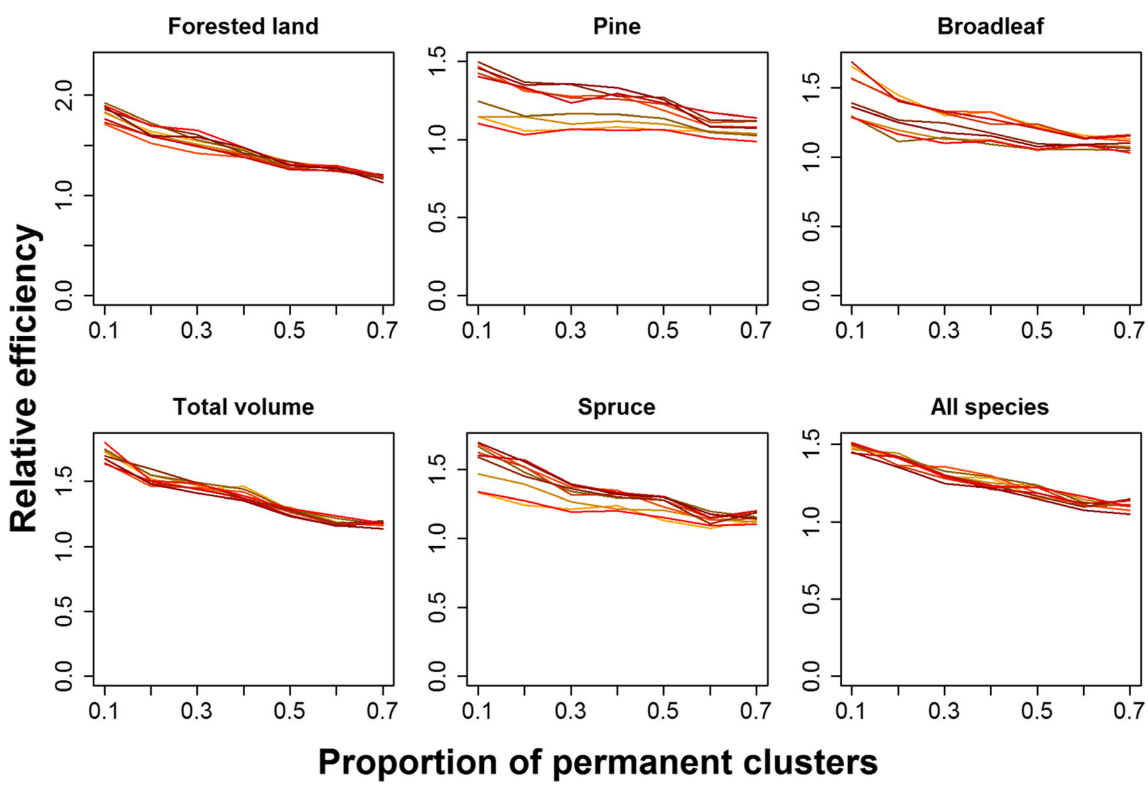

Fig. 5 Relative efficiency when temporary and permanent cluster populations are both separately sampled with local pivotal method with the same auxiliary variables

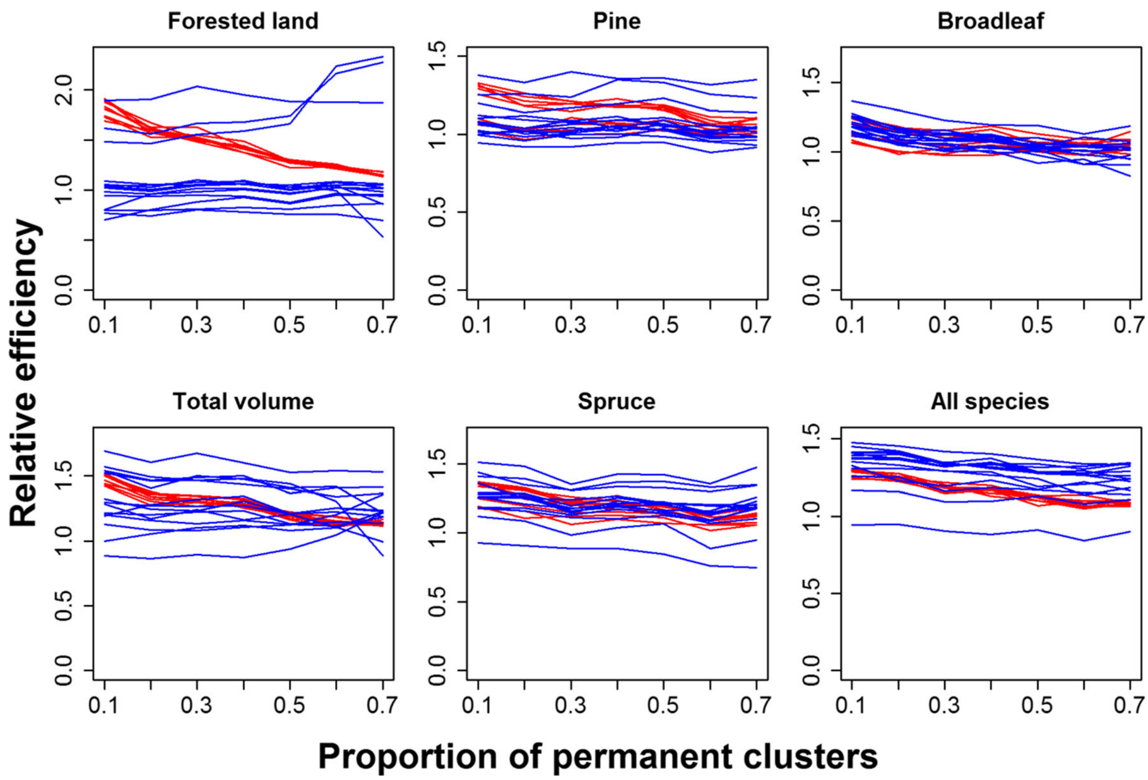

Fig. 6 Relative efficiencies of stratified sampling designs (blue) and local pivotal method utilizing auxiliary information (red)

permanent plots when selecting the sample from temporary population with LPM would be an optimal solution.

Both datasets MS-NFI10 and NFI11 had their own error sources and inaccuracies, for example, locating the sample plots in NFI and MS-NFI has inaccuracy of some meters and therefore given center coordinates might have fallen into an adjacent pixel in the MS-NFI auxiliary data raster with pixel size of 20 × 20 m (Tomppo et al. 2012). On top of that, sample plots of changing radius (angle-gauge measurements) of maximum of 12.52 m are usually spreading to the adjacent pixels (Korhonen et al. 2017). Therefore, we did not choose only the pixel where the sample plot center falls in but also the adjacent pixels for auxiliary information estimation. Thus, we could be surer that we had chosen a pixel which describes the conditions of the sample plot, but at the same time, we also could have included pixels which were describing the forest conditions of adjacent stands. These position errors may decrease the RE, but do not cause bias.

The auxiliary variables were defined at cluster level which brought challenges to the simulation. Having all auxiliary information aggregated from single pixels to mean values for clusters faded the extremes of the multi-dimensional auxiliary variable distribution. This was compensated by adding an auxiliary variable which describes the amount of within cluster variation, i.e., variance of total growing stock volume, but the variation could also originate from distribution of land use or tree species compositions as well as from other site conditions like altitude, which were not included as auxiliaries in our study. Instead of mean values, different kinds of metrics to describe the distances between the clusters in the multi-dimensional auxiliary space or the variation and distribution of auxiliary variables within the clusters as well as variance estimator (Grafström and Schelin 2014; Grafström et al. 2017a; Grafström and Matei 2018) could also be studied further.

5 Conclusion

Increasing proportion of permanent sample plots did not have an effect on the RE of stratified sampling designs, though their result depended on the chosen variables used in stratification. Contrarily, with spatially balanced sampling designs, the REs decreased being about 10% for the mean growing stock when proportion of permanent plots in the sample increased to 60%. When permanent plots were changed to semi-permanent plots which were, instead of using systematic sampling, allocated in the similar manner as temporary plots, i.e., based on auxiliary information, the loss in RE experienced in spatially balanced

Table 6 Relative efficiency of sampling designs when both temporary and permanent clusters were chosen with local pivotal method utilizing auxiliary information

LPM design						Relative efficiency					
Auxiliary variables											
All tree species, x_1	Pine, x_2	Spruce, x_3	Broadleaf, x_4	Variance, x_5	Forested land, x_6	Forested land	Total volume	Mean volume			
								Pine	Spruce	Broadleaf	All tree species
$p = 0.1$											
X					X	2.11	1.85	1.08	1.39	1.27	1.57
X	X				X	2.08	1.86	1.56	1.60	1.42	1.57
X		X			X	2.08	1.91	1.29	1.77	1.27	1.60
X				X	X	2.06	1.83	1.16	1.45	1.21	1.53
	X	X			X	2.04	1.78	1.53	1.82	1.45	1.52
X			X		X	2.00	1.82	1.17	1.37	1.60	1.53
X	X	X	X		X	1.98	1.79	1.48	1.70	1.63	1.52
	X	X	X		X	1.89	1.80	1.52	1.70	1.60	1.49
X	X	X	X	X	X	1.83	1.76	1.49	1.74	1.61	1.57
$p = 0.3$											
X					X	2.19	1.83	1.04	1.29	1.12	1.49
X		X			X	2.11	1.81	1.19	1.54	1.15	1.51
X	X				X	2.09	1.76	1.50	1.49	1.25	1.45
X			X		X	2.08	1.86	1.17	1.32	1.51	1.52
	X	X			X	2.03	1.68	1.47	1.65	1.24	1.40
X				X	X	1.98	1.70	1.13	1.33	1.14	1.38
	X	X	X		X	1.96	1.75	1.47	1.54	1.51	1.43
X	X	X	X		X	1.93	1.73	1.47	1.60	1.42	1.47
X	X	X	X	X	X	1.81	1.66	1.46	1.59	1.44	1.44
$p = 0.6$											
X					X	2.09	1.70	1.02	1.22	1.10	1.39
X	X				X	2.07	1.62	1.45	1.48	1.18	1.38
	X	X			X	2.05	1.57	1.44	1.52	1.15	1.30
X		X			X	2.04	1.73	1.19	1.54	1.15	1.49
X			X		X	1.98	1.63	1.14	1.22	1.38	1.39
	X	X	X		X	1.96	1.59	1.35	1.53	1.39	1.35
X				X	X	1.93	1.64	1.07	1.31	1.04	1.37
X	X	X	X		X	1.93	1.67	1.40	1.55	1.39	1.40
X	X	X	X	X	X	1.80	1.60	1.36	1.54	1.31	1.40

designs disappeared. Therefore, the result challenges to consider sampling strategies with shorter term permanent sample plots which, however, might not be optimal regarding long-term changes, e.g., the effect of forest management on the forest structure. On the other hand, further development of spatially balanced sampling methods could also solve the problem how to take into account the permanent sample when selecting temporary sample.

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Data availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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