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Using auxiliary data to rationalize smartphone-based pre-harvest forest mensuration

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Accurate mensuration of forest stands for pre-harvest planning will pose high costs if carried out by a professional forester as an on-site evaluation. The costs could be reduced if a person with limited mensuration expertise could collect the required data using a smartphone-based system such as TRESTIMA® Forest Inventory System. Without prior information, the field sample with sufficient number of measurement points over the whole stand should be selected, so that the entire variation will be covered. We present and test a rational framework based on selecting the sampling locations according to auxiliary data. As auxiliary variables, we use various spatial data sources indicating forests' structural or spectral variation, as well as previously predicted inventory variables. We construct two variants of sampling schemes based on the local pivotal method, weighted by the auxiliary data, and compare the results to simple random sampling (SRS) with corresponding sample sizes. According to our findings, the benefits of auxiliary data depend on the considered stand, species and timber assortment. The use of auxiliary data leads generally to improved results and up to three times higher efficiency (i.e. lower variance) as compared with SRS. We conclude that the framework of applying auxiliary data has high capabilities in rationalizing the sampling efforts with little drawbacks, consequently providing potential to improve the results with similar sample size and possibility to use of non-specialists for the pre-harvest inventory.

Introduction

Roundwood procurement for the Nordic forest industry is based on cut-to-length harvesting, in which the trees are cut to timber assortments in the forest. The Nordic forestry is characterized by a high proportion of private forest ownership and, for example, in Finland as much as 83 per cent of the industrial roundwood removals came from non-industrial private forests in 2019 (Luke, 2020). Timber transactions are typically based on bids or a customer contract with a forest company. From the perspective of the buyer, pre-harvest information on the species-specific log length–diameter distribution and quality of the logs are needed. These are required to determine the bids according to the applicable harvesting methods and demands for the end use.

Information collected for tactical forest management planning has not been found accurate for this purpose (Haara *et al.*, 2019; Holopainen *et al.*, 2010; Vergara *et al.*, 2015). Other publicly available sources for pre-harvest information include thematic layers from multi-source national forest inventories (MS-NFIs) (Kangas *et al.*, 2018) and airborne laser scanning (ALS) (Vauhkonen *et al.*, 2014; Barth *et al.*, 2015), which may be combined with harvester data (Barth and Holmgren, 2013; Maltamo *et al.*, 2019) and bucking simulators (Sanz *et al.*, 2018; Vähä-Konka *et al.*, 2020), but these data either lack accuracy or feasibility to have become commonly utilized in wood sourcing. Further improvements by means of terrestrial/mobile laser scanning or drones with subsequent data analysis are possible (Liang *et al.*, 2016; Kotivuori *et al.*, 2020). Locally manoeuvered measurement devices however rely on an experienced field operator, which similarly to an on-site evaluation by a wood sourcing professional, will lead to high mensuration costs. To decrease these costs, one solution would be to emphasize strategies that enable the collection of applicable and standardized pre-harvest information by means of simple tools and relatively low level of expertise. This would allow, e.g. the non-professional forest owner to perform the actions needed for on-site data collection.

TRESTIMA® Forest Inventory System (Trestima 2020; later referred as Trestima), based on employing a mobile application and smartphone camera for measurements, has been developed to offer a solution and lower the costs. The application guides the user to take several photos, which are considered as samples of the targeted forest. These samples are analyzed by detecting visible trees and their species using a Bitterlich-type relascope principle (angle-count sampling) (Bitterlich, 1984; Rouvinen, 2014; Trestima, 2020). Based on the detected trees, basal area and diameter distribution for each species are calculated on the stand, which provides sufficient pre-harvest mensuration data and can be used for further timber procurement planning (Siipilehto *et al.*, 2016).

Regardless of the applied strategy or the level of expertise employed for collecting the pre-harvest data, field evaluation is slow and prone to errors (Kangas *et al*., 2004). These errors derive from either the inaccuracies of the initial measurements, or the inability of the sample to adequately capture the underlying variation. For example, the experience of the surveyor in allocating the sample to properly cover within-stand variation as well as include non-dominant species may affect the results (Laasasenaho and Päivinen, 1986; Haara, 2003; Haara and Korhonen, 2004; Islam *et al*., 2009). As for the Trestima system, the quality of the results relies on the performance of the underlying algorithms and requires that an adequate number of samples, depending on the complexity of the forest structure, is taken under sufficient visibility. At the moment, a Trestima user can determine the number of samples in two ways. The first alternative is to subjectively select a number of sampling locations from different parts of the stand, relying on the internal performance measures calculated by the application. These measures inform the user on the standard errors estimated from the images, but do not consider the possible variation on areas outside of the sample photos. The second alternative is to allocate the sample points in a regular grid form, which may result in a high number of photos on larger stands and be inefficient in terms of sampling resources.

One solution to ensure the efficient sampling is to use auxiliary data, such as MS-NFI or ALS. In this context, on-site data collection efforts can be narrowed down by rationalizing the sample selection so that the given sample would cover the variation in the auxiliary feature space as adequately as possible (Junttila *et al*., 2013; Grafström *et al*., 2014). This relies on the correlation of auxiliary data with the variables to be measured and aims at a more representative sample with lower level of randomness and smaller errors as compared with simple random sampling (SRS) of similar size (Grafström and Schelin, 2014). Various materials derived from ALS, satellite images, or enhanced products based on these data have earlier been used as auxiliary information for this purpose (Pesonen *et al*., 2009; Tomppo *et al*., 2014; Räty *et al*., 2018). These data sources can be continuous or classified variables, as long as they provide information on forest variation to rationalize the sample selection.

The Trestima system has been tested in Finland both for sample plot measurements (Vastaranta *et al*., 2015) and stand-level inventories (Siipilehto *et al*., 2016), but without auxiliary data to guide the sample selection. Smartphone-based measurements based on Trestima or other software have also been tested in Russia (Rybakov *et al*., 2018), Slovenia (Ficko, 2020) and Spain (Aguilera *et al*., 2021). For each mentioned country, in addition to optical remote sensing data sources (aerial and satellite images), there are regional to national coverages of LiDAR data available for auxiliary information as reported by Kauranne *et al*. (2017), Čeru *et al*. (2017) and Arias-Rodil *et al*. (2018), respectively. Even though the applicability of the proposed methods should be verified case by case, using auxiliary data for smartphone-based forest inventory as such is not restricted to the context of our study, but would be applicable over a wide range of conditions and locations.

We test the applicability of auxiliary data to assist the Trestima application in a pre-harvest evaluation of mature stands marked for cutting. The applied auxiliary information is collected from publicly available remote sensing data sources and used to constitute a supervised sample selection procedure. The samples used for Trestima calculation are subsets from a large number of photos, taken initially in a regular grid design over the whole analyzed stand. We test three sampling methods, namely, SRS and two variants of local pivotal method (LPM), which utilize the auxiliary data in sample selection (Deville and Tillé, 1998; Grafström *et al*., 2012). The LPM-based selection is driven by the underlying variation of the auxiliary data but does not depend on the data source or its acquisition strategy as such, as long as the data have relevance for forest mensuration. We assume that LPM variants will produce more reliable predictions and lower variance than SRS. The results are evaluated with respect to efficiency (samples required) as well as correctness of harvesting value and stem distribution predictions.

Materials and methods

Test sites

The photo-based sampling tests were conducted in July–August 2019 using three stands of mature boreal forest in Finland (Figure 1, Table 1), having areas between ~6 and 12 ha and located in Pohjois-Savo, Etelä-Savo and Päijät-Häme provinces. In terms of species, evaluation concerned Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) H. Karst.), silver birch (*Betula pendula* Roth.) and downy birch (*Betula pubescens* Ehrh.), of which the latter two were pooled and considered as a single birch species. Of the three stands, the first one was structurally the most homogeneous and relatively open, having the lowest stem count and basal area as compared with the other two stands. It was co-dominated by Norway spruce and Scots pine but characterized by the highest proportion of photos with trees of only single species identified. Stand 2 had considerably more variation, containing large areas dominated by mature Scots pines but also dense patches of young Norway spruces, which were growing principally as understory trees. This heterogeneity is reflected by the markedly highest stem count and the lowest proportion of single-species photos of all the stands. Stand 3 had intermediate structural complexity as compared with the other stands and was dominated mainly by uneven-aged Norway spruces with scattered trees of other species. In terms of proportion of single-species photos, basal area, stem count and total volume, stand 3 was ranked between the two other focused stands.

Auxiliary data

Auxiliary data sources included two forest-related data sets, ALS data, and ortho images (Table 2). Forest resource data (FRD) from the Finnish Forest Centre (Finnish Forest Centre, 2020) and the MS-NFI data from the Natural Resources Institute Finland (Mäkisara *et al*., 2019) are both predicted based on field measurements and remote sensing data and distributed as 16 x 16 m raster data sets with matching dimensions and orientation. The first is intended at supporting management decisions of privately owned forests, and the latter producing inventory data for all the forested land. The difference between them is that construction of FRD utilizes ALS, which is three-dimensional data (3D) whereas

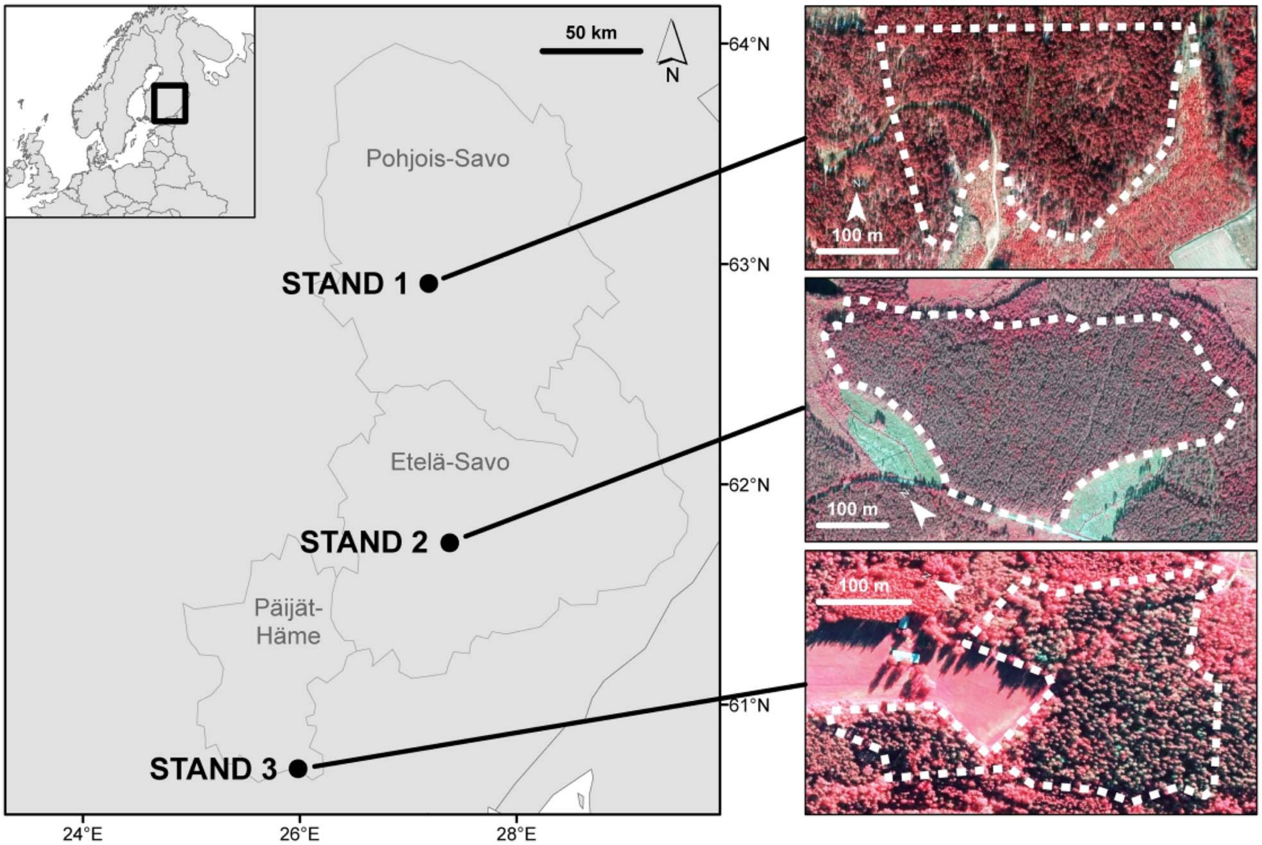

Figure 1 Location of the stands and their borders overlayed on aerial images (map sources: EuroGeographics/UN-FAO, National Land Survey of Finland 2021).

Table 1 General characteristics of the stands, derived from the Trestima results using all the available sample photos (BA = basal area, V = volume, σ = standard deviation). For single species photos, only species with predicted basal areas of 1 m^2ha^{-1} or more were included in the evaluation.

Stand	Size (ha)	Photos	Single species photos (%)	BA; total (m^2ha^{-1})	BA; σ (m^2ha^{-1})	Stems (ha^{-1})	Total V (m^3ha^{-1})	Pine V (%)	Spruce V (%)	Birch V (%)	Other V (%)
1	8.56	300	38.2	22.8	10.1	645	206.8	34.6	56.2	7.2	2.1
2	12.30	460	19.5	32.5	9.51	1380	283.5	70.1	18.3	9.5	2.1
3	5.99	208	26.4	27.5	11.7	688	271.6	20.0	65.8	8.9	5.3

MS-NFI is based only on two-dimensional (2D) data sources, primarily satellite images. Both data were available from the targeted stands as updated between 2016 and 2019, and a set of variables with expected high importance on the sampling procedure was selected from them.

The two remaining data sets, ALS and ortho images, were both produced by the National Land Survey of Finland. ALS data had been acquired in 2010–2012 and ortho images in 2017–2018. The time gap between the ALS scanning and photographing was expected to have some effect on the results, but the data were still regarded applicable for indicating the most important variation on the studied stands. Variables derived from both ALS data and ortho images, as described below, were calculated using the same 16 x 16 m cells as the forest data sets.

The ALS data were scanned at a relatively low density of 0.5 points per m^2, and its height values were first normalized to the ground level using a digital elevation model at 2 m resolution. A set of the extracted variables, as presented in Table 2, was determined based on previous forest resource studies in similar conditions (Gobakken *et al.*, 2015; Nilsson *et al.*, 2017; Tomppo *et al.*, 2017).

Ortho images, having a ground resolution of 0.5 m per pixel, had been captured mostly in the spring during leaf-off time due to their primary use for terrain mapping. Variables calculated from them included spectral values as well as textural features according to grey level co-occurrence matrix (GLCM), which were utilized to describe both spectral and spatial within-stand variation (Haralick *et al.*, 1973; Packalén, 2009; Tuominen *et al.*, 2014).

Table 2 Auxiliary variables used in the study.

Data set	Producer	Type	Extracted variables
Forest resource data (FRD)	The Finnish Forest Centre	Raster	- Basal area of pine, spruce and deciduous trees—volume of pine, spruce and deciduous trees—average age of pine, spruce and deciduous trees—basal area, volume and average age of all trees
Multi-source NFI (MS-NFI)	Natural Resources Institute Finland (Luke)	Raster	- Basal area of pine, spruce, birch and other deciduous trees—basal area and volume of all trees—average diameter, height and age of all trees
Airborne laser scanning (ALS) data	National Land Survey of Finland (NLS)	Point cloud	- Mean, max and standard deviation of the first-of many and only return z values—ratio of first-of-many and only returns to all returns—proportion of ground returns (LAS 2.0 class 2 based on all returns)—proportion of canopy returns ($z > 1.3$ m, all returns)—10%, 50%, 75%, 90% and 95% percentiles of all returns' z values
Ortho images	National Land Survey of Finland	Raster	- Mean and standard deviation values of green, red and near-infrared bands—image textures from grey level co-occurrence matrices, including correlation, second moment, entropy, dissimilarity, contrast, homogeneity and variance

GLCM textures were calculated as a mean value of directions 0°, 45°, 90° and 135°.

Photographs

To cover the within-stand variation and provide enough material for sub-sampling, photographs needed as Trestima input data were taken throughout the stands in a regular grid design, following the cell size and orientation of the auxiliary data. Figure 2 illustrates the photographing spots on stand 1, and their actual deviation from the regular grid as recorded in the field by a smartphone GPS. Photographing spots were set to every second corner of the auxiliary data cells, i.e. 32 m apart from each other in cardinal directions, which was considered a suitable distance according to the assumed visibility within the stands and easing the match between the sample photos and the auxiliary data. From each spot, photos were taken towards the north-east, south-east, south-west and north-west directions, therefore totalling four photos per spot. This setup resulted in 52–115 separate spots and 208–460 photos taken from each stand, respectively, depending on the stand size and shape. Average time used for photographing was 151–167 seconds per spot, including transitions.

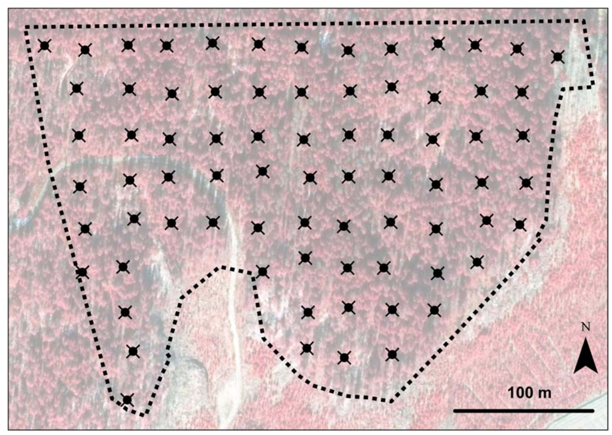

Figure 2 Realized locations of the photographing spots (points) as recorded by the smartphone GPS receiver and directions of single sample photos (lines), visualized for stand 1 (map source: National Land Survey of Finland 2021).

Trestima processing

Trestima calculates species-wise basal areas for each photo using a relascope-type approach with multiple basal area factors, and extracts stem diameters at breast height (DBH) by proprietary methods with assistance of image orientation at the moment of photo capture. Then, using the results of the single photos and further processing algorithms, stem distribution is produced for the whole stand, indicating the number of stems divided by species and condensed into DBH classes at 2 cm lags. Stem distribution is in the operative application additionally smoothed to provide a more realistic outcome, but this smoothing functionality was disabled in our study to provide better comparability between the sampling runs. For the analyses, we used the image-wise basal areas for each of the detected species as well as the final stand-wise stem distribution.

Photos were inserted to the Trestima system using subsamples of all the available photos. Sample sizes were defined proportionally to the total number of photos, therefore differing between the stands but having approximately similar density per areal unit. The primary sample size on each run was decided to be 7.5 per cent of all the photos, which still can be considered as a small enough sampling fraction to reveal the differences

Table 3 Number of photographing spots and individual photos on different sampling levels (L1–L3).

	L1		L2		L3	
Stand	Spots	Photos	Spots	Photos	Spots	Photos
1	3	12	4	16	2	8
2	6	24	8	32	4	16
3	9	36	12	48	6	24

between the sampling methods. Thus, each photo in the sample corresponded to about 0.35 ha of stand area. To better evaluate the effect of sample size regarding to the different sampling methods, additional sample sizes were tested with multiplication factors of 0.5 (i.e. 3.75 per cent of all the photos) and 1.5 (11.25 per cent). The three sampling levels are later referred as L1, L2 and L3, as from the smallest to the largest.

Sample units for selection were whole photographing spots including four individual photos shot at different directions, which resulted to the closest match with the targeted sampling levels. This was intended at first, confirming a better inclusion of different photographing directions in the sample, and second, enabling selection of spots using averaged values of the auxiliary variables. It was therefore reducing both the uncertainties related to photographs (slightly incorrect locations or directions) and auxiliary data (effects of anomalous pixel values, or inaccuracies in georectification). All the applied sample sizes, as presented in Table 3, also fulfilled the recommended minimum number of photos for the Trestima analysis.

Sampling procedure

Three sampling methods were used: SRS with no assistance of auxiliary variables, and LPM with equal inclusion probabilities, which was applied with and without optimization. For each stand and sampling level, 3000 SRS samples were first generated to calculate the reference values for evaluation, as no field-measured reference data was available. This procedure was based on the assumption that the applied Trestima algorithms depend partially on the number of images and, therefore, comparison of the results is unbiased only within a similar sample size.

LPM targets to a sample, in which the distributions of auxiliary variables in the chosen sample and the whole population are similar in all dimensions of the auxiliary data. The sample selection in LPM is performed by promoting and impeding similar population units in respect to auxiliary data. For the two LPM variants, separate runs were performed for all the individual auxiliary data sets as well as using a combination of them, thus permitting evaluation and comparison of potential differences between the auxiliary variables. Results were generated by running Trestima calculations 1000 times for each stand, sampling level, applied method and auxiliary data source.

LPM sampling without optimization refers to picking a single LPM-based sample to initialize a Trestima calculation. For optimized version, however, $S = 2000$ LPM samples were generated prior to a Trestima run, and only the best sample according to the following criterium was chosen to be used:

$$\min_{S}\left(\sum_{j=1}^{a}\sum_{i=1}^{3}\left|Q_i^{(p,j)} - Q_i^{(s,j)}\right|\right), \tag{1}$$

where s is sample, p is population, j is a dimension of auxiliary data, Q is a quantile of auxiliary data distribution. In the measure only quantiles $i = 1,2,3$ corresponding to 25 per cent, 50 per cent and 75 per cent of cumulative distribution, respectively, were considered. The best sample had the smallest absolute distance in auxiliary data distribution from the population in chosen cumulative points (Eq. 1). In addition, given the limited number of population units and therefore potential for picking similar samples repeatedly, the chosen sample for optimized LPM was only accepted if it was not selected before.

For LPM-based selection, dimensionality of the auxiliary space was reduced by selecting four stand-specific variables for each set of runs. These variables were expected to correlate with the inter-stand forest variation but not significantly with each other. Variable selection was carried out with the following procedure:

1. The Trestima analysis for the given stand was run using all the available sample photos. This resulted in photo-wise predictions of basal areas for all the detected species, which were summed for each photographing spot (four photos taken to different directions) at the levels of individual species, as well as the total basal area.
2. Correlations between the predicted basal areas and the auxiliary values of interest, averaged from four 16 x 16 m pixels surrounding the spot, were calculated.
3. Auxiliary variables were arranged starting from the strongest absolute correlation with any of the basal area strata, which determined their importance order.
4. Four most important individual variables were selected, and their cross-correlations were calculated.
5. If any of the absolute correlations exceeded a value of 0.75, or several selected variables were referring to the same species (concerning the two forest-related data sets), the variable among these with smallest initial correlation with Trestima basal areas was dropped out and replaced by the next one on the importance order.

This procedure was continued until the conditions were satisfied, or there were no more variables left to replace. The fifth LPM variant, i.e. combination of the auxiliary data sources, was constructed similarly with exception that the selected variables always included one from each of the four initial data sets, and

Table 4 Selected variables at their importance order (1–4) for each stand and auxiliary data set (BA = basal area, V = volume). Data sets, their abbreviations and details on the single variables are presented in Table 2.

Stand	Data set	Variable 1	Variable 2	Variable 3	Variable 4
1	FRD	BA pine	BA spruce	BA total	V total
	MS-NFI	Average diameter	BA birch	BA spruce	BA other deciduous trees
	ALS	Mean of first return *z* values	Maximum of first return *z* values	Proportion of first returns	10% percentile of *z* values
	Ortho images	Mean value of red band	Standard deviation of near-infrared band	Contrast	Second moment
	Combined	BA pine (FRD)	Mean of first return *z* values (ALS)	*V* all trees (MS-NFI)	Mean value of red band (Ortho)
2	FRD	*V* pine	BA spruce	BA deciduous trees	BA total
	MS-NFI	Average diameter	BA birch	BA spruce	BA other deciduous trees
	ALS	Mean of first return *z* values	Proportion of first returns	10% percentile of *z* values	90% percentile of *z* values
	Ortho images	Mean value of red band	Standard deviation of near-infrared band	Entropy	Correlation
	Combined	BA spruce (FRD)	Mean of first return *z* values (ALS)	BA birch (MS-NFI)	Entropy (Ortho)
3	FRD	BA pine	*V* spruce	BA total	*V* total
	MS-NFI	Average diameter	BA birch	BA spruce	BA pine
	ALS	Mean of first return *z* values	Maximum of first return *z* values	Proportion of first returns	75% percentile of *z* values
	Ortho images	Standard deviation of green band	Standard deviation of near-infrared band	Variance	Contrast
	Combined	*V* spruce (FRD)	Mean of first return z values (ALS)	BA pine (MS-NFI)	Contrast (Ortho)

potential replacements were made only within the respective set. The selected variables for each stand and auxiliary data set are presented in Table 4.

Evaluation of the results

After completing the sample based Trestima runs, the results were evaluated primarily using two different strategies, which focused on indicating the differences between the SRS and LPM sampling methods. First, stem distributions of each stand, sampling level, sample selection method and applied auxiliary data (for LPM-based samples) were compared for all the focused tree species. This was based on modified Reynold's error index (EI), proposed by Reynolds et al. (1988) and scaled to relative frequencies by Packalén and Maltamo (2008). Index calculation for one Trestima run was as follows:

$$e = \sum_{i=1}^{k} 0.5 \left| \frac{f_i}{N} - \frac{\hat{f}_i}{\hat{N}} \right|, \qquad (2)$$

where f_i and $\hat{f}_i$ are the reference and predicted number of stems in a single DBH class, N and $\hat{N}$ reference and predicted number of stems over all the DBH classes, and k is the number of classes, respectively. Multiplying the frequency differences by 0.5 will scale the result between 0 (perfect fit) and 1 (totally non-overlapping distributions). It should, however, be emphasized that the applied EI formula compares only the similarity of relative distributions but will not indicate potential differences in the total stem counts.

To make the evaluation strategy less susceptible for focusing on minor distribution differences, initial reference distribution DBH classes at 2 cm lags were combined to larger 6 cm lags. Then, the final EI result was calculated by averaging the value e of all the Trestima runs ($n = 1000$). To calculate the EI value for SRS, only a subset of 1000 first runs out of 3000 (as used for calculating the reference values) were applied to correspond to the size of the LPM sample. In case Trestima had predicted no stems of the focused tree species, therefore making the second denominator zero, a value of 1 was assigned to the respective e. In addition to calculating EI values separately for the three species, distributions were also compared similarly at the level of all the stems.

The second evaluation strategy focused on the monetary value of the stand, i.e. indicating the correctness of the detected stems with emphasis on large trees, having the highest importance for harvesting plans. As the applied Trestima results did not include tree heights, the sample tree data bank from the Finnish National Forest Inventory was used. First, we estimated taper curve for each NFI sample tree, using species, field-measured DBH and tree height as regressors (Laasasenaho, 1982). The taper curve was applied to calculate the volumes of saw log (at least 400 cm long with diameter of 15 cm or more) and pulpwood (at least 200 cm long with diameter of 7 cm or more) assortments of the respective tree. Then, species-wise relationships between the DBH and the two assortment volumes were modelled using cubic splines. These spline-based models were further applied to estimate the assortment volumes of a single tree for each Trestima-detected stem distribution class by using the respective mean diameter. Finally, stem distributions deriving from Trestima runs were converted to assortment-wise and total volumes of the stand by multiplying these values by the number of stems and prices paid of the respective timber assortments in 2018 (Luke, 2019). In addition to Scots pine, Norway spruce and the two birch species (also combined in the statistics), Trestima recognized a small number of other broadleaved trees. For them, the saw log and pulpwood volumes were calculated similarly to birch, and with price corresponding to 50 per cent value of birch derived from their low industrial importance.

Reference monetary values for each timber assortment and total stand value were averaged from all the SRS runs ($n = 3000$). Comparative statistics between the SRS and different LPM-based sampling methods were calculated using relative efficiency (RE), derived from mean-squared error (MSE):

$$\mathrm{RE}_i = \frac{\mathrm{MSE}_{srs}}{\mathrm{MSE}_i}, \tag{3}$$

where MSE_{srs} and MSE_i are the MSEs of 1000 first SRS-based runs and the LPM samples under investigation, respectively. Further, to evaluate the significance of differences between the three methods, the RE values of each stand and sampling level were compared using *t*-tests. Evaluation between the LPM and SRS strategies was based on one sample *t*-tests, examining whether the RE values of the respective LPM variant differed significantly from 1 (i.e. the level of SRS regarding to MSEs, as derived from Equation 3). All the RE values of different timber assortments and auxiliary data sets were included with equal weights, with intention of evaluating the methods as such rather than their ability to find high-value timber products in this particular case, or performance of any single auxiliary data source. To evaluate the differences of the two LPM variants, two-sample *t*-tests were applied to compare their means. All the significances were calculated as one-tailed tests, expecting RE values to increase SRS < non-optimized LPM < optimized LPM.

In addition to calculating EI and RE, distribution of monetary values over all the Trestima runs were visualized as histograms for two selected cases.

Results

The EI values (Figure 3) varied principally according to the tree species abundance and the applied sample size. Errors were always highest for birch, which was the least common species with 7.2–9.5 per cent proportion depending on the stand, and lowest for either Norway spruce or Scots pine depending on their dominance. Variation in the absolute levels of EI values between the stands derived largely from the number of photos used in the Trestima calculation, as indicated by the total stem distribution (Figure 4). The results of using optimized LPM sampling were characterized by relatively high variation depending on the applied auxiliary data, which extended the EI range to both improving and deteriorating directions as compared with SRS.

RE (Table 5) indicated improvements initiated by the LPM methods, i.e. use of auxiliary data, which varied considerably between the targeted stands, focused timber assortments, and sampling levels, respectively. Generally, auxiliary data improved the evaluation of stand value ($\mathrm{RE} > 1$) and in several cases more than halved the sample-based variance ($\mathrm{RE} > 2$). On the contrary, however, not all the timber assortments were benefitting from applying the LPM sampling ($\mathrm{RE} \approx 1$), and part of the results were even deteriorated as compared with SRS. For most of the evaluated individual timber assortments, optimized LPM performed better than non-optimized. The reference values had some variation depending on the sampling level due to their calculation separately for each sample size. As averaged from n Trestima runs, the reference level appeared to stabilize after approximately $n = 500$–1000 with relatively little oscillation and was therefore regarded as a suitable value for comparison at the given sample size.

The assistance of auxiliary data was more obvious on stands 1 and 3 as compared with stand 2. In terms of the forest characteristics, stand 2 differed from the other two sites by having the largest total area and the highest stem count, in addition to be the only one dominated by Scots pine. Stand 2 also appeared to benefit from LPM mainly at sampling level 1 whereas the two other stands rather indicated improvements at proportionally larger sample sizes. It should however be noted that the absolute sample sizes (i.e. the number of individual photos) for stand 2 were also larger compared with other stands, e.g. $n = 16$ at sampling level 1 as compared with $n = 12$ for stand 1 and $n = 8$ for stand 3, respectively. The highest RE values on stand 2 were also mainly concentrated on the logs of non-dominant species (Norway spruce and birch), which were not further reflected to the total value of the stand. In general, total value will not average the single assortments due to its dependence on correct detection of the high-value assortments but lower sensitivity for species distribution. For stands 1 and 3, LPM sampling improved both the evaluation of most individual timber assortments as well as the total stand value. On average, evaluation of Norway spruce log was the most successful among the focused timber assortments and the only one reaching RE values of over 3, but differences between the stands were however large.

Regarding to the auxiliary data sources, highest average RE values were associated to combined use of the applied data sets, which was closely followed by the FRD by the Finnish Forest Centre. They were also the only data sets where features were derived from both 2D (spectral/textural) and 3D (height) information. Of the remaining data sets, ALS performed slightly better than MS-NFI, and the weakest of the single auxiliary data sources were ortho images. Within single stands, most of the data sets had however mixed performance, thus generally lacking the potential to improve the results of all the individual timber assortments.

Based on RE, the differences between the sampling methods were significant (Table 6). For every stand and sampling level, applying any LPM-based sampling method instead of SRS improved efficiency values highly significantly. In most cases, optimized LPM strategy also outperformed the non-optimized version significantly ($P < 0.05$), with exception of sampling level

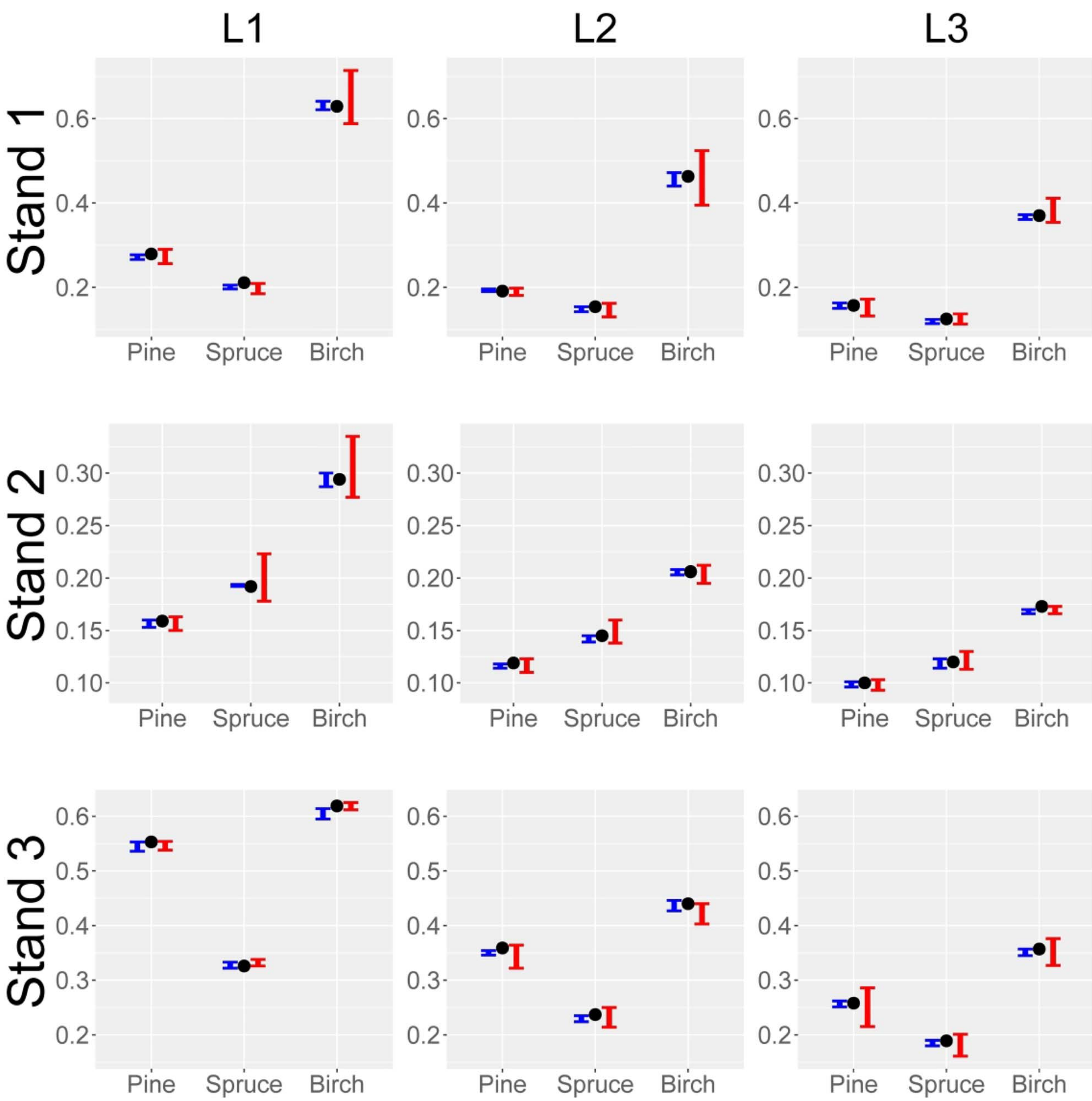

Figure 3 Reynold's error index statistics for all the stands, sampling levels, and targeted tree species. In each subplot, the error index value for SRS is presented as a black dot, and the ranges of LPM values with different auxiliary data sources as bars, including both non-optimized (blue, left) and optimized (red, right) sampling strategies.

1 on stand 3, which had the smallest absolute number of photos of all the samples.

To understand the differences between the sampling methods and effects of the auxiliary data, two common cases of sample-based value distributions are presented in Figure 5. Case A (left) is the targeted behaviour of the LPM method as compared with SRS, presenting the total value of stand 1 at sampling level 2. In this case, LPM works efficiently with assistance of ALS in order to narrow down the sample variation and concentrate more samples close to the reference value. This tendency is particularly notable with the optimized LPM, which shortens the distribution tails and reduces the likelihood of strong under- or overestimates of the stand value, resulting in a RE of 2.90. On the contrary, case B (right) receives little help from applying the LPM-based sampling. It presents the Scots pine log value on stand 2 at sampling level 2, and indicates a typical case associated with low RE: histograms between the different sampling methods are relatively similar, and LPM optimization shifts the distribution mean further away

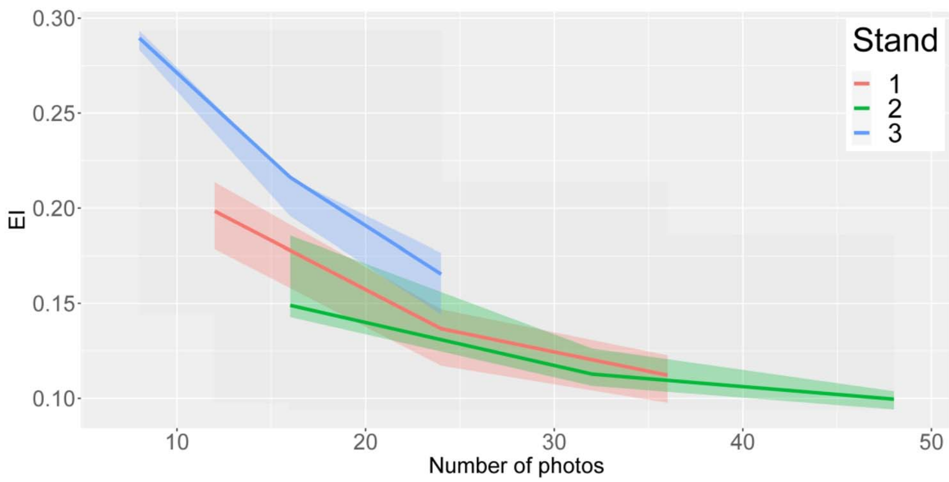

Figure 4 Reynold's error index statistics for the total stem distribution, presented for all the stands as a function of the number of individual photos. Error index values based on SRS are presented as solid lines, and ranges of the respective LPM values (both non-optimized and optimized) with different auxiliary data sources as shaded areas.

from the reference value. As this consequently increases the MSE, RE drops to 0.85. Many of the low RE values were associated to overestimated stem count rather than errors related to diameter distribution.

Discussion

Prediction of timber assortments in this study follows the widely applied scheme in Finland, i.e. first predicting the diameter distribution of trees, and then converting representative trees of the distribution into tree-wise timber assortments with assistance of taper curve functions (Kangas and Maltamo, 2002). The use of the Trestima application will make this procedure effortless for a user, as collecting the required data needs no specific measurement skills but only taking photos using a smartphone according to easy-to-follow instructions. If no auxiliary data are used, the representativeness of the sample photos is ensured by the spatially dispersed selection of photographing locations. As forest stands are generally relatively small and homogeneous in Finland, even a random sample would often lead to sufficiently accurate results. But in some cases, as presented in this study, these predictions can be biased, and auxiliary data can assist in lowering the variance of estimates. Given that photographing locations in our study were predetermined and not following Trestima instructions regarding to the selection of sites or shooting directions, the actual Trestima results are not likely to be as dispersed as the values presented, e.g. in Figure 5. The calculated statistics, however, are expected to be applicable over various sample selection procedures, given that the primary challenge is related to picking an unbiased sample to cover all the essential stand variation.

As shown by the RE statistics, application of auxiliary data can substantially improve the sampling procedure and ensure selecting a more representative sample as compared with SRS. RE-related advantages of LPM sampling may not be gained at very small or large sample sizes, but rather at intermediate levels which enable covering the most essential variation without allocating resources for repetitive sampling. This tendency would however be expected to be shifted toward larger sample sizes with increased within-stand variation, given the larger range of conditions needed to be covered for gaining an unbiased sample. Regardless of the sampling level, LPM optimization distributes the sampling locations more efficiently according to the local variation, therefore gaining higher RE. Differences of the efficiency between the three stands are likely to be connected to their structural characteristics as well as the evaluation strategy by monetary value. The best results for stand 1 would be explained by its relatively homogeneous composition of mature Scots pine and Norway spruce without widespread undergrowth, both of which having high importance for timber and pulp assortments. Considerably worse RE of stand 2, however, are likely to derive from dense concentrations of young Norway spruces, which may hinder Trestima's image-based evaluation and initiate structural variation within the stand. These Norway spruces however have low importance in terms of monetary value, which further leads to unimproved or even deteriorated RE of LPM-based sampling as compared with SRS.

It should be acknowledged that the results presented in this study are based on DBH distributions derived by means of image analysis and pre-existing data on their relationships with other stem dimensions but lacking independent data on these factors. This includes various uncertainties related both to underlying data as well as its processing. Siipilehto et al. (2016) found Trestima-based predictions accurate and unbiased as compared with a number of other prediction alternatives, but prone to underestimation of diameters and basal areas, particularly if a small number of photos was used. The study setup of Siipilehto et al. (2016) is however not comparable with our study due to fundamentally different photo sampling and modelling. Further, our study ignores technical tree quality. Recently, Vähä-Konka et al. (2020) compared timber assortment estimates, derived directly from the FRD data and aggregated to the stand level, against actual logging data recorded by harvesters. They found

Table 5 RE statistics and reference (Ref.) monetary values for all the stands, sampling levels (L1–L3) and auxiliary data sets, divided by species-wise timber assortments as well as indicated as total value. Minor quantities of other broadleaved species are not individually presented but included in the total value, thus not equalling the sum of single assortments. Data sets and their abbreviations are presented in Table 2.

A. Stand 1

		Ref. €ha^{-1}	Non-optimized local pivotal method					Optimized local pivotal method				
			FRD	MS-NFI	ALS	Ortho	Combined	FRD	MS-NFI	ALS	Ortho	Combined
L1	Pine log	2966	1.07	0.89	0.93	0.89	1.12	1.33	1.12	0.89	0.84	1.49
	Pine pulp	371	1.41	1.09	1.06	1.07	1.31	1.60	0.71	1.54	1.15	1.68
	Spruce log	5319	1.41	1.46	1.34	1.00	1.36	1.73	1.21	2.52	1.19	1.72
	Spruce pulp	561	1.29	1.14	1.18	1.07	1.23	1.38	0.94	1.20	1.22	1.59
	Birch log	525	1.16	1.02	1.15	1.15	1.22	1.30	1.89	1.19	0.65	1.60
	Birch pulp	67	1.02	1.03	0.94	0.93	1.08	1.72	0.91	2.19	1.67	1.80
	Total value	9868	1.40	1.25	1.44	1.01	1.31	1.77	1.03	2.74	1.04	1.54
L2	Pine log	3058	1.24	1.06	1.01	1.05	1.34	1.61	1.40	0.94	1.14	1.72
	Pine pulp	362	1.53	1.17	1.37	1.26	1.53	2.80	1.10	2.17	1.29	1.57
	Spruce log	5392	1.50	1.58	1.57	1.20	1.61	2.34	2.29	1.50	1.32	2.07
	Spruce pulp	542	1.30	1.22	1.20	1.22	1.46	1.12	1.16	0.94	1.21	1.32
	Birch log	532	1.23	1.15	1.29	1.14	1.22	1.53	1.44	1.54	1.20	1.42
	Birch pulp	69	0.93	0.94	0.95	1.08	1.03	2.06	1.11	0.66	1.23	1.98
	Total value	10019	1.43	1.48	1.87	1.05	1.44	2.16	2.02	2.90	1.13	2.07
L3	Pine log	3139	1.30	1.09	1.14	1.15	1.50	1.68	0.91	1.29	1.33	1.85
	Pine pulp	350	1.80	1.26	1.34	1.25	1.48	1.95	0.77	1.75	1.50	1.92
	Spruce log	5534	1.78	1.83	1.67	1.22	1.57	2.15	1.71	2.19	1.15	2.06
	Spruce pulp	524	1.15	1.15	1.22	1.19	1.35	0.93	1.30	1.19	1.31	1.12
	Birch log	535	1.14	1.21	1.25	1.04	1.23	1.50	1.64	1.30	0.93	1.54
	Birch pulp	65	1.05	0.90	1.00	1.10	0.94	1.35	1.20	1.49	1.04	1.93
	Total value	10212	1.64	1.67	1.76	1.19	1.43	1.77	2.16	2.30	0.64	1.82

B. Stand 2

		Ref. €ha^{-1}	Non-optimized local pivotal method					Optimized local pivotal method				
			FRD	MS-NFI	ALS	Ortho	Combined	FRD	MS-NFI	ALS	Ortho	Combined
L1	Pine log	10602	1.05	1.01	1.00	1.12	1.18	1.28	1.35	1.08	1.44	1.32
	Pine pulp	444	0.92	1.09	0.92	1.12	1.00	0.99	0.88	1.13	1.09	1.06
	Spruce log	1392	1.03	1.25	1.08	1.07	1.19	3.15	2.80	2.52	2.58	2.71
	Spruce pulp	598	1.15	1.12	0.99	1.17	1.15	1.42	1.10	1.26	0.90	1.36
	Birch log	829	1.16	1.01	0.92	1.10	1.13	1.94	2.31	0.62	2.12	1.73
	Birch pulp	238	0.95	1.04	1.03	1.10	1.15	1.01	1.41	1.37	1.07	0.82
	Total value	14185	0.95	0.96	1.00	1.03	1.07	1.06	1.12	0.96	1.07	1.04
L2	Pine log	10592	1.18	1.12	1.19	1.26	1.23	1.31	0.85	1.50	1.40	1.34
	Pine pulp	443	0.99	0.98	1.00	1.14	1.01	1.16	0.93	1.10	1.13	0.85
	Spruce log	1401	1.12	0.99	1.11	1.28	1.16	1.19	1.12	1.36	1.27	1.27
	Spruce pulp	580	1.08	1.10	1.21	1.26	1.18	1.21	0.94	1.34	1.07	1.10
	Birch log	825	1.17	1.25	1.28	1.29	1.26	1.97	1.23	1.53	2.02	1.35
	Birch pulp	234	1.13	1.05	1.05	0.90	1.01	1.09	1.45	1.10	1.19	1.04
	Total value	14165	0.91	0.96	0.99	1.00	1.04	1.01	0.83	1.13	1.15	1.13
L3	Pine log	10688	1.26	1.14	1.21	1.18	1.23	1.41	0.90	1.33	1.33	1.30
	Pine pulp	433	1.09	1.04	1.23	1.09	1.08	1.23	1.09	1.16	1.37	1.04
	Spruce log	1420	1.19	1.07	1.07	1.34	1.20	1.34	1.10	0.93	1.27	1.21
	Spruce pulp	575	1.15	1.11	1.21	1.18	1.11	1.14	1.25	1.34	1.16	1.17
	Birch log	827	1.26	1.15	1.18	1.12	1.10	1.31	1.20	1.34	1.62	1.41
	Birch pulp	232	1.05	1.10	1.10	1.08	0.96	1.04	1.33	1.06	1.24	1.19
	Total value	14268	0.95	0.96	0.96	1.06	1.03	1.05	0.78	0.99	1.04	1.03

(Continued)

Table 5 Continued.

C. Stand 3

		Ref. €ha[-1]	Non-optimized local pivotal method					Optimized local pivotal method				
			FRD	MS-NFI	ALS	Ortho	Combined	FRD	MS-NFI	ALS	Ortho	Combined
L1	Pine log	2804	1.17	1.14	1.07	1.04	1.17	1.10	1.12	1.02	0.99	1.16
	Pine pulp	90	0.99	1.05	1.27	1.31	0.96	1.04	1.13	1.05	1.04	1.07
	Spruce log	8773	1.23	1.12	1.17	1.07	1.38	1.28	1.20	1.18	1.09	1.30
	Spruce pulp	489	1.04	1.30	1.04	1.10	1.30	1.06	1.17	1.14	1.22	1.18
	Birch log	818	0.95	1.24	0.97	1.23	1.16	1.05	1.07	0.98	1.26	1.14
	Birch pulp	112	1.02	1.19	1.07	1.33	1.07	1.07	1.10	1.00	1.28	1.15
	Total value	13266	1.20	1.09	1.24	1.03	1.37	1.20	1.10	1.23	1.03	1.20
L2	Pine log	2900	1.40	1.41	1.15	1.22	1.60	1.90	2.48	1.25	1.33	2.22
	Pine pulp	80	1.06	1.17	1.07	1.05	1.11	1.15	1.53	1.12	1.38	1.67
	Spruce log	9022	1.33	1.30	1.44	1.13	1.60	1.92	1.96	2.39	1.24	3.51
	Spruce pulp	471	0.87	0.98	1.06	0.92	1.01	0.99	1.18	1.00	1.23	1.33
	Birch log	855	1.02	1.35	0.90	1.16	1.07	1.48	1.60	1.18	1.67	1.55
	Birch pulp	121	1.24	1.31	1.07	1.39	1.37	2.17	2.62	1.25	1.70	1.87
	Total value	13628	1.41	1.21	1.73	1.10	1.62	1.67	1.36	2.61	1.19	2.91
L3	Pine log	2921	1.54	1.61	1.12	1.26	1.65	2.17	2.04	1.13	1.12	2.04
	Pine pulp	76	1.25	1.20	1.07	1.27	1.16	0.94	1.54	1.73	1.11	1.26
	Spruce log	9140	1.39	1.35	1.29	0.97	1.66	1.38	1.91	2.08	1.03	2.93
	Spruce pulp	463	0.90	0.90	0.93	0.96	1.04	1.04	0.88	1.02	1.73	1.47
	Birch log	847	1.33	1.71	1.09	1.43	1.25	1.96	1.58	1.20	1.73	1.50
	Birch pulp	123	1.37	1.45	1.09	1.40	1.48	1.52	1.62	1.04	1.72	1.74
	Total value	13753	1.37	1.20	1.62	0.93	1.61	1.48	1.38	1.30	1.07	2.34

Table 6 RE of different timber assortments (Table 5), condensed as mean values for each stand, sampling level (L1–L3) and LPM variant. The *P*-values derive from one-tailed *t*-tests, expecting RE values to increase SRS < non-optimized LPM < optimized LPM.

		Non-optimized LPM		Optimized LPM		
		Mean RE value	Difference to SRS (*P*-value)	Mean RE value	Difference to SRS (*P*-value)	Difference to non-optimized LPM (*P*-value)
Stand 1	L1	1.155	<0.001	1.431	<0.001	0.001
	L2	1.276	<0.001	1.585	<0.001	0.001
	L3	1.314	<0.001	1.505	<0.001	0.015
Stand 2	L1	1.063	<0.001	1.459	<0.001	<0.001
	L2	1.111	<0.001	1.219	<0.001	0.015
	L3	1.121	<0.001	1.191	<0.001	0.019
Stand 3	L1	1.145	<0.001	1.126	<0.001	0.778
	L2	1.224	<0.001	1.703	<0.001	<0.001
	L3	1.281	<0.001	1.535	<0.001	0.003

the data otherwise reliable but to overestimate particularly the sawlog volume. This result was mainly because of inability to consider tree technical quality, affecting the factual recovery of the timber assortments and related to poor quality reduction models (Karjalainen *et al.*, 2019). The measures for timber assortments may further depend on the applied bucking parameters which come from the contemporary needs of the sawmills (Malinen *et al.*, 2001; Malinen *et al.*, 2006). The evaluation of theoretical assortment values as presented in this paper, in contrast, rather promotes the role of auxiliary data in covering the essential stand variation especially with respect to the dominant trees that contribute mostly to the sawlog volume and timber value.

In terms of the EI values, LPM-based sampling strategies appear to contribute only to relatively minor improvements (Figures 3 and 4). In addition, the use of optimized LPM leads to high variation depending on the applied auxiliary data, which may partially derive from the applied precondition of accepting only samples not selected before. The apparently low LPM performance as compared with SRS may however derive from a few important reasons. First, as there was no exact validation data for the studied forest stands, we used the Trestima results as the reference values. While this was the most applicable strategy for our study, it is also vulnerable to Trestima-based prediction errors and potential non-detections. A particular problem is

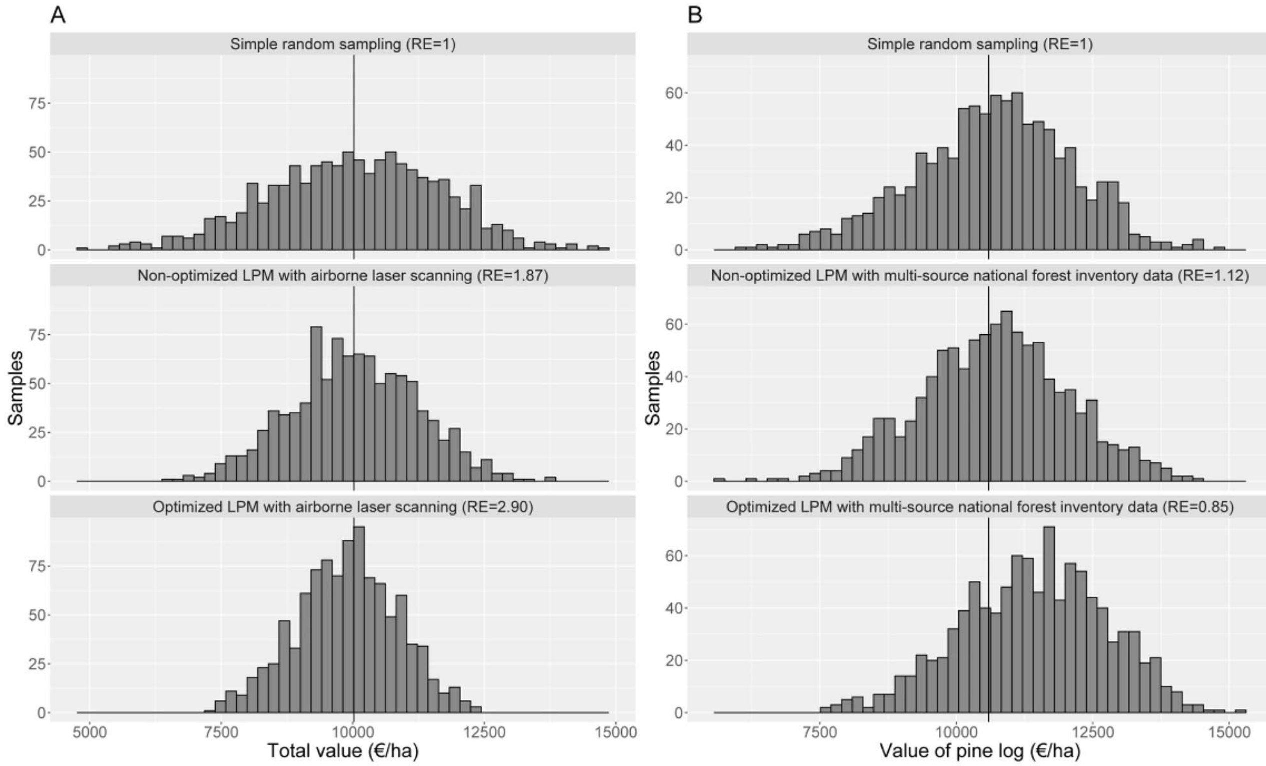

Figure 5 Two case distributions of sample-based total monetary values ($n = 1000$) and their RE values using the three sampling methods, i.e. SRS and two LPM variants. Reference value in each distribution is indicated by a black horizontal line.

caused by younger and denser parts of the stand, which may be often included in the LPM samples, but cause problems for reliable image-based detection. Focusing sample selection on these locations, which are likely to contain higher proportion of problematic images and non-detected trees, will not emphasize the potential advantages of LPM. Second, comparing the stem distributions with equally weighted DBH classes will not separate whether a given sample lacks a tree of 4 cm or 40 cm, which however makes a great difference in terms of tree volume and harvesting opportunities. And third, the applied calculation methodology of EI values was focused on relative distribution differences instead of absolute ones. That is, a correctly shaped distribution with a highly erroneous stem count would gain a lower error as compared with a skewed distribution with a correct number of stems. For these reasons, RE statistics with capabilities of reacting to the number and size of the stems should be emphasized from the perspective of the focused application.

Of the auxiliary data sets used for LPM sampling, the one combining all the data sources provided generally the highest improvement. Its construction was based on selecting one variable from each data source, which may not ensure the optimal performance but however offers an importance ranking through the selection order. This order was similar for all the stands, i.e. FRD–ALS–MS-NFI–Ortho (see Table 4), which is a logical result. Auxiliary sources containing 3D data (FRD and ALS) instead of applying only 2D-derived information (MS-NFI and Ortho) improve the sampling efficiency most. Prediction of the FRD data includes ALS data, ortho images and extensive field measurements, which makes them the most comprehensive single data source applied in this study, but at the cost of expensive and tedious production. ALS-derived information will primarily provide data on tree heights, which however correlates strongly with their volumes and monetary values, whereas spectral 2D data assists in detecting differences in species composition. Similarly, field plot data have been applied in the prediction of the MS-NFI data set, but they are primarily based on optical satellite images and lack a 3D data source, which lead to a poorer performance. This also corresponds to the results of Kankare et al. (2015) and Vauhkonen (2018), which emphasize the better performance of ALS-derived features to predict forest biophysical attributes as compared with 2D-derived MS-NFI. Further, the applicability of ALS for guiding the sampling design has been proved in several other studies (Pesonen *et al*., 2009; Grafström and Ringvall, 2013; Yang *et al*., 2019).

Regarding to the importance of single FRD variables, those related to Scots pine and Norway spruce—the two main tree species—are always the most significant. For MS-NFI, however, stronger correlation of average diameter instead of single species could be due to its higher degree of spectral robustness or spatial autocorrelation, given the differing background data of MS-NFI as compared with FRD. This refers particularly to the inclusion of ALS in the construction of FRD, which will not only provide 3D information but also enhances capturing the actual variation within the focused raster cell. As compared with this, MS-NFI is more vulnerable to suffer from variable image quality as well as non-matching resolution and pixel borders between the input and output data. Inaccuracies of the MS-NFI data at a single pixel level are also increased by its optimization to minimize the variance and RMSE of pixel values, which does not always retain the variation of field variables (Katila and Tomppo, 2001;

Katila, 2006; Tomppo *et al*., 2008). For using ALS data alone, the most important output appears to be related to the average tree height (mean of first-or-many or only return *z* values) whereas orthophotos emphasize species distribution (spectral data instead of textural information). The ortho data however have generally relatively poor performance, deriving assumedly from image acquisition in the spring, i.e. during leaf-off time and before growing season, which deteriorates their applicability as auxiliary data source.

Conclusions

Distributing the Trestima photo locations evenly throughout the stand or selecting diverse spots subjectively may provide reasonably good pre-harvest information based on simple tools and no particular requirements for forest mensuration skill. Such strategies are however vulnerable to unintentional bias due to poorly or excessively sampled strata, particularly if the sampling locations are purposively selected. According to our results, various freely available spatial data sources can be applied as auxiliary data to enable objective and rational sampling design and facilitate efficient allocation of inventory resources. Auxiliary variables concentrated on structural variation, i.e. containing 3D information are more efficient as compared with 2D spectral data, but combining various auxiliary data sources will assist in optimizing the performance. Moreover, auxiliary data can also assist better detection of marginal strata, which may have significance depending on the application. The best solution depends on the stand and its primary sources of variation (for example, age or species composition), but gaining a RE of 1.5–2 as compared with SRS appears to be generally feasible.

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Conflict of interest statement

None declared.

Data availability statement

The data underlying this article will be shared on reasonable request to the corresponding author.

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