Estimating Timber Volume using Harvester Data and Airborne Laser Scanner Data from Multiple Acquisitions

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1. Introduction

Airborne laser scanning (ALS) data have played a central role in the field of forest inventory over the last decades (White et al. 2016). Forest attributes are commonly estimated from ALS data by linking field reference data to ALS metrics in statistical models (Næsset 2002). Herein, accurately georeferenced field data are essential, and remain a main cost component in operational forest inventories (Gobakken and Næsset 2008).

In the context of cost saving, data recorded by forest harvesters are emerging as a potential supplement to, or replacement for, traditional field measurements in operational forest inventories (Lindroos et al. 2015). Cut-to-length harvesters measure and store large amounts of data on the dimensions and characteristics of harvested logs. In addition, harvesters are commonly equipped with Global Navigation Satellite System (GNSS) receivers which provide a spatial reference and time stamp for each harvested tree (Olivera 2016).

Newly developed harvester positioning systems enable georeferencing of individual trees with submeter accuracy (Hauglin et al. 2017; Noordermeer et al. 2021). Previous studies have shown that accurately georeferenced harvester data can be linked to ALS data to estimate timber volume (Hauglin et al. 2018) and stem diameter distributions (Maltamo et al. 2019). The mentioned studies used ALS data from a single acquisition, and experimentally installed sensors to monitor the position of the harvester head relative to the machine. Recently developed technology in cut-to-length harvesters of several manufacturers allows for measuring and recording coordinates of harvested trees automatically with standardized sensor hardware (Westerberg 2014; Bhuiyan et al. 2016; La Hera and Morales 2019), enabling extensive and automatic georeferenced tree-level data collection. These data may prove beneficial to a range of inventory applications that fall outside the scope of periodic forest inventories, such as short-term planning of timber harvesting within a region in which a harvester operates. It is therefore important to assess the suitability of data collected by harvesters equipped with industry standard positioning systems for volume estimation, using ALS datasets acquired with different scanners and over multiple years.

The aim of this study was to assess the accuracy of timber volume estimated from harvester data obtained using industry standardized crane sensor systems and differential GNSS positioning, and ALS data acquired over multiple years.

2. Data and Methods

2.1 Harvester data

Harvester data were collected from 33 logging operations between March 2019 and June 2021 using a single-grip Komatsu 931XC harvester. The operations were located in Innlandet county in southeastern Norway. As optional equipment supplied by the manufacturer, a sensor was mounted on the crane which measured the angle between the inner and outer boom (Bhuiyan et al. 2016), enabling improved crane tip positioning. In addition, we replaced the harvester's standard GNSS with a real-time kinematic Septentrio AsteRx-U GNSS receiver, with which tree positions were georeferenced with submeter accuracy (Noordermeer et al. 2021). Harvester production report (HPR) files were exported in StanFord 2010 format (Arlinger et al. 2012) which, among other things, included log volumes and coordinates of crane tip positions during fellings. We summed log volumes for each harvested stem and linked the volumes to the corresponding crane tip positions.

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2.2 ALS Data

ALS data were acquired in the years 2013, 2016, 2017, 2019 and 2020 (Table 1) covering different areas which in some cases overlapped. Therefore, the delay between ALS and harvester data acquisition varied from one to eight years. For each logging site, we clipped the most recently acquired ALS data from within the spatial extent of the site, and classified the laser echoes as ground or non-ground. We then normalized the ALS data, i.e., the height above ground was calculated for all echoes classified as non-ground.

Table 1. Airborne laser scanning acquisition parameters.

Year	Instrument	Time period	Pulserate (kHz)	Scan rate (Hz)	Flying altitude (m)	Echo density (m^{-2})
2013	TopEye S/N 444	May-July	200	92	1500	7.7
2016	Riegl LMS Q-1560	September	400	100	2900	3.2
2017	Riegl VQ-1560 I	July	700	240	2300	6.8
2019	Leica ALS70-HP	August	495	69	1150	5.9
2020	Riegl VQ-1560 II	June	749	158	1100	10.4

2.3 Enhanced area approach

We generated hexagonal grids by tessellating the logging sites into 200 m^2 cells, and segmented individual trees within the logging sites from the ALS data using the itcSegment package in R (Dalponte 2016). We used the obtained crown segments to adjust grid cell borders as proposed by Packalen et al. (2015) to improve correspondence between harvester and ALS data (Figure 1). In contrast to the mentioned study, however, we labelled trees as “in” or “out” based on the proportion of tree crown area overlapping the sampling area, and not the position of the detected tree apex falling in- or outside the sampling area boundary. We then extracted harvester stem volume data from within the adjusted grid cells, and calculated cell-level volumes as the sum of timber volumes recorded by the harvester, scaled to a per ha unit. From the laser echoes that fell within the spatial extent of the adjusted grid cells, we computed canopy metrics from echoes of all categories (first, intermediate and last) with a height > 2 m above the ground. The canopy metrics included the heights at the 10th, 20th, … and 90th percentile of echo height distributions, and the mean height, standard deviation, skewness and coefficient of variation of echo heights. We also computed canopy density metrics by dividing the height range between 2 m and the 95th percentile into 10 fractions of equal height, and computing the proportion of echoes between the lower limit of each fraction to the total number of echoes.

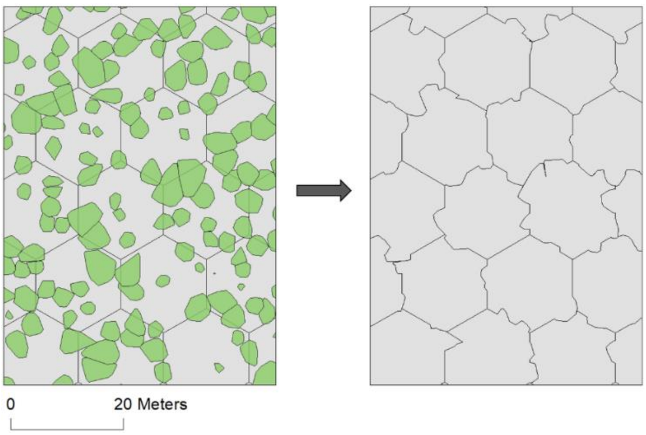

Figure 1. The enhanced area based approach used in this study. A hexagonal sampling grid overlaid with tree crowns segmented from the ALS data (left) and grid cells adjusted for segmented trees crowns (right).

2.4 Timber Volume Estimation

We estimated the mean timber volume per ha for the 33 logging operations in a leave-one-operation-out fashion. We removed one operation from the dataset, and fitted a random forest model with data from the remaining operations. We used the model to predict timber volume for grid cells within the testing operation, and repeated the procedure until all grid cells obtained predictions. We estimated the mean timber volume per ha for each operation as the mean of volume predictions, and compared these values to the mean timber per ha recorded by the harvester. To assess the accuracy of timber volume estimates, we computed the root mean square error between harvester and ALS estimates relative to the mean recorded by the harvester (RMSE%). Finally, we tested whether the year of ALS data acquisition had a statistically significant effect on the prediction errors using an analysis of variance (ANOVA) test.

3. Results and Discussion

Figure 2 shows mean timber volumes recorded by the harvester plotted against corresponding values estimated from the ALS data for the 33 logging operations. The leave-one-operation-out cross validation procedure revealed a RMSE% of 11.4. This level of accuracy was comparable to the results obtained by Packalén and Maltamo (2007), who estimated timber volume at stand level by using manually measured field plots and ALS data from a single acquisition, and obtained a RMSE% of 10.4. We obtained better accuracies than Saukkola et al. (2019) who estimated timber volume at stand level by using harvester data georeferenced with an autonomous GNSS, i.e., without differential GNSS positioning, and ALS data from a single acquisition, and obtained a RMSE% of 25.9.

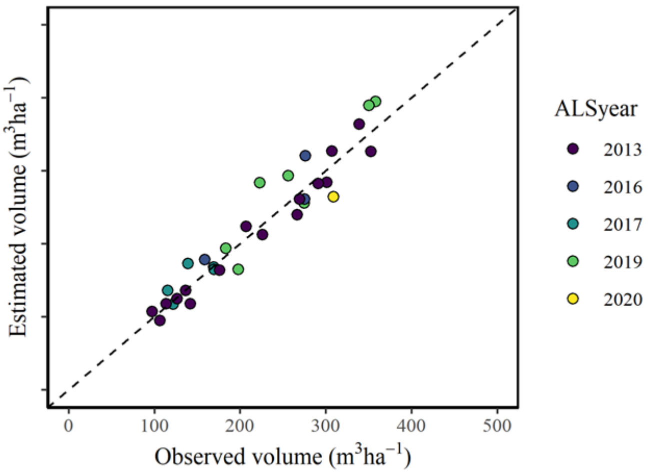

Figure 2: Timber volume recorded by the harvester plotted against timber volume estimated from airborne laser scanner data for the 33 logging operations.

Even though data from five different ALS acquisitions were used, and the number of years between ALS acquisition and harvesting varied considerably from one to eight years, the ANOVA test showed that the year of ALS acquisition did not have a statistically significant effect on prediction errors obtained for grid cells ($p = 0.37$). Thus, a single random forest model fitted with data from all years provided a practical solution for predicting and subsequently estimating timber volume.

The proposed approach can be used for updating operational forest inventories in situations where field data are not available, and timely data is needed for short-term operational planning. Harvester and ALS data may prove particularly useful for operational planning, where volume estimates are typically needed within a short time frame, for example for the selection of stands for harvesting in the near future. Such decisions typically require data with greater spatial and temporal resolution than those provided by periodic forest management inventories, which are commonly only carried out every 10-15 years.

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