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The use of dual-wavelength airborne laser scanning for estimating tree species composition and species-specific stem volumes in a boreal forest

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ABSTRACT

The estimation of species composition and species-specific stem volumes are critical components of many forest inventories. The use of airborne laser scanning with multiple spectral channels may prove instrumental for the cost-efficient retrieval of these forest variables. In this study, we scanned a boreal forest using two channels: 532 nm (green) and 1064 nm (near infrared). The data was used in a two-step methodology to (1) classify species, and (2) estimate species-specific stem volume at the level of individual tree crowns. The classification of pines, spruces and broadleaves involved linear discriminant analysis (LDA) and resulted in an overall accuracy of 91.1 % at the level of individual trees. For the estimation of stem volume, we employed species-specific k-nearest neighbors models and evaluated the performance at the plot level for 256 field plots located in central Sweden. This resulted in root-mean-square errors (RMSE) of 36 m^3/ha (16 %) for total volume, 40 m^3/ha (27 %) for pine volume, 32 m^3/ha (48 %) for spruce volume, and 13 m^3/ha (87 %) for broadleaf volume. We also simulated the use of a monospectral near infrared (NIR) scanner by excluding features based on the green channel. This resulted in lower overall accuracy for the species classification (86.8 %) and an RMSE of 41 m^3/ha (18 %) for the estimation of total stem volume. The largest difference when only the NIR channel was used was the difficulty to accurately identify broadleaves and estimate broadleaf stem volume. When excluding the green channel, RMSE for broadleaved volume increased from 13 to 26 m^3/ha. The study thus demonstrates the added benefit of the green channel for the estimation of both species composition and species-specific stem volumes. In addition, we investigated how tree height influences the results where shorter trees were found to be more difficult to classify correctly.

1. Introduction

Species-specific stem volume is a commonly requested forest attribute of high importance for both timber estimations and biodiversity monitoring. From an industry standpoint, it contains crucial information for estimating the forest value, its potential use, and for what management decisions to take. Ecologists can use species-specific volumes to assess biodiversity and map wildlife habitats (Löfstrand et al., 2003).

Airborne laser scanning (ALS) captures the 3-dimensional structure of trees and is now used as a standard technology for retrieving forest variables in the Nordic countries. The National Land Survey in Sweden has scanned most of the country from high altitude resulting in point densities of 0.5–1.0 pulses/m^2. These data have been used to produce raster maps (12.5 × 12.5 m^2 cell size) of mean tree height, basal area, stem volume, and above ground tree biomass (Nilsson et al., 2017). Tree species mapping is more difficult, and often seen as a bottleneck in forest inventories using remote sensing (Michałowska & Rapiński, 2021). Species classification is commonly conducted using multi- or hyperspectral imagery, sometimes in combination with ALS (Fassnacht et al., 2016; Shi et al., 2020). For example, Sentinel-2 imagery combined with ALS were utilized for the nationwide mapping of land cover including forest types in Sweden at a cell size of 10 × 10 m^2 (Ahlcrona et al., 2019). Passive optical sensors can capture differences in foliage reflectance across multiple wavelengths, as well as differences in phenology in the case of multi-temporal imagery (Axelsson et al., 2021).

The emergence of multispectral laser scanners brings the possibility to capture both the geometry and reflectance features of the scanned trees from a single platform. This technology could prove ideal for retrieving species-specific stem volumes of the scanned forest. Several studies have shown promising results for species detection using

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multispectral ALS (Axelsson et al., 2018; Budei et al., 2018; Leclère et al., 2022; Yu et al., 2017). The potential to detect tree species accurately depends on the heterogeneity of the forest and whether some species are grouped together. In general, conifers have proven easier to classify than distinguishing between a mixture of broadleaf species (Prieur et al., 2022). Boreal forests in the Nordic countries are relatively homogenous with a high dominance of Scots pine and Norway spruce. These two species also hold the highest commercial value from a forest industry standpoint. Species detection in these forests often focuses on separating between pines, spruces, and a general category of broadleaves (Kukkonen et al., 2019). Both the geometry and reflectance of the tree crowns contain important species-related information. Holmgren et al. (2008) showed that the crown base height was useful for detecting Scots pine, and treetop sharpness contributed to distinguishing between Scots pine, Norway spruce and broadleaved trees. The intensity of the backscattered signal depends on the reflectance, density, and orientation of the foliage (Korpela et al., 2010), and has proven valuable for distinguishing between species. In addition, multispectral ALS enables the creation of intensity features from the combination of intensities in multiple channels. Budei et al. (2018) found that spectral vegetation indices based on backscattered intensities in the green and infrared channels were the most important predictors of species in a Canadian forest.

While species-detection from multispectral ALS can be conducted using area-based approaches (Lindberg et al., 2021), it is often carried out at the level of individual tree crowns (ITC). ITC also necessitates higher point densities. While the cost of high point densities can be inhibitory, technological improvements in laser scanners have led to higher pulse repetition frequency. This development has enabled scanning with high point densities from increasingly higher altitudes and over larger areas. Analysis at the level of individual trees is preceded by a segmentation step that partitions the canopy into individual crown segments. This usually results in some level of systematic over- or under-segmentation. Since the tree crown structure varies with species, a segmentation algorithm may over-segment some species while under-segmenting others. This could potentially lead to biased results (Peuhkurinen et al., 2011), where systematic errors at the level of individual trees propagate as trees are aggregated to larger areas. It is therefore important to use methods that do not assume that crowns are segmented correctly and are insensitive to these errors. In this context, Breidenbach et al. (2010) proposed the semi-ITC method where segments may contain any number of trees. To predict the content of target segments, the method imputes ground truth data from the most similar reference segments. The semi-ITC method has proved to reduce biases when compared to traditional ITC, and has also outperformed area-based models for species-specific volume (Kandare et al., 2017).

The main objective of this study was to investigate the utility of dual-wavelength ALS using green and near infrared (NIR) channels for estimating species-specific stem volumes in a boreal forest in central Sweden. A second objective was to determine the additional contribution of the green wavelength, and thus the benefit of using a dual-wavelength scanner.

2. Materials and methods

An overview of the main steps in the methodology is presented in Fig. 1. We employed a two-step modelling approach: (1) linear discriminant analysis (LDA) to classify segments into dominant species,

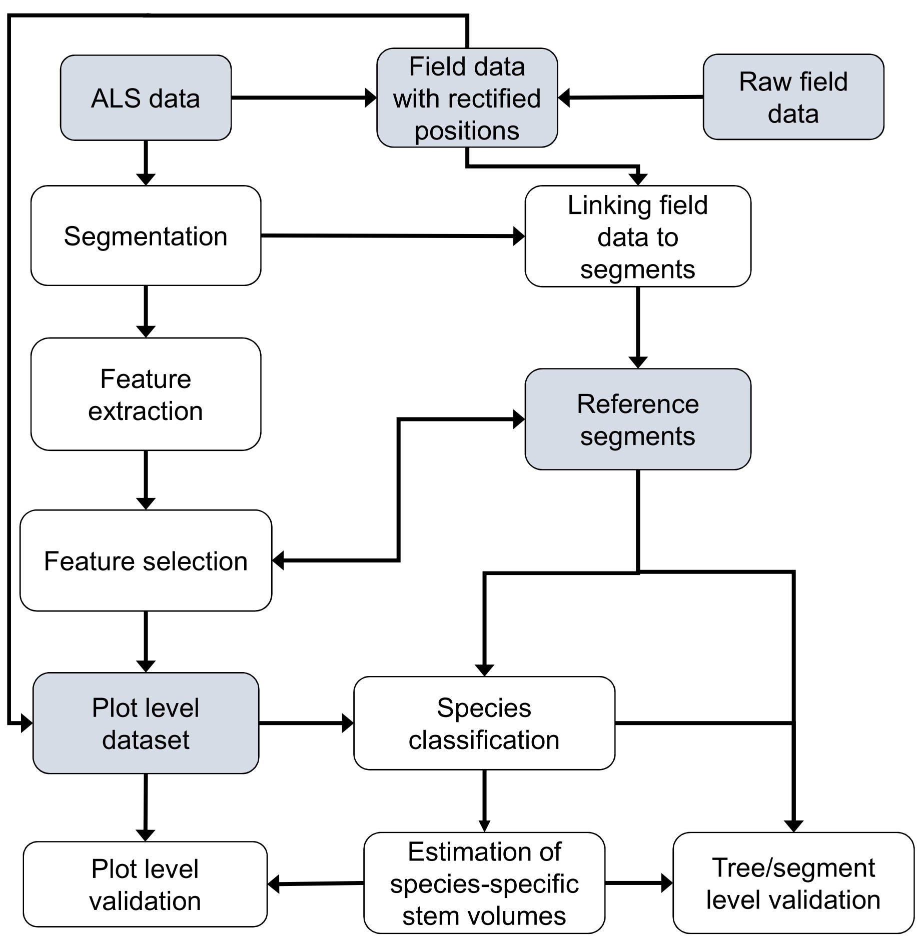

Fig. 1. Workflow of the main steps in the analysis. White boxes represent processing steps and gray boxes represent datasets.

and (2) species-specific k-nearest neighbors models for the estimation of stem volumes. The estimated species-specific stem volumes were validated at the plot level for 256 field plots. The analysis followed the semi-ITC method where each segment may contain any number of trees (Breidenbach et al., 2010).

2.1. Study area and field data

The Siljansfors experimental forest is situated in central Sweden (60°53́ N, 14°24́ E) and covers an area of 1520 ha. It is dominated by Scots pine (60 %) and Norway spruce (35 %) mixed with some broadleaf species (5 %), of which most are birches. The field work was carried out between September 2019 and June 2020. Field data were collected at 291 circular plots distributed in a systematic sampling pattern (Fig. 2). Most of these had a radius of 10 m, but in some cases with dense young forest they were given a smaller radius. At each field plot center, the position was recorded using an R8 GNSS receiver (Trimble, USA) that used corrections from permanent reference stations to improve the accuracy. The accuracy, as reported by the receiver, was often in the cm range and in all cases less than 50 cm. Stem diameters at 1.3 m above ground (DBH) and stem positions relative the plot center were measured using a DP II caliper with the DP PosTex add-on (Haglöf, Sweden). Tree species, DBH, and stem position were recorded for all trees with a DBH of at least 4 cm. In addition, the height of some of the trees were measured with a Vertex Laser Geo range finder (Haglöf, Sweden). Of the original 291 plots, we used data from 256. Plots were excluded where the plot radius was less than 10 m (for consistency), contained lodgepole pines or larch trees (which are normally very rare in Swedish forests), and where the field data could be matched reliably to the ALS data.

Stem volumes were calculated from DBH and height using species-specific models for northern Sweden (Brandel, 1990). The heights (H) were estimated from DBH according to Equation (1) (Persson & Fransson, 2017), where the species-specific coefficients, β_0, β_1 and β_2 were calibrated using the field data trees where height had been measured (n = 1223).

$$\ln(H) = \beta_0 + \beta_1 DBH + \beta_2 \ln(DBH) \quad (1)$$

2.2. Airborne laser scanning

The study area was scanned from an airplane at an altitude of 800 m and at a speed of 213 km/h on June 27, 2019. The Riegl VQ-1560i-DW scanner used two wavelengths: 532 nm (green) and 1064 nm (near infrared). The field of view was 40° and each wavelength was scanned with a pulse rate of 1 MHz and a scan rate of 206 lines per second. The average point densities were 40.5 and 48.8 points per m^2 for the green and near infrared wavelengths respectively. The densities of first returns were 26.6 and 29.7 points per m^2. The ALS data were delivered with intensity values calculated from the amplitude of the returned signal. In addition to x, y, z coordinates and intensity values, each point had a return number and the total number of returns from the emitted laser pulse.

During pre-processing of the ALS point cloud, we used the TerraScan software (Terrasolid, Finland) to derive a digital terrain model (DTM) with 0.5 m cell size, which was used to calculate the normalized elevation (height above ground) for all points. The DTM together with a canopy height model (cell size 0.25 m) were used to identify and remove underground and above-canopy noise.

2.3. Segmentation and linking of field data

The segmentation algorithm used was developed by Holmgren et al. (2022) and creates a model fit surface raster (cell size 0.25 m) by matching the ALS data in each cell to a tree crown density model derived from reference trees of different species. This step was followed by a watershed algorithm that delineated the segments (Fig. 3). The field data at each sample plot were then overlaid with the local segments and a canopy height model. This enabled us to manually rectify the position of the field inventoried trees and to spot potential errors in the field data. Links between field measured trees and segments were established where it was clear which tree belonged to which segment. When several trees were linked to the same segment, the species of the segment was set to that of the tree with the largest stem diameter. The mean number of tree stems per segment was 1.6. The linked tree segments (n = 5,163)

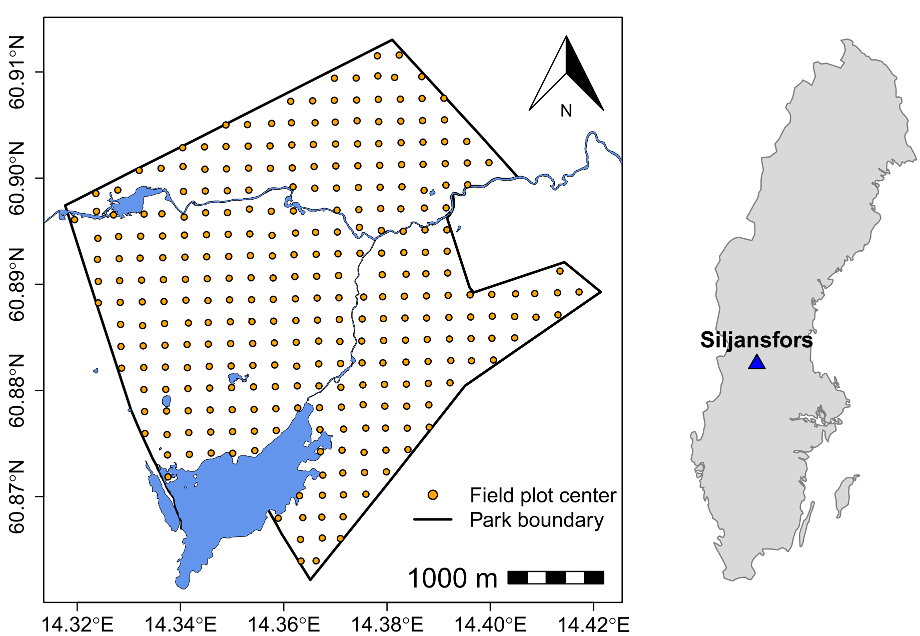

Fig. 2. Map of the Siljansfors experimental forest in central Sweden with the 291 sample plots distributed in a systematic pattern.

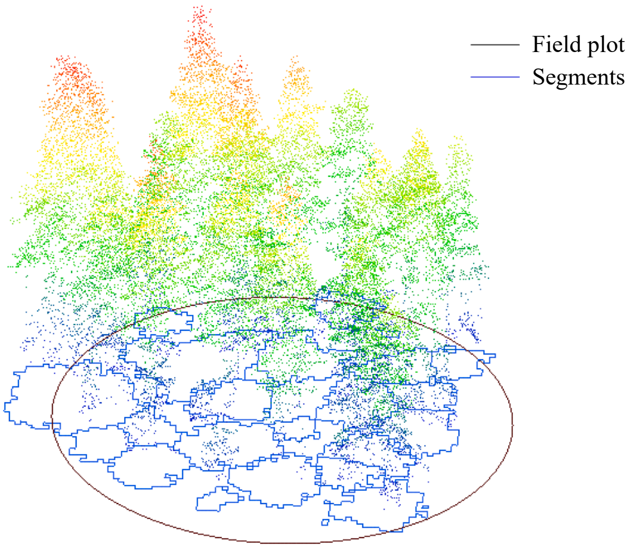

Fig. 3. ALS data and segments for one of the field plots. The colors of the ALS point cloud represent height.

Table 1
The reference segments (n = 5,163) divided into species groups.

Group	Pine	Spruce	Broadleaf	
Species	Scots pine	Norway spruce	Birch	Other broadleaf
Number	3,506	1,269	371	17

constituted the training data during the modelling of tree species and volume. The tree population was composed of Scots pine, Norway spruce, birch, and a small number of other broadleaf species. The broadleaves were combined into a single category (Table 1) in order to get a sufficient sample size for each species class.

2.4. Feature extraction

Several features were extracted from the point cloud of the reference segments and evaluated as predictors for species classification and stem volume estimation. The following descriptions provide examples of the different types of features used in the analysis. They can be categorized into geometric features (relating to spatial variation), intensity features (radiometric variation), and return type features (based on proportions of different return types). The geometric features were derived from the combined point clouds of green and near infrared data points. Some geometric features were used with the aim to capture the shape of the crown, for example relative height percentiles, vertical skewness, and height-to-width ratio of the crown. We also used geometric features that captured variation inside the crown structure, such as the standard deviation of the number of points in voxels. Other geometric features were aimed at capturing tree size, e.g., maximum height, crown volume, profile and footprint area of the crown. Intensity features included the maximum and standard deviation of the intensity, and the ratio between the mean intensity in the near infrared channel and the mean intensity in the green channel. Features based on return number included the proportion of first returns among all returns and the proportion of single returns among all first returns. There were also features using both intensity and return number, e.g. the summarized intensity of first returns divided by the summarized intensity of all returns. Before calculating any of the features, we removed all points below two meters from the ground.

2.5. Selection of features for modelling species and volume

When extracting features from the reference segments, some smaller segments contained too few points for the calculation of some features. Since robust features are preferable, we excluded those that could not be calculated for more than 1 ‰ of all reference segments. To identify the most important features for classifying species, we employed stepwise feature selection for an LDA-model (stepLDA method in caret R package). We excluded non-normalized geometric features, such as height and crown volume, since we wanted the species classification to be independent of tree size. Features that were important for modelling the volume were identified using stepwise linear regression with forward selection (leapForward method in caret R package).

In order to investigate the contribution of the green wavelength we also created feature sets for species classification and volume estimation that were solely based on the NIR wavelength. All features based on intensity or return type of the green wavelength were excluded during this selection process. These second feature sets represented the use of a monospectral NIR scanner in the analysis.

2.6. Classification of tree species and estimation of stem volume

Prediction of species-specific volume followed a two-step approach: (1) classification of the dominant species of each segment using LDA (MASS R package), and (2) estimation of stem volume using species-specific k nearest neighbors models (yaImpute R package). We set the parameter k to 5, meaning the estimated tree volumes are a weighted mean of the five nearest neighbors. Both the total and species-specific volumes were simultaneously imputed from the most similar neighbors. While a segment was classified according to the species of the most dominant tree, it may thus contain stem volumes of several species.

The distance to the neighbors can be calculated using different methods. We compared results for Euclidean distance, most similar neighbor (MSN) distance, and random forest distance to identify which method performed best. The Euclidean distance is calculated using the normalized independent variables and the MSN distance is calculated in a projected canonical space. Random forest distance depends on the proportion of random forest trees that contain both the target segment and reference segment in the same leaf node.

2.7. Validation

The imputation was validated at the plot level for the 256 plots using leave one plot out cross-validation. This approach was selected as it maximizes the use of the available data for model training. Although we did have many samples in total, the number of broadleaf reference trees was relatively small. For a specific sample plot, an LDA model was trained using reference data from all the other plots and applied to predict the species of each segment. The procedure was then repeated for all sample plots. Species-specific knn models were applied to impute the stem volumes using reference segments from all the other plots. Predictions were made for all segments with centroids inside the plot. The combined imputed species-specific volumes at each plot were then compared to the volumes of all the field-measured trees within the plot boundaries.

The results of the species classification are presented in graphs and confusion matrices. We added confusion matrices for data sets with balanced sample sizes for a better comparison between the species. Here, we used all 388 broadleaf samples and added the same number of randomly selected pine and spruce samples. All the other results are, however, based on the full dataset with imbalanced sample sizes. To quantify the accuracy of the volume estimates we used root-mean-square error (RMSE) and bias (estimated volume minus observed volume). Relative RMSE and relative bias were calculated through division by the mean of the observations.

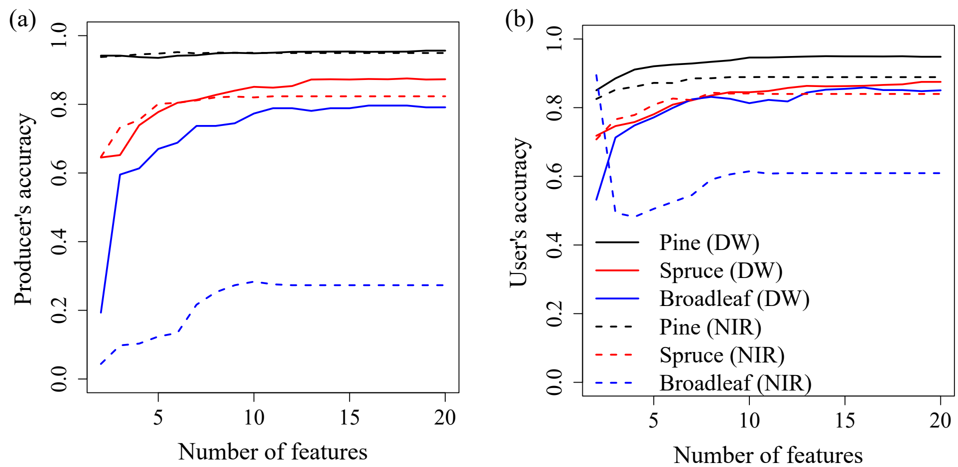

Fig. 4. Producer's accuracy (left) and user's accuracy (right) for the three species groups in relation to the number of features used during classification. Dashed lines represent results from only using features based on the NIR channel. Based on these results, 10 features were used in the species modelling.

3. Results

3.1. Feature selection

To evaluate how many features to use we ran the models with an increasing number of features and plotted the results (Figs. 4 and 5). For species classification (Fig. 4), we chose to use 10 features as there was only a minor accuracy improvement with additional features. Descriptions of the selected features and their selection order are detailed in Table 2. The high number of pines meant that the model was more inclined to classify uncertain cases as pine (Graves et al., 2016), and producer's accuracy for pines stayed at a high level throughout the range of features.

In the case of stem volume estimation (Fig. 5), we chose to use five features. These five features were the same whether utilizing the green wavelength or not (Table 3), and additional features provided only small improvements in stem volume estimations. There was only a small difference in performance between the three methods for calculating the distance to the neighboring reference segments. We decided to continue with the MSN method, which performed equally well or better than Euclidean distance and random forest distance. One drawback with the

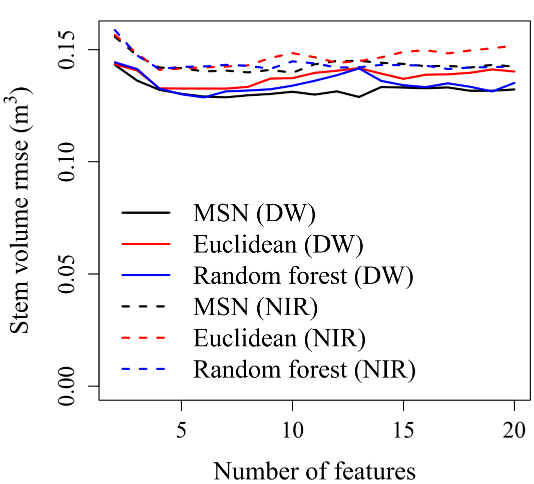

Fig. 5. Variation in stem volume RMSE in relation to the number of features used in the imputation. We compared three methods for finding the nearest neighbors: MSN, Euclidean and random forest distance. The estimations were made on the individual tree segments after classification of species. The reason for the marginally lower error when using the full dual-wavelength (DW) dataset was the more accurate species classification that also improved the estimation of stem volume.

Table 2
Features used as predictors during the species classification for the predictions based on dual-wavelength data (DW) or only the NIR channel data. The numbers to the right show in which order the features were selected and thus their relative importance.

Geometric features	DW	NIR
Standard deviation of the number of points in 20 cm voxels in the crown top[1].	(7)	
Standard deviation of the number of points in 40 cm voxels in the crown top[1].	(9)	
L-transformed Ripley's K at 20 cm calculated on the profile (x and z coordinates) of the crown top1.		(4)
The height at which 50 % of the points fall below divided by the maximum height.	(2)	(2)
The height at which 80 % of the points fall below divided by the maximum height.		(10)
Crown height divided by crown width of the crown top[1], where the width was calculated as the diameter of the smallest enclosing circle.		(8)
Skewness of the z coordinates in the crown top[1].		(9)
Skewness of the z coordinates in the top 2 m of the crown.	(10)	(7)
Return type and intensity based features	DW	NIR
Proportion of single returns among first returns in the NIR data.	(6)	(5)
Proportion of points with NumberOfReturns[2] above two among all NIR points.	(8)	(6)
The summarized intensity of single returns divided by the summarized intensity of all first returns in the NIR data.	(5)	(3)
The summarized intensity of first returns divided by the summarized intensity of all returns in the green data.	(4)	
Mean intensity among NIR points.		(1)
Standard deviation of the intensity among both green and NIR points.	(1)	
Ratio between the mean intensity per emitted pulse in the NIR and green channels. The mean intensity per emitted pulse was calculated as the summarized intensity of all points divided by the number of first returns.	(3)	

[1] Crown top refers to points located above half of the maximum height.
[2] NumberOfReturns refers to the number of returns that were registered for a single emitted pulse.

Table 3
Features used as predictors for the estimation of stem volume. The numbers to the right show at which position the features were selected and thus their importance. For both DW and NIR, the profile area was the most important feature for modelling stem volume.

Geometric features	DW	NIR
Maximum height.	(4)	(4)
Volume of an alpha shape created from the crown top[1].	(2)	(2)
Profile area of the crown top[1]. The mean area of convex hulls around the x and z coordinates and the y and z coordinates.	(1)	(1)
Coefficient of variation of the z coordinates.	(5)	(5)
Return type and intensity based features	DW	NIR
Mean NumberOfReturns[2] of all infrared points.	(3)	(3)

[1] Crown top refers to all points that were located above the maximum height/2.
[2] NumberOfReturns refers to the number of returns that were registered for a single emitted pulse.

random forest method was the longer model training time, which can become an issue due to the many iterations of leave one plot out cross-validation.

3.2. Species classification of individual tree crown segments

The overall classification accuracy for the DW dataset when using 10 features was 91.1 %. Pines had the highest user's and producer's accuracies, followed by spruces and broadleaves (Table 4). However, the balanced dataset with the same number of samples per species resulted in similar accuracies for the three species. Classification results from using 10 features and only information in the infrared channel resulted in an overall accuracy of 86.8 %. In relation to using both channels, the largest difference was the significantly lower accuracy for broadleaves. (Table 4). The green wavelength is thus especially important for separating broadleaf trees from coniferous trees. The lower classification accuracies when excluding the green channel also negatively affected the estimation of stem volume, which used species-specific models that relied on the initial species classification (Fig. 5).

Fig. 6 shows the relationship between tree height and classification accuracy. In general, shorter trees (<10 m) were the most difficult to classify correctly but there were differences between the species. In the case of spruces, classification accuracy increased with tree height. Pines had the highest producer's accuracy in the medium height categories (10–20 m), reflecting the distribution of the reference trees.

3.3. Estimation of stem volumes at the segment and plot levels

Predictions of stem volumes at the level of individual tree segments (Table 5, Fig. 7) resulted in relative RMSE of 38 % (total volume), 70 % (pine volume), 136 % (spruce volume), and 291 % (broadleaf volume). For the species-specific volumes, misclassifications appeared as points falling on or close to one of the axes (Fig. 7). The biases were consistently low, which is crucial for scaling up the predictions to the plot and stand level. At the plot level (Table 6, Fig. 8) the relative errors were lower

Table 4
Confusion matrices for species classification using 10 features and evaluated on the reference trees using leave one plot out cross-validation. The results are calculated for the full dual-wavelength dataset (top), and only the NIR channel data (bottom). We also added results for balanced sample sizes where each tree species had 388 samples (right). PA is producer's accuracy and UA is user's accuracy.

Dual-wavelength					Dual-wavelength, balanced sample sizes				
	Pine	**Spruce**	**Broadleaf**	**UA (%)**		**Pine**	**Spruce**	**Broadleaf**	**UA (%)**
Pine	3325	144	47	95	**Pine**	347	21	23	89
Spruce	157	1079	41	84	**Spruce**	30	346	24	86
Broadleaf	23	46	300	81	**Broadleaf**	11	21	341	91
PA (%)	95	85	77	**91.1**	**PA (%)**	89	89	88	**88.8**
NIR					NIR, balanced sample sizes				
	Pine	**Spruce**	**Broadleaf**	**UA (%)**		**Pine**	**Spruce**	**Broadleaf**	**UA (%)**
Pine	3330	197	219	89	**Pine**	323	18	58	81
Spruce	137	1040	59	84	**Spruce**	19	325	58	81
Broadleaf	38	31	110	61	**Broadleaf**	46	45	272	75
PA (%)	95	82	28	**86.8**	**PA (%)**	83	84	70	**79.0**

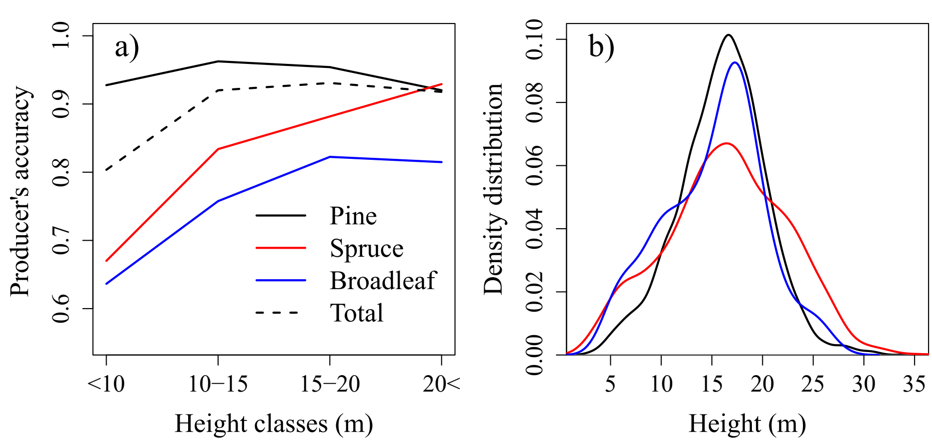

Fig. 6. a. producer's accuracy in relation to height classes based on the maximum heights in the ALS data. There is a relationship between tree height and classification accuracy where the largest differences in producer's accuracy were observed among spruces. b. shows differences in the height distribution of the species groups among the reference trees.

Table 5
Results for stem volume estimations of tree segments.

Data	Channels	RMSE (m^3)	Bias (m^3)
Total	DW	0.128 (38.2 %)	−0.00496 (−1.48 %)
Pine	DW	0.154 (70.2 %)	−0.00719 (−3.28 %)
Spruce	DW	0.132 (136.0 %)	0.00289 (2.98 %)
Broadleaf	DW	0.053 (291.4 %)	−0.00057 (−3.12 %)
Total	NIR	0.140 (41.7 %)	−0.00084 (−0.25 %)
Pine	NIR	0.185 (84.5 %)	0.00565 (2.58 %)
Spruce	NIR	0.127 (131.4 %)	0.00264 (2.73 %)
Broadleaf	NIR	0.082 (444.8 %)	−0.00889 (−48.48 %)

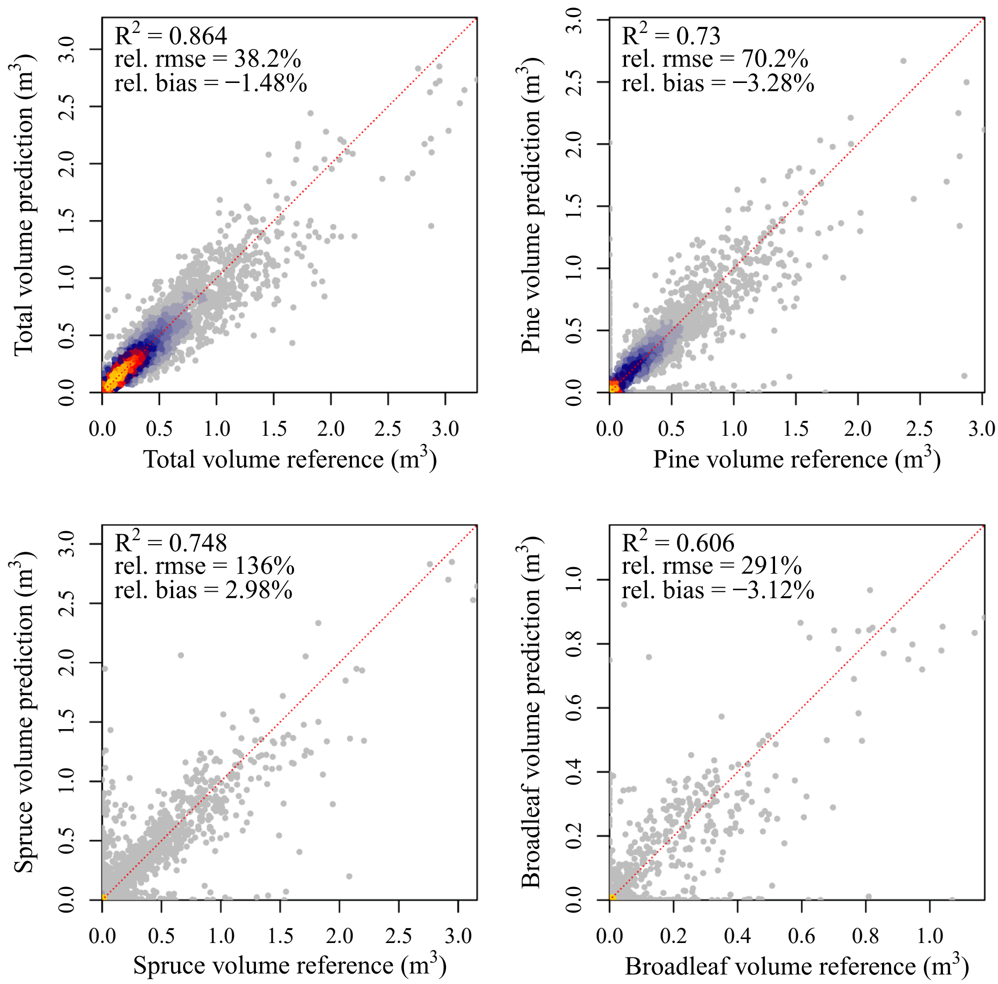

Fig. 7. Volume predictions at the segment level using the full dual-wavelength dataset. Species misclassifications appear as points close to the x- and y-axes.

Table 6
Results for stem volume estimations at the plot level.

Data	Channels	RMSE (m^3/ha)	Bias (m^3/ha)
Total	DW	36.2 (15.9 %)	3.80 (1.67 %)
Pine	DW	39.7 (27.2 %)	0.45 (0.31 %)
Spruce	DW	31.7 (47.8 %)	2.06 (3.11 %)
Broadleaf	DW	13.1 (87.0 %)	0.66 (4.36 %)
Total	NIR	40.7 (17.9 %)	6.81 (3.00 %)
Pine	NIR	56.4 (38.7 %)	10.21 (7.00 %)
Spruce	NIR	30.5 (46.0 %)	2.96 (4.47 %)
Broadleaf	NIR	25.7 (170.8 %)	−6.83 (−45.34 %)

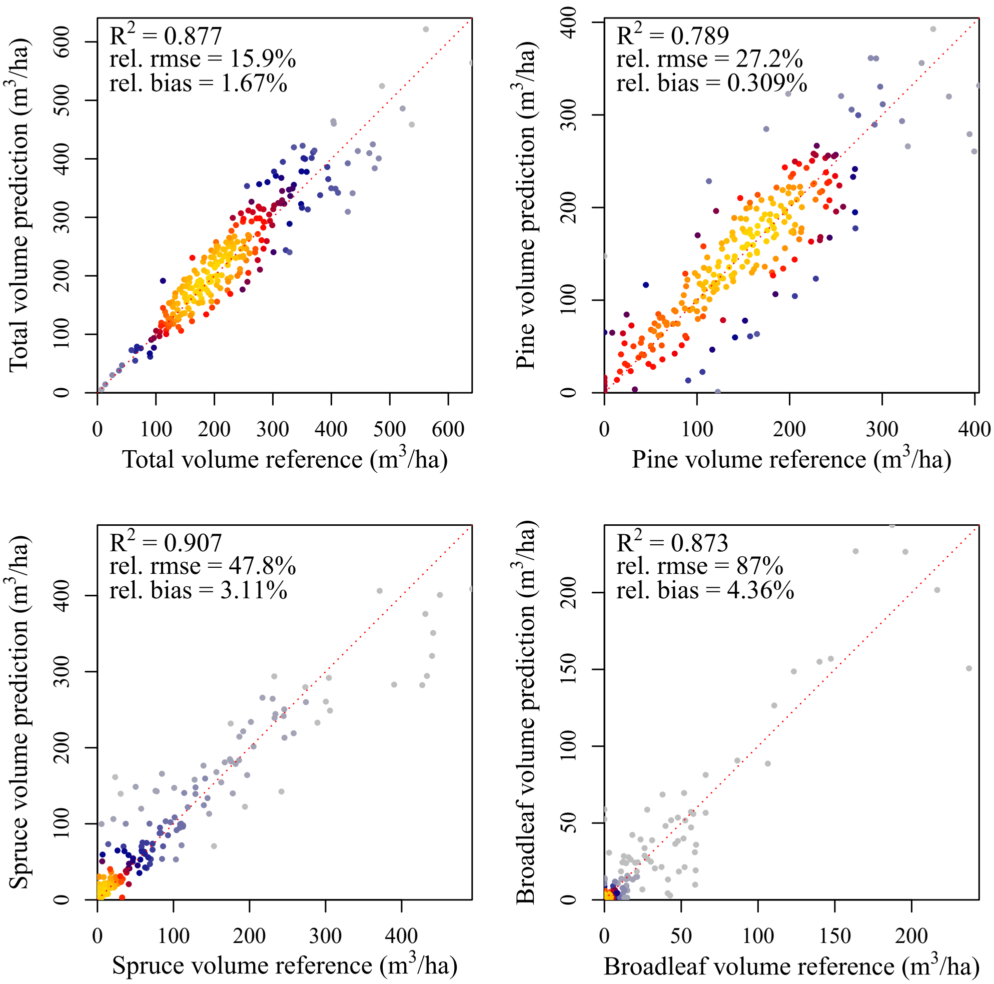

Fig. 8. Species-specific stem volumes at the plot level using the full dual-wavelength dataset. When trees were aggregated to the plot level, the errors shrank and there were few signs of misclassification.

compared to the relative errors of predictions of the individual tree segments. There were only a few indications of misclassifications. The estimates of species-specific volumes thus improved as trees were aggregated to larger areas.

Estimation errors for total stem volume from only using features based on the infrared channel (Tables 5 and 6) were marginally higher but comparable to using both channels. The largest difference when excluding the green channel was related to the inferior estimation of broadleaf volumes, which reflected the poor classification accuracy of broadleaves.

4. Discussion

This study demonstrates the use of dual-wavelength ALS for classifying species and estimating species-specific stem volumes. To the best of our knowledge, this is the first study to utilize dual- or multi-wavelength ALS to estimate species-specific stem volumes for individual tree crown segments. One novelty was the two-step approach with an initial segment level species classification followed by species-specific stem volume estimations using the MSN method. We tested a variety of ALS features for their ability to classify species, including geometric, intensity-based, and features using the return number and total number of backscattered returns. All these types of features proved useful for separating between pines, spruces, and broadleaves. The intensity-based features were the most important for identifying species with four of the first five features making use of the intensity (Table 2, DW case).

The classification model using both channels resulted in producer's accuracies of 95 %, 85 % and 77 % for pines, spruces and broadleaves, respectively (Table 4). These results reflected the varying number of samples for the species. When we used a dataset with balanced sample sizes, there was little difference in user's and producer's accuracies between the three species. For the NIR dataset, the broadleaf user's and producer's accuracies were however clearly lower also in the case of balanced sample sizes.

The estimation of species-specific volumes was based on the complete imbalanced dataset and resulted in lower relative errors for pines than for spruces and broadleaves. Similar to the study by Breidenbach et al. (2010), we achieved low levels of bias which might be due to the use of the semi-ITC method. The relative errors were lower when trees were aggregated to the plot level, and the low levels of bias were key for accurate estimates at larger areas.

Models created using data only from the NIR channel produced good results for total, pine, and spruce volumes, but underestimated broadleaf volumes due to difficulties in separating them from the coniferous species. This resulted in negative biases for the estimation of broadleaf volumes (−48 % and −45 % at the segment and plot level respectively). Features based on the green wavelength thus proved especially important for the identification of broadleaves and estimation of broadleaf stem volumes in the forest.

Similar results were observed in Kukkonen et al. (2019) which compared monospectral and multispectral ALS and how the inclusion of aerial imagery improved the classification results. They found that the use of multispectral ALS (including the 532 nm green channel) significantly improved the classification of broadleaved trees and they concluded that multispectral ALS is comparable in performance to the combination of monospectral ALS and aerial imagery for estimating species-specific volumes. It is clear that multispectral ALS is suitable for species classification, and it also offers some benefits over the fusion of monospectral ALS with multi- or hyperspectral imagery. These include avoiding potential misregistration between the datasets, which is especially important when estimations are conducted at the individual tree level, and the fact that aerial imagery is dependent on daylight and favorable weather conditions (Kukkonen et al., 2019).

One factor that influences overall classification results is the tree size distribution (Fig. 6). Shorter trees are generally more difficult to classify correctly and a height distribution skewed towards smaller trees can negatively affect classification results. While the overall classification accuracies were lowest for the short trees (less than10 m), pines had reduced accuracy for the tallest trees (greater than20 m). This may be a result of the lower proportion of pines in that range. Most of the reference trees were between 10 and 20 m and the models were optimally tuned for classifying trees of that size.

In this study, we extracted a large number of features from an ALS point cloud and tested them for their ability to predict species-specific stem volumes in a relatively small study area. A greater goal, however, is to apply the methodology in operational forest inventories over larger areas. This requires the utilization of robust features that are transferable between different acquisitions and over varied forest conditions (Navarro et al., 2020; Rana et al., 2022). In future research, we therefore aim to combine and compare data from multiple geographically distant sites.

5. Conclusions

This paper demonstrates the estimation of species composition and species-specific volumes from dual-wavelength ALS data at the level of individual trees. We showed how ALS features from dual-wavelength NIR and green channels improved the species classification compared to using a monospectral infrared scanner. The added use of the green channel proved especially important for the classification of broadleaf trees, which in turn improved the estimation of broadleaf stem volumes in the forest. Furthermore, we showed how tree height influences the results with lower accuracies for the shorter trees.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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