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Estimating the conservation value of boreal forests using airborne laser scanning

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ABSTRACT

In sustainable forest resource management, establishing forest conservation areas is important to maintain forest biodiversity. However, assessing the conservation value of forests is challenging because the target areas are often both large and remote. We explored using dense airborne laser scanning (ALS) data to estimate conservation values. Field data were collected at sites in Sweden for standing deadwood (S trees), laying deadwood (L trees), and trees considered particularly important for conserving biodiversity (N trees), and forest conservation values were determined using a commonly employed method in the field. A template matching method was then used to detect L, S and N trees from ALS data. L trees were identified from linear features in the point cloud above the ground, with a 52 % detection error rate. S and N trees were identified from unusually small or large crown diameters, with 71 % and 83 % error rates, respectively. We also tested the relationships between the three types of indicator tree, their summed values and the field inventory-assessed conservation values. Regressions between the assessed conservation values and ALS indicators were most robust comparing the three test sites when using the summed number of L, S, and N trees. A wall-to-wall map covering a 3 km × 4 km area was generated using Kernel density estimation of the summed number of ALS-derived indicators, to represent relative conservation values. The map was validated using 10 1-ha plots, and yielded an R^2 value of 0.6 for predicted conservation values at the plot level. We conclude that ALS data can be used to map forest conservation values and inform decisions about which forests should be used for timber production and which should be set aside as conservation areas. The maps could also be used as a data source for habitat analysis.

1. Introduction

A range of environmental and social values can be assigned to forests. In order to support sustainable and responsible ecological, social and economic management of forests and their resources, the concept of "high conservation value forests" (HCVFs) was proposed by the Forest Stewardship Council (FSC) in 1999. HCVFs are characterized by one or several of the following attributes: they (1) represent a significant concentration of biodiversity values, (2) are significantly large forests at a landscape level, where populations of autochthonous species exist in their natural form in terms of distribution and density, (3) contain rare, threatened or endangered ecosystems, (4) provide basic natural services in critical situations, for example as water catchments, erosion control, and barriers to destructive fire, (5) are fundamental to the basic needs of local communities, (6) and a critical component of local communities' traditional cultural identity (FSC Principles and Criteria, February 2000). Forest managers should identify HCVFs and implement management plans that maintain and enhance their value. In Sweden, forest harvesting requires an assessment of the biodiversity potential of forest stands to determine whether they can be harvested or should be set aside to conserve their value. In addition, patches of high conservation value within stands that are to be harvested need to be identified and retained, i.e. a green tree retention policy should be implemented. Therefore, estimating the forest biodiversity potential is important for sustainable forest resource management.

However, comprehensive information on biodiversity is rarely

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available, and gathering such information is extremely time-consuming and costly. Hence, assessed conservation values are commonly based on surrogates for biodiversity, i.e. easily recognizable structures or species the presence of which indicates high biodiversity (Lindenmayer et al. 2015). Numerous surrogates, or sets of surrogates, have been suggested as indicators of conservation value (Noss, 1990; Lindenmayer and Likens, 2011; Hunter et al., 2016; Yong et al., 2018). In Sweden, the most widespread method is based on the presence of various habitat characteristics or structures, e.g. senescent/large trees and deadwood, and disturbance processes, such as signs of natural disturbance (Drakenberg and Lindhe, 2001). All surrogate methods rely on field-derived sample data for the occurrence/abundance of the surrogates. To reduce the risk of biologically valuable areas being overlooked, there is a need for wall-to-wall maps of forest conservation values (Zhao et al., 2005) that represent the complete area of interest rather than just sample plots distributed within the area.

Remote sensing, including airborne laser scanning (ALS), can be applied in forestry and ecology studies to obtain information more efficiently and accurately than field inventory, and most importantly, can be used to generate a comprehensive estimate (i.e. wall-to-wall map) of forest attributes. ALS data usually covers large areas and provides vertical information about forests, and full 3D representations of forest can provide insights into ecologically relevant features (Onojeghuo and Onojeghuo, 2017). ALS data used for habitat studies includes canopy openness, foliage height diversity, and microhabitats (Santopuoli et al., 2020), as well as the height and species of individual trees (Müller and Vierling, 2014). Laser scanning has been used to map forest structure diversity (Adhikari et al., 2020; Adnan et al., 2019; Schneider et al., 2020), tree species diversity (Mohammadi et al., 2020), and functional diversity (Zheng et al., 2021), all of which are highly related to forest biodiversity values (Ehbrecht et al., 2017; van Kane et al., 2011; Sterеńczak et al., 2020). However, we are not aware of any studies that have explored the possibility to use remote sensing data to construct indices from detailed 3D reconstruction of different types of tree objects from dense ALS data. Therefore, the potential of remote sensing needs to be further explored, and if reliable, the assessment method would be more efficient than field-based inventory, and more comprehensive to cover the whole area.

In this study, we aim to test the potential of using ALS to map forest conservation values regarding the biodiversity (HCVF attribute 1), based on the premise that dense ALS data can provide information about forest structures relevant to biodiversity, such as the quantity of standing and lying deadwood and the number of trees with high conservation values (i.e., biodiversity indicators). We tested how well the number of ALS-derived indicator trees is correlated with field-assessed conservation values, the latter assigned using the surrogate method currently employed in Sweden and elsewhere. We developed a method for detecting biodiversity indicators from dense ALS data, to which we assigned a conservation value. We then produced a wall-to-wall map showing the distribution of the biodiversity indicators, and tested if an ALS-derived map can be used to successfully identify forests with a high conservation value.

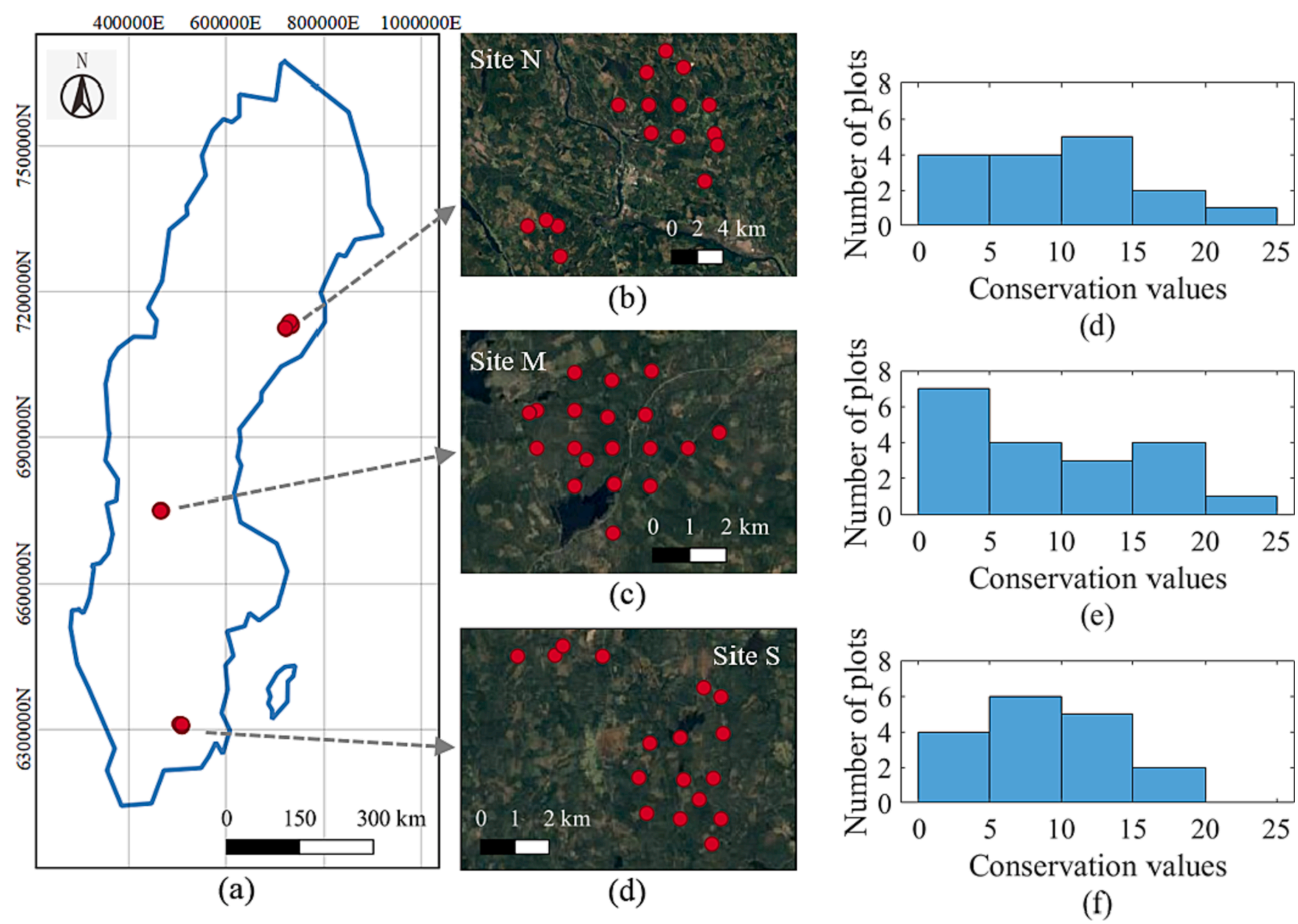

Fig. 1. The location of the study sites in Sweden (a), the 1-ha field plots at Krycklan (b, Site N), Siljansfors (c, Site M), and Attsjö (d, Site S), and the distribution of the assessed conservation values based on the field-inventories conducted at Site N (d), Site M (e), and Site S (f). The conservation value assessments were made in circular 1 ha plots distributed within the three sites according to panels b-d.

2. Study area and data collection

2.1. Study sites

The study sites, Krycklan (site N; Lat. 64.2° N, Long. 19.8° E; 6 780 ha), Siljansfors (site M; Lat. 60.9° N, Long. 14.3° E; 1500 ha), and Attsjö (site S; Lat. 56.9° N, Long. 15.1° E; 350 ha), were located in northern, middle, and southern Sweden, respectively (Fig. 1). The sites were covered with managed boreal or hemi-boreal forests (Ahti et al., 1968), and the most common tree species were Scots pine (*Pinus sylvestris*), Norway spruce (*Picea abies*), and birch (*Betula* spp.).

2.2. Study sites and field inventory data

During the summer of 2019, the forest biodiversity potential of the study sites was assessed by taking field inventories within 1-ha circular plots (15 plots per site). The decision for the specific plot size and plot density were based on the same type of constraints that practitioners face when assessing conservation values, i.e. the need to balance the cost (time) and precision (plot density). In our specific case, we had to limit the field inventory to one week per site, and to balance the time constraints with the need to get a reasonable representation of the variation in conservation value across a site we decided to survey 15 of 1 ha plots within each site. To define a 1-ha plot, the ArcMap tool "Buffer" was used with a radius of 56.4 m, and to randomize the inventory the centers of the 1-ha plots were placed in a systematic grid using the tool "Create fishnet". If a plot was positioned so that part of the 1 ha plot ended up in a habitat (e.g. on a mire) that did not fulfill the criteria for being forested (crown cover exceeding 10 % of the ground), it was manually moved to the nearest location so that the entire plot area represented forested conditions. To increase the likelihood that some of the plots included a high range of conservation values, two plots that were situated in either key woodland habitats or a nature reserve (i.e. areas already identified for their high conservation value or as a reserve) were added to each study site, resulting in an overall total of 17 plots per site. This implies that the grid used was close to, but not exactly a systematic grid.

Within each of the 1-ha plots, we assessed the conservation value following the methodology developed by Skogsbiologerna AB (Drakenberg and Lindhe, 2001). This method is widely used to assess forest conservation values, has been demonstrated to produce reliable estimates of forest biodiversity, and can be used without specialized training to measure the biodiversity of any type of forest (Hekkala et al. unpublished). The surveyor uses a score sheet and systematically searches for the presence of certain stand characteristics, processes, and structures, such as the age distribution of the stand, presence of downed and standing dead trees, trees with holes, other microhabitats, vegetation type, and signs of forest fires or other natural disturbance. The survey is divided into six sections, site (with 12 variables), dynamics (13), microhabitats (15), trees (12), structures (13), and deadwood (15), and is usually conducted at the stand level (0.5–10 ha when the stand is uniform). For this study, the presence of each characteristic (with a maximum of 80) was recorded, and the sum of all the recorded characteristics provided a value that represented the potential conservation value of the stand. Generally, stands with values exceeding 15–20 represent forest of high conservation value.

In addition to assessing the conservation value, we used a hand-held global positioning system (GPS) to record the position of all the lying deadwood (L trees) longer than 1.5 m with a diameter exceeding 10 cm in the basal end, and standing deadwood with a diameter at breast height (DBH) > 10 cm (S trees) within each 1-ha plot. We also recorded the position of trees of special importance for preserving biodiversity (N trees). The identification of N trees followed the criteria described by the Swedish Forestry Agency (Naturvårdsverket, 2012); they tended to be old large trees with characteristics typical of old-growth forests (a flattened tree crown, dead branches, coarse bark, etc.), trees containing a bird nest, or trees of an uncommon species. All the identified L, S and N trees were thereafter referred to as indicator trees. The distribution of indicator trees in each study sites is presented in Fig. 2.

2.3. ALS data

ALS data was collected on June 28, 2019, using a Riegl VQ 1560i-DW (Riegl, 2020) scanner at 800 m above the ground. The scanner recorded two channels (CH): CH1 set at 532 nm (Green) and CH2 at 1064 nm (near-infrared (NIR)). The average density of the first returns was 26.5 m^{-2} for each channel. The point cloud was normalized from a ground model derived in TerraScan (version 019) (Terrasolid Ltd, 2023). We then created a normalized digital surface model (nDSM) at a resolution of 0.25 m from the tallest points of the normalized point clouds.

3. Data analysis methodology

The framework of the data analysis and methodology is presented in Fig. 3. Object detection and data analyses were conducted in MATLAB (The MathWorks Inc., 2021). The parameters used in the object detection were heuristically designed without training and tuning.

3.1. Detection of lying deadwood (L trees)

Downed deadwood (L trees) was detected using a template matching algorithm (Nyström et al., 2014; Huo and Lindberg, 2020). The steps were as follows.

Step 1. Rasterization. Point clouds were sliced into [0.2, 0.5], [0.4 – 0.7], [0.6 – 0.9] and [0.2 – 1.0] m height intervals (above ground), and rasterized (cell pixels with laser points taking a value of 1, and pixels without laser points taking a value of 0) at a resolution of 0.25 m.

Step 2. Creation of templates. Linear filters at a resolution of 0.25 m were defined with a length of 25 pixels (6.25 m) and a width of 1 or 2 pixels (0.25 m or 0.50 m). The filters had 0 – π horizontal angles at 0.01 π intervals (denoting the directions of the templates, as shown in Fig. 4).

Step 3. Template matching. The rasters of the sliced point clouds were convoluted using the templates. After convolution, pixels within the slices with values larger than *Th* were marked as potential locations (denoted as *Set A*) of deadwood, and the directions of the templates were recorded for the next step (*Set A* $\{(x, y, z, \alpha)\}$, where x,y, z were the coordinates, and α was the direction of the template that resulted in a convoluted pixel value larger than *Th*). *Th* was set at 0.4 times the length × width (25 × 1 or 25 × 2 pixels) of the template. The same location could appear in different directions. We added the coordinates of all potential directions into *Set A*.

Step 4. Determination of deadwood positions. After Step 3, *Set A* included the positions of downed deadwood (denoted as *Set A1*) detected in all the slices, and other linear objects on the ground such as bushes (*Set A2*). We observed that *Set A1* usually contained positions with the same x and y and similar α in different slices, while *Set A2* usually contained isolated positions. Therefore, we determined a location to be *Set A2* when there was no other location with a similar α (α differences ≤

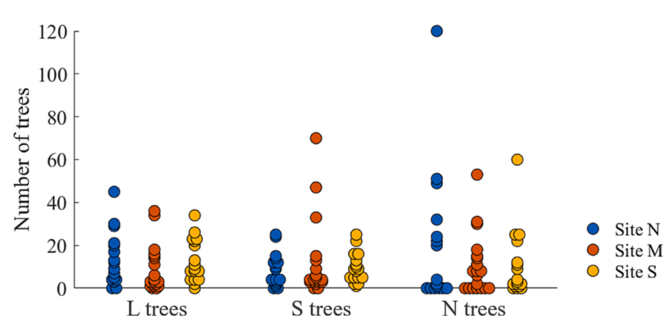

Fig. 2. The distribution of indicator trees, signifying trees important for preserving biodiversity, within the three study sites.

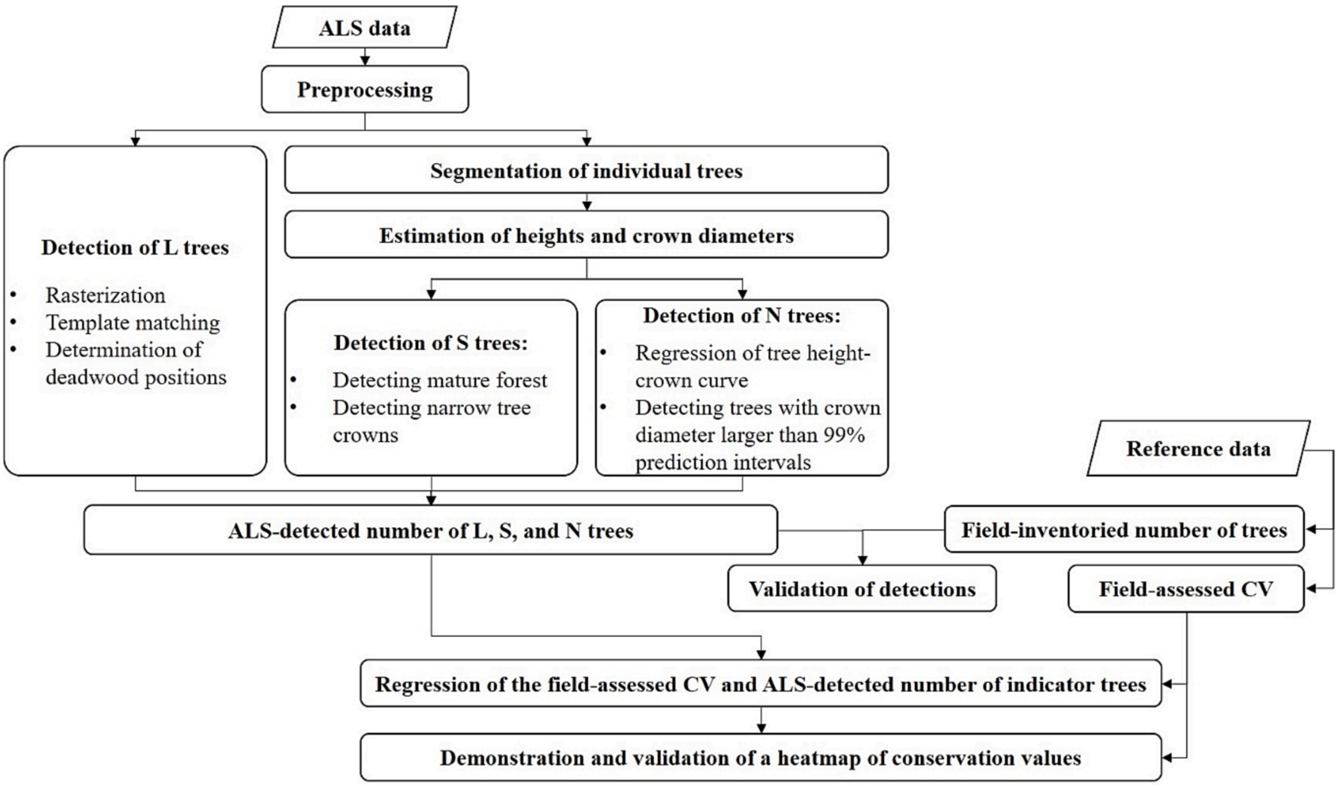

Fig. 3. Framework of the data processing and analysis.

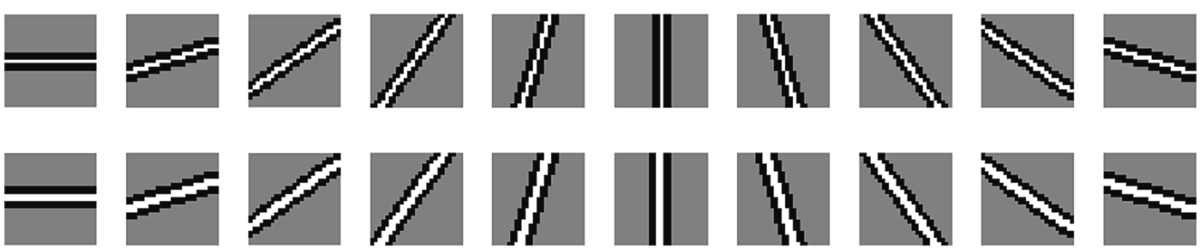

Fig. 4. Examples of the linear filters (templates). The templates were 0.25 m (first row) or 0.50 m (second row) wide. Values of 1, –1, and 0 were assigned to white, black, and grey pixels, respectively.

0.02 π) in the surrounding 1 m. We remove *Set A2* from *Set A* to define *Set A1*. We then merged the elements in *Set A1* that belonged to the same deadwood, by using a Mean Shift Clustering algorithm on *Set A1*, to cluster elements with similar *x*,*y*, and α values. The algorithm assigns the points to the clusters iteratively by shifting points towards the highest density of points in the region, and it is commonly used to cluster laser points that belong to the same objects (Xiao et al., 2019; Melzer, 2007; Huo and Lindberg, 2020). The average *x*,*y* values for each cluster were taken to represent the positions of deadwood (Fig. 5).

3.2. Segmentation of individual trees

We used the local maxima from the nDSM as tree heights, and circular templates to estimate the crown diameters (Huo and Lindberg, 2020). The templates were 3 × 3, 5 × 5, 7 × 7, and 33 × 33 pixels at a resolution of 0.25 m, corresponding to 0.75 m, 1.25 m, 1.75 m to 8.25 m. The nDSM was filtered using a Gaussian smoothing kernel with a *Sigma* standard deviation to reduce over- and under-segmentation. We initially used *Sigma* = 2 pixels to detect the local maxima for the dominant trees, and used all the templates to estimate the crown diameters. This setting reduced the over-segmentation of dominant trees, but promoted under-segmentation of smaller trees including S trees. Therefore, we then used *Sigma* = 1 pixel to detect the local maxima, and the templates for 0.75 m and 1.25 m to detect narrower crowns. The detected local maxima with *Sigma* = 1 pixel could be from big branches of dominant trees, so we tested the segmentation from the point cloud using points with horizontal distances ≤ 0.5 m from the local maxima. If the points were scattered only at the top, rather than being distributed at height intervals, the local maximum was identified as a branch and the segment was removed. This step could be achieved using different settings. We took points from the upper 1/3 of the heights, and divided the points into 0.5-m height intervals. If the points occupied less than 50 % of the height intervals, we identified them as branches. The parameters in this step were set up based on experience without optimization, and the sensitivity analysis was not limited by referencing. Fig. 6a shows an example of detected tree crowns.

3.3. Detection of standing deadwood (S trees)

We developed our method based on the observation that standing deadwood usually has an unusually narrow tree crown compared to the surrounding trees (Fig. 6b). We first detected young forest and excluded it from deadwood detection bearing in mind that (1) young forest usually has low conservation value, and (2) the distribution of crown

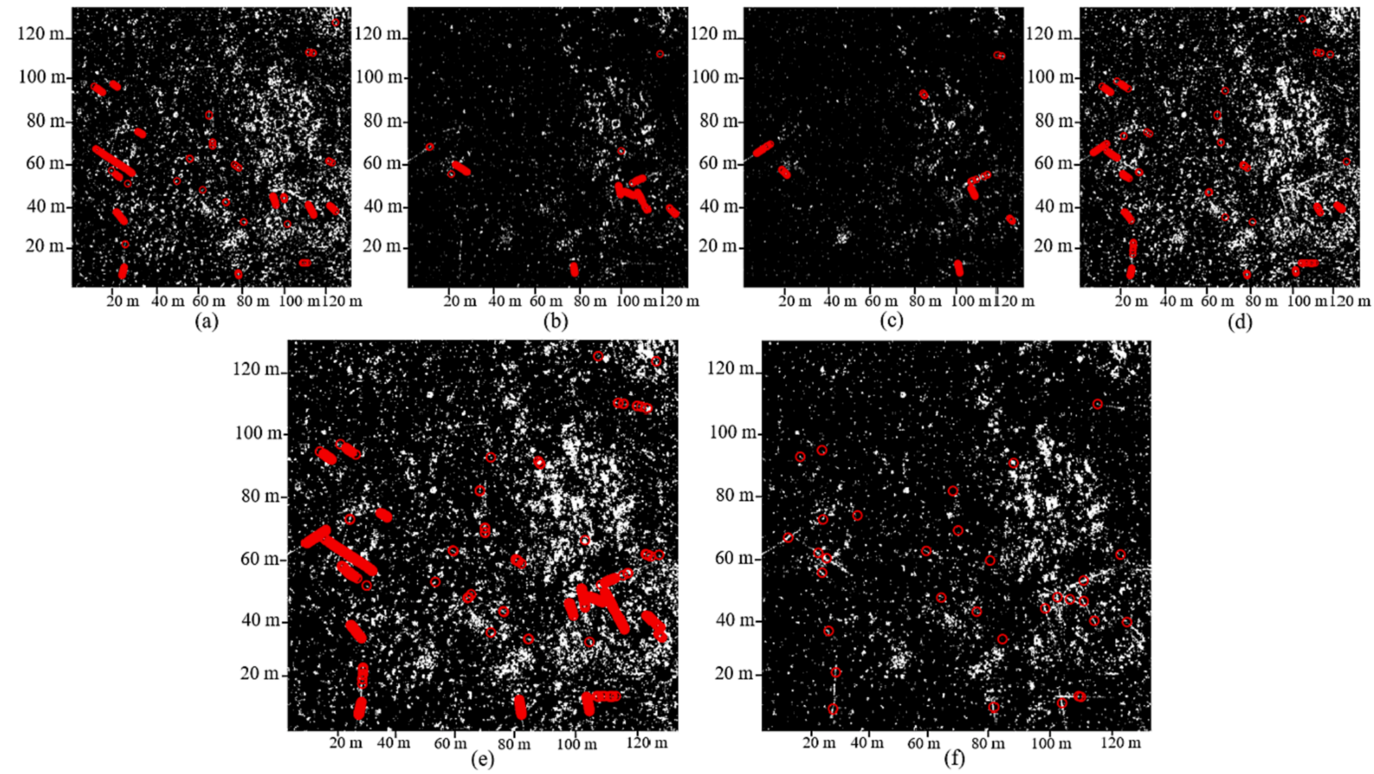

Fig. 5. The process of detecting downed deadwood. (a - d) Rasters detected at [0.2, 0.5], [0.4 – 0.7], [0.6 – 0.9] and [0.2 – 1.0] height intervals. (e) Potential positions based on all identified rasters (*Set A*). (f) The final positions of deadwood.

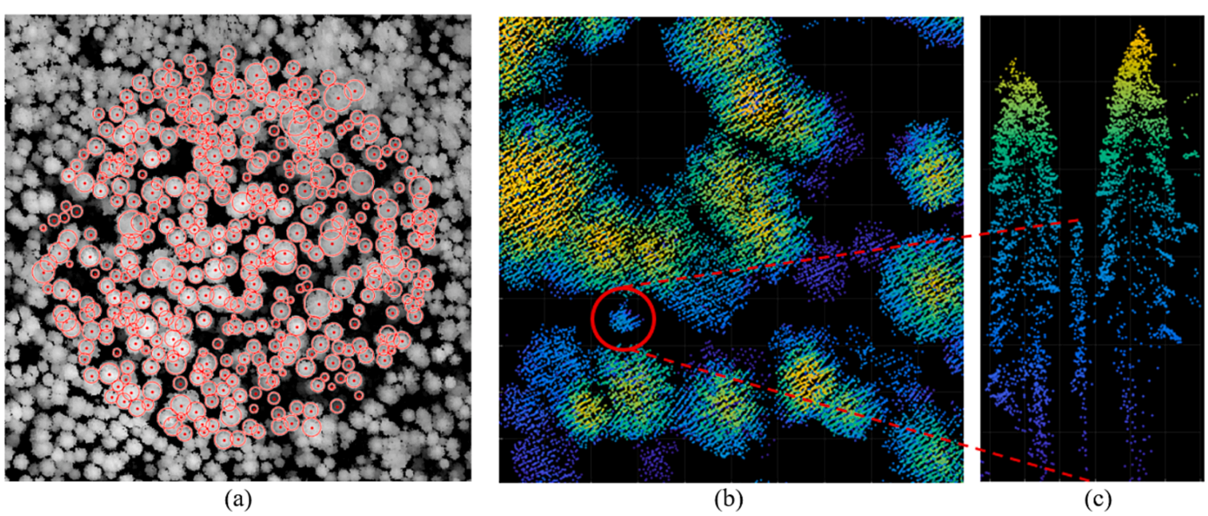

Fig. 6. An example of detected tree crowns (a), and standing deadwood detected from an aerial view (b) and from a side view (c).

diameters (CDs) usually differs between young and mature forest. Thus the method was based on the CD distribution of mature forest. For each tree with a narrow crown (a CD value of 0.75 m or 1.25 m), we calculated the 95 % percentile of the heights (H_{95}) and CD (C_{95}) of the surrounding trees in a 15-m radius. Narrow trees were determined to be in a mature forest stand when $H_{95} > 20$ m or $C_{95} > 3.5$ m. For narrow trees in mature forest stands, we then calculated the mean and standard deviation of the CDs in a 50-m radius (denoted as C_{mean} and C_{std}), and defined a crown diameter as narrow (C_o) if a) the crown diameter was 0.75 m or 1.25 m, and b) $C_o < C_{mean} - C_{std}$.

3.4. *Detection of trees with high conservation value (N trees)*

In Sweden, trees of high conservation value are routinely identified and preserved as part of a strategy to conserve biodiversity. Trees considered to be of high conservation value are typically old trees (remnants of an older tree generation) with wide and flattened crowns, and core bark, and trees that have woodpecker nesting holes or harbor many wood-decaying fungi. We used unusually large crowns as an indicator of trees of special importance for preserving biodiversity (N trees), and tested whether they could be used to predict conservation values. We first fit the tree heights and crown diameters (Fig. 7), derived from the individual tree segmentation in step 1 of S tree detection, for each study site using Equation (1):

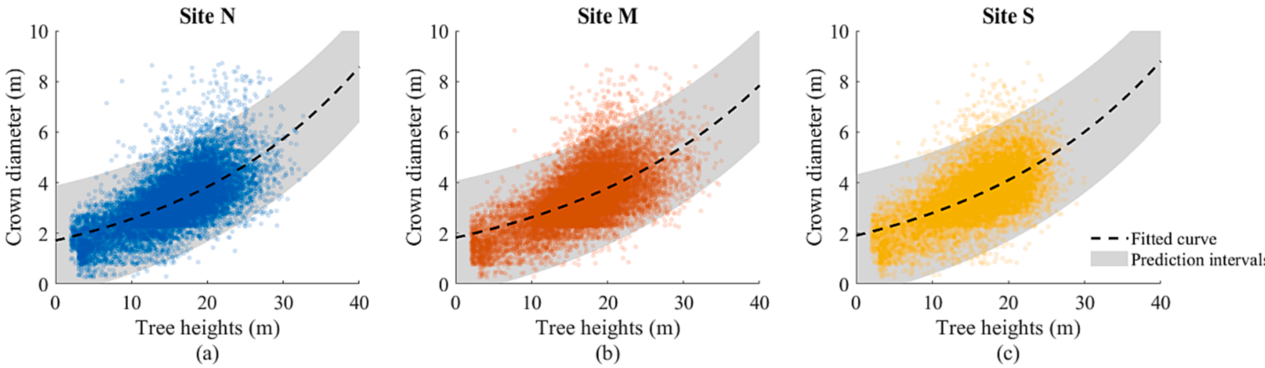

Fig. 7. Fitted curves for tree heights and crown diameters and the 99% prediction intervals for (a) Site N, (b) Site M, (c) Site S.

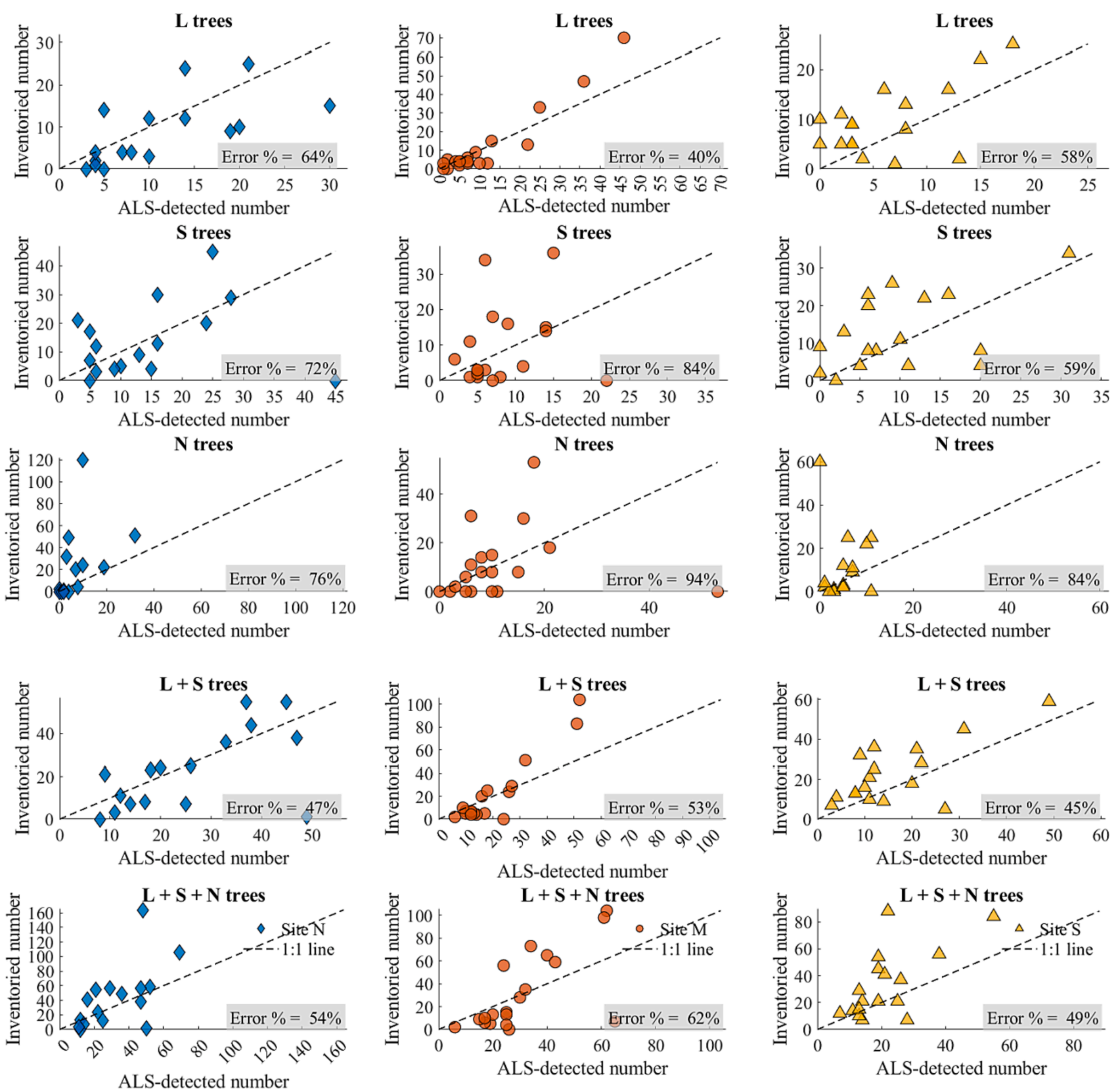

Fig. 8. The ALS-detected and field-inventoried numbers of indicator trees and the error rate for each study site (from left to right Site N, M and S).

$$C = ae^{bH} \tag{1}$$

where a and b are coefficients, C is the crown diameter, and H is the tree height. We identified a tree as an N tree when the crown diameter was larger than the 99 % prediction intervals, i.e. had significantly larger crowns than predicted by height using a generalized tree-height model.

3.5. Estimation of conservation values and validation

We validated the detection results by comparing the number of L, S, and N trees detected by ALS and the inventoried number from the field, and calculated the detection error rate (%) as:

$$\text{Error}\,(\%) = \frac{\sum_{i=1}^{n}|Y_{ALS} - Y_{Field}|}{\sum_{i=1}^{n}Y_{Field}} \tag{2}$$

where Y_{ALS} and Y_{Field} are the ALS and inventoried numbers of indicator trees, respectively, and i and n are the index of the plots and the number of plots, respectively.

We regressed the conservation values using the ALS-detected number of L trees, S trees, and N trees, and the sum of L and S trees (L + S trees), and the sum of all indicator trees (L + S + N trees), using Equation (3):

$$CV = a \times \ln(Y_{ALS} + 1) + b \tag{3}$$

where CV is the conservation value estimated from the field inventory,

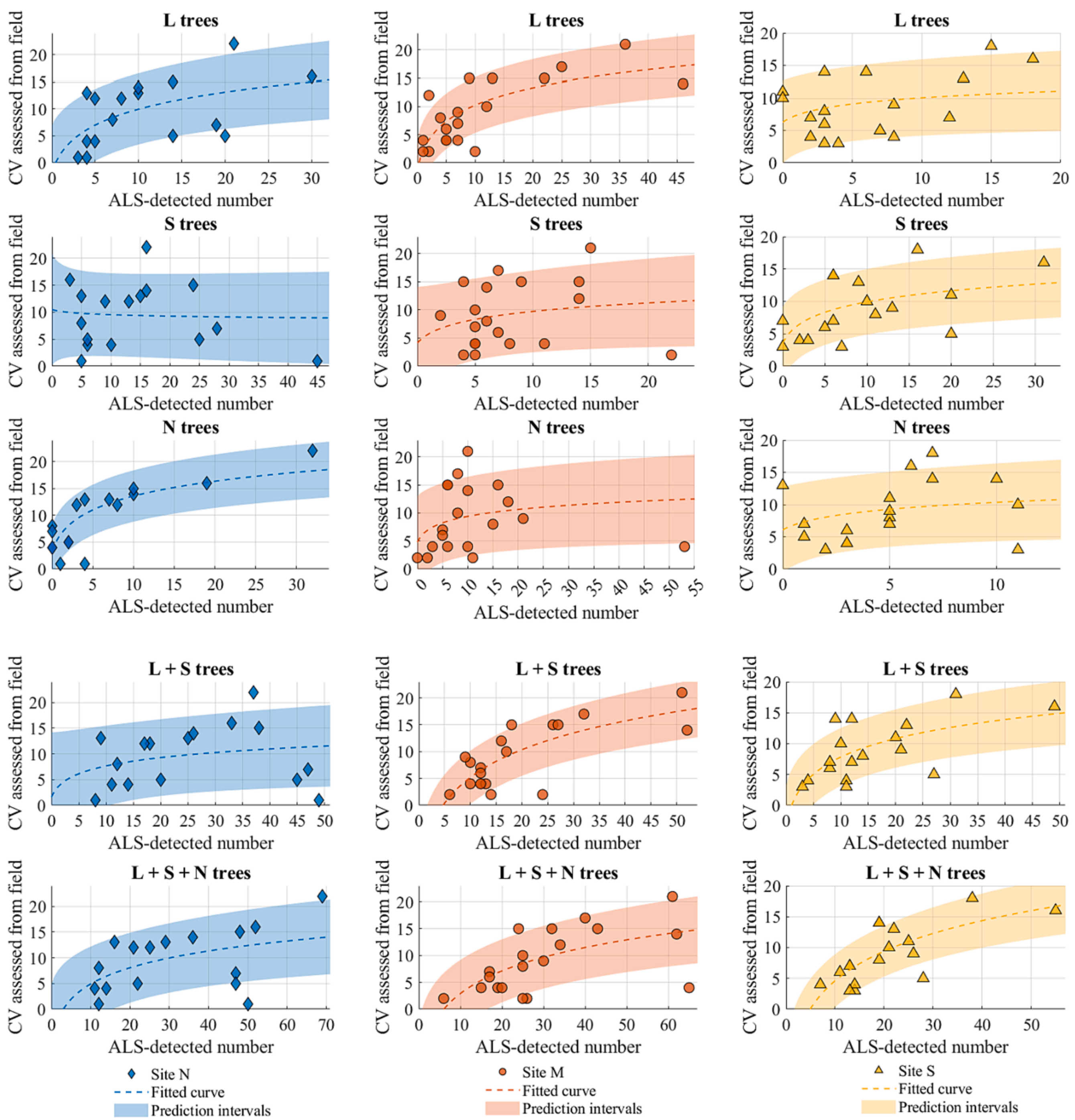

Fig. 9. Regression of the field-assessed conservation values (CV) and the ALS-detected number of indicator trees, with 75% prediction intervals.

and a and b are the coefficients. A value of 1 was added to Y_{ALS} before taking the natural logarithm to avoid negative infinity.

To demonstrate an application of the methodology, we generated maps based on the numbers of indicator trees to show the relative conservation values of the study area. The maps covered a 3 km × 4 km area at Site S, and included ten plots and one key woodland habitat identified by the Swedish Forest Agency. We implemented a detection algorithm using the ALS data to derive the locations of the indicator trees. We then generated heatmaps using kernel density estimation in QGIS, which indicated the density of indicator trees within a 56-m radius. The radius was set to match our field plot size. The resolution of the maps was 10 m. We determined the average pixel values for the ten plots from the heatmaps and tested the linear relationship between the values derived from the map and the CVs assessed from the field data.

4. Results

4.1. Detection of L, S, and N trees

The distributions of the ALS-derived tree heights and crown diameters for each plot, derived from 3.2 Segmentation of individual trees, are presented in Appendices A and B to show the structural characteristics. The detection accuracies using ALS data for the L trees by Section 3.1, S trees by Section 3.3, and N trees by Section 3.4 are presented in Fig. 8. The identification of L trees had a relatively small detection error rate, with the detected and inventoried numbers distributed along the 1:1 line, while the identification of S trees and N trees displayed larger detection errors (Fig. 8). There were also differences in detection accuracies between the different study sites (Fig. 8). By summing the ALS-detected number of indicator trees, however, the difference in detection errors between the sites decreased, resulting in similar detection accuracies across all sites (Fig. 8).

4.2. Regression of field-assessed CV

The regression of CV using ALS-derived L, S, and N trees varied between the three test sites (Fig. 9). The best fit between ALS-derived indicators and CV assessed from the field survey was in site M using L trees (intermediate latitude). Not all indicator trees derived from ALS data predicted conservation values successfully, e.g. S trees at Site N. However, the relationship between the number of indicator trees derived from ALS and assessed conservation values from the field was stronger when the different types of indicator tree were summed, especially when all three were summed together. A higher ALS detection accuracy did not, however, always lead to better prediction (Table 1). Our interpretation is that the detection error was not constant across tree type, and that a lower detection error for one tree type could compensate for the higher error of another. The performances differed less between the study sites when all types of indicator tree were used, suggesting the summed values provided a more generic and robust estimate than individual values.

4.3. Heatmaps of conservation values and hotspots

To demonstrate the potential of the proposed methods for large area mapping, we generated heatmaps of the ALS-derived indicator trees (Fig. 10) to indicate the relative conservation values. The heatmaps generally distinguished areas with high and low conservation values (Figs. 10 and 11), and the values from the maps showed a positive correlation with the field-assessed CVs for all ten plots. When using all types of indicator trees, the map-derived values had a linear relationship with the CVs, the largest R^2 value being 0.6 and the smallest RMSE of the CV scores being 2.9. We thus concluded that a heatmap derived from ALS-detected indicator trees can represent relative forest conservation values.

5. Discussion

This study has explored the potential of ALS data for mapping forest conservation values. The key technique was detecting indicator trees from point clouds and regressing the conservation values using the number of detected indicator trees. The indicator trees included lying deadwood (L trees), standing deadwood (S trees), and trees with a high conservation value (L trees). To detect L trees, we used a template matching method to identify linear objects above the ground with specific widths. Possible errors were identified, however. (1) When the canopy was too dense, or the field- or bush-layer vegetation sheltered the L trees, there could be insufficient point cloud data for L trees to be detected. (2) When there was field- or bush-layer vegetation with linear shapes, e.g. bushes along the road, the algorithm did not distinguish them from L trees, resulting in an over-estimation. (3) When snags decomposed into two or several pieces, it could also result in an over-estimation. This agrees with the challenges to detecting L trees from ALS data identified by others (Heinaro et al., 2021; Lindberg et al., 2013), and our approach resulted in a lower accuracy than studies using terrestrial laser scanning (TLS). For example, Yrttimaa et al. (2019) used TLS to detect downed deadwood and standing stem volume and achieved an overall completeness of 33 % and correctness of 76 %, respectively. However, although ALS data has a lower accuracy rate compared to TLS data, the advantage is that ALS data can be used to cover much larger areas for mapping.

Although we used a simple method for detecting S and N trees, we could predict the conservation values derived from field surveys. One way to improve the accuracy could be to incorporate species recognition algorithms, e.g. utilizing intensity information from multispectral laser scanning data (Axelsson et al., 2018; Amiri et al., 2019) and multi-temporal ALS data, and combining them with optical data (Kamińska et al., 2018). This would, however, require reference data from field inventories of individual trees to train the models.

Although the detection of L trees had a higher degree of accuracy than detection of S and N trees, the conservation values were predicted more accurately when all three ALS-derived indicators were combined. When used together (by summing the numbers of all three indicators), the weight of the detection error caused by each type of detection was 1/3 of the weight when using one alone. The different study sites also

Table 1
The detection error rate and regression performance of ALS indicator trees.

Indicator trees	Site N			Site M			Site S			All sites		
	Detection	Regression		Detection	Regression		Detection	Regression		Detection	Regression	
	Error [%]	R^2	RMSE*	Error [%]	R^2	RMSE*	Error [%]	R^2	RMSE*	Error	R^2	RMSE*
L	64	0.27	5.3	40	0.55	4.0	58	0.08	4.7	52	0.27	4.7
S	72	0.00	6.2	84	0.04	5.9	59	0.30	4.1	71	0.06	5.3
N	76	0.63	3.8	94	0.08	5.8	84	0.07	4.7	83	0.20	4.9
L + S	47	0.06	6.0	53	0.56	4.0	45	0.40	3.8	48	0.27	4.7
L + S + N	54	0.23	5.5	62	0.37	4.8	49	0.53	3.3	55	0.32	4.5

*RMSE of the estimated CV, which were distributed from 1 to 22 in our study area as measured by the field inventory.

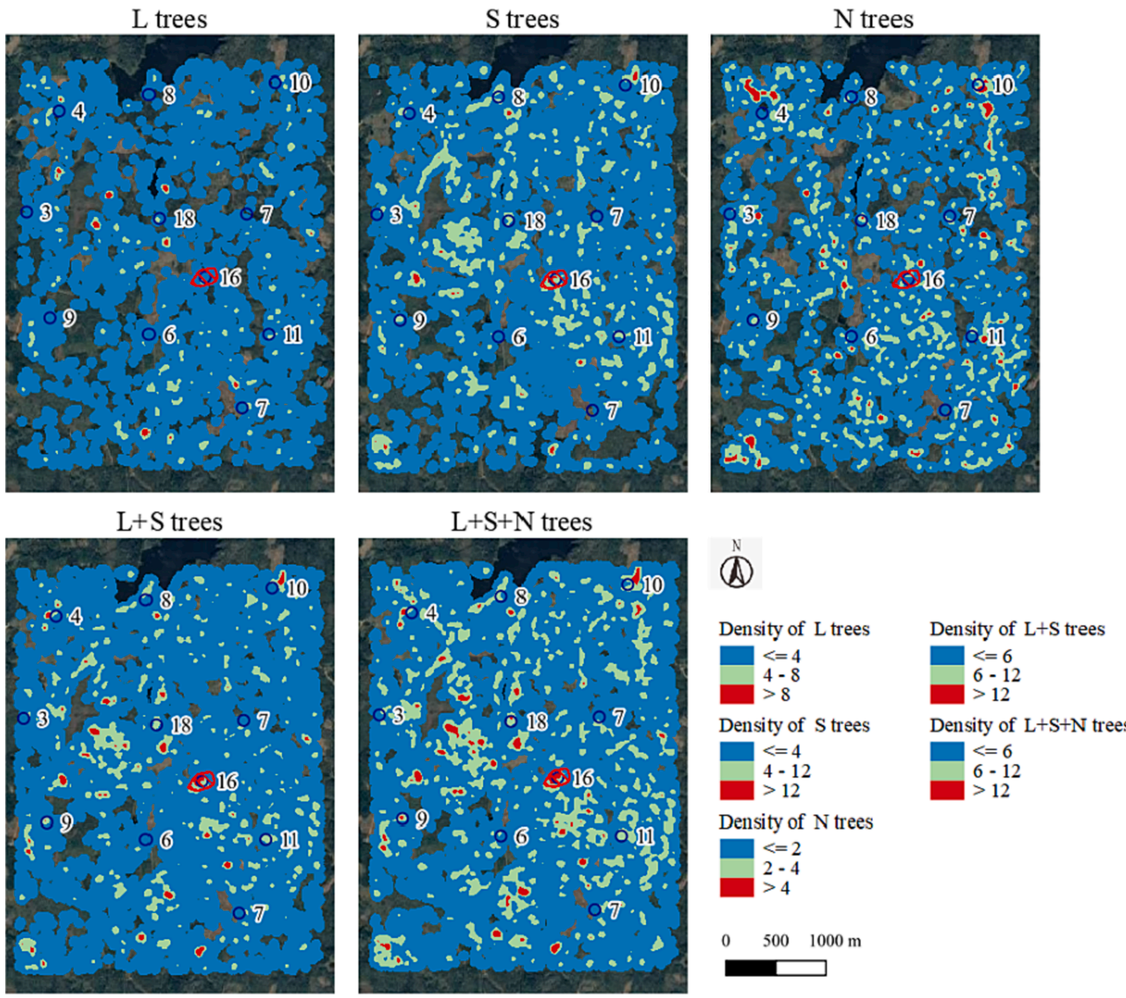

Fig. 10. Heatmaps using different types of indicator tree. The blue circles represent the field plots, and the adjacent numbers are the conservation values based on field inventories (low values = low potential for biodiversity, high values = high potential for biodiversity). The red polygon is an area identified as a key woodland habitat (an area especially important for the conservation of biodiversity) by the Swedish Forest Agency. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

responded differently to single indicators, while all test sites responded to the sum of all three indicators. Using three indicators is therefore more generic and can be applied to different types of site. When mapping the conservation values of an unknown area, we expect the performance to be more stable when all three indicators are used.

This study indicates that the amount of deadwood is an efficient predictor of assessed conservation values. The availability of deadwood is a widely used surrogate of biodiversity, supported by positive correlations between species richness of saproxylic organisms and deadwood availability (Similä et al., 2006; Djupström et al., 2010; Abrego and Salcedo, 2013; Ylisirniö et al., 2016). The volume of deadwood itself can be used as an indicator of forest species diversity. For example, a deadwood volume ≥ 6 m^3/ha is one of the five conditions that characterizes a boreal forest as having high biodiversity (Kallio et al., 2008). L trees have been detected from ALS data using 3D reconstruction methods (Lindberg et al., 2013; Mücke et al., 2013) and statistical methods based on the canopy structure (Tanhuanpää et al., 2015). Using deadwood as an indicator of conservation value is also proposed by Skogsbiologerna, using their method for obtaining reference data. The innovation of our study is applying the detection of deadwood using laser scanning data to estimate conservation values.

We propose a framework for using ALS data to generate wall-to-wall maps of conservation values, with many potential practical applications. Forest managers can use such maps for planning at several spatial scales. Although it is unlikely that they could replace field-based assessments of conservation value, the maps can provide important supporting information for such assessments. For example, using heatmaps could ensure that potential within-stand hotspots of biodiversity are checked during field inventories, or assist green infrastructure management at a landscape level (e.g. when selecting where in the landscape management should focus on wood production and where the focus should be conservation-oriented management). Furthermore, heatmaps could help authorities decide the locations and borders of conservation areas, taking into account the size and distribution of HCVFs and economic impacts. The maps could provide a dataset for habitat and ecological analyses, such as habitat connectivity, ecological corridors (Morandi et al., 2020; Wu et al., 2021), and habitat fragmentation (Ahmad et al., 2018; Chibeya et al., 2021; Nurfatimah et al., 2018), based on the locations of indicator trees detected using ALS data, and the density of indicator trees within a certain radius. Different radii could be used for different ecological analyses, considering the habitat area required for different species or the specific ecological processes of conservation interest (Fig. 12).Fig. A13.Fig. B14..

It should also be possible to derive forest structure information from the ALS data, and previous studies have shown that forest structure diversity can be used to estimate habitat heterogeneity (Sverdrup-Thygeson et al., 2016), biodiversity (Coops et al., 2016), the potential of forest ecosystem services (Vauhkonen, 2018), and conservation values

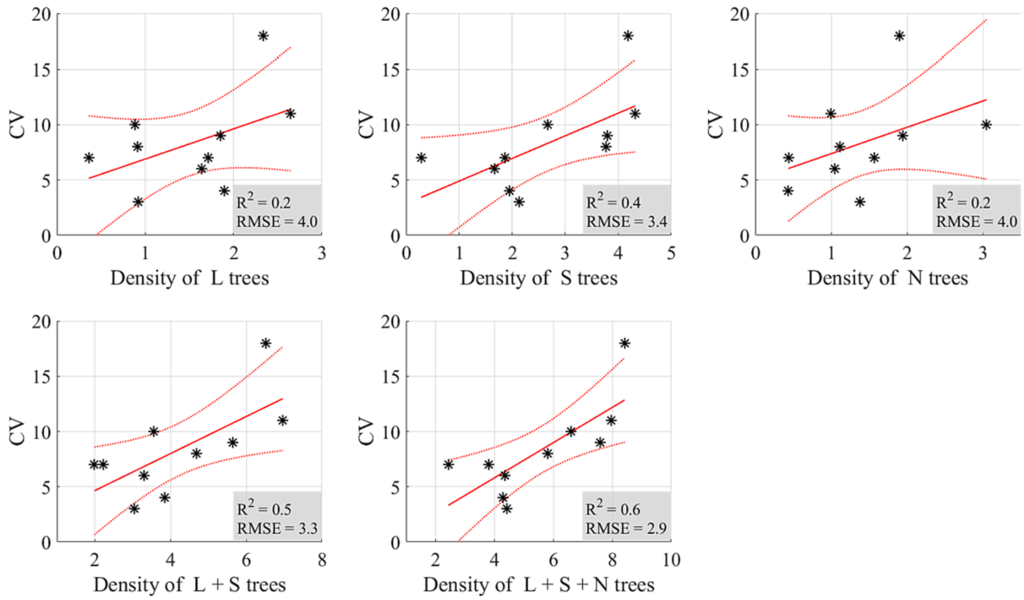

Fig. 11. Average densities of indicator trees derived from the heatmaps, and the linear regression with the conservation values (CV) assessed in the field. The red lines are the regression lines, and the dashed lines are the 95% confidence bounds. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

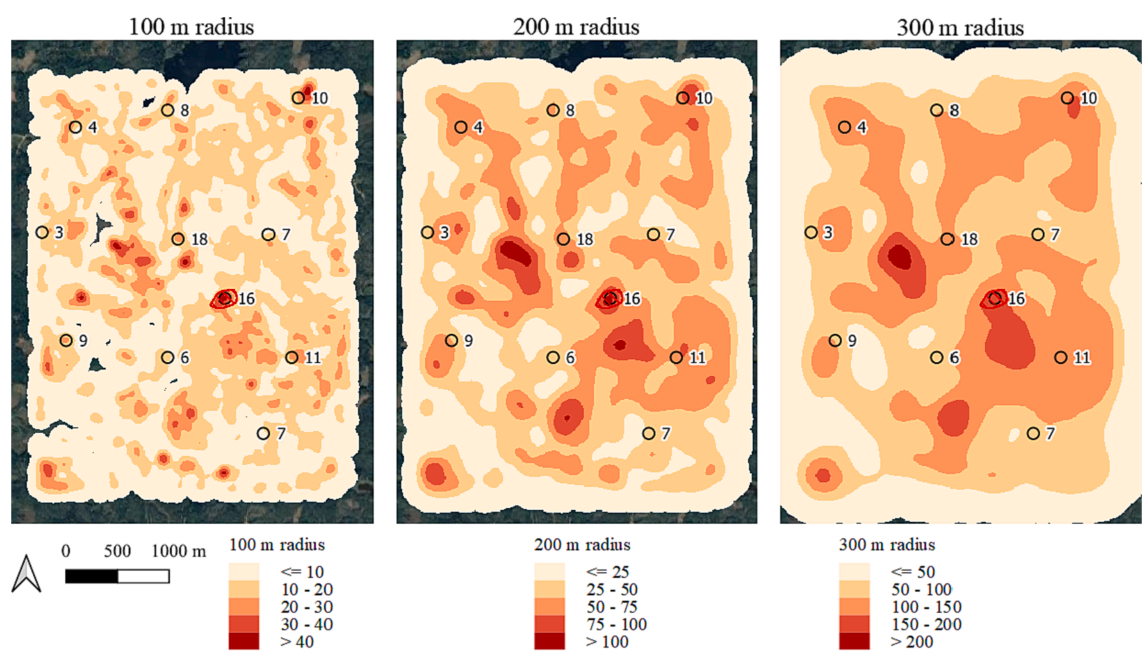

Fig. 12. Heatmaps generated using different radii for the number of indicator trees.

(Munteanu et al., 2022), according to the habitat heterogeneity hypothesis (Tews et al., 2004; Rödig et al., 2017; Lundholm, 2009; Pommerening et al., 2020). However, although we determined the distribution of tree heights and crown diameters from the ALS data, the distributions were often similar between plots with high and low CVs (Appendixes A and B). We used a systematic sampling method when setting up the plots, thus many different forest types were included in our samples, with different species compositions, ages, densities, layers, and management. All these factors added noise to the structural indicators, causing them to be less sensitive to conservation values. The indicator trees used, the L, S and N trees, were less influenced by the noise factors than the structural indicators, and showed more stable correlations with the conservation values. Besides the proposed method, another possible solution is to classify the forest into different types or functional groups first (Edman et al., 2011; Szantoi et al., 2016; Juutinen et al., 2008; Coops et al., 2016; Fuhr et al., 2022), and then compare conservation values within the same type using the structural indicators. This would require a larger dataset than the one used in this study, and should be the focus of future studies.

In addition, this study used dense ALS data to identify indicator trees, although such dense scanning is yet not available for large areas such as region or national level. Therefore, the dense laser scanning and the proposed methods can be used in selected study areas to derive wall-to-wall maps and conduct connectivity analysis for biodiversity. If less dense scanning is used to cover larger areas, we expect that the accuracy of identifying L trees would be lower, while identifying S and N trees

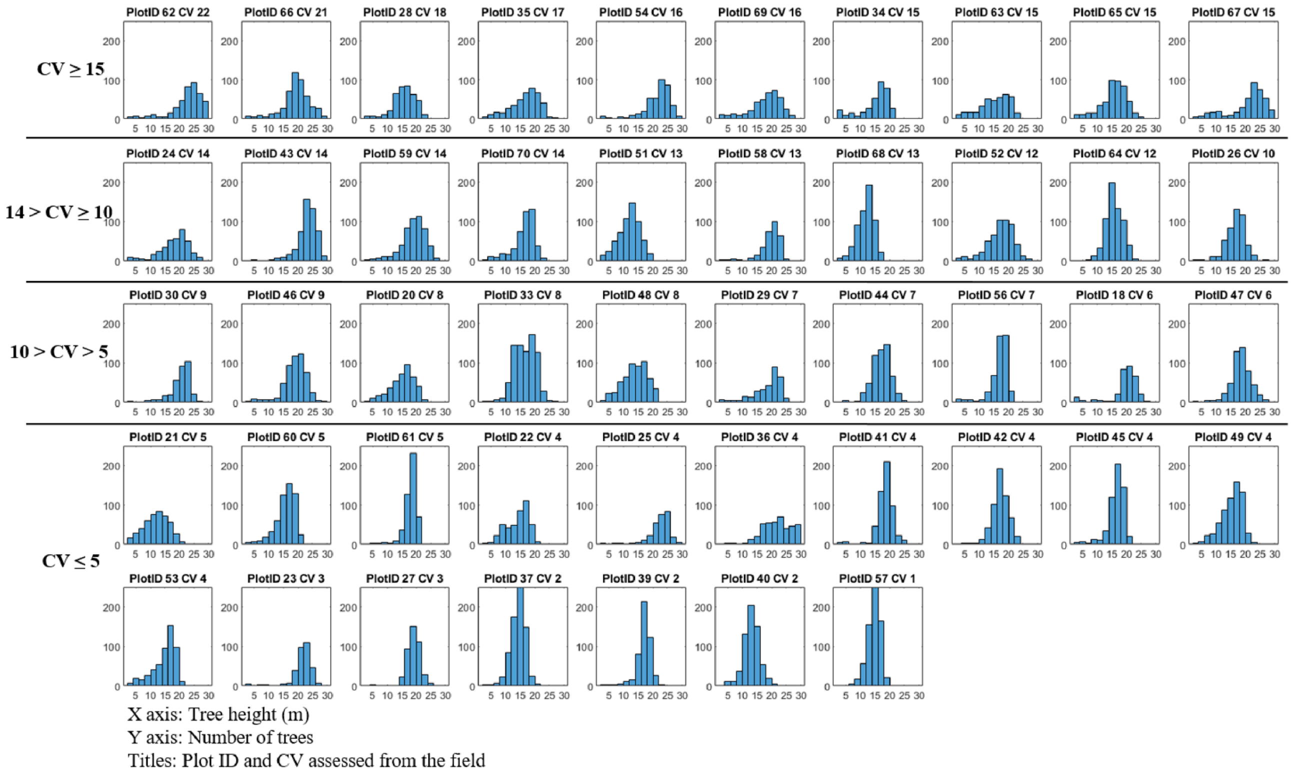

Fig. A13. The distribution of ALS-derived tree heights in each plot.

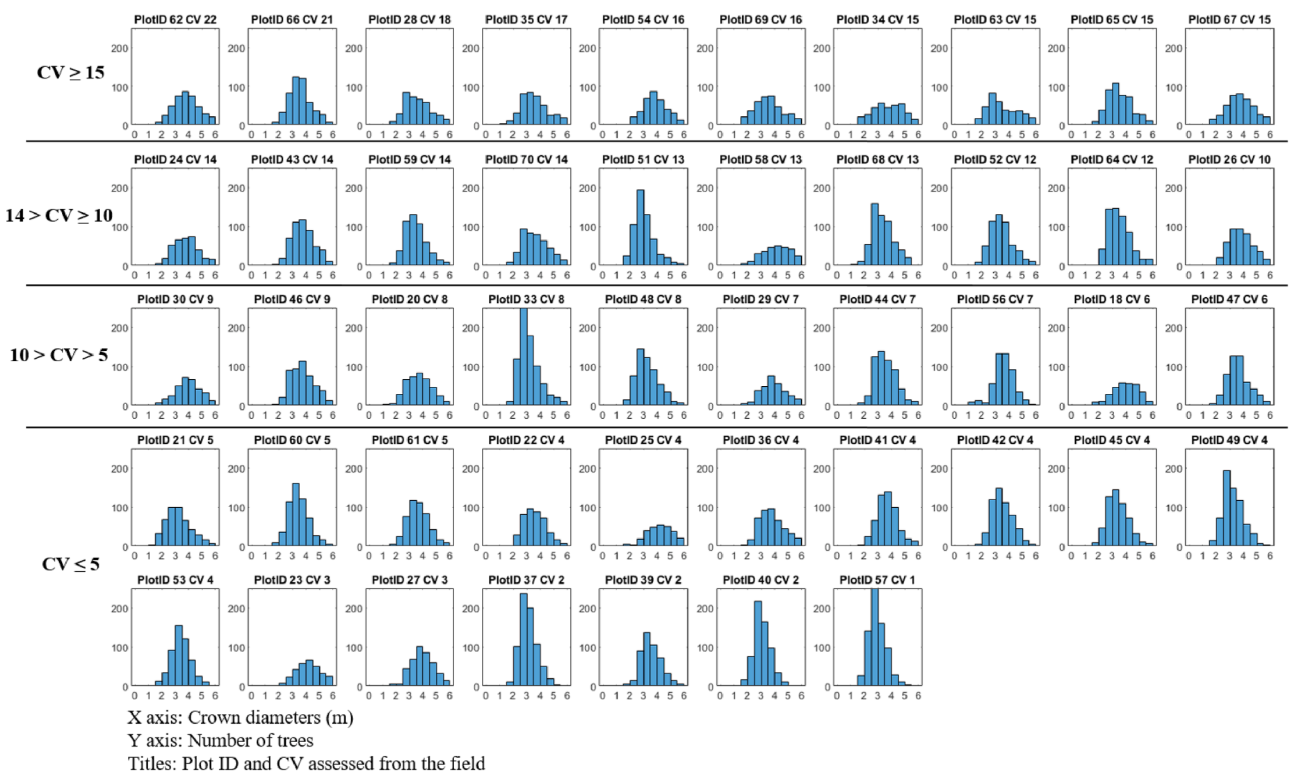

Fig. B14. The distribution of ALS-derived crown diameters in each plot.

should be relatively stable. It would thus be possible to map conservation areas using S and N trees. In future studies, it would be valuable to test the mapping performance using less dense ALS data that are available for large areas such as region or national level.

6. Conclusions

After evaluating methods for mapping forest conservation values, we recommend using the ALS-detected number of lying deadwood (L trees), standing deadwood (S trees), and trees especially important for conserving biodiversity (N trees). ALS estimates were more robust (better at predicting field-assessed conservation values) for all three study sites when the sum of all three indicators (L, S, and N trees) was used. The proposed method could be used for operational mapping of forest conservation values over larger areas, and building wall-to-wall maps to support the identification of conservation hotspots in the landscape. Such maps could be used to inform forest management and direct conservation efforts, thereby supporting the development of more sustainable forest management practices.

CRediT authorship contribution statement

Langning Huo: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Joachim Strengbom:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Tomas Lundmark:** Conceptualization, Funding acquisition. **Per Westerfelt:** Conceptualization, Methodology, Writing – review & editing. **Eva Lindberg:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Funding acquisition.

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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