Airborne laser scanning and digital stereo imagery measures of forest structure: comparative results and implications to forest mapping and inventory update

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Abstract. Airborne laser scanning (ALS) has demonstrated utility for forestry applications and has renewed interest in other forms of remotely sensed data, especially those that capture three-dimensional (3-D) forest characteristics. One such data source results from the advanced processing of high spatial resolution digital stereo imagery (DSI) to generate 3-D point clouds. From the derived point cloud, a digital surface model and forest vertical information with similarities to ALS can be generated. A key consideration is that when developing forestry related products such as a canopy height model (CHM), a high spatial resolution digital terrain model (DTM), typically from ALS, is required to normalize DSI elevations to heights above ground. In this paper we report on our investigations into the use of DSI-derived vertical information for capturing variations in forest structure and compare these results to those acquired using ALS. An ALS-derived DTM was used to provide the spatially detailed ground surface elevations to normalize DSI-derived heights. Similar metrics were calculated from the vertical information provided by both DSI and ALS. Comparisons revealed that ALS metrics provided a more detailed characterization of the canopy surface including canopy openings. Both DSI and ALS metrics had similar levels of correlation with forest structural attributes (e.g., height, volume, and biomass). DSI-based models predicted height, diameter, basal area, stem volume, and biomass with root mean square (RMS) accuracies of 11.2%, 21.7%, 23.6%, 24.5%, and 23.7%, respectively. The respective accuracies for the ALS-based predictions were 7.8%, 19.1%, 17.8%, 17.9%, and 17.5%. Change detection between ALS-derived CHM (time 1) and DSI-derived CHM (time 2) provided change estimates that demonstrated good agreement ($r = 0.71$) with two-date, ALS only, change outputs. For the single-layered, even-aged stands under investigation in this study, the DSI-derived vertical information is an appropriate and cost-effective data source for estimating and updating forest information. The accuracy of DSI information is based on a capability to measure the height of the upper canopy envelope with performance analogous to ALS. Forest attributes that are well captured and subsequently modeled from height metrics are best suited to estimation from DSI metrics, whereas ALS is more suitable for capturing stand density. Further investigation is required to better understand the performance of DSI-derived height products in more complex forest environments. Furthermore, the difference in variance captured between ALS and DSI-derived CHM also needs to be better understood in the context of change detection and inventory update considerations.

Résumé. Le scanneur laser aéroporté (SLA) a démontré son utilité dans les applications en foresterie et a suscité un intérêt renouvelé pour d'autres formes de données de télédétection, en particulier celles qui capturent les caractéristiques tridimensionnelles (3D) de la forêt. Une telle source de données résulte du traitement avancé d'images numériques stéréoscopiques (INS) à haute résolution spatiale pour générer des nuages de points en 3D. À partir du nuage de points...
Introduction

The capacity to acquire information characterizing the three-dimensional (3-D) structure of forests has invigorated forest mapping. Airborne laser scanning (ALS) data have emerged as a primary data source for 3-D information on forest vertical structure (e.g., Naesset et al., 2004; McRoberts et al., 2010; Walder et al., 2012). ALS has proven to be an information-rich asset for forest managers, enabling the generation of highly detailed digital terrain models (DTM) and the estimation of a range of forest inventory attributes including height, basal-area, stem volume, and aboveground biomass (Naesset et al., 2004). The most used method to estimate forest inventory attributes is the area-based approach, in which ALS point clouds are generalized into metrics that are then used as independent variables in models developed using co-located ground plot measurements (Naesset, 2002a).

The utility and accessibility of ALS data has renewed the forestry community’s interest in alternate forms of remotely sensed data, especially those with 3-D sensing capacity. One such technology is the advanced processing of high spatial resolution digital stereo imagery (DSI) to generate digital surface models (DSMs) (e.g., Bohlin et al., 2012; Järnstedt et al., 2012; Nurminen et al., 2013; Straub et al., 2013) from which vertical information with similarities to ALS can be produced. DSI have been used to measure tree and stand characteristics. Tree heights of individual trees were measured semi-automatically using DSI by Gong et al. (2002). Naesset (2002b) used automatic image matching to determine mean stand height. Fujita et al. (2003) and Véga and St-Onge (2008) have shown the potential of using multitemporal DSI in monitoring long-term canopy dynamics and height growth using DSI. In a process analogous to that applied to an ALS-derived DSM, forest canopy height measurements are generated by subtracting ground elevations from the DSI-derived DSM (resulting in a canopy height model or CHM), with the accuracy and precision of these height measurements being a function of the quality of the DTM that is used. For this application, a DTM must be accurate and have a sufficiently high spatial resolution (e.g., <2 m). Such detailed DTMs, particularly in forested areas, are typically only available operationally from ALS (e.g., St-Onge et al., 2004; Nurminen et al., 2013). With a high spatial resolution DTM, it has been shown that tree heights can be measured accurately using DSI (St-Onge et al., 2004). It is also shown that canopy height models derived from DSI and ALS are highly correlated (St-Onge et al., 2008). The approach for deriving photogrammetric DSMs has a lineage to digital softcopy processing of large-scale photography, with current advances being largely related to computer processing capacity, algorithm development, and the availability of high spatial resolution elevation data (Hirschmugl, 2008; Leberl et al., 2010).

The creation of image-derived DSMs requires high-resolution aerial images with stereo coverage (Hirschmugl, 2008; Leberl et al., 2010). The use of digital aerial cameras has enabled a substantial increase in the number of overlapping images that are acquired for on-going forest inventory or monitoring programs. In forested regions, the availability of many overlapping images provides the multi-image information required to produce a DSM and reduces the impact of
occlusions (i.e., shadows), which occur more frequently when there is less image overlap (Haala et al., 2010). The film-to-digital transition has resulted in improvements to the radiometric properties of the images, whereas advances in computing technology have made complex algorithms for image matching practical (Leberl et al., 2010). These technological advances have greatly enhanced the quality of DSMs derived from stereo-photogrammetric processing, improving the characterization of detailed structures. The digital image resolution is defined by the Ground Sampling Distance (GSD), which depends on various factors (Nelson et al., 2001), most importantly the flying height and the specifications of the camera (instrument) used. Flying heights between 550 m and 4800 m have been used with 60%–90% forward overlap and 30%–60% side overlap for forestry applications, resulting in GSDs ranging from 0.05 m to 0.5 m (e.g., Hirschmugl, 2008; Bohlin et al., 2012; Järnstedt et al., 2012; Nurminen et al., 2013).

Several countries are currently using ALS for creating or updating regional or nation-wide DTMs, and industrial forest management organizations and jurisdictional resource management agencies are also collecting ALS data over large areas. As a result, areas with ALS-derived DTMs are increasingly common and available to provide the high spatial resolution ground elevations required for generation of DSI-based forest height information. For forest mapping and monitoring purposes, it may therefore be possible to acquire ALS data intermittently (i.e., every 10 or 20 years, depending on forest and management considerations), with DSI used to update forest information in the intervening periods (White et al., 2013). The practical implications of this scenario are the subject of active research, although DSI has already proven to be suitable for reconstruction of height growth (Veiga and St-Onge, 2008) and for mapping of long-term canopy dynamics (Fujita et al., 2003).

ALS surveys require lower flying altitudes and slower flying speeds relative to a photogrammetric survey, thereby contributing to increased costs that are typically associated with ALS surveys (Leberl et al., 2010). In addition, the swath widths of photogrammetric surveys are generally wider as a function of their higher flying altitudes, meaning that a single photogrammetric swath covers a larger area than a typical ALS swath. Thus, with the same number of flying hours, a larger area can be covered with a photogrammetric survey. However, ALS surveys are not constrained, as photogrammetric surveys are, by the need for optimal sun angles, particularly in northern forest areas (Baltsavias, 1999).

In operational forest mapping, DSI-derived information could be used instead of ALS data in the area-based approach. To date, there are a limited number of studies that have used DSI-derived height information to predict forest inventory attributes in conjunction with an ALS-derived DTM (White et al., 2013). Bohlin et al. (2012) predicted tree height, stem volume, and basal area for forest stands using canopy height, density, and texture metrics derived from DSI. The ALS data used in their study had a resolution of seven pulses per square metre, and the DSI GSD ranged from 0.12 m to 0.48 m, depending on the flying altitude. Estimation was done following the area-based approach (Næsset, 2002a), and stand-level accuracy was validated using 24 stands. With varying image acquisition parameters, the predicted accuracies (root mean squared error (RMSE) %) for tree height, stem volume, and basal area were 8.1–8.8%, 13.0%–20.1%, and 12.6%–19.6%, respectively. These results are comparable with results obtained by other studies that have used ALS data for estimation (e.g., Næsset et al., 2004; Næsset, 2007; van Leeuwen and Nieuwenhuis, 2010). Järnstedt et al. (2012) compared plot-level estimates of diameter, basal area, mean height, dominant height, and volume from ALS and DSI. ALS resolution was 10 pulses per square metre and the DSI GSD was approximately 0.25 m. ALS-based estimates had a lower RMSE for all attributes estimated. For example, volume was estimated with an RMSE of 31.3% with ALS and 40.4% with DSI. Nurminen et al. (2013) studied the effect of forward overlap and off-nadir angle in DSI-based estimation of forest characteristics. According to their results, the higher forward overlap (80% vs. 60%) only slightly improved the estimation accuracy, whereas change in the off-nadir angle (0–20°) did not effect the estimation accuracy. Straub et al. (2013) used DSI and ALS for estimating timber volume and basal area in mixed central European forests. They obtained root mean square (RMS) accuracies of 37.9% and 35.3% for timber volume and basal area, respectively, using DSI in conjunction with ALS-derived DTM. The respective accuracies using ALS only were 31.9% and 30.2%.

In this study, we investigated DSI capabilities in capturing the variation in the most commonly estimated forest attributes and canopy structure in managed forest conditions typical in Finland. Comparisons of DSI estimates are made to ALS equivalents. Our objective was to better understand the strengths and limitations of DSI for estimating forest inventory attributes with an area-based approach. This study is a continuation of the Järnstedt et al. (2012) study, where a basic suite of forest inventory attributes were predicted using metrics extracted from DSI and ALS. In this research, we also compared ALS and DSI-derived CHMs to determine the capacity for change detection (in this case, over 3 years). Determining the capacity of DSI to provide information in support of forest mapping and inventory update was a key aim of our current research, and we discuss the implications of our results for operational forestry applications.

**Materials**

**Study area**

The study area is located at Evo, Finland (61.19°N, 25.11°E). The area belongs to the southern Boreal Forest
Zone and comprises approximately 2000 ha of managed forest. Evo is also a popular recreation area, which distinguishes it from other entirely homogenous managed forests, and it represents a range of stand conditions from natural to intensively managed southern boreal forests. Stands are mainly even aged and single layer, with an average stand size of slightly less than 1 ha. The elevation of the area varies from 125 m to 185 m above sea level. Scots pine (Pinus sylvestris, L.) and Norway spruce (Picea Abies (L.) H. Karst.) are the dominant tree species in the study area, contributing 44.7% and 33.5% of the total volume, respectively. The percentage of deciduous trees is 21.8% of the total volume.

Ground truth

The field data consisted of individual tree measures for 500 circular plots, each with a radius of 9.77 m. Sampling of the field plots was based on pre-stratification of existing stand inventory data to distribute plots over various site types, tree species, and stand development classes. The plots were located with a GEOXM 2005 Global Positioning System (GPS) device (Trimble Navigation Ltd., Sunnyvale, Calif., USA), and the locations were post-processed with local base-station data resulting in an average error of approximately 0.6 m. Field measurements were collected in 2007 and 2009. The following variables were measured for trees with a diameter at breast height (dbh) larger than 7 cm: location, tree species, dbh, and height. Stem volumes and tree-level aboveground biomass values were calculated according to models developed by Laasasenaho (1982) and Repola (2008, 2009). Both models used the same predictors as follows: tree species, dbh, and height. Plot-level estimates were obtained by summing the tree-level data. The SIMO forest management planning calculation system (Rasinmäki et al., 2009) was used for adding growth to the plots measured in 2007. The statistics of the forest variables in the plots are presented in Table 1.

Aerial images

The aerial imagery was acquired in August 2009. The imaging sensor used was a Microsoft UltracamXp with stereoscopic forward overlap of 70% and side overlap of 50%. The area was covered by 51 images in total. Images were taken from three separate flight lines covering 17 images each. The GSD was approximately 0.25 m. The images were delivered as 16-bit RGB (red, green, blue) and color infrared (CIR) composites. The image orientation was completed by the data vendor (FM International Oy, Helsinki, Finland). Based on the image orientation report provided, the RMS accuracy of the orientation (validated with seven ground control points) was 4.3 cm, 3.1 cm, and 9.1 cm in the X, Y, and Z directions, respectively.

Airborne laser scanning

ALS data were acquired in 2006 and 2009. Our main analyses were based on ALS data acquired in July 2009 using a Leica ALS50-II SN058 system (Leica Geosystems AG, Heerbrugg, Switzerland). In addition, we used ALS data acquired in July 2006 with an Optech ALTM3100C-EA system (Optech Inc., Vaughan, Ont., Canada) to provide an initial state (T1) for change detection. For the 2009 ALS campaign, the flying altitude was 400 m with a speed of 80 knots, a scan angle of 30°, a beam divergence of 0.15 mrad (1/e), and a pulse rate of 150 kHz. The density of the first pulse echoes returned within the plots was 10 hits per m². The 2006 ALS data were acquired with a flying altitude of 1900 m at a speed of 146 knots, a scan angle of 28 degrees, beam divergence of 0.3 mrad (1/e), and a pulse rate of 70 kHz. The density of the first pulse echoes returned within the plots was 1.8 hits per m². In both of the datasets, a DTM and, consequently heights above ground level, were computed by the data provider. The expected accuracy of the ALS-derived DTM varies in boreal forest conditions by around 10–50 cm (Hyppä et al., 2009).

Methods

Generation of the DSI-based surface and canopy height model

For the development of a high spatial resolution DSI-based DSM, the Next-Generation Automatic Terrain Extraction (NGATE) module of the software SOCET SET (from BAE Systems) was used. NGATE combines area-based and feature-based methods to calculate similarity measurements on the basis of a cross-correlation approach (DeVenecia et al., 2007). The algorithm iterates seven times, using the pyramid levels of the images, proceeding from coarse resolution (1:64) to the original image resolution (1:1). Different correlation strategies for different image contents (e.g., urban, flat homogenous, hilly, and steep areas) are provided by the software vendor. The size of the correlation windows, the threshold for spikes (slope limit), and the minimum correlation coefficient difference are the most important differences between correlation strategies. For this study, a modified steep strategy was used that allowed for high elevation changes between matched points (slope limit 60° or 85° depending on the iteration), thereby ensuring that individual trees and borders between stands were not filtered out. Correlation window size was

<table>
<thead>
<tr>
<th>Table 1. Summary of forest plot characteristics (n = 500).</th>
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<tr>
<td>Mean height (H), m</td>
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<td>Mean dbh (D), cm</td>
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<tr>
<td>Basal area (G), m²/ha</td>
</tr>
<tr>
<td>Total stem volume (V), m³/ha</td>
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<td>Aboveground biomass (AGB), t/ha</td>
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object to be modelled is 2 point measurements, meaning that the minimum size of an object to be modelled is \(2n \times 2n\), where \(n\) is the original grid spacing (Baltsavias et al., 2008). Based on a GSD of 0.25 m therefore, the resolution of the resulting DSM was set to 0.5 m. No multi-image matching was used. For more detailed description of the DSM production see Järnstedt et al. (2012). The ALS-based DTM from 2009 was subtracted from DSI-based DSM to create CHM.

**Extraction of metrics**

For investigation of the performance of the DSI-based height information in capturing variation in the forest variables, several statistical metrics describing canopy structure were extracted for the sample plots. The DSI-derived CHM raster layer was treated as an XYZ-point cloud. First, heights over 2 m were classified as vegetation (Nilsson, 1996) and then a vegetation ratio (vege) was calculated as a ratio between vegetation heights and all heights within a plot. The other extracted metrics were: maximum (Hmax), average (Hmean), standard deviation (Hstd), and coefficient of variation of heights (CV); height at 10%–90% percentiles (h10–h90), and canopy cover metrics as a proportion of heights below a certain relative canopy height (p10–p90). Only the heights belonging to vegetation (that is, height over 2 m) were used in calculation of these metrics. The same metrics were extracted from the ALS data using first returns only.

**Predictions and accuracy evaluation**

Height, diameter, basal area, stem volume, and biomass were predicted by means of DSI and ALS metrics using the nearest neighbour (NN) approach. Forest variables measured in the field (stem volume, biomass) were used as target observations and plot-specific metrics derived from DSI and ALS data were used as predictors. The Random Forest approach (RF, Breiman, 2001) was applied in the NN search. Based upon the quality of results and desirable statistical characteristics (i.e., the capability to predict multiple response variables simultaneously, use a large number of predictors without the problem of overfitting, and evaluate accuracy with built-in functionality), the use of RF in NN estimation of forest variables is increasingly common (e.g., Hudak et al., 2008; Breidenbach et al., 2010; Vauhkonen et al., 2010; Latifi et al., 2010; Falkowski et al., 2010; Yu et al., 2011). Hudak et al. (2008) and Latifi et al. (2010) demonstrated that the RF method is more robust and flexible for forest variable prediction when compared with other NN distance measures, such as Euclidian distance, Mahalanobis distance, or Canonical Correlation Analysis. In the RF method, several regression trees are generated by drawing by replacement from two-thirds of the data for training and one-third for testing for each tree. The samples that are not included in training are called out-of-bag samples, and they can act as a testing set in the approach. The measure of nearness in RF is defined, based on the observational probability of ending up in the same terminal node in classification. The R statistical computing environment (R Core Team, 2012) and yaImpute library (Crookston and Finley, 2008) were applied in the RF predictions. The yaImpute library is tailored to NN forest attribute estimation.

In the present study, 1000 regression trees were generated and the square root of the number of predictor variables was picked randomly at the nodes of each regression tree. Randomness was taken into account by running the RF method 100 times. The final result was the average of these runs. In this study, predictors and target observations were available for all of the test plots. Therefore, the accuracy of the predicted variables was evaluated by calculating bias and RMSE using out-of-the-bag samples. The relative bias and RMSE were calculated according to the sampled mean of the variable in question. The number of neighbours for imputation was set to five.

**Change detection**

The capacity to detect change over time, that is between 2006 and 2009, was investigated using ALS and DSI-derived CHMs. Changes between ALS data acquired in 2009 and 2006 were compared with changes between DSI (acquired in 2009) and ALS acquired in 2006. Differences in change, as captured between the two subsequent ALS surveys (noted as Change\(_{\text{ALS}}\)) and the DSI and ALS (noted as Change\(_{\text{DSI}}\)), were characterized. Change\(_{\text{ALS}}\) and Change\(_{\text{DSI}}\) were both calculated as a CHM 2009 – CHM 2006.

**Results**

**Comparison of DSI and ALS metrics**

Height distribution metrics between DSI and ALS were similar (Figure 1); however, there is a general trend that lower height percentiles are greater in DSI, whereas higher height percentiles are almost equal. Mean differences between h70, h80, and h90 were under 0.2 m, whereas the mean difference for h10 was 2.4 m. In a paired Student’s \(t\) test, the DSI and ALS height metrics between h10 and h60 were significantly different (\(p < 0.05\)). For the DSI, 93.8% of the height observations were classified as coming from vegetation (i.e., height > 2 m), whereas only 65.5% of the ALS heights were > 2 m.
Canopy cover metrics between DSI and ALS were less similar than height metrics (Figure 2). In general, values for ALS canopy cover metrics were greater than their DSI counterparts, indicating that more observations were below a certain relative canopy height in ALS compared with DSI. Median differences in canopy cover metrics decreased with increased relative height. The mean difference at p10 was 0.31, whereas the mean difference at p90 was 0.24. In a paired Student’s t test, all the DSI and ALS canopy cover related metrics were found to be significantly different (p < 0.05).

Tree height is directly measured by both ALS and DSI. DSI metrics that were most strongly correlated with plot mean height were h90 (r = 0.85) and Hmax (r = 0.82) (Table 2). ALS metrics that were most strongly correlated with plot mean height were h90 and h80 (for both, r = 0.93). ALS-derived h90 was, on average, 0.13 m higher than DSI-derived h90 across all plots. DSI and ALS-derived Hmax are strongly correlated (r = 0.91) (Figure 3) and both of them are capable of capturing the entire range of variation in mean height (Table 1 and Figure 1).

Basal area and stem volume are both dependent on tree stem density and size (diameter and height) and neither variable is measured directly by DSI or ALS. ALS canopy cover metrics such as proportion of returns below a certain height (p10–p90), describe canopy cover and are highly correlated with basal area. In our data, ALS-derived p30 and p40 (for both, r = −0.67) provided the best correlations with basal area. For DSI, the proportion of returns below a certain height (p10–p90) provided correlations between −0.45 and −0.59; however, h10 (r = 0.68) and h20 (r = 0.67) were the most correlated with basal area (Figure 4). For comparison, ALS-derived h10 and h20 correlations with basal area were 0.39 and 0.48, respectively.

ALS is capable of penetrating the forest canopy and can capture small openings in the canopy structure. Occlusions

Figure 2. Box-and-whisker plot of DSI and ALS metrics describing proportional densities at various heights. The bottom and top of the box are the lower and upper quartiles, and the band near the middle of the box is the median. The end of the whiskers represents the minimum and maximum values.

Table 2. Correlation coefficients between ALS- and DSI-derived metrics and forest variables.

<table>
<thead>
<tr>
<th></th>
<th>Mean height (m)</th>
<th>Basal area (m²/ha)</th>
<th>Total stem volume m³/ha</th>
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<tr>
<td></td>
<td>ALS</td>
<td>DSI</td>
<td>ALS</td>
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<tr>
<td>Hmax</td>
<td>0.88</td>
<td>0.82</td>
<td>0.31</td>
</tr>
<tr>
<td>Hmean</td>
<td>0.85</td>
<td>0.69</td>
<td>0.48</td>
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<tr>
<td>Hstd</td>
<td>0.67</td>
<td>0.47</td>
<td>0.01</td>
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<tr>
<td>CV</td>
<td>0.16</td>
<td>0.10</td>
<td>−0.31</td>
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<tr>
<td>h10</td>
<td>0.35</td>
<td>0.40</td>
<td>0.39</td>
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<td>h20</td>
<td>0.49</td>
<td>0.48</td>
<td>0.48</td>
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<td>h30</td>
<td>0.60</td>
<td>0.54</td>
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<td>h40</td>
<td>0.70</td>
<td>0.60</td>
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<td>h50</td>
<td>0.76</td>
<td>0.66</td>
<td>0.49</td>
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<td>h60</td>
<td>0.83</td>
<td>0.71</td>
<td>0.46</td>
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<tr>
<td>h70</td>
<td>0.90</td>
<td>0.76</td>
<td>0.38</td>
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<tr>
<td>h80</td>
<td>0.93</td>
<td>0.81</td>
<td>0.34</td>
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<tr>
<td>h90</td>
<td>0.93</td>
<td>0.85</td>
<td>0.31</td>
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<tr>
<td>vege</td>
<td>−0.20</td>
<td>−0.18</td>
<td>0.64</td>
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<td>p10</td>
<td>0.24</td>
<td>0.18</td>
<td>−0.63</td>
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<td>p20</td>
<td>0.23</td>
<td>0.14</td>
<td>−0.66</td>
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<tr>
<td>p30</td>
<td>0.19</td>
<td>0.06</td>
<td>−0.67</td>
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<td>p40</td>
<td>0.13</td>
<td>−0.05</td>
<td>−0.67</td>
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<td>p50</td>
<td>0.04</td>
<td>−0.14</td>
<td>−0.65</td>
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<td>p60</td>
<td>−0.08</td>
<td>−0.20</td>
<td>−0.61</td>
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<td>p70</td>
<td>−0.19</td>
<td>−0.20</td>
<td>−0.55</td>
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<td>p80</td>
<td>−0.26</td>
<td>−0.16</td>
<td>−0.46</td>
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<tr>
<td>p90</td>
<td>−0.25</td>
<td>−0.13</td>
<td>−0.26</td>
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</table>
(i.e., shadows) prevent DSI from detecting small canopy openings. In general, when approximately 40% of ALS first returns are less than 2 m (canopy cover ratio), all DSI observations are already above that threshold. In other words, DSI observations are concentrated on the outer canopy envelope only, whereas ALS returns are distributed throughout the vertical extent of the canopy. This is an important distinction between ALS and DSI data, with the latter incapable of penetrating the canopy in the same manner as ALS data. The trend can be seen in Figure 5, where ALS and DSI vegetation ratios (vege) are plotted against field measured basal area. DSI vegetation ratio reaches its maximum at relatively low basal area values (i.e., 10–20 m²/ha). The mean height metric from DSI ($r = 0.80$) and ALS ($r = 0.72$) had the strongest correlation with stem volume (Figure 6).

**Predictions for height, basal area, and stem volume**

The predicted accuracies for DSI- and ALS-derived estimates of height, diameter, basal area, stem volume, and biomass are presented in Table 3. $H_{mean}$, $h_{40}$, $h_{50}$, and $h_{60}$ were the most powerful predictors from all the plot-specific metrics derived from DSI and ALS data based on RF’s scaled importance values. This is supported by finding that $H_{mean}$ had the strongest correlation with the stem volume. For all attributes, the predictions from ALS data were more accurate than those from DSI, and bias for both ALS and DSI were low.

**Comparison of canopy height models derived from ALS and DSI**

The similarity of the CHMs at the plot level was investigated (Figure 7). DSI minimum CHM values were on average 4 m higher than ALS CHM minimum values. Investigations of minimum values also revealed that ALS was more capable of penetrating canopy openings (Figure 8). For ALS CHMs, the minimum height was less than 0.5 m for 95.8% of the ground plots, whereas only 44.2% of ground plots had a minimum height less than 0.5 m in the DSI CHM. The ALS-derived CHM also had greater variation in stand heights, with a mean standard deviation in ALS canopy heights of 6.2 m compared with 3.8 m for the DSI-derived CHM. Plot-level CHM minimum, mean, maximum, and standard deviation for the DSI and ALS CHMs were statistically different based on paired student’s $t$ test ($p < 0.05$).

When undertaken at the plot level, mean change in CHMs using $\text{Change}_{\text{ALS}}$ and $\text{Change}_{\text{DSI}}$ were 3.03 m and 4.10 m, respectively.
respectively, with standard deviations of 1.82 m and 2.75 m. \(\text{Change}_{\text{ALS}}\) and \(\text{Change}_{\text{DSI}}\) were reasonably correlated (\(r = 0.71\)) indicating good agreement between the two change outputs (Figure 9). In Figure 10, negative changes indicate clear-cuttings, thinning, or wind damage. As a stand replacing disturbance, clear-cutting can be readily detected from both of the change pairs, although \(\text{Change}_{\text{ALS}}\) is capable of providing more detail as seen in Figure 8.

**Table 3.** Accuracies in Random Forest predictions using DSI and ALS metrics.

<table>
<thead>
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<th></th>
<th>Bias</th>
<th>Bias (%)</th>
<th>RMSE</th>
<th>RMSE (%)</th>
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<tr>
<td>Mean height (m)</td>
<td>DSI</td>
<td>-0.07</td>
<td>-0.35</td>
<td>2.13</td>
</tr>
<tr>
<td></td>
<td>ALS</td>
<td>-0.03</td>
<td>-0.16</td>
<td>1.47</td>
</tr>
<tr>
<td>Mean dbh (cm)</td>
<td>DSI</td>
<td>-0.15</td>
<td>-0.65</td>
<td>5.13</td>
</tr>
<tr>
<td></td>
<td>ALS</td>
<td>0.00</td>
<td>0.00</td>
<td>4.51</td>
</tr>
<tr>
<td>Basal area (m²/ha)</td>
<td>DSI</td>
<td>0.08</td>
<td>0.37</td>
<td>4.86</td>
</tr>
<tr>
<td></td>
<td>ALS</td>
<td>0.09</td>
<td>0.39</td>
<td>3.65</td>
</tr>
<tr>
<td>Total stem volume (m³/ha)</td>
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<td>0.42</td>
<td>0.22</td>
<td>46.1</td>
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<tr>
<td></td>
<td>ALS</td>
<td>0.49</td>
<td>0.26</td>
<td>33.64</td>
</tr>
<tr>
<td>Aboveground biomass (t/ha)</td>
<td>DSI</td>
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<td>0.35</td>
<td>22.56</td>
</tr>
<tr>
<td></td>
<td>ALS</td>
<td>0.14</td>
<td>0.15</td>
<td>16.64</td>
</tr>
</tbody>
</table>

**Figure 5.** Relationship between DSI vegetation ratio, ALS vegetation ratio, and basal area. DSI reaches its maximum values with low basal areas.

**Figure 6.** Relationship between DSI \(H_{\text{mean}}\) and stem volume (left) and ALS \(H_{\text{mean}}\) and stem volume (right).

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Discussion

DSI versus ALS

DSI and ALS are both capable of producing metrics that provide similar levels of correlations with studied forest attributes. Metrics describing tree heights are powerful predictors for height, basal area, and stem volume (e.g., Næsset, 2002a; Maltamo et al., 2006). DSI and ALS are both capable of capturing variation in plot mean height. Both methods also provide metrics that are moderately correlated with basal area and stem volume. However, ALS can provide more metrics that are not correlated with each other if basal area or stem volume are modelled using many predictors. This means that in addition to height, which is captured by both of the methods, ALS metrics are capable of providing a more detailed description of canopy cover (e.g., Vastaranta et al., 2011; Korhonen et al., 2011). Based on our results, ALS captures more variation in height measures and enables a more detailed description of the canopy surface than DSI, because ALS is more capable of penetrating small canopy openings. Occlusions, which can be common in forest canopies, can make it difficult to detect small canopy openings in the DSI-derived CHM. Consider that the DSI-derived vegetation ratio (vege) reached its maximum at relatively low basal areas. In general, forests in Evo are managed and we did not have many plots in seedling stands. Thus it can be assumed that stands with low basal area will also have more ground visible from above.

It should be noted that multi-image matching was not used in the production of the DSI-derived DSM; multi-image matching could improve the level of detail of the DSI-derived DSM (Leberl et al., 2010). Our predictions using DSI were obtained using one image data set and one image-matching algorithm. Both image quality (including image acquisition conditions, such as illumination conditions and wind) and the image-matching algorithms used will influence the quality of the final DSI-derived DSM (Gruen, 2012). No spatial adjustment was applied between the DSI-derived DSM and ALS-derived DTM, which may have caused some height errors. However, since our study area was relatively flat and we used an area-based approach in the estimation of forest attributes, our analyses were not sensitive to small errors in spatial alignment between the

![Figure 7](image_url). Box-plot from DSI- and ALS-derived canopy height model statistics calculated at the plot level. The bottom and top of the box are the lower and upper quartiles, and the band near the middle of the box is the median. The end of the whiskers represents the minimum and maximum values.

![Figure 8](image_url). Differences in DSI- and ALS-derived canopy height models in mature Scots pine stand. Small canopy openings are missing from the DSI.
DSI- and ALS-derived layers. Our study provides knowledge about the accuracy of the DSI-based predictions of forest attributes and the quality of the DSI-based CHM, when assuming that the image supplier has already carried out the orientation of the images and that an accurate, high spatial resolution DTM is on hand.

### Forest mapping

In this study, predictions of height, diameter, basal area, stem volume, and aboveground biomass were more accurate using ALS. However, the accuracies of the DSI estimates were comparable to those attained in the same study area using ALS with a lower pulse density than what was used in this present study (Holopainen et al., 2008, 1.8 hits per m²; Yu et al., 2010, 2.6 hits per m²). The attribute estimates generated from DSI in this study were more accurate than those generated from a previous study in the same study area (Järnstedt et al., 2012). For example stem volume was predicted with a RMSE accuracy of 40.4% with DSI in Järnstedt et al. (2012), whereas the RMSE for stem volume in this study was 24.5%. There are several factors that may have contributed to this difference. First, we used a greater number of ground plots (500 versus 468) and the mean stem volume (187 m³/ha versus 160.1 m³/ha), height (19.0 m versus 17.9 m), and basal area (20.6 m²/ha versus 17.6 m²/ha) were greater than those in the plots used by Järnstedt et al. (2012). Secondly, our model building and validation procedures were different: we used RF in a k-NN mode and evaluated the prediction accuracy using RFs out-of-the-bag samples, whereas Järnstedt et al. (2012) used sequential forward selection for feature selection followed by a k-NN estimation approach (with weighting by inverse squared Euclidean distance) and cross-validation. Our results were in line with results obtained in Bohlin et al. (2012) and Nurminen et al. (2013) where the accuracy of stem volume predictions varied from 13.0% (stand level) to 22.7% (plot level).

It would appear that for even-aged, single layer stands such as those that dominate in this study area, 3-D information extracted from DSI is capable of estimating mean height, dbh, basal area, volume, and aboveground biomass with accuracies comparable with those of ALS-derived estimates. Overall the performance of DSI in the prediction of forest variables was promising. This is notwithstanding the fact that the information from the DSI is primarily characterizing the outer canopy envelope and detection of the small canopy openings is limited. The lack of penetration capacity and insensitivity to the small canopy openings limits the variety of metrics that may be generated from the DSI when compared with the broad range of metrics that may be calculated from the ALS data. Thus, ALS is seen as offering more opportunities for modeling (see also Bohlin et al., 2012). However, it should be noted that aerial images also provide spectral information that is useful in tree species classification. In addition, Bohlin et al. (2012) investigated the usefulness of height texture metrics as compensation for the lack of information on vertical height distribution captured by DSI. They concluded that height texture metrics improved estimates of stem volume and basal area. Straub et al. (2013) used DSI and ALS for estimating timber volume and basal area in mixed central European forests with more complex structures. They obtained RMS accuracies of 37.9% and 35.3% for timber volume and basal area, respectively, using DSI in conjunction with an ALS-derived DTM. The accuracies for volume and basal area using ALS only were 31.9% and 30.2%, respectively. Based on the results of Straub et al. (2013), the difference in estimation accuracy between DSI and ALS in more complex forest conditions is comparable with the results obtained in Nordic forest conditions (Bohlin et al., 2012; Järnstedt et al., 2012; Nurminen et al., 2013).

### Forest monitoring

Change detection using ALS and DSI-derived CHMs is seen as an intriguing and cost-efficient option for forest monitoring and mapping. When comparing Change_{ALS} and Change_{DSI} for a three year time interval (2006–2009), both methods provided change estimates that correlated relatively well overall, but with some exceptions. ALS- and DSI-derived CHMs characterize the canopy surface differently. For example, small openings in the canopy that can be detected with high pulse density ALS are missing from DSI (Figure 8). This leads to different canopy closure estimates (see also St-Onge et al., 2008). If the initial time point (T1) in change detection is captured with ALS, and the second time point (T2) is captured using DSI, much of the identified change will result from these aforementioned differences.
that are inherent to the differences in how the ALS and DSI CHMs characterize the canopy, especially canopy closure. Thus, calibration of the canopy closure estimates is important for reliable change detection. Differences in height measures can be calibrated for example using a subset of field trees (St-Onge et al., 2004; Vega and St-Onge, 2008). The question of how best to calibrate ALS and DSI for change detection purposes warrants further investigation; however, for the purposes of updating forest operations for stand replacing disturbances such as storm damage or harvesting, Change\textsubscript{DSI} seems promising. Honkavaara et al. (2013) developed a method based on ALS (T1) and DSI (T2) to detect wind damage. Their result showed that the approach was sensitive enough to detect damage where more than 10 trees had fallen within a 1 ha area with 100% accuracy. Monitoring of nonstand replacing disturbances such as thinnings and other individual tree-level changes with DSI requires further research. The results of this study demonstrate that for the even-aged, single-layer stands in this study area, DSI is capable of estimating forest inventory attributes with accuracies similar to that achieved with ALS and therefore could be used in the generation of a second independent inventory (see results in Table 2). However, as with ALS, ground plots need to be measured and a high spatial resolution bare earth DTM is required to normalize the DSI-derived elevations.

**Outlook**

We remain circumspect on recommendations regarding the use of DSI in other forest types, particularly in mixed-aged, multi-layered stands, and other management regimes. The relatively homogeneous stand conditions found in the study area result in limited variance and facilitated strong relationships between both the ALS and DSI metrics and the ground plot measurements.

Looking forward, it certainly appears that there are opportunities for DSI in forest management and planning. The capacity of DSI to achieve estimates with accuracies
similar to ALS needs to be tested in a broader range of forest conditions, particularly in larger, more complex stands (White et al., 2013). Furthermore, practitioners should be clear about what information needs are driving the data collection choices. For instance, in an update mode, practitioners should be mindful of having greater variance in T1 (ALS) than in T2 (DSI). In this scenario, it is possible that more change could have occurred than could be detected: There would be fewer canopy openings in T2 and an apparent increase in average growth over the stand.

Opportunities for monitoring and inventory update applications are foreseen for jurisdictions where large-area ALS coverages have been acquired, imagery is routinely collected, and numerous well-distributed ground plots are present. Sweden, for instance, with its notable collection of ALS data combined with its routine national collection of imagery to meet a wide-range of resource management needs, is well positioned to take advantage of emerging DSI opportunities.

**Conclusion**

The results of this study indicate that DSI have notable potential as a cost-effective method of estimating and updating forest inventory information. Accuracies similar to ALS were obtained from DSI for the managed, even-aged, single-layered forests characterized in this study. The accuracy of DSI is based on the capacity to measure the height of the upper canopy with the same degree of accuracy as ALS. The lack of penetration into the sub-canopy afforded by the DSI may impact the estimation of attributes that rely more strongly on density metrics or height distributions within the canopy as opposed to heights of only the upper canopy (e.g., stand complexity for habitat assessments, characterization of understory or determination of base to live crown for fire management). ALS is better able to characterize vegetation density through the complete vertical height distribution of the stand. Another caveat associated with the use of DSI is the requirement for a spatially detailed DTM to normalize obtained heights to heights above ground level. Change detection using a combination of ALS and DSI requires further investigation, particularly with regards to calibration between the two data sources.

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