Estimating vertical canopy cover using dense image-based point cloud data in four vegetation types in southern Sweden

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ABSTRACT
This study had the aim of investigating the utility of image-based point cloud data for estimation of vertical canopy cover (VCC). An accurate measure of VCC based on photogrammetric matching of aerial images would aid in vegetation mapping, especially in areas where aerial imagery is acquired regularly. The test area is located in southern Sweden and was divided into four vegetation types with sparse to dense tree cover: unmanaged coniferous forest; pasture areas with deciduous tree cover; wetland; and managed coniferous forest. Aerial imagery with a ground sample distance of 0.24 m was photogrammetrically matched to produce dense image-based point cloud data. Two different image matching software solutions were used and compared: MATCH-T DSM by Trimble and SURE by nFrames. The image-based point clouds were normalized using a digital terrain model derived from airborne laser scanner (ALS) data. The canopy cover metric vegetation ratio was derived from the image-based point clouds, as well as from raster-based canopy height models (CHMs) derived from the point clouds. Regression analysis was applied with vegetation ratio derived from near nadir ALS data as the dependent variable and metrics derived from image-based point cloud data as the independent variables. Among the different vegetation types, vegetation ratio derived from the image-based point cloud data generated by using MATCH-T resulted in relative root mean square errors (rRMSE) of VCC ranging from 6.1% to 29.3%. Vegetation ratio based on point clouds from SURE resulted in rRMSEs ranging from 7.3% to 37.9%. Use of the vegetation ratio based on CHMs generated from the image-based point clouds resulted in similar, yet slightly higher values of rRMSE.

1. Introduction
Vertical canopy cover (VCC) is the area of the ground covered by a vertical projection of the canopy (Jennings, Brown, and Sheil 1999). In vegetation mapping, VCC is of vital importance for the separation of open areas from forest, based in part on definitions which include VCC. For example, the Forest and Agriculture Organization of the United
Nations (FAO) definition of forest areas is based on areas with tree cover with potential to reach 10% VCC and 5 m height. Accurate and non-biased field measurements of VCC are time-consuming (Korhonen et al. 2006) while studies have shown that VCC can be estimated using airborne laser scanner (ALS) data (Holmgren et al. 2008; Korhonen et al. 2011). The vegetation ratio (VR), calculated as the proportion of first and single ALS returns above a specified height above ground, has an almost 1:1 relationship with field measured VCC (Korhonen et al. 2011). Korhonen et al. (2011) produced estimates of VCC, which had an absolute root mean square error (RMSE) of less than 5% with an over-estimation of 3–5% when using ALS data with a maximum scan angle of 15°. Large scan angles of the ALS data resulted in larger overestimations, due to the increased proportion of returns from the canopy (Holmgren 2003; Holmgren et al. 2008; Montaghi 2013). The accuracy of VR derived from low scan angle ALS data allows it to be used as reference data for estimation of VCC, when lacking field measurements (Korhonen, Heiskanen, and Korpela 2013; Korhonen, Ali-Sisto, and Tokola 2015). However, ALS data are an expensive alternative for repeated measurements.

Image-based point clouds obtained by image matching of digital aerial images have proven to be useful for deriving explanatory variables for estimation of tree heights and other forest variables that are correlated with tree height (Bohlin, Wallerman, and Fransson 2012; Gobakken, Bollandssås, and Næsset 2015; Granholm et al. 2015; Järnstedt et al. 2012; Nurminen et al. 2013; Pitt, Woods, and Penner 2014; Vastaranta et al. 2013; White et al. 2013, 2015). A recent study demonstrated the successful generation of a nationwide digital surface model (DSM) in Switzerland by image matching countrywide coverage of digital aerial stereo-imagery (Ginzler and Hobi 2015). Using this national DSM, normalized with a digital terrain model (DTM) from ALS data, Waser et al. (2015) produced a wall-to-wall forest cover map for Switzerland via a workflow including classification of areas into forest or non-forest based on vegetation height. A similar approach could be used in Sweden, considering that the national coverage of digital stereo-imagery is at present updated every third year on average, and that Lantmäteriet (the National Land Survey of Sweden) is producing a DSM based on aerial images acquired in 2016 and onwards. The prerequisite for deriving a normalized DSM, i.e. a canopy height model (CHM), is an accurate DTM, preferably derived from ALS data (Baltsavias 1999; St Onge et al. 2008). Such a DTM made from ALS exists in Sweden. Regularly updated nationwide image-based point cloud data would provide data for vegetation mapping (e.g. Granholm et al. 2015; Reese et al. 2015; Waser et al. 2015) and change detection (e.g. Waser et al. 2008; Wang, Ginzler, and Waser 2015). Such data would for instance be beneficial for the National Inventory of Landscapes in Sweden (NILS) programme (Ståhl et al. 2011), which aims to monitor the condition and changes in the Swedish landscape. NILS would benefit from affordable metrics for estimation of VCC to separate open areas from forested areas, based on a threshold of 10% VCC and vegetation height ≥3 m (Lindgren et al. 2015). Currently, such measurements are done manually by aerial photo interpretation (Allard et al. 2003). An alternative method would be to replace the interpreted VCC by an estimate derived from ALS data. A more affordable alternative would be to derive such an estimate from image-based point clouds, or surface models, which could be regularly updated considering the frequent
aerial image acquisition. Accurate estimates of VCC would be useful both for separation of open area from forest, i.e. at 10% VCC (FAO 2010; Lindgren et al. 2015), but also for use in studying habitat and biodiversity (Bergen et al. 2009), which is linked to canopy cover (Müller and Vierling 2014). The raster-based method used by Waser et al. (2015) in the production of a forest map resulted in overall accuracy of 97%, with lower accuracies along forest borders and at altitudes above 1400 m above sea level. The errors along forest borders were due to limitations in the classification method, while the errors at high altitude were caused by a combination of lower resolution of imagery, less distinct forest borders, and dominance of tree species with small and narrow crowns (Waser et al. 2015). In a mixed boreal forest in eastern Canada, single tree detection using a CHM from image-based point cloud data as compared to ALS data revealed that fewer trees were detected in the image-based CHM (St Onge, Audet and Begin 2015). In addition, this study showed that the crown area derived from the image-based CHM was generally lower than the corresponding crown area from ALS data due to occlusion of the far side of the tree in the image-based CHM. Vastaranta et al. (2013) found that VR derived from an image-based CHM, calculated as the proportion of raster cells above 2 m height, reached 100% when the VR based on ALS was approximately 40%, in a relatively homogeneous, managed boreal coniferous forest. The omission of small gaps within canopy, due to shadows, was described as the main limitation of the image-based CHM (Vastaranta et al. 2013). Previous studies have pointed out that the lack of ground returns in image-based point cloud data (due to the inability of aerial images to penetrate forest canopies), in comparison to ALS point data, is a drawback for the use of image-based point clouds in estimation of forest variables (White et al. 2013; Vastaranta et al. 2013). However, Straub et al. (2013) found that combining height and canopy cover metrics derived from image-based point clouds improved estimations of timber volume and basal area in a mixed European forest, and that stratified estimation, by separating coniferous and deciduous forest, improved the prediction accuracy. White et al. (2015) calculated the number of ALS returns above the mean return height divided by the total number or ALS returns (CCmean) and compared this to CCmean based on image-based point cloud data. The comparison was applied to the full range of canopy cover in a heterogeneous, coastal boreal forest in western Canada, and it was found that the correlation was low (White et al. 2015). This result may be due to the difference in height distribution between ALS point clouds and image-based point clouds (Baltsavias 1999). Stepper, Straub, and Pretzsch (2015) estimated growing stock in a European broadleaf-dominated forest by using explanatory variables derived from image-based point cloud data and found that adding canopy cover metrics, such as CCmean, resulted in models with reduced RMSE. These results indicate that the utility of canopy cover metrics derived from image-based point cloud data is influenced by tree species composition.

Apart from the studies by Waser et al. (2015), canopy cover metrics derived from image-based point cloud data and ALS data have not been used for vegetation mapping in pasture areas, or in unmanaged forests in non-productive areas such as wetland or bedrock outcrops. These vegetation types are relatively common in a landscape context. Trees outside of forest are interesting for estimation of natural resources in a global context, such as above ground biomass (Schnell et al. 2015), and using image-based point clouds to detect trees outside of forest would improve such estimates at an
affordable cost. As Stepper, Straub, and Pretzsch (2015) points out, there is value in examining the utility of using standard aerial images from regularly updated surveys for forest inventory and planning, and this applies to the needs of landscape monitoring as well.

Operational prediction of VCC using image-based point cloud data would need reference data. This could be obtained via aerial photo interpretation, or field measurements of sample plots, which would still be more efficient compared to manual aerial photo interpretation of the area to be mapped.

The objective for this study was to investigate the utility of image-based point clouds for the estimation of VCC. The investigation was done in four different vegetation types in the hemi-boreal zone in Sweden, such as managed coniferous forest to enable a comparison to previous studies, but also in pasture areas with deciduous tree cover, as well as in wetland and unmanaged forest in a nature reserve area. Two different approaches were used: first by calculating VR as the proportion of points above a height threshold in image-based point cloud data, and second by using VR calculated as the proportion of grid cells above a height threshold in a CHM from image-based point cloud data. Two different commercially available image matching software solutions were used to derive the image-based point cloud data, thus enabling a comparison.

Functions for estimating VCC using image-based point cloud data, given the different methods and vegetation types, were estimated by linear regression using the VR from low scan angle ALS data as the dependent variable.

2. Methods

2.1. Study area

The study area is approximately 5 km × 8 km, and located in the hemi-boreal zone in southern Sweden at 58° 30’ N, 13° 40’ E (Figure 1). Visual interpretation of stereo aerial images was used to detect reference plots in four vegetation types:

(1) ‘Unmanaged’: pristine, non-productive forest in a nature reserve, dominated by Scots Pine (Pinus sylvestris L.) growing on nutrient poor moraine, coarse boulders, and rocky outcrops. The tree cover is fragmented, with small canopy gaps.

(2) ‘Deciduous’: areas used as pasture for cattle and sheep, with a mix of broad-leaved trees, mostly Oak (Quercus robur L.) and Lime (Tilia cordata L.), other deciduous tree species such as Birch (Betula spp. L.) and Alder (Alnus glutinosa (L.) Gaertner), and occasionally Norway spruce trees (Picea abies (L.) Karst.). The trees have large, wide crowns, and the tree cover is fragmented, with single trees or clusters of trees.

(3) ‘Wetland’: dominated by pristine ombrotrophic bogs in a nature reserve area. The tree cover, dominated by Scots Pine, is highly fragmented and sparse with small crowns.

(4) ‘Managed’: intensively managed forest dominated by Scots Pine, Norway spruce and Birch in different successional stages from clear cut to mature forest, growing on fertile sites. The tree cover ranges from sparse to dense.
2.2. Remote-sensing data

ALS data with a strip overlap of 60% and mean pulse density of 32 pulses m$^{-2}$ within reference plots was acquired in September 2014 by a contractor using a Riegl LMS Q680i scanner mounted on a helicopter flying at an altitude of 440 m. Aerial images covering the study area were acquired in July 2014 by Lantmäteriet using a Vexcel UltraCam Xpwa camera at an altitude of 2800 m above ground, resulting in pan sharpened CIR aerial images with a ground sample distance (GSD) of 0.24 m, and stereo overlap ratio of 60% along-track, and 27% across-track. The aerial imagery was acquired by Lantmäteriet as part of their regular survey.

2.3. Reference data

Visual stereo interpretation of the aerial CIR UltraCam Xpwa images was used to manually detect suitable locations for reference plots within the four vegetation types, based on interpreted canopy cover, tree species, and land use such as grazing or forest management. Subjective sampling was used to avoid reference plots being placed at the border between different vegetation types, which is likely with systematic sampling, and to collect reference plots representing the available range of VCC in each of the four vegetation types. The size of the reference plots, 20 m radius, was an accommodation to the field plot size used for tree cover estimates in the

Figure 1. The location of the study area in southern Sweden at 58° 30′ N, 13° 40′ E. The study area covered by a canopy height model (CHM), derived from ALS data, in greyscale where low vegetation is dark grey and higher vegetation is lighter grey. Reference plots are coloured by vegetation type; unmanaged = black; deciduous = green; wetland = blue; and managed forest = red. © Lantmäteriet.
NILS programme (Gallegos-Torell and Rydin 2015) as well as an adaptation to the largest tree crown size in order to reduce the risk of only capturing partial tree crowns. The broadleaved trees in the vegetation type ‘Deciduous’ had particularly large crowns, approximately 20 m wide. The reference plot selection was restricted to the area covered by ALS data with a maximum scan angle of 10°, since VR based on ALS data was used as reference data, and unbiased estimates of VR are derived from ALS data with low scan angle (Korhonen et al. 2011; Montaghi 2013). A total of 288 reference plots were allocated. The restriction to low scan angle of ALS data combined with the reference plot size led to a low number of reference plots in the less common vegetation types ‘Unmanaged’ and ‘Wetland’. A review of the tree height in the vegetation type ‘Wetland’ led to the exclusion of four of the sample plots due to possible influence of mineral soil or drainage. Thus the number of sample plots was reduced to 284. The large reference plot size in relation to the relatively sparse tree cover, as well as small crown size of the dominant Scots Pine trees, in the ombrotrophic bogs in ‘Wetland’ resulted in a lack of plots with VCC above 71.5%. The plot size was also larger than the canopy gap size in the vegetation type ‘Unmanaged, leading to a lack of reference plots with VCC below 24.6% (Table 1 and Figure 2). Potential changes in the canopy, due to difference in acquisition date, were sought for by visual stereo interpretation of the CIR UltraCam Xpwa images and simultaneous comparison to high spatial resolution (0.04 m GSD) CIR orthophotos generated from aerial imagery acquired at the same time as the ALS data. No changes were observed in the reference plots.

### 2.4. Processing of the ALS data

The ALS point cloud was classified into other vegetation and ground hits using the algorithm by Axelsson (1999, 2000). The ALS point cloud was used to generate a DTM covering the entire study area. LAStools (Isenburg 2015) was then used to process the ALS point cloud; flight line overlap was removed and the height of the laser returns was normalized to above ground. All returns but first and single returns were dropped from the ALS point cloud, which was then thinned down to one point per 0.5 m × 0.5 m grid cells, where one randomly selected point for each cell was kept. This was done in order to avoid effects of uneven point densities.

The thinned ALS point cloud was clipped to each plot and a reference $\text{VR}_{\text{ALS}}$ was calculated per plot, defined as the number of returns above a height threshold divided by the total number of returns (Nilsson 1996; Korhonen et al. 2011). Three different height thresholds were tested, namely 1, 2, and 3 m above ground to produce three separate $\text{VR}_{\text{ALS}}$, $\text{VR}_{\text{ALS}1}$, $\text{VR}_{\text{ALS}2}$, and $\text{VR}_{\text{ALS}3}$.

### 2.5. Image matching

The image matching software solutions MATCH-T DSM version 6.1 by Trimble (Anonymous 2014a), and SURE version 1.1.1.3 by nFrames GmbH (Anonymous 2014b; Rothermel et al. 2012) were used for producing two different sets of image-based point cloud data out of the UltraCam images, which are described in the following paragraph.
### Table 1. Characteristics of the reference plots per vegetation type.

| Characteristic          | Unmanaged | Deciduous | Wetland | Managed forest |
|-------------------------|-----------|-----------|---------|----------------|
| Number of reference plots | 23        | 74        | 38      | 149            |
| Range of p90 (m)        | 9.9–21.2  | 0.0–24.8  | 1.3–14.1| 1.4–30.6       |
| Mean of p90 (m)         | 15.4      | 16.1      | 7.8     | 14.6           |
| SD of p90 (m)           | 2.6       | 5.4       | 3.1     | 7.4            |
| Range of VR (%)         | 24.6–81.2 | 0.0–92.2  | 0.0–71.5| 0.0–99.0       |
| Mean VR (%)             | 58.0      | 33.2      | 29.2    | 52.7           |
| SD of VR (%)            | 15.4      | 23.0      | 21.7    | 30.2           |
| Dominant tree species   | Scots pine| Broadleaved trees, Birch spp. | Scots pine | Norway spruce, Scots pine, Birch spp. |

Height and vegetation ratio derived from ALS data. p90 = height percentile 90.
VR = vegetation ratio. SD = standard deviation.
MATCH-T DSM was used with the default settings for production of a DSM or image-based point cloud data; Terrain type = Extreme, Smoothing = Low, Feature Density = Dense, and Point Cloud Density = 1, These settings mean that every pixel was used for the extraction of 3D points. The software used a combination of feature-based matching and cost-based matching (Anonymous 2014a), which resulted in an image-based point cloud with mean point density of 2.8 points m$^{-2}$ within reference plots.

SURE was used for producing a second set of image-based point cloud data, with the default settings for production of dense DSM point cloud data (Anonymous 2014b). SURE uses an algorithm similar to Semi-Global Matching (SGM) by Hirschmüller (2008); (Rothermel et al. 2012), which resulted in an image-based point cloud with mean point density of 11.6 points m$^{-2}$ within reference plots.

The two image-based point cloud datasets will from now be referred to as MATCH-T and SURE, respectively.

2.6. Processing of the image-based point clouds

LAStools (Isenburg 2015) was used for further processing of the image-based point clouds. The height of each point cloud was normalized to above ground by using the DTM from ALS data. Then, the image-based point clouds were clipped to the reference plots. VR$_{M}$ was calculated per plot, defined as the number of points above a height threshold divided by the total number of points. Three different height thresholds, namely 1, 2, or 3 m above ground, were used to produce VR$_{M1}$, VR$_{M2}$, and VR$_{M3}$ per image-based point cloud dataset.

If no data areas in image-based point clouds are assumed to represent gaps rather than canopy in dense forest, then the lack of ground heights could be compensated for by converting the point cloud to a grid where empty grid cells are assigned ground level height. To test this, the normalized image-based point clouds were used.
to generate CHMs where the grid cells received the height value of the highest point within each cell, and cells wherein no points fell received zero height above ground. Grid cell sizes of 0.50; 0.75; 1.00; and 2.00 m were used, resulting in four image-based CHMs each per image-based point cloud dataset. The image-based CHMs were clipped to the reference plots and \( V_{\text{CHM}} \) was calculated per plot as the number of grid cells above a height threshold of 3 m, divided by the total number of grid cells per plot.

### 2.7. Estimation of VCC

\( V_R \) derived from MATCH-T and SURE was plotted against \( V_{\text{ALS}} \). Linear models were fitted with the reference \( V_{\text{ALS}} \) as the dependent variable and substitute for VCC. The \( V_R \) derived from MATCH-T, and SURE, respectively, was used as a predictor variable, as in Equation (1):

\[
VCC = a + \beta V_R + \varepsilon.
\] (1)

Linear models were fitted using the ordinary least squares method, first by using all reference plots \((n = 284)\) and second per vegetation type. Regression analysis was performed by matching VR derived with the different height thresholds (1, 2, and 3 m), in a way that the \( V_{\text{ALS}}^1 \) was used for \( V_R^1 \), and so on. The R statistical software (R Core Team 2015) was used for the regression analysis. leave-one-out cross-validation was used for accuracy estimation and the results were evaluated using the adjusted coefficient of determination \((\text{adj. } R^2)\), as well as the RMSE of predictions, the relative RMSE \((\text{rRMSE})\), and BIAS (Equations (2)–(4)):

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}, \quad (2)
\]

\[
\text{rRMSE}(\%) = \frac{\text{RMSE}}{\bar{y}_i} \times 100, \quad (3)
\]

\[
\text{BIAS} = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)}{n} \quad (4)
\]

where \( y_i \) is \( V_{\text{ALS}} \), \( \hat{y}_i \) is the estimated VCC, \( n \) is the number of reference plots, and \( \bar{y}_i \) is the mean of \( V_{\text{ALS}} \). The value of \( q \), the square root of the ratio between the predicted sum of squares of residuals and the ordinary sum of squares of residuals, was calculated to test for possible over-fitting of the models.

Estimation of VCC using the \( V_{\text{CHM}} \) was done by fitting linear models with \( V_{\text{ALS}} \) as the dependent variable, as in Equation (1). The \( V_{\text{CHM}} \) was used as the predictor variable, replacing \( V_R \) in Equation (1). Linear models were fitted for each combination of grid cell size (0.50; 0.75; 1.00; 2.00 m) per matching method, using the ordinary least squares method. First by using all reference plots \((n = 284)\) and secondly per vegetation type. leave-one-out cross-validation was used for accuracy estimation and the results were evaluated using adj. \( R^2 \), RMSE, rRMSE, and BIAS (Equations (2), (3), and (4)). The value of \( q \) was calculated to test for possible over-fitting.
Paired Student’s t-test were used to test for significant difference between VRM derived by MATCH-T or SURE, for each of the four vegetation types and on the entire dataset (n =284).

3. Results

3.1. Image-based point cloud data

The image matching resulted in two sets of image-based point cloud data, referred to as MATCH-T, and SURE, respectively. The points within MATCH-T were evenly distributed with a distance of approximately 0.6 m, while the points in SURE were evenly distributed on rather flat areas such as the ground (distance of 0.2 m) and more clustered in the canopies (Figures 3 (a–f) and 4(a–f)). No data areas in the image-based point cloud datasets were observed in areas that were in deep shadow, or were occluded (such as behind or between trees). It was observed that in areas with sparse tree cover, entire trees were sometimes missed in the image-based point cloud datasets while they were visible in the ALS point cloud data, as can be seen in Figures 3(a–f). In reference plots with dense cover, there were often no data areas but few or no points on the ground in canopy gaps in the image-based point cloud datasets.

3.2. Estimation of VCC using point based vegetation ratio

Comparing the results of linear regression showed that there was very little difference in accuracy, maximum 1% in rRMSE, between models based on VRM derived from image-based point cloud data using height threshold of 1, 2, or 3 m. The presentation of results from the statistical analysis is therefore restricted to using a height threshold of 3 m, which is also the height threshold for classifying ligneous vegetation as trees specified by the NILS programme (Allard et al. 2003).

Figure 3. Normalized and height coloured point clouds clipped to a ‘Wetland’ plot with partial tree cover of Scots Pine. Upper row is horizontal view. Bottom row is view from above. No data areas are white. The plots are circular with a radius of 20 m. (a) and (d) ALS point cloud, VRALS = 34.5%, p90ALS = 8.0 m; (b) and (e) MATCH-T, VRM = 13.7%, p90 = 7.2 m; (c) and (f) SURE, VRM = 6.6%, p90 = 7.4 m. Height threshold = 3 m.
Scatterplots of \( VR_M \) derived from image-based point clouds against \( VR_{ALS} \) showed that \( VR_M \) underestimated \( VR_{ALS} \) at low canopy cover and that \( VR_M \) overestimated \( VR_{ALS} \) at high canopy cover. The \( VR_M \) seemed to behave linearly in the interval of approximately 15–85% canopy cover (Figure 5). General statistics of \( VR_M \) per image-based point cloud and vegetation type showed small differences between MATCH-T and SURE (Table 2).

The paired Student’s t-test applied to the \( VR_M \) derived from MATCH-T versus SURE for the full dataset \((n = 284)\) gave \( p < 0.05 \), thus they differed significantly. Linear regression results showed small differences between using \( VR_M \) derived from MATCH-T or SURE, with the latter yielding slightly higher values of RMSE and rRMSE for the estimation of VCC (Table 3).

Applying linear regression per vegetation type led to improved results for the vegetation types ‘Unmanaged’ and ‘Deciduous’. The models fitted for reference plots in the vegetation type ‘Wetland’, with fragmented cover of small Scots Pine trees, yielded the highest rRMSE for the estimation of VCC. Plots with standardized residuals exceeding 2, or below –2, were present in every vegetation type and in the full range of \( VR_{ALS} \) (Figures 6(a–d)), but none of the plots were removed.

### 3.3. Estimation of VCC using pixel-based vegetation ratio

Linear regression using \( VR_{CHM} \) resulted in models with similar or slightly greater values of RMSE and rRMSE for the estimation of VCC (Table 4) compared to the models fitted to \( VR_M \). Using the full dataset \((n = 284)\) and grid cell size of 0.75 m yielded the best results in
Figure 5. Vegetation ratio derived from airborne laser scanner data (VRALS) plotted against vegetation ratio derived from image-based point cloud (VRM) per vegetation type and at a height threshold of 3 m above ground, with a 1:1-line as reference. Top row: VRM based on image-based point cloud data by MATCH-T, and bottom row: VRM based on image-based point cloud data by SURE.

Table 2. Characteristics of the vegetation ratio based on image-based point cloud data (VRM) per matching method and per vegetation type at a height threshold of 3 m.

| Image matching method | Statistic | VRM (%) | Unmanaged | Deciduous | Wetland | Managed forest |
|-----------------------|-----------|---------|-----------|-----------|---------|----------------|
| MATCH-T              | Range     | 5.0–98.6| 0.0–100.0 | 0.0–88.7  | 0.0–100.0|                |
|                      | Mean      | 61.5    | 30.6      | 24.8      | 61.8    |                |
|                      | SD        | 27.5    | 29.2      | 28.9      | 42.1    |                |
| SURE                 | Range     | 3.2–100.0| 0.0–100.0 | 0.0–99.9  | 0.0–100.0|                |
|                      | Mean      | 55.4    | 28.0      | 22.3      | 62.3    |                |
|                      | SD        | 32.3    | 30.5      | 29.9      | 42.5    |                |

SD: standard deviation.

Table 3. Results of linear regression with vegetation ratio derived from airborne laser scanner data (VRALS) as dependent variable and vegetation ratio derived from image-based point cloud data (VRM) as independent variable.

| Dependent variable | Independent variable | Model statistics | Full dataset | Unmanaged | Deciduous | Wetland | Managed |
|--------------------|----------------------|------------------|--------------|-----------|-----------|---------|---------|
| VRALS (%)          | VRM (%) MATCH-T      | adj. $R^2$       | 0.91         | 0.95      | 0.93      | 0.85    | 0.90    |
|                    |                      | RMSE             | 8.4          | 3.5       | 6.0       | 8.6     | 9.5     |
|                    |                      | rRMSE (%)        | 18.7         | 6.1       | 18.2      | 29.3    | 18.1    |
|                    |                      | BIAS             | −0.003       | −0.024    | −0.010    | 0.114   | 0.002   |
|                    |                      | $\alpha$         | 11.6         | 24.6      | 9.9       | 12.0    | 10.5    |
|                    |                      | $\beta$          | 0.68         | 0.54      | 0.76      | 0.70    | 0.68    |
|                    |                      | $q$              | 1.01         | 1.08      | 1.03      | 1.05    | 1.01    |
| VRALS (%)          | VRM (%) SURE         | adj. $R^2$       | 0.88         | 0.93      | 0.90      | 0.76    | 0.89    |
|                    |                      | RMSE             | 9.7          | 4.3       | 7.5       | 11.1    | 10.1    |
|                    |                      | rRMSE (%)        | 21.6         | 7.3       | 22.4      | 37.9    | 19.2    |
|                    |                      | BIAS             | −0.004       | −0.066    | −0.017    | −0.212  | 0.001   |
|                    |                      | $\alpha$         | 14.0         | 32.5      | 13.2      | 15.0    | 10.9    |
|                    |                      | $\beta$          | 0.65         | 0.46      | 0.71      | 0.64    | 0.67    |
|                    |                      | $q$              | 1.01         | 1.08      | 1.03      | 1.05    | 1.01    |

VR was calculated using a height threshold of 3 m above ground. All coefficients were statistically significant with $p$-value <0.001 for the t-test. Full dataset corresponds to all sample plots ($n = 284$). $\alpha =$ intercept. $\beta =$ coefficient of VRM (%).
linear regression with VR<sub>CHM</sub> from MATCH-T. For VR<sub>CHM</sub> derived from SURE, the grid cell size of 1 m yielded the best results. The paired Student’s t-test applied to the VR<sub>M</sub> versus VR<sub>CHM</sub> derived from MATCH-T for the full dataset (n =284) gave p < 0.05, thus they differed significantly. The corresponding paired Student’s t-test for the VR<sub>M</sub> versus VR<sub>CHM</sub> derived from SURE gave p < 0.05, thus they also differed significantly.

Linear regression per vegetation type gave results similar to those received with VR<sub>M</sub>, with MATCH-T yielding slightly lower values of RMSE and rRMSE for the estimation of VCC (Table 4). VR<sub>ALS</sub> plotted against VR<sub>CHM</sub> showed underestimation of VR<sub>ALS</sub> at low canopy cover, and overestimation of VR<sub>ALS</sub> at high canopy cover (Figure 7).
Table 4. Results of linear regression with vegetation ratio derived from airborne laser scanner data (\(VR_{ALS}\)) as dependent variable and vegetation ratio derived from canopy height models (CHMs) based on image-based point cloud data (\(VR_{CHM}\)) as independent variable.

| Dependent variable | Independent variable | Model statistics | Full dataset | Unmanaged | Deciduous | Wetland | Managed |
|--------------------|----------------------|------------------|--------------|-----------|-----------|---------|---------|
| \(VR_{ALS}\) (%) | \(VR_{CHM}\) (%)     | adj. \(R^2\)     | 0.91         | 0.95      | 0.94      | 0.86    | 0.90    |
| MATCH-T 0.75 m    | RMSE                 | 8.5              | 3.6          | 5.9       | 8.4       | 9.8     |
|                   | rRMSE (%)            | 18.9             | 6.2          | 17.8      | 28.6      | 18.5    |
|                   | BIAS                 | -0.002           | -0.016       | -0.006    | -0.110    | 0.005   |
|                   | \(\beta\)            | 10.9             | 23.5         | 9.3       | 11.6      | 9.6     |
|                   | \(\alpha\)           | 0.68             | 0.55         | 0.76      | 0.68      | 0.69    |
|                   | \(q\)                | 1.01             | 1.08         | 1.03      | 1.05      | 1.01    |
| VR_{ALS} (%)      | VR_{CHM} (%)         | adj. \(R^2\)     | 0.88         | 0.87      | 0.89      | 0.83    | 0.87    |
| SURE 1.0 m        | RMSE                 | 10.1             | 5.7          | 7.7       | 9.4       | 11.1    |
|                   | rRMSE (%)            | 22.4             | 9.9          | 23.1      | 32.2      | 21.1    |
|                   | BIAS                 | -0.001           | -0.044       | 0.021     | -0.177    | 0.008   |
|                   | \(\beta\)            | 9.8              | 27.2         | 7.4       | 12.2      | 7.1     |
|                   | \(\alpha\)           | 0.71             | 0.54         | 0.79      | 0.69      | 0.73    |
|                   | \(q\)                | 1.01             | 1.11         | 1.03      | 1.08      | 1.01    |

The height threshold was 3 m above ground. Out of the different tested grid cell sizes, the best case per matching method is presented. All coefficients were statistically significant with \(p\)-value <0.001 for the \(t\)-test. Full dataset corresponds to all sample plots (\(n = 284\)). \(\alpha\) = intercept. \(\beta\) = coefficient of \(VR_{CHM}\) (%).

Figure 7. Vegetation ratio derived from airborne laser scanner data (\(VR_{ALS}\)) plotted against vegetation ratio derived from CHMs based on image-based point cloud data (\(VR_{CHM}\)) per vegetation type and with a height threshold of 3 m above ground, with a 1:1-line as reference. The selection of grid cell sizes is based on the best results of linear regression. Upper row is \(VR_{CHM}\) (%) based on image-based point cloud data derived by MATCH-T, with grid cell size 0.75 m, and bottom row is \(VR_{CHM}\) (%) based on image-based point cloud data derived by SURE, with grid cell size 1 m.

4. Discussion

The results show that VR derived from image-based point cloud data is potentially useful for estimation of VCC, considering the high values of the adj. \(R^2\). However, the accuracy is low when canopy cover values are low, as well as high. The underestimation at low
canopy cover can be explained by missing trees in the image-based point clouds in sparsely covered areas. This was especially common with the small Scots pine trees in the vegetation type ‘Wetland’, similar to the small trees in the alpine treeline zone in the study by Waser et al. (2015). Another example of omission of trees was single Scots pine seed trees in the vegetation type ‘Managed’. Another reason for underestimation was occlusion of the far side of the trees, which was observed in several vegetation types, and was also reported in Vastaranta et al. (2013) and in St Onge, Audet and Begin (2015). The overestimation at high canopy cover, as seen in the densely covered reference plots in the Norway spruce dominated vegetation type ‘Managed’, was likely due to the lack of canopy gaps caused by inter-tree occlusion, as well as the crown shape of the dominant tree species (e.g. St-Onge, Audet, and Begin 2015).

Little difference was found between the different height thresholds applied (1, 2, or 3 m), which is likely caused by the lack of matched points closer to the ground in dense forest, since the aerial images only show the upper surface of the canopy.

Using the grid-based metric VRCHM resulted in estimations with similar or slightly lower accuracies. Therefore, we conclude that adding ground heights by assigning zero height above ground to no data cells does not suffice to compensate for the lack of ground heights in dense forest. Furthermore, no data areas in image-based point cloud data appear not only in canopy gaps, but also in areas covered by shadows and otherwise occluded areas which could potentially have vegetation cover.

Separating the reference plots into different vegetation types based on land cover, land use, and tree species composition, resulted in improved accuracy of estimation of VCC in the vegetation types ‘Unmanaged’ and ‘Deciduous’. The improvement in the vegetation type ‘Unmanaged’ might be misleading considering the limited number of reference plots and the lack of reference plots at canopy cover below 25%. In addition, the value of q, 1.08, indicated over-fitting of the models for this vegetation type. The improvement within the vegetation type ‘Deciduous’ might be partly explained by factors such as the dominant tree species and the crown shape. For instance, St-Onge, Audet, and Begin (2015) found that tree species composition combined with oblique view angles influenced the quality of the image-based point cloud. Occlusion was more common, or rather the visibility of trees was poorer, in forest dominated by boreal coniferous tree species with an elongated shape viewed from oblique angle when compared to mixed forest (St-Onge, Audet, and Begin 2015). Another possible explanation for the higher accuracy of the estimation of VCC in the vegetation type ‘Deciduous’ is grazing, which generally leads to lack of small trees and shrubs as well as a low canopy cover. The proportion of sample plots with low canopy cover was higher in the vegetation type ‘Deciduous’ compared to the other vegetation types. These factors could also have led to more successful image matching, due to less inter-tree occlusion, and thus higher accuracy of the estimation of VCC. Though the results in the vegetation type ‘Managed’ were less accurate than for the full dataset, they were better compared to a previous study which reported that the vegetation ratio derived from a CHM based on image-based point cloud data reached 100% cover already at a basal area of 10–20 m² ha⁻¹ (Vastaranta et al. 2013). Both metrics used in this study, the point-based VRM as well as the grid-based VRCHM, performed better. Considering this, there is potential in using image-based point clouds for estimation of VCC. The methods used in this study produced most accurate estimation of VCC in pasture areas with relatively low canopy cover of deciduous trees. The methods are however not useful for the separation of forest
from open areas at 10% VCC due to the underestimation of VCC at low canopy cover. Further development is needed to find methods which provide accurate results at both low and high canopy cover.

The results also showed that there was a difference in the image-based point clouds produced by MATCH-T DSM and SURE. This was expected considering the difference in matching algorithms as well as in the post-processing of the extracted homologous points. However, the metrics based on the image-based point cloud datasets performed equally well. The limited accuracy of the estimations using $VR_M$ and $VR_{CHM}$ might be caused by the aerial images used in this study. These had an along-track stereo overlap of 60%, which is the standard used by Lantmäteriet, but lower than the 80% overlap along-track recommended as optimal for the production of image-based point clouds (Anonymous 2014a; and 2014b). The results by St-Onge, Audet, and Begin (2015) are seen as a sign of the potential utility of image-based point clouds in mapping forest, since individual tree detection and classification was done successfully using image-based point clouds derived from aerial images with an along-track overlap of 80% and a slightly higher spatial resolution compared to the images used in this study. It was also found that near nadir view angles led to more accurate results (St-Onge, Audet, and Begin 2015). This study did not consider view angle per reference plot.

Our results are limited to a relatively small set of reference plots. They have nonetheless provided information about the effect of tree species and crown shape on image matching results. This study has also demonstrated the utility of stereo aerial imagery available for the major part of Sweden, and which are regularly updated, thus it is of great value and interest for users in vegetation mapping and forestry. Further research is needed and should test using aerial imagery with greater stereo overlap, and over larger areas, in different geographical regions, and in a variety of vegetation types.

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References

Allard, A., B. Nilsson, K. Pramborg, G. Ståhl, and S. Sundquist. 2003. *Manual for Aerial Photo Interpretation in the National Inventory of Landscapes in Sweden*, NILS. Umeå: Department of Forest Resource Management, Swedish University of Agricultural Sciences.

Anonymous 2014a. *Reference Manual of the Software Package MATCH-T DSM 6.0*. Inpho *software, Trimble*. Stuttgart, Germany.

Anonymous. 2014b. *SURE - Photogrammetric Surface Reconstruction from Imagery. Manual, Version 12/5/14*. nFrames. Stuttgart, Germany.

Axelsson, P. E. 1999. “Processing of Laser Scanner Data — Algorithms and Applications.” *ISPRS Journal of Photogrammetry and Remote Sensing* 54 (2–3): 138–147. doi:10.1016/S0924-2716(99)00008-8.

Axelsson, P. E. 2000. “DEM Generation from Laser Scanner Data Using Adaptive TIN Models.” *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XXXIII (B4/1): 110–117.

Baltsavias, E. P. 1999. “A Comparison between Photogrammetry and Laser Scanning.” *ISPRS Journal of Photogrammetry and Remote Sensing* 54 (2–3): 83–94. doi:10.1016/S0924-2716(99)00014-3.

Bergen, K. M., S. J. Goetz, R. O. Dubayah, G. M. Henebry, C. T. Hunsaker, M. L. Imhoff, R. F. Nelson, G. G. Parker, and V. C. Radeloff. 2009. “Remote Sensing of Vegetation 3-D Structure for Biodiversity and Habitat: Review and Implications for Lidar and Radar Spaceborne Missions.” *Journal of Geophysical Research: Biogeosciences* 114 (G2): 1–13. doi:10.1029/2008JG000883.

Bohlin, J., J. Wallerman, and J. E. S. Fransson. 2012. “Forest Variable Estimation Using Photogrammetric Matching of Digital Aerial Images in Combination with a High-Resolution DEM.” *Scandinavian Journal of Forest Research* 27: 692–699. doi:10.1080/02827581.2012.686625.

FAO (Food and Agriculture Organization of the United Nations). 2010. “Global Forest Resource Assessment 2010 Main Report.” *FAO Forestry Paper 163*. Rome: Food and Agriculture Organization of the United Nations. http://www.fao.org/docrep/013/i1757e/i1757e.pdf

Galllegos-Torell, Å., and M. Rydin. 2015. *Fältinstruktion För Nationell Inventering Av Landskapet I Sverige, NILS 2015*. Umeå: SLU.

Ginzler, C., and M. L. Hobi. 2015. “Countrywide Stereo-Image Matching for Updating Digital Surface Models in the Framework of the Swiss National Forest Inventory.” *Remote Sensing* 7 (4): 4343–4370. doi:10.3390/rs70404343.

Gobakken, T., O. M. Bollandsás, and E. Næsset. 2015. “Comparing Biophysical Forest Characteristics Estimated from Photogrammetric Matching of Aerial Images and Airborne Laser Scanning Data.” *Scandinavian Journal of Forest Research* 30 (1): 73–86. doi:10.1080/02827581.2014.961954.

Granholm, A., H. Olsson, M. Nilsson, and A. Allard. 2015. “The Potential of Digital Surface Models Based on Aerial Images for Automated Vegetation Mapping.” *International Journal of Remote Sensing* 36 (7): 1855–1870. doi:10.1080/01431161.2015.1029094.

Hirschmüller, H. 2008. “Stereo Processing by Semi-Global Matching and Mutual Information.” *IEEE Transactions on Pattern Analysis and Machine Intelligence* 30 (2): 328–341. doi:10.1109/TPAMI.2010.1166.

Holmgren, J. 2003. “Estimation of Forest Variables Using Airborne Laser Scanning.” *Acta Universitatis Agriculturae Sueciae, Silvestria* 278. Doctoral thesis. Umeå: Department of Forest Resource Management and Geomatics, Swedish University of Agricultural Sciences.

Holmgren, J., F. Johansson, K. Olofsson, H. Olsson, and A. Glimskär. 2008. “Estimation of Crown Coverage Using Airborne Laser Scanning.” In *Proceedings of Silvilaser 2008: 8th International Conference on Lidar Applications in Forest Assessment and Inventory. September 17-19, 2008*, edited by R. A. Hill, J. Rosette, and J. Suárez, 50–57. Edinburgh: Heriot-Watt University, UK.

Isenburg, M. 2015. *Lastools - Efficient Tools for Lidar Processing. Version 150526*, http://lastools.org.
Järnstedt, J., A. Pekkarinen, S. Tuominen, C. Ginzler, M. Holopainen, and R. Viiitala. 2012. “Forest Variable Estimation Using a High-Resolution Digital Surface Model.” *ISPRS Journal of Photogrammetry and Remote Sensing* 74: 78–84. doi:10.1016/j.isprsjprs.2012.08.006.

Jennings, S. B., N. D. Brown, and D. Shell. 1999. “Assessing Forest Canopies and Understorey Illumination: Canopy Closure, Canopy Cover and Other Measures.” *Forestry* 72 (1): 59–74. doi:10.1093/forestry/72.1.59.

Korhonen, L., D. Ali-Sisto, and T. Tokola. 2015. “Tropical Forest Canopy Cover Estimation Using Satellite Imagery and Airborne Lidar Reference Data.” *Silva Fennica* 49 (5): 1–18. doi:10.14214/sf.1405.

Korhonen, L., J. Heiskanen, and I. Korpela. 2013. “Modelling Lidar-Derived Boreal Forest Canopy Cover with SPOT 4 HRVIR Data.” *International Journal of Remote Sensing* 34 (22): 8172–8181. doi:10.1080/01431161.2013.833361.

Korhonen, L., K. T. Korhonen, M. Rautiainen, and P. Stenberg. 2006. “Estimation of Forest Canopy Cover: A Comparison of Field Measurement Techniques.” *Silva Fennica* 40 (4): 577–588. doi:10.14214/sf.315.

Korhonen, L., I. Korpela, J. Heiskanen, and M. Maltamo. 2011. “Airborne Discrete-Return LIDAR Data in the Estimation of Vertical Canopy Cover, Angular Canopy Closure and Leaf Area Index.” *Remote Sensing of Environment* 115: 1065–1080. doi:10.1016/j.rse.2010.12.011.

Lindgren, N., P. Christensen, B. Nilsson, M. Åkerholm, A. Allard, H. Reese, and H. Olsson. 2015. “Using Optical Satellite Data and Airborne Lidar Data for a Nationwide Sampling Survey.” *Remote Sensing* 7: 4253–4267. doi:10.3390/rs70404253.

Montaghi, A. 2013. “Effect of Scanning Angle on Vegetation Metrics Derived from a Nationwide Airborne Laser Scanning Acquisition.” *Canadian Journal of Forest Remote Sensing* 39: S152–S173. doi:10.5589/m13-052.

Müller, J., and K. Vierling. 2014. “Assessing Biodiversity by Airborne Laser Scanning.” In *Forestry Applications of Airborne Laser Scanning: Concepts and Case Studies. Managing Forest Ecosystems*, edited by M. Maltamo, E. Naesset, and J. Vauhkonen, 27: 357–374. Dordrecht, Netherlands: Springer.

Nilsson, M. 1996. “Estimation of Tree Heights and Stand Volume Using an Airborne Lidar System.” *Remote Sensing of Environment* 56: 1–7. doi:10.1016/0034-4257(95)00224-3.

Nurminen, K., M. Karjalainen, X. Yu, J. Hyppä, and E. Honkavaara. 2013. “Performance of Dense Digital Surface Models Based on Image Matching in the Estimation of Plot-Level Forest Variables.” *ISPRS Journal of Photogrammetry and Remote Sensing* 83: 104–115. doi:10.1016/j.isprsjprs.2013.06.005.

Pitt, D. G., M. Woods, and M. Penner. 2014. “A Comparison of Point Clouds Derived from Stereo Imagery and Airborne Laser Scanning for the Area-Based Estimation of Forest Inventory Attributes in Boreal Ontario.” *Canadian Journal of Remote Sensing* 40 (3): 214–232. doi:10.1080/07038992.2014.958420.

R Core Team. 2015. *R: A language and environment for statistical computing. R Foundation for Statistical Computing*. Vienna, Austria. http://www.R-project.org/

Reese, H., K. Nordkvist, M. Nyström, J. Bohlin, and H. Olsson. 2015. “Combining Point Clouds from Image Matching with SPOT 5 Multispectral Data for Mountain Vegetation Classification.” *International Journal of Remote Sensing* 36 (2): 403–416. doi:10.1080/2150704X.2014.999382.

Rothermel, M., K. Wenzel, D. Fritsch, and N. Haala. 2012. “SURE: Photogrammetric Surface Reconstruction from Imagery.” In *Proceedings LC3D Workshop, December 2012*, edited by F. Neitzel and R. Reulke, 1-9. Berlin, Germany.

Schnell, S., D. Altrell, G. Ståhl, and C. Kleinn. 2015. “The Contribution of Trees outside Forests to National Tree Biomass and Carbon Stocks—A Comparative Study across Three Continents.” *Environmental Monitoring and Assessment* 187 (1): 1–18. doi:10.1007/s10661-014-4197-4.

Ståhl, G., A. Allard, P.-A. Esseen, A. Glimskär, A. Ringvall, J. Svensson, S. Sundquist, et al. 2011. “National Inventory of Landscapes in Sweden (NILS) - Scope, Design, and Experiences from Establishing a Multiscale Biodiversity Monitoring System.” *Environmental Monitoring and Assessment* 173: 579–595. doi:10.1007/s10661-010-1406-7.
Stepper, C., C. Straub, and H. Pretzsch. 2015. “Using Semi-Global Matching Point Clouds to Estimate Growing Stock at the Plot Level and Stand Levels: Application for a Broadleaf-Dominated Forest in Central Europe.” Canadian Journal of Forest Research 45: 111–123. doi:10.1139/cjfr-2014-0297.

St-Onge, B., F.-A. Audet, and J. Begin. 2015. “Characterizing the Height Structure and Composition of a Boreal Forest Using an Individual Tree Crown Approach Applied to Photogrammetric Point Clouds.” Forests 6 (11): 3899–3922. doi:10.3390/f6113899.

St-Onge, B., C. Vega, R. A. Fournier, and Y. Hu. 2008. “Mapping Canopy Height Using a Combination of Digital Stereo-Photogrammetry and Lidar.” International Journal of Remote Sensing 29: 3343–3364. doi:10.1080/01431160701469040.

Straub, C., C. Stepper, R. Seitz, and L. T. Waser. 2013. “Potential of Ultracamx Stereo Images for Estimating Timber Volume and Basal Area at the Plot Level in Mixed European Forests.” Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere 43 (8): 731–741. doi:10.1139/cjfr-2013-0125.

Vastaranta, M., M. Wulder, J. C. White, A. Pekkarinen, S. Tuominen, C. Ginzler, V. Kankare, M. Holopainen, J. Hyyppä, and H. Hyyppä. 2013. “Airbornelaser Scanning and Digital Stereo Imagery Measures of Forest Structure: Comparative Results and Implications to Forest Mapping and Inventory Update.” Canadian Journal of Remote Sensing 39 (5): 382–395. doi:10.5589/m13-046.

Wang, Z., C. Ginzler, and L. Waser. 2015. “A Novel Method to Assess Short-Term Forest Changes Based on Digital Surface Models from Image-Based Point Clouds.” Forestry 0: 1–12. doi:10.1093/forestry/cpv012.

Waser, L. T., E. Baltsaviais, K. Ecker, H. Eisenbeiss, E. Feldmeyer-Christe, C. Ginzler, M. Kuechler, and L. Zhang. 2008. “Assessing Changes of Forest Area and Shrub Encroachment in a Mire Ecosystem Using Digital Surface Models and CIR Aerial Images.” Remote Sensing of Environment 112 (5): 1956–1968. doi:10.1016/j.rse.2007.09.015.

Waser, L. T., C. Fischer, Z. Wang, and C. Ginzler. 2015. “Wall-To-Wall Forest Mapping Based on Digital Surface Models from Image-Based Point Clouds and a NFI Forest Definition.” Forests 6: 4510–4528. doi:10.3390/f6124386.

White, J. C., C. Stepper, P. Tompalski, N. C. Coops, and M. A. Wulder. 2015. “Comparing ALS and Image-Based Point Cloud Metrics and Modeled Forest Inventory Attributes in a Complex Coastal Forest Environment.” Forests 6 (10): 3704–3732. doi:10.3390/f6103704.

White, J. C., M. A. Wulder, M. Vastaranta, N. C. Coops, D. Pitt, and M. Woods. 2013. “The Utility of Image-Based Point Clouds for Forest Inventory: A Comparison with Airborne Laser Scanning.” Forests 4 (3): 518–536. doi:10.3390/f4030518.