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Bitemporal aerial laser scans as an alternative to site index estimation: A case study in the Bohemian Switzerland National Park

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Abstract

In this work, we present a study about the application of bi-temporal, large interval aerial laser scans for constructing of tree growth models and estimating site index quality based on the measured increments from the laser scans. We compared two LiDAR scans with 14 years of difference in the national park area, where most areas are unmanaged. We derived the increment curve based on the Chapman-Richard growth formula. We used site index estimates from forest management plans from the national scale as the ground truth (both absolute and relative). We constructed three predictive models for site index estimates from bi-temporal scans, in modalities with and without stand age. Including the stand age improved all models, but even without the age, the models performed relatively well for differentiation between better and worse sites. At this moment, it is not directly possible to estimate age from remotely sensed data, but consistent monitoring, with laser scanning or photogrammetry, undoubtedly detects the harvest or dieback, so in the future, age can be considered as a variable easily estimated from remotely sensed data and so remote sensed material are viable source for understanding of forest growth and production.

Key words: site index; empirical models; bi-temporal laser scanning; machine learning; height growth

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1. Introduction

Knowledge about forest growth and development is one of the key pieces of information for sustainable forest management. Since the first inventories were based on permanent plots and their repeated measurements, the technology for estimating forest/tree growth has developed through dendrochronological methods till sophisticated 3D techniques based on architecture measurements (Antonelli 1992).

As the mensuration technologies developed, so have developed prediction techniques for forest growth. According to (Kurth & Anzola Jürgenson 1997), three main groups of models can be distinguished: empirical (also termed as aggregated), process-based, and morphological. The empirical models are mostly based on direct observation of the modeled variable like height, dbh, etc., and use mathematical functions from relatively simple ones (Richards 1959; Zhao-Gang & Feng-Ri 2003; Nigul et al. 2021) to sophisticated mathematical methods allowing prediction of variety of behavior (Cieszewski et al. 2000; Cieszewski 2001; Cieszewski & Strub 2018). The second class of models is called process based or often mechanistic because of the underlying models for mechanism and processes including photosynthesis, respiration, etc. The third class, according to (Kurth & Anzola Jürgenson 1997), is called the morphological group of models which belongs to the description of plant's structure and development and systems aiming to provide structural information with the possibility of prolonging the prediction of future. Each of the modeling techniques can be differently linked to data. Authors generally use an empirical approach with variables directly estimated from remotely sensed material. To improve the forest inventory, it is advisable to include negative or zero values of height increment in the dataset. When predicting height increment, the difference in modeled heights – can be improved by using random effects models that explicitly account for observations of negative or zero height increments. Uncategorized these values can lead to models that are not fully representative of the entire population of trees being measured (Woo et al. 2020).

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In recent years, LiDAR technology has gained great significance in the forestry sector (Muhamad-Afizzul et al. 2019; Goodbody et al. 2021) describe several possibilities of incorporating airborne laser scanning into sustainable forest management and describing how the LiDAR is increasingly important as a meaningful method for sustainable management, not only from productive point of view but also from point of view of biodiversity mapping, forest structure, ecosystem services and others. With the help of ALS, we can also obtain very accurate height estimates. If we also know what dominant species is expected in a stand, even if we do not have more detailed information about species composition, accurate volume estimates can be generated (Tompalski et al. 2014). However, several challenges could still be focused on in the future so that data from remote sensing is used more in forest inventory and monitoring programs (Fassnacht et al. 2023). Remote sensing provides opportunities to gather a wealth of information on forest attributes. In the last decade, advances in these processing technologies and algorithms have been rapid (White et al. 2015), enabling and facilitating the use of this data in forest monitoring. High-resolution three-dimensional data are useful in forest inventory (Vauhkonen et al. 2014). LiDAR technology is also suitable for clearcut detection. LiDAR technology is also suitable for clearcut detection. When we compare the technology of highly detailed image point clouds (IPCs) from aerial stereo images (which is usually cheaper than LiDAR) and LiDAR, this technology can detect major changes in the vegetation but is incapable of detecting minor changes, similar to LiDAR data (Ali-Sisto & Packalen 2017).

At present, the impact of global climate change and the ever-increasing concentration of CO_2 in the air emphasize its sequestration. Forest ecosystems bind more carbon than all other terrestrial ecosystems (Næsset et al. 2011). Data from laser scanning has also found application in this area, where we can estimate aboveground and underground biomass (Silva et al. 2013). We can use the data difference from two time intervals to detect the change in biomass (Bollandsås et al. 2013). Reliable estimates of carbon stocks are also affected by the field plot size. From the technical point of view, increasing the plot size is relatively more efficient when ALS is used to enhance the estimates (Mauya et al. 2015).

Repeated measurements (separated by a time interval) of the same tree or stand can assess growth from remote sensing. Time differences in remote sensing data usually indicate growth directly or indirectly. LiDAR data, with the help of which we can derive the age, we can divide it into bitemporal (Ma et al. 2018) or multitemporal (Yu et al. 2005). Repeated measurements may be a substitute for measurements from permanent or temporary sample plots. It can be expected that with the improvement of technology and the reduction of costs, the accuracy of the estimate of height increments will increase (Socha et al. 2017). The first mentions in the current literature can be found in the work (Næsset & Gobakken 2005), where the authors compare a shorter interval with a difference of 2 years (1999 and 2001) and evaluated the change in forest conditions using LiDAR data and found the difference in 50th and 90th height percentile with the help of which they predicted a change in height, basal area, and volume. These data could predict the growth of variables over two years, even though the accuracy of measurements was low. There are two methods for deriving forest information from airborne laser scanning: Individual Tree Detection (IDT) (Yu et al. 2010) and Area Based Approach (ABA) (Tompalski et al. 2015c). The above-mentioned area-based approach for processing data from laser scanning for forest inventory has been used in Scandinavia since 2002 (Patočka & Mikita 2016).

The new approach was tested by utilizing airborne laser scanning (ALS), where (Tompalski et al. 2016) derived forest stand attributes to determine future growth and yield. A combination of ALS and DAP can be used to estimate growth and yield. The use of a combination of laser scanning data and digital photogrammetry to model growth and yield was described in the article (Tompalski et al. 2018), where used two three-dimensional point cloud datasets from ALS (airborne laser scanning) and DAP (digital aerial photogrammetry). ALS can also be used in combination with satellite time series (Tompalski et al. 2015a) or aerial hyperspectral images (Bollandsås et al. 2019). LiDAR data is also suitable for estimating site index (SI). The authors (Noordermeer et al. 2018) used the estimation of heights from bitemporal laser data to estimate the site index of the area-based approach. The use of bitemporal data and an area-based approach proved to be suitable for estimating site index with reasonable accuracy. Utilizing bitemporal ALS data for site index determination necessitates the undisturbed height growth of dominant trees. The data effectively distinguished disturbed from undisturbed forest areas with moderate to high accuracy in complex temperate mixed wood forests. The exclusion of disturbed forest areas substantially improved the fit statistics of SI prediction models (Moan et al. 2023).

In this work we try to estimate the site index (absolute and relative) from repeated LiDAR scan, and we hypothesize that the initial and differential rasters can be sufficiently predicting these site indices and forest growth. We also hypothesize that forest age can increase the accuracy of the models, though it is not at the moment directly accessible variable from remote sensing, in future with continuous long term it might be possible to estimate age from remote sensing materials. For estimation of site index we used linear regression and machine learning (random forest) for comparison of performance.

2. Material and methods

2.1. Study area

Our area of interest for our research is The Bohemian Switzerland National Park. It is in the north-west of the Czech Republic, where the state border separates it from Germany and the Saxon Switzerland National Park (Fig. 1) (50°53'0.7"N, 14°23'21.6"E). The altitude ranges from 120 m above sea level (Labe near Hřensko) to 619 m above sea level (Růžovský vrch). The average rainfall here is 600 to 800 mm per year, and the average temperature is between 7 and 8 °C. There are mostly acid soils formed on sandstones with the predominant soil type cambium. Forest vegetation stages are in this area: oak-beech 32.7%, fir-beech 60.3%, spruce-beech 7.0%. The park is 79.23 km^2 and it is a partially uncultivated area.

Remnants of the original forests have been preserved in the form of so-called relict pines and in deep ravines where the original form of spruce can still be found. In some places, remnants of deciduous forests have also survived, including beech forests, warm-loving oak forests and floodplain forests that are linked to watercourses.

Bi-temporal data from the Bohemian Switzerland National Park were used in our research. The first laser data was from 2005, acquired by the Technical University of Dresden (TU Dresden) made company TopoSys Topographische Systemdaten GmbH, Biberach. The density of points during laser scanning was in, on average, 4 points/m^2. The second laser data was from 2019, acquired by commercial company Primis. The density of points during laser scanning was, on average, 15 points per m^2.

2.2. Processing of data

The laser data from 2005 was in binary data format 3d3 and 3d3i (format from TopoSys) and has a structure according to the type of scanner used. Therefore, for further processing, the data in these formats were converted to text format using TopoSys Converter V.2.2.0. Because it was a large amount of data, it was necessary to divide the territories into smaller parts and convert it gradually. With this software, the data were exported to a basic text file with records for each point in the form X, Y, Z, T (time), I (intensity, for the data of the last reflection) (Bruna et al. 2012). The disordered point cloud, which has about 12 billion points, must be filtered and classified.

Point cloud filtering, classification rasterization and generating a DTM

Filter and classification were done in the software environment PDAL running on Anaconda. PDAL, used to classify ground, returns the Simple Morphological Filter (SMRF) technique, which is based on finding the minimum z-value in a chosen buffer and angle connection to the closest point. The algorithm discriminated the points into two groups, ground and non-ground. First, the outlier filter merely classifies outliers with a Classification

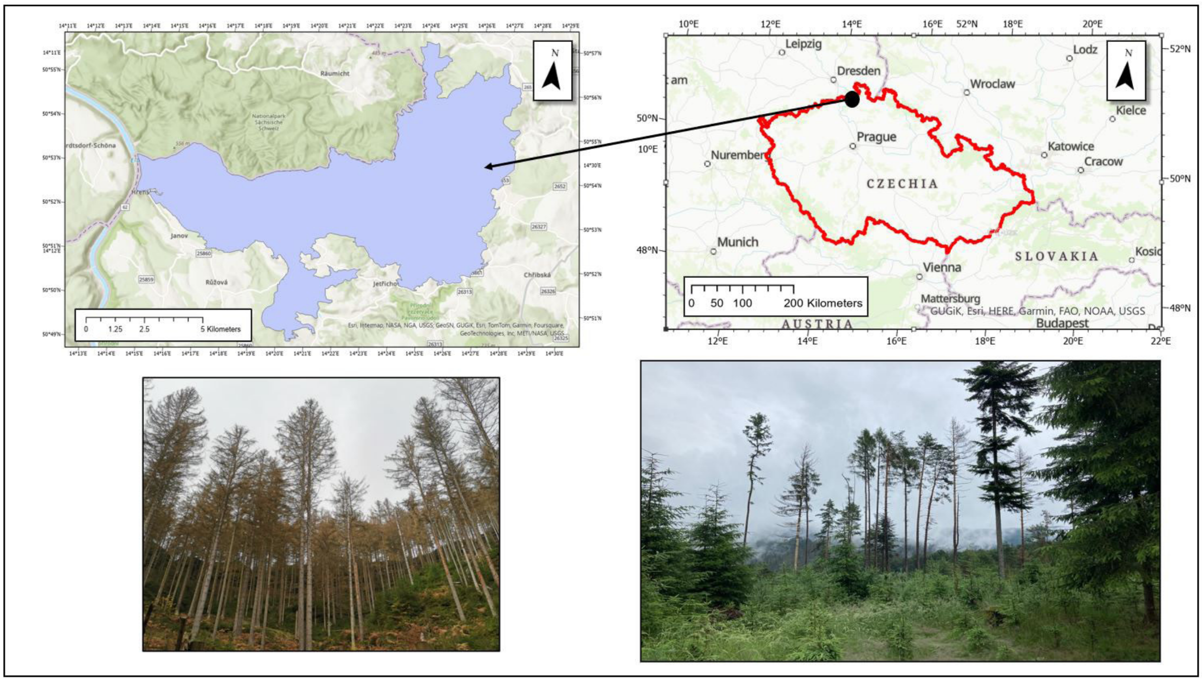

Fig. 1. The study is in the context of the Czech Republic, and examples of dead and alive forest stands.

value 7. These outliers are then ignored during SMRF processing with the ignore option. Finally, we added a range filter to extract only the ground returns (i.e. Classification value of 2) (PDAL 2022a).

We used PDAL to generate a raster surface using a fully classified point cloud with PDAL's writers.gdal. PDAL capability to generate rasterized output is provided by the writers.gdal stage (PDAL 2022b).

(PDAL 2022b) PDAL was used to generate an elevation model surface using the output from the filtering. PDAL's writers.gdal operation, and GDAL to generate an elevation and hillshade surface from point cloud data (PDAL 2022c).

The spatial analysis was done using ArcGIS Pro Esri® (Fig. 2). The minus subtracts the value of the second input raster from the value of the first input raster on a cell-by-cell basis.

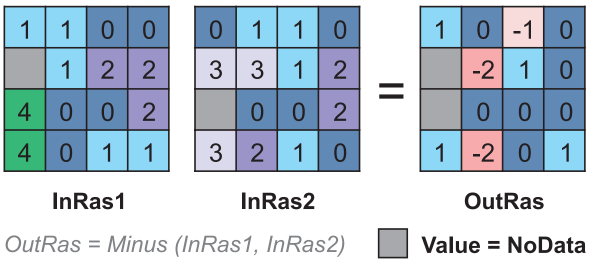

Fig. 2. Illustration of Minus function in software ArcGIS Pro Esri ® (Minus (Spatial Analyst, ArcGIS Pro 3.2)).

For estimation of pure biomass expansion, we eliminated data where the increment was larger than 15 meters, which corresponds to the largest increments found in Czechia growth and yield tables (Černý et al. 1993). We also eliminated negative increment, which can be understood as either harvested area or influenced by some kind of disturbance causing decreased height (tree top break, snow damage, etc.).

ArcGIS Change Detection function

The geo-processing tools within the Change Detection toolset enable the execution of basic change detection analyses between raster datasets. Additionally, the Compute Change raster function can be employed for real-time change detection between two raster datasets.

For change detection across a time series of raster images, one can utilize either the Analyze Changes Using CCDC tool or the Analyze Changes Using LandTrend tool. Each tool can be linked with the Detect Change Using Change Analysis Raster tool to ascertain details about the timing and extent of changes for each pixel time series (Change Detection in ArcGIS Pro, ArcGIS Pro 3.2).

We used Zonal statistics as data source for numerical descriptions of changes in the two periods. The following variables are obtained automatically as potential predictors:

MEAN – The average of all cells in the value raster that belong to the same zone as the output cell;
MAXIMUM – The largest value of all cells in the value raster that belong to the same zone as the output cell;
MEDIAN – The median value of all cells in the value raster that belong to the same zone as the output cell;
MINIMUM – The smallest value of all cells in the value raster that belong to the same zone as the output cell;
PERCENTILE 90 – The percentile of all cells in the value raster that belong to the same zone as the output;
RANGE – The difference between the largest and smallest value of all cells in the value raster that belong to the same zone as the output cell;
STANDARD DEVIATION – The standard deviation of all cells in the value raster that belong to the same zone as the output cell;
SUM – The total value of all cells in the value raster that belong to the same zone as the output cell;
VARIETY – The number of unique values for all cells in the value raster that belong to the same zone as the output cell (Zonal Statistics as Table (Spatial Analyst, ArcGIS Pro 3.2).

Verification data

In the Czech Republic, to assess site quality, site index is used. Currently, the most used variable is stand height, based on the mean or dominant height of the stand. Site index can be absolute or relative. Relative site index expresses the relative quality of the site, while absolute site index directly indicates the values of the mean heights of stands, usually at 100 years.

Statistical modelling and machine learning based model creation

The statistical analysis was done using software R version 4.2.3 (R Core Team 2023). Firstly, increments were modeled over the age and mean height, respectively. The nonlinear package (nls2) was used to fit the incremental form of the Chapman-Richards function (equation 1) (Richards 1959).

$$y = a(1 - e^{-bt})^c \qquad [1]$$

The function is one of the potential candidates for such work, and future work may include more detailed analysis and deployment of other functions available (Kuželka & Marušák 2015). For linear model creation, we used forward stepwise regression, with starting variables all available from remotely sensed data: first set from 2005 and second from the difference between 2005 and 2019 (the variables are standard zonal statistics variables from ArcGIS Zonal toolbox). The machine learning approach for model creation was done by deploying the RandomForest package v 4.7-1.1. The model's accuracy was estimated by confusion matrix and by the accuracy provided from the model. For both cases (absolute and relative site index), the values were transformed into factors and modelled as discrete classes.

3. Results

The distribution of all changes between 2005 and 2019 is shown on the map (Fig. 3). The larger red areas represent clearcuts resulting from the preliminary removal of bark beetle-attacked areas, an approach which was later abandoned in favor of natural evolution.

The Chapman-Richards growth model was used in its incremental (first derivative) form to fit the increment data. The data based on age are displayed in Fig. 4 left and based on mean height in Fig. 4 right.

It is possible to observe that the overall known and expected dynamics of the increments follow the typical nonlinear shape, with lower starting values, immediately followed by the high values (young age), and then continuously decreasing to low values where it usually stabilizes. Such behavior is expected in all the growth curves as it describes the typical biological evolution of the organism, and most of the growth curves can easily be fitted over such data.

There are significant similarities when comparing increments over age and over height in 2005. The left chart shows increments from 2005 related to age status in 2019, and the right chart shows increments from 2005 related to the height in 2005. Such growth models could be utilized for rough estimates of future height incre-

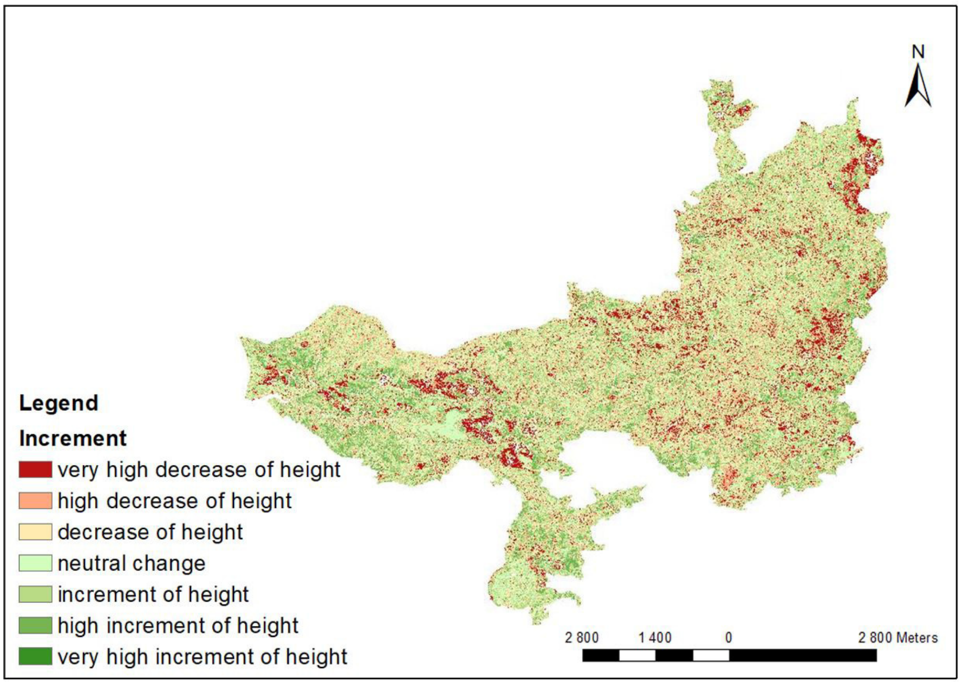

Fig. 3. The distribution of height changes between years 2005 and 2019.

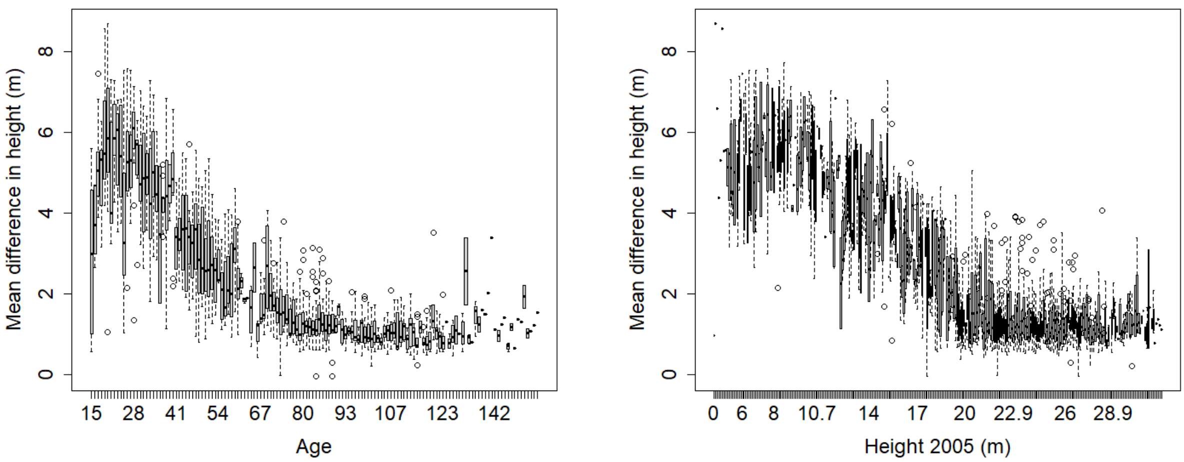

Fig. 4. The Chapman-Richards growth model input data. The left part shows the data based on age, and the right part shows the data based on mean height.

Table 1. The data for the Chapman-Richards growth model based on the age are shown on the left and based on mean height are on the right.

Growth model parameters for age:

	Estimate	Std. error	t – val	Pr (> |t|)
a	3.23e+02	378e+01	23.468	< 2e–16
b	2.69e–02	1.3e–03	20.241	< 2e–16
c	1.57e+00	1.6e–01	9.798	< 2e–16
AIC = 2,248.75				

Growth model parameters for height:

	Estimate	Std. error	t – val	Pr (> |t|)
a	1.03e+02	4.6e+00	22.174	< 2e–16
b	1.192e–01	4.7e–03	24.923	< 2e–16
c	1.916e+00	2.0e–01	9.437	< 2e–16
AIC = 2,302.181				

ments, for example, mentioned by (Woo et al. 2020). As the authors also mentioned in their study, it is also good to incorporate negative or zero height increment observation into the model so that the resulting models better represent the total population of tree measurements.

The resulting coefficients of the function fit are shown in Figure 5, upper row left and right, for age and mean height, respectively. The creation of height increment models is an interesting and important challenge. Especially local models for smaller areas might be of interest for estimating site index and determining better and worse growth sites compared to the local average. On the other hand, given the existence of a global state site index system, the possibility of this growth curve might not be sufficient for the estimation and assessment of the nationwide site index scale. On the other hand, the state site index is available in the ground truth data from Forest Management Plan, as mentioned in the Methods section. Therefore, the classical statistical approach using linear regression can be evaluated for the assessment of the site index.

Distribution of values of absolute site index values. Fig. 6 shows the approximate normal distribution of the values, and it is also expected that the phenomena itself has a normal distribution in general. Despite this, the machine learning approach was also tested in model 2 for the absolute site index.

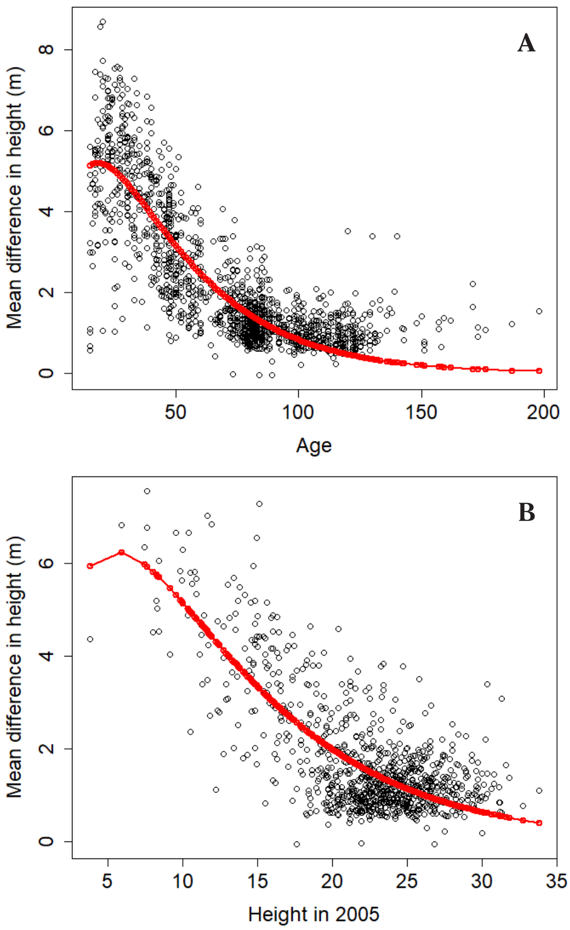

Fig. 5. Comparing increments over age and heights in 2005. The chart A shows increments from 2005 related to age status in 2017, and the chart B shows increments from 2005 related to the height in 2005.

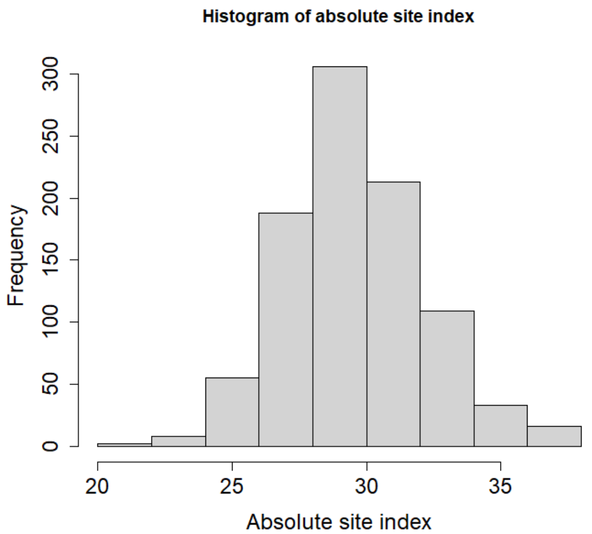

Fig. 6. The approximate normal distribution of the absolute site index values.

Model 1 – Regression model only using LiDAR for absolute site index estimation

This model was created for absolute site index estimation using a linear model approach. The resulting variables (those which are most significant to describe the fit are shown in Table 1). The most important predictors are median, mean, and 90th percentile differences.

The coefficient of determination of this model (R2) is equal to 0.277, which signals a significant correlation, though not very strong. On the other hand, the fact that there is a trend between variables found as significant predictors and predicted site index means that better and worse sites might be differentiated by the LiDAR only.

Table 2. The significant resulting variables of the model for absolute site index estimation without age. Multiple R-squared: 0.2825, Adjusted R-squared: 0.2771, p-value: < 2.2e–16.

	Estimate	Std. error	t – val	Pr (> |t|)	significance
(Intercept)	2.20E+01	7.66E–01	28.678	0	***
diff_MEDIAN	4.79E+00	6.36E–01	7.535	1.17E–13	***
r2005_PCT90	–2.08E–02	7.29E–02	–0.285	0.77576	
diff_MEAN	–5.28E+00	9.38E–01	–5.631	2.38E–08	***
diff_PCT90	1.13E+00	2.30E–01	4.922	1.02E–06	***
r2005_SUM	–4.42E–06	1.64E–06	–2.697	0.00713	**
r2005_MAX	1.03E–01	3.35E–02	3.086	0.00209	**
r2005_MEDIAN	1.51E–01	5.72E–02	2.647	0.00826	**

Table 3. The significant resulting variables of the model for absolute site index estimation with age. Multiple R-squared: 0.4439, Adjusted R-squared: 0.4384, p-value: < 2.2e–16.

	Estimate	Std. error	t – val	Pr (> |t|)	significance
AGE	–6.71E–02	4.11E–03	–16.335	2.00E–16	***
r2005_PCT90	–4.40E–02	7.36E–02	–0.598	0.550229	
diff_MEDIAN	2.73E+00	5.87E–01	4.655	3.71E–06	***
r2005_MEDIAN	3.19E–01	5.92E–02	5.382	9.36E–08	***
r2005_STD	2.65E–01	7.54E–02	3.515	0.000461	***
r2005_MAX	1.18E–01	2.96E–02	3.972	7.67E–05	***
r2005_SUM	–4.92E–06	1.45E–06	–3.395	0.000715	***
diff_MEAN	–2.64E+00	8.50E–01	–3.100	0.001993	**

Model1a – Regression model using LiDAR and age for absolute site index estimation

In this model the AGE variable obtained from Forest Management Plan was included among predictors.

The selected variable is again the median from the difference raster, but now the initial median and other starting predictors. The age was included by stepwise regression, and its inclusion increased the coefficient of determination to 0.438, which is approximately 0.16 more. It is a significant improvement, and as mentioned before, the age of a stand or tree is not directly detectable from remotely sensed data, but in long term monitoring, it is possible to detect by the detection of clearcut or individual tree breakdown.

Model2 – Model using machine learning for absolute site index without age

For comparison of model quality with relative site index, which does not have a normal distribution and is also not possible to be modeled by linear regression approach, we also constructed a predictive model for absolute site index using machine learning, more precisely random forest method.

The accuracy of the model is 0.3474. From the variable importance table, it is possible to observe that again, as in the linear model, the median of differences is selected as the most important variable, and approximately ten other variables alternatively from the starting year, and the difference contributes more than 50 percent to the final model.

Model2a – Model using machine learning for absolute site index with age

The model includes age in the predictors in this scenario, and similarly, as in the linear regression model, age is the most important predictor.

Table 4. The most important variables of the random forest model for absolute site index estimation without age. Overall Statistics: Accuracy: 0.3474, 95% CI: (0.2799, 0.4197.

diff_MEDIAN	100
r2005_MIN	87.8
diff_PCT90	72.5
diff_MEAN	71.6
r2005_SUM	67.0
diff_STD	63.8
diff_SUM	59.3
r2005_STD	56.9
r2005_MEDIAN	54.9
r2005_MAX	52.5
diff_MIN	50.1
r2005_PCT90	35.7
r2005_MEAN	34.1
r2005_RANGE	34.0
diff_RANGE	4.0
diff_MAX	0.0

Table 5. The most important variables of random forest model for absolute site index estimation with age. Overall Statistics: Accuracy: 0.4105, 95% CI: (0.3398, 0.484).

Age	100
r2005_MIN	41.9061
r2005_MAX	33.8553
r2005_STD	31.8844
r2005_PCT90	30.9755
r2005_MEDIAN	30.6710
r2005_SUM	30.2382
r2005_MEAN	25.3025
diff_MIN	25.2751
diff_STD	22.8977
diff_SUM	18.6345
r2005_RANGE	17.7695
diff_MEDIAN	14.9402
diff_PCT90	13.2787
diff_MEAN	4.9568
diff_RANGE	0.3649

Model3 – Model using machine learning for relative site index without age

In this model, we estimated the relative site index (bonita) with fewer levels than the absolute site index; the relative one has only nine classes, which are not linearly connected as the absolute site index. Though it is possible to say that 1st class is better than 2nd class, it is not possible to claim that 1st class is twice as better as 2nd class. Therefore, the problem cannot be easily solved by linear modeling, and machine learning offers a much better approach.

Table 6. The most important variables of the random forest model for relative site index estimation without age. Overall Statistics: Accuracy: 0.5105, 95% CI: (0.4371, 0.5836).

diff_MEDIAN	100
diff_MEAN	93.046
diff_PCT90	69.911
diff_STD	43.772
r2005_SUM	42.786
r2005_PCT90	28.869
r2005_MEDIAN	28.711
r2005_MEAN	28.552
r2005_MAX	27.237
r2005_RANGE	25.614
diff_SUM	24.352
r2005_STD	21.983
r2005_MIN	15.022
diff_MAX	5.627
diff_RANGE	2.337
diff_MIN	0

This model has the highest accuracy of all models so far; again, among the most important variables is the median difference between the two scans.

Model3a – Model using machine learning for relative site index with age

In this model, similarly to previous models, age was incorporated into predictor variables. Also, it was selected as the most important predictor variable.

Table 7. The most important variables of the random forest model for relative site index estimation with age. Overall Statistics: Accuracy: 0.5368, 95% CI: (0.4632, 0.6093).

Age	100
diff_MEDIAN	43.81
r2005_MEDIAN	32.90
r2005_MAX	27.37
r2005_MEAN	26.17
r2005_STD	23.99
diff_MEAN	22.46
r2005_SUM	22.25
r2005_MIN	22.21
r2005_PCT90	21.09
diff_PCT90	15.91
r2005_RANGE	15.17
diff_SUM	13.82
diff_STD	11.65
diff_MIN	11.39
diff_RANGE	0.64

Despite using age as a predictor with the highest importance, this model did not improve as much as the previous one. The resulting accuracy is the highest among all possible models, age is the most important predictor, and the median of differences is among the most influential variables. On the other hand, the difference to the model without age is, in this case, rather small.

4. Discussion

Estimating site index quality using empirical growth models is of essential use for practical forestry. Previous studies show the potential of ALS data for modeling and observation of forest characteristics, especially site index (Guerra-Hernández et al. 2021). Tompalski et al. (2015a) estimated height from remote sensing to developed site productivity estimates. For the estimation of the dominant height of the stand, they used ALS. Landsat time series was used to identify disturbances areas for stand age estimation. For fit, a site productivity guide curve was used for nonlinear regression for stands aged 7 to 32. Site productivity models were validated by Remote sensing, inventory data, and existing and developed models. This method of data estimation is more suitable for young stands in areas lacking wall-to-wall forest inventory data.

After deriving the Site Index, we can predict the height of the stand at a given age. The authors (Tompalski et al. 2015b) investigated the accuracy of height derivation from traditional site index (SI) curves and those measured using Airborne Laser Scanning (ALS) data. Their investigations showed a significant difference between the compared stand heights, influenced by factors such as stand complexity and canopy cover. On the other hand, the characteristics of elevation, slope, and aspect had less of an impact on site index estimation.

Parametric and non-parametric models can be used to model site index. According to a study (Watt et al. 2015) parametric models have higher accuracy. It may also be the case that age information is not always available, although this value improves the accuracy of the model. In our study, we added age, and the results show that adding age increases the accuracy of the model.

For mapping and predicting, the site index is also used with repeated laser scanning (Noordermeer et al. 2020; Socha et al. 2020). Socha et al. (2017) in their study, using airborne laser scanning data, they derived a site index for site-specific growth trajectories. Already, a five-year interval between data collection has proven to be sufficient.

It has been several years since the use of ALS technology in forest inventories, and we can now use repeated scans with a time interval of up to 15 years (Noordermeer et al. 2019). Besides that, laser scanning can accurately detect the vertical distribution of forest vegetation components. Detecting understory vegetation is possible with direct return and full-waveform recording methods but significantly more accurately with full-waveform (Crespo-Peremarch et al. 2020). In our work, 14-year-interval showed successful estimates of site index for fine-scale (in case of absolute site index) to coarser scale in case of relative site index.

Repeated laser scanning (fifteen years) can also be used in site index estimation using direct and indirect methods. In the direct method, field observations can be a regress of age-height site index against canopy height metrics derived from ALS data from the first point in time and changes in ALS metrics reflecting canopy height growth during the observation period. The two points in time were firstly modeled Hdom using the respective ALS metrics as predictors SI, derived from the initial Hdom, the estimated Hdom increment, and the length of the observation period using empirical SI curves. Both approaches yield a satisfactory site index estimation (Noordermeer et al. 2018). In our study, instead, we used the mean height of the stand, and we proved that in all cases, the median height of LiDAR measurements was always among the most important predictors. On the other hand, in all modalities (regression, machine learning), the age proved to be improved by including variable age. At first glance, the age does not appear directly accessible by remote sensing materials. However, consistent long-term monitoring can delineate clear-cuts or disturbances and define the starting period for a new generation of tree cover. Such mapping can nowadays also easily be done (Melichová et al. 2023), and clearcut areas with very high-resolution mapping can be analyzed for prediction of vegetation survival (Hüttnerová et al. 2024).

Bollandsås et al. (2019) have compared the accuracy of site index modeling based on single-time hyperspectral data with different types of processing, bitemporal laser scans, and their combination. The aerial laser scan (ALS) data used in this study were obtained at two-time intervals with a twelve-year difference. Hyperspectral data were obtained by the same flight as ALS data in 2011. Using a combination of ALS data and hyperspectral images, the results showed that the contribution of hyperspectral data was negligible compared to using only bitemporal ALS data. In the cases where only spectral data are available, it is still possible to construct predictive models of the H40 site index (which is used in Norway to represent forest productivity). They also found that models constructed with normalized hyperspectral data showed lower RMSE values than models constructed with atmospheric correction and that pixel selection based on NDVI did not improve results compared to using all pixels.

Even today, the financial aspect is important when deciding what data will be used. Direct methods, using bi-temporal ALS and DAP data, demonstrated testing the highest accuracy and the lowest total cost (Noordermeer et al. 2021).

5. Conclusions

This study used distant bitemporal datasets from aerial laser scanning to estimate growth and site index quality. Initial and differential rasters were used as input data for models, and ground truth from Forest management plans was used to evaluate the accuracy of the outputs. We demonstrated that machine learning (random forest method) could estimate both absolute and relative site indices and that linear regression can also be used to model absolute site index successfully. In all three modalities of models, including age as a predictive variable, accuracy improved significantly by 3 to 15 percent. Age is a logical predictor for site index estimation because it relates to growth trajectory. In the future, age can be easily estimated from remotely sensed material as a moment when canopy height is reduced to zero, either by harvest or natural disturbance. Continuous remote sensing monitoring may contribute to a better understanding of forest growth status and conditions.

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References

Ali-Sisto, D., Packalen, P., 2017: Forest Change Detection by Using Point Clouds from Dense Image Matching Together with a LiDAR-Derived Terrain Model. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10:1197–1206.

Antonelli, P. L., 1992: The Algorithmic Beauty of Plants (Przemyslaw Prusinkiewicz and Aristid Lindenmayer). SIAM Review, 34:142–143.

Bollandsås, O. M., Gregoire, T. G., Næsset, E., Øyen, B. H., 2013: Detection of biomass change in a Norwegian mountain forest area using small footprint airborne laser scanner data. Statistical Methods and Applications, 22:113–129.

Bollandsås, O. M., Ørka, H. O., Dalponte, M., Gobakken, T., Næsset, E., 2019: Modelling site index in forest stands using airborne hyperspectral imagery and Bi-temporal laser scanner data. Remote Sensing, 11:1020.

Bruna, V., Elznicova, J., Pacina, J., 2012: Využití geoinformačních technologií pro hodnocení krajiny přeshraniční oblasti Česko-Saské Švýcarsko. Ústí nad Labem, Univerzita J. E. Purkyně v Ústí nad Labem, Fakulta životního prostředí, 104 p. (In Czech).

Černý, M., Pařez, J., Malík, Z., 1993: Růstové modely hlavních dřevin České republiky (smrk, borovice, buk, dub) – 2. etapa. Zpráva o výsledcích řešení za rok 1993. Skupina ekologického monitoring, PYRUS, 66 p. (In Czech).

Cieszewski, C. J., Harrison, M., Martin, S. W., 2000: Practical methods for estimating non-biased parameters in self-referencing growth and yield models. PMRC Technical report. Georgia, University of Georgia. 11 p.

Cieszewski, C. J., 2001: Three methods of deriving advanced dynamic site equations demonstrated on inland Douglas-fir site curves. Canadian Journal of Forest Research, 31:165–173.

Cieszewski, C. J., Strub, M., 2018: Comparing properties of self-referencing models based on nonlinear-fixed-effects versus nonlinear-mixed-effects modeling approaches. Mathematical and Computational Forestry and Natural-Resource Sciences, 10:46–57.

Crespo-Peremarch, P., Fournier, R. A., Nguyen, V. T., van Lier, O. R., Ruiz, L. Á., 2020: A comparative assessment of the vertical distribution of forest components using full-waveform airborne, discrete airborne and discrete terrestrial laser scanning data. Forest Ecology and Management, 473:118268.

Fassnacht, F. E., White, J. C., Wulder, M. A., Næsset, E., 2023: Remote sensing in forestry: current challenges, considerations and directions. Forestry: An International Journal of Forest Research, 97:11–37.

Goodbody, T. R. H., Coops, N. C., Luther, J. E., Tompalski, P., Mulverhill, C., Frizzle, C. et al., 2021: Airborne laser scanning for quantifying criteria and indicators of sustainable forest management in Canada. Canadian Journal of Forest Research, 51:972–985.

Guerra-Hernández, J., Arellano-Pérez, S., González-Ferreiro, E., Pascual, A., Sandoval Altelarrea, V., Ruiz-González, A. D. et al., 2021: Developing a site index model for P. Pinaster stands in NW Spain by combining bi-temporal ALS data and environmental data. Forest Ecology and Management, 481:118690.

Hüttnerová, T., Muscarella, R., Surový, P., 2024: Drone microrelief analysis to predict the presence of naturally regenerated seedlings. Frontiers in Forests and Global Change, 6:1329675.

Kurth, W., Anzola Jürgenson, G., 1997: Triebwachstum und Verzweigung junger Fichten in Abhängigkeit von den beiden Einflußgrößen "Beschattung" und "Wuchsdichte": Datenaufbereitung und -analyse mit GROGRA. In: Pelz, D. (ed.): Deutscher Verband Forstlicher Forschungsanstalten, Sektion Forstl. Biometrie u. Informatik, 10. Tagung Freiburg i. Br. 24.–26. 9. 1997, Ljubljana, Biotechn. Fakultät, p. 89–108. (In German).

Kuželka, K., Marušák, R., 2015: KORFit: An efficient growth function fitting tool. Computers and Electronics in Agriculture, 116:187–190.

Ma, Q., Su, Y., Tao, S., Guo, Q., 2018: Quantifying individual tree growth and tree competition using bi-temporal airborne laser scanning data: a case study in the Sierra Nevada Mountains, California. International Journal of Digital Earth, 11:485–503.

Mauya, E. W., Hansen, E. H., Gobakken, T., Bollandsås, O. M., Malimbwi, R. E., Næsset, E., 2015: Effects of field plot size on prediction accuracy of aboveground biomass in airborne laser scanning-assisted inventories in tropical rain forests of Tanzania. Carbon Balance and Management, 10:10.

Melichová, Z., Pekár, S., Surový, P., 2023: Benchmark for automatic clear-cut morphology detection methods derived from airborne LiDAR data. Forests, 14:2408.

Moan, M. Å., Noordermeer, L., White, J. C., Coops, N. C., Bollandsås, O. M., 2023: Detecting and excluding disturbed forest areas improves site index determination using bitemporal airborne laser scanner data. Forestry: An International Journal of Forest Research, 97:48–58.

Muhamad-Afizzul, M., Siti-Yasmin, Y., Hamdan, O., Tan, S. A., 2019: Estimating stand-level structural and biophysical variables of lowland dipterocarp forest using airborne LiDAR data. Journal of Tropical Forest Science, 31:312–323.

Næsset, E., Gobakken, T., 2005: Estimating forest growth using canopy metrics derived from airborne laser scanner data. Remote Sensing of Environment, 96:453–465.

Næsset, E., Gobakken, T., Solberg, S., Gregoire, T. G., Nelson, R., Ståhl, G. et al., 2011: Model-assisted regional forest biomass estimation using LiDAR and InSAR as auxiliary data: A case study from a boreal forest area. Remote Sensing of Environment, 115:3599–3614.

Nigul, K., Padari, A., Kiviste, A., Noe, S. M., Korjus, H., Laarmann, D. et al., 2021: The possibility of using the Chapman-Richards and Näslund functions to model height-diameter relationships in hemiboreal old-growth forest in Estonia. Forests, 12:1–15.

Noordermeer, L., Bollandsås, O. M., Gobakken, T., Næsset, E., 2018: Direct and indirect site index determination for Norway spruce and Scots pine using bitemporal airborne laser scanner data. Forest Ecology and Management, 428:104–114.

Noordermeer, L., Økseter, R., Ørka, H. O., Gobakken, T., Næsset, E., Bollandsås, O. M., 2019: Classifications of forest change by using bitemporal airborne laser scanner data. Remote Sensing, 11:2145.

Noordermeer, L., Gobakken, T., Næsset, E., Bollandsås, O. M., 2020: Predicting and mapping site index in operational forest inventories using bitemporal airborne laser scanner data. Forest Ecology and Management, 457:117768.

Noordermeer, L., Gobakken, T., Næsset, E., Bollandsås, O. M., 2021: Economic utility of 3D remote sensing data for estimation of site index in Nordic commercial forest inventories: a comparison of airborne laser scanning, digital aerial photogrammetry and conventional practices. Scandinavian Journal of Forest Research, 36:55–67.

Patočka, Z., Mikita, T., 2016: Využití plošného přístupu ke zpracování dat leteckého laserového skenování v inventarizaci lesa. Zprávy lesnického výzkumu, 61:115–124. (In Czech).

Richards, F. J., 1959: A flexible growth function for empirical use. Journal of Experimental Botany, 10:290–301.

Silva, C. A., Klauberg, C., De Pádua Chaves Carvalho, S., Rodriguez, L. C. E., 2013: Estimation of aboveground carbon stocks in Eucalyptus plantations using LIDAR. International Geoscience and Remote Sensing Symposium (IGARSS), 21–26 July 2013, Melbourne, VIC, Australia, p. 972–974.

Socha, J., Pierzchalski, M., Bałazy, R., Ciesielski, M., 2017: Modelling top height growth and site index using repeated laser scanning data. Forest Ecology and Management, 406:307–317.

Socha, J., Hawryło, P., Stereńczak, K., Miścicki, S., Tymińska-Czabańska, L., Młocek, W. et al., 2020: Assessing the sensitivity of site index models developed using bi-temporal airborne laser scanning data to different top height estimates and grid cell sizes. International Journal of Applied Earth Observation and Geoinformation, 91:102129.

Tompalski, P., Coops, N. C., White, J. C., Wulder, M. A., 2014: Simulating the impacts of error in species and height upon tree volume derived from airborne laser scanning data. Forest Ecology and Management, 327:167–177.

Tompalski, P., Coops, N. C., White, J. C., Wulder, M. A., Pickell, P. D., 2015a: Estimating forest site productivity using airborne laser scanning data and Landsat time series. Canadian Journal of Remote Sensing, 41:232–245.

Tompalski, P., Coops, N. C., White, J. C., Wulder, M. A., 2015b: Augmenting site index estimation with airborne laser scanning data. Forest Science, 61:861–873.

Tompalski, P., Coops, N. C., White, J. C., Wulder, M. A., 2015c: Enriching ALS-derived area-based estimates of volume through tree-level downscaling. Forests, 6:2608–2630.

Tompalski, P., Coops, N. C., White, J. C., Wulder, M. A., 2016: Enhancing forest growth and yield predictions with airborne laser scanning data: Increasing spatial detail and optimizing yield curve selection through template matching. Forests, 7:1–20.

Tompalski, P., Coops, N. C., Marshall, P. L., White, J. C., Wulder, M. A., Bailey, T., 2018: Combining multi-date airborne laser scanning and digital aerial photogrammetric data for forest growth and yield modelling. Remote Sensing, 10:1–21.

Vauhkonen, J., Ørka, H. O., Holmgren, J., Dalponte, M., Heinzel, J., Koch, B., 2014: Tree species recognition based on airborne laser scanning and complementary data source. In: Maltamo, M., Næsset, E., Vauhkonen, J. (eds.): Forestry applications of airborne laser scanning. Managing Forest Ecosystems. Springer, Dordrecht., p. 135–156.

Watt, M. S., Dash, J. P., Bhandari, S., Watt, P., 2015: Comparing parametric and non-parametric methods of predicting Site Index for radiata pine using combinations of data derived from environmental surfaces, satellite imagery and airborne laser scanning. Forest Ecology and Management, 357:1–9.

White, J. C., Stepper, C., Tompalski, P., Coops, N. C., Wulder, M. A., 2015: Comparing ALS and image-based point cloud metrics and modelled forest inventory attributes in a complex coastal forest environment. Forests, 6:3704–3732.

Woo, H., Eskelson, B. N. I., Monleon, V. J., 2020: Tree height increment models for national forest inventory data in the Pacific Northwest, USA. Forests, 11:2.

Yu, X., Hyyppä, J., Kaartinen, H., Hyyppä, H., Maltamo, M., Rönnholm, P., 2005: Measuring the growth of individual trees using multi-temporal airborne laser scanning point clouds. ISPRS WG III/3, III/4, V/3 Workshop "Laser scanning 2005", 12–14 September 2005, Enschede, the Netherlands, p. 204–208.

Yu, X., Hyyppä, J., Holopainen, M., Vastaranta, M., 2010: Comparison of area-based and individual tree-based methods for predicting plot-level forest attributes. Remote Sensing, 2:1481–1495.

Zhao-Gang, L., Feng-Ri, L., 2003: The generalized Chapman-Richards function and applications to tree and stand growth. Journal of Forestry Research, 14:19–26.

Other sources

Change detection in ArcGIS Pro. Available at https://pro.arcgis.com/en/pro-app/latest/help/analysis/image-analyst/change-detection-in-arcgis-pro.htm.

Minus (Spatial Analyst). Available at https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/minus.htm.

PDAL. (2022a). Available at https://pdal.io/en/2.4.3/workshop/exercises/analysis/ground/ground.html.

PDAL. (2022b). Available at https://pdal.io/en/2.4.3/workshop/exercises/analysis/rasterize/rasterize.html.

PDAL. (2022c). Available at https://pdal.io/en/2.4.3/workshop/exercises/analysis/dtm/dtm.html.

R Core Team, 2023. R Core Team. R: A Language and Environment for Statistical Computing; R Foundation for Statistical Computing: Vienna, Austria, 2023; Available at https://www.R-project.org/ (accessed on 7 December 2023).

Zonal Statistics as Table (Spatial Analyst). Available at https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/zonal-statistics-as-table.htm.