

Urban Tree Species Classification with Multispectral Airborne LiDAR

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Abstract: Urban tree species provide various essential ecosystem services in cities, such as mediating urban temperature, isolating noise, fixing carbon, and mitigating the urban heat island impact. The quality of these services is influenced by species diversity, tree growth status, and the distribution and composition of trees. Traditionally, data about urban trees has been gathered through field data collection and manual interpretation of remote sensing images. In this study, we evaluate the capacity of using Multispectral Airborne Laser Scanning (ALS) data to classify 24 common urban roadside tree species in Espoo, Finland. We utilized tree crown structure information, intensity features, and spectral information for classification. 8 different machine learning algorithms were used in our study and Extra trees (ET) performed best with an overall accuracy of 71.7% using multispectral LiDAR data, highlighting that combining structural and spectral information in a single frame could enhance classification accuracy. In the future, we will focus on identifying the most important features in species classification and finding algorithms with higher efficiency and accuracy.

Key words: Multispectral Airborne LiDAR, Tree species classification

PACS:

基于多光谱机载激光雷达的城市树种分类研究

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摘要:城市树种可为城市提供各种基本的生态系统服务, 如调节城市温度、隔离噪音、固定碳以及减轻城市热岛效应。这些服务的质量受到物种多样性、树木生长状况以及树木分布和组成的影响。传统上, 有关城市树木的数据都是通过实地数据收集和人工解读遥感图像收集的。在这项研究中, 我们评估了使用多光谱机载激光扫描(ALS)数据对芬兰 Espoo 市 24 种常见城市路边树种进行分类的能力。我们利用树冠结构信息、强度特征和光谱信息进行分类。我们在研究中使用了 8 种不同的机器学习分类算法, 其中 Extra Tree (ET) 的性能最佳, 其使用多光谱激光雷达数据的总体准确率为 71.7%, 这表明在集成一体的高光谱激光雷达中扫描结合结构和光谱信息可以提高分类准确率。未来, 我们的重点将是确定物种分类中最重要的特征, 并找到效率更高、准确率更高的算法。

关 键 词: 多光谱机载激光雷达; 树种分类

1 INTRODUCTION

Today, some 56% of the world's population - 4.4 billion inhabitants - live in cities. Urban trees are outsized in driving global climate change[1] and are uniquely susceptible to climate change impacts. Urban Forest Effects model[2], [3] is commonly implemented in urban areas worldwide to produce citywide estimates of urban forest structure, species diversity, and ecosystem

function. However, urban forest inventory is labour-intensive, particularly on private properties, and the results are not spatially explicit. Although remotely sensed data have been widely used for forest applications, traditional optical remote sensing techniques lack the ability to capture three-dimensional forest structures, particularly in unevenly aged, mixed species forests with multiple canopy layers[4].

Airborne laser scanning (ALS) is effective for extracting biophysical variables and revising forest inventory maps. The successful use of ALS data has been demonstrated for various applications. For example, ALS has been used to estimate tree height [5], [6], identify tree species [7], [8], [9], and estimate tree volume biomass [10], [11], and growth [12], [13]. Tree species information at an individual tree level is particularly useful in growth and yield estimates and has been primarily studied for forest applications, such as updating forest inventories. Tree species classification using ALS has not been intensively studied compared with studies on the successful use of ALS for other forest attribute mapping because of the lack of spectral information.

Previous studies have also revealed that combining multispectral information with 3D ALS data can improve the accuracy of tree extraction and tree species classification, as we can take advantage of both datasets. However, challenging factors limit the effective operational use of the fused datasets [14], [15]. For example, geometric and radiometric registration between two datasets is demanding because data are normally acquired at different times using different sensors. The recently developed multispectral laser scanning technique is becoming an attractive option for forest mapping because it can provide not only a dense point cloud but also spectral information, which can simplify data processing and facilitate the interpretation of data.

Given the challenges with traditional optical remote sensing in capturing three-dimensional forest structures, it is worthwhile to explore the potential of multispectral laser scanning for urban tree inventories, particularly for species classification. This study aims to evaluate the feasibility of using multispectral Airborne Laser Scanning (ALS) data for urban tree species classification and to investigate the information content of features derived from point cloud and intensity data.

2 MATERIALS AND METHODS

2.1 Study Area and Establishment of Sample Plots

The MLS datasets used in this study were acquired in a suburban area in Espoo, southern Finland (60° 9' 18" N, 24° 38' 24" E) in the southern Boreal Forest Zone. We choose around 822 trees in this area as our field dataset. The land area is approximately 5 km². In our research, we concentrated solely on the vegetated areas, excluding the sea using a water mask created from topographic map data. The area included a diverse range of boreal tree species.

The points were updated through visual interpretation of Titan data and open datasets from the City of Espoo, the National Land Survey of Finland, Google Maps, and Google Street View. Field checks validated the analysis and resolved uncertainties. The reference points' attributes included species, geographic location, living conditions, tree height, and planting date for each tree.

2.2 Multispectral ALS data

Multispectral Optech Titan data (Teledyne Optech, To-

ronto, ON, Canada) for the study area were collected in May and June 2016 in collaboration with TerraTec Oy (Helsinki, Finland) from a 650 m flight high. The data acquisition was carried out using a fixed-wing aircraft flying at the same sea level. The sensor comprises three Titan channels: green (532 nm), NIR (1064 nm), and short wave infrared (1550 nm). Each channel provided as separate point clouds. In our preprocessed dataset, the point densities over land areas are roughly 9 points/m² for Channel 1, 9 points/m² for Channel 2, and 8 points/m² for Channel 3.

TerraScan (TerraSolid Oy, Helsinki, Finland) was used to preprocess our ALS data and differentiate between ground and nonground points using a standardized procedure.

This procedure involved removing noise, such as points detected below the ground level or above the canopy. Subsequently, the point clouds were height normalized. We subtracted the ground elevation from the point cloud height measurements, employing a digital terrain model. The digital terrain model was created from the classified ground points of three separate channels to eliminate potential discrepancies.

Radiometric calibration of ALS intensity is crucial to ensure successful classification (Kaasalainen et al., 2011). Therefore, in this study we implemented relative radiometric calibration. We found that the intensity value is higher in the middle flight route than the other and it also decreased with the scanning height. So a range correction was applied to eliminate of such effects:

$$I_c = I \times \frac{D_i^2}{D_{ref}^2}$$

I_c is the modified intensity, I is the original intensity, D_i is the distance from the LiDAR to the point cloud and D_{ref} is the flying altitude (650 m).

2.3 Creating Canopy Height Model and single tree detection

Individual trees were detected using a minimum curvature-based algorithm, which started with creating a canopy height model (CHM). According to our field dataset of each tree coordination, we set the potential crown area within 5 m². A local maximum filtering algorithm was used to find the treetops in this area. Subsequently, the watershed segmentation method was used to delineate tree crown boundaries without setting a flow threshold in the CHM. Eventually, the point cloud of each tree from the multispectral ALS dataset was created. In the segmentation process, the shape and position of individual tree crowns were identified using the segment boundaries and the location of the highest point within each segment. In this study, first return points from all three channels were utilized to generate the canopy height model (CHM).

2.4 Multispectral ALS data Feature extraction

In this experiment, the features were primarily divided into two types: intensity features and geometric features. The maximum height (H_{max}) of each tree was calculated from the highest point of all point cloud in each tree segment.

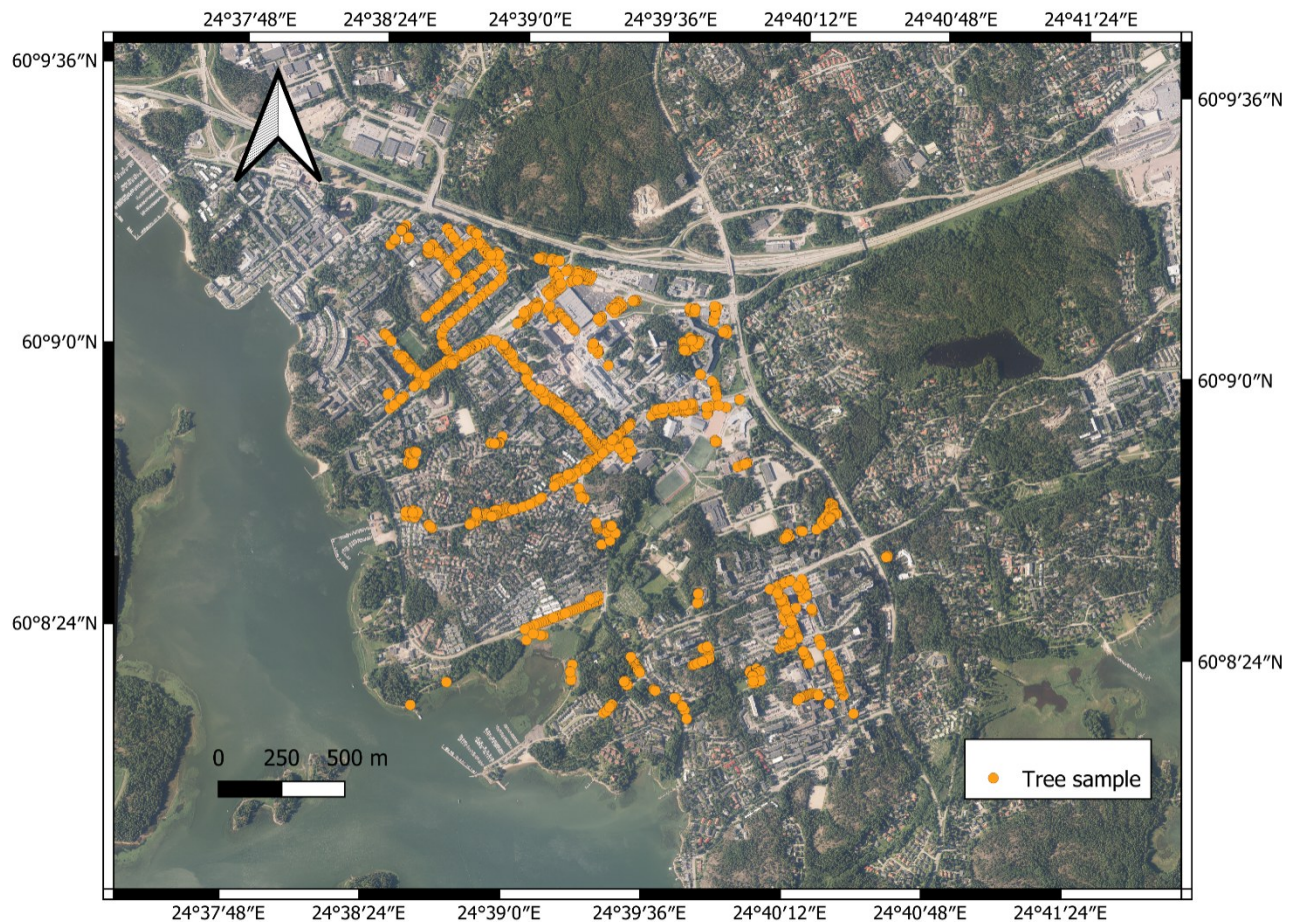


Figure 1 Map of the study area and tree samples in the research area.
图 1 研究区和研究区的树木样本

Simultaneously, we got 137 features in each channel from the multispectral ALS data.

2.5 Tree species classification and accuracy evaluation

In this study, we use 8 machine learning algorithms to compare the classification of tree species: Extra trees (ET), random forest (RF), K-nearest neighbour (KNN), logistic regression (LR), Linear Discriminant Analysis (LDA), Classification And Regression Tree (CART), Naive Bayes (NB), support vector machine (SVM). Tree species were estimated based on prediction models by 8 machine learning algorithms using tree features as predictors and tree species as a response for correctly detected trees.

3 RESULTS

3.1 Accuracy of Classification

As presented in Figure 2, using all the intensity and geometric features, the overall tree species classification performed best in the Extra tree algorithm and reached 71.7%. When we only use channel 1 features for classification, overall values can only reach 65.7%. Only using features from channel 2 yielded overall values that can only reach 68.3%. Only using features from channel 3 yielded overall values that can only reach 64.8%. The

accuracy of all the classifications for each species is shown in Figure 3.

3.2 Feature Importance Analysis

We also investigated which input features and channels are most relevant for tree species classification based on the measure provided by the RF algorithm for assessing feature importance. If a feature influences the prediction, permuting its values should affect the model error. If a feature is not influential, then permuting its values should have little or no effect on the model error. Table 3 lists the top three features in the classifications based on different combinations of the features. The most important features in the classification based on point cloud features were penetration and higher-level percentiles. Two density-related features at higher and middle layers were also scored as important as higher percentiles. In the case of classification using single-channel features, the 1064nm wavelength (Channel 2) appears to provide the most valuable information for distinguishing between pine, spruce, and birch species. This is followed by the 1550nm wavelength (Channel 1) and then the 532nm wavelength (Channel 3).

4 DISCUSSION

Multispectral LiDAR data improved the classification ac-



Figure 2 Titan intensity image of Study area in Espoo (Red: Channel 1; Green: Channel 2; Blue: Channel 3).
图2 埃斯波拉赫蒂研究区,背景为泰坦强度影像(红色:Channel 1;绿色:Channel 2;蓝色:Channel 3)。

curacy by approximately 5% to 10% for all channels compared to each channel. This proves our hypothesis about the ability of mALS features in classification. For example, the overall accuracy of 71.7% was obtained in multispectral LiDAR all channel data and was 65.7%, 68.3% and 64.8% when using only channel 1, channel 2 and channel 3, respectively. Our findings demonstrated the advantage of combining multichannel features over each single channel in classifying urban trees. Additionally, the sample size of each tree species in the sample of this experiment is uneven, which may affect the model's accuracy when trained. Consequently, a larger and more representative sample will be selected for the experiment in future research. In this experiment, the measurement samples were not well balanced, which led to a considerable reduction in classification accuracy to some extent. Therefore, in the future research, we will improve the balance of the samples.

In this study, 8 machine learning algorithms were evaluated for their classification performance, each demonstrating distinct strengths and limitations in tree species classification. The selection of an appropriate classification algorithm depends on the specific characteristics of

the dataset, including size, dimensionality, and the underlying relationship between features and class labels. Extra Trees (ET) and Random Forests (RF) proved effective in our study and they are professional in handling large, high-dimensional datasets, offering robustness against overfitting which fit the conditions of our study dataset. Naive Bayes (NB) was efficient and scalable, especially for high-dimensional data, but its assumption of feature independence limits its applicability in cases with high feature correlation.

It's also important to note that overall accuracy (OA) is influenced by factors such as species composition, stand structure, age, and the methods used to select the best features, which vary among studies. In this research, however the intensity of laser returns was not calibrated. There are two reasons to explain for it. Firstly, in the future research, we can investigate if the calibrated intensity would have effect on the classification result. Secondly, we use MCI features to mitigate potential variations in intensity.

In conclusion, the ability of mALS compared to SCI-Ch ALS data to characterize tree species in urban areas was assessed in this study. Our classification results indicate

Table 1 List of all features from Multispectral ALS data. (*i* refers to channel numbers, and subscript *F* represents the single-channel intensity feature used)
表 1 从激光回波中得出的所有特征列表 (*i* 代表通道编号, 下标 *F* 指使用的单通道强度特征)

Feature	Definition
Single-channel Intensity (SCI) features	
I_{\max}	Maximum intensity
I_{\min}	Minimum intensity
I_{mean}	Mean intensity
I_{std}	The standard deviation of intensity
I_{cov}	Coefficient of variation (i. e. , relative standard deviation) of intensity
I_{sk}	Skewness of intensity
I_{range}	Range of intensity
I_{kut}	Kurtosis of intensity
I_5 to I_{95}	Percentiles of intensity values of points above the ground threshold from 5% to 95% in 5% increments
Multi-channel Intensity (MCI) features	
$R_i^F = I_i^F / (I_1^F + I_2^F + I_3^F)$	Ratios of intensity features in each channel
$\text{gNDVI}^F = (I_2^F - I_3^F) / (I_2^F + I_3^F)$	Green normalized differential vegetation index (gNDVI)
$\text{gSRF} = I_2^F / I_3^F$	Green simple ratio vegetation index (gSR)
Geometric features	
H_{\max}	Maximum of the heights of all points
H_{mean}	Arithmetic mean of the height of all points above 1 m threshold
H_{std}	Standard deviation of height of all points above 1 m threshold
H_{range}	Range of normalized height of all points above 1 m threshold
<i>P</i>	Penetration as a ratio between the number of returns below 1 m and total returns
<i>CA</i>	Crown area as the area of the convex hull in 2D
<i>CV</i>	Crown volume as the convex hull in 3D
<i>CD</i>	Crown diameter calculated from crown area considering crown as a circle
HP_{10} to HP_{90}	Percentiles of the points above 1 m height from 10% to 90% at 10% incremental.
D_1 to D_{10}	$D_i = N_i/N_{\text{total}}$, where <i>i</i> = 1 to 10, <i>N_i</i> is the number of points within the <i>i</i> th layer when tree height was divided into 10 intervals starting from 1 m, <i>N_{total}</i> is the number of all points.

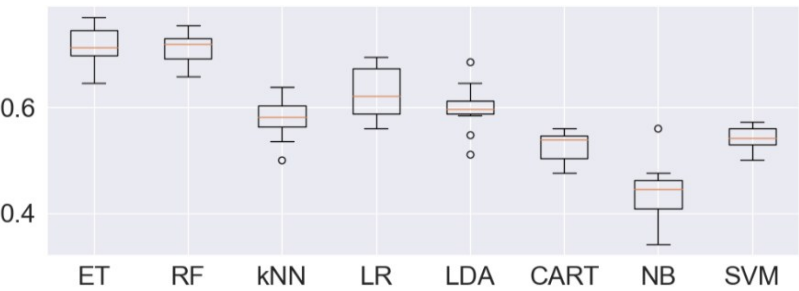


Figure 3 The comparison of classification accuracy of 24 tree species: Extra trees (ET), random forest (RF), K-nearest neighbour (KNN), logistic regression (LR), Linear Discriminant Analysis (LDA), Classification And Regression Tree (CART), Naive Bayes (NB), support vector machine (SVM).
图 3 树种的分类准确率比较: 额外树(ET)、随机森林(RF)、K-近邻(KNN)、逻辑回归(LR)、线性判别分析(LDA)、分类回归树(CART)、奈夫贝叶斯(NB)、支持向量机(SVM)。

that mALS data provided more accurate results than each SCI-Ch for the classification of urban tree species.

Table 2 List of tree sample
表 2 树木样本清单

Tree spe- cies	The in- dex num- ber	Number of Trees	Tree spe- cies	The in- dex num- ber	Number of Trees
<i>Pinta-ala</i>	1	2	<i>Populus</i>	13	16
<i>Abies</i>	2	13	<i>Prunus</i>	14	10
<i>Acer</i>	3	249	<i>Quercus</i>	15	23
<i>Alnus</i>	4	5	<i>Ribes</i>	16	5
<i>Betula</i>	5	26	<i>Salix</i>	17	4
<i>Fallopia</i>	6	1	<i>Sambucus</i>	18	1
<i>Fraxinus</i>	7	2	<i>Sorbus</i>	19	84
<i>Juglans</i>	8	5	<i>Syringa</i>	20	1
<i>Larix</i>	9	11	<i>Taxus</i>	21	4
<i>Malus</i>	10	8	<i>Thuja</i>	22	2
<i>Picea</i>	11	15	<i>Tilia</i>	23	88
<i>Pinus</i>	12	84	<i>Ulmus</i>	24	163

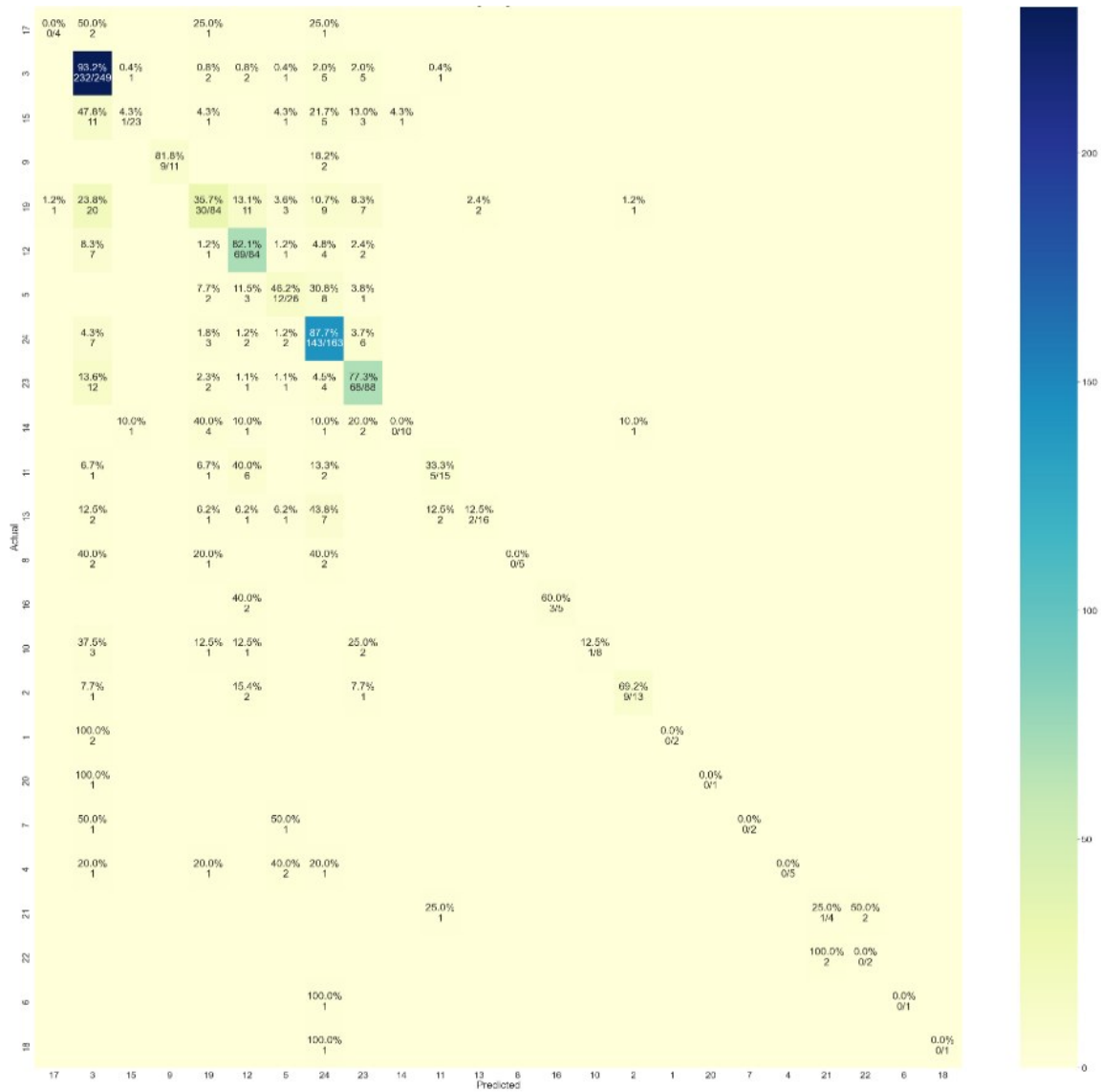


Figure 4 The Confusion matrix of classification has geometric and intensity features for each species.
图 4 利用几何特征和强度特征对每个物种进行分类的混淆矩阵。

Table 3 The features have the most predictive power in different classification scenarios.
表 3 在不同的分类场景中预测能力最强的特征值。

Cases	Top 3 features
All features	I^2_{min} , $P_{1.5}$, I^3_{min}

reference

[1] A. Schneider, M. A. Friedl, and D. Potere, "Mapping global urban areas using MODIS 500-m data: New methods and datasets based on 'urban ecoregions,'" Remote Sens Environ, vol. 114, no. 8, pp. 1733 - 1746, Aug. 2010, doi: 10.1016/J.RSE.2010.03.003.

[2] J. H. Lee and K. W. Bang, "Characterization of urban stormwater runoff," Water Res, vol. 34, no. 6, pp. 1773 - 1780, Apr. 2000, doi: 10.1016/S0043-1354(99)00325-5.

[3] F. J. Escobedo and D. J. Nowak, "Spatial heterogeneity and air pollution removal by an urban forest," Landsc Urban Plan, vol. 90, no. 3 - 4, pp. 102 - 110, Apr. 2009, doi: 10.1016/J.LANDURBPLAN.2008.10.021.

[4] D. J. Nowak, D. E. Crane, J. C. Stevens, R. E. Hoehn, J. T. Walton, and J. Bond, "A Ground-Based Method of Assessing Urban For-

est Structure and Ecosystem Services," Arboriculture & Urban Forestry (AUF), vol. 34, no. 6, pp. 347 - 358, Nov. 2008, doi: 10.48044/JAUF.2008.048.

[5] J. L. Lovell, D. L. B. Jupp, D. S. Culvenor, and N. C. Coops, "Using airborne and ground-based ranging lidar to measure canopy structure in Australian forests," Canadian Journal of Remote Sensing, vol. 29, no. 5, pp. 607 - 622, Oct. 2003, doi: 10.5589/M03-026.

[6] E. Næsset, T. Ø.-R. S. of Environment, and undefined 2002, "Estimating tree height and tree crown properties using airborne scanning laser in a boreal nature reserve," Elsevier, Accessed: Sep. 11, 2023. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0034425701002437>

[7] M. Clark, D. Clark, D. R.-R. S. of Environment, and undefined 2004, "Small-footprint lidar estimation of sub-canopy elevation and tree height in a tropical rain forest landscape," Elsevier, doi: 10.1016/j.rse.2004.02.008.

[8] J. Holmgren and Å. Persson, "Identifying species of individual trees using airborne laser scanner," Remote Sens Environ, vol. 90, no. 4, pp. 415 - 423, Apr. 2004, doi: 10.1016/S0034-4257(03)00140-8.

[9] T. Brandtberg, "Classifying individual tree species under leaf-off and leaf-on conditions using airborne lidar," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 61, no. 5, pp. 325 - 340, Jan. 2007, doi: 10.1016/J.ISPRJPRS.2006.10.006.

[10] E. ; Lindberget al., "Delineation of tree crowns and tree species

- classification from full-waveform airborne laser scanning data using 3-D ellipsoidal clustering," *ieeexplore.ieee*. LindbergorgE, EysnL, HollausM, HolmgrenJ, N PfeiferIEEE Journal of Selected Topics in Applied Earth Observations and, 2014•*ieeexplore.ieee.org*, vol. 7, no. 7, pp. 3174 - 3181, 2014, doi: 10.1109/JSTARS.2014.2331276.
- [11] J. Hyypä, O. Kelle, ...Hyypä M. L. -I. T. on, and undefined 2001, "A segmentation-based method to retrieve stem volume estimates from 3-D tree height models produced by laser scanners," *ieeexplore.ieee.*, KelleO, LehtikainenM, M InkinenIEEE Transactions on geoscience and remote sensing, 2001•*ieeexplore.ieee.org*, Accessed: Sep. 11, 2023. [Online]. Available: <https://ieeexplore.ieee.org/abstract/document/921414/>
- [12] R. Ahmed, P. Siqueira, S. H. -R. sensing of environment, and undefined 2013, "A study of forest biomass estimates from lidar in the northern temperate forests of New England," Elsevier, Accessed: Sep. 11, 2023. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0034425712004476>
- [13] M. Hollaus, W. Wagner, B. Maier, K. S. - Sensors, and undefined 2007, "Airborne laser scanning of forest stem volume in a mountainous environment," *mdpi.com* M Hollaus, W Wagner, B Maier, K SchadauerSensors, 2007•*mdpi.com*, Accessed: Sep. 11, 2023. [Online]. Available: <https://www.mdpi.com/1424-8220/7/8/1559>
- [14] X. Yu, J. Hyypä, H. Kaartinen, M. Maltamo, and H. Hyypä, "Obtaining plotwise mean height and volume growth in boreal forests using multi-temporal laser surveys and various change detection techniques," *Int J Remote Sens*, vol. 29, no. 5, pp. 1367 - 1386, Mar. 2008, doi: 10.1080/01431160701736356.
- [15] X. Yu, J. Hyypä, A. Kukko, M. M. -... & R. Sensing, and undefined 2006, "Change detection techniques for canopy height growth measurements using airborne laser scanner data," *ingentaconnect. YucomX, HyypäJ, KukkoA, MaltamoM, H KaartinenPhotogrammetric Engineering & Remote Sensing*, 2006•*ingentaconnect.com*, 2006, Accessed: Sep. 11, 2023. [Online]. Available: <https://www.ingentaconnect.com/content/asprs/pers/2006/00000072/00000012/art00001>