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Urban tree species classification based on multispectral airborne LiDAR

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Abstract: Urban tree species provide various essential ecosystem services in cities, such as regulating urban temperatures, reducing noise, capturing carbon, and mitigating the urban heat island effect. The quality of these services is influenced by species diversity, tree health, and the distribution and the composition of trees. Traditionally, data on urban trees has been collected through field surveys and manual interpretation of remote sensing images. In this study, we evaluated the effectiveness of multispectral airborne laser scanning (ALS) data in classifying 24 common urban roadside tree species in Espoo, Finland. Tree crown structure information, intensity features, and spectral data were used for classification. Eight different machine learning algorithms were tested, with the extra trees (ET) algorithm performing the best, achieving an overall accuracy of 71. 7% using multispectral LiDAR data. This result highlights that integrating structural and spectral information within a single framework can improve the classification accuracy. Future research will focus on identifying the most important features for species classification and developing algorithms with greater efficiency and accuracy.

Key words: multispectral airborne LiDAR, machine learning, tree species classification

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。利用树冠结构信息、强度特征和光谱信息进行分类。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；机器学习；树种分类

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Introduction

Today, approximately 56% of the world's population —4.4 billion people—live in cities. Urban trees play a significant role in mitigating global climate change[1] and are uniquely susceptible to climate change impacts. Urban Forest Effects model[2,3] is widely used in urban areas globally to estimate urban forest structure, species diversity, and ecosystem functions. However, conducting urban forest inventories is labor-intensive, especially on private properties, and the results are often not spatially detailed. While remotely sensed data is commonly used in forest applications, traditional optical remote sensing methods struggle to capture three-dimensional forest structures, especially 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[7-9], 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 limitations of traditional optical remote sensing in capturing three-dimensional forest structures, it is essential to explore the potential of multispectral laser scanning for urban tree inventories, particularly for species classification. This study aims to assess the feasibility of using multispectral ALS data for urban tree species classification and to analyze the information content of features derived from point clouds and intensity data.

1 Materials and methods

1.1 Study area and establishment of sample plots

The MLS datasets used in this study were acquired in a suburban area in Espoolahti, 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 km^2. 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.

1.2 Multispectral ALS data

Multispectral Optech Titan data (Teledyne Optech, Toronto, 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 height. The data acquisition was carried out using a fixed-wing aircraft flying at a constant altitude. The sensor comprises three Titan channels: green (532 nm), near-infrared (1 064 nm), and shortwave infrared (1 550 nm). Each channel provided separate point clouds. In our preprocessed dataset, the point densities over land areas were approximately 9 points/m^2 for Channel 1, 9 points/m^2 for Channel 2, and 8 points/m^2 for Channel 3.

TerraScan (TerraSolid Oy, Helsinki, Finland) was used to preprocess the 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. Ground elevation was subtracted from the point cloud height measurements using a digital terrain model created from the classified ground points of the three channels to eliminate potential discrepancies.

Radiometric calibration of ALS intensity is crucial to ensure successful classification. Therefore, in this study, we implemented relative radiometric calibration. We observed that the intensity values were higher in the middle of the flight path compared to other areas and decreased with scanning height. A range correction was applied to mitigate such effects.

$$I_c = I \times \frac{D_i^2}{D_{\mathrm{ref}}^2} \quad , \quad (1)$$

where 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).

1.3 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 m^2. 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

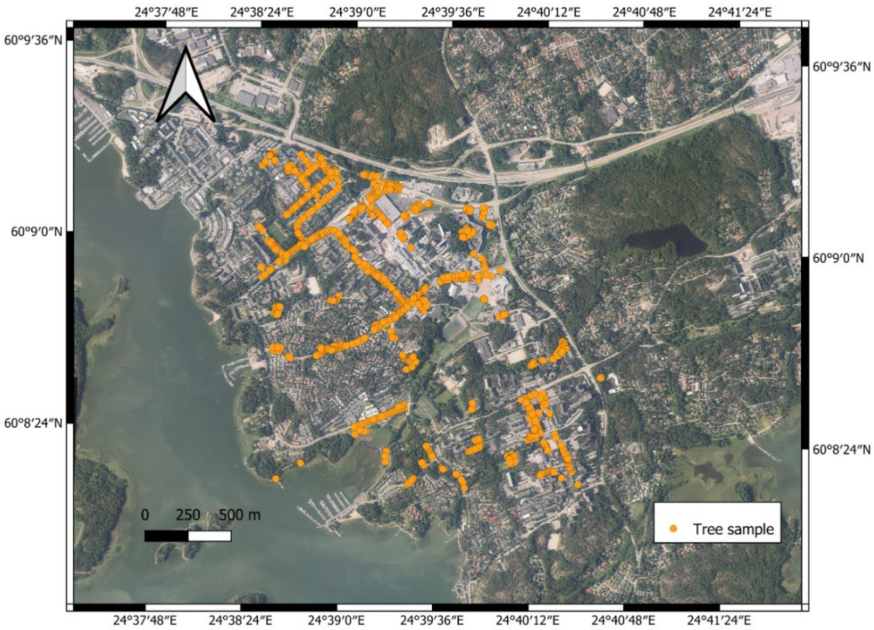

Fig. 1　Map of the study area and tree samples in the research area.
图 1　研究区和研究区的树木样本

Fig. 2　Titan intensity image of Study area in Espoolahti (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)。

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 CHM.

1.4　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.

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

1.5　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.

2　Results

2.1　Accuracy of classification

As presented in Fig. 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 Fig. 3.

The confusion matrix analysis reveals a model that performs well for most classes but struggles with a few, particularly *Quercus* and *Sorbus* according to Table 2 and Fig. 4. Certain classes, such as *Acer*, *Larix*, and *Thuja*, exhibit high accuracy (≥93%), indicating the model's ability to correctly classify instances for these classes.

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
$\mathrm{gNDVI}^F = (I_1^F - I_3^F)/(I_2^F + I_3^F)$	Green normalized differential vegetation index (gNDVI)
$\mathrm{gSRF} = (I_2^F/I_3^F)$	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
P	Penetration as a ratio between the number of returns below 1 m and total returns
CA	Crown area as the area of the convex hull in 2D
CV	Crown volume as the convex hull in 3D
CD	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}	$D_i = N_i/N_{total}$, where i = 1 to 10, N_i is the number of points within the ith layer when tree height was divided into 10 intervals starting from 1 m, N_{total} is the number of all points.

By addressing these shortcomings through feature refinement, data augmentation, and model optimization, the overall classification accuracy can be significantly improved. Future work should focus on integrating domain-specific knowledge to enhance feature representation and reduce class overlap.

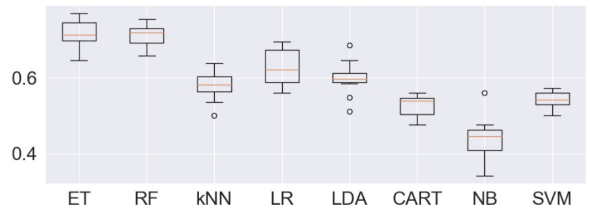

Fig. 3 The comparison of classification accuracy of 24 tree species: ET, RF, KNN, LR, LDA, CART, NB, SVM
图 3 树种的分类准确率比较：额外树、随机森林、K-近邻、逻辑回归、线性判别分析、分类回归树、奈夫贝叶斯、支持向量机

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

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

2.2 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 percen-

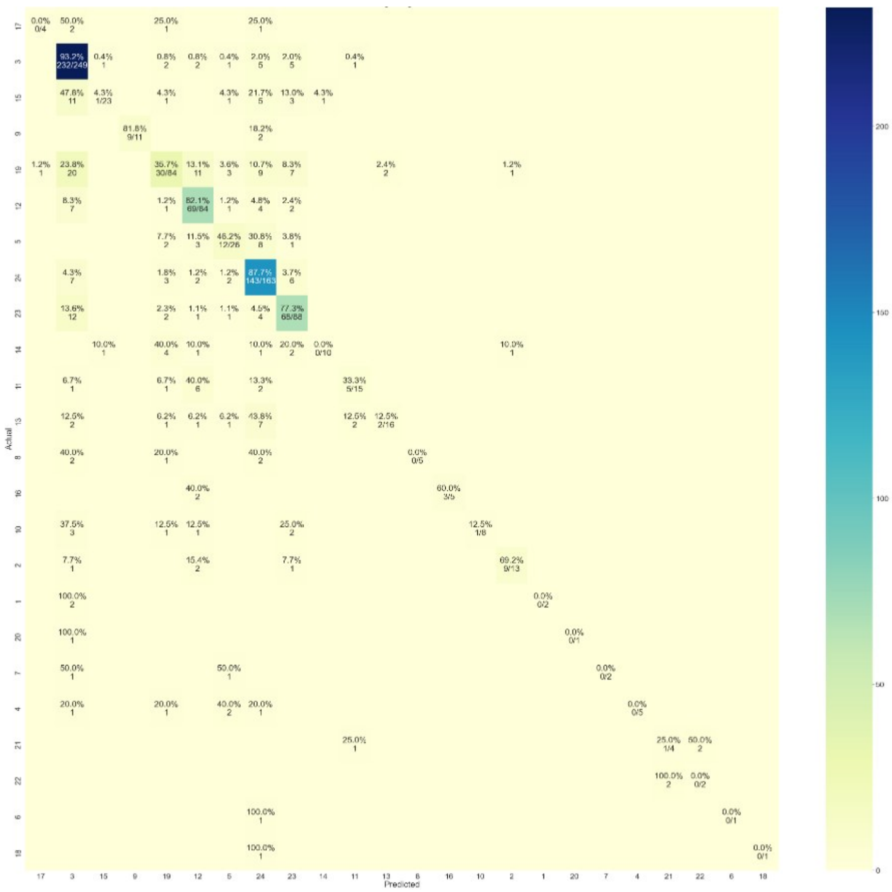

Fig. 4 The confusion matrix of classification with geometric and intensity features for each species.
图 4 利用几何特征和强度特征对每个物种进行分类的混淆矩阵。

tiles. In the case of classification using single-channel features, the 1 064nm wavelength (Channel 2) appears to provide the most valuable information for distinguishing between pine, spruce, and birch species. This is followed by the 1 550nm wavelength (Channel 1) and then the 532nm wavelength (Channel 3).

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	$I^2_{\min}$, $P_{1.5}$, $I^3_{\min}$

3 Conclusions

Multispectral LiDAR data improved the classification accuracy 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, while accuracies of 65.7%, 68.3%, and 64.8% were achieved when using only Channel 1, Channel 2, and Channel 3, respectively. Our findings demonstrated the advantage of combining multichannel features over single-channel data in classifying urban trees. However, the sample size of each tree species in this experiment was uneven, which may have affected the model's accuracy. Consequently, a larger and more representative sample will be used in future research. The imbalance in measurement samples reduced classification accuracy to some extent. Addressing this limitation will be a key focus in subsequent studies.

In this study, eight machine learning algorithms were evaluated for their classification performance, each demonstrating distinct strengths and limitations. 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 due to their ability to handle large, high-dimensional datasets and their robustness against overfitting, which suited the conditions of our dataset. Naive Bayes (NB) was efficient and scalable, especially for high-dimensional data, but its assumption of feature independence limited its applicability in cases with high feature correlation.

It is 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. This limitation can be addressed in future studies. First, we can investigate whether calibrated intensity affects classification results. Second, the use of MCI features in this study mitigated potential variations in intensity.

In conclusion, the ability of mALS compared to single-channel ALS (SCI-Ch) data to characterize tree species in urban areas was assessed in this study. Our classification results indicate that mALS data provided more accurate results than single-channel ALS data for urban tree species classification.

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