

IMPROVING URBAN TREE SPECIES CLASSIFICATION WITH LIDAR-DERIVED METRICS

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ABSTRACT

Urban tree species mapping provides valuable insights into the green infrastructure management of cities. However, information on the spatial distribution of tree species in urban areas is usually acquired with costly procedures such as field surveys. Remote sensing combined with field data provides an efficient way to obtain spatially explicit information on tree species distribution over broad spatial extents. In this study, we investigate the utility of light detection and ranging (LiDAR) metrics to improve tree species classification in a highly diverse tropical urban setting. LiDAR metrics were estimated using a statistical approach that retrieved surface normals. Moreover, we explore the use of LiDAR reflectivity intensity and canopy height to discriminate among species. The results show that intensity and canopy height improve the classification accuracy, while the use of surface normals reduces it. However, more research is needed to evaluate the utility of surface normals since the species have highly variable patterns, particularly in the nz direction.

***Key words** – Surface normals, LIDAR intensity, Canopy structure.*

1. INTRODUCTION

Urban trees provide essential ecosystem services such as air quality improvement and surface temperature reduction [1]. Information on the spatial distribution of tree species in urban environments is increasingly needed to plan and develop green infrastructures in cities. However, this information is usually acquired with ground-based surveys, which is costly and operationally prohibitive if performed in large cities ($>$ 1 million inhabitants). A promising way to obtain spatially explicit information on tree species over broad spatial extents is by integrating field data with remote sensing images.

Tree species mapping at the individual tree crown (ITC) level requires very-high-resolution (VHR) images (pixel $<$ 1 m). While the potential VHR satellite images combined with machine learning methods to automatically discriminate among tree species in urban and forest environments has been demonstrated [2–4], the potential of aerial photographs remains poorly investigated, particularly in tropical urban settings. Aerial photographs are acquired with only four (red, green, blue, and near-infrared) channels, thus providing limited spectral information on the ground objects. When spectral information is poorly available, it is worth using other types of data to retrieve species-specific characteristics that may improve the classification accuracy.

For example, LiDAR data can be used to extract structural characteristics of ITCs, such as the arrangement of leaves and branches or tree height. LiDAR sensors emit tens of thousands of laser pulses ($\approx$ 900 nm wavelength) per second and measure the time delay from pulse emission to return, enabling the modeling of the canopy structure in three dimensions (3D). 3-D point clouds can be used to describe the geometric surface properties of the tree crowns. To do this, one can compute surface normals of tree leaves and estimate species-specific leaf angle and orientation. Surface normals are important attributes of 3-D point clouds. It has been widely used in various tasks, such as point cloud registration, classification, segmentation, etc.

In this work, we investigate the utility of surface normals in 3-D point clouds to improve tree species classification in a highly diverse tropical urban setting. Moreover, we explore other LiDAR-derived metrics, such as reflectivity intensity and canopy height, to classify urban trees.

2. MATERIAL AND METHODS

2.1. Study area

The study area comprises the urbanized domain of the Grajaú neighborhood in Rio de Janeiro, Brazil. The site has about 325 ha, and more than 100 tree species [5]. The mean annual temperature is 23.2$\pm$5.5°C, and yearly precipitation is 1,278 mm.

2.2. Aerial photographs and airborne LiDAR data

The aerial photographs were taken in October 2019 under clear sky conditions with the aerial digital camera UltraCam-Eagle Prime (Vexcel, Inc.). The photographs were taken with four channels (red, green, blue, and near-infrared, RGBNIR) with a ground sample distance of 0.15 m. The photogrammetric flight was planned to collect photographs with an endlap and sidelad of 80% and 40%, respectively. The overlapping photographs were used to generate a digital surface model (DSM) employed for orthorectification. LiDAR data was acquired with the Trimble Harrier 68i (Trimble Germany GmbH) sensor. The sensor fires laser pulses with a frequency of 400 kHz and has a field of view (FOV) of 60°. For LiDAR data acquisition, the flight height was about 700 m, which resulted in point clouds with a density of 12 points/m^2.

2.3. Individual tree crown dataset

The ITC dataset was adapted from [5]. Several ITCs were manually outlined in RGB compositions of the aerial photographs on a scale of 1:250. The ITCs were identified to the species level in the field by a botanical specialist. Since the work of [5] was based on aerial photographs acquired in 2015, we removed ITCs that were not present in 2019. A total of 283 ITCs were outlined, comprising nine species, as shown in Table 1.

Species	Nº ITCs
Terminalia catappa	130
Pachira aquatica	35
Licania tomentosa	45
Senna siamea	24
Tamarindus indica	24
Caesalpinia pluviosa	25

Table 1: Tree species and number of individual tree crowns (ITCs)

2.4. LiDAR-derived metrics

We computed several metrics for each point in the LiDAR point cloud and produced rasters with the same resolution (pixel size = 0.15 meters) as the aerial photographs. To do this, we computed the mean of the LiDAR metrics of points within cells on size 0.15×0.15 meters.

2.4.1. Estimating surface normals in 3-D point clouds

For a given 3-D point cloud χ, we used the first order 3-D plane fitting method [6] to estimate surface normals of tree leaves. Our approach works in two steps. Initially, the neighboring points i of a query point p_i are determined with a predefined radius of a sphere s, as proposed by [7]. Subsequently, the normal of a plane tangent to the surface (see Fig. 1) is estimated in a least-square sense. In practice, since p_i is on a plane, its coordinates satisfy the equation:

$$d_i = \vec{n} \cdot (p_i - \frac{1}{k}\sum_{i=1}^{k} p_i) \tag{1}$$

where k is the number of neighbors to the query point, the $\vec{n} = [n_x, n_y, n_z]^T$ denotes the normal vector, and d_i represents the distance from a point $p_i \in q$ to the plane.

Since tree leaves change both its orientation and position during the LiDAR scanning (e.g., leaf motion due to wind), a closed-form solution based on eigenvector and eigenvalue correspondences from covariance matrix $M \in \Re^{3x3}$ is the method of choice for the normal estimation, as it is invariant to rigid motion:

$$M = \frac{1}{k}\sum_{i=1}^{k}(p_i - \frac{1}{k}\sum_{i=1}^{k} p_i) \cdot (p_i - \frac{1}{k}\sum_{i=1}^{k} p_i)^T \tag{2}$$

As a result, a normal vector is assigned for each p_i. The normal vector can be decomposed by orientation in the *nx*, *ny*, and *nz* directions. In addition, we can also compute an

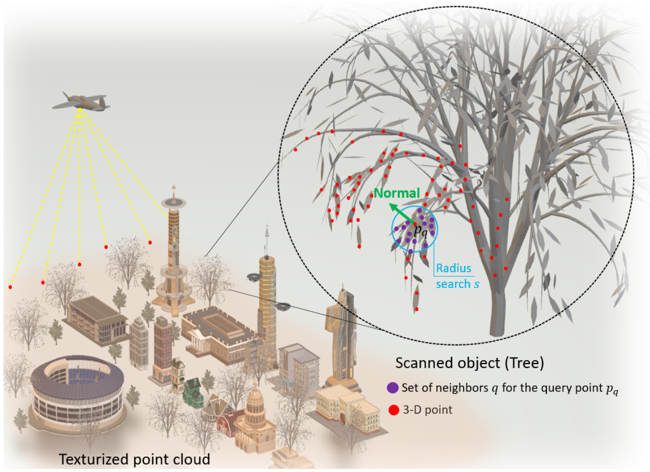

Figure 1: Surface normals estimation scheme.

approximation of the surface curvature around p_i using the eigenvalues λ_j of M, as follows [7]:

$$curv = \frac{\lambda_0}{\lambda_0 + \lambda_1 + \lambda_2} \tag{3}$$

2.4.2. Intensity and canopy high model

LiDAR intensity is a measure of the reflectivity of the laser pulse and is measured for every point. Intensity is a function of the wavelength used and is proportional to the strength of the returns, varying with the composition of the surface objects. Canopy height models (CHM) represent the actual height of the objects. They are computed by subtracting the digital terrain model (DTM) from a LiDAR point cloud to create a normalized dataset in which the ground points equal zero.

2.5. Experimental set-up

2.5.1. Selection of training and testing samples

Labeled pixels from the manually delineated ITCs (Section 2.3) were extracted from the image to compose a dataset with 10 attributes (red, green, blue, NIR, *nx*, *ny*, *nz*, curvature, intensity, and CHM) and 283 ITCs (Table 1). Then, we computed the mean of each attribute per ITC to reduce computational cost. This dataset was randomly partitioned into 70% of the ITCs for training and the remaining 30% for testing. We repeated the above splitting procedure 1000 times, randomly choosing ITCs to train and test the classifier at each realization. Systematic changes in the selection of training and testing crowns allowed us to assess the robustness of the classification models and better understand the relevance of LiDAR-derived metrics to classify the species.

2.5.2. ITC-level classification

Aiming to verify if the LiDAR-derived metrics improve the accuracy of tree species classification, we performed ITC-level classification using support vector machines with the radial basis function (SVM-RBF) kernel, which proved useful in previous studies (e.g., [4]). We optimized the SVM-RBF

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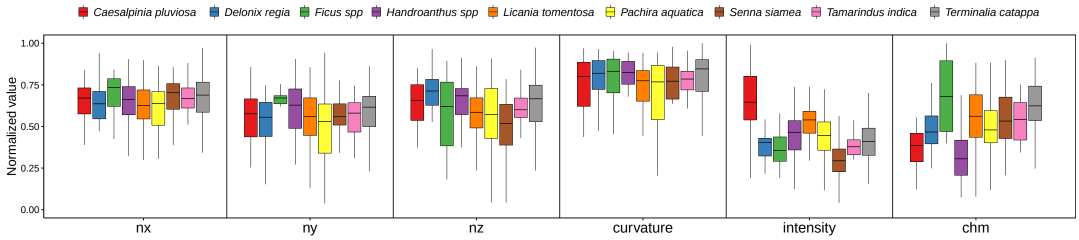

Figure 2: Boxplots showing the variability of the LiDAR-derived metrics of each tree species. The central lines within each box are the medians. The boxes' edges represent the upper and lower quartiles. The values were normalized in the [0, 1] range.

parameters C and γ using a grid search strategy and trained the model with the RGBNIR bands alone and in combination with the LiDAR metrics, one at a time. We assessed the classification accuracy by computing the Kappa index.

3. RESULTS AND DISCUSSION

Table 2 shows the Kappa values obtained for the urban tree species classification with SVM-RBF. Using only the RGBNIR bands, the Kappa was 0.486±0.059. After including the surface normals (*nx*, *ny* and *nz*) and curvature in the classification process, we observed a decrease in Kappa of up to 0.062. Among the surface normal metrics, *nz* provided the best results but decreased Kappa compared to the RGBNIR dataset. The highest increase in Kappa was observed after combining *intensity* and CHM with the RGBNIR bands.

Dataset	Kappa (mean±SD)
RGBNIR	0.486±0.059
RGBNIR_nx	0.437±0.063
RGBNIR_ny	0.424±0.060
RGBNIR_nz	0.440±0.058
RGBNIR_curv	0.439±0.064
RGBNIR_intensity	0.499±0.064
RGBNIR_chm	0.504±0.065

Table 2: Mean±Standard deviation of Kappa obtained after classifying urban tree species with SVM-RBF. The classification was performed using RGBNIR bands and LiDAR-derived metrics.

Fig. 2 shows the distribution of the LiDAR-derived metrics for each species. One can note that the median of *nz*, intensity, and CHM is highly variable among the species. Intensity and CHM, in particular, can capture species-specific differences in canopy structure, thus improving the classification accuracy.

We perform species classification by computing the mean of each feature (RGBNIR bands and LiDAR-derived metrics) per ITC. Thus, the spatial context was not considered in the classification process. In future studies, we intend to use convolutional neural networks (CNNs), a deep learning method that uses convolutional operations for feature extraction. CNNs explore the spatial relationship between neighboring pixels and have been successfully used to classify tree species [8].

4. CONCLUSIONS

This study aimed to improve urban tree species classification with LiDAR-derived metrics. We found that LiDAR intensity and canopy height with RGBNIR bands provide the best results. The use of surface normals reduced the classification accuracy. However, more research is needed to evaluate the utility of surface normals because of the species' highly variable patterns, particularly in the *nz* direction. Future studies will focus on using CNNs and different approaches to fuse RGBNIR bands with LiDAR-derived metrics.

5. ACKNOWLEDGMENTS

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