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HIGH-RESOLUTION MAPPING OF VEGETATION TYPES, STRUCTURE, HEIGHT, AND DENSITY IN THE USAMV CLUJ-NAPOCA CAMPUS USING LiDAR, PHOTOGRAMMETRY AND MULTISPECTRAL SENSING

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Abstract

Metropolitan areas are most often affected by the weak presence of „green" infrastructure so that the climate can be affected. This work aims to evaluate the vegetation within the UASVM Cluj-Napoca campus, in terms of its spatial distribution, the types of vegetation and their characteristics. In an attempt to overcome the disadvantages of classical vegetation assessment methods, an approach that integrates several types of geospatial data was proposed. More specifically, LiDAR technology was used to determine, among other things, the height of forest vegetation and its density, aerial photogrammetric technology was used for contextual and texture information, and multispectral sensors helped to differentiate vegetation types. Data acquisition was carried out using the DJI MAVIC 3M, respectively the South SF 1200 with SG130 scanner. Data processing was carried out using various software. This research highlights the advantages brought by the use of the most modern geodetic and topographic technologies in the evaluation of green areas within large urban areas and their contribution to the most correct management of green areas.

Key words*: LiDAR, multispectral, photogrammetry, vegetation.*

INTRODUCTION

The contemporary landscape is undergoing continuous transformation under the influence of natural processes and increasing anthropogenic pressures (Ali et al., 2026).

Romania has some of the largest remaining areas of old-growth forests in the European Union. This represents a very important part of the country's natural heritage. These forests continue to face increasing pressure due to inadequate management practices, despite their ecological significance, resulting in a gradual decline of their extent over recent decades. In this context modern surveying and monitoring technologies have become valuable tools for integrating spatial and descriptive data (Moatăr et al., 2026).

Rapid urbanization, land-use changes, and climate variability are altering the composition, structure, and spatial distribution of vegetation, highlighting the need for accurate and up-to-date monitoring approaches (Liang et al., 2020; Rai & Singh, 2026).

Traditional field-based vegetation surveys provide valuable information but are often time-consuming, labor-intensive, and difficult to implement over large or heterogeneous areas (Goebel & Iwaszczuk, 2026; Mohamad & Tahar, 2026).

Vegetation mapping with high accuracy is essential for monitoring plant distribution and for assessing ecosystem dynamics. Remote sensing has become one of the most effective methodologies in ths regard, being rapid and also cost efficient (Guan et al., 2019; Mohamad & Tahar, 2026).

Sattelite imagery has moderate spatial resolution being suitable for broad land cover classification, but high-resolution multispectral imagery which is also often combined with LiDAR data enables vegetation mapping with greater accuracy (Fernández-Guisuraga et al., 2018; Goebel & Iwaszczuk, 2023).

Equipped with a multitude of sensors, such as photogrammetric sensors, multispectral sensors and LiDAR, Unmanned Aerial Vehicles have become one of the most important technologies when it comes to remote sensing. Due to their ability to aquire high resolution spatial data, in a relatively short period of time, at relatively low cost, UAVs become essential tools in modern

vegetation assessment and monitoring (Hyyppä et al., 2020; Liu et al., 2026).

The objective of this study is to develop a high-resolution vegetation mapping framework for the UASVM Cluj-Napoca campus through 1the integration of UAV-based LiDAR, photogrammetric, and multispectral data. Specifically, the study aims to assess vegetation structure, estimate vegetation height and density, and generate a detailed vegetation inventory that can support future environmental monitoring and landscape management activities.

MATERIALS AND METHODS

The investigated area covers approximately 26 hectares, with an elevation range of about 100 m, varying between 330 m and 440 m above sea level.

The study area consists of the USAMV Cluj-Napoca campus, Cluj County, Romania and a section of the adjacent Iuliu Prodan Park located in its immediate proximity.

The study site is characterized by an urban environment that includes numerous buildings, primarily dedicated to educational activities, while also containing extensive forest and horticultural vegetation. These characteristics, together with the easy and rapid access to the area, were the main reasons for selecting it as the case study site for this research.

LiDAR data were acquired using the South SF 1200 Unmanned Aerial System with SG130, which is 2kg aerial LiDAR system that combines a 45/61MP RGB camera with precise IMU/GNSS tracking. It has a ± 3 cm absolute accuracy. It features a 360° FOV, captures up to 800,000 pts/sec with 12 returns.

Photogrammetric and multispectral data was acquired using a DJI Mavic 3 Multispectral UAS equipped with an RTK-GNSS module providing positioning accuracies of approximately ± 0.10 m in both the horizontal and vertical components. The system integrates a 20 MP RGB camera for high-resolution photogrammetry and a 4-band 5 MP multispectral sensor (Green, Red, Red Edge, and NIR).

To complement the structural assessment, a series of spectral vegetation indices (Șuba et al., 2025) from the multispectral imagery were calculated, namely:

-NDVI (Normalized Difference Vegetation Index): It evaluates vegetation vigour, greenness, and photosynthetic activity based on red and near-infrared reflectance ((NIR - Red)/(NIR + Red));

-GNDVI (Green Normalized Difference Vegetation Index): It is sensitive to chlorophyll content and plant physiological condition through the use of the green spectral band. ((NIR - Green)/(NIR + Green));

-NDRE (Normalized Difference Red Edge Index): It assesses chlorophyll concentration and nitrogen status using the red-edge spectral region ((NIR - RedEdge)/(NIR + RedEdge));

-LCI (Leaf Chlorophyll Index): It estimates leaf chlorophyll content and vegetation productivity. ((NIR - RedEdge)/(NIR + Red));

-MCARI (Modified Chlorophyll Absorption Ratio Index): It enhances sensitivity to chlorophyll absorption and vegetation stress while reducing background effects ([(RedEdge - Red) - 0.2 (RedEdge - Green)]/times (RedEdge/Red));

-SIPI (Structure Insensitive Pigment Index): It evaluates pigment balance and vegetation stress while minimizing canopy structure influence ((NIR - Blue)/(NIR - Red)) (Șuba et al., 2025).

The workflow (Figure 1) which starts with UAV-based LiDAR, RGB, and multispectral data acquisition, followed by direct GNSS georeferencing.

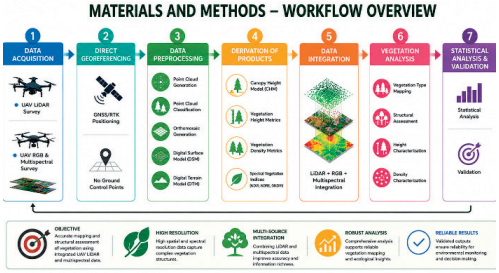


Figure 1. Workflow overview

After preprocessing, both structural and spectral vegetation metrics were derived, such as canopy height, density, and vegetation indices. These datasets were integrated and analysed together to provide a detailed assessment of vegetation.

RESULTS AND DISCUSSIONS

In the first stage, a colorized LiDAR point cloud was generated from the acquired UAV data. This point cloud can be seen in Figure 2.



Figure 2. Colorized point cloud

Subsequently, the point cloud was analyzed based on elevation values, allowing the visualization and assessment of height variations across the study area and providing valuable information on vegetation structure and terrain morphology.

The LiDAR point cloud was subsequently classified into several categories, including ground points (brown), buildings (orange), and vegetation (green).

The classification was performed automatically using the Maximum Likelihood Estimation (MLE) algorithm (Figure 3).

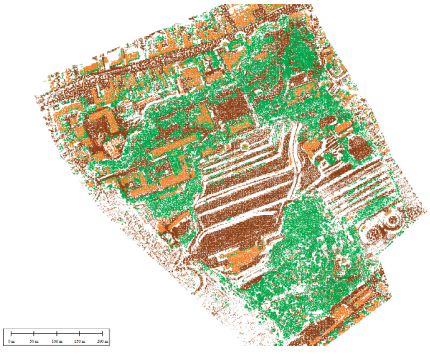


Figure 3. Ground points (brown), Buildings (orange), Vegetation (green)

Other valuable outputs derived from the LiDAR survey are the vertical cross-sections through the point cloud. These cross-sections provide detailed information on the vertical structure of vegetation and can support species identification (Figure 4).

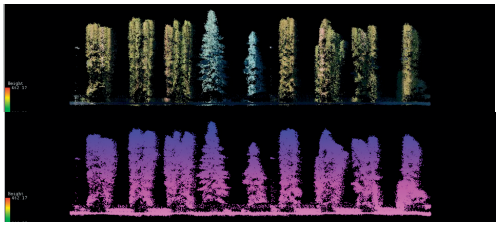


Figure 4. Thuja and spruce trees identified in the vertical cross-section

Tree and canopy extraction was also performed automatically using the Maximum Likelihood Estimation (MLE) algorithm combined with MultiScale Classification. This approach enabled the identification and delineation of individual trees and their crowns based on the structural characteristics of the LiDAR point cloud. The extracted tree attributes included elevation, tree height, mean crown diameter, and maximum crown diameter, providing detailed quantitative information for each identified tree (Figure 5).

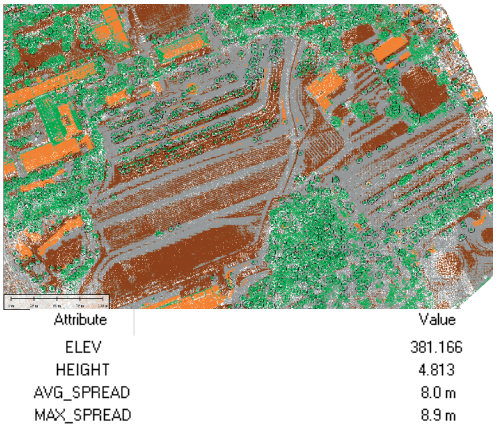


Figure 5. Tree and canopy extraction

The automated extraction of trees and canopy boundaries also presents several limitations, particularly regarding canopy delineation accuracy and trunk positioning. For example, large tree crowns may be divided into two or more individual trees, as major branches can be interpreted as separate crowns.

In Figure 6 it can be seen the Elevation-based representation A total of 1,645 trees exceeding 2.5 m in height were identified within the study area. The detected trees were distributed across different height classes, providing an overview of the vertical structure and composition of the vegetation.

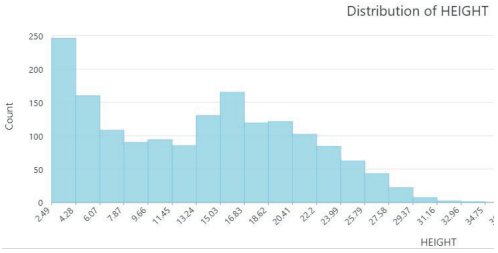


Figure 6. Elevation-based representation

Tree density map showing the distribution of trees per square meter across the study area is presented in Figure 7.

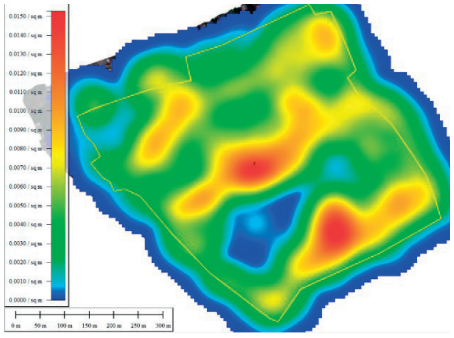


Figure 7. Tree density map

Multispectral images were acquired according to a predefined flight plan. A total of 2,796 images (RGB, Green band, Red band, Red Edge band) were collected during the survey. The study area covered approximately 262,330 m² (26.23 ha). Following image processing, a high-resolution orthomosaic was generated (Figure 8).

GNDVI quantifies vegetation health and vigour by comparing the reflectance recorded in selected spectral bands. Higher GNDVI values (approaching +1) indicate vegetation with elevated chlorophyll concentrations and intense photosynthetic activity, characteristics commonly associated with dense and healthy plant cover.



Figure 8. High-resolution orthomosaic

Intermediate GNDVI values correspond to areas with partial vegetation cover, such as grasslands or sparsely cultivated fields, where vegetation condition and density may vary. Lower GNDVI values (around 0) generally represent bare soil, built-up areas, or locations with limited vegetation cover. Negative GNDVI values are typically associated with water bodies, barren surfaces, or other non-vegetated land covers (Figure 9).

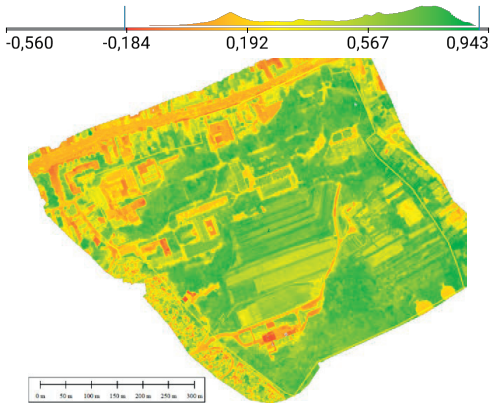


Figure 9. GNDVI

The Leaf Chlorophyll Index (LCI) is derived from the Near Infrared (NIR) and Red Edge spectral bands (Figure 10). The NIR band is particularly responsive to leaf internal structure and water content, whereas the Red Edge band is closely related to chlorophyll concentration, enabling an accurate assessment of vegetation condition. Low LCI values (grey to dark orange) generally indicate low chlorophyll concentrations and are commonly associated with bare soil, non-vegetated areas, or

vegetation affected by severe physiological stress. Moderate LCI values (yellow to light green) correspond to areas with partial vegetation cover, where reduced chlorophyll content may reflect nutrient limitations or environmental stress conditions. High LCI values (bright green) represent vigorous and healthy vegetation characterized by high chlorophyll concentrations, active photosynthesis, and strong plant development.

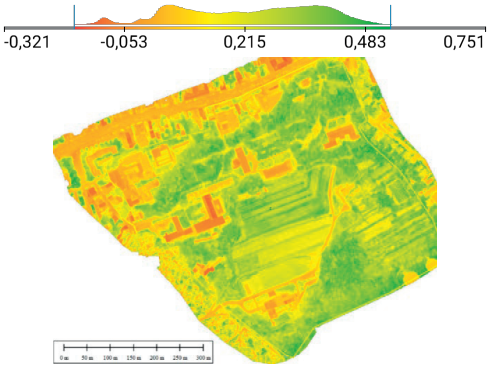


Figure 10. LCI

MCARI is highly responsive to changes in chlorophyll concentration and the Leaf Area Index (LAI), making it an effective indicator for evaluating vegetation health and detecting plant stress. High index values (dark to light green) are associated with elevated chlorophyll concentrations, reflecting healthy, vigorous vegetation with high photosynthetic activity. Moderate values (yellow to orange) indicate intermediate chlorophyll levels and may suggest the presence of mild plant stress or the onset of nutrient deficiencies. Low values (dark orange to red) are characteristic of vegetation with reduced chlorophyll content and are often linked to physiological stress, chlorosis, or diminished photosynthetic performance (Figure 11).

Because the NDRE index incorporates the Red Edge spectral band, it is particularly effective at identifying subtle changes in vegetation health before visible symptoms become apparent.

This capability makes it especially useful for precision agriculture applications, including crop health assessment, stress detection, and continuous crop monitoring. Negative values or values approaching zero (grey to dark orange) generally correspond to bare soil, non-vegetated surfaces, or vegetation in poor health.

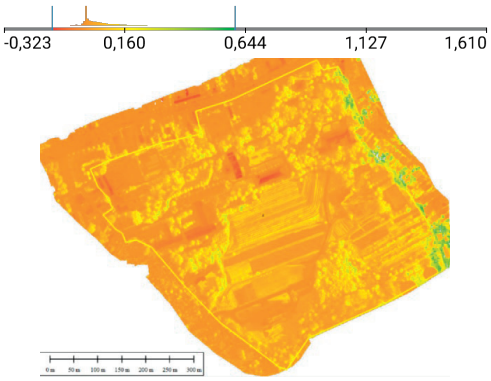


Figure 11. MCARI

Moderate values (yellow to light green) indicate the presence of vegetation with intermediate chlorophyll levels, which may reflect physiological stress or reduced plant vigour. High values (bright green) are characteristic of dense and healthy vegetation with high chlorophyll activity, indicating vigorous plant growth and optimal physiological condition (Figure 12).

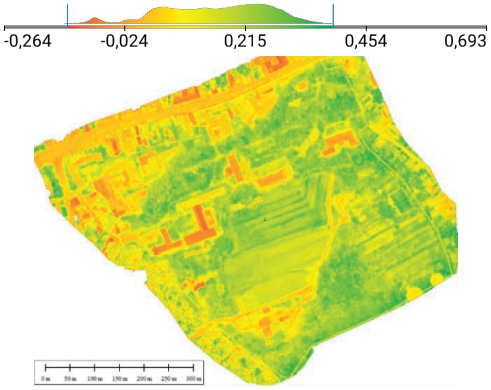


Figure 12. NDRE

In Figure 13 the NDVI applied on the studied area can be seen. High NDVI values (approaching +1) indicate dense, healthy vegetation with abundant chlorophyll content and active photosynthesis. On NDVI maps, these areas are typically displayed in bright green. Moderate NDVI values (around 0) are generally associated with sparse vegetation, grasslands, or areas with relatively low chlorophyll concentrations. These regions are commonly represented by yellow or light green shades. Low NDVI values (approaching −1)

correspond to bare soil, exposed rock, or other non-vegetated surfaces where vegetation is absent. On NDVI maps, these areas usually appear in brown or reddish colours.

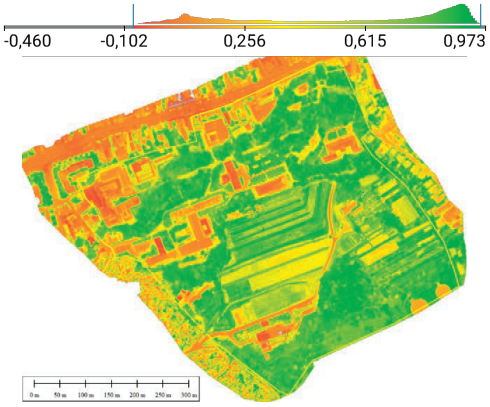


Figure 13. NDVI

The Structure Insensitive Pigment Index 2 (SIPI_2) (Figure 14) evaluates plant stress and pigment composition, particularly the carotenoid-to-chlorophyll ratio. Because it is less influenced by leaf structure, it provides a reliable assessment of vegetation health and photosynthetic performance.

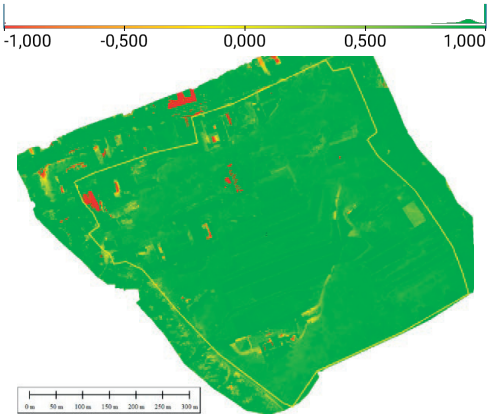


Figure 14. SIPI_2

The predominance of green areas indicates that most of the analysed vegetation is healthy and in good physiological condition.
Mean GNDVI values were calculated for each identified tree crown.
It can be observed that most trees fall within the higher GNDVI value range, indicating a generally good vegetation condition and relatively high chlorophyll content (Figure 15).

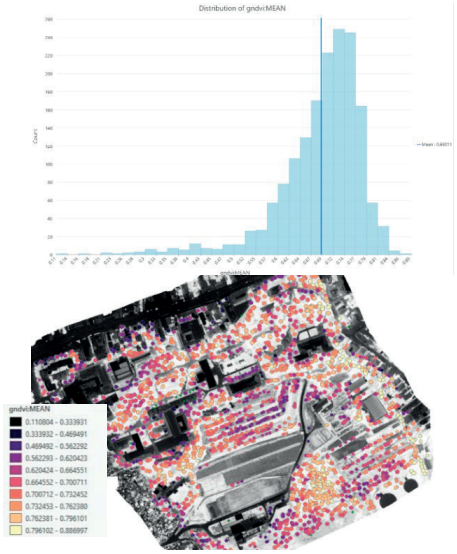


Figure 15. (Up) Mean GNDVI Values per Tree and (Down) Symbology of Mean GNDVI Values per Tree

The distribution of mean LCI values (Figure 16) appears relatively uniform across the study area, with a similar number of trees exhibiting values below and above the overall mean. This pattern suggests a relatively homogeneous distribution of chlorophyll content and vegetation condition among the identified trees.

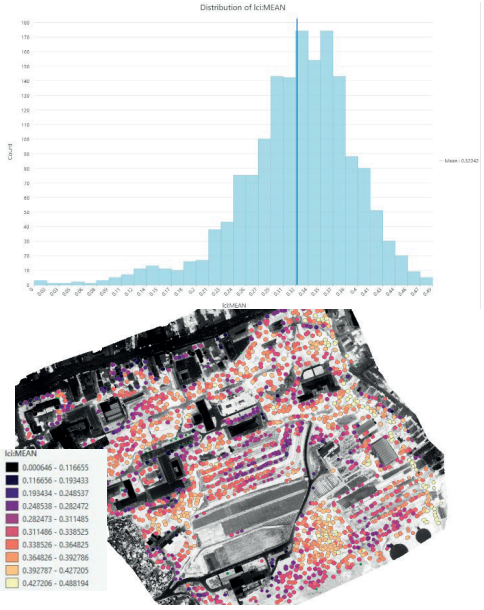


Figure 16. (Up) Mean LCI Values per Tree and (Down) Symbology of Mean LCI Values per Tree

The distribution of MCARI values (Figure 17) indicates that most trees are characterized by values below the overall mean. In addition, the range of values is relatively narrow, resulting in limited differentiation between distinct value classes across the study area.

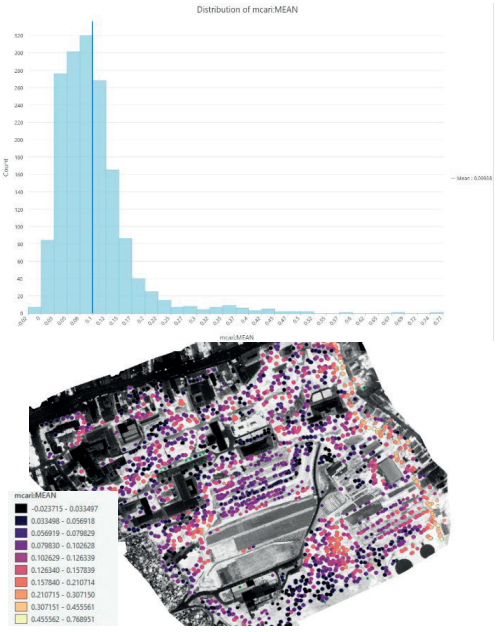
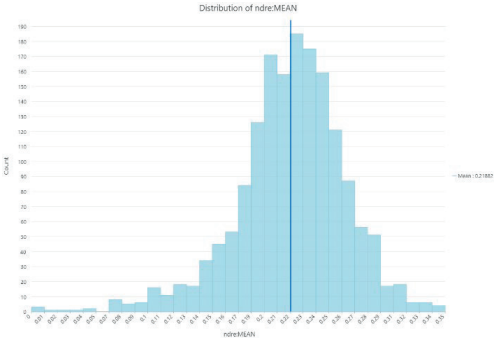


Figure 17. (Up) Mean MCARI Values per Tree and (Down) Symbology of Mean MCARI Values per Tree

The distribution of mean NDRE values (Figure 18) appears relatively uniform across the study area, with a similar number of trees exhibiting values below and above the overall mean.



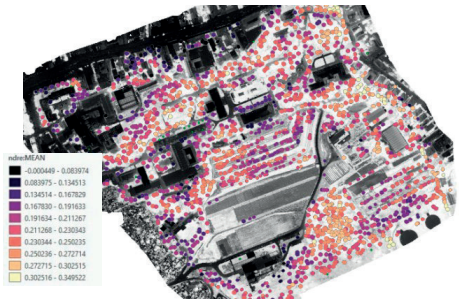
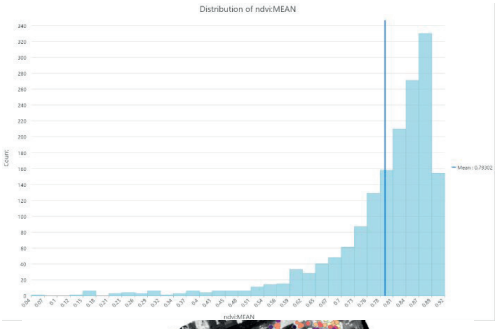


Figure 18. (Up) Mean NDRE Values per Tree and (Down) Symbology of Mean NDRE Values per Tree

The distribution of NDVI values (Figure 19) indicates that the majority of trees exhibit values above the overall mean. This suggests generally healthy vegetation conditions and a high level of photosynthetic activity throughout the study area.



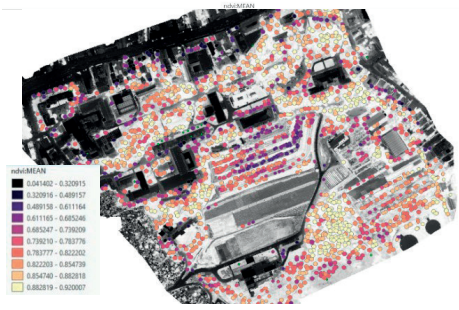


Figure 19. (Up) Mean NDVI Values per Tree and (Down) Symbology of Mean NDVI Values per Tree

The distribution of mean SIPI values (Figure 20) appears relatively uniform across the study area, with a similar number of trees exhibiting values below and above the overall mean.

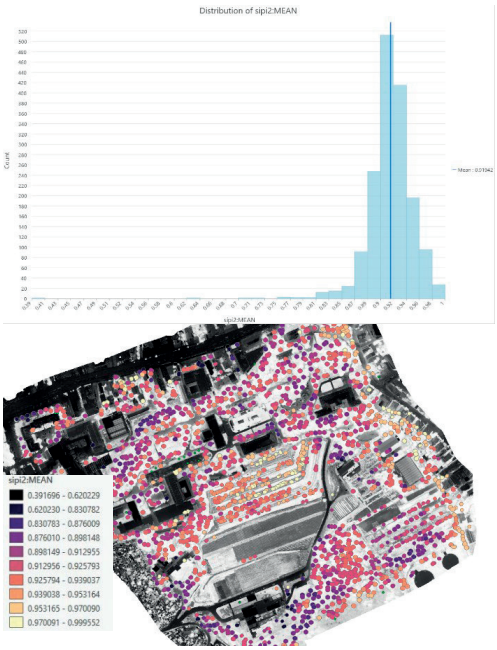


Figure 20. (Up) Mean SIPI_2 Values per Tree and (Down) Symbology of Mean SIPI_2 Values per Tree

All indices have median values close to 0 (distributed between -1 and +1, which also confirms their compliance with the theoretical thresholds), which is expected after standardization (Figure 21).

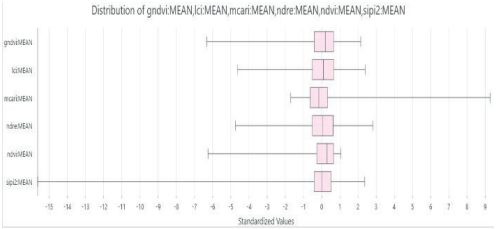


Figure 21. Boxplot Representation of Standardized Vegetation Indices

The boxplots are relatively narrow and similar in size, suggesting that most trees exhibit relatively homogeneous vegetation responses.
The main differences are observed in the length of the whiskers, which indicate the presence of trees with values that differ considerably from the rest of the population. This is most likely due to different species and unique specimens, especially those located within the agro-botanical garden area, although it may also result from canopy delineation errors.

CONCLUSIONS

The LiDAR survey showed detailed information on both terrain and vegetation structure, thus being able to generate multiple high-value products from a single dataset. The automatic classification successfully separated ground, buildings, and vegetation, while tree and canopy extraction allowed the estimation of key dendrometric parameters, including tree height and crown dimensions.
Although the automated workflow proved efficient for processing large datasets, certain limitations were observed in the matter of canopy delineation, where large crowns were occasionally segmented into multiple individual trees. Nevertheless, the identification of 1,645 trees higher than 2.5 m and the generation of elevation and tree density maps demonstrate the potential of UAV-based LiDAR data for rapid and detailed forest inventory, vegetation analysis, and environmental monitoring.
Based on the images (in the following order: GNDVI → LCI → MCARI → NDRE → NDVI → SIPI2), a visual analysis of the consistency of tree classification can be performed.
There is no perfect correspondence between trees assigned to different classes across all images. The same tree that appears in a high-value class for one index may appear in a medium or even low-value class in another index. This is expected, as each index measures a different aspect of vegetation condition.
A partial correlation can be observed among the indices. Many trees maintain their general trend (high or low values) across several maps; however, they are not classified identically in all cases.
LCI and NDRE – The two maps exhibit a very similar distribution of values, indicating a strong correlation in identifying trees with different chlorophyll levels.
NDVI and GNDVI – Values are distributed similarly across most areas, highlighting a good correlation between vegetation vigor and chlorophyll content.
MCARI – This index reveals more pronounced differences among trees, and its results are only

partially similar to those obtained from NDVI and NDRE.

SIPI2 – The distribution of values differs the most from the other indices, suggesting that it captures distinct physiological characteristics, particularly those associated with vegetation stress.

A potential direction for future research is the correlation of vegetation indices with ground-collected data for tree species identification and condition assessment. By comparing GNDVI, LCI, MCARI, NDRE, NDVI, and SIPI2 values with direct field observations regarding species, health condition, stress level, defoliation, or the presence of degradation symptoms, it may be possible to determine whether certain species exhibit specific spectral signatures and whether they respond differently to stress factors. Such an approach would contribute both to improving species identification and to developing remote sensing–based models for monitoring tree health.

ACKNOWLEDGEMENTS

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USE OF GENERATIVE ARTIFICIAL INTELLIGENCE (GenAI)

The authors declare the use of Generative Artificial Intelligence (GenAI) tools in the preparation of this manuscript. GenAI was used exclusively for language editing and text refinement and for the visual refinement of the sketch in Figure 1, which was previously drafted by the authors. All scientific content, data analysis, and interpretations were developed and verified by the authors.

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