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Urban Vegetation Volume Estimation from LiDAR Point Clouds

A Data-Driven Approach for Large-Scale 3D Analysis

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***Abstract*—Urban green space is typically assessed using two-dimensional indicators such as land cover percentage, which do not reflect the structural complexity or ecological value of vegetation. This study presents a data-driven method for estimating three-dimensional vegetation volume using widely available, pre-classified LiDAR point cloud data. To address the challenges of large datasets, efficient processing techniques are applied to extract vegetation classes and convert them into raster formats, including terrain and vegetation height layers. Vegetation is segmented into low, medium, and high, enabling the calculation of corresponding volumetric indicators. The results demonstrate that volumetric metrics provide a more accurate representation of urban greenery and offer improved potential for environmental analysis, including carbon-related assessments, compared to conventional area-based approaches.**

Keywords—LiDAR; point cloud processing; urban vegetation; 3D analysis; GeoTIFF; big data; urban sustainability; environmental modelling

I. INTRODUCTION

Urban green infrastructure plays a critical role in improving environmental quality [1], mitigating climate change, and enhancing human well-being [2,3]. Vegetation in cities contributes to carbon sequestration, air pollution reduction, urban heat island mitigation [4,5], and stormwater regulation. As a result, urban planning policies commonly include quantitative requirements for green space provision. However, these requirements are typically based on two-dimensional indicators, such as the percentage of vegetated land area within a parcel, which do not adequately reflect the ecological performance or structural complexity of urban greenery.

This limitation has been widely discussed in the fields of urban ecology and remote sensing. Studies have shown that vegetation structure, including height, density, and canopy volume, is a key determinant of ecosystem services such as carbon storage and microclimate regulation [6,7]. Two urban areas with identical green surface percentages may differ significantly in their environmental impact depending on whether vegetation consists of low grass cover or mature trees [8]. Therefore, moving from planar to volumetric metrics is essential for a more accurate representation of urban green systems.

Recent advances in remote sensing technologies, particularly airborne Light Detection and Ranging (LiDAR), provide new opportunities to quantify vegetation in three dimensions. LiDAR systems generate dense point cloud datasets that capture the vertical structure of the surface and above-ground objects with high precision. These datasets have been successfully applied in forestry and ecological studies to estimate tree height, canopy structure, and biomass [9,10]. Increasingly, national and regional LiDAR datasets are becoming openly available and are often pre-classified into ground, vegetation, and built environment classes, significantly reducing preprocessing requirements.

Despite these advances, the application of LiDAR data for routine urban planning metrics remains limited. One of the primary challenges is the large size of point cloud data, which can consist of hundreds of millions of points and require substantial computational resources for processing and analysis. Efficient data handling strategies and scalable workflows are therefore essential to enable practical use of LiDAR in urban-scale assessments [11].

This study addresses these challenges by proposing a data-driven methodology for extracting vegetation volume from large-scale, pre-classified LiDAR datasets. The approach focuses on efficient processing techniques to convert point cloud data into raster-based representations, including digital terrain models and vegetation height layers. Vegetation is categorized into low, medium, and high strata, allowing the calculation of volumetric indicators that better describe the spatial distribution and structural characteristics of urban greenery.

The proposed method aims to bridge the gap between advanced remote sensing capabilities and current urban planning practices by introducing volumetric vegetation metrics as a more informative alternative to conventional area-based indicators. Such metrics can support improved environmental assessment and decision-making, particularly in the context of climate change mitigation and sustainable urban development.

II. LITERATURE REVIEW

Urban green space assessment has traditionally relied on two-dimensional indicators, such as green area ratios, land cover classifications, and vegetation indices derived from optical imagery. These approaches are widely used in planning regulations due to their simplicity and ease of interpretation. However, numerous studies have highlighted their limitations in representing the ecological functionality of vegetation. In particular, surface-based metrics fail to account for vertical structure, which is a key factor influencing ecosystem services such as carbon storage, shading, and evapotranspiration [12].

Remote sensing techniques such as the Normalized Difference Vegetation Index (NDVI) have been extensively applied to map vegetation presence and health [13,14]. While effective for large-scale monitoring, NDVI and similar indices provide limited insight into vegetation height and volume, especially in heterogeneous urban environments where built structures and mixed vegetation types complicate interpretation. Consequently, there is increasing recognition that two-dimensional representations are insufficient for capturing the true spatial and functional characteristics of urban greenery.

Light Detection and Ranging (LiDAR) has emerged as a key technology for capturing three-dimensional information about the Earth's surface. By emitting laser pulses and measuring their response time, LiDAR systems generate high-density point clouds that accurately represent terrain and above-ground objects. This capability has made LiDAR particularly valuable in forestry and ecological research, where it is used to estimate tree height, canopy structure, and biomass [12,15].

In urban contexts, LiDAR has been applied to map building geometry, detect vegetation, and analyze urban morphology. Studies have demonstrated its effectiveness in distinguishing between ground, low vegetation, and high vegetation classes, especially when datasets are pre-classified. LiDAR-derived products such as Digital Terrain Models (DTMs), Digital Surface Models (DSMs), and Canopy Height Models (CHMs) provide a basis for quantifying vertical vegetation structure [16,17].

A growing body of research has focused on deriving quantitative measures of vegetation structure from LiDAR data. Common approaches include the use of canopy height models and voxel-based representations to estimate vegetation density and volume [18]. Voxelization techniques divide space into three-dimensional grid cells, enabling detailed analysis of vegetation distribution and structure [19]. Such methods have been successfully applied in forest environments to estimate biomass and carbon stocks.

In urban studies, however, the application of volumetric metrics remains less developed. Existing research often focuses on tree detection or canopy cover rather than full volumetric assessment. Some studies have explored simplified approaches by integrating height information over area units to approximate vegetation volume [20], but these methods are not yet widely adopted in planning practice. This gap highlights the need for scalable and reproducible workflows that can translate LiDAR data into meaningful volumetric indicators for urban analysis.

Despite the potential of LiDAR, its practical application is often constrained by the data size and complexity of point cloud datasets. Large-scale LiDAR surveys can produce billions of points, requiring efficient data management, processing, and storage solutions [21]. Traditional workflows may struggle with memory limitations and computational performance [22], particularly when applied at city or national scales.

To address these challenges, recent studies have explored optimized data processing techniques, including spatial indexing, tiling, parallel processing, and rasterization methods [23,24]. Converting point cloud data into raster formats, such as GeoTIFF, is a common strategy that reduces data complexity while preserving essential spatial information [25]. This approach enables integration with geographic information systems (GIS) and supports efficient analysis of large datasets.

III. PROBLEM FORMULATION

Although significant progress has been made in LiDAR-based vegetation analysis, a gap remains between advanced three-dimensional methodologies and their application in urban planning and policy. Current regulations still rely predominantly on two-dimensional indicators, overlooking the volumetric and structural properties of vegetation. At the same time, existing LiDAR-based approaches are often either computationally intensive or tailored to forestry applications rather than urban environments.

This study contributes to the field by proposing a practical and scalable method for extracting vegetation volume from pre-classified LiDAR datasets. By focusing on efficient processing and clear categorization of vegetation layers, the approach aims to facilitate the integration of volumetric green metrics into urban analysis and decision-making.

Urban planning and environmental assessment practices predominantly rely on two-dimensional indicators to quantify green infrastructure, most commonly expressed as the proportion of vegetated area within a land parcel. While such metrics are simple to compute and widely standardized, they fail to capture the vertical structure and spatial complexity of vegetation. As a result, significantly different vegetation configurations—such as low grass cover versus dense tree canopies—may be evaluated as equivalent, despite their substantially different ecological functions, including carbon sequestration, shading, and microclimate regulation.

With the increasing availability of airborne LiDAR data, it is now possible to represent urban environments in three dimensions and to derive volumetric characteristics of vegetation. Many national LiDAR datasets are openly accessible and pre-classified into classes such as ground, low vegetation, medium vegetation, and high vegetation. However, the transformation of such large-scale point cloud data into consistent and meaningful volumetric indicators remains a computational and methodological challenge.

A. *Mathematical Formulation of Vegetation Volume*

Let the LiDAR point cloud be defined as a set of points:

$$P = \{(x_i, y_i, z_i)\}_{i=1}^{N}$$

where x_i, y_i are spatial coordinates and z_i is the elevation of each point.

A Digital Terrain Model (DTM) is used to represent the ground surface. Let the terrain elevation at location (x, y)be:

$$z_{ground}(x, y)$$

The **normalized height** of each LiDAR point above ground is then defined as:

$$h_i = z_i - z_{ground}(x_i, y_i)$$

Vegetation points are filtered based on classification and height thresholds. Let the set of vegetation points be:

$$P_v = \{i \in P \mid h_i > 0\}$$

To derive volumetric information, the spatial domain is discretized into a regular grid of cells (pixels) with area:

$$A_{cell} = \Delta x \cdot \Delta y$$

Each cell accumulates vegetation height values. The vegetation height function within a cell can be approximated as:

$H(x, y) = \max(h_i)$for all points i within the cell

Alternatively, an average height can be used:

$$H(x, y) = \frac{1}{n}\sum_{i=1}^{n} h_i$$

where $n$is the number of points in the cell.

The **vegetation volume** within a given land parcel $D$is then approximated by integrating the height over the area:

$$V = \iint_D H(x, y)\, dA$$

In discrete form, this becomes:

$$V \approx \sum_{j=1}^{M} H_j \cdot A_{cell}$$

where:

- $M$is the number of grid cells within the parcel,
- $H_j$is the vegetation height value in cell j.

B. *Stratified Vegetation Volume*

To better reflect vegetation structure, the total volume can be decomposed into height-based layers:

- Low vegetation: $0 < h \leq h_1$
- Medium vegetation: $h_1 < h \leq h_2$
- High vegetation: $h > h_2$

The volume for each category is computed as:

$$V_k = \sum_{j \in S_k} H_j \cdot A_{cell}$$

where:

- $S_k$is the set of cells belonging to vegetation class k,
- $k \in$ {low,medium,high}.

The total vegetation volume is then:

$$V_{total} = V_{low} + V_{medium} + V_{high}$$

C. *Problem statement*

The core problem addressed in this study is the development of a scalable and computationally efficient method to compute vegetation volume from large-scale, pre-classified LiDAR datasets. The method must:

1. Efficiently process large point clouds containing millions to billions of points,
2. Utilize existing classification to minimize preprocessing effort,
3. Convert point cloud data into structured raster representations,
4. Accurately compute volumetric vegetation indicators using the formulations defined above,
5. Provide stratified outputs (low, medium, high vegetation) suitable for urban analysis and planning.

By addressing these challenges, the proposed approach enables the transition from traditional two-dimensional green area metrics to more informative three-dimensional volumetric indicators, supporting improved assessment of urban environmental quality.

Fig. 1.

IV. METHODOLYGY

The proposed methodology focuses on the transformation of large-scale LiDAR point cloud data into raster-based vegetation indicators using a fully automated and scalable workflow. The approach leverages pre-classified LiDAR datasets and applies the Point Data Abstraction Library (PDAL) to efficiently generate GeoTIFF outputs for different vegetation classes.

A. *Data Structure and Input Preparation*

The input data consists of LiDAR point clouds distributed as compressed .zip archives, each containing multiple tiles in LAS or LAZ format. The datasets are typically pre-classified, with vegetation represented by standardized classification codes:

- Low vegetation: class 3
- Medium vegetation: class 4
- High vegetation: class 5

This classification enables direct filtering of vegetation points without requiring additional machine learning or classification steps.

B. *Workflow Overview*

The processing pipeline follows these main steps:

1. Selection of input directory containing LiDAR .zip files
2. Iteration through all compressed datasets
3. Extraction of individual LiDAR tiles
4. Filtering of vegetation classes using classification attributes
5. Rasterization of point clouds into GeoTIFF format using PDAL
6. Storage of outputs separated by vegetation type and dataset

This workflow ensures efficient handling of large datasets while maintaining modularity and scalability.

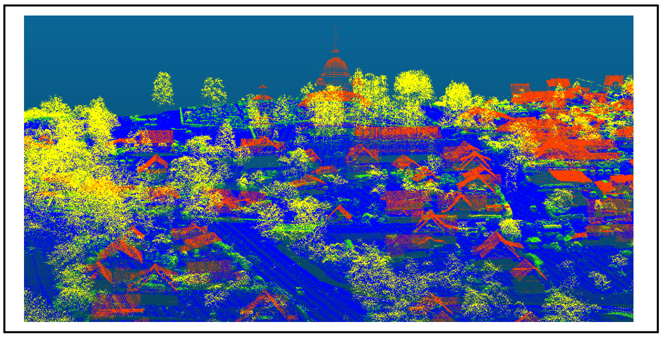

Fig. 1. Classified LiDAR data showing vegetation grouped into low, medium, and high vegetation, while buildings are included for contextual reference.

C. *PDAL-Based Rasterization*

The core of the methodology relies on the use of the Point Data Abstraction Library (PDAL), which enables high-performance processing of LiDAR data. A predefined PDAL pipeline is used to convert classified point clouds into raster (GeoTIFF) format.

Vegetation filtering is performed using classification limits:

$$\text{Classification} \in \{3,4,5\}$$

Each vegetation class is processed separately, producing three independent raster datasets corresponding to:

- Low vegetation
- Medium vegetation
- High vegetation

D. *Python Implementation*

```
import zipfile
import os
import tempfile
import subprocess
from tkinter import Tk, filedialog

# Select LiDAR dataset folder
Tk().withdraw()
zip_folder =
filedialog.askdirectory(title="Select
folder with LiDAR zip files")
if not zip_folder:
    exit("No folder selected.")

# Define vegetation classes
veg_classes = {
    "low_vegetation": 3,
    "medium_vegetation": 4,
    "high_vegetation": 5
}

# Create output directories
output_folders = {}
for veg_name in veg_classes:
    folder = os.path.join(zip_folder,
veg_name)
    os.makedirs(folder, exist_ok=True)
    output_folders[veg_name] = folder

# Path to PDAL pipeline
pipeline_json =
r"C:/path/to/vegetation_pipeline.json".r
eplace("\\", "/")

# List all ZIP files
zips = sorted([f for f in
os.listdir(zip_folder) if
f.lower().endswith(".zip")])
print(f"Found {len(zips)} zip files.")

# Process each ZIP file
for z in zips:
    zip_path = os.path.join(zip_folder,
z)
    print(f"\nProcessing zip: {z}")

    with zipfile.ZipFile(zip_path, 'r')
as zip_ref:
        tiles = [f for f in
zip_ref.namelist() if
f.lower().endswith((".laz", ".las"))]
```

```
        with
tempfile.TemporaryDirectory() as
tmp_dir:
            for tile_name in tiles:

zip_ref.extract(tile_name, tmp_dir)
                temp_tile_path =
os.path.join(tmp_dir,
tile_name).replace("\\","/")

                for veg_name, veg_class
in veg_classes.items():

                    zip_output_folder =
os.path.join(

output_folders[veg_name],

os.path.splitext(z)[0]
                    )

os.makedirs(zip_output_folder,
exist_ok=True)

                    output_path =
os.path.join(

zip_output_folder,

f"{os.path.splitext(os.path.basename(til
e_name))[0]}.tif"
                    ).replace("\\","/")

                    subprocess.run([
                        "pdal",
"pipeline", pipeline_json,
                        f"--
readers.las.filename={temp_tile_path}",
                        f"--
filters.range.limits=Classification[{veg
_class}:{veg_class}]",
                        f"--
writers.gdal.filename={output_path}"
                    ],
capture_output=True, text=True)
```

E. *Output Data Structure*

The output of the process consists of three sets of GeoTIFF raster files corresponding to vegetation height distributions:

- low_vegetation/
- medium_vegetation/
- high_vegetation/

Each raster represents spatially distributed vegetation derived directly from classified LiDAR point clouds.

These rasters can be further used to compute:

- Vegetation area (2D)
- Vegetation height distribution
- Vegetation volume (3D integration of raster values)

F. *Advantages of the Proposed Approach*

The proposed methodology offers several advantages:

- Scalability: Efficient processing of large LiDAR datasets using tile-based processing
- Automation: Fully automated pipeline with minimal manual intervention
- Reuse of Existing Data: Utilizes pre-classified LiDAR datasets
- Compatibility: Outputs in GeoTIFF format, compatible with GIS software
- Extensibility: Can be extended to compute volumetric indicators and additional spatial metrics.

Unlike traditional approaches that rely on direct point cloud analysis, this method transforms LiDAR data into raster-based vegetation representations using PDAL. This enables efficient handling of large datasets while preserving spatial structure, making it suitable for large-scale urban and environmental analysis.

G. *Raster Clipping by GIS Boundaries (Python Implementation)*

After generating the raster datasets a further step is required to enable meaningful spatial analysis in urban contexts since planning and environmental assessment are typically performed at the level of defined spatial units such as land plots cadastral parcels or administrative boundaries the raster outputs must be divided according to these GIS based entities This is achieved by integrating vector boundary layers into the workflow where each polygon represents a specific land unit the raster data is then overlaid with these geometries and clipped so that only the values within each boundary are retained before this operation it is necessary to ensure that both raster and vector datasets share the same coordinate reference system for accurate spatial alignment as a result each land unit is represented by an individual raster dataset containing only the vegetation information within its boundaries

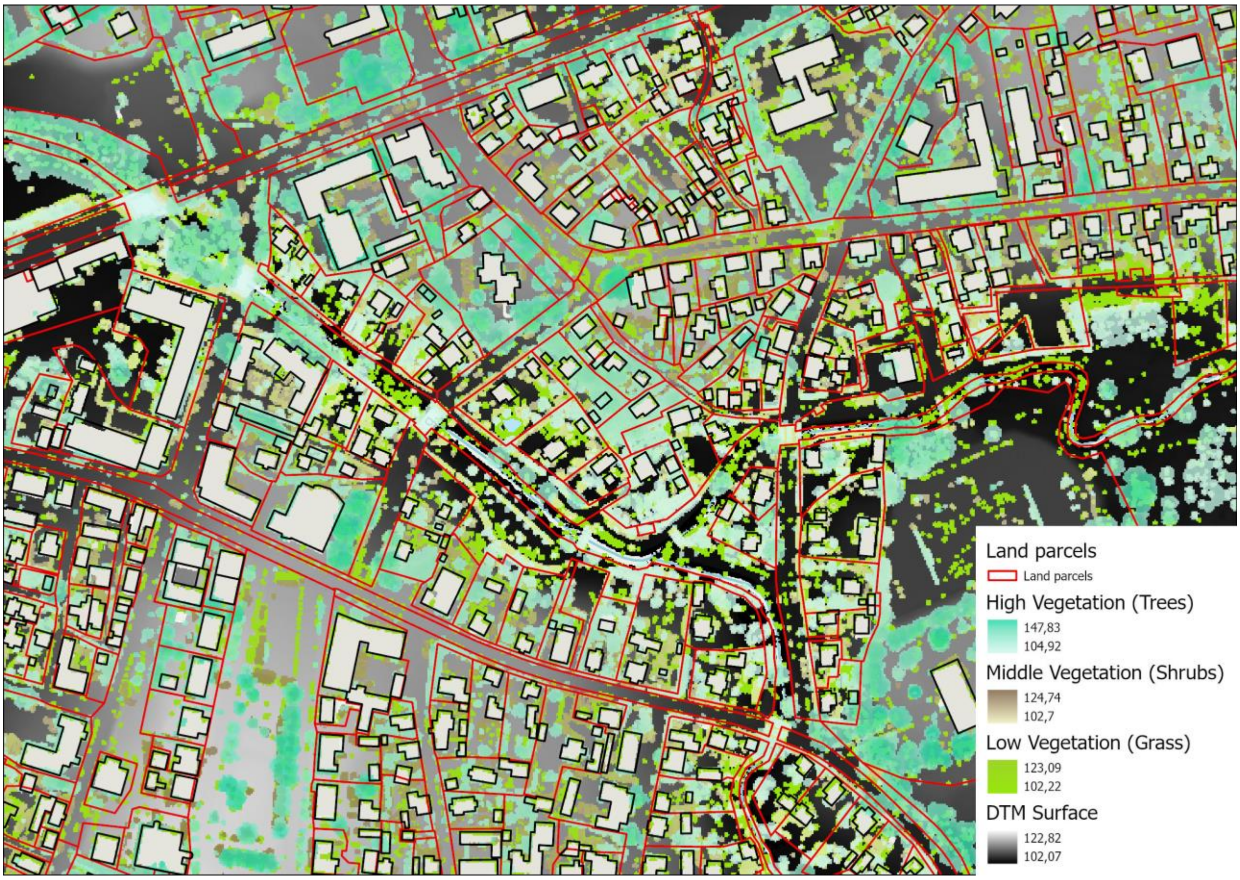

Fig. 2. Raster TIF representations of low, medium, and high vegetation together with the DTM derived from LiDAR data.

Once the raster data is partitioned in this way it becomes possible to calculate vegetation indicators for each spatial unit the vegetation volume can be computed by summing the raster values within each polygon and multiplying by the area of a single raster cell:

$$V_k = \sum_{i \in k} H_i \cdot A_{cell}$$

```
def calculate_volume(raster_file,
cell_size):
    with rasterio.open(raster_file) as
src:
        data = src.read(1)
        data = np.nan_to_num(data)
        return np.sum(data) * (cell_size
** 2)

cell_size = 1.0  # match raster
resolution
volume =
calculate_volume("parcel_1.tif",
cell_size)
print(volume)
```

This approach provides a direct way to quantify vegetation in three dimensions while maintaining compatibility with standard GIS workflows and administrative data structures the resulting outputs can then be used for further spatial analysis comparison between land units and integration into urban planning and environmental assessment systems.

V. CONCLUSIONS

This study presented a scalable and data-driven methodology for extracting and quantifying urban vegetation volume from large-scale, pre-classified LiDAR point cloud datasets. The proposed workflow demonstrates that it is possible to move beyond traditional two-dimensional green area metrics and derive three-dimensional indicators that better reflect the structural and ecological complexity of urban vegetation. By leveraging existing LiDAR datasets and using PDAL-based rasterization, the method enables efficient processing of very large datasets while minimizing the need for additional preprocessing such as classification.

The results of this approach show that vegetation can be effectively represented as raster-based GeoTIFF outputs separated into low, medium, and high vegetation classes. This stratification allows for a more detailed understanding of urban green infrastructure and provides a practical way to compute volumetric indicators. By further integrating GIS-based spatial boundaries, such as land plots or administrative units, the methodology enables the calculation of vegetation volume at the level of meaningful spatial entities, which is essential for urban planning and policy applications.

The transition from area-based to volume-based vegetation metrics represents a significant improvement in how urban greenery is quantified and assessed. Volumetric indicators provide additional insight into the vertical structure of vegetation, which is closely related to key environmental functions such as carbon sequestration, shading, and microclimate regulation. This makes them particularly relevant in the context of climate change mitigation and sustainable urban development.

The main limitation of the proposed approach lies in the reliance on the quality and availability of pre-classified LiDAR data, as well as the computational requirements associated with processing large datasets. However, the increasing global availability of LiDAR data and advances in computing power make this approach increasingly feasible for large-scale applications.

Future work may focus on refining volumetric metrics, integrating additional environmental parameters, and developing standardized indicators that can be adopted in urban planning regulations. In particular, the concept of vegetation volume has strong potential to complement or even replace traditional green area requirements, providing a more accurate and meaningful measure of urban sustainability.

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