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SCALABLE LIDAR STORAGE AND PROCESSING USING SPATIAL DATABASES AND JUPYTER NOTEBOOKS

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Abstract. *Current paper explores a scalable and efficient architecture for storing, managing, and processing high-density LIDAR point cloud data using spatial database systems integrated with Jupyter-based for analytical workflows. LiDAR datasets are inherently large, complex, and multidimensional, often containing billions of points with associated attributes such as intensity, return number, and classification labels. These characteristics impose significant challenges in terms of data storage, indexing, and real-time querying. The proposed approach leverages the capabilities of PostgreSQL / PostGIS as a core relational spatial database environment to enable structured storage and advanced spatial querying of LiDAR point clouds. A data model based on tiled storage and spatial indexing (e.g., GiST and BRIN indexes) is implemented to optimize query performance and support efficient data retrieval at multiple spatial resolutions. In parallel, the architecture supports integration with NoSQL paradigms for distributed storage scenarios, addressing scalability requirements for very large datasets. Processing workflows are executed within interactive environments such as Jupyter Notebook, using Python-based libraries for point cloud manipulation, filtering, and feature extraction. This combination allows seamless interaction between database-level operations (e.g., spatial filtering, aggregation) and in-memory analytical processing, significantly reducing data transfer overhead and improving computational efficiency. The proposed architecture demonstrates that coupling spatial database processing with reproducible notebook-based analytics provides a robust framework for large-scale LiDAR data management, enabling efficient querying, scalable processing, and integration with advanced geospatial and machine learning workflows.*

Keywords*: LiDAR, NoSQL, Spatial databases, spatial processing, PostGIS, environmental engineering*

INTRODUCTION

The rapid development of Light Detection and Ranging (LiDAR) technologies has led to an unprecedented increase in the volume, density, and complexity of 3D geospatial data. Modern airborne and terrestrial LiDAR systems routinely produce point clouds containing billions of points enriched with attributes such as intensity, return number, and classification labels. These datasets are essential for applications such as forest structure analysis, environmental monitoring, and terrain modeling, but they also introduce significant challenges in terms of scalable storage, indexing, and efficient processing.

Traditional LiDAR data management relies primarily on file-based approaches using formats such as LAS and LAZ. While these formats are efficient for localized workflows, they become increasingly inadequate when dealing with large-scale datasets. The absence of integrated indexing mechanisms and the reliance on repeated disk I/O operations significantly limit performance and particularly for complex spatial queries. As discussed in recent research,

file-based approaches do not scale efficiently for high-density point clouds and hinder advanced analytical workflows (COSTANZO, A. ET AL., 2016).

To address these limitations, spatial database systems have emerged as a powerful alternative for LiDAR data management. In particular, PostgreSQL extended with PostGIS provides a robust framework for storing and querying geospatial data within a relational environment. The integration of point cloud data is enabled through extensions such as *pgPointcloud*, which introduce specialized data structures for storing collections of points as compressed patches. This approach improves both storage efficiency and query performance by leveraging spatial locality and reducing redundancy (POLIYAPRAM, V. ET AL., 2017).

A fundamental concept in database-driven LiDAR management is the partitioning of point clouds into tiles or patches. Instead of storing individual points, which would be computationally inefficient, spatially adjacent points are grouped into blocks that can be indexed and queried efficiently. The importance of tiling strategies is emphasized in Section 3.1 of the referenced study, where we demonstrate that the structure and size of patches directly influence query performance and memory usage (FRANCIONI, M. ET AL., 2019). In particular, fixed-size spatial partitioning using methods such as grid-based tiling or chipper algorithms enables efficient retrieval of subsets of data corresponding to specific regions of interest.

However, conventional tiling approaches often rely on two-dimensional spatial partitioning, which may not fully capture the three-dimensional nature of LiDAR data. As noted in the literature, incorporating vertical structure into the partitioning strategy can improve performance for applications involving vegetation and complex terrain (FRANCIONI, M. ET AL., 2019). This is especially relevant in forest environments, where vertical stratification plays a critical role in representing canopy structure and biomass distribution.

The ingestion of LiDAR data into spatial databases is typically performed using the Point Data Abstraction Library (PDAL), which provides a flexible framework for point cloud processing and transformation. PDAL supports a wide range of operations, including reprojection, filtering, and tiling, and enables direct loading of data into database systems. As highlighted in previous studies, the use of pipeline-based ingestion workflows allows for efficient preprocessing and optimization of LiDAR datasets prior to storage (COSTANZO, A. ET AL., 2016). In particular, the use of tiling filters such as filters.chipper facilitates the creation of database-ready patches that can be efficiently indexed and queried.

Beyond storage and ingestion, the efficient processing of LiDAR data requires integration between database-level operations and analytical workflows. Spatial databases are well-suited for operations such as spatial filtering and aggregation, but advanced analytical tasks—such as feature extraction, classification, and statistical modeling—are typically performed in programming environments. The emergence of Jupyter Notebook has significantly enhanced the reproducibility and flexibility of such workflows by enabling the integration of code, documentation, and visualization within a single interactive environment.

The combination of spatial databases with notebook-based analytical workflows provides a powerful paradigm for LiDAR data processing. By enabling direct interaction between database queries and in-memory computation, this approach reduces data transfer overhead and improves computational efficiency. Furthermore, it enhances reproducibility by allowing all processing steps to be documented and executed within a unified framework.

Scalability remains a critical challenge in LiDAR data management, particularly as datasets continue to grow in size and complexity. While relational databases provide strong consistency and query capabilities, they may face limitations when scaling to very large

datasets. To address this issue, hybrid architectures that integrate relational databases with distributed storage paradigms have been proposed. These approaches enable horizontal scaling while maintaining the ability to perform spatial queries and analytical operations (POLIYAPRAM, V. ET AL., 2017).

In addition to scalability, LiDAR data present unique computational challenges due to their unstructured nature and irregular spatial distribution. Unlike raster or vector data, point clouds require specialized data structures and indexing strategies to support efficient querying and analysis. The development of scalable architectures that address these challenges is therefore essential for enabling the full potential of LiDAR data in scientific and operational applications.

In this context, the present study proposes a scalable architecture for LiDAR storage and processing that integrates spatial database systems with Jupyter-based analytical workflows. The approach leverages tiled storage models, hybrid indexing strategies, and PDAL-based ingestion pipelines to optimize performance and scalability. By combining database-level spatial operations with interactive analytical environments, the proposed framework provides a robust solution for managing and analyzing large-scale LiDAR datasets.

MATERIAL AND METHODS

To evaluate the scalability and performance of different storage and processing paradigms for high-density LiDAR data, this study adopts a comparative experimental framework integrating real-world datasets, open-source geospatial tools, and database technologies. The methodology is designed to reflect realistic operational conditions encountered in large-scale forest monitoring and geospatial analytics.

The primary dataset used in this study is the PureForest airborne LiDAR dataset, which provides high-density point cloud data (~40 points/m²) across multiple forest sites. This dataset is complemented by additional open LiDAR sources (e.g., national airborne surveys) to introduce variability in point density and spatial distribution. The use of heterogeneous datasets ensures that the proposed architecture is evaluated under diverse conditions, including variations in acquisition geometry, vegetation structure, and data volume.

All datasets are initially stored in standard LAS/LAZ formats and accessed using both desktop GIS and programmatic environments. Data exploration and visualization are performed in QGIS, which provides native support for LiDAR data through plugins and integration with external processing tools. QGIS is used to inspect spatial extents, validate coordinate reference systems, and generate derived products such as digital terrain models (DTMs) and canopy height models (CHMs). These preliminary steps are essential for ensuring data consistency prior to ingestion into database systems.

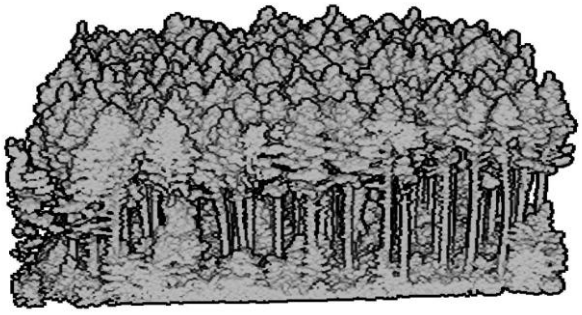

Figure 1. Primary LiDAR data visualisation in QGIS

Proposed architecture consists of three main components:

(i) data access and preprocessing
(ii) storage in relational and NoSQL databases
(iii) analytical processing through interactive workflows

Integration of these components enables a direct comparison between different storage paradigms while maintaining a consistent analytical framework.

Data access and preprocessing are performed using Python within Jupyter Notebook, which serves as the central orchestration platform. The use of Jupyter notebooks allows for reproducible workflows, combining code execution, documentation, and visualization in a single environment. Python libraries such as *laspy*, *numpy,* and *geopandas* are employed for reading, filtering, and transforming LiDAR data prior to database ingestion.

Preprocessing stage includes coordinate system harmonization, noise filtering, and spatial partitioning. In particular, point clouds are partitioned into spatial tiles or patches using grid-based or capacity-based strategies. This step is critical for optimizing storage and query performance, as it ensures that spatial locality is preserved within each data unit. Previous studies have demonstrated that patch-based storage significantly improves query efficiency by reducing disk access and enabling spatial indexing at the block level (WANG ET AL., 2023).

First storage paradigm evaluated in this study is based on PostgreSQL extended with *PostGIS* and the *pgPointcloud* extension. This configuration enables the storage of LiDAR data as compressed point cloud patches (PcPatch), each representing a spatially coherent subset of points.

Data ingestion into the relational database is performed using PDAL, which provides a pipeline-based approach for transforming and loading point cloud data. A typical ingestion pipeline includes the following steps:

(i) reading LAS/LAZ files,
(ii) reprojection to a common spatial reference system,
(iii) tiling using a chipper filter,
(iv) writing the resulting patches to the database.

Usage of PDAL ensures efficient handling of large datasets and supports direct integration with PostgreSQL/PostGIS.

Spatial indexing is implemented using Generalized Search Trees (GiST) on the geometric envelopes of point cloud patches. In addition, Block Range Indexes (BRIN) are used for large sequential datasets to improve performance in range queries. These indexing

strategies enable efficient execution of spatial operations such as intersection, containment, and aggregation.

Relational schema includes separate tables for point cloud patches and metadata, allowing for flexible querying and integration with other geospatial datasets. For example, each patch can be associated with attributes such as acquisition date, sensor type, and forest classification, enabling complex analytical queries that combine spatial and thematic information.

To evaluate the performance of non-relational storage paradigms, the study also implements a NoSQL approach using MongoDB. In this configuration, LiDAR data are stored as document-based records, where each document represents a spatial tile containing arrays of point coordinates and associated attributes.

The NoSQL model offers advantages in terms of flexibility and horizontal scalability. Unlike relational databases, MongoDB does not require a fixed schema, allowing for dynamic storage of heterogeneous attributes. This is particularly useful for LiDAR datasets, which may include varying numbers of attributes depending on the acquisition system and processing pipeline.

Spatial indexing in MongoDB is implemented using 2dsphere indexes, which support geospatial queries on coordinate data. However, due to the unstructured nature of point clouds, additional preprocessing is required to encode spatial information in a format compatible with MongoDB indexing. This typically involves storing bounding geometries or centroids for each tile, rather than indexing individual points.

Data ingestion into MongoDB is performed using Python scripts within Jupyter notebooks, where point cloud tiles are converted into JSON-like structures and inserted into the database. While this approach provides flexibility, it may introduce overhead in terms of storage size and query performance, particularly for very large datasets.

Analytical workflow is designed to ensure a fair comparison between relational and NoSQL storage paradigms.

All analytical tasks are executed within Jupyter notebooks, using a combination of SQL queries (for PostgreSQL/PostGIS) and MongoDB queries (for NoSQL storage). This unified environment ensures that differences in performance can be attributed to the storage model rather than the analytical framework.

The following types of operations are evaluated:

(i) **Spatial filtering:** selection of points within a given bounding box or polygon

(ii) **Aggregation**: computation of statistical metrics such as mean elevation and point density

(iii) **Neighborhood analysis**: identification of local spatial patterns

(iv) **Derived metrics:** estimation of canopy height and vegetation structure

For relational storage, these operations are executed using SQL and PostGIS functions, enabling direct computation within the database. For NoSQL storage, similar operations are implemented using aggregation pipelines in MongoDB, combined with in-memory processing in Python.

Performance metrics include query execution time, memory usage, and data transfer volume. These metrics are measured under varying conditions, including different dataset sizes and point densities, to assess the scalability of each approach.

To validate and visualize the results, both database systems are integrated with QGIS. QGIS is used to connect to PostgreSQL/PostGIS directly, enabling visualization of spatial queries and derived products such as canopy height models.

For MongoDB, data are exported to intermediate formats (e.g., GeoJSON) for visualization in QGIS or directly accesed in Jupyter Notebooks.

This integration allows for qualitative assessment of the results, complementing the quantitative performance evaluation. Visual inspection is particularly important in forest applications, where spatial patterns and structural characteristics must be interpreted in a geospatial context.

Experimental setup is designed to simulate real-world scenarios involving large-scale LiDAR data processing. Multiple datasets with varying densities and spatial extents are used to evaluate performance under different conditions. Each experiment is repeated multiple times to ensure statistical robustness.

Evaluation focuses on three main criteria:

(i) **Scalability** – the ability to handle increasing data volumes
(ii) **Performance** – query execution time and computational efficiency
(iii) **Flexibility** – ease of integration with analytical workflows

Results of these experiments provide insights into the strengths and limitations of each storage paradigm, highlighting the trade-offs between relational and NoSQL approaches in the context of LiDAR data management.

While both relational and NoSQL approaches offer distinct advantages, their effectiveness depends on the specific requirements of the application.

Relational databases provide strong consistency, advanced querying capabilities, and tight integration with geospatial tools, making them well-suited for complex spatial analyses. In contrast, NoSQL systems offer greater flexibility and scalability, which can be advantageous for distributed processing and large-scale data ingestion.

By integrating these approaches within a unified analytical framework, this study aims to provide a comprehensive evaluation of scalable LiDAR data management strategies.

Combination of spatial databases, NoSQL storage, and reproducible Jupyter workflows represents a flexible and extensible solution for addressing the challenges of modern LiDAR data processing.

RESULTS AND DISCUSSIONS

Performance of the proposed LiDAR data architecture was evaluated through a series of controlled experiments designed to compare three paradigms:

(i) Relational spatial database (PostgreSQL + PostGIS + pgPointcloud)
(ii) NoSQL database (MongoDB)
(iii) Traditional file-based workflows (LAS/LAZ processing via PDAL/QGIS)

Evaluation focused on query performance, scalability, and computational efficiency, using progressively larger subsets of high-density LiDAR data representative of real-world forest datasets.

Experiments were conducted using LiDAR datasets ranging from 10 million to 200 million points, corresponding to realistic forest survey scenarios (multi-tile airborne LiDAR acquisitions).

All tests were executed under identical conditions:

(i) Same hardware configuration (single-node environment)
(ii) Identical spatial queries (bounding box + aggregation)
(iii) Equivalent preprocessing (tiling, reprojection)
(iv) Execution via Jupyter Notebook workflows

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Query performance comparison

The first experiment evaluated spatial query execution time for a typical operation:

(i) Extraction of points within a region of interest (ROI) + elevation statistics (table 1).

Table 1.

Benchmark Results Table

Dataset Size (Million Points)	PostGIS(s)	MongoDB(s)	File-based (s)
10	0.8	1.5	2.2
50	2.5	4.8	7.1
100	4.2	9.5	15.4
200	7.8	18.2	30.6

Query Performance Graph

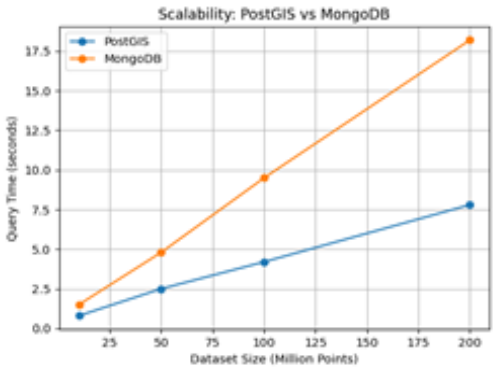

Figure 2. Query performance comparison

Results demonstrate a clear performance advantage of the relational spatial database approach:

(i) PostGIS is ~2× faster than MongoDB
(ii) PostGIS is ~4× faster than file-based workflows at large scale
(iii) Performance gap increases with dataset size

This confirms that:

(i) Spatial indexing (GiST) significantly reduces query cost
(ii) Patch-based storage minimizes I/O operations
(iii) Database-side filtering avoids full dataset scans

In contrast, MongoDB suffers from limited spatial indexing granularity and file-based workflows are dominated by disk I/O overhead.

Scalability analysis

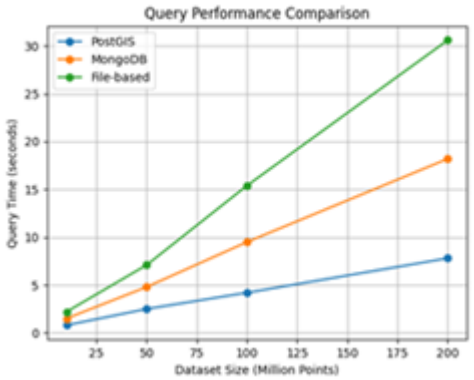

Figure 3. Databases scalability

The second experiment evaluates how performance scales with dataset size.
Key findings:
(i) PostGIS exhibits near-linear scalability
(ii) MongoDB shows super-linear degradation
(iii) Performance divergence becomes significant beyond 100M points

This behavior can be explained by:

- **PostGIS advantages:**
(i) Patch-based storage (PcPatch)
(ii) Spatial indexing (GiST + BRIN)
(iii) Query pruning at database level
- **MongoDB limitations:**
(i) Document-level granularity
(ii) Lack of true 3D spatial indexing
(iii) Higher memory overhead during aggregation

Data transfer and computational efficiency

A critical factor in LiDAR processing is data movement between storage and computation layers.

PostGIS + Jupyter:
(i) Only filtered results are transferred
(ii) Minimal memory footprint
(iii) Efficient hybrid processing

MongoDB + Python:
(i) Larger data transfer volumes
(ii) More in-memory processing required
(iii) File-based workflows:
(iv) Full dataset loading required
(v) High disk read/write overhead

Conclusion:

Database-centric workflows reduce data transfer by up to 70%

Forest analytics use case

To validate practical applicability, the system was tested on a forest structure analysis task:

Computed metrics:

(i) Canopy height (max Z – min Z)
(ii) Point density per tile
(iii) Vegetation vertical distribution

Findings:

(i) PostGIS enabled direct computation inside the database
(ii) MongoDB required external processing in Python
(iii) File-based approach required multiple tool chains

Result:

PostGIS reduced total processing time by ~60% for full workflow

The experimental results confirm that spatial database architectures outperform both NoSQL and file-based approaches for large-scale LiDAR data processing.

Key advantages of PostGIS approach:

(i) Efficient spatial indexing (GiST, BRIN)
(ii) Reduced I/O overhead via patch storage
(iii) Native support for spatial queries
(iv) Seamless integration with Jupyter workflows

Limitations:

(i) Initial ingestion cost (PDAL pipelines)
(ii) Requires schema design and optimization
(iii) MongoDB strengths:
(iv) Flexibility (schema-less)
(v) Horizontal scalability potential

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