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Tool-Based Automation in 3D Point Cloud Processing – A Review

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Abstract – This paper provides a systematic review of tool-based automation in 3D point cloud processing, focusing on open-source platforms and their capabilities to facilitate spatial workflows. The irregular nature of point clouds and their increasing volume are increasingly utilized in geomatics, construction, agriculture, and heritage documentation, making manual processing impractical. Scalability, accuracy, and usability, therefore, require automation. It was a systematic review based on Scopus, IEEE Xplore, and Web of Science (2019-2025). A total of 36 articles were located using keywords, including automation, machine learning, open-source tools, and point cloud processing, which applied automation in a tool or platform. The results are organized into three domains: segmentation, classification, and reconstruction. In segmentation, voxel-based partitioning and transformer networks have been implemented in platforms such as CloudCompare and Open3D to enhance scalability and detail capture. In classification, tools are increasingly instruments that integrate machine learning with other forms of contextual reasoning, and forestry and UAV applications are examples of their potential. Reconstruction studies show an increasing relationship between BIM and heritage workflows, enabled by tools such as Cloud2BIM and Open3DGen. Although these methods reduce manual labor and increase efficiency, they still have limitations in terms of compatibility, benchmark standardization, and cross-domain applicability. The review, in general, synthesizes progress but also points out a lack of consistency in current advances. It also helps guide future point cloud research by clarifying the strengths and gaps in creating more compatible, benchmarked, and domain-flexible tool-based automation.

Keywords *– Automation, machine learning, open-source tools, point cloud processing, segmentation*

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1.0 Introduction of Point Cloud

Point clouds are three-dimensional (3D) digital models of real-world objects or environments that portray detailed information, including geometry, surface texture, and RGB (Red, Green, Blue) colour values (Razali et al., 2020, 2023). They are often produced using LiDAR technologies, such as terrestrial laser scanners (TLS), or photogrammetric methods that employ cameras and sensors (Saptari et al., 2019). Due to their ability to represent precise, dense spatial data, point clouds have become essential across many fields. They are the foundation in geomatics and surveying, as well as mobile mapping and urban modelling. Point clouds can be used in the architecture, engineering, and construction (AEC) industry to facilitate Building Information Modelling (BIM) and digital twin (Schwarz, 2010; Tang et al., 2010; Wang et al., 2015). In addition to these, they are used in robotics, autonomous vehicles, augmented and virtual reality, and 3D manufacturing (Bello et al., 2020a).

Despite the versatility, point clouds pose unique challenges. They are non-grid, sparse, and irregular, unlike 2D images. Attributes such as intensities or surface normals (Sazaly et al., 2022) are invariant to transformations. They can be present at each point, whereas the lack of regular structure makes it more difficult to apply conventional algorithms. Traditional deep learning architectures, designed to handle structured data, often underperform on raw 3D point clouds. This has motivated researchers to either tune existing models or develop new architectures, including PointNet and graph neural networks, specialized for irregular 3D data.

Traditionally, analysis was based on handcrafted features, such as manually defined scriptors to describe geometric patterns (Bello et al., 2020a). These techniques worked well with small datasets and where computational requirements were minimal. Still, they failed to scale to point cloud data collection due to the extensive reach and availability of point cloud data. The advent of deep learning, based on artificial neural networks (Hinton, 1989), has brought a major shift to the field, enabling models to learn directly from data rather than being engineered manually. This change has been accompanied by an increase in lower-cost scanning technology, which is now capable of producing large volumes of 3D information at increasingly high resolutions and over extended fields of view.

Against this background, automation in point cloud processing has become a given. The manual process is becoming unrealistic for large-scale or complex data, especially when repetitive tasks such as segmentation, classification, and reconstruction are required. Automation, particularly tool-based automation, is a potentially beneficial approach to handling such problems, and tools, particularly open-source ones, can make processes more predictable, efficient, and scalable. However, there are still doubts about the extent to which existing tools have been developed, their applicability to new areas of research, and where the most urgent gaps lie. This paper answers these questions by conducting a systematic review of 36 recent articles on tool-based automation in point cloud processing to shed light on the current capabilities, limitations, and future trends.

2.0 The Relevant Research of Automation in Point Cloud Data Processing

Automation has become primary to managing the complexity of 3D point cloud data, yet recent studies show that its outcomes are not uniform across domains. While automation improves efficiency, reduces manual labor, and enables scalable workflows, debates remain about dataset consistency, segmentation reliability, and computational costs. Comparative studies highlight that segmentation and classification accuracy often depend on the benchmark used (Sai & Pande, 2024; Zachar et al., 2023) while reconstruction approaches vary in scalability (Bassier et al., 2020; Lyu et al., 2020). This section reviews recent work, emphasizing both contributions and contradictions in how automation addresses challenges such as data volume, computational efficiency, segmentation, classification, unstructured data, and open-source tool development.

2.1 The Importance of Automation in Processing Point Cloud Data

Automation in point cloud processing supports critical domains such as construction, smart cities, and cultural heritage by reducing manual work and enabling repeatable results. Machine learning methods are primary here. Mirzaei et al. (2022) demonstrated the use of Convolutional Neural Networks (CNNs) for wall defect detection, while K-means clustering supported quality control of construction sites (Abreu et al., 2023). These methods, implemented through toolkits such as TensorFlow, Pyroflash, and Open3D, illustrate how automated inspection and monitoring can turn raw 3D data into operational use.

However, performance varies by dataset. For example, a framework for indoor segmentation using S3DIS reports an overall success rate above 98% (Mahmoud et al., 2025). By contrast, Luo et al. (2023) introduced a multi-constraint graph clustering (MCGC) approach that performed well in restoring indoor scene details, but its adaptability to outdoor datasets was not tested. Likewise, Zhang et al. (2024) demonstrated that the Convolutional Multi-Granularity Fusion Network (CMGF-Net) significantly outperformed Kernel Point Convolution (KPConv) in semantic segmentation on the Semantic3D and SensatUrban outdoor datasets, suggesting that the choice of benchmark influences reported performance. Together, these studies show that automation increases accuracy and efficiency, but results remain context dependent.

Other domains illustrate similar tensions. Zeybe (2021) applied a random forest algorithm to UAV-based point clouds, achieving high classification accuracy, though the method relied heavily on radiometric features, limiting applicability. Lu et al. (2025) shifted the focus to scalability, proposing a geometry compression model trained on ShapeNet and validated on the KITTI and ScanNet datasets. Their work highlights that while compression algorithms improve efficiency, transferability between synthetic CAD models and real-world scans remains a concern. Thus, automation is advancing rapidly, but challenges of domain adaptation, benchmark variability, and scalability remain at the forefront.

2.2 The Challenges Addressed by Automation

This section discusses the challenges addressed by automation that include issues on handling large data volumes, computational efficiency, accuracy of automated classification and segmentation, unstructured data and applicability of existing tools.

2.2.1 Data Volume Management through Automated Structuring

Processing large point cloud datasets is an ongoing challenge, particularly in heritage sites and urban scans, where billions of points must be processed. Strategies based on automated structuring, such as voxel-based partitioning, octrees, and clustering, enable algorithms to operate on smaller spatial units, which supports the preservation of geometric accuracy but lowers memory load (Poux & Billen, 2019). Escudero et al. (2024) voxel-partitioned 4 billion points from the Metropolitan Cathedral of Valencia, and the resulting 98.7% reduction in file size was relatively small in terms of detail. The additional clustering algorithms (DBSCAN and K-means) also cluster points based on density and spatial connectivity, which is useful for automated floor, wall, and other structure segmentation. However, the dataset's characteristics can influence performance. Dense or hierarchical datasets, such as CENAGIS-ALS and the airborne LiDAR benchmark dataset (Zachar et al., 2023), are harder to cluster using standard techniques, indicating a lack of applicable volume management method(Sai & Pande, 2024).

The large volume and disorganized format of point cloud data have led to the development of methods, including real-time 3D point cloud environmental contour modelling (Wu et al., 2024). The approach by Wu et al. (2024) uses structured edge-based features derived from LiDAR point distributions to generate high-density environmental maps. It selectively removes temporary objects, such as vehicles, using various LiDAR-image matching methods. This method preserves the geometric recognizability of the environment, achieves close-to-real-time processing without pre-structured point clouds, and offers an effective balance between efficiency and adaptability. Most importantly, although the approach can address storage and computational constraints, its reliance on edge-based contour extraction might not be as robust as volumetric or AI-based classification models in highly cluttered or occluded environments. Besides, omitting unstable objects presupposes high detection reliability, which may limit its applicability to dynamic or densely populated scenes. However, the contribution by Wu et al. provides a practical direction for real-time processing of massive unstructured data, complementing voxel-based and deep learning-based approaches (Escudero et al., 2024; Park & Cho, 2022).

The same cases are reported in building fields. According to Park & Cho (2022), point clouds are typically composed of millions of points; the researchers gathered 9 laser-scanned point clouds with more than 20 million points at a real construction site. Such volumes of data could not be handled manually. Their framework of Point Cloud Information Modeling (PCIM) utilised deep learning models, specifically PointNet++, to automate classification and efficiently process large datasets with minimal human intervention. They found, as reported, that PointNet++ trained in channel format (XYZ coordinates, RGB, and original intensity values) was the most appropriate for classifying the data, making it suitable for working with large volumes of data. PCIM framework significantly decreased manual segmentation and computational inefficiency by recognizing and classifying objects directly upon raw point clouds (through automatic object recognition and classification) instead of the traditional approaches (solid modelling or manual classification) that are time-intensive and resource-intensive.

Beyond computational trade-offs, the issue of interpretability is far from solved. Holzinger et al. (2025) argue that the development of theoretical explanations for 3D point clouds is still in its earliest stages, largely due to the high dimensionality and geometric complexity involved. They further note that LiDAR datasets often contain “natural noise inherent to LiDAR scanning processes,” such as reflections and artifacts, which complicates analysis and demands more robust approaches for large, noisy data.

Taken together, these findings suggest that while automated structuring enables significant reduction and even parallelized processing of massive datasets, scalability and interpretability remain open challenges. This contrast between voxel- and clustering-based approaches (Escudero et al., 2024), contour-based real-time modeling (Wu et al., 2024), and deep learning-driven frameworks (Park & Cho, 2022) reflects an ongoing debate in the field, whether efficiency in volume management is best achieved through geometry-preserving partitioning, edge-based contour mapping, or AI-based classification pipelines.

2.2.2 Computational Efficiency

One of the largest constraints in large-scale point cloud automation is computational efficiency. Billions of unstructured points require algorithms optimized for and hardware-accelerated. Unstructured data are processed directly using deep learning models, including PointNet and Multi-Layer Perceptrons (MLPs), requiring minimal processing and eliminating the need to consider computational overhead (Ding et al., 2023; Tychola et al., 2024). Transformer-based networks also achieve better efficiency because they can capture global dependencies, though their memory requirements can be prohibitive with terabyte-scale datasets.

Voxel grid downsampling, Normal Distribution Transform (NDT), and Principal Component Analysis (PCA) are popular preprocessing methods to reduce computational load before learning-based applications (Ding et al., 2023; Poux & Billen, 2019). For example, NDT partitions the space into probabilistic cells, enabling efficient computation of features with structural accuracy. Such hybrid methods are now typical of pipelines that process both indoor (S3DIS, ScanNet) and outdoor (Semantic3D, KITTI) datasets.

Here, an important point of reference is provided by Anand et al. (2020), who compare the performance of Central Processing Unit (CPU) and Graphics Processing Unit (GPU) for LiDAR point cloud processing. Their experiments, which employed the repetitive multiplication of data from a Velodyne VLP-32C sensor with 65,536 points, demonstrate the significant effectiveness of GPUs for parallel processing. The time spent processing the data decreased significantly with the number of threads, even with more GPUs, and the process could be performed almost in real time using multiple iterations on the same data set. This finding confirms that parallel processing can dramatically enhance scalability and efficiency, particularly for applications requiring rapid or continuous point cloud analysis. Nevertheless, Anand et al. (2020) also emphasize that these improvements are not without challenges. Limitations in memory bandwidth and GPU core size continue to restrict scalability as LiDAR sensors generate increasingly dense datasets. At the same time, the inherently iterative and conditional nature of many point cloud algorithms complicates their parallelization. Real-time constraints, such as the need to process frames within 0.1 seconds at 10 fps, pose additional challenges, particularly when multiple data streams are involved.

Furthermore, high-performance GPUs remain costly and power-intensive, making them difficult to use in edge devices or resource-limited environments. These trade-offs underscore that while GPU acceleration significantly enhances computational efficiency, its broader adoption will depend on algorithmic adaptation and ongoing improvements in hardware design.

Comparative studies illustrate the balance between speed and accuracy. Bassier et al. (2020) compared 2D vs. 3D reconstruction of wall geometry, showing that 3D methods are more accurate but slower, while Lyu et al. (2020) proposed a segmentation strategy to reduce computation time while maintaining surface quality. Cloud computing infrastructure, often GPU-accelerated and paired with 5G data transfer, now enables near-real-time processing of large point clouds (Tychola et al., 2024).

Beyond raw processing, computational efficiency is increasingly tied to explainability and theoretical generation. Holzinger et al. (2025), citing Levi & Gilboa (2024), highlight a “fast and easy-to-explain” method that accelerates interpretability by at least three orders of magnitude compared to conventional approaches. Their framework emphasizes rapid calculation of the importance of each point, which is essential in safety-critical domains like autonomous driving, where interpretability delays can undermine decision-making. The authors argue that explicit adjustment policies provide a scalable alternative to computationally expensive gradient-based models.

Finally, these insights underscore a widening scope of computational efficiency, not only reducing training and inference times for large datasets but also enabling real-time, interpretable explanations. The critical challenge is balancing fine-grained explanatory depth with feasible computation, an area where current point cloud frameworks still face significant limitations.

2.2.3 Automation of Segmentation and Classification

Segmentation and classification are fundamental to deriving actionable information from point clouds, but they are also the subject of controversy in the field of automation. Poux & Poncian (2020) reported that ontology-based models could achieve almost perfect precision 99.99% with planar-dominant classes when applied to voxel clustering and rule-based semantic classification in the absence of labels. In comparison, deep learning methods, including CMGF-Net (Zhang et al., 2024) and MCGC (Luo et al., 2023), demonstrated higher performance in more complex, large-scale outdoor scenarios, indicating that various approaches perform better in different settings.

Structural markers are usually used in segmentation algorithms, including planes, convexity, and colour (Luo et al., 2023; Zhang et al., 2024). To illustrate this, MCGC uses a combination of geometric constraints to retrieve finer details in indoor settings. In contrast, the Convolutional Multi-Granularity Fusion Network (CMGF-Net) uses colour and multi-scale features to segment semantics outdoors. The use of hybrid approaches combining classical clustering methods and deep learning involves a trade-off between accuracy and applicability, especially in scenarios where numerous benchmark datasets must be used (Sai & Pande, 2024).

Historically, point cloud object and material classification was based on either manual interpretation or rule-based algorithms, which were time-intensive and often domain-specific. Park & Cho (2022) proposed the PCIM framework, which automates this process using hierarchical deep learning methods. Their study employed a systematic PointNet++ model in which the first stage extracted material information using laser intensity values, followed by object classification based on this material data. As they note, "This study employs a systematic PointNet++ in which the material information is extracted first with laser intensity values, and then construction objects are classified with the material information." This automation streamlines segmentation, reduces manual effort, and increases classification accuracy. One of the core contributions of PCIM is bypassing traditional feature extraction by deploying neural network architectures that directly recognize and classify construction components. As emphasized by the authors, "The classification modules in PCIM utilize deep learning algorithms that automatically recognize material types and element categories, bypassing manual feature engineering and enhancing the speed and accuracy of segmentation."

The type of features selected also depends on classification accuracy. UAV-related research demonstrates that random forests, combined with radiometric and geometric characteristics, yield high classification accuracy (Zeybek, 2021), yet this method is less effective in indoor or densely populated environments. Likewise, hybrid AI methods (Wettewa et al., 2024; Xia et al., 2022) combining local descriptors, machine learning, and graph neural networks (GNNs) can now identify complex structural features, indicating the future potential of semantic reasoning alongside automated learning.

Interpretability has more recently been introduced to the discourse of automated segmentation and classification. Holzinger et al. (2025) describe a framework that produces meaningful theoretical scenarios through optimization and expert-guided adjustment. They use a multi-criteria optimization that trades off similarity, validity, and sparsity of theoretical, automating the interpretability procedure without using computationally intensive gradient-based generative models. This is an indication of a larger trend to human-in-the-loop systems in which automated classification is steered by domain knowledge. Nonetheless, it also raises questions about scalability: can expert-informed adjustments effectively capture the full complexity of varied real-world datasets, or will automation still threaten to oversimplify in highly dynamic environments?

In general, segmentation and classification remain context-specific, with ontology-based rules especially effective in structured and planar environments, deep learning superior in complex outdoor images, and theoretically grounded explainability starting to transform how findings are justified and understood. The contribution of Park & Cho (2022) illustrates how systematic deep learning can reduce manual intervention while improving classification performance. Still, their PCIM framework also highlights an emerging debate: whether task-specific pipelines can scale effectively across domains, or whether more applicable architectures are needed to balance accuracy, efficiency, and interpretability.

2.2.4 Handling Unstructured Data

Automation is especially challenging in unstructured point clouds, such as those encountered in plant phenotyping, forestry, or complex archaeological sites. These point clouds, unlike regular CAD-based datasets, are not inherently organized; techniques that can preserve consistency and handle variable densities, occlusions, and rotational variance are needed. Li et al. (2022) developed

DeepSeg3DMaize, which uses PointNet and multi-view image acquisition to segment plant organs, achieving F1-scores of more than 0.90. Another application to be part of their system was the semi-automatic Label3DMaize annotation tool, which reduced manual labeling while not compromising the level of training.

ResTreeNet (Kaleab Taye et al., 2025) has presented an automated classification of tree species based on terrestrial LiDAR, and Chen et al. (2019) integrated personal laser scanning with SLAM to fingerprint tree trunks and diameters in a time-saving manner. Based on these methods, Li et al. (2023) propose a holistic framework for forestry point clouds that addresses specific issues related to dense foliage occlusion, irregular sparsity, and large data volumes. Their approach presents a point cloud annotation strategy that relies on single-tree positioning, substantially increasing labeling efficiency and enabling the generation of a semantic segmentation dataset comprising 1259 scenes and over 214 billion points across 4 classes. The PointDMM model combines tree properties with a Deep Multimodal Module (DMM), builds important segmentation graphs using energy-based segmentation functions, and uses a cutpursuit algorithm to perform pre-segmentation. Multi-layer perceptron (MLP) and locally extracted features are finally fused and segmented using a lightweight PointNet, achieving 93% accuracy on the large-scale DMM-3 dataset. It also represents a 21% improvement in standing tree recognition over previous means, highlighting the benefits of customized structures in complex forestry settings.

Critically, while Li et al. (2023) demonstrate the effectiveness of combining advanced annotation strategies with deep learning, limitations remain. Reliance on dense TLS-acquired data may limit transferability to sparser UAV or mobile LiDAR datasets, and the computational requirements of such massive datasets could hinder real-time or edge deployment. Additionally, extreme terrain variability or underrepresented forest structures may still challenge the framework, underscoring the need for adaptive, scalable algorithms that can generalize across diverse forestry environments.

Deep learning architectures have also been extensively reviewed for their application in LiDAR point clouds, focusing on tasks such as segmentation, detection, and classification. These architectures are particularly crucial for autonomous driving, where processing unstructured, noisy, and massive 3D point clouds remains a significant challenge (Zhang et al., 2023). In heritage and urban contexts, unstructured scans of historic buildings or complex infrastructures require flexible methods that adapt to uneven sampling and noise. The combination of preprocessing (noise reduction, voxel downsampling) with advanced segmentation models allows for robust handling of these irregular datasets (Escudero et al., 2024; Zachar et al., 2023). However, even the most sophisticated frameworks must cope with domain-specific constraints, emphasizing that automation is not a one-size-fits-all solution.

Unstructured point cloud data also retains rich information such as colour, surface texture, and deformation, but traditional modeling methods often lose these details during conversion to meshes or CAD representations. Park & Cho (2022) address this challenge with their PCIM framework, which preserves semantic richness by storing information hierarchically within the raw point cloud itself. As they note, "PCIM can automatically recognize construction objects and their properties and store information in the original point cloud data with a hierarchical structure." This avoids the costly, error-prone processes of solid modeling while maintaining the accuracy of the raw data. By directly integrating semantic properties into the point cloud, such as material type, colour, or shape deformation, PCIM preserves the detailed, reality-based information necessary for accurate construction site modeling. In this way, PCIM demonstrates that unstructured data can be both automated and semantically enriched without sacrificing the original geometric and visual detail.

Adding another dimension, Holzinger et al. (2025) emphasize the geometric complexity and high-dimensional nature of point clouds, which make classical theoretical approaches less effective for unstructured datasets. Their framework introduces interpretable, domain-informed adjustment policies that explicitly account for geometric structure, unlike gradient-based or black-box methods. While this improves interpretability, it also introduces a dependency on expert knowledge: explicitly defining adjustments requires substantial domain expertise, potentially limiting scalability or full automation in highly complex environments such as forestry ecosystems or heritage reconstructions.

2.2.5 Role of Open-Source Tools in Addressing Automation Challenges

Open-source tools remain an important element in translating research into practice. Mesh generation and deviation analysis: CloudCompare is still popular for these tasks (Majid et al., 2024), and its automation capabilities are often workflow-based rather than fully embedded. Open3D is a general-purpose Python API that supports clustering algorithms such as DBSCAN and BIRCH (Szutor, 2020), whereas Open3DGen supports real-time 3D model-reconstruction pipelines (Niemirepo et al., 2021).

Newer devices focus on automation by domain. cLASpy_T can process 10 million points in less than two minutes to perform large-scale coastal classification (Pellerin Le Bas et al., 2024). Cloud2BIM (Zbirovský & Nežerka, 2025) directly transforms point clouds into an IFC-compliant BIM representation, dividing slabs and walls without the computationally intensive RANSAC. Its stated capacity to calculate 40 million points within 30 minutes marks a new step for architectural automation.

Specialized domains also benefit from tool-based solutions. In a previous study (Özkan et al., 2025), automated timber structure modeling outperformed manual approaches in early-stage assessments. In construction, UAV point clouds have been used for progress monitoring (Chengtao et al., 2021) and automated scaffolding inspection (Zhao et al., 2024). These applications confirm that while tools differ in focus—general-purpose libraries versus domain-specific platforms—all advance automation by balancing accuracy, efficiency, and accessibility.

While Park & Cho (2022) do not directly focus on open-source tool development, they highlight the use of existing point cloud frameworks such as pptk and Extensible Markup Language (XML) schemas to enable visualization and modification. The automation achieved through these supporting tools supports compatibility and customization, suggesting that even when patented frameworks like PCIM are applied, leveraging open tools enhances accessibility and adaptability. Critically, their study implies that greater integration with open-source ecosystems could democratize advanced automation techniques, making them more widely transferable across projects and domains.

Adding another perspective, Holzinger et al. (2025) discuss integrating multi-objective optimization algorithms into open-source platforms such as jMetalPy to generate diverse theoretical results, thereby promoting transparency, accessibility, and community engagement. Their framework claims to provide “a diversity of theoretical candidates” simultaneously, thereby enhancing user trust and enabling iterative analysis, in contrast to gradient-based methods that often offer less diverse explanations. While the reliance on open-source tools supports reproducibility and democratization of methods, it may also constrain applicability in real-time systems where computational resources are limited or expert input is not readily available.

3.0 Materials and Methods

This section describes the process undertaken to produce this review. It introduces the review protocol applied in this study and explains the study selection process, including the number of papers identified, screened, excluded, and included at each stage.

3.1 Research Design

The review utilizes a systematic method organized according to the PRISMA 2020 framework (Haddaway et al., 2022). The study was tailored to discover, filter, and critically evaluate peer-reviewed articles on tool-based automation in 3D point cloud processing, with a view to mapping the application of automation across segmentation, classification, and reconstruction. To have conceptual clarity, the review identifies three levels of automation that are related yet different. Full automation can be defined as workflows that are fully computer-controlled and require minimal or no human effort. Semi-automation refers to the use of automated tools under human supervision, with parameters adjusted or corrected as needed. Tool-based automation is a solid combination of software platforms, algorithms, and hybrid pipelines that make automation applicable in real workflows. These differences enable a more sophisticated assessment of the studies that differ in the level and the extent of automation attained.

3.2 Identification of Studies

A comprehensive search strategy was implemented to capture relevant studies from major academic databases, including Scopus, Web of Science, IEEE Xplore, and SpringerLink. Search strings combined terms such as “point cloud,” “automation,” “segmentation,” “classification,” “reconstruction,” and “tool,” with Boolean operators used to maximize retrieval. Only publications written in English and published between 2019 and 2025 were considered eligible. The search offered a total of 75 records. No additional publications were obtained from trial registers, organizational repositories, or citation chasing.

3.3 Screening and Selection Process

The records (n=75) were imported into a reference management system, which automatically identified and eliminated redundant records. At this point, four duplicates were filtered out, leaving only 71 distinct records for screening of title and abstract. The predefined inclusion and exclusion criteria were used to screen the subjects. Only eligible studies were included in peer-reviewed journals or conferences, published between 2019 and 2025, and that directly covered 3D point cloud automation or semi-automation workflows. To be included, studies were also required to cover at least one of the three types of segmentation, classification, or reconstruction and to be sufficiently detailed to be methodologically replicated.

Studies were excluded if they did not address tool-based automation (15 records), lacked sufficient methodological detail to enable replication (10 records), or were not directly related to 3D point cloud processing (9 records). Following this process, 36 studies were retained for full-text review and synthesis.

3.4 Data Extraction and Analysis

Each of the 36 studies underwent structured data extraction to enable systematic comparison. The information recorded for each study included the authorship and year of publication, the tool, framework, or method employed, the automation category to which the study contributed, and the specific contribution or focus, such as accuracy, efficiency, scalability, or workflow innovation.

To address computational overhead, the decision was made to include both software tools (e.g., CloudCompare or Open3D) and methodological approaches (e.g., Random Forest or voxel partitioning). In the field of point cloud processing, automation rarely arises from tools or algorithms in isolation; rather, it emerges from the interplay between computational frameworks and algorithmic strategies. By considering both, the review preserves an accurate representation of how automation is operationalized in practice. The extracted data were consolidated in a tabular form to provide a comprehensive overview of the included studies.

3.5 PRISMA Flow Diagram

The entire process of study selection and inclusion followed PRISMA 2020 guidelines. A PRISMA flow diagram (Figure 1) was generated using the PRISMA2020 R package and Shiny app (Haddaway et al., 2022), which ensured transparent reporting of each step from the initial identification of 75 records through screening and eligibility assessment to the final inclusion of 37 studies. The diagram is presented below.

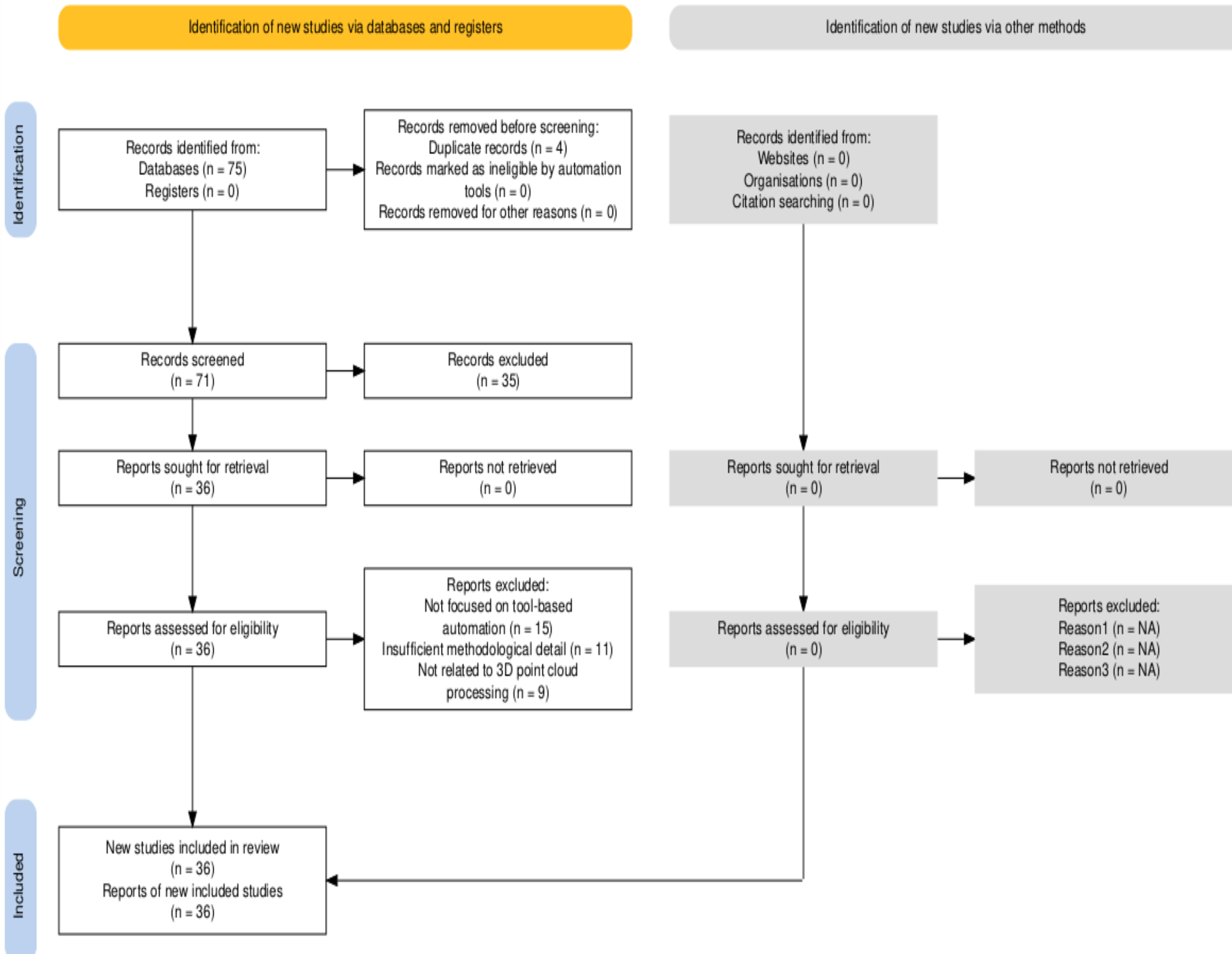

Figure 1: PRISMA flow diagram

3.6 Summary of Included Studies

The remaining 36 studies represent a broad range of automation strategies. 18 papers concerned with segmentation, with applications to indoor scene segmentation, forestry analysis, and heritage recording. 12 studies focused on classification, including tasks such as detecting structural elements, material recognition, plant phenotyping, and tree species identification. Seven studies were included in the reconstruction, covering building information modeling (BIM), real-time reconstruction pipelines, and historical timber structure modeling.

Segmentation studies were shown to be very successful when fed benchmark datasets, but in many cases, their effectiveness was limited when applied to complex or varied environments. Classification experiments achieved high task-specific accuracy, but depended on domain-specific datasets and thus had limited applicability to other contexts. Reconstruction research has advanced the automation of BIM and similar processes, but computational load and data volume remain limiting factors for large-scale use. Table 1 presents a structured summary of the included studies, outlining the tool or method employed, the automation category, and the study's main contribution.

Table 1: Summary of studies on tool-based automation in point cloud processing

No.	Domain / Application Field	Author(s) / Year	Tool/Method	Category	Contribution/Focus
1	Benchmark / Dataset Studies	Zachar et al., 2023	Benchmark datasets (CENAGIS-ALS)	Segmentation	Compared segmentation reliability across benchmarks; highlighted dataset dependency
2	Benchmark / Dataset Studies	Sai & Pande, 2024	Benchmark comparison	Segmentation	Analyzed segmentation/classification accuracy variation across datasets
3	Construction	Mirzaei et al., 2022	CNN	Classification	Automated wall defect detection using CNNs
4	Construction	Abreu et al., 2023	K-means clustering	Classification	Quality control of construction sites using clustering
5	Construction	Park & Cho, 2022	PCIM framework (PointNet++)	Classification	Automated object/material recognition in construction point clouds
6	Construction	Chengtao et al., 2021	UAV point clouds	Classification	Automated progress monitoring in construction
7	Construction	Zhao et al., 2024	UAV scaffolding inspection	Classification	Automated detection of scaffolding structures
8	Reconstruction / Scalability	Bassier et al., 2020	2D vs. 3D reconstruction	Reconstruction	Trade-off between speed (2D) and accuracy (3D) for wall geometry
9	Reconstruction / Scalability	Lyu et al., 2020	Divide-and-conquer segmentation	Segmentation	Scalable approach reducing computation

					while preserving quality
10	Reconstruction / Scalability	Lu et al., 2025	Geometry compression (ShapeNet, KITTI, ScanNet)	Reconstruction	Improved scalability; noted CAD vs. real-world transfer limits
11	Reconstruction / Heritage	Poux & Billen, 2019	Voxel partitioning	Segmentation	Reduced dataset size while maintaining detail; applied to heritage datasets
12	Reconstruction / Heritage	Escudero et al., 2024	Voxel partitioning (Cathedral of Valencia)	Segmentation	98.7% file size reduction with minimal detail loss
13	Reconstruction / Heritage	Majid et al., 2024	CloudCompare	Reconstruction	Mesh generation and deviation analysis; workflow-dependent automation
14	Reconstruction / Heritage	Niemirepo et al., 2021	Open3DGen	Reconstruction	Real-time 3D reconstruction pipelines
15	Reconstruction / Heritage	Özkan et al., 2025	Automated timber modeling	Reconstruction	Outperformed manual methods for heritage timber structures
16	Coastal / Specialized	Pellerin Le Bas et al., 2024	cLASpy_T	Classification	Large-scale coastal classification (10M pts in <2 min)
17	Indoor / Segmentation	Mahmoud et al., 2025	Indoor segmentation (S3DIS)	Segmentation	Success rate above 98% for indoor datasets
18	Indoor / Segmentation	Luo et al., 2023	Multi-Constraint Graph Clustering (MCGC)	Segmentation	Reconstructed fine indoor scene details; outdoor generalization not tested
19	Outdoor / Segmentation	Zhang et al., 2024	CMGF-Net vs. KPConv	Segmentation	Outperformed KPConv on Semantic3D & SensatUrban outdoor datasets
20	UAV / Remote Sensing	Zeybek, 2021	Random Forest	Classification	UAV-based classification with radiometric features; limited applicability

21	Forestry / Agriculture	Li et al., 2022	DeepSeg3DMaize + Label3DMaize	Segmentation	Automated plant organ segmentation with F1 > 0.90; reduced labeling effort
22	Forestry / Agriculture	Kaleab Taye et al., 2025	ResTreeNet (Terrestrial LiDAR)	Classification	Automated tree species classification
23	Forestry / Agriculture	Chen et al., 2019	Personal laser scanning + SLAM	Segmentation	Efficient tree trunk and diameter inventory
24	Forestry / Agriculture	Li et al., 2023	PointDMM framework	Segmentation	Forestry semantic segmentation (1259 scenes, 214B points, 93% accuracy)
25	Autonomous Driving / LiDAR	Zhang et al., 2023	Deep learning architectures	Segmentation	Reviewed LiDAR deep learning methods for autonomous driving
26	Real-Time / Edge / Efficiency	Wu et al., 2024	Real-time edge-based contour modeling	Segmentation	Real-time processing of unstructured LiDAR; excluded temporary objects
27	Real-Time / Edge / Efficiency	Ding et al., 2023	PointNet + preprocessing	Segmentation	Improved efficiency with downsampling and PCA preprocessing
28	Real-Time / Edge / Efficiency	Tychola et al., 2024	Transformer-based networks	Segmentation	Captured global dependencies for large-scale datasets
29	Real-Time / Edge / Efficiency	Anand et al., 2020	CPU vs. GPU benchmark	Efficiency	Demonstrated GPU parallelism benefits for LiDAR datasets
30	Real-Time / Edge / Efficiency	Levi & Gilboa, 2024	Theoretical interpretability	Classification	Accelerated interpretability 1000x compared to conventional methods
31	Explainable AI / Hybrid Methods	Holzinger et al., 2025	Theoretical adjustment policies	Classification/Segmentation	Enhanced interpretability with domain-informed adjustments
32	Explainable AI / Hybrid Methods	Poux & Ponciano, 2020	Ontology-based semantic classification	Segmentation	99.99% precision for planar classes without labeled data

33	Explainable AI / Hybrid Methods	Xia et al., 2022	Hybrid AI (local descriptors + ML)	Classification	Detected complex structures with combined semantic reasoning
34	Explainable AI / Hybrid Methods	Wettewa et al., 2024	Graph Neural Networks (GNNs)	Classification	Structural detection using hybrid AI + GNNs
35	Tools / Open-Source	Szutor, 2020	Open3D (DBSCAN, BIRCH)	Segmentation	Provided clustering functions for automation
36	Tools / Open-Source	Zbirovský & Nežerka, 2025	Cloud2BIM	Reconstruction	IFC-compliant BIM automation; processed 40M points in 30 mins

4.0 Review Findings

This section summarizes the results of the 36 articles incorporated into this review. It systematizes them into 3 areas of tool-based automation in 3D point cloud processing: segmentation, classification, and reconstruction. Whereas previous reviews have focused mostly on the advancement of algorithms (Bello et al., 2020b; P. Li et al., 2020; Tychola et al., 2024), the current analysis explores how these techniques are implemented through tools and workflows. This attention enables further evaluation of usability, scalability, and integration possibilities - aspects that ultimately lead to the migration of automation beyond academic prototypes to viable implementation in geospatial and engineering environments.

4.1 Segmentation

Segmentation remains the most extensively studied area, with more than half of the reviewed papers addressing it. The methods range from voxel-based approaches (Escudero et al., 2024; Poux & Billen, 2019) to advanced machine learning architectures such as transformers (Tychola et al., 2024) and multi-constraint graph clustering (Luo et al., 2023).

Classical techniques like voxelization are effective at reducing data volume while preserving sufficient structural information. An example of such a study is that conducted by Escudero et al. (2024), who reported 98.7% decrease in file size for heritage datasets with only a slight loss of information. These methods are recommended for dynamic data collection when there are enormous data volumes but minimal scene variability. This context sensitivity shows that scalability is not a technical issue of efficiency but a conceptual one, as techniques that perform well in small datasets, typically in indoor settings, are seldom applicable to the complex conditions of the outdoors. Voxelization, however, is not as effective in complex or rough outdoor conditions. More recent learning-based models have developed this weakness by learning to capture dependencies across global scenes and finer-grained object features. Concurrently, they are limited in their general applicability due to their heavy reliance on large training datasets and substantial computational resources.

Comparing algorithms through benchmarks reveals inconsistencies in segmentation results. Zachar et al. (2023) have shown that accuracy can vary dramatically across datasets, and Sai & Pande (2024) have also established that a model that performs well on one benchmark can perform poorly on another. These results highlight the continuing problem of applicability and indicate that the claims of superiority in single experiments should be viewed cautiously. This problem is reinforced by the lack of cross-domain benchmarking, which makes it unclear whether performance improvements are due to methodological improvements or to dataset-specific fine-tuning.

Another line of research highlights the trade-off between processing speed and segmentation accuracy. Wu et al. (2024) developed a real-time edge-based method capable of segmenting unstructured LiDAR data, though this came at the cost of excluding temporary objects. In contrast, methods such as those by Luo et al. (2023) and Zhang et al. (2024) achieved high-quality segmentation but required significant preprocessing and GPU acceleration. This contrast illustrates the tension between achieving operational efficiency and maximizing precision.

Segmentation has also seen increasing specialization within domains. Y. Li et al. (2022) developed DeepSeg3DMaize for agricultural datasets, achieving high accuracy with reduced labeling demands. Similarly, forestry-focused frameworks such as PointDMM (J. Li et al., 2023) demonstrated strong performance across large datasets. These cases illustrate both the value of targeted approaches and the difficulty of translating them to broader contexts.

Taken together, segmentation research demonstrates substantial progress, but results remain heavily dataset- and domain-dependent. Advances in hybrid approaches that combine the efficiency of geometric methods with the adaptability of machine learning may offer a way forward. However, standardization of datasets and benchmarks remains an unmet need.

4.2 Classification

The second most common research design used in this review was classification, with 13 studies. The tools included both classical machine learning models and deep neural networks and hybrids. Previous methods, such as Random Forests (Zeybek, 2021) and K-means clustering (Abreu et al., 2023), have been proven useful for UAV-based mapping and construction monitoring but have limitations in manual feature engineering and in cross-context transferability. Improved models, including CNNs (Mirzaei et al., 2022) and Forestry-specific models such as ResTreeNet (Kaleab Taye et al., 2025), achieved higher accuracy and often compete with human annotation.

One recent effort is to make classification models more interpretable. Holzinger et al. (2025) proposed theoretical adjustment policies to provide an understanding of a model's decision-making, and Levi & Gilboa (2024) demonstrated that interpretability can be computationally more efficient. These contributions address growing concerns about the lack of understanding of the black-box properties of deep learning models, an obstacle to their use in practice when accountability is needed. However, these solutions are still experimental; their integration into standard tools is not yet well developed, and it is unclear whether interpretability will be given priority in commercial or operational applications.

Hybrid approaches also reflect an important shift in the field. Xia et al. (2022) combined local geometric descriptors with machine learning to capture complex structural patterns, while Wettewa et al. (2024) demonstrated the utility of combining graph neural networks with semantic reasoning. Such frameworks go beyond raw pattern recognition to incorporate contextual knowledge, resulting in more robust classification across diverse domains.

Nevertheless, the reviewed studies reveal that classification methods remain scattered. Different domains often rely on unique datasets and metrics, hindering comparability and slowing the development of cross-domain solutions. This lack of standardization limits scalability and complicates efforts to evaluate progress across the field.

Overall, classification research is moving toward more interpretable, hybrid, and domain-aware methods. Without standardized benchmarking frameworks, the field risks producing a patchwork of highly accurate but non-transferable models, undermining the promise of automation at scale.

4.3 Reconstruction

Ten papers focused on reconstruction, including both classic geometric constructions and more recent domain-oriented models. At the algorithmic level, researchers such as Bassier et al. (2020) have emphasized the trade-off between 2D and 3D reconstruction: the former is efficient, while the latter is more accurate at a higher computational cost. The compression-based approaches (Lu et al., 2025) also addressed the scalability problem but showed a decline in performance when applied to real-world data.

The importance of open-source platforms, which is continually emphasized in the reviewed literature, is also emphasized. An example of this is CloudCompare, which Majid et al. (2024) demonstrated as enabling quality mesh generation and deviation analysis. However, the results were still strongly influenced by the workflow options and parameter optimization. Other tools, such as Open3DGen (Niemirepo et al., 2021) and Cloud2BIM (Zbirovský & Nežerka, 2025), provided more integrated pipelines, with the latter being IFC-compliant BIM automation capable of objectively working with large-scale data.

Heritage-focused applications provided additional insights into the benefits of automation. Özkan et al. (2025) demonstrated that automated timber modeling could outperform manual workflows, while Escudero et al. (2024) showed that voxel partitioning improved the processing of irregular scans in architectural settings. However, these domain successes often come at the cost of broader adaptability, since methods optimized for heritage or timber structures may not generalize to infrastructure or urban contexts. These examples illustrate the practical utility of reconstruction automation in domains where manual methods are prohibitively time-intensive.

Across the reviewed work, reconstruction tools appear to be advancing toward domain-specific integration, but remain limited in their applicability. This reliance on domain-specific tailoring also reveals a structural weakness: reconstruction pipelines are rarely modular, meaning segmentation or classification limitations cascade into reconstruction errors, limiting their robustness across workflows.

4.4 Cross-Cutting Challenges

Across the three domains, several challenges reappear. Scalability remains a pressing issue, with GPU acceleration shown to be critical for large datasets (Anand et al., 2020), yet not universally supported across open-source platforms. Dataset dependency continues to undermine applicability, as evidenced in segmentation and classification benchmarks (Sai & Pande, 2024; Zachar et al., 2023). Reconstruction tools, while increasingly effective, often remain locked into specific workflows without broader compatibility. This isolation prevents knowledge transfer between domains and limits opportunities for cumulative innovation, as advances in one sector (e.g., forestry) rarely influence progress in another (e.g., urban mapping).

Another overarching limitation is the absence of standardized evaluation protocols. The lack of consistency across datasets, domains, and performance measures makes it difficult to compare tools or synthesize results meaningfully. While widely used benchmarks such as S3DIS, Semantic3D, and KITTI have driven significant progress, they remain highly domain-specific. The fragmentation is particularly visible in the datasets used for evaluation, which, while necessary for progress, have inadvertently reinforced narrow specialization. Table 2 summarizes the common datasets used in recent studies, highlighting their contributions and limitations.

Table 2. Benchmark Datasets Commonly Used in 3D Point Cloud Automation Research

Dataset	Domain/Focus	Typical Applications	Limitations
S3DIS (Stanford Large-Scale 3D Indoor Spaces)	Indoor scenes	Indoor segmentation, object recognition	Limited to office-type layouts; not representative of diverse indoor environments
Semantic3D	Outdoor urban LiDAR	Semantic segmentation, urban modeling	Static scenes only; lacks temporal dynamics
SensatUrban	Large-scale aerial/urban	Outdoor segmentation and classification	High variability but annotation inconsistencies
KITTI	Autonomous driving	Road scene segmentation, object detection	Focused on the automotive context; limited to roadside perspectives
ScanNet	Indoor RGB-D scans	3D reconstruction, semantic segmentation	Strong for indoor benchmarking; lacks outdoor variability
ShapeNet	Synthetic CAD models	Geometry learning, reconstruction	Synthetic → poor transfer to real-world data
CENAGIS-ALS	Airborne LiDAR benchmarks	Segmentation reliability comparison	Dataset-specific biases; not yet widely adopted

Label3DMaize	Agricultural/plant structures	Automated plant segmentation	Highly domain-specific; low applicability

As Table 2 illustrates, benchmark datasets have been necessary in driving progress, but their domain-specific nature has reinforced fragmentation. The lack of cross-domain datasets not only limits the comparability of tools but also hinders their scalability beyond the niche contexts in which they were developed.

Ontology-based approaches (Poux & Ponciano, 2020) suggest one possible path forward by integrating semantic reasoning into workflows, but these remain underexplored in combination with recent advances in deep learning. Without broader, standardized benchmarks that extend across domains, tool development risks remaining scattered and difficult to evaluate on common ground.

4.5 Future Potential

In the future, some directions are particularly promising for the further development of tool-based automation of 3D point cloud processing. The creation of open, standardized benchmarks spanning fields such as indoor mapping, forestry, agriculture, and heritage is a primary focus. In the absence of such structures, comparative assessments are isolated, and tool development occurs in isolation as well. It is also important to include strategies for geometry and semantics. To illustrate, voxel partitioning and transformer-based architectures might be combined to address the shortcomings of both geometric and learning-only approaches to automation, achieving a more robust, context-sensitive automation.

One consistent issue is the inability of current tools to interoperate, thus compelling practitioners to implement ad hoc solutions. The research should then focus on developing more integrated toolchains to bridge the gap between general-purpose platforms (such as CloudCompare) and specialized systems (such as Cloud2BIM). The interoperability of these platforms would enable workflows to be more easily transferred across BIM, GIS, and visualization systems, so that ad hoc data conversions and manual modifications are not necessary. Scalability and advancements in real-time processing are also extremely important. The use of GPUs and cloud computing, along with compression algorithms that balance efficiency and accuracy, will be needed to ensure that automation can scale to larger point cloud datasets.

Finally, lessons learned from successful domain-specific applications, such as DeepSeg3DMaize in agriculture or ResTreeNet in forestry, need to be translated into more applicable frameworks. While domain tailoring has proven effective for achieving high accuracy, the field will benefit most from approaches that can adapt flexibly across diverse contexts. Achieving this balance between specialization and generalization will be key to ensuring that tool-based automation moves beyond niche applications and into mainstream geospatial practice.

4.6 Analysis

A combination of reviewed studies demonstrates that tool-based automation in 3D point cloud processing has improved since 2019. The methods of segmentation are becoming more precise and effective, classification models are being shifted towards interpretability and hybrid rationale, and reconstruction tools are being integrated into real-world processes. However, progress is conditional: approaches can usually be effective within limited fields but tend to be ineffective in terms of generalization, scaling, and cross-platform compatibility.

The strengths and weaknesses of tools differ drastically across disciplines, as summarized in Table 3. Voxel-based methods are useful for reducing the size of structured datasets, but not for representing complex outdoor variability in segmentation. In contrast, deep learning methods can capture fine details but require expensive computational resources. In classification, the transition to hybrid, interpretable deep learning models is evident, though the lack of standardized benchmarks undermines comparability. Open-source tools like CloudCompare and Open3DGen are mentioned in reconstruction as a means of accessible automation; more specific tools like Cloud2BIM demonstrate efficiency in a BIM process, but commonly at the expense of greater flexibility.

In contrast to earlier reviews that mostly list algorithmic innovations, this work notes the realities of tool-driven automation, where dataset dependency, computational demands, and the persistence of semi-automated workflows dilute success stories. When acquiring the future, a focus on standardized benchmarks, hybrid strategies, and integrative toolchains will be needed to make dried-up research results scalable, transferable, and industry-accessible. In that regard, it is no longer just a technical issue but an institutional one: unless researchers, industry, and standards organizations converge on benchmarks and compatibility, the danger of scattered development and isolated advancement is great.

Table 3. Overview of Tool-Based Automation in 3D Point Cloud Domains

Domain	Tools/Frameworks	Strengths	Weaknesses	Typical Applications
Segmentation	Voxelization (Escudero et al., 2024; Poux & Billen, 2019); Transformers (Tychola et al., 2024); Graph clustering (Luo et al., 2023)	Efficient at dataset reduction; transformers capture global context; graph methods handle structural complexity	Voxelization struggles with irregular outdoor data; learning-based methods require large training datasets and high compute power	Heritage datasets; large-scale outdoor mapping
Classification	Random Forests, K-means (Abreu et al., 2023; Zeybek, 2021); CNNs (Mirzaei et al., 2022); ResTreeNet (Kaleab Taye et al., 2025); Hybrid GNN-semantic (Wettewa et al., 2024)	Traditional ML is simple and interpretable; deep learning achieves high accuracy; hybrid methods incorporate context; recent work emphasizes interpretability	Traditional ML requires manual feature engineering; DL methods are “black box” and domain-dependent; lack of standardized benchmarks	Forestry monitoring, UAV mapping, construction
Reconstruction	CloudCompare (Majid et al., 2024); Cloud2BIM (Zbirovský & Nežerka, 2025); Open3DGen (Niemirepo et al., 2021); Compression (Lu et al., 2025)	Open-source tools are accessible; BIM-compliant workflows; compression improves scalability; strong domain-specific performance (heritage, architecture)	Performance drops in real-world vs. synthetic data; heavy parameter tuning; tools often locked into specific workflows	Heritage documentation, BIM-GIS integration, infrastructure modeling

5.0 Conclusion

Point cloud processing automation has become a growing critical consideration as the size and variety of 3D datasets exceed the capacity of manually driven methods. This review presents a synthesis of tool-based automation, with a special focus on open-source platforms and their contribution to accessible, replicable, and efficient workflows. Reviewing recent research in 2019-2025, the review identified three broad areas of development: segmentation, classification, and reconstruction, and how tools such as CloudCompare, Open3D, Cloud2BIM, and cLASpy_T have enhanced automation in real-world applications such as indoor mapping, infrastructure inspection, forestry, and agriculture.

The most important lesson is that automation is no longer an experimental algorithm but is woven into systems that practitioners interactively use. Computational efficiency and segmentation accuracy have been enhanced by machine learning and deep learning techniques, especially voxel-based structuring, connected-component clustering, and ontology-based classification, while minimizing reliance on manual processing. Nevertheless, there are still sustained difficulties. Most tools are incompatible, and practitioners have to settle for ad hoc conversions and disorganized workflows. Hardware requirements and scalability limitations may still hamper real-time processing, and the lack of standardized benchmarks makes cross-domain evaluation and comparability impossible.

The field's future looks promising in three interconnected directions. First, greater attention should be paid to compatibility to enable general-purpose platforms and specialized systems to work more closely together, facilitating the harmonization of workflows across BIM, GIS, and visualization systems. Second, future tools should focus on balancing semantic intelligence and geometric robustness, combining ontology-driven reasoning and learning-based systems to generate more context-aware automation. Third, the scalability of point cloud data, enabled by GPU acceleration, cloud computing, and data compression, will play a vital role in managing the fast-growing volume. These objectives cannot be realistically achieved solely through technical innovation, but also through the transition to open, standardized frameworks that enable benchmarking, validation, and the reuse of results across fields.

In general, this review shows that tool-based automation has become an essential facilitator of effective 3D analysis. Although there are still considerable hurdles, the research trend indicates a consistent move towards more intelligent, compatible, and scalable solutions. The critical synthesis of existing trends and identification of gaps make this study a contribution to a better understanding of the current state of automation and where it should go to achieve its full potential in geospatial science and related fields.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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