GEOMATICS AND ENVIRONMENTAL ENGINEERING • Volume 20 • Number 4 • 2026

https://doi.org/10.7494/geom.2026.20.4.123

Point Cloud Technologies for Smart Cities: Acquisition, Processing, and Applications

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Abstract: Recent progress in LiDAR, UAV, and photogrammetric systems has made spatial data collection faster and more accessible. These tools enable the acquisition of detailed point clouds that form the foundation for many smart city applications. Efficient processing of these datasets is now a practical necessity, especially for everyday tasks such as monitoring roads and bridges, managing traffic, or building 3D city models used in digital twins. This paper reviews both classical and deep learning-based processing methods, data acquisition techniques, and multi-sensor integration strategies. Furthermore, the paper highlights applications beyond infrastructure, such as environmental monitoring of green areas and the analysis of pedestrian and bicycle networks. Despite the significant progress achieved in recent years, several open challenges remain. Among the most important are the need for standardized data formats, improved computational efficiency, and robust fusion of heterogeneous sensor data. Overcoming these difficulties is key to ensuring that digital twins and AI-based analysis become useful tools in practical urban management. Ultimately, continued progress in this field can make a meaningful contribution to the development of smarter and more sustainable cities.

Keywords: point clouds, smart cities, LiDAR, machine learning, digital twin

Received: October 13, 2025; accepted: May 1, 2026

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1. Introduction

1.1. The Development of Smart Cities

Urban areas are growing rapidly, increasing pressure on public services and infrastructure. These challenges are clear in many European cities, including Krakow, where sustainable resource management is becoming a priority. The smart city idea materializes via the integration of information and communication technologies (ICT), the Internet of Things (IoT), artificial intelligence (AI), and advanced geospatial systems [1] into urban governance and service delivery frameworks. Through this integration, cities can plan resources more effectively, repair infrastructure before it fails, and build applications that react to real-time changes in traffic or weather [2–5]. With information from sensors and networks, cities can take proactive steps rather than responding only after issues arise in mobility, energy use, waste management, and public safety.

At the core of these capabilities is 3D spatial modeling, which accurately represents the shapes of urban objects and surfaces. Point clouds consist of millions to billions of points, each with spatial coordinates (X, Y, H) and attributes such as return intensity or RGB color. When integrated with IoT-derived metrics (air quality, traffic flow, energy consumption), these geometric datasets form the foundation for digital twins: virtual replicas of physical cityscapes that support scenario-based simulations and impact assessments. These digital twins allow planners to see how new developments, climate resilience projects, or transport plans might affect the city before committing resources [1, 6–8].

1.2. Point Clouds: Sources and Applications in Smart Cities

Point clouds are generated by diverse technologies, each contributing unique strengths. LiDAR (Light Detection and Ranging) systems emit laser pulses and measure the time of flight of the emitted laser pulses to derive precise distance measurements, making them essential for large-scale urban mapping, bridge scanning, and detailed façade reconstruction [6, 7]. RGB-D cameras capture synchronized color imagery and depth maps via Time-of-Flight or stereovision, providing cost-effective solutions for indoor mapping and small-scale urban surveys [9]. Photogrammetry reconstructs 3D geometry from overlapping optical images, enabling high-resolution terrain and building modeling from aerial or terrestrial photos [10]. Multi-sensor platforms combine LiDAR, RGB-D, drone imagery, GNSS/INS modules, and IoT sensor networks to produce comprehensive spatial datasets. However, it remains challenging to standardize formats and synchronize data from multiple sources [1, 11, 12].

These point clouds form the foundation for many smart city applications that require accurate and dynamic spatial models. 3D city modeling with digital twins enables the visualization and analysis of urban infrastructure, including buildings and transport networks [13, 14]. In infrastructure monitoring and management, point clouds are used to assess the technical condition of buildings, roads, and bridges [15, 16]. They also play a crucial role in urban planning, where detailed 3D models support decision-making in land use and city development [1]. In the field of autonomous vehicles, navigation systems rely on point cloud data for obstacle detection and route planning [17–19]. Additionally, spatial data analysis supports environmental protection by facilitating the monitoring of green urban areas and predicting environmental changes [14, 20].

1.3. Technologies in Point Cloud Processing

Recent progress in point cloud acquisition and processing is largely powered by specialized deep learning methods that address the limitations of traditional techniques such as Iterative Closest Point (ICP). The PointNet model introduced a new idea: it could analyze raw 3D points directly, without first arranging them into grids or voxels. It applies shared multilayer perceptrons (MLPs) to each point coordinates and features, then aggregates the results via a symmetric max-pooling function, guaranteeing permutation invariance and enabling end-to-end learning of both global shape descriptors and per-point semantic scores [21, 22]. In practice, PointNet is rarely used alone; researchers often combine it with voxel-based preprocessing to improve stability.

Building on this idea, KPConv defines a continuous convolution operator on point clouds by placing a small set of "kernel points" in each local neighborhood and learning weight functions that deform to match the underlying geometry. This deformable kernel allows KPConv to capture fine-grained spatial patterns (edges, corners, and surface curvatures) while maintaining translation equivariance and parameter efficiency that make grid-based convolutions so powerful in image analysis [22].

RandLA-Net addresses the challenge of scaling deep learning to millions of points typical in urban scans. It employs a fast, random sampling strategy to progressively downsample the input cloud, coupled with Local Feature Aggregation modules that aggregate neighborhood information via attentive pooling. This design retains salient geometric details while dramatically reducing computational cost, enabling RandLA-Net to perform efficient, high-accuracy semantic segmentation on city-scale point clouds [23]. Together, models such as PointNet, KPConv, and RandLA-Net show how quickly neural networks are changing the way we process 3D point clouds.

1.4. Research Challenges and Article Objectives

Despite significant progress in point cloud acquisition and processing, several research challenges remain. The integration of data from heterogeneous sensors lacks standardized methods for efficiently merging information from various sources [24, 25]. Computational efficiency also remains a concern, as processing large datasets requires advanced algorithms and robust computational infrastructure [26, 27]. Additionally, incomplete data, often characterized by gaps and noise, create difficulties for practical applications [20, 28]. System scalability is another challenge, as point cloud processing systems must be capable of handling the demands of large cities [11, 29].

The aim of this review article is to present existing technologies for acquiring and processing point clouds and to discuss methods for integrating data from various sensors, along with their applications in smart cities. It also seeks to identify research gaps and potential future directions that could support the continued development of smart cities [30].

2. Technologies for Point Cloud Acquisition in Smart Cities

Advances in spatial data acquisition technologies enable precise 3D point cloud representations of urban environments. These datasets are a key resource for various smart city applications, including infrastructure monitoring, urban planning, and environmental modeling. This section explores the main technologies used for point cloud acquisition, focusing on LiDAR systems, RGB-D cameras, and multisensor data integration.

2.1. LiDAR (Light Detection and Ranging)

LiDAR is a widely used technology for acquiring high-precision 3D point clouds. It operates by emitting laser pulses and measuring the time it takes for them to return to the sensor, enabling accurate distance calculations and spatial positioning of objects [31]. Depending on the application, LiDAR systems can be classified into airborne, UAV-based, mobile, and terrestrial platforms.

Airborne LiDAR, mounted on manned aircraft, is commonly used for large-area mapping, including regional topography, urban planning, and infrastructure management. It allows rapid acquisition over thousands of square kilometers, providing extensive coverage that makes it cost-effective for large-scale projects. However, operational costs remain high due to the need for specialized aircraft, certified pilots, and suitable weather conditions. Airborne LiDAR typically provides decimeter-level accuracy, depending on acquisition conditions [12, 31]. UAV-based LiDAR operates at lower altitudes and is suitable for smaller areas requiring higher spatial detail, such as city districts, corridors, or construction sites. UAV platforms are generally less expensive than manned aircraft, but covering large areas becomes time-consuming and increases operational costs. Therefore, UAV surveys are most efficient for detailed mapping, urban modeling, vegetation assessment, and infrastructure inspection, rather than regional-scale coverage. Due to lower flight altitude, UAV-based LiDAR can achieve higher accuracy, typically at the centimeter level [32]. Mobile LiDAR, mounted on vehicles, is particularly useful for mapping road networks and assessing infrastructure conditions, providing detailed street-level scans. Mobile LiDAR achieves, on average, centimeter-level accuracy depending on positioning quality and trajectory estimation [33, 34]. Terrestrial LiDAR, set up on tripods, is used for high-precision scanning of specific objects, such as historical buildings and bridges. It delivers dense, accurate point clouds, but it is time-consuming and requires multiple measurement setups. This method provides the highest accuracy among LiDAR techniques, typically at the millimeter level [34, 35]. It is worth noting that mobile and terrestrial laser scanning have a limited effective range.

LiDAR sensors are often used in autonomous vehicle navigation, as they provide critical data for obstacle detection and route planning [6, 18, 36]. Camera-only and radar-centric systems are also viable alternatives. Relevant alternatives are discussed in the literature on sensor technology for autonomous systems [19, 37].

2.2. RGB-D Cameras and UAV

RGB-D cameras simultaneously capture both color (RGB) and depth (D) information, using technologies such as Time-of-Flight (ToF) and stereovision to generate point clouds. These cameras are increasingly used in indoor and small-scale urban applications due to their cost-effectiveness and ease of deployment [9, 38].

SLAM (Simultaneous Localization and Mapping) techniques are crucial in mobile robotics and autonomous vehicle navigation, enabling real-time environmental mapping and pose estimation [39]. A representative application of RGB-D cameras is the reconstruction of building interiors, where they enable the creation of detailed 3D models for architectural analysis and virtual reality applications [40, 41], as described in dense 3D mapping studies [42]. SLAM is also applied in handheld or mobile LiDAR scanners, enabling 3D mapping of indoor and complex environments [43].

In robotics, these cameras enhance navigation systems by providing depth data for obstacle detection and environmental mapping, where RGB-D supports SLAM [44, 45]. Furthermore, RGB-D cameras play a role in intelligent surveillance systems, allowing for real-time monitoring of pedestrian and vehicle movements in urban areas, particularly in indoor or robotic navigation contexts [46, 47]. Benchmark datasets such as SUN RGB-D [40] provide standardized environments for testing segmentation, detection, and localization algorithms using RGB-D data, aiding the development of robust perception systems.

In addition to ground-based deployments, RGB-D cameras are increasingly mounted on unmanned aerial vehicles (UAVs) to complement photogrammetry and LiDAR. UAV platforms enable flexible data acquisition in hard-to-reach and smaller areas [31, 48, 49]. Their key advantage is the simultaneous capture of color and depth, which facilitates segmentation and object recognition without the need for complex stereo reconstruction [50]. Despite these benefits, UAV-mounted RGB-D sensors face important challenges. Their effective depth range is limited, and strong sunlight can reduce measurement accuracy, which is typically at the centimeter level under controlled conditions but degrades significantly in outdoor environments, making them mostly reliable in semi-controlled settings or for close-range inspections [50, 51]. Moreover, payload and energy constraints on UAVs require careful integration of lightweight cameras, stabilizing gimbals, and efficient onboard processing to ensure both data quality and flight safety.

Current applications demonstrate their potential in infrastructure inspections (bridge or aircraft fuselage scanning), indoor mapping of large halls, and filling occlusion gaps in photogrammetric surveys. Hybrid workflows are especially promising, where UAV LiDAR or structure-from-motion pipelines capture the overall geometry, and RGB-D data provide dense local depth and semantic details. Future research should aim to improve the outdoor performance of RGB-D sensors, advance robust multi-sensor fusion techniques, and establish standardized UAV-specific processing workflows [48–51].

2.3. Data Integration from Multiple Sensors

To make point clouds more accurate and complete, data from multiple sensors is often combined. By fusing LiDAR, RGB-D cameras, drone imagery, and GNSS/INS data, comprehensive spatial models can be generated from these point clouds, with improved resolution and reliability [7, 24, 29].

Various methods are used for data integration, including the ICP algorithm, which aligns point clouds by minimizing the distance between corresponding points. Feature-based algorithms enhance registration accuracy by identifying distinctive object features [28, 29]. More recently, deep learning-based approaches, such as voxel-based and GNN-based (Graph Neural Network) methods, have been developed to optimize sensor fusion, leveraging neural networks to merge heterogeneous data sources effectively [22, 52, 53].

Table 1. Comparison of technologies and methods

Technology / Method	Description	Advantages	Limitations	Smart city applications	Accuracy
LiDAR	Laser pulses for precise 3D scans (aerial, mobile, terrestrial)	High to moderate accuracy, large-scale coverage	Expensive, weather-sensitive, mobile scanners have a limited range	3D city models, digital twins, roads, infrastructure, and autonomous cars	dm for ALS mm for TLS cm for MLS
RGB-D cameras	Capture color + depth via ToF or stereovision	Cheap, easy setup, good for real-time mapping	Short range, poor outdoor performance	Indoor mapping, VR/AR, robotics, surveillance	≤1 GSD for *XY* ≤2 GSD for *Z*
RGB-D on UAVs	Drones with RGB-D for depth + color mapping	Flexible, fills gaps, adds semantic detail	Limited outdoor performance, payload & battery issues	Bridge / building scans, large halls, hybrid with LiDAR	≤1–2 GSD for *XY* ≤2–3 GSD for *Z*
Multi-Sensor Integration	Fusion of LiDAR, RGB-D, UAV, GNSS/INS data	More complete and accurate models	No standardization, scalability issues	Urban 3D models, traffic monitoring, autonomous driving	Depending on methods

The integration of multiple sensors is crucial in various smart city applications. For instance, combining LiDAR and RGB-D camera data allows for the generation of highly detailed 3D urban models. In intelligent transportation systems, the fusion of LiDAR and GNSS/INS data enhances traffic monitoring and autonomous vehicle navigation [25, 40, 54]. Despite these advancements, challenges remain in standardizing sensor fusion methodologies and ensuring scalability for large urban environments [11, 27]. Table 1 presents a comparison of the methods and technologies mentioned.

3. Point Cloud Processing Techniques

Despite their precision and detailed spatial content, point clouds must be processed with advanced techniques to be truly useful. The processing workflow consists of multiple stages, including registration, filtering, segmentation, classification, and 3D reconstruction. These steps are crucial for smart city applications, as they enable detailed analysis of urban environments, infrastructure monitoring, and the integration of data from diverse sources. This section introduces the main techniques for point cloud processing, highlighting the differences between classical methods and deep learning approaches [24, 30, 54, 55]. Figure 1 shows the point cloud processing pipeline for smart city applications.

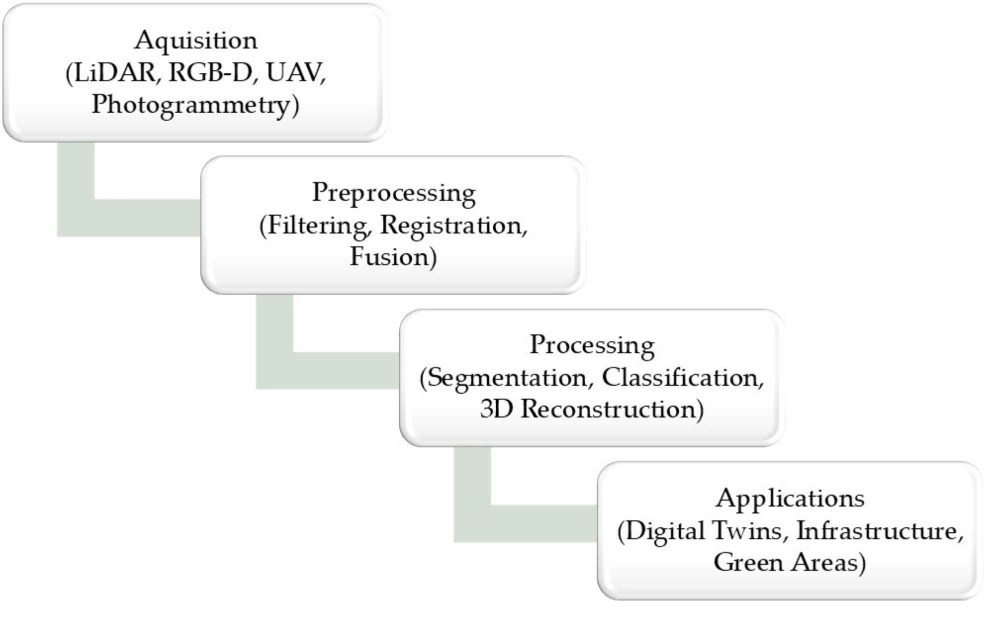

Fig. 1. Overview of the point cloud processing pipeline for smart city applications

3.1. Point Cloud Registration

Accurate registration of multiple scans into a common coordinate system is foundational for sensor fusion, change detection, and multi-temporal analysis. The classical ICP algorithm iteratively minimizes point-to-point distances but is sensitive to initial alignment and noise, often converging to local minima when the overlap is limited. The Normal Distribution Transform (NDT) improves robustness by matching statistical distributions of local surface patches rather than individual points, facilitating alignment under significant displacements [29]. Feature-based methods extract descriptive signatures. Fast Point Feature Histograms (FPFH) capture local geometric variations, while Signature of Histograms of OrienTed normals (SHOT) establishes correspondences even in complex urban topologies [28]. Recent deep learning methods, including Deep Closest Point (DCP) and 3DMatch, learn feature representations and matching patterns directly from training data, resulting in higher accuracy and better resilience to occlusions, varying point densities, and sensor noise in real-world scenarios [56, 57]. For example, 3DSmoothNet, an advanced deep-learning descriptor evaluated on the 3DMatch benchmark, achieves an average recall of around 94.9%, outperforming traditional handcrafted methods by more than 20 percentage points. Similarly, DCP demonstrates significantly better alignment accuracy on ModelNet40 compared to ICP and PointNetLK, showing the effectiveness of learned features in predicting 3D transformations even under challenging conditions [58, 59].

3.2. Point Cloud Filtering

Filtering improves data quality by removing noise, outliers, and redundant points, thereby making subsequent processing more efficient. Statistical outlier removal evaluates the distribution of neighbor distances and discards any point whose average distance to its k-nearest neighbors exceeds a set threshold [55]. Density-based filters adjust to local point concentrations, keeping fine details in sparse regions while eliminating false returns in dense clusters. Voxel grid downsampling divides space into uniform cells and keeps representative centroid points, significantly reducing the dataset size while preserving its overall structure [6, 60]. Adaptive downsampling refines this approach by dynamically adjusting cell sizes based on curvature or surface variation, ensuring that critical geometric features (edges, corners, junctions) remain well represented in large-scale urban scans [26, 61].

3.3. Point Cloud Segmentation

Segmentation breaks point clouds into semantically or geometrically consistent regions, allowing focused analysis of structural elements. Region-growing techniques initiate clusters from seed points and expand by aggregating neighboring points with similar normals and curvature, effectively isolating planar surfaces such as facades, roads, and sidewalks. RANSAC (Random Sample Consensus) fits parametric models (planes, cylinders, spheres) to data, robustly detecting objects such as poles, street furniture, and columns amidst noise [62]. In many urban cases, classical methods such as RANSAC still outperform neural models, especially when training data are limited. Deep learning methods have revolutionized segmentation by directly ingesting raw point sets. PointNet learns global and local features for semantic labeling, while variants like RandLA-Net and KPConv achieve high accuracy in urban scenes by capturing both local geometry and large-scale context [21, 22, 63]. Instance-level segmentation frameworks, including 3D-MPA [64] and hierarchical aggregation strategies [65], generate multiple object proposals, merge overlapping hypotheses, and combine multi-scale features to delineate individual instances in dense environments, as validated on benchmarks such as SemanticKITTI and ScanNet [66, 67].

3.4. Point Cloud Classification

Point cloud classification is a crucial step in processing 3D data. The main goal is to assign semantic labels to each point, for example, building, tree, or road surface. Traditional approaches relied on geometric descriptors and statistical methods, which proved effective in smaller areas but became less robust in complex urban environments [68].

Recent progress in deep learning has significantly improved classification accuracy. Models like PointNet++, RandLA-Net, and KPConv learn directly from raw 3D data, which makes them practical for analyzing large urban scenes [21–23]. Their ability to capture both global context and local detail has enabled new applications such as vegetation monitoring, building façade detection, and automatic mapping of street furniture. An important direction is multimodal fusion: combining point clouds with multispectral or hyperspectral imagery improves class separability. Recent surveys confirm that deep learning with multimodal inputs is reshaping point cloud classification [69].

3.5. 3D Reconstruction Using Point Clouds

3D reconstruction is the process of turning raw point cloud data into continuous surfaces and detailed models of urban environments. Traditional methods, such as Poisson Surface Reconstruction (PSR), are still widely used because they generate complete, watertight meshes useful for visualization, mapping, and planning [70]. These models help represent buildings, roads, and infrastructure in a way that is both accurate and easy to interpret.

Newer approaches, such as 3DPointCaps++ and 3D-R2N2, use deep learning to reconstruct geometry from incomplete or noisy data [71, 72]. These models are especially helpful in cities, where buildings and objects often block sensors, making full scans difficult. By learning patterns from existing shapes, these methods can fill in missing parts and improve the quality of the final model.

Such techniques are increasingly used in digital twin creation, infrastructure monitoring, and smart city simulations. They allow planners and engineers to work with more complete and realistic representations of urban spaces [73].

It is worth noting that quantitative metrics (such as accuracy) are commonly reported in the literature, but their values are highly dependent on the dataset, point density, scene complexity, and evaluation protocols. As a result, direct comparisons between different methods are often unreliable and may lead to misleading conclusions.

In practice, the effectiveness of point cloud processing methods depends not only on the algorithms themselves, but also on the characteristics of the input data and the application context. Classical approaches work well in structured environments and with limited training data, but they often struggle with complex urban scenes. Deep learning methods, on the other hand, perform better in such cases by learning spatial and semantic patterns, although they require large, annotated datasets and may not generalize well across different sensors [22].

A comparison of the technologies mentioned is presented in Table 2.

Table 2. Comparison of point cloud processing techniques

Technique	Purpose	Accuracy	Classical methods	Deep learning methods	Smart city use
Registration	Align scans in one system	mm/cm (TLS/MLS) cm/dm (ALS) 1–2 GSD (photo)	ICP, NDT	DCP, 3DMatch	Multi-sensor fusion, change detection
Filtering	Clean data, remove noise	cm (MLS/TLS) cm/dm (ALS)	Outlier removal, voxel grid	Adaptive downsampling	Faster processing of infrastructure scans
Segmentation	Divide into objects	80–95% depending on the data and methods used	Region growing, RANSAC	PointNet, RandLA-Net, KPConv	Roads, buildings, vegetation
Classification	Label each point	80–95% depending on the data and methods used	Geometry descriptors	PointNet++, multimodal fusion	Trees, roads, façades
3D Reconstruction	Build surfaces / models	cm/dm, depending on the data and methods used	Poisson reconstruction	3DPointCaps++, 3D-R2N2	Visualization, mapping, and planning

4. Applications of Point Clouds in Smart Cities

4.1. 3D City Modeling

The most common use of point clouds in smart cities is 3D city modeling. These models form the foundation of digital twins and are increasingly applied in energy and mobility planning. Integrating point cloud data with IoT sensor data, air-quality monitors, energy-consumption records, and traffic-analysis systems enables the creation of comprehensive urban models. These models support spatial planning, infrastructure management, and the assessment of environmental and socio-economic factors affecting urban development [2, 3, 5, 13, 14]. Another interesting example involves procedural building model generation, where Župan et al. [74] demonstrated the integration of airborne LiDAR with OpenStreetMap to automate the reconstruction of urban geometries, enhancing urban mapping in large-scale digital twin initiatives. In a related study, Garnett and Adams [75] demonstrated how LiDAR can support climate resilience planning in urban environments by enabling scenario-based modeling of metropolitan infrastructure under future climate risks.

One practical case is the Virtual Singapore project. It combines LiDAR scans, aerial photos, and other spatial data to build a detailed 3D model of the city [76]. The model supports urban simulation, energy optimization, disaster management, and transportation planning. Authorities use it to analyze the effects of climate change, optimize building performance, and improve mobility strategies. Importantly, the platform is also designed as an interactive tool accessible to both policymakers and citizens, which makes it an exemplary case of a participatory digital twin initiative. Similarly, smart city frameworks increasingly integrate point cloud datasets, LiDAR, and IoT technologies to support energy efficiency and transport management. The combination of IoT, artificial intelligence, and digital twins enables applications such as traffic management, energy system optimization, and environmental monitoring, facilitating both real-time analysis and long-term urban planning [77].

4.2. Monitoring and Managing Infrastructure

Point clouds play a critical role in assessing the technical condition of buildings, bridges, and other essential urban structures. By analyzing point cloud data, engineers can detect structural damage, such as cracks, deformations, and material degradation, ensuring public safety and efficient maintenance planning. In China, UAVs equipped with LiDAR and photogrammetry systems are used for real-time bridge inspections [78]. These methods enable engineers to detect microcracks and other forms of damage that conventional inspections might miss. By combining aerial and ground-based scans, authorities can create detailed structural health models and plan predictive maintenance. This example illustrates how point clouds can support proactive safety management, reduce risks, and extend the lifespan of critical infrastructure.

Automating infrastructure inspections is another key benefit of point cloud technology. Autonomous drones and mobile LiDAR systems facilitate rapid, efficient inspections, reducing operational costs and improving safety. Cities such as Amsterdam have implemented automated monitoring solutions that use LiDAR and RGB-D cameras. These monitoring systems keep constant watch over infrastructure, enabling early detection of cracks, surface damage, or structural deformations, while reducing the cost and risk associated with manual inspections. Additionally, integrating point cloud data with environmental indicators, such as noise and air pollution, allows for a holistic assessment of urban infrastructure and its impact on residents [19, 79–81].

4.3. Autonomous Vehicle and Navigation

In the realm of smart transportation, point clouds are fundamental for enabling autonomous vehicles to navigate complex urban environments. High-resolution 3D mapping derived from LiDAR and other sensors allows autonomous vehicles to detect obstacles, recognize road elements, and adapt to changing traffic conditions in real time. A prominent example is Waymo and its Waymo Open Dataset, which documents the use of multi-sensor LiDAR and camera systems to create detailed maps and support research in perception for urban driving [82].

The integration of point cloud data with intelligent transportation systems further improves traffic management. By providing precise road mapping, real-time traffic monitoring, and weather condition analysis, point clouds support adaptive traffic control and congestion mitigation. In the Virtual Singapore project, point cloud-based systems are utilized to monitor road traffic, optimize signal timing, and improve overall transport efficiency, contributing to a more seamless and sustainable urban mobility ecosystem [76], including traffic monitoring aspects and sensor fusion methodologies.

4.4. Pedestrian and Bicycle Network Analysis

Recent studies have demonstrated that point clouds can be leveraged to evaluate and optimize pedestrian and bicycle networks by capturing detailed surface geometry, identifying obstacles, and quantifying accessibility. Balado et al. [83] introduced a direct path-finding method that uses urban point clouds to detect barriers such as street furniture, poles, and curb edges, and to compute terrain slopes and discontinuities. Their algorithm constructs a weighted graph from the 3D data, assigning high traversal costs to steep gradients or obstructed segments, and then solves for the lowest-cost pedestrian routes, ensuring continuous paths that avoid architectural barriers and unsafe inclines.

Building on this, Jahromi et al. [84] developed a fuzzy-based, adaptive weighting framework specifically for wheelchair users. They extract four core metrics from high-resolution point clouds: walkway width, surface slope, pavement roughness, and curb presence. Each metric is fuzzified into linguistic variables (e.g., "narrow," "moderate," "wide") and weighted according to user profiles and mobility requirements. The resulting accessibility index reflects real-world travel comfort and safety, correlating strongly with field-measured user satisfaction scores, and enabling fine-grained prioritization of sidewalk improvements.

Mi et al. [85] focused on automated extraction and vectorization of road and sidewalk boundaries. Their machine learning pipeline classifies each point based on features such as relative height above the road surface and LiDAR intensity returns. Boundary points are then connected via spline-based vectorization, producing continuous, topologically correct polylines that delineate sidewalks, curb lines, and roadway edges. This approach supports rapid GIS updates, change detection over successive surveys, and integration with urban asset management systems.

When used together, these methods form a complete workflow for studying sidewalks and bike paths. High-density mobile LiDAR scans along corridors capture surface details at centimeter-level resolution, which can then be segmented and classified into sidewalks, curbs, roads, and obstacles using either feature-based or learning-based methods. Multi-criteria accessibility scores are calculated through fuzzy inference, integrating geometric factors such as width and slope with surface quality metrics, including roughness and curb height. Automated vectorization of infrastructure boundaries further enables updates to GIS layers and supports the analysis of temporal changes in the network. Such an approach gives planners clear quantitative measures of how continuous or comfortable a route is. It also helps them decide where to repair or design new bike lanes. Although these approaches are promising, in practice, data quality and urban clutter can still limit their reliability.

4.5. Urban Green Areas in Smart Cities

Green spaces such as parks, street trees, and green corridors are an essential part of modern smart cities. They enhance air quality, help mitigate the urban heat island effect, and support biodiversity. Equally important, they provide social and health benefits to city residents. With new tools such as airborne LiDAR, UAV-based photogrammetry, and high-resolution satellite imagery, it is now possible to monitor these areas in detail and regularly [12].

Point clouds make it possible to measure features such as tree height, crown volume, and canopy cover. They also allow the calculation of indicators such as the Green View Index, which describes how much greenery is visible from the street. Another important metric frequently derived from LiDAR is the Leaf Area Index (LAI), which quantifies leaf surface area relative to ground area and is widely used to assess the environmental and climatic functions of urban vegetation, including shading, evapotranspiration, and carbon exchange [86]. This type of information helps city planners detect changes over time, track tree health, or identify where green corridors are missing. Recent studies show that these methods work not only in global projects but also in local contexts, including Polish cities [87].

Research teams in Poland have shown how LiDAR can be used for practical landscape monitoring and quality-of-life studies in urban areas. Their work highlights the value of combining 3D data with spatial indices to understand how greenery affects everyday life in the city [88, 89]. Future work should focus on integrating LiDAR with multispectral data, automating tree-level change detection, and developing common standards for comparing green areas across cities.

Figure 2 shows a graphical overview of these five applications.

Fig. 2. Overview of point cloud applications for smart cities

5. Research Challenges and Future Directions

Integrating point clouds into smart city applications involves several technical and methodological challenges. These arise from the heterogeneity of data sources, the high computational demands of processing large datasets, and the need for standardized methods to ensure both interoperability and accuracy. This section examines the main research challenges and outlines potential directions for future work in the field.

5.1. Integration of Heterogeneous Data from Multiple Sensors

A major challenge in using point clouds for smart cities is integrating data from heterogeneous sensors, such as LiDAR, RGB-D cameras, GNSS, IoT devices, and environmental monitoring systems. Because these sensors operate at different spatial and temporal resolutions and produce continuous data streams, synchronizing and aligning their outputs requires advanced methods that can handle variations in acquisition times, sensor positions, and environmental conditions. This is especially difficult for mobile platforms like drones and autonomous vehicles, where real-time synchronization is critical for accurate urban modeling [24, 27, 29, 52].

Another important challenge is data quality, as sensors differ in accuracy and can be affected by noise or interference. For instance, LiDAR data may contain errors due to reflections, occlusions, or atmospheric conditions, while GNSS positioning can be unreliable in dense urban areas. To improve the reliability and completeness of point clouds, advanced error detection, denoising, and interpolation methods are required [26, 61, 90, 91].

Furthermore, managing large datasets remains an obstacle. The continuous collection of high-resolution point cloud data generates vast amounts of information that must be efficiently stored, processed, and analyzed. Developing scalable architectures capable of handling real-time data streams is essential to support large-scale smart city implementations [11, 92].

5.2. Computational Efficiency in Processing Large Datasets

Processing point clouds in real time is demanding; it takes powerful computers and well-optimized algorithms. Tasks such as filtering, segmentation, and 3D reconstruction are inherently complex and often depend on parallel processing or cloud-based solutions to meet performance demands [16, 17, 36, 67].

Machine learning techniques can further improve efficiency by dynamically adapting processing pipelines to the characteristics of incoming data, ensuring high performance without sacrificing quality [30, 65, 93].

In the context of smart city applications, real-time processing is particularly critical. Rapid analysis of point cloud data enables immediate decision-making for traffic monitoring, air quality assessment, hazard detection, and other time-sensitive tasks. Consequently, developing lightweight algorithms capable of processing point clouds in real time remains a key research priority, with significant implications for the efficiency and responsiveness of urban management systems [24, 94, 95].

5.3. Additional Challenges

Real-world point clouds frequently suffer from incomplete coverage, noise, and artifacts arising from sensor occlusions, reflective materials, or adverse environmental conditions. Traditional hole-filling algorithms interpolate missing geometry by fitting local surface patches, yet they often introduce smoothing artifacts and fail to preserve sharp edges in complex urban structures [96]. Robust interpolation filters improve results by weighting adjacent points based on proximity and normal consistency, but their performance degrades when point distributions are highly irregular or sparse [97]. Deep generative models provide an alternative to traditional approaches. They learn typical scene patterns from large datasets and can automatically predict missing geometry, producing more coherent reconstructions even in highly cluttered environments [70–72].

The LAS format has been widely adopted for geospatial point clouds for over two decades, with broad software support, and its compressed counterpart, LAZ, provides efficient storage without compromising compatibility. In contrast, PLY is primarily used for reverse engineering and small-scale object modeling rather than large-scale urban or municipal datasets. Despite the standardization of LAS, interoperability challenges persist due to variations in attribute schemas, semantic labeling, and versioning across datasets. Libraries such as the Point Cloud Library (PCL) facilitate reading, writing, and transforming diverse formats, yet they do not fully resolve differences in metadata or semantics. Establishing best practices for semantic tags, version management, and attribute conventions is therefore critical for enabling seamless data exchange, collaborative workflows, and the integration of point cloud technologies in smart city operations [3, 14, 26].

6. Conclusion and Final Remarks

Point cloud technology has become a fundamental tool in the development of smart cities, offering unprecedented precision in 3D spatial modeling, infrastructure monitoring, autonomous navigation, and urban planning. The ability to capture and analyze large-scale spatial data provides cities with valuable insights into their environments, enabling more effective decision-making and improved management of urban systems. However, despite significant progress, several technical and methodological challenges must be addressed to fully harness the potential of point clouds in real-world applications.

6.1. Key Conclusions

Based on the reviewed literature and analyzed applications, several key conclusions can be identified regarding the role of point clouds in smart city development. These conclusions emphasize both the technical challenges of data acquisition and processing, as well as the broader opportunities for improving urban planning, infrastructure management, and environmental sustainability.

1. Point cloud integration and fusion of heterogeneous data
   The effective use of point clouds in smart cities depends on the seamless integration of data from multiple sources, including LiDAR, RGB-D cameras, IoT sensors, and GIS systems. Professional systems, such as ALS/MLS and

UAVs with GNSS timestamps, already provide reliable spatial and temporal referencing. Nevertheless, variability in sensor characteristics, data formats, and acquisition conditions still requires advanced fusion techniques to synchronize and merge heterogeneous datasets while preserving consistency [24, 29]. The growing use of UAVs with RGB-D cameras enhances flexibility and resolution in urban mapping yet demands advanced synchronization to effectively integrate aerial and ground data.

2. Optimization of processing algorithms for large-scale data
   The computational demands of point cloud processing remain a significant challenge, particularly in real-time applications such as autonomous vehicles and dynamic urban monitoring. The adoption of artificial intelligence, deep learning, and edge computing solutions will be crucial for optimizing data-processing workflows, reducing computational costs, and enabling scalable, high-performance analysis of large datasets [17, 30].
3. Ensuring data quality and completeness
   Noise, missing data, and inconsistencies in point clouds continue to limit their practical applications. Improving data reliability through advanced filtering, interpolation, and reconstruction methods is essential to enhancing the accuracy and usability of spatial models. A useful next step would be to design sensor-fusion algorithms that can handle real-time urban data from multiple sources [70, 85, 90].
4. Interoperability and best practices
   The lack of universally accepted data standards can make it harder to integrate and exchange point cloud data across platforms and urban management systems. For smart city applications, the focus is often on derived products, such as vector data, 3D models, or GIS layers, rather than raw point clouds. Still, having agreed standards for metadata, semantic labeling, and interoperability can help increase the use of point clouds and support smooth collaboration between municipalities, private companies, and research institutions [3, 11, 26].
5. Applications for sustainable and resilient urban development
   Beyond infrastructure monitoring and navigation, point clouds offer significant potential in supporting sustainable urban planning. Some applications, such as real-time traffic monitoring or disaster response, require timely data, while others, such as environmental monitoring, energy efficiency analysis, and resource management, can work with processed datasets. Recent examples show that point clouds support inclusive mobility planning by mapping pedestrian and cycling infrastructure. LiDAR-based vegetation analysis also aids climate adaptation by assessing the structure and distribution of urban green spaces. As 3D scanning and analysis keep improving, cities will be able to plan more flexibly and respond faster to the needs of their residents [2, 5, 13, 14].

6.2. Final Outlook

Point cloud technology has become a key tool in digital urban transformation, providing the basis for creating detailed 3D models. These models can be used for a wide range of applications, including high-fidelity digital twins for urban simulation and planning [1, 11, 76], structural health monitoring of bridges and buildings [78], intelligent transportation systems that rely on precise road and traffic mapping [26], and environmental analytics such as green-space assessment and air-quality monitoring [16]. UAVs enable dynamic data collection over wide areas, improving traffic and crowd monitoring. Their integration supports both real-time applications, such as traffic monitoring, and offline applications, such as environmental or energy analysis. By integrating dense geometric data with sensor-derived metrics, point clouds enable city managers and engineers to visualize complex scenarios, predict infrastructure performance, and optimize resource allocation in a coherent, data-driven framework.

Realizing the full potential of point cloud methodologies requires addressing several key challenges. The first major issue is that different sensor types (LiDAR, RGB-D cameras, and photogrammetry) produce data at varying spatial and temporal resolutions, making seamless data fusion difficult [25, 26]. Second, the large size of urban point-cloud datasets creates significant computational and storage challenges, highlighting the need for efficient compression and streaming methods that reduce bandwidth and storage requirements while preserving geometric accuracy [90]. Third, standardized metadata and format conventions are crucial to ensure interoperability and reproducibility. Common definitions for attributes and semantic labels are essential [3, 14]. Additionally, real-world scans often have occlusions, noise, and sparse sampling, so processing methods need to handle uncertainty, estimate errors, and fill in missing data without creating artifacts [61, 91]. In dense urban areas, data limitations can make it difficult to detect pedestrian and cycling routes. Robust reconstruction ensures accurate infrastructure mapping, while error-tolerant algorithms are vital for assessing vegetation in incomplete scans.

Future research should focus on:

– developing adaptive fusion algorithms that harmonize multi-sensor streams in both real-time and offline urban applications;
– designing efficient frameworks for real-time and offline data processing and delivery;
– defining standardized metadata and format protocols to ensure interoperability and traceability of point-cloud datasets;
– creating uncertainty-aware reconstruction methods that balance accuracy with robustness to noise and incomplete coverage, supporting both raw point clouds and derived products;
– addressing the variability of data quality across different acquisition methods, which directly affects the reliability of point cloud processing algorithms.

Addressing these challenges gradually will allow cities to use point cloud tools more effectively for planning, maintenance, and adapting to environmental change. While deep learning methods are advancing rapidly, current technologies still do not allow fully automated processing of point cloud data (without human intervention), especially in complex urban environments. Limitations related to data quality, sensor variability, and the need for reliable interpretation make such fully autonomous systems difficult to achieve in practice. Therefore, hybrid workflows that combine classical geometry-based methods with learning-based approaches are expected to play an important role alongside emerging end-to-end solutions.

Funding

The article was prepared under the research subvention of AGH University of Krakow No. 16.16.150.545.

Declaration of Competing Interests

The author declares that she has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

No data was collected or analyzed in this paper.

Use of Generative AI and AI-Assisted Technologies

ChatGPT (OpenAI, GPT-5 model) was used to assist in paraphrasing and summarizing information from the literature during manuscript preparation. Zotero was used for reference management.

Acknowledgments

The author gratefully acknowledges the supervisor’s guidance and support, as well as the reviewers’ constructive feedback that helped enhance the quality of this manuscript.

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