ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume X-1/W2-2025
13th International Conference on Mobile Mapping Technology (MMT 2025)
"Mobile Mapping for Autonomous Systems and Spatial Intelligence", 20–22 June 2025, Xiamen, China

High resolution 3D data for Pavement Condition Assessment in a Digital Twin perspective

Vittorio Scolamiero [1,2], Piero Boccardo [2]

[1] DICEA, Department of Civil, Building and Environmental Engineering, Sapienza Università di Roma, Via Eudossiana, 18, 00184 Rome, Italy – vittorio.scolamiero@uniroma1.it
[2] DIST, Interuniversity Department of Regional and Urban Studies and Planning, Polytechnic of Torino, Viale Pier Andrea Mattioli, 39, 10125 Turin, Italy – vittorio.scolamiero@polito.it , piero.boccardo@polito.it

Keywords: Mobile Mapping System, LiDAR Point Cloud, Road asset management, Road pavement condition, Urban Infrastructures, BIM

Abstract

The use of Mobile Mapping Systems (MMS) has revolutionized urban road infrastructure management, offering unprecedented precision and efficiency in data acquisition and analysis. This study focuses on the application of the RIEGL VMY-2 MMS to assess pavement conditions in an urban environment. The RIEGL VMY-2 system, equipped with dual LiDAR sensors and spherical cameras, enabled the collection of high-density point clouds enriched with RGB and intensity values. These attributes were critical for the automated detection and characterization of pavement defects, such as cracks, potholes, and deformations. Advanced algorithms processed the MMS data to classify the point cloud, extract surface features, and attribute semantic information, such as defect severity and location. Additionally, the study integrates Building Information Modeling (BIM) methodologies to enhance urban infrastructure management. By incorporating the processed geospatial data into a BIM environment, municipalities can create comprehensive digital representations of road assets, facilitating improved planning, maintenance, and lifecycle management. The BIM model serves as a dynamic repository that links geometric and semantic data, offering a more structured and interactive approach to infrastructure monitoring. The results demonstrate the potential of MMS technologies in creating actionable geospatial datasets for urban infrastructure management. The geospatial database generated through this workflow includes detailed pavement condition maps and the Pavement Condition Index (PCI), enabling municipalities to prioritize maintenance interventions and optimize resource allocation. This study underscores the critical role of MMS technologies in modernizing urban infrastructure management, bridging the gap between raw geospatial data and actionable insights for sustainable urban planning.

1. Introduction

The effective management of road infrastructure has become a pressing challenge for modern cities, especially as urban environments grow in complexity and scale. Road networks, as critical components of urban infrastructure, play a pivotal role in ensuring safety, mobility, and economic vitality. However, traditional methods of road asset management often fall short in addressing the demands of contemporary urban areas due to their labour-intensive nature, limited scalability, and lack of real-time insights.
In this context, MMS have emerged as a transformative technology, revolutionizing the way cities monitor and manage road infrastructure. By integrating advanced sensors such as LiDAR, cameras, Global Navigation Satellite System (GNSS), and Inertial measurement unit (IMU), MMS enable the precise, real-time collection of geospatial data as vehicles traverse urban road networks. These systems excel in capturing detailed three-dimensional models of road surfaces and surrounding infrastructure, allowing for millimeter-level accuracy in detecting defects such as potholes, cracks, and deformations.
Beyond surface monitoring, MMS contribute to a comprehensive understanding of urban road environments by cataloguing critical elements like traffic lights, signage, barriers, drainage systems, and sidewalks (Sairam et al., 2016). This capability not only supports road maintenance and asset management but also ensures that infrastructure complies with regulatory and safety standards. The ability to seamlessly integrate data from MMS into DT frameworks further enhances their value, enabling cities to perform advanced analyses, simulate future scenarios, and prioritize interventions with greater precision. Furthermore, this integration enable the Predictive Maintenance (PdM), in fact the use of LiDAR point cloud and panoramic imagery allows not only to identify existing distress on road surface, but also to implement a predictive system able to anticipate future deterioration and optimize the management of road infrastructures. The PdM can be integrated into an interactive GIS, allowing local authorities to view critical areas on dynamically updated thematic maps, while a BIM model, built from MMS data, can be enriched with time information to simulate the evolution of degradation and optimize intervention planning.
As urban areas continue to evolve, the adoption of MMS represents a pivotal step toward sustainable and intelligent transportation systems. This paper explores the integration of MMS data into multi-source workflows, demonstrating its potential to address the challenges of modern urban road management through precise data acquisition, automated analyses, and actionable insights.

1.1 Case Study

The work described here is part of the broader Turin Digital Twin (DT) initiative, a collaborative effort between the municipality of Torino and the Politecnico di Torino, which began in 2022. This initiative initially relied on aerial hybrid data acquisition, conducted using the Leica CityMapper-2 system, to create an accessible and navigable digital representation of the city (Boccardo et al., 2024). The aerial data provided a comprehensive large-scale perspective of the urban environment, capturing key features such as road layouts, building rooftops, and general urban morphology.
The case study presented focuses on an urban area encompassing a portion of the Cit Turin neighbourhood, located within the 3rd district of Turin. This area is distinguished by the presence of the Spina Centrale, a transformative infrastructure project that has significantly reshaped Turin's urban landscape. The study area also hosts key public infrastructures, including the city's courthouse, a bus terminal, multiple metro stations, a public park, and a neighbourhood market. The dense urban

fabric, combined with the presence of shaded streets, as illustrated through an orthophoto obtained from aerial surveys, underscores the complexity of this urban environment and its challenges for detailed analysis (figure 1).
In this context, a MMS was deployed to assess its capability for capturing high-resolution, multi-dimensional data and integrating it with existing datasets. This approach aligns with the multi-level and multi-sensor strategy underpinning the Turin DT project, which aims to create a comprehensive digital representation of the city. While aerial data offers a large-scale perspective of the urban environment, its limitations in capturing ground-level details emphasize the necessity of complementing it with terrestrial datasets, such as those acquired via MMS (Scolamiero et al., 2025).

Figure 1. Cit Turin neighbourhood. The orthophoto illustrates, with a zoomed area, the urban environment with dense shading caused by closely buildings and narrow streets.

2. Materials and Methods

This section presents the methodology used to transform raw geospatial data into actionable information for road infrastructure management. By combining LiDAR point clouds, panoramic imagery from MMS, and municipal geospatial data, the approach offers a comprehensive analysis of road conditions. Figure 2 summarizes the entire workflow—from data acquisition to the integration of results into both the municipal geodatabase and a BIM environment—highlighting the modular structure of the process and its adaptability to municipal planning needs.

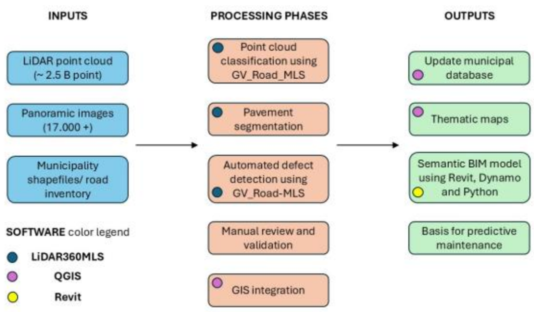

Figure 2. Flowchart

2.1 MMS for road infrastructure monitoring

In recent years, MMS for road monitoring have seen remarkable advancements, driven by the integration of state-of-the-art technologies such as LiDAR, GNSS, IMU, high-resolution cameras, and artificial intelligence (AI) algorithms. These systems now enable highly accurate detection of road defects, including potholes, cracks, ruts, and surface deformations, while also facilitating the detailed cataloguing of infrastructure elements such as traffic signs, streetlights, barriers, and sidewalks.
This technological evolution has proven particularly impactful in urban environments, where dense and complex infrastructures demand high-precision mapping. MMS solutions are capable of achieving millimeter-level accuracy, allowing for detailed assessments of road surfaces and ensuring compliance with safety regulations. The integration of AI algorithms further enhances their functionality by automating the recognition and classification of road features and defects. This automation significantly improves the efficiency of road maintenance planning and urban infrastructure management. Modern MMS systems are highly versatile and adaptable to a variety of use cases, offering solutions that range from handheld and wearable devices for accessing hard-to-reach areas to vehicle-mounted systems designed for large-scale road monitoring. Vehicle-mounted systems, in particular, deliver unparalleled efficiency and scalability, making them indispensable for extensive urban projects such as the Turin DT initiative.
A MMS mounted on a vehicle for urban applications comprises several key components engineered to collect high-precision spatial data in real time. Central to these systems are LiDAR sensors, which emit laser pulses to measure distances to surrounding objects, generating detailed 3D representations of the environment. A GNSS receiver provides accurate geolocation by utilizing satellite signals, while an IMU tracks the vehicle's orientation and motion. Together, the GNSS and IMU data ensure continuous and precise positioning, even in challenging environments such as tunnels or urban canyons, by compensating for signal interruptions or sudden movements (Elhashash et al, 2022).
High-resolution cameras are another integral component, capturing detailed imagery of the surroundings to complement the LiDAR data. These images provide essential visual context, enhancing the analysis and interpretation of the acquired geospatial data. A central computing unit processes the data from all sensors in real time or stores it for post-processing, ensuring seamless integration and management of the collected information. The coordinated operation of these components enables detailed mapping and monitoring of urban road infrastructure, delivering the accuracy and efficiency necessary for applications such as road condition assessments, asset inventory creation, and urban planning.
MMS are revolutionizing road maintenance management by offering significant advantages over traditional methods such as manual inspections. One of the primary benefits of MMS is its speed and efficiency in data collection. Mounted on a vehicle, the system captures road condition data in real time as the vehicle moves, enabling extensive sections of the road network to be surveyed quickly. This rapid data acquisition allows for more frequent updates on road conditions, enabling cities to address issues promptly and carry out maintenance operations in a timely and efficient manner. Another key advantage of MMS lies in its potential to reduce costs and mitigate risks. Traditional manual inspections are often labour-intensive, time-consuming, and expensive, requiring extensive fieldwork. MMS dramatically reduces the need for such efforts, cutting down on labour costs and streamlining the data collection process. Furthermore, the high-resolution 3D data collected by MMS enables more precise planning of maintenance activities, reducing the likelihood of costly emergency repairs and optimizing resource allocation. The versatility of MMS data is another critical benefit, as it can be seamlessly integrated into Geographic Information Systems (GIS) and BIM. This integration facilitates the creation of comprehensive databases of road infrastructure, supporting a wide range of applications, from detailed maintenance planning to traffic simulations

(Pavard et al., 2023). By providing accurate and detailed geospatial information, MMS empowers decision-makers with the tools necessary to enhance the efficiency and effectiveness of urban infrastructure management.
In summary, MMS represents a transformative approach to road maintenance management. By combining advanced technologies, MMS delivers precise, efficient, and cost-effective solutions that improve the planning and execution of maintenance tasks, ensuring better-maintained road infrastructure and long-term cost savings.

2.2 Data acquisition

The MMS utilized is the RIEGL VMY-2 (figure 3), a highly advanced dual-scanner mobile mapping system tailored for urban environments. Equipped with two high-resolution RIEGL miniVUX-HA LiDAR sensors, the system was designed to capture dense and accurate 3D point clouds. The sensors, mounted in an angled configuration, enabled comprehensive spatial coverage and precision, ensuring detailed mapping of urban road infrastructure.
The RIEGL VMY-2 system supports data acquisition at an impressive rate of up to 300 scan lines per second with a pulse repetition rate of 600 kHz. This capability results in high-density point clouds, achieving an average of 1100 points per square meter on pavement surfaces even at speeds of up to 80 km/h. The system’s LiDAR sensors provide a full 360-degree field of view with a range accuracy of 10 mm, capturing intricate details essential for analysing road surfaces, vertical infrastructure, and surrounding urban features.
In addition to LiDAR data, the system integrates a spherical camera (figure 4)—in this case, the FLIR Ladybug6—to capture high-resolution panoramic images. These images complement the geometric data from the LiDAR sensors, providing rich visual context for feature identification and classification. The Ladybug6 excels in capturing 360-degree images with precise stitching and exceptional clarity, making it ideal for documenting the urban environment in real time.
The data acquisition workflow produced two primary outputs:

- LiDAR Point Clouds: High-density, millimeter-accurate 3D datasets representing road surfaces, infrastructure elements, and surrounding urban features. The dataset consists of approximately 2,538,189,873 points. These point clouds (figure 5) serve as the foundation for analyses such as pavement condition assessments and asset inventory creation.
- Panoramic Images: High-resolution 360-degree imagery providing visual details of the captured environment (figure 6). A total of 17,641 panoramic images were collected, enhancing the interpretation of LiDAR data and supporting advanced analyses, such as the detection of road markings and defects.

Figure 3. The LiDAR sensor Riegl VMY-2, from this image is possible recognize the GNNS antenna, the dual RIEGL miniVUX-HA LiDAR with the GNNS/IMU unit, the control unit covered by a protective cover and the roof mount

Figure 4. The spherical camera Teledyne FLIR Ladybug, from the image is possible recognize the six high quality 6.94 mm focal length lenses

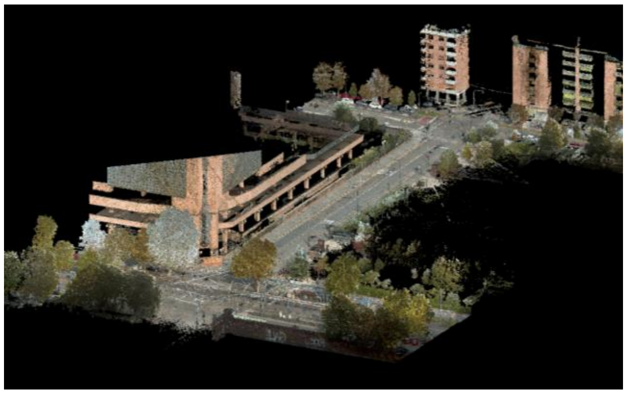

Figure 5. Portion of the LiDAR point cloud

Figure 6. Example of a panoramic image

Together, the integration of LiDAR point clouds and panoramic images forms a comprehensive dataset. This multi-dimensional output supports detailed urban infrastructure analysis, enabling precise and efficient workflows for road condition monitoring and management.
Despite the numerous advantages of MMS in capturing high-precision geospatial data for road infrastructure management, the presence of obstacles in urban environments poses significant challenges during the data acquisition phase. Elements such as parked vehicles, street furniture, vegetation, and other urban structures can create occlusions that hinder the completeness and accuracy of the collected dataset.
One of the most common obstacles encountered during MMS data acquisition is parked cars, which can obstruct critical road features such as pavement defects, road markings, and drainage elements. Moreover, trees, bushes, and other forms of vegetation can further complicate data acquisition by obstructing visibility and distorting sensor readings. LiDAR beams may penetrate some types of vegetation, but dense foliage can scatter or absorb signals, leading to incomplete or noisy point clouds that require additional processing for correction. In addition to physical obstacles, dynamic elements such as moving vehicles and pedestrians can introduce

temporary occlusions, resulting in gaps or inconsistencies in the dataset. Urban infrastructure elements, including traffic signs, lampposts, and overhanging structures, can also partially obscure the scanned environment, necessitating multiple passes to ensure comprehensive coverage.

2.3 Pavement damage recognition

The process begins with the classification of the point cloud, where major elements such as ground, buildings, vegetation, and facilities are identified (figure 7). From this classified dataset, the ground class is further segmented to focus specifically on the road surface. The segmentation was carried out extracting ground points from the rest of the point cloud. These analyses are critical for evaluating the functionality and safety of road infrastructure, enabling the identification of essential features and conditions. By isolating and examining these specific elements, the study highlights the potential of advanced geospatial datasets to streamline road management and support the development of targeted maintenance strategies.

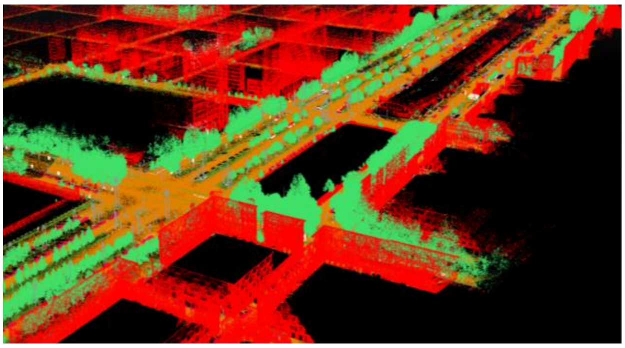

Figure 7. Classified Point Cloud, color legend: red_building, orange_ground, green_vegetation, grey_facilities,

The analyses utilized both the point cloud and panoramic images acquired via the MMS, adopting a fully automated approach. This methodology was implemented using LiDAR360MLS, a specialized software developed by GreenValley International for road infrastructure analysis. The analysis of the point cloud focused on intensity values, which play a crucial role in identifying surface-level details such as cracks, potholes, and other irregularities. These values were instrumental in assessing pavement conditions, providing precise insights into the structural integrity of the road surface.
Simultaneously, panoramic image analysis utilized a deep learning model to efficiently extract visual features.
The automated defect detection was carried out using the "GV_Road_MLS" module within the LiDAR360MLS software suite, developed by GreenValley International. This module applies proprietary algorithms specifically designed for road surface analysis from MLS data. Although the internal workings of the model are not publicly documented, it operates by analysing LiDAR intensity values and topographic features to identify surface-level defects such as cracks and potholes.
Despite the proprietary nature of the algorithm, the workflow allows for explicit configuration of several key parameters. These include:

- Tolerance: a threshold value used to filter shallow surface anomalies; any damage with a depth less than this value is excluded from detection.
- Minimum Area: defines the smallest surface area that qualifies as a valid defect; damage with an area below this threshold is automatically disregarded.
- Fit Length: the length of the analysis strip used during defect detection, typically corresponding to the width of a single traffic lane. For larger damage patterns, this parameter can be increased to ensure full coverage.

The module outputs a classified shapefile containing defect locations, typologies, and severity levels, which was validated and post-processed.
This integrated approach demonstrated the ability of automated techniques to handle large datasets efficiently, accelerating the detection process while maintaining precision. The synergy between LiDAR-derived intensity values and advanced image-based analyses underscored the potential of combining multi-modal data for comprehensive road infrastructure assessments. The analyses yielded critical outputs, including: the typology of detected damages, their geospatial position, the extent of affected areas and the severity of each issue (figure 8).

Figure 8. Visualization of the damage analysis phase. From left to right: LiDAR point cloud, panoramic image, and attribute table of the damage vectors. Red vectors represent the identified defects, while blue markers indicate the positions of the panoramic images utilized in the analysis. This figure illustrates the integration of multi-sensor data to accurately detect and geolocate road surface damages.

Additionally, the methodology provided the PCI, a globally recognized metric for assessing road conditions. The PCI serves as a statistical measure that offers a comprehensive evaluation of a pavement section's overall condition. It is calculated based on the survey and analysis of the number, types, and severity of various surface distresses. By aggregating individual defect information across a given section, the PCI enables a transition from isolated point-specific assessments to a holistic evaluation of the road segment.
To evaluate the accuracy of the automated defect detection, the results obtained from the MMS-based workflow were compared with manual annotations performed over a representative road section. Table 1 presents the performance metrics—true positives (TP), false positives (FP), false negatives (FN), precision, recall, and F1-score—computed for three common defect types: cracks, potholes, and repairs. Importantly, the manual annotations used as ground truth were carried out directly on the rasterized version of the same point cloud used by the automated detection system. This ensured full spatial alignment between the reference data and the algorithm's input, minimizing positional discrepancies and enabling a consistent and reliable comparison between the two approaches.
The system showed moderate performance in detecting potholes, with an F1 score of 0.45 and relatively balanced precision and recall. In contrast, the detection of cracks and repairs was affected by a high number of false positives, likely due to surface noise or confusion with construction joints and previously repaired areas. Overall, while the system effectively identifies prominent defects such as potholes, further refinement is needed to improve fine-grained classification and reduce false detections in complex urban contexts. These results confirm the utility of the MMS-based approach as a preliminary screening

tool, while also highlighting the need for manual validation and model calibration for operational deployment.
This validation process included a manual review (Figure 9) to identify and correct any incoherent or erroneous detections in the dataset. By cross-referencing the automated results with manual annotations, this step ensured that the final defect map accurately reflected the actual condition of the road surface, thereby increasing the reliability of the outputs for infrastructure management. The final result was delivered as a geospatial vector file containing all extracted and validated information, ready for integration into infrastructure management systems or further analysis, and serving as a solid foundation for the development of a comprehensive road asset geodatabase.

Damage Type	TP	FP	FN	Precision	Recall	F1 Score
Crack	46	207	59	0.18	0.44	0.26
Pothole	13	14	18	0.48	0.42	0.45
Repair	15	50	26	0.23	0.37	0.28

Table 1 Validation metrics for automated damage detection compared to manual annotations

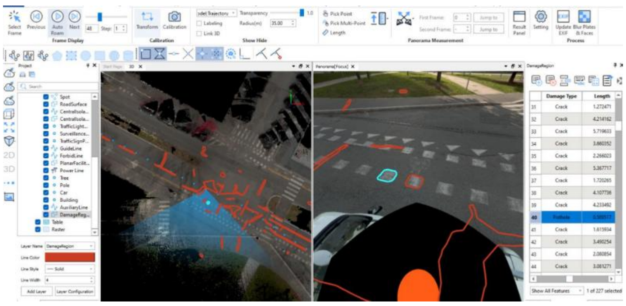

Figure 9. Manual review phase, in blue is highlighted an example of an incoherent detection (a road marker was detected as a pothole)

2.4 Integration into Municipality geodatabase

Following the identification of pavement damage within the study area, the next objective of this work was to integrate the extracted information into a structured geodatabase for the Municipality of Turin. This phase was carried out in collaboration with technicians from the Department for Major Public Works, Infrastructures, and Mobility. The continuous exchange of expertise between researchers and municipal professionals played a crucial role in refining the procedures for data integration, ensuring that the collected information was effectively structured and aligned with municipal standards. This collaborative approach not only enhanced the accuracy and usability of the dataset but also contributed to the development of a more standardized and scalable methodology for road infrastructure management.
The geodatabase serves as a centralized resource, making all relevant information readily accessible to municipal authorities for informed decision-making and planning. To achieve this integration, the outputs from the MMS-based analysis were recalibrated to align with the municipality's specific guidelines. Notably, the municipality does not use the PCI as a standard metric. Instead, a locally defined condition index is employed. Therefore, PCI values—ranging from 0 (worst) to 100 (best) and organized into seven standard categories—were translated into four qualitative classes used operationally by the municipality: "good", "partially degraded", "degraded", and "very degraded" (figures 10). These categories also reflect the type of maintenance strategy typically associated with each condition level.

Once this translation was completed, the dataset underwent a thorough quality assurance process, including cross-referencing with the municipal road inventory and a series of on-site inspections conducted by municipal technicians. These manual surveys provided an important opportunity for validating the automated analysis.
Approximately one year after the MMS-based survey, the municipal office conducted a manual inspection on a two segment of the same area within the Cit Turin district. Although this inspection was performed using standard visual assessment methods and occurred a significant time after the original data acquisition, it allowed for a significant comparison. Several anomalies detected through the semi-automated MMS-based workflow corresponded to locations where more severe defects had developed over time, reinforcing the potential of the methodology to identify early-stage degradation (figure 11).

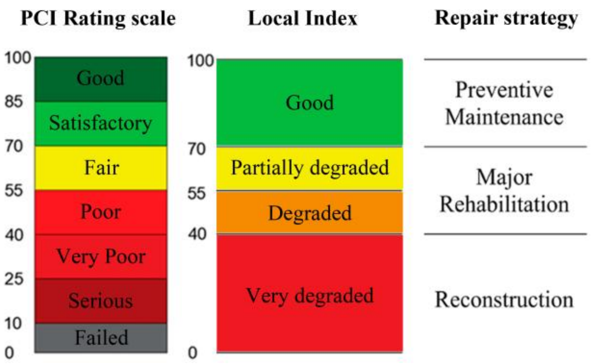

Figure 10. This figure illustrates how the Local Index is derived from the PCI categories and aligned with typical repair strategies.

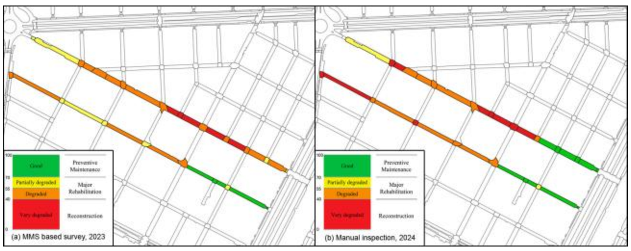

Figure 11. Comparison between automated damage detection results from the 2023 MMS survey (left) and the 2024 ground inspection conducted by the Municipality of Turin (right).

This validation confirmed a coherent spatial alignment between PCI-based pavement condition mapping and the degradation patterns documented by the municipality, especially in zones identified as requiring urgent maintenance. It also demonstrated the capacity of the workflow to serve as a predictive support tool for infrastructure monitoring and maintenance scheduling.
It should be noted that the time gap between the MMS data collection and the municipal ground survey introduces inherent uncertainties due to ongoing surface wear, weather exposure, and traffic-induced deterioration. Moreover, the manual inspection was limited in spatial extent and did not follow a georeferenced acquisition protocol, making precise metric comparison unfeasible. Nonetheless, the strong alignment of identified damage locations provides robust support for the reliability of the proposed method.

2.5 Urban Infrastructure Management through GIS and BIM integration

Effective management of urban road infrastructure is crucial for ensuring safety, mobility, and long-term sustainability within cities. The integration of pavement condition data into the municipal geodatabase represents a significant step toward data-driven infrastructure management. Beyond pavement analysis, the collected dataset enables the cataloguing of additional urban features, such as horizontal road markings, utility poles, and other critical road assets (figure 12), which play a crucial role in traffic organization and public safety. By leveraging these enriched datasets, municipalities can transition from reactive maintenance strategies to proactive and predictive approaches, optimizing resource allocation and improving service life. Furthermore, municipalities can achieve a more comprehensive mapping of the urban environment, identifying elements such as crosswalks, directional arrows, lane markings, and traffic control features. This level of detail enhances the ability to monitor compliance with traffic regulations, plan for upgrades, and prioritize maintenance interventions based on real-world conditions. A well-structured road asset management strategy relies on continuous monitoring, timely maintenance interventions, and strategic planning based on comprehensive data analysis. The integrated dataset not only facilitates the identification of critical maintenance needs but also enables prioritization based on factors such as road usage, economic impact, and safety considerations.

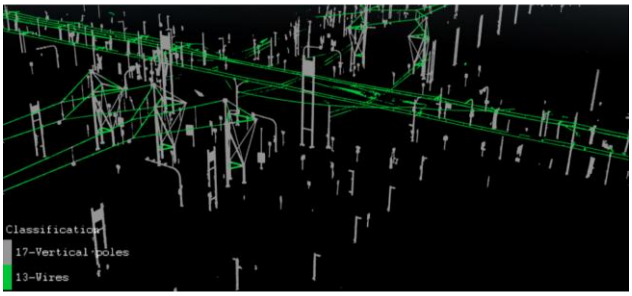

Figure 12. Cataloguing of additional urban features

The use of GIS and BIM in urban infrastructure management further enhances these capabilities by offering integrated visualization tools that allow stakeholders to analyse and interact with the data more effectively. BIM methodologies, in particular, can significantly improve road maintenance activities by creating an informative model that consolidates all extracted data from previous steps into a unified digital representation (Castaneda et al., 2024). This model serves as a dynamic repository of road asset conditions, facilitating more informed decision-making and optimizing maintenance schedules.

The combination of GIS and BIM provides a multi-dimensional perspective, supporting strategic planning for future urban developments and infrastructure resilience. By integrating geospatial data into BIM platforms, municipalities can achieve greater interoperability, enhancing collaboration across departments and improving overall infrastructure lifecycle management.

A crucial aspect of GIS and BIM integration is ensuring interoperability and seamless data exchange between the two systems. Different data formats and modeling approaches can create barriers to efficient collaboration, making standardized workflows essential (Noardo et al., 2020).

To achieve this integration, a methodology was developed to incorporate the geospatial data acquired with the MMS and all the extracted information from previous analytical steps. The core concept of this approach is to derive value-added information from geometric data and build a semantic informative model. Specifically the generation of the BIM model of the road section is a combination of a geometric representation derived from a 3D mesh and semantic attributes extracted from a shapefile within the municipal geodatabase. The process began with the classified point cloud, focusing specifically on the ground class. A road section, identified from the informative layer provided by the municipality, was segmented into distinct geometric elements (figure 13). Subsequently, a mesh surface was generated from the point cloud to create a continuous representation of the road section. The mesh surface was decimated from 244,890 to 11,926 faces to optimize handling within the BIM environment, ensuring an efficient balance between accuracy and computational performance (figure 14).

The processed mesh surface was then imported into the BIM environment using Autodesk Revit software. This integration was facilitated through Dynamo, a visual programming tool, and custom Python scripts. These tools enabled the creation of the BIM model while associating the semantic information derived from the municipal database and the road section analyses (figure 15-16). The result is an enriched BIM model containing both geometric and semantic attributes, supporting comprehensive urban infrastructure management and enhancing data accessibility for decision-makers.

Furthermore, the resulting BIM model was exported in Industry Foundation Classes (IFC) format, a widely used open standard for data exchange in the AEC (Architecture, Engineering, and Construction) industry. The IFC format enhances interoperability by allowing BIM models to be visualized and analyzed in GIS platforms such as ArcGIS Pro. This capability enables urban planners and infrastructure managers to access and interact with BIM models within their existing GIS workflows, fostering a more integrated approach to road asset management.

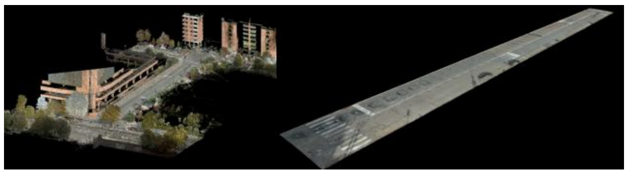

Figure 13. Segmentation of road section from the LiDAR point cloud

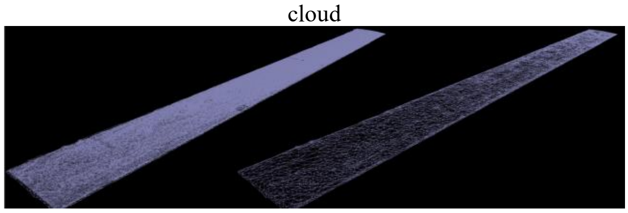

Figure 14. 3D Mesh generation and subsequent decimation of the road section

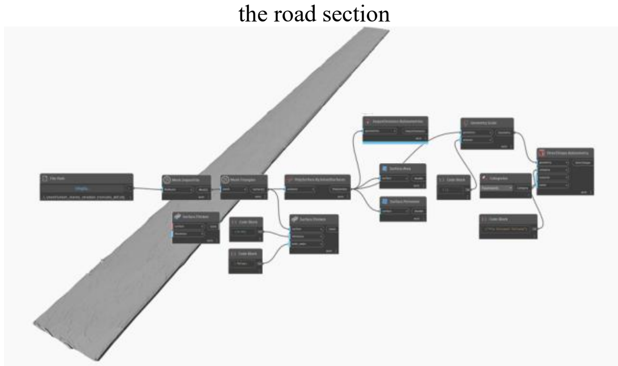

Figure 15. Creation of BIM model using DYNAMO, visual graphic language, and PYTHON scripts

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
https://doi.org/10.5194/isprs-annals-X-1-W2-2025-123-2025

3. Results

A key outcome of this study is the development of a thematic map (Figure 16) that visualizes pavement conditions across the study area. The map categorizes road segments from "good" to "very degraded", enabling municipalities to prioritize maintenance activities based on real-world conditions and to support long-term planning strategies. During interactions with municipal stakeholders, this output was identified as a critical tool to support not only technical assessments but also communication with decision-makers and the public.
The enriched geodatabase improves prioritization and budget allocation by providing a clear overview of infrastructure conditions. Integrated into a GIS dashboard, it allows municipal staff to visualize pavement data, filter by defect severity, and generate customized thematic layers for targeted interventions. Feedback from the Municipality of Turin highlighted that the dashboard has simplified coordination between technical departments and improved the efficiency of annual maintenance planning. Specifically, the thematic classification aligned with the municipality's internal index system, making the outputs immediately usable in ongoing asset management workflows.

Figure 16. Thematic mapping of the municipal information layer integrating the data extracted from pavement condition analysis, limited to the area surveyed with the MMS

In addition to the geodatabase, a BIM model of the road section was created using Revit and Dynamo, starting from a classified point cloud and a decimated 3D mesh (figure 17). Semantic attributes extracted from the GIS layer were associated with geometric elements, ensuring an accurate and informative digital representation. The model was exported in IFC format to facilitate interoperability with GIS platforms, supporting spatial analysis and infrastructure maintenance planning.

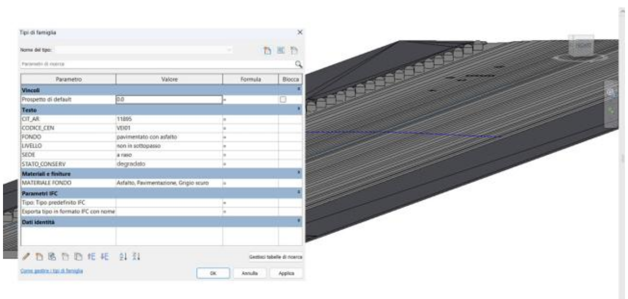

Figure 17. The 3D informative model developed within the BIM environment, enriched with semantic information for enhanced analysis and decision-making

This integration of GIS and BIM methodologies provides a multi-faceted approach to road asset management. The combination of spatial mapping and parametric modeling enhances the municipality's capacity for data-driven decision-making and structured maintenance operations. In practice, this approach has enabled the city to reclassify intervention priorities across several blocks of the Cit Turin district based on objective data, reducing reliance on manual inspections and ensuring more equitable resource distribution.
In terms of system performance, the MMS-based workflow successfully processed over 2.5 billion LiDAR points and more than 17,000 panoramic images within a time-efficient pipeline. The automated defect detection system was able to identify the majority of major surface anomalies, particularly potholes, with moderate accuracy. However, validation results revealed a substantial number of false positives for more subtle damage types such as cracks and surface repairs. Minor classification errors, often related to shaded or occluded areas, were mitigated through cross-verification with panoramic imagery and manual review. These findings confirm the operational scalability of the workflow, while highlighting the need for manual refinement and future improvements in detection accuracy.The study also lays the foundation for predictive maintenance (PdM). By leveraging MMS-derived geospatial data and time-series analysis, deterioration trends can be anticipated and intervention schedules optimized. This predictive approach shifts infrastructure management from reactive to proactive, increasing resilience and operational efficiency.

4. Discussion

The integration of MMS, GIS, and BIM provides a robust framework for enhancing modern urban infrastructure management. By combining precise 3D data acquisition with semantic modeling, this study demonstrates how local authorities can move toward proactive, data-driven strategies for road asset monitoring, maintenance, and long-term planning.
A central strength of the proposed workflow lies in its interoperability and alignment with municipal systems. The successful integration into the City of Turin's geodatabase—including the translation from PCI values to local qualitative descriptors—highlights the method's adaptability. By leveraging both thematic maps and parametric BIM models, the approach facilitates transparency, budget optimization, and operational planning across departments.
The BIM model, generated through Revit and Dynamo and enriched with semantic attributes from GIS, was exported in IFC format. This enables not only seamless integration with GIS platforms like ArcGIS Pro but also potential extensions toward broader standards such as CityGML. Future developments may consider full BIM-GIS-CityGML interoperability, enabling unified representations of road infrastructure in city-wide digital twins and supporting urban-scale asset management frameworks.
Despite these advantages, several challenges remain. Data occlusions caused by parked vehicles, vegetation, and dynamic objects can compromise acquisition completeness, especially in narrow urban contexts. These limitations can be mitigated through optimized survey planning (e.g., off-peak hours), multi-pass acquisition, and data fusion with complementary sources like UAV or static terrestrial scans.
The automated defect detection process also presents challenges. While MMS data and AI techniques offer robust solutions, complex surface textures and subtle forms of degradation may reduce classification reliability. Future refinements should focus on improving detection granularity and reducing false positives through validation with ground

truth and further model training. Furthermore, a known limitation of this study is the reliance on a proprietary black-box algorithm for damages detection. While the GV_Road_MLS module demonstrated effective performance, full reproducibility and fine-grained control remain constrained by limited algorithmic transparency. Future work could involve the development or benchmarking of open-source detection tools to further validate and expand on the methodology presented here.

Importantly, this study establishes a foundation for PdM. By integrating MMS-derived geospatial datasets with time-series analysis and machine learning algorithms, municipalities can transition from reactive to anticipatory maintenance strategies. Over time, deterioration trends can be modeled based on historic and real-time inputs, optimizing scheduling and reducing emergency interventions.

Looking forward, PdM frameworks could be further enhanced through IoT sensor networks and real-time monitoring technologies. By embedding sensors into pavement layers or key infrastructure points, cities could generate alerts as degradation thresholds are approached. These advancements would enable near-continuous updates of geospatial and BIM databases, pushing infrastructure management toward true digital twin implementations.

In conclusion, the combined use of MMS, GIS, and BIM—as demonstrated in this study—constitutes a scalable and interoperable solution for urban pavement management. The workflow not only addresses present infrastructure needs but also opens avenues for predictive modeling, integration with smart city platforms, and alignment with international data exchange standards, supporting resilient and sustainable urban development.

Acknowledgements

The authors would like to thank the Department for Major Public Works, Infrastructures, and Mobility of the Municipality of Turin and all those who contributed to the work, especially to Giulia Di Vinci for her works during the pavement damage recognition phase.

References

Arseni, M., Roman, O., Cucoara, C. & Georgescu, L.P. (2024) Application of Mobile Mapping System for a Modern Topography. Journal of Applied Engineering Sciences, Sciendo, vol. 14 no. 2, pp. 186-193.

Biancardo, S.A., Intignano, M., Veropalumbo, R., et al. (2023) BIM approach for stone pavements in Archaeological Sites: The case study of Vicolo dei Balconi of Pompeii, Transportation Research Interdisciplinary Perspectives, Volume 17, 100755.

Bertolini, L., D'Amico, F., Napolitano, A., Bianchini Ciampoli, L., Gagliardi, V., Romer Diezmos Manalo, J. (2023) A BIM-Based Approach for Pavement Monitoring Integrating Data from Non-Destructive Testing Methods (NDTs). Infrastructures, 8, 81.

Boccardo, P., La Riccia, L., & Yadav, Y. (2024) Urban echoes: exploring the dynamic realities of cities through digital twins. Land, 13(5), 635.

Castaneda, K., Sánchez, O., Herrera, R.F., Gómez-Cabrera, A., Mejía, G. (2024) Building Information Modeling Uses and Complementary Technologies in Road Projects: A Systematic Review. Buildings, 14,563.

Cepa, J.J., Alberti, M.G., Pavón, R.M., Calvo, J.A. (2024) Integrating BIM and GIS for an Existing Infrastructure. Appl. Sci., 14, 10962.

Cepa, J.J., Pavón, R.M., Alberti, M.G., & Caramés, P. (2023) TOWARDS BIM-GIS INTEGRATION FOR ROAD INTELLIGENT MANAGEMENT SYSTEM. Journal of civil engineering and management. 29(7), 621–638.

de Bortoli, A., Baouch, Y., Masdan, M., (2023) BIM can help decarbonize the construction sector: Primary life cycle evidence from pavement management systems, Journal of Cleaner Production, Volume 391, 136056.

Di Vinci, G. (2025) Utilizzo di dati ad alta risoluzione geometrica per l'analisi del dissesto stradale. Politecnico di Torino,Torino.https://webthesis.biblio.polito.it/secure/34601/1/tesi.pdf

D'Amico, F., Bianchini Ciampoli, L., Di Benedetto, A.; Bertolini, L., Napolitano, A.(2022) Integrating Non-Destructive Surveys into a Preliminary BIM-Oriented Digital Model for Possible Future Application in Road Pavements Management. Infrastructures, 7,10.

Elhashash, M., Albanwan, H, & Qin, R.. (2022) A Review of Mobile Mapping Systems: From Sensors to Applications. Sensors, 22(11), 4262.

Javanmardi, M., Javanmardi, E., Gu, Y., & Kamijo, S. (2017) Towards High-Definition 3D Urban Mapping: Road Feature-Based Registration of Mobile Mapping Systems and Aerial Imagery. Remote Sensing, 9(10), 975.

Made, I.D., Karyawan, A., Hariyadi, H., Iskandarsyah, D., Mahendra, M. (2023) INTEGRATING MMS AND GIS TO IMPROVE THE EFFICIENCY AND SPEED OF MAPPING OF URBAN ROAD DAMAGE CONDITIONS IN MATARAM, INDONESIA. Geographia Technica.

Maltinti, F., Curreli, L., Quaquero, E., Rubiu, G., Coni, M. (2021). Applying Building Information Modeling to Road Pavements Management. In: Gervasi, O., et al. Computational Science and Its Applications – ICCSA 2021. ICCSA 2021. Lecture Notes in Computer Science(), vol 12958. Springer, Cham.

Noardo, F., Harrie, L., Arroyo Ohori, K., Biljecki, F., Ellul, C., Krijnen, T., ... & Stoter, J. (2020). Tools for BIM-GIS integration (IFC georeferencing and conversions): Results from the GeoBIM benchmark 2019. ISPRS international journal of geo-information, 9(9), 502.

Oreto, C., Massotti, L., Biancardo, S.A., Veropalumbo, R., Viscione, N., Russo, F. (2021) BIM-Based Pavement Management Tool for Scheduling Urban Road Maintenance. Infrastructures, 6, 148.

Pavard, A., Dony, A., Bordin, P., (2023) ROAD MODELLING FOR INFRASTRUCTURE MANAGEMENT – THE EFFICIENT USE OF GEOGRAPHIC INFORMATION SYSTEMS. Journal of Information Technology in Construction (ITcon), Vol. 28, pg. 438-457.

Sairam, N., Nagarajan, S., & Ornitz, S. (2016): Development of Mobile Mapping System for 3D Road Asset Inventory. Sensors, 16(3), 367.

Samadzadegan, F., Dadrass Javan, F., Ashtari Mahini, F., Gholamshahi, M., Nex, F. (2024) Automatic Road Pavement Distress Recognition Using Deep Learning Networks from Unmanned Aerial Imagery. Drones, 8, 244.

Schwarz, K.P., El-Sheimy, N., (2004) Mobile mapping systems—State of the art and future trends. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 35, 10.

Scolamiero, V., Boccardo, P., & La Riccia, L. (2025). Mobile Mapping System for Urban Infrastructure Monitoring: Digital Twin Implementation in Road Asset Management. Land, 14(3), 597.

Sohaib, M., Najeeb, A., Umair, M. et al. (2024) Improving urban road infrastructure analysis and design using an integrated BIM-GIS and traffic microsimulation framework. Innov. Infrastruct. Solut. 9, 285.

Soilán, M., Justo, A., Sánchez-Rodríguez, A., Lamas, D.R., & Riveiro, B. (2021) 3D POINT CLOUD DATA PROCESSING AND INFRASTRUCTURE INFORMATION MODELS: METHODS AND FINDINGS FROM SAFEWAY PROJECT. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. XLIII-B2-239-246.

Tang, F., Ma,T., Zhang, J., Guan, Y., Chen, L., (2020) Integrating three-dimensional road design and pavement structure analysis based on BIM, Automation in Construction, Volume 113, 103152.

Wang, C., Wen, C., Dai, Y., Yu, S., Liu, M. (2020) Urban 3D modeling using mobile laser scanning: A review. Virtual Reality & Intelligent Hardware, 2(3): 175—212.