CityGML 3.0 as a Hub: Integrating BIM, GIS, and Point Cloud Data for 3D Streetspace Modeling Comprising Roads, Bridges and Tunnels

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Abstract

In recent years, semantic 3D city models have been increasingly used for large scale urban analysis in urban digital twins and smart cities. As a crucial component, semantic 3D streetspace models have gained attention due to the growing availability of road and transportation infrastructure data. However, these models exist in various data formats, such as point cloud data and BIM models, each designed for different use cases, making integration and management challenging when diverse models need to be utilized together for further applications. To address this, we develop a workflow to transform heterogeneous streetspace component representations into an integrated semantic 3D model based on the international standard CityGML 3.0, which serves as a hub for integrating different geometric and semantic features. A case study in Munich, Germany was conducted by integrating BIM, GIS, and point cloud data. The case study area features complex streetspace components, including roads, bridges, and tunnels. This study demonstrates the feasibility of harmonizing complex urban environments with multiple types of models for streetspace components. Challenges encountered in the transformation process are discussed, along with future research directions to further enhance the integration of semantic 3D streetspace models.

1. Introduction and Related work

Semantic 3D city models have recently gained significant attention from both researchers and the public due to their wide range of applications in urban digital twins (Biljecki et al., 2015). However, most existing semantic 3D city models primarily emphasize buildings. Semantic 3D streetspace models are essential for maintaining consistency and connectivity across different components of the urban environment. With the advancement of technologies such as autonomous driving, there is a growing shift in focus toward the development of semantic 3D streetspace models (Beil et al., 2020). Streetspace models represent transportation systems, including not only roads but also other essential components that interact, share functions, and occupy space (Beil and Kolbe, 2020). Therefore, modeling semantic 3D streetspace models should extend beyond roads to include other complex components relevant to 3D streetspace representation. In complex scenarios, elements such as bridges and tunnels must be integrated into semantic 3D streetspace models, as many use cases require a comprehensive representation of all interconnected components. Figure 1 illustrates examples of semantic 3D streetspaces (Beil and Kolbe, 2024).

Nowadays, there are multiple ways to model streetspace components, driven by advancements in data acquisition technologies. For instance, mobile mapping provides detailed geometric information in the form of point cloud data (Xu and Stilla, 2021). Additionally, government agencies offer 2D and 3D GIS data, some of which are available through paid services such as Google Maps (Google Earth Engine Team, 2024). Designers can also use BIM authoring tools to model existing streetspace components, providing the flexibility to create models of components that do not yet exist in the real world. These different methods offer flexibility in modeling semantic 3D streetspace, each excelling in specific domains and providing unique advantages tailored to particular applications.

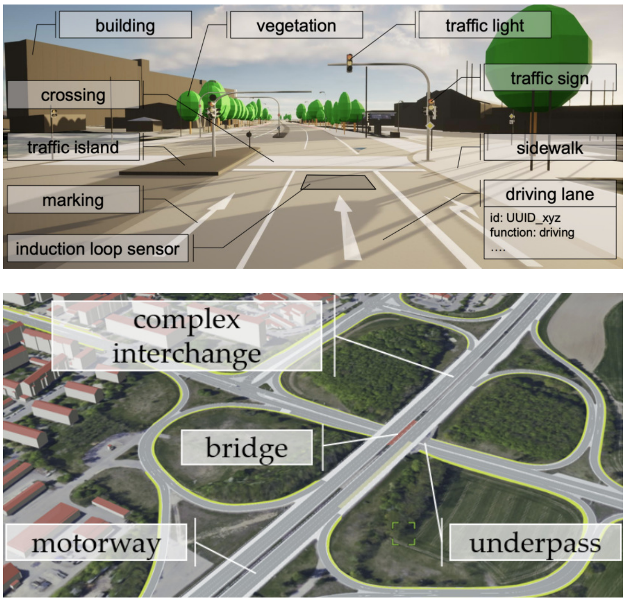

Figure 1. The upper image illustrates the components of a semantic 3D streetspace, including not only the road but also relevant components that share functional interactions. The lower image depicts a semantic 3D streetspace in a complex interchange, incorporating both a bridge and an underpass as part of the overall semantic 3D streetspace.

However, these variations present challenges in managing a geometrically, topologically and semantically integrated model, particularly in semantic 3D streetspace, where all components play a crucial role in downstream applications such as traffic simulation and road safety analysis. There are mainly three key research questions. First, given the existence of multiple standards for streetspace modeling, it is essential to identify the

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most suitable representation for the integration of these models. Second, in complex scenarios involving multiple components such as roads, bridges, and tunnels, redundancies often exist across different models stored in various data formats. These redundancies increase the overall file size, consume unnecessary computing time, and negatively impact the performance of downstream applications. Finally, achieving an automatic and precise transformation of various models remains a critical challenge in developing an integrated and efficient semantic 3D streetspace model.

To address these challenges, researchers are actively exploring efficient methods for achieving data integration. Kolbe and Donaubauer discussed semantic 3D city modeling and Building Information Modeling, explaining their relationship, modeling methods, and key differences (Kolbe and Donaubauer, 2021). Significant efforts have been made in this field. For instance, Stouffs et al. proposed a Triple Graph Grammar for the automatic semantic and geometric conversion of IFC models to CityGML (Stouffs et al., 2018). However, most research in this domain still focuses on buildings. In the context of infrastructure, buildingSMART has expanded its scope to include various infrastructure domains. It currently defines IfcFacility as the parent class for IfcBridge, IfcRailway, and IfcRoad, with future developments planned, including IfcTunnel and other extensions (buildingSMART, 2024). In this context, Cepa et al. examined a use case in the infrastructure domain, specifically an experiment conducted in Spain on the integration of BIM and GIS for the operation and maintenance of large scale existing infrastructure (Cepa et al., 2024). Modern streetspace modeling encompasses a broader range of models at a larger scale. For instance, GIS data is widely used for 3D road network modeling. Wang et al. introduced a method for automatically generating 3D road networks by integrating GIS data with road semantic information (Wang et al., 2021). To address the limitations of complex 3D road network modeling, Chen et al. proposed a rule-based approach that accurately represents intricate areas using open-source data (Chen et al., 2022). Point cloud data can serve as an augmentation of 3D geometric information in the data integration process. For instance, Brea et al. proposed an effective method using indoor mobile laser scanners for geometric quality control in construction, enabling the rapid detection of structural deviations based on LiDAR data (Brea et al., 2024). Existing BIM and GIS integration methods have been well developed and extensively researched. Other models, such as point cloud data, are increasingly being incorporated into data integration efforts. Although extensive research has been conducted, most existing approaches primarily focus on transforming individual models, without addressing complex scenarios that demand the geometric and semantic integration of multiple components.

Beil et al. provided a detailed discussion of standards relevant to semantic 3D streetspace modeling, specifically examining the capabilities of the CityGML 3.0 Transportation module (Beil et al., 2020). CityGML 3.0 also includes additional streetspace related modules, such as Bridge and Tunnel, providing an ideal standard for integrating various streetspace models (Kolbe et al., 2024). Thus, the objective of this study is to treat CityGML 3.0 as a hub for semantic 3D streetspace modeling. By integrating various models related to streetspace components, this research ensures the generation of a fully georeferenced, geometrically and semantically consistent 3D streetspace model. Bridge BIM models in IFC, GIS data (e.g., shapefiles and digital elevation models), and point cloud data in LAS are processed, semi-automatically transformed, and integrated into a CityGML 3.0 representation. Simultaneously, different representations can complement each other during the transformation process, which helps to remove redundancies and noise across these representations. The key contributions of this research include:

1. Insights into CityGML 3.0's role in harmonizing various components within streetspace.
2. A workflow for the semi-automatic transformation of heterogeneous streetspace models into a detailed 3D CityGML 3.0 representation.
3. Remove redundancies and noise in heterogeneous streetspace models to enhance efficiency in downstream 3D streetspace applications.

A case study was conducted in a complex transportation area in Munich, Germany, involving the transformation of diverse models representing roads, bridges, and tunnels. Recent study categorizes urban data fusion into three integration levels: Level 1 extends the conceptual data model; Level 2 ingests data into a shared repository; and Level 3 postpones integration until the visualization or client layer (Jeddoub et al., 2024). Our work aligns with Level 2, where heterogeneous sources are harmonized through transformation into a common target schema.

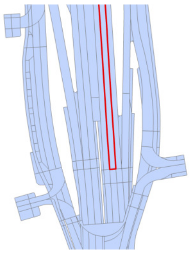
2. Case Study Approach

2.1 Study Area

The case study was conducted in Munich, Germany. As a large city in the Germany, Munich has a large-scale and highly developed road network. Consequently, its streetspace has become increasingly complex, featuring numerous multilevel structures, such as bridges and tunnels. This complexity necessitates the use of various models for streetspace modeling. For instance, numerous bridge designs exist, and with advancements in mobile mapping technologies, point cloud data has become more prevalent due to its ease of acquisition and cost-effectiveness. Additionally, the City of Munich is actively developing a standardized and unified representation of the semantic 2D lane model, providing a comprehensive and precise depiction of streets while incorporating official semantic information. These factors make Munich an ideal study area for evaluating the proposed workflow. The case study focuses on the streetspace surrounding Donnersberger Bridge and Trappentreu Tunnel in central Munich.

2.2 Data Sources and Existing Models

Different digital models are available in the test area: semantic 2D lane models of the study area, a BIM model of a conceptual (non-existing) bridge in IFC, and mobile mapping point cloud data of the tunnel. The semantic 2D lane model, developed by the City of Munich, contains rich semantic information, including lane type, material, level, and other relevant attributes. It is composed of multiple polygons, with semantic information stored within each polygon. These models are based on extensive survey data and existing geospatial information. Geometrically, these polygons define the 2D shape of the lane, as shown in Figure 2. The bridge BIM model, created as part of a student project, serves solely as a redesign of an existing bridge and does not represent a real world structure. The mobile mapping point cloud data was captured at a resolution of 2000 points per square meter, providing detailed spatial information for tunnel modeling. Additionally, aerial point cloud data is available at the resolution of 6 points per square meter, covering the entire case study area and capturing surface features from an overhead perspective. Existing models are illustrated in Figure 4.



Semantic information of the highlighted polygon	
Lane ID	372
Lane Type	Driving Lane
Lane Material	Asphalt
Speed Limit	50 km/h
Elevation Level	1

Figure 2. A section of the semantic 2D lane model with an illustration of the semantic information stored within the highlighted red polygon.

As different models currently exist in silos, streetspace data in this area is highly unorganized. The BIM model primarily represents detailed structural components and provides precise geometric and semantic information for infrastructure design and management (Bradley et al., 2016). The semantic 2D lane models serve as a standardized representation of road networks and are crucial applications for such as transportation planning. Mobile mapping point cloud data captures high resolution spatial information. In contrast, aerial point cloud data provides large scale spatial coverage (Javanmardi et al., 2017). Thus, from a semantic perspective, missing semantic information (e.g., in point cloud data) or inconsistent semantic mappings due to different naming conventions pose challenges in achieving seamless semantic integration. From a geometric perspective, different models are represented using various geometries, such as points, surfaces, or volumetric forms. Managing these models separately often leads to conflicting information and errors. Another issue we identified is geometric redundancy. Geometries may be unnecessarily duplicated across models or may not contribute meaningful information. For instance, the mobile mapping point cloud data capturing the tunnel contains many redundant points that either exceed the extent of the tunnel or do not accurately represent its structure. Finally, downstream applications, such as traffic simulation, increasingly require semantically and geometrically integrated 3D streetspace models to accurately reflect real-world conditions. These demands highlight the growing need for an integration workflow capable of geometrically and semantically integrating different models across various data formats in streetspace.

3. The Semantic CityGML 3.0 Data Model

Different models offer a range of capabilities across geometric, semantic, topological, and visual aspects, and are typically developed to support specific use cases (Beil and Kolbe, 2024). Therefore, it is necessary to identify a suitable standard that can bridge the gaps between these 2D and 3D models when geometric and semantic integration is required. Such a standard should, on the one hand, support various streetspace modeling modules, including bridges, tunnels, and roads. On the other hand, it should enable the integration of these components within a consistent semantic 3D model.

Beil et al. have already conducted a thorough comparison of standards and data formats for representing streetspace across various model types (Beil et al., 2020). Based on their analysis, CityGML emerged as a suitable choice. The international OGC standard CityGML 3.0 is thematically organized into a core module, which defines the fundamental concepts and structures of CityGML, and eleven extension modules that support various thematic aspects of 3D city modeling. As illustrated in Figure 3, this modular structure allows for a standardized representation of diverse urban elements. Among these, the Bridge Module, Tunnel Module, and Transportation Module are particularly relevant to the modeling and integration of streetspace components in the case study. The Bridge Module in CityGML 3.0 consists of AbstractBridge, a superclass that defines shared attributes. The Bridge class represents the entire bridge structure, while BridgePart defines its subdivisions. These classes include elements such as BridgeConstructiveElement, BridgeInstallation, and BridgeFurniture. Similarly, the Tunnel Module follows the same structure, with AbstractTunnel as the superclass, while Tunnel and TunnelPart represent the main tunnel structure and its subdivisions. Internal components include TunnelFurniture and TunnelInstallation. In the Transportation Module, Roads are divided into Sections and Intersections, which are further segmented into AuxiliaryTrafficSpaces and TrafficSpaces, bounded by AuxiliaryTrafficAreas and TrafficAreas to define their spatial extent relative to the ground.

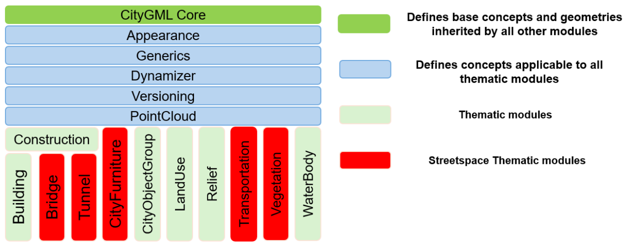


Figure 3. Modular structure of the CityGML 3.0 standard

Thus, CityGML 3.0 provides a well-structured and standardized framework for managing various streetspace modules. It serves as a viable solution for addressing the challenges associated with the management and storage of diverse streetspace data representations within a consistent semantic model. In this study, three key components, bridge, lane model, and tunnel, were transformed into CityGML 3.0 representations to evaluate its capability for the geometric and semantic integration of complex streetspace scenarios.

4. Data Integration Workflow

The proposed workflow is designed to transform existing models into a geometrically and semantically integrated CityGML 3.0 representation. The transformation process is divided into three main stages: preprocessing, geometric alignment, and semantic mapping. Preprocessing varies depending on the model type. For the bridge BIM model, it primarily involves coordinate system alignment and georeferencing. For the lane and tunnel models, preprocessing consists of point cloud data classification. Geometric alignment focuses on converting geometries into formats compatible with CityGML 3.0. Semantic mapping involves assigning feature classes based on semantic information. After the transformation, the modules are imported into the 3DCityDB V5 (Yao et al., 2018). The workflow is illustrated in Figure 5.

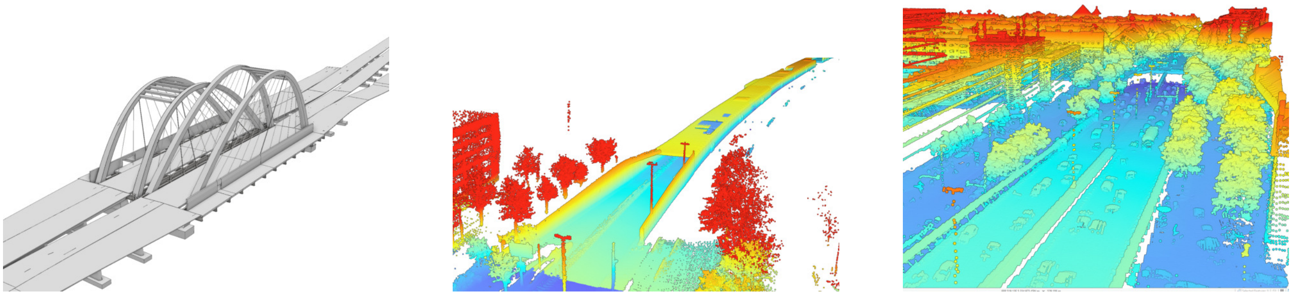


Figure 4. Visualization of the existing models. The left figure presents a redesigned bridge model, created as part of a student project. This model does not exist in reality but represents a conceptual design. The middle figure displays mobile mapping point cloud data of the tunnel. The right figure presents aerial point cloud data, covering the case study area and capturing surface features.

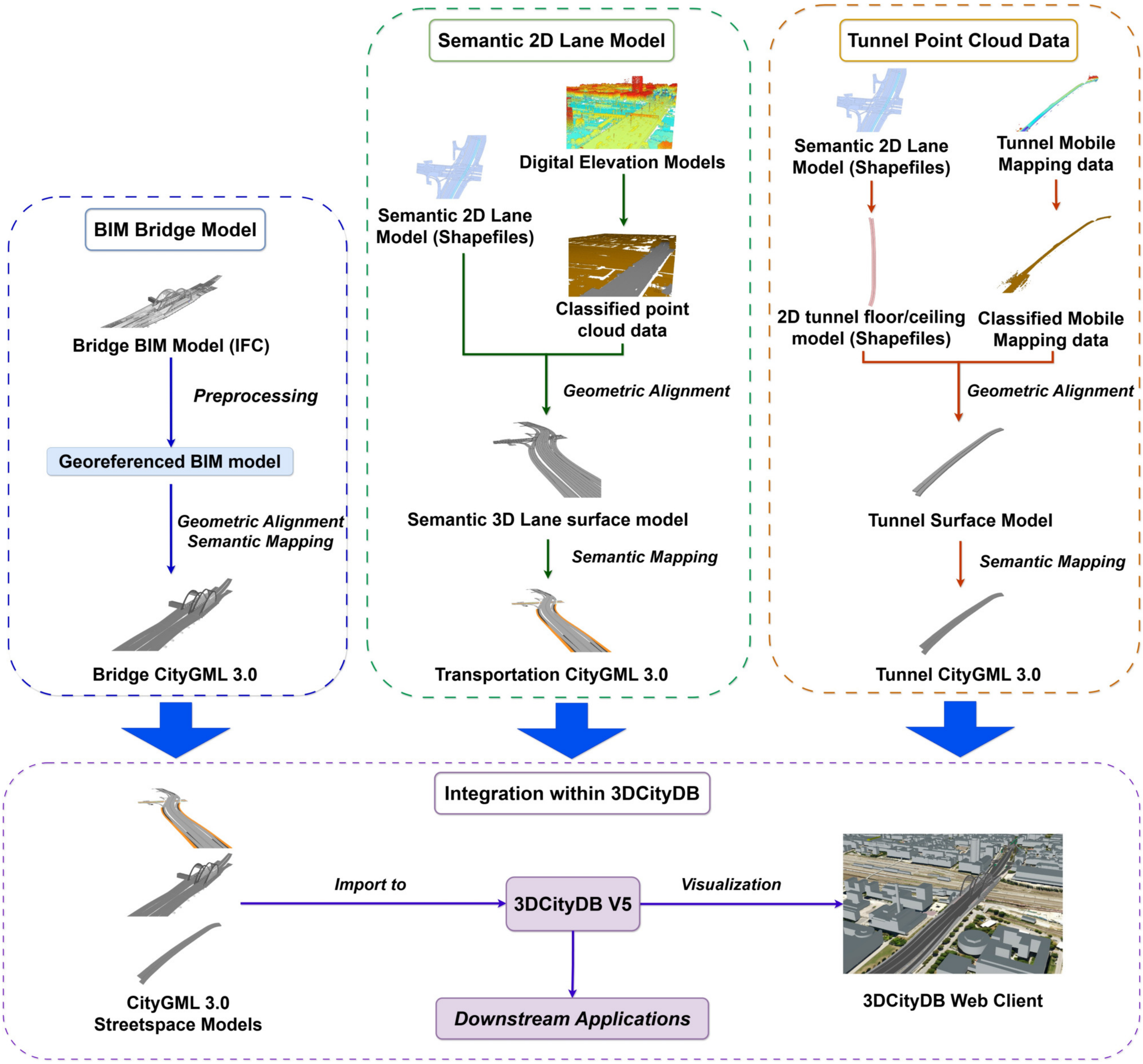


Figure 5. The workflow for bridge, lane and tunnel models integration.

4.1 Preprocessing

A crucial preprocessing step is ensuring that the bridge BIM model is correctly positioned. The procedure begins by setting the appropriate coordinate system in a GIS software environment. The BIM model is then imported and projected onto the designated coordinate system. Next, a control point within the BIM model is matched to a corresponding real-world location in the GIS. This process can be described using a transformation matrix T, which integrates translation, rotation, and scaling operations, defined as $T = T_{\text{translation}} \cdot T_{\text{rotation}} \cdot T_{\text{scale}}$ (Isikdag and Zlatanova, 2009). A specific control point is selected and aligned with its corresponding coordinate in the GIS.

Apart from the BIM model, point cloud data also requires preprocessing. One of the primary challenges associated with point cloud data is the lack of semantic information. Therefore, a critical preprocessing step involves noise removal and classification. Aerial and mobile mapping point cloud data is classified into different categories using a pre-trained model, which assigns each point clusters to predefined classes based on location and elevation information. To streamline the processing pipeline within a unified environment, a pre-trained model based on the PointCNN architecture which is available in GIS software was utilized for pipeline alignment (Esri, 2024). The ground class within the point cloud data is identified as the ground surface, while irrelevant structures and noise are filtered out to enhance data quality and accuracy.

4.2 Geometric Alignment

Geometrically, the CityGML data model does not support parametric representations. As a result, implicit geometries created through parameterized modeling methods, such as Constructive Solid Geometry (CSG), must be converted into explicit representations, i.e., boundary representations (B-Rep) (Donkers et al., 2016). In this step, the geometries from BIM models are first extracted, then decomposed and reconstructed. For the geometric alignment of lane models and tunnels, we developed a transformation method. The semantic 2D lane model provides semantic information and spatial positioning, where attributes such as elevation levels are embedded within the polygons. Specifically, elevation level 1 represents lanes on bridges, level 0 corresponds to ground level lanes where height information aligns with the terrain, and level -1 denotes underground lanes. Using this information, the semantic 2D lane model is transformed into a 3D by interpolating each level's elevation information from 3D representations onto the 2D lane model.

After preprocessing, the classified point cloud data contains clusters of ground points that hold elevation information corresponding to their spatial positions. To extract elevation values for each level, the elevation information from the point cloud data is converted into a 2.5D raster representation, where each grid cell stores its corresponding elevation value. To further refine the lane model and remove noise, an interpolation function Spline is applied to fill voids and create a smooth, continuous elevation raster. Finally, the elevation values from grid cells are interpolated to the 2D lane model polygons to generate a 3D multi-polygon representation. This process can be fully automated using two approaches. The first approach utilizes model-building tools within a GIS software environment. The second approach involves a Python script. Both approaches enable execution with the semantic 2D lane model and digital elevation models as inputs, producing semantic 3D multi-polygon lane models as the output.

Building on this, we developed an automatic reconstruction algorithm for 3D tunnel modeling based on mobile mapping point cloud data. This process also incorporates the semantic 2D lane model. As previously mentioned, the tunnel floor surface should align with the lane model. Specifically, level -1 2D polygons in the lane model represent underground lanes, directly corresponding to the tunnel floor surface. To reconstruct the tunnel floor, a new set of 2D polygons identical to the level -1 polygons is generated, with new created semantic attributes specifically defining as the tunnel floor surface. Using the classified mobile mapping point cloud data, we apply the same transformation process used for the level -1 lane model, producing 3D multi-polygon representations of the tunnel floor which aligned with lane models. Beyond the floor surface, tunnels also consist of walls and a ceiling. To model these components, new 2D polygons are generated to represent the tunnel ceiling surface, geometrically mirroring the layout of the tunnel floor. Since mobile mapping point cloud data accurately reflects real-world conditions, the highest points in the unclassified mobile mapping point cloud data correspond to the ceiling surface and contain relevant elevation information. By applying the 3D transformation process once again, replacing the input 2D polygon with the newly created ceiling polygon and using the unclassified point cloud data, the tunnel ceiling surface is reconstructed. For the tunnel walls, 3D multi-polygon representations are generated by extruding the boundary lines between the reconstructed floor and ceiling surfaces. This entire process can be implemented using model-building tools in the GIS software environment or Python scripting to create a custom function for automated 3D tunnel reconstruction. The required inputs for this workflow are classified mobile mapping point cloud data and level -1 lane models, ensuring the alignment of the tunnel floor surface with the lane model. Moreover, only the necessary portions of the tunnel are used and transformed from the mobile mapping point cloud data, which significantly reduces redundancy.

4.3 Semantic Mapping

From a semantic perspective, IFC to CityGML semantic object type mapping is performed to transfer element types, attributes, and relationships from the IFC object model to the CityGML model (Tan et al., 2023). For the bridge model, the mapping process involves two key aspects: IFC spatial structure elements and IFC physical objects. IFC spatial structure elements act as hierarchical containers within the IFC model, including elements such as IfcProject and IfcSite. In contrast, CityGML 3.0 provides feature classes that serve as root elements, such as CityModel and CityObjectGroup. The second aspect pertains to IFC physical objects, which are typically defined by detailed object names such as IfcColumn or IfcWall. In contrast, CityGML 3.0 does not classify objects at such a granular level. Instead, it aggregates similar components into more generalized feature classes. For example, multiple IFC object types like IfcColumn and IfcWall are mapped to the broader class BridgeConstructiveElement in the CityGML Bridge module. In our case study, we designed a mapping for IFC Bridge to the CityGML Bridge Module features. The detailed mapping of object types is illustrated in Figure 6.

For the lane model, each polygon encapsulates rich semantic information, including lane type, function, material, and other attributes. In the CityGML 3.0 Transportation Module, roads are decomposed into specific feature classes, optimizing the data structure by avoiding redundancy and improving clarity, which is shown in Figure 7. By leveraging the semantic details embedded in the lane model and the feature classes of the CityGML 3.0 Transportation Module, we established a systematic mapping that transforms the semantic 3D surface representation into a structured CityGML 3.0 data model. Specifically, during the CityGML 3.0 transformation process, the 3D multi-polygons were first mapped to CityGML 3.0 TrafficArea and AuxiliaryTrafficArea based on the semantic attribute lane type. The lane type represents the function of the lane within the road network. The corresponding mapping is detailed in Table 1.

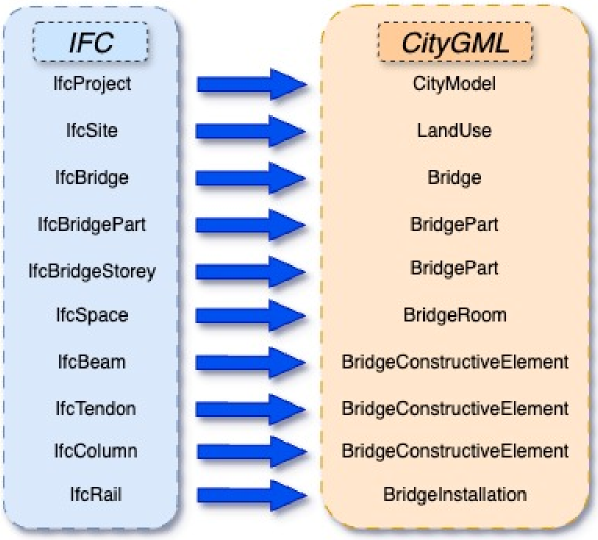


Figure 6. Mapping of IFC Bridge Object Types to CityGML Bridge Module Features.

Following this, manual adjustments were necessary to map sections and intersections. A Section is a transportation segment that can be clearly assigned to a single Road, whereas an Intersection is a shared transportation space that serves as a common segment for multiple Roads or other transportation objects. Thus, in the case study area, junctions within the lane model are classified as intersections, while all other segments are considered sections. Due to the complexity of the test area and the original format of the lane model and the Junction feature class being in 2D, automatically identifying sections and intersections proved challenging, especially for bridges and viaducts, which require definition in the vertical dimension. To address this, we compared the data with real world conditions using the 2D Junction feature class, where intersection and section features were manually identified and assigned to the reconstructed 3D multi-polygon. These features were then mapped back into CityGML 3.0 for the Section and Intersection feature classes. Furthermore, since these features were originally decomposed from the Road feature class based on road names, they were later unified into the Road class through real world validation. For tunnels, the mapping process is more straightforward. During the creation of the 3D multi-polygon representation, the floor and ceiling names were assigned, allowing direct mapping based on these attributes. The TunnelPart is bounded by FloorSurface, CeilingSurface, and InteriorWallSurface.

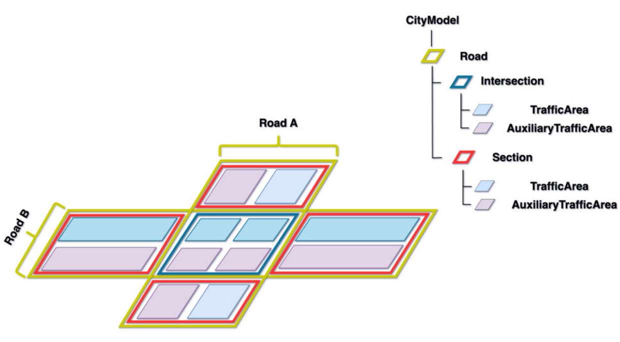


Figure 7. Visualization of CityGML 3.0 Transportation Module.

Table 1. Mapping of Lane Types to CityGML 3.0 Objects.

Lane Types	CityGML 3.0 Objects
driving_lane footpath cyclepath combined foot-/cyclepath square parking_lay_by rail rail_road_combined crosswalk bus_lay_by motorway emergency_lane road_works unknown	TrafficArea
shoulder green_area kerbstone restricted traffic_island raised_median low kerbstone border road_channel	AuxiliaryTrafficArea

4.4 Integration into 3DCityDB

The case study primarily utilized ArcGIS Pro, FME, and 3DCityDB. ArcGIS Pro was primarily used for preprocessing and geometric alignment of the lane and tunnel models. FME was used for geometric alignment and semantic mapping of the bridge model, as well as for semantic mapping of the lane and tunnel models. Following the transformation, several CityGML 3.0 models relevant to semantic 3D streetspace were generated, including the Transportation Module features, Bridge Module features, and Tunnel Module features. However, these models initially existed as standalone entities without explicit relationships between them. To address this, 3DCityDB V5 was used for CityGML 3.0 feature management, visualization, and interaction. It was also used for the storage, management, and analysis of large scale semantic 3D streetspace models. The 3DCityDB citydb-tool was used to import each CityGML 3.0 model into a unified database, ensuring centralized management of all models. For visualization, the models were exported in 3DTiles and visualized in the 3DCityDB web client.

5. Results and Discussion

By utilizing CityGML 3.0 as a hub, we successfully integrated streetspace models from various data formats. The case study area comprises multiple complex components, including lane models, bridge model, and tunnel model. We semi-automatically transformed these three different models into CityGML 3.0, ensuring geometric and semantic consistency. To illustrate the integration process, we imported the original models into the ArcGIS Pro environment, as shown in Figure 9. This visualization clearly demonstrates that the three models initially exist as entirely separate entities. Geometrically, when visualized by absolute height, the BIM model and point cloud data are represented in 3D, whereas the lane model is stored in a 2D format. Semantically, the point cloud data lacks structured attributes, as it consists purely of unstructured points, while the BIM and lane models follow different semantic schemas. In their raw form, these models remain disconnected, lacking inherent relationships.

Bridge Entrance | Main Bridge | Bridge Exit

Viaduct Section | Tunnel Entrance | Tunnel Exit

Figure 8. Visualization of the semantic 3D streetspace model in 3DCityDB web client.

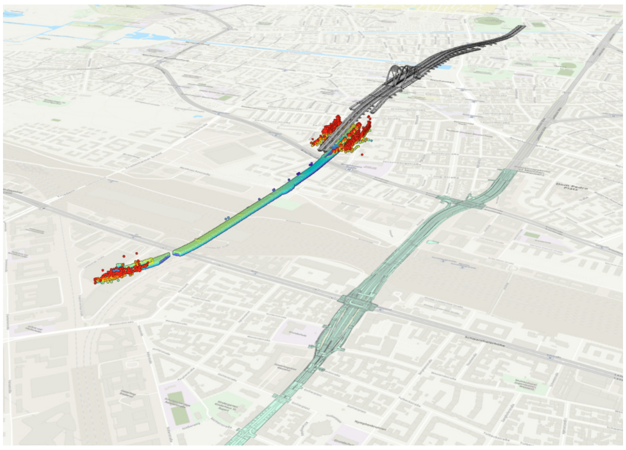


Figure 9. Visualization of the existing models, which exist as separate entities with no explicit relationships between them.

The original models were transformed into corresponding CityGML 3.0 module features, specifically Bridge, Tunnel, and Transportation. Using the 3DCityDB V5 citydb-tool, all CityGML 3.0 data was stored in a single database. The visualization results are presented in Figure 8. When visualized, individual components remain interactable, demonstrating the capability of CityGML 3.0 to serve as a hub for the geometric and semantic integration of heterogeneous streetspace models. Table 2 compares the file sizes of the original models with their transformed CityGML 3.0 representations, as well as the final exported integrated streetspace model in CityGML 3.0 representation. After the transformation process, the overall size of the streetspace model was significantly reduced. This reduction is primarily due to the removal of irrelevant, noisy, and redundant data from the original point cloud data.

Table 2. File size comparison

Component	Original File Size	Transformed File Size (CityGML 3.0)
Bridge	IFC: 404 MB	449 MB
Road	LAS and Shapefiles: 1125 MB	84 MB
Tunnel	LAS: 437 MB	19 MB
StreetSpace Model	IFC, LAS and Shapefiles: 1966 MB	376 MB

In the workflow illustrated in Figure 5, the transformation process consists of 9 steps, including preprocessing, geometric alignment, and semantic mapping for each of the three components. Among these steps, manual interventions are limited to BIM model preprocessing and lane model semantic mapping. The remaining steps can be automated using Python scripts or model-building tools, demonstrating a semi-automated process for transforming heterogeneous streetspace models into a detailed 3D CityGML 3.0 representation.

6. Conclusions

In conclusion, this study integrates various models in different data formats within the streetspace into a geometrically and semantically integrated semantic 3D model based on CityGML 3.0 representation. The test area encompasses a complex environment containing multiple digital models, including BIM models, semantic 2D lane models, and point cloud data. First, by treating CityGML 3.0 as a hub, this study enables the management and storage of diverse models within a unified framework, facilitating a more accessible and manageable semantic 3D streetspace model. The approach also demonstrates the capability of CityGML 3.0 to serve as an integration platform for heterogeneous semantic 3D streetspace representations. Second, the proposed workflow effectively extends beyond traditional building models to include infrastructure components such as bridges and tunnels. Finally, the transformation process can be performed semi-automatically, further enhancing operational efficiency.

However, several limitations were identified and addressed during this research. First, although the tunnel can be topologically aligned with the lane model, the topological alignment between the bridge and the lane model remains a challenge. Ideally, the bridge surface should align with the lane model as well. However, due to the separate design of the bridge, redesigning the bridge lane to achieve alignment is time-consuming. Additionally, the attribute mapping of roads, intersections, and sections in CityGML 3.0 was performed manually, requiring us to verify roads based on real world conditions. To improve automation, the semantic structure of the 2D lane model should be further refined. Specifically, adding a junction attribute and integrating it with elevation levels would enable a more automated and efficient process. During the tunnel model transformation process, the mobile mapping point cloud data was incomplete, capturing only a unidirectional view of the tunnel, whereas in reality, it is a bidirectional structure. To compensate, we artificially generated the opposite side of the tunnel. Additionally, we simplified the tunnel structure by reconstructing only the inner space.

Moving forward, additional features from other modules can be incorporated into streetspace modeling, such as the CityFurniture module and other relevant extensions. Furthermore, it is worth exploring the application of this approach in additional areas that involve multiple digital models represented in various data formats. Additionally, we aim to enhance the integration of bridge and road models to further reduce redundancy and improve consistency. To evaluate the effectiveness of this approach, we plan to test the process in various locations with a broader range of components and establish a more systematic evaluation framework to assess the integration method.

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