MSc thesis in Geomatics

Structuring Semantics in Smart Point Clouds Using an HBIM Ontology for Heritage Objects with Propagation to Gaussian Splatting

Zhuoyue Wang

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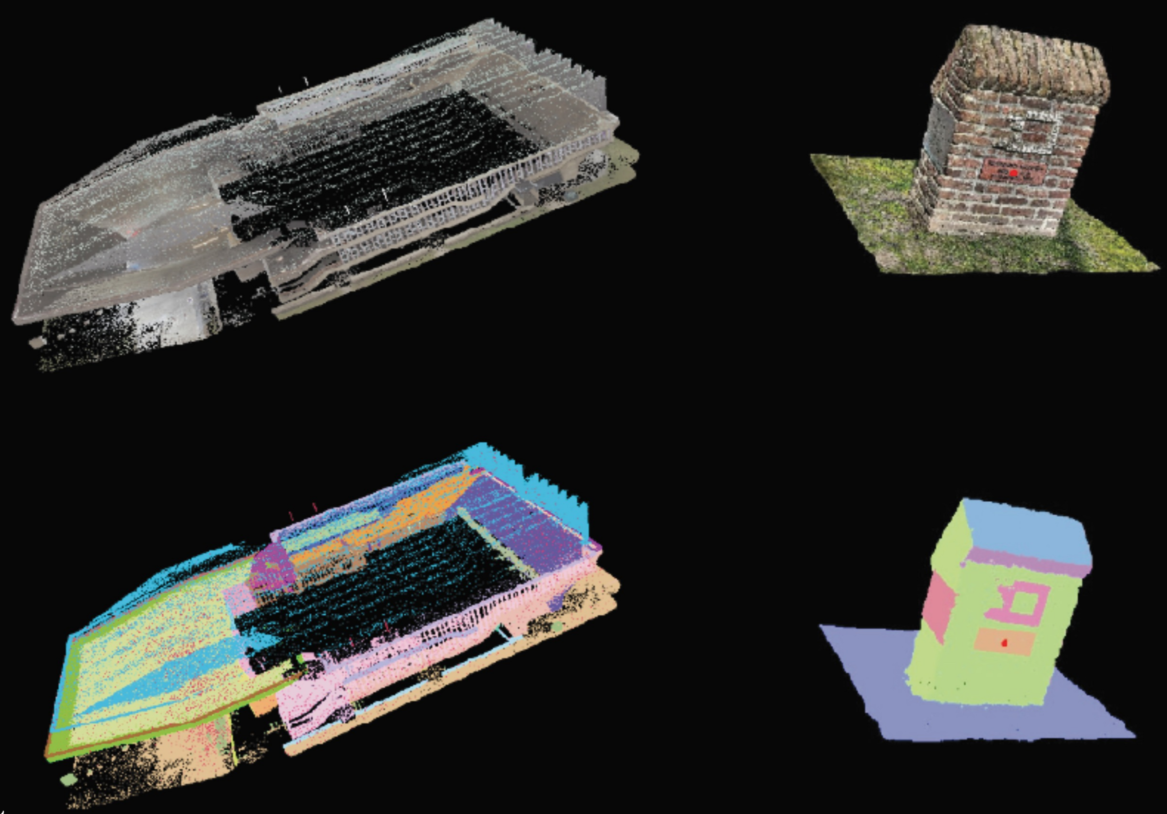

TU Delft

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Structuring Semantics in Smart Point Clouds Using an HBIM Ontology for Heritage Objects with Propagation to Gaussian Splatting

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Zhuoyue Wang: *Structuring Semantics in Smart Point Clouds Using an HBIM Ontology for Heritage Objects with Propagation to Gaussian Splatting* (2025)

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Abstract

This thesis proposes a structured and scalable workflow for semantically enriched Smart Point Cloud (SPC) grounded in Heritage Building Information Model (HBIM) ontology. Rather than representing the heritage object with vector-based parametric models, this approach treats the smart point cloud itself as a valid HBIM geometry representation, preserving geometric fidelity while attaching multi-layered semantic information at the patch level. A structured semantic model is defined through a literature-based ontology review, encompassing structural, material, historical, cultural, and conservation-related characteristics. The SPC workflow is implemented and tested on two heritage case studies: the Herdenkingsmonument Kartuizerklooster and the Aula of TU Delft. Each case demonstrates the generality of the method under different geometric and semantic complexities. The semantic annotations are stored externally in structured JSON files, ensuring modularity, version control, and future interoperability. A lightweight web-based viewer was developed using Three.js to support interactive visualization and interpretation, enabling users to explore structure, material, and cultural information directly in the browser. Although full integration with 3D Gaussian Splatting (3DGS) could not be achieved due to current toolchain limitations, the thesis outlines strategies for propagating patch-level semantics to 3DGS centers, as well as segmenting and visualizing per patch with Gaussian Splatting, establishing groundwork for future research in full semantically integrated rendering. Overall, this study contributes a reproducible methodology for documenting, interpreting, and disseminating heritage datasets in a way that aligns with HBIM objectives while minimizing modeling overhead. The data processing and the visualization platform are shared on Github by https://github.com/Zhuoyuee/thesis and https://github.com/Zhuoyuee/spc_viewer/tree/main.

Keywords: Smart Point Cloud, HBIM, semantic enrichment, Gaussian Splatting, cultural heritage

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To my friends, classmates, and extended family. You made the tough parts survivable and the good parts much sweeter.

Lastly, limited assistance from large language models was used to refine grammar and phrasing. All substantive content was written and developed by the author.

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1. Introduction

1.1. Background

Heritage conservation plays a critical role in preserving the cultural identity, historical continuity, and social meaning of places and structures. These heritage sites not only embody architectural and technological achievements of the past but also support education, identity formation, and tourism-based economies. Yet, many of these assets face ongoing threats from environmental degradation, urban pressure, neglect, and catastrophic events such as fire or conflict. In response, digital documentation has emerged as a key strategy for preservation, research, and public dissemination (UNESCO, 2024; Wagner & de Clippele, 2023).

Despite increased access to heritage archives through initiatives like United Nations Educational, Scientific and Cultural Organization (UNESCO), Documentation and Conservation of Monuments and Sites of the Modern Movement (DOCOMOMO), and *Europeana*, most platforms remain limited in terms of their digital formats. While scanned documents and photographs are widely available, structured 3D representations are often missing or isolated from semantic content. Even when 3D models exist, they are typically passive: simple point clouds rendered with Potree, or vectorized models with no semantic interaction, limiting their usefulness for conservation or education. Additionally, differences in format and purpose (e.g., mesh vs. Industry Foundation Classes (IFC) vector-based BIM vs. raw point cloud) result in fragmented workflows and reduced interoperability.

To address these gaps, Heritage Building Information Modeling (HBIM) has been proposed as a solution that combines geometric documentation with structured metadata. However, most HBIM workflows remain reliant on parametric modeling based on the IFC standard. This approach requires the conversion of raw data (e.g., point clouds) into idealized vector geometries — a process that introduces abstraction, geometric loss, and significant manual overhead. Furthermore, there is no consensus on what constitutes HBIM in practice. Semantics are often project-specific, and there is no formal ontology that defines which attributes (structural, material, symbolic, historical) should be consistently included across heritage modeling efforts (Murphy et al., 2013; Pocobelli et al., 2018).

Smart Point Cloud (SPC) offers an alternative that maintains the original geometric fidelity of the point cloud while enabling semantic enrichment through segmentation and metadata attachment. By treating point clouds not only as measurement data but as the main modeling medium, SPCs can fulfill the goals of HBIM—such as structured information, interpretability, and lifecycle tracking—without the need for rigid parametric reconstruction. Prior works such as Poux et al. (2017) have demonstrated the potential of patch-based point cloud segmentation and structured enrichment in various domains, yet most implementations remain domain-specific or theoretical.

This thesis contributes to this growing field by designing a modular, generalizable workflow for creating semantically enriched SPCs guided by a literature-based HBIM ontology. Unlike conventional HBIM pipelines, which convert point clouds into IFC vector-based models, this workflow takes the SPC as the final output and focuses on linking semantic attributes directly to geometric patches. A structured information model is built based on a systematic literature review, which informs both the categories and levels of semantic annotation. The resulting SPCs are visualized in a lightweight, web-based viewer that supports interactive exploration and structured interpretation.

In terms of visualization, this thesis also investigates the potential of integrating SPCs with 3D Gaussian Splatting (3DGS) — a recent rendering technique known for its photorealistic output and real-time performance. Although full semantic integration with 3DGS could not be demonstrated due to technical limitations in current tools, the thesis laid the ground for semantic integration by semantically propagating from SPC to 3DGS, also exploring strategies for future linkage. These efforts set the foundation for future research in combining high-fidelity visualization with semantic interaction for heritage datasets.

In summary, this research develops a semantically structured SPC workflow grounded in HBIM ontology and tests its application through two case studies of varying complexity. It proposes web-based dissemination tools to enhance accessibility and begins exploring the integration of new visualization methods like 3DGS. By doing so, it addresses long-standing gaps in HBIM standardization, semantic clarity, and public dissemination of 3D heritage data.

1.2. Research Gap, Research Questions, and Scope

While many digital heritage platforms provide access to cultural information, they often lack structured 3D representations or meaningful semantic integration. Traditional HBIM workflows rely on parametric modeling that can be labor-intensive and geometrically reductive, especially for irregular heritage forms, missing details important for analysis and monitoring. Moreover, semantic structures in HBIM are fragmented and lack a standardized ontology, making cross-project consistency and reuse difficult. Although SPC offers a promising alternative by retaining raw geometry and enabling semantic annotation, its application in heritage remains underdeveloped. Finally, emerging techniques like Gaussian Splatting offer high-fidelity visualization but currently operate without semantic awareness. This thesis addresses these gaps by proposing a lightweight and scalable workflow for modeling and disseminating SPCs enriched with HBIM-informed semantics.

Therefore, this thesis is guided by the main research question: **How can HBIM ontology be integrated into smart point clouds with semantic enhancement to improve the visualization and conservation of heritage objects?**

It is further divided into the following sub-questions:

1. **What are the defining characteristics of HBIM, and which additional characteristics are critical for heritage conservation?**
2. **What does an effective HBIM information model look like, and how can it incorporate essential heritage attributes?**
3. **How can point clouds be segmented and semantically enriched with HBIM attributes?**
4. **What strategies can support web-based interactive visualizations of semantically enriched smart point clouds?**

The scope of this thesis is to develop and evaluate a structured workflow for integrating HBIM characteristics into semantically enriched SPC for heritage documentation and visualization. The research begins with a literature review to identify core HBIM ontology categories and uses these findings to design an information model suitable for point cloud annotation. This model is then tested and implemented across two case studies, representing different heritage complexities. A web-based viewer is developed to visualize the annotated SPCs, enabling semantic interpretation and public dissemination through an interactive platform.

The study does not aim to develop new point cloud segmentation algorithms or propose novel computer vision techniques. While segmentation is a necessary step in the SPC workflow, the focus remains on defining, structuring, and linking semantic information rather than solving low-level perception problems. Similarly, although the integration of 3DGS is discussed and preliminary results are reviewed, the thesis does not resolve the technical challenges in generating or aligning Gaussian splats from SPC—instead, it outlines potential future directions for combining the two representations and the possibility of propagate the semantics from SPC to Gaussian Splatting. The work is therefore situated at the intersection of semantic modeling, heritage ontology design, and web-based dissemination, rather than computer vision or machine learning development.

1.3. Overview of the Chapters

This thesis is structured into six chapters. Chapter 2 reviews the state of the art in heritage documentation, HBIM workflows, ontology design, and recent advancements in point cloud enrichment and rendering. Chapter 3 presents the methodology, including the design of a semantic information model, the implemented SPC workflow, the initial integrative workflow plan, and a description of the case studies and data sources. Chapter 4 details the technical implementation, covering pre-processing, segmentation, semantic structuring, format handling, web-based visualization, and the exploratory semantic propagation and segmentation of Gaussian splatting. Chapter 5 presents results from the segmentation and visualization stages, discusses limitations and semantic outcomes, and reflects on the research questions. Finally, Chapter 6 summarizes the main conclusions and proposes directions for future work.

2. Related Work

This chapter of the related work presents the previous theories and findings of HBIM, SPC, and Gaussian Splatting. It starts with the existing heritage documentation platforms and methods like UNESCO or DOCOMOMO, examining their limitations in structure, semantics, and scalability. The chapter then shifts to the concept of HBIM, which is widely used to digitally reconstruct heritage objects. By reviewing the current workflows, we see that HBIM adds more structure and metadata than general 3D models, but it often involves complex software workflows and remains focused on parametric modeling. From the gap caused by the lack of structurally defined semantics, a literature review was done to summarize the five main categories of characteristics that were included in previous HBIM definitions. Following this, the chapter introduces the idea of SPC, which offers an alternative: instead of converting point clouds into idealized BIM models, SPC keeps the raw geometry while adding semantic information directly to the data, as well as connecting it to the defined HBIM ontology by explaining how point clouds can be segmented and enriched using this structure. The rest of the chapter outlines the theories and algorithms behind Gaussian Splatting and the current web-based point cloud visualization platforms. Finally, it presents the research gap identified from the related work and the research questions that this thesis is going to answer.

2.1. Heritage Documentation Methods and Semantic Needs

Heritage represents cultural identity, memory, and meaning. Yet many heritage sites face the risk of damage, destruction, or inaccessibility — whether due to environmental threats, urban development, or political neglect. In this context, conservation and accessibility are not only end goals but also active strategies: they guide how we document, preserve, and share heritage in digital form.

Many attempts have been made to digitally archive heritage objects. The most well-known example is the UNESCO World Heritage List, which presents a full list of heritage sites defined by the World Heritage Committee. These are considered to have outstanding universal value. The list includes descriptions of cultural value, links to documents such as reports, conservation plans, evaluations, and galleries of photographs (Centre, n.d.). However, the available materials, such as conservation plans and reports, tend to remain formal and descriptive rather than richly detailed. The content is largely limited to photographs, with limited inclusion of other media formats such as 3D models or immersive visualizations.

One of the most important organizations on a global scale is the International Committee for Documentation and Conservation of Monuments and Sites of the Modern Movement (DOCOMOMO). DOCOMOMO plays a key role in this process, particularly in safeguarding the legacy of the modern movement. It monitors threats to important modernist buildings across the globe, while also fostering international dialogue on conservation methods, historical knowledge, and educational approaches. Beyond protecting physical structures, the organization seeks to cultivate public awareness and professional responsibility toward the architectural innovations and cultural significance of 20th-century modernism (DoCoMoMo, n.d.). Unlike UNESCO's broad public-oriented approach to globally recognized heritage, DOCOMOMO focuses more narrowly on modern architecture through academic networks and expert contributions, which also means its era (only modern) and domain coverage are more limited. Figure 2.1 shows the screenshots of the DOCOMOMO websites, the international one and the local one in the Netherlands.

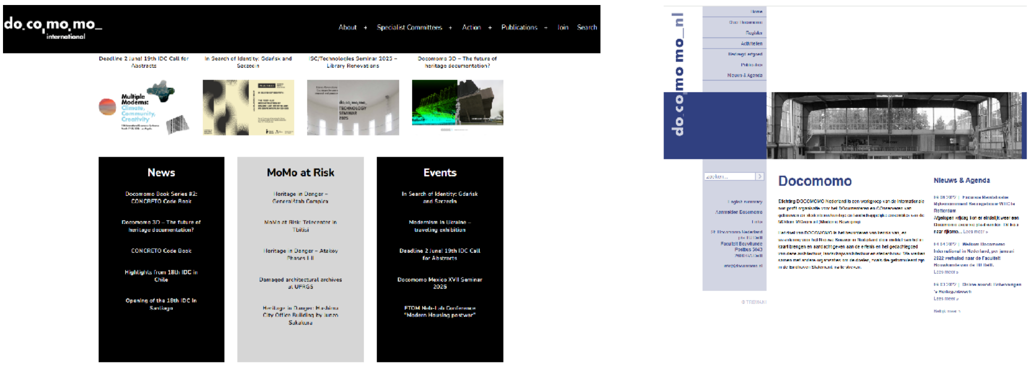


Figure 2.1.: Screenshots of DOCOMOMO international and DOCOMOMO Netherlands website. https://docomomo.com/

Its digital archive is an openly accessible resource that allows users to explore and contribute to projects based on criteria such as architect, location, and type. The archive includes photographs, drawings, and related materials, preserving the architectural legacy digitally (DoCoMoMo, n.d.). Despite its significant efforts and contributions to heritage documentation and conservation, there are several limitations in this process. The archive relies on submissions from member organizations and volunteers, which can result in gaps in documentation types and quality. For the same reason, there is no guarantee of frequent updates. Furthermore, the archive mainly consists of scanned historical document images and floor plans, but lacks 3D geometry information that is critical for understanding the spatial characteristics of heritage objects. This limits the ability to visualize heritage in 3D and reduces its effectiveness in dissemination for educational purposes.

A regional platform, Europeana, has started to host 3D model archives of selected heritage objects. It already contains a wide collection of older materials such as maps, artworks, and manuscripts. In its new 3D model section, *Twin it! A Pan-European Collection of 3D Heritage Models* (https://www.europeana.eu/nl/galleries/15694-twin-it-a-pan-european-collection-of-heritage-3-d-models) , member states of the European Union were invited by the European Commission and the Europeana initiative to select and share at least one emblematic, high-quality 3D model of cultural heritage to be included in a shared European data space ("Twin it! Een pan-Europese verzameling van 3D-erfgoedmodellen", n.d.). See Figure 2.2 for the screenshots of this website and the interactive page for the 3D model.

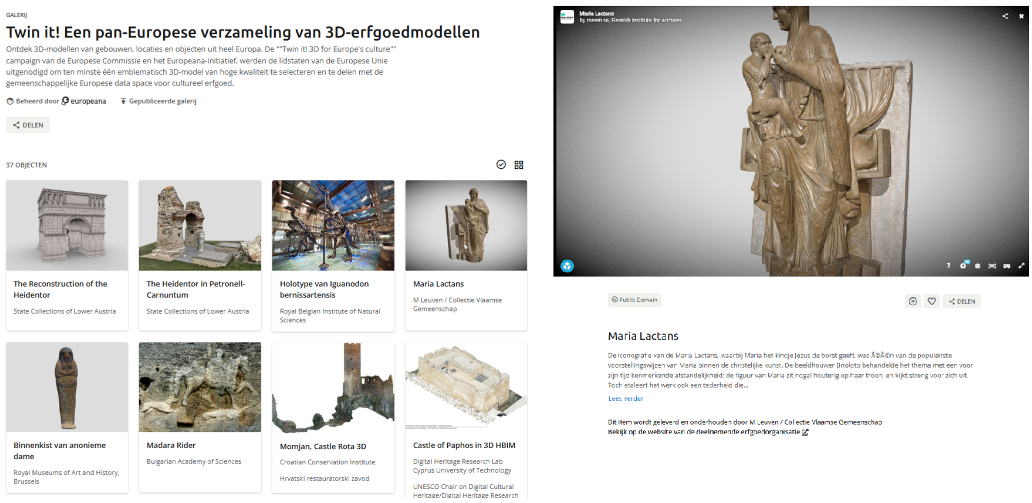


Figure 2.2.: Screenshots of Europeana 3D archive and the interactive page of a 3D model.

Three examples illustrate different types of documentation and visualization approaches. The first is the Heidentor in Petronell-Carnuntum in Austria, reconstructed from survey data into a mesh with annotations (in German) visible directly during visualization (State Collections of Lower Austria, 2024a). This is a good example of combining semantic information directly in the model interface. The second is the reconstruction of the Heidentor, also shared through Europeana (see Figure 2.3), which represents a parametric BIM model, but without interaction in the web-based viewer (State Collections of Lower Austria, 2024b). The third example is the Castle of Paphos in Cyprus (See Figure 2.3.c), where the point cloud is georeferenced and integrated into a 2D basemap (UNESCO and ERA Chairs on Digital Cultural Heritage - Digital Heritage Research Lab, Cyprus University of Technology and EU ERA Chair on Digital Cultural Heritage - MNEMOSYNE, n.d.). A dropdown menu allows switching between views, but it seems that no attributes are stored in the 3D layer itself. Due to the limitations of Potree, the visualization is not interactive.

(a) Annotated mesh: Heidentor, Austria

(b) BIM-based reconstruction: Heidentor, Austria

(c) Georeferenced point cloud of the Castle of Paphos integrated into a 2D basemap, Cyprus.

Figure 2.3.: Examples from Europeana's 3D heritage archive.

Accessible global platforms often lack 3D data or only provide passive viewing. However, these platforms offer a strong foundation for making heritage more accessible. In this context, geospatial information plays an essential role in recovery, dynamic updates, and monitoring of heritage sites, enabling better visualization and dissemination. Emerging solutions such as laser scanning, photogrammetry, and the integration of 3D data into heritage workflows offer a shift toward more comprehensive digital documentation methods.

There are growing initiatives to share 3D heritage models, but a lack of protocols and standards remains. Various data formats are used, mostly without interactive functions or semantic annotation. The model and its associated semantics often remain separated. Smart interactive models with semantics needed, not only to improve the accuracy and detail of heritage visualizations but also enhance their usability for education, conservation, and public engagement.

2.2. HBIM: Current Workflow, Semantics, and Limitations

Despite not often being seen in global heritage digital archives, there is a generally uniform 3D modeling for creating the digital twin of the artifacts from geometrical data - HBIM (sometimes also referred to as Historical or Historic BIM). On top of the visual representation, they also aimed to contain semantics for heritage management. The concept of HBIM emerged originally from the architectural and documentation community. The goal was usually to reconstruct heritage structures digitally by creating a Building Information Modeling (BIM), often following International Organization for Standardization (ISO) standards. In this section, HBIM workflows are reviewed from a geospatial perspective, and acknowledging that point cloud is the core and SPC is a model itself, instead of serving only as the survey data nor an intermediate step.

Current HBIM Workflows.
HBIM, first coined by Murphy in 2009, as the Historic BIM, stated its preliminary purpose - to use laser scanning data and imagery for creating a parametric model for its historic structure. It is BIM-based, software-reliant, and the point cloud is only described as survey data and an intermediate step for making a parametric-based 3D model.

Throughout the years, the H meaning for HBIM has been evolving gradually to a bigger context of heritage instead of only historical, but the workflow and end product remained similar. Through reviewing the definition and usage of the heritage or historic/historical BIM from the literature, it is believed that when use the word historic, the spatial and physical attributes are usually the focus. While heritage BIM not only includes these features but also focuses on the general way of conserving and communicating the culture and identity of the monuments (Yu et al., 2025). HBIM focuses on documenting and digitally reconstructing existing heritage buildings, which is called the "reverse engineering process", as it instead of being used for monitoring and managing the construction of new buildings in architecture. This workflow for generating HBIM usually involves collecting, processing, modeling, and organizing semantic information from different sources critical to the cultural heritage, finally managing them in a structured way (Biagini et al., 2016; Donato et al., 2017; Pocobelli et al., 2018).

From the usual HBIM workflows illustrated in many previous studies, the first step is acquisition, where the usual technologies employed include Terrestrial Laser Scanning (TLS) or Mobile Laser Scanning (MLS), and the use of Unmanned Aerial Vehicle (UAV). Images captured during this process typically undergo Structure-from-Motion (SfM) or other computer vision techniques to acquire the sparse point cloud (Donato et al., 2017; Lovell et al., 2023; Yastikli, 2007). After acquiring the point cloud, the workflow often diverges into constructing different 3D representation methods. The most common approach involves creating a BIM with added heritage information. This is often achieved using the Scan-to-BIM method, which converts point cloud data to BIM semi-automatically through Autodesk Revit plug-ins such as PointSense and Scan-to-BIM (Fryskowska & Stachelek, 2018; Giuliani et al., 2024; Penjor et al., 2024). However, this process still remains not fully integrated, and heavily software-based for generating HBIM (Logothetis et al., 2017). Statistics have shown that the level of automation in the entire format conversion process (point cloud to BIM, mesh to BIM, and object recognition and segmentation) remains low. It shows that the current BIM software does provide great aid for the basic elements recognition from BIM standards, with mainly a semi-automatic process, and the rest fully automatic. However, it also illustrates that there is no automatic operation to turn point cloud directly to BIM, that it relies heavily on semi-automatic and even sometimes manual processing (Bruno et al., 2018).

Semantic and Structure

The semantic structure in HBIM is mostly fundamentally derived from conventional BIM standards, which have been adapted to fit the particularities of heritage documentation. Concepts such as Level of Development (LoD) and Level of Information (LoI) are originally defined in the context of BIM, where they form the basis for controlling both the graphical and non-graphical aspects of a model. In HBIM workflows, these definitions are not simply transferred but adapted to deal with issues like incomplete data, uncertain sources, and the historical stratification of architectural elements. Despite its origin, since HBIM is a process usually documenting or motinoring existing buildings or monuments, the definition of Level of Detail (LoD) has been adapted and redefined to Detail instead of Development (Garcia-Gago et al., 2022; Mora et al., 2021). Though it is still different from the LoD definition in cityGML, which is used in an urban setting (Biljecki et al., 2016). LoD, in its adapted form for HBIM, refers to the graphical richness of the model—geometry, dimensions, and spatial alignment—but the expected accuracy is often tied to the data source (e.g., laser scan, archival drawing). LoI remains focused on associated metadata, such as material properties or construction phases, but may also include archival references, historical photos, or restoration records—types of information not typically found in standard BIM models. These information layers are commonly stored as metadata linked to model elements, although the method of association varies significantly across tools and projects (Pocobelli et al., 2018).

Another foundational concept inherited from BIM is the Building Object Model (BOM), which defines structural components as topologically connected entities. In BIM, BOMs are predefined types (e.g., wall, slab, beam) that are instantiated with geometric and material properties. Each is referenced within a coordinate system and linked hierarchically to form a complete model. In HBIM, this structure is retained, but often with more flexibility: elements can be modeled as approximations, based on scan data or visual interpretation, and may include components unique to historical structures that do not have direct counterparts in IFC or commercial BIM libraries (Donato et al., 2017).

In alternative workflows, especially those focusing more on visualization than strict parametric modeling, mesh-based models are created from point clouds using surface reconstruction algorithms such as Poisson or Ball Pivoting (Bruno et al., 2018). These do not rely on object-level semantics, but rather group surface information into geometric patches, which can then be manually annotated or linked to external data sources.

Some HBIM projects borrow semantic class hierarchies from urban modeling standards such as CityGML, yet require supplementary references to capture the full complexity of historical structures (Pocobelli et al., 2018). While the IFC schema offers a structured framework for BIM, its use in HBIM is often limited by a lack of heritage-specific classes, unclear mappings for certain architectural features, and insufficient support for uncertain or layered information (Mora et al., 2021).

Despite these adaptations, several limitations remain. LoD and LoI definitions, while helpful, are still not standardized for HBIM, leading to inconsistent practices. Metadata integration is often ad hoc, lacking structured storage or querying methods. The reliance on BOMs and IFC-type structures limits modeling flexibility and hampers the representation of non-standard components. Finally, the interoperability between HBIM tools and other heritage-focused platforms is still underdeveloped, affecting both collaboration and long-term data preservation.

Interoperability and Scalability limitations.
Current HBIM workflows are predominantly ad hoc and project-specific. Each project defines its own modeling scope, level of detail, and semantic depth based on immediate conservation, restoration, or documentation goals. For example, Mora and colleagues (2021) defined HBIM by specifying two aspects: the Level of Detail (LoD) for geometric information and the Level of Information (LoI) for non-graphical metadata. The LoD is largely adapted from architectural BIM standards, typically ranging from 100 to 300, depending on the project's needs. One difficulty in reaching a consensus on the definition of HBIM is the lack of clear and unified use cases across different heritage applications. With the tremendously varying shapes in buildings, especially ornamental parts, different purposes of HBIM — such as long-term monitoring, restoration planning, or visualization—may require different levels of detail or different ontology for this modeling process (Donato et al., 2017; Mora et al., 2021). Consequently, there is no general standard guiding the creation of HBIM models across different heritage cases.

Because workflows are improvised for specific projects, they inherently lack scalability. Processes that work for one building, object, or site cannot be readily transferred or reused for others. Each project starts from scratch in defining modeling assumptions, file structures, and semantic categories. Due to these reasons, interoperability remains a major technical barrier. BIM models with heritage information are often confined within proprietary BIM software environments, limiting the accessibility and broader application of the data. For example, heritage-related metadata such as material properties, architectural styles, or construction phases are typically archived inside BIM platforms like Revit, while point cloud data (in formats like LiDAR Data Exchange Format (las) or Polygon File Format / Stanford Triangle Format (ply)) must be converted and restructured through tools such as Autodesk Recap to be used in BIM workflows (Donato et al., 2017; Garcia-Gago et al., 2022; Pocobelli et al., 2018). Furthermore, modeling non-standard or complex heritage features such as sculptures, decorative elements, or organic forms often forces the use of hybrid approaches, combining vector BIM structures with triangulated mesh models (Fryskowska & Stachelek, 2018). These conversions are not seamless: they introduce overhead, potential errors, and can lead to loss of important geometric or metadata details. Heritage BIM models are often locked within proprietary ecosystems, making long-term reuse and interdisciplinary collaboration more difficult.

Semantic definitions in HBIM workflows are equally fragmented. There is no agreed standard on what should be modeled—whether only major structural components like walls and roofs, or also smaller features like ornaments, inscriptions, or construction phases—and how these elements should be semantically described. This lack of standardization affects the consistency, depth, and interoperability of heritage data.

Modeling non-standard or irregular heritage features presents additional challenges. Unlike new buildings, heritage structures often contain sculptures, decorations, and organic forms that do not fit neatly into the plane-based, parametric frameworks of traditional BIM. Even though BIM standards, such as the BOM, offer well-defined object classes for conventional elements, they struggle to accommodate the complexity and irregularity of cultural artifacts. As a result, hybrid workflows combining vector-based BIM elements with triangulated meshes are sometimes used (Fryskowska & Stachelek, 2018), although these further complicate file management and standardization.

In summary, the current practices for generating HBIM models are fragmented, non-scalable, and suffer from significant technical and conceptual gaps. Without a unified standard for geometry, semantics, and interoperability, the broader application of HBIM for heritage documentation and management remains limited.

These workflows often focus more on the technical aspects of data acquisition and integration rather than on the semantic enrichment of the models. Though some tried to segment the model, automatically or manually semantically segment BIM, the semantics are not enriched in detail in the model. Especially under the limitation of the lack of consensus on the heritage characteristics needed for heritage conservation. They emphasize the architectural management of heritage structures without delving into the semantic aspects that are critical for developing a comprehensive HBIM.

As such, forcing the creation of semi-parametric HBIM models from these point clouds introduces unnecessary abstraction and information loss. Surfaces that are not perfectly planar, features that are eroded or damaged, and complex historical stratifications become flattened into regularized objects, compromising authenticity.

A clear and operational definition is still needed for HBIM, both regarding what type of information is included and how it is systematically integrated. From a non-architectural perspective, it is important to observe that most previous works treat the generation of a BIM-standard model containing heritage information as the end goal. However, the lack of a formal HBIM definition makes it difficult to distinguish between a BIM model enriched with some heritage information and a true HBIM model where heritage knowledge is fully integrated and structured according to the object's cultural significance.

Point Cloud as an HBIM Format

In this context, this thesis does not view HBIM as a mandatory process of remodeling point clouds into vector-based models. Rather, the focus shifts to retaining the HBIM characteristics while maintaining the original point cloud geometry with no loss of its details. The "BIM" in HBIM is interpreted as a structured, queryable information system attached to heritage objects, rather than a strict parametric model.

This reinterpretation is consistent with the evolving needs of heritage conservation, where maintaining authentic geometry, damage patterns, and context is more critical than reconstructing idealized building elements. Thus, enriching point clouds with structured semantics fulfills many of the traditional goals of HBIM (structured storage, interoperability, lifecycle tracking), while better respecting the reality of historic fabric.

In summary, while BIM in its classical form implies parametric models, in heritage documentation a Smart Point Cloud carrying rich HBIM-style attributes can serve as an equally valid, and often more authentic, alternative geometry representation compared with vector-based HBIM.

In this research, the results are primarily stored and modeled as SPC for heritage objects. This approach preserves both the detailed geometric information and the structured semantics derived from HBIM principles, while bypassing many of the bottlenecks associated with rigid BIM platforms. The detailed information model for the heritage SPC will be defined in the following sections.

2.3. Five Categories of HBIM Ontology Defined: A Literature Review

Semantic enrichment plays a foundational role in HBIM because it enables a meaningful connection between visual models and layered heritage knowledge. Beyond just 3D geometry, heritage documentation requires multiple levels of interpretation: for example, identifying a statue is not only about its shape, but also its spatial relation within a building, its role in the site's history, and the archival documents or photos associated with it. Without semantic links, such contextual relationships remain implicit and unstructured.

However, the definition of HBIM and the heritage characteristics it should model are still inconsistently addressed in the field. A critical step is thus to ask: what exactly should be modeled? This question motivates the review of prior HBIM work to uncover which aspects of heritage — whether structural, historical, or material—have received focused attention in modeling and conservation. These findings directly inform the semantic layers embedded in SPC for this thesis.

Although not central to the research focus here, the terminology surrounding HBIM warrants brief clarification. This thesis adopts the term *Heritage BIM*, consistent with prevailing usage in the literature and a related article currently under review (Yu et al., 2025). Some studies instead use *Historic BIM* or *Historical BIM*, often to signal a focus on authenticity, archival research, or scholarly interpretation. These variants emphasise temporal layering or stylistic accuracy. (Banfi et al., 2019; Brumana et al., 2018; Cicalo, 2016; Iovane & Cera, 2016). Though there are differences in how the "H" in HBIM is expanded, most research is directed toward the documentation, conservation, and long-term management of culturally valuable built environments. The practical objectives across the literature typically align with heritage-driven concerns. As such, the "H" has, in practice, largely converged on "Heritage," reflecting the field's broader emphasis on preserving cultural assets rather than merely referencing the past or cataloguing historical change (Yu et al., 2025). The difference between heritage and historic BIM has been discussed in the last section.

The Ontology of HBIM Defined

Due to the lack of well-defined characteristics that should be consistently included in HBIM documentation, there is a need for a formalized structure — an ontology — to clarify what information belongs within the HBIM domain. Such an ontology serves to define the relevant characteristics of HBIM across all possible representations, including IFC-based models and SPC environments. To inform the development of this ontology, a structured literature review was conducted. A total of 86 peer-reviewed publications were gathered from the Web of Science and Scopus databases, limited to articles published after 2015. Papers were selected based on whether they explicitly discussed the definition of HBIM or described which characteristics should be modeled within an HBIM framework. The complete list of reviewed studies can be found in Appendix B.

Table 2.1 organizes the HBIM ontology into five overarching categories: Structural, Material, Historical, Cultural & Artistic, and Restoration & Conservation Information. Each of these domains captures a specific dimension of knowledge essential for modeling, preserving, and managing built heritage. Their inclusion in the ontology is not only grounded in theoretical relevance but also supported by recurring themes across recent literature.

Structural Information is the most frequently emphasized domain in HBIM literature, reflecting its foundational role in digital heritage representation. The focus on geometry, structure, and formal articulation is especially prominent in scan-to-BIM workflows and parametric modeling approaches. The study Brumana et al. (2018) illustrates how structural hierarchies and architectural articulation are encoded in the HBIM environment to support both preservation and intervention. Similarly, the work Fregonese et al. (2017) demonstrates the modeling of mechanical behavior such as deformation and structural response, especially for vaulted and irregular geometries. These studies show how HBIM enables the representation of load-bearing behavior and spatial hierarchies, forming a baseline for both documentation and conservation analysis.

Material Information, though less dominant in the literature, is vital for conservation-related applications. It includes the documentation of construction materials, their condition, and behavior over time. In the study Sutherland et al. (2023), the integration of infrared thermography with HBIM workflows reveals decay patterns and surface delamination, demonstrating how material analysis informs ongoing risk assessment. The paper Moropoulou et al. (2022) emphasizes the role of multispectral data in diagnosing material heterogeneity and decay, which are subsequently modeled in the HBIM platform. These approaches enable the monitoring of weathering and deterioration, and support material-specific interventions grounded in visual and scientific evidence.

Historical Information captures the temporal dimensions of heritage, such as original construction phases, past modifications, and integration of documentary sources. Studies in this domain often aim to reconstruct semantic timelines or embed historical sources into digital representations. For instance, Banfi et al. (2021) exemplifies how historical cartographic and archival material are incorporated into HBIM to reconstruct now-vanished architectural elements. The paper Adami et al. (2019) presents a method for integrating 3D survey data with interpretations of past structural phases, creating layered representations of building evolution. These contributions show how HBIM can serve as a structured repository of historical semantics, offering both temporal depth and documentary linkage.

Cultural and Artistic Information is the least represented in existing HBIM work, yet it addresses the vital domain of intangible and symbolic value. This category includes artistic detailing, iconography, and culturally significant ornamentation. The study Cicalo (2016) focuses on the documentation of stylistic and decorative elements such as mosaics, bas-reliefs, and wrought ironwork, making the case for their inclusion as primary semantic components rather than auxiliary annotations. Similarly, El Barhoumi and Hajji (2024) demonstrates how integrating symbolic content and extended reality techniques can enhance public understanding of heritage significance. These studies underscore the need for structured, semantic encoding of aesthetic features and narrative meanings into HBIM environments.

Restoration and Conservation Information is the second most explored domain and focuses on deterioration mapping, documentation of past interventions, and ongoing conservation planning. For instance, García-Valldecabres et al. (2021) outlines strategies for embedding long-term maintenance workflows directly into HBIM structures, supporting lifecycle-based management. Furthermore, Oreni et al. (2017) integrates structural assessment, restoration history, and decay conditions into a unified HBIM model that guides future reinforcement work. Moreover, Laohaviraphap and Waroonkun (2024) explores how HBIM environments can incorporate live environmental data streams to trigger condition-based interventions. These studies demonstrate that HBIM is not only a documentation tool but an active platform for managing the conservation of built heritage.

2.4. From Raw Data to Smart Point Cloud

Semantic enrichment is a crucial process in transforming raw point clouds into meaningful data structures such as vector HBIM, supporting the documentation and conservation of heritage objects. In many previous works, this typically involves the recognition of established BIM components during the Scan-to-BIM process, where elements like doors, roofs, and windows are identified based on geometric features and mapped to predefined parametric objects. However, heritage-specific elements—such as historically significant columns or sculptural fragments—are often modeled using custom or local components with manually added semantics. This reliance on BIM's standard structure limits the expression of cultural or stylistic detail. Moreover, semantic attribution is often done manually, making the process time-consuming and inconsistent across projects (Fryskowska & Stachelek, 2018).

Smart Point Cloud

The concept of SPC has emerged as a potential solution of managing and utilizing unstructured point cloud data. Introduced by Poux et al. (2017), proposes a three-level data model to enrich raw point clouds with semantics. SPCs refer to enhanced 3D point clouds that integrate semantic information, enabling more efficient data analysis and interaction. Unlike traditional point clouds, which consist solely of spatial coordinates and possibly color data, SPCs incorporate additional metadata—such as object classifications, relationships, and attributes—facilitating advanced processing and decision-making. Unlike traditional BIM or IFC models that rely on predefined geometry or parametric elements, SPCs embed semantics directly within the point cloud structure, allowing a bottom-up organization of meaning, starting from the raw data (Poux et al., 2016).

Level 0 – Semantic Patch Structure At the base of the model, individual points are grouped into `semanticPatch` entities. Each patch includes not only the spatial extent and point count, but also key attributes that describe its statistical or geometric characteristics. These may include curvature, reflectance, color intensity, or roughness—captured under `sAttribute` and used for generalization. Semantic patches can be seen as enriched segments of the point cloud with localized metadata, forming the first semantic unit.

Table 2.1.: Overview of HBIM ontology categories and subcategories

Category	Subcategory	Description
Historical Information	Building Origin	Construction period, historical background, cultural significance.
	Architectural Style	Architectural style classification (e.g., Gothic, Baroque, Neoclassical).
	Chronological Changes	Modifications, expansions, demolitions, and restorations over time.
	Historical Documents	Historical archives, paintings, manuscripts, maps, and photographs.
	Functional Evolution	Changes in building use over time (e.g., religious site to museum).
Structural Information	Building Hierarchy	Overall structure $\rightarrow$ substructures $\rightarrow$ components $\rightarrow$ materials.
	Building Components	Foundation, walls, roofs, floors, beams, columns, windows, doors.
	Mechanical Properties	Load-bearing structure, seismic resistance, stress analysis.
	Construction Techniques	Traditional techniques such as vaulting, wooden joinery, stone masonry.
	Damage Conditions	Cracks, deformation, peeling, corrosion, erosion, infestation.
Material Information	Material Types	Types of materials used: stone, wood, metal, concrete, etc.
	Material Provenance & Processing	Material origin, processing methods.
	Aging & Deterioration	Physical and chemical changes such as weathering, corrosion, decay.
	Restoration Material	Details of past restorations, materials used, and techniques applied.
Cultural & Artistic Information	Decorative Elements	Carvings, murals, stained glass, mosaics, ornamental details.
	Symbolism	Religious symbols, family crests, historical event-related decorations.
	Craftsmen & Architects	Information on architects, craftsmen, and artists involved in construction.
Restoration & Conservation Information	Restoration Techniques	Methods for restoration (reinforcement, joining, filling, etc.).
	Conservation History	Past conservation efforts, large-scale restoration history.
	Monitoring Data	Real-time environmental monitoring (humidity, temperature, weathering).
	Legal & Regulations	Protection laws, UNESCO certification, national/local conservation measures.
	Structural Stability	Mechanical analysis of structure stability and potential risk assessment.

Semantics here is not added externally but organized internally through metadata stored directly at the patch level. Attributes such as material or status (e.g., degraded, restored) can be attached here.

Level 1 – Connection Layer

Above the patch level, Level 1 structures the spatial and logical relationships between patches. Each patch is linked into higher-level groupings called `ConnectedElements` or `AggregatedElements`, which correspond to coherent objects like a wall, arch, or ornament.

The model introduces topological notions such as "part-of" or "adjacent-to", enabling spatial reasoning within the cloud. The intermediate layer functions as a bridge between low-level data-driven patches and domain-specific concepts.

Level 2 – Domain Adaptation Layer

Level 2 brings in domain knowledge. In the example of indoor architectural scenes, domain-specific classes such as `WindowElement`, `WallElement`, or `Arch` are defined. These inherit from `WorldObject` or `SubSpace`, linking them back to the lower levels. Semantics are encoded through class hierarchies and property inheritance, enabling flexible specialization across domains.

This tier allows the integration of cultural, historical, or material meaning to 3D components. For instance, a segment identified as a column can be further classified as "Ionic" based on stylistic rules, or linked to conservation status.

The model is well-structured and provides a solid foundation for organizing large, unstructured datasets into semantically meaningful units. In particular, its clear formalization of connectivity—how patches relate spatially and topologically—offers a robust groundwork for higher-level interpretation. This allows for modeling adjacency, inclusion, and other spatial logics, which are crucial in domains such as indoor mapping, structural integrity assessment, or conservation planning.

However, there are practical considerations. Because patches are often small and spatially uniform, many attributes may be repeated across them, leading to redundancy. Attributes like reflectance and intensity are useful at the sensor interpretation level, but may be less informative for domain-specific tasks, such as identifying cultural or stylistic features in heritage objects. In such cases, these raw attributes may require further abstraction before they can support meaningful classification. Nevertheless, the patch-level design is essential: it segments the data in a way that is both scalable and structured, and serves as the bridge from raw measurements to semantic reasoning.

SPC framework offers a solid structural foundation, but it does not yet embed domain-specific semantics natively. For it to be fully applicable in heritage or archaeological contexts, domain knowledge still needs to be defined and connected externally. Ontologies and standardized vocabularies play an important role here, enabling the classification of elements not just by geometry or attributes, but by cultural meaning or historical significance. In the later work, as will be mentioned below in the segmentation method, Poux and Billen (2019) and Poux et al. (2018) had several applications in the heritage and archaeological context, introducing the case-specific semantics. An ontology that can be applied to a more general case for heritage still needs to be defined and integrated into the SPC framework.

Segmentation Method

Four main segmentation approaches were reviewed to assess their suitability for semantic modeling in Smart Point Clouds. Rule-based and ontology-based methods rely on handcrafted features and expert-defined rules. They offer transparent logic and good performance in structured scenes, especially when domain ontologies guide classification, but they lack flexibility and are difficult to scale. Geometry-based methods operate without training data, segmenting surfaces based on spatial continuity and geometric primitives. These are efficient for pre-segmentation but provide no semantic context. Unsupervised clustering (e.g., DBSCAN, k-means) detects patterns in geometric or radiometric features and is useful for irregular elements like vegetation or damage but requires manual interpretation to assign meaning. Finally, supervised and deep learning approaches demonstrate strong performance on urban datasets but struggle in heritage contexts due to limited annotated data and high variability in structure and material. They remain computationally demanding and are not yet generalizable across heritage use cases.

1. Rule-based / Ontology-based

Rule-based segmentation methods rely on manual rules derived from geometric or radiometric features such as curvature, intensity, color, and voxel adjacency (after applying octree structure on point cloud to use the points in a voxel as the unit of points). One of the representative examples is the voxel-based segmentation method developed by Poux and Billen (2019). It begins by constructing an octree-based voxel grid from the point cloud, recursively subdividing the bounding box into voxels until a defined maximum depth is reached. From each voxel, features are extracted in two layers. The first includes shape-based descriptors, subdivided into eigen-based descriptors (e.g., eigenvalues, planarity, sphericity) and geometrical features (e.g., mean, variance, number of points). The second layer includes relational and connectivity features based on 26-connectivity between voxels. These relationships are modeled as a directed graph. The extracted features then serve to categorize voxels into semantic groups such as primary elements (walls, floors), secondary elements (beams, doors), transition elements (edges), and remaining elements. Connected-component labeling is used to group voxels into clusters based on shared attributes and spatial adjacency, resulting in semantically segmented components. This approach demonstrated high accuracy in structured environments, such as a room dataset, and was benchmarked against deep learning methods like PointNet.

Another example is the ontology-based segmentation tested on mosaic tesserae (Poux et al., 2018). This method uses formalized domain knowledge encoded in ontologies (e.g., OWL/RDF) to guide segmentation and classification. Classes (e.g., Tessera, Faience, Gold), properties (e.g., hasMaterial, hasColor), and rules (e.g., if color = gold and area ¡ threshold then classify as *Golden Tessera*) are predefined. Segmentation is first performed, and then segments are evaluated against ontology rules. While effective for this specific case, such methods depend heavily on the accuracy of prior observations and rule definitions. Scaling up to more complex or less regular cases would require redesigning rules and more extensive data analysis. Despite these constraints, the method demonstrates a way to assign semantic labels to raw point cloud data without relying on parametric modeling or machine learning.

These rule-based methods are often tailored to archaeological and heritage applications, aligning closely with the goals of semantic segmentation in this paper and the concept of Smart Point Clouds. However, these ontologies remain case-specific (e.g., mosaics or indoor furniture), and they lack abstraction or structural hierarchies. To adapt to broader cases, new rules must be authored, and rule quality significantly affects outcomes. While effective in structured scenes, these methods often struggle with unstructured geometry and require manual tuning (Dong et al., 2022).

2. Geometry-based Methods

These methods rely solely on geometric cues without requiring training data or semantic context. Random Sample Consensus (RANSAC) is commonly used to fit primitive shapes, such as planes or cylinders, to extract structured surfaces. Region Growing algorithms segment the point cloud by grouping points based on proximity and similarity in surface normals or curvature. Connected Components analysis clusters adjacent voxels based on spatial adjacency, identifying coherent regions without prior labeling.

As noted by X. Yang et al. (2020), these algorithms are often limited to building facades or structured surfaces, assuming regular geometry. A recent region-growing system (Poux et al., 2022) addresses some of these limitations by avoiding manual thresholds and focusing on spatial continuity, enabling its integration into heritage workflows like HBIM modeling. It supports clean pre-segmentation of elements such as walls and floors, though it does not produce semantic labels directly. Such geometric clustering must be linked manually to domain knowledge, and performance may degrade in the presence of ornamentation or deterioration.

Geometry-based methods are strong in structured scenarios and require no training data. However, their semantic granularity is limited—they distinguish geometry (e.g., planar) but not meaning (e.g., column). They are best used as a pre-segmentation tool before higher-level semantic annotation.

3. Clustering-based / Unsupervised Machine Learning (ML)
This includes techniques like DBSCAN, k-means, hierarchical clustering, or clustering in PCA-reduced space. These are fast, do not require labeled data, and are effective for identifying irregular features such as damage or vegetation. However, they lack semantic precision. Laser scanning attributes like return numbers or amplitude work well to distinguish object types (e.g., tree vs. building), but not detailed architectural parts. These methods group similar features without understanding their meaning and require manual interpretation for semantic labeling (X. Yang et al., 2020).

4. Supervised ML / Deep Learning
Supervised methods like Random Forests rely on handcrafted features (e.g., curvature, texture) and annotated datasets. Though effective, they struggle with the complexity and density of point clouds. Annotating high-quality training data is time-consuming, error-prone, and often infeasible (Poux & Billen, 2019).

Deep learning directly processes 3D data and has transformed semantic segmentation. In a recent review (Yan et al., 2025), deep learning methods are categorized into several approaches. Point-based networks such as PointNet++ capture local and global geometric features through hierarchical learning structures (Qi et al., 2017). Image-based approaches, such as the Dynamic Graph Convolutional Neural Network and Multi-View Convolutional Neural Networks, leverage 2D projections or graph-based relationships to infer 3D semantics. Voxel-based methods convert point clouds into structured 3D voxel grids and apply three-dimensional convolutional neural networks. Fusion-based approaches combine multiple data modalities or representations, aiming to integrate geometric and visual cues into a unified learning framework.

However, deep learning methods are resource-intensive and require large labeled datasets. They may fail to capture fine details or generalize across heritage sites due to variability in materials, structure, and cultural semantics (Buldo et al., 2024; S. Yang et al., 2021; Zhao et al., 2023). Most DL models are trained on urban data and perform poorly in heritage contexts (Yan et al., 2025). Further, they risk misclassifying similar geometries from different periods, and surface-based data limits segmentation to visible areas only (Murphy et al., 2013; Poux et al., 2016; S. Yang et al., 2023).

In summary, while DL methods show promise, they are not yet broadly applicable in cultural heritage without significant domain-specific training and adaptation. Rule-based and geometric methods remain more accessible and interpretable for structured segmentation but require manual effort and often lack scalability. There is currently no solution that generalizes well across varied heritage sites without manual intervention.

2.5. Visualization and Dissemination

Web-based visualization tools have been widely used for presenting point cloud data online. Among them, Potree and Three.js are the most relevant in the context of heritage applications.

Potree is specifically designed for rendering large-scale point clouds in the browser. It supports `.laz` and `.las` formats and uses an octree-based level-of-detail structure to optimize performance. Potree includes a range of built-in tools, such as measurements, clipping boxes, and annotations. It also allows users to visualize attributes stored in the point cloud file, such as classification or intensity (Schütz et al., 2020). However, Potree has limitations when it comes to semantic enrichment. It does not support external semantic models or custom mappings between points and labels, which makes it difficult to visualize or interact with semantics beyond what is already embedded in the file. Moreover, its architecture is not intended to be easily extended to support structured semantic workflows. For example, Europeana and affiliated platforms use Potree to present heritage sites online. In this example, the Paphos Castle model is visualized using Potree, where the point cloud is georeferenced and mapped. However, the implementation remains limited to geometric visualization—it does not incorporate semantic enrichment or interactive querying of attributes (UNESCO and ERA Chairs on Digital Cultural Heritage - Digital Heritage Research Lab, Cyprus University of Technology and EU ERA Chair on Digital Cultural Heritage - MNEMOSYNE, n.d.).

Three.js, in contrast, is a general-purpose 3D rendering library based on WebGL (Three.js Contributors, 2010). Although it does not offer point cloud-specific functions by default, it provides full control over the rendering logic, user interactions, and data structures. This flexibility makes it possible to develop tailored viewers that connect point cloud data with external metadata, such as JSON files that contain semantic labels or object-level descriptions. With Three.js, developers can implement features like toggling between semantic layers, highlighting selected components, or displaying labels and linked documents. Compared to Potree, Three.js requires more development effort, but it allows semantic information to be structured and visualized in a more meaningful and extensible way.

2.6. Rendering Improvements: Integration of Gaussian Splatting

Traditional visualization techniques for cultural heritage, such as creating triangulated surface meshes with color and texture, often fail to fully capture intricate geometrical details, such as ornamental features or subtle material variations. These limitations can be partially addressed by incorporating higher LoI into models; however, the challenge of achieving photorealistic and detailed visualization remains (Mora et al., 2021; Pocobelli et al., 2018). To address the limitations of visualization, 3DGS has emerged and is experiencing high attention. This approach is particularly effective for preserving fine details and handling complex lighting conditions, making it suitable for heritage visualization by accurately depicting fragile or inaccessible structures and offering a photorealistic experience for both documentation and public engagement (Balloni et al., 2024; Dahaghin et al., 2024).

Mathematical Foundation and Rendering Pipeline

3DGS is a real-time rendering technique that models a scene using a set of 3D anisotropic Gaussians instead of traditional surface meshes or neural volumetric fields (Kerbl et al., 2023). Each Gaussian is defined by a set of learnable parameters: a spatial mean $\boldsymbol{\mu}_i \in \mathbb{R}^3$, a covariance matrix $\Sigma_i \in \mathbb{R}^{3\times 3}$ controlling shape and orientation, an opacity α_i, and a color function modeled via spherical harmonics.

During rendering, the Gaussians are projected onto the image plane using known camera intrinsics and extrinsics parameters. These camera parameters are derived from SfM. Instead of tracing rays through the scene, the method rasterizes the 2D projections of the Gaussians using a differentiable tile-based renderer. The contribution of each splat to the final pixel color is computed using α-blending and sorted front-to-back in depth order. The projection also involves transforming the 3D covariance Σ_i into screen space using a Jacobian derived from the ray-space transformation (Kerbl et al., 2023).

The color of each Gaussian is made view-dependent through a spherical harmonics expansion. Each color channel is represented as a weighted sum of basis functions up to degree $\ell_{\max}$:

$$C(\theta, \phi) = \sum_{\ell=0}^{\ell_{\max}} \sum_{m=-\ell}^{\ell} a_{\ell m} Y_\ell^m(\theta, \phi), \tag{2.1}$$

where Y_ℓ^m are the spherical harmonics and $a_{\ell m}$ are the learned coefficients for each channel.

The training pipeline begins with a sparse point cloud and camera poses obtained via SfM. Initial Gaussians are seeded from the sparse point cloud. Optimization is performed over the parameters (μ, Σ, α, C) using stochastic gradient descent, minimizing a combination of $\mathcal{L}_1$ and D-SSIM losses between the rendered and ground-truth images. See Figure 2.5 for the overall algorithm. To maintain visual fidelity and efficiency, the method applies adaptive density control. Figure 2.4 shows the visual process of the density control of the under- or over-reconstruction. Gaussians with negligible opacity or overly large footprint are pruned, while regions with insufficient detail are densified by duplicating or splitting Gaussians.

Gaussians overlapping the same tile are sorted front-to-back using a GPU-accelerated radix sort, after which compositing is performed in parallel per tile (Kerbl et al., 2023).

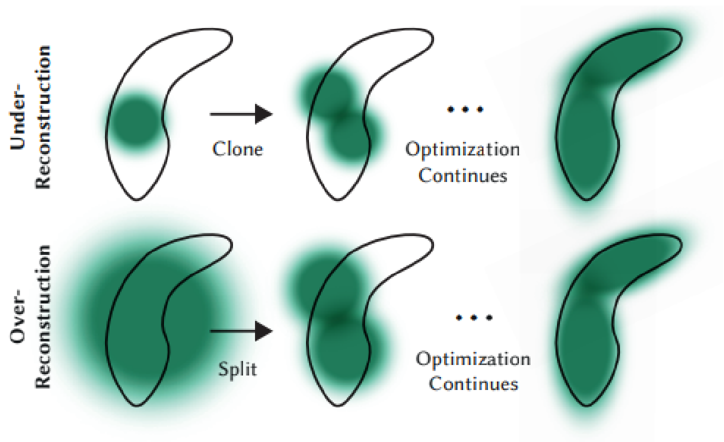


Figure 2.4.: Density control process during the reconstruction of Gaussian Splatting *Source: (Kerbl et al., 2023, p. 6).*

The final rendered image is produced by blending the contributions of all visible Gaussians at each pixel location (x, y) using:

$$I(x,y) = \sum_i \alpha_i \cdot \exp\left(-\frac{1}{2}(\mathbf{p}_{xy} - \pi(\mu_i))^\top \Sigma_i^{-1}(\mathbf{p}_{xy} - \pi(\mu_i))\right) \cdot c_i, \tag{2.2}$$

where $\pi(\mu_i)$ is the projection of the 3D Gaussian center into image space, Σ_i determines the splat's shape in screen space, and c_i is the color (often view-dependent via spherical harmonics (Kerbl et al., 2023).

Algorithm 1 Optimization and Densification
w, h: width and height of the training images

```
M ← SfM Points                                    ▷ Positions
S, C, A ← InitAttributes()        ▷ Covariances, Colors, Opacities
i ← 0                                       ▷ Iteration Count
while not converged do
    V, Î ← SampleTrainingView()          ▷ Camera V and Image
    I ← Rasterize(M, S, C, A, V)                      ▷ Alg. 2
    L ← Loss(I, Î)                                      ▷ Loss
    M, S, C, A ← Adam(∇L)                    ▷ Backprop & Step
    if IsRefinementIteration(i) then
        for all Gaussians (μ, Σ, c, α) in (M, S, C, A) do
            if α < ε or IsTooLarge(μ, Σ) then          ▷ Pruning
                RemoveGaussian()
            end if
            if ∇_p L > τ_p then                 ▷ Densification
                if ||S|| > τ_S then       ▷ Over-reconstruction
                    SplitGaussian(μ, Σ, c, α)
                else                     ▷ Under-reconstruction
                    CloneGaussian(μ, Σ, c, α)
                end if
            end if
        end for
    end if
    i ← i + 1
end while
```

Figure 2.5.: Algorithm for the optimization and densification pipeline of 3D Gaussian Splatting. *Source: (Kerbl et al., 2023, p. 13).*

Semantic Use of Gaussian Splatting Despite its advantages, Gaussian Splatting lacks inherent semantic integration, meaning that while the technique excels at rendering visual detail, it does not associate objects with contextual or historical metadata. This gap limits the technique's potential in heritage applications, where semantic understanding is crucial. Furthermore, the application of 3DGS on a large scale is hindered by excessive computational requirements due to the management of a large number of Gaussians (W. Liu et al., 2024).

As for the semantic enrichment of 3DGS, tests were divided into two workflows based on current theories: geometry-based and image-based. The first approach was tested by a previous group from a synthesis project (van Arnhem et al., 2024), in which the authors used the 3DGS centers as a sparse point cloud and explored transferring segmentation from a clustered point cloud to the Gaussian representation. They tested this idea on a small example—one façade of a building. Several clustering or segmentation methods were applied to the dense point cloud data, generating visually coherent clusters. These clusters were then aligned spatially with the 3DGS centers, and a nearest-neighbor approach was used to associate each Gaussian with a cluster label. Notably, they did not use the sparse point cloud generated from SfM to construct the 3DGS as described in the pipeline by Kerbl et al. (2023), but instead relied on precomputed Gaussian splats from tools such as Polycam and INRIA's implementation (van Arnhem et al., 2024). Additionally, there was no intermediate alignment between the SfM-derived sparse point cloud and the dense GeoSLAM point cloud; rather, the segmentation information was transferred directly from the dense point cloud to the Gaussian centers following coordinate registration. Furthermore, they also explored the direct application of clustering algorithms to the 3DGS centers themselves. The resulting clusters were visualized using the Blender plugin for 3DGS (van Arnhem et al., 2024).

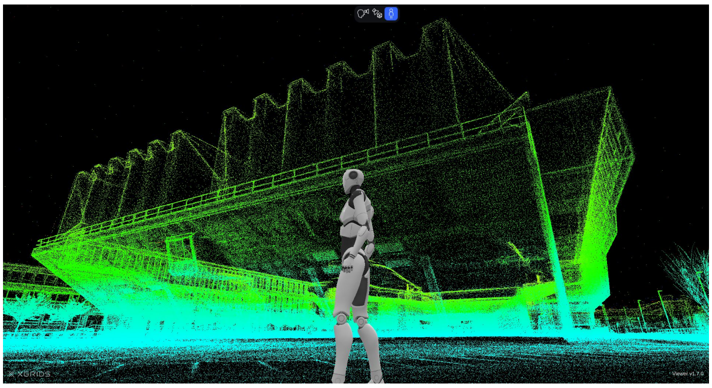
Although some limitations were observed—such as imprecise boundaries or mixed segments when clustering was applied directly to the 3DGS—the conceptual workflow of associating cluster information from a dense point cloud to Gaussian centers demonstrates a feasible method for enriching 3DGS with semantic categories. It is possible to generate semantically labeled Gaussian splats by identifying spatial correspondences between the two representations. This approach provides a practical basis for integrating segmentation results into 3DGS and is supported by publicly available code.

Another way is image-based, recent works such as Segment Any 3D GAussians (SAGA) and Segment Anything for Gaussian Diffusion (SAGD) propose applying 2D foundation models on individual rendered views of 3DGS. SAGA focuses on integrating 2D segmentation capabilities into 3DGS for rapid, multi-granularity segmentation, but may struggle with boundary precision (Cen et al., 2025). SAGD builds upon SAGA by introducing a boundary refinement technique that enhances segmentation accuracy without additional training overhead. Both methods employ the Segment Anything Model (SAM) on multiple camera views, generating masks per image and aggregating results through label voting. This approach leads to clear object boundaries and visually compelling segmentations that match the image-based essence of 3DGS rendering (Hu et al., 2025).

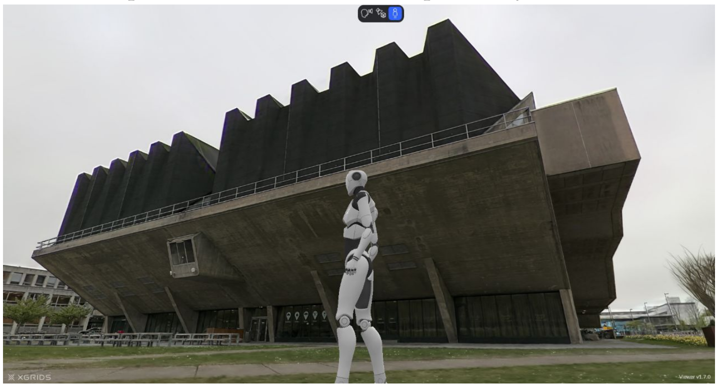
However, despite the visual quality, neither paper integrates the segmentation results back into the Gaussians as part of a structured data model. While each Gaussian may receive a label via multi-view voting, the information is not retained or embedded in a way that supports structured interaction or semantic querying. These methods focus on visualization, not on enriching the underlying representation with persistent semantics. For integration into SPC workflows, which require semantically structured representations, this remains a major gap. To align with SPC goals, such segmentation must be converted into consistent, queryable attributes per Gaussian or patch, linked to a knowledge structure or ontology.

Until then, these techniques remain effective visual tools but do not yet contribute to the development of smart or semantically aware 3DGS representations.

Commercial Use: Combining Laser Scanning with GS



(a) AULA: point cloud visualization captured by XGRIDS Lexils.



(b) AULA: Gaussian splatting result captured and processed by XGRIDS Lexils.

Figure 2.6.: Point cloud and 3DGS of AULA generated by one integrated workflow by XGRIDS Lexils.

In this section, internal test results are used to illustrate an integrative semantic enrichment approach for 3DGS. The visualization presented in Figure 3.9 includes both point cloud and Gaussian splatting data obtained using the custom system developed by XGRIDS LCC. This system integrates a laser scanner for capturing dense point clouds and a panoramic imaging setup. Rather than relying on SfM, their algorithm derives depth maps directly from the point cloud and registers them with known camera positions. This method avoids the typical SfM pipeline and enables more efficient and structured 3DGS generation. This example is public and can be viewed here from the LCC viewer from xgrids: https://lcc-viewer.xgrids.com/pub/dbahri-auladelft.

The example shown in Figure 2.6 is taken from the Aula of TU Delft. The resulting model is interactive and includes initial semantic layers, such as walkable ground surfaces and obstacles like walls. According to the developers, the use of a sparse point cloud in this process significantly improves both the visual quality and rendering speed of the generated Gaussian splats. This inspires the potential integration of Gaussian splatting into the Smart Point Cloud workflow, to enhance the photorealistic visualization of semantically structured scenes.

2.7. Research Gap

While multiple efforts have been made to document, digitize, and disseminate cultural heritage, several critical gaps remain unaddressed across existing workflows.

First, although many heritage platforms such as UNESCO, DOCOMOMO, and Europeana provide access to cultural information, they often lack structured 3D representations or only offer passive models without semantic enrichment. The formats vary, ranging from plain point clouds rendered in Potree to vector-based HBIM models or static meshes. From the review, we can notice that there is currently no standardization for the agreed in the domain of heritage, thus an information model is needed. Also, there are yet none providing unified, interactive platforms with embedded semantic understanding. These limitations reduce their effectiveness for conservation, analysis, or interactive learning. A scalable digital infrastructure that supports both 3D representation and semantic layers is still missing.

Second, HBIM workflows typically require converting raw data into IFC-based parametric models, which introduces abstraction, manual overhead, and geometric loss—especially for non-standard heritage features. While the term HBIM is widely used, its exact definition, expected contents, and modeling priorities remain inconsistent across projects and disciplines.

Third, the semantics used in HBIM are fragmented and often project-specific. There is a lack of a formal ontology to define which heritage characteristics (e.g., structure, material, symbolic meaning) should be consistently modeled. Semantics in HBIM still lack standardization and regulation, which can be modeled by a UML class diagram. Ontologies used are usually developed based on case-specific needs, making them difficult to generalize. This thesis responds to that by proposing a structured semantics derived from a literature review, grounded in recurring elements across HBIM publications. However, broader consensus in the domain of architectural heritage and alignment with standard vocabularies are still needed.

Fourth, SPC offers a promising geometrical alternative to vector-based HBIM for representing heritage objects, preserving raw geometry while enabling semantic structuring. However, domain-specific ontologies are not yet systematically embedded in SPCs. Prior work has focused more on the data structure than on meaningful enrichment for heritage applications.

Fifth, semantic segmentation of point clouds—necessary to implement SPCs with HBIM attributes—remains limited by method generalizability and automation. Rule-based, geometry-based, or deep learning methods each have trade-offs or need manual process, and none currently offer scalable solutions for multi-layered heritage semantics.

Sixth, Gaussian Splatting has emerged as a powerful real-time rendering technique, enabling photorealistic heritage visualization. However, current applications lack semantic integration. There is no established method to propagate structured semantics from SPCs to 3DGS representations, limiting their interpretability despite their visual fidelity.

In summary, there is a need for a unified, scalable, and semantically rich workflow that:

1. Treats point clouds as valid HBIM geometry representations without requiring parametric remodeling.
2. Applies a structured and literature-based ontology to define relevant heritage semantics.
3. Links semantic layers to segmented point clouds in an extensible format.
4. Bridges visualization and semantic interpretation through web-based tools and real-time rendering techniques such as Gaussian Splatting.

This thesis addresses these gaps by proposing a Smart Point Cloud workflow that integrates HBIM-informed semantics, offers structured point-level and patch-level annotation, and supports dissemination via interactive web visualization.

2.8. Research Questions Revisited

The main question guiding this research is: **How can HBIM ontology be integrated into smart point clouds with semantic enhancement to improve the visualization and conservation of heritage objects?** This research seeks to address the integration of heritage-specific semantic information into smart point clouds, with the aim of developing a lightweight and scalable workflow that enriches point clouds with HBIM-informed attributes. By doing so, it supports improved visualization, analysis, and documentation of heritage structures.

The main research question is divided into sub-questions aiming to address different challenges in the process:

1. **What are the defining characteristics of HBIM, and which additional characteristics are critical for enhancing heritage conservation efforts?** This sub-question involves conducting a literature review to understand the scope of HBIM and identify the key characteristics—including elements, relationships, and attributes—that are essential for heritage documentation and conservation. It also explores typical information sources such as historical records, expert insights, and previous case studies, helping to establish a grounded and structured semantic foundation.

2. **What does an effective HBIM information model look like, and how can it incorporate essential heritage attributes?** This question focuses on developing a semantic structure that accommodates both object-level and component-level attributes. It investigates how semantics can be attached to segments of the point cloud (e.g., via patch identifiers), and how the data can be organized and stored to remain usable, extensible, and compatible with broader heritage documentation practices.

3. **How can point clouds be segmented and semantically enriched with HBIM attributes?** This sub-question examines the segmentation of raw point clouds into meaningful components and their subsequent annotation with HBIM-derived semantics. While the development of new segmentation methods is not the focus, the study considers rule-based and data-driven approaches to enable a generalizable pipeline, and reflects on the practical limitations and potential of current segmentation techniques in heritage contexts.

4. **What strategies can be employed to create web-based interactive visualizations using semantically enriched smart point clouds?** This question addresses how semantically structured point clouds can be disseminated and interacted with through the web. It includes the design of a Three.js-based viewer that allows toggling between attribute layers, querying metadata, and supporting dissemination for education, research, and conservation planning.

3. Methodology

This chapter explains the methods and the rationale behind the methods for solving the research questions. It starts with illustrating the information model for structuring the HBIM ontology for SPC for heritage objects. A UML diagram is used for modeling the attributes and relations in this matter. Then, a general workflow for SPC is described, from capturing data to visualization. Then, another information model is proposed for integrating the semantic structure in different models, like IFC BIM and Gaussian Splatting. Within this integrative model, the semantic propagation from SPC to 3DGS, as well as the segmentation of the 3DGS, were described in detail as it was tested out. Finally, the case studies, equipment and dataset used were explained. Two modern heritage objects were chosen based on their different size and cultural significance.

3.1. Information Model - HBIM ontology

Smart Point Clouds typically offer a highly detailed geometric and spectral RGB representation of heritage assets but often lack structured semantics that make them reusable for analysis, documentation, or conservation. Without a formal model, the encoding of such information remains ad hoc and inconsistent, leading to interoperability issues and fragmented workflows. The information model ensures that HBIM characteristics —derived from the literature-based ontology — are organized in a clear, extensible way, aligned with the needs of both documentation and analysis.

A model-based approach allows semantic attributes to be not only recorded but also formally structured in a machine-readable and human-understandable format. This is especially critical in the context of SPC, where traditional BIM platforms (e.g., Revit or IFC-based systems) are not always compatible with raw or rendered point data. By creating a standalone information model, semantics can be integrated into the SPC pipeline independently, while still aligning with HBIM principles.

The information model is expressed in Unified Modeling Language (UML) class diagram, which is a standardized way to describe software and data structures. UML is widely used in the geospatial and heritage domains for defining conceptual schemas because it visually conveys class hierarchies, data types, and relationships. It also provides a pathway toward formal encoding in formats like GML or JSON schemas, if needed for implementation.

As can be seen in Figure 3.1, the UML model is centered around the concept of a `Heritage Object`, which serves as the top-level entity and is defined by both historical and restoration-related information, as well as a collection of associated `PointCloud` instances. Each `PointCloud` represents one scan linked to the heritage object, but a heritage object can be consist of more than one scans. This way, it can deal with partial scans for large-sized buildings, as well as the temporal changes of the same point cloud. The `PointCloud` includes metadata such as ID, format, reference system, and spatial extent. In addition, bi-temporal attributes are introduced to track both the system registration time (`systemStart`, `systemEnd`) and the real-world validity period (`validFrom`, `validTo`). This enables changes, corrections, or updates to be recorded without overwriting earlier states (Thompson & van Oosterom, 2021).

The classes `Historical` and `restorationandConservation` are directly associated with the `HeritageObject` as defining attributes. The `Historical` structure includes attributes such as building Origin, architectural Style, chronological Changes, historical Documents, and `functionalEvolution`, allowing the temporal and interpretative aspects of a heritage building to be captured. Apart from the time attribute, which represents when the object was built, all the other attributes in the Historical feature type are optional. The building can have more than one architectural style; in the meantime, it can have no defined style recorded as this attribute is not the core that defines the object. The function evolution, for instance, this model allows it to have none or more than one function evolved, which are included in the codelist.

Legal and conservation-related metadata are organized under `restorationandConservation` feature type, which includes subfields for restoration Technique, monitoring Data, conservation History, legal Status, and structural Stability. This structure enables the integration of preventive maintenance planning, environmental monitoring, and compliance requirements into the SPC-based modeling workflow. However, if one heirtage object has not gone through any conservation or restoration process, or its legal status has not been defined by organizations yet, this whole feature can be unknown or left empty. Therefore, all the attributes related to restoration are optional, noted by the [0..*] or [0..1].

Each `PointCloud` is composed of individual points, each defined by the `Point` class, which stores only minimal attributes such as coordinates (`x`, `y`, `z`), and color (`r`, `g`, `b`). Per-point information is not considered semantically meaningful on its own. Instead, each point is mapped to a semantic context via the `semanticPatch`, using an integer-based unique `patchID`. Each `PointCloud` can contain a number of `semanticPatch` units (at least one as indicated by 1..*). It allows the documentation and storage of unsegmented point clouds to be stored, so it can have no semantic patches yet (indicated by 0..* on the association of the semantic patch side). At the same time, one semantic patch can be associated with more than one point cloud. It is allowed when a patch happens to be on the edge of two partial scans of the same object. These semantic patches are the key containers for encoded domain semantics. They link to three major feature types—`Material`, `Structural`, and `CultureandArtist` — corresponding directly to the ontology categories defined earlier. The association to `semantic Patch` is version-dependent, meaning that each patch is linked to a specific point cloud scan instance. In addition, the model supports recursive aggregation of `semanticPatch` instances, allowing patches to be composed of sub-patches. This design enables hierarchical representation of semantics across different levels of detail, which is particularly valuable for complex architectural elements. For example, a semantic patch may represent a complete building wing, while sub-patches correspond to the roof, facade, or interior walls. These may be further divided into specific elements such as windows, ornaments, or decorated panels. The aggregation structure ensures that semantic information remains organized and traceable across scales, supporting both top-down and bottom-up interpretation in Smart Point Cloud workflows.

The `Structural` feature type holds attributes such as `building Hierarchy`, `componentType` (e.g., wall, roof, beam), `mechanicalProperties`, `construction Techniques`, and `damage Conditions`, with controlled vocabularies defined through accompanying code lists. Among these attributes, the component type is the core one, while the others are optional. It is because the structural component is always the core for modeling the different parts of a building or object, as the whole scan-to-BIM method is mainly about modeling the structure. Similarly, `Material Type` covers semantic properties like material classification (e.g., wood, stone, metal), provenance, deterioration patterns, and restoration records. `Historical Type`, although connected at the object level, conceptually complements the patch-level semantics by describing temporally evolving attributes. Meanwhile, `Culture and Artist Type` captures intangible and symbolic values, including `decorativeElements`, `artistName`, and `symbolism`, enabling the encoding of narrative, iconographic, and authorial information into the Smart Point Cloud structure.

It is worth noting that the `restorationandConservation`, `Historical`, and `CultureandArtist` are designed flexibly and can be connected either at the object level or at the patch level. This decision depends on whether the relevant characteristic applies uniformly to the entire heritage object or only to specific components. For example, if the same restoration technique were applied consistently to the entire building, it could be attached at the object level to avoid redundancy. Likewise, if the building was designed entirely by the same architect, this information can be linked directly to the `HeritageObject`. However, in cases where only a specific part—such as a sculpture or a decorative panel — was restored differently or created by a different artist, those semantics can be separately assigned at the patch level for more precise annotation.

The result is a flexible yet formally constrained structure that allows both the visual and semantic dimensions of heritage objects to be modeled within Smart Point Cloud environments, fully aligned with HBIM ontology defined in related work and extensible for future use cases.

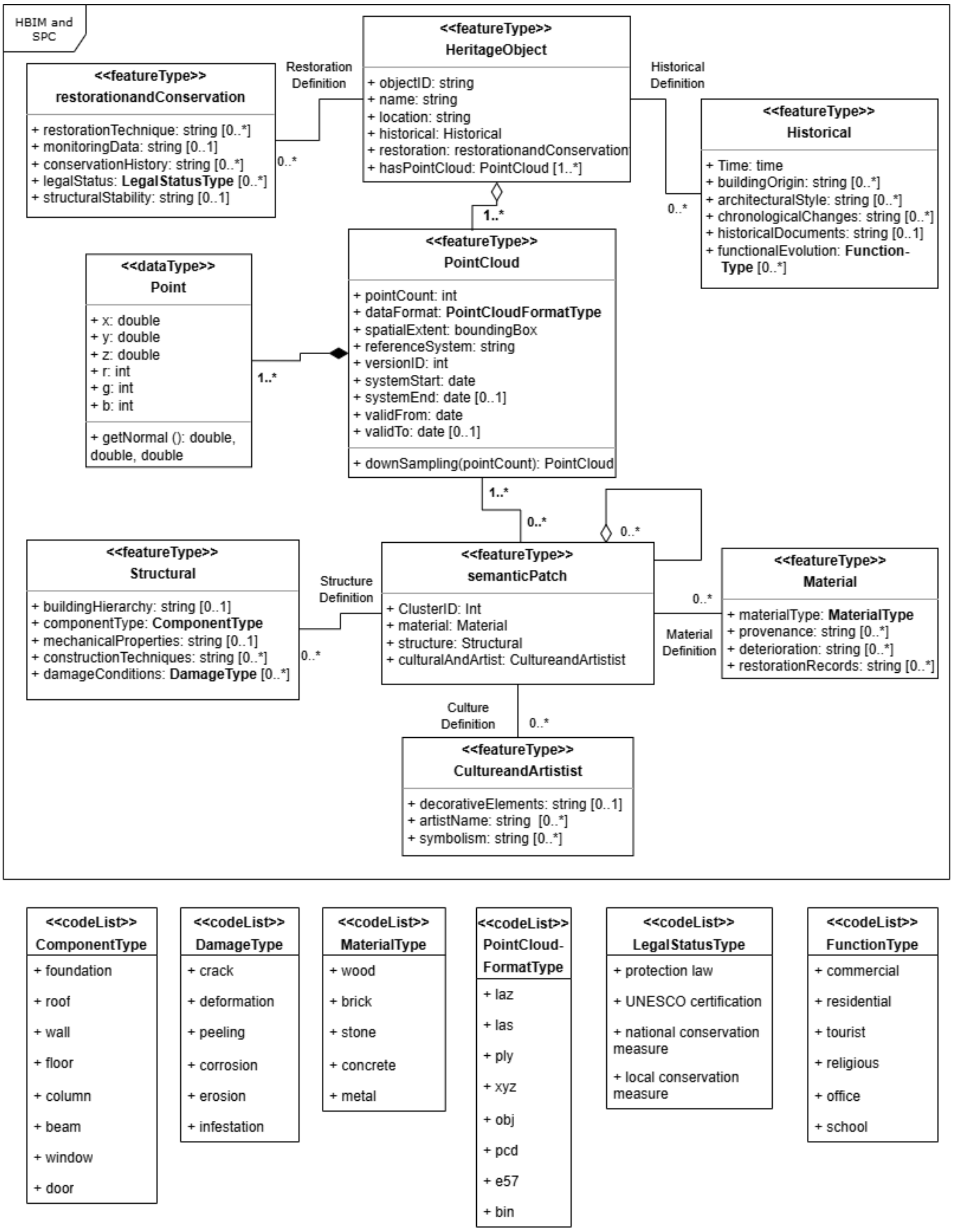


Figure 3.1.: UML class diagram for the information model of smart point cloud for architectural heritage.

3.2. Implemented SPC Workflow

Figure 3.2 illustrates the actual workflow implemented in this thesis to generate semantically enriched SPC for heritage documentation and visualization. The process begins with data collection from various scanning methods, which can include TLS, MLS, and Airborne Laser Scanning (ALS). After merging and cleaning the data in a pre-processing step, the point cloud undergoes semantic segmentation using geometry-based and manual methods to assign patch identifiers (`patchID`) to meaningful components. Parallel to this, semantic information is derived from historical documents and archival sources, structured according to the HBIM-informed ontology, and encoded in a `.json` format mapped to the same patch IDs. The SPC composed of spatial data and linked semantics—is then integrated into a web-based visualization tool built using Three.js, enabling interactive access, querying, and interpretation of both geometric and semantic content. The following subsections elaborate on each phase of this workflow.

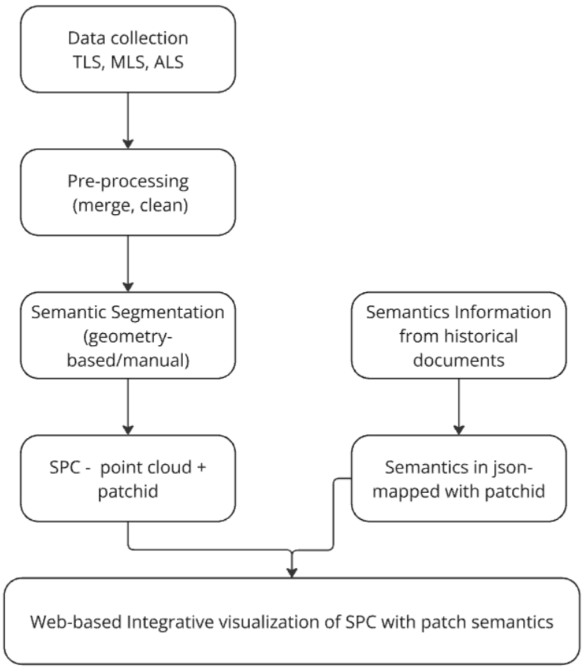


Figure 3.2.: The implemented workflow for structuring semantics in SPC and visualization.

Data Collection

The point clouds used in this study were collected through a combination of terrestrial, mobile, and aerial laser scanning methods, depending on the size and accessibility of the heritage object. For small objects, mobile LiDAR-based scans from consumer devices such as smartphones were found to be sufficient. For larger structures like the Aula of TU Delft, MLS and ALS were combined to capture a comprehensive dataset. This merging allows the complementary strengths of each method to be used: ALS provides complete roof coverage and contextual geometry, while MLS captures detailed façades and accessible surfaces.

High-resolution images were also captured using UAVs to support the generation of 3DGS models. Although 3DGS was initially planned to play a central role in visualization, it was only implemented in a limited capacity. Images were processed using SfM to produce sparse point clouds and camera poses, later used in an attempt to create Gaussian splats. While direct generation using PostShot succeeded, integration with SfM outputs through open-source workflows proved technically challenging and was ultimately unsuccessful.

Semantic Enrichment

The semantic enrichment process was guided by a structured HBIM ontology derived from the literature. Instead of converting point clouds into IFC-based BIM models using Scan-to-BIM plugins in Revit, the project focused on assigning semantics directly to the point cloud using a custom-designed information model. The key innovation is that semantic attributes were applied to spatial patches within the point cloud itself, allowing smart point clouds to serve as lightweight alternatives to traditional HBIM without requiring parametric modeling.

Due to computational constraints and lack of training data, no machine learning-based segmentation or annotation methods were used. Instead, semantics were assigned manually, supported by visual inspection and external documentation. Attributes such as material, structure, and decorative elements were encoded into JSON files, mapped to patch identifiers assigned during segmentation.

Point Cloud Segmentation

Point clouds were segmented using geometry-based methods. Due to the time limitation and lack of training data, supervised machine learning and deep learning based methods were not considered in this process. Though if these methods can yield better or quicker results, it can enhance this workflow greatly. Furthermore, the two modern chosen cases have relatively flat planes and medium complex structure (for Aula TUDelft), thus the author decided that geometry-based methods with manual adjustment can deal with the issue in a quicker and accurate manner in order to carry on the work further. The workflow relied heavily on plane detection using RANSAC and manual selection in CloudCompare. For planar elements like walls, slabs, and plaques, RANSAC with parameters such as a 5mm distance threshold and 500 inlier minimum provided effective results. For non-planar or thin components that were geometrically indistinct from their background (e.g., metal plates on concrete walls), manual polygon selection was used.

Each patch was assigned a unique integer identifier, stored as a custom attribute `patch_id` in the point cloud. Other attributes, such as RGB were preserved, but all text-based semantics were stored externally in JSON format. To reconcile patch IDs with the original point cloud, a k-d tree nearest-neighbor search was applied so that each point in the segmented subset could update the corresponding point in the full dataset.

Format compatibility presented a major challenge during segmentation. PDAL was used to convert `.laz` files to `.ply`, and PCL utilities were used to convert `.ply` to `.pcd` as required by segmentation tools. However, float64-to-float32 casting and 16-bit RGB normalization had to be performed in Open3D before processing. The final semantic point cloud was stored in `.ply` format, which is compatible with web visualization frameworks and allows embedding of custom fields such as `patch_id`.

Semantic Mapping and Structuring

After segmentation, patch-level semantics were manually assigned using external knowledge and inspection. Each patch ID was mapped to a dictionary of attributes in a JSON file, including material type, structural function, surface role, and condition. For example, a wall patch might be labeled as brick material, structural wall, and fair condition.

In addition to patch-level metadata, object-level semantics were collected from heritage websites and archival sources. This included artist name, construction date, historical function, and commemorative purpose. Both object-level and patch-level semantics were structured according to the predefined UML information model. This ensured compatibility across levels and provided a modular structure for storing and referencing heritage attributes.

Visualization and Dissemination

Visualization was implemented as a web-based viewer using Three.js. The point cloud was loaded using `PLYLoader`, while a parallel pass parsed the patch ID values. These values were linked to metadata using JSON files, enabling interactive queries and dynamic color updates.

Users can interactively explore the model by rotating, zooming, and translating the view. Patch-level information is shown upon clicking any point, and object-level metadata is always visible in a side panel. Buttons allow toggling between different semantic views, such as material-based or structure-based coloring. A floating highlight sphere shows the center of the selected patch, computed as the average of all included points. This visualization workflow allows semantic smart point clouds to be disseminated as interactive, browser-based tools, extending their value beyond documentation into education, analysis, and heritage storytelling. All rendering, metadata access, and interactivity are handled client-side. Deployment was tested locally using Vite and can be extended to server-based systems like Apache Tomcat for broader access. However, due to the large size of the file and the conflicting systems, the deployment has not been successful yet.

3.3. Semantic Integration and Propagation to Gaussian Splatting

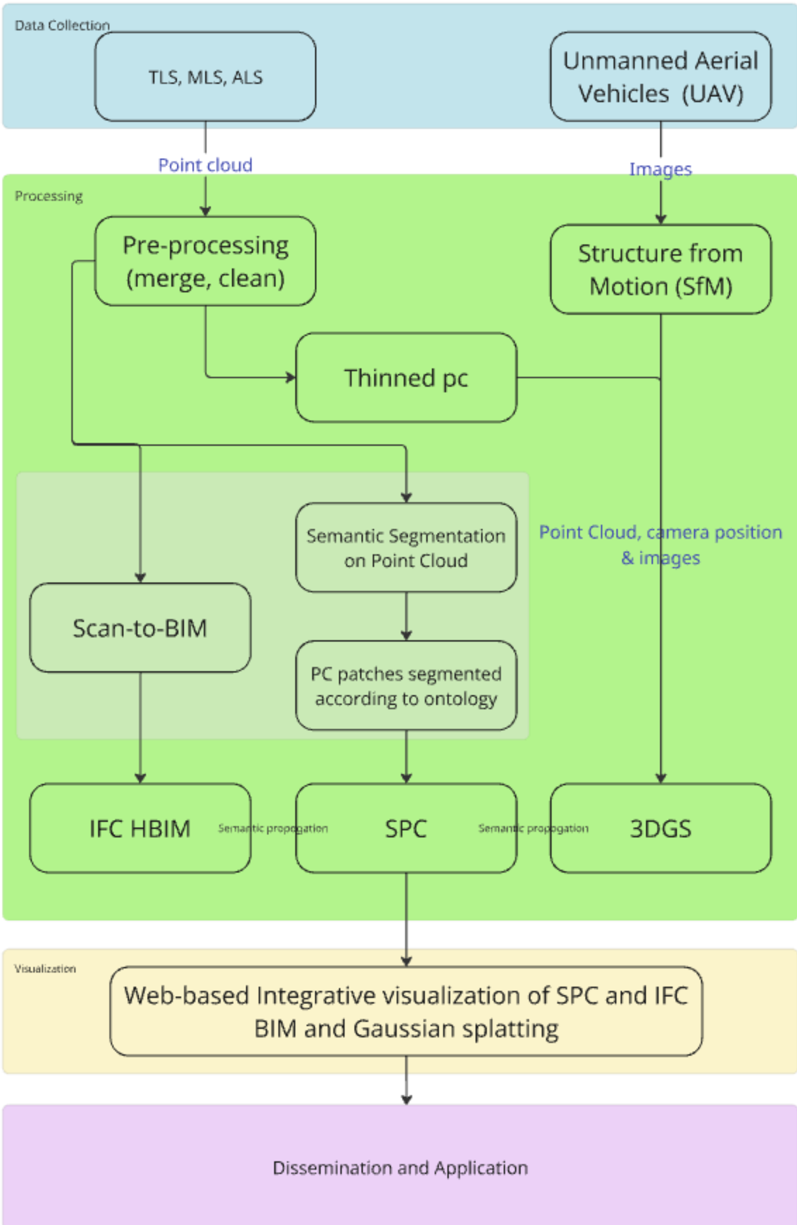


Figure 3.3.: The initial workflow for integrative 3DGS and SPC for heritage objects.

The initial plan for this research aimed to establish a comprehensive, integrative workflow that connects three representations of heritage data: SPC, IFC-based HBIM models, and 3DGS. The central hypothesis was that each representation could serve complementary roles in conservation and visualization, while semantic consistency could be maintained through propagation mechanisms aligned via patch identifiers or geometric alignment.

The first major component was the acquisition and preprocessing of data. Point clouds were to be acquired by the same methods described in the previous workflow, and images from UAV would be used for photogrammetric reconstruction through SfM. The flow from the thinned point cloud to 3DGS is an alternative method inspired by and is successfully implemented in the industry already (xgrids equipment described in 2). It provides the possibility of deriving the depth of the images directly from the laser-scanned point cloud, instead of going through SfM. The point clouds, either from SfM or directly from laser scanners, are then combined with camera positions and the original images for 3DGS generation.

Semantic segmentation was to be performed on the cleaned point clouds through both rule-based and geometry-based algorithms; dl methods were also tested. Ideally, more advanced methods such as voxel-based segmentation (Poux & Billen, 2019) and deep learning-based models (e.g., RandLA-Net, KPConv) would also be tested. However, due to practical and technical limitations, only geometric and manual segmentation were ultimately used and produced meaningful results in the implemented workflow.

From this segmentation, patches were defined within the SPC and assigned semantic labels using a manually curated ontology. At the same time, the Scan-to-BIM process was intended to convert point clouds into parametric IFC HBIM models, attaching common BIM attributes. All these representations—SPC, IFC HBIM, and 3DGS—would then receive semantic annotations based on a unified structure, enabling integrative visualization and querying.

To support this vision, a UML class diagram information model (Figure 3.4) was designed to integrate diverse 3D representations of heritage objects and support semantic propagation through spatial alignment. The central class is the `HeritageObject`, which represents a single cultural asset and links to external documentation via the `Documents` class. Each document instance is associated with a specific `DocumentType` such as report, conservation plan, architectural drawing, or historical archive, enabling traceability and source tracking.

The geometry of the heritage object is handled through an abstract superclass called `3DRepresentation`. This class defines shared metadata across representations, including the version tracking features that contains both system time and valid time, which was discussed earlier in Figure 3.1. The spatial alignment is presented through the attribute `spatialReferenceType`,

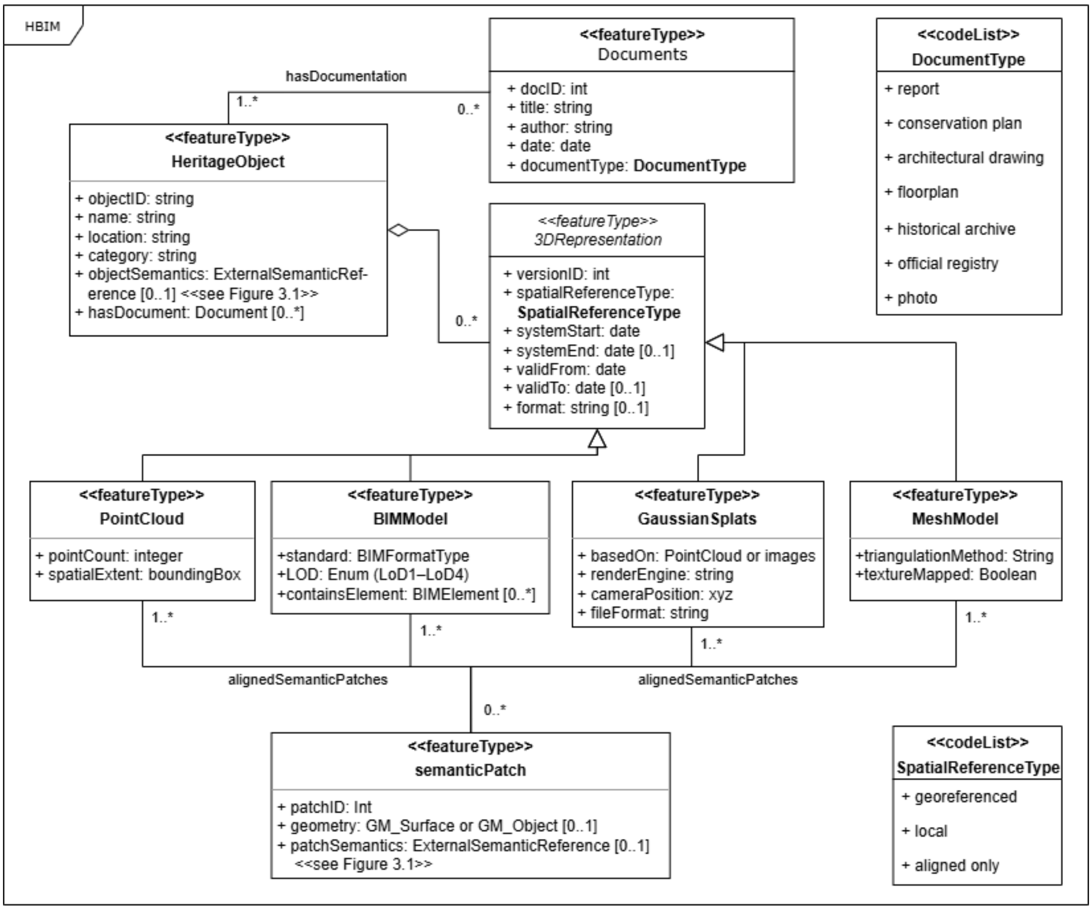


Figure 3.4.: The UML diagram of the integrative 3DGS and SPC structure.

which uses a controlled vocabulary to distinguish between georeferenced, local, and relatively aligned coordinate systems. The `format` and `referenceSystem` fields further clarify the technical structure of the datasets.

Four specialized representations inherit from `3DRepresentation`: `PointCloud`, `BIMModel`, `GaussianSplats`, and `MeshModel`. Each serves a different purpose in the modeling pipeline. `PointCloud` includes point count and bounding box information and is commonly used as the raw input for segmentation. `BIMModel` supports additional metadata such as BIM standards, level of detail (LOD), and a list of contained `BIMElement` instances. `GaussianSplats` accommodates recent splatting-based rendering pipelines and includes parameters like camera position, rendering engine, and source (e.g., point cloud or images). `MeshModel` represents conventional surface geometry and supports metadata about triangulation and texture mapping.

Each of these representation types links to one or more `semanticPatch` instances through the association `alignedSemanticPatches`. This association allows shared semantic annotations to be reused across models, as long as their geometry has been aligned. The `semanticPatch` is defined as a `dataType` and includes a unique `patchID`, a spatial geometry (e.g., `GM_Surface` or `GM_Object`), and an optional reference to a detailed semantic description ExternalSemanticReference, which is defined in a separate domain-specific UML (Figure 3.1).

In this way, semantic regions such as a roof, beam, or ornamental facade can be modeled once and linked across multiple aligned geometric models. The result is a lightweight but extensible structure that accommodates version control, provenance tracking, and semantic integration without overloading any single representation with redundant data.

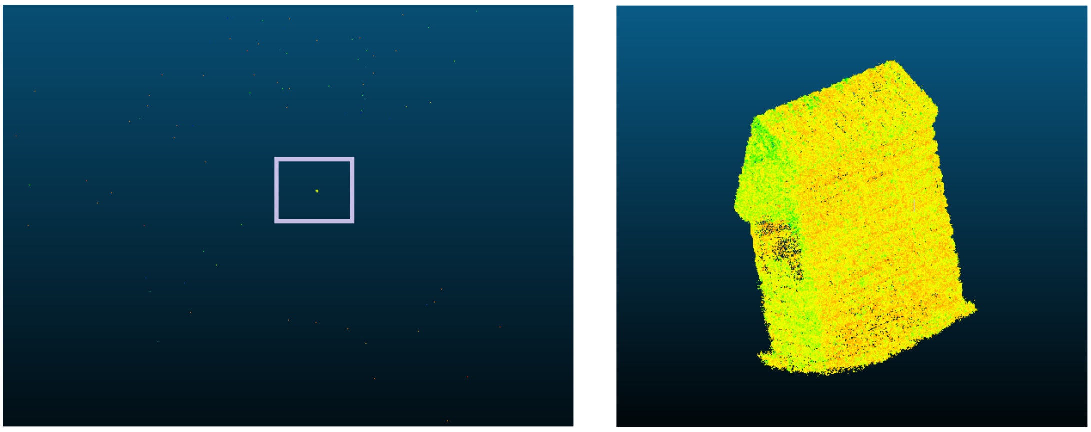


Figure 3.5.: The noise of Gaussian centers and its distance to the object, and the gaussian centers viewed in CloudCompare.

The detailed process to align SPC patches with Gaussian splat centers is byusing spatial registration techniques. See Figure 3.6 for the SPC and Gaussian Splatting of the case study. Corresponding points (such as those on the corners) were identified, and the transformation matrix was calculated and applied to the SPC. Once aligned, patch-level semantics would be transferred to splats which do not contain semantic labels natively. The 3D coordinates of both the point cloud and the Gaussian splats are aligned. Since the Gaussian splat attributes are closely related to the visualization and camera position, meaning that if we only align the XYZ coordinates of Gaussian centers to the point cloud, the new Gaussian splatting will not render well. Therefore, the point cloud was aligned to Gaussian splatting using least square adjustment by corresponding points. This alignment ensures that the coordinate systems are consistent while leaving the Gaussian rendering parameters (such as covariance matrices, spherical harmonics, and opacity) untouched.

For each Gaussian center, the closest point in the point cloud is identified using a KD-Tree-based nearest-neighbor search for computational efficiency. The corresponding patch ID (semantic label) is assigned from the nearest point to the Gaussian center, by adding a

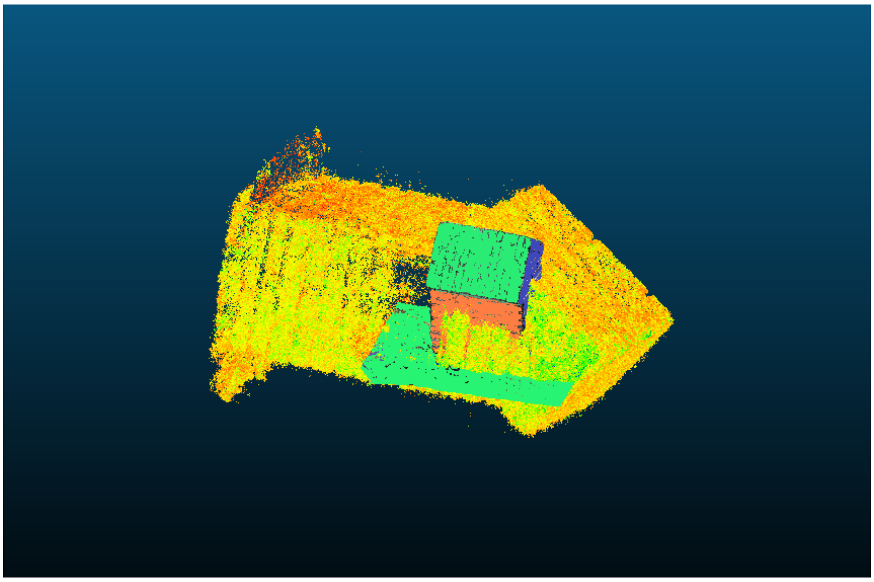


Figure 3.6.: The unaligned Gaussian Splat centers and SPC of case study HK visualized in CloudCompare.

new feature in the 3DGS ply file as in the SPC. Based on the integer patch ID, each patch can be separated and rendered on its own, and connected to the semantics by the patch ID. This method is tested on the prototype of the small monument, the result contains the separated parts of the Gaussian splatting based on the segmentation on the SPC. The segmentation process successfully isolates structural components such as ground, facade, and roof elements, demonstrating that the semantic information can be transferred and applied directly to the Gaussian splat representation.

By structuring semantic information externally and referencing it across different 3D models, this workflow facilitates consistent documentation and visualization of heritage objects. The model supports future developments where 3DGS rendering tools may evolve to support custom attribute linking, enabling full integration with semantically enriched smart point clouds.

3.4. Case Studies, Equipment, and Datasets Used

Case Studies - Aula TUDelft and Herdenkingsmonument Kartuizerklooster

The workflow was tested with two heritage objects in the Netherlands, encompassing different architectural styles and complexities. Each stage of the workflow, from data collection to

Figure 3.7.: The SfM point cloud (and camera positions) and Gaussian Splatting generated and viewed in Postshot.

visualization, will be validated based on criteria such as accuracy, scalability, and the ability to represent and integrate semantic information effectively.

This methodology provides a comprehensive approach to heritage documentation, combining traditional and advanced techniques to validate the potential of semantically enriched SPC with HBIM characteristics.

Located in Mekelweg 5, 2628 CC, Delft (as seen in Figure 3.8), Aula plays a central role in university life. The building includes a large auditorium with 1300 seats, four trapezoidal lecture halls ranging from 250 to 350 seats, the senate hall, and the main university canteen. It stands out as a rare and clear example of brutalist architecture in the Netherlands and is widely seen as a landmark of Dutch modernism. The design pays tribute to the ideals of the modern movement—architecture intended to serve a social purpose, evoke a sense of cosmic spatiality, and express organic form. In 2015, the building was officially recognized as a National Monument. ("Keeping It Modern", 2021; www.architectuur.org, n.d.). A conservation management plan exists, addressing issues ranging from concrete damage and code compliance to energy efficiency and defining surface colors. The plan was supported by the

Getty Foundation and serves as one of the first pilot projects of its kind in the Netherlands, aiming to guide the conservation of culturally significant buildings on the TU Delft campus and elsewhere. However, the full text of the conservation management plan is currently under embargo until 2030 and was not available for review at the time of writing (de Jonge et al., 2023).

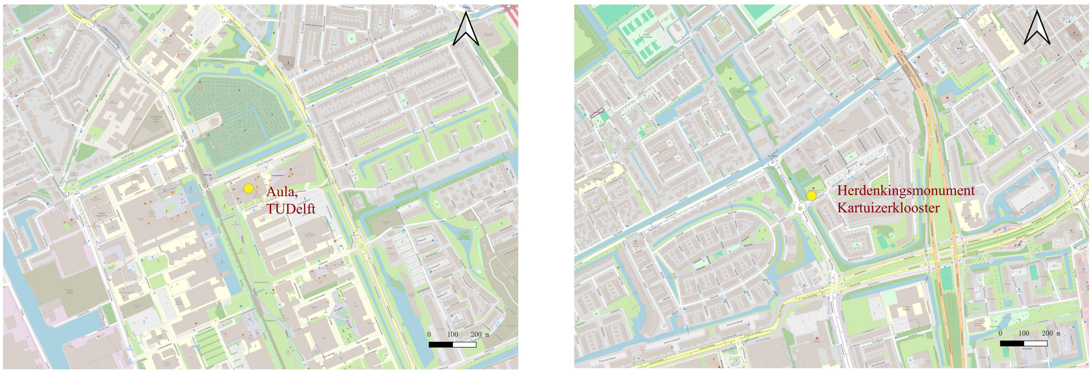


Figure 3.8.: Location of Aula TUDelft and HK on map.

Apart from its cultural significance, Aula TUDelft is a suitable case study for three main reasons. First, its structure consists of distinct parts that correspond well with the concept of patches, making it a good example to illustrate the distinction between object-level and patch-level semantics. Its unique features include a cantilevered roof and pre-stressed concrete ribs. Second, its large scale introduces practical challenges such as limitations in data collection from the ground level and the need to integrate additional point cloud data. The segmentation process becomes more demanding due to its complex geometry and extended processing time. Finally, the building is locally accessible in Delft, which facilitates data collection and information gathering for metadata, while also ensuring relevance for the broader community.

The other example, the Herdenkingsmonument Kartuizerklooster (Carthusian Monastery Memorial, abbreviated as HK in this paper), is also located in Voordijkshoorn, 2614 HL Delft. This small monument commemorates the remains of the Carthusian monastery 'St. Bartholomew in Jerusalem', which stood on this site from 1469 to 1572. The monastery was destroyed during the Eighty Years' War, and the monument was later donated by the Royal Dutch Society for the Promotion of Medicine (KNMG) to the (then new) hospital ("Art Guard - Delft", n.d.).

Unlike Aula TUDelft, HK was chosen as the first prototype due to its small scale. It is well-suited for testing because data can be collected entirely from the ground using a mobile phone and a scanner, without the need for integrating external sources. Various segmentation methods were tested without extensive processing time. The structure is clear, and geometric planes are easily detectable, which simplifies the analysis.

(a) Aula TUDelft (drone photo by author).

(b) HK (phone photo by author).

Figure 3.9.: Case study: (a) Aula TUDelft(drone photo), taken by author; (b) Herdenkingsmonument Kartuizerklooster (HK), captured by phone by the author.

In summary, the two case studies represent two types of monuments that differ in scale and complexity but are both culturally significant and accessible in Delft. While the small monument and the brutalist building offer relevant contrasts, they also share certain limitations: minimal decorative elements, simple to moderate architectural complexity, and relatively intact conditions. Their modern origins also mean that, compared to older monuments, they present fewer conservation challenges at this stage.

Equipment and Data Used

The UAV used for image acquisition is a DJI Mini 3, which includes a Global Navigation Satellite System (GNSS) module. Each image is geotagged with location data; however, orientation data per image is not recorded. Due to the drone's incompatibility with the DJI SDK, access to raw sensor data is limited. For mobile laser scanning, a GeoSLAM ZEB Horizon RT was used , offering up to 6 mm relative accuracy and a 100-meter range. It supports real-time feedback and is suitable for both indoor and outdoor mapping workflows, using a SLAM-based algorithm. iPhone models later than version 12 were also used for capturing images and 3D scans via the Polycam app (https://poly.cam/), which leverages the built-in LiDAR sensor for dense reconstruction. See Figure 3.13 (b) .

For Aula TUDelft, approximately 450 UAV images were collected over two days, though lighting variations affected the usability of some images for SfM. GeoSLAM scans were conducted for the TUDelft Aula building and the adjacent library, see Figure 3.11 for the data collected. We can see that, data is relatively complete for the parts that the ground-level scan can reach, aula library is clear, but the roof of the aula is missing.

Additionally, AHN5 tile 37EN2_11 was obtained from GeoTiles.nl, which includes satellite-colored LiDAR point clouds, see the screenshot of the data in Figure 3.12. First thing to

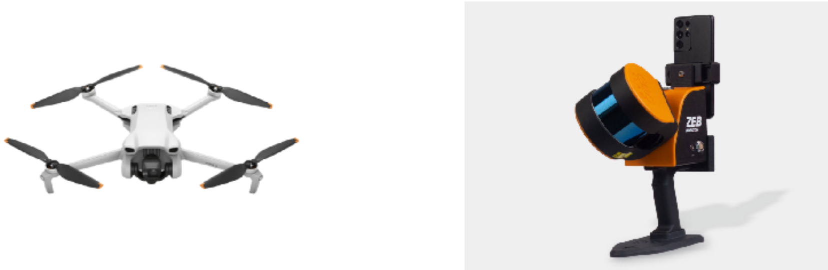


Figure 3.10.: Equipments used: DJI mini 3 and GeoSLAM ZED Horizon RT.

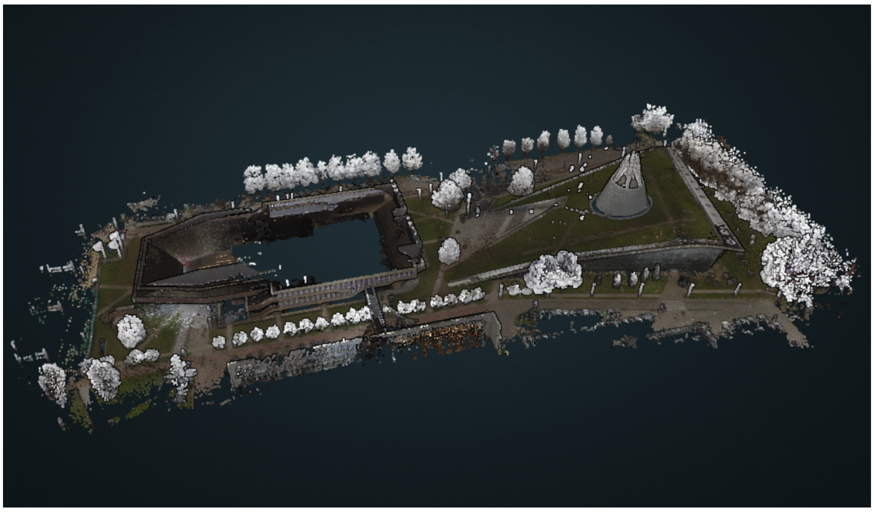


Figure 3.11.: The point cloud data of Aula TUDelft collected by GeoSLAM ZED Horizon RT.

notice is the color difference in Geotiles compared with MLS data. Due to the integration of satellite imagery, the whole color scale is greener. Furthermore, we can see the misalignment of the imagery and the point cloud, which is especially obvious on the edge of the TUDelft Library, where we can see that the roof color is projected on the ground (it is a limitation pointed out by the authors of Geotiles). Most importantly, it is mainly the point cloud roof that was collected, and a small part of the side. The overhanging structure of Aula and the walls on the other side are missing.

For HK, image data was collected with both the iPhone and UAV, with the DJI offering higher resolution (4K HDR). The iPhone-based LiDAR scans were exported in PLY format, while GeoSLAM data was exported in LAZ format. See Figure 3.13 for the two point cloud data captured for HK.

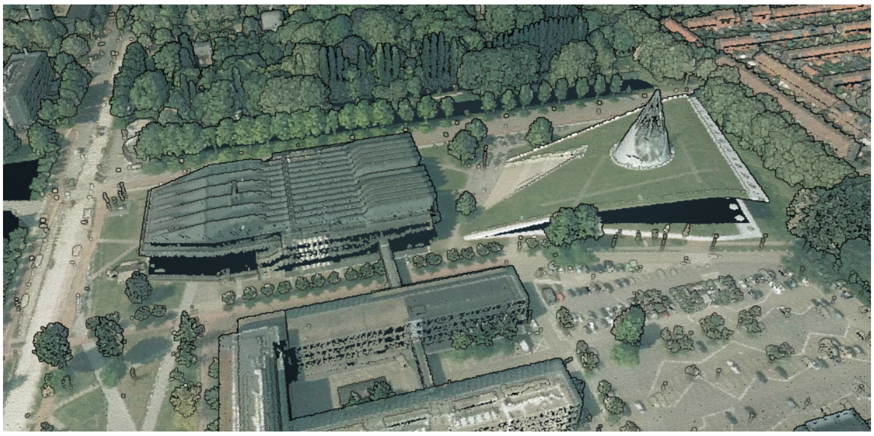
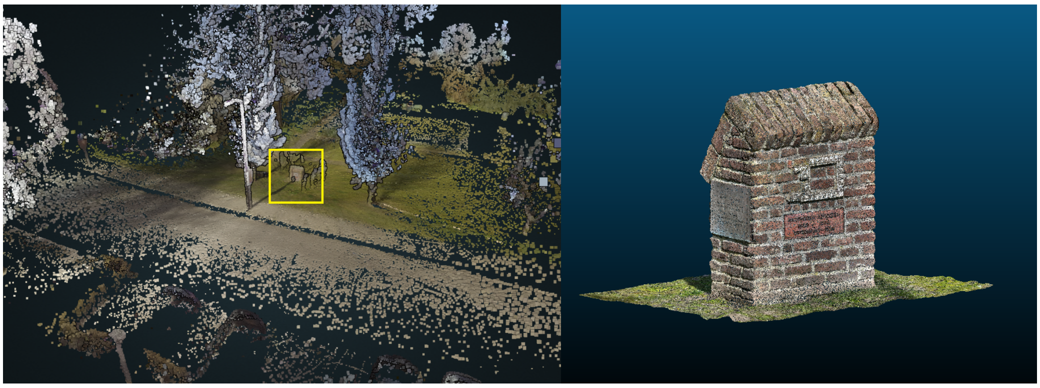


Figure 3.12.: The point cloud data of a tile of Delft from Geotiles (AHN and color from satellite imagery.



(a) The point cloud data of HK collected by GeoSLAM ZEB Horizon RT.

(b) The point cloud data of HK collected by iPhone (Polycam).

Figure 3.13.: Case study: (a) GeoSLAM point cloud of HK with yellow square; (b) iPhone-based point cloud of HK (Polycam).

Table 3.1.: Overview of data used in this study

Name or Description	Type	Source	Format
Aula TUDelft images	Image set	UAV (DJI Mini 3)	JPG
Aula TUDelft point cloud	Point cloud	GeoSLAM ZEB Horizon RT	LAZ
AHN5 tile 37EN2_11	Point cloud	GeoTiles.nl (colored AHN5)	LAZ
Aula TUDelft semantics	Metadata table	Hand annotation, Kunstwacht	JSON
HK images	Image set	UAV (DJI Mini 3) and iPhone (Polycam)	JPG
HK point cloud	Point cloud	GeoSLAM ZEB Horizon and iPhone (Polycam app)	LAZ, PLY
HK semantics	Metadata table	Hand annotation, heritage documents	JSON

4. Implementation

The chapter of implementation includes all the technical details that were described in the methods, and it focuses more on how the results were achieved. It starts with the preprocessing of the point cloud captured by the MLS, mainly the alignment and combination of the two complementary datasets for AULA TUDelft. After the preprocessing, the point clouds went through several tests for the segmentation process. Mainly geometry-based segmentation methods were tested out, and the success or failed results and the corresponding parameters were explained. Then, the segmented point cloud patch is connected with the semantics. Details are provided for how the semantics are structured and connected to the patch by the patchid. This link is further explained by the design of the web-based visualization platform using Three.js to show how the patch semantics can be viewed per patch in an interactive way. Finally, the tested workflows of Gaussian Splatting were presented. It includes the steps for transferring the semantics from the SPC to the 3DGS, as well as the two failed workflows which tried to generate Gaussian Splatting from SfM point cloud.

4.1. Data Pre-processing

This section outlines the essential pre-processing steps required to make the point cloud usable for semantic segmentation and integration into a structured model. The codebase used for data processing, segmentation, and web-based visualization is published at: https://github.com/Zhuoyuee/thesis.

Point clouds require pre-processing for noise removal and downsampling to optimize the segmentation process. Furthermore, for large heritage objects, data acquired from different sources must undergo several steps to be aligned and merged. For example, for the Aula at TU Delft, we have ALS from Actueel Hoogtebestand Nederland (AHN) (from the geotiles.nl project, AHN with satellite color) and MLS data. This serves as an example of integrating multiple sources into a single model using open data and handheld, ground-based MLS, instead of UAV-mounted LiDAR systems designed for tailored scene acquisition. The following steps were applied to the Aula and Library dataset:

1. **Geo-reference the MLS point cloud**: The MLS point cloud is in local coordinates, while AHN is georeferenced in EPSG:7415 (RD New + NAP). We identify corresponding features and points, such as building corners and streetlight poles, that are visible in both point clouds, despite their limited overlap. These must be permanent, immobile, and identifiable in both datasets. Then, a transformation matrix is computed. An example matrix is shown below:

   ```
   "type": "filters.transformation",
   "matrix": "0.870089 0.490798 0 85589.92
             -0.489936 0.868996 0 446476.01
              0 0 1 -0.625
              0 0 0 1"
   ```

   This matrix represents a 3D affine transformation, including rotation (first two rows), translation (fourth column), and height adjustment. The matrix is then applied to all points in the local coordinate system using the `pdal` library via its JSON API in Python. This transformation ensures that both datasets share the same spatial reference frame, which is crucial for accurate merging. If the alignment is not sufficient, the process can be repeated for fine-tuning.

   The reason for aligning both datasets to real-world coordinates is to preserve geographic location, which is beneficial for integration into larger-scale point cloud datasets in the future.

2. **Merging point clouds**: Once aligned, the two point clouds can be merged using the `pdal` API:

   ```
   {"type": "filters.merge"}
   ```

   Although tolerance settings can be used when merging, applying nearest-neighbor tolerance check results in memory issues due to limited Random Access Memory (RAM). However, because of the minimal overlap, a simple merge does not introduce excessive point duplication.

3. **Noise removal**: Noise includes floating points or non-building elements. Both point clouds capture the surroundings of the buildings, which are unnecessary for modeling the digital twin. The method is to crop the buildings using a 2D mask created from the coarse classification in AHN, which correctly outlines the roof structure, effectively bounding the building footprint. Using `pdal`:

```
"type": "filters.range",
"limits": "Classification[6:6]"
```

This filters only the building-classified points from AHN. We need to generate a 2D mask of the building area. First, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is applied using `sklearn` with parameters: `alpha = 1.5`, `clustering_eps = 2.0`, and `min_samples = 30`. The DBSCAN parameters control the cluster shape and density sensitivity: a higher `alpha` preserves more detail in irregular outlines, while `clustering_eps` defines the spatial reach for connecting points into clusters. The purpose is to isolate 2D clusters of buildings for further processing.

To extract the polygon geometry of each cluster, both the convex hull and alpha shape methods were tested:

```
MultiPoint(cluster_points).convex_hull
alphashape.alphashape(cluster_points, alpha)
```

Convex hull returns the tightest convex polygon that encloses all points, but it cannot represent concavities. In contrast, alpha shapes allow the reconstruction of non-convex boundaries and provide more control over detail by adjusting the alpha parameter (Edelsbrunner & Mücke, 1994). For this use case, alpha shapes were preferred, as they better capture the actual shape of buildings. The resulting polygons are saved as Well-Known Text (WKT). Polygons are sorted by area: in this case, the largest is the Aula, and the second largest is the Library. The rest are small clusters and are omitted. The goal is to isolate building regions accurately while minimizing the inclusion of noise or surrounding structures.

Using the separated 2D masks for each building, we can clip the overall merged point cloud with these polygons. Cropping is done using `pdal`'s polygon WKT crop function.

For floating-point noise within the point cloud, 3D DBSCAN was attempted, but caused memory issues. Therefore, SOR (Statistical Outlier Removal) from `pdal` was used instead.

4. **Downsampling**: This is crucial for reducing the dataset size to avoid computational bottlenecks during further processing. In `pdal`, a sampling filter can be used:

```
"type": "filters.sample",
"radius": sample_radius
```

Alternatively, in PCL:

```
pcl::VoxelGrid<pcl::PointXYZRGB> sor;
sor.setInputCloud(cloud);
float base_leaf_size = 0.08f;
sor.setLeafSize(base_leaf_size, base_leaf_size, base_leaf_size);
sor.filter(*cloud_filtered);
```

The downsampling radius must be chosen carefully to reduce point density without compromising the object's geometric fidelity.

See Figure 4.1 for the two separate objects after preprocessing. If the target point cloud comes from a single data source, the first two steps (geo-referencing and merging) can be omitted.

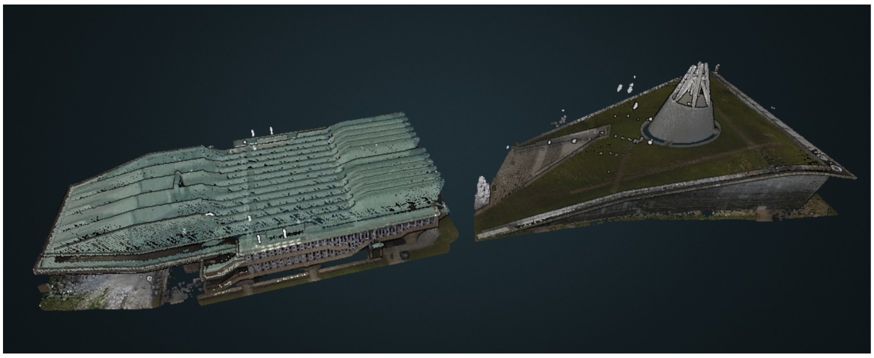


Figure 4.1.: Point cloud of AULA and library after preprocessing.

4.2. Point Cloud Segmentation

Segmentation methods for point clouds can be broadly categorized into rule-based, geometry-based, cluster-based unsupervised learning , and dlsupervised learning approaches. Geometry-based methods, such as plane fitting or region growing rely on spatial structure, while learning-based approaches require annotated training data, which was not available in this case.

DL methods were considered to automate semantic segmentation without manual labeling. Open3D-ML was selected and added to the project environment to access models such as PointNet and RandLA-Net. The plan was to build Open3D from source with PyTorch support. A Python virtual environment was created, and Open3D was compiled using CMake and Visual Studio, attempting to enable ML modules. However, persistent issues during the build—such as missing dependencies (MKL, libcurl), broken external libraries, and failed PyTorch linking—prevented proper integration. Despite multiple rebuilds with adjusted

CMake flags and dependency updates, Open3D raised runtime errors indicating that it was ”not built with PyTorch support.” As a result, DL-based segmentation could not be tested or incorporated into the Smart Point Cloud workflow.

Due to the failure of the DL-based methods, a fallback to classical segmentation techniques was necessary. The Point Cloud Library (PCL) library (Rusu & Cousins, 2011) was selected for its range of geometry-based segmentation methods and its reliability. Although PCL only supports the `.pcd` format, requiring format conversions, it allowed direct testing of multiple algorithms within a stable C++ environment.

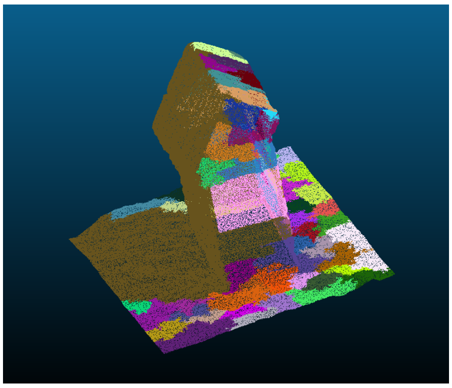
Several segmentation methods were tested in PCL, including region growing based on RGB similarity, region growing based on surface normals, and RANSAC plane fitting. Region growing with RGB similarity initially used tight thresholds, leading to severe over-segmentation with hundreds of small clusters. Relaxing thresholds improved the result but still produced noise-sensitive segmentations. For example, see in Figure 4.2, we can see that this segmentation algorithm is very sensitive the lighting and the RGB difference from different point cloud data sources.

Another algorithm was also tested - region growing with surface normals. We can see from Figure 4.3 some of the segmentation results. It works better than the previous one with RGB involved. However, there are many unclassified points (grey ones), especially around boundaries and noisy regions. Tuning the threshold is also tricky. As if it is not sensitive, some structures cannot be detected, like the plate on the side. However, with details detected, it comes with over-clustering of unwanted areas, like the inclined plane. This way, it needs manual tuning, but it still cannot segment according to the semantic rules

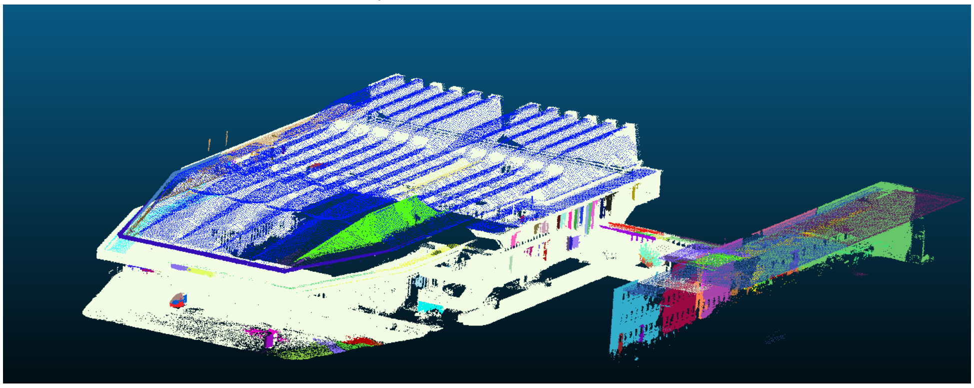
RANSAC plane fitting was the most viable method, but still produced unstable results when applied to large building-scale datasets. Adjustments to distance thresholds and iteration limits could not fully resolve issues of over-fragmentation and missed surfaces. CloudCompare's qRANSACSD plugin offered a better alternative. After importing the PLY-format point cloud into CloudCompare, normals were optionally computed to enhance plane fitting. RANSAC plane detection was executed using parameters such as a maximum distance threshold of around 5 mm and a minimum of 500 support points. Each detected plane was saved as a separate subset, while residual points were grouped for manual processing.

Further manual steps were necessary. Fragmented or overlapping planes were merged interactively. Thin features such as plaques and metal plates, which could not be isolated by RANSAC due to geometric co-planarity with the background, were segmented manually using polygon selection.

Each plane or feature subset received a unique integer `patch_id`, assigned through CloudCompare's scalar field tools. Residual unclassified points were initially assigned a place-



(a) Lighting sensitive result of applying region growth rgb segmentation on HK case study



(b) Noise sensitive result of applying region growth rgb segmentation on AULA case study

Figure 4.2.: Not ideal results after applying RGB region growth on case studies.

holder ID (e.g., 99). After segmentation, all subsets were merged into a single point cloud, preserving coordinates, RGB values, optional normals, and the newly created patch IDs.

A KD-tree nearest-neighbor pass was applied: every point in the residual set was assigned the nearest classified patch ID to ensure no point remained unsegmented. Normals were optionally propagated in the same way.

The final point cloud structure was:

```
x  y  z  r  g  b  nx  ny  nz  patch_id
```

Semantics were stored externally, linking each patch ID to a relational semantic table. This design avoided duplicating semantic text in the point cloud and allowed attribute versioning independently of geometry.

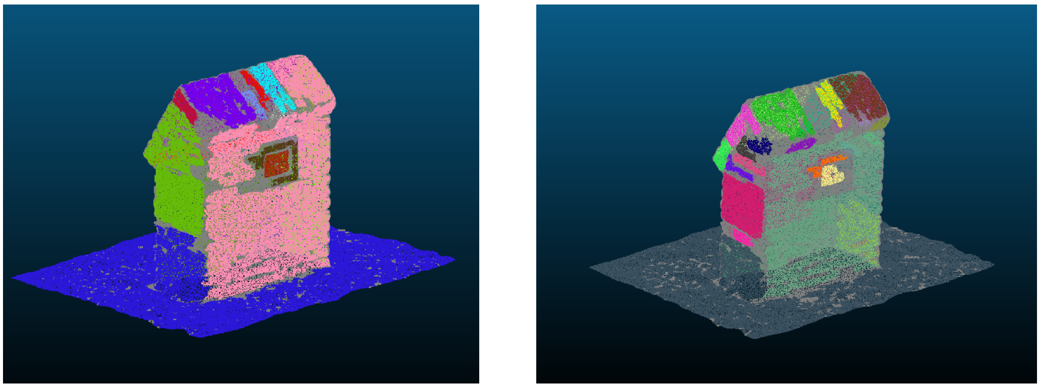


Figure 4.3.: Segmentation result of case study HK using region growth normals

In summary, segmentation was achieved through a combination of RANSAC plane detection, manual refinement, KD-tree-based patch assignment, and external semantic linking. This method proved reliable for datasets up to ~ 0.6 million points and maintained compatibility with both desktop tools and web visualization frameworks.

4.3. Point Cloud Format and Conversion

Throughout the implementation, multiple point cloud formats were used and converted depending on the tools involved. The choice of format affects both processing and compatibility, especially when using libraries such as Point Data Abstraction Library (PDAL), PCL, and visualization frameworks like Three.js JavaScript 3D Library (Threejs).

The standard output from most LiDAR scanners is in the Compressed LiDAR Data Exchange Format (laz) format—a compressed version of the las format. It typically includes spatial coordinates (`x, y, z`), return intensity, classification codes, GPS time, and sometimes RGB and NIR values, depending on the sensor and processing. laz is efficient for storage but not always directly supported for manipulation in C++-based libraries. A reference for the format is provided by the ASPRS specification https://html.asprslas.org/en/latest/01$_{i}ntro.html$.

For smaller objects, the point cloud was acquired using an iPhone via Polycam. The output is in ply format, with minimal attributes, as shown below:

```
format binary_little_endian 1.0
comment Created by Polycam
element vertex 584320
property double x
property double y
```

```
property double z
property uchar red
property uchar green
property uchar blue
```

Although uncompressed, the Polycam file includes optimized noise reduction during capture, which is suitable for visualization and small-scale geometry. Compared to the scan acquired using the GeoSLAM Horizon RT, which performs better in large-scale environments, the iPhone scan produced cleaner results for small objects. The GeoSLAM scanner, while more accurate in open spaces, introduced closely connected dangling points in small objects, which negatively impacted segmentation and were not easily removed. (An example figure illustrating this difference may be added.)

For processing with the PCL library in C++, the point cloud must be in the `.pcd` format. Conversion workflows are therefore necessary:

- PDAL is used to convert `.laz` to `.ply`
- PCL utilities convert `.ply` to `.pcd`
- There is no direct converter from `.laz` to `.pcd`

Another technical limitation encountered was related to file formats. Input `.ply` files captured by Polycam store coordinates as `float64` (`double`) types, while PCL expects `float32` fields. Direct conversion to `.pcd` failed, with errors indicating missing fields. This issue was solved by preprocessing the files in Python using Open3D, converting `float64` coordinates to `float32` and preserving RGB attributes.

As a result, the final SPC is stored in **PLY!** (**PLY!**) format. This format is widely supported across APIs and tools, including Threejs for web-based visualization, and allows for inclusion of geometric and color data along with a custom integer `patch_id` field used for linking semantics.

During the implementation, several point cloud formats were handled based on technical requirements and library compatibility. No unified format could be maintained throughout, and conversions were necessary at different stages.

- **LAZ to PLY**: Possible using PDAL. Required because PCL does not directly support reading `.laz` files.
- **PLY to PCD**: Possible using PCL utilities. Required because all PCL segmentation algorithms require input point clouds in `.pcd` format.

- **LAZ to PCD**: Not directly possible. No existing tool provides a stable and simple conversion from `.laz` to `.pcd` in one step.
- **PCD to PLY**: Possible using PCL utilities. Used to export the segmented point clouds back into a more widely supported format after processing.

The choice of formats was not based on optimization but on forced compatibility:

- `.laz` files were necessary as input because PDAL provides robust tools for reading and manipulating LiDAR datasets.
- `.pcd` format had to be used for processing with PCL because the segmentation methods do not accept any other input format.
- `.ply` format was selected for final storage and visualization because it is compatible with web visualization frameworks such as Threejs and can embed custom attributes.

Additional format issues encountered during the conversion include:

- Type mismatch between `float64` coordinates in `.ply` files and `float32` expected by PCL.
- Color channel normalization required during conversion from `.laz` files to ensure valid RGB values.

Issues with Float Precision

PLY files exported from Polycam stored coordinates as `float64` (`double`) types, whereas PCL expects `float32`. Directly loading these PLY files into PCL failed with errors such as that it failed to find match for field 'x' 'y' 'z'.

This was solved by preprocessing the PLY files using Python and Open3D, manually casting coordinate fields from `float64` to `float32` while preserving the `r, g, b` color attributes.

Color Normalization Problems

During `.laz` to `.ply` conversion using PDAL, it was observed that some color fields (`Red, Green, Blue`) were stored in 16-bit integer format (0–65535). Since standard visualization and segmentation workflows expect 8-bit (0–255) RGB, color values needed to be scaled down by dividing by 256.

Without this manual normalization step, colors appeared oversaturated or incorrect during visualization or later processing.

Loss of Non-Geometric Attributes

While laz files often contained rich information, including intensity, classification, number of returns, etc. And during the process, only basic attributes (`x, y, z, r, g, b`) were preserved during the conversion to `.ply` and `.pcd` for segmentation. This was a deliberate decision to simplify the dataset and focus on geometry and visual attributes, at the cost of losing extra metadata.

Memory Limitations During Processing

Segmenting large clouds (more than 30 million points) using PCL often led to crashes or termination with memory allocation failures, even on a machine with 32 GB RAM.

To handle this, VoxelGrid downsampling was applied to reduce the point density. A compromise was made between voxel size and geometric detail retention: Too small voxel size (e.g., 0.01 m) caused no meaningful reduction in point number. While too large voxel size (e.g., 0.2 m) resulted in excessive loss of surface detail and poor segmentation results.

Final Format for Dissemination

While `.pcd` was used during intermediate processing steps with PCL, the final Smart Point Cloud was exported to `.ply` format. This format was chosen for several reasons: broader compatibility with web-based visualization frameworks like Threejs; the ability to easily add custom attributes such as `patch_id`; and its simplicity for archiving and sharing across different software platforms.

4.4. Semantic Mapping and Structuring

After the segmentation process, semantics were manually mapped to the segmented point clouds based on human inspection and external information gathering.

Patch-to-Semantics Assignment

Each segmented patch was assigned a semantic label manually. After RANSAC or manual segmentation, patches were visually inspected. Observed properties such as material, structure, and surface function were noted. A `patch_id` integer was maintained consistently across the point cloud. Semantic attributes were then recorded into a `.json` file, with `patch_id` as the linking key.

An example structure of the JSON file:

```
{
  "1": {
    "Material": "Concrete",
    "SurfaceFunction": "Wall",
    "Condition": "Good"
  },
  "2": {
    "Material": "Brick",
    "SurfaceFunction": "Decorative",
    "Condition": "Fair"
  }
}
```

This JSON structure provides a lightweight, extensible way to store patch-level semantics independently from the point cloud geometry.

Collection of Object-Level Semantics

For complete documentation, object-level metadata was gathered separately. Public heritage sources such as art guard Delft were consulted. Properties such as artist, year of construction, and historical context were extracted.

An example of object-level JSON:

```
{
  "ObjectName": "Herdenkingsmonument Kartuizerklooster",
  "Artist": "Henk Tieman",
  "Year": 1969,
  "Material": "Brick and Concrete",
  "HistoricalContext": "Commemoration of Kartuizer Monastery"
}
```

Structuring Semantics Based on the Information Model

The semantic attributes were organized according to the UML information model designed earlier. Object-level and patch-level semantics are stored separately but share a logical linkage through the point cloud. No modification was made to the `.ply` geometry file apart from embedding `patch_id`. Further semantic integration (e.g., linking dynamically to patches in visualization) is handled in the dissemination phase. Thus, the semantic information is decoupled from the point cloud, maintaining flexibility for different applications such as visualization, queries, or analytics.

4.5. Web-based Visualization Platform

To support interactive exploration and semantic dissemination of heritage point cloud datasets, a web-based visualization platform was developed using Three.js and standard web technologies. The front-end is composed of a single-page HTML application (index.html) with modular JavaScript (main.js) controlling scene logic, data loading, and user interaction. The viewer renders .ply point cloud files and overlays structured semantic metadata via an accompanying .json file. The overall setup supports both object-level and patch-level semantics.

The rendering pipeline initializes a Three.js Scene with a PerspectiveCamera, WebGLRenderer, and OrbitControls for intuitive navigation. A .ply file containing patch-level color and identifier information is loaded using PLYLoader. The pipeline extracts position and color attributes and associates each point with a semantic patch_id, which is parsed from the 9th column of the ASCII .ply file. Semantic metadata is loaded from a JSON file that contains both high-level attributes of the heritage object (e.g., name, location, material, artist, historical documents) and per-patch annotations (e.g., material type, structural role, decorative elements).

An info panel persistently displays object-level metadata, and A popup panel is dynamically shown when a user clicks on a patch, revealing detailed patch-level semantics. For each patch, the 3D centroid is computed by averaging the spatial coordinates of its constituent points. These centroids are later used to place highlighting markers during interaction.

Interactive functionalities are added using the `Raycaster` from Three.js. When a user clicks on the point cloud, the corresponding patch is identified through the `patch_id` array, and a floating panel appears showing detailed semantic information of that patch. The floating panel can be closed manually, and it automatically updates if a new patch is clicked.

Multiple UI buttons are provided to allow users to switch between different color views: original RGB, patch ID coloring, grouping by material, and grouping by structure. Switching views is implemented by updating the `color` attribute of the point cloud's geometry on the fly.

For deployment, the visualization setup can be bundled using `Vite` for local testing and preview. For wider dissemination, the files and viewer can be hosted on a server-based web application where the static files are served to clients over Hypertext Transfer Protocol (HTTP), supporting multi-user access. However, the local system vite has a conflict with the deployment platform, as it relies on three.js heavily, which is not usually operated on the server side. Tests were performed on Netlify webapp, as well as a directly GitHub deployment. Apart apart from the conflicting nature between jekyll, which GitHub relies on for deployment, the large point cloud size is also an obstacle for the file storage and sharing.

4.6. Integration and Propagation to Gaussian Splatting and IFC HBIM to SPC

3DGS generated from UVA images.
The initial 3DGS models were successfully generated using PostShot software directly from images captured by UAV-mounted cameras. This process largely utilized the default settings provided by the software, requiring minimal user intervention and parameter tuning. The default pipeline generated Gaussian splatting models, exporting them in PostShot's proprietary format (`.psht`) as well as **PLY!** files for further examination and visualization. The Gaussian Splatting models are shown in Figure 4.4. Although a sparse point cloud was visualized during processing, it could not be exported and thus was not usable. The exported `.ply` files contain attributes representing the Gaussian parameters used for rendering (e.g., position, covariance matrix, color, opacity).

Figure 4.4.: 3DGS of the case studies generated by Postshot.

In this study, the Gaussian splatting outputs generated by PostShot were stored in the widely used **PLY!** format. The resulting Gaussian splatting PLY files contained the following fields:

- `x, y, z`: Spatial coordinates of Gaussian centers.
- `nx, ny, nz`: Surface normals at Gaussian centers.
- `f_dc_0, f_dc_1, f_dc_2`: Color coefficients.
- `opacity`: Transparency values for each Gaussian.
- `scale_0, scale_1, scale_2`: Scaling factors of Gaussian ellipsoids.
- `rot_0, rot_1, rot_2, rot_3`: Quaternion rotation defining Gaussian orientations.

This structure allows detailed, oriented, and visually realistic rendering based on the camera viewpoint.

Semantic propagation - from SPC to 3DGS using coordinates from splat centers.
The implementation begins by preprocessing the GS file generated from Postshot. It is worth noting that the raw output often contains numerous small, scattered Gaussians—noise artifacts that are disproportionate to the scale of the heritage object. In Figure **??**, the splat centers are indicated by the sqaure in the zoomed out position, almost as the same size as the noise points. These artifacts are typically located far from the actual geometry and cannot be fully removed through manual cleaning within Postshot. Therefore, the GS `.ply` file was first rendered in a point cloud viewer—CloudCompare was used—to visually inspect and isolate the region of interest. A general bounding box was manually determined based on visual observation, then applied to crop the Gaussian data and retain only the relevant structure. Also worth noticing is that in this visualization, the color of the points does not represent anything meaningful. It is the result of rendering the Gaussian Splatting ply file as a point cloud, for which, the visualization platform took the 4th to 6th column, which usually records the RGB of the point cloud, but in this case, the color coefficients have a different scale for color.

Next, alignment was performed by identifying corresponding reference points between the SPC and the GS file. This follows the same logic as aligning ALS and MLS data in other heritage case studies such as the AULA. Once the coordinate systems were matched, a spatial query was conducted using `scipy`'s `cKDTree` to efficiently perform nearest-neighbor searches across millions of points.

Each Gaussian center was queried against the SPC to find its closest labeled point. The patch ID from the nearest SPC point was then propagated to the Gaussian center and stored as a new attribute column (as a `int`, to avoid compatibility issues with some `.ply` readers). The updated GS file was exported with the patch ID appended, while preserving all original GS attributes such as position, scale, rotation, and spherical harmonics.

To complete the pipeline, the updated GS file was segmented further. It was split into separate `.ply` files, each corresponding to a unique patch ID. Each of these segmented GS files retains the full set of Gaussian attributes, with filtering applied only on the semantic level. Although the bounding box and alignment steps involve some manual preprocessing, the semantic propagation and segmentation processes are fully automated.

Workflows tested for deriving corresponding SfM point cloud and Gaussian Splatting. For the practical implementation of 3DGS, two major workflows were tested. First, direct 3DGS generation from image datasets, and second, attempts to generate Gaussian splats from SfM sparse point clouds.

To explore the integration possibilities suggested by the initial plan, additional experiments aimed at generating 3DGS from reconstructed sparse point clouds and camera poses derived from SfM were carried out using two separate workflows:

1. **Colmap-based SfM and GSplat Python library:** Colmap was used to perform SfM on the provided image datasets. The process involved standard feature extraction, matching, and sparse reconstruction steps, using primarily default parameters in Colmap. The output from Colmap included camera intrinsics, extrinsics (camera poses), and sparse point clouds, all stored in binary (`.bin`) files.

   Subsequently, the open-source Python package GSplat (Ye et al., 2025), which claims efficient GPU-based Gaussian splatting reconstruction directly from Colmap SfM results, was tested. Setting up the package involved significant troubleshooting, with issues encountered including library dependencies, GPU compatibility problems, and unexpected errors during runtime.

   Initially, the GSplat library could not run successfully due to missing or invalid camera positions in the imported Colmap model. To address this, the GSplat source code was modified to introduce a fallback mechanism: when a camera pose was missing or invalid, the system would default to using the first available valid camera pose instead. This allowed the training process to continue past the initial blocking error.

   However, even after resolving this primary issue, two critical problems remained unsolved:

   - **Camera Intrinsics Handling:** The initial Colmap reconstruction was performed with the "Shared Intrinsics" option enabled, meaning all images shared identical intrinsic parameters. GSplat, however, expects unique intrinsic matrices per image. A second attempt was made by rerunning the Colmap reconstruction without the ”Shared Intrinsics” option. Despite this adjustment, Colmap automatically detected and enforced the shared intrinsics configuration due to inherent camera consistency in the dataset. Thus, the attempt to achieve per-image intrinsics failed, potentially causing systematic projection inaccuracies in GSplat training.

- **Scene Scale Problem:** GSplat requires both sparse point clouds and camera poses to be in a realistic metric scale. The Colmap model, however, produced outputs in an arbitrary scale. Without reliable scaling factors available from external references, the original arbitrary scale was retained during the training. This mismatch between expected and actual scene scale likely contributed to unstable training behavior and negatively impacted the resulting reconstruction quality.

Despite considerable efforts to correct input formats, camera pose settings, and scale issues, the GSplat reconstructions remained unsuccessful, producing corrupted or unusable outputs for the tested heritage objects.

2. **RealityCapture-based SfM to PostShot pipeline:** RealityCapture (by Epic Games) was tested as an alternative SfM tool, again using images from the UAV-based camera. Following the software's recommended procedure, the intrinsic parameters were set as shared for all images, leveraging the consistent camera characteristics. Other parameters remained at default settings. The outputs generated by RealityCapture included sparse point clouds and precise camera positions (extrinsics), all exported in binary format.

   Based on a method described in an external video tutorial[1], RealityCapture outputs were manually formatted and combined with original images in a single folder structure. According to this approach, PostShot should be able to ingest this structured data and produce Gaussian splatting models directly from the RealityCapture-generated sparse point clouds and camera poses. However, this workflow consistently resulted in corrupted or invalid Gaussian splats, which could not be toggled or visualized correctly within PostShot. The outputs appeared as scattered points rather than coherent Gaussian splatting representations.

In summary, although direct image-based Gaussian splatting generation via PostShot succeeded(see Figure 4.4), attempts to link Gaussian splatting to SfM-derived sparse point clouds using existing open-source and commercial workflows encountered critical technical challenges. These issues indicate significant current limitations in the practical pipeline from sparse SfM reconstructions to functional 3DGS models for heritage-scale datasets.

[1] http://youtube.com/watch?v=Nt5_RBx8dmo

During the setup and compilation of the SAGA framework, several critical technical obstacles were encountered:

- **Missing CUDA Runtime Library (`cudart64_118.dll`):** Although CUDA 11.8 was nominally installed, the essential runtime library `cudart64_118.dll` was missing. Attempts to reinstall the CUDA 11.8 toolkit produced only `cudart64_110.dll`, suggesting an incomplete or outdated installer.
- **MSVC and CUDA Compiler Version Conflict:** The installed Microsoft Visual Studio 2022 (MSVC 14.42) was too new for CUDA 11.8. The updated C++ Standard Library (STL) enforced strict version checks, causing compilation errors such as:

  ```
  error STL1002: Unexpected compiler version, expected CUDA 12.4 or newer.
  ```

- **Dynamic Linking Problems:** Even after manually compiling CUDA extensions (e.g., `simple-knn`), runtime errors persisted because Windows could not correctly locate `cudart64_118.dll`, leading to repeated `DLL load failed` and `ImportError` messages.
- **Package Compatibility:** Libraries such as PyTorch3D and Open3D-ML were tightly coupled to PyTorch 2.0 and CUDA 11.8. Upgrading to CUDA 12.4 was impractical without breaking compatibility with the segmentation pipeline.

The core issue stemmed from an incompatibility between the newer Microsoft Visual Studio compiler (MSVC 14.42) and the older CUDA 11.8 toolkit required by SAGA. This mismatch simultaneously caused missing CUDA runtime libraries and prevented successful compilation of native CUDA extensions, unless major downgrades or manual patching were performed.

Due to these critical compatibility issues and time limitations, the SAGA workflow could not be fully implemented in this project.

5. Result and Discussion

This chapter shows the results in three parts and includes the discussion for the contributions and limitations of the research. The first part of the result shows the structured semantics of the case studies. Then, the web-based viewer shows how the semantics and the patch are linked and viewed. Last but not least, the Gaussian Splatting segmentation result based on the semantic patches from SPC.

5.1. Point Cloud and Semantic Structure

The result for structuring semantics in SPC can be divided into two parts: the point cloud itself and the structured semantics. The two parts are mapped by the foreign key of the semantic `patch_id`.

As described in the information model UML (see Figure 3.1), the point cloud can contain the minimum of the following attributes: `xyz`, `RGB`. In the case studies, the attributes used include `xyz`, `rgb`, `nx`, `ny`, `nz`, and `patch_id`. Below is an excerpt from the PLY file of the HK case study:

```
format ascii 1.0
element vertex 584320
property float x
property float y
property float z
property uchar red
property uchar green
property uchar blue
property float nx
property float ny
property float nz
property int patch_id
end_header
-0.1443 -0.2129 0.6120 85 86 78 0.9787 -0.1426 -0.1476 0
```

```
-0.1444 -0.2147 0.6144 99 100 92 0.9922 -0.08316 -0.09227 0
...
```

Normals are included as they are required by `PLYLoader.js`. The `patch_id` serves as a foreign key to map each point to the semantics. We can also observe that the coordinates are local in the HK dataset, as the data originates from a single laser scanner. In contrast, the Aula dataset is georeferenced to `EPSG:7415` (RD New + NAP).

One benefit of this design is its structural simplicity. To avoid redundancy, only one semantic attribute, `patch_id`, is stored in the point cloud. The entire point cloud is also linked to object-level semantics, avoiding the need to embed rich semantic metadata directly into the geometry file.

This single-layer structure for the case studies in this thesis is case-adapted, but can be also generalized to multiple layers as stated in the original design by Poux (2019). In this design, if all properties are identical for a group of points, and the points are geometrically proximate, they form a semantic patch. For example, symmetrical structures—like two opposite walls that share semantic meaning but are not adjacent—are considered two separate patches.

Semantics are stored in JSON and linked back to the `patch_id` in the point cloud. The structure of the JSON follows the ontology defined in the UML (see Figure 3.1). The first layer includes object-level information: object ID, name, location; cultural and artistic details (if they apply to the entire object); historical data such as architectural style and documents; and restoration and conservation records. Each patch in the JSON includes structural and material information (mainly `componentType` and `materialType` in the case studies). The full semantics JSON file can be found with this link: https://github.com/Zhuoyuee/spc_viewer/blob/main/spc_viewer/public/HK_full_description.json.

Listing 5.1: High-level structure of the semantic JSON file

```
{
  "heritageObject": {
    "objectID": "...",
    "name": "...",
    "location": {...},
    "culturalAndArtist": {...},
    "historical": {...},
    "restorationAndConservation": {...}
  },
  "patches": {
    "1": {
```

```
      "structure": {...},
      "material": {...},
      "culturalAndArtist": {...}
    },
    "2": {
      "structure": {...},
      "material": {...}
    },
    ...
  }
}
```

The HK case is small in scale, modern, and has a clear structure. It has not undergone restoration or major transformations and is not a building, so its semantic structure is simpler and does not include all ontology-defined categories. Historical and cultural/artist information is only represented at the object level. In contrast, the Aula case is on a much larger scale and includes conservation initiatives, although they have not yet been formally published (de Jonge et al., 2023):

Listing 5.2: Example JSON structure of Restoration and Conservation Information

```
"restorationAndConservation": {
  "restorationTechnique": "Restoration research led by TU Delft's
  Campus & Real Estate and Heritage & Architecture department.",
  "monitoringData": "Funded by the Getty Foundation under the
  Keeping It Modern initiative.",
  "conservationHistory": "Restoration supported by the Getty
  Foundation's Keeping It Modern initiative recognizing post-war
  campus architecture.",
  "legalStatus": "national conservation measure",
  "structuralStability": "Focus on long-term usability, material
  conservation, and stewardship for post-war campuses."
}
```

A sculpture by Carel Visser also demonstrates layered semantics. There are two valid interpretations: cultural and artist-type information can either be attached to the object level or stored per patch, as shown below:

Listing 5.3: Example of Patch-level semantic example for Carel Visser sculpture

```
"43": {
  "material": {
    "materialType": "concrete"
```

```
  },
  "structure": {
    "componentType": "sculpture",
    "buildingHierarchy": "independent",
    "mechanicalProperties": "cast-in-place",
    "constructionTechniques": "precast concrete blocks"
  },
  "culturalAndArtist": {
    "decorativeElements": "abstract concrete sculpture",
    "artistName": "Carel Visser",
    "symbolism": "embodiment of brutalist aesthetics and integration
    of art and architecture"
  }
}
```


The full semantics JSON file can be found with this link: https://github.com/Zhuoyuee/spc_viewer/blob/main/spc_viewer/public/aula_patchid_semantics.json

5.2. Web-Based Viewer

The developed viewer is built using **Three.js** for real-time 3D rendering and orbit controls, and uses the `PLYLoader` module to parse `.ply` point cloud files. It loads both the point cloud and its semantic metadata, the latter provided as a structured JSON file as described in earlier. The viewer parses the patch ID stored per point and links each patch to its corresponding semantic information. This enables interactive inspection of both geometric and semantic properties. The code for the web-based SPC viewer can be found here: https://github.com/Zhuoyuee/spc_viewer

As shown in 5.1 and 5.2, the object-level semantics (e.g., name, location, historical background) are presented in a dedicated panel on the right-hand side. This panel also includes clickable hyperlinks to external historical documents. On the top left, users can switch between datasets (e.g., HK and Aula), and the viewer automatically updates both the 3D content and associated object metadata.

The viewer includes several key features that enable **semantic exploration**:

1. **Interactive Patch Semantics**
   Users can interactively click on individual patches within the point cloud. When a patch is selected, its centroid is marked with a red sphere (see HK dataset example in 5.1), and its semantic attributes —such as material, structure, and decorative

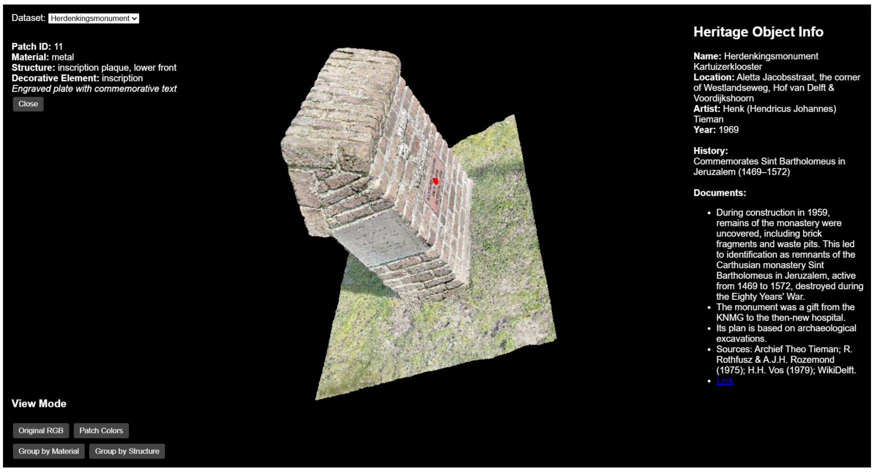


Figure 5.1.: Full view of SPC of HK rendered on the web-based viewer.

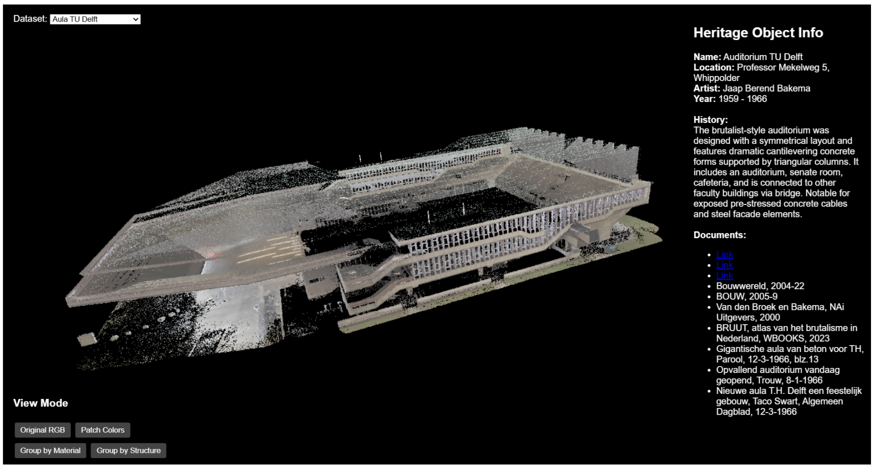


Figure 5.2.: Full view of SPC of AULA rendered on the web-based viewer.

elements—are displayed in a panel at the top left corner. Clicking on a new patch updates this panel accordingly. A close button allows the user to dismiss the panel if desired.

2. Toggle Between Visual Modes
   The viewer supports toggling between three visual modes using buttons located at the **bottom left corner**:

   - **Real RGB values** from the point cloud, shown by default.
   - **Patch ID coloring**, where each patch is assigned a unique color.
   - **Semantic groupings** based on shared material or structural type.

As shown in 5.45.3, this allows users to easily identify non-contiguous patches that belong to the same semantic group. For example, in the Aula dataset, all patches with the structural type *"curtain wall"* are rendered in the same color. In contrast, in the HK dataset, each patch has a unique structural role, so patch and structure groupings yield visually identical results.

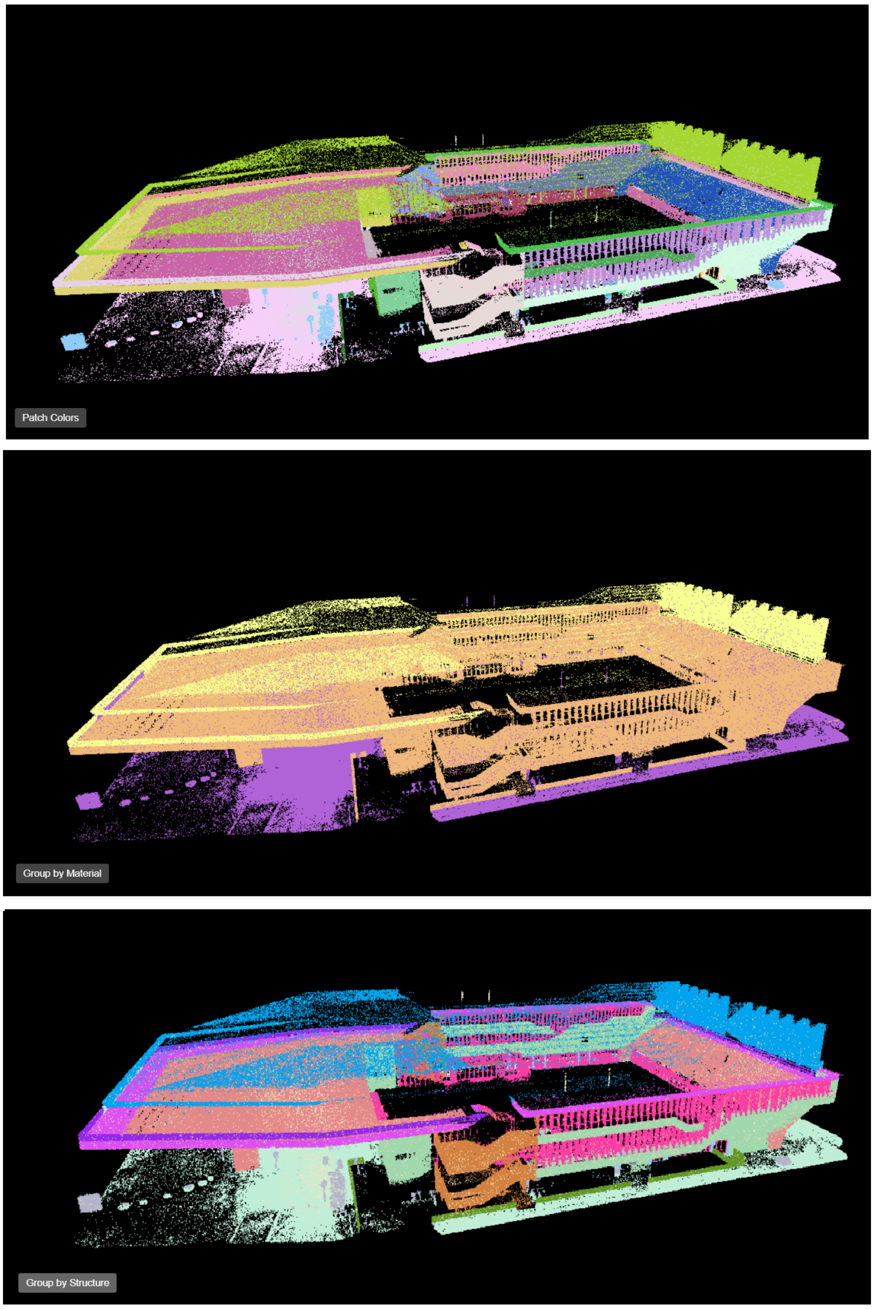


Figure 5.3.: Color by semantic patch, color by material, and color by structure type on the SPC of AULA.

This implementation provides a lightweight and web-based method for inspecting complex heritage point cloud data without requiring specialized software. The viewer can handle multiple datasets with different coordinate systems and metadata structures, provided that

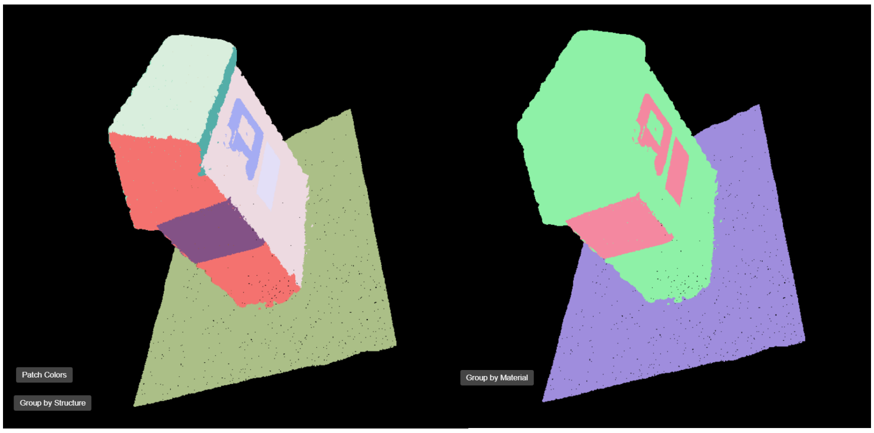


Figure 5.4.: Color by semantic patch and color by material on the SPC of HK rendered on the web-based viewer.

they conform to the JSON schema.

The patch-centric interaction model bridges the gap between raw 3D data and human-readable semantics, which is particularly relevant in the heritage domain where interpretation is key. In future iterations, features like search/filter by semantic attributes, grouped patch highlighting, or camera bookmarks could further enhance usability.

Finally, the design choices—such as using color to represent ontology groups—enable visual comparison of conceptual elements, rather than just geometric proximity, which is particularly useful for reasoning about building functions, restoration planning, or stylistic analysis.

5.3. Semantic Propagation and Gaussian Splatting Segmentation

Though generated from different workflows—and still limited by the unavailability of the corresponding sparse point cloud used to generate the 3DGS—the Gaussian Splatting centers retain sufficient geometric fidelity to be aligned with the SPC. By using a nearest-neighbor method to semantically propagate the patch ID information from the SPC to the 3DGS, the Gaussian Splatting can be segmented, and each part can be linked to semantic information.

Figure 5.5 and Figure 5.6 show the details of the segmentation of two surfaces of the monument HK, based on the patch IDs from the SPC. In general, the patches correspond well with the SPC, and the surface boundaries are clear—thanks to the high density of Gaussian centers (over 100,000, compared to 40,000 in the point cloud). In Figure 5.5, some blurry areas can still be seen; however, these do not appear to lie on the surface itself but rather reflect Gaussians that captured internal structures. These blurry parts do not affect the main message of each segmentation and can be manually removed if needed. In the same figure, the segment of the plate at the bottom left shows slight misalignment, revealing some brick textures instead of a clean cut along the plate's edge. This is due to the semi-automatic segmentation—therefore, the quality of the segmented GS also depends on the accuracy of the alignment process.

Figure 5.6 shows the other surface, which has a better visual result, possibly due to its simpler and straighter structure. However, this figure also highlights a limitation of the GS data: due to a lack of lighting (this part was in shadow), the system failed to capture the text on the plate.

Figure 5.5.: Color by semantic patch, color by material, and color by structure type on the SPC of AULA.

Figure 5.6.: Color by semantic patch and color by material on the SPC of HK rendered on the web-based viewer.

5.4. Discussion

This thesis contributes a structured and reproducible approach to modeling and visualizing Smart Point Clouds enriched with HBIM ontology-defined semantics.

First of all, instead of remodeling the geometry into IFC-based structures, this work treats SPC themselves as a valid geometry representation of HBIM, with no geometry remodel while attaching semantics through `patch_id` identifiers. The process of reconstructing IFC-standard parametric geometry introduces considerable modeling effort and can result in the abstraction of geometric detail. In contrast, this approach retains the point cloud as the primary representation, allowing each geometric subset to be annotated directly. This fulfills key HBIM objectives—structured, queryable, interpretable data — while avoiding typical bottlenecks related to parametric modeling, especially for complex or non-standard heritage geometries.

The semantic structure applied is grounded in HBIM literature and built from a generalized ontology. It follows a layered model distinguishing between object-level and patch-level attributes, supporting both holistic and component-specific interpretation. Object-level metadata (e.g. artist, historical function, conservation records) reflects global information applicable to the entire heritage object, while patch-level attributes (e.g. structural role, material type) are assigned to local geometric clusters derived from segmentation. This layered strategy ensures flexibility in representing both macro and micro-level characteristics.

Design choices emphasize modularity and scalability. Semantic data is stored externally in a structured JSON format, allowing annotations to be edited, expanded, or versioned without altering the point cloud. The PLY format used for geometry is compatible with common tools and preserves patch identifiers, while the semantic files can be parsed in Python, JavaScript, or database environments. This separation supports generalizability and integration into heritage infrastructures or linked data systems.

The final output — consisting of a structured point cloud and a semantic JSON file - are open-format, lightweight, and well-structured. These outputs are suitable not only for visualization but also for archival, educational, or documentation purposes. The modular pipeline is extensible and can accommodate additional semantic layers or link to institutional heritage databases and digital twin platforms. The current viewer architecture is prepared for integration of features such as time filtering or multi-user annotation tools.

This thesis also proposes a full workflow for creating Smart Point Clouds of heritage objects—from data collection to semantic annotation and dissemination. The workflow is designed for general applicability and does not rely on highly specialized equipment like UAV-mounted laser scanners. It supports data integration from heterogeneous sources, such as the varying density and RGB quality found in AHN and MLS, and handles incomplete geometries (e.g. hollow sections between roofs and floors) by maintaining flexibility in data use. The non-perfect data was also reflected on the lighting and shadow during collection, rgb region growth - RGB might be one of the closes raw attribute to reflect on material segmentation, due to lighting difference still cannot automatic segment. It reflects on the problems we might encounter with self-collected data when reproduce the workflow. Two full-scale case studies were completed to demonstrate the generality and adaptability of the workflow. The first, the Herdenkingsmonument Kartuizerklooster, is a small-scale, modern monument with clear structural logic and no known conservation record. The second, the Aula TU Delft, is a large, historically significant structure featuring multiple volumetric elements, attached artworks, and embedded restoration narratives. Together, these cases reflect a wide range of object types and semantic richness, showing that the proposed SPC framework can be reused in different locations with comparable scanning setups and disseminated in a uniform manner on the web.

Although the final implementation focused on SPC-based workflows, the initial design of the project envisioned a broader integration between Smart Point Clouds, IFC HBIM models, and Gaussian Splatting. A dedicated UML-based information model was developed to support this integration, enabling semantic propagation across multiple 3D representations of the same heritage object. The intention was to allow enriched patch-level semantics to be reused not only in SPC visualizations but also within parametric BIM environments and high-fidelity 3DGS renderings. While practical limitations such as scale mismatch, camera pose inconsistencies, and software compatibility prevented full realization of this pipeline, the conceptual groundwork has been laid. The model remains extensible and technically feasible with future tools, offering a scalable and cross-platform semantic framework for heritage documentation.

Semantic propagation from SPC to 3DGS allows researchers to use mature methods to segment the point cloud and link semantics. Then, with simple alignment, the corresponding GS can also be segmented according to the SPC. There is no need to directly apply segmentation methods to the GS itself. The separated parts of GS remain valid GS files and can be rendered normally without requiring plugins. Just like the semantic structure of the SPC, the semantics are linked externally with no attributes stored in the file. In this way, Gaussian Splatting retains its photorealistic nature without sacrificing its advanced visual achievements. This approach shows great potential for future implementation—by doing all processing in point clouds and then propagating and linking the results to the GS, we move toward achieving Smart Gaussian Splatting.

Finally, the work contributes to broader efforts in heritage dissemination and open access to 3D data. The current web platform supports interaction with structured semantic content, and has the potential to be integrated into DOCOMOMO's 3D dissemination infrastructure.

This demonstrates the applicability of Smart Point Cloud methodologies beyond technical environments and supports long-term digital accessibility of cultural heritage.

5.5. Limitations

Internal structure and visible modeling scope.
SPC as implemented in this study only model the geometry and semantics of what is visible in the collected data. The current focus was on outdoor surfaces, and no internal scans were included. Within each patch, only the surface geometry is represented, not internal substructures such as the core of walls or embedded reinforcements. For example, in HK, only bricks are visible in the point cloud, although historical records indicate an inner concrete core. Similarly, in the Aula TU Delft, columns appear as concrete externally but contain tensioned steel cables internally, which are not captured or modeled. As a result, SPC cannot yet fulfill the expectations of architectural models in representing full internal compositions or structural functions. From the perspective of HBIM definition, this limits its linkage to structural or mechanical analysis components expected in traditional HBIM systems.

Ontology scope and adaptability.
The HBIM ontology used for semantic enrichment in this thesis was developed from a literature-based review. However, the ontology reflects what past studies considered important or feasible to model, and is sometimes shaped by the specific needs or data of individual cases. Therefore, it remains a dynamic and evolving definition. As heritage documentation expands in scope and technology, new characteristics or semantic layers may become relevant, requiring updates to the structure and definition of the ontology used in SPC.

Another important point is that even under the same attribute, like the structure segmentation, there might be different opinions from experts who might agree on different patch divisions. The information model, for now, cannot address the diverse opinions on the patches, which might be a common discussion in real life.

Segmentation limitations and scalability.
Although this thesis does not focus on segmentation algorithms, it is important to acknowledge that semantic segmentation is a necessary step in any SPC pipeline and presents nontrivial limitations. The segmentation methods required to divide point clouds based on HBIM ontology (e.g., by structure or material) are often case-specific and not easily generalizable. Rule-based or supervised learning methods require labeled data or case-specific rules and thus lack scalability. Moreover, geometric features alone do not always correspond to semantic distinctions: the same material or function may appear under different shapes,

and vice versa. Deep learning methods can be computationally expensive and system-dependent, and most do not address layered semantics. The aim of associating segmentation results with multiple semantic layers—function, structure, material—is rarely addressed in existing methods.

From the practical level, the attempted integration of Open3D-ML to support deep learning-based semantic segmentation did not succeed due to unresolved build errors and the absence of PyTorch support. Despite multiple attempts using CMake, Visual Studio, and adjusted dependencies, the library could not be compiled successfully. As a result, no deep learning segmentation model (e.g., RandLA-Net, PointNet) could be integrated into the current SPC workflow.

Limitations in case studies.
Both case studies focused on relatively modern heritage objects with largely planar structures. However, limitations in the point cloud quality affected segmentation granularity and semantic annotation. In Aula, data collection was incomplete in certain areas due to obstructions or inaccessible zones, such as beneath overhangs. Because of this incompleteness and lack of details, hierarchical patch grouping was not applied, although it may become necessary for more complex or multi-level heritage models. Additionally, while the implemented semantic structure included key HBIM categories, not all dimensions—such as mechanical analysis or multispectral condition data—could be covered due to the simplicity or incompleteness of the available data.

Integration with HBIM and 3DGS models.
One of the original goals of this study was to demonstrate the integration of SPC with IFC-based HBIM and 3DGS. This would have enabled semantic propagation across different 3D representations without repeating the segmentation process. Though this step was done successfully, the web-based visualization and semantic interactive ability were not finished. Furthermore, IFC-based HBIM models follow different geometric standards—such as allowing self-intersecting or non-watertight volumes—that are incompatible with requirements in Geomatics and cannot be directly converted to valid solids suitable for alignment with SPC. As a result, the extraction of semantic geometry failed, and no usable geometric alignment could be performed.

For both case studies, 3DGS models were generated using images only from Postshot, unable to export the sparse point clouds from the same reference system. Multiple workflows promising to generate 3DGS from sparse point clouds, camera positions, and images failed by producing corrupted or incomplete outputs. Therefore, the originally proposed path from structured point cloud to 3DGS-based visualization could not be realized. While current implementations remain limited, semantic enrichment of 3DGS remains a promising future direction, especially for immersive heritage visualization and interaction.

In the tested example of HK, the boundary on the surface is clear, but there also Gaussians from some inward positions has some blurry retaining parts, but it does not affect the visualization of the clarity of the texts on the surface. Due to the unavailability of the matching SfM point cloud, geometries from Gaussian Splatting centers are used to semi-automatically align with existing SPC. The visualization and dissemination of segmented gaussian splatting is not there yet, and the semantics linked to each part cannot be viewed like the platform for SPC yet. Due to the limitations in open-source web-based gaussian splatting applications. Nevertheless, it still possesses great potential.

6. Conclusion

This thesis set out to develop a structured and generalizable approach for enriching point cloud representations of heritage objects with semantics derived from HBIM literature. Instead of translating captured geometries into parametric IFC models — which often involves extensive manual work and abstraction — this research treats SPC as valid and complete HBIM geometric representations in themselves. The proposed method enables semantic enrichment directly on segmented point clouds, structured by `patch_id`, to preserve the geometric authenticity of the original scans while supporting HBIM - like interpretability and lifecycle tracking.

A core contribution lies in the definition and implementation of a layered semantic model, grounded in an extensive literature review on HBIM definitions and attribute categories. This model distinguishes between object-level and patch-level semantics and is designed for scalability and reusability. Semantic data is stored externally in structured JSON files and mapped to point cloud segments, allowing patch-based interpretation without embedding metadata in proprietary formats. The semantic structure includes HBIM-relevant attributes such as construction technique, material type, symbolic meaning, and restoration history, and was implemented across two real-world case studies of varying complexity and scale.

To support the interaction and dissemination of these semantic point clouds, a lightweight web-based viewer was developed using Three.js. The viewer enables users to explore the dataset by toggling between RGB and semantic color modes, grouping patches by shared attributes, and viewing detailed semantics for each patch. These functionalities demonstrate that SPCs can serve as a foundation for semantically interpretable, easily shareable, and accessible documentation tools for cultural heritage.

The entire SPC workflow—from data collection and segmentation to semantic annotation and web-based visualization — was implemented for two case studies: the Herdenkingsmonument Kartuizerklooster and the Aula TU Delft. The former demonstrates applicability to small-scale, modern heritage objects with simpler semantics, while the latter addresses a larger, more complex architectural structure with restoration history and embedded artistic elements. Both cases validate that the pipeline can be adapted to different heritage contexts without requiring highly specialized equipment or formats.

While IFC-based HBIM models remain dominant in architectural documentation, the SPC approach presented here offers a lightweight alternative point-based geometry that maintains a link to HBIM ontologies without reproducing their full parametric complexity usually from survey data. The results demonstrate that such an approach can facilitate not only visualization but also structured knowledge organization and dissemination of heritage data. With further development, SPCs enriched with HBIM semantics can integrate more tightly with institutional databases, participatory annotation platforms, and advanced rendering methods such as Gaussian Splatting.

6.1. Research Questions and Answers

The following section reflects on the four research sub-questions that guided this thesis. Each question corresponds to a major component of the proposed workflow and collectively contributes to answering the main research question: **How can HBIM ontology be integrated into smart point clouds with semantic enhancement to improve the visualization and conservation of heritage objects?**

1. **What are the defining characteristics of HBIM, and which additional characteristics are critical for heritage conservation?**
   A structured literature review identified five main semantic categories relevant to HBIM: structural, material, historical, cultural/artistic, and conservation-related information. These were distilled into a formal ontology tailored for heritage documentation. While the ontology reflects a synthesis of prior definitions, it also highlights the need for evolving standards and integration of non-visible characteristics like internal structure and chronological changes.

2. **What does an effective HBIM information model look like, and how can it incorporate essential heritage attributes?**
   Based on the ontology, a UML-based information model was developed to link semantics to smart point clouds at both object and patch levels. The model supports structured, extensible representation of HBIM attributes without converting to IFC-based geometry, thereby enabling lightweight and interoperable documentation. The use of patch IDs allows direct mapping between semantic units and spatial subsets of the point cloud.

3. **How can point clouds be segmented and semantically enriched with HBIM attributes?**
   The thesis did not propose new segmentation algorithms but emphasized the critical role of segmentation in any SPC workflow. Mainly geometry-based methods were

used to divide the case studies into patches, combined with minimal manual refinement. These patches were then semantically labeled using the defined ontology. Limitations related to segmentation scalability, accuracy, and modeling of internal components were discussed, especially regarding their impact on semantic completeness. The use of existing methods was positioned as a practical step forward, and their outputs could serve as training data for future machine learning-based segmentation tailored to HBIM semantics.

4. **What strategies can support web-based interactive visualizations of semantically enriched smart point clouds?**
   A browser-based viewer was developed using Three.js to support public access and interaction with semantically enriched SPCs. The viewer enables toggling between RGB and semantic views, querying metadata by patch, and visualizing structure or material groups. It demonstrates that SPCs can serve as both documentation and dissemination tools, bridging the gap between raw point clouds and semantic understanding.

Together, these answers demonstrate that it is feasible to semantically enrich smart point clouds using HBIM-derived ontology and an independent information model, and to visualize them interactively on the web. While limitations remain—especially in segmentation automation and the modeling of internal or temporal properties—the research presents a generalizable and scalable workflow that contributes to the semantic structuring, visualization, and dissemination of heritage data beyond the constraints of traditional HBIM platforms.

6.2. Future Directions

Semantic gaps: internal structure and temporal data. Some heritage attributes defined in HBIM literature—such as chronological changes, internal construction details, or monitoring data—cannot be directly linked to geometric patches in SPC. For example, a column may visibly appear as concrete in the point cloud but may contain hidden steel tension cables that are not captured geometrically. Similarly, temporal changes like restorations or degradation over time cannot be expressed in the current static point cloud representation. Future work could explore complementary layers (e.g., time-tagged annotations, mesh overlays, or cross-referenced CAD models) to extend SPC toward temporally-aware or structurally-augmented representations.

Linking semantics to standards and external ontologies. The current semantic structure, while grounded in HBIM literature, remains an internal schema and is not formally aligned with institutional vocabularies such as CIDOC CRM, ifcOWL, or other linked data standards. This limits semantic interoperability across platforms and datasets. A promising direction is to formalize key classes and properties in RDF and establish URI-based links to authoritative vocabularies. This would allow SPC-based models to become part of broader semantic web infrastructures and facilitate integration with digital heritage archives, cultural databases, and museum systems.

Towards automated, ontology-driven segmentation. Semantic segmentation remains one of the most critical bottlenecks for scalable SPC workflows. Future work should develop or adapt machine learning techniques that can segment point clouds based on HBIM-derived ontologies, ideally distinguishing layers such as material, structure, or function. The case studies produced in this thesis already provide labeled segmentation data, which can serve as the foundation for training supervised models. Beyond model development, integration of active learning or human-in-the-loop correction could enhance reliability while maintaining adaptability to diverse heritage geometries.

Integration with institutional databases and participatory tools. Dissemination can be strengthened by enabling SPC metadata to interoperate with institutional or public databases such as DOCOMOMO, UNESCO heritage registers, or local archives. Metadata fields such as object name, construction year, location, and architect could be linked automatically, enriching both datasets. In parallel, the web-based viewer can evolve into a participatory platform by allowing users to comment, validate, or flag uncertainties in the semantic content. This would support collaborative knowledge building and crowd-sourced validation for heritage documentation.

Extending workflows to semantic 3D Gaussian Splatting. Although the current attempt to integrate Gaussian Splatting was only partially successful due to technical limitations, the approach remains promising for real-time heritage visualization. Future implementations could revisit preprocessing steps such as dense mesh generation or normal estimation to support better alignment between point cloud patches and Gaussian centers. Semantic labels could be propagated using nearest-neighbor clustering or learned association methods. This would allow 3DGS to carry semantic attributes, opening up possibilities for immersive and meaning-aware exploration of cultural heritage scenes.

In summary, this thesis contributes an interoperable and extensible framework for Smart Point Cloud representation of heritage objects, capable of supporting HBIM-informed semantics and accessible through web-based visualization. It offers a practical and conceptual bridge between geometric fidelity, semantic modeling, and public dissemination—meeting the needs of heritage documentation beyond traditional parametric constraints.

Bibliography

Adami, A., Fregonese, L., Rosignoli, O., Scala, B., Taffurelli, L., & Treccani, D. (2019). GEOMETRIC SURVEY DATA AND HISTORICAL SOURCES INTERPRETATION FOR HBIM PROCESS: THE CASE OF MANTUA CATHEDRAL FAÇADE. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2/W11*, 29–35. https://doi.org/10.5194/isprs-archives-XLII-2-W11-29-2019

Aksin, M., & Karaş, İ. R. (2021). A REVIEW OF THE DISTINGUISHING FEATURES OF THE HISTORICAL BUILDINGS IN SAFRANBOLU REGION FOR THE PURPOSE OF CLASSIFICATION FOR SEMANTICALLY ENHANCED 3D BUILDING MODEL. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLVI-4/W5-2021*, 39–42. https://doi.org/10.5194/isprs-archives-XLVI-4-W5-2021-39-2021

Ariza-Lopez, F., Reinoso-Gordo, J., Garcia-Balboa, J., & Ariza-Lopez, I. (2022). Quality specification and control of a point cloud from a TLS survey using ISO 19157 standard. *AUTOMATION IN CONSTRUCTION*, *140*. https://doi.org/10.1016/j.autcon.2022.104353

Art Guard - Delft. (n.d.).

Baarimah, A. O., Alaloul, W. S., Liew, M. S., Kartika, W., Al-Sharafi, M. A., Musarat, M. A., Alawag, A. M., & Qureshi, A. H. (2021). A Bibliometric Analysis and Review of Building Information Modelling for Post-Disaster Reconstruction [Number: 1]. *Sustainability*, *14*(1), 393. https://doi.org/10.3390/su14010393

Baarimah, A. O., Idrissi Gartoumi, K., Alaloul, W. S., Liew, M. S., Alawag, A. M., & Bahamid, R. A. (2023). Applications of Heritage Building Information Modeling (HBIM): A Bibliometric Review and Future Trends. *2023 International Conference on Sustaining Heritage: Innovative and Digital Approaches (ICSH)*, 104–111. https://doi.org/10.1109/ICSH57060.2023.10482844

Bagnolo, V., Argiolas, R., & Cuccu, A. (2019a). HBIM FOR ARCHAEOLOGICAL SITES: FROM SFM BASED SURVEY TO ALGORITHMIC MODELING. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2/W9*, 57–63. https://doi.org/10.5194/isprs-archives-XLII-2-W9-57-2019

Bagnolo, V., Argiolas, R., & Cuccu, A. (2019b). DIGITAL SURVEY AND ALGORITHMIC MODELING IN HBIM. TOWARDS A LIBRARY OF COMPLEX CONSTRUCTION ELEMENTS. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-4/W12*, 25–31. https://doi.org/10.5194/isprs-archives-XLII-4-W12-25-2019

Balloni, E., Ceka, D., Pierdicca, R., Paolanti, M., Mancini, A., & Zingaretti, P. (2024). Comparative assessment of Neural Rendering methods for the 3D reconstruction of complex heritage sites in the inner areas of the Marche region - Italy. *Digital Applications in Archaeology and Cultural Heritage*, *35*, e00371. https://doi.org/10.1016/j.daach.2024.e00371

Banfi, F., Bolognesi, C. M., Bonini, J. A., & Mandelli, A. (2021). THE VIRTUAL HISTORICAL RECONSTRUCTION OF THE CERCHIA DEI NAVIGLI OF MILAN: FROM HISTORICAL ARCHIVES, 3D SURVEY AND HBIM TO THE VIRTUAL VISUAL STORYTELLING. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLVI-M-1-2021*, 39–46. https://doi.org/10.5194/isprs-archives-XLVI-M-1-2021-39-2021

Banfi, F., Brumana, R., & Stanga, C. (2019). A CONTENT-BASED IMMERSIVE EXPERIENCE OF BASILICA OF SANT'AMBROGIO IN MILAN: FROM 3D SURVEY TO VIRTUAL REALITY. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2/W11*, 159–166. https://doi.org/10.5194/isprs-archives-XLII-2-W11-159-2019

Barrile, V., Fotia, A., Candela, G., & Bernardo, E. (2019). INTEGRATION OF 3D MODEL FROM UAV SURVEY IN BIM ENVIRONMENT. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2/W11*, 195–199. https://doi.org/10.5194/isprs-archives-XLII-2-W11-195-2019

Bartolomei, C., Ippolito, A., & Vizioli, S. H. T. (Eds.). (2022). *Digital Modernism Heritage Lexicon*. Springer International Publishing. https://doi.org/10.1007/978-3-030-76239-1

Bastem, S., & Cekmis, A. (2022). Development of historic building information modelling: A systematic literature review [Number: 5]. *BUILDING RESEARCH AND INFORMATION*, *50*(5), 527–558. https://doi.org/10.1080/09613218.2021.1983754

Biagini, C., Capone, P., Donato, V., & Facchini, N. (2016). Towards the BIM implementation for historical building restoration sites. *Automation in Construction*, *71*, 74–86. https://doi.org/10.1016/j.autcon.2016.03.003

Bianconi, F., Filippucci, M., Amoruso, G., & Bertinelli, M. (2019). FROM THE INTEGRATED SURVEY OF HISTORIC SETTLEMENTS TO THE PATTERN BOOK WITHIN THE BIM. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2/W9*, 135–142. https://doi.org/10.5194/isprs-archives-XLII-2-W9-135-2019

Biljecki, F., Ledoux, H., & Stoter, J. (2016). An improved LOD specification for 3D building models. *Computers, Environment and Urban Systems*, *59*, 25–37. https://doi.org/10.1016/j.compenvurbsys.2016.04.005

Bolognesi, C., & Garagnani, S. (2018). FROM A POINT CLOUD SURVEY TO A MASS 3D MODELLING: RENAISSANCE HBIM IN POGGIO A CAIANO. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2*, 117–123. https://doi.org/10.5194/isprs-archives-XLII-2-117-2018

Bolognesi, C., & Villa, D. (Eds.). (2021). *From Building Information Modelling to Mixed Reality*. Springer International Publishing. https://doi.org/10.1007/978-3-030-49278-6

Borkowski, A., & Kubrat, A. (2024). Integration of Laser Scanning, Digital Photogrammetry and BIM Technology: A Review and Case Studies [Number: 4]. *ENG*, *5*(4), 2395–2409. https://doi.org/10.3390/eng5040125

Bródka, J., & Walek, M. (2022). DIGITAL SURVEY OF THE LATE 1960'S VILLA IN USTRON: CREATING A VIRTUAL MODEL OF A HERITAGE SITE OF POLISH POST-WAR MODERNIST ARCHITECTURE [Number: 3]. *ARCHITECTURE CIVIL ENGINEERING ENVIRONMENT*, *15*(3), 13–22. https://doi.org/10.2478/acee-2022-0027

Brumana, R., Banfi, F., Cantini, L., Previtali, M., & Della Torre, S. (2019). HBIM LEVEL OF DETAIL-GEOMETRY-ACCURACY AND SURVEY ANALYSIS FOR ARCHITECTURAL PRESERVATION. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2/W11*, 293–299. https://doi.org/10.5194/isprs-archives-XLII-2-W11-293-2019

Brumana, R., Della Torre, S., Previtali, M., Barazzetti, L., Cantini, L., Oreni, D., & Banfi, F. (2018). Generative HBIM modelling to embody complexity (LOD, LOG, LOA, LOI): Surveying, preservation, site interventionthe Basilica diCollemaggio (L'Aquila) [Number: 4]. *APPLIED GEOMATICS*, *10*(4), 545–567. https://doi.org/10.1007/s12518-018-0233-3

Brumana, R., Oreni, D., Raimondi, A., Georgopoulos, A., & Bregianni, A. (2013). From survey to HBIM for documentation, dissemination and management of built heritage: The case study of St. Maria in Scaria d'Intelvi. *2013 Digital Heritage International Congress (DigitalHeritage)*, 497–504. https://doi.org/10.1109/DigitalHeritage.2013.6743789

Bruno, S., De Fino, M., & Fatiguso, F. (2018). Historic Building Information Modelling: Performance assessment for diagnosis-aided information modelling and management. *Automation in Construction*, *86*, 256–276. https://doi.org/10.1016/j.autcon.2017.11.009

Buldo, M., Agustín-Hernández, L., & Verdoscia, C. (2024). Semantic Enrichment of Architectural Heritage Point Clouds Using Artificial Intelligence: The Palacio de Sástago in Zaragoza, Spain [Number: 12 Publisher: Multidisciplinary Digital Publishing Institute]. *Heritage*, *7*(12), 6938–6965. https://doi.org/10.3390/heritage7120321

Castagnetti, C., Dubbini, M., Ricci, P. C., Rivola, R., Giannini, M., & Capra, A. (2017). CRITICAL ISSUES AND KEY POINTS FROM THE SURVEY TO THE CREATION OF

THE HISTORICAL BUILDING INFORMATION MODEL: THE CASE OF SANTO STEFANO BASILICA. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-5/W1*, 467–474. https://doi.org/10.5194/isprs-archives-XLII-5-W1-467-2017

Cen, J., Fang, J., Yang, C., Xie, L., Zhang, X., Shen, W., & Tian, Q. (2025). Segment Any 3D Gaussians [_eprint: 2312.00860].

Centre, U. W. H. (n.d.). UNESCO World Heritage Centre - World Heritage List.

Chenaux, A., Murphy, M., Pavia, S., Fai, S., Molnar, T., Cahill, J., Lenihan, S., & Corns, A. (2019). A REVIEW OF 3D GIS FOR USE IN CREATING VIRTUAL HISTORIC DUBLIN. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2/W9*, 249–254. https://doi.org/10.5194/isprs-archives-XLII-2-W9-249-2019

Chiabrando, F., Sammartano, G., & Spanò, A. (2016). HISTORICAL BUILDINGS MODELS AND THEIR HANDLING VIA 3D SURVEY: FROM POINTS CLOUDS TO USER-ORIENTED HBIM. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLI-B5*, 633–640. https://doi.org/10.5194/isprsarchives-XLI-B5-633-2016

Cicalo, E. (2016). B.I.M. for representing historical building heritage. The survey of Liberty and Art Deco decorated facades [Number: 16]. *DISEGNARECON*, *9*(16).

Cogima, C. K., Paiva, P. V. V., Dezen-Kempter, E., Carvalho, M. A. G., & Soibelman, L. (2019). The Role of Knowledge-Based Information on BIM for Built Heritage. In I. Mutis & T. Hartmann (Eds.), *Advances in Informatics and Computing in Civil and Construction Engineering* (pp. 27–34). Springer International Publishing. https://doi.org/10.1007/978-3-030-00220-6_4

Corrao, R., Campisi, T., Colajanni, S., Saeli, M., & Vinci, C. (Eds.). (2025). *Proceedings of the 11th International Conference of Ar.Tec. (Scientific Society of Architectural Engineering): Colloqui.AT.e 2024 - Volume 1* (Vol. 610). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-71855-7

Dahaghin, M., Castillo, M., Riahidehkordi, K., Toso, M., & Bue, A. D. (2024, September). Gaussian Heritage: 3D Digitization of Cultural Heritage with Integrated Object Segmentation [arXiv:2409.19039 [cs] version: 1]. https://doi.org/10.48550/arXiv.2409.19039

D'Amico, A., & Currà, E. (2017). From TSL survey to HBIM, issues on survey and information modeling implementation for the built heritage The case study of the Temple di Bacco Ravello. In A. Fioravanti, S. Cursi, S. Elahmar, S. Gargaro, G. Loffreda, G. Novembri, & A. Trento (Eds.), *Sapienza University Rome* (pp. 39–48).

Daniotti, B., Gianinetto, M., & Della Torre, S. (Eds.). (2020). *Digital Transformation of the Design, Construction and Management Processes of the Built Environment*. Springer International Publishing. https://doi.org/10.1007/978-3-030-33570-0 de Jonge, W., Clarke, N., & Kerkhoven, C. W. (2023). *TU Delft Aula Conservation Management Plan*. Delft University of Technology.

Delpozzo, D., Appolonia, L., Scala, B., & Adami, A. (2022). FEDERATED HBIM MODELS FOR CULTURAL HERITAGE: SURVEY MODEL AND CONCEPTUAL MODEL. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLVI-2/W1-2022*, 191–197. https://doi.org/10.5194/isprs-archives-XLVI-2-W1-2022-191-2022

Di Stefano, F., Gorreja, A., Malinverni, E. S., & Mariotti, C. (2020). KNOWLEDGE MODELING FOR HERITAGE CONSERVATION PROCESS: FROM SURVEY TO HBIM IMPLEMENTATION. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLIV-4/W1-2020*, 19–26. https://doi.org/10.5194/isprs-archives-XLIV-4-W1-2020-19-2020

Diara, F. (2022). HBIM Open Source: A Review [Number: 9]. *ISPRS INTERNATIONAL JOURNAL OF GEO-INFORMATION*, *11*(9). https://doi.org/10.3390/ijgi11090472

DoCoMoMo. (n.d.). Digital Archives – Docomomo International.

Donato, V., Biagini, C., Bertini, G., & Marsugli, F. (2017). CHALLENGES AND OPPORTUNITIES FOR THE IMPLEMENTATION OF H-BIM WITH REGARDS TO HISTORICAL INFRASTRUCTURES: A CASE STUDY OF THE PONTE GIORGINI IN CASTIGLIONE DELLA PESCAIA (GROSSETO – ITALY) [Conference Name: WG V/1, WG V/2, WG II/8 & CIPA¡br¿GEOMATICS & RESTORATION – Conservation of Cultural Heritage in the Digital Era (Volume XLII-5/W1) - 22–24 May 2017, Florence, Italy Publisher: Copernicus GmbH]. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-5-W1*, 253–260. https://doi.org/10.5194/isprs-archives-XLII-5-W1-253-2017

Dong, Y., Li, Y., & Hou, M. (2022). The Point Cloud Semantic Segmentation Method for the Ming and Qing Dynasties' Official-Style Architecture Roof Considering the Construction Regulations [Number: 4 Publisher: Multidisciplinary Digital Publishing Institute]. *ISPRS International Journal of Geo-Information*, *11*(4), 214. https://doi.org/10.3390/ijgi11040214

Edelsbrunner, H., & Mücke, E. P. (1994). Three-dimensional alpha shapes. *ACM Trans. Graph.*, *13*(1), 43–72. https://doi.org/10.1145/174462.156635

El Barhoumi, N., & Hajji, R. (2024). HBIM AND EXTENDED REALITY FOR CULTURAL MEDIATION OF HISTORICAL HERITAGE: A REVIEW. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLVIII-4/W9-2024*, 125–132. https://doi.org/10.5194/isprs-archives-XLVIII-4-W9-2024-125-2024

Farghaly, K., Soman, R., & Zhou, S. (2023). The evolution of ontology in AEC: A two-decade synthesis, application domains, and future directions. *JOURNAL OF INDUSTRIAL INFORMATION INTEGRATION*, *36*. https://doi.org/10.1016/j.jii.2023.100519

Fregonese, L., Taffurelli, L., Adami, A., Chiarini, S., Cremonesi, S., Helder, J., & Spezzoni, A. (2017). SURVEY AND MODELLING FOR THE BIM OF BASILICA OF SAN

MARCO INVENICE. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2/W3*, 303–310. https://doi.org/10.5194/isprs-archives-XLII-2-W3-303-2017

Fryskowska, A., & Stachelek, J. (2018). A no-reference method of geometric content quality analysis of 3D models generated from laser scanning point clouds for hBIM. *Journal of Cultural Heritage*, *34*, 95–108. https://doi.org/10.1016/j.culher.2018.04.003

Galassi, S., Bigongiari, M., Tempesta, G., Rovero, L., Fazzi, E., Azil, C., Di Pasquale, L., & Pancani, G. (2022). Digital Survey and Structural Investigation on the Triumphal Arch of Caracalla in the Archaeological Site of Volubilis in Morocco: Retracing the Timeline of Collapses Occurred during the 18th Century Earthquake [Number: 6]. *International Journal of Architectural Heritage*, *16*(6), 940–955. https://doi.org/10.1080/15583058.2022.2045387

Galera-Rodríguez, A., Angulo-Fornos, R., & Algarín-Comino, M. (2022). SURVEY AND 3D MODELLING OF UNDERGROUND HERITAGE SPACES WITH COMPLEX GEOMETRY: SURFACE OPTIMISATION FOR ASSOCIATION WITH HBIM METHODOLOGY [Number: 1]. *SCIRES-IT-SCIENTIFIC RESEARCH AND INFORMATION TECHNOLOGY*, *12*(1), 177–190. https://doi.org/10.2423/i22394303v12n1p177

Garcia-Gago, J., Sánchez-Aparicio, L. J., Soilán, M., & González-Aguilera, D. (2022). HBIM for supporting the diagnosis of historical buildings: Case study of the Master Gate of San Francisco in Portugal. *Automation in Construction*, *141*, 104453. https://doi.org/10.1016/j.autcon.2022.104453

García-Valldecabres, J., Pellicer, E., & Jordan-Palomar, I. (2016). BIM Scientific Literature Review for Existing Buildings and a Theoretical Method: Proposal for Heritage Data Management Using HBIM. In J. Perdomo-Rivera, A. Gonzalez-Quevedo, C. Lopez DelPuerto, F. Maldonado-Fortunet, & O. Molina-Bas (Eds.), *Universitat Politecnica de Valencia* (pp. 2228–2238).

García-Valldecabres, J., Galiano-Garrigós, A., Meseguer, L. C., & López González, M. C. (2021). HBIM WORK METHODOLOGY APPLIED TO PREVENTIVE MAINTENANCE: A STATE-OF-THE-ART REVIEW, 157–169. https://doi.org/10.2495/BIM210131

Garozzo, R., & Santagati, C. (2021). DIGITAL SURVEY AI AND SEMANTICS FOR RAILWAY MASONRY BRIDGES HEALTH ASSESSMENT. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLVI-M-1-2021*, 249–255. https://doi.org/10.5194/isprs-archives-XLVI-M-1-2021-249-2021

Germanà, M. L., Akagawa, N., Versaci, A., & Cavalagli, N. (Eds.). (2024). *Conservation of Architectural Heritage (CAH): Developing Sustainable Practices*. Springer International Publishing. https://doi.org/10.1007/978-3-031-33222-7

Giuliani, F., Gaglio, F., Martino, M., & De Falco, A. (2024). A HBIM pipeline for the conservation of large-scale architectural heritage: The city Walls of Pisa [Publisher: Nature Publishing Group]. *Heritage Science*, *12*(1), 1–20. https://doi.org/10.1186/s40494-024-01141-4

Gspurning, J., Sulzer, W., Held, D., & Landl, N. (2022). Surveying 3D Data as Basis of a HBIM for the Management of Cultural Heritage Objects [Number: 4]. *BALTIC JOURNAL OF MODERN COMPUTING*, *10*(4), 776–783. https://doi.org/10.22364/bjmc.2022.10.4.10

Hou, H., Lai, J., Wu, H., & Wang, T. (2024). Digital twin application in heritage facilities management: Systematic literature review and future development directions [Number: 8]. *ENGINEERING CONSTRUCTION AND ARCHITECTURAL MANAGEMENT*, *31*(8), 3193–3221. https://doi.org/10.1108/ECAM-06-2022-0596

Hu, X., Wang, Y., Fan, L., Luo, C., Fan, J., Lei, Z., Li, Q., Peng, J., & Zhang, Z. (2025). SAGD: Boundary-Enhanced Segment Anything in 3D Gaussian via Gaussian Decomposition [_eprint: 2401.17857].

Iovane, D., & Cera, V. (2016). 3D SURVEY AND HBIM FOR THE KNOWLEDGE AND VALORIZATION OF ARCHEOLOGICAL HERITAGE. THE CASE STUDIES OF THE CAPUA AND TELESIA AMPHITHEATRES. In J. Lerma & M. Cabrelles (Eds.), *University of Naples Federico II* (pp. 464–467).

Janisio-Pawlowska, D. (2021). Analysis of the Possibilities of Using HBIM Technology in the Protection of Cultural Heritage, Based on a Review of the Latest Research Carried out in Poland [Number: 10]. *ISPRS INTERNATIONAL JOURNAL OF GEO-INFORMATION*, *10*(10). https://doi.org/10.3390/ijgi10100633

Keeping It Modern: Grants Awarded 2018 (Getty Foundation). (2021, June).

Kerbl, B., Kopanas, G., Leimkühler, T., & Drettakis, G. (2023). 3D Gaussian Splatting for Real-Time Radiance Field Rendering [_eprint: 2308.04079].

Laohaviraphap, N., & Waroonkun, T. (2024). Integrating Artificial Intelligence and the Internet of Things in Cultural Heritage Preservation: A Systematic Review of Risk Management and Environmental Monitoring Strategies [Number: 12]. *Buildings*, *14*(12), 3979. https://doi.org/10.3390/buildings14123979

Laumain, X., Muñoz, V., & Sabater, A. (2023). STUDIES OF THE NOLLA PALACE. FROM SURVEY TO HBIM MANAGEMENT [Number: 19]. *EGE-REVISTA DE EXPRESION GRAFICA EN LA EDIFICACION*, (19), 96–116. https://doi.org/10.4995/ege.2023.20825

Lin, G., Giordano, A., & Sang, K. (2020). FROM SITE SURVEY TO HBIM MODEL FOR THE DOCUMENTATION OF HISTORIC BUILDINGS: THE CASE STUDY OF HEXINWU VILLAGE IN CHINA. *CONSERVATION SCIENCE IN CULTURAL HERITAGE*, *20*, 111–123.

Liu, J., Willkens, D., López, C., Cortés-Meseguer, L., García-Valldecabres, J. L., Escudero, P. A., & Alathamneh, S. (2023). COMPARATIVE ANALYSIS OF POINT CLOUDS ACQUIRED FROM A TLS SURVEY AND A 3D VIRTUAL TOUR FOR HBIM DEVELOPMENT. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLVIII-M-2-2023*, 959–968. https://doi.org/10.5194/isprs-archives-XLVIII-M-2-2023-959-2023

Liu, J., & Li, B. (2024). Heritage Building Information Modelling (HBIM): A Review of Published Case Studies [Conference Name: ISPRS TC I Mid-term Symposium "Intelligent Sensing and Remote Sensing Application" - 13–17 May 2024, Changsha, China Publisher: Copernicus GmbH]. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLVIII-1-2024*, 387–393. https://doi.org/10.5194/isprs-archives-XLVIII-1-2024-387-2024

Liu, W., Guan, T., Zhu, B., Ju, L., Song, Z., Li, D., Wang, Y., & Yang, W. (2024, April). EfficientGS: Streamlining Gaussian Splatting for Large-Scale High-Resolution Scene Representation [arXiv:2404.12777 [cs]]. https://doi.org/10.48550/arXiv.2404.12777

Lo Turco, M., Mattone, M., & Rinaudo, F. (2017). METRIC SURVEY AND BIM TECHNOLOGIES TO RECORD DECAY CONDITIONS. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-5/W1*, 261–268. https://doi.org/10.5194/isprs-archives-XLII-5-W1-261-2017

Logothetis, S., Delinasiou, A., & Stylianidis, E. (2015). BUILDING INFORMATION MODELLING FOR CULTURAL HERITAGE: A REVIEW. In Y. Yen, K. Weng, & H. Cheng (Eds.), *Aristotle University of Thessaloniki* (pp. 177–183). https://doi.org/10.5194/isprsannals-II-5-W3-177-2015

Logothetis, S., Karachaliou, E., & Stylianidis, E. (2017). FROM OSS CAD TO BIM FOR CULTURAL HERITAGE DIGITAL REPRESENTATION. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2/W3*, 439–445. https://doi.org/10.5194/isprs-archives-XLII-2-W3-439-2017

Lovell, L. J., Davies, R. J., & Hunt, D. V. L. (2023). The Application of Historic Building Information Modelling (HBIM) to Cultural Heritage: A Review [Number: 10 Publisher: Multidisciplinary Digital Publishing Institute]. *Heritage*, *6*(10), 6691–6717. https://doi.org/10.3390/heritage6100350

Luigini, A. (Ed.). (2019). *Proceedings of the 1st International and Interdisciplinary Conference on Digital Environments for Education, Arts and Heritage: EARTH 2018* (Vol. 919). Springer International Publishing. https://doi.org/10.1007/978-3-030-12240-9

Lumini, A. (2023). The integrated digital survey of the Florence Air Warfare School. HBIM-based protocols for documentation and information management [Number: 30]. *DISEGNARECON*, *16*(30). https://doi.org/10.20365/disegnarecon.30.2023.11

Martín-Lerones, P., Olmedo, D., López-Vidal, A., Gómez-García-Bermejo, J., & Zalama, E. (2021). BIM Supported Surveying and Imaging Combination for Heritage Conservation [Number: 8]. *REMOTE SENSING*, *13*(8). https://doi.org/10.3390/rs13081584

Monaco, S., Siconolfi, M., & Di Luggo, A. (2019). EXISTING-BIM: INTEGRATED SURVEY PROCEDURES FOR THE MANAGEMENT OF MODERN ARCHITECTURE. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2/W9*, 495–500. https://doi.org/10.5194/isprs-archives-XLII-2-W9-495-2019

Mora, R., Sánchez-Aparicio, L. J., Maté-González, M. Á., García-Álvarez, J., Sánchez-Aparicio, M., & González-Aguilera, D. (2021). An historical building information modelling approach for the preventive conservation of historical constructions: Application to the Historical Library of Salamanca. *Automation in Construction*, *121*, 103449. https://doi.org/10.1016/j.autcon.2020.103449

Moropoulou, A., Georgopoulos, A., Doulamis, A., Ioannides, M., & Ronchi, A. (Eds.). (2022). *Trandisciplinary Multispectral Modelling and Cooperation for the Preservation of Cultural Heritage: Second International Conference, TMM_ch 2021, Athens, Greece, December 13–15, 2021, Revised Selected Papers* (Vol. 1574). Springer International Publishing. https://doi.org/10.1007/978-3-031-20253-7

Moropoulou, A., Georgopoulos, A., Ioannides, M., Doulamis, A., Lampropoulos, K., & Ronchi, A. (Eds.). (2023). *Transdisciplinary Multispectral Modeling and Cooperation for the Preservation of Cultural Heritage: Third International Conference, TMM_ch 2023, Athens, Greece, March 20–23, 2023, Revised Selected Papers* (Vol. 1889). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-42300-0

Murphy, M., McGovern, E., & Pavia, S. (2013). Historic Building Information Modelling – Adding intelligence to laser and image based surveys of European classical architecture. *ISPRS Journal of Photogrammetry and Remote Sensing*, *76*, 89–102. https://doi.org/10.1016/j.isprsjprs.2012.11.006

Nespeca, R. (2018). TOWARDS A 3D DIGITAL MODEL FOR MANAGEMENT AND FRUITION OF DUCAL PALACE AT URBINO. AN INTEGRATED SURVEY WITH MOBILE MAPPING [Number: 2]. *SCIRES-IT-SCIENTIFIC RESEARCH AND INFORMATION TECHNOLOGY*, *8*(2), 1–14. https://doi.org/10.2423/i22394303v8n2p1

Oreni, D., Brumana, R., Della Torre, S., & Banfi, F. (2017). SURVEY, HBIM AND CONSERVATION PLAN OF A MONUMENTAL BUILDINGDAMAGED BY EARTHQUAKE. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-5/W1*, 337–342. https://doi.org/10.5194/isprs-archives-XLII-5-W1-337-2017

Palestini, C., Basso, A., & Graziani, L. (2018). INTEGRATED PHOTOGRAMMETRIC SURVEY AND BIM MODELLING FOR THE PROTECTION OF SCHOOL HERITAGE, APPLICATIONS ON A CASE STUDY. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2*, 821–828. https://doi.org/10.5194/isprs-archives-XLII-2-821-2018

Paris, L., Rossi, M., & Cipriani, G. (2022). Modeling as a Critical Process of Knowledge: Survey of Buildings in a State of Ruin [Number: 3]. *ISPRS INTERNATIONAL JOURNAL OF GEO-INFORMATION*, *11*(3). https://doi.org/10.3390/ijgi11030172

Paris, L., & Wahbeh, W. (2016). Survey and representation of the parametric geometries in HBIM [Number: 16]. *DISEGNARECON*, *9*(16).

Penjor, T., Banihashemi, S., Hajirasouli, A., & Golzad, H. (2024). Heritage building information modeling (HBIM) for heritage conservation: Framework of challenges, gaps, and existing limitations of HBIM. *Digital Applications in Archaeology and Cultural Heritage*, *35*, e00366. https://doi.org/10.1016/j.daach.2024.e00366

Pocobelli, D. P., Boehm, J., Bryan, P., Still, J., & Grau-Bové, J. (2018). BIM for heritage science: A review. *Heritage Science*, *6*(1), 30. https://doi.org/10.1186/s40494-018-0191-4

Poux, F., Hallot, P., Neuville, R., & Billen, R. (2016). SMART POINT CLOUD: DEFINITION AND REMAINING CHALLENGES. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *IV-2/W1*, 119–127. https://doi.org/10.5194/isprs-annals-IV-2-W1-119-2016

Poux, F., Mattes, C., Selman, Z., & Kobbelt, L. (2022). Automatic region-growing system for the segmentation of large point clouds. *Automation in Construction*, *138*, 104250. https://doi.org/10.1016/j.autcon.2022.104250

Poux, F. (2019). The Smart Point Cloud: Structuring 3D intelligent point data [Publisher: ULiège - Université de Liège].

Poux, F., & Billen, R. (2019). Voxel-based 3D Point Cloud Semantic Segmentation: Unsupervised Geometric and Relationship Featuring vs Deep Learning Methods [Number: 5 Publisher: Multidisciplinary Digital Publishing Institute]. *ISPRS International Journal of Geo-Information*, *8*(5), 213. https://doi.org/10.3390/ijgi8050213

Poux, F., Neuville, R., Hallot, P., & Billen, R. (2017). MODEL FOR SEMANTICALLY RICH POINT CLOUD DATA. *ISPRS Annals of the Photogrammetry Remote Sensing and Spatial Information Sciences*, (IV-4/W5), 107–115. https://doi.org/10.5194/isprs-annals-IV-4-W5-107-2017

Poux, F., Neuville, R., Nys, G.-A., & Billen, R. (2018). 3D Point Cloud Semantic Modelling: Integrated Framework for Indoor Spaces and Furniture [Number: 9 Publisher: Multidisciplinary Digital Publishing Institute]. *Remote Sensing*, *10*(9), 1412. https://doi.org/10.3390/rs10091412

Psaltakis, D.-I., Kalentzi, K., Mariettaki, A.-P., & Antonopoulos, A. (2019). 3D Survey of a Neoclassical Building Using a Handheld Laser Scanner as Basis for the Development of a BIM-Ready Model [Series Title: Communications in Computer and Information Science]. In A. Moropoulou, M. Korres, A. Georgopoulos, C. Spyrakos, & C. Mouzakis (Eds.), *Transdisciplinary Multispectral Modeling and Cooperation for the Preservation of Cultural Heritage* (pp. 119–127, Vol. 961). Springer International Publishing. https://doi.org/10.1007/978-3-030-12957-6_8

Qi, C. R., Yi, L., Su, H., & Guibas, L. J. (2017, June). PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space [arXiv:1706.02413 [cs]]. https://doi.org/10.48550/arXiv.1706.02413

Quintilla Castán, M., & Agustín Hernández, L. (2021). 3D survey and virtual reconstruction of heritage. The case study of the City Council and Lonja of Alcañiz [Number: 2]. *VITRUVIO - International Journal of Architectural Technology and Sustainability*, *6*(2), 12–25. https://doi.org/10.4995/vitruvio-ijats.2021.16567

Radanovic, M., Khoshelham, K., & Fraser, C. (2020). Geometric accuracy and semantic richness in heritage BIM: A review. *Digital Applications in Archaeology and Cultural Heritage*, *19*, e00166. https://doi.org/10.1016/j.daach.2020.e00166

Ramírez Eudave, R., & Ferreira, T. M. (2021). On the suitability of a unified GIS-BIM-HBIM framework for cataloguing and assessing vulnerability in Historic Urban Landscapes: A critical review [Number: 10]. *International Journal of Geographical Information Science*, *35*(10), 2047–2077. https://doi.org/10.1080/13658816.2020.1844208

Rodrigues, B. N., Favoreti, A. L. F., Borges, K., Gomes, P. H., Dionizio, R. F., Menzori, M., Jr Molina, V. E., & Dezen-Kempter, E. (2023). Digital survey applied to the assessment of pathological manifestations in the architectural heritage of monte alegre in Piracicaba/SP. *Journal of Building Pathology and Rehabilitation*, *8*(1), 60. https://doi.org/10.1007/s41024-023-00306-1

Rolim, R., López-González, C., & Viñals, M. (2024). Analysis of the Current Status of Sensors and HBIM Integration: A Review Based on Bibliometric Analysis [Number: 4]. *HERITAGE*, *7*(4), 2071–2087. https://doi.org/10.3390/heritage7040098

Roman, O., Farella, E., Rigon, S., Remondino, F., Ricciuti, S., & Viesi, D. (2023). FROM 3D SURVEYING DATA TO BIM TO BEM: THE INCUBE DATASET. In D. Iwaszczuk, B. Hejmanowska, K. Bakula, & F. Remondino (Eds.), *Fondazione Bruno Kessler* (pp. 175–182). https://doi.org/10.5194/isprs-archives-XLVIII-1-W3-2023-175-2023

Rusu, R. B., & Cousins, S. (2011). 3D is here: Point Cloud Library (PCL). *IEEE International Conference on Robotics and Automation (ICRA)*.

Salvador García, E., García-Valldecabres, J., & Viñals Blasco, M. J. (2018). The use of HBIM models as a tool for dissemination and public use management of historical architecture: A review [Number: 01]. *International Journal of Sustainable Development and Planning*, *13*(01), 96–107. https://doi.org/10.2495/SDP-V13-N1-96-107

Sanseverino, A., Limongiello, M., & Fiorillo, F. (2022). UAV photogrammetric survey and Image-Based elaborations for an Industrial Plant [Number: 29]. *DISEGNARECON*, *15*(29), D1–D10. https://doi.org/10.20365/disegnarecon.29.2022.15

Sanseverino, A., Messina, B., Limongiello, M., & Guida, C. (2022). An HBIM Methodology for the Accurate and Georeferenced Reconstruction of Urban Contexts Surveyed by UAV: The Case of the Castle of Charles V [Number: 15]. *REMOTE SENSING*, *14*(15). https://doi.org/10.3390/rs14153688

Santagati, C., Laurini, C. R., Sanfilippo, G., Bakirtzis, N., Papacharalambous, D., & Hermon, S. (2019). HBIM FOR THE SURVEYING, ANALYSIS AND RESTORATION OF THE SAINT JOHN THE THEOLOGIAN CATHEDRAL IN NICOSIA (CYPRUS). *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2/W11*, 1039–1046. https://doi.org/10.5194/isprs-archives-XLII-2-W11-1039-2019

Santos, D., Sousa, H., Cabaleiro, M., & Branco, J. (2023). HBIM Application in Historic Timber Structures: A Systematic Review [Number: 8]. *INTERNATIONAL JOURNAL*

OF ARCHITECTURAL HERITAGE, *17*(8), 1331–1347. https://doi.org/10.1080/15583058.2022.2034071

Scandurra, S., Pulcrano, M., Cirillo, V., Campi, M., Di Luggo, A., & Zerlenga, O. (2018). INTEGRATED SURVEY PROCEDURES FOR THE VIRTUAL READING AND FRUITION OF HISTORICAL BUILDINGS. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-2*, 1037–1044. https://doi.org/10.5194/isprs-archives-XLII-2-1037-2018

Schütz, M., Ohrhallinger, S., & Wimmer, M. (2020). Fast Out-of-Core Octree Generation for Massive Point Clouds [Publisher: John Wiley & Sons, Inc.]. *Computer Graphics Forum*, *39*(7), 1–13. https://doi.org/10.1111/cgf.14134

Sentürk, H., & Simsek, C. (2024). A review on HBIM modelling process from 3D point clouds by applying artificial intelligence algorithms in cultural heritage Kültürel mirasta yapay zeka algoritmaları uygulayarak 3B nokta bulutlarından HBIM. *JOURNAL OF POLYTECHNIC-POLITEKNIK DERGISI*. https://doi.org/10.2339/politeknik.1503631

Shehata, A., Farsangi, E., Mirjalili, S., & Yang, T. (2024). A State-of-the-Art Review and Bibliometric Analysis on the Smart Preservation of Heritages [Number: 12]. *BUILDINGS*, *14*(12). https://doi.org/10.3390/buildings14123818

Shishehgarkhaneh, M., Keivani, A., Moehler, R., Jelodari, N., & Laleh, S. (2022). Internet of Things (IoT), Building Information Modeling (BIM), and Digital Twin (DT) in Construction Industry: A Review, Bibliometric, and Network Analysis [Number: 10]. *BUILDINGS*, *12*(10). https://doi.org/10.3390/buildings12101503

State Collections of Lower Austria. (2024a). The Heidentor in Petronell-Carnuntum.

State Collections of Lower Austria. (2024b). The Reconstruction of the Heidentor.

Sun, Z., & Zhang, Y. (2018). Using Drones and 3D Modeling to Survey Tibetan Architectural Heritage: A Case Study with the Multi-Door Stupa [Number: 7]. *Sustainability*, *10*(7), 2259. https://doi.org/10.3390/su10072259

Sutherland, N., Marsh, S., Priestnall, G., Bryan, P., & Mills, J. (2023). InfraRed Thermography and 3D-Data Fusion for Architectural Heritage: A Scoping Review [Number: 9]. *REMOTE SENSING*, *15*(9). https://doi.org/10.3390/rs15092422

Teppati Losè, L., Diara, F., Spadaro, A., & Chiabrando, F. (2024). FROM 3D METRIC SURVEY TO HBIM MODEL. TESTING OF DIFFERENT SCAN2BIM APPROACHES FOR THE ARCHAEOLOGICAL DOCUMENTATION. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLVIII-2/W4-2024*, 437–444. https://doi.org/10.5194/isprs-archives-XLVIII-2-W4-2024-437-2024

Thompson, R., & van Oosterom, P. (2021). Bi-temporal foundation for LADM v2: Fusing event and state based modelling of Land administration data 2D and 3D. *Land Use Policy*, *102*, 105246. https://doi.org/10.1016/j.landusepol.2020.105246

Three.js Contributors. (2010). Three.js – JavaScript 3D Library.

Twin it! Een pan-Europese verzameling van 3D-erfgoedmodellen. (n.d.).

UNESCO. (2024, July). *Operational Guidelines for the Implementation of the World Heritage Convention* (tech. rep. No. WHC.24/01). https://doi.org/10.34685/HI.2022.25.22.001

UNESCO and ERA Chairs on Digital Cultural Heritage - Digital Heritage Research Lab, Cyprus University of Technology and EU ERA Chair on Digital Cultural Heritage - MNEMOSYNE. (n.d.). Castle of Paphos in 3D (HBIM).

van Arnhem, M., Yang, Q., Tew, S., Zhao, X., & Kahn, W. (2024). Integrating Gaussian Splatting with Semantic Labels for Heritage BIM.

Vuoto, A., Funari, M., & Lourenco, P. (2024). Shaping Digital Twin Concept for Built Cultural Heritage Conservation: A Systematic Literature Review [Number: 11]. *INTERNATIONAL JOURNAL OF ARCHITECTURAL HERITAGE*, *18*(11), 1762–1795. https://doi.org/10.1080/15583058.2023.2258084

Wagner, A., & de Clippele, M.-S. (2023). Safeguarding Cultural Heritage in the Digital Era – A Critical Challenge. *International Journal for the Semiotics of Law - Revue internationale de Sémiotique juridique*, *36*(5), 1915–1923. https://doi.org/10.1007/s11196-023-10040-z

www.architectuur.org. (n.d.). Auditorium Technische Universiteit, Delft, Van den Broek en Bakema — Architectuurgids.

Yan, H., Lau, A., & Fan, H. (2025). Evaluating Deep Learning Advances for Point Cloud Semantic Segmentation in Urban Environments. *KN - Journal of Cartography and Geographic Information*, *75*(1), 3–22. https://doi.org/10.1007/s42489-025-00185-1

Yang, S., Hou, M., & Li, S. (2023). Three-Dimensional Point Cloud Semantic Segmentation for Cultural Heritage: A Comprehensive Review [Number: 3 Publisher: Multidisciplinary Digital Publishing Institute]. *Remote Sensing*, *15*(3), 548. https://doi.org/10.3390/rs15030548

Yang, S., Hou, M., Shaker, A., & Li, S. (2021). Modeling and Processing of Smart Point Clouds of Cultural Relics with Complex Geometries [Number: 9 Publisher: Multidisciplinary Digital Publishing Institute]. *ISPRS International Journal of Geo-Information*, *10*(9), 617. https://doi.org/10.3390/ijgi10090617

Yang, X., Grussenmeyer, P., Koehl, M., Macher, H., Murtiyoso, A., & Landes, T. (2020). Review of built heritage modelling: Integration of HBIM and other information techniques. *Journal of Cultural Heritage*, *46*, 350–360. https://doi.org/10.1016/j.culher.2020.05.008

Yastikli, N. (2007). Documentation of cultural heritage using digital photogrammetry and laser scanning. *Journal of Cultural Heritage*, *8*(4), 423–427. https://doi.org/10.1016/j.culher.2007.06.003

Ye, V., Li, R., Kerr, J., Turkulainen, M., Yi, B., Pan, Z., Seiskari, O., Ye, J., Hu, J., Tancik, M., & Kanazawa, A. (2025). Gsplat: An open-source library for Gaussian splatting. *Journal of Machine Learning Research*, *26*(34), 1–17.

Yu, Y., van Oosterom, P., Pottgiesser, U., Verbree, E., & Wang, Z. (2025). Rethinking HBIM: Definition and Technological Integration for Architectural Heritage.

Zhang, Z., & Zou, Y. (2022). Research hotspots and trends in heritage building information modeling: A review based on CiteSpace analysis [Number: 1]. *HUMANITIES & SOCIAL SCIENCES COMMUNICATIONS*, *9*(1). https://doi.org/10.1057/s41599-022-01414-y

Zhao, J., Hua, X., Yang, J., Yin, L., Liu, Z., & Wang, X. (2023). A REVIEW OF POINT CLOUD SEGMENTATION OF ARCHITECTURAL CULTURAL HERITAGE. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *X-1/W1-2023*, 247–254. https://doi.org/10.5194/isprs-annals-X-1-W1-2023-247-2023

A. Reproducibility self-assessment

A.1. Marks for each of the criteria

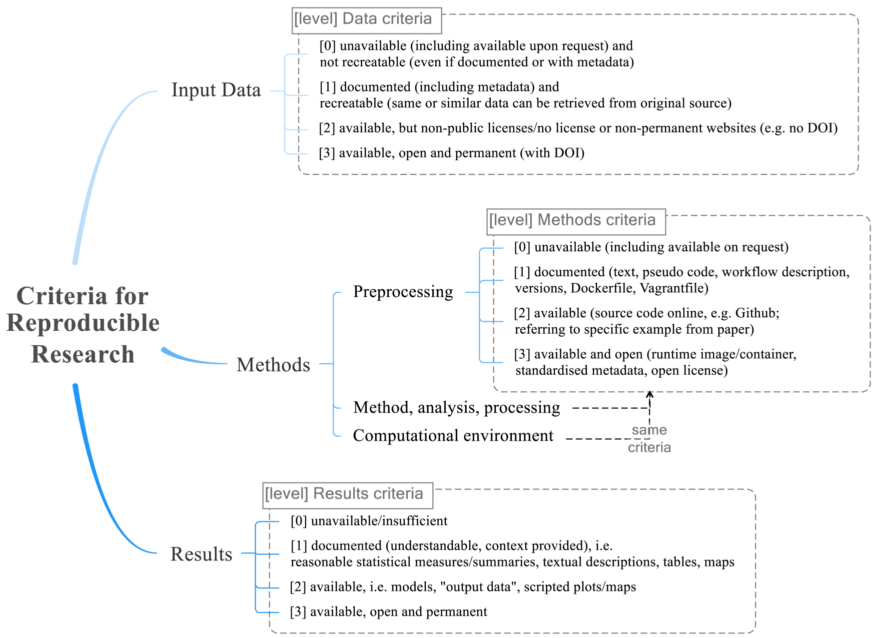


Figure A.1.: Reproducibility criteria to be assessed.

1. input data: level 0 and level 3
2. preprocessing: level 2
3. methods: level 2
4. computational environment: level 2
5. results: level 2

A.2. Self-reflection

Most of the input data, including the MLS-acquired and smartphone-acquired point cloud and UVA-acquired images, is at level 0, as it was collected independently using school's or our own devices. Due to the size of the datasets, licensing limitations, and practical storage restrictions, full open access, including the full metadata, cannot be uploaded to spatial data infrastructures. However, it can be shared upon request. Furthermore, the data acquisition protocols, sensor parameters, and case study contexts are documented in detail to allow similar data collection in future replication efforts. The other part of the data - AHN dataset is available, open, and permanent with DOI, thus reaching level 3.

Full runtime packaging using Docker was not implemented, as the time investment for learning, building, and validating Docker images exceeded the scope of this thesis work. Instead, the computational pipeline, including all scripts and instructions, is made available through GitHub, achieving Level 2 reproducibility. Though it is also worth nociting that there are also some manual processes, especially during preprocessing, as the attributes depends on the different attributes per building, also the scale of the case studies. Nevertheless, these manually processed parameters are documented in the code, like the matching points, and thus is reproducible in this case. Due to the large file size of input point clouds, raw datasets are not hosted online but are described in detail for potential re-use with similar datasets.

Final semantic point clouds (in ply), annotation files (in JSON), and web visualization code are mostly available for replication, with the GitHub link availableble for reproducing the visualization platform architecture. The largest point cloud data of Aula TUDelft is too big to be uploaded to GitHub. Due to the limitations with large files and conflicting server issues between the localhost and the deployment, a higher level of reproducibility is hard to achieve. Nevertheless, the information models, and the structured semantics examples are available from the thesis. The small web-based prototype can be cloned from Github and tested out locally with all the configuration included.

B. HBIM ontology literature review

Table B.1.: Classification of Articles by Attribute Category

No.	Structural	Material	Historical	Cul.&Art.	Rest.&Cons.	Reference
1	+++	+++	+++	+++	+++	(Banfi et al., 2019)
2	+++	++	+++	-	++	(Iovane & Cera, 2016)
3	+++	++	++	-	-	(Psaltakis et al., 2019)
4	+++	++	++	-	++	(Sentürk & Simsek, 2024)
5	+++	++	++	++	+++	(Shehata et al., 2024)
6	+++	++	++	+	+	(Chenaux et al., 2019)
7	+++	++	+	+	+++	(Rolim et al., 2024)
8	+++	++	++	++	+++	(Janisio-Pawlowska, 2021)
9	++	+	++	+++	-	(Cicalo, 2016)
10	++	+	+++	++	++	(García-Valldecabres et al., 2016)
11	+++	++	++	++	++	(Sanseverino, Messina, et al., 2022)
12	+++	++	+++	++	+++	(Castagnetti et al., 2017)
13	++	+	++	+	+++	(Bastem & Cekmis, 2022)
14	+++	++	++	+	+++	(Martín-Lerones et al., 2021)
15	++	+	++	++	++	(Logothetis et al., 2015)
16	+++	++	+	+	++	(J. Liu et al., 2023)
17	++	-	+	-	+++	(Hou et al., 2024)
18	+++	++	+	-	++	(Monaco et al., 2019)
19	+++	+	++	++	+++	(Delpozzo et al., 2022)
20	+++	+	++	++	+	(Bagnolo et al., 2019b)
21	+++	++	++	+	+++	(Bródka & Walek, 2022)
22	+++	++	++	++	+++	(D'Amico & Currà, 2017)
23	+++	++	+++	++	+++	(Brumana et al., 2018)
24	++	+	+	-	++	(Roman et al., 2023)

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Table B.1 – continued from previous page

No.	Structural	Material	Historical	Cul.&Art.	Rest.&Cons.	Reference
25	+++	++	++	++	+++	(Lin et al., 2020)
26	+++	++	+++	+++	+++	(Bianconi et al., 2019)
27	+++	+	++	++	++	(Bagnolo et al., 2019a)
28	+++	+++	+++	++	+++	(Santagati et al., 2019)
29	+++	++	++	+	+++	(Brumana et al., 2019)
30	+++	++	+++	++	+++	(Adami et al., 2019)
31	++	+	++	+++	++	(El Barhoumi & Hajji, 2024)
32	+++	++	+++	++	+++	(Murphy et al., 2013)
33	+++	++	++	+	+++	(Santos et al., 2023)
34	++	+	++	++	++	(Diara, 2022)
35	+++	++	+	-	++	(Borkowski & Kubrat, 2024)
36	+++	++	+++	++	+++	(Chiabrando et al., 2016)
37	++	+++	+	+	+++	(Sutherland et al., 2023)
38	+	+++	+	+	+++	(Laohaviraphap & Waroonkun, 2024)
39	+++	++	++	+	+++	(Barrile et al., 2019)
40	++	+	+	+	++	(Zhang & Zou, 2022)
41	+++	+++	+++	++	+++	(Di Stefano et al., 2020)
42	+++	++	+	+	++	(**gil˙machine˙202**)
43	+++	+++	++	+	+++	(Lo Turco et al., 2017)
44	++	++	+	-	+++	(Ariza-Lopez et al., 2022)
45	+++	+++	+++	++	+++	(Oreni et al., 2017)
46	+++	+++	+++	+++	+++	(Laumain et al., 2023)
47	+++	++	+++	+	++	(Galera-Rodríguez et al., 2022)
48	+++	+++	++	+++	+++	(Fregonese et al., 2017)
49	++	++	++	++	+++	(Vuoto et al., 2024)
50	++	+++	++	+++	+++	(Moropoulou et al., 2023)
51	++	+	+	-	++	(Farghaly et al., 2023)
52	+++	++	++	+	+++	(Gspurning et al., 2022)
53	+++	+	++	++	++	(Paris & Wahbeh, 2016)
54	+++	++	++	++	+++	(Lovell et al., 2023)
55	+	+	-	-	++	(Shishehgarkhaneh et al., 2022)
56	+++	+++	+++	++	+++	(Lumini, 2023)

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Table B.1 – continued from previous page

No.	Structural	Material	Historical	Cul.&Art.	Rest.&Cons.	Reference
57	+++	++	+++	+++	+++	(Nespeca, 2018)
58	+++	+++	++	++	+++	(Sanseverino, Limongiello, & Fiorillo, 2022)
59	+++	++	+++	++	+++	(Paris et al., 2022)
60	+++	++	+++	+++	++	(Banfi et al., 2021)
61	+	+	++	+	++	(Baarimah et al., 2023)
62	++	++	+++	++	+++	(Ramírez Eudave & Ferreira, 2021)
63	+++	++	+++	++	++	(Bolognesi & Garagnani, 2018)
64	++	+++	++	+	++	(Aksin & Karaş, 2021)
65	+	+	-	-	++	(Baarimah et al., 2021)
66	+	+	++	+++	+++	(Germanà et al., 2024)
67	++	++	++	+	+++	(Daniotti et al., 2020)
68	+	+	++	+++	+	(Luigini, 2019)
69	++	+	++	+	+++	(García-Valldecabres et al., 2021)
70	+++	++	++	++	++	(Teppati Losè et al., 2024)
71	+++	+++	+++	++	+++	(Brumana et al., 2013)
72	+++	++	+++	++	++	(Galassi et al., 2022)
73	+	+	++	+++	++	(Salvador García et al., 2018)
74	+++	++	++	+	+++	(Garozzo & Santagati, 2021)
75	+++	++	++	+	+++	(Corrao et al., 2025)
76	+++	-	-	-	-	(J. Liu & Li, 2024)
77	+++	-	-	-	-	(Cogima et al., 2019)
78	++	+	++	++	++	(Sun & Zhang, 2018)
79	+++	++	++	+	+++	(Palestini et al., 2018)
80	++	+	++	+	++	(Radanovic et al., 2020)
81	++	++	++	++	+++	(Rodrigues et al., 2023)
82	+++	+++	+++	+++	+++	(Quintilla Castán & Agustín Hernández, 2021)
83	+++	++	++	++	++	(Scandurra et al., 2018)
84	++	++	++	+	+++	(Pocobelli et al., 2018)

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Table B.1 – continued from previous page

No.	Structural	Material	Historical	Cul.&Art.	Rest.&Cons.	Reference
85	++	++	++	+++	++	(Bolognesi & Villa, 2021)
86	++	++	+++	+++	++	(Bartolomei et al., 2022)

Colophon

This document was typeset using LaTeX, using the KOMA-Script class `scrbook`. The main font is Palatino.