Enriched Semantic 3D Point Clouds: An Alternative to 3D City Models for Digital Twin for Cities?

Imane Jeddoub, Zouhair Ballouch, Rafika Hajji, and Roland Billen

Abstract Digital Twins (DTs) for cities represent a new trend for city planning and management, enhancing three-dimensional modeling and simulation of cities. While progress has been made in this research field, the current scientific literature mainly focuses on the use of semantically segmented point clouds to develop 3D city models for DTs. However, this study discusses a new reflection that argues on directly integrating the results of semantic segmentation to create the skeleton of the DTs and uses enriched semantically segmented point clouds to perform targeted simulations without generating 3D models. The paper discusses to what extent enriched semantic 3D point clouds can replace semantic 3D city models in the DTs scope. Ultimately, this research aims to reduce the cost and complexity of 3D modeling to fit some DTs requirements and address its specific needs. New perspectives are set to tackle the challenges of using semantic 3D point clouds to implement DTs for cities.

Keywords Digital twin · Semantic point cloud · Semantic segmentation · 3D city model · Urban simulations

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1 Introduction

3D city models (3DCMs) and Digital Twins (DTs) for cities have gained significant interest in the urban and geospatial fields (Ellul et al. 2022; Ferré-Bigorra et al. 2022; Mylonas et al. 2021). Both approaches are created based on the combination of various datasets and techniques, i.e., basically 3D reality capture and surveying technologies (Deng et al. 2021b; Ledoux et al. 2021; Lehner and Dorffner 2020). 3D point cloud data from laser scanning has proven its potential as an input layer to create 3D semantic city models and geospatial Digital Twins (Bacher 2022; Beil et al. 2021; Lehner and Dorffner 2020; Lehtola 2022; Lu 2019; Nys et al. 2020; Scalas et al. 2022; Xue et al. 2020). Indeed, point clouds have a simple and easy-to-handle structure that replicates all the physical city features based on point geometries. They are considered a point-based model, where entities are represented as a set of points. Furthermore, their discrete representation, as well as the lack of structure, topology, and connectivity, make them easy to handle, but at the same time, they require costly processing, especially to enrich them with semantic information by applying, for example effective knowledge-based approaches (i.e., Machine Learning (ML) and Deep Learning (DL) approaches) (Döllner 2020; Richter 2018). The current emergence of Artificial Intelligence (AI) is revolutionizing the field of 3D semantic segmentation and yielding highly satisfactory results (Su et al. 2022; Wilk et al. 2022). Nevertheless, the success of newly developed DL approaches relies heavily on the semantic richness of training data.

In the context of implementing semantic 3D city models, most recent works were carried out to optimize the automatic reconstruction of 3D city models. They essentially combine elevation data coming from LiDAR (airborne, terrestrial or mobile) or photogrammetry along with 2D building footprints to generate the city model (Dukai et al. 2019; Ledoux et al. 2021; Nys et al. 2020; Ortega et al. 2021; Pađen 2022; Peters 2022). For instance, 3dfier is an automatic framework that allows the reconstruction of a LoD1.2 model with respect to some specific set of rules (Ledoux et al. 2021). Another related work develops an automatic workflow that segments roof surfaces from point cloud data and generates buildings at LoD2.1 (Nys et al. 2020). Although various methods are in practice to generate accurate semantic 3D city models to perform various spatial and thematic analyses, the city modeling process is still tedious and time consuming (Girindran et al. 2020; Naserentin and Logg 2022).

Following the classic modeling pipeline to automatically generate a 3D city model from LiDAR point clouds, two phases are crucial (Ballouch and Hajji 2021). The first step requires a semantic segmentation of the point cloud to extract the semantic classes that will be used in the second phase (i.e., automatic modeling). However, it will be interesting to investigate if the initial phase in the processing pipeline already has something to offer to DTs for cities instead of going through the modeling process. In fact, an enriched 3D semantic point cloud would help to better manipulate and interpret the 3D data as well as fulfill the DT's needs (Lehtola 2022). First, the initial geometrical accuracy is maintained, which certainly opens new opportunities to perform simulations directly on point clouds instead of creating surface models. Second, point cloud data should be seen as a preliminary level of DTs as they fulfill their minimum conditions (i.e., replicating all city entities such as buildings, roads, vegetations, terrain, etc.). Finally, it is important to highlight that point clouds can be easily updated over time to reflect changes in the urban environment, whereas updating a 3D city model can be more complicated due to its hierarchical structure.

In this paper, reflections about the use of semantic 3D point cloud data in urban DTs are presented. The questions that are raised here are: how DTs for cities can benefit from enriched semantically 3D point cloud data while meeting the requirements of urban simulations and analysis that goes beyond visual interpretations? And is semantic point cloud data sufficient to fit the DTs analysis instead of a semantic 3D city model?

The paper structure is as follows: Sect. 2 briefly introduces the mainstream uses of semantic point clouds in urban applications. Section 3 discusses to what extent the point cloud may be an alternative to the 3D city model in the context of creating DTs for cities. The same section reflects the requirements of DTs and compares them with the potentialities of semantic point clouds. The advantages and the limitations of both 3D city model and point cloud are highlighted. Then, we conclude the section by giving an overview of the main findings and introducing the future perspectives. Section 4 concludes this work.

2 Mainstream Uses of Point Clouds in Urban Applications

The use of 3D LiDAR point clouds is becoming increasingly relevant in various emerging urban applications, including urban simulations, Virtual and Augmented Reality (VR and AR), Building Information Modeling (BIM), 3D urban mapping, Smart Cities (SCs), Urban Digital Twins (UDTs), and many others. Point clouds can be collected faster than other surveyed data, so enabling regular updates for specific urban applications. They provide a detailed digital representation of urban settings with accurate spatial information and large-scale coverage, especially when acquired through airborne sensors. Besides, the rapid development of LiDAR acquisition techniques has made it possible to create high-precision 3D point cloud representations of urban environments at an affordable cost. These point clouds are capable of depicting objects of varying sizes, providing remarkably lifelike depictions of cities and other landscapes. Moreover, with the increased capacity of GPUs, high density 3D point clouds can be efficiently rendered and displayed instantaneously.

One of the mainstream uses of point clouds in urban applications is for autonomous driving. The recent advancements in DL techniques have enabled the reliable navigation and decision-making required in autonomous driving through the use of dense, geo-referenced, and accurate 3D point cloud data provided by LiDAR. This data provides real-time environment perception and allows for the creation of high-definition maps and urban models, making it an indispensable technology for autonomous vehicles (Li et al. 2021). Another application of point clouds in urban environments is 3D change detection, which is made possible through the implementation of point clouds (Kharroubi et al. 2022). Recent advancements in computer vision and machine learning have further enhanced the automatic and intelligent detection of changes in urban settings. Moreover, point clouds are suitable for use in virtual and augmented reality applications due to their ability to provide a more immersive way of perceiving 3D digital objects (Alexiou et al. 2017). Furthermore, 3D point cloud data has been used as reference data for city modeling (Badenko et al. 2019; Huang et al. 2022; Nurunnabi et al. 2022; Nys et al. 2020; Wang et al. 2019; Yan et al. 2019). For example, 3D BAG[1] has multiple Level of Details (LoDs) of 3D buildings as an up-to-date data set for the whole city of the Netherlands. The datasets are generated based on the building footprints from the BAG and the height data from AHN acquired by airborne laser scanning (ALS) (Dukai et al. 2019, 2021; Dukai 2020; León-Sánchez et al. 2021). Additionally, several cities around the world have acquired 3D point cloud data to model their buildings. For instance, Helsinki used classified ALS point cloud data to determine the elevation position and the roof shapes of the buildings (Hämäläinen 2021). The city has also used classified point clouds to map, update, and maintain the City Information Model. Another deployment of point cloud data is in the context of creating UDTs for city-state Singapore called "Virtual Singapore". The authors proposed an automatic tree modeling framework at multiple LoDs combining airborne and mobile LiDAR scanning datasets with different remote sensing data to address the limitations of each acquisition technique (Gobeawan et al. 2018). In addition, to create a CityGML model for the city, 3D building models were created using aerial images and airborne point cloud data (Soon and Khoo 2017).

In recent years, considering BIM models as one of the input layers to implement an UDTs (Deng et al. 2021a; Lehtola 2022; Stojanovic et al. 2018), many approaches in the Architecture Engineering Construction (AEC) field have been discussed to automate and support the process of creating a BIM model from a point cloud for several applications known as the Scan-to-BIM workflow (Hellmuth 2022). The use of Scan-to-BIM practices has led to highly accurate data and faster project delivery in the construction industry (Perez-Perez et al. 2021; Soilán et al. 2020). To further improve this process, the industry and academia are exploring ways to automate the segmentation of point clouds into individual building components and model them using continuous surfaces of solid geometries (Perez-Perez et al. 2021). However, the process is still facing challenges that are partially solved, and the approaches still require some manual modeling and are based on proprietary modeling software (Deng et al. 2021a). The LiDAR point clouds were used also to generate derived products such as DTM, DSM or mesh models which will be used in turn for 3D city modelling and visualizations purposes (Biljecki et al. 2015; Guth et al. 2021). Thus, several improvements were made to effectively render massive point cloud data through the web allowing seamless data access (Oosterom 2015; Richter 2018). In addition, some tools are in common use that directly work with point cloud data, bypassing the complex and expensive approaches of deriving 3D city models from point cloud. More and more point cloud data are available and relevant. However,

[1] https://3dbag.nl/en/viewer.

working with point cloud data in the 3D city modeling and UDTs scopes remain challenging. Although the new improvement of CityGML 3.0 allows the use of point cloud data to mimic the city objects, the semantic information is not handled, and some approaches are proposed to extend the semantic capabilities of 3D point cloud data (Kutzner et al. 2020).

The raw point clouds are widely used, their usefulness can be limited due to their unstructured nature. Semantic point clouds, on the other hand, provide a semantic label associated with each point, which allows for a better understanding of the scanned urban scene and opens new possibilities for a range of urban applications (Ballouch et al. 2022; Ballouch and Barramou 2022). Semantic point cloud plays a crucial role in creating 3D urban models that form the primary basis of DTs. It offers an accurate basis for the creation of semantic models in different formats such as CityGML and its encoding CityJSON, or (IFC) Industry Foundation Classes (Beil et al. 2021). The use of semantic point clouds enables precise extraction of urban objects, which is an essential step in the 3D modeling process of cities. With a semantic point cloud, automated object modeling is simplified. For instance, buildings can be extracted and matched with the corresponding building footprints to generate the corresponding 3D models (Kong et al. 2022). Furthermore, an enriched semantic point cloud enhances the enrichment of 3D models by providing richer and more detailed information about the urban environment. Besides, the semantic richness of semantic point clouds can be useful to quickly identify objects relevant to a specific task or application in the context of urban applications. Recent advances in 3D semantic segmentation allow for the extraction of maximum semantic information that comprises the urban environment, such as vegetation, roads, railways, etc. This semantic information can be used to create the basis for the DT of a given city, i.e., the geometric model onto which other data can be integrated. In addition, it is important to regularly update the digital model to accurately reflect real-time changes in the urban environment and keep urban applications up to date. Besides, the use of semantic point clouds is an interesting source of data for training DL models for semantic segmentation tasks. By using semantically segmented point clouds, precise datasets can be formed to achieve high performing pretrained models in different urban contexts to meet the requirements of plenty of urban applications. Additionally, semantic point clouds can be used to extract building footprints, which is crucial for the 3D modeling of buildings. Similarly, airborne sematic point clouds can be used to extract roofs, enabling the creation of accurate models of building roofs that can be used to meet the specific requirements of urban applications. In addition, incorporating structured knowledge and semantics into 3D point cloud (beyond semantic segmentation) are beneficial in meeting the needs of urban applications (Poux and Billen 2019).

To conclude, 3D LiDAR point clouds in urban applications have grown increasingly important due to their rapid and cost-effective means of gathering accurate spatial information of urban settings. These point clouds capture the real-time state of the city for almost all spatial entities at various scales, depending on the laser scanning survey methods employed, whether airborne, terrestrial, or mobile. Enriched 3D semantic point clouds play a crucial role in creating 3D urban models, automating object modeling, extracting maximum semantic information, and updating urban application models.

Up to date, there are no initiatives that rely on enriched semantic 3D point cloud data to meet the DT requirements since they are primarily used as input data for urban modeling. Thus, deployed in the generation of semantic 3D city models. Indeed, using semantic point clouds as a fundamental input layer to build DTs deserves consideration. To better understand this, we must first identify the requirements of DTs for cities, the performance of semantic point clouds to address the limitations of 3D city models, and the possibilities of studying semantic point clouds as an alternative to perform simulations directly on point clouds without going to 3D models.

3 Is a Semantic 3D Point Cloud an Alternative to 3D City Model for DT Applications?

To address this key research question, we will split it into two sub-questions. Firstly, does the point cloud meet the DTs' requirements? (Sect. 3.1); Secondly, is the point cloud a good alternative to 3D city models? (Sect. 3.2). We finally give some research guidelines related to extending the use of semantic point clouds in DTs for cities (Sect. 3.3).

3.1 Semantic Point Cloud: An Input Layer to DTs for Cities

The presence discourse in the urban and geospatial context is predominantly about the relevance and the potentiality of considering semantic 3D city models as an input layer to create DTs for cities (Alva et al. 2022; DImitrov and Petrova-Antonova 2021; Ketzler et al. 2020; Würstle et al. 2022). However, it is worth considering the potentialities and advantages of semantic point clouds to serve DTs needs as a fundamental input layer without going through the 3D city modeling process.

To tackle this research question, it is interesting to identify the requirements of DTs for cities. Indeed, DTs for cities are conceptualized as a risk-free, living virtual ecosystem that mimics all the city elements to generate knowledge, assist urban decision-making through the city lifecycle, and provide outcomes at the city level (Hristov et al. 2022; Nguyen and Kolbe 2022; Würstle et al. 2022). Furthermore, from technical perspective, most of the research led to a tacit agreement on what constitutes a DT for cities in the geospatial domain and the Smart Cities initiatives previously announced by Stoter et al. (2021). Thus, DTs for cities are based on (1) 3D city models enriched with geometrical and semantic information, (2) often incorporate heterogenous data namely coupled with historical and sensor data in near or real time (at an appropriate rate of synchronization), thus enabling (3) a link (e.g., data flow between the real counterpart and the virtual twin and vice versa), (4) allowing updates and analysis through a set of simulations, predictions, and visualization tools, and (5) providing an integrated view of the multiple datasets and models through their life cycle, enabling to manage and adapt cities' current and future states.

If we intend to unpack the DT definition, we will first start from the assumption that the DT for cities is a digital realistic city replica that incorporates all its city features. Thus, we can clearly validate this characteristic since a point cloud by nature is a high geometrically 3D representation of urban environments such as cities and other landscapes. However, back to definition, a DT must have semantic and geometrical information. This is completely accurate from geometrical dimension of a point cloud but is not applicable for semantics. In this regard, various approaches are proposed to enrich the point cloud and extend its semantic capabilities, whether through 3D semantic segmentation (Hu et al. 2021), or a conceptual data model called "Smart Point Cloud Infrastructure" (Poux 2019), or data integration (GIS data, 3D city models) (Beil et al. 2021).

Although possibilities exist to tackle the lack of semantics in point cloud data, the enrichment of such data remains critical and challenging. Indeed, the current advancement in the scope of building DTs for cities is more focused on data integration approaches, including the association and integration of both point cloud data and semantic 3D city models using for example the new "PointCloud" module of CityGML 3.0 (Beil et al. 2021). This module provides a new concept to bridge the gap between the geometrically detailed point cloud data and the enriched 3D semantic model. The integration of both datasets intuitively assigns sets of points to the corresponding objects. The existing approach in CityGML 3.0 provides an alternative for extending point cloud data to cover more semantic information beyond classification using various methods. Thus, integration of point cloud data with different data sets from GIS, BIM, and 3D city models helps to overcome the limitations of each approach and meet the DT requirements.

At the same time, a widespread algorithm and approaches have emerged to extract 3D objects automatically and effectively by semantically segmenting LiDAR point clouds using supervised learning methods, including Machine Learning-based segmentation, as well as Deep Learning-based segmentation such as multi-view-based methods, voxel-based methods, and direct methods that consume point clouds directly. Recent advances in semantic segmentation allow the extraction of the main urban features, such as buildings, vegetation, roads, railways (Zhou et al. 2023), and many more that are relevant for DT's applications (Döllner 2020; Lehtola 2022; Masoumi et al. 2023).

In another hand, 3D semantic segmentation is relevant to update DTs for cities and track the changes at city-scale. That said that 3D semantic point cloud data enable the identification of the changes as they appear in the real world and updating corresponding information. For example, point cloud data allows to have a realistic and big picture of the status of an urban object under construction, especially if the current project does not have the necessary elements to generate a 3D model (i.e., lack of definitive footprint that is mandatory to generate accurate model). This says that the semantic point cloud can help in urban planning and management which is one of the common use cases of DTs for cities. In addition, the advantage of enriched semantic point cloud data is that almost all urban classes are extracted (i.e., static, and dynamic objects) and for specific applications, classes that are required or need to be updated are simply retained. Nevertheless, the classes that are not crucial are neglected. It is worth mentioning as well that for different use cases, different classes are deployed, which is completely in line with the DT's requirements that replicate all the city objects as one snapshot, and for each use case, the data will be derived. Hence, semantic 3D point cloud enables us to precisely define the urban classes, thus augmenting the performance of the semantic extendibility, improving modeling capabilities, giving new interpretability of the data from different perspectives, and opening new doors for various simulations and urban analysis.

Turning to one of the promising characteristics of a DT (i.e., the simulation feature), yet the available processes and simulation tools that involve the direct use of 3D point clouds are still limited. Few studies are conducted to explore the potential of this type of data. For example, the authors of Peters et al. (2015) introduced a new approach based on the medial axis transform to performing visibility analysis. The approach could be used for any typical airborne LiDAR data, which gives more realistic results and effectively handles the missing parts of the point cloud (e.g., walls and roofs). Furthermore, performing visibility analysis is more insightful when working with point cloud data, as vegetation is considered. Another study case on an urban scale performs the visibility analysis for both surface model and point cloud data and puts them together for in-depth analysis according to their efficiency and accuracy. To ensure intervisibility between the reference points (i.e., the observer and target points), the authors of Zhang et al. (2017) generate cubes for each point to block the sight lines. The study concludes that consistent input data (i.e., dense and classified point clouds) will certainly improve the findings.

On the other hand, solar radiation is a relevant use case in 3D urban modeling. Historically, solar irradiance was measured using DSM. However, 3D city models gained a significant amount of interest to improve the sun exposition estimations. In addition, the authors have developed a tool that uses point cloud data to model illumination and solar radiation (Pružinec and Ďuračiová 2022). The algorithm is based on voxels and has shown its capabilities for green areas as well as urban environments.

Figure 1 depicts an illustrative example from our research works, demonstrating the simulation of solar radiation performed on semantic point clouds. The point cloud data utilized in the study was acquired in the Flanders region of Belgium. The pre-trained RandLA-Net model (Hu et al. 2020) on the Semantic3d dataset (Hackel et al. 2017) was used for semantic segmentation of point clouds. The relevant semantic classes that have the potential to impact solar radiation were extracted, including high vegetation, low vegetation, buildings, and scanning artifacts. To perform the simulation, the "pcsrt" function proposed by Pružinec and Ďuračiová (2022) was used. The source code for this tool was adapted from its publicly available version on GitHub as an open-access resource (https://github.com/hblyp/pcsrt, accessed on August 2, 2022).

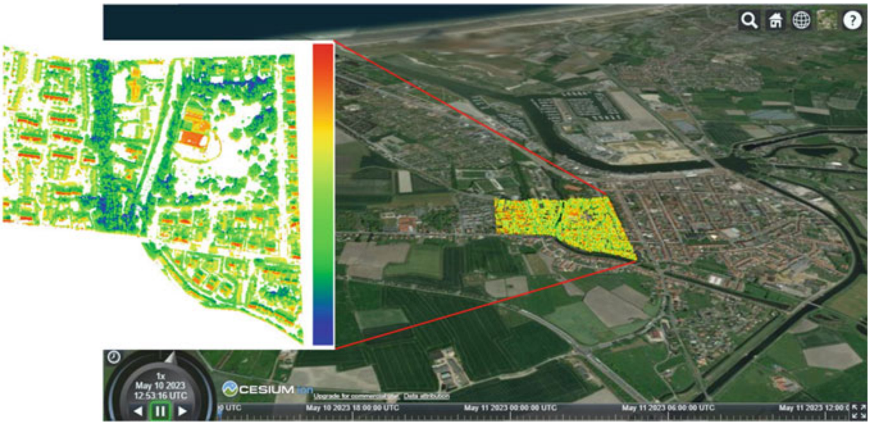

Fig. 1 Example of solar radiation performed on semantic point cloud

A further characteristic of DTs that is undoubtedly satisfied, is the visualization and the interactivity aspects. Point cloud data is supported through various visualization tools (i.e., web applications and game engines platforms). Additionally, point clouds are considered as a form of natural communication used as an input data to enhance immersivity and interactivity of Virtual Reality or Augmented Reality experiences. Moreover, for enhancing visualization, most of DT's initiatives tend to foster the ability to process, store, handle, and disseminate massive point clouds through the web, namely using the CesiumJS WebGL virtual globe. For instance, the Digital Twin of the City of Zurich sets a research agenda where further developments of the DTs for city are required namely, how to benefit from the derived mobile mapping point cloud data to improve the façades of the buildings as well as how to incorporate vegetation acquired from point cloud into the DTs. It is worth pointing that some visualization applications do not demand rich semantics, while others need specific attributes to perform simulations (Schrotter and Hürzeler 2020).

While the state of the art is well developed regarding the applications of 3D city models, some urban applications do not necessarily need a semantic 3D city model. Hence, enriched 3D semantic point cloud will certainly give new opportunities to perform some sophisticated analysis for DTs instead of creating surface models.

3.2 Semantic Point Cloud and Semantic 3D City Models: Advantages and Limitations

While it is out of the scope of this article to compare 3D semantic model-based DTs and enriched semantic point cloud-based DTs, we will nevertheless highlight certain advantages and limitations of both semantic 3D city model and semantic 3D point clouds.

3D city models nowadays exhibit significant differences due to various factors including data acquisition, processing, storage, dissemination, use, and maintenance, as well as technical, socio-economic, political, and cultural variations. Consequently, it has become challenging to identify best practices, assess the quality of 3D city models, foster their appropriateness for specific use cases, and integrate effectively diverse datasets. Moreover, comparing multiple datasets present some difficulties, creating ambiguity in selecting the most suitable one. These concerns have implications for urban DTs, which rely on 3D city models as a key component (Lei et al. 2022). Despite the availability of advanced 3D representation techniques and methods for creating 3D city models (Toth and Jóźków 2016), significant challenges remain in achieving accurate and interactive 3D modeling of the urban environment. It is not just a matter of representing the environment in 3D, but also ensuring that the model is closer to the real world by attempting to represent as many urban objects of the physical world as possible without being restricted to a specific feature (i.e., buildings as they represent the identity of the city).

Research has identified several problems associated with 3D modeling (Stoter 2020), including limited data collection capabilities (Ledoux et al. 2021), reduced levels of automation (Park and Guldmann 2019), the lack of established modelling standards and rules (Eriksson et al. 2020), and limited applications for visualizing city models (Liamis and Mimis 2022). There are three types of modeling techniques: geometric modeling, mesh modeling, and hybrid modeling. Geometric modeling uses simple geometric primitives (planes, cylinders, lines, etc.) to represent objects, which reduces the volume of generated data and allows for semantic data to be embedded in the model. However, this method is dependent on the algorithms used and the resulting representation may lack fine details. Mesh modeling is useful for representing fine surface details, but the generated data remains voluminous, making interpretation and manipulation laborious for the user. Furthermore, 3D mesh models have limited analytic capabilities. However, few studies are conducted to improve the usability and applicability of mesh models by integrating semantic 3D city models with 3D mesh models (Willenborg et al. 2018). Another related work enhances semantic segmentation of urban mesh using a hybrid model and a feature-based approach for semantic mesh segmentation in an urban scenario using real-world training data (Tutzauer et al. 2019). While meshes alone do not inherently allow semantic data to be embedded in the model since no shape or element recognition is performed. Semantic information could be introduced by modifying them or storing them using specialized data formats such as CityJSON that support semantics.

3D city modeling has different challenges that limit their full automation and usage. Firstly, there is an inconsistency between models generated using heterogenous dataset, reconstruction methods, and software, which affects geometry, appearance, and semantics. Standardization is the second challenge. Up to date, there are no common standards that are established to handle DTs for cities from a technical point of view. However, we should take advantage of the existing standards by enabling convergence between them in a meaningful way with respect to the discrepancies (different geometries, semantics, structures and various spatial scales). Data quality is a major obstacle to create 3D city models, with many existing models containing errors that prevent their use in other software and applications. Data interoperability involves converting 3D models from one format to another. Language barriers may hinder understanding and interoperability. Indeed, public administrations often do not provide integrated and standardized 3D city models, making further analysis difficult. In addition, datasets may be managed in different standards and have different sets of information, making them unqualified for particular use cases. There is a lack of means to characterize data and their fit for purpose. In addition to the challenge posed by the heterogeneous nature of 3D city models in terms of making comparisons, another issue arises from the data integration approaches (Lei et al. 2022). Data maintenance/governance is also a challenge, with governmental organizations lacking strategies for updating and maintaining different versions of the data. Lastly, implementing 3D data in the real world requires more precise definitions of specifications, validation mechanisms, clear semantics to address knowledge and skills gaps and integration of public and private sector models (Stoter et al. 2021).

It is well known that in the scientific literature and in practice, the point cloud is considered a primary resource for reconstructing a semantic 3D city model. Indeed, 3D city models are by definition, a simplification of the real world (i.e., an abstraction at a certain LoD). With this in mind, 3D city models do not aim to represent all the features of the real world in the same detail as point cloud data. Thus, point cloud allows to avoid the abstraction needed for 3D city models, and objects such as trees are correctly rendered instead of being generalized according to city modeling standards. Furthermore, for a given point cloud, different 3D semantic model could be generated according to the use case, the standards and the quality of the acquired data. Moreover, recent advances in semantic segmentation and point cloud processing have made significant progress toward optimizing the algorithms and approaches.

Another particularity of point cloud data is the lack of a specific standard to generate and process them. However, there may be variations in format and representation (e.g., voxels). In contrast, for 3D city models, there are many standards deployed to generate a semantically rich 3D model, namely CityGML and its JSON encoding, CityJSON. These standards are recognized as the foundation of DTs for cities. The existence of a range city modeling standards raises data interoperability issues. This does not mean that the standardization efforts are irrelevant, but this standard heterogeneity makes data integration challenging especially in the context of creating DTs in practice. This is also justified by having several 3D city models for the same urban scale from different stakeholders, but there is usually a single national LiDAR acquisition. Of course, for some cities, we may find more than one acquisition, however they are captured at different timescale having overlapped regions. It is also sometimes collected to fill some missing information for large scale aeras (i.e., urban land expansion). This extension of point cloud data to the temporal scale serves in the context of DTs given a 4D point cloud. However, this point cloud requires a high storage infrastructure, and detecting the changes is tricky since point-to-point corresponding is problematic.

Regarding the point cloud, another challenge that hinders its full potentials is the lack of topology, which can make simulating object behavior challenging.

For instance, connections between different urban objects are difficult to represent without topology, which is why 3D models with a surface model are preferred for such representations, which are relevant for simulations namely for Computational Fluid Dynamics (CFD). Furthermore, 3D city models offer the possibilities to store attributes for objects (e.g., buildings) but also for surfaces, to build hierarchy (Building + Building Part) and to store the type of surfaces (namely used for energy modelling). It is also worth mentioning that 3D city models are significantly taking less space (compared to a raw point cloud, which is more than 10pts/m2 nowadays).

To conclude, semantic point clouds and semantic 3D city models are both great inputs to build DTs for cities. Both bring new opportunities but still have some weaknesses. However, all DT initiatives invest in hybrid models, enabling them to bridge the gap between different approaches and compensate for the limitations of the others.

3.3 Semantic Point Cloud: A New Research Field for DTs

The potential benefits of implementing this new research path include reducing the cost of modeling, computation time, to take advantage of the semantic richness of the semantic point cloud since frequently we make large-scale acquisitions and heavy processing operations to end up exploiting only the buildings class in 3D modeling without other details of the urban environment (i.e., vegetation, roads). This approach also avoids the complexities of 3D modeling, particularly for other urban objects than buildings like transportation infrastructure and vegetation. It's also advantageous for updating urban DTs and conducting specific simulations that require accurate and detailed information about the urban environment. The proposed reflection challenges the frequently used approach of relying solely on 3D modeling for DTs applications and suggests that semantic point clouds can be a viable alternative, particularly for addressing the limitations of 3D models and meeting the needs of DTs in an easy and effective way. However, it is important to note that while semantic 3D point clouds may be a useful input layer for some DT applications, they may not be a complete replacement for 3D city models in all cases. The choice between using semantic 3D point clouds or 3D city models as an input layer for DT applications will depend on the specific application purposes, the available resources, and the required level of accuracy and detail.

Further research is needed to explore the potential of semantic point clouds and develop new approaches for integrating them into DTs applications.

As a first step of our reflection, we investigated the feasibility of some simulations that can be performed directly on point clouds. In the next steps, we will evaluate and validate our approach by comparing it with 3D city models that utilize the same data, in order to affirm its effectiveness and accuracy.

This work also suggests some perspectives to meet the requirements of DTs:

- Future research should focus on exploring the potential of semantic point clouds and developing integration methods for their use in DTs applications.
- It is important to consider the specific requirements of the application, available resources, and desired level of accuracy and detail when choosing between semantic 3D point clouds and 3D city models as an input layer for DT applications.
- Establishing standards for DTs could bring several benefits. Firstly, it would enable increased interoperability among different systems applying this concept, thereby facilitating collaboration and data exchange. Additionally, clearly defined standards could help ensure the security and protection of data, as well as the quality of the created models.
- Defining a preliminary LoD for semantic point clouds can help ensure the quality and usability of data for specific DTs applications.
- Developing new approaches and algorithms that enable the direct simulation of urban environments using semantically rich point clouds instead of generating 3D model, more precisely for sophisticated simulations such as computational fluid dynamics.
- Studying change detection and updating of DTs with semantically rich point clouds.

4 . Conclusions

In this paper, we have proposed a research reflection on the use of semantic 3D point clouds as an alternative to 3D city models for DTs needs. We have introduced the limitations and performance of both 3D city models and semantic point clouds. Furthermore, we explain how semantic point clouds can overcome the limitations of 3D city models to create a DTs. We then presented the initial guidelines of the suggested reflection, which aims to answer the research question of whether a point cloud can meet the requirements of DTs by going beyond considering a semantic point cloud as input for modeling and performing simulations directly on it without resorting to 3D modeling. This research direction should be further explored to match point clouds to DTs' requirements and extend their urban applications. In short, semantic 3D point clouds appear as potential data that goes beyond the current deployment of creating 3D city models, which puts them at the forefront of new needs in urban simulations.

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