Reviewing Open Data Semantic 3D City Models to Develop Novel 3D Reconstruction Methods

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Abstract

Structured semantic 3D city models are pivotal in creating urban 3D digital twins. The wide adoption of such models has been primarily enabled by robust, model-based, and automatic 3D reconstruction methods. However, these methods impose requirements on the reconstruction, mainly restricting the solution space to several model types and relying on accurate 2D footprints. Recent research shows that deep-learning-based methods promise highly generic solution space and are footprint-free. Yet, the current training and test datasets are limited, hindering the methods' development. In this work, we analyze the ubiquity of already existing, open 3D city model datasets and their potential to serve as a large-scale training and test set for 3D reconstruction, where 27 potential dataset collections have been identified. Our review shows that more than 215 million building models are readily available. We firmly believe that this review will facilitate further research on robust automatic 3D city model reconstruction and serve as a reference for benchmarking 3D city models.

1. Motivation

Semantic 3D city models are crucial in many applications, such as simulating urban floods, estimating building solar potential, and predicting building energy demands, among others (Biljecki et al., 2015). Unlike mesh-based models, structured 3D models are characterized by watertight geometry, object-level modeling, and hierarchical semantics at various Levels of Detail (LODs), frequently following the CityGML standard and its encodings in GML (Gröger et al., 2012, Kutzner et al., 2023) and CityJSON (Ledoux et al., 2019).

For many years, the automatic and robust reconstruction of semantic 3D city models has been considered essential for providing worldwide semantic 3D city model accessibility. Nowadays, there are well-established automatic Level of Detail (LOD)1 and 2 building reconstruction approaches, as underscored by adoption in both open-source and commercial software (Muñumer Herrero et al., 2022). Yet, deep learning approaches for LOD1 and 2 reconstructions are set to become a vital factor for more accurate reconstruction methods' development, which, however, necessitate a great deal of high-quality and high-variability worldwide data (Wang et al., 2023). Recent years have also witnessed a renewed importance in at-scale LOD3 reconstruction, which, however, lacks ground-truth data (Wysocki et al., 2023).

The limited knowledge about the models' availability and the absence of actual data hamper the development of novel 3D reconstruction methods. One of the main traits facilitating the research concerning semantic 3D city models is their global and free-of-charge availability. However, to date, there has not been any comprehensive scientific publication devoted to analyzing the potential of semantic 3D city models for training and testing of deep-learning-based models for 3D object reconstruction (Figure 1). Consequently, the open-data semantic 3D model distributions remain primarily unknown, along with their per-dataset characteristics.

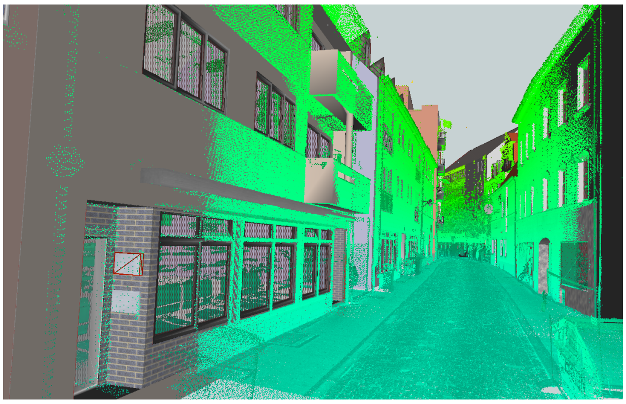

Figure 1. The object reconstruction at various Levels of Detail LOD requires on par 3D measurements. Here, the street-level mobile mapping point cloud enabled modeling of LOD3 building models characterized by facade elements.

In this paper, our contributions are as follows:

- Analyzing openly available semantic 3D city model datasets worldwide.
- Evaluating object-level statistics of semantic 3D city models with the object type distinctions.
- Identifying potential datasets for testing 3D reconstruction of semantic 3D building models.

2. Related Works

Much research has been devoted to benchmarking semantic 3D city models, considering their various aspects. Biljecki et al., present use cases and applications of semantic 3D city models based on the analysis of research publications and practical implementations (Biljecki et al., 2015). Their publication and the following works (Willenborg et al., 2018, Schwab and Kolbe, 2019), show that the semantic models can be deployed in applications such as estimating heating demand, analyzing photovoltaic potential, simulating traffic, or assessing natural hazards risk, among others.

Other publications have been devoted to proposing assessment criteria for 3D city models (Jeddoub et al., 2023, Uggla et al., 2023, Biljecki, 2020). For instance, Lei et al., propose a metric called "3D City Index", which aims to rank 3D city models around the globe under 47 different aspects, allowing for their performance benchmarking (Lei et al., 2023).

Analogously to the semantic 3D city models' availability research, the 3D reconstruction research has witnessed numerous publications listing and ranking 3D reconstruction test sets (Rottensteiner et al., 2014, Yeshwanth et al., 2023). Wang et al., introduce the Building3D dataset, where the comparison list to other popular 3D-reconstruction-related datasets is shown (Wang et al., 2023). In this research community, terms such as wireframe and lightweight model reconstruction are often used (Wang et al., 2023, Nan and Wonka, 2017), which can be related to the so-called boundary representation (B-Rep), frequently utilized for semantic 3D city models (Kolbe and Donaubauer, 2021).

The important aspect of 3D reconstruction is often the 3D semantic scene understanding, whereby the type of sensor data shall match the respective envisioned LOD reconstruction (Figure 1). As shown in the ArCH (Matrone et al., 2020) or in the TUM-FAÇADE (Wysocki et al., 2022b) datasets, the semantically enriched point clouds can have a direct link to the semantic 3D reconstruction classes. Also, in these studies, available test sets are ranked based on various aspects. They also discuss the potential of street-level measurements for reconstructing high-detail building models, e.g., LOD3 (Wysocki et al., 2022a).

However, to date, the existing works lack a detailed joint analysis of open data semantic 3D city models and their 3D measurement data in the context of 3D reconstruction evaluation. In this research area, a count of city model objects, along with the type of 3D measurement data, is essential for having a potential 3D reconstruction test set; this information has not yet been assessed to the best of our knowledge.

3. Method

In our analysis, we follow the approaches of such comprehensive reviews as (Biljecki et al., 2015, Lei et al., 2023). The systematic scoping analysis concerns related research publications, Internet web-sources, and geoportals. We also include presentations, interviews, and publications on leading 3D urban and computer vision conferences, e.g., the 3D GeoInfo 2023, Munich, Germany, or the Computer Vision and Pattern Recognition 2023, Vancouver, Canada. Additionally, region- and country-specific information geoportals are analyzed. Another leading source of information is the official repository of the CityGML standard that links to multiple implementations, datasets, and other related resources (OGC, 2024). To list the potential datasets for 3D building reconstruction, we also analyze whether the existing models include any additional open data enabling 3D reconstruction, such as aerial laser scanning and images, terrestrial observations, and building footprints.

We understand that such lists are subject to change with time. Therefore, we include all the dataset references in the OGC-recognized open repository entitled "Awesome CityGML"[1]. We aim to regularly update the list and the respective links and invite the community to contribute to the repository.

3.1 Terminology

We define "semantic 3D city models" as urban models comprising object-level geometry and semantics stored in a hierarchical data model that also describes the object-to-object relationship (Kolbe and Donaubauer, 2021). The so-called virtual reality models, which represent a geometry just by a set of 3D meshes with appearance, are excluded. Unlike virtual reality models, the semantic models are commonly represented by watertight geometry, enabling volumetric space understanding by accumulating outer-observable surfaces of boundary representation (B-Rep). Often encountered direction in the 3D reconstruction community is the wireframe reconstruction, which, however, deals with reconstructing vertices and their connecting lines, which finally represent object edges but do not describe surfaces nor solids (Wang et al., 2023). We also differentiate the semantic 3D city models from the Building Information Modeling (BIM) models: The former deals with district-, city- and country-wide models, while the latter focuses rather on single sites. Furthermore, the modeling paradigm differs, as BIM models frequently follow the constructive solid geometry (CSG) approach. For an elaborate discussion on the differences, see (Kolbe and Donaubauer, 2021).

3.2 The OGC Standard CityGML

When referring to the LOD of building models, we follow the typical division proposed by the CityGML standard (see Figure 2), which is issued by the Open Geospatial Consortium (OGC) and stands as the primary specification for semantic 3D city modeling. CityGML is used as the official standard for representing semantic 3D city models in many countries and regions, for example, Japan (Seto et al., 2023), Sweden (Uggla et al., 2023), Singapore (Soon and Khoo, 2017), Vienna (Lehner et al., 2024), Helsinki (Rossknecht and Airaksinen, 2020) or Germany (Roschlaub and Batscheider, 2016). Many datasets are available as open data and modeled according to CityGML version 2.0 (Gröger et al., 2012). CityGML version 3.0 was published in 2021 and contains revised and extended modeling concepts (Kolbe et al., 2021). The standard has a modular structure with spatial-semantic concepts for representing different thematic components of semantic 3D city models such as buildings, bridges, transportation, vegetation, city furniture, the terrain, or waterbodies. The conceptual model of CityGML can be implemented using different encodings such as GML, JSON, OWL, or relational databases.

4. Review

4.1 Current Requirements for Reconstructing Semantic 3D City Models

The established approach to automatically reconstruct semantic 3D city models assumes the availability of two types of data sources, namely a) 3D observations (laser- or image-based point clouds) and b) 2D non-overlapping object footprints. The latter minimizes the reconstruction space and segments objects, while the former provides 3D shape cues. Such an approach has been adopted in both commercial and open software and largely

[1] https://github.com/OloOcki/awesome-citygml

https://doi.org/10.5194/isprs-archives-XLVIII-4-2024-493-2024 | © Author(s) 2024. CC BY 4.0 License.

Table 1. Semantic 3D city models provided and updated as open CityGML datasets by public authorities (country, state, or municipal level) categorized by country and spatial extent. The *CityGML modules* number totals the repositories that contain objects of the respective module (e.g., a repository can comprise objects of the Building as well as the Vegetation module). The Relief column includes separate digital terrain files.

Country		**# Repositories by spatial extent**				**# CityGML modules**						
#	Name	$\sum$	country	region	city(ies)	Building	Transportation	Bridge	Vegetation	Relief	CityFurniture	Multiple epochs
AT	Austria	2	–	–	2	2	–	–	–	–	–	–
BE	Belgium	1	–	–	1	1	–	1	–	–	–	–
CA	Canada	1	–	–	1	1	–	–	–	1	–	–
CZ	Czech Republic	1	–	–	1	1	–	–	–	1	–	–
EE	Estonia	1	1	–	–	1	1	–	–	1	–	–
FI	Finland	4	–	–	4	4	1	1†	1	1	1	1
FR	France	1	–	–	1	1	–	1	–	–	–	1
DE	Germany	15	–	12	3	15	–	7†	–	6	–	1
JP	Japan*	1	–	–	1	1	1	1	1	1	1	1
LV	Latvia	1	–	–	1	1	–	–	–	–	–	–
LU	Luxembourg	2	–	–	2	2	–	–	–	–	–	–
NL	Netherlands	3	1	1	1	2	1	1	1	1	–	–
PL	Poland	3	1	–	2	2	–	–	2	1	1	1
CH	Switzerland	1	–	–	1	1	–	1†	–	–	–	–
US	United States of America	1	–	–	1	1	–	–	–	–	–	–
	Total: 15	38	3	13	22	36	4	13†	5	13	3	5

* *Japan's project PLATEAU currently covers over 200 cities, towns, and wards (Seto et al., 2023) and is counted as a single repository here.*
† *Repositories contain bridge objects that are not assigned to the Bridge module but to another module, such as the Building module.*

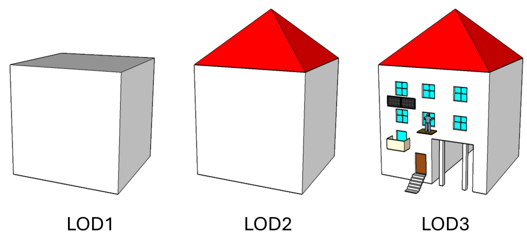

Figure 2. Level of Detail (LOD) in semantic 3D building models, where LOD1 is characterized by a cuboid model, LOD2 is enriched in specific roof shape, and LOD3 comprises additionally facade elements.

enabled semantic 3D city models adoption (Muñumer Herrero et al., 2022, Roschlaub and Batscheider, 2016, Haala and Kada, 2010). For instance, given their footprint and a respective point cloud, the open source software ”3Dfier” automatically reconstructs seven urban object classes at LOD1: Building, Terrain, Road, Water, Forest, Bridge, Separation (Ledoux et al., 2021).

The prominent branch that has been established within the city model reconstruction is the semantic 3D building reconstruction, owing to the prominence of buildings in cities and their wide range of applications. Here, in addition to the approaches mentioned above, a footprint-free paradigm emerged, showing promising results (Nan and Wonka, 2017). On the other hand, researchers and practitioners have also explored observation-free methods, where 3D building models are extruded using only footprints and the estimated height, e.g., using a count of stories (Biljecki et al., 2017).

The current research and practice show that LOD1 and LOD2 building models can be automatically reconstructed using a model-based approach comprising a set of region-typical building shapes, given the aerial 3D observations, usually airborne laser scanning (ALS) due to its robustness, and cadastre footprints (Roschlaub and Batscheider, 2016). The cadastre footprints are crucial to the reconstruction as they define strict boundaries between various objects based on the cadastre-derived ownership, easing partitioning of 3D observations per entity, especially in the case of city blocks or terraced houses where pure geometric differences are hardly recognizable. Such trait is essential for maintaining synchronized 3D and 2D cadastral records.

However, the high reliance on error-free footprints hampers further worldwide adoption in countries where cadastre is unavailable or unreliable (Biljecki, 2020). Also, the model-based approach restricts the solution to the set of predefined primitives, which reduces its adaptability to out-of-distribution building shapes.

To tackle these challenges, researchers have recently commenced investigating the machine and deep learning models for up to LOD2 building reconstruction (Wang et al., 2023, Chen et al., 2023). Such a data-driven strategy promises higher adaptability of reconstructed 3D shapes and reconstruction without prior footprints. This trend is underscored not only by publications but also by a recent CVPR Workshops challenge focusing on such data-driven reconstruction (CVPR Workshop, 2024). Nevertheless, this research direction remains still in its infancy.

Simultaneously, the research shows that recent novel methods have been devoted to automatic LOD3 reconstruction, which has not yet been widely applied in the practical scenarios and software. Here, the vital components for the automatic reconstruction are street-level 3D measurements and existing LOD1 or 2 building models (Pantoja-Rosero et al., 2022, Wysocki et al., 2022a, Huang et al., 2020). One of the main issues hampering the development of these methods is the scarcity of ground-truth LOD3 models for training and testing methods (Wysocki et al., 2023).

A research direction that is also worth mentioning is satellite-based 3D model reconstruction, primarily with optical (Sun et al., 2024) and Synthetic Aperture Radar (SAR) (Bagheri et al., 2019) observations. However, this approach is beyond the scope of this publication.

4.2 Semantic 3D City Models Availability

Our results indicate that 15 countries offer governmental semantic 3D city models at no cost. We present the results in

Table 1, where the number of repositories providing administrative data on semantic 3D city models according to the CityGML standard for each country is listed. Furthermore, Table 1 indicates whether datasets are available nationwide or in individual states or cities. Additionally, the availability of different thematic modules such as buildings, transportation, or vegetation is indicated. Several countries also offer datasets representing different epochs.

While building models are frequently represented, semantic 3D models of transportation infrastructure are gaining relevance. This trend is due to the increased availability of source data, e.g., from mobile mapping campaigns, improved 3D reconstruction methods, and requirements of new and emerging applications and use cases such as automated driving or urban digital twins (Schwab and Kolbe, 2019). Thus, in addition to the availability of 3D building models, openly available semantic road and streetspace models are included and analyzed in this publication as well.

4.2.1 Semantic 3D Building Models 3D models of buildings are the most commonly represented component of semantic 3D city models and are available for all locations summarized in Table 1. In total, 38 repositories providing (official) semantic 3D city models as open data in the CityGML format have been identified, including 36 repositories containing representations of buildings. Countries such as Estonia or the Netherlands provide country-wide building models as open data. Still, semantic 3D building models, according to the CityGML standard, are only regionally available in other locations. In Germany, for example, currently, 14 out of 16 states already provide building models in LOD1 and LOD2 as open data. Some cities provide additional building models, often represented at a higher LOD and with image-based textures. Table 2 provides a more detailed overview of the total number of individual building objects available in different countries and regions. Depending on the available LOD, individual building models contain further semantic information on the individual roof-, wall- or ground surfaces (LOD2) or information on doors, windows, and more detailed roof structures (LOD3).

4.2.2 Semantic 3D Transportation Models While most available datasets still focus on models of buildings, representations of other thematic components of cities are increasingly available. This representation includes transportation infrastructure such as road networks (Beil et al., 2020). The available open data on roads provided according to CityGML is usually limited to individual cities or regions. The newest version, 3.0 of CityGML, provides revised and extended concepts for modeling road objects and introduces a Level of Granularity (LoG) concept for indicating the degree of semantic decomposition of roads and other transportation infrastructure. This concept includes LoG ”area” for objects representing the entire width of a road, LoG ”way” for individual carriageways, or LoG ”lane” for lane-level representations.

While some of the existing open data on roads are available according to CityGML 2.0 and thus does not explicitly provide information on the contained level of granularity, this information is analyzed and provided for each dataset in Table 3. This Table showcases the semantic capabilities of these datasets and only includes representations of roads that are available according to CityGML. In some regions, CityGML data is available according to version 2.0 and version 3.0. Due to revised and extended concepts in the newer version of the standard, the increased number of available object types and attributes leads to large

Table 2. Total number estimates of semantic 3D building models for selected countries from public authorities and third parties marked with an asterisk, such as research institutes. All the references available under the ”Awesome CityGML” repository.

Country	Total	LOD	Source
Czech Republic	0.1 M	2	housing statistics
Estonia	0.8 M	1,2	dataset
Germany			
Bavaria	9.8 M	2	federal agency report
Berlin	0.6 M	2	federal agency report
Brandenburg	2.4 M	1,2	federal agency report
Bremen/Bremerhaven	0.3 M	1,2	federal agency report
Hamburg	0.4 M	1,2	federal agency report
Hesse	5.0 M	2	federal agency report
Ingolstadt*	56	3	dataset
Lower Saxony	6.9 M	1,2	federal agency report
North Rhine-Westphalia	11.4 M	1,2	federal agency report
Saxony	2.2 M	1,2	federal agency report
Saxony-Anhalt	1.8 M	1,2	federal agency report
Schleswig-Holstein	2.4 M	1,2	federal agency report
Thuringia	2.3 M	1,2	federal agency report
tum2twin*	28	3	dataset
Japan: PLATEAU project			
$>$ 150 cities	18.3 M	1,2	(Seto et al., 2023)
Kasukabe City	29	3	dataset
Kawasaki City	9	3	dataset
Kofu City	8	3	dataset
Kyoto City	138	3	dataset
Niigata City	30	3	dataset
Numazu City	472	3	dataset
Osaka City	15	3	dataset
Sarabetsu Village	14	3	dataset
Tamana City	4	3	dataset
Tokyo: Minato Ward	92	3	dataset
Tsukuba City	3	3	dataset
Yokohama City	37	3	dataset
Netherlands	10.0 M	2	(Peters et al., 2022)
Poland			
Country	15.5 M	1,2	federal agency report
Poznań	0.1 M	1,2	dataset
Poznań	14	3	dataset
Switzerland			
Zurich	57.1 K	2	dataset
United States of America			
Open City Model*	125.0 M	1	dataset description
New York City	1.1 M	1,2	dataset
TOTAL	216.5 M		

Table 3. Number of semantic transportation objects and their parts, available Level of Granularity (LoG) and CityGML version. All the references available under the "Awesome CityGML" repository.

Country	City / Region	LoG	# Objects	Version
DE	Brunswick	lane	121,143	2.0
DE	Brunswick	lane	171,217	3.0
DE	Highway A9	lane	2,341	2.0
DE	Highway A9	lane	3,321	3.0
DE	Ingolstadt	lane	4,877	2.0
DE	Ingolstadt	lane	7,867	3.0
JP	Japan: PLATEAU project			
JP	$>$ 50 cities	area		2.0
JP	Gifu City	way	823	2.0
JP	Kasukabe City	lane	132	2.0
JP	Kawachinagano City	way	901	2.0
JP	Kumagaya City	way	1,823	2.0
JP	Kyoto City	way	64	2.0
JP	Niigata City	way	2,718	2.0
JP	Numazu City	lane	1,206	2.0
JP	Sarabetsu City	way	1,614	2.0
JP	Shinagawa City	way	1,781	2.0
JP	Tamana City	way	17	2.0
JP	Tokyo*	area	200,334	2.0
JP	Tokyo: Takeshiba model	lane	124,086	2.0
JP	Tokyo: Minato Ward	way	18,675	2.0
JP	Tsukuba City	lane	851	2.0
JP	Yokohama City	lane	379	2.0
AU	Melbourne	way	137,106	2.0
US	New York City	area	149,292	2.0
US	New York City	way	459,742	2.0
DE	Wolfsburg	lane	16,350	2.0
DE	Wolfsburg	lane	23,054	3.0

object numbers in datasets utilizing concepts of CityGML 3.0. The given number of objects per dataset includes all individual transportation-related objects such as Roads, TrafficAreas, or AuxiliaryTrafficAreas.

Using the open source OpenDRIVE to CityGML converter r:trån, any openly available OpenDRIVE data can be converted to CityGML (2.0 and 3.0) automatically (Schwab et al., 2020), which is how the data of Brunswick, the highway A9 in Germany, Ingolstadt and Wolfsburg was created. In addition to this data, open data on roads of Melbourne, New York City, and Tokyo can be found for download[2].

While there exist further CityGML-compliant datasets representing semantic road models for other locations such as Singapore (Soon and Khoo, 2017) or Vienna (Lehner et al., 2024), this data is not openly available. A growing number of cities in Japan also provide road models as open data, which were created in the PLATEAU project (Seto et al., 2023). While most of the data currently is provided in granularity "area", some selected roads are modelled up to level of granularity "way" or "lane". Selected examples of Japanese cities providing road models in higher levels of granularity are included separately in Table 3. However, the data is provided in a 3D compound coordinate reference system, combining horizontal geographic coordinates in degrees and a vertical part using a metric reference system. Thus, datasets must first be transformed into a projected coordinate system to work with the data more conveniently. This was done for the example data of Tokyo* in granularity "area", which is included separately in the Table and available for download via the provided source link.

[2] https://go.tum.de/531120

It is worth noting that the city of Espoo in Finland also provides CityGML road models via Web Feature Service (WFS). CityGML-compliant models of other transportation, such as (real-world) railway networks, are mostly not openly available so far. Yet, point cloud segmentation datasets concentrating on railways are emerging (Kharroubi et al., 2024).

4.3 Miscellaneous

Semantic 3D city models can include not only buildings and streetspace models but also other thematic components such as vegetation, city furniture, waterbodies, bridges, railways, land use, or the terrain. Individual thematic modules within the CityGML standard specify these object-type parts. While semantic 3D models representing this kind of city object are typically only available for a limited spatial extent, some examples of open CityGML datasets provide this information. For instance, the Japanese PLATEAU project provides CityGML-compliant models on bridges, vegetation, city furniture, waterbodies, land use and the relief for a large number of cities. Generalized models of bridges in LOD1 are available in Germany, Switzerland, Finland, or the Netherlands. Some datasets in Table 3 also include 3D information on city furniture and vegetation objects (e.g., Ingolstadt). Other notable examples include Estonia, which offers official LOD1 bridge models for the entire country, and the Polish Opolskie voivodeship providing LOD1 tree models.

5. Potential for Developing Deep Learning 3D Building Reconstruction Methods

Owing to the abundance of semantic 3D building models (Table 1) and maturity of the building reconstruction methods, we concentrate our analysis on this part of city models. As shown in Table 4, there are 27 datasets with the identified potential for the training and testing of 3D building reconstruction methods. Our criteria while selecting the datasets are a) having at least LOD1 building models according to the CityGML standard, b) having at least one source of aerial or terrestrial 3D measurements; we include only digital surface model (DSM) and point clouds with the ground sampling distance of less than $1\,\mathrm{m}^2$.

Most of the datasets (23) hold the potential to train and validate reconstruction methods up to LOD2, at the national- (3), regional- (7), and city- (13) levels. This trait is enabled by the availability of aerial point clouds from ALS or multi-view stereo (MVS), and roof-detailed LOD2 building models. Note the partial availability for Poland of LOD2 in Table 4: Approximately half of the country is available at LOD2, while the whole country is at LOD1. The increasing interest in the LOD3 building reconstruction is worth noting, reflected by small-scale projects in cities such as Munich, Germany (tum2twin), Ingolstadt, Germany, and Poznań, Poland. We expect an increasing amount of such data owing to a) the increasing availability of mobile mapping point clouds offering street-level measurements capturing the facade details, which are the essential part of LOD3 building models; b) increasing robustness of LOD3 reconstruction methods (Wysocki et al., 2023, Huang et al., 2020, Pantoja-Rosero et al., 2022). For example, the city of Vienna, Austria, has already publicly released its mobile mapping point clouds. However, the LOD3 models are not present.

Our analysis also shows that some of the datasets have already been adapted for training and testing of deep-learning-based 3D building reconstruction methods, i.e., 16 cities in Estonia stand

Table 4. List of datasets revealing potential for training and validation of deep learning building reconstruction methods, where the feature is present (✓), absent (✗), and partially available (∼). The links are available under the open repository "Awesome CityGML" and will be successively updated.

Name	Country	Size	Aerial?	Terrestrial?	Footprints?	LOD3	LOD2	LOD1	Validation up to
tum2twin	DE	city block	✓	✓	✓	✓	✓	✓	LOD3
Ingolstadt	DE	city block	✓	✓	✓	✓	✓	✓	LOD3
Poznań	PL	city	✓	∼	✓	∼	✓	✓	∼LOD3
Vienna	AT	city	✓	✓	✓	✗	✓	✓	LOD2
Prague	CZ	city	✓	✗	✓	✗	✓	✓	LOD2
Diekirch/Bastendorf	LU	city	✓	✗	✓	✗	✓	✓	LOD2
Riga	LV	city	✓	✗	✓	✗	✓	✓	LOD2
Espoo	FI	city	✓	✗	✓	✗	✓	✓	LOD2
Helsinki	FI	city	✓	✗	✓	✗	✓	✓	LOD2
Lyon	FR	city	✓	✗	✓	✗	✓	✓	LOD2
Berlin	DE	city	✓	✗	✓	✗	✓	✓	LOD2
Bremen/Bremerhaven	DE	city	✓	✗	✓	✗	✓	✓	LOD2
Potsdam	DE	city	✓	✗	✓	✗	✓	✓	LOD2
Rotterdam	NL	city	✓	✗	✓	✗	✓	✓	LOD2
Zurich	CH	city	✓	✗	✓	✗	✓	✓	LOD2
New York	US	city	✓	✗	✓	✗	✓	✓	LOD2
Bavaria	DE	region	✓	✗	✓	✗	✓	✓	LOD2
Brandenburg	DE	region	✓	✗	✓	✗	✓	✓	LOD2
North Rhine-Westphalia	DE	region	✓	✗	✓	✗	✓	✓	LOD2
Saxony	DE	region	✓	✗	✓	✗	✓	✓	LOD2
Saxony-Anhalt	DE	region	✓	✗	✓	✗	✓	✓	LOD2
Schleswig-Holstein	DE	region	✓	✗	✓	✗	✓	✓	LOD2
Thuringia	DE	region	✓	✗	✓	✗	✓	✓	LOD2
Netherlands	NL	country	✓	✗	✓	✗	✓	✓	LOD2
Poland	PL	country	✓	✗	✓	✗	∼	✓	∼LOD2
Estonia	EE	country	✓	✗	✓	✗	✓	✓	LOD2
USA	US	country	✓	✗	✓	✗	✗	✓	LOD1
$\sum$ 27									

as a test set for ALS-based reconstruction of building roofs (Wang et al., 2023). We also recognize that the listed datasets can serve different purposes than sole 3D reconstruction. For example, the city of Lyon, France, and its multi-epoch models have been utilized for generating simulated point clouds and served as experimental data for developing change detection algorithms (de Gélis et al., 2023).

Notably, the analysis revealed that other datasets were excluded based on our criteria, which yet hold the potential to serve in the future as a validation set: They either lacked semantic 3D building models or aerial observations freely available. For example, the UK and Denmark provide ALS datasets at no cost; however, no building models are available. The International Society for Photogrammetry and Remote Sensing (ISPRS) Vahingen, Germany, and Toronto, Canada, datasets used to develop the now established building reconstruction methods, provide only geometry in DWG files (Rottensteiner et al., 2014). Similarly, the whole of Switzerland is covered in 3D building models. However, only DXF and File Geodatabase are free of charge, while the CityGML dataset is available for a fee. Yet another dataset of Victoria, Australia, provides ALS point clouds covering approximately 60% of the state and 99% of the state's populated areas. However, only a few selected regions are available at no cost. The complete list of datasets with links and references is available under the open repository[3].

Also noteworthy are datasets stemming from a satellite-based reconstruction, such as the ones in China (Sun et al., 2024), which offer 3D building models but not the source satellite images.

5.1 Limitations and Challenges

This work aims to analyze the worldwide availability of semantic 3D city models and related source data. Although we have identified and analyzed multiple datasets, we acknowledge that the list can still be extended in the future.

One of the primary obstacles we observe is the heterogeneity of the geoportals: Their layout and download tools vary significantly from country to country and even from city to city. Also, some of the portals provide functionality to download the data directly from a geoportal (e.g., Poland), while the others offer a separate download page (e.g., Bavaria). Another challenge is the language barrier: Most geoportals and related websites offer their services in the country-native language, with several exceptions offering duo-lingual services (e.g., native and English language). Furthermore, the metadata are frequently absent or incomplete (as indicated in Tab. 2); thus deriving object-level statistics proves cumbersome. We aim to mitigate the limitation by contributing and providing an open repository "Awesome CityGML", where each interested party can contribute with their own dataset. We firmly believe that the collaborative community spirit can ensure the list comprehensivness.

6. Conclusions

In this work, we present an elaborate analysis aiming to maximize the awareness and accessibility of the open city models, facilitating the development of novel 3D reconstruction methods:

[3] https://github.com/OloOcki/awesome-citygml

Developing new city models depends on robust reconstruction methods; Conversely, robust reconstruction methods can only be developed utilizing high-quality, high-diversity ground-truth data.

As we show in Table 4, the abundance of training samples stemming from governmental and other sources allows us to believe that reconstruction methods can be tested on the international scale using more than 215 M building models. On the other hand, the LOD3 reconstruction testing is possible on a city-block-scale, with the recently generated datasets totaling around 100 building instances in Germany and Poland, and further potential 857 objects in Japan. We expect that such datasets will be extended in the upcoming works given the increasing interest in LOD3 reconstruction. We also present an analysis focusing on the transportation models (Tab. 3), which have gained increased attention in recent years owing to their diverse applications.

Acknowledging that the listed datasets are subject to change with time, we maintain and update an open list of semantic 3D city models "Awesome CityGML" (Wysocki et al., 2024) in the presence of emerging datasets. In future work, we plan to extend our analysis to other types of objects, such as 3D tree reconstruction.

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[4] https://3d.bk.tudelft.nl/opendata/opencities/

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