Evaluating the development of open 3D city models: a multidimensional assessment

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Abstract

Adopting 3D City Index, a comprehensive 3D data scoring framework encompassing four categories — data portals, model descriptions, thematic content, and semantic information, we assess and benchmark currently available 3D city models made accessible openly by governments worldwide. The 2025 update, including 47 datasets, reveals both the current situation and advancements in the open 3D data landscape since the previous benchmark 3 years ago. The heterogeneous landscape continues, with European cities demonstrating sustained progress, such as the datasets of Helsinki and Espoo. Japan as a country, performs well in the large-scale availability of 3D geoinformation. The trend analysis between 2022 and 2025 highlights measurable progress in the development of open 3D city models. Among the 28 datasets assessed in both years, 11 models show improvement, with an average increase of 2.5 points. While in general there is an improvement, many aspects declined, such as data portals and semantic richness. Further, the analysis implies an emerging trend toward large-scale harmonised initiatives at the state or national level, such as the PLATEAU project in Japan and Digital Twin Victoria in Australia. Such efforts indicate promise for standardised modelling, interoperability, and collaboration between governments, companies and research institutions. Understanding the current status and development of 3D city models, this work aims to inform improvements of 3D geoinformation and support broader adoption of 3D city models in research and practice.

1. Introduction

3D city models have become an increasingly prevalent tool to support urban management and facilitate efficient decision-making (Biljecki et al., 2015, Chen, 2011, Kolbe and Donaubauer, 2021, Palliwal et al., 2021). Modelling primarily buildings, and optionally other features such as vegetation, roads, and other urban assets, 3D city models support a variety of studies, e.g. visibility analysis (Wysocki et al., 2023a), solar energy potential calculations (Katal et al., 2022, Ma et al., 2023), or wind simulation (García-Sánchez et al., 2021). The availability of 3D city models is key to provide up-to-date information and support use cases widely. However, properties of 3D city models vary across cities and countries, together with the nature of their initiatives and purposes. Such heterogeneity and different practices are not explored thoroughly, which presents a challenge for usability and for local governments who are yet to establish their 3D initiatives.

This issue is compounded by the increasing importance of urban digital twins, which 3D city models are a pillar of (Ferré-Bigorra et al., 2022, Lei et al., 2024, Badwi et al., 2022, Dimitrov and Petrova-Antonova, 2021). The quality of 3D city models plays a role in the effectiveness of designing and implementing urban digital twins, but how 'good' it is, and what the difference is among different practices around the world, is not fully clear.

From data collection (e.g. level of detail) to model management (e.g. frequency of updates), there are numerous factors that impact the usability of 3D city models. However, approaches to examining and monitoring 3D data remain limited. The work (Lei et al., 2023b) introduced 3D City Index, the first instrument to assess 3D city models holistically and comprehensively. When applied to several datasets, it enables comparisons among them and deducing the state of the art of 3D city models. While this work, based on datasets openly available in 2022, provides insights into the properties of 3D city models, given the continuously released data, it may be outdated and not fully capture the most recent advancements in the field. Further, since then, several studies investigated specific aspects of 3D city models, e.g. reconstruction (Wysocki et al., 2024) and thematic specifications (Uggla et al., 2023), serving as useful references for interpreting model characteristics. Yet, there remains a research gap in outlining the trends, spatially and temporally, e.g. identifying new 3D city models across different regions and evaluating how the properties have developed over time.

Building on the framework proposed by (Lei et al., 2023b) and the results obtained in 2022, this work updates the assessment of 3D city models openly available in 2025, thereby establishing the *3D City Index 2025*, and compares the results to infer trends. We address three research questions: (1) What is the current state of the art in 3D city models worldwide? (2) What are the prevailing trends in the development of 3D city models? and (3) How has 3D geoinformation progressed regarding various aspects such as portals, model description, thematic coverage, and semantic information? Our assessment includes both geographies from the previous benchmark and newly added ones, and it enhances the framework by recasting some approaches. For example, while the previous study assessed several Japanese cities independently, the nationwide PLATEAU initiative[1] has led to the harmonisation of 3D city models for 56 cities following a standardised framework. In this case, we evaluate Japan as a single model in this study, reflecting the consistent efforts implemented nationwide, rather than assessing each city independently, and keeping the framework updated with the latest practices. Focusing on the comparative analysis of data from 2022 and 2025, first, we visualise the

[1] https://www.mlit.go.jp/en/toshi/daisei/plateau_en_2.html

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changes over the three-year period, delivering an overview of which cities have updated their 3D city models and which have not; and second, we conduct a category-level analysis to examine increases and decreases in individual criteria across cities, thereby highlighting trends in how different jurisdictions have prioritised enhancements in their 3D datasets.

2. Methodology

We adopt the framework from (Lei et al., 2023b), comprising four categories and 47 criteria, including the dataset and accompanying elements such as data portal and documentation. This work is documented in a publicly available GitHub Repository [2]. The first category (Category 1) includes six criteria evaluating the data portal, focusing on the general information accessible to the public for understanding and engaging with the dataset. For example, this category assesses whether a 3D web viewer is available, whether multiple language options are provided, and whether users are able to leave feedback or contact the data provider. The second category (Category 2) involves 15 criteria to investigate the basic description of 3D city models, such as downloadability, license, and data lineage. Meanwhile, this category examines the temporal dimension of the datasets, in particular, the age of the models and the plan for updates, thereby assessing their currency. Category 2 also evaluates structural characteristics, e.g. alignment with open standards, LODs, formats, and whether the model is structured as a mesh or information-based model. The third category (Category 3) focuses on the thematic completeness (Gröger and Plümer, 2012), e.g. the inclusion of terrain model, vegetation model, bridge, water bodies, etc. The last category (Category 4) assesses the diversity and richness of semantic information (Milojevic-Dupont et al., 2023, Zhang et al., 2025), examining attributes such as number of storeys, building height, and roof type.

Following previous efforts in cataloguing available datasets (Lei et al., 2023b, Wysocki et al., 2024), we examine currently available 3D city models and incorporate additional updates and extensions. We acknowledge a number of 3D datasets developed by research institutions and companies, many of which demonstrate good modelling practices and incorporate detailed semantic information (Dukai et al., 2020, Peters et al., 2022, Wysocki et al., 2023b, Biljecki, 2020). However, regarding the access, we include only 3D city models that are made openly accessible by governments, enabling detailed investigation into their properties. A total of 29 datasets are included in both the 2022 and 2025 assessments. Incorporating the list from (Wysocki et al., 2024), we identify 18 new datasets for inclusion in the 2025 update. Meanwhile, four datasets from the 2022 assessment that are no longer available have been excluded from the current collection.

We base the work on the list of datasets identified in the initial research a few years ago and expand it. For example, we update the jurisdictional classification of several datasets to better reflect their actual geospatial coverage. For example, all Japanese cities are evaluated as a single entry in the 2025 update instead of being assessed independently, as they are developed under the same nationwide initiative. Likewise, the entry for ‘Tallinn’ is updated to ‘Estonia’, as the nationwide model encompasses the city and provides broader coverage beyond municipal boundaries. We incorporate newly identified 3D city models while also retaining the datasets developed by different levels of authorities, even in cases of overlapping spatial coverage. For example, the dataset for Victoria, Australia, is included as a new entry at the state level. However, the city of Melbourne remains assessed independently, as its model is developed by a different agency, leading to differences in data collection and model maintenance. Therefore, despite overlapping geospatial extents, we evaluate these models as separate entities to compare inconsistencies across authority levels.

For each criterion, we follow a binary evaluation scheme of ‘Yes’ or ‘No’, consistent with the methodology used in (Lei et al., 2023b). For example, if the model is available for download, the response to the criterion ‘Is it downloadable?’ will be marked as ‘Yes’. Further, we introduce a third option ‘Partially Yes’, capturing cases where the criterion is only partially satisfied. When examining semantic information for each model, we found that in some cases, attributes were inconsistently applied across buildings. For example, in some models, height information is available for only a subset of buildings. In this case, we assign the response ‘Partially Yes’ to the criterion — ‘Does it contain the height of buildings?’, reflecting the partial availability of this characteristic. Meanwhile, while 3D city models in Japan are developed by a coordinated national initiative, there are variations in model characteristics across different cities and regions. For example, Tokyo’s model contains bridges as part of its thematic content, whereas they are absent elsewhere in the country. Therefore, in this case, the response to the bridge-related criterion is marked as ‘Partially Yes’ to reflect the inconsistency within the initiative. Hence, in the updated benchmarking process, we assign a score of 1 to ‘Yes’, 0.5 to ‘Partially Yes’, and 0 to ‘No’, producing updated total scores that reflect recent changes in the evaluation criteria.

Evaluating the properties in detail, we download each dataset in its available formats and examine their specifications and attributes through visualisation and manual inspection using various tools. For example, we use ‘azul’ to visualise and explore semantic 3D models (Arroyo Ohori, 2020), such as in CityGML and CityJSON (Gröger and Plümer, 2012, Yao et al., 2018, Ledoux et al., 2019, Nys and Billen, 2021, Kolbe and Donaubauer, 2021). For mesh models (e.g. OBJ and FBX formats), we visualise the model and inspect the file using a code editor (e.g. UltraEdit) to assess their content. The resulting scores in Category 3 and 4 reflect the diversity and richness of the thematic and semantic information contained in each 3D city model.

3. Results

3.1 Landscape of open 3D city models

We collected information on 47 datasets — 29 of which are from the previous index, 18 are newly identified, and 4 are no longer available. Their spatial distribution is shown in Figure 1 — most existing and newly found datasets continue to be found in Europe. For example, Germany has released several state-level 3D city models, which, when combined with existing datasets, have the potential to provide coverage for the entire country. Meanwhile, there are two new models from Australia: the city of Adelaide, and the state of Victoria. In recent years, the state has launched the Digital Twin Victoria initiative [3]), integrating various datasets (e.g. geospatial information

[2] `https://github.com/binyulei/3D-City-Index`

[3] https://www.land.vic.gov.au/maps-and-spatial/digital-twin-victoria

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and sensor data) into one single platform for diverse demonstrations. A 3D city model constitutes a key component of the platform, covering the entire jurisdiction.

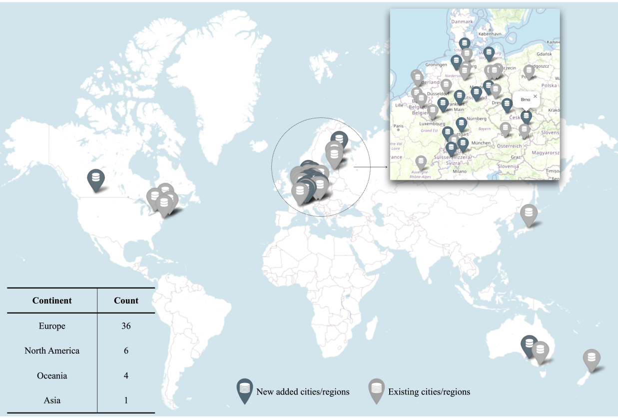

Figure 1. Geographic distribution of the 47 evaluated 3D city models in the 2025 update. Most of the datasets are found in Central Europe. Basemap: (c) OpenStreetMap contributors.

The spatial distribution reveals two trends. First, an increasing number of governments demonstrate a willingness to publicly release their 3D city models, enabling access for 3D visualisation, download and application. Compared to the collection assessed three years ago (Lei et al., 2023b), we notice that while there are new initiatives, many existing models are also actively maintained and improved. This trend reflects the ongoing expansion of the 3D city modelling landscape, as well as suggests their sustainability in practice. Second, a growing body of 3D city models are being developed at broader spatial scales beyond the city level, such as nationwide models from Japan, Switzerland, and Estonia, as well as state-level models from Germany and Australia. This trend implies that governments are moving toward more integrated efforts, serving as strong examples of how to promote information consistency and interoperability across jurisdictions (Jeddoub et al., 2023, Jeddoub et al., 2024, Lehner and Dorffner, 2020). Such integration also facilitates efficient model maintenance and helps reduce resource demands, such as manpower and time associated with data updates and management (Eriksson and Harrie, 2021, Yan et al., 2022). At the same time, we identify independent and concurrent developments of 3D city models for the same area (i.e. the case of Melbourne mentioned in the previous section), indicates that coordination, integration and standardisation of initiatives still have room for improvement.

3.2 3D City Index 2025: Assessment and benchmarking

We implemented the scoring system on the identified datasets to assess them (Figure 2). Helsinki continues the best performance (30.5), suggesting its comprehensive efforts across four categories. In total, 11 city models score more than half of the maximum score (47), with Japan being the only entry from outside Europe among them. Notably, three of these improved models are developed at the country level, i.e. Japan, Switzerland, and Liechtenstein. For example, in the PLATEAU project in Japan, led by the Ministry of Land, Infrastructure, Transport and Tourism, (Seto et al., 2023), 3D city models have been developed for 200 Japanese cities, all of which are openly accessible for visualisation, download, and downstream applications.

The scores across all 3D city models remain quite variable, suggesting that there is no convergence of initiatives around the world towards commonly established practices.

In general, Europe continues to indicate active participation in 3D city modelling (Caprari et al., 2022, Lehtola et al., 2022). For example, cities such as Helsinki, Espoo, and Rotterdam demonstrate good cases where governments commitment to 3D city modelling is complemented by multistakeholder engagement, open data policies, practices, and a dedicated effort toward public accessibility and practical value (Hämäläinen, 2021, Attard et al., 2015, de Juana-Espinosa and Luján-Mora, 2019, Nguyen and Kolbe, 2021). At the same time, North America and Oceania are making progress in developing 3D city models, however, they include comparatively fewer cities that perform well across all evaluation categories. The underperforming models often lack standardised data descriptions and rich semantics (e.g. specifications and attributes), limiting their usability in both practical applications and research contexts. The implications suggest a room for improvement in model development and quality management.

A complementary analysis is presented in the right plot, illustrating the distribution of scores across the four categories. In the first category of website information, more than half of the 3D city models perform well in delivering a comprehensive portal to provide general information about the dataset, e.g. a 3D web viewer and language options. However, several cities and regions fail to satisfy a broader range of criteria.. For example, Nordrhein-Westfalen state and Rheinland-Pfalz state score 16.7% in Category 1, due to the absence of dedicated data portals and online 3D visualisation tools. This lack of accessible web infrastructure presents challenges in understanding the purpose, content, and potential applications of the datasets, and may present barriers to those not acquainted with 3D GIS. Notably, while 3D city models in Calgary (Canada) and Brno (Czechia) do not achieve high overall scores, their local governments demonstrate commendable efforts in certain aspects, e.g. developing and maintaining dedicated data portals. These portals represent a promising approach to integrating essential information, thereby enhancing public understanding and encouraging broader use by practitioners and researchers.

Building on Category 1, the second category focuses on the descriptive aspects of 3D city models, offering a high-level overview without investigating the detailed content of the datasets. In the assessment of Category 2, the majority of 3D city models perform well in describing the dataset, whereas some models show a slight reduction in scores, reflecting minor fluctuations in specific criteria. In particular, Linz (Austria), Kuopio (Finland), and Hannover (Germany) meet 14 out of 15 criteria (93.3%), indicating a good access to downloadability, various formats and LODs, and metadata, as well as up-to-date information. Grouping by the criterion of 2C7 — 'Is it generated using open data standard?', we found that 39 3D city models are generated using open data standards (mostly CityGML). This finding suggests a positive shift toward the adoption of international standards, promoting the consistency and interoperability across datasets, and advancing the development of semantic city models.

Category 3 evaluates thematic content of 3D city models, where Espoo achieves 63.4% of the relevant criteria, standing out in this category. Meanwhile, cities and regions such as Rotterdam, Switzerland, Liechtenstein, and Melbourne also perform well by incorporating more specifications. The inclusion of more thematic components enhances the informational value of a 3D city model, thereby showing the potential to expand its

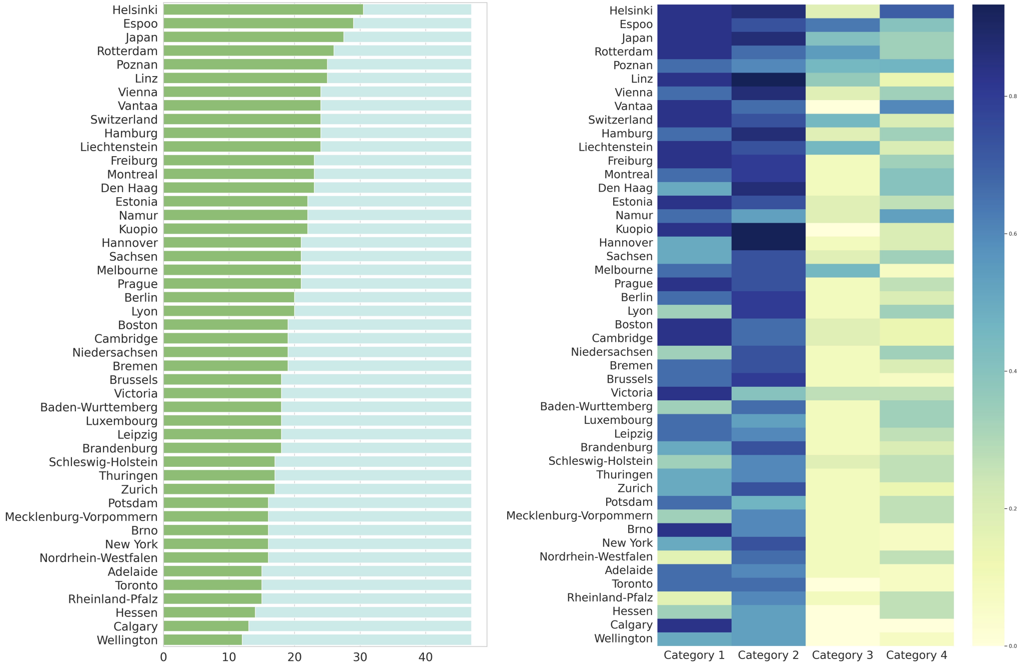

Figure 2. Evaluation of 47 open 3D city models in 2025, including total scores and category-level performance. The 3D City Index evaluates an extensive set of properties of 3D city models, thus, higher scores do not necessarily mean better 3D city models, as the notion of the quality of models is subject to different interpretations and downstream applications.

applicability across various domains. A diverse set of thematic elements contributes to the versatility of 3D datasets and their usability in a long term. For example, modelling vegetation can support urban heat analysis and simulate microclimate conditions (Fujiwara et al., 2024, Xu et al., 2021, Li et al., 2023). In Category 4, it is explicit that the richness of attribute information varies across initiatives. Helsinki achieves a score of 10.5 out of 15, indicating the most comprehensive semantics among all assessed 3D city models, such as building texture, height information, and roof details. Further, Vantaa (Finland), Namur (Belgium) and Poznan (Poland) also make notable efforts to enhance the semantic quality of their 3D city models, supporting a wider range of use cases beyond basic 3D visualisation.

3.3 Progress and trends in 3D city model development

Analysing the differences between the two assessments (2022 and 2025) provides an opportunity to infer trends and analyse how the 3D city modelling landscape (at least among openly released authoritative datasets) has evolved. Therefore, we compare datasets that are included in both the 2022 and 2025 assessments — a total of 28 datasets. We group cities by their score changes across years, distinguishing between those with increasing and decreasing scores (see in Figure 3). Datasets that demonstrate improvement gain an average of 2.5 points, whereas those that decline experience an average decrease of 1.5 points. A total of 11 3D city models show improvement, while two models — Vienna (24) and Luxembourg (18) keep the same scores as in the previous assessment. However, the results do not imply that these 3D datasets have no progress. Instead, updates may have been made, but changes in specific criteria can offset improvements elsewhere, such as enhanced semantic richness accompanied by new download restrictions, leading to an unchanged total score. Among the improved datasets, the 3D city model of Boston suggests a significant progress, increasing its score from 14 in 2022 to 19 in 2025. Similarly, Hamburg (24) and Linz (25) demonstrate notable advancements, each achieving a 4-point improvement and rising to scores of 24 and 25, respectively. At the same time, we found that improved 3D city models from 2022 reveals continued progress. For instance, Espoo satisfies three additional criteria in the 2025 assessment, increasing its total score from 27 to 29. The findings align with earlier observations, indicating a positive trend in the continuous development of 3D city models, particularly in terms of accessibility, semantic richness, and data quality.

Within the decreasing group, 15 3D city models indicate slight decrease in overall performance. The dataset for Toronto introduces the most notable reduction, with a four-point drop compared to its 2022 score. Brandenburg (18), Lyon (20) and Nordrhein-Westfalen (16) each fall by two points in the 2025 assessment. However, the majority of score reductions are relatively minor, with most datasets decreasing by only 0.5 to 1 point. It is important to pay attention that introducing the new scoring option, ‘Partially Yes’, allows for a more nuanced evaluation than the previous index. While such an addition enhances the precision of the assessment, it contributes to slight reductions in total scores for some models as well.

3.4 Category-level analysis of 3D city models

Further, we investigate how 3D city models evolved across four categories between 2022 and 2025 (Figure 4). Complementing the trend analysis in Section 3.3, this section aims to highlight improvements and declines within each category, offering insights into the factors influencing these changes. The below plot shows an aggregated result of all datasets across four evaluation categories from 2022 to 2025. Category 2 suggests the most substantial improvement (increased by 13 points), while the other categories experience modest overall declines. To better understand these patterns, we examine the evaluation criteria within each category across datasets.

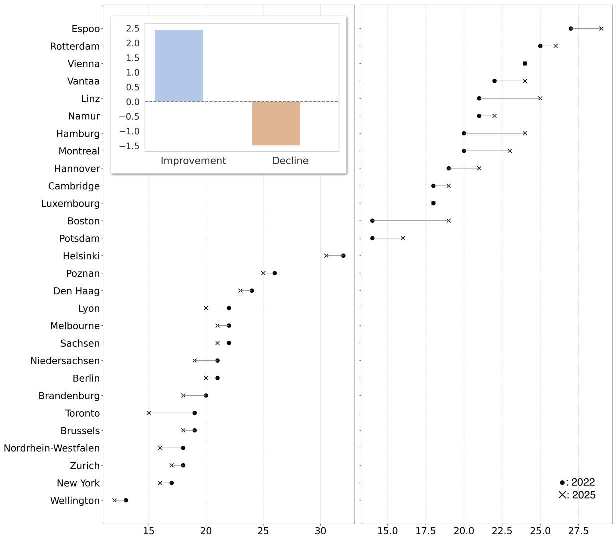

Figure 3. Comparison of total scores in 2022 and 2025 for 28 3D city models available in both years.

For each category, we calculate the percentage increase or decrease relative to the 2022 scores. The 3D city models included in both the 2022 and 2025 assessments demonstrate varying degrees of change across categories. In several cases, local governments modify or replace their data portals, resulting in the removal of previously available features, such as 3D viewers or multilingual support. For example, the 3D city model of Nordrhein-Westfalen drops by two points, considering its insufficient website management, for example, its data portal is no longer available compared to the 2022 assessment. A similar issue is noticed in the case of Wellington, lacking a dedicated portal, which would make the dataset better accessible and understandable to users. In contrast, Vantaa demonstrates significant improvement by establishing a dedicated data website, enabling users to easily access and explore information of interest. In the second category, 42.9% of 3D datasets reflect positive changes, albeit 32.1% models show decline in providing detailed dataset descriptions. One reason is that some models now require registration for data download, negatively affecting the availability and downloadability (and questioning whether these datasets can still be considered truly open data), such as the datasets for Zurich and Amsterdam. Meanwhile, criteria related to timeliness play a significant role in Category 2 (e.g. the integration of up-to-date information, and a plan for future updates), and these criteria are not consistently satisfied across all models.

From the aspect of thematic specifications (Category 3), 11 3D city models suggest slight decreases in including various urban subject types. For example, cities such as Toronto and Rotterdam exhibit a decline in scores; however, their models continue to represent a diverse range of urban features (e.g. bridges and vegetation). The decline reflects a reduction that is related to partial omission or inconsistent updates, rather than a fundamental lack of thematic diversity. However, Linz presents clear improvement, incorporating additional thematic elements in its updated 3D dataset to provide a more comprehensive representation of the urban environment. When examining the changes in Category 4, ten models show improvement, while nine exhibit a decline in the provision of rich attribute information. Nevertheless, the magnitude of these changes is generally modest across all 3D city models. Helsinki indicates a slight

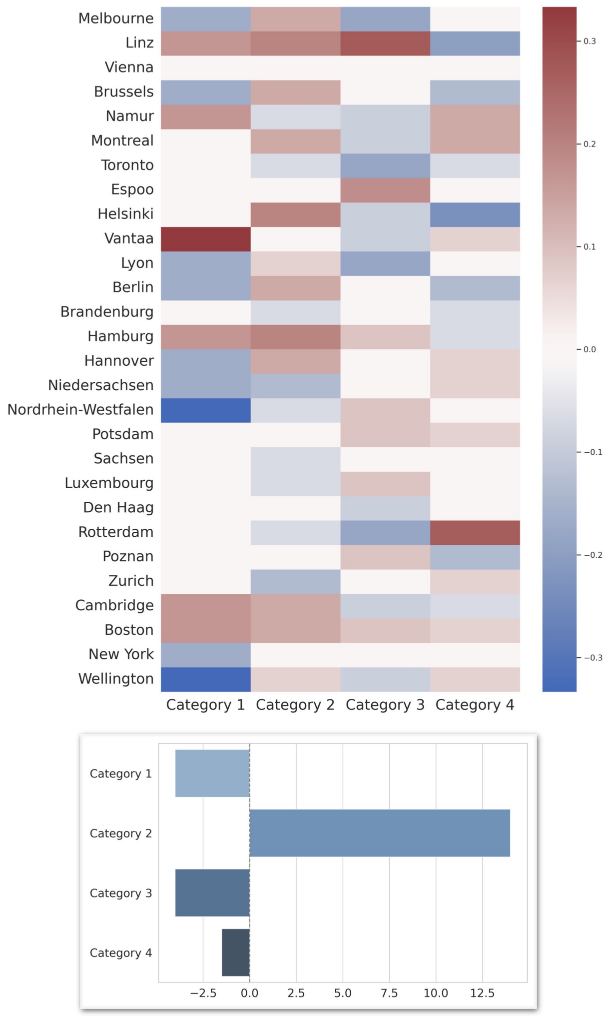

Figure 4. Category-level score changes between 2022 and 2025 for 28 3D city models. The heatmap shows the change in each category for individual dataset, and the bar chart aggregates total score changes by category.

decrease in semantic richness, which may be associated with the updated scoring framework and the uneven distribution of attributes within the dataset. In contrast, Rotterdam demonstrates progress in addressing previous gaps in semantic data when compared to its 2022 performance. For example, while the dataset contains only height information in the 2022 assessment, additional building characteristics are included in the update 2025, such as the year of construction and the number of storeys.

The category-based comparison highlights varying efforts and strategies in developing 3D city models across evaluation criteria. Moreover, this analysis outlines the dynamic landscape of 3D datasets and implies potential interventions or policies that may be conducted to further advance the growth of 3D city models. For example, the slight decreases in Categories 1, 3, and 4, suggest a need for maintaining the data portals and improving semantic richness in the datasets.

4. Discussion

This work presents a systematic analysis of openly available 3D city models released and maintained by authorities worldwide, offering insights into their current status and developments between 2022 and 2025. Applying an updated scoring index, we visualised variations in performance across datasets, highlighting the differences among various initiatives. Further, this work provides a new understanding of 3D city models — not only their geographic distribution but also their temporal trends.

Notably, European cities continue to lead the proliferation of 3D city models, which may be thanks to policies, standardised framework, and data infrastructures (Tai, 2021, Gao et al., 2023, Matheus et al., 2021). Another potential catalyst is their evolving usability for various downstream studies, serving as a key motivation for local and national governments to maintain and enhance the model availability and quality (Ansari et al., 2022, Ferré-Bigorra et al., 2022). Further, we observed a growing trend of 3D city models being developed at broader administrative levels, such as state or national scales, for example, Japan's PLATEAU initiative and Digital Twin Victoria in Australia. Such large-scale initiatives demonstrate significant potential to standardise 3D city modelling and facilitate interoperability across broader jurisdictions. These developments imply a positive tendency towards effectively integrating resources and efforts, fostering harmonious collaboration among various data stakeholders, as well as creating more comprehensive, consistent, and accessible 3D geoinformation (Janssen et al., 2012, Zuiderwijk and Janssen, 2014, Haraguchi et al., 2024), which can be further explored in the future work (e.g. gathering insights from the practice and liking to local policy development). However, initiatives that demonstrate a decline in total score or across categories highlight the challenges and vulnerabilities inherent in 3D city modelling, for example, shifting priorities, funding limitations, or administrative barriers (Lei et al., 2023a, Hu et al., 2021).

At the same time, scores should be interpreted according to the context. This work is meant to be general rather than focused on specific use cases and local needs. For example, a 3D city model with a high score may be less usable for a particular use case than another one that has a lower score but was developed with a specific application in mind that it serves very well. Meanwhile, while this study aims to provide a broad and up-to-date overview of open 3D city models, we acknowledge that the dataset collection is not exhaustive. Despite systematic efforts to identify publicly available 3D city models, some datasets might have been missed in this assessment, e.g. due to language barriers and some initiatives being inconspicuous.

Future research can take a further step by examining how policy frameworks (e.g. related to data sharing and management) contributes to the proliferation and usability of 3D city models, and explore how social and legal factors influence the development of these models (Zuiderwijk et al., 2012). Such insights will be invaluable for guiding policymakers, practitioners and researchers towards available, semantically rich and sustainable 3D city models. Our work serves as a benchmark to capture the state of the art in 3D geospatial datasets, enabling comparisons across years and regions. But it does not regard their use case and usability. A promising direction for future work is to similarly investigate practical use cases of 3D city models, particularly the frequency of their applications in urban planning and environmental management, and tangible impact on policy-making.

5. Conclusion

Building on 3D City Index, a multi-dimensional framework to benchmark 3D city models (Lei et al., 2023b), we conduct a new round of assessment to evaluate the state of 3D city models in 2025 and compare it to the situation in 2022. This is the first study that systematically analyses the trends and developments of open 3D data across time.

This work focuses primarily on the datasets and accompanying infrastructure (e.g. data portals). A collection of 47 3D city models covering four continents has been identified, which are all from open government data. Seven cities and regions are newly included in the index, alongside updates to the previous assessment, such as the integration of many cities in Japan into a single nationwide initiative. From a geospatial perspective, Europe continues to lead in contributing to 3D datasets, as evidenced by the growing number of 3D city models released by European municipalities. Applying the framework to 47 datasets, we examined their data portals (Category 1) and model descriptions (Category 2), as well as downloaded and visualised their thematic content (Category 3) and attribute information (Category 4). During the benchmarking process, we manually conducted 2,209 individual evaluations — scoring 47 criteria across 47 3D city models. As a result, we establish the *3D City Index 2025*.

From the perspective of total scores, the 3D city model of Helsinki (30.5) continues to satisfy the highest number of evaluated aspects among all datasets, followed by another Finnish city, Espoo (29), which has shown notable improvement to secure second place. Japan, the only entry from Asia, also performs strongly with a score of 27 out of 47 points. The global assessment highlights the ongoing and substantial contributions of European cities to 3D city modelling, both in terms of the number of datasets published and their overall availability. Outside of Europe, other regions (e.g. Oceania) are also advancing in 3D city model development. A prominent example is the initiative of Digital Twin Victoria, demonstrating a growing regional interest in comprehensive urban data infrastructures. The category-based analysis provides deeper insights into how the total scores are composed. While in general there is an improvement, many aspects declined, such as data portals and semantic content. Improved models demonstrate consistency in satisfying more criteria across four categories, particularly in Category 1 and Category 4, suggesting a focus on improving accessibility and enriching model attributes. However, many city models underperform in Category 3, requiring the need to expand thematic specifications to support a more comprehensive representation of urban environments.

Given that the same assessment was conducted a few years ago, an analysis is conducted to understand the changes in the developments between 2022 and 2025. Visualising score progression over the years and grouping cities by increasing or decreasing performance, the findings reveal diverse paths. Cities such as Boston, Hamburg and Linz have made substantial advancements, as reflected in significant increases in their total scores. While some cities exhibit a decline, the changes are minor, not indicating major setbacks. Explaining the trend in detail, we visualised score changes across four categories. The 3D city models of Wellington and Nordrhein-Westfalen show decreases in Category 1, reflecting reduced efforts in maintaining dedicated data portals. However, Vantaa indicates substantial improvement in this category. In the area of dataset description (Category 2), many cities have made progress in providing clear and detailed information, reflecting the commitment to open data. All 3D city models suggest varying degrees of improvement in thematic content (Category 3) and attribute content (Category 4). For example, Linz has the best performance in expanding thematic coverage (e.g. terrain, bridge and vegetation). Considering semantic richness, Rotterdam has enhanced the quality and depth of its attribute data, while Helsinki indicates a slight decline in this category due to the inconsistency in the dataset.

While this work includes scoring and comparing initiatives, it is by no means intended to serve as a competition or exhaustive metric of quality of data and success of initiatives. Ultimately, how good a 3D city model is depends on many aspects, primarily how well it can serve (its intended) use cases, and how successful an initiative is, depends on whether it delivered its promise of being used among various stakeholders. These matters are out of scope of this paper. Understanding a dataset's usability and actual impact on policy-making is a direction for future work.

Acknowledgments

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