Automatic DEM-infused 2D to 3D LoD1 Urban Morphology Python Framework

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Abstract

The generation of 3D urban morphology models from 2D urban morphology maps has been widely explored. Traditional methods use modelling software, such as Rhino, which lack georeferencing, elevation, and automation. In this study, we developed an open-source Python framework for automatic generation of 3D city blocks, including elevation, from 2D colour-graded building heightmaps and urban morphology input. We utilised the UT-GLOBUS and GlobalBuildingAtlas building datasets to generate heightmaps and retrieved other urban morphology features, such as waterbodies, parks, roads, and trees, from OpenStreetMap to form the input raster patches. The framework generates height and colour maps based on the input features, which are extruded in 3D and exported into multiple standard 3D GIS formats such as CityGML and CityJSON. Six global cities: Sydney, New York, London, Rio de Janeiro, Hong Kong, and Singapore, were modelled to demonstrate the framework's applicability. Validation includes qualitative comparison with Google Earth 3D data and quantitative comparison against official LiDAR-derived DSMs for four cities. Quantitative results show moderate height errors and good spatial agreement of building footprints, reflecting the expected differences between simplified LoD1 block models and detailed DSM representations. Our framework results show promising potential in the field of 2D to 3D mapping for the creation of 3D city models for urban climate modelling and environmental analysis. The generated 3D models can be downloaded at https://doi.org/10.5281/zenodo.17620303.

1. INTRODUCTION

Urban climate research is increasingly relying on three-dimensional (3D) city models, georeferenced digital representations of urban areas, to capture the complex morphology of urban areas. A 3D city model is a digital model of an urban environment with a three-dimensional geometry of urban structures (Girindran et al., 2020). Such models support analyses of phenomena like solar irradiation, urban heat islands, wind flow, noise, and energy demand (Girindran et al., 2020; Park et al., 2021). For example, recent studies have used detailed 3D city representations to quantify how building and tree shading affect local surface temperatures (Park et al., 2021). By enabling computation of shadows, sky view factors, and flow obstructions, 3D models have become essential in urban energy and microclimate simulations (Biljecki et al., 2015).

In practice, city models are generated at multiple levels of detail (LoD). The international CityGML standard defines LoDs 0 through 4 (Biljecki et al., 2014). In particular, Level of Detail 1 (LoD1) represents buildings as simple block models: each footprint is extruded to a uniform height with a flat roof (Arroyo-Ohori et al., 2018). CityGML describes LoD1 as a block model that is usually derived by extruding a footprint to a uniform height (Biljecki et al., 2014; Arroyo-Ohori et al., 2018). LoD1 models are typically used for city- or regional-scale datasets, since they capture volumetric form without complex roof geometries (Girindran et al., 2020). As researchers note, LoD1 provides a realistic representation of the urban form without excessive computational cost (Biljecki et al., 2014; Girindran et al., 2020). As higher LoDs greatly increase data size and processing time, many urban climate and energy applications rely on LoD1. many applications of 3D city models require only a low level of detail like LOD1 (e.g., vulnerability models, disaster mitigation, climate change and energy models) (Girindran et al., 2020). In other words, LoD1 strikes a balance between representational fidelity and tractability in environmental modelling. For example, Park et al. (2021) constructed a 3D urban model (LoD1) to simulate how building and vegetation shades influence urban heat, finding that a realistic 3D digital representation of urban and suburban landscapes is needed to capture shade effects (Park et al., 2021). Zhou et al. (2023) generated 3D LoD1 models by using AI-generated 2D urban morphology maps from cities' Local Climate Zones maps, providing valuable insights for city planners to enhance the local climate using 3D models (Zhou et al., 2023).

Until recently, constructing 3D city models has typically required commercial tools or intensive photogrammetry, which can be prohibitive. Conventional workflows often use software like Rhino or Autodesk's CityEngine to extrude 2D GIS data into 3D, but these tools are expensive and tied to proprietary formats. In addition, stereophotogrammetric methods (using aerial or satellite imagery) require significant cost and effort. Girindran et al. (2020) pointed out that stereo-derived city models can be an expensive, as well as time and labour-consuming process (Girindran et al., 2020), so large-scale 3D data tend to exist only in wealthier countries with national mapping programs. This creates barriers for reproducibility and limits access for many researchers.

Open-source and open-data approaches can overcome these barriers. By using publicly available 2D footprint data such as OpenStreetMap and global elevation datasets, it is possible to generate LoD1 city models without proprietary software. Prior work has demonstrated this concept: for instance, Bagheri et al. (2019) fused open building footprints with satellite DSMs to derive simple prismatic (LoD1) building models (Bagheri et al., 2019). Girindran et al. (2020) went further by developing a fully open workflow: they combined global digital surface models (e.g. ASTER, SRTM, AW3D) with building footprints to produce a 3D city model in LoD1 (Girindran et al., 2020).

Building on these ideas, our work introduces an open-source Python framework for 3D city model generation from 2D urban footprints. Python's rich geospatial ecosystem (e.g. GDAL, Shapely, GeoPandas, PyVista, CityJSON libraries) enables end-to-end processing: from 2D vector footprints and terrain elevation rasters to extruded 3D meshes. By automating footprint extrusion and terrain integration, our pipeline creates LoD1 building models that can feed directly into urban climate tools. In doing so, we provide a cost-free alternative to commercial tools, enhancing reproducibility and accessibility. More broadly, the framework contributes to ongoing efforts in urban data science by establishing an open, reproducible workflow for large-scale 3D city model generation from 2D footprints, facilitating comparative studies and cross-city analyses. Our framework generalises these ideas in a unified, extensible way.

In summary, 3D city models (especially LoD1 block models) are a fundamental input for urban climate analysis. However, high costs and closed software have constrained their use. By leveraging Python and open spatial data, we can automate the conversion of 2D GIS data into LoD1 city models. This paper details such a workflow, covering data preprocessing, 3D building generation, and visualisation, and demonstrates its utility for urban climate studies. The resulting open-source framework aims to improve reproducibility, scalability, and accessibility of urban environmental modelling.

2. METHODS

2.1 Data

The framework described in this study is applied to six diverse cities around the world: New York, London, Rio de Janeiro, Singapore, Hong Kong and Sydney. The cities were chosen based on their varied morphology features such as dense high-rise buildings, hilly and mountainous areas, and extensive water bodies.

Building footprint maps of central blocks from New York, London, Singapore, Rio de Janeiro, and Sydney were developed using building height data from UT-GLOBUS, a global building heights dataset for urban studies that provides coverage for more than 1,200 cities around the world (Kamath et al., 2024). The Global Building Atlas dataset was used for mapping building footprints for Hong Kong. Global Building Atlas is a building footprint dataset covering the entire globe with provided building heights (Zhu et al., 2025). It is used for Dubai and Hong Kong as they are not included in the UT-GLOBUS dataset. The buildings are mapped using a red colour-coded scheme based on their height. Antialiasing is not applied to avoid building edges having different colours/heights than the inner pixels.

The 2D urban morphology maps were developed by supplementing the building footprint maps with other urban features such as parks, trees, roads and water bodies from OpenStreetMap (OpenStreetMap, 2025). Each feature is loaded with a unique colour and marker size/line width. The compiled maps are then resampled and rasterised to a spatial resolution of 2 metres using the projected coordinate reference system (UTM) for each city. Digital elevation model (DEM) data were downloaded for each of the cities from several fine-resolution data sources and resampled to 2-meter resolution to match the urban morphology's extent. An example of the 2D urban morphology and the 2D DEM input maps for Sydney are illustrated in Figure 1.

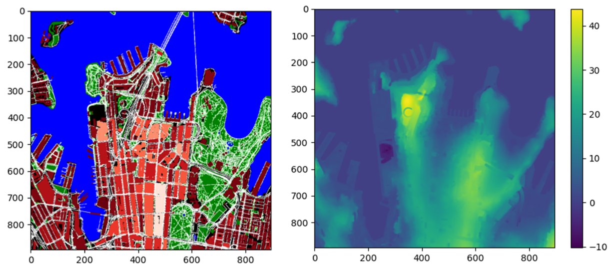

Figure 1. 2D urban morphology (left) and 2D DEM layer (left) for Sydney's central business district (CBD).

2.2 The framework

The open-source Python framework uses a dual input of 2D urban morphology and DEM to generate height map and colour map rasters. The framework starts with the segmentation of different urban features into separate masks as illustrated in Figure 2.

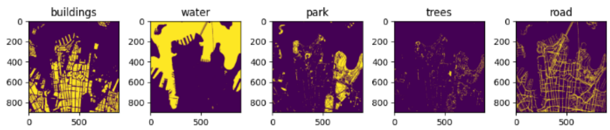

Figure 2. Segmentation of different urban features for Sydney.

The buildings mask is then passed to a function that extract each individual building and average the DEM pixels underneath it to estimate building base elevation in order to generate uniformly extruded buildings. The extracted building footprint maps are presented in Figure 3.

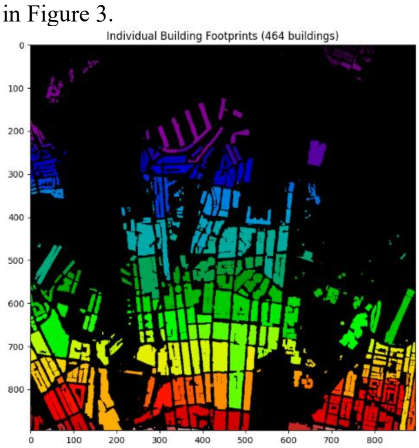

Figure 3. Extracted building footprints in Sydney.

The segmented masks are then used to calculate the heightmap value for every pixel in the image using the information in Table 1. The parks were assumed to have a height of two metres above the ground, representing vegetation, and the trees were assumed to have a fixed height of five metres. The colourmap is generated based on the following colour plate: Buildings: white, Roads: black, Parks: light green, Trees: dark green, Waterbodies: blue. An example output showing the generated heightmap and colourmap for Sydney is presented in Figure 4.

Table 1. Height table.

Feature	Type	Height
Buildings	Per footprint	Average DEM+ footprint height
Parks	Per pixel	DEM + 2m
Trees	Per pixel	DEM + 5m
Roads	Per pixel	DEM
Waterbodies	Per pixel	DEM

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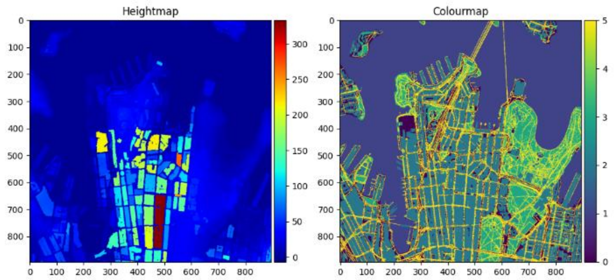

Figure 4. Generated height and colour maps of Sydney from the 2D to 3D Python framework.

2.3 Extrusion and exporting

The generated heightmaps for the six cities are used to extrude LoD1 3D polygons in Python by applying the heightmap's pixel value and using the colourmap's pixel value to apply the required colour to the 3D model. In addition, the extrusion function multiplies the X and Y axes by the 2D raster's spatial resolution (2m) to properly scale the 3D model. The generated 3D mesh is then exported in the following formats: Polygon (PLY), Object (OBJ), CityGML (GML), CityJSON (JSON). An example of Sydney CBD plotted using the Matplotlib library in Python is illustrated in Figure 5.

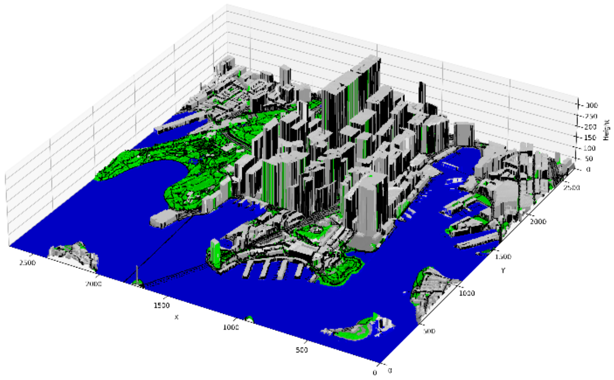

Figure 5. Plotted 3D LoD1 model of Sydney's CBD in Python.

3. RESULTS

3.1 Data collection

The details of data retrieval for the six cities used in this study are presented in Table 2.

Table 2. Details of the data used to generate the inputs in this study.

City	Buildings	Other Features	Elevation
Sydney	UT-GLOBUS	OpenStreetMap	Australian 5m DEM
Hong Kong	GlobalBuildingAtlas	OpenStreetMap	HK GOV Open Data
Singapore	UT-GLOBUS	OpenStreetMap	Copernicus DEM GLO-30
Rio de Janeiro	GlobalBuildingAtlas	OpenStreetMap	NASA SRTM Digital Elevation 30m
London	UT-GLOBUS	OpenStreetMap	England 1m Composite DTM
New York	UT-GLOBUS	OpenStreetMap	USGS 3DEP 1m National Map

3.2 Generated 3D models

The framework inputs, 2D outputs and extruded and rendered 3D models for the six cities are presented in Figure 6.

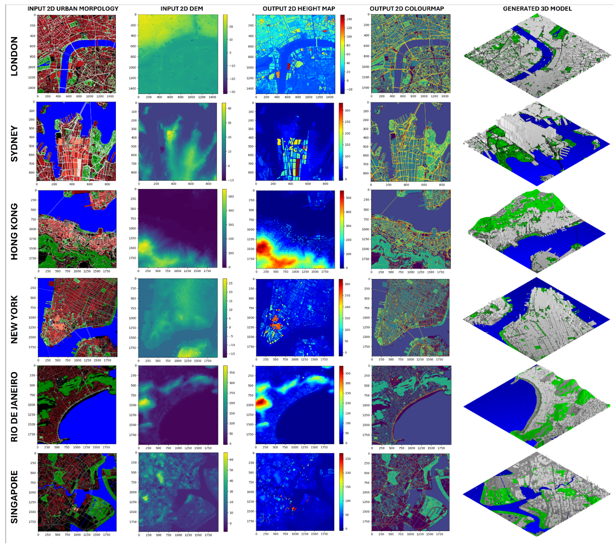

Figure 6. Framework results for the six study cities.

3.3 Exporting to 3D GIS formats

The models are exported in several formats, including open 3D GIS formats such as CityGML and CityJSON, by extracting individual footprints from the height and colour maps and categorising them into relevant urban features, as illustrated in the examples in Figures 7 and 8, respectively. The 3D models can be downloaded from the following repository (https://doi.org/10.5281/zenodo.17620303).

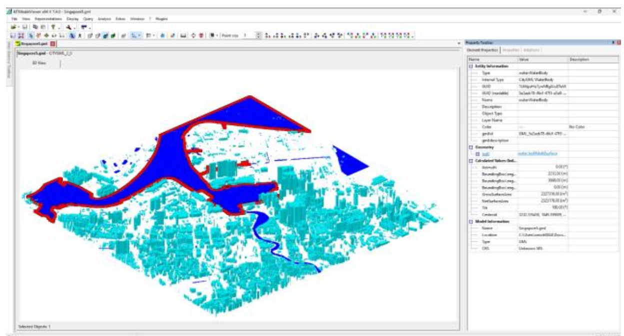

Figure 7. Singapore's urban features (CityGML 2.0) visualised by FZKViewer.

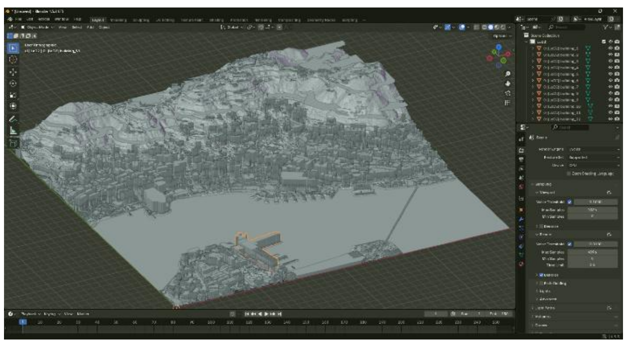

Figure 8. Hong Kong's urban features (CityJSON) visualised by Blender.

3.4 Visual Comparison

To assess the realism and spatial accuracy of the generated 3D urban morphology models, a qualitative visual validation was conducted using Google Earth 3D buildings and terrain as reference data (Figure 9). Google Earth's 3D layer provides photogrammetrically reconstructed urban surfaces derived from aerial and satellite imagery, offering a globally consistent visual benchmark for assessing the morphological plausibility of synthetic models. Previous studies have demonstrated the suitability of Google Earth imagery and 3D content for evaluating the spatial alignment and geometric fidelity of city-scale models (Wirth et al., 2015; Soleimani Vostikolaei & Jabari, 2023; Župan et al., 2023; Campoverde et al., 2024) and for general positional accuracy checks within urban settings (Wirth et al., 2015).

While Google does not publish formal vertical accuracy specifications for its 3D dataset, several investigations have found its positional and height consistency to be within a few meters, making it appropriate for qualitative or relative validation. Consequently, side-by-side comparisons were made between the generated models and Google Earth 3D scenes for six major cities representing diverse morphological and topographic conditions.

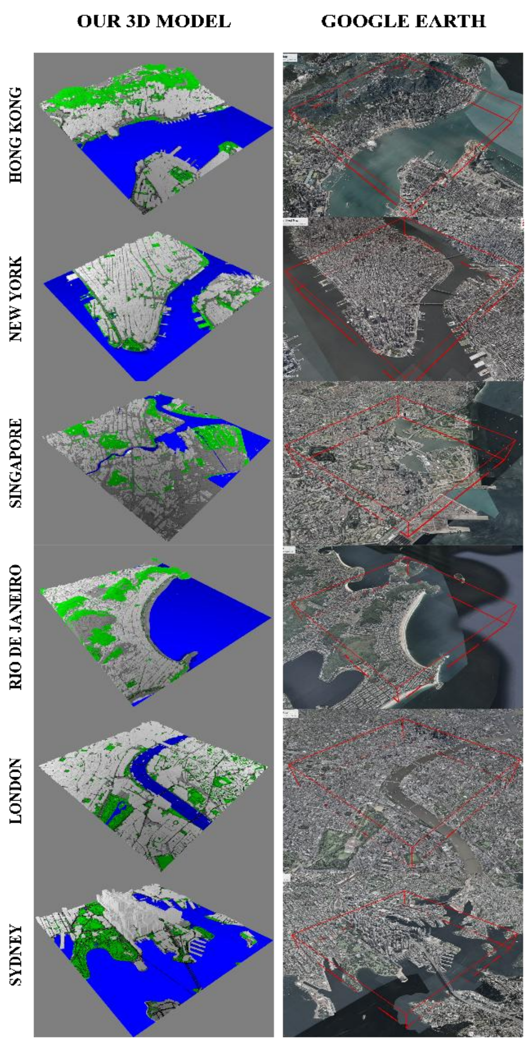

Figure 9. Our generated 3D models (left) and Google Earth buildings and terrain (right).

Visual side-by-side comparisons between the generated 3D models and Google Earth 3D scenes (Figure 9) show strong morphological agreement across the six case-study cities. In Hong Kong and New York, the high-rise clusters and overall skyline patterns are faithfully reproduced, with dense vertical zones clearly distinguishable from adjacent low-rise or open-space areas. Singapore and London show good spatial alignment and relative height differentiation among built-up, vegetated, and waterfront zones, though individual building geometries appear simplified due to the extrusion-based modelling approach.

The Lower Manhattan panel (New York) exhibits particularly close correspondence: building locations, block morphology, and the vertical clustering of skyscrapers in the financial district are reproduced with high fidelity, which reflects the high quality of the UT-GLOBUS building-height inputs used for New York in this study. In both planimetric and oblique views the modelled extrusions align with the Google Earth massing, indicating that UT-GLOBUS height values provide a reliable basis for extruded LOD1 representations in dense urban cores.

The Hong Kong and Rio de Janeiro panels demonstrate that large-scale topographic structures, including steep slopes and mountainous backdrops adjacent to built-up areas, are captured well by the framework: ridgelines, slope breaks, and the abrupt change from high ground to coastal plains are evident in the modelled surfaces and correspond closely to the photogrammetric terrain in Google Earth. Conversely, the Singapore Marina Bay Sands Resort building highlights a systematic limitation of the 2D to 3D extrusion approach: the iconic Marina Bay Sands complex is represented in our output as three separate extruded volumes (the tower blocks) without the continuous rooftop podium and cantilevered roof structure visible in Google Earth. This simplification illustrates how roof-top superstructures and complex multi-part buildings are not fully recovered from the colour-graded 2D heightmaps and urban morphology rasters alone.

In Rio de Janeiro, Hong Kong and Sydney, the framework successfully captured complex coastal morphology and large-scale topographic variation, including elevation gradients around bays and ridges. Minor discrepancies are observable along steep or heavily vegetated terrain where elevation interpolation may under- or over-estimate local height variations.

3.5 Quantitative Validation

Quantitative validation was conducted for four cities where official government LiDAR-derived DSM data were available (New York: OTI (2017), Hong Kong: CSDI (2020), Sydney: ICSM (2024), and London: Agency (2022)). The generated LoD1 models were compared against these DSMs using height-based error metrics (RMSE and MAE) and spatial agreement of building footprints measured by intersection-over-union (IoU) as presented in Table 3.

Table 3. Quantitative validation results

City	DSM RMSE (m)	DSM MAE (m)	Building RMSE (m)	Building MAE (m)	Building IoU
New York	33.8	6.7	17.0	13.2	0.618
Hong Kong	22.2	5.3	23.9	14.5	0.536
Sydney	41.1	8.5	27.5	26.9	0.904
London	24.6	16.6	21.0	20.8	0.620

It is crucial to emphasise that the ground truth DSMs provide highly detailed representations of the urban surface, including roof structures, vegetation, fine terrain variation, and small vertical features, whereas the proposed framework produces simplified LoD1 representations composed of extruded buildings derived from AI-based global building datasets and planar representations of trees, roads, parks, and water bodies. As such, the validation assesses agreement in bulk urban morphology rather than pixel-level surface correspondence. Across the four cities, DSM RMSE values range from 22.2 m to 41.1 m, while DSM MAE values are substantially lower, between 5.3 m and 16.6 m, indicating that most height differences between the generated LoD1 surfaces and the reference DSMs are moderate, with RMSE being inflated by a smaller number of large discrepancies caused by features not represented in LoD1 models, such as detailed roof geometry, tall vegetation, or features not included in the LoD1 models such as bridge decks. These differences are expected given the fundamental representational mismatch between simplified block models and high-resolution DSMs.

When restricting the comparison to building areas only, building-height RMSE values range from 17.0 m to 27.5 m and building MAE values from 13.2 m to 26.9 m. These errors are generally lower than or comparable to the full-DSM errors, indicating that a significant portion of the DSM discrepancy arises from non-building elements and fine-scale surface detail rather than from errors in the building height estimates themselves. This supports the conclusion that the framework captures relative building heights and volumetric structure reasonably well at the LoD1 scale. In addition, spatial agreement of building footprints shows IoU values between 0.536 and 0.904 across the four cities. Higher IoU values indicate strong correspondence in building location and extent, while lower values are likely influenced by differences between the 2 building datasets-derived footprints and official building representations, particularly in dense, vertically complex urban environments. High footprint agreement combined with moderate height errors demonstrates that the framework successfully reproduces large-scale urban morphology, even where exact surface matching with DSMs is not expected.

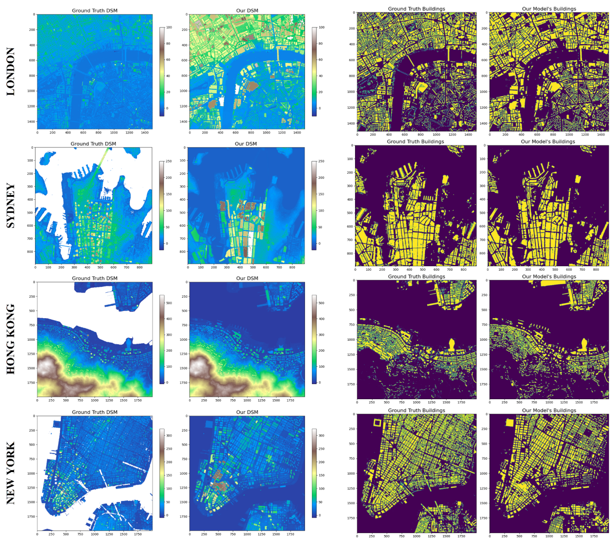

Figure 10: Ground truth DSM vs Our model's DSM (right) Ground truth buildings vs Our model's buildings (left)

A visual comparison between ground truth DSMs, buildings and our models' DSMs and buildings are illustrated in Figure 10. The quantitative results confirm that the proposed framework generates georeferenced LoD1 city models that are structurally consistent with real-world urban form. While discrepancies with DSMs are unavoidable due to differences in level of detail and represented features, the observed error ranges are consistent with the intended application of LoD1 models for urban climate modelling and environmental analysis, where accurate representation of building distribution, relative height patterns, and overall morphology is more critical than fine surface detail.

3.6 Limitations and planned improvements

Overall, the qualitative agreement and quantitative validation confirm that the proposed open-source framework reproduces the essential spatial and morphological characteristics of real urban environments, validating its utility for large-scale 2D to 3D mapping for climate modelling, and urban environmental analysis. Nevertheless, several limitations are apparent from the visual checks. First, structural roof details and complex architectural elements (e.g., the Marina Bay Sands roof and other non-extruded rooftop forms) are lost by the flat-extrusion method; these instances should be treated as known simplifications when applying the models to analyses sensitive to roof geometry. Second, transport infrastructure such as bridge decks and elevated roads are not modelled correctly in the current workflow because roads are rendered by overlaying vector/ raster road masks on top of the DEM surface, where bridges cross valleys or waterways the roadway geometry should be represented above the terrain rather than conforming to it. To address this, future development will incorporate a road-type classification step in the 2D inputs (distinguishing ground-level roads, elevated roads/bridges, and tunnel segments) so that different extrusion and elevation rules can be applied per road class, producing more faithful bridge and elevated-road geometries.

In addition, the framework produces simplified LoD1 block models by design, so it will never reproduce fine roof geometry, façade detail, or the microtopography captured by LiDAR/DSM; quantitative disagreements with DSMs therefore reflect representational differences rather than failures of the pipeline. The quality of outputs depends strongly on input datasets: AI-derived height maps from the UT-GLOBUS and GlobalBuildingAtlas datasets and OSM features carry their own errors, temporal mismatches, and coverage gaps; where these inputs are incomplete or biased, building footprints and heights will be correspondingly affected. Comparisons to reference DSMs are sensitive to temporal mismatch; without co-temporal, pre-processed DSMs, some portion of measured error may be attributable to dataset mismatches rather than modelling error.

As the framework's pipeline prioritises automation and broad applicability over per-building calibration, the current implementation treats trees, roads, parks and water bodies as planar or height-approximated raster layers and does not model vegetation volume or canopy structure explicitly, limiting suitability for applications that require accurate vegetation morphology or rooftop-level detail.

Finally, The CityJSON exported models, represent land-use areas such as parks and vegetation zones primarily as 2D surfaces draped over the terrain, rather than full volumetric objects. As a result, parks tend to appear geometrically flat, without detailed features such as varying ground textures, slopes, or vegetation structure. Similarly, trees are encoded only as simplified points or surfaces, lacking true 3D geometry such as trunks, crowns, or volumes. These limitations make CityJSON efficient and lightweight, but they also restrict the visual and semantic richness of natural features in high-detail urban models. We are currently working on enhanced modelling workflows to overcome these limitations and provide richer, more realistic representations of natural features.

4. DISCUSSION

This framework significantly lowers the barrier to generating 3D city models by enabling a streamlined conversion of 2D urban morphology data into detailed 3D representations using only open-source tools. Unlike traditional modelling workflows that rely on commercial software, this approach requires no proprietary licenses, making it especially valuable for researchers and practitioners operating in resource-limited environments. The process of extrusion is automated and efficient, allowing users to go from urban morphology raster and elevation data to a textured 3D model with minimal technical overhead. The integration of terrain, building height data, and land use features into a cohesive 3D model highlights the framework's potential as an accessible alternative to more complex and costly solutions.

A key strength of the framework lies in its ability to leverage fully open-access datasets. By incorporating global building height datasets such as UT-GLOBUS and GlobalBuildingAtlas alongside OpenStreetMap data, the framework ensures global applicability while maintaining consistency and reliability. These datasets provide building geometries, elevation profiles, and land use classifications at sufficient resolution to support meaningful 3D reconstructions. The reliance on open data also supports reproducibility and transparency, which are critical for scientific and policy-driven research. This data-driven approach ensures that users can generate models for a wide variety of urban contexts without incurring data acquisition costs or facing usage restrictions.

The quantitative comparisons against official LiDAR-derived DSMs confirm that the framework reliably captures the large-scale distribution of building footprints and bulk-height patterns while predictably diverging from DSMs at fine surface detail. These results neither contradict nor diminish the framework's value; rather they clarify its representational envelope: it is fit for applications that depend on correct building locations, relative heights, volumes, and morphological context such as urban climate modelling, large-area exposure and vulnerability assessments, scenario visualisation, and rapid multi-site comparisons, but not for tasks requiring roof-level, façade-level, or sub-meter vertical accuracy such as detailed structural design, or cadastral surveying. The measured height errors largely reflect expected differences between simplified LoD1 extrusions and high-resolution DSM detailed surfaces, so where higher fidelity is required the framework can be combined with co-temporal LiDAR, photogrammetry, or targeted local refinements to improve per-building accuracy without losing the pipeline's automation and open-data advantages.

The applicability of this framework to urban climate research is particularly noteworthy. Accurate 3D models are essential for simulating urban heat islands, solar radiation, wind flow, and energy consumption. By providing detailed representations of buildings, roads, parks, trees, and water bodies, the models produced by this framework can be directly integrated into urban climate modelling tools such as ENVI-met and UMEP. The inclusion of key morphological elements allows for realistic assessments of shading, ventilation, and surface energy balances, enhancing the accuracy and relevance of simulation results. Furthermore, the framework's efficiency allows for rapid generation of models across large areas, facilitating multi-scenario analysis and enabling iterative design and policy exploration.

An additional advantage of the framework is its support for widely accepted output formats, including PLY, OBJ, CityGML, and CityJSON. These formats ensure compatibility with a broad range of visualisation, simulation, and data management tools. CityGML and CityJSON, in particular, allow for semantic encoding of urban features, enabling users to retain feature-level information such as building heights, types, and land use attributes. This granularity is essential for tasks ranging from energy modelling to disaster risk assessment. The availability of structured and interpretable output formats also enhances data interoperability, allowing the models to be integrated into broader urban data ecosystems and shared across platforms and institutions.

The framework's real-world applicability has been demonstrated through its deployment across six major cities: New York, London, Rio de Janeiro, Singapore, Hong Kong, and Sydney. These case studies span diverse climates, urban and terrain forms, and data availability contexts, showcasing the framework's flexibility and robustness. Despite the differences in urban structure and scale, the tool was able to generate complete, high-quality 3D models in each case, highlighting its generalisability. The processing time remained low across all cities, underscoring the framework's scalability and suitability for large-scale or time-sensitive projects.

5. CONCLUSIONS

In summary, our open-source Python framework represents a substantial step forward in facilitating access to 3D urban modelling from 2D footprints. By combining open data, efficient processing, and support for standard 3D output formats, it provides a powerful tool for researchers, planners, and policymakers engaged in urban environmental analysis and design to generate accurate 3D urban morphology in regions where there is no access to expensive LiDAR/scanning technologies. Future work should integrate the addition of more urban features to the five features used, improving the exported CityGML/CityJSON features and test the generated 3D models using urban climate modelling tools.

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