

# VoxCity: A Seamless Framework for Open Geospatial Data Integration, Grid-Based Semantic 3D City Model Generation, and Urban Environment Simulation

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## Abstract

Three-dimensional urban environment simulation is a powerful tool for informed urban planning. However, the intensive manual effort required to prepare input 3D city models has hindered its widespread adoption. To address this challenge, we present VoxCity, an open-source Python package that provides a one-stop solution for grid-based 3D city model generation and urban environment simulation for cities worldwide. VoxCity's 'generator' subpackage automatically downloads building heights, tree canopy heights, land cover, and terrain elevation within a specified target area, and voxelizes buildings, trees, land cover, and terrain to generate an integrated voxel city model. The 'simulator' subpackage enables users to conduct environmental simulations, including solar radiation and view index analyses. Users can export the generated models using several file formats compatible with external software, such as ENVI-met (INX), Blender, and Rhino (OBJ). We generated 3D city models for eight global cities, and demonstrated the calculation of solar irradiance, sky view index, and green view index. We also showcased microclimate simulation and 3D rendering visualization through ENVI-met and Rhino, respectively, through the file export function. Additionally, we reviewed openly available geospatial data to create guidelines to help users choose appropriate data sources depending on their target areas and purposes. VoxCity can significantly reduce the effort and time required for 3D city model preparation and promote the utilization of urban environment simulations. This contributes to more informed urban and architectural design that considers environmental impacts, and in turn, fosters sustainable and livable cities. VoxCity is released openly at <https://github.com/kunifujiwara/VoxCity>.

**Keywords:** Urban morphology, Digital Twin, Thermal environment, Ray-tracing, Thermal comfort, Built environment, View factor

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## 1. Introduction

Three-dimensional urban environment simulations facilitate assessing various conditions including outdoor heat stress [1, 2], wind flow [3], visual perception [4, 5], building energy demand [6, 7], air quality [8], and noise propagation [9, 10], at high spatial and temporal resolution. Their results help diverse applications including policy-making, urban planning, city management, architectural and landscape design [11, 12, 13]. Such urban environment simulations require 3D city models with semantic information for diverse elements. For example, microclimate simulation uses heat-related parameters such as heat conductivity, solar reflectance, transmittance, and evaporation coefficients for each object [14, 15]. Therefore, models need to define semantic

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classes of objects, such as buildings, roads, vegetation, and water bodies, that determine these parameters. Simulation of visual perception also requires similar semantic information to evaluate visibility of greenery or buildings [16, 17, 18]. However, in most cases of urban environment simulations, researchers and engineers must prepare such 3D city models themselves due to a lack of available data sources [19, 20]. The intensive manual effort required to create or adapt these models has been a significant bottleneck for urban environment simulations. Although some cities have prepared open 3D city models with semantic attributes, the coverage of such data is currently limited. Moreover, existing models may not be simulation-ready because of issues such as incompatible data formats, unsealed solid geometries, and insufficient semantic information [3, 21, 19].

Meanwhile, increasing global geospatial data relevant to 3D city models has been openly released in the last few years, largely due to rapid advancements in deep learning techniques [22, 23, 24, 25]. For instance, Sirk et al. [26] released building height data with a 4 m spatial resolution for the Global South; Tolan et al. [23] published global canopy height data at a 1 m resolution; Zanaga et al. [24] released land cover data with worldwide coverage at a 10 m resolution; and Hawker et al. [25] created global terrain elevation data with a 1 Arc-second (30.9 m at the equator) resolution, based on Copernicus DEM, canopy height and building footprint data. We can use these open geospatial datasets to create 3D city models with semantic information regarding buildings, trees, land cover, and terrain. However, while these datasets can reduce the efforts required to collect necessary information and increase the coverage, they still require intensive manual efforts to integrate them and reconstruct 3D city models of sufficient quality for advanced uses such as simulations. Each dataset has different data types, such as raster and vector, and varying spatial resolutions, making the data integration process complex. To scale applications of urban environment simulation globally, it is desirable to automate these manual efforts for data integration. Moreover, even with simulation-ready models, working in simulation software remains time-consuming, particularly for tasks such as data import, boundary condition settings, and result data export.

Several open-source packages have been developed to address these challenges. 3dfier [27] and City4CFD [21, 3] automate the integration of land use and point cloud data to generate semantic 3D city models. They enable users to prepare input 3D city models for urban environmental simulations; however, point cloud data is not available for most cities, and they do not incorporate tree canopies. UMEP [28] offers functionality to simulate urban thermal and wind environments using 3D city models; however, users need to prepare input datasets including building digital surface models (DSMs) and vegetation DSMs, which require manual efforts, and are, moreover, not available for most cities. Additionally, to the best of our knowledge, there are no open packages that provide seamless functionality encompassing open geospatial data integration, 3D city model generation, and urban environment simulation.

To bridge the gap between 3D model generation and urban environment simulation, a meshing process fundamentally needs to be incorporated. Many urban environment simulation methods include the process where 3D city models are split into meshes with certain scales. For example, Computational Fluid Dynamics (CFD) for wind environment simulation requires volume meshes for fluid (air) domains and surface meshes for solid objects, such as buildings and ground [29]. Ray-tracing for solar irradiance simulation requires surface meshes of solid objects, where solar radiation is reflected or absorbed [30]. There are two principal methods for the meshing process: structured meshing and unstructured meshing. Structured meshing is a grid-based approach to create cuboid volume meshes and rectangular surface meshes [31, 32]. Unstructured meshing does not rely on a grid and generates polyhedral volume meshes and triangular surface meshes, allowing for more flexibility in shape and proportion [33, 29]. Numerous software packages employ structured meshing due to its lower computational load for both calculation and memory, as well as its stability in numerical simulations. Unstructured meshing has the advantage of incorporating curved surfaces; however, it can generate low-quality meshes with overly sharp or blunt vertex angles, leading to divergence or low accuracy in numerical simulations. For city-scale applications, structured meshing should be more desirable than unstructured meshing. More specifically, the voxel-based approach, which applies the same mesh size for the entire domain in structured meshing [34, 35], offers advantages in simplicity, as a single 3D array and a specified

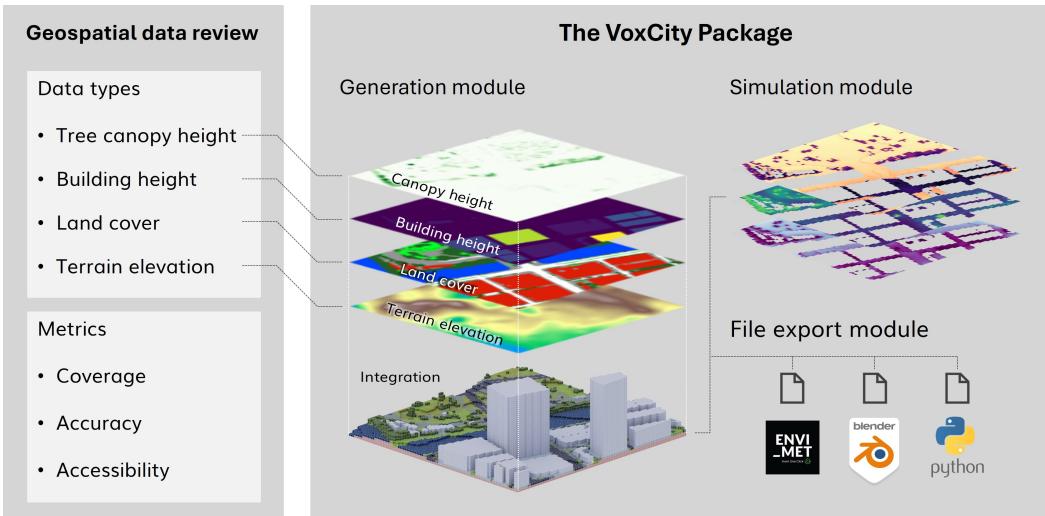


Figure 1: Framework of the development of VoxCity.

voxel size can represent the entire mesh. Moreover, voxels have better compatibility with raster formats that are commonly used in geospatial data, such as land cover, tree canopy height, and terrain elevation.

Therefore, this paper introduces ‘VoxCity’, an open-source Python package that provides a seamless solution for voxel-based geospatial data integration, 3D city model generation, and urban environment simulation. The framework is illustrated in Figure 1. We review open geospatial data, including building height, tree canopy height, land cover, and terrain elevation data types, and select appropriate data sources for our 3D city model generator based on metrics such as coverage, accuracy, format and accessibility. VoxCity automates the process of downloading, voxelizing, and integrating geospatial data from the selected sources to generate voxel-based 3D city models with semantic information. The package includes a subpackage for urban environment simulation, providing users an end-to-end workflow from data acquisition and integration through model generation and simulation. Furthermore, VoxCity supports multiple export file formats, ensuring compatibility with various external 3D modeling and simulation software packages.

## 2. Background and Related Work

### 2.1. Urban Environment Simulation

Climate change [36] has intensified heat-related challenges like frequent heat waves [37, 38] and urban heat island effects [39], spurring increased assessment of outdoor heat stress and thermal comfort through CFD [40, 2], radiation transfer models [1, 41, 42], and heat conduction and energy balance analyses [43]. The objectives of microclimate simulations have encompassed not only heat-related health issues but also other diverse aspects such as energy consumption for heating, ventilation, air conditioning (HVAC), and lighting [6, 7, 44, 45, 46], air quality [27, 8], wind comfort [47, 48], wind pressure on building surfaces [49, 50], and sunlight and ultraviolet exposure focusing on human skin health [51]. Additionally, numerous studies have reported impacts of buildings [52, 53, 54, 55], trees [56, 57, 58, 59, 60], low vegetation [61, 62, 63], water bodies [64, 65, 66, 67, 68], and terrain morphology [69] on the microclimate, indicating the importance of including these urban elements in 3D city models for simulations.

Meanwhile, many studies have conducted urban environment simulations to assess the visual comfort of streetscapes [4, 5] and window views [70]. Specifically, sky view factor (SVF) or sky view index (SVI) [71] and green view index (GVI) [72] have mainly been evaluated as quantitative indicators using 3D city models with buildings, trees, and low vegetation land covers. Numerous studies have employed street view imagery and computer vision techniques instead of simulations with 3D city models to evaluate view indices [73, 74, 75, 76]. This enables view analysis without preparing detailed 3D city models; however, such analysis cover only viewpoints along street

networks, and furthermore, not all streets have sufficient imagery. These view indicators have been assessed focusing not only on visual comfort but also on walkability [77, 74] and bikeability [78] of streets, the well-being of city dwellers [79], and the preference of residents and real-estate prices [80, 81]. The visibility of water features, including the ocean, lakes, and rivers, has also been discussed in the same context [82].

Our literature review revealed that buildings, trees, land cover, water bodies, and terrain elevation have been included as essential information in 3D city models across different simulation objectives.

## 2.2. Creation of 3D city models

Numerous studies have prepared their 3D city models by processing point clouds acquired through LiDAR measurements [41, 83, 84, 27], or by processing polygon data acquired through photogrammetry methods [85]. While these methods can reduce the manual effort required for 3D city model preparation, their input data—point cloud data from LiDAR or multi-view photography—is not readily available in most cases.

Meanwhile, an increasing number of studies have employed open 3D city models that have been individually released by countries or cities [86, 87, 88, 89, 90]. However, in most cases, we still need to create 3D city models ourselves because cities with such available models are limited [19]. Furthermore, the data, even when openly available, is not always directly compatible with urban environment simulations. For instance, while 3D city models fundamentally include building data, only a portion of them have other semantic information, including trees and land cover [20]. Many software solutions for urban environment simulation require their own input file formats for 3D city models, such as INX for ENVI-met<sup>1</sup> and MSH for ANSYS<sup>2</sup>. Additionally, some simulations require high completeness in geometry for their meshing processes. Software for CFD simulations tends to require precise watertight geometries for solid objects and does not accept polygons with gaps and intersections [3, 21]. Therefore, even for studies targeting areas with open 3D city models, many of them need to add missing information from other data sources, convert file formats, or modify to meet quality standards.

Our review of the preparation of 3D city models highlights the significant lack of available 3D city models with sufficient quality for urban environment simulations, while there is a strong demand for methods to generate 3D city models from openly available data sources for many cities.

## 2.3. Related work

There are several open tools to generate 3D city models. For instance, 3dfier [27] is an open-source software to generate 3D building models from point cloud data and building footprints. BlenderGIS<sup>3</sup> is a plug-in tool for Blender<sup>4</sup>, a free and open-source 3D modeling software, which generates 3D city models by combining building data from OpenStreetMap<sup>5</sup> and terrain elevation from Shuttle Radar Topography Mission (SRTM) [91]. However, we were unable to find any open-source tools that could generate 3D city models containing all essential elements and attributes, including buildings, vegetation, water bodies, and terrain.

Several previous studies suggest a potential solution to the demand for a semantic 3D city model generator. Ding et al. [92] and Li and Wang [42] integrated multiple geospatial data to create 3D city models with semantic information and conducted microclimate simulations using the generated models. Specifically, Ding et al. [92] combined data on building height, land cover, and terrain elevation, while Li and Wang [42] combined building height and tree canopy height. Although Ding et al. [92] and Li and Wang [42] created land cover data using aerial imagery and building data using aerial LiDAR data respectively, they directly use openly available data sources for other data types. If these methods can be extended to encompass all essential data types—building height, land cover, canopy height, and terrain elevation—and if all these data can be

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<sup>1</sup><https://envi-met.com/>

<sup>2</sup><https://www.ansys.com/>

<sup>3</sup><https://blender-addons.org/blendergis-addon/>

<sup>4</sup><https://www.blender.org/>

<sup>5</sup><https://www.openstreetmap.org>

collected from openly and globally available data sources, such a tool would be highly beneficial for many researchers and engineers working on urban environment simulations.

Existing open datasets vary considerably in their spatial coverage, accuracy, and resolutions. Despite the importance of these factors for application in 3D city modeling and urban environment simulation, we were unable to find any studies offering a systematic comparison for such datasets. This gap underscores the importance of cataloging available open geospatial data, evaluating their quality, and their applicability in generating semantic 3D city models. However, no studies have reviewed open geospatial data from this perspective.

Meanwhile, increasing studies have proposed open-source tools as Python packages [27, 93, 94, 95, 96, 97]. For example, Yap et al. [93] introduced the Python package ‘Urbanity’ to automate the construction of feature-rich urban networks at any geographical scale and any location. Gholami et al. [94] developed a Python-based approach to assess microscale human thermal stress in urban environments. Python is one of the most dominant programming languages for data science, especially in machine learning. Many Python users openly share their scripts and packages through platforms such as GitHub<sup>6</sup> and PyPI<sup>7</sup>, facilitating easier and more scalable distribution of developed tools.

Therefore, we propose a tool that offers three key contributions: reducing the manual effort required to prepare 3D city models for urban environment simulations, and enabling broader applications of these simulations in environmental research and urban-architectural design projects. To achieve these contributions, we present three main developments:

1. Review of open geospatial data. We review publicly available geospatial datasets—including building height, tree canopy height, land cover, and terrain elevation—focusing on crucial metrics for 3D city modeling, such as coverage, spatial resolutions, and accuracy. We identify suitable data sources for the 3D city model generation process and compile them into a comprehensive catalog. This catalog will assist researchers and practitioners in selecting appropriate data sources for 3D city model preparation and urban environment simulation, depending on their purposes and target areas.
2. Integration of open geospatial data. We propose a tool that automates the integration of publicly available geospatial data to generate semantic 3D city models. This approach enables users to prepare 3D city models and conduct urban environment simulations for cities worldwide with minimal manual effort.
3. Open-source Python package. We release our tool as an open-source Python package, allowing users to easily adopt, modify, and combine it with other Python libraries. Through this release, we aim to streamline 3D city model preparation and encourage broader collaboration and innovation within the community.

### 3. Review of open geospatial data

In this section, we review open geospatial data related to building height, tree canopy height, land cover, and terrain elevation, comparing spatial coverage, resolution, platform, and file format. Sections 3.1 to 3.4, discuss each data type in detail. Based on the review, we present a comprehensive data catalog in Section 3.5 to guide readers in selecting suitable data sources for specific target areas and research purposes.

#### 3.1. Building height

We first screened open building height datasets using two criteria: (1) global or multi-national coverage and (2) horizontal resolution finer than 10 m. The 10-meter threshold ensures sufficient granularity to represent urban morphology, including small-scale buildings and street canyons. During the screening process, we excluded datasets that cover only one country or city [98, 99, 100, 101] or have coarser than 10 m resolution [102, 103, 104]. As a result, we selected OpenStreetMap<sup>8</sup>

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<sup>6</sup><https://github.com/>

<sup>7</sup><https://pypi.org/>

<sup>8</sup><https://www.openstreetmap.org>

(OSM), Overture<sup>9</sup>, EUBUCCO v0.1<sup>10</sup> [105], UT-GLOBUS [22], Open Buildings 2.5D Temporal dataset (OB2.5DT) [26], and Microsoft Building Footprints (MSBF) [106]. Table 1 summarizes their characteristics. None of these sources provides complete, worldwide coverage, underscoring the importance of selecting a dataset that best suits the target city.

Table 1: Comparison of building height data sources.

Dataset	Spatial Coverage	Resolution /Accuracy	Platform /File format	Source /Data Acquisition
OpenStreetMap	Worldwide completeness in city centers [107])	(24% (24% / Not provided	API / JSON (vector)	Volunteered / updated continuously
Overture	Worldwide	- / Not provided	API / JSON (vector)	OpenStreetMap, Esri Community Program, Google Open Buildings, etc. / updated continuously
EUBUCCO v0.1 [105]	27 EU countries and Switzerland (378 regions and 40,829 cities)	- / Not provided	Files on the official website ( <a href="https://eubucco.com/">https://eubucco.com/</a> ), Zenodo / GPKG (vector)	OpenStreetMap, government datasets / 2003-2021 (majority is after 2019)
UT-GLOBUS [22]	Worldwide (more than 1200 cities or locales)	- / 7.8 m (RMSE, height)	Files on Zenodo / GPKG (vector)	Prediction from building footprints, population, spaceborne nDSM / not provided
Microsoft Building Footprints [106]	North America, Europe, Australia	- / Not provided	List of download links with QuadKey / GeoJSON (vector)	Prediction from satellite or aerial imagery / 2018-2019 for the majority of the input imagery
Open Buildings 2.5D Temporal dataset [26]	Africa, Latin America, and South and Southeast Asia	4 m / 1.5 m (MAE, height)	Google Earth Engine, Google Cloud Storage / GeoTIFF (Raster)	Prediction from satellite imagery / 2016-2023

Figure 2 illustrates building height maps from the reviewed sources for Paris, Rio de Janeiro, and Nairobi. In OSM, some buildings lack footprints, and some footprints lack height attributes, reflecting its nature as Volunteered Geographic Information (VGI) [108]. Moreover, while OSM has higher coverage for footprints and heights in central areas of major cities (e.g., Paris and Rio de Janeiro), coverage in rural areas (e.g., Nairobi) is often poor. Overture displays coverage similar to OSM in Paris and Rio de Janeiro, but differs in footprint geometries and height values. For Nairobi, it offers substantially better footprint coverage than OSM. We attribute such differences to Overture’s data acquisition strategy: it uses OSM as a baseline and augments coverage with other sources, including MSBF, Google Open Buildings, and the Esri Community Maps Program (as detailed in their documentation: <https://docs.overturemaps.org/guides/buildings>). EUBUCCO exhibits higher completeness than both OSM and Overture in Europe, often providing more detailed footprints. This is partly due to the inclusion of governmental datasets in addition to those from OSM. OB2.5DT covers most buildings and suggests reasonably good height accuracy for low- and mid-rise buildings; however, it underestimates tall buildings exceeding 100 m. In contrast, MSBF and UT-GLOBUS tend to have lower footprint accuracy than OSM, Overture, and EUBUCCO; some footprints deviate significantly from actual building outlines, and multiple buildings can appear as a single merged footprint.

Overall, OSM, Overture, and EUBUCCO demonstrate sufficient quality for many applications, whereas MSBF, UT-GLOBUS, and OB2.5DT are less suited as sole sources for 3D city model generation. They can, however, serve as complementary data for missing building height in EUBUCCO, OSM, and Overture. In Figure 2, the panels labeled “OSM + [dataset]” and “Overture + [dataset]” illustrate the integration of OSM or Overture footprints with either MSBF, UT-GLOBUS, or OB2.5DT. Where OSM or Overture footprints lack a height value, the missing

<sup>9</sup><https://overturemaps.org>

<sup>10</sup><https://eubucco.com/>



Figure 2: Examples of building height maps for Paris, Rio de Janeiro, and Nairobi. Gray indicates buildings without height data. Basemap: © OpenStreetMap contributors, © CARTO. Imagery: Google satellite tiles.

attribute is retrieved from the intersecting footprints in a complementary data source. If a building intersects multiple footprints, the final height is determined by a weighted average based on intersection area. The resulting combined data exhibit more complete height coverage than OSM or Overture alone.

Based on this review, we decided to use EUBUCCO, OSM, and Overture as base building height data. OB2.5DT, UT-GLOBUS, and MSBF are used as complementary sources to fill in missing values.

### 3.2. Land cover

We filtered open land cover datasets using the following criteria: (1) worldwide coverage, (2) land cover classes suitable for general urban environment simulations, and (3) horizontal resolution finer than 10 m. We excluded datasets that cover only a single city or country [109, 110], are restricted to specific land cover types (e.g., ice, crop, or forest) [111, 112, 113, 114], or have resolution coarser than 10 m [115, 116, 117].

As a result, we selected ESA World cover (ESA) [24], ESRI 10m Annual Land Cover (2017-2023) (Esri) [118], Dynamic World V1 (DW) [119], OpenStreetMap<sup>11</sup> (OSM), OpenEarthMap Japan (OEMJ) [120], and UrbanWatch (UW) [121] for our further review. Although OEMJ and UW each cover only one nation, we included them because of their exceptionally high (1 m) resolution. Table 2 compares key metrics for these sources.

Table 2: Comparison of land cover data sources.

Dataset	Classes	Spatial Coverage	Resolution /Accuracy	Platform /File format	Source /Data Acquisition
ESA World Cover 10 m 2021 V200 [24]	Tree cover, Shrubland, Grassland, Cropland, Built-up, Bare/Sparse vegetation, Snow and ice, Permanent water bodies, Herbaceous wetland, Mangroves, Moss and lichen	Worldwide	10 m / 76.7%	Google Engine, Earth Zenodo / GeoTIFF (Raster)	Prediction from satellite imagery / 2021
ESRI 10m Annual Land Cover (2017-2023) [118]	Water, Trees, Flooded Vegetation, Crops, Built Area, Bare Ground, Snow/Ice, Clouds, Rangeland	Worldwide	10 m / 85%	Google Engine / GeoTIFF (Raster)	Prediction from satellite imagery / 2017-2023
Dynamic World V1 [119]	Water, Trees, Grass, Flooded vegetation, Crops, Shrub and scrub, Built, Bare, Snow and ice	Worldwide	10 m / 73.8%	Google Engine, Earth Zenodo / GeoTIFF (Raster)	Prediction from satellite imagery / updated continuously
OpenStreetMap	Bare rock, Rock, Sand, Desert, Grass, Park, Industrial, Construction, Railway, Parking, Highway, Wood, Forest, Tree, Water, Waterway, Bay, Ocean, Farmland, Building, etc.	Worldwide	- / provided	API / (vector)	Volunteered / updated continuously
OpenEarthMap Japan [120]	Bareland, Rangeland, Developed space, Road, Tree, Water, Agriculture land, Building	Japan	~1 m / 80%	Webmap (downloadable as tiles) / PNG (Raster)	Prediction from aerial imagery / 1974-2022 (mostly after 2018 in major cities)
UrbanWatch [121]	Building, Road, Parking Lot, Tree Canopy, Grass/Shrub, Agriculture, Water, Barren, Other	22 major cities in the US	1 m / 92%	Google Engine, Google Drive / GeoTIFF (Raster)	Prediction from aerial imagery / 2014-2017

Figure 3 shows example land cover maps from the reviewed datasets for Osaka, Los Angeles, and São Paulo. To allow direct comparisons, we harmonized the class definitions across all datasets using the conversion rules presented in Table 3. Overall, OEMJ (for Osaka) and UW (for Los Angeles) most closely match the actual land cover when compared to aerial imagery. OSM also aligns well but tends to miss smaller patches of vegetation (particularly trees). ESA captures major water bodies and broad vegetation patterns but is less detailed than OEMJ, UW, or OSM. In OSM, some areas (e.g., São Paulo) lack detail in spatial variation, indicating lower completeness than

<sup>11</sup><https://www.openstreetmap.org>

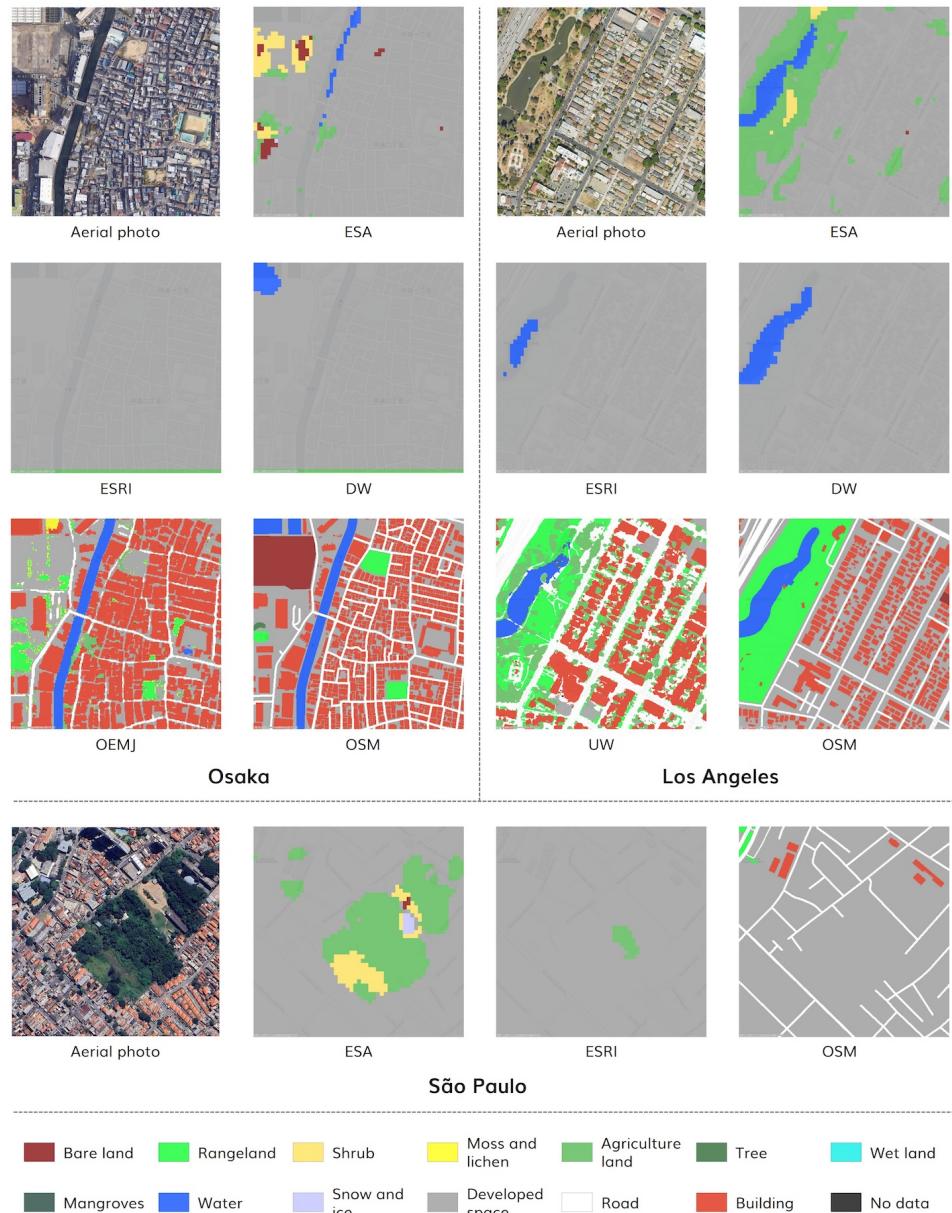


Figure 3: Examples of land cover data for Osaka and Los Angeles. Basemap: © OpenStreetMap contributors, © CARTO. Imagery: Google satellite tiles.

ESA, ESRI and DW indicate low completeness, classifying most pixels as “Developed space” despite these areas actually containing diverse classes. We attribute the relatively low performance of ESRI and DW to their primary focus not being on urban areas, resulting in training and validation data that lacks detailed annotations for urban regions.

Table 3: Class definition harmonization across different land cover data sources.

Class	Allocated classes					
	ESA	ESRI	DW	OEMJ	UW	OSM
Bareland	Barren/sparse vegetation	Bare Ground	Bare	Bareland	Barren	quarry, brownfield, bare_rock, scree, shingle, rock, sand, desert, landfill, beach
Rangeland	Grassland	Grass	Grass	Rangeland	Grass/Shrub	grass, meadow, grassland, heath, garden, park
Shrub	Shrubland	Scrub/Shrub	Shrub and Scrub	Shrub	–	scrub, shrubland, bush, thicket
Agriculture land	Cropland	Crops	Crops	Agriculture	Agriculture	farmland, orchard, vineyard, plant_nursery, greenhouse_horticulture, flowerbed, allotments
Tree	Trees	Trees	Trees	Tree	Tree Canopy	wood, forest, tree, tree_row
Moss and lichen	Moss and lichen	–	–	–	–	moss, lichen, tundra_vegetation
Wet land	Herbaceous wetland	Flooded Vegetation	Flooded Vegetation	Wetland	–	wetland, marsh, swamp, bog, fen
Mangrove	Mangroves	–	–	Mangrove	–	mangrove, mangrove_forest, mangrove_swamp
Water	Open water	Water	Water	Water	Water, Sea	water, waterway, reservoir, basin, bay, ocean, sea, river, lake
Snow and ice	Snow and ice	Snow/Ice	Snow and Ice	Snow	–	glacier, snow, ice, snowfield, ice_shelf
Developed space	Built-up	Built Area	Built	Developed	Parking Lot	industrial, retail, commercial, residential, construction, railway, parking, islet, island
Road	–	–	–	Road	Road	highway, road, path, track, street
Building	–	–	–	Building	Building	building, house, apartment, commercial_building, industrial_building
No Data	–	No Data, Clouds	–	–	Unknown	unknown, no_data, clouds, undefined

Based on this review, we excluded ESRI and DW, and included the remaining datasets as data source options in our package.

### 3.3. Tree canopy height

We screened tree canopy height datasets according to: (1) global coverage, (2) resolution finer than 10 m, (3) coverage that includes urban areas, and (4) no restriction to specific tree species. During this screening, we excluded datasets that cover only particular cities or nations [122], have resolutions coarser than 10 m [123], or focus on forested regions or specific tree species [124, 125]. We also considered open tree inventories, which typically include a database of individual trees (e.g., location, size, age, species) [126, 127, 128]. However, each city or country tends to maintain its own tree inventory format, and coverage rarely extends beyond one locality [129, 130, 131]. Hence, no standardized globally comprehensive tree inventory dataset was identified. Ultimately, we selected High Resolution 1 m Global Canopy Height Maps (META) [23] and ETH Global Sentinel-2 10 m Canopy Height (2020) (ETH) [132] for further review. Table 4 provides details on these data sources.

Table 4: Comparison of tree canopy height data sources

Dataset	Coverage	Resolution /Accuracy	Platform /File format	Source /Data Acquisition
High Resolution 1 m Global Canopy Height Maps [23]	Worldwide	1 m / 2.8 m (MAE)	Google Earth Engine / GeoTIFF (Raster)	Prediction from satellite imagery / 2009 and 2020 (80% are 2018-2020)
ETH Global Sentinel-2 10 m Canopy Height (2020) [132]	Worldwide	10 m / 6.0 m (RMSE)	Google Earth Engine / GeoTIFF (Raster)	Prediction from satellite imagery / 2020

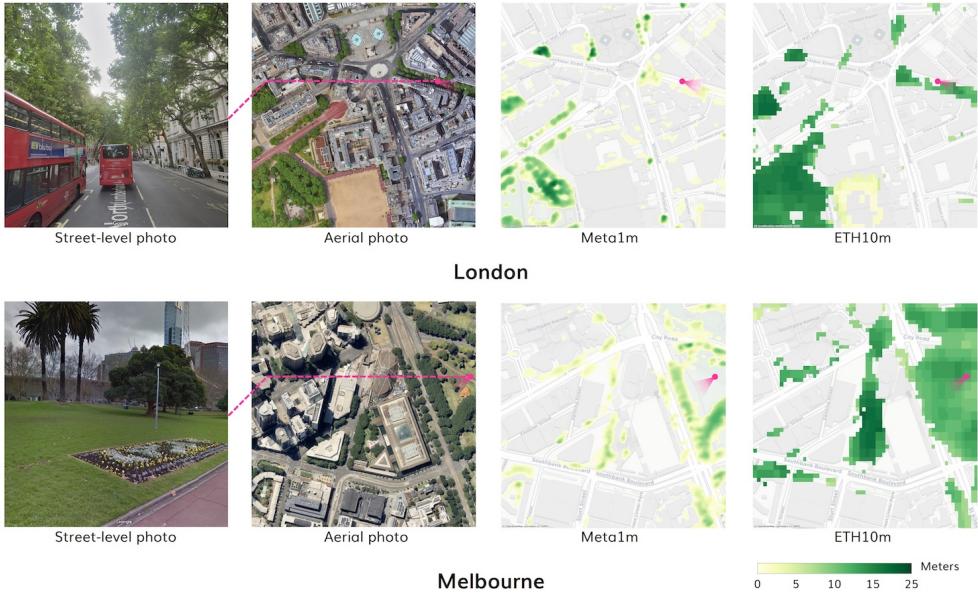


Figure 4: Examples of canopy height data for London and Melbourne. Basemap: © OpenStreetMap contributors, © CARTO. Imagery: Google street view, Google satellite tiles.

Figure 4 compares canopy height maps from META and ETH for areas in London and Melbourne, alongside corresponding street-level and satellite images. In London, the street-level photo indicates trees over 10 m tall (judging from the height of double-decker buses), while META reports around 3 m and ETH 12 m for the same location, suggesting underestimation by META and more accurate performance by ETH. Meanwhile in Melbourne, ETH detects a canopy height of around 10 m at a location that is primarily grass in street-level and aerial imagery, whereas META shows almost no canopy. In this case, META appears more accurate, and ETH overestimates. In short, META and ETH underestimate and overestimate canopy height, respectively, in certain situations. Neither dataset consistently outperforms the other, so the choice depends on regional characteristics and research requirements. We therefore include both options in our package, allowing users to select according to their needs.

#### 3.4. Terrain elevation

We filtered Digital Elevation Model (DEM) and Digital Terrain Model (DTM) sources according to: (1) a horizontal resolution of at least 1 Arc second (30.9 m at the equator), and (2) a bare-earth model that excludes buildings and vegetation (i.e., a DTM rather than a Digital Surface Model, DSM). Datasets with 3 Arc seconds resolution [133], as well as DEMs or DSMs that retain building and vegetation heights [134, 135, 136, 137] were excluded. Consequently, we selected FABDEM [25], DeltaDTM [138], USGS 3DEP 1m DEM (USDEM) [139], England 1m Composite DTM (ENGDTM) [140], Australian 5M DEM (AUSDEM) [141], and RGE Alti (FRADEM) [142] for further review.

Table 5 summarizes the characteristics of the selected datasets. FABDEM provides the most extensive worldwide coverage, followed by DeltaDTM, which covers global coastal areas. While the other datasets are limited to country-scale coverage, they offer superior horizontal resolutions ranging from 1 to 5 m—significantly finer than those of FABDEM and DeltaDTM.

Figure 5 illustrates example terrain elevation maps for London and New York City derived from the reviewed sources. ENGDTM and USDEM show more detailed spatial variation than the other datasets, consistent with their finer resolutions. The London maps display similar elevation values across all sources, whereas the New York City maps show significant discrepancies, particularly between FABDEM and USDEM. We attribute these differences to the varying methods and resulting accuracy in removing building heights in areas with dense high-rise constructions.

Table 5: Comparison of terrain elevation data sources

Dataset	Coverage	Resolution /Accuracy	Platform /File format	Source /Data Acquisition
FABDEM [25]	Worldwide	30 m / Built-up areas: 1.12 m, forests: 2.88 m (MAE)	Google Earth Engine / GeoTIFF (Raster)	Correction of Copernicus DEM using canopy height and building footprints data / 2011-2015 (Copernicus DEM)
DeltaDTM [138]	Worldwide (Only for coastal areas below 10m + mean sea level)	30 m / 0.45 m (MAE)	Google Earth Engine / GeoTIFF (Raster)	Copernicus DEM, spaceborne LiDAR / 2011-2015 (Copernicus DEM)
USGS 3DEP 1m DEM [139]	United States	1 m / Not provided	Google Earth Engine, government website / GeoTIFF (Raster)	Aerial LiDAR / 2004-2024 (mostly after 2015)
England Composite DTM [140]	England	1 m / 0.15 m (RMSE, a vertical accuracy of LiDAR used)	Google Earth Engine, government website / GeoTIFF (Raster)	Aerial LiDAR / 2000-2022
Australian 5M DEM [141]	Australia	5 m / 0.30 m (error metric not specified)	Google Earth Engine, government website / GeoTIFF (Raster)	Aerial LiDAR / 2001-2015
RGE Alti [142]	France	1 m / 0.2 m (RMSE, coastal areas), 0.5 m (RMSE, large forest areas)	Google Earth Engine / GeoTIFF (Raster)	Aerial LiDAR / Not provided

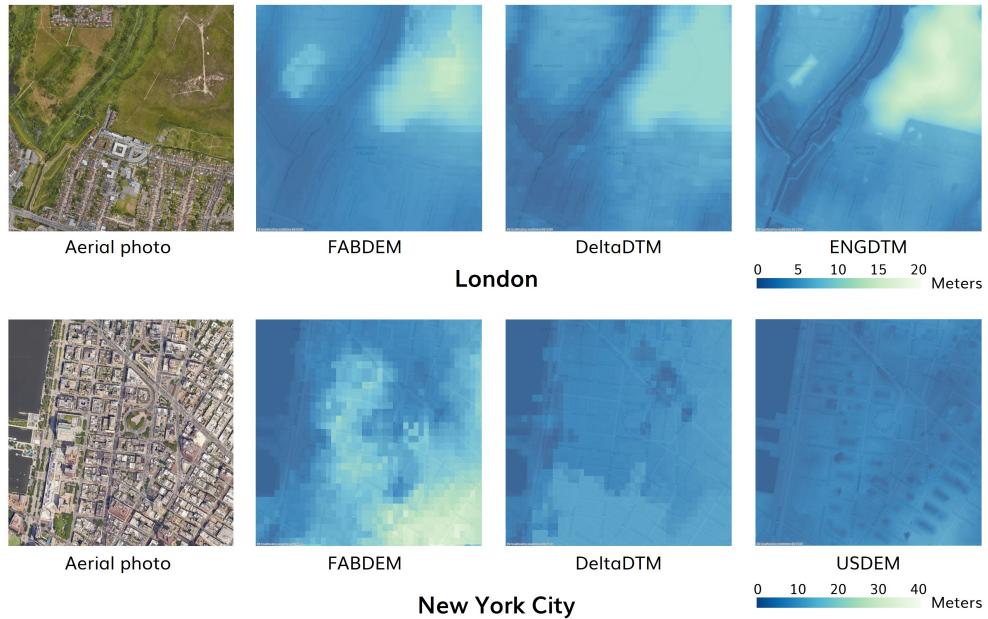


Figure 5: Examples of terrain elevation data for London and New York City. Basemap: © OpenStreetMap contributors, © CARTO. Imagery: Google satellite tiles.

Based on the observed advantages and disadvantages of each dataset in terms of coverage and resolution, we decided to include all reviewed sources as options in our package.

### 3.5. Data catalog with guidelines for data selection

After reviewing data sources for building height, land cover, tree canopy height, and terrain elevation, we compile a comprehensive data catalog for our package (Table 6). This catalog includes guidelines to select appropriate data sources for each data type. Users can refer to this catalog to identify the most suitable data sources based on their specific target areas and research objectives.

Table 6: Catalog of data types for 3D city model generation.

Type	Data sources	Guidelines for selection
Building height	Base: EUBUCCO [105], OSM, Overture Complementary: OB2.5DT [26], UT-GLOBUS [22], MSBF [106]	(1) Use EUBUCCO for EU countries; for other regions, employ OSM or Overtures as the base source. (2) If the target area is covered by any complementary dataset (MSBF for the USA, Europe, and Australia; OB2.5DT for the Global South; UT-GLOBUS for 1,200 global cities), use it as the complementary source.
Land cover	UW [121], OEMJ [120], OSM, ESA [24]	(1) Use UW for U.S. cities and OEMJ for Japanese cities, where available. (2) For all other regions, rely on OSM by default. (3) If OSM coverage is insufficient, switch to ESA.
Canopy height	META [23], ETH [132]	Select either META or ETH according to the target areas and research objectives, keeping in mind that META typically underestimates canopy height while ETH tends to overestimate.
Terrain elevation	USDEM [139], ENGDGM [140], AUSDEM [141], DeltaDTM [138], FABDEM [25]	(1) For cities covered by high-resolution datasets (ENGDGM, USDEM, AUSDEM, and FRADEM), use those data sources. (2) For other regions, use FABDEM or DeltaDTM. Note that, in areas with dense high-rise buildings, these data may include significant errors.

## 4. The VoxCity package

In this section, we introduce ‘VoxCity’, an open-source Python package for open geospatial data integration, grid-based 3D city model generation, and urban environment simulation. Figure 6 illustrates the framework of VoxCity. Users start the process by specifying the target area and voxel size and selecting data sources from our catalog. The workflow consists of four main subprocesses: (1) 3D city model generation, (2) simulation, (3) file export, and (4) visualization. In (1) 3D city model generation, VoxCity downloads building height, land cover, tree canopy height, and terrain elevation data from the selected sources within the specified target area. It then voxelizes all the downloaded data and integrates them into a semantic 3D city model. In (2) simulation, the output models can be used directly to conduct urban environment simulations through VoxCity’s built-in simulation functions. In (3) file export, VoxCity can export the output model in multiple file formats that are compatible with external software. In (4) visualization, VoxCity offers 3D visualization functionality for not only generated city models but also simulation results. The following subsections provide more details on these sub-processes.

### 4.1. 3D city model generation

#### 4.1.1. Download

VoxCity automatically downloads the required data within a target area through either file links or API depending on selected data sources. Users can define the target area as a rectangular region. Downloaded data are saved in users’ environments and utilized in subsequent processes. Vector and raster data are saved as GeoJSON and GeoTIFF files, respectively. Users who need these intermediate files can also use VoxCity solely as a downloader for various geospatial datasets, similar to OSMnx [96], which often serves as a downloader for road networks from OSM.

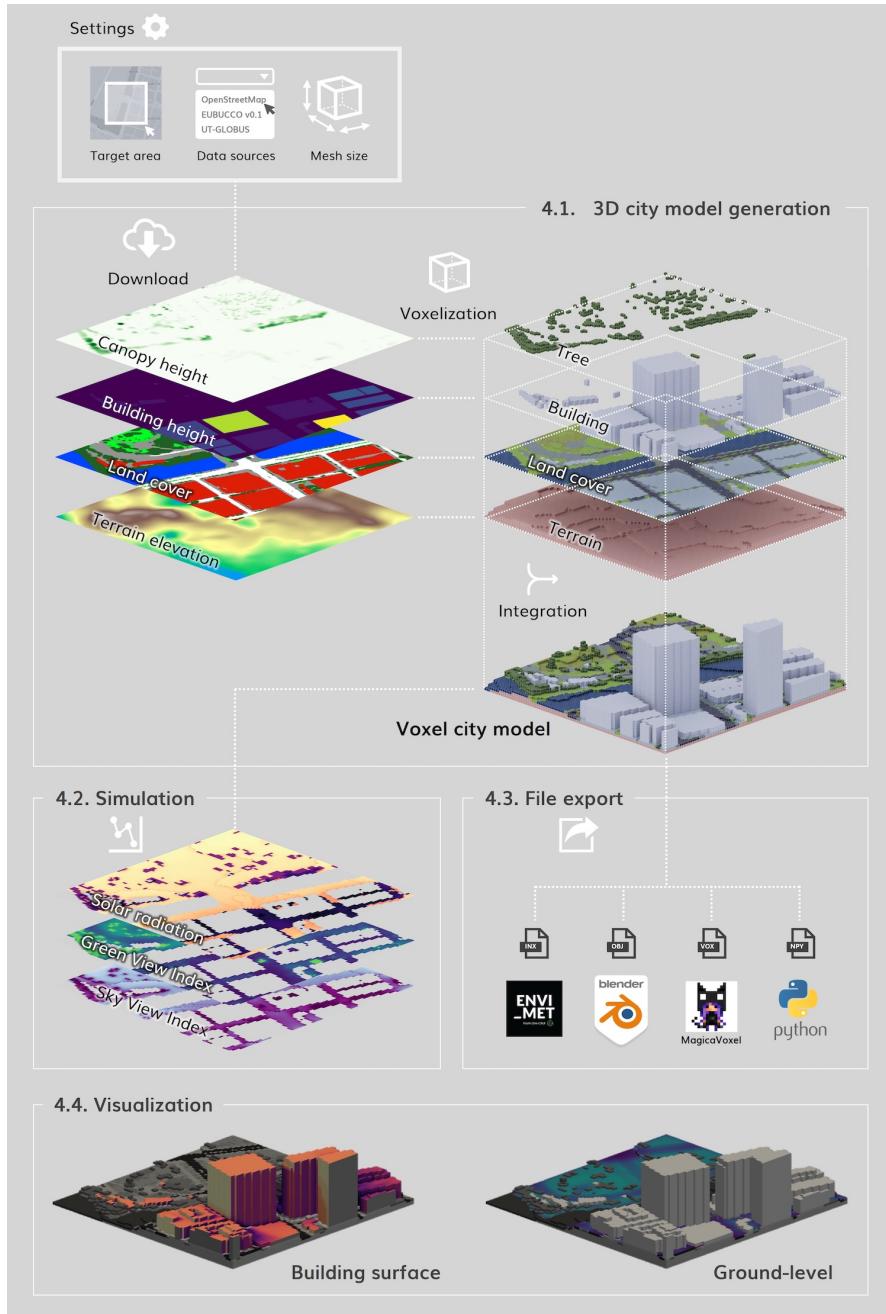


Figure 6: Workflow of data processing in 'VoxCity' – from bringing together disparate urban data sources to conducting complex multi-modal simulations – all in a single software package.

#### *4.1.2. Voxelization and integration*

Downloaded data are then voxelized using voxel units through the following processes.

VoxCity first aggregates values using a two-dimensional horizontal grid defined by the voxel size (in meters). For building height, tree canopy height, and land cover, each cell's value is determined by the dominant value within that cell. For instance, focusing on land cover, when a cell includes multiple classes, the class that covers the largest area is assigned as its representative value of the cell. In this process, the land cover class harmonization shown in Table 3 is applied, enabling users to easily compare the generated 3D models across different data sources and select the desirable sources. For terrain elevation, the representative value of a cell is calculated as the average within the cell.

A voxel model is then generated for each data type by extruding the aggregated cell values. For building height, tree canopy height, and terrain elevation, two-dimensional grids are extruded corresponding to the value of each cell and its voxel size. For example, if a cell representing building height has a value of 50 m and the voxel size is 5 m, it is extruded into 10 ( $=50/5$ ) voxels vertically. Tree and terrain voxels are generated using the same method. For trees, the canopy height value includes a gap between the terrain surface and the bottom of the canopy. Tree voxels occupy only the space between the top and bottom of the canopy, while void voxels fill the space below the canopy. The height of this gap is determined by multiplying the canopy height by a trunk height ratio, which can be adjusted to reflect different regions or tree species. For land cover, the topmost (surface) terrain voxel in each cell of the 2D grid is replaced with a land cover voxel.

Finally, voxel models of buildings, trees, and terrain with land cover are integrated into a single 3D city model. In this integration process, building and tree models are placed on top of the land cover voxels (the surface voxels of the terrain model).

In OSM, some buildings consist of multiple footprint polygons with detailed height information for both the top and the bottom. Such footprints represent more complex building shapes than simple extrusions based on terrain surfaces. For these buildings, our method uses both top and bottom height values to fill building voxels only between the two heights, leaving voxels between the terrain surface and the building's bottom as void (see Figure 7-Singapore as an example). Additionally, VoxCity generally does not support civil engineering structures such as bridges and elevated highways, except for some rare cases where such objects are registered with height values in OSM.

VoxCity's 3D city models are structured as three-dimensional arrays, whose dimensions correspond to the geospatial x, y, and z axes. Each cell corresponds to a voxel, and its value represents an element type such as a building, tree, or water.

#### *4.1.3. Example outputs*

Figure 7 shows example 3D city models generated by VoxCity. These include models of Singapore, Tokyo, Paris, New York City, Rio De Janeiro, Abu Dhabi, Sydney, and Cape Town, demonstrating VoxCity's capability to generate 3D city models worldwide and in varied urban morphologies. These outputs also illustrate VoxCity's ability to represent building configurations more complex than simple extrusions of building outlines. This is particularly evident in the Singapore model, which features a rooftop park supported by three towers.

Additionally, VoxCity's outputs capture the morphological characteristics of each city by combining building shapes and arrangements, land covers, tree canopies, and terrain elevations. Notable examples include the radiating block arrangements and street networks around Arc de Triomphe in Paris; dense skyscrapers surrounded by water in Lower Manhattan, New York City; tightly packed houses on a mountainside in Rio de Janeiro; and sparse high-rise buildings set amid sandy terrain in Abu Dhabi.

The approach is efficient. In our environment—equipped with an Intel Core i9-13900 processor and an internet connection with a measured download speed of 180 Mbps—VoxCity took 25 seconds to download the required data and generate the 3D city model of Singapore shown in Figure 7. However, it is important to note that processing times can vary substantially depending on the selected data sources.

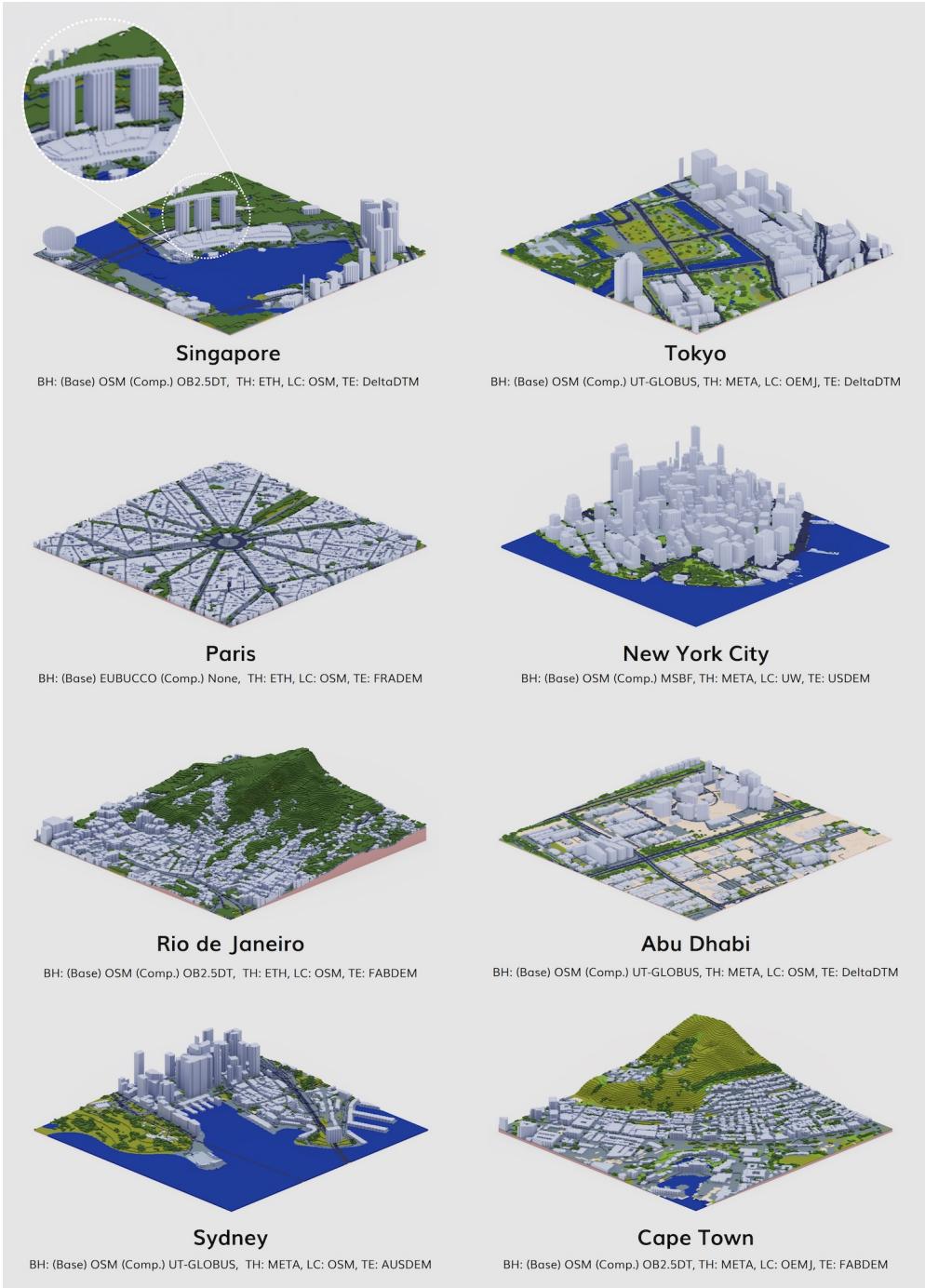


Figure 7: Examples of output 3D city models from VoxCity. 3D rendering performed in MagicaVoxel. BH, TH, LC, and TE represent building height, tree canopy height, land cover, and terrain elevation, respectively.

## 4.2. Simulation

VoxCity includes a built-in subpackage ‘simulator’ that calculates solar irradiance, view indices, and landmark visibility in 3D city models. Combined with the ‘generator’ subpackage, VoxCity provides a one-stop solution for everything from 3D city model preparations to urban environment simulations, reducing the manual effort typically required to transfer data between 3D modeling software and specialized simulation tools. The following subsections detail methodologies used for each simulation.

### 4.2.1. Solar radiation

A module, ‘solar’, provides functionality for calculating global irradiance at ground-level and on building surfaces. Solar radiation is a critical factor influencing outdoor heat stress [143], thermal comfort [144, 145], urban farming [146], photovoltaic power generation [147, 148], and building energy consumption by HVAC and lighting [149, 150]. Consequently, it has profound impacts on urban sustainability and the well-being of city dwellers—underscoring its importance in urban and architectural planning. The ‘solar’ module offers two calculation options: (1) instantaneous solar irradiance ( $\text{Wm}^{-2}$ ) at a specific timestamp and (2) cumulative solar irradiance ( $\text{Whm}^{-2}$ ) over a specific period. For instantaneous value, the module first calculates solar azimuth and elevation angles using the location (longitude and latitude) of the target area and the target timestamp, employing a Python package ‘astral’<sup>12</sup>. Direct and diffuse irradiance are then calculated using a ray-tracing technique, incorporating the computed sun position as well as direct normal and diffuse horizontal irradiance that is not affected by shading. In the ray-tracing process, a transmittance determined by the Beer-Lambert law (Equation 1) is incorporated when rays pass through tree voxels:

$$\tau = e^{-K \cdot LAD \cdot l} \quad (\text{Monsi and Saeki [151]}) \quad (1)$$

where  $\tau$  is the transmittance of solar radiation through tree canopies,  $e$  is the base of the natural logarithm,  $K$  is the extinction coefficient,  $LAD$  represents the leaf area density ( $\text{m}^2 \text{ m}^{-3}$ ), and  $l$  is the path length through tree voxels (m). In this paper, we employed  $K = 0.5$ , and  $LAD = 1.0 \text{ m}^2 \text{ m}^{-3}$ .

For cumulative value, the module calculates instantaneous irradiance at each timestamp from the start to the end of a specified period and then sums the results. To incorporate locally relevant climate conditions (including direct normal and diffuse horizontal irradiance), the module can use Energy Plus Weather (EPW) files. Users may supply their own EPW files; otherwise, the module can automatically download the nearest EPW file from Climate.OneBuilding.Org<sup>13</sup>.

Figure 8a illustrates example results of ground-level cumulative solar irradiance for three target areas: New York City, Paris, and Abu Dhabi. These simulations used the same 3D city models shown in Figure 7 and employed the nearest EPW files downloaded from Climate.OneBuilding.Org. Each target area exhibits distinct spatial variations in solar irradiance, reflecting differences in urban morphology, climate, and weather conditions. These results demonstrate the potential of VoxCity’s simulation subpackage for evidence-based urban and architectural design that accounts for local conditions.

Additionally, VoxCity provides a feature to aggregate grid-based simulation results along the edges of road networks, as shown in Figure 8b. The functionality uses OSMnx to download road networks from OSM, enabling various network analyses within simulated urban environments—including not only solar irradiance but also view indices and landmark visibility, which is detailed in Section 4.2.2.

### 4.2.2. View index

A module, ‘view’, provides functionality for conducting view index analyses, where the ratio of specific object types—such as vegetation, sky, and buildings—visible from a given location is quantitatively evaluated. The module calculates the view index by applying a ray-tracing technique to 3D city models. Users can specify the target object type, the vertical angle of view (i.e., the

<sup>12</sup><https://github.com/sffjunkie/astral>

<sup>13</sup><https://climate.onebuilding.org/>

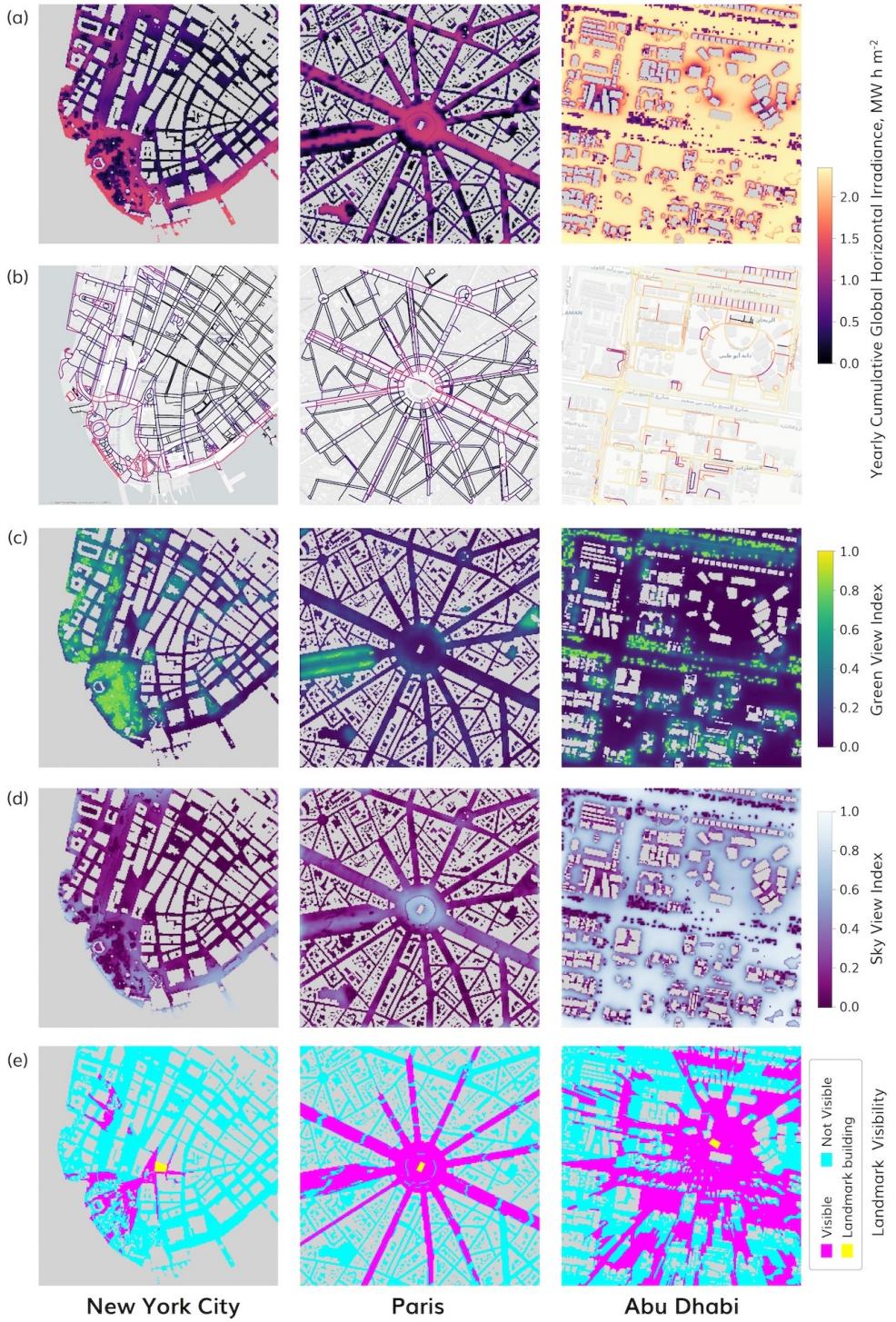


Figure 8: Example urban environment simulations conducted using 3D city models from VoxCity. (a, b) Solar irradiance. (c) Green View Index, GVI. (d) Sky View Index, SVI. (e) Landmark Visibility. Panel (b) employed walking path networks downloaded from OpenStreetMap. Basemap: © OpenStreetMap contributors, © CARTO.

ranges in which rays are cast), and the total number of rays. The horizontal angle of view is set to 360 degrees, assuming uniform visibility in all directions.

We demonstrated the calculations of the Green View Index (GVI) and Sky View Index (SVI) using the module on 3D city models for Paris, New York City, and Abu Dhabi, as shown in Figure 8c and d. For GVI, our method casts 600 rays per location, covering 60 degrees vertically. Specifically, the vertical angles range from -30 to +30 degrees, with the horizontal direction defined as 0 degrees. Rays are cast at six-degree intervals both horizontally and vertically, resulting in  $60 \times 10 = 600$  rays per location. In contrast, for SVI, areas below the horizon do not influence the results; therefore, the vertical angle of view is set from 0 to +30 degrees. This configuration produces 300 rays per location. We employed the same 3D city models shown in Figure 7. The results reflect the distinct urban morphological features of the target areas: New York City exhibits a notably low SVI due to its dense high-rise buildings, whereas Abu Dhabi shows a relatively low GVI and high SVI, aligning with its limited greenery and more sparse buildings.

The view module also provides functionality for evaluating the visibility of specified landmark buildings from ground-level locations using a ray-tracing technique. This enables users to understand from which locations within a target area the landmark buildings can be seen. Figure 8e shows example visibility maps. Landmarks play important roles in pedestrians' perception and wayfinding [152, 153], influencing visual comfort and walkability [154, 155]. The access to the view of landmarks is proved to adding property value [156]. The visibility simulations could support informed urban planning considering such effects of landmarks.

#### 4.3. File export

VoxCity's 'exporter' subpackage can save the generated 3D city model data in several file formats to support downstream applications and data exchange. The available file formats include INX for ENVI-met [157, 158], OBJ for 3D modeling software, VOX for MagicaVoxel<sup>14</sup>, and NPY for Python. ENVI-met is a widely used microclimate simulation software. MagicaVoxel offers GPU-accelerated 3D rendering for voxel models. NPY files enable model data transfer between different Python environments without any format conversion. When using the NPY format, the data is directly saved as a three-dimensional NumPy [159] array. For other formats, the data is first converted to each format's specific data structure. In the case of VOX, the 3D array from VoxCity is reformatted into the VOX structure, including color palette information corresponding to voxel classes. The subsequent subsections describe the export functionality for the INX and OBJ formats in more detail.

##### 4.3.1. INX for ENVI-met

Building height and terrain elevation from VoxCity are directly converted to the INX format, while canopy height and land cover data are translated into corresponding vegetation ID and material ID in ENVI-met before being integrated into the INX format. Additionally, users can specify the trunk height ratio relative to total canopy height and the leaf area density (LAD) of trees. These tree-specific settings are then exported separately as a project database (EDB) file.

Figure 9 shows microclimate simulation examples using the widely-used ENVI-met code (V5.7.1, ENVI-met GmbH, Essen) in two characteristic sites, high-rise Al Zahiya district in Abu Dhabi and low-rise residential in Greenbelt, MD (USA). Since ENVI-met is based on the structured mesh (i.e., Cartesian coordinate), VoxCity can provide basic 3D geometries (Figures 9a and 9b) for the simulation. The calculation domains were 800 m × 800 m × 310 m for Abu Dhabi, and 500 m × 500 m × 50 m for Greenbelt. They comprised inner areas with buildings and trees with horizontally homogeneous grid spacing (4 m for Abu Dhabi and 2 m for Greenbelt here), which is off-the-shelf from VoxCity. Because perimeter margins are necessary for ENVI-met simulation to avoid unphysical results (as detailed in their documentation: <https://envi-met.com/tutorials-plugins-faqs-helpful-info/>), VoxCity provides a function to remove perimeter buildings and trees. For vertical grid spacing, VoxCity provides options that use the same size for the horizontal grid or set an arbitrary number of layers. Here, we

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<sup>14</sup>[https://ephtracy.github.io/index.html?page=mv\\_main](https://ephtracy.github.io/index.html?page=mv_main)

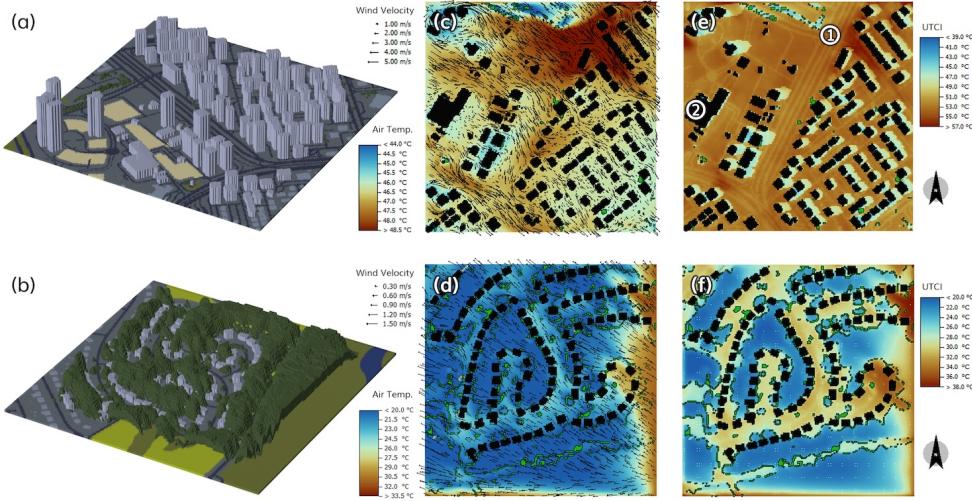


Figure 9: Examples of ENVI-met microclimate simulation in Abu Dhabi and Greenbelt. (a, b) 3D models and land-use land-cover maps obtained from VoxCity. (c, d) Horizontal wind vectors and air temperature, and (e, f) universal thermal climate index (UTCI) distributions at the 1.5-m height on typical summer afternoons.

set 19 layers for the Greenbelt case and 50 for the Abu Dhabi case. One should note that before running the simulation, ENVI-met automatically resizes the meshes within the five layers near the ground to a finer resolution. We also note that ENVI-met V5.7.1 often predicts unphysical results for complex terrains (as detailed on their website: <http://www.envi-hq.com/>), so we strongly recommend VoxCity users not to obtain DEM when conducting ENVI-met simulation.

As mentioned above, VoxCity automatically sets default values of the thermal properties of buildings, ground, and trees by providing the INX file. Although overwriting the INX file, e.g., setting detailed building surface materials, can give more accurate predictions, we show the results with the default values here to verify their adequacy. For meteorological forcings, we used the 2004–2018 typical meteorological year data of the Energy Plus Weather file (<https://www.ladybug.tools/epwmap/>) and selected the nearest weather stations for each site.

Figures 9c–9f show thermal environments at 1.5 m height on typical summer afternoons (2:00 p.m.), namely the horizontal wind vectors and the universal thermal climate index (UTCI) (derived from the air temperature, humidity, radiation, and wind speed) predicted by ENVI-met. In the Abu Dhabi case, the inlet wind was the northwesterly sea breeze from the Persian Gulf. The speed was relatively high above the roads and the open areas and reached 5 m/s at the maximum (Figure 9c), probably because the city block pattern is along the direction of the inlet wind. However, the inlet air temperature was 44°C, hotter than the human body, and therefore, as seen around point ① in Figure 9e for example, the increase in wind speed rather increased UTCI by convective heat transfer (see Fig. 7 of Bröde et al. [160]). Shading effects of buildings and trees on UTCI are evident, and the difference between sunlit and shaded areas reached  $> 20$  °C (Figure 9e). Weak and complex diverged flows with lower air temperature and UTCI values are found in the leewards of the buildings (e.g., around building ② in Figures 9c and 9e and the southeast city block), indicating cooler above-roof air moved to the ground level by the downdrafts. In the Greenbelt case, the wind speed was generally lower than the inlet value (1.5 m/s) due to the momentum sink by trees (Figure 9d). The UTCI distribution seems to correspond simply to the shading pattern, and the contrast between roads and under-tree areas is evident (Figure 9f). Overall, these results seem to be reasonable and suggest the adequacy of the INX file obtained from VoxCity.

#### 4.3.2. *OBJ for 3D modeling and rendering*

The 3D array from VoxCity is converted into surface polygons of the voxel model and then formatted according to the OBJ structure. Colors corresponding to voxel classes are assigned to polygons, and the color palettes are saved as MTL files. This allows 3D modeling software to automatically apply the assigned surface colors when loading OBJ files and helps preserve semantic information that is not native to OBJ [161].

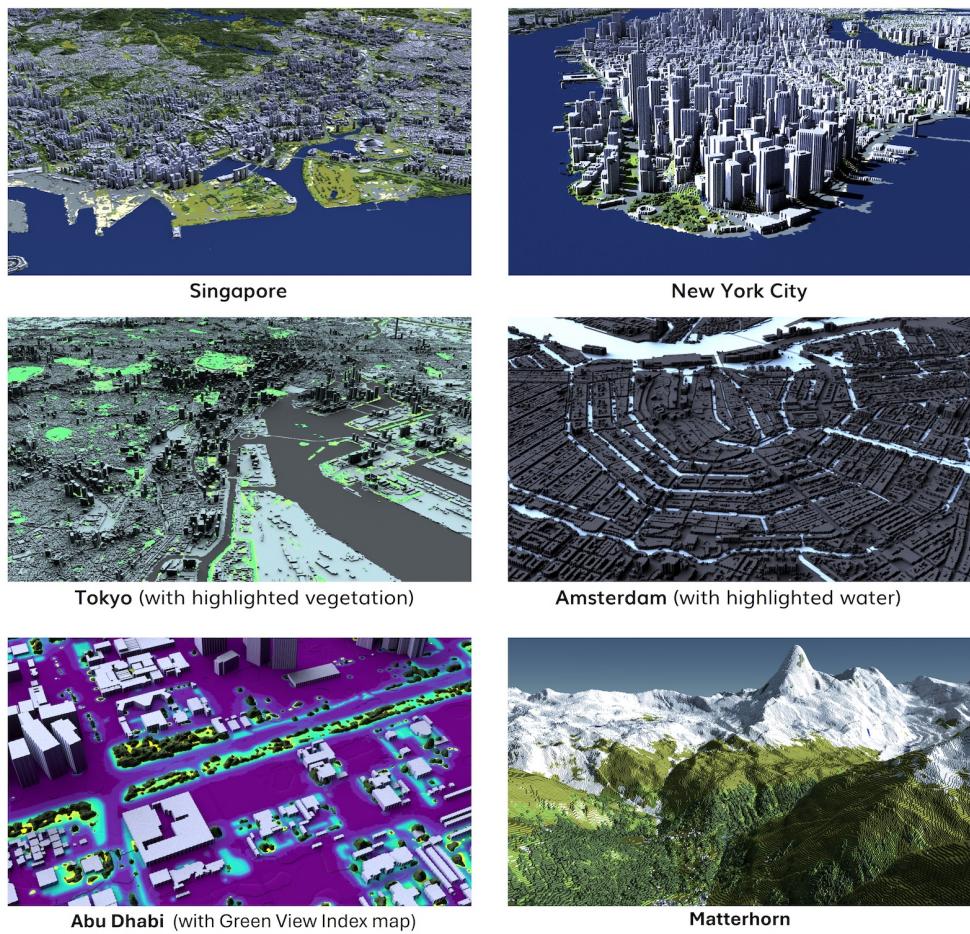


Figure 10: Examples of 3D renderings created in Rhino using output 3D city models from VoxCity.

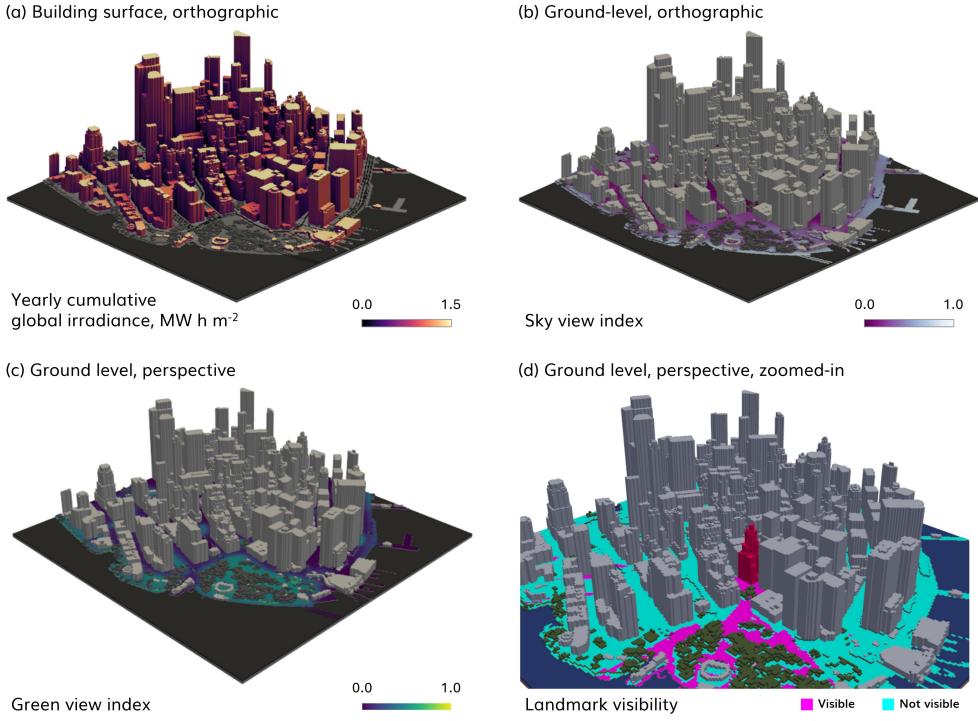


Figure 11: Example outputs for New York City produced by VoxCity’s built-in 3D visualization function.

Figure 10 shows examples of OBJ outputs rendered in Rhino 7, illustrating VoxCity’s capabilities to produce diverse visualization styles for different purposes. The renderings for Singapore and New York City aim to provide photo-realistic visualization of large-scale urban morphologies. Those for Tokyo and Amsterdam employ vibrant colors for specific urban objects, vegetation, and water, highlighting distinct urban morphological features. The example of Abu Dhabi demonstrates how urban environment simulation results can be integrated with 3D city models by exporting simulation data as OBJ files. This makes it easier for viewers to understand the relationship between simulated environments and the underlying urban morphology. Although VoxCity primarily focuses on urban areas, it can also be used to visualize natural environments. In the Matterhorn example, VoxCity accurately captures the mountain’s sharp peak and ice-covered terrain.

#### 4.4. Visualization

VoxCity provides a built-in function for 3D visualization. Figure 11 shows example outputs produced by this functionality. Users can visualize generated 3D city models as well as simulation results. For instance, Figure 11a, b, c, and d indicate the yearly cumulative global irradiance on building surfaces, the ground-level sky view index, the ground-level green view index, and the ground-level landmark visibility, respectively. Additionally, users can specify projection types from two options: ‘orthographic’ and ‘perspective’, adjust the zoom factor, and change the camera position and angle.

### 5. Limitations and future direction

#### 5.1. Support and integration of existing semantic 3D city models

Considering the aspiring role of VoxCity in 3D GIS, an integration of advanced 3D data models (e.g., CityGML and CityJSON) could facilitate its broader interdisciplinary adoption. In this section, we will discuss such integration in two aspects — (1) incorporating semantic 3D models as input data sources; and (2) extending export outputs to standardized 3D data formats.

First, integrating 3D models has the potential to enrich geospatial information embedded within VoxCity, contributing to more comprehensive and tailored research. VoxCity currently generates 3D city models from a series of openly available 2D and 2.5D datasets, which can result in a lack of semantic and geometric details especially for research at block or building scale. Integration of publicly available 3D city models as supplementary input may be beneficial for such cases. For example, 3D datasets, such as 3DBAG in the Netherlands [162, 163, 84] offer higher levels of detail achieved through advanced acquisition techniques (e.g., high-resolution airborne laser scanning) and state-of-the-art reconstruction algorithms. Such 3D datasets can address current limitations in semantics and geometry, particularly in the representation of building forms (e.g., roof-related semantics) and vegetation (e.g., classification) [164]. Nevertheless, the integration of detailed semantic 3D models introduces certain trade-offs in the future development of VoxCity. Large and complex 3D datasets often entail substantial computational demands, which may hinder overall efficiency. Future research needs to evaluate the balance between the benefits of enhanced semantic detail and the associated technical costs when scaling to an extensive city scale.

Second, in the current implementation, VoxCity provides four export formats (i.e., NPY, VOX, INX, and OBJ) to interface with downstream applications. Fostering data standardization and interoperability, in the future, we plan to implement additional export options (e.g., CityGML or CityJSON). For example, exporting 3D city models in standardized formats is of value for use cases that involve data exchange and sharing with practitioners or systems, which require compliance with established schemas. Offering CityGML or CityJSON as export options, VoxCity can enhance compatibility and ensure broader usability across various domains. Further, VoxCity incorporates semantic information during the generation process, preserving these attributes through standardized formats is important. Formats such as CityJSON are ideal for this purpose, providing a compact, structured, and easy-to-use approach to storing and managing semantic data [162]. Therefore, such properties can be retained and effectively communicated for downstream practices. For example, a recent study by Lei et al. [165] extended the CityJSON schema to accommodate human perception of architectural appearance in 3D buildings, enabling potential use cases. In this work, VoxCity features its novelty in automatic generation and tangible usability. Enabling standardized export can strengthen the role of VoxCity as a versatile tool, supporting the consistent interoperable development of 3D city models. However, challenges should be considered, such as the complexity of translating a voxel-based representation into a hierarchical structure, as well as computational and storage costs compared to current formats (e.g., NPY or OBJ).

### 5.2. *Integration of building surface material information*

Integrating building surface attributes, such as surface materials and window-to-wall ratio (WWR), to VoxCity is another promising direction for the next iteration of the package. VoxCity currently does not support the integration of building surface attributes, primarily due to limitations in data sources. To the best of our knowledge, no global open datasets currently provide surface attributes for individual buildings. While some buildings in OSM include material information, the proportion is relatively small [108]. However, building materials and WWR can significantly influence the surrounding microclimate and building energy consumption in various ways, including heat transfer, air leakage or ventilation, and offsetting daylighting demand [166, 167, 168]. This highlights the importance of incorporating material and WWR information in 3D city model generation for detailed urban environment simulations. A potential approach to address this gap is to use computer vision techniques on street view imagery to infer facade features.

In light of this, we conducted a trial to incorporate (1) building surface materials and (2) WWR information into VoxCity’s 3D city model generation. Figure 12 provides an overview of the process. First, street view images were obtained from Mapillary for a target area in Houston, United States. OpenFACADES pipeline [169] is then employed to geolocate and detect buildings within the street view images, assigning them to their corresponding building footprints. Building on previous facade classification studies [170, 171, 172], we applied fine-tuned models to categorize the building materials depicted in these images [173, 174], with each footprint linked to multiple images. For WWR, window pixels were identified using the Grounded Segment Anything [175],

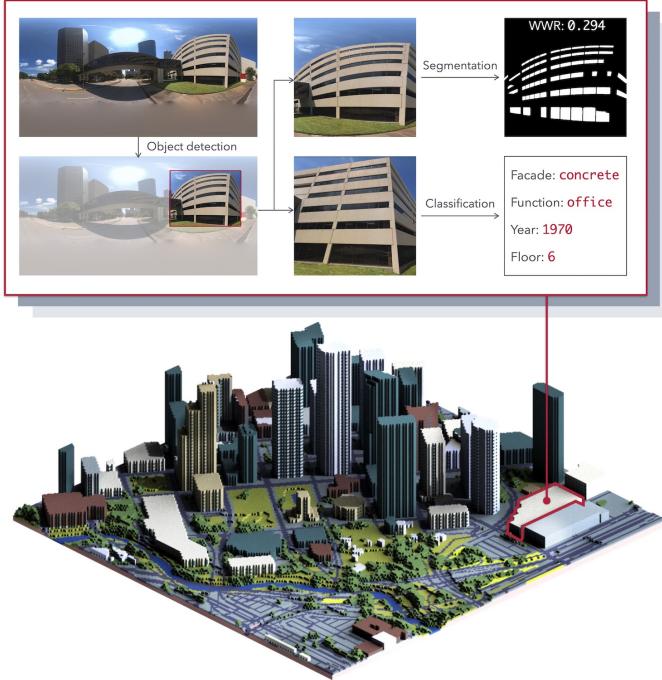


Figure 12: 3D city model of a target area in Houston, United States, from a trial incorporating building surface materials and window ratio information extracted from street view imagery. Image source: Mapillary. 3D rendering performed in Rhino.

and the percentage of window pixels within the building walls was calculated. Based on the inferred materials and WWR, we assigned categorical values to building voxels (e.g., 10 for glass, 11 for concrete, 12 for brick, and 13 for wood).

3D city models with detailed building material attributes can improve the accuracy of these simulations and expand their range of potential applications. Consequently, we plan to develop an additional subpackage that provides this functionality, after refining the methods and conducting a thorough validation.

### 5.3. Coverage of open geospatial data

In Section 4, we have demonstrated VoxCity’s capability to generate 3D models of a variety of cities worldwide. However, it cannot be used to generate models for every urban area, mostly because existing open datasets for building footprints and heights remain incomplete, and VoxCity does not incorporate all available data sources. Consequently, users may find it challenging to produce accurate models for regions beyond its current scope. We are addressing this challenge by continuously updating VoxCity and expanding the range of datasets it supports. Meanwhile, to broaden the utilization of building data, efforts to combine individual local datasets into comprehensive global collections—such as EUBUCCO [105]—should be further encouraged.

### 5.4. Incorporation of tree inventory

Our method currently considers only tree canopy height and does not account for variations in shape and density, which can differ by species, season, and health condition. For an accurate assessment of urban environments, it is crucial to include these factors. However, such detailed information is often unavailable in most cities, although some have created tree inventories containing data on individual trees. We plan to add functionality to parse such inventories and incorporate them into model generation. As mentioned in Section 3.3, no globally comprehensive tree inventory datasets or standardized data formats currently exist. Both the integration of local inventories into a global repository and the development of standardized data structures must be pursued in parallel.

## 6. Conclusions

Urban environment simulations using 3D city models are powerful instruments for informed urban planning and policymaking, particularly for assessing environmental benefits and risks that affect the health and well-being of city dwellers. However, the intensive manual effort required to prepare 3D city models, complicated application-specific data requirements, and fragmented data availability often hinder their broader utilization. To address this, we developed ‘VoxCity’, a one-stop Python package for open geospatial data integration, 3D city model generation, and urban environment simulation. Focusing on four key data types—building height, tree canopy height, land cover, and terrain elevation—we reviewed existing open datasets and compiled them into a catalog. VoxCity automatically downloads these datasets, voxelizes buildings, trees, land cover, and terrain, and creates an integrated voxel-based city model ready for a variety of environmental simulations. Additionally, VoxCity enables users to perform urban environment simulations through its built-in simulation subpackage and to export the generated 3D models in various file formats compatible with external software. The key contributions of this holistic and integrated work are as follows.

1. This paper presents a review of globally available geospatial data relevant to 3D city models—including building height, tree canopy height, land cover, and terrain elevation. This review not only helps VoxCity users select appropriate datasets but also provides readers with an overview of such datasets.
2. VoxCity provides a streamlined and automatic method to prepare 3D city models. This is particularly advantageous in cities without openly available 3D city models. Additionally, VoxCity’s capability to generate ready-to-use models for urban environment simulations benefits even those cities with existing 3D city models.
3. VoxCity can integrate four geospatial data types — building height, tree canopy height, land cover, and terrain elevation — to generate semantic 3D city models. Users can conduct simulations that account for buildings, vegetation, water bodies, and terrain geometry, all of which significantly affect urban environments.
4. VoxCity’s built-in simulation and visualization functions provide a comprehensive, end-to-end solution—from 3D city model generation to running urban environment simulations including solar irradiance and visibility analyses and visualizing the simulation results—thereby significantly reducing the time and effort required for such tasks.
5. By leveraging data from OSM, which is continuously updated, VoxCity helps its 3D city models remain current. Many open 3D city models are not regularly updated and can quickly become obsolete; VoxCity addresses this limitation by providing a more up-to-date representation of the urban form.
6. VoxCity can also serve as a comprehensive data downloader, sourcing information from various providers for users who require only intermediate data.

## CRediT authorship contribution statement

**Kunihiko Fujiwara:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – original draft, Writing – review & editing. **Ryuta Tsurumi:** Formal analysis, Investigation, Data Curation, Writing – review & editing. **Tomoki Kiyono:** Formal analysis, Investigation, Data Curation, Writing – original draft, Writing – review & editing. **Zicheng Fan:** Formal analysis, Investigation, Data Curation, Writing – original draft, Writing – review & editing. **Xiucheng Liang:** Formal analysis, Investigation, Data Curation, Writing – original draft, Writing – review & editing. **Binyu Lei:** Writing – original draft, Writing – review & editing. **Winston Yap:** Methodology, Software, Writing – review & editing. **Koichi Ito:** Software, Writing – review & editing. **Filip Biljecki:** Conceptualization, Methodology, Supervision, Project administration, Funding acquisition, Writing – review & editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## **Declaration of Generative AI and AI-assisted technologies in the writing process**

During the preparation of this work the authors used ChatGPT in order to proofread the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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## **Data availability**

The scripts developed for our method are openly available at a GitHub repository (<https://github.com/kunifujiwara/VoxCity>).

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