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Developing a 3D geometry for Urban energy modelling of Indian cities

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Abstract

The advancement in the field of Urban Building Energy Modelling (UBEM) is assisting urban planners and managers to design and operate cities to meet environmental emission targets. The usefulness of the UBEM depends upon the quality and level of details (LoD) of the inputs to the model. The inadequacy and quality of relevant input data pose challenges. This paper analyses the usefulness of different methodologies for developing a 3D building stock model of Ahmedabad, India, recognizing data gaps and heterogenous development of the city over time. It evaluates the potentials, limitations, and challenges of remote sensing techniques namely (a) Satellite imagery (b) LiDAR and (c) Photogrammetry for this application. Further, the details and benefits of data capturing through UAV assisted Photogrammetry technique for the development of the 3D city model are discussed. The research develops potential techniques for feature detection and model reconstruction using Computer vision on the Photogrammetry reality mesh. Preliminary results indicate that the use of supervised learning for Image based segmentation on the reality mesh detects building footprints with higher accuracy as compared to geometry-based segmentation of the point cloud. This methodology has the potential to detect complex building features and remove redundant objects to develop the semantic model at different LoDs for urban simulations. The framework deployed and demonstrated for the part of Ahmedabad has a potential for scaling up to other parts of the city and other Indian cities having similar urban morphology and no previous data for developing a UBEM.

Introduction

This section discusses pertinent aspects of a UBEM ranging from its application, specifications, data collection and processing techniques for the 3D model to the relevance of this research.

UBEM has emerged as a powerful tool for exploring opportunities to address the challenges of rapid urbanisation. Combining the data generated in cities with energy simulations, UBEMs help in the identification, support, and improvement of sustainable urban development measures and policies. During the last decade, bottom-up UBEMs have been extensively researched due to their suitability for urban and regional analyses when more integrated energy supply-demand scenarios are being investigated (Johari, Peronato, Sadeghian, Zhao, & Widén, 2020). UBEM's growing popularity and importance as a planning tool has encouraged the exploration of this research and its application in Indian cities. While statistical models are more reliable at estimating energy use, they have limitations in excessive requirement of existing & historic data and not being able to adopt for design modifications (Abbasabadi and Mehdi Ashayeri 2019). For application in Indian cities where this type of data is scarce (Khosla and Janda 2019; Shnapp and Laustsen 2013), such a modelling approach can be challenging. Thus, simulation-based modelling can be promising as it doesn't rely heavily on metered electricity data. It requires detailed inputs for individual buildings, which is used in obtaining reliable energy use estimates.

Need for a semantic 3D city model

Like BEM, Simulation based UBEMs also require a description of the geometry of the buildings and their surroundings to account for the operational energy and thermal performance (Johari et al. 2020). These models are integrated with the Cadastral data to define energy related semantic attributes including building use, age, no. of properties, occupancy patterns, mechanical system and construction details. (Krüger & Kolbe, 2012). The geometry defines the building's volume with the surfaces for the thermal interaction of the envelop with the external and internal loads. It defines interactions between outdoor exposed surfaces with the conditioned space, adjacencies between different buildings and exposure to radiation from the sky, sun and the urban context. Thus, application of 3D city models for UBEMs extend beyond visualization purposes to a Semantic city 3D model. These models can be developed with Levels of detail (LoD) ranging from 0 to 4 (Biljecki 2013). The suitability of developing different LoD 3D models for a UBEM varies with their application, indented outcomes and the available data.

Data collection & Model Reconstruction

Data for 3D city models can be acquired from Photogrammetric Digital Surface Models (DSM) or Light Detection and Ranging (LiDAR) data or extruded from orthophotos and vector building footprints that are often provided by cadastral or topographic maps (Moreia, Nex, Agugiaro, Remondino, & Lim, 2013). Methods also extend to the use of synthetic aperture radar, architectural models and drawings, handheld devices, and volunteered geoinformation (Biljecki et al. 2015). In addition to building geometry, the other components of 3D city models are topography and vegetation. Topography can be generated from Digital Elevation Models (DEM), which are widely accessible in most locations. Vegetation can be reconstructed using LiDAR data or georeferenced databases providing the characteristics of trees (Johari et al. 2020).

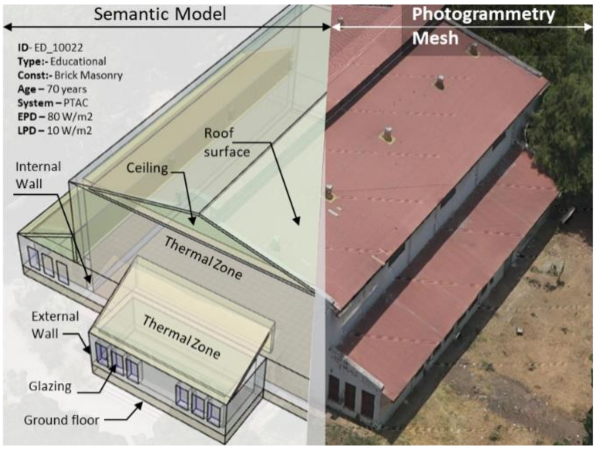


Figure 1- Semantic model generated from Photogrammetry, linked with Cadastral data for performing simulations

The output generated from these data collection methods needs specific processing to generate 3D models. Due to their simple data structure, these models lack analytical capabilities. Moreover, the individual objects in the model can be recognized by the human eye but cannot be distinguished by computer systems (Willenborg, Pültz, and Kolbe 2018) which is essential for analysis, particularly energy simulations. Extracting building features and defining their geometry as points, lines, surfaces and polygons in 3D space is required for the model to be usable in energy simulations. Thus, outputs generated from these methods are re-constructed and linked to other datasets to generate semantic models. This reconstruction defines the city objects into semantic classes like buildings, transportation, water bodies, vegetation, and terrain, that are individually identified and operated. The model needs to provide required attributes and decomposed representation of the buildings with their thematic surfaces; walls, ground, and roof shape, etc. as shown in Figure 1.

City GML is one such globally accepted inter-operable format for storing semantic 3D city models in thematic classes that can be used in several applications (Gröger and Plümer 2012). Open Street Maps (OSM) is another open source database that provides building 3D models with crowdsourced semantic data on properties like use type, No. of floors, building age and other relevant information. OSM models are readily accepted by GIS based applications and can be used to create 3D shapefiles of the city's buildings. Due to their easy availability and ready to use formats, the outputs from both these platforms are extensively used as input data for a number UBEM projects globally, as reflected in Table 1.

Relevance of the research

The challenge however is for Indian cities where such datasets are unavailable or have too many data gaps. 2D cadastral data for many Indian cities do not exist in a digitized format on open source platforms. Hence not only the 3D geometry of buildings and urban structures but their semantic attributes like use-type, age, etc. along with model processing is required. Thus, data collection, understanding different building attributes, and associating their behaviour, are all significant challenges in haphazardly developed Indian cities (Tanzeem, Aswal, and Saini 2019). The LoD which can be achieved in 3D building reconstruction also depends on the quality of the input data. The higher the LoD, the longer is the time required to produce a 3D model, as the amount of manual editing and checks grow considerably (Moreia et al., 2013). Also, fully automatic and reliable reconstruction of 3D models is challenging beyond LoD2.

Analysis of existing projects indicates several methodologies to reconstruct buildings to form semantic 3D models as highlighted in the following sections. However extensive data, computational knowledge and manual efforts are required in those techniques. In most of the UBEM projects reviewed in Table 1, an existing GIS dataset with building footprints and semantic attributes is required as a base to extract building polygons from remote sensing data. In the absence of such data, more than one method of data collection like LiDAR and Photogrammetry are combined to generate accurate building geometry. This is followed by manual digitization of semantic attributes in the buildings.

This research evaluates different model development and reconstruction methodologies for their suitability in Ahmedabad. To simplify data collection and feature extraction in the absence of previous datasets, a case study is presented to discusses the application of Photogrammetry-based Reality mesh models coupled with Computer vision using the Bentley Systems – Context Capture software (Bentley 2017). The proposed methodology uses supervised machine learning algorithms, built in the software to train an image based detector and thematically classify different urban features, eg- buildings, vegetation, landscape etc. The application of the computer vision can potentially be extended to classify archetypes for semantic attributes to buildings based on their appearance. Classification of archetypes will assign characteristics like construction assembly, operational schedules and mechanical systems to the buildings. Thus, with limited cadastral data, the generated 3D model can be enriched semantically to fill the necessary data gaps for its utilization in UBEM simulations.

Review of existing methods

A comprehensive literature review was carried out to identify the different methods available and adopted for data collection and reconstruction of building geometries. Their advantages, limitations and applicability in Ahmedabad are detailed below and in Table 2.

Using aerial imagery with DEM/DTM data: - This process involves feature extraction using satellite or UAV based orthographic imagery for detecting building footprints and use of Digital elevation/terrain models (DEM/DTM) for height information. This method typically generates LoD1 models. Tanzeem et al., (2019) used this methodology to generate an LoD1 model of Khanjarpur Area of Roorkee, Uttarakhand, India. High resolution orthophotos taken from a UAV were used to digitize building footprints using the Quick shift segmentation algorithm, which is based on the pixel value of the coloured image. These footprints were linked to a DSM model generated through LiDAR to obtain mean heights of the buildings and extrude the LoD1 model. These models can be linked to the cadastral dataset to generate semantic models as performed by (New et al. 2018) to automatically generate a UBEM for 130,000 buildings. A specially developed API was used to source all publicly available cadastral information available in GIS format to link the semantic attributes to the buildings and thereafter a series of assumptions and heuristics for estimating building type and properties from available data sources was applied to fill data gaps. These building models were then simulated on Energy Plus engine for the UBEM.

Using Photogrammetry & LiDAR data: - Aerial photogrammetry captures several oblique and orthogonal photos to generate a 3D reality mesh model. Photogrammetry models are often combined with DTM generated from LiDAR or previously existing 2D GIS shapefiles to reconstruct semantic city 3D models. City GML models are also developed using this technique. Typically, LoD2 & LoD3 models have been generated from this approach. Various UBEMs have used LoD2 CityGML models for simulations, like Helsinki, (Willenborg et al. 2018) Berlin (Kaden and Kolbe 2013) and Switzerland (Fonseca et al. 2016).

Using only Photogrammetry with advanced computer vision algorithms: - The advent of UAV with high resolution oblique camera payloads has increased the popularity and accuracy of photogrammetry models. With the help of reality modelling software, photogrammetry models can be generated and geo-referenced to give accurate measurements, heights and elevations. These tools also allow these models to be converted into both point clouds like LiDAR and triangulation surfaces or meshes. Increasing computational power and advanced machine learning algorithms have improved computer vision to abstract semantic models from reality meshes. Stathopoulou & Remondino, (2019) presented a method for image-based 3D reconstruction with semantic labelling, similar to the method discussed in this paper. A trained Convolutional Neural Network (CNN) on building façade images was used. The results of this study are promising, with an improved performance on the quality of the 3D reconstruction. Hensel, Goebbels, & Kada, (2019) used photogrammetry models on existing LoD2 models to generate LoD3 models by adding façade details like exact window and door locations. Abstracting actual window / glazing on the façade improves UBEM's accuracy in simulation. They used deep neural networks to detect bounding boxes on the actual glazing on the façade and then reconstructed it to enhance the existing 3D city model.

Data availability for the area of interest

An attempt was made to review the suitability of the existing datasets for Ahmedabad prepared the Urban Local Bodies and research institutes. (Rawal et al., 2018) used the administrative data along with satellite imagery to extract building footprints and develop a GIS database. Similarly as shown in Figure 2 manual digitization and field survey to assign semantic attributes to buildings was performed by CEPT University to generate a GIS database for Ahmedabad. Along with this, publicly avaialble OpenStreetMap dataset was also extracted, as shown in Figure 3. However, there are several gaps and inaccuracies in these available datasets as discussed:-

1. The building footprints extracted didn't match the plot boundaries and overestimated building area by including projections like balconies, porch, temporary structures and unoccupied areas like lift/staircase cores, shafts & corridors.

2. Building heights were estimated based on maximum permissible FSI or visual inspection of the number of floors and not on the actual building as existing.

3. The validity of semantic attributes like building use and age is questionable due to approximation errors.

3. The Address on the property tax assessment data is insufficient to locate the property on the GIS map for many properties, thereby tagging semantic attributes that were performed manually.

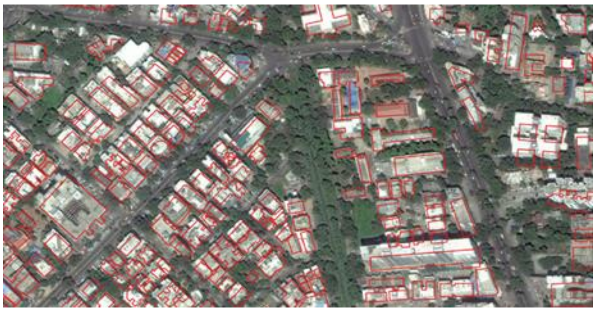


Figure 2- GIS data collected by CEPT university overlaid (in red) on satellite imagery

Figure 3- OpenStreetMaps for Ahmedabad overlaid (in orange) on satellite imagery. Many buildings are missing here.

Table 1-Application of different data sources in UBEM projects globally

Primary source	Secondary source	UBEM projects			
		Examples	**Location**	**Model LoD**	**No of Projects reviewed**
GIS shapefiles (Geometry and Cadastral data)	Public Datasets	(Hong et al. 2016)	San Francisco, USA	1	19
	Field survey	(Saran et al., 2015)	Dehradun, India	2, 3	1
Open Street Maps	-	(Wang et al., 2019)	Nanjing, China	1	2
City GML	-	(Kaden & Kolbe, 2014)	Berlin, Germany	2	12
LiDAR	GIS shapefiles	(Evans et al., 2017)	London, UK	1	8
Photogrammetry	GIS shapefiles	(Julin et al., 2018)	Helsinki, Finland	2	4
	LiDAR	(New et al. 2018)	Tennessee, USA	1	2
Aerial imagery	LiDAR (DEM)	(Ratti et al., 2005)	London, UK	1	3

Table 2- Evaluating the challenges and potential of different methodologies for developing a semantic model for Ahmedabad UBEM. The dots represent a score of High (6-5), medium (4-3) and low (2-1).

Methodology		Inputs				Outcomes		Limitations
Data collection	**Processing / Reconstruction**	**Input data**	**Economic viability**	**Effort required**	**Compu-tation**	**Accuracy**	**Suitability**	
Ariel Imagery	Manual digitization of footprint	●○○○○○	●○○○○○	●●●●●●	●○○○○○	●●○○○○	●●○○○○	Extensive manual effort Prone to human error
	RGB / Multispectral Reflectance value-based segmentation of high-resolution images to extract footprints	●●●○○○	●●●●○○	●●●○○○	●●●○○○	●●●○○○	●●●○○○	Requires very high resolution orthophotos and an algorithm to detect buildings. Requires DEM for building heights
LiDAR	Geometry based segmentation of point cloud	●●●○○○	●●●●○○	●●○○○○	●●●●○○	●●●○○○	●●●●○○	LiDAR devices are expensive. An algorithm to detect buildings from height or reflectance values needs to be developed for processing.
	RGB / Reflectance value-based segmentation of Point cloud	●●●○○○	●●●●○○	●●○○○○	●●●●○○	●●●●○○	●●●●○○	
LiDAR DEM + 2D GIS	LiDAR to generate DEM - for building heights & 2D GIS data for footprints and semantic attributes	●●●●●○	●●●○○○	●●●○○○	●●●○○○	●●●●●○	●●●●○○	Needs more than one dataset. 2D GIS data has many gaps and error (Fig 4)
Photogra mmetry mesh + 2D GIS	Point cloud to generate DEM & 2D GIS data for footprints and semantic attributes	●●●●●○	●●●○○○	●●●○○○	●●●●○○	●●●●○○	●●●●○○	
Photogra mmetry mesh + LiDAR	LiDAR for 3D geometry, photogrammetry with image processing for other building features	●●●●●●	●○○○○○	●●●●○○	●●●●●●	●●●●●○	●●●○○○	Needs multiple devices for conducting the data collection.
Photogra mmetry	RGB value-based segmentation of Point cloud	●●●○○○	●●●●●○	●●●●○○	●●●●○○	●●●●○○	●●●●○○	Limited accuracy, requires specific algorithms for detection, Cannot detect objects hidden below foliage
	Geometry based segmentation of point cloud	●●●○○○	●●●●●○	●●●●○○	●●●●○○	●●●○○○	●●●●○○	
	Image based segmentation of Reality mesh using ML algorithms (supervised learning)	●●●○○○	●●●●●○	●●●●●○	●●●●●○	●●●●○○	●●●●●●	Extensive requirement of labelled images for training the algorithm

Establishing a suitable methodology

It was judged that the existing database from Open Street Maps has too many data gaps, thus making it unfit for UBEM application. The GIS data developed by the academic institute is collected and digitized manually and thus required extensive human resources and is prone to several errors and assumptions. However, it is by far the best dataset for Ahmedabad readily available. Another challenge apart from geometric data is the collection and linking of semantic data from public records to the model. As discussed above the property's address is insufficient to locate it geographically. Moreover, a lot of cadastral data with the Urban Local Bodies (ULB) is not digitized. Thus, these challenges along with the technological and human resources make data collection and processing even more difficult. Evaluating the methodologies, it is evident that an extensive remote sensing exercise through either LiDAR or Photogrammetry needs to be carried out exclusively for Ahmedabad to develop the geometry. Along with this validating the semantic attributes and digitizing public records must be carried out. The scope of this paper is limited to the geometry extraction method adopted for Ahmedabad. Parallel research is also being dedicated to generating and linking semantic attributes for the UBEM.

Methodology

The UAV assisted photogrammetry method was selected after this review. The application of Computer Vision with photogrammetry-based reality mesh was explored to extract building footprints for application in the UBEM of Ahmedabad. To develop the reality mesh, a state-of-the-art method comprising of the latest Real-time kinematic (RTK) enabled UAV with a hybrid oblique imaging camera was selected to capture the aerial images which were later processed in Context Capture (CC) (Bentley 2017). As a pilot study to test this methodology an area of 1.2 km^2 was selected within Ahmedabad city. As shown in Figure 4 The first step of the data-collection includes preparing a flight mission plan for the pilot area. The required input of the flying height, photo overlap (front and side), which are important for the resolution of the model (GSD) are entered in the UAV software. The second step is the actual data collection of the pilot area by flying the UAV. Simultaneously the Ground Control Points (GCP), which are used to enhance the accuracy of the resultant model were also collected manually on the ground. After the collection and compilation of both image data and GCPs, both were imported to the Context Capture software. Due to the scale of the data collected, a grid/cluster setup of high-performance computers was used to process the reality mesh in less time. The image processing is conducted in two steps. First is the Aero-triangulation which prepares a rudimentary model to be reviewed. Second is the 3D model reconstruction, where the actual model is prepared as per the users desired output. After 62 hours of processing of nearly 10000 images the photogrammetry software developed a reality mesh in *.3mx format. The cleaning process was also carried out on the model to discard the distorted parts of the model. The reality mesh along with the .3mx format was also converted into *.las: point cloud format and the *i3s or Esri3d: portable 3D model format to be used in ArcGIS Pro and the Ortho DSM raster format for visual verification of obtained shapefile from the footprint extraction exercise.

Extraction of Building Footprints

The next step after developing the model is to utilize the model for extracting usable building footprint in UBEM. In this study, two techniques are being explored for building footprint extraction i.e.: -

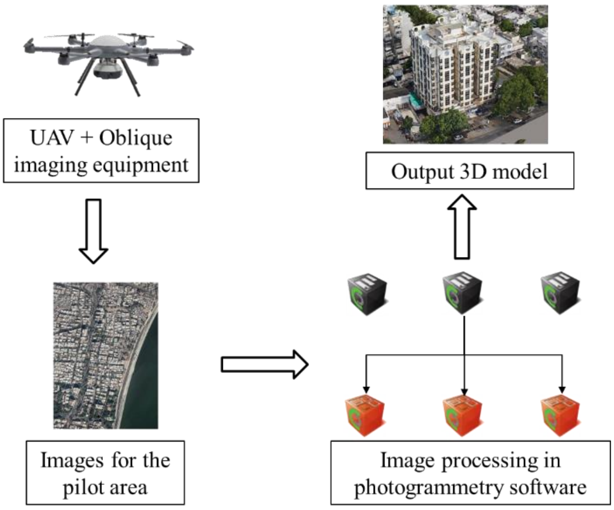
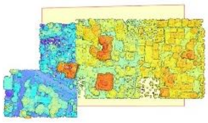
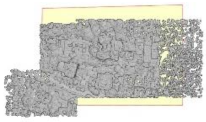
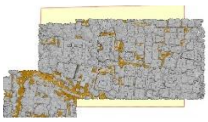
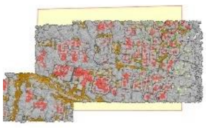


Figure 4- Data collection through UAV and processing to generate 3D models

1. Elevation and area-based classification of the point cloud model generated in the. las format using the classification codes defined by the American Society for Photogrammetry and Remote Sensing (ASPRS,2015) in the ArcGIS software and the coordinates of the point.
2. Image-based segmentation in the CC Insights machine learning extension by training a detector with relevant training images to identify building rooftops.

Both the methodologies are evaluated with their workflow and the preliminary results of building footprint and model extraction in Table 3.

Table 3 - Comparison of the two methodologies adopted to extract building footprints from Photogrammetric reality mesh model

Method	Geometric classification of the point cloud model		Image-based segmentation using computer vision
Data Required	Point cloud model from the reality mesh needs to be generated separately and stored in the .las format along with .i3s format for its use in ArcGIS pro		Aero-triangulated block. Some images from the UAV need to be processed as training data. Manual classification of rooftops in the trained images is required to develop the initial classification algorithm.
Software used	Context Capture centre edition for generating reality mesh & ESRI ArcGIS Pro for footprint extraction and 3D reconstruction		Context Capture centre edition for generating reality mesh & Insights extension in the software for developing the trained detector. ContextCapture editor to export the detected rooftop polygons into a *.shp shapefiles
Steps followed		Importing point-cloud in ArcGIS pro. The model auto-classifies based on the point's elevation as per presets of ASPRS	Model is aerotriangulated after the manual identification of GCPs A separate block or a new file is made and only the limited images that are required for training the detector are imported in that block.
		Changing point display from height based to class based using LAS classification tools in ArcGIS pro	An appropriate method of training the detector i.e. object based or image segmentation is now selected. The image segmentation is selected for this study.
		Classification of ground surface based on the 16 point classes defined as per ASPRS	A new Insight file is created. Roof polygons are manually drawn over the selected images for training the detector The detector is uploaded on the server for training
		Classifying vegetation into high & low densities	The detector is applied to a small test area to check its consistency. After necessary quality assurance, the detector runs on a larger testing data set.
		Filtering Building rooftop points with a minimum height of 3.5 m & area of the shape more than 20 sqm.	The detector runs to identify building rooftops in the images. On obtaining satisfactory results the images are exported to generate the segmented reality mesh model.
Post Processing	The obtained roof polygons from post-processing are converted first into raster images and then to vector format. Then Building footprint regularization command is run to extract the polygons. Manual editing is done to remove redundant polygons		Manual editing and re-training of the detector is required to improve its accuracy. Building rooftops obtained can be exported and vectorized to obtain the *.shp shapefiles.
Preliminary results (Building footprints)			
Challenges & Limitations	• Additional time is required to converted *.3mx to *.las and to DSM and *i3s • A lot of manual classification is required and many times the results are not accurate • ArcGIS is an additional cost		• Processing time is more than ArcGIS • The quality assurance and training the detector can take more time • Results are as accurate as the quality of the trained images
Prospects	• Overall processing time is less • If the sweet spot of everything can be obtained, like point sampling distance for the model, and other input in the steps of vectorizing the footprints, it can be a promising method.		• Result accuracy is higher than the point cloud method. • Ability to expand classification beyond the standard 16-point classes • Features like temporary structures can be removed

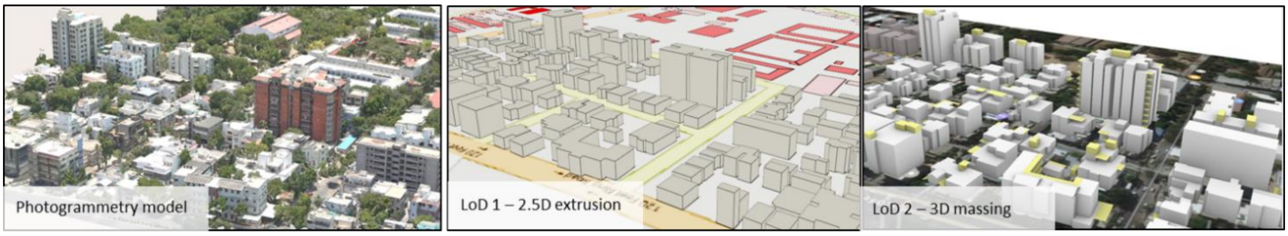


Figure 5-Proposed methodology will result in a semantic 3D model at different LoDs for their application in UBEM of Ahmedabad

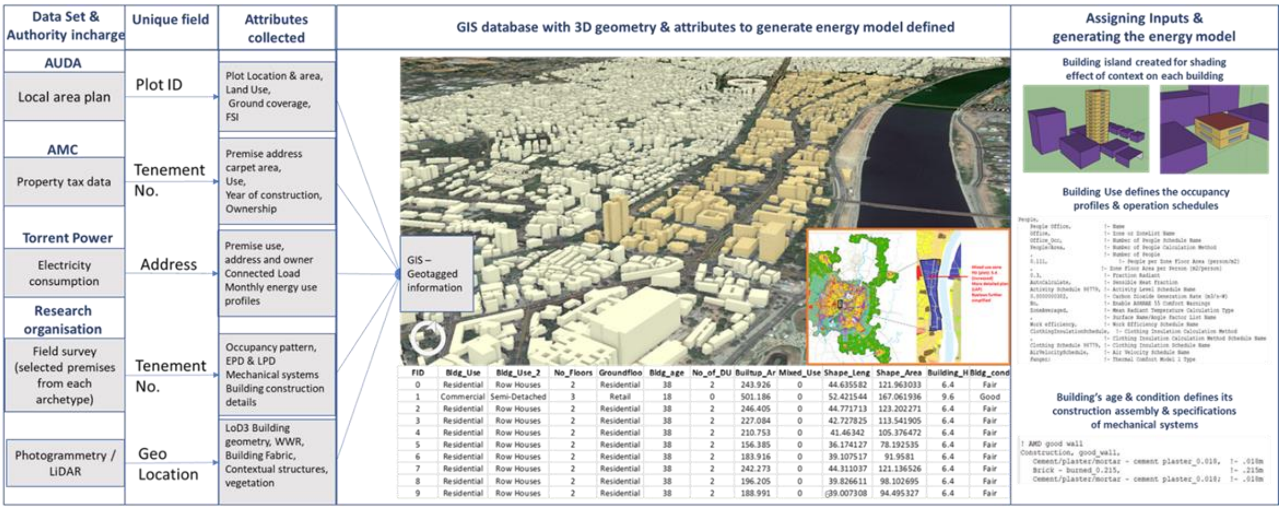


Figure 6 - Proposed framework to link datasets into the semantic 3D model and performing UBEM simulations

Conclusion

The preliminary results indicate the potential of using Image based segmentation for building footprint extraction. These footprints can now be linked to the DEM for building heights to generate an LoD1 geometry of the urban area. The challenges currently being faced are primarily linked to enriching the training data and accounting for finer details and peculiarity in the urban fabric of Ahmedabad. As evident in the results that due to similarity in textures of roofing materials and paving materials the latter is also getting detected as a building. However, with more feature classes created for separate urban components like roads, vehicles, trees, humans and furniture, the accuracy of the detector to remove these objects from the building class will increase. The algorithm can potentially be trained further to extract building features like balconies, overhangs, canopies and porches and identifying the exact glazing ratios on each façade of the building. This will enable extracting the geometry at different LoDs as shown in Figure 5.

Prospects for this study

The 3D city model thus developed would be data semantically enriched with cadastral and energy data different public/private sources to create a single database as shown in Figure 6. Each building would be linked to different datasets through the unique fields / IDs as described in the framework. This City energy model is proposed to be made available on an open source online platform for assisting in various analysis and planning exercises by the Local government. By linking more such publicly collected data, the model can be enriched to ultimately serve as a City Information Model.

The use of computer vision along with photogrammetry models for the UBEM of Ahmedabad will allow the model's application in other analyses as well. The most promising application that can be explored is appearance-based assignment of building archetype properties. As previously stated, that linking of semantic data to the building geometry is another challenge for Ahmedabad. Thus, for the framework proposed in Figure 6, the application of Computer vision can fill the data gaps by identifying buildings of similar use-type based on their physical appearance. This will also help in identifying the building's age and physical condition to assign properties like construction material, the efficiency of mechanical systems and equipment installed etc. The potential of Photogrammetry models can also be extended to link and map the municipal service network into the UBEM. Thus, a holistic analysis of urban scale energy consumption can be achieved. Apart from energy-based applications, these models are capable of application in areas like: - management of infrastructure and public assets, planning transport networks, and developing strategies for the city's resilience towards extreme climate events and preparedness for the pandemic scenario.

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