Automating 3D Building Modeling: A Comparative Study of Data- and Model-Driven Methods

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Abstract

Accurate and efficient 3D building reconstruction from airborne point clouds is crucial for a wide range of applications, from urban planning to navigation and microscale simulations. This paper review and evaluate model- and data-driven approaches for building modeling, using two baselines' methods and introducing two new implementations: an augmented, data-driven variant of Kinetic Shape Reconstruction (KSR) and a model-driven approach under development named RoofGenerator. Experiments use a dataset available among the open-data of SwissTopo, featuring diverse building types and varying slopes, with manually reconstructed reference 3D building models providing a reliable ground truth for evaluation. The results show that data-driven methods offer greater flexibility and capture finer details but require careful parameter tuning and are sensitive to point density and segmentation accuracy. In contrast, model-driven approaches are computationally efficient and robust but constrained by predefined shape libraries, limiting their ability to model specific roof structures. Additional challenges include reconstruction consistency, footprint dependency and the lack of standardized evaluation metrics. The choice of the evaluation method depends on specific application needs, data quality and scalability requirements.

1. INTRODUCTION

Digital reconstruction of urban environments has become a cornerstone in various scientific and practical fields, including photogrammetry, computer vision and remote sensing. An increasing number of decision-makers recognize that three-dimensional (3D) city models are set to become indispensable as central information hubs accessible to everyone. They play a crucial role in diverse range of uses including urban and development planning, microscale simulations, city marketing, navigation and facility management (Toschi et al., 2017; Stoter et al., 2020; Widl et al., 2021; Pađen et al., 2024).

Due to the broad exploitation of building models and the large effort required for their manual reconstruction, numerous methods have been developed in recent years to automate the modeling process (Haala and Kada, 2010; Wang, 2013; Gui and Qin, 2021). Existing approaches are generally categorized as model-driven (top-down) and data-driven (bottom-up), although hybrid bottom-up, top-down approaches (Mehranfar et al., 2022) and learning-based methods (Pan et al., 2023) were recently proposed.

Model-driven top-down methods rely on predefined parametric shapes that are assembled and optimized based on estimated parameters (Xiong et al., 2015; Buyukdemircioglu and Kocaman, 2020; Zhang et al., 2021; Župan et al., 2023). These approaches often employ rule-based generation, shape grammars or template matching, making them well-suited for structured environments with repetitive architectural patterns. Their reliance on fixed templates, however, limits adaptability to urban landscapes with complex, irregular or non-Manhattan geometries. Consequently, they struggle to generalize to urban environments with diverse architectural styles or dense historical districts where predefined shapes fail to capture unique building structures.

In contrast, data-driven approaches reconstruct building geometries directly from LiDAR or photogrammetric point clouds (Xiong et al., 2013; Li et al., 2016). These methods prioritize geometric fidelity and adaptability, allowing for greater flexibility in modeling diverse architectural styles. A widely used data-driven strategy involves detecting planar segments corresponding to building roofs and facades from the input point cloud. These planes are identified using spatial geometric analysis (Rabbani et al., 2006; Schnabel et al., 2007) or by applying neural architectures (Jiang et al., 2020; Zhang and Fan, 2022). Once detected, planes are assembled into structured building meshes using either connectivity graphs that capture the topological relationships between elements (Jarzabek-Rychard and Borkowski, 2016; Wang et al., 2020; Xu et al., 2021), or space decomposition techniques (Bauchet and Lafarge, 2020; Nan and Wonka, 2017). While these methods ensure high accuracy, they often fail to enforce geometric regularity, leading to small, redundant facets and irregular connectivity at roof intersections. Another branch of data-driven methods focuses on simplifying an initially reconstructed dense mesh derived from the input point cloud (Kazhdan and Hoppe, 2013; Li and Nan, 2021; Wang et al., 2021). These methods aim to reduce computational complexity while preserving essential building structures. Excessive simplification may however result in loss of structural accuracy and violation of key planarity constraints, reducing the usability of these models in high precision applications.

Finally, learning-based methods (Park and Guldmann, 2019; Li et al., 2022; Liu et al., 2024) have recently shown promising results by addressing the limitations of both model- and data-driven methods. These methods learn implicit building priors from large-scale datasets, enabling automatic feature extraction, robustness to noise, and adaptability to diverse urban environments. However, their effectiveness depends on the availability of high-quality training data, and they often face challenges in generalization across different geographic regions and scanning conditions.

Despite advancements in 3D building reconstruction, the lack of standardized evaluation frameworks remains a critical challenge. Many proposed methods are tested on small-scale datasets or specific urban environments, often lacking comprehensive reference models. This inconsistency leads to subjective performance assessments, making it difficult to fairly compare methods and to determine which approaches are most suitable for particular applications. While some methods perform well in structured environments with regularized building layouts, their effectiveness diminishes in historic city centers or heterogeneous urban landscapes. Standardized benchmarks, such as the ISPRS benchmark for 3D building reconstruction (Rottensteiner et al., 2014), played a crucial role in ensuring fair and reproducible evaluations by providing consistent datasets and standardized assessment metrics. As urban modeling applications evolve, there is an increasing need for more comprehensive and large-scale evaluation frameworks that assess not only geometric accuracy of the results but also consider efficiency and scalability of methods, robustness of their employment from user perspective, and the practical usability of reconstructed models in real-world applications.

Recognizing these gaps, this study aims to bridge the divide between existing methodologies and real-world applicability. The objective of the presented work is multi-fold and focuses on:

- Evaluating and comparing 3D building reconstruction methods representing both data- and model-driven approaches;
- Developing two new reconstruction algorithms;
- Stepping into a preparation of a new benchmark dataset for assessing the performance of 3D building reconstruction methods;
- Exploring the generalization and scalability potential of building modeling methods.

2. BUILDING MODELING METHODS

The study primarily investigates the automatic generation of polygonal building models from airborne point clouds in large-scale urban environments. We analyze both model- and data-driven approaches, using two in-house implementations: Roof Generator and Augmented KSR, and comparing them against two baselines' methods representing each category, respectively: City3D by Huang et al. (2022) and BREC by Virtual City Systems (2025). A key aspect of this evaluation is capturing the precise geometry of roof structures, which plays a crucial role in Level of Detail 2 (LoD2) modeling.

City3D is a data-driven approach based on the hypothesis-and-selection framework of PolyFit (Nan and Wonka, 2017). It generates a set of potential building faces by intersecting planar segments detected from the point cloud and additional vertical planes inferred from the input data. The final model is generated by selecting the optimal subset of building faces through binary integer linear programming optimization, considering criteria such as simplicity, compactness, regularity, and fit to the input data. Although City3D is also available as an open-source software, for this study we used its core algorithmic code, allowing for greater control over processing parameters, input data handling and output storage.

BREC: Building Reconstruction (Virtual City Systems, 2025) is a model-driven approach, released as a commercial software, that reconstructs buildings using a predefined library of parametric roof shapes. Roof types are automatically classified in airborne point clouds based on extracted geometric features and the most suitable template is selected and fitted to the data. The method enforces planarity and topological consistency, ensuring that reconstructed models adhere to well-defined geometric rules. The software also supports manual post-processing of the reconstructed models and direct export into CityGML 2.0 with flexible attribute mapping.

RoofGenerator is an in-house model-driven approach that reconstructs 3D building models as a combination of predefined standard roof shapes (flat, pyramid, gabled, hip) available in an internal library of geometric structures. The method consists of two main stages: (i) roof type identification in orthophotos by means of machine learning techniques; (ii) roof model generation, according to the identified shape, supported by the airborne point cloud.

Augmented KSR is an in-house data-driven implementation builds upon Kinetic Shape Reconstruction (KSR) (Bauchet and Lafarge, 2020), which uses planes detected in the input point clouds to compute a polyhedral decomposition by leveraging a kinetic data structure. Instead of performing exhaustive planar slicing, the method allows detected planes to expand at a uniform rate until they intersect, forming meaningful polyhedral partitions. The cells are classified as either inside or outside based on the orientation of point normals. Kinetic space partition enhances shape assembly efficiency by reducing both processing time and the number of generated shapes.

A general major challenge in airborne (LiDAR-based) 3D building reconstruction is the often incompleteness of vertical walls due to limited scanning or imaging angles or occlusions from surrounding structures. Since airborne LiDAR primarily captures roof geometries, in data driven-approaches these gaps cause severe topological inconsistencies, preventing proper model closure, leading to unreliable structural representations, or in some cases, make reconstruction entirely impossible - as frequently observed in KSR. To mitigate these limitations, we apply a data augmentation strategy that enhances building representation by generating synthetic 3D points to compensate for missing walls (Figure 1). The key steps in this process include: (i) detecting vertical discontinuities in 3D point clouds; (ii) extracting line segments using Hough Transform on the rasterized data; (iii) projecting 3D roof edges into 3D space and extruding vertical planes.

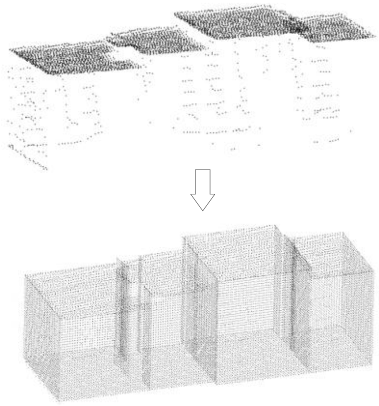

Figure 1. Data augmentation in the proposed augmented KSR.

3. EXPERIMENTS AND COMPARISONS

3.1 Data and setup

The comparative analysis is conducted using a dataset obtained from the open data of the Swiss Federal Office of Topography (SwissTopo, 2025). In the experiments, we use aerial LiDAR point cloud (with a declared minimum density of 5 pts/m^2), along with orthophotos, building footprints and manually reconstructed vector-based building models. The 3D models feature simplified facades but realistic roof geometries, conforming to Level of Detail (LoD) 2.3, as defined by Biljecki et al. (2016). These models serve as high-quality ground truth for evaluating reconstruction accuracy. The study area, located in Pfäffikon, Switzerland, spans 1 km × 1.5 km and includes buildings of diverse shapes and sizes, situated on terrain with varying slopes (Figure 2).

Figure 2. Benchmark dataset: manually generated reference 3D building models.

To facilitate the reconstruction process of data-driven approaches, we preprocess input data using vectorized building footprints to partition the airborne point cloud into subsets corresponding to individual buildings. On the other hand, model-driven methods are directly applied to the point cloud of the whole area.

3.2 Results and evaluation

The comparative analysis highlights the strengths and limitations of data- and model-driven approaches. The evaluation is structured into three key components:

- Key aspects of the evaluated methods performance are summarized in Table 1;
- A selection of representative building samples from the dataset is used for visual comparison, allowing for a qualitative assessment of the reconstruction results (Table 2);
- Deviation analyses, comparing reconstructed models to manually reconstructed ground truth, are presented in Figure 3.

Parameter sensitivity: data-driven methods (City3D and Augmented KSR) are highly sensitive to the chosen values of the reconstruction parameters. Their performance depends heavily on the results of point cloud segmentation into planes, which influence reconstruction accuracy and structural completeness. Minor parameter adjustments can lead to significant differences in results, requiring careful tuning, which might be challenging for non-expert users. Moreover, there is no single optimal parameter set for the whole data. In Table 2, we compare Augmented KSR under two scenarios: (i) balanced parameter configuration applied to the entire dataset and (ii) individually tuned parameter settings for each presented building. The balanced configuration often limit reconstruction detail but yields plausible results for the entire benchmark area. Customizing parameters for a specific building can significantly improve its reconstruction results, but at the same time it degrades or even prevents successful reconstruction of other buildings.

Footprint dependency: except for City3D, all methods rely on predefined building footprints used for building detection. While this ensures structured inputs and controlled boundaries, it also limits method autonomy. The potential integration of automated contouring algorithms (Jarzabek-Rychard, 2012; Bauchet and Lafarge, 2019) could reduce dependencies but would introduce additional computational complexity. Another key challenge arises when footprints belonging to a single building are subdivided according to roof segments. While such partitions benefit model-driven methods by isolating simpler, well-defined structures, they can complicate data-driven approaches by imposing unnecessary subdivisions in the reconstructed mesh.

Density sensitivity: model-driven approaches (BREC and RoofGenerator) demonstrate higher resilience to lower-density point clouds as they rely on predefined geometric primitives rather than dense, detailed point data. By contrast, data-driven methods (City3D and Augmented KSR) require higher point densities to accurately capture structural details, particularly in complex roof geometries. At lower densities - around 5 pts/m² - reconstructions often show missing elements and structural ambiguities. While the precise density threshold varies depending on the complexity of the scene and the chosen parameters, higher densities consistently give more reliable outcomes for data-driven techniques.

Roof type variety: data-driven approaches theoretically offer unlimited roof shape variety, adapting flexibly to diverse architectures. However, this flexibility introduces irregularities, particularly in unconstrained scenarios. In contrast, model-driven methods enforce predefined templates, ensuring standardized and consistent outputs. While this templating can restrict the range of possible roof shapes, it can be well-suited for regions where local roof types are well-defined and incorporated into the template library.

Mesh simplicity: while dense, detailed meshes are beneficial for applications such as visualization and immersive environments, many large-scale applications, such as urban simulations, physical modeling, and real-time navigation, require lightweight, structured 3D representations. In these scenarios, buildings should be represented by low-polygon surface meshes, maintaining geometric fidelity while ensuring computational efficiency. Model-driven approaches inherently address this

Method	Type	Footprints	Param	Density sensitiv.	Roof type variety	Mesh simplicity	Efficiency	Details reconstr.	Repeatability
City3D	data-driven	optional	####	##	#####	#	#	####	##
BREC	model-driven	required	#	#	###	####	####	##	######
Augmented KSR	data-driven	required	###	##	#####	###	###	####	##
RoofGenerator	model-driven	required	#	#	#	####	####	#	#####

Table 1. Comparative score from the lowest (#) to the highest (#####) values.

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Reference	**City3D**	**BREC**	**Augmented KSR**	**Augmented KSR** indiv. tuned param.	**RoofGenerator**

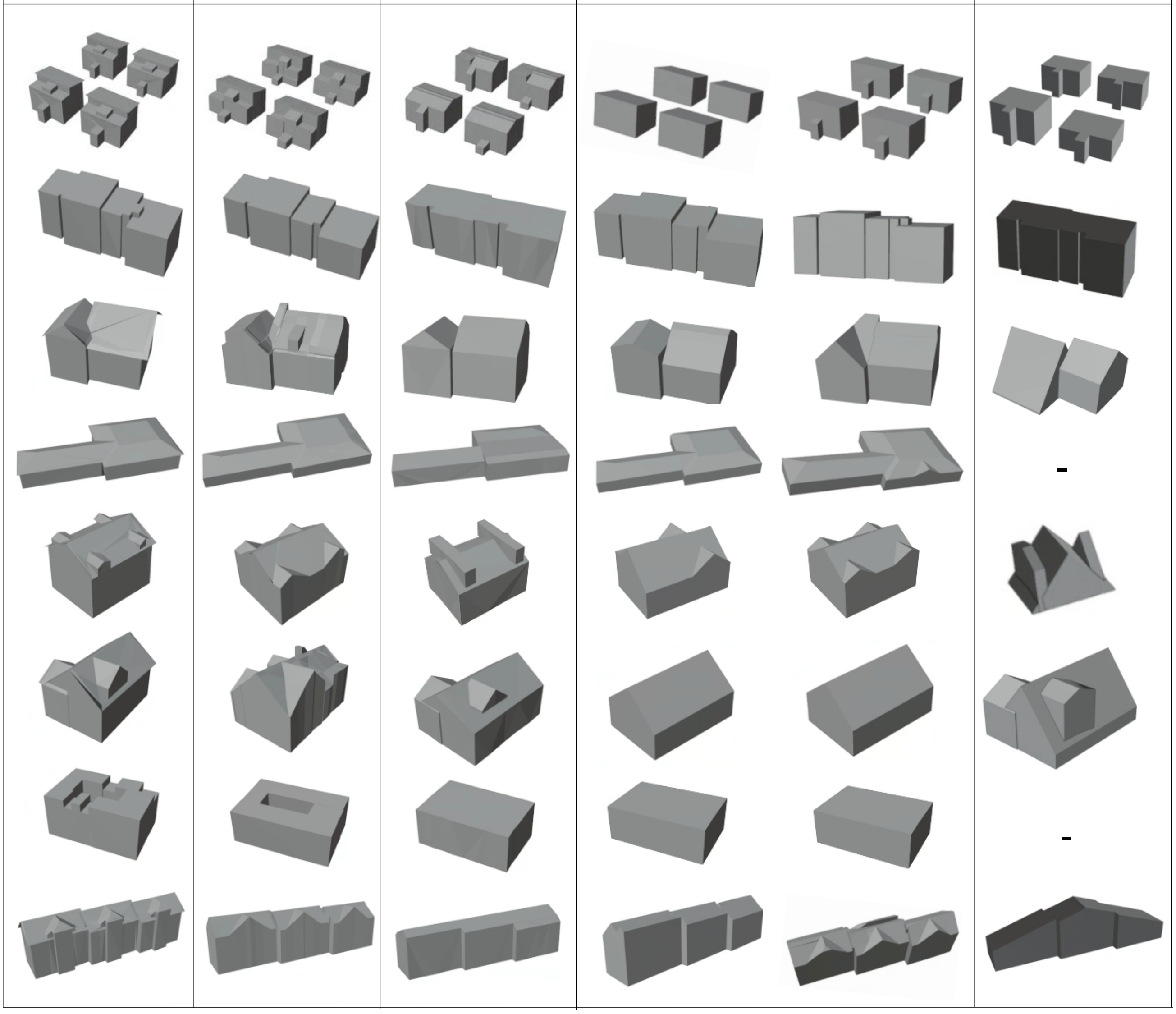

Table 2. Comparative evaluation of 3D reconstruction methods on selected building samples.

challenge by generating simplified, predefined polygonal structures. Data-driven City3D tends to produce overly complex polygonal structures, breaking roof surfaces into numerous smaller facets. In contrast, Augmented KSR generates low-polygon meshes closely resemble model-driven reconstructions, significantly improving efficiency while maintaining structural integrity.

Efficiency: model-driven BREC and RoofGenerator exhibit the highest computational efficiency among the tested methods. By contrast, City3D’s optimization-based strategy can significantly extend processing time, sometimes requiring several hours for a single complex building. Second data-driven method, Augmented KSR, proves substantially faster - often by an order of magnitude.

Details reconstruction: model-driven approaches rely on predefined shape libraries, which naturally restrict the level of detail by focusing on the template shapes provided. In contrast, data-driven methods can capture and preserve finer geometric nuances - although this comes at the cost of sensitivity to point density and segmentation quality. Considering that depending on the application additional complexity is not always beneficial, simpler meshes may be also preferable in some practical scenarios.

Repeatability: an important limitation of data-driven methods based on hypothesis-selection and space partitioning, is their general inconsistency across multiple runs. Even when using identical parameters, reconstructions may vary due to stochastic processes. This issue manifests in two forms: (i) inconsistency within a single run, when despite identical building geometries indicated by segmentation results, the reconstructed models differ significantly, revealing a lack of stability in processing similar structures; (ii) inconsistency across multiple runs - where the same input data leads to slightly different outputs across multiple executions, highlighting algorithmic randomness. Such variability poses challenges for large-scale, repeatable city modeling workflows and multi-temporal applications.

Reconstruction accuracy: considering the geometric properties of the reconstructed models, we perform a mesh-to-mesh comparison by evaluating the reconstruction outputs of each method against manually created reference 3D buildings.

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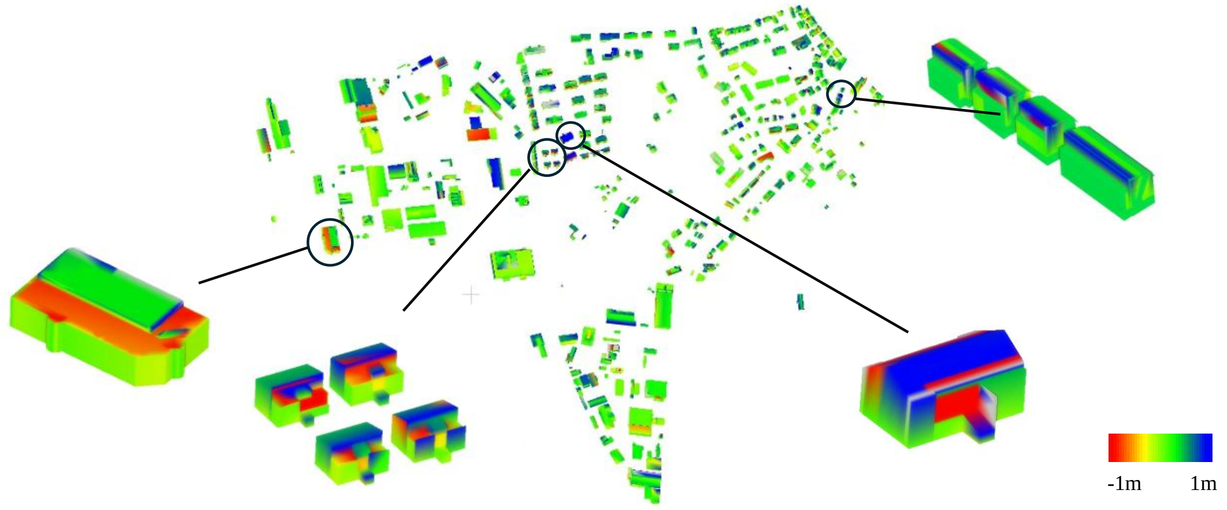
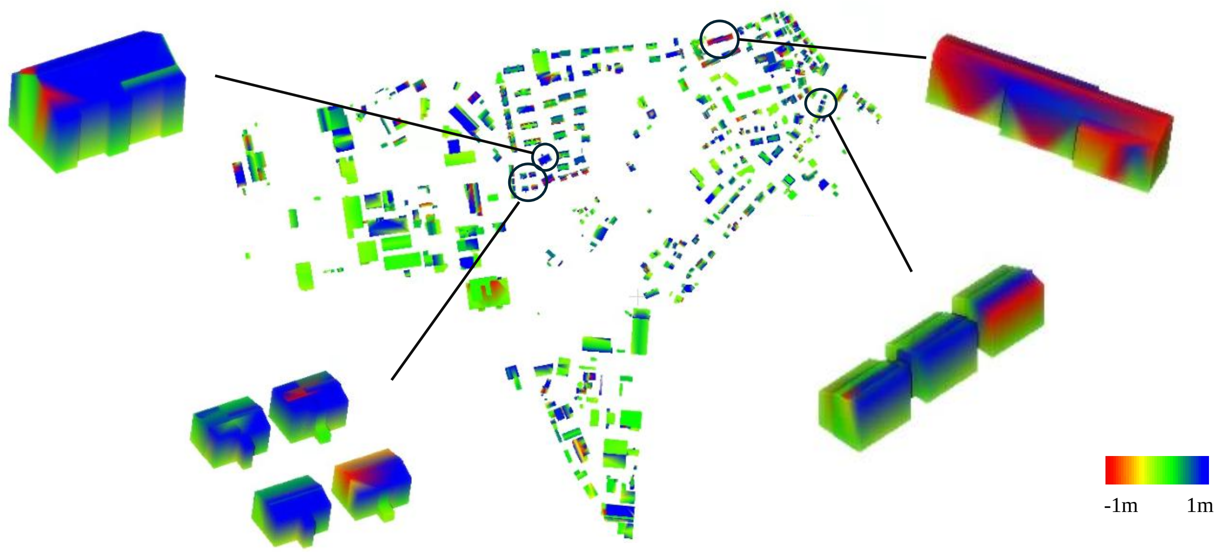
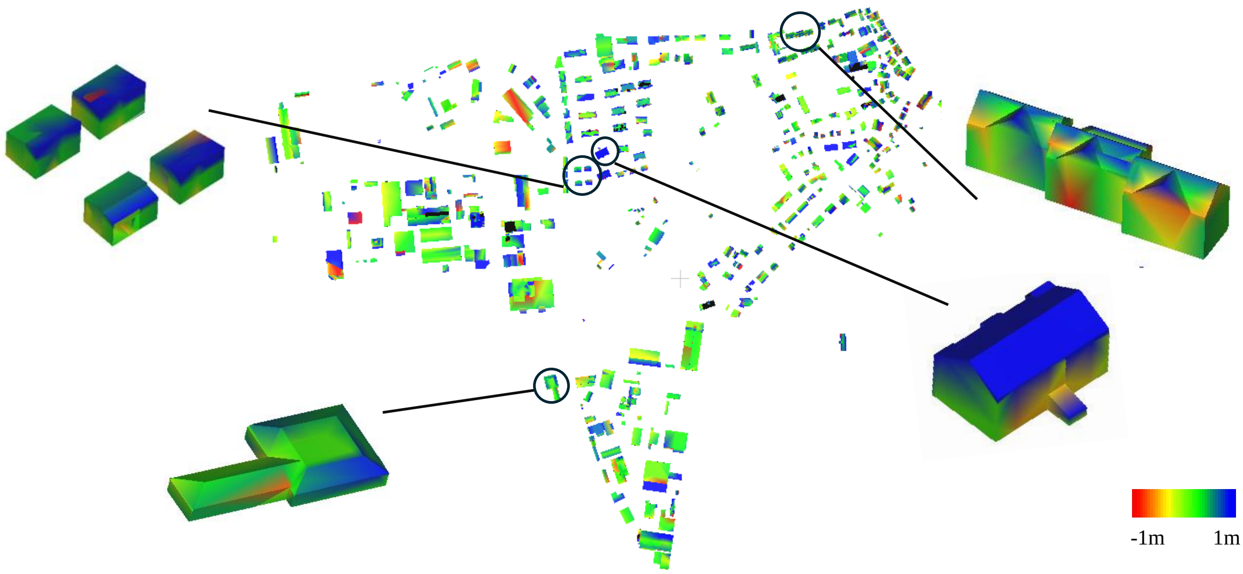


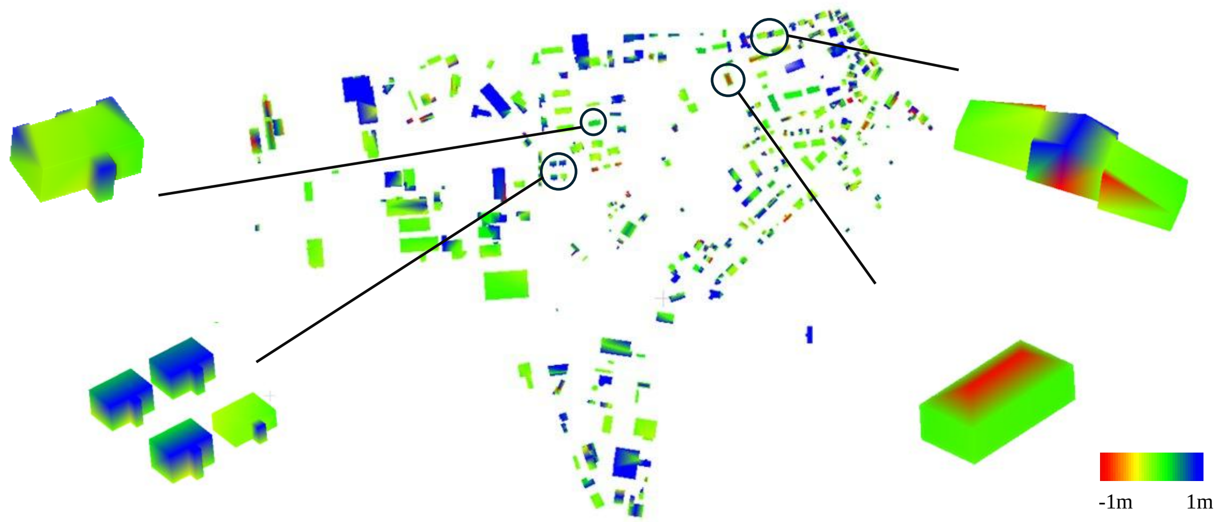
(a) City3D results



(b) BREC results



(c) Augmented KSR results



(d) RoofGenerator

Figure 3. Spatial deviations between 3D reference models and the 3D reconstruction results of the evaluated methods.

Metrics are computed as signed distances between the two meshes (Fig.3). The accuracy distribution varies significantly across methods. While data-driven methods reconstruct intricate roof details, they may introduce noise or minor misalignments. Conversely, model-driven methods prioritize structural correctness but lack flexibility in irregular roof formations. Consequently, City3D and Augmented KSR demonstrate higher fidelity in capturing complex roof structures but exhibit localized deviations in areas with insufficient point density. BREC and RoofGenerator enforce strong geometric regularization, leading to larger deviation between the reconstructed models and reference objects.

4. CONCLUSIONS

In this work, we reviewed the task of automatic 3D building reconstruction from airborne point clouds and proposed two new implementation - one data- and one model-driven - which we compared against established baselines. Our results confirm that 3D building modeling remains an active field with no universal solution. Data-driven methods can capture rich details but require careful parameter tuning and accurate plane segmentation - any errors here can yield incomplete or overly complex models. By contrast, model-driven approaches are generally faster and more robust, yet rely on predefined shape libraries that limit adaptability and upscaling. The final choice of method should be driven by application needs (e.g., high-detail heritage documentation vs. large-scale urban simulation), data quality (point density, sensor type, and alignment with footprints), and practical requirements like runtime and ease of parameter tuning. As future work, we aim to enhance our modeling methods by integrating a semantic layer to the mesh, based on classification information from the input 3D points. We also plan to evaluate reconstruction performance under varying point-cloud densities, to employ validation tools to ensure defect-free meshes, and to refine evaluation metrics - particularly those computed in 3D space - to provide a more comprehensive assessment of reconstruction accuracy and reliability. The created benchmark / dataset will be also released.

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