Towards Precise Building Models: LOD Generation from Airborne Multi-Source Point Clouds

Shahoriar Parvaz, Felicia Teferle, Abdul Nurunnabi

Geodesy and Geospatial Engineering, Faculty of Science, Technology and Medicine, University of Luxembourg,
6, rue Richard Coudenhove-Kalergi, L-1359 Luxembourg (shahoriar.parvaz, rebecca.teferle)@uni.lu, pyal1471@yahoo.com

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Abstract

The demand for accurate, lightweight 3D building models is rapidly growing in urban analysis, digital twins, and geospatial information systems. Single-source airborne point clouds, such as airborne laser scanning (ALS) or dense image matching (DIM), often suffer from geometric incompleteness, uneven density, and misalignments, limiting the reliability of Level of Detail (LOD) building reconstructions. While substantial progress has been made in single-source building reconstruction and multi-source fusion, fully automated LOD generation pipelines that effectively exploit cross-source airborne data remain limited. This paper presents an automated workflow for generating precise LOD building models from cross-source fused point clouds, leveraging the precision of ALS and the high resolution of DIM to improve model fidelity. Using point clouds obtained from a slice-to-slice fusion approach, experiments on Luxembourg datasets demonstrate a reduced model standard deviation of 0.17 m compared to 0.20 m for ALS, 0.29 m for DIM, and 0.27 m for conventional ICP-based fused point clouds. The results show that our workflow, combined with a polygon fitting algorithm and cross-source fused data, significantly enhances building model accuracy and geometric completeness, highlighting the value of multi-source integration for automated 3D city modeling.

1. Instructions

The generation of precise 3D building models is fundamental to the evolution of urban digital twins, smart city management, spatial analytics, and sustainable development (Mandlburger et al., 2017; Li et al., 2016b; Nurunnabi et al., 2022; Toschi et al., 2018). The Level of Detail (LOD) concept provides a standardized framework for representing model complexity, where higher LODs correspond to greater geometric detail. The quality and utility of these models, however, are fundamentally dependent on the characteristics of the underlying source data and the methods used for their reconstruction.

Despite steady advances, the majority of current urban 3D reconstruction approaches have relied heavily on single-source data, such as airborne laser scanning (ALS) or light detection and ranging (LiDAR) and photogrammetry driven dense image matching (DIM) point clouds (Haala et al., 2015; Mandlburger et al., 2017; Verdie et al., 2015; Huang et al., 2022; Xiong et al., 2014). Although ALS is recognized as a state-of-the-art method for topographic mapping due to its ability to provide dense and reliable height information, especially through vegetation, such single-source datasets often suffer from inherent limitations. These limitations typically include incomplete coverage, varying point densities, and insufficient semantic information (Li et al., 2016b,a; Xiong et al., 2014). Consequently, relying solely on these conventional datasets often leads to inaccuracies when reconstructing complex urban structures.

The limitations inherent in single-source data necessitate a move towards integrating complementary information. Recent advancements in remote sensing have highlighted the significant potential of integrating multi-source or cross-source data to enhance model fidelity (Mandlburger et al., 2017; Toschi et al., 2018, 2021). Point cloud fusion plays a pivotal role in this process by leveraging the strengths of both modalities, combining the precise ranging capabilities of LiDAR with the potentially higher resolution and detailed texture information available from photogrammetry (Parvaz et al., 2024; Huber et al., 2003). This fusion mitigates the limitations of individual datasets, enabling the reconstruction of more complete, reliable, and detailed 3D representations of the urban environment.

Recent research in 3D urban modeling has focused on generating geometrically accurate and semantically consistent building representations across different LOD (Li et al., 2016a; Liu et al., 2024). Advances in large-scale point cloud reconstruction have significantly improved the reliability and completeness of urban structures at various modeling scales (Huang et al., 2022). Polygonal surface reconstruction methods emphasize planar fitting and geometric regularity, enabling compact yet structurally coherent representations of complex building surfaces (Nan and Wonka, 2017). Furthermore, robust reconstruction frameworks integrate multi-primitive fitting strategies to enhance model stability and precision under noisy or heterogeneous conditions (Li and Shan, 2022).

Despite the clear benefits of data fusion, the systematic evaluation of combining airborne cross-source point clouds for the automated generation of building models remains underexplored. This paper addresses this critical research gap. The objective is to investigate how the fusion of multi-source airborne point clouds can substantially improve the detail and automation of urban building reconstruction, ultimately providing a pathway toward generating a more robust geospatial database. To this end, we propose a workflow that begins with fusing ALS and DIM datasets to produce a geometrically consistent fused point cloud. This fused data then undergoes semantic classification, individual building separation via clustering, and subsequently, structural reconstruction involving plane primitive detection and polygonal surface reconstruction. This rigorous pipeline aims to create lightweight, manifold 3D building models with the necessary precision for high LOD generation.

2. Related Work

In recent literature, numerous studies have proposed various approaches for 3D building reconstruction from airborne 3D point clouds for urban digital twin development (Li et al., 2016a; Huang et al., 2022). The field has progressed from manual, template-driven approaches to automated model generation that handles massive and irregular data. Here, we present a brief review of related technological development and key challenges encountered when using heterogeneous ALS and DIM enable richer input for building reconstruction.

2.1 3D Building Reconstruction from Airborne Single-Source Data

Airborne LiDAR is widely used for building modeling due to accurate geometry and vegetation penetration (Li and Shan, 2022; Vosselman and Dijkman, 2001). Early methods used geometric primitives and model libraries to estimate standard roofs, but these struggled with irregular or complex architecture (Zhang et al., 2021). Algorithms like City3D introduced robust roof segmentation and topological refinement to create detailed urban meshes (Huang et al., 2022).

Recent deep learning methods, such as Point2Building and BWFormer, reconstruct polygonal meshes directly from point clouds using transformer-based networks, reducing error propagation from multi-stage pipelines and improving adaptability to diverse structures (Liu et al., 2025, 2024). Point clouds from DIM offer fine detail, but are more sensitive to noise and occlusions, making them less reliable as a sole source (Xiong et al., 2014; Mandlburger et al., 2017; Haala et al., 2015).

2.2 Multi-Source Point Cloud Fusion

The fusion of airborne cross-source or multi-source point clouds can only be effective if the datasets are precisely registered to eliminate geometric inconsistencies between the sources (Huber et al., 2003; Toschi et al., 2021; Yang et al., 2021). This process involves estimating either a rigid or non-rigid transformation that best aligns corresponding points between the source and target datasets (Li et al., 2021). However, most existing approaches primarily address rigid transformation, such as the widely used Iterative Closest Point (ICP) algorithm (Besl and McKay, 1992), which assumes uniform transformation across the entire dataset. In contrast, non-rigid alignment addresses local deformations and sensor-induced discrepancies, but remains an active research area with slower progress. Recently, slice-to-slice adjustment methods have demonstrated enhanced robustness in aligning cross-source point clouds by applying localized transformations to each point, thereby minimizing geometric discrepancies and improving overall alignment accuracy (Parvaz et al., 2024).

2.3 Semantic Segmentation and Planar Primitive Detection

Semantic segmentation of point clouds plays a crucial role in isolating building structures from airborne data, paving the way for 3D city model generation by classifying points into meaningful categories such as building, ground, tree, and other urban objects. Many methods have been developed over the years for semantic segmentation in relevant research fields such as computer vision, photogrammetry, and machine learning (Nurunnabi et al., 2016; Duran et al., 2021). However, they often struggle with noise and occlusions in urban environments. In recent years, deep learning has been recognized as the most powerful approach, revolutionizing the domain through architectures like PointNet that facilitate hierarchical feature learning for semantic labeling of large-scale airborne point clouds (Charles et al., 2017; Nurunnabi et al., 2021; Agoub et al., 2019).

After segmentation, planar primitive detection is a cornerstone of 3D building reconstruction in urban scenes, where rooftops and façades are approximated by piecewise planar surfaces extracted from noisy, cluttered point clouds. Planar model fitting typically begins with RANSAC, which estimates a plane by iteratively sampling minimal point sets and validating consensus (Fischler and Bolles, 1981). For large-scale urban point clouds, the Efficient RANSAC algorithm accelerates hypothesis generation and verification through spatial indexing and lazy score evaluation, enabling robust detection of multiple geometric primitives (Schnabel et al., 2007; Zuliani et al., 2005). In our experiment, we use this approach with manual validation.

2.4 Polygonal Surface Reconstruction and LOD Generation

Urban building or polygonal surface reconstruction transforms noisy and sparse point clouds into structured 3D meshes for urban modeling. This reconstruction went through hierarchical simplifications, as demonstrated by progressive approaches to balance geometric accuracy and computational efficiency in large-scale scenes (Li and Shan, 2022; Verdie et al., 2015; Li et al., 2016a). Manhattan-world assumptions further enhance reconstruction by enforcing orthogonal alignments, producing clean polygonal surfaces and automated LOD hierarchies for improved rendering performance (Li et al., 2016b).

Polygonal surface reconstruction produces watertight meshes with accurate building topology. PolyFit formulates this as a hypothesis selection problem, generating optimal face sets directly from points for robust and lightweight results (Nan and Wonka, 2017). City3D (Huang et al., 2022) scales this approach, incorporating hierarchical segmentation to generate at various levels of detail in city scale from only using ALS data. However, City3D relies on predefined footprint information, and the quality of the final model is sensitive to its accuracy. Generating precise building footprints from airborne LiDAR remains an ongoing challenge (Nurunnabi et al., 2022). Additionally, City3D tends to produce building models with a higher number of faces, which can increase computational demands in subsequent analysis stages.

3. Methodology

This study introduces an automated workflow (Figure 2) to generate higher LOD building models (LOD2 and above), ensuring precise alignment of roof and facade structures with the input point clouds. The workflow addresses major deficiencies in single-source 3D urban modeling in five stages from data fusion to polygonal surface reconstruction.

1. Cross-source point cloud fusion: The process begins with cross-source fusion of ALS and DIM point clouds (Figure 1). To tackle common challenges of density imbalance and geometric discrepancies, the slice-to-slice adjustment method is deployed (Parvaz et al., 2024). Compared to conventional registration or fusion methods, the slice-to-slice approach yields a geometrically consistent and complete fused point cloud that is ready for further semantic analysis.

2. Classification: With the fused dataset prepared, semantic segmentation is conducted to separate building points from

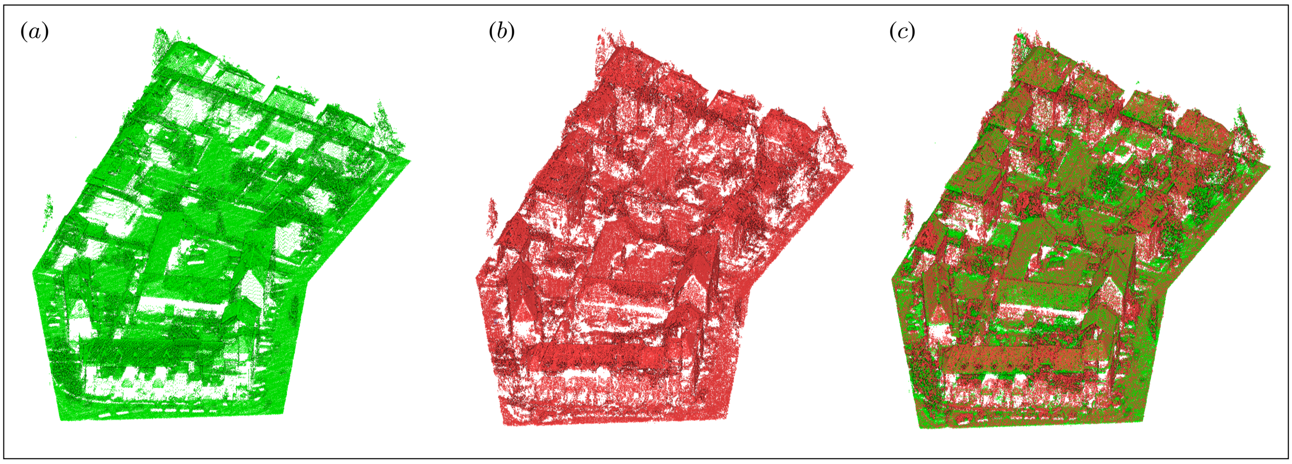


Figure 1. Sample aerial (a) LiDAR, (b) DIM and (c) fused point clouds.

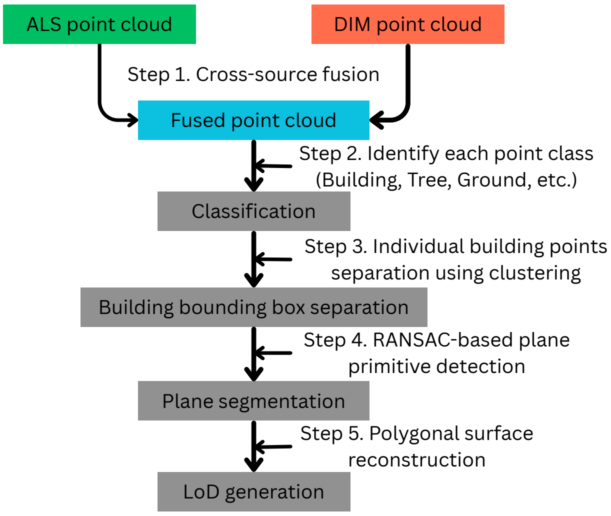


Figure 2. Overview of the proposed building reconstruction workflow. The process starts with a fused point cloud and results in a lightweight, manifold 3D building model.

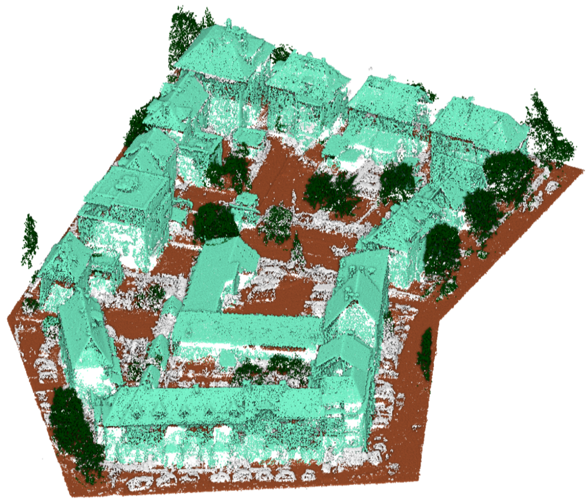


Figure 3. Classification result of the fused point cloud showing four classes: building, tree, ground, and unclassified.

ground, vegetation, and other urban features (Figure 3). This ensures that subsequent modeling stages focus strictly on relevant architectural data. Recent research investigates many methods that may be used, with the aim of delivering a clean, building-specific point cloud (Charles et al., 2017; Duran et al., 2021).

3. Individual building extraction: From the building class identified through semantic segmentation, points corresponding to individual buildings are isolated using clustering algorithms (Figure 4). We used the density-based spatial clustering of applications with noise (DBSCAN) algorithm (Ester et al., 1996) to extract individual building point clouds. DBSCAN groups densely populated regions in the point cloud, efficiently separating each building's structure from the entire building class, which enables downstream steps to focus on each building separately.

4. Plane segmentation: After extracting individual building point clouds, the workflow applies a RANSAC-based approach to segment dominant planar primitives (Figure 5) associated with roof and facade surfaces (Schnabel et al., 2007). RANSAC iteratively fits planes to subsets of points and evaluates inlier consensus, robustly handling outliers, occlusions, and irregular

Figure 4. Individual building point cloud extracted from the building class using DBSCAN clustering.

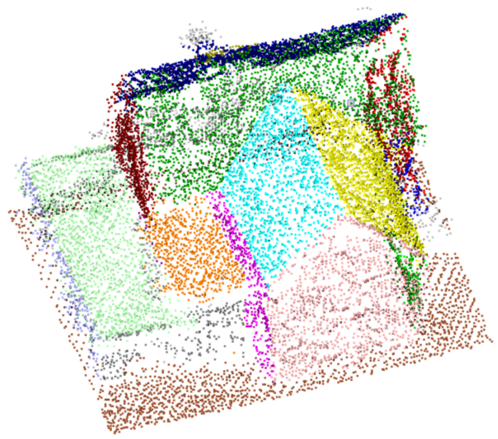


Figure 5. Randomly colored planar segments extracted from an individual cluster or selected building point cloud.

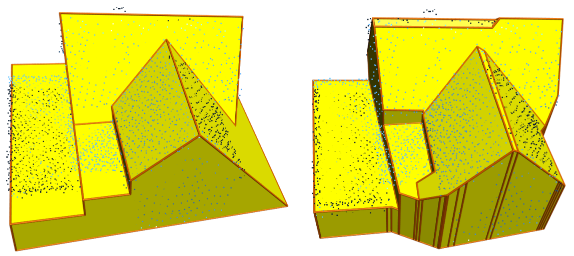


Figure 6. Building reconstruction from ALS point cloud using PolyFit (left) and City3D (right) algorithm.

point distributions.

5. Polygonal surface reconstruction: The next stage involves polygonal surface reconstruction (Figure 6) using a hypothesis-and-selection algorithm (Nan and Wonka, 2017; Huang et al., 2022). Considering the workflow's emphasis on simplicity and automation through cross-source integration, PolyFit was adopted as the reconstruction algorithm. In fact, City3D outperforms PolyFit in handling incomplete or sparse data, particularly on vertical surfaces such as facades. Therefore, we use the City3D algorithm for ALS data to keep this relevant when comparing with other reconstruction results.

The output of the pipeline is a compact, accurate building model, suitable for use in urban databases and analytics. This proposed workflow ensures the mitigation of the discrepancy between the generated building model and the input point cloud. In sum, our proposed workflow gives a framework for handling the limitations of airborne point clouds for the generation of an automated and accurate 3D city model.

4. Results and Evaluation

To illustrate the proposed workflow for building reconstruction from airborne cross-source data, we selected a representative tile from the airborne LiDAR and DIM point cloud datasets acquired during the 3D survey of the Luxembourg territory by the Administration of Cadastre and Topography (ACT). Using our proposed pipeline, we extracted a single building under four scenarios: LiDAR-only, DIM-only, conventional ICP-based fusion, and our proposed slice-to-slice fusion. This design allows a controlled comparison of geometric accuracy, completeness, and model compactness across different strategies.

4.1 Visual Evaluation

Visual comparisons (Figure 8) show clear distinctions among the tested scenarios. The LiDAR-only model features accurate roof ridges but lacks full coverage on facades because of the sparse data on vertical surfaces. The DIM-only model achieves greater surface detail, but this comes at the expense of increased noise and fragmented planes due to matching artifacts and occlusions. Fused data with a classic ICP approach modestly improves building completeness, but persistent misalignments remain visible around corners. In contrast, the reconstruction result using the point cloud from the slice-to-slice fusion algorithm produces well-aligned, watertight models with minimal faces or distortions. This results in visually plausible and topologically consistent models suitable for urban analysis and visualization.

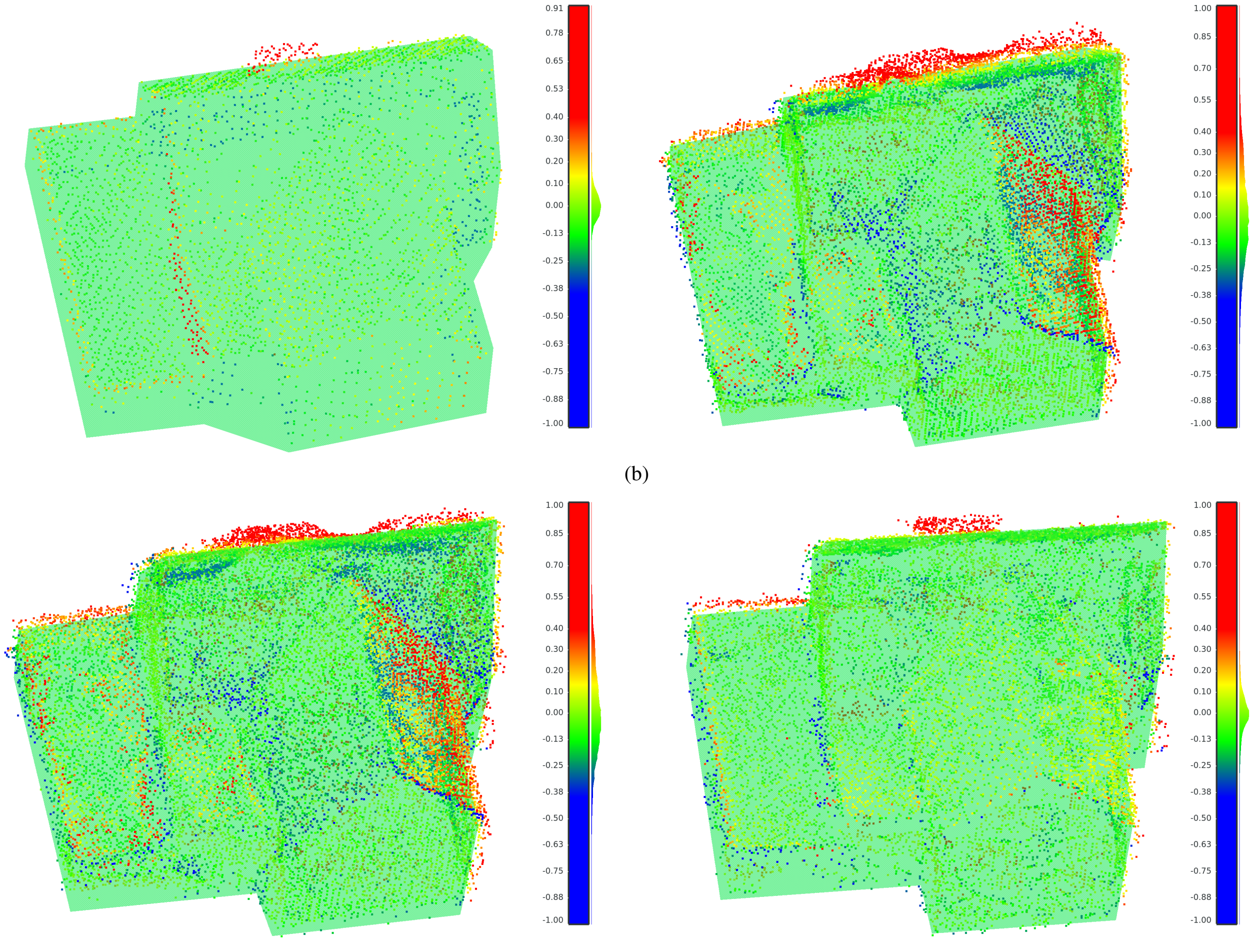
Furthermore, Figure 7 presents a color-coded visualization of the discrepancies between the reconstructed building model and the corresponding input datasets. Notably, the deviations for ALS points are minimal compared to the DIM dataset, owing to DIM's inherent lower accuracy and high noise artifacts from airborne acquisition, which manifest as significant distortions under and over the fitted roof surfaces. This issue persists in rigid ICP fusion, as the method applies a uniform transformation without accounting for individual point variations during ALS and DIM alignment. In contrast, our slice-to-slice fusion approach effectively mitigates these discrepancies, substantially reducing the distances between the reconstructed model and input points. Nevertheless, across all scenarios, localized discrepancies persist around small architectural features such as chimneys, skylights, and dormers, where insufficient point density and complex geometry challenge automated plane detection and model fitting algorithms.

4.2 Statistical Evaluation

To further assess model fidelity, we evaluated the proposed method's effectiveness through key metrics, including mean points-to-model distance, standard deviation (SD), and the number of faces in the resulting building (Table 1). The reconstructed building derived from the slice-to-slice fusion method consistently outperformed all alternatives, achieving the lowest mean distance of 0.013 m and SD of 0.17 m, in comparison to LiDAR-only (-0.018 m mean distance and 0.20 m SD), DIM-only (0.020 m mean distance and 0.29 m SD), and ICP fusion (0.018 m mean distance and 0.27 m SD). This superior performance demonstrates that cross-source fusion leads to tighter alignment between the reconstructed model and input points, thereby enhancing overall geometric accuracy for the building model.

Although the DIM point cloud provides a better representation of building structures and enables the generation of a more sensible reconstruction model compared to LiDAR input (Figure 8), it suffers from noise, resulting in a high SD of 0.29 m. On the other hand, the reconstructed models generated using the slice-to-slice fused point cloud exhibit notably lower SD than any other input source, underscoring the method's ability to utilize LiDAR accuracy and DIM point cloud resolution and completeness.

Collectively, both the visual evaluations and these quantitative analyses confirm that the proposed method achieves state-of-the-art accuracy and model compactness, as evidenced by the



(a) (b) (c) (d)

Figure 7. Color-coded differences (in meters) between reconstructed building from (a) LiDAR, (b) DIM, (c) ICP fusion, and (d) Slice-to-slice fusion datasets.

Dataset Source		# Points	# Faces	Mean Distance (m)	Standard Deviation (m)
LiDAR		4161	91	-0.018	0.20
DIM		17479	17	0.020	0.29
Fusion	ICP	21640	17	0.018	0.27
	Slice-to-slice	14382	16	0.013	0.17

Table 1. Statistics on the reconstructed buildings shown in Figure 8. For each dataset from different sources, the number of points in the input, the number of final building model faces, and model fitting error (mean distance and SD) are listed.

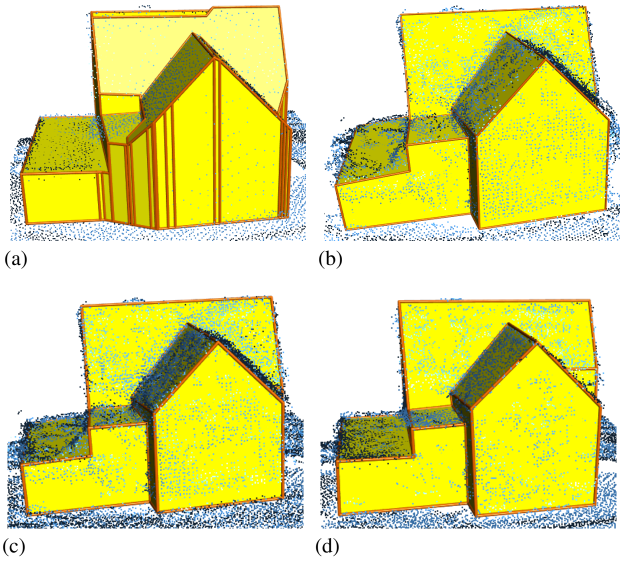


Figure 8. The reconstruction results of a building from (a) LiDAR, (b) DIM, (c) ICP fusion, and (d) Slice-to-slice fusion datasets.

lowest face count while maintaining superior fitting metrics. This ensures both geometric fidelity and practical efficiency, offering substantial benefits for automated, city-scale 3D building modeling in diverse urban environments.

5. Conclusions

This work demonstrates that integrating multi-source 3D point clouds in a unified pipeline can substantially improve automated building reconstruction for city-scale applications. By leveraging the complementary strengths of airborne LiDAR for precise geometry and DIM for completeness, our strategy produces building models with greater accuracy. The workflow from cross-source fusion and semantic classification to robust plane fitting and the PolyFit algorithm reconstructed building models that are both compact and reliable for higher LOD generation.

Comparative evaluations against single-source baselines indicate consistent gains in accuracy and completeness. The reconstruction based on the fused point cloud significantly reduces point-to-model discrepancies, lowering the mean distance from 0.018 m to 0.013 m and the SD from 0.27 m to 0.17 m. It effectively mitigates artifacts caused by occlusions and sampling gaps, while producing more compact polygonal representations without compromising accuracy. These improvements make it a state-of-the-art method and highlight the scalability for large-area mapping and its suitability for downstream tasks such as change detection, energy modeling, and exposure assessment.

Further research will focus on automation at the city scale, extending the approach to handle complex roof features and detailed façade architecture. We also plan to investigate more robust approaches, such as region growing for plane segmentation, and include other shape primitives like cylinders, cones, or curves. Together, these directions aim to deliver a robust, reproducible, and resource-efficient pathway to high quality 3D urban models.

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