

# A Semi-Automatic Roof Type-Driven Workflow for LoD2 Building Reconstruction from Orthophotos and Photogrammetric Point Clouds

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## Research Article

**Keywords:** LoD2 building model, roof type, semi-automatic, CityGML, CityJSON, Boundary Representation

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# A Semi-Automatic Roof Type-Driven Workflow for LoD2 Building Reconstruction from Orthophotos and Photogrammetric Point Clouds

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## Abstract

Level of Detail 2 (LoD2) building models provide explicit roof geometry and basic semantic subdivision and are widely used in urban analysis, 3D GIS, and remote sensing applications. However, generating LoD2 models from orthophotos and photogrammetric point clouds remains challenging, particularly due to variable data quality, complex roof forms, and dense urban structures. This study proposes a semi-automatic, roof type driven workflow for LoD2 building reconstruction that combines interactive digitized roof outlines and roof shape labels with rule based Boundary Representation (BREP) reconstruction in Python. Derived roof outlines from orthophotos are classified into five roof types (flat, gable, hip, shed, pyramid), while Digital Terrain Model (DTM), Digital Surface Model (DSM), normalized DSM, slope, and aspect layers derived from point clouds are used to infer roof height and roof plane orientation. The novelty of this study lies in a roof type driven semi-automatic workflow that explicitly uses roof type knowledge as the main driver of reconstruction rules, integrates orthophotos based roof outlines with elevation derivatives from point clouds, and generates complete BREP based LoD2 building models in CityJSON with CityGML conversion. The method is implemented to reconstruct 371 buildings into semantically structured LoD2 models stored in CityJSON and convertible to CityGML. Visual accuracy is evaluated for 30 buildings using completeness, correctness, and quality metrics derived from a confusion matrix comparing reconstructed roof planes with orthophotos reference data, yielding average values of 100% for completeness and 98.33% for both correctness and quality. Geometric accuracy is assessed by comparing selected model dimensions with point clouds based reference measurements, resulting in a *Root Mean Square Error* of 0.90 m, which satisfies the LoD2 tolerance adopted in this study. Overall, the results show that a roof type based semi-automatic workflow can deliver interpretable, semantically coherent, and interoperable LoD2 building models from photogrammetric data while maintaining explicit control over roof geometry and compatibility with existing 3D city model standards.

**Keywords:** LoD2 building model; roof type; semi-automatic; CityGML; CityJSON; Boundary Representation

## 1. Introduction

Three dimensional (3D) building models with sufficient geometric and semantic detail have become central to contemporary geomatics, remote sensing, and urban analytics because the importance to support many applications such as spatial visualization, urban morphology analysis, solar potential estimation, and cultural heritage documentation

(Biljecki et al., 2016; Morlighem et al., 2022; Arif & Harintaka, 2025). Within standardized 3D city modelling frameworks, Level of Detail 2 (LoD2) is particularly important because it represents roof geometry with basic building semantics, providing substantially more information than LoD1 models, which are generally limited to footprint extrusion (Biljecki et al., 2016; Biljecki & Dehbi, 2019). The CityGML conceptual model and its JSON based implementation CityJSON have further strengthened the role of LoD2 models by defining interoperable representations for ground surface, wall surface, roof surface, and related building components (Gröger et al., 2012; Biljecki & Dehbi, 2019; OGC, 2021).

Despite these advances, the efficient and accurate production of LoD2 building models remains challenging, especially when the source data consist of photogrammetric digital surface models (DSM) and airborne or terrestrial point clouds affected by variations in density, noise, and acquisition geometry (Alganci et al., 2018; Duran et al., 2021). Accuracy assessments of DSM and derived digital elevation models have shown that vertical errors and mixed uncertainties in slope and aspect can strongly influence downstream analyses and geometric modelling (Alganci et al., 2018; Zhang et al., 2025). LoD2 reconstruction, therefore requires not only the recovery of roof geometry but also careful handling of elevation derivatives such as DTM, DSM, and normalised DSM (nDSM) or Object Height Models (OHM), as well as aspect and slope, which encode the dominant orientation and steepness of roof planes (Lee et al., 2020; Zhang et al., 2025).

Some researchs have addressed 3D building reconstruction through geometric approaches based on point clouds and elevation surfaces. Amini et al. (2014) demonstrated that directional plane intersections applied to LiDAR data can reconstruct gabled and hipped roof structures by intersecting vertical and horizontal planes. Kong et al., (2023) developed methods for detecting roof vertices from airborne laser scanning (ALS) point clouds, and later combined vertex detection, constrained Delaunay triangulation, and graph theory to generate 3D building models directly from ALS data (Kong et al., 2024). These geometric methods can recover roof geometry with high fidelity when roof planes are distinct and point clouds quality is high, but they often focus on roof extraction rather than complete, semantically structured LoD2 solids, and may be sensitive to point clouds noise and complex roof forms (Amini et al., 2014; Duran et al., 2021; Kong et al., 2024).

Procedural and rules based approaches represent another major research stream for LoD2 generation. Zhang et al. (2022) showed that GIS based procedural modelling using Computer Generated Architecture (CGA) can support 3D urban design by generating LoD2 buildings from building footprints, heights, and rule sets. Usta et al. (2023) proposed a deep learning aided, web based procedural modelling workflow in which semantic city models are generated using grammar rules guided by building segmentation results. Morlighem et al. (2022) reconstructed historical 3D city models using CGA rules applied to historical data, while Nursyahrial & Ilmawan (2025) demonstrated semi-automated 3D modelling of rooftop types (flat, gable, hip, shed, pyramid) from aerial photos in CityEngine using CGA. These studies highlight the efficiency and scalability of procedural modeling, but they also show that CGA outputs depend strongly on rule design and platform specific ecosystems, which may limit interoperability and the tight coupling between observed roof outlines and generated roof geometry (Zhang et al., 2022; Morlighem et al., 2022; Nursyahrial & Ilmawan, 2025).

In parallel, artificial intelligence (AI) assisted and hybrid methods have been increasingly applied for point clouds reconstruction and classification. Duran et al. (2021) compared machine learning algorithms for classifying

photogrammetric and airborne LiDAR point clouds into land cover classes, demonstrating that learning based approaches can improve separation between building and non building points. Li et al. (2025) proposed an outdoor LiDAR point clouds classification algorithm based on multilevel point cluster feature fusion, achieving robust separation of structural elements in complex scenes. Vostikolaei & Jabari (2023) introduced a deep multimodal feature fusion framework for large scale LoD2 building modeling, combining imagery and LiDAR data to improve roof segmentation and model generation. More recently, (Andaru et al. (2026) presented CASCADE-3D, a GUI-driven framework for automated 3D building model reconstruction that integrates segmentation, DTM/DSM extraction, and LoD1-LoD2 model generation within a single workflow. These AI and hybrid systems demonstrate strong geometric performance and scalability, but they often involve complex processing chains, can act as black boxes with limited interpretability, and may require substantial computational resources (Duran et al., 2021; Vostikolaei & Jabari, 2023; Andaru et al., 2026).

Alongside fully automatic approaches, several studies emphasize the role of semi-automatic workflows that combine manual or interactive interpretation with rule based reconstruction. Biljecki & Dehbi (2019) argued that LoD2 models can be generated without full aerial survey pipelines by leveraging machine learning and existing data, highlighting the importance of alternative workflows that balance automation and explicit control over roof geometry. Nursyahrial & Ilmawan (2025) showed that semi-automatic, CGA based modelling guided by rooftop type classification can achieve high visual accuracy for five roof classes, while Arif & Harintaka (2025) demonstrated that combining Structure from Motion-Multi View Stereo (SfM-MVS) and neural radiance fields can support interoperable 3D heritage models. These studies suggest that interpretability, reproducibility, and semantic richness remain important criteria alongside automation and accuracy.

Overall, the literatures indicate that three methodological gaps remain. First, there is limited work on semi-automatic workflows that reconstruct complete Boundary Representation (BREP) based LoD2 building solids from orthophotos and photogrammetric point clouds while treating roof type as the central driver of reconstruction rules. These workflows should clarify how each roof class maps to specific rule sets and maintain interoperability with CityGML and CityJSON (Gröger et al., 2012; Biljecki & Dehbi, 2019). Second, the potential of elevation derivatives such as DTM, DSM, OHM, aspect, and slope as explicit inferential variables for roof height and roof plane orientation across multiple roof classes remains underexplored compared with their more common use as support data for segmentation or classification (Alganci et al., 2018; Lee et al., 2020; Zhang et al., 2025). Third, many recent approaches emphasize high levels of automation or platform specific procedural but offer limited transparency for roof type specific reconstruction logic and limited coupling between observed roof outlines and generated geometry (Zhang et al., 2022; Usta et al., 2023; Vostikolaei & Jabari, 2023).

In response to these gaps, this study develops and evaluates a roof type driven, semi-automatic workflow for generating LoD2 3D building models from orthophotos and photogrammetric point clouds. The workflow combines interactive roof outline digitization and roof type classification with rule based geometric reconstruction using elevation derivatives such as DTM, DSM, OHM, aspect, and slope as inferential parameters to estimate roof height and plane orientation for five common roof classes: flat, gable, hip, shed, and pyramid, as shown in Fig. 1. For each roof class, the reconstruction rules define how the observed roof outline is transformed into the corresponding roof geometry. The resulting geometry is organized into BREP based LoD2 solids with semantic surfaces and exported as CityJSON, then

converted to CityGML, providing interpretable, semantically structured, and interoperable 3D building models that  
 bridge roof shape classification, geometric rule formation, and standardized 3D city modeling.

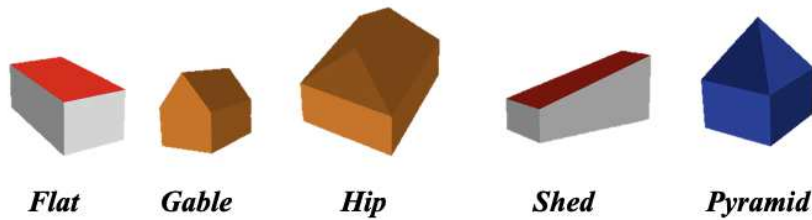


**Fig. 1** Roof types of building. Data sources: concept adopted from Biljecki & Dehbi (2019), modified by authors.

## 2. Material and Method

### 2.1. Study area

This study was conducted in 3 locations: Jawa Subdistrict, Singkawang City, West Kalimantan, Indonesia, covering an area of 67.41 ha, as shown in Fig. 2. Each study area is characterized by low rise urban development with a mixture of residential and commercial buildings, providing diverse but still interpretable roof geometries which suitable for LoD2 reconstruction. The area was selected because it contains roof shape variations representing the five roof classes addressed in this research, which are flat, gable, hip, shed, and pyramid.

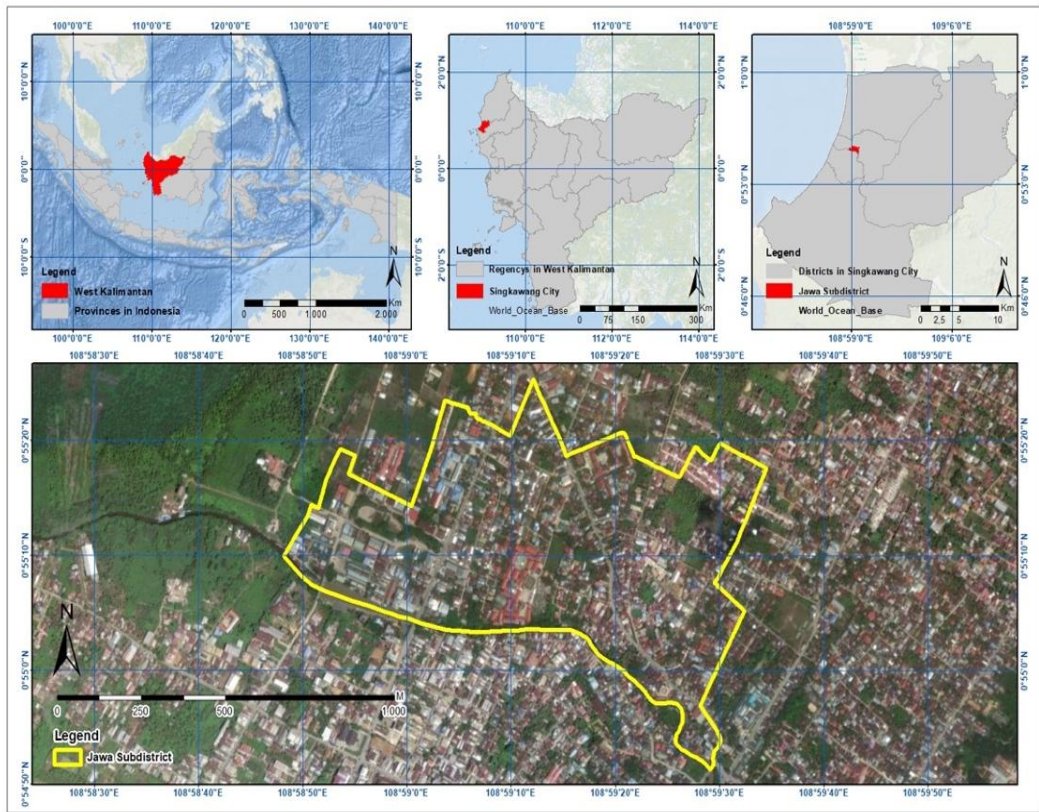


**Fig. 2** Study area  
 (Image source: upper - World Ocean Base; lower - Land Office of Singkawang City)

## 2.2. Data collection

The data used in this study consisted of the administrative boundary, orthophotos data, and point clouds data, which are depicted in Fig. 3. All datasets were acquired in 2024 as part of an aerial survey campaign over the study area. The orthophotos has a ground sampling distance of 7.5 cm and the point clouds has a density of approximately 4 points/m<sup>2</sup>, which was sufficient for roof outline delineation and for deriving elevation information and building surface geometry.

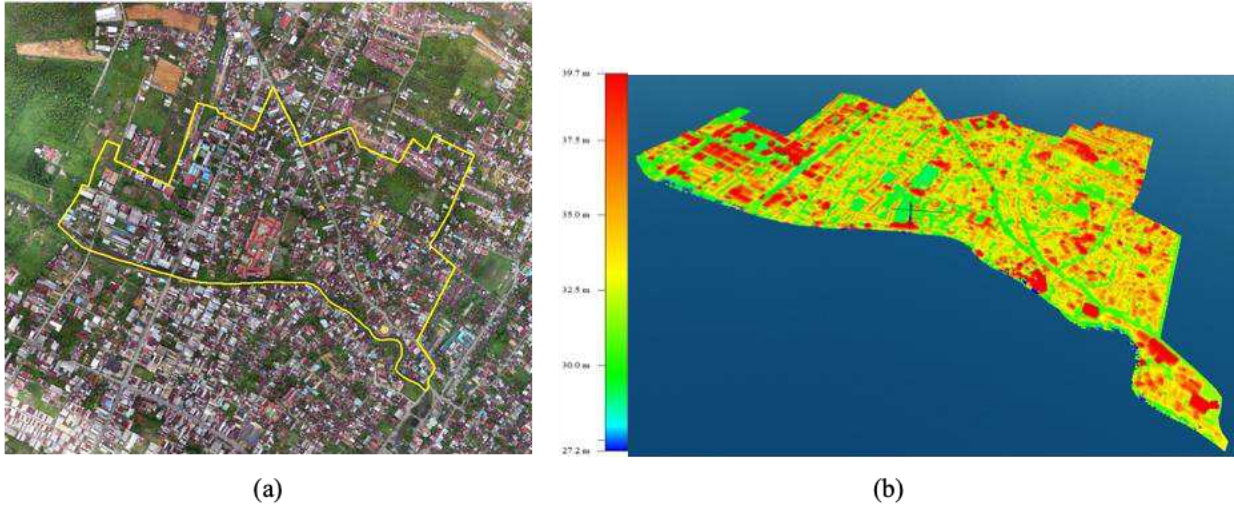


**Fig. 3** Data collection (a) orthophotos and administrative boundary of Jawa subdistrict and (b) point clouds  
(Image source: Land Office of Singkawang City)

## 2.3. Method

The initial stage of the study was a literature review of recent methods for 3D building reconstruction, roof geometry characterization, Boundary Representation (BREP) modeling, and visual and geometric accuracy assessment approaches. This stage was used to establish the study's conceptual basis, identify relevant parameters, and design an appropriate semi-automated workflow. After that, secondary data were collected, including digital administrative boundaries, orthophotos, and point clouds data.

The proposed method consists of three main stages: elevation extraction, roof outline digitization and roof type classification, and automatic LoD2 reconstruction, as summarised in Fig. 4. Point clouds were first classified to derive DTM and DSM surfaces, from which nDSM, slope, and aspect layers were generated. Roof outlines were then interactively digitized from the orthophotos and labeled into one of five roof types. These labeled polygons served as structured inputs for Python based BREP reconstruction, producing LoD2 building models in CityJSON format.

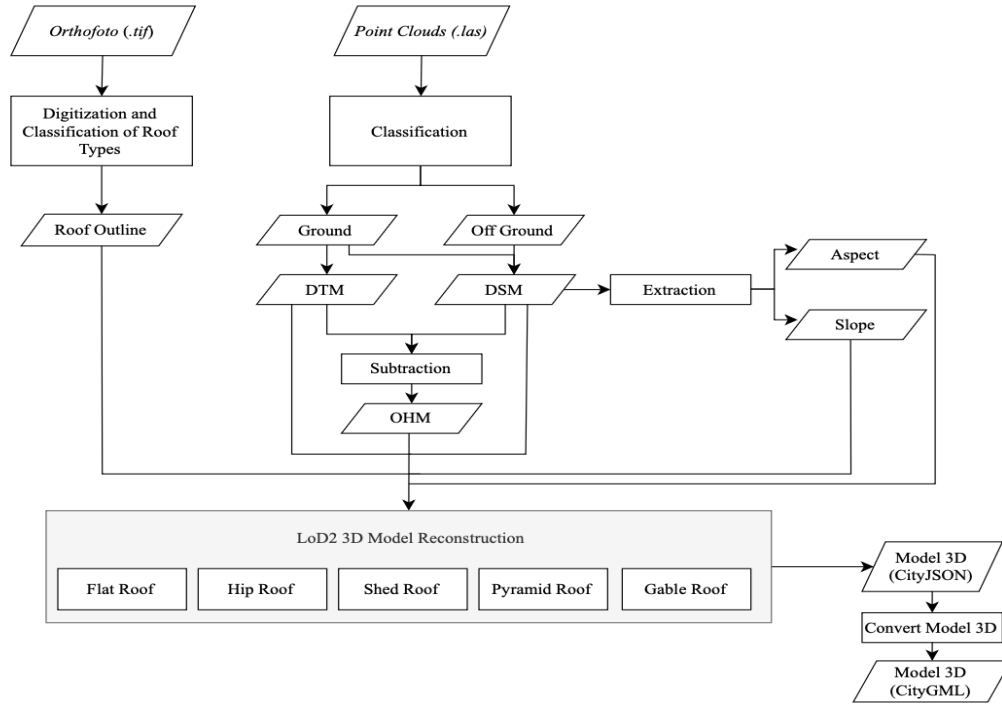


**Fig. 4** Workflow of the proposed roof type driven semi-automatic LoD2 building reconstruction

## 2.4. Elevation extraction

Data processing was initiated by extracting elevation models from the point clouds. Point clouds classification was first carried out to separate ground and non ground points. Ground points were used to generate the DTM, whereas all points were used to generate the DSM. This separation was required because the DTM was intended to represent bare earth elevation, whereas the DSM was intended to represent the highest surface elevation, including terrain, buildings, vegetation, and other objects. From these two models, the object height model (nDSM) was derived by subtracting the DTM from the DSM. This parameter was selected because the relative object height above ground was required as the basis for estimating building height in LoD2 reconstruction. In addition, slope and aspect parameters were derived from the DSM. The slope parameter was selected because it describes the magnitude of roof surface inclination, whereas aspect was selected because it indicates its orientation. Both parameters were used to support the inference of roof geometry and orientation, particularly for sloped roofs such as gable and shed roofs.

## 2.5. Roof outlines and roof types

The next stage consisted of roof outline digitization and roof type classification. Roof outlines were digitized interactively from the orthophotos by following visible roof edges, resulting in polygons representing roof footprints. This approach was adopted because the LoD2 geometry was constructed from roof geometry rather than merely from building footprints on the ground. Each digitized polygon was then assigned a roof-type attribute corresponding to one of the five roof classes. Examples of interactively digitized roof outlines for the five roof types are shown in Fig. 5. The

classification was performed visually based on roof geometry characteristics observed in the orthophotos, ensuring that each class reflected its distinctive roof shape. The resulting digitized and classified polygons were then exported in GeoJSON format for use as input to the automatic reconstruction stage.

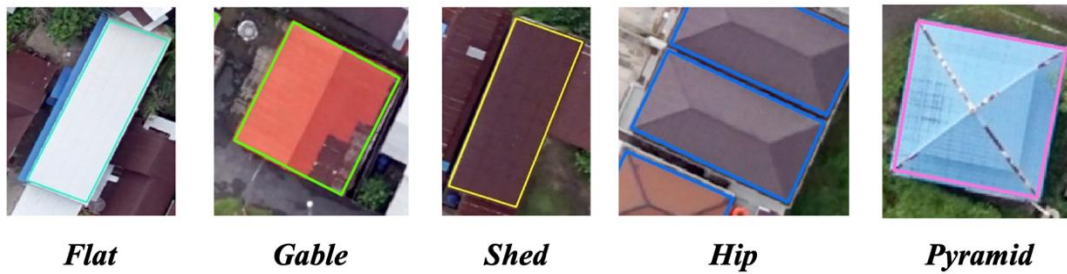


**Fig. 5** Roof outline digitization

## 2.6. Rule based BREP reconstruction

LoD2 building reconstruction was carried out semi-automatically using Python scripts. At this stage, the geometry of each roof outline polygon was first read to obtain the two dimensional coordinates ( $x,y$ ) of each vertex. Raster statistics from the DTM and DSM were then extracted for each polygon to obtain the mean ground surface elevation ( $z_{ground}$ ) and the mean roof surface elevation ( $z_{roof}$ ). These parameters were selected because the base and roof elevations were required to determine the initial three dimensional coordinates ( $x,y,z$ ). Based on these values, base vertices were formed at ground elevation, and roof vertices were formed at roof elevation, and these vertices were then used to construct wall and roof surfaces. The conceptual structure of the BREP based building model, including vertices, edges, and faces linked to the semantic surfaces *GroundSurface*, *WallSurface*, and *RoofSurface*, is illustrated in Fig. 6. Subsequently, reconstruction rules were applied according to roof type.

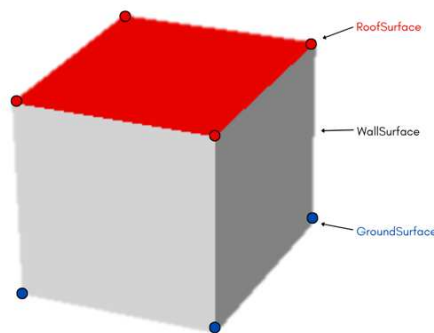


**Fig. 6** Boundary Representation (BREP)

### 2.6.1. Flat Roofs

Roof geometry of flat roof was generated directly from the roof outline at a constant elevation. The mean roof surface elevation  $z_{roof}$  was assigned to all roof vertices, while the mean ground surface elevation  $z_{ground}$  was used for the base vertices, so that a single horizontal roof plane was formed above the ground surface. This configuration reflects the geometric characteristic of flat roofs and provides a reference case against which the sloped roof reconstruction rules can be compared.

### 2.6.2. Gable Roofs

Roof polygon of gable roof was first rotated to align with the coordinate axes and then subdivided into four equal sub-polygons. Median aspect values were extracted for each sub-polygon and grouped into two dominant orientation clusters, as shown in Fig. 7a. These two clusters represent the two main roof planes on either side of the ridge. After the ridge line had been identified from the intersection of these two plane orientations (Fig. 7b), the ridge elevation  $Z_{ridge}$  was calculated. The additional height  $h$  above the object height is computed using equations (1) and (2).

$$h = d \times \tan \theta \quad (1)$$

$$Z_{ridge} = Z_{ground} + OHM + h \quad (2)$$

Where  $d$  denotes the horizontal distance from the eave to the ridge along the roof plane,  $\theta$  is the roof slope angle derived from the slope layer,  $Z_{ground}$  is the mean ground elevation within the roof outline, and OHM is the nDSM. The term  $h$  therefore represents the additional elevation required to raise the roof apex above the object height so that the ridge line is consistent with the observed slope and aspect. This procedure ensures that the two opposing roof planes meet along a ridge whose position and height are constrained by both the planimetric roof outline and the point clouds derived elevation derivatives.

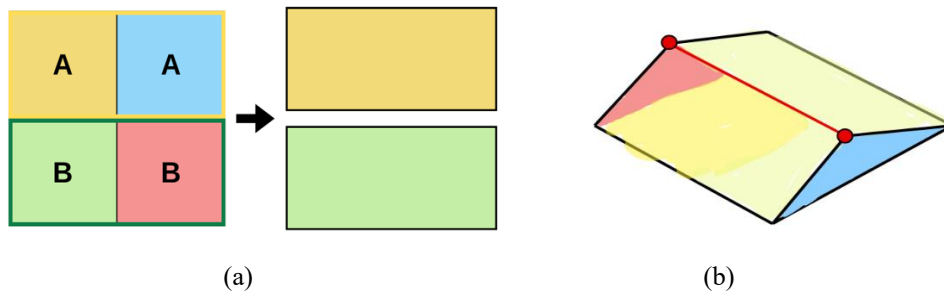


**Fig. 7** Forming the ridge of gable roof (a) classification of aspect values into two cluster and (b) Identification of ridge points

Fig. 7 illustrates the main steps used to form the ridge of a gable roof. In Fig. 7a, the rotated roof polygon is divided into four sub-polygons and their median aspect values are classified into two clusters (labelled A and B), which correspond to the two dominant roof planes. In Fig. 7b, the ridge line is defined as the intersection between these two plane orientations, and the ridge points are positioned at the locations where the two planes meet once the ridge elevation  $Z_{ridge}$  has been computed using equations (1) and (2).

### 2.6.3. Hip roofs.

The roof structure was generated from the inward sloping pattern along the entire building perimeter toward a ridge, in accordance with the geometric characteristics of this roof type. Candidate ridge lines were first defined by connecting opposite edges of the roof outline polygon through the centroid, as shown in Fig. 8a. DSM values were then sampled at regular intervals along each candidate ridge line (Fig. 8b), and the segment with the highest elevation was identified as the ridge segment (Fig. 8c). This procedure ensures that the ridge location is constrained both by the footprint geometry and by the maximum roof elevation observed in the DSM. The relationship between the eave sides and the ridge for the final hip roof configuration is depicted in Fig. 9: the long eave sides run parallel to the ridge, while

the short eave sides are perpendicular to it, and the ridge endpoints  $r_1$  and  $r_2$  are positioned along the line connecting the corresponding eave corners  $e_1$ - $e_4$ .

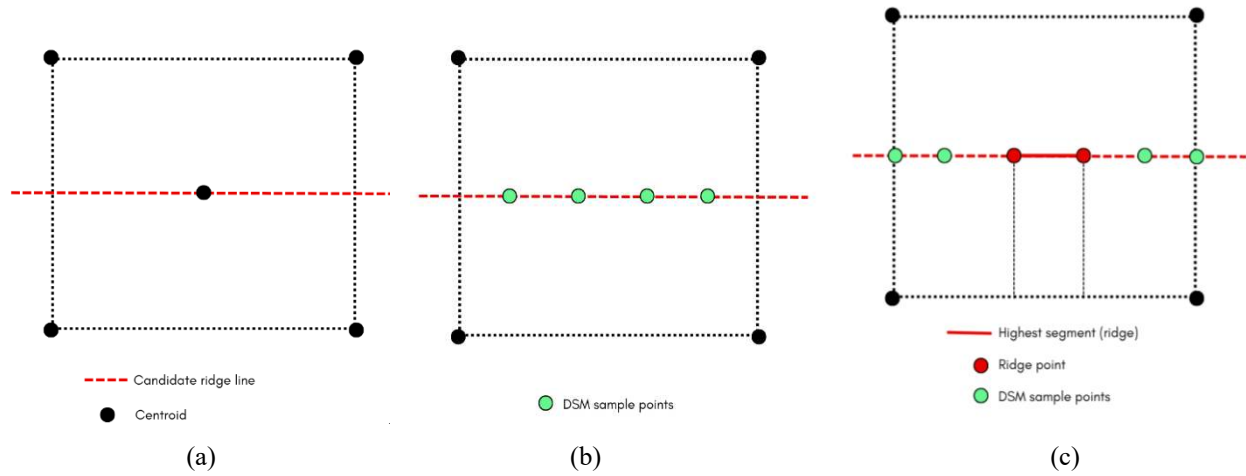


**Fig. 8** Determining the start and end points of the ridge (a) candidate ridge line and centroid, (b) sampling DSM along the candidate ridge line, and (c) identifying the highest elevation ridge segment

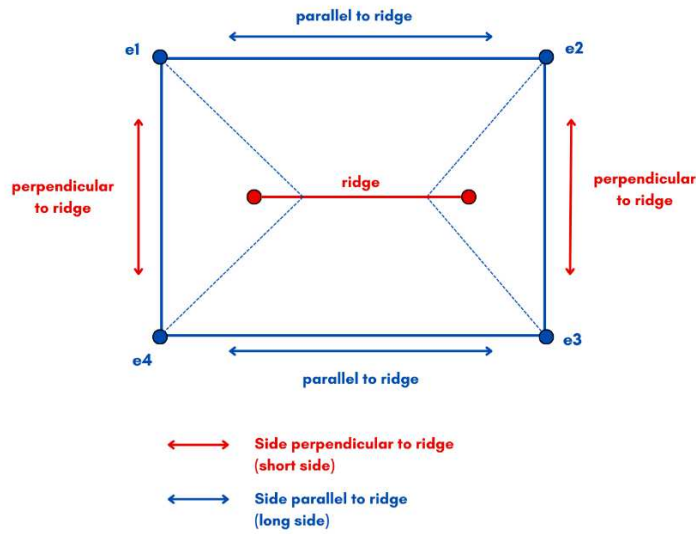


**Fig. 9** Relationship between eave sides and the ridge for a hip roof

#### 2.6.4. Shed Roofs

The slope direction was determined from the lowest elevation eave edge toward the highest elevation eave edge. Once this dominant slope direction had been identified, the elevation of each roof vertex was calculated by linear interpolation between the mean eave elevation  $z_{eave}$  and the mean roof edge elevation  $z_{roof}$ . The detection of the slope direction and the definition of the eave and ridge elevations are illustrated in Fig. 10a, while the resulting interpolated vertex elevations and roof planes are shown in Fig. 10b.

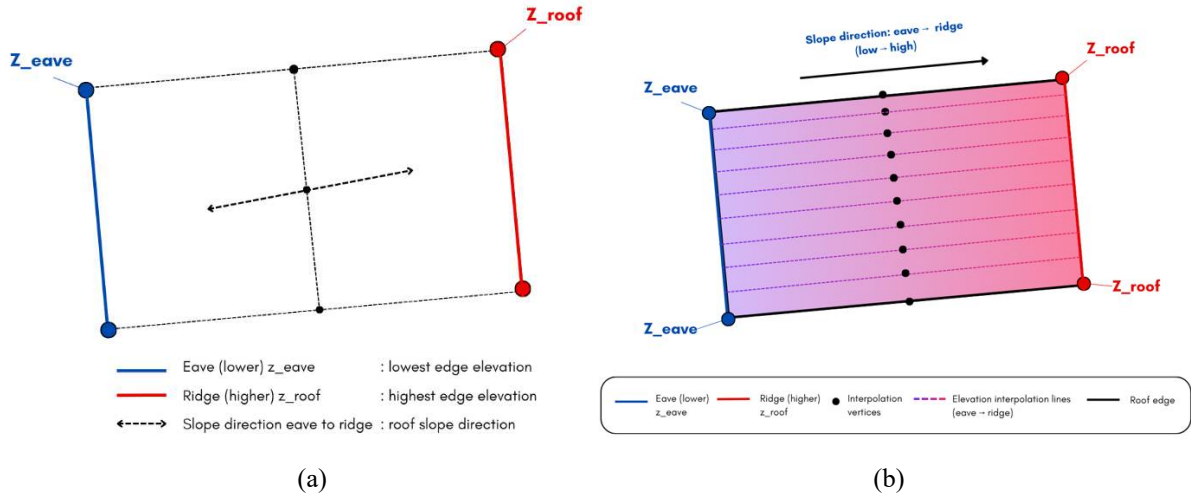


**Fig. 10** Forming of a shed roof slope (a) detection of slope direction and (b) linear interpolation of roof elevation

### 2.6.5. Pyramid Roofs

Pyramid roofs, define the apex at the centroid of the roof outline polygon and use it as the central top vertex with elevation  $z_{roof}$ . Each roof side was then connected from the eave vertices with elevation  $z_{eave}$  to this apex, forming four roof planes that converge at a single point, as illustrated in Fig. 11.

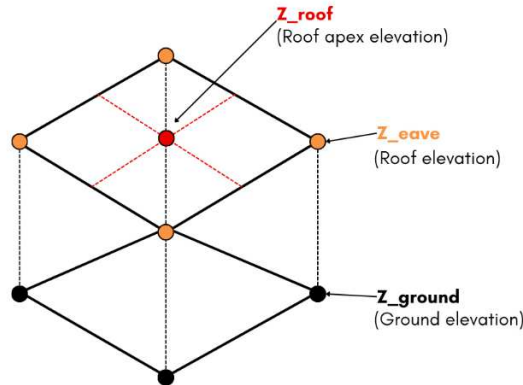


**Fig. 11** Determination the apex point at the centroid of the roof outline polygon

All generated geometry was organized into the semantic structure of *GroundSurface*, *WallSurface*, and *RoofSurface* using the BREP concept, exported in CityJSON format, and converted into CityGML to support interoperability. For each roof type, specific reconstruction rules were defined: flat roofs were generated with constant roof elevation, gable roofs with two main planes separated by a ridge line derived from aspect and slope, hip roofs with inward sloping planes toward a ridge or apex system, shed roofs with a single dominant slope direction and linearly interpolated vertex elevations, and pyramid roofs with four planes converging at a central apex. This rule set ensured that all buildings were reconstructed using consistent, roof type specific geometric logic before accuracy assessment.

## 2.7. Accuracy assessment

In three dimensional building modeling, the success of Level of Detail 2 (LoD2) representation depends on the model's ability to explicitly represent roof structures rather than merely extruding building footprints. According to Nursyahrial & Ilmawan (2025), the quality of 3D building models can be evaluated through a visual accuracy assessment by comparing the 3D model with orthophotos data in terms of roof shape, using completeness, correctness, and quality as evaluation parameters. Conceptually, LoD2 evaluation can therefore be carried out through semantic visual accuracy tests that assess the consistency and completeness of LoD2 roof structure representation against orthophotos used as reference data. Visual accuracy is typically quantified using a confusion matrix consisting of *True Positives* (TP), *False Positives* (FP), *True Negatives* (TN), and *False Negatives* (FN), where each component describes correct or incorrect predictions for positive and negative categories (Arif & Harintaka, 2025). Minimum acceptance thresholds of 85% for these accuracy indicators have been suggested in previous studies on 3D models and classification evaluation (Zheng et al., 2017).

In addition to visual assessment, geometric accuracy tests evaluate the dimensional fidelity of 3D building models by comparing the length, width, or height of buildings measured in the reconstructed model with the corresponding dimensions in the reference data. Geometric accuracy in CityGML based LoD2 building models is commonly expressed using the Root Mean Square Error (RMSE), in line with the accuracy standards defined in the CityGML specification (OGC, 2021). For LoD2 building models, RMSE values are generally expected to remain below 2 m to comply with CityGML accuracy recommendations (Gröger et al., 2012).

## 3. Result and Discussion

### 3.1. Elevation extraction

Elevation derived products were generated from the point clouds dataset, including the Digital Terrain Model (DTM), Digital Surface Model (DSM), normalized Digital Surface Model (nDSM), aspect, and slope layers. The DTM, DSM, and nDSM derived from the point clouds are presented in Fig. 12a-c, while the corresponding aspect and slope layers are shown in Fig. 13a-b. The DTM represents the ground surface after the removal of above-ground objects such as buildings and vegetation, whereas the DSM represents the upper surface, including terrain, buildings, vegetation, and other objects. In the study area, DTM elevation values range from 14.0217 m to 34.8761 m, while DSM values range from 14.8823 m to 52.2272 m.

Following the generation of the DTM and DSM, the nDSM was calculated as the difference between the DSM and DTM to represent object height above the ground surface. The resulting nDSM values range from 0 m to 29.411 m in the study area. This layer was used to represent relative object height and to support the identification of building height in the subsequent LoD2 reconstruction process, in line with common practices in photogrammetric 3D building modeling (Alganci et al., 2018).

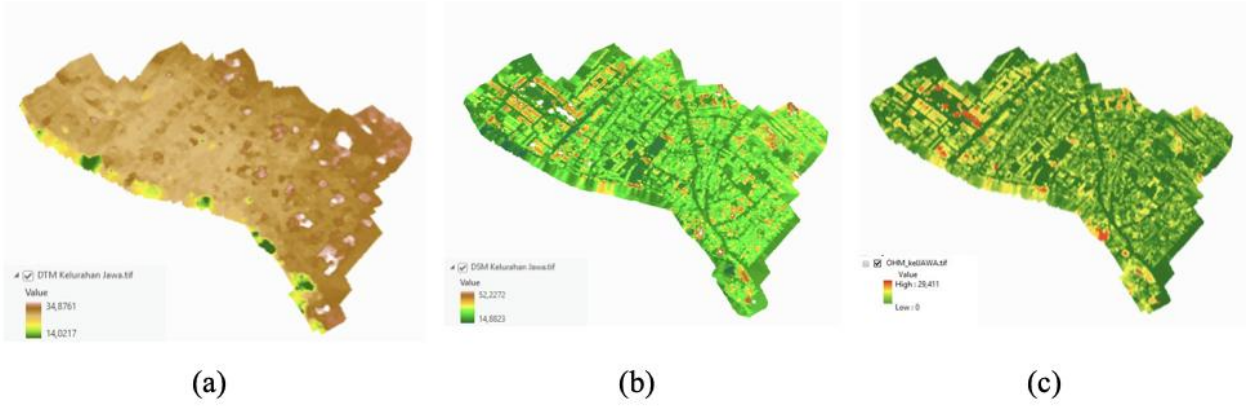


**Fig. 12** Result of extraction (a) DTM, (b) DSM, (c) nDSM

In addition, aspect and slope layers were derived from the DSM as supporting parameters for roof reconstruction. The aspect values range from  $0^{\circ}$  to  $360^{\circ}$ , representing the orientation of the surface relative to azimuth, while slope values range from  $0^{\circ}$  to  $84.5^{\circ}$ , indicating variation in surface inclination from relatively flat to steeply sloping terrain. These derived products were used to support the identification of roof orientation and roof inclination, particularly in the reconstruction of sloped roof types such as gable roofs. The observed value ranges reflect moderate terrain variation within the study area and building heights typical of low rise urban environments, which are consistent with the building stock observed in the orthophotos (Nursyahrial & Ilmawan, 2025).

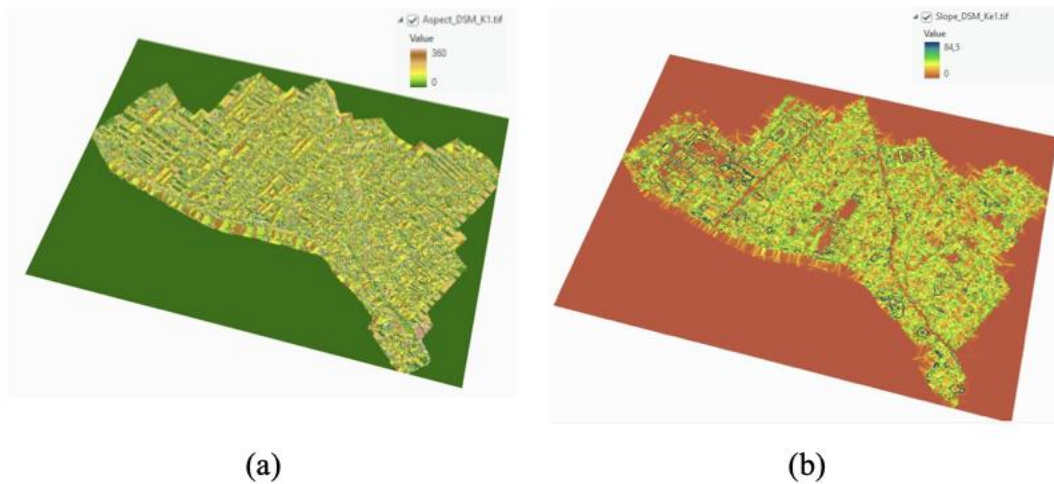


**Fig. 13** Result of extraction (a) aspect and (b) slope

The study further suggests that derived surfaces such as DTM, DSM, nDSM, aspect, and slope are not merely auxiliary elevation products, but can function as inferential parameters for encoding roof geometry and supporting roof form reconstruction logic across the five roof classes considered in this study. In this sense, the proposed workflow provides a practical link between roof-shape classification, geometric rule formation, and CityJSON/CityGML based semantic modeling for LoD2 building reconstruction in geospatial applications (Gröger et al., 2012).

### 3.2. Roof classification

Roof outlines were digitized interactively from the orthophotos by visually interpreting roof edges, resulting in polygon features representing roof footprints. Each polygon was then assigned to one of five roof classes, which are flat, gable, hip, shed, and pyramid, based on the observable roof geometry in the orthophotos. The final classified dataset, summarised in Table 1, contains 371 buildings: 22 flat roofs, 265 gable roofs, 56 hip roofs, 18 shed roofs, and 10 pyramid roofs. Table 1 also reports the proportion of each class, showing that gable roofs dominate the study area (71%), followed by hip roofs (15%), while flat, shed, and pyramid roofs each account for less than 10% of the total building stock. These classified roof outline polygons were then exported in GeoJSON format for use as structured inputs in the subsequent reconstruction stage.

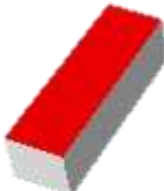
**Table 1** Distribution of digitized buildings by roof type

| Roof type    | Quantity   | Percentage (%) |
|--------------|------------|----------------|
| Flat         | 22         | 6              |
| Gable        | 265        | 71             |
| Hip          | 56         | 15             |
| Shed         | 18         | 5              |
| Pyramid      | 10         | 3              |
| <b>Total</b> | <b>371</b> | <b>100</b>     |

### 3.3. Reconstruction output

All 371 digitized buildings were reconstructed into LoD2 three dimensional building models using a semi-automated Python workflow. The models were semantically structured into GroundSurface, WallSurface, and RoofSurface and stored in CityJSON format. The dataset was then converted to CityGML to verify interoperability with standard 3D city modeling platforms. Table 2 summarises the number of reconstructed buildings for each roof type, their availability in CityJSON and CityGML, and representative LoD2 examples of flat, gable, hip, shed, and pyramid roofs.

**Table 2** Representative LoD2 building models by roof type in CityJSON and City GML

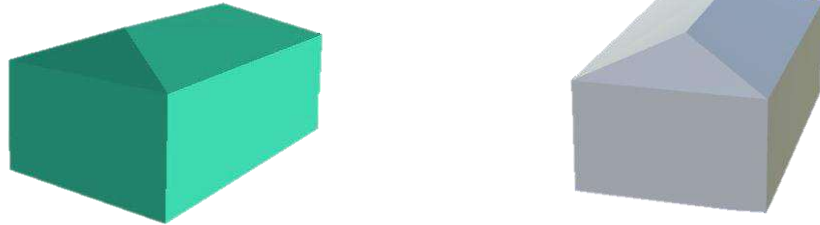
| Roof Type   | Model 3D<br>(CityJSON)                                                              | Model 3D<br>(CityGML)                                                                 |
|-------------|-------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------|
| <i>Flat</i> |  |  |

---

*Gable*



*Hip*



*Shed*



*Pyramid*



330  
331 These findings support the argument that LoD2 reconstruction does not necessarily depend on fully automated  
332 pipelines or exclusively on procedural modeling frameworks. A roof type driven, rule based approach, combined with  
333 elevation derivatives from point clouds, can also produce semantically structured and interoperable 3D building models  
334 (Amini et al., 2014; Kong et al., 2024).  
335 The successful reconstruction of all 371 digitized buildings indicates that the proposed workflow is operationally  
336 feasible at the subdistrict scale, particularly for buildings whose roofs can be assigned to the five predefined roof classes.  
337 In addition, using CityJSON and converting it to CityGML provides an important implementation advantage by enabling  
338 interoperability with OGC oriented platforms, web based spatial systems, and potential urban digital twin applications  
339 (Biljecki et al., 2016).  
340 Visual examples of the reconstructed LoD2 buildings were produced in CityGML using the Cesium ion platform,  
341 showing their spatial distribution and semantic structure within the study area (Fig. 14). These visualizations show that

the roof type specific reconstruction rules generate coherent LoD2 building geometries and that the CityJSON to CityGML conversion preserves the GroundSurface, WallSurface, and RoofSurface subdivision.



**Fig. 14** Visualization of LoD2 3D building models in CityGML format (Source: image by Land Office of Singkawang City; processed by authors)

### 3.4. Visual accuracy

Visual accuracy was assessed using 30 building samples, selected through stratified random sampling to represent the five roof classes. The evaluation relied on counts of *True Positives* (TP), *False Positives* (FP), and *False Negatives* (FN) derived from comparisons between reconstructed roof surfaces and the orthophotos reference data, in line with standard confusion matrix based accuracy assessment for 3D building models (Nursyahrial & Ilmawan, 2025; Zheng et al., 2017). An example of the visual semantic evaluation, showing the comparison between reconstructed roof planes and the orthophotos reference, is provided in Fig. 15.

The mean completeness across the 30 samples was 100%, and the mean correctness and quality were both 98.33%. Of the evaluated samples, 29 buildings achieved 100% completeness, correctness, and quality, indicating that all roof planes were correctly reconstructed and matched the reference data. One gable roof sample yielded TP = 2, FP = 2, and FN = 0, corresponding to 100% completeness, 50% correctness, and 50% quality, because the model generated two additional roof planes not present in the orthophotos reference. Overall, the mean completeness, correctness, and quality values are well above the commonly suggested 85% threshold for visual accuracy evaluation (Zheng et al., 2017), demonstrating high semantic consistency with the orthophotos reference data.

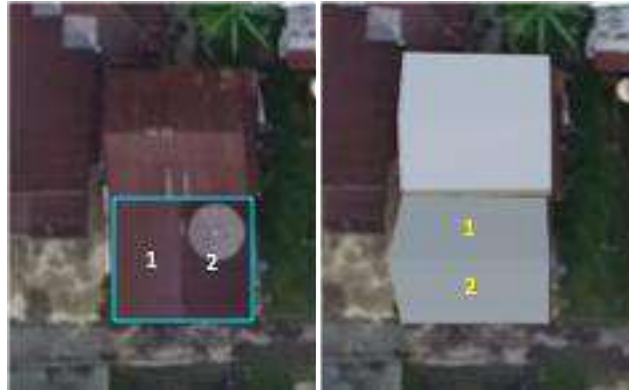


**Fig. 15** Visual evaluation of reconstructed roof planes against the orthophotos reference. (Source: image by Land Office of Singkawang City; processed by authors)

### 3.5. Geometric accuracy

Geometric accuracy was evaluated using 30 building samples by comparing reconstructed model dimensions with corresponding dimensions measured from the point clouds. The measured dimensions included identifiable building length, width, or height, depending on the sample and the availability of clearly observable edges in both the 3D model and the point clouds. An example of the dimension measurement procedure is illustrated in Fig. 16.

The resulting RMSE for the dimensional differences was 0.90 m, where RMSE is the root mean square error of the dimensional differences, with a total squared difference of 24.30 and a mean absolute difference of 0.81 m, where the mean absolute difference is the average absolute dimensional difference. The smallest dimensional difference was 0.09 m in samples 11 and 29, whereas the largest difference was 2.55 m in sample 14. Both negative and positive differences were recorded across the sample set, indicating that some reconstructed dimensions were lower than the reference values and others were higher, which is consistent with the combined effects of roof outline digitization, point clouds noise, and interpolation in the elevation derivatives (Alganci et al., 2018). Overall, the RMSE of 0.90 m remains below the 2 m threshold commonly adopted for LoD2 building models in the CityGML specification, and is therefore acceptable for many urban applications (Gröger et al., 2012; OGC, 2021).

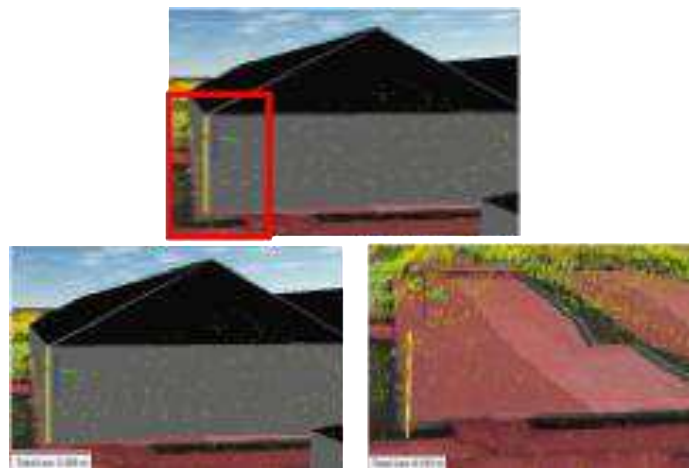


**Fig. 16** Measurement of building dimensions on the 3D model and the point clouds

The high completeness and strong geometric performance observed in this study can be attributed to the division of labor between interactive and automated stages. Interactive roof outline digitization reduces boundary ambiguity at the most sensitive stage of LoD2 reconstruction, while automatic rule based generation enforces consistency in roof topology, wall formation, and semantic encoding. This balance appears particularly effective for common roof classes with interpretable geometry, such as flat, gable, hip, shed, and pyramid roofs, which aligns with previous findings that semi-automatic workflows can provide robust results for well-defined roof typologies (Nursyahrial & Ilmawan, 2025; Biljecki & Dehbi, 2019).

Compared with purely geometric roof extraction methods, the proposed workflow reconstructs complete LoD2 building solids rather than only roof surfaces and does so within an interoperable CityJSON framework (Amini et al., 2014; Kong et al., 2024). Compared with CGA based procedural approaches, it is more tightly constrained by observed roof outlines and point clouds derived elevation cues, thereby reducing the risk of overly generic roof generation (Zhang et al., 2022; Usta et al., 2023). Compared with fully automatic AI-driven systems, the workflow is less scalable in its current form, but it is also more transparent and easier to control for roof type specific logic, echoing concerns about interpretability in deep learning based reconstruction pipelines (Duran et al., 2021; Vostikolaei & Jabari, 2023; Andaru et al., 2026).

The proposed workflow achieved strong visual consistency and a complete reconstruction of all manually prepared building inputs, while the RMSE remains below the 2 m threshold commonly adopted for LoD2 building models in the CityGML specification (Gröger & Plümer, 2012; OGC, 2021). These factors support the workflow's practical usefulness for medium scale LoD2 production.

Overall, these aspects highlight the novelty of the proposed workflow as a roof type driven, semi-automatic approach that integrates orthophotos interpretation, point clouds derived elevation derivatives, and BREP based CityGML modeling into a single interpretable LoD2 reconstruction framework. A key methodological contribution of this study is that roof type is treated not merely as an attribute but as the central driver of reconstruction rules. This design makes the workflow interpretable, reproducible, and extensible. Each roof class can be refined independently, and additional roof classes can be introduced as new rules rather than requiring a complete redesign of the system. The use of CityJSON further strengthens the workflow by providing lightweight, machine-readable, semantically structured outputs that are compatible with CityGML conversion and future extensions to more complex roof typologies.

#### **4. Conclusion**

This paper presents a semi-automatic workflow for LoD2 building reconstruction from orthophotos and photogrammetric point clouds. It combines interactively interpreted roof outlines and roof labels with automatic BREP based reconstruction in Python to produce semantically structured LoD2 building models in CityJSON, with CityGML conversion capability. The workflow successfully reconstructed 371 buildings across five roof classes and achieved strong validation results, with mean values of 100% completeness, 98.33% correctness, 98.33% quality, exceeding the 85% threshold. Geometric accuracy testing yielded an RMSE of 0.90 m, below the tolerance limit ( $< 2$  m) for LoD 2, indicating that the model dimensions fulfill the CityGML standard requirements. These results show that a semi-automatic, rule based strategy can provide a robust middle ground between manual modeling and fully automatic

pipelines, especially when the aim is to generate interpretable, semantically structured, and interoperable LoD2 building models from photogrammetric data.

Beyond the specific case study, the proposed workflow can be adapted to other areas with similar data availability, provided that roof outlines and roof types can be interpreted reliably from orthophotos. Future development should target automatic roof outline extraction and roof type classification using deep learning or hybrid human in the loop methods, building on recent advances in learning based roof and building detection from imagery and point clouds (Duran et al., 2021; Andaru et al., 2026). The rule base should also be extended to include more complex roof categories, such as multi ridge and composite roofs, so that the workflow can accommodate a wider range of urban building typologies. In addition, larger benchmark datasets and cross city experiments would strengthen claims about transferability and allow more comprehensive comparison with recent fully automatic LoD2 pipelines (Vostikolaei & Jabari, 2023; Andaru et al., 2026). Such developments would build on the current workflow while addressing its main limitations in scalability and generalization identified in this study.

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## 6. Author Contribution

N.A.L. contributed to data acquisition, processing and analysing data, model implementation, experimental analysis, visualization, and original manuscript writing. H. contributed to the conceptualization, supervision in data processing and analysis, methodological development and validation, validation the result, manuscript review, and finalization the manuscript . A.R.S. contributed to data acquisition, data preprocessing, and visualization. All authors read and approve the final manuscript.

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## 8. Data availability

The data of this study are available upon reasonable request.

## 9. Declarations

**Competing interests.** The authors declare no competing interests.

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