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Semi-automated indoor geometry reconstruction for daylight simulation

Nima Forouzandeh^{a,*}, Jin Huang^b, Liangliang Nan^b, Eleonora Brembilla^a, Jantien Stoter^b

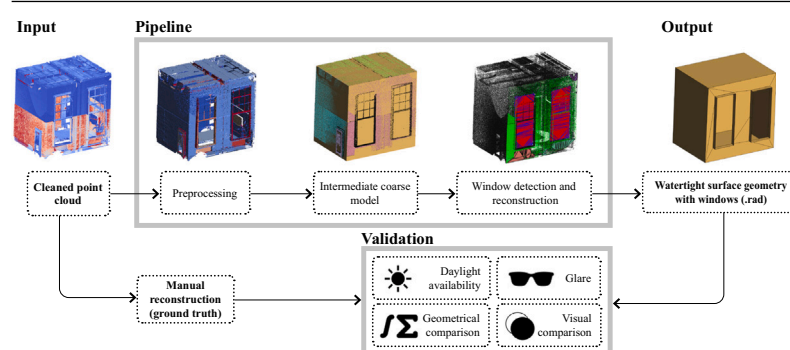
^a Department of Architectural Engineering and Technology, Faculty of Architecture and the Built Environment, TU Delft, Delft, Netherlands

^b Department of Urbanism, Faculty of Architecture and the Built Environment, TU Delft, Delft, Netherlands

HIGHLIGHTS

- Semi-automated pipeline for window-containing watertight indoor surface models from point clouds.
- Reduced user interaction to guide reconstruction algorithm.
- Mean TAI bias of less than 16 % across all rooms.
- sDA bias of less than 5 % and ASE bias of less than 6 %.
- Errors within 4 % in glare prediction.

GRAPHICAL ABSTRACT



ARTICLE INFO

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ABSTRACT

This study presents a semi-automatic pipeline for reconstructing indoor geometries from point cloud data for daylight simulation. The pipeline generates watertight models of permanent architectural surfaces with window boundaries through three steps: (1) preprocessing, (2) permanent structure reconstruction, and (3) window boundary extraction. The pipeline was evaluated in four rooms of varying complexity against manually reconstructed models using visual and geometrical comparisons, and by comparing daylight availability and glare metrics calculated from *Radiance* results. Geometric deviations in terms of Chamfer Distance (CD) were found to be smaller than one centimetre for regular rooms and up to 51 cm for complex rooms. Across annual daylight metrics, sDA and ASE showed less than 6 % bias, while UDI_d exhibited spatial biases ranging from approximately -2 % to 40 %, and the mean TAI bias remained below 16 % in all rooms. The Daylight Glare Probability (DGP) error remained under 4 %, and the modelling time did not exceed 5 min for any scenario. The approach enables rapid generation of simulation-ready models with acceptable accuracy for Climate-based daylight modelling (CBDML).

1. Introduction

Although simulation-based design methodologies and pipelines are well-developed, studies on real buildings with occupant participation remain limited [6]. Simulated models of advanced façades systems show

significant potential for energy savings and occupants' comfort [40], yet alignment with real-world performance is often lacking. Obtaining accurate digital daylight models for existing buildings can substantially reduce the effort required for reliable monitoring and, therefore, building management. As building-control algorithms advance rapidly,

* Corresponding author.

Email addresses: n.forouzandeh@tudelft.nl (N. Forouzandeh), j.huang-1@tudelft.nl (J. Huang), liangliang.nan@tudelft.nl (L. Nan), E.Brembilla@tudelft.nl (E. Brembilla), J.stoter@tudelft.nl (J. Stoter).

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efficient methods to generate valid digital representations of existing buildings are essential to align simulations with real-world performance.

Indoor geometry is an essential input for these digital models. It can be modelled in different Geometrical Levels of Detail (GLODs) as proposed in previous work [10]. In such a framework, GLOD0 only contains the permanent objects of an indoor space and is the basis for simulation-based decision making. Permanent objects determine the daylight potential of the room and remain constant irrespective of short-term changes, e.g., redecoration, and long-term interventions, e.g., retrofit actions. Higher GLODs 1–4 include non-permanent objects with size thresholds that incrementally get smaller. On average GLOD0 introduces errors of 18.05 % on Total Annual Illumination (TAI) although it halves the simulation time.

Unlike newly-built buildings, where geometrical properties are digitally defined at the design stage and can be used for daylight assessments, redesigning existing buildings requires reliable geometrical models that are acquired on-site. This is often done manually, requiring substantial on-site labour. Laser scanning technology was invented to address this in the 1960s, and it became popular in engineering applications by the late 1990s. Since then, various on-site scanning workflows have evolved beyond passive scanning of scenes or objects—some of which are described later in more detail in the Section 2. These workflows include scanning combined with physical manipulation of objects, active scene illumination, and the integration of LiDAR sensor data with other sensor information, all aimed at achieving a geometrically accurate representation of objects, better suited to their physical characteristics [48]. These methods provide users with dense and redundant geometric information about the scene, including at least a point cloud that contains the 3D coordinates of points.

Daylight simulation, like other simulations, requires a detailed surface model, rather than raw point cloud data. Surface models can be reconstructed from points manually using CAD interfaces [34], but the downside is significant manual labour. Several surface reconstruction algorithms and techniques have been proposed in the literature to automate all or parts of the workflow to reconstruct surfaces from point clouds [41]. In general, developing an efficient reconstruction pipeline for indoor applications, often referred to as ‘scan-to-BIM’ in the AECO industry, is fully dependent on the final application. For indoor daylight simulation, this pipeline typically involves the reconstruction of three key components: (1) a watertight structure of permanent surfaces, which is a closed set of surfaces representing the room shell (i.e., walls, floor, and ceiling), (2) window boundaries, and (3) furniture.

1.1. Aim of this study

In this paper, a three-step semi-automatic indoor geometry reconstruction pipeline is developed to generate the window-containing geometry of the rooms from raw point cloud data with reduced user interactions, which includes (1) preprocessing, (2) reconstruction of a window-less watertight indoor model, and (3) reconstruction of windows. This GLOD0 geometry of the room provides a stable representation of the room. In most refurbishment and retrofit projects, furniture layouts are typically undecided whereas permanent elements are not, and excluding furniture reduces processing time and user input while representing the room’s overall daylight potential.

This work offers an open-source and practical middle-ground solution between manual and fully automated scan-to-BIM methods. Unlike manual modelling, which is labour-intensive and time-consuming (often requiring hours per room), the proposed pipeline reduces modelling time to under five minutes per room. Unlike so-called fully automated techniques, which often rely on rigid geometric priors and can fail under partial occlusions or noisy scans, the proposed approach includes reduced user input to guide and validate window detection.

This approach has practical relevance for building retrofit projects, where accurate digital geometry is needed for retrofit actions such as lighting upgrades or envelope interventions [23]. It is also applicable

in facility management contexts, where reliable 3D models can inform the design and control of daylight systems, improve visual comfort, and reduce energy consumption [13]. Finally, the method supports post-occupancy evaluation studies [22] by enabling rapid creation of simulation-ready models that can be used to link measured performance with simulations.

2. Literature review

Synchronous survey of light and geometrical properties of indoor spaces has been approached using both HDR and LiDAR data. Kim and Tzempelikos [17] proposed a semi-automated technique to reconstruct the luminance distribution within the occupant’s field of view by re-projecting HDRs luminance maps onto a three-dimensional model. In a subsequent and related study, the same authors experimentally validated this approach under controlled laboratory conditions, demonstrating that the DGP error of the re-projected luminance maps remained within acceptable limits [18]. Rodrigue et al. [35] conducted surveys of actual buildings using HDR imaging for luminance capture and LiDAR scanning as a complementary source for acquiring geometric data. Kurkela et al. [19] applied photogrammetry techniques to reconstruct three-dimensional luminance point clouds of indoor spaces, relying solely on HDR imaging. In another study, they utilized LiDAR technology in combination with colour targets to measure indoor luminance directly from geometry [20]. Finally, Cai [4] performed synchronous measurements of indoor luminance and geometry using HDR imaging techniques. These studies are limited to a single point-in-time analysis—corresponding to the time when the survey campaign takes place—although they provide a measure of both geometry and light.

Another approach is to use point cloud data from geometric surveys as input for daylight simulations, as previously proposed by Bognár et al. [3] in urban domain. Indoor surface reconstruction is applied in building physics and simulation domains, including indoor acoustics simulation [26], and energy simulation [1,12,43]. Although there are not many studies dedicated to simulating daylight or other building physics applications, many of them are relevant when addressing the above key requirements, i.e., watertight permanent structures, including window boundaries. These studies are presented in this section with an emphasis on permanent structures and window boundaries and a summary of reconstruction algorithm steps in these studies is presented in Table 1.

- **Permanent structure.** Real-world building surfaces are typically planar. Many building surface reconstruction algorithms leverage this assumption to segment points on the ceiling, wall, and floor prior to surface reconstruction. This geometric pattern informs the reconstruction pipeline and allows the use of planar segmentation algorithms like PCA and RANSAC for detecting points belonging to these surfaces [2,7,41].
- **Window boundaries.** Daylight simulation results are highly sensitive to the accuracy of window boundaries, making their precise reconstruction critical. Various studies have approached this, in most of which, windows are assumed to be rectangular holes within wall point clouds. This prior is commonly used to identify potential openings. Edge points of such openings are detected using alpha shape or Canny edge detection algorithms [21,28,37,44], followed by clustering to form regions as candidate openings [28,36,42]. To distinguish actual openings from other types of occlusions, shape priors are employed. For instance, Smit [37] and Jung et al. [15] apply rectangle fitting, while Michailidis and Pajarola [28] use RANSAC-based line fitting. Beyond rule-based methods, artificial intelligence techniques have been adopted for differentiating between the two types of openings, i.e., windows and doors [11,31]. More advanced approaches leverage semantic and instance segmentation using deep learning networks such as YOLO [32,49]. The output of these networks is then used

Table 1

A summary of the reconstruction algorithms. The listed works are not applied to daylight simulation.

Reference	Algorithm
Wei et al. [44]	(1) Extraction of alpha shape for the opening-containing wall to extract edge points, (2) Regularization of edge points with Semantic-constrained optimization.
Xiaojuan et al. [47]	(1) Detection of the occlusion area on the wall segment by constructing scanning rays, (2) Extraction of wall edge points, (3) Extraction of the feature line of the wall according to the point density, (4) Forming a cell complex by the intersection of feature lines, (5) Extraction of the doors and windows by graph cut based on Ford Fulkerson.
Michailidis and Pajarola [28]	(1) Alpha shape computation of wall segment, (2) RANSAC line fitting, (3) Mean-shift clustering, (4) Forming a cell complex, (5) Graph-cut cell segmentation.
Li et al. [21]	(1) Wall Surface Detection, (2) Extraction of candidate opening boundary points with alpha shape, (3) Opening Edge Fitting, (4) Opening Reconstruction.
Previtali et al. [33]	(1) Extraction of holes in planar wall segments, (2) Filtering false positives using geometric constraints, (3) Refine the opening boundaries using edge detection or histogram projection, (4) Assign opening types (e.g., windows, doors) based on position, size, and semantic rules, (5) Reconstruction of openings as bounded voids in wall geometry or as separate mesh components.
Jung et al. [15]	(1) Rectangular hole extraction from the segmented wall point segments, (2) Refinement.
Shi et al. [36]	(1) Gridding 2D projected data to identify low-density areas, (2) Applying region growing to group empty areas and pruning occlusions, (3) Extracting geometric and density-based features for each cluster, (4) Formulating an object-based graph cut problem, (5) Minimizing an energy function combining data term (point density likelihood) and smoothness term (area, floor-ceiling proximity, and shape linearity), (6) Classifying resulting objects into windows, doors, or virtual openings.
Tang et al. [42]	(1) Tagging RGB-D frames near openings based on camera trajectory and scan timestamps, (2) Segmentation of vertical planes from tagged frames, (3) Computing the convex hull of each segmented plane and filling it with synthetic points, (4) Comparing original and filled planes using octree-based KNN search to detect vacant regions, (5) Clustering vacancy regions using Euclidean distance, (6) Reconstructing each opening by combining 3D boundary data with 2D line fitting.
Assi et al. [2]	(1) Transform planar wall point segments to 2D image, (2) Image cleaning, (3) Clustering regions with region growing, (4) Calculate energy function with geometric terms (e.g., proximity to ceilings, size, and proportions) to determine openings.
Smit [37]	(1) Calculate Euclidean distances, (2) Mercator Projection, (3) Point cloud → 3D Histogram → 2D image, (4) CLAHE, (5) Canny edge detection, (6) Contour Extraction, (7) Rectangle validation, (8) Cluster ROIs to deduce window regions.
Pan et al. [32]	(1) Semantic segmentation, (2) Applying voxel growing, (3) Classification of voxels into void and non-void, (4) Fitting rectangles on empty voxels corresponding to openings.
Zhong et al. [49]	(1) Instance segmentation network to separate elements (doors, windows), (2) Hierarchical grouping of points to merge semantically segmented points into multi-scale groups.
Kellner et al. [16]	(1) Computing geometric features (e.g., planarity, linearity, surface variation) for points, (2) Using networks (PointTransformer, RandLA-Net, KpConv) for semantic segmentation, (3) Bounding box fitting for each opening.
Fotsing et al. [11]	(1) Extraction of holes from wall segments based on point density in a grid fitted to wall points, (2) Classification separating windows and doors via deep learning.
Mehranfar et al. [27]	(1) Detection of door and window bounding boxes in open, semi-open, and closed states with YOLOv8 trained on 214 RGB images and 89 projected wall images, (2) Replacement with 3D models from a library.
Wong et al. [46]	(1) Semantic segmentation using YOLOv8 to acquire pixel-wise class information of building elements from video frames (HBD dataset), (2) Projection of the mask onto the wall.
Ochmann et al. [31]	(1) Determination of ray intersections with walls emitted from scanner location, (2) Clustering of intersection points, (3) Classification of openings as windows or doors with supervised learning.

to reconstruct window geometries either through bounding box fitting [16], projection of detected masks onto wall geometry [46], or by replacing them with pre-modelled window objects from libraries [27].

Díaz-Vilariño et al. [7] propose a reconstruction pipeline for indoor daylight simulation. To reconstruct opaque surfaces, the authors use PCAs and region growing to detect the surface planes and later intersect them. For openings, by assuming a low density of points in the openings, they use PCAs for linear edge detection. The labelling of the openings on the walls is achieved through user interactions. Their technique is not validated against manually reconstructed models. Therefore, the error associated with their geometrical modelling is not known.

Although these methods rely on hardcoded or learned priors, they do not guarantee complete reconstruction of window boundaries. For

daylight simulations, geometric accuracy must be verified before use. Therefore, rather than depending on fully automated pipelines, the approach proposed in this paper incorporates reduced user input to guide the workflow and validate window geometry.

In summary, existing approaches either demand extensive manual effort or depend heavily on assumptions that may not hold in practice. This work introduces a pipeline that reduces modelling time without sacrificing geometric reliability. It produces watertight, window-containing room models suitable for daylight analysis.

3. Methodology

The proposed methodology addresses the difficulty in reconstructing watertight window-containing surface models from point cloud data, suitable for daylight simulations. This work integrates existing methods to create a semi-automated pipeline for generating simulation-ready

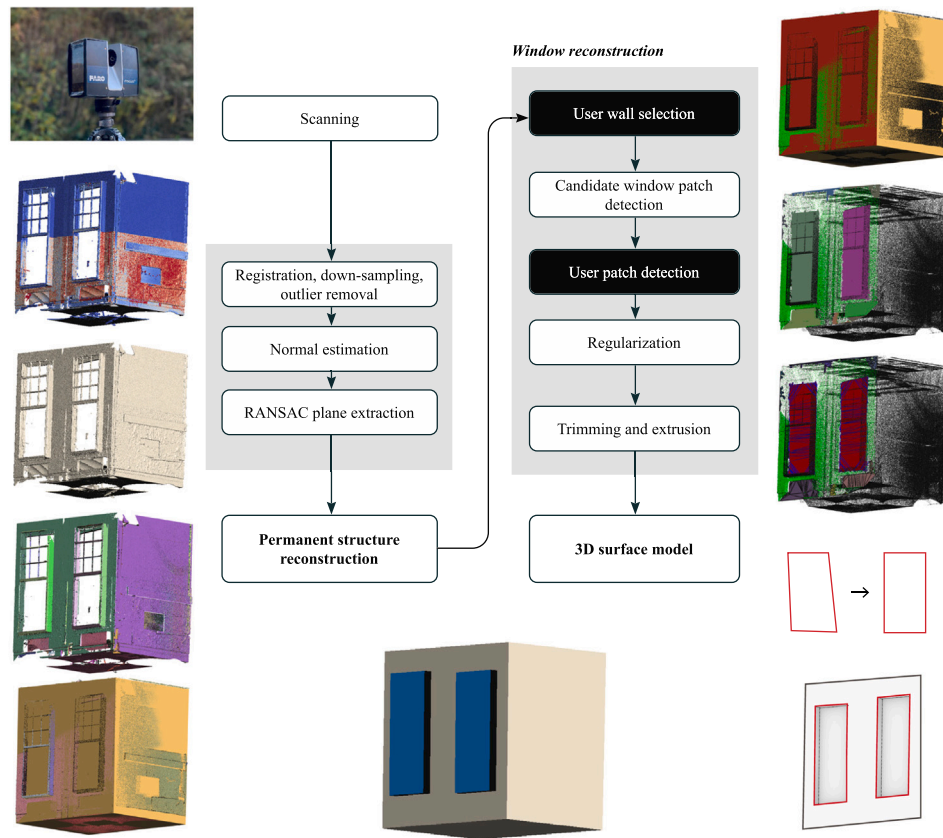


Fig. 1. Reconstruction pipeline. Manual steps are shown in black, and automated steps are shown in white. Visual examples beside each block illustrate the corresponding stage of the process, from raw scanning to final 3D model generation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

geometry with reduced user interaction to ensure complete window detection. The key contribution lies in the introduction of a three-step pipeline for daylight simulation studies. The method is tested on five rooms of varying sizes and surface properties, and validated against manually reconstructed room geometries over several performance metrics relevant to daylight simulations.

3.1. Reconstruction pipeline

The reconstruction pipeline, as shown in Fig. 1, includes three key steps: (1) preprocessing, (2) reconstruction of the permanent structure, and (3) reconstruction of window boundaries, each described in separate subsections, followed by a description of geometrical and daylight comparison methods.

3.1.1. Preprocessing

After registering the scans, the outlier points, *i.e.*, the ones outside the room, are manually deleted. Next, the point cloud is randomly down-sampled to reduce the processing time in the subsequent steps. Afterwards, the point normals are estimated with a neighbour size of 16. In this context, the neighbour size refers to the number of nearby points used to locally estimate the surface orientation required by the RANSAC plane detection. This is followed by a RANSAC plane extraction, whose hyperparameters are listed in Table 2. Such values are listed for repeatability. More explanations about the RANSAC process and its hyperparameters are laid out by [9]. This point cloud is then used as input for *PolyFit*—a surface reconstruction algorithm that generates watertight polygonal models by fitting planar segments to point cloud data using optimization [30].

Table 2

RANSAC parameters used in this work for plane extraction.

Parameter	Value
Minimum support	1,000–4,000
Distance threshold	0.005
Bitmap resolution	0.02
Normal threshold	0.8
Overlook probability	0.001

3.1.2. Permanent structure reconstruction

This step reconstructs the watertight permanent structure, *i.e.*, walls, ceiling, and the floor of the room, using *PolyFit* [30]. An example is shown in Fig. 2.

3.1.3. Window reconstruction

As the first step of the window reconstruction pipeline, *i.e.*, the *wall selection* step, the user is asked to select the surfaces containing windows with a single click per window-containing wall (Fig. 2). The program stores these selected walls with their corresponding planes and points from the previous step.

During *candidate window patch detection*, for each of the picked walls, the corresponding points are first mapped onto their underlying plane, and then a Delaunay triangulation is applied to these 2D points to establish local connectivity between neighbouring samples. In this triangulation, points are connected into non-overlapping triangles such that no point lies inside the circumcircle of any triangle. This is followed by automatic detection of *holes*, *regions*, and *candidate window patches*. A *hole* is defined as a face in the Delaunay triangulation where all edges

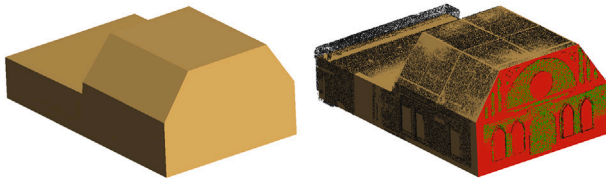


Fig. 2. An example of permanent structure reconstructed using *PolyFit* [30] (left) and user wall selection. The red wall is selected by the user (right). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

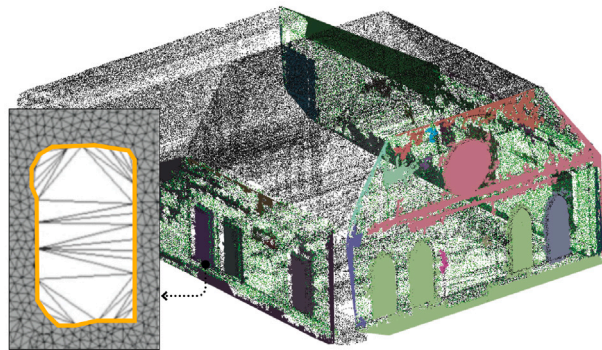


Fig. 3. Candidate window patch detection workflow. Triangles exceeding the edge-length threshold from the Delaunay triangulation are classified as *holes* (white faces), while the remaining faces are non-hole faces (grey faces). Connected hole faces are grouped into labelled *regions*, and regions that satisfy the area criterion are identified as *candidate window patches* (yellow edge). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

have lengths greater than a specified threshold. This threshold is empirically set to 8 cm. A *region* is a connected group of *hole* faces from the previous step, where each *region* is assigned a unique label. The detection process involves grouping adjacent *hole* faces into distinct *regions*. *Candidate window patches* are *regions* that meet a user-specified area criterion (10 cm^2 in this work). *Regions* with an area smaller than this threshold are excluded from being *candidate window patches* (Fig. 3).

The edge-length threshold of 8 cm defines the minimum gap size considered as an opening. Edges shorter than this value are considered part of opaque wall surfaces rather than holes. Likewise, regions with an area smaller than 10 cm^2 are excluded from window detection, as they typically result from occlusions, missing data near edges, or measurement noise. These thresholds make the visualization algorithm ignore small, non-window gaps so the user can focus on identifying actual openings during *user window patch selection*. The values were determined empirically based on the scan resolution and building dimensions in this study, assuming that windows are much larger than 10 cm^2 . Both parameters are adjustable in the program to match different room types and scan qualities.

Next, during *user window patch selection*, the faces corresponding to one window are picked with a lasso tool in separate stages per wall. The lasso tool allows the user to freely select a region on the desired faces (Fig. 4).

As the initially extracted window boundaries are inevitably irregular, a *window boundary regularization* proposed by Huang et al. [14] is adopted. Lastly, during *trimming and extrusion*, the regularized boundaries are trimmed from the corresponding walls and defined as the window boundary layer, and a user-defined extrusion is applied to carve the windows from the walls. The final 3D surface model is then used directly for daylight simulation, as the polygonal mesh representation sufficiently describes the planar geometry of the reconstructed rooms.

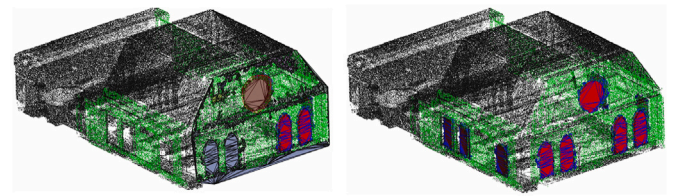


Fig. 4. User window patch selection, while user draws the lasso tool (left) and completed selection (right).

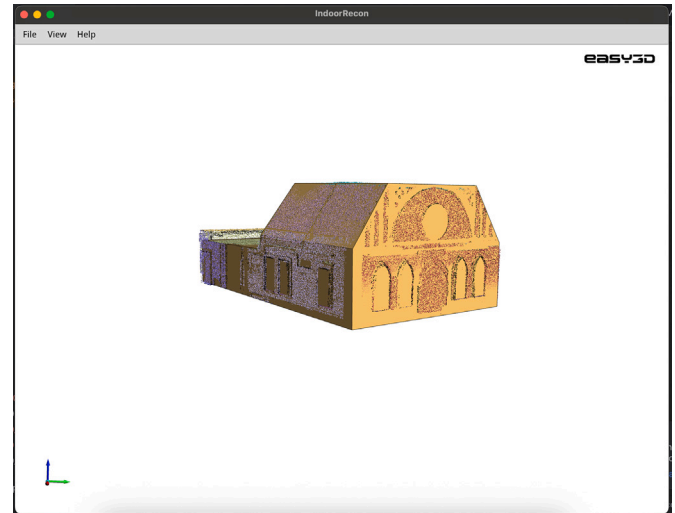


Fig. 5. A screen shot of the program during the user interaction.

3.2. Implementation

The pipeline is implemented in C++. Core geometry processing, visualization and user interaction are performed using the *Easy3D* library [29]. A screenshot of the program interface during user interaction is shown in Fig. 5. Watertight surface reconstruction is carried out using *PolyFit* [30]. The software follows a modular architecture, separating components for permanent-structure reconstruction and window-boundary extraction. The *CGAL* library is utilized for Delaunay triangulation and related geometric operations [8].

The pipeline uses 3D point cloud data as its primary input. Raw point clouds are stored as PLY files containing XYZ coordinates and normal information for each point, estimated during preprocessing. After plane detection, the processed point clouds are saved as BVG files, which include segmented planar regions and associated metadata required for surface reconstruction. The data are acquired using terrestrial laser scanning, capturing dense spatial samples of indoor environments. All input point clouds are subsampled to approximately 100,000 points to reduce processing time while preserving sufficient geometric detail for accurate surface reconstruction and window detection.

All reconstructions were performed on a MacBook Pro (13-inch, Apple M1 chip, 16 GB RAM) running macOS Sequoia 15.7.1.

3.3. Use case rooms

In this study, individual rooms are used as the unit of analysis for both reconstruction and simulation. A room is defined as a single enclosed indoor space bounded by permanent architectural surfaces (walls, floor, ceiling) and containing window openings that connect it to the exterior. This focus allows for consistent comparison across cases and ensures that the reconstructed geometry represents the primary spatial enclosure relevant to daylight performance.

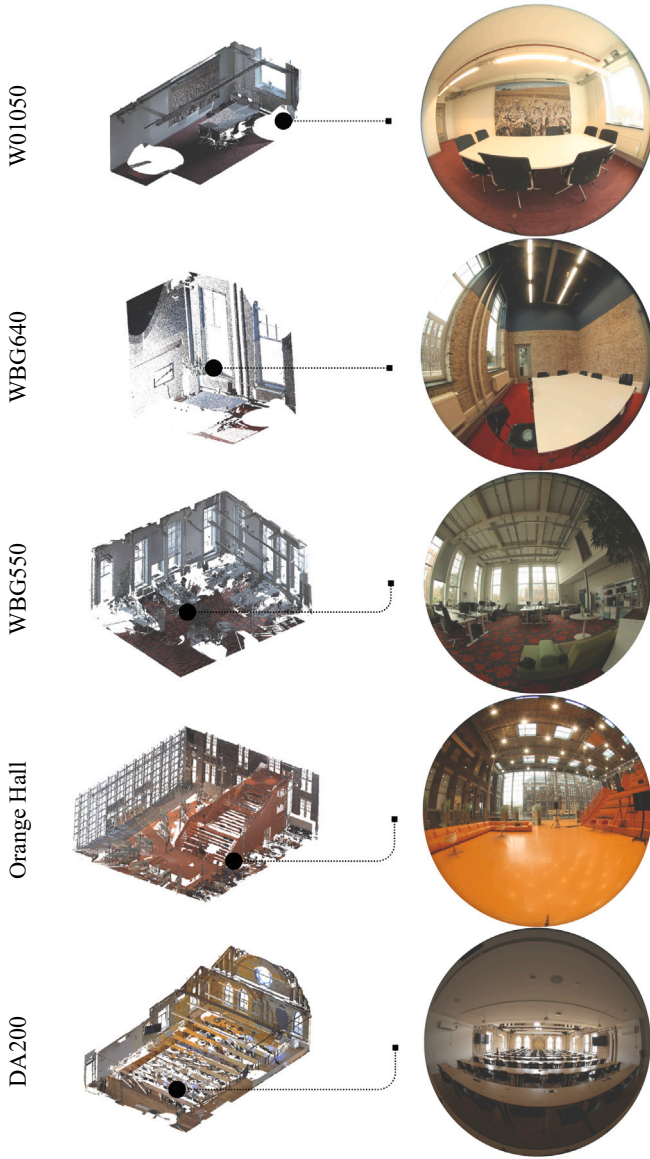


Fig. 6. Point clouds and an indoor view from the five rooms used for this study.

Table 3

Description of the rooms.

Space ID	Location	Room use	Dimensions [m*m*m]	WFR [%]
W01050	Delft, NL	Meeting room	5.8 × 4.4 × 5.8	9.1
WBG640	Delft, NL	Meeting room	7.2 × 3.4 × 2.6	40.9
WBG550	Delft, NL	Open office	12 × 9.8 × 5.8	29.4
DA200	Toronto, CA	Classroom	16.6 × 10.6 × 3.5–6.7	9.1
OrangeHall	Delft, NL	Faculty public hall	33 × 30 × 13	40

Five rooms with varying sizes, shapes, and window complexity were chosen to cover both typical and challenging room geometries for reconstruction. The rooms are shown in Fig. 6 and described in Table 3. The test set includes three office/meeting spaces (W01050, WBG640, WBG550) with orthogonal envelopes, rectangular windows, and moderate window–floor ratios; one classroom (DA200) with non-rectangular openings and non-orthogonal geometry; and one large public hall (OrangeHall) with a large size, lots of clutter, and a complex form.

3.4. Performance evaluation

Visual comparisons. All rooms have been reconstructed using the proposed semi-automatic approach and are qualitatively compared with the manually reconstructed models.

Geometrical accuracy. To quantitatively complement the visual comparison and assess the geometric fidelity between the manually and semi-automatically reconstructed meshes, the geometric differences between the manually and semi-automatically reconstructed models are measured using two symmetric metrics:

1. *Chamfer Distance (CD)* compares the two meshes in both directions by averaging the squared nearest-neighbour distances between uniformly sampled point sets on each mesh (manual → reconstructed and reconstructed → manual).
2. *Hausdorff Distance (HD)* captures the worst-case deviation as the maximum of the two directed nearest-neighbour distances.

Each mesh was uniformly sampled to 80,000 points; nearest-neighbour queries were evaluated with k-d trees.

Daylight availability. To quantify the simulation error associated with manual and semi-automatic reconstruction pipelines, the annual illuminance values are compared in terms of:

1. Spatial Daylight Autonomy (sDA) percentage of the floor area that receives at least 300 lx of daylight for at least 50 % of occupied hours over the year.
2. Annual Sunlight Exposure (ASE) percentage of the floor area exposed to direct sunlight exceeding 1000 lx for more than 250 hours per year. These two metrics are widely used in daylight-related certification schemes such as LEED for evaluating daylight performance.
3. Per-point Total Annual Illumination (TAI) as described in Eq. (1). TAI is used as a cumulative indicator of illuminance bias at each sensor location.

$$TAI_g = \frac{1}{1000} \sum_{t=1}^H (E_t) \quad (1)$$

Where TAI_g is the Total Annual Illumination in klx.hour/year at point g , E_t is illuminance value at time step t , and H is the total number of sun-up hours in the simulation.

4. UDI for time-aggregated annual performance, with 300 lx and 3000 lx as thresholds to divide the three UDI ranges: insufficient, autonomous, and exceeding. The choice of the thresholds is based on the most recent updates from the original author of this metric, now implemented in recent simulation tools [24,25,38]. In contrast to sDA and ASE, UDI provides a more comprehensive view of annual performance by capturing both underlit and overlit illuminance hours within a single framework.

Temporal bias is defined here as the illuminance Relative Bias (RB) across all annual time steps as in Eq. (3).

$$RB_t = \frac{E_{t,semi-auto} - E_{t,manual}}{E_{t,manual}} \times 100 \quad (2)$$

$$TMRB = \frac{1}{N_{sun}} \sum_{t=1}^{N_{sun}} RB_t \quad (3)$$

Where $E_{t,semi-auto}$ and $E_{t,manual}$ are the illuminance values at time step t from the semi-automatic and manual simulations, respectively, and N_{sun} is the number of sun-up hours.

A reflectance value of 0.5 is assumed equally across the three colour channels for opaque surfaces and a transmittance of 0.75 for glazings. The choice of the same reflectance value for all surfaces is not realistic, but was deliberately made to isolate the errors associated with only the geometrical differences as much as possible.

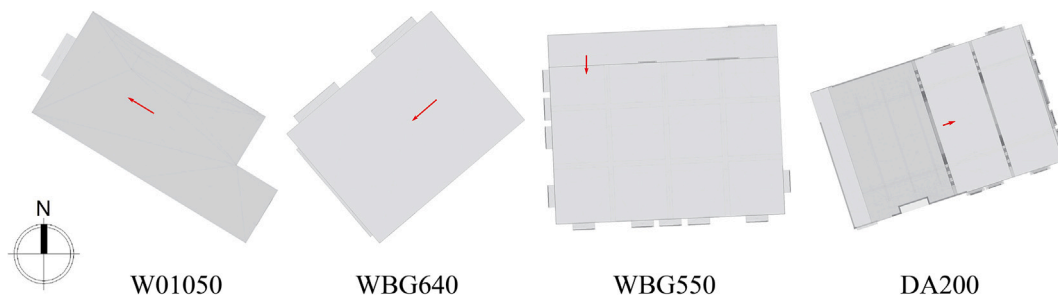


Fig. 7. Selected views for glare analysis.

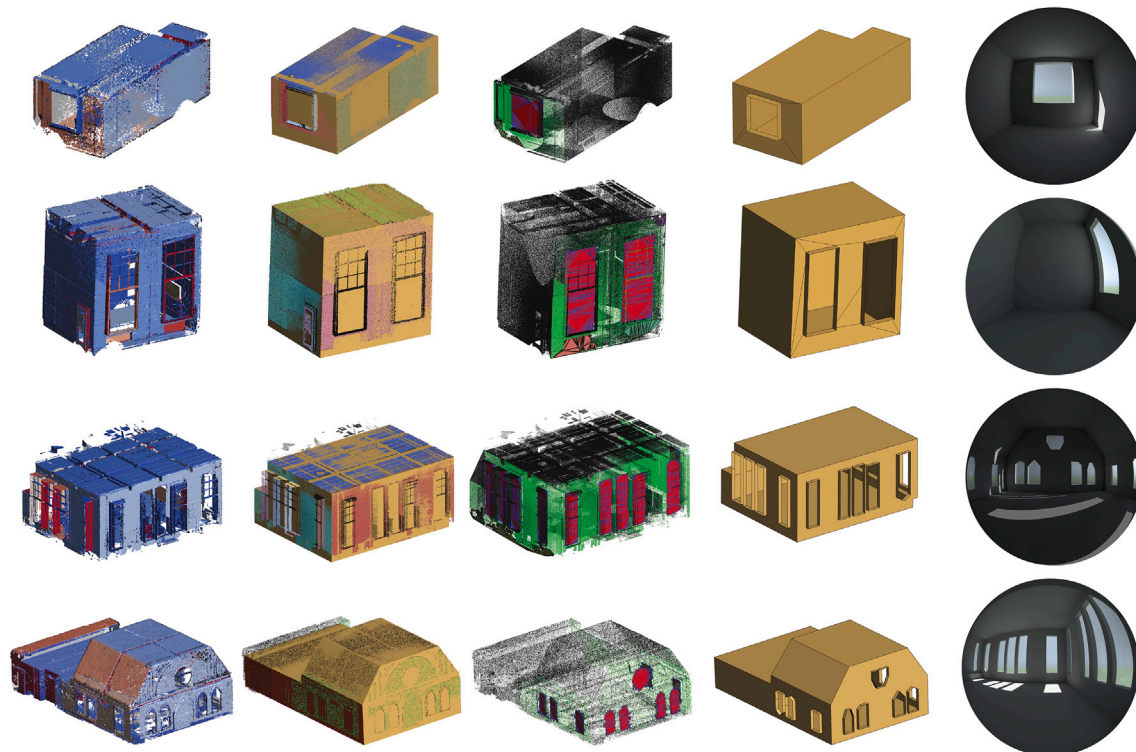


Fig. 8. Intermediate and final visualizations from the four successful reconstruction cases. From left to right: input point cloud, visible points and surfaces prior to user wall selection, user-marked window region, final 3D model, a fisheye render from the flare views corresponding to Fig. 7.

Work-plane illuminance was simulated on a grid with 0.30–1.00 m spacing in both perpendicular directions at a work-plane height of 0.80 m for both the automatically and manually reconstructed geometries. Simulations were performed by *Honeybee* which uses the *Radiance* engine, and has been validated against on-site measurements [39]. The *Radiance* parameters of “-ad 2048 -as 1024 -aa 0.5 -ar 1024 -ab 6” and the Perez All-Weather sky model were selected. Hourly annual simulations assuming a full occupancy—with 4397 and 4400 sun-up hours for Delft and Toronto, respectively—were conducted using weather data retrieved from *Climate.OneBuilding.org* for the stations closest to Delft and Toronto [5].¹

Visual comfort. A sitting head pose was chosen for each use case as shown in Fig. 7. DGP was calculated using *evalglare* [45] from fisheye HDR renderings generated with the *Radiance* engine. Each rendering used the same parameters as the work-plane illuminance simulations, with a hemispherical fisheye view (-vth) at 180° horizontal

and vertical field of view, and a resolution of 1000 × 1000 pixels. The default glare source identification (-r 0.2 -b 2000) was used without applying peak extraction thresholds or task area definitions. DGP was computed for 9 AM, 12 PM, and 3 PM on both solstices and equinoxes under a standard CIE clear sky, resulting in 12 time steps per room.

4. Results

Successful planar reconstruction was achieved using *PolyFit* for four out of five rooms, with both intermediate and final geometries presented in Fig. 8. Reconstruction of the *OrangeHall* was not successful due to its geometrical complexity as illustrated in Fig. 9. Specifically, this room contains large stairs with a unique and irregular shape in the middle and many large exhibition objects. There are a large number of points on these surfaces which are therefore picked by the optimization step in *PolyFit* (see Fig. 6).

For all successfully reconstructed cases, the total modelling time, comprising both user interaction and automated processing, remained under 5 min.

¹ EPW file names: NLD_ZH_Rotterdam.The.Hague.AP.063440_TMYx.epw and CAN_ON_Toronto.City.715080_CWEC2016.epw.

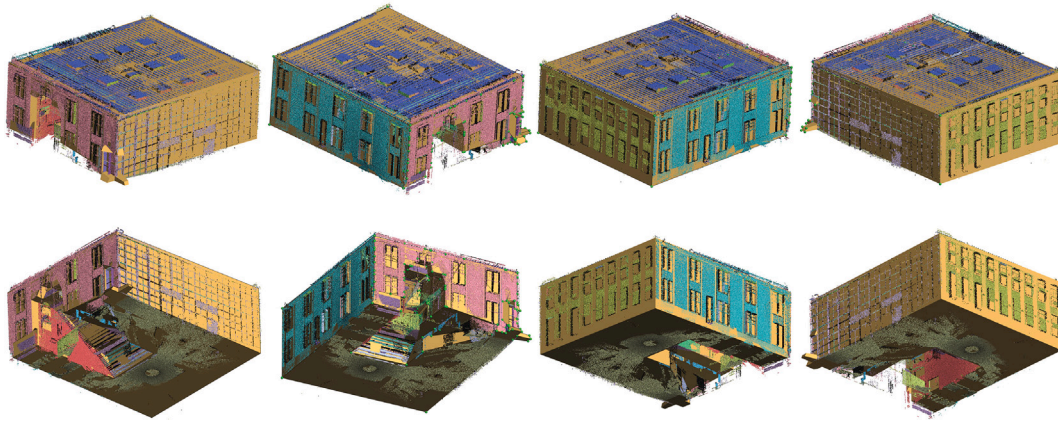


Fig. 9. A failure case. The *OrangeHall* contains a large number of points capturing interior objects, such as large exhibition objects and large staircases, resulting in undesired permanent structure reconstructed by *PolyFit*.

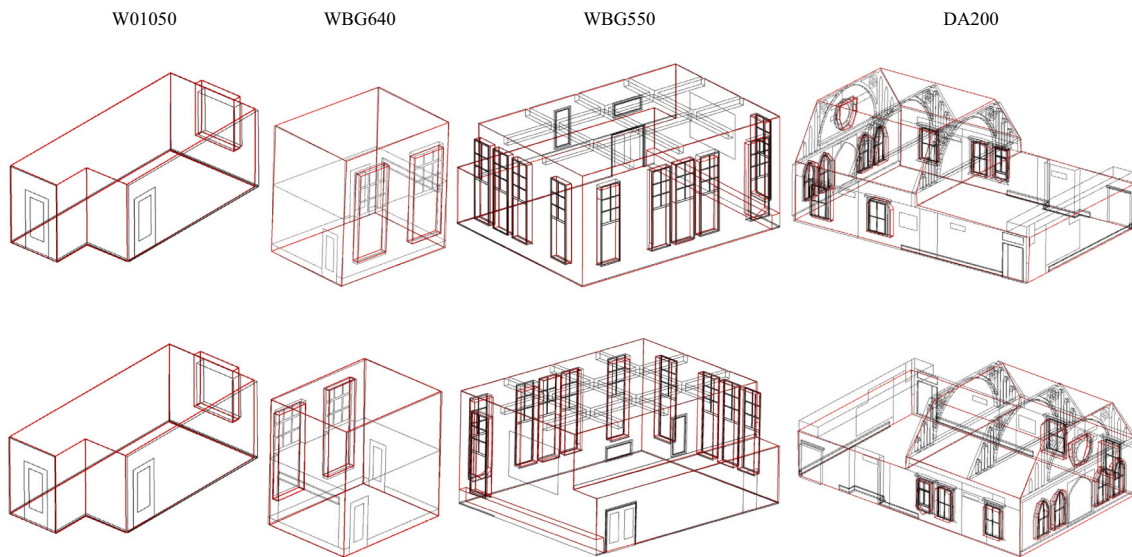


Fig. 10. Comparison of manually reconstructed (in black) with the proposed semi-automatic technique (in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.1. Visual comparison

Manual and semi-automatically reconstructed rooms are visually compared in Fig. 10. The overall shape of the rooms aligns well with the ground truth—manually reconstructed—geometries. A similar level of agreement is observed for the windows, although mullions are not reconstructed in rooms WBG640 and WBG550. Additionally, the arched and curved geometry of the windows in room DA200 is not fully captured by the reconstruction method.

4.2. Geometrical comparison

The geometric accuracy of the semi-automatic reconstructions was evaluated against the manually modelled ground truth using symmetric squared Chamfer (mean of directed terms) and HD (Table 4). Rooms WBG640 and W01050 show sub-centimetre mean deviations, which indicate close correspondence in walls and window boundaries. WBG550 presents slightly higher deviations, and DA200 exhibits the largest discrepancies.

4.3. Daylight availability

Table 5 compares ASE and sDA between the manual and semi-automatic models. In W01050, sDA increases from 32 % to 36 %, while

Table 4

Geometric comparison between manually and semi-automatically reconstructed models (distances in metres).

Room	CD	HD
W01050	0.0041	0.157
WBG640	0.0014	0.169
WBG550	0.0187	1.015
DA200	0.5189	3.905

ASE rises from 0.57 % to 2.46 %. In WBG640, sDA stays at 100 % for both models, with ASE increasing slightly (0.30 % → 0.89 %). In WBG550, sDA remains at 100 %, while ASE increases by 6 % (87.9 % → 93.8 %). In DA200, sDA increases from 52.0 % to 54.0 %, and ASE changes from 2.49 % to 2.59 %.

The spatial relative biases of UDI are summarised in Table 6. UDI_i shows negative mean biases in all rooms, UDI_a exhibits large variation with mean biases ranging from approximately −1.5 % to 40 %, and UDI_e shows positive mean biases in every case. This indicates an overall tendency toward overprediction of daylight availability. The large standard deviations, particularly for WBG550 and for UDI_a in W01050, indicate

Table 5
ASE and sDA results.

Room	ASE [%]		sDA [%]	
	Manual	Semi-auto	Manual	Semi-auto
W01050	0.57	2.46	32	36
WBG640	0.30	0.89	100	100
WBG550	87.94	93.82	100	100
DA200	2.49	2.59	52	54

Table 6
Spatial relative bias of UDI for (i)nsufficient, (a)utonomous, and (e)xceeding ranges.

Room	UDI _i		UDI _a		UDI _e	
	Mean [%]	Std [%]	Mean [%]	Std [%]	Mean [%]	Std [%]
W01050	-5.71	3.70	39.73	205.29	6.44	37.56
WBG640	-16.09	33.00	6.36	19.93	3.77	21.12
WBG550	-3.09	113.55	-1.54	45.32	25.84	42.11
DA200	-3.67	2.13	8.97	38.93	15.70	67.32

Table 7
Summary of spatial relative bias for TAI.

Room	Mean [%]	STD [%]
W01050	15.97	3.39
WBG640	11.91	1.36
WBG550	14.93	7.34
DA200	9.52	2.49

that these biases are not spatially uniform but are concentrated in specific regions of the sensor grid. The corresponding absolute UDI and TAI results are summarised in [Appendix A](#).

In terms of TAI, the mean and Standard Deviation values are summarised in [Table 7](#). The results indicate a systematic overprediction across all rooms, primarily attributable to the larger reconstructed window areas and the omission of mullions in the semi-automatic models. The mean remains below 20 % in all cases. The spatial distribution of this overprediction, shown in [Fig. 11](#) (top row), shows that the bias is most

pronounced near window regions, gradually decreasing with distance from the façade.

[Fig. 12](#) shows the annual variability of temporal RB values for a single sensor in the middle of each room along with the corresponding TMRB. This analysis shows that the bias is highly variable throughout the year. In addition to the temporal analysis, spatial variability of TMRB values was also examined. However, no clear spatial trend was observed, and these results are therefore not presented. The spatial statistical summary for all rooms is presented in [Appendix B](#).

4.4. Glare

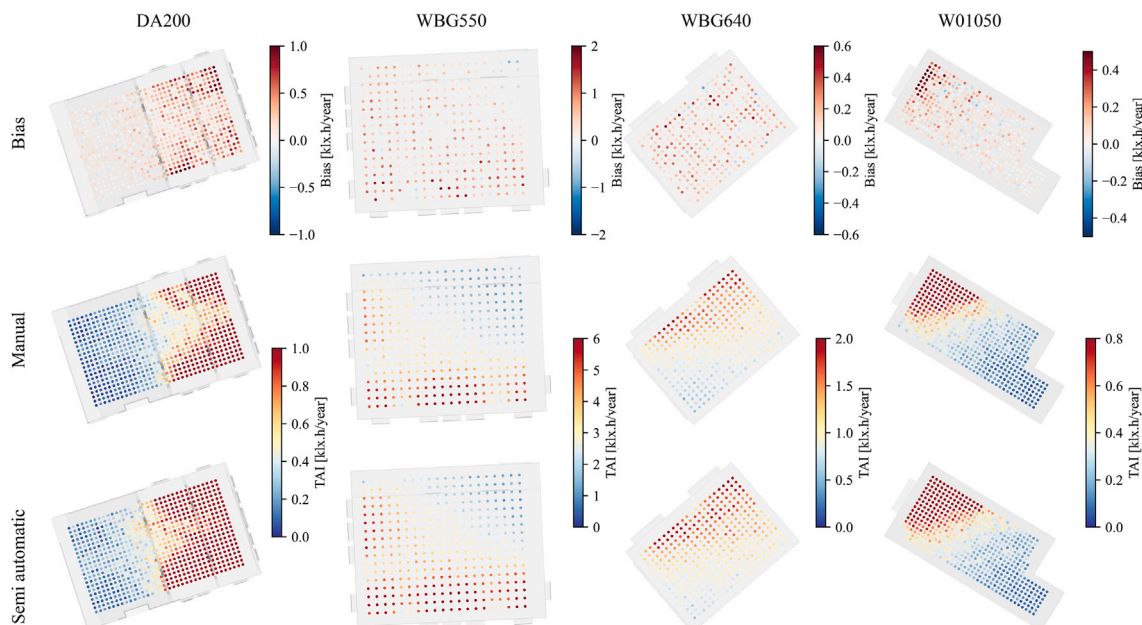
[Fig. 13](#) shows false colour luminance renderings for 21st of June at 15:00 under clear sky conditions, and [Fig. 14](#) compares DGP from manual and semi-automatic models across all the rendered time steps. The RMSE values are 0.0399, 0.0034, 0.0152, and 0.0220 for W01050, WBG640, WBG550, and DA200, respectively.

5. Discussion

5.1. Advantages

A key advantage of the proposed approach is the significantly reduced modelling time. For all four successfully reconstructed rooms, the total modelling time remained under 5 min. This is substantially shorter than the time required to manually model the rooms used as ground truth in this study. The manual modelling process took approximately 15 hours per room on average (including furniture), reconstructing only the GLoD0 would presumably take about half of that time, which still far exceeds the duration of the proposed pipeline.

A concurrent advantage of this small user interaction is that it mitigates the ambiguity introduced by the assumption that windows appear as holes in point clouds. Most of the fully automated methods reviewed in [Section 2](#) rely on heuristics to identify window candidates, such as rectangularity, edge linearity, proximity to floor and ceiling planes, and alignment patterns. These assumptions are not robust, particularly in the presence of occlusions or incomplete scans. By incorporating brief user input during the window selection stage, the proposed method reduces the risk of false detections and ensures that only valid window regions are processed, improving both the accuracy and robustness of the reconstruction pipeline.

**Fig. 11.** TAI heat map for semi-automatic (bottom) and manual (middle) geometries, along with its bias (top).

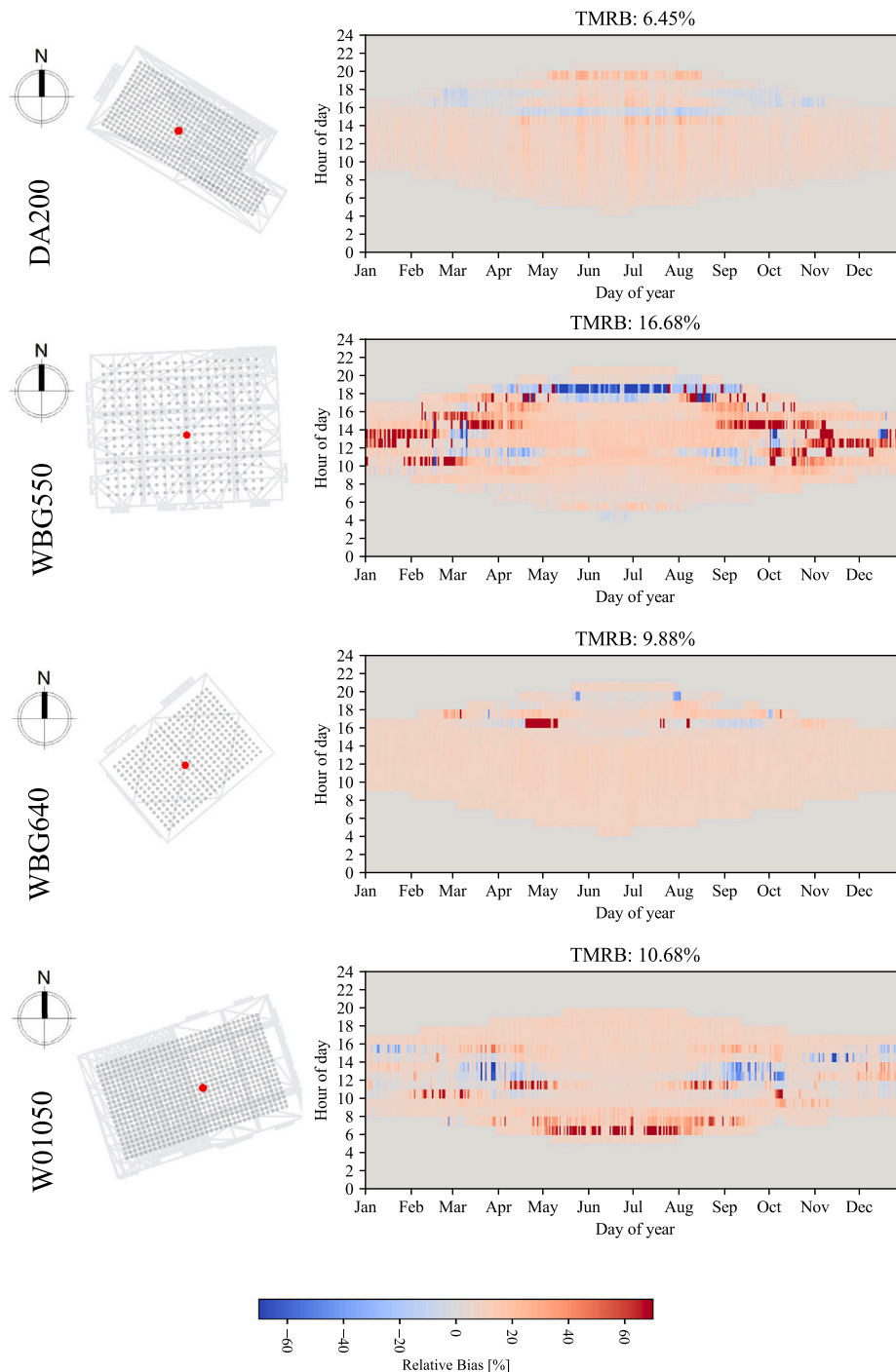


Fig. 12. Temporal illuminance relative bias across rooms. Left: sensor locations. Right: corresponding relative bias (RB) temporal maps for the same sensors.

A third advantage is the guaranteed water tightness. GLoD0 is the simplest resolution of indoor geometry for any type of daylight analysis, and remains unaffected by changes in indoor configurations. Water tightness is an important and basic requirement for indoor daylight models to ensure that simulated daylight permeates the room only through the transparent surfaces. This requirement is assured by the design of the proposed algorithm.

A fourth advantage is the inclusion of window extrusion in the reconstructed models. Window details are critical for daylight simulation,

e.g., window frames or sills may cause glare or significant reflected luminance. This work has therefore included an extrusion of windows so that these effects are captured in the output. This is an efficient approach compared to extruding the whole wall, which potentially adds unnecessary complexity to the model.

A fifth advantage is that the proposed algorithm assumes that the windows are individually symmetrical. Unlike similar studies in the literature that take a more specific prior, *i.e.*, rectangularity of windows, the symmetry assumption is a more robust architectural prior,

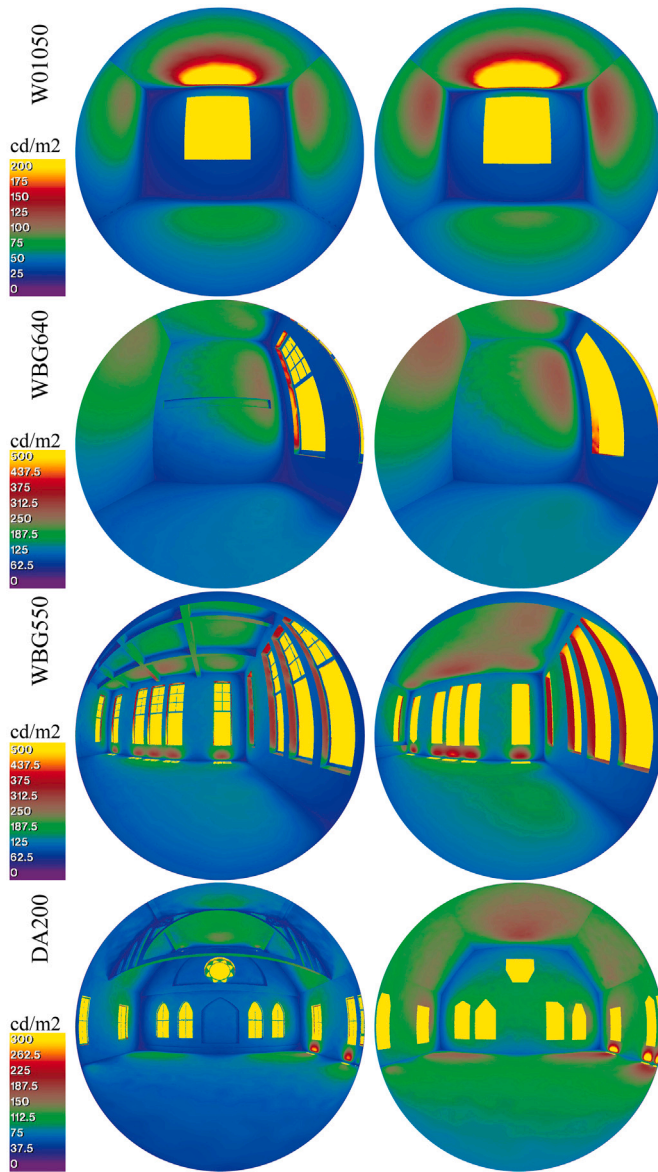


Fig. 13. False colour images of the summer solstice time step for manual (left) and semi-automatic (right) geometries. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

given that many windows in historic buildings are symmetrical and not rectangular.

The sixth advantage is the overall alignment between the semi-automatic and manual geometries, which is promising. The sDA results show less than 5 % bias and ASE less than 6 % bias, while TAI remains below 16 % relative bias across all rooms. The geometric comparison also shows a close agreement for rectilinear cases, with CD of less than one centimetre in *W01050* and *WBG640*, and discrepancies of up to 51 centimetres in more complex rooms. Although UDI shows larger deviations (up to 39 %) and higher variability, this behaviour is inherent to the metric due to its categorical binning.

Finally, the glare evaluation using DGP showed consistent performance. The RMSE of DGP values between the manual and semi-automatic models remained below 0.04 in all cases, indicating good agreement in predicting occupant visual comfort. This suggests that,

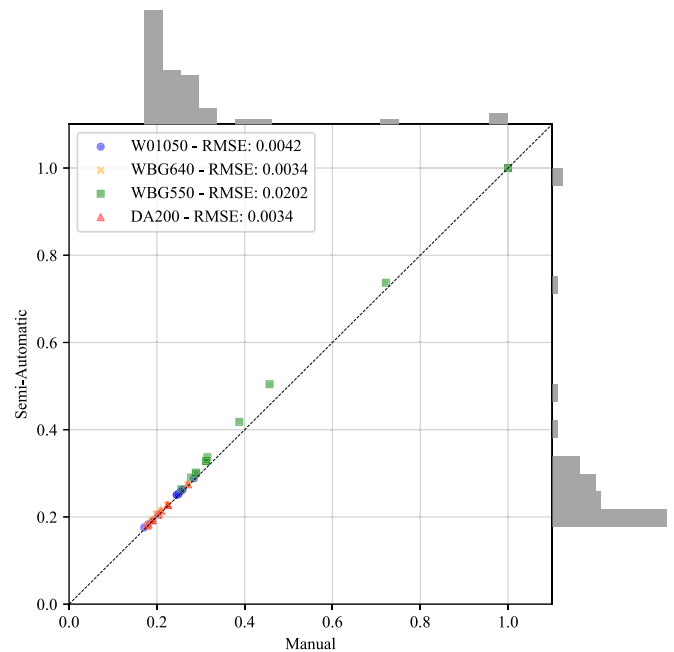


Fig. 14. DGP for manual and semi-automatic reconstruction pipelines.

despite geometric simplifications, the reconstructed models capture the primary geometric features that influence daylight availability and visual comfort in a sufficient manner.

5.2. Limitations

This study has limitations that highlight directions for future work.

The most fundamental assumption underlying the proposed reconstruction algorithm is that indoor surfaces are planar. This assumption originates from the reliance on the *PolyFit* method, which operates on planes extracted using RANSAC. While this is valid for most architectural elements such as walls, floors, and ceilings, it does not hold for spaces with curved or irregular geometries.

The reconstruction pipeline also inherits limitations from *PolyFit*. As noted by the original authors, this technique is suited to simple polygonal (piecewise-planar) surfaces and may encounter bottlenecks with large or complex geometries [30]. This was evident in the *Orange Hall* case, where geometrical and topological complexities produced an excessive number of candidate faces, causing the reconstruction to fail. Furthermore, the non-rectangular and arched window geometries in *DA200* challenged the boundary regularization step, increasing daylight-availability errors, though the impact on visual comfort remained minimal. Isolating the errors attributable to specific reconstruction shortcomings such as missing mullions and curved boundaries would be among the first steps toward remedies in future work.

Additionally, mullions—vertical or horizontal dividers within window frames—are not reconstructed. Their absence can lead to overestimated daylight entry areas and thus to higher simulated illuminance values. Similarly, the algorithm does not detect co-planar subsurfaces. In cases where surfaces share a plane but differ in material or reflectance (e.g., partially painted walls or embedded panels), users must manually define these areas if they significantly influence daylight distribution.

Furthermore, some other architectural elements, such as beams and columns, are not reconstructed. This choice aligns with the pipeline's focus on watertight room enclosures, but in rooms where such features obstruct light near window levels or cast prominent shadows, their absence may result in noticeable simulation errors. If such features

are expected to affect daylight performance significantly, an additional manual modelling step may be necessary.

Besides, the current approach has been validated on individual, single-room point clouds. Its scalability to more complex configurations, such as multi-room layouts or multi-storey buildings, remains untested.

Moreover, although a total modelling time of under 5 min is observed on one test machine, a formal timing study or a multi-user sensitivity analysis is not conducted to assess stability across users. This can be done by asking multiple users to repeat the wall/window selection on identical scans and compare results to the manual ground truth using geometric error metrics (e.g., Chamfer Distance, Hausdorff Distance) to establish expected error bounds and the variance attributable to user input.

Another limitation is that the algorithm does not detect co-planar subsurfaces. In spaces where surfaces share the same geometric plane but differ in material properties or reflectance—such as partially painted walls or embedded panels—this limitation may lead to inaccuracies in simulation. Users must manually define such subsurfaces if the reflectance contrast is expected to influence the daylight distribution significantly.

Lastly, in this work, points lying outside the target room were removed manually during preprocessing. While this is not always a strict input requirement—for instance, when acquisition already isolates the room or the reconstruction tolerates outliers—automating the room-isolation step would further reduce user effort and improve repeatability. The development and evaluation of such routines are left to future work.

6. Conclusion

In this paper, a semi-automatic pipeline for reconstructing indoor geometries is presented, primarily aimed at CBDM. The method focuses on generating GLOD0 models, which represent the window-containing watertight enclosure of indoor spaces with reduced manual effort. The pipeline includes three main steps, i.e., (1) preprocessing, (2) reconstruction of watertight surfaces, and (3) adding regularized window boundaries through reduced user interaction. This pipeline significantly reduces the processing time required to generate indoor geometry for daylight simulations.

The reconstruction approach was evaluated across four rooms of varying complexity. Results demonstrate that the reconstructed models yield daylight availability and glare outcomes with promising accuracy for many applications: sDA shows less than 5 % bias, ASE remains within 6 %, and TAI stays below 16 % relative bias across all cases. Although UDI shows larger deviations (up to 39 %) due to its binning logic, glare predictions remain consistent, with DGP RMSE below 0.04. These findings confirm that the pipeline captures the dominant daylight-driving geometrical features despite geometric simplifications and assumptions.

Nevertheless, limitations remain. The method is constrained to planar surfaces, does not reconstruct mullions or co-planar subsurfaces, and has not been validated on multi-room configurations. While these constraints limit its standalone applicability in some cases, the approach can serve as an efficient initial step for global analysis. It enables rapid generation of baseline models, which can subsequently be refined using more detailed methods when higher accuracy is required.

CRedit authorship contribution statement

Nima Forouzandeh: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Jin Huang:** Writing – review & editing, Visualization, Software. **Liangliang Nan:** Writing

– review & editing, Supervision. **Eleonora Brembilla:** Writing – review & editing, Supervision, Resources. **Jantien Stoter:** Supervision, Resources.

Declaration of competing interest

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

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Appendix A. UDI and TAI simulation results

In Tables A.8–A.11 the full simulation results are presented.

Table A.8
TAI [klx.hr/year].

Room	Manual		Semi-auto	
	Mean	STD	Mean	STD
W01050	0.40	0.47	0.47	0.55
WBG640	1.11	0.98	1.25	1.10
WBG550	3.23	2.51	3.75	2.90
DA200	0.57	0.49	0.82	0.69

Table A.9
UDI_i [%].

Room	Manual		Semi-auto	
	Mean	STD	Mean	STD
W01050	65.90	22.88	60.82	24.17
WBG640	15.53	32.83	13.81	31.52
WBG550	13.38	28.74	12.18	27.70
DA200	59.47	22.92	48.31	25.41

Table A.10
UDI_a [%].

Room	Manual		Semi-auto	
	Mean	STD	Mean	STD
W01050	33.10	21.45	37.87	22.41
WBG640	81.11	32.87	82.14	32.00
WBG550	60.47	26.84	55.09	27.61
DA200	38.11	21.16	47.86	22.96

Table A.11
UDI_e [%].

Room	Manual		Semi-auto	
	Mean	STD	Mean	STD
W01050	0.98	3.34	1.28	4.16
WBG640	3.33	10.03	4.03	11.58
WBG550	26.13	22.15	32.71	26.65
DA200	2.40	3.99	3.80	5.87

Appendix B. TMRB

In Table B.12 the TMRB results for all the rooms are presented.

Table B.12
Summary of spatial TMRB values.

Room	Mean [%]	STD [%]
WBG640	14.20	13.06
WBG050	14.03	13.71
WBG550	28.93	40.39
DA200	22.40	145.76

Data and code availability

Data and code for this study can be found at <https://github.com/tudelft3d/Indoor-window-reconstruction>.

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