# A pipeline for automatic building reconstruction for Digital Twins in complex urban environments

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**Abstract**

Automatic building reconstruction is a strategic component for creating urban Digital Twins (DTs), enabling the generation of accurate and interoperable Level of Detail 2 (LOD2) models. These models provide an essential standard for applications such as Geographic Information Systems (GIS), energy and hydraulic simulations, and urban planning. To address these needs, the MEDUSA (MEDiterraneo: Uso Sostenibile dell'Ambiente) project, promoted by the University of Salerno and funded by the Italian Space Agency (ASI), developed an innovative pipeline. The method was optimized to model areas with complex geometries and articulated roofs, utilizing the Amalfi Coast as a test area. The developed workflow is based on the City3D algorithm, integrating LiDAR (Light Detection And Ranging) data with building footprints derived from the Regional Topographic Database (RTDB). The process involves point cloud segmentation to isolate buildings and the generation of a Triangulated Irregular Network (TIN) mesh. Roof contours are identified using edge detection operators, simplified into polylines, and regularized using geometric constraints like parallelism and orthogonality to ensure LOD2 compliance. Finally, polygons are vertically extruded and optimized through the PolyFit framework, ensuring closed and topologically correct polygonal models. To overcome computational challenges and LiDAR data variability, significant improvements were introduced, including process parallelization, alignment with the Digital Terrain Model (DTM), and batch management of GeoJSON files. These enhancements successfully increased the pipeline's robustness and efficiency. The enriched pipeline produces high-quality LOD2 models, laying a solid foundation for next-generation urban modeling capable of meeting the scalability and interoperability requirements of future smart cities.

## 1. Introduction

In the past decade, photogrammetry and remote sensing for digital 3D recording have grown significantly. Advances in computer vision algorithms and high-performance computing have enabled automated processing of large spatial datasets and accelerated 3D model generation. Techniques such as Structure from Motion (SfM), multi-view stereo reconstruction, and LiDAR (Light Detection And Ranging) acquisition have improved the modeling of complex environments with high geometric accuracy. Consequently, urban reconstruction from spatial data has become more efficient and automated.

The diffusion of airborne and UAV-based (Unmanned Aerial Vehicle) LiDAR sensors has enhanced the acquisition of dense point clouds over large areas. LiDAR datasets provide detailed geometric information and are widely used for city modeling. Integrating LiDAR data with photogrammetric techniques and Geographic Information Systems (GIS) has enabled 3D city models capable of supporting applications such as urban planning, infrastructure monitoring, environmental analysis, and urban process simulation (Vosselman and Maas, 2010).

Recently, these developments contributed to the emergence of the Digital Twin (DT) concept. Urban DT create dynamic representations of cities by integrating spatial data, sensor information, and numerical models. These environments allow monitoring urban processes and support data-driven decision-making in infrastructure management and energy analysis. Accurate 3D models of the built environment are fundamental here. Buildings constitute the primary structural elements of urban landscapes, providing essential data for visibility analysis, hydraulic modeling, and energy simulations (Yan et al., 2019).

To support these applications, building reconstruction must satisfy specific standards. Level of Detail 2 (LOD2) models are widely adopted in 3D city modeling, which include simplified building volumes with realistic roof geometries. This level provides a balance between geometric detail and computational efficiency, making it suitable for large-scale analysis in GIS and DT platforms (Biljecki et al., 2016; Peters et al., 2022). Reliable LOD2 models require methodologies capable of extracting structures while maintaining geometric regularity and topological consistency. Without this foundation, DT applications such as scenario analysis and urban optimization may be limited.

Automatic building reconstruction has thus become a key research topic. Early studies focused on identifying planar surfaces within LiDAR point clouds and assembling them into roof structures via region-growing or plane-fitting (Rottensteiner et al., 2005; Tarsha-Kurdi et al., 2008). These approaches laid the foundation for modern reconstruction methods.

Recent research focuses on improving robustness and scalability in complex urban environments. Model-driven approaches incorporate geometric constraints and topological rules to improve consistency (Haala and Kada, 2010). Data-driven approaches combine LiDAR point clouds with building footprints from cadastral datasets, enabling consistent reconstruction at the city scale. Among recent developments, the City3D algorithm (Huang et al., 2022) represents a significant contribution, integrating point cloud processing with footprint information through a workflow of segmentation, mesh generation, edge detection, and geometric regularization.

Despite these advances, automatic reconstruction in complex environments remains challenging. Dense building clusters and complex roof geometries introduce difficulties during segmentation. Buildings in historical areas frequently present irregular shapes, multi-level roofs, and heterogeneous structures that complicate feature extraction. Additionally, LiDAR datasets may present variations in point density and incomplete facade information, which can negatively affect reconstruction quality.

Within this context, this study is developed within the framework of the MEDUSA project (MEDiterraneo: Uso Sostenibile dell’Ambiente), promoted by the University of Salerno and funded by the Italian Space Agency (ASI) as part of Earth observation and sustainable resource management initiatives. This work aims to support reliable urban models for DT applications, aligning with national and European policies for ecological and digital transition. It presents an automated reconstruction pipeline specifically optimized for complex environments, using the built environment of the Amalfi Coast—characterized by dense building clusters and articulated roof structures—as a testbed. The broader MEDUSA initiative integrates advanced remote sensing technologies, numerical modeling, and geographic information systems into a DT platform capable of representing and simulating coastal and marine ecosystem dynamics in real time.

The development of this DT relies on the exploitation of satellite data, drawing on reference missions from ASI—including the hyperspectral PRISMA and the COSMO-SkyMed SAR constellation—alongside Earth observation data from ESA’s Copernicus program.

The proposed pipeline generates LOD2 building models suitable for Digital Twins (DTs) by integrating aerial or UAV LiDAR point clouds with footprint information from official regional cartography. The process includes point cloud segmentation to isolate structures, generation of a Triangulated Irregular Network (TIN) mesh, detection of roof contours through edge detection, and geometric regularization. Regularized polygons are then extruded into volumetric models, with final optimization performed using the PolyFit framework to ensure geometric coherence and topological consistency.

Additional improvements enhance the robustness and scalability of the workflow, including parametric adjustments for LiDAR variability, Python modules for automatic model export, parallelization of processing steps, and alignment with the Digital Terrain Model (DTM). Together, these allow the pipeline to process large datasets efficiently while maintaining the geometric quality required for DT applications.

## 2. Methods

The developed pipeline adapts the City3D algorithm (Huang et al., 2022) as a reference, tailoring it to our data. It integrates LiDAR data acquired from aerial or UAV platforms with building footprints derived from official regional cartography, specifically the Regional Topographic Database (RTDB) (Figure 1).

The workflow begins by importing the point cloud and segmenting it to isolate building points. From these, a TIN mesh is generated, providing a preliminary 3D representation of each structure. Edge detection operators, such as Canny, are then applied to the mesh to outline roof contours, which are subsequently simplified into closed polylines to reduce geometric complexity in preparation for regularization (Xia et al., 2020).

Regularization is a crucial step: geometric constraints—including parallelism, orthogonality, and collinearity—are enforced to ensure polyline consistency and compliance with LOD2 standards. The regularized polygon is then vertically extruded to generate closed building volumes. Final optimization is handled by the PolyFit framework (Nan and Wonka, 2017), which assembles planar surfaces and selects faces through an integer optimization process that balances adherence to data, model simplicity, and preference for upper surfaces, ultimately yielding closed and topologically correct polygonal models. The last step consists of exporting models in GIS-compatible formats, ready for integration into advanced urban analyses.

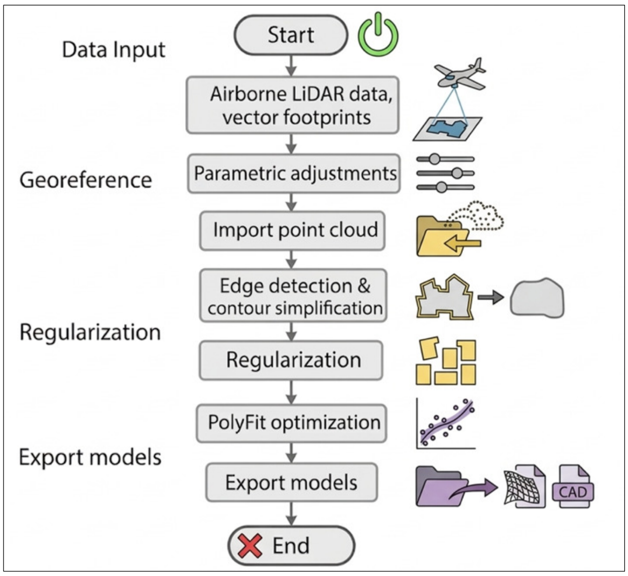


Figure 1. Processing workflow diagram.

Although robust, the method presents some challenges related to incomplete vertical facades, LiDAR data variability, and computational complexity. To overcome these issues, significant improvements were introduced, including:

- Parametric adjustment to handle data variability;
- Development of Python modules for automatic model export;
- Process parallelization and logging to ensure monitoring, increase scalability, and reduce computation time;
- Alignment with the DTM to ensure altimetric consistency;
- Batch management of GeoJSON files to reduce computational load and optimize workflow;

### 2.1 Data Preprocessing

In the context of urban modeling for DTs, defining an accurate and standard-compliant base geometric model is essential to ensure the reliability of downstream analyses. The literature highlights that the LOD2 represents an optimal trade-off between geometric complexity and operational applicability (Biljecki et al., 2016).

Unlike LOD1, which is limited to flat volumetric extrusions, LOD2 represents geometries realistically, including roof pitches, overhangs, and architectural articulations. This level of detail serves as the backbone that anchors the semantic and dynamic data of the DT, and is indispensable for energy simulations, visibility analyses, emergency management, and the optimization of urban flows.

To meet these needs, the pipeline reconstructs LOD2 models starting from aerial LiDAR point clouds. Although LiDAR offers high point density on horizontal surfaces, it provides sparse acquisition of vertical facades. To overcome this critical issue, the City3D algorithm (Huang et al., 2022) was adopted and adapted. The preprocessing workflow begins with importing the point cloud and separating the buildings using vector footprints derived from RTDB (Figure 2). This constrained segmentation reduces the search space and provides the exact planimetric boundaries for the subsequent inference of the missing vertical walls.

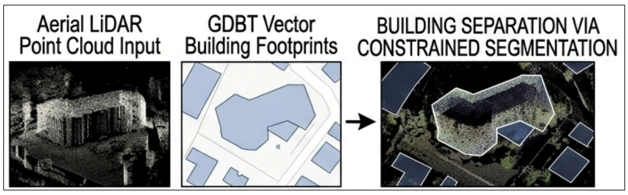


Figure 2. Point Cloud Extraction.

In data preprocessing, correct georeferencing and precise spatial alignment between LiDAR point clouds and vector building footprints are essential to prevent topological errors in the subsequent 3D reconstruction.
For this reason, a crucial phase involved the standardization of the coordinate reference systems, aligning the heterogeneous datasets to the official ETRF2000 system (epoch 2008.0), in compliance with national standards and the INSPIRE directive. This optimization was automated using an ArcPy script that employed the official IGM grids and the ITALGEO2005 geoid model to ensure a rigorous planimetric and altimetric transformation (Di Benedetto et al., 2022). The validation of the process, conducted against the official Verto3k software, confirmed sub-millimeter accuracy in the coordinate transformation, ensuring spatial consistency required for the DT.

### 2.2 Facade Inference and Roof Extraction

The second phase focuses on inferring the 3D structure of each building from roof data alone. For each segmented building, a height map H(x,y) is generated in the form of a TIN mesh, which provides a continuous and adaptive surface bounded by the extracted points.

To identify the sharp contours of the roofs (ridge lines, hip lines, and eaves), the Canny edge detection operator is applied to the surface (Canny, 1986). This involves computing the gradient magnitude of the height map, defined as:

$$\| \nabla H \| = \sqrt{\left(\frac{\partial H}{\partial x}\right)^2 + \left(\frac{\partial H}{\partial y}\right)^2} \tag{1}$$

followed by non-maximum suppression to isolate precise edge locations. The extracted contours, often affected by noise and irregularities due to LiDAR sampling, undergo a geometric simplification process that converts them into closed polylines. This step is governed by advanced mathematical principles, specifically the framework of optimal transport (De Goes et al., 2011; Huang et al., 2022). The simplification algorithm seeks a reduced geometric representation by minimizing the p-Wasserstein distance $W_p$ between the point distribution of the original noisy contour μ and the distribution of the simplified polyline ν. This optimization problem is formulated as:

$$W_p(\mu,\nu) = \left( \inf_{\gamma \in \Pi(\mu,\nu)} \int_{\mathbb{R}^2 \times \mathbb{R}^2} \| x - y \|^p \, d\gamma(x,y) \right)^{1/p} \tag{2}$$

where Π(μ, ν) denotes the set of all joint probability measures γ (transport plans) with marginals μ and ν, and ||x - y|| represents the Euclidean distance. By solving this optimization, the method effectively minimizes the spatial deviation between the simplified polyline and the original points. This significantly reduces the topological complexity of the roof polygon while strictly preserving its core shape, optimally preparing it for subsequent geometric regularization.

Figure 3 provides an overview of the building reconstruction workflow, structured into four main phases: (a) generation of the TIN mesh surface, (b) edge detection using the Canny operator, (c) geometric simplification based on optimal transport, and (d) visualization of the final simplified closed polyline.

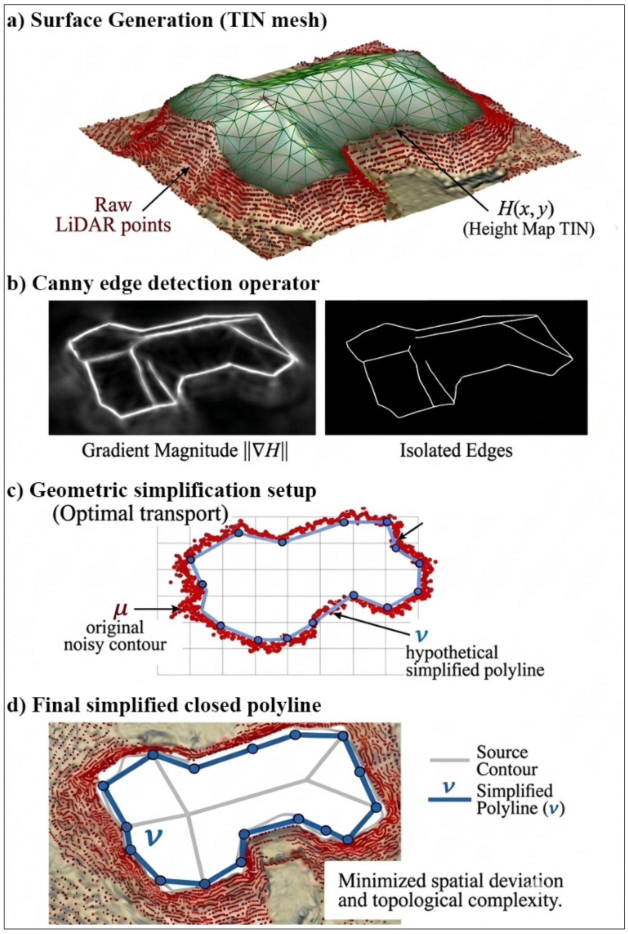


Figure 3. Workflow illustrating the extraction of the roof polygon.

### 2.3 Geometric Regularization and 3D Optimization via PolyFit

To ensure compliance with LOD2 standards (Biljecki et al., 2016; Peters et al., 2022), geometric regularization imposes strict spatial constraints on the simplified polylines (Figure 4a). This is formulated as a constrained optimization problem where vertices are adjusted to restore parallelism, orthogonality, and collinearity, by penalizing deviations from the dominant orientation angles of the building footprint. Topological priors are also applied to enforce specific roof structures (e.g., single-pitch or gable roof). Subsequently, the regularized polygon undergoes a vertical extrusion toward the ground elevation (DTM) to generate the exterior walls, thus providing a preliminary closed building volume (Figure 4b).

The final optimization of the 3D model is performed using the PolyFit framework (Nan and Wonka, 2017). This algorithm generates a comprehensive set of planar polygonal face hypotheses by intersecting the dominant planes extracted from the point cloud (Figure 4C). The selection of the optimal watertight subset of faces is cast as a Binary Integer Programming (BIP) problem. Let $x \in \{0,1\}^N$ be a vector of binary variables where $x_i = 1$ if the *i-th* candidate face is selected, and 0 otherwise. The objective function minimized by PolyFit consists of three weighted energy terms:

$$E(x) = \lambda_{data} E_{data}(x) + \lambda_{comp} E_{comp}(x) + \lambda_{roof} E_{roof}(x) \quad (3)$$

where $E_{data}$ measures the data fitting error (the geometric distance from LiDAR points to the selected faces), $E_{comp} = \sum x_i$ represents the total number of selected faces, acting as a penalty to favor simpler geometric models, and $E_{roof}$ encourages the selection of upper covering surfaces. To ensure the final model is topologically correct and free of self-intersections, hard constraints are enforced. Specifically, the watertightness of the model is guaranteed by the topological constraint:

$$\mathbf{A}x = 0 \quad (4)$$

where A represents the edge-face incidence matrix. This constraint mathematically ensures that every active edge is shared by exactly two active faces, yielding a perfectly closed, LOD2-compliant polygonal model ready for advanced GIS environments (Figure 4d).

### 2.4 Scalability, Automation, and Topological Alignment

Despite the precision of the parametric reconstruction, applying the pipeline on a territorial scale introduces critical challenges related to the high spatial variability of LiDAR point density and the exponential growth of computational load. To ensure scalability and execution efficiency, the workflow was extensively optimized at the algorithmic and architectural levels. Firstly, a dynamic parameter tuning strategy was introduced: instead of relying on global thresholds, identification parameters —such as region-growing tolerances and edge—detection sensitivities—are adaptively adjusted based on the local point cloud density and noise distribution, ensuring robust extraction across heterogeneous urban morphologies.

Regarding the software architecture, a spatial partitioning strategy was implemented for the batch processing of GeoJSON files. By leveraging spatial indices (e.g., R-tree bounding volume hierarchies) and chunking the dataset into computationally tractable tiles, the memory footprint was significantly reduced, preventing memory overflow (out-of-memory) errors during the processing of massive urban scenes (Elseberg et al., 2013; Richter and Döllner, 2014). Furthermore, the processes were parallelized using multiprocessing frameworks to distribute the workload across multiple CPU cores. This architecture is coupled with an advanced logging and checkpointing system, which continuously records the execution state. This fault-tolerant design is essential not only for the real-time monitoring of computational bottlenecks but also for enabling automatic state recovery, allowing the pipeline to resume operations seamlessly from the last processed tile in the event of system interruptions.

Finally, to ensure full interoperability with advanced GIS environments and spatial databases, a dedicated Python-based module was developed for the automated export of the generated 3D models into standard semantic formats (e.g., CityJSON, multipatch shapefiles) (Ledoux et al., 2019).

This module integrates a rigorous altimetric alignment system with the DTM. Rather than applying a simple uniform vertical translation, the algorithm computes the exact intersection between the regularized building footprint and the underlying DTM grid, performing a constrained Z-axis projection. This step ensures that the base of each generated building accurately snaps to the varying terrain morphology, effectively eliminating topological anomalies such as floating structures or subterranean intersections (Ledoux and Meijers, 2011), thereby finalizing the creation of a semantically enriched and geometrically coherent Urban DT (Mazzetto, 2024).

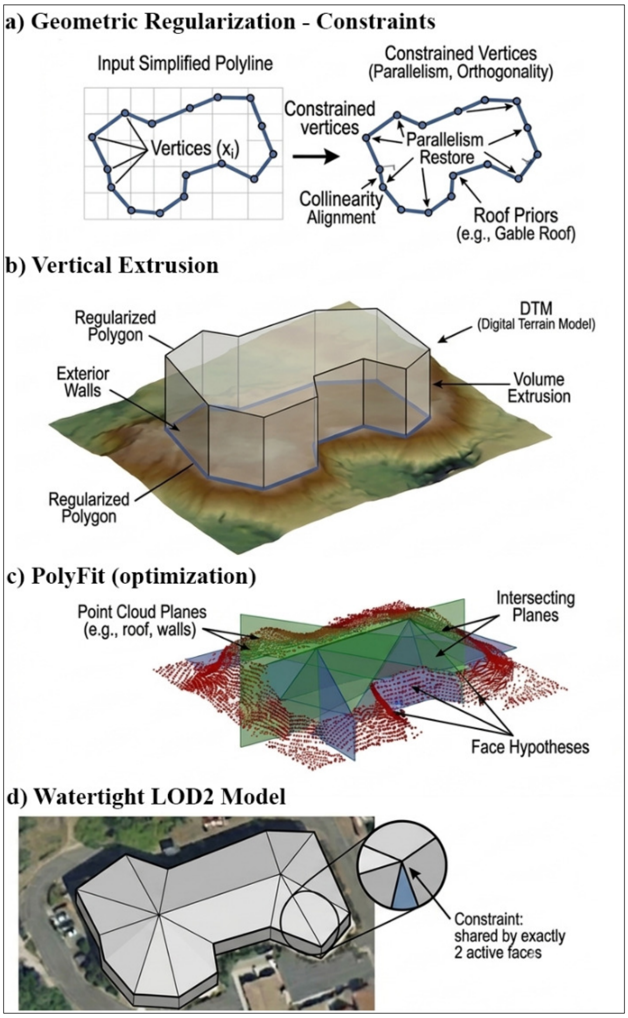


Figure 4. Workflow of Geometric Regularization and 3D Optimization.

## 3. Results

The enriched pipeline constitutes a solid approach for automatic building reconstruction in urban contexts, successfully applied to the highly complex morphological case study of the Amalfi Coast within the framework of the MEDUSA project. The methodology was validated across several municipalities, including Vietri sul Mare, Cetara, Maiori, Minori, and Amalfi. The resulting accurate and interoperable LOD2 models form the basis for advanced DT applications, energy simulations, visibility analysis, and urban planning (Yan et al., 2019).

The combination of LiDAR data, such as the 1m resolution MASE (Ministero dell'Ambiente e della Sicurezza Energetica) dataset, regularization, and optimization algorithms lays the foundation for next-generation urban modeling. Specifically, the implementation of the City3D method and the PolyFit framework enabled the automatic extrusion of building volumes from vector footprints, generating topologically correct LOD2 models featuring realistic roof geometries, rather than simple flat volumes. This approach meets the precision, interoperability, and scalability requirements of future smart cities, ensuring that all data are rigorously aligned to official reference systems.

Figure 5 illustrates the results of the 3D geometric reconstruction obtained by integrating the ministerial LiDAR data (e.g., MASE) and the vector footprints extracted from the RTDB. A critical analysis of the output highlights the algorithm's effectiveness in handling the intrinsic limitations of the input vector data. Notably, the RTDB polygons were often under-segmented, representing not single building units, but complex structural aggregates or entire continuous blocks. Despite this critical issue, the algorithmic pipeline demonstrated high topological robustness, successfully segmenting, and correctly parameterizing the multiple roof pitches of the entire agglomerate, reconstructing their slopes and ridge lines with considerable reliability.

However, the application on a morphologically challenging territory such as the coastal area revealed some technical challenges that require specific mitigation strategies:

1. Overhanging Vegetation Interference: in several areas, the presence of dense tree vegetation partially or totally overhanging the buildings generated occlusions and geometric noise in the point cloud, causing occasional artifacts in the generation of the roof planes. This spatial anomaly can be mitigated by refining the preprocessing phase, implementing advanced semantic classification filters for the point cloud (e.g., algorithms based on Cloth Simulation or the analysis of local roughness and return echoes) capable of accurately distinguishing and excluding the high vegetation class from the candidate building points.

2. Buildings Embedded in Rocky Contexts: A second challenge concerns structures partially attached to or embedded in sub-vertical rocky cliffs, typical of the extreme orography of the Amalfi Coast. In these specific cases, the spatial resolution (points/m²) of traditional aerial LiDAR and the nadir scanning angle struggle to provide a clear distinction between the anthropogenic planar surfaces and the natural discontinuities of the bare rock. Experimental analysis confirmed that this limitation can be overcome through a data fusion strategy: by integrating the LiDAR cloud with ultra-high-resolution UAV surveys (oblique photogrammetry or drone LiDAR), the increase in spatial density and the better acquisition geometry allow the planar region-growing algorithms to successfully segment the roof pitches, clearly distinguishing them from the complex morphology of the adjacent cliff.

The accurate parameterization of these complex structural aggregates holds strategic value for the preservation and management of historical and architectural heritage, which is particularly dense and vulnerable in contexts such as the Amalfi Coast. Having LOD2 models that are faithful to the geometric reality of the site—capable of accurately representing complex roof configurations rather than relying on simple flat extrusions—makes it possible to overcome the approximations inherent in conventional cartographic representations. This level of three-dimensional detail is crucial for enhancing the reliability of computational analyses. The use of realistic geometries, modeled on actual roof pitches, makes simulations—whether for energy performance, visual impact assessments, urban microclimate modeling, or vulnerability studies—significantly more precise. Consequently, this provides decision-makers with the fundamental analytical support needed to plan targeted and sustainable conservation interventions.

Quantitative validation on a larger test set is currently underway and will be reported in future work.

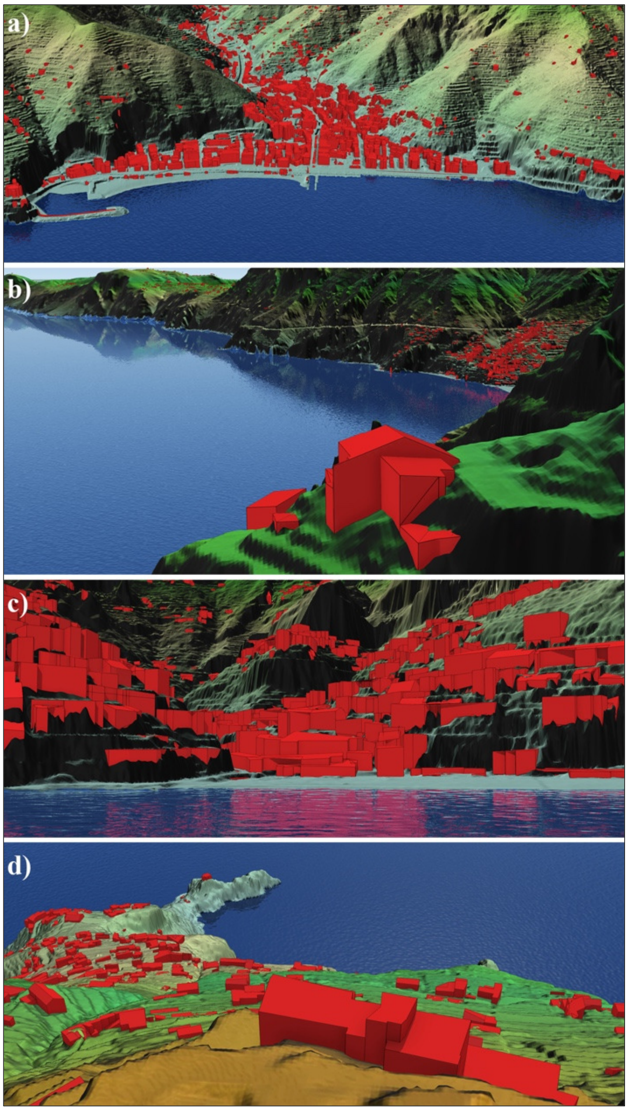


Figure 5. 3D building polygons on the Amalfi Coast DTM and visualized in the DT platform.

## 4. Conclusions

The proposed approach aligns with the growing interest in high-fidelity urban modeling, essential for supporting data-driven decision-making processes. The pipeline goes beyond generating 3D geometries, introducing a paradigm oriented toward interoperability and scalability— key elements for building urban DT. The integration of LiDAR data, high-resolution UAV photogrammetry, and official cartography allows for accurate models even in areas with severe morphological constraints, such as the Amalfi Coast. Furthermore, the adoption of regularization algorithms ensures compliance with international standards (LOD2), promoting the use of models in advanced applications such as risk analysis, energy simulations, and resilient planning.

Future developments and ongoing implementations focus on further automation and integration with dynamic monitoring systems. Currently, the Amalfi Coast DT is being enriched with sub-daily data from IoT environmental sensors (measuring temperature, humidity, and brightness) installed in pilot heritage sites, such as the Torre Vicereale in Cetara, the Arsenale in Amalfi, and the Villa Romana in Minori. Supported by a scalable hybrid-cloud architecture, this large-scale application enables the creation of resilient and intelligent urban digital ecosystems, maintaining geometric quality as a key strength.

This work thus represents a methodological and technological contribution to the digital transition of cities, paving the way for full automation and real-time operational support.

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