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Research Article

Automatic Building Vectorization from Photogrammetric Point Clouds for GIS-based Spatial Analysis

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Abstract

Photogrammetry has played an essential role in creating visually interesting three-dimensional (3D) models thanks to unmanned aerial vehicle (UAV) images in recent years. Photogrammetry and GIS are widely used together to produce and analyze 3D models. This study successfully created 3D models of buildings using photogrammetry and transferred them to GIS for analysis. UAVs were utilized to capture images, which were then processed to generate a dense point cloud. The point cloud was classified using rule-based classification. Buildings were vectorized and textured, and the resulting models were analyzed in commercial GIS software. The study proposed the classification process and automatic vectorization of buildings in the photogrammetric point clouds. In the study, buildings were classified with 90% accuracy, and the obtained building point clouds were vectorized and transferred to a GIS environment. The use of UAVs expedited data collection and improved data quality, while the detailed analysis of the point enabled precise analysis for many applications such as urban planning and land management. The integration of building models into GIS facilitated more accurate and efficient work processes.

Keywords: Photogrammetry, GIS, Point Cloud, Classification, UAV

Introduction

Object detection and classification studies using photogrammetric data have recently become an important research topic. These studies can be applied in various fields such as monitoring urban changes and developments, urban planning, map production, property assessment, and disaster management. Object detection in urban areas primarily focuses on buildings, which are the most prominent and visually striking objects compared to others (Chen, et al., 2012). The rapid and accurate automated extraction of up-to-date building data is crucial in creating city models. The hierarchical steps involved in automated building extraction include (I) Data preparation, (II) Point cloud generation, (III) Point cloud classification, (IV) Building separation, (V) 3D modeling, and (VI) Validation. Data preparation involves collecting, organizing, and preprocessing drone imagery and other relevant data. Point cloud generation processes the input data to create a point cloud, involving data processing, filtering, and resampling. Point cloud classification assigns different classes to each point in the point cloud, such as buildings, trees, roads, and terrain. Building separation is used to distinguish buildings from other objects in the point cloud. 3D modeling is the process of creating 3D models of buildings. Validation is used to verify the accuracy of automatically extracted buildings (Sirmacek and Gulec, 2017; Büyüksalih et al., 2018; Yildirim et al., 2021). Studies in the literature indicate that most methods used for automated building extraction do not achieve total accuracy in point cloud classification. Factors that negatively affect the accuracy of point cloud classification such as insufficient point density, occlusion, noise, lighting conditions, and ground characteristics.

Analyzing 3D model data using GIS software is important for understanding and interpreting the data. In GIS, analysis and modeling processes can be performed on 3D data, including 3D visualization, volume calculation, slope analysis, viewshed analysis, shading analysis, etc. The interpretation and reporting of results involve analyzing and reporting the analysis results, which can be presented in the form of 3D models, tables, and graphs (Lu, et al., 2019).

In this study, very high-resolution UAV imagery was used, obtained through the nadir method. The nadir method involves positioning the drone vertically to the Earth's surface during flight, allowing it to capture the top and sides of objects and obtain high-resolution and detailed imagery (Wang et al., 2019). A dense point cloud was generated from the acquired imagery using structure form motion (SFM). The point cloud was edited, noise was removed, a macro was created to automatically classify and manually correct misclassified point clusters. Buildings were converted to vector format, and texture processing was performed. The resulting textured buildings were analyzed using GIS tools.

Related Works

Many studies have been published in the literature on point cloud classification (Atik et al., 2021; Duran et al., 2021; Aljumaily et al., 2023; Pellerin et al., 2024; Atik et al., 2024). Machine learning-based methods have been widely used in the last decade for point cloud classification. However, there are significant limitations such as high hardware requirements and large training data. For this reason, it is preferred for point cloud classification in parametric and rule-based unsupervised classification. Although LiDAR point clouds are mostly used, studies on photogrammetric point clouds are increasing. In the article published by Haithcoat et al. (2001), it was aimed to conduct a study on automatic building footprint extraction and retrieving the three-dimensional (3D) view of these buildings from LIDAR (Light Detection and Ranging) data. Creating the building footprint; Creating a building footprint consists of three steps: DEM production, footprint extraction and footprint simplification. In the study published by Zhang et al. (2020), the footprint and height information of each building in three study areas located on the main campus of Universitas Negeri Makassar (UNM) were extracted using aerial photographs and LiDAR data. LIDAR data was used to produce Digital Surface Model (DEM) and Digital Terrain Model (SAM). Park and Gundman (2019) aimed to create a three-dimensional city model with building roof footprints within the study area located in the City of Columbus and Franklin. It aimed to present a point cloud classification methodology that assigns LIDAR points to different classes, detects points that reflect a roof surface, and estimates building heights using only those points. Each point is characterized by a set of features and classified by a machine learning algorithm. In the study conducted by Duran et al. (2022), four different classes, one of which was a building, were detected in the urban area through photogrammetric and LiDAR point clouds. Each point is defined using geometric features. Machine learning algorithms have been used for classification. Chen et al. (2020) proposed a new approach for extracting object information such as individual tree locations and building footprints from photogrammetric point cloud. Supervised machine learning algorithms have been analyzed using different point descriptors. Huang et al. (2022) proposed a fully automatic approach to reconstruct 3D building models from airborne point clouds. In the study, building sample segmentation was carried out by separating buildings separately using vectorized building footprint data. Additionally, using preliminary information about the structures of the buildings, their vertical planes were determined. Nys et al. (2020) aim for automatic reconstruction of consistent 3D city buildings formatted according to CityJSON. It is ensured that the models created from the airborne LiDAR point cloud have a reliable geometric and topological structure to store information and be used consistently in complex calculations. Shirowzhan and Sepasgozar (2019) proposed a new approach to extract landmarks using autocorrelation-based algorithms for accurate detection of building structures in hilly urban areas. Thanks to the digital elevation model (DEM) created using ground points, ground points are eliminated from the point cloud and used to eliminate ground height from building height. Widyaningrum et al. (2019) proposed a new sequential point-assisted Hough Transform (OHT) to extract high-quality building outlines from an airborne LiDAR point cloud using sequential building edge points. Sharma and Garg (2023) extracted buildings from point clouds using machine learning classifiers and geometric features. Building points were separated by applying K-means clustering to the obtained classified point cloud. Finally, building footprints were vectorized from the point clouds of the buildings. However, building facades were not modeled in the study. Kang (2023) proposed an approach to automatically generate building mass and facade information on the GIS platform from airborne laser scanning (ALS) data. With the proposed approach, a holistic approach for Scan to BIM mapping has been presented. 3D models have been created in the GIS environment, considering building heights and footprints. However, texture information has not been included in the study. In another study (Karsli et al., 2024), building footprints were extracted from photogrammetric and LiDAR point clouds with the Improved-Octree approach. Building footprints were extracted from both data types using ground filtering, clustering and vectorization/regulation, but no analysis was performed in a GIS environment. In this study, all of the building footprint, facade and texture information from point clouds were transferred to the GIS environment and analyses were performed. Thus, an end-to-end approach was presented to the literature.

Materials and Methods

Study Area and Data Captured

UAV images are application data belonging to the neighborhood of Alibeyköy, located in the Eyüp district of Istanbul province, covering an area of approximately 48,500 square meters.

Fig. 1. Study area.

The data used in the application consists of images captured with a Phantom 4 RTK drone in the area, using a nadir (usually at an angle close to 90 degrees) perspective. Moreover, the ground sampling distance (GSD) is about 2 cm, all the flights were carried out at an altitude of 80 m. Sample images are presented in Figure 2. A 60-80% overlap during image capture enhances the linkage of images, resulting in high-accuracy orthophotos and 3D models.

Fig. 2. Sample images of the study area taken from UAV.

RTK is a positioning technology used with global positioning systems (GPS, GLONASS, etc.). This method provides high-precision location information and enables real-time positioning capabilities (Smith, et al., 2021). This technology can reduce or eliminate the need for Ground Control Points (GCP) in photogrammetric processes, as it directly provides geographic reference position data for each photo, significantly reducing post-processing workload. RTK operates through collaboration between a base station and at least one rover (portable device). The base station is placed in a fixed location and sends reference signals that provide high-precision location information. On the other hand, the rover is a mobile device that receives the reference signals from the base station to determine its position. The fundamental principle of RTK is to utilize the signal differences between the base station and the rover to achieve fast and accurate positioning. These differences are used to correct atmospheric effects and other errors. The most significant feature of RTK is its ability to obtain high-precision location information in real-time (Smith, et al., 2021)

Point Cloud Generation and Digital Elevation Model

The point cloud, digital elevation model (DEM) and orthomosaic are generated using SFM. SFM calculates the 3D coordinates of an object based on epipolar geometry by measuring the corresponding points between two overlapping images. SFM automatically estimates camera positions and orientation to create object geometry. The initially estimated values are iteratively improved using non-linear least squares adjustment (Westoby et al., 2012).

Image matching was performed by loading the nadir angle images (a total of 95 images) into the software. This process finds similar points by using the images' overlapping regions and common features. The software calculated the camera parameters using the similar points obtained from the image-matching process and known control points. These parameters include the camera's intrinsic and extrinsic parameters. The intrinsic parameters represent the optical characteristics of the camera (e.g., focal length, lens distortion), while the extrinsic parameters transform the camera's position and orientation into the world coordinate system. To create a denser point cloud, the software performs dense point matching using the matched points. This process converts each pixel in the images into 3D points, resulting in a point cloud. After the dense point matching, a 3D point cloud is generated. This point cloud contains dense 3D coordinates derived from the images. DEM is a representation of the Earth's surface topography or terrain. It is a three-dimensional model that provides information about the elevation or height values of the Earth's surface at regularly spaced intervals. A DEM is typically represented as a grid of elevation values, where each cell in the grid corresponds to a specific geographic location and contains the elevation value for that location.

DEM is produced by applying inverse distance weighted (IDW) interpolation to the dense point cloud produced as a result of SfM. IDW performs a surface interpolation based on the weighted average of the support points, which lose weight as they move away from the point to be interpolated (Yanalak, 2002). DEM of the region has been generated (Figure 3). After the DEM is generated, the height variations of each object in the study area have been determined. The red areas represent the highest points, while the blue areas represent the lowest.

Orthophoto Generation

An orthophoto image is a geometrically corrected aerial or satellite image that has been adjusted to remove distortions caused by the perspective and relief of the terrain. Unlike regular aerial or satellite images, which may have distortions due to the angle of capture and terrain variations, orthophotos have a uniform scale and can be used to measure distances, areas, and angles accurately. Orthophotos are widely used in various fields, including mapping, urban planning, agriculture, environmental analysis, and infrastructure development. After the DEM was produced, the distortions that occurred due to the height in each image were removed and an orthophoto was produced. The generated dense point cloud and DEM are presented in Figure 4.

Point Cloud Classification

Rule-based classification method was preferred for point cloud classification. Classification was achieved by defining a set of discriminant rules based on height and color information. The K-nearest neighbors (KNN) algorithm was used for the classification process. This algorithm is a classification method based on the nearest neighbors to determine the class of the data. In short, the KNN algorithm classifies a data point in a dataset based on its proximity to previously observed data points. It is one of the most fundamental examples of instance-based learning methods. Instance-based learning performs the learning process by relying on the data in the training set and utilizing the similarities between these data points. Each data point $(x, (f(x))$ in the training set is added to the training examples. For each x_q to be classified, the following rules are applied: The k nearest examples (x_1 , x_2 , … , x_k) to the x_q point in the training set are found, and based on these examples, the class of xq is determined (Özcan, K., 2021).

$$\hat{f}(x_q) = \text{argmax}_{v \in V} \sum_{i=1}^{k} \delta\big(V, f(x_i)\big) \qquad (Eq. 1)$$

In the equation, if a and b are equal, $\delta(a, b) = 1$, otherwise $\delta(a,\ b) = 0$. The key parameters that affect the performance of the KNN algorithm are the distance metric, the number of neighbors (k), and the weighting. Different distance metrics such as Minkowski, Euclidean, Manhattan, Chebyshev, and Dilca can be used. The Minkowski distance is defined as follows:

$$\left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{\frac{1}{p}} \qquad (Eq.2)$$

In the KNN algorithm, classification is done based on the specified number of neighbors (k). By assigning weight values to the neighbors, closer neighbors are expected to contribute more to the voting process during classification (Özcan, K., 2021). Upon examining Figure 5, it is clearly evident that there are structures with elevations lower than the road level. When automatic classification was applied in Figure 5, it was observed that certain building classes were incorrectly assigned to ground and default classes.

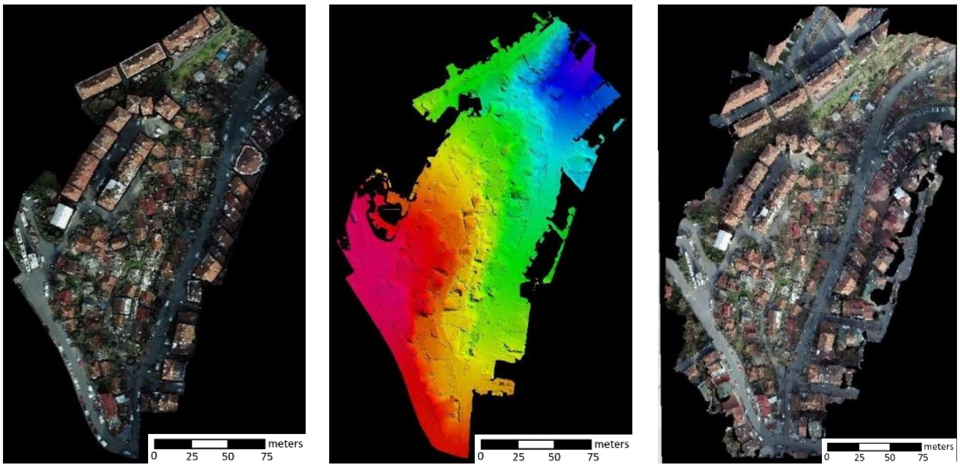


Fig. 3. Colored Dense Point Cloud, Digital Elevation Model (DEM) and Orthomosaic.

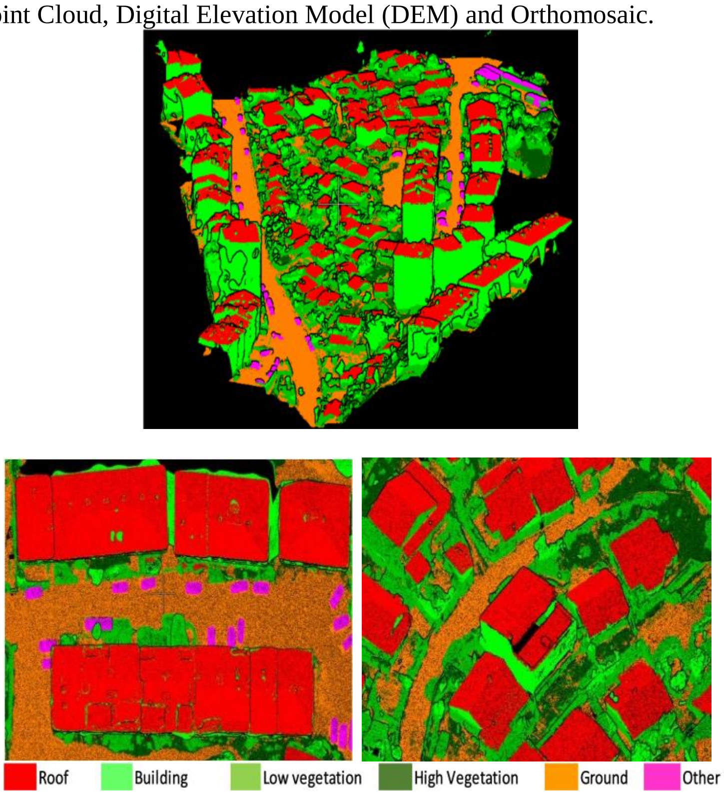


Fig. 4. Classified point cloud.

This issue has been largely resolved through color-based classification. Color-based classification is a process that utilizes the color information based on point cloud data. In this method, each point in the point cloud includes not only 3D positional information but also color information. Color-based classification can be used to recognize and classify different objects or features by utilizing the color properties of the points. In other words, color-based classification assigns points with the same color in the colored point cloud to specific classes. For example, the roofs in the area mostly have the same color, and the classification of buildings using color-based classification has significantly improved the classification accuracy. In Figure 4, color-based classification was applied to the study area, effectively addressing the issues related to elevation differences.

Results and Discussion

Accuracy Assessment of Point Cloud Classification

Point cloud classification accuracy is a measure of the ability to correctly classify point cloud data. This criterion evaluates the assignment process of point cloud data to different object or surface types (e.g., buildings, trees, roads, water) (Limandal, 2019). Typically, a classification algorithm is used to classify point cloud data, and then these classification results are compared with the ground truth class labels. Through this comparison, the number of points correctly classified by the classification algorithm is determined (Park and Guldmann, 2019). The accuracy value is calculated as the ratio of the number of points correctly classified to the total number of points (Equation 1).

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ samples} \qquad \text{(Eq.3)}$$

The accuracy value is typically expressed as a value between 0 and 1 or represented as a percentage. A high accuracy value indicates that the classification algorithm accurately reflects the ability to classify the data correctly. The colored point cloud was used as a reference to evaluate the accuracy of the point cloud classification and validate the classification results. In this context, 200 randomly selected points from the roofs of buildings were checked to determine whether these points were correctly classified into the "building" class after the classification process. This accuracy assessment process was repeated 10 times on different sets of 200 points. The accuracy results obtained for each repetition were recorded, and the average of these results was calculated to obtain an overall accuracy value. In Table 1, the class information, the number of points taken as reference from the colored cloud, the number of points correctly classified in the classification results, and the accuracy values for each set are provided. The classification accuracy was calculated as 0.90 when each cluster's average accuracy values was considered (Table 1).

Table 1. Classification accuracy for the point cloud.

Test	Number of points	Correctly Classified	Accuracy
1	200	178	0.89
2	200	169	0.81
3	200	194	0.97
4	200	186	0.93
5	200	191	0.95
6	200	173	0.87
7	200	197	0.98
8	200	156	0.78
9	200	188	0.94
10	200	194	0.97
Average			**0.90**

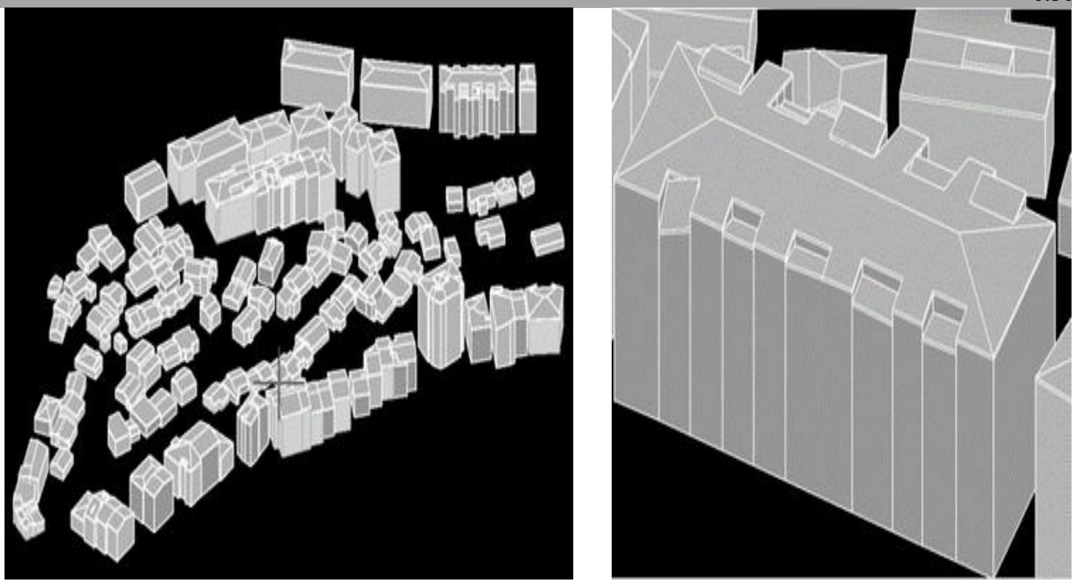


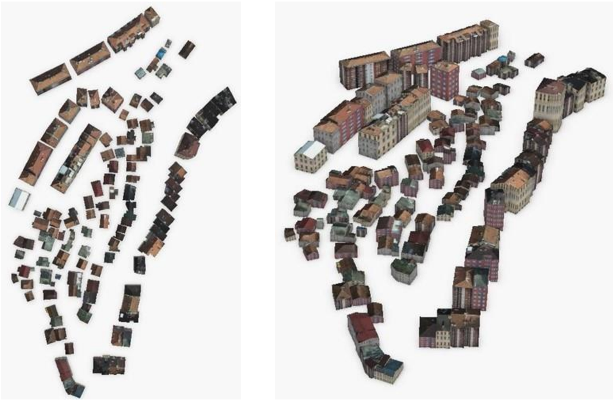
Fig. 5. Building vectorization.

Building Vectorization

The first step of the building vectorization process involves preparing the data source to be vectorized. Point clouds belonging to buildings are filtered from the classified point cloud. Then it is transferred to the software used. With the automatic vectorization tool, the boundaries of each building are converted into vector data. Finally, the accuracy and completeness of the vectorized building are checked. Based on these checks, it was observed that the automated process achieved an approximate accuracy of 85%. Generally, wrong vectors can occur at the boundaries of adjacent buildings. Areas that were incorrectly vectorized were manually corrected and compared against the reference data. The vectorized buildings are represented in Figure 5.

Building Texture Generation

Firstly, data importation involves transferring building geometry and texture data. Then, the building and texture data are merged, which entails combining the building geometry with the texture data. Next, the adjustment of texture coordinates takes place, where texture coordinates are set for applying textures to building surfaces. Then, texture processing and editing occur, involving modifications to the textures such as color adjustments, resizing, rotation, and other transformations (Figure 6). Lastly, the texture output transfers the processed texture data to the desired file format.



(a) (b)

Fig. 6. 3D model with building texture. (a) nadir view; (b) oblique view.

Integration with Geographic Information System (GIS)

After the provision of building textures, the data was transferred to the GIS environment for analysis (Figure 9). It became possible to access attribute data for each building, such as building number, number of floors, and coordinate information (Figure 7).

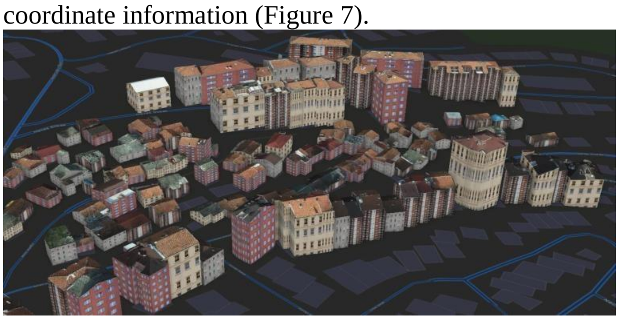


Fig. 7. 3D model after exporting to GIS environment.

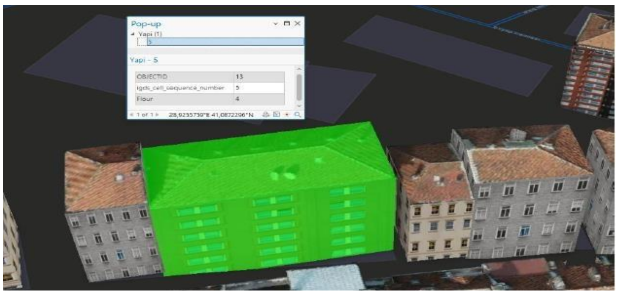


Fig. 8. Displaying attribute data in GIS environment.

Additionally, it is possible to make additions to the existing attribute data, such as the total number of units within the building, the number of registered individuals, individuals' information, physical characteristics of the structure, and more (Figure 8).

Conclusions

According to the results of this project, it has been possible to successfully extract 3D models of buildings using photogrammetry methods and transfer them to GIS. Dense point clouds have been generated from aerial images obtained through the use of drone technologies and processed to convert them into a vector format. Furthermore, texture processing has been applied to the buildings and they are suitable for GIS analysis.

The outcomes of this study contribute significantly to the field of remote sensing and GIS. Using drone technologies has accelerated the data collection process and improved data quality. The obtained dense point clouds and classified point clouds enable detailed analyses to be performed. These analyses can be utilized in various areas such as urban planning, land management, and structural deformation detection. The transfer of building models to GIS facilitates more accurate and efficient workflow execution. GIS plays a crucial role in the positioning, analysis, and management of buildings. The obtained building models assist in better planning and management of tasks, leading to increased efficiency and accuracy. In conclusion, this study successfully demonstrates the integration of remote sensing, photogrammetry, and GIS technologies. The obtained building models and analyses can provide significant contributions to various application areas and serve as inspiration for future research.

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