Gümüşhane University Journal of Science and Technology

GUFBD / *GUJS* (2026) 16(2): 350-361 doi: 10.17714/gumusfenbil.1856457 Research Article

Automatic detection of illegally constructed buildings using single epoch UAV data

Hayrettin ACAR*[1,2]

[1]*Karadeniz Technical University, Engineering Faculty, Department of Geomatics, 61080 Trabzon, Turkey*

[2]*AcarTech Software and Engineering Limited Company, 61080 Trabzon, Turkey*

• Received: 05.01.2026 • Accepted: 27.03.2026

Abstract

Rapid urbanization has led to an increase in construction activities, making it necessary that buildings are constructed in compliance with approved projects and current legal regulations. Buildings constructed in accordance with expert approved designs can maintain their structural integrity, particularly during natural disasters. This plays a significant role in ensuring the safety of life and property. In addition, buildings constructed based on approved projects provide important economic contributions to the public budget through taxation systems. In this context, the regular monitoring of urban areas and keeping spatial data up to date are of great importance for planning, inspection, and legal property management. This study aims to automatically detect illegal buildings that are constructed in violation of approved projects or are not legally permitted. Within this scope, building detection was carried out using three dimensional (3D) data obtained by Unmanned Aerial Vehicles (UAVs), and the results were analyzed with respect to cadastral data. As input data, a 3D point cloud produced from optical images acquired during single period UAV flights and 1:1000 scale base maps obtained from the Arsin Municipality of Trabzon were used. After eliminating vegetation and ground points, building roof points were automatically identified. Then, building polygons and roof points are analyzed in a three dimensional environment using a rule based approach to automatically identify illegal structures. The proposed approach successfully detected all the buildings that were manually identified by the municipality within the study area and additionally identified 7 extra illegal structures or building extensions. Preventive measures based on automatic illegal building detection may help reduce the number of people affected by natural disasters and prevent or reduce property related tax losses faced by public institutions.

Keywords: 3D Point cloud, Illegal building detection, UAV

1. Introduction

Cities are complex socio spatial systems that concentrate population, economic activities, and infrastructure. They are rapidly urbanizing while facing major challenges, including climate change, population growth, and resource limitations around the world. By integrating advanced technologies, smart cities can provide innovative solutions that foster smarter, greener, and more livable urban environments (Kaiser & Deb, 2025). In order to establish smart cities and ensure their sustainability, it is essential that buildings are constructed in a planned, safe, and controlled manner in compliance with approved projects and current technological standards. The construction of buildings in accordance with project standards and their regular monitoring give rise to various legal requirements. Illegal buildings that are constructed in violation of zoning plans, without proper design, without compliance with approved projects, or without obtaining the necessary permits not only contradict existing regulations but also fail to provide sufficient resistance to natural disasters such as earthquakes and fire hazards (Fan, 2024; Xu et al., 2024). These types of structures pose serious risks to life and property safety, while also negatively affecting the effectiveness of the taxation system and leading to losses in public revenues. For these reasons, the effective and systematic detection of illegal buildings is of great importance for achieving planned, safe, and sustainable urban development (Kaiser & Deb, 2025).

Illegal construction has emerged as a major problem, particularly in cities experiencing rapid population growth and unplanned urbanization (Kaiser & Deb, 2025). Such development often leads to spatial disorder within the urban fabric and causes significant infrastructure related problems. According to reports published in 2025, the total number of residential units registered within the Address Based Population Registration

* Hayrettin ACAR; h_acar@ktu.edu.tr

System was approximately 42.2 million (SBB, 2025). Following the zoning amnesty program, for which the application period ended on 15 June 2019, building registration certificates were issued for approximately 7.238 million illegal independent structures. These figures indicate that nearly 20% of the building stock in Türkiye consists of illegal constructions (SBB, 2025).

Under the current legal framework for Türkiye, the property taxation system is largely based on declarations made by property owners, which results in several deficiencies. Failure to submit declarations or the submission of incomplete declarations leads to significant tax losses and leakages within the property tax system. Within this context, the rapid and automatic detection of buildings subject to tax losses or unregistered values remains limited under existing practices. Pursuant to Article 102 of Law No. 6183, "A public receivable becomes time-barred if it is not collected within five years from the beginning of the calendar year following the calendar year in which its due date falls" (AATUHK, 1953). Accordingly, unpaid taxes related to detected illegal buildings can be claimed retroactively for a maximum period of five years from the date of declaration. Consequently, each period during which illegal structures or unreported taxable values remain undetected results in substantial financial losses for municipalities.

Although zoning plans introduce various regulations, such as building boundaries and floor numbers, the full and effective implementation of these plans in the field is challenging in many cities. Therefore, the continuous monitoring of settlement areas and their evaluation using up to date spatial data constitute a critical requirement for both spatial planning and legal property management. In this regard, the rapid detection and regular monitoring of illegal buildings are of great importance. The literature includes a wide range of approaches for detecting illegal buildings, based on different data types and methods. These approaches vary depending on the type of data used and the applied analysis techniques. Commonly used data sources in the literature include multitemporal (two period) satellite imagery, aerial photographs, and laser scanning (LiDAR) data (Varol et al., 2019). Methods developed for illegal building detection generally focus first on identifying building locations or temporal changes, followed by an analysis to determine whether these structures are illegal (Mehta et al., 2024).

Many studies focusing on building extraction have been reported in the literature. Many of these studies make direct use of LiDAR data, photogrammetric 3D point clouds, or remotely sensed imagery. Some studies rely solely on 3D point cloud data (Awrangjeb et al., 2014; Acar et al., 2019), while others perform building detection by integrating LiDAR data with orthophotos and multispectral imagery (red, green, blue, and near infrared) (Awrangjeb et al., 2010; Matikainen et al., 2010; Ullo et al., 2020; Wierzbicki et al., 2021). In addition, the literature includes studies in which building detection and change analysis are jointly evaluated using different data types. Some of these studies identify changes in buildings by analyzing 3D point clouds or remotely sensed imagery acquired at two different time periods (Khalili Moghadam et al., 2015; Xu et al., 2015; Du et al., 2016; Awrangjeb et al., 2018; Pang et al., 2018; Tran et al., 2018; Zhang et al., 2019; Zięba-Kulawik et al., 2020).

An examination of topic specific studies in the literature shows that Digital Elevation Model (DEM) datas are extensively used for detecting illegal buildings in conjunction with three dimensional changes in topography, vegetation cover and built up areas (Nebiker et al., 2014; Pang et al., 2014; Varol et al., 2019; Lyu et al., 2020). The studies that focus on evaluating DEM data from two different periods, generated either from historical stereo imagery or from previously produced 3D point clouds, to detect changes over time (Nebiker et al., 2014; Pang et al., 2014; Varol et al., 2019; Lyu et al., 2020). With recent technological advances, convolutional neural networks (CNNs) and deep learning models within the field of artificial intelligence have been widely applied to building extraction, change detection, and illegal building identification. Using pre trained datasets derived from LiDAR data, photogrammetric point clouds, Synthetic Aperture Radar (SAR), satellite imagery, and aerial photographs, it is possible to detect different classes (e.g., buildings and vegetation), analyze temporal changes, and identify illegal structures (Ji et al., 2019; Li et al., 2019; Pirasteh et al., 2019; Jiang et al., 2020; Du et al., 2024; Fan, 2024; Yildirim et al., 2024; Xu et al., 2024).

An examination of studies on building detection, change analysis, and illegal building identification indicates that most approaches rely on the direct use of bitemporal aerial photographs or 3D point clouds, or on evaluations based on derivative datasets (e.g., DEMs) generated from these sources. When two period LiDAR data or photogrammetric 3D point clouds with high positional accuracy are jointly analyzed, precise and automated detection of changes or illegal buildings is achievable. However, acquiring high resolution bitemporal data is not always feasible, particularly when analyses of older periods are required. In studies employing artificial intelligence or CNN based methods, the need for training data and the inability to achieve consistently high accuracy across all study areas constitute notable limitations.

In this study, unlike existing approaches in the literature, a contemporary single-period 3D point cloud dataset, together with base maps covering nearly the entire country, is employed as input data. This obviates the need for datasets from multiple time periods. As the initial period data comprise building polygon layers, analyses can be initiated from the production date of the base map. Moreover, since the proposed methodology is rule based, it offers the advantage of not requiring training data or multispectral imagery, in contrast to deep learning based approaches.

2. Methodology

In this study, illegal buildings are automatically detected by processing 3D point clouds generated from stereo images acquired through UAV flights together with relevant data obtained from public institutions (e.g., cadastral maps and land registry information). In the initial stage, buildings that are legally constructed but subject to property tax losses or unreported values particularly of concern to municipalities are automatically identified. Subsequently, compliant and noncompliant buildings are automatically distinguished. The input data used in the study consists of base maps produced as a standard for all settlement areas within the study region and dense 3D point clouds generated from high resolution stereo images acquired through a UAV flight over the same area. Through this approach, processes that are traditionally performed manually are carried out automatically and much more rapidly.

The 3D point clouds generated from stereo images acquired during UAV flights consist of millions of points, resulting in very large data volumes. Identifying and removing ground and vegetation classes from the main dataset significantly reduces the data volume. Reducing data size without compromising data quality is crucial for decreasing processing time and system requirements. The elimination of ground and vegetation points can reduce the data volume by nearly 50%. For ground point classification, the progressive TIN (Triangulated Irregular Network) densification algorithm, one of the most widely used methods, was employed (Axelsson, 2000). To identify vegetation points, the Visible Band Difference Vegetation Index (VDVI) was used (Xiaoqin et al., 2015). Using software developed in the MATLAB environment, vegetation points were detected in three dimensions based on the VDVI (equation 1). G refers to the green band, R represents the red band, and B defines the blue band in Equation 1.

$$VDVI = \frac{2G-R-B}{2G+R+B} \qquad (1)$$

After eliminating points belonging to the vegetation class to reduce the data volume, the process involved the automatic detection of building roof points. For the identification of building roof areas, the parameters proposed by Acar (2018) were refined and applied. Some of the parameters used in this study include: minimum building roof area (A) > 5 m²; point density on planar surfaces (d) > 100 points/m²; surfaces with a distance between planes (s) of less than 1 m are considered to belong to the same roof; for the generated photogrammetric point clouds, the distance of points above and below the planes to the plane (plane thickness, k) < ±10; the building width (a) to length (b) ratio (a/b) > 0.1; the height difference between the building roof and the ground (h) > 5 m; and the angle (α) between the plane normals and the zenith (α > 80°) (Acar, 2018). To enable the evaluation of the automatically detected building roof points using information such as base maps, property tax declarations, and land registry shares obtained from relevant institutions, a second algorithm was developed. This algorithm automatically selects information related to building layers from up to date base map data and assesses the consistency of declared property taxes, as well as automatically detects illegal buildings that are not present in the base maps but are subject to taxation. The workflow of the proposed method is illustrated in Figure 1.

Equations (2, 3 and 4) will be used to evaluate the overall accuracy of the detected buildings at the pixel level (Rutzinger et al., 2009; Shufelt, 1999). In these equations, Corr (Correctness) represents the matching rate in equation 2, Comp (Completeness) denotes the automatic detection rate in equation 3, and Quality (equation 3) indicates the overall quality percentage of the study.

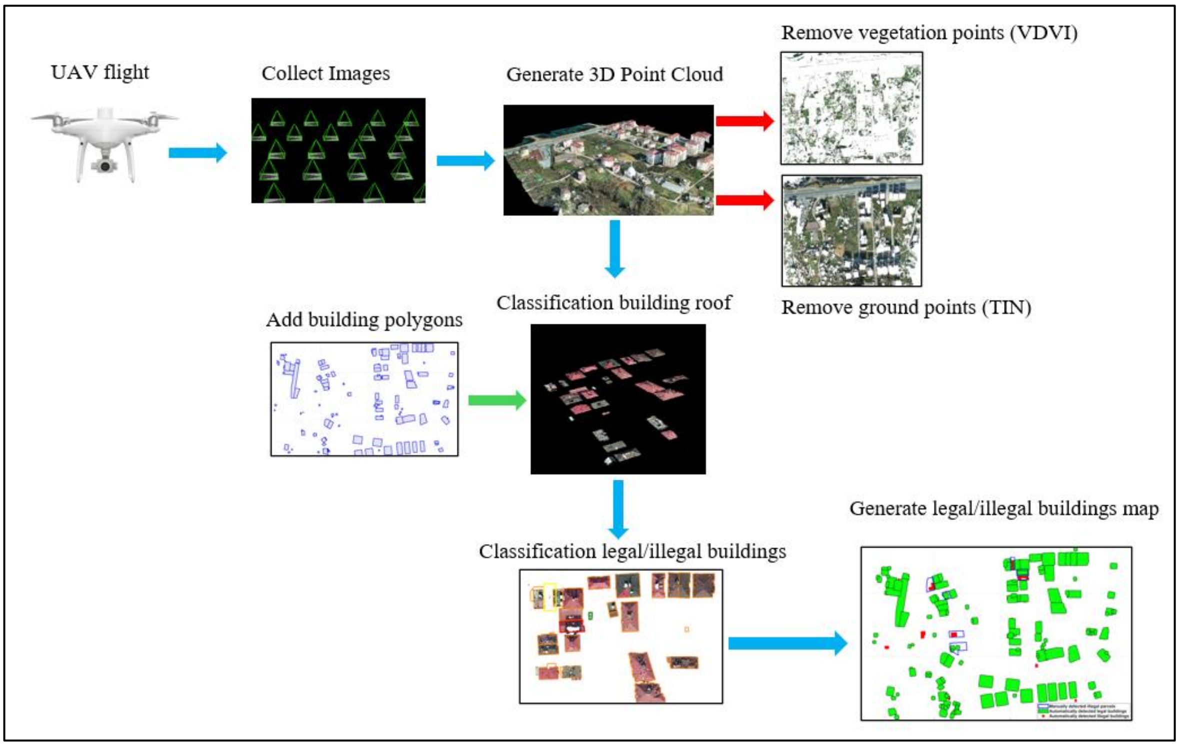

Figure 1. The workflow of the proposed method

TP refers to the matching value of features that are present in the reference image and are also correctly detected by the algorithm, FN represents objects that are present in the reference data but are not detected by the algorithm, and FP defines features that are detected by the algorithm but are not present in the reference data.

$$Corr = \frac{TP}{TP+FP} \tag{2}$$

$$Comp = \frac{TP}{TP+FN} \tag{3}$$

$$Quality = \frac{TP}{TP+FN+FP} \tag{4}$$

Quantitative evaluations regarding unauthorized structures were conducted based on a comparison between the number of structures manually identified by the municipality and the number of structures detected by the proposed method.

2.1. Study area

As the study area, a region in Arsin District of Trabzon Province, where illegal building detection had previously been carried out manually by the relevant municipality, was selected (Figure 2). The building stock in the study area comprises structures with heights varying between one and ten storeys. Roof types of buildings vary, including gable, hip, flat, shed and dormer shaped forms in the study area. In addition, the study area starts at sea level and rises to an elevation difference of 50 meters.

2.2. UAV and Data Specifications

In the study area, autonomous UAV flights were conducted at an altitude of 100 m using a DJI Phantom 4 RTK (20 MP, 1″ CMOS, 8.8/24 mm) platform available in the inventory of AcarTech Software & Engineering. The flights were carried out nearly 50 hectares with 70–80% image overlap and 330 images were obtained. Based on the acquired data, an orthophoto with an approximate ground sampling distance (GSD) of 2.7 cm and a photogrammetric dense 3D point cloud with a density of approximately 200 points/m² were generated with DJI Terra software with the highest iteration in 1 hour (Figure 3).

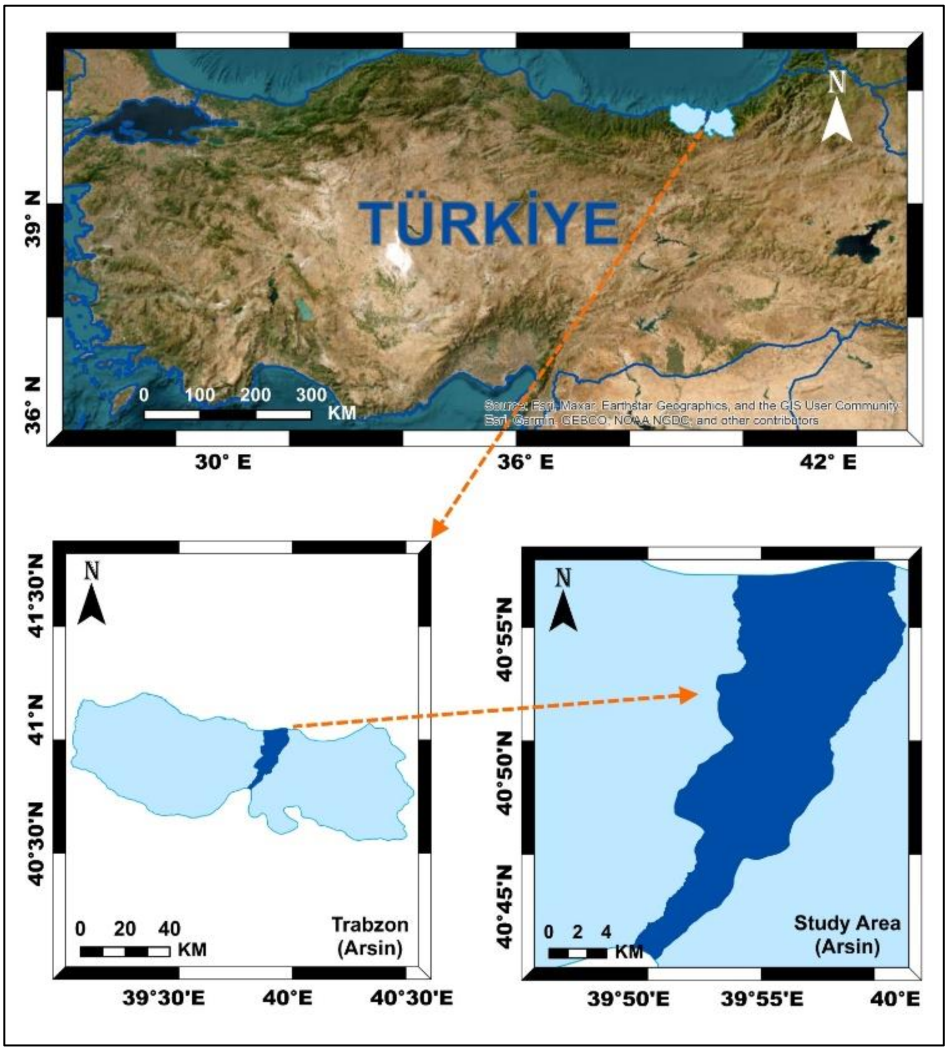

Figure 2. Study area

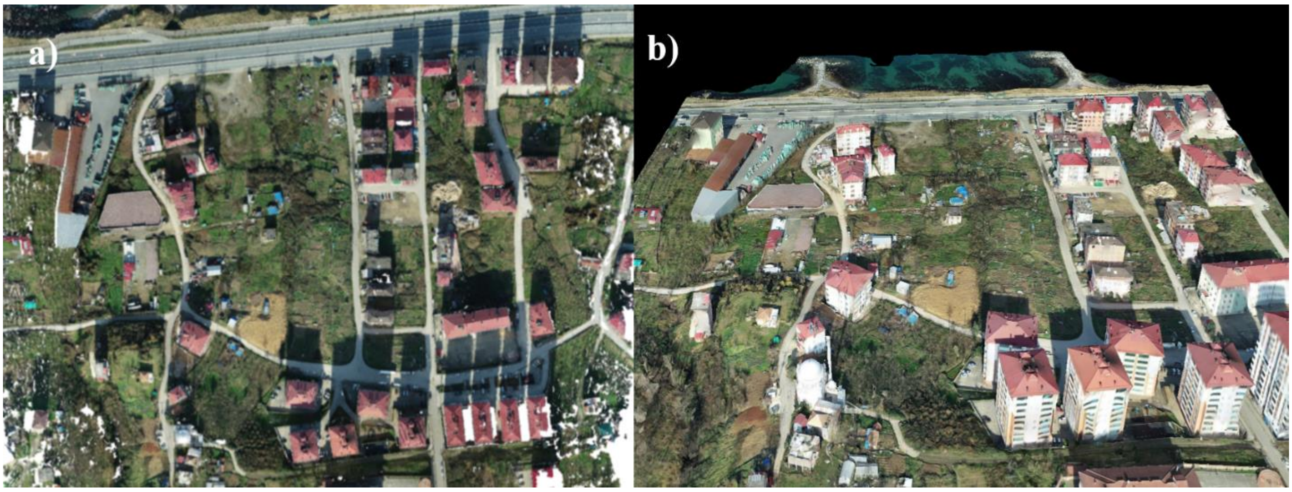

Figure 3. The dense 3D photogrammetric point cloud generated for the study area: a) 2D view, b) 3D view

The figures below present the base map of the study area obtained from Arsin Municipality (Figure 4) and the enlarged boundary polygons representing only the buildings (Figure 5).

For the analyses to be conducted, the building footprint in the cadastral base map were expanded by 50 cm from each boundary in order to prevent them from being affected by 3D points belonging to other features located near the building edges (trees, points belonging to adjacent buildings, facades, etc.).

Figure 4. The part of cadastral map for the study area

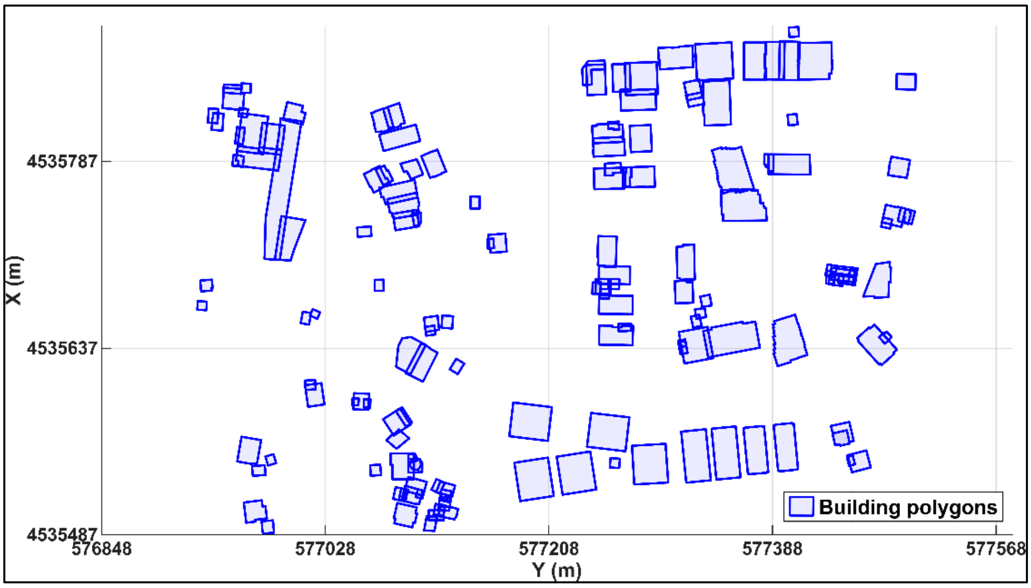

Figure 5. The enlarged building footprint polygons of the study area

3. Results and discussion

To reduce the data volume of the raw point cloud and eliminate unnecessary detail points, ground and vegetation points must be removed. Therefore, points belonging to the ground and vegetation classes were identified. Ground points extracted from the 3D point cloud of the study area were detected using the TIN (triangulated irregular network) based approach with LAStools software (Figure 6). Considering that the study area is slightly sloped, contains buildings, and is characterized by a dense photogrammetric point cloud, the parameters were determined as follows; step size 15, -extra_fine and -bulge 1.5.

Figure 6. The 3D ground points of the study area

For the automatic detection of vegetation points, an analysis based on the VDVI index (equation 1) was performed using software developed in the MATLAB environment. For each point, VDVI values were calculated within the range of −1 to +1, and points with values greater than 0.05 were classified as vegetation and removed from the raw dataset. The 3D vegetation points extracted from the point cloud of the study area are shown in Figure 7.

Figure 7. The 3D vegetation points of the study area

As the VDVI relies on visible spectral bands, it identifies many green and green toned points as vegetation. Consequently, some points belonging to building roofs with green or green like colors were also classified as vegetation. However, since the roof points exhibiting a cyan color were still present in the base dataset, roofs with that specific color could be successfully detected. After the detected vegetation and ground points were removed from the main 3D point cloud dataset, the data volume was reduced. Finally, the 3D points belonging to building roofs were automatically detected using the parameter conditions described in the methodology section (Figure 8).

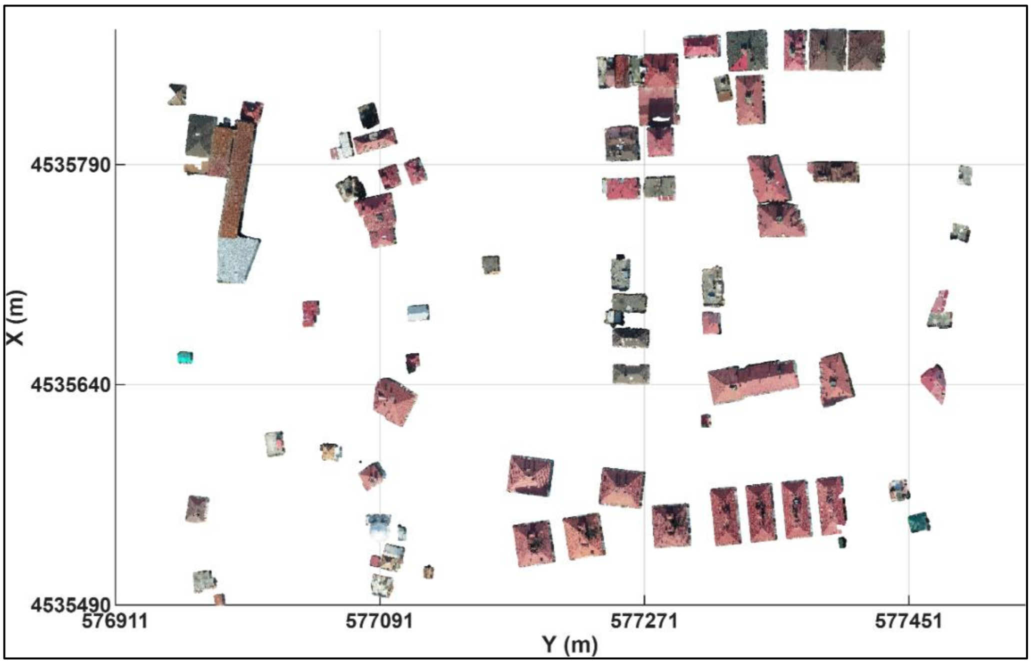

Figure 8. The building roof points detected from the 3D point cloud data

Accuracy assessment was conducted for the detected 3D building roof points and. To perform the accuracy analysis, the automatically detected building layers and the manually digitized building roof layers were converted into binary raster format (Figure 9).

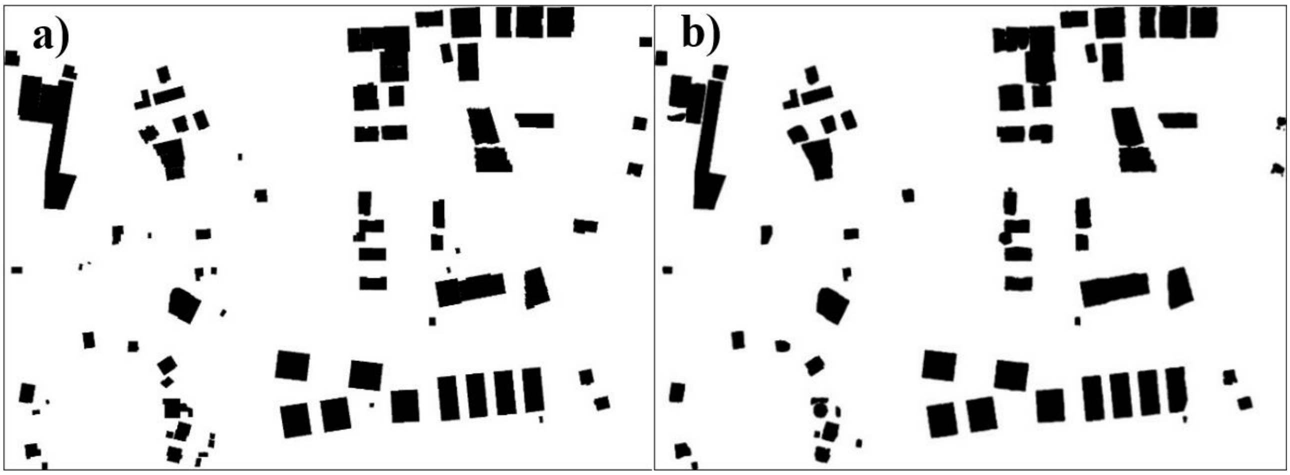

Figure 9. The accuracy assessment data: a) reference building roof layer for the study area, b) building layer automatically detected using the proposed method

Within the scope of this study, an accuracy assessment was conducted by comparing the reference data and the automatically generated data. For the detected buildings, the Corr, Comp, and Quality percentage values were calculated as 92.39%, 94.46%, and 87.64%, respectively. The study area includes a heterogeneous mix of very small and very large building roofs. The high number of small sized buildings in the study area, as well as gaps in the point cloud data particularly near the boundaries of the study area led to the incomplete detection of some building roofs. Despite these challenges, the achieved accuracy values exceeded 87%.

In the final stage, the largely automatically detected building roof points were evaluated together with the building boundary polygon layer obtained from relevant institutions. For each detected building roof, the centroid coordinates and outer boundaries were computed for further analysis using the developed algorithm. The centroid coordinates of the building polygons and the hundreds of automatically detected roof points located in close three-dimensional proximity to this centroid are evaluated jointly. As a result of this evaluation, two possible cases are identified. First, if the automatically detected roof points are located within the cadastral expanded building polygons and the elevation values of the points surrounding the centroid are close to the centroid's elevation value, the structure is classified as a legal building. Second, if the automatically detected roof points are not located within the cadastral building polygon and the elevation values of the points surrounding the centroid differ significantly, the structure is classified as an illegal building or an unauthorized building extension. By jointly analyzing the building attribute data (centroid coordinates and roof boundary polygons) and the building boundary polygons derived from base maps in a three dimensional (3D) environment, illegal buildings were automatically identified.

Some buildings include verandas that form enclosed spaces in the cadastral data of the study area. These verandas are therefore considered in the evaluation of illegal structures (Figure 10).

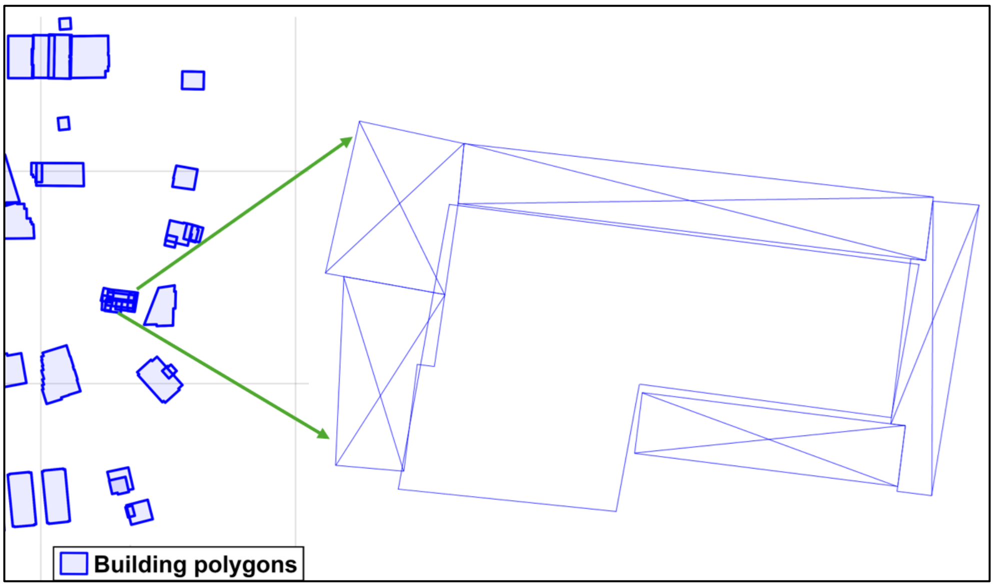

Figure 10. The appearance of a sample building with numerous verandas.

To remove points along building boundaries that do not belong to the buildings, the boundaries were expanded by 50 cm. Consequently, overlaps between some buildings and verandas can be observed in the final visual outputs (Figure 11).

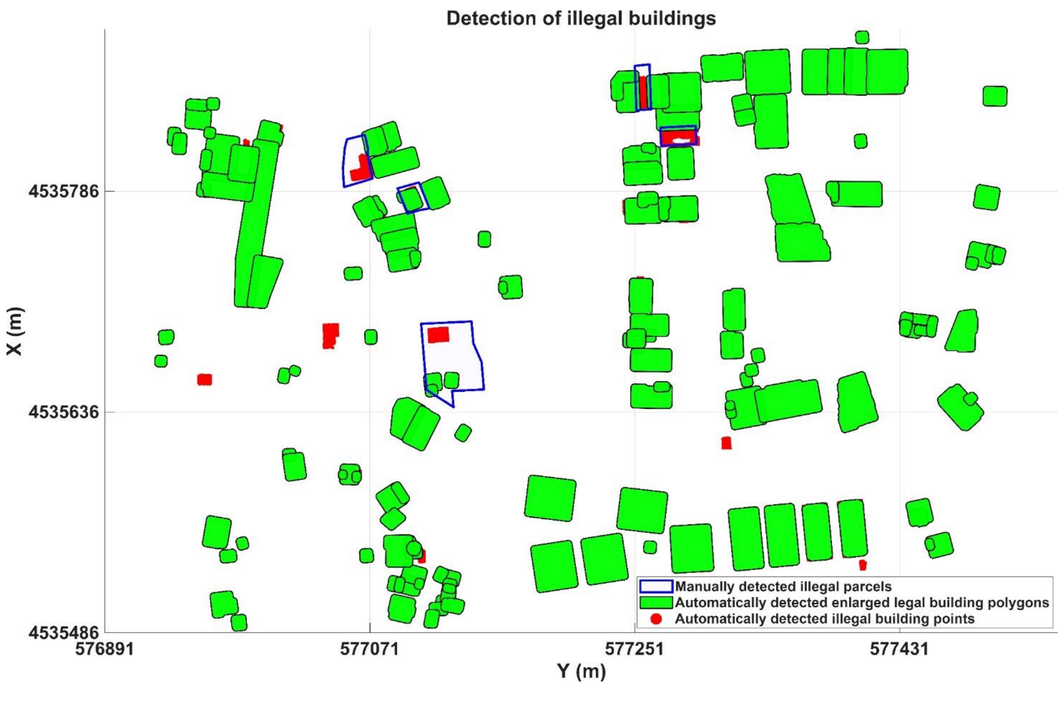

Figure 11. The visualization of automatically detected illegal structures (red), legal buildings (green), and parcels containing illegal buildings identified manually by the municipality (blue).

In the visualization presented in Figure 11, illegal buildings and building extensions are shown in red, legal buildings are shown in green, and the parcel boundaries representing problematic structures identified through manual inspections conducted by the municipality are shown in blue. As illustrated in the figure, the proposed method not only identifies structures located within areas previously detected by mobile inspection teams through manual surveys but also reveals additional problematic buildings that could not be identified during field inspections.

Analysis of the results shows that, the 5 parcels containing illegally constructed buildings identified manually. The algorithm correctly identified all parcels corresponding to these manually detected illegal buildings (5 illegal buildings) and additionally detected 7 more illegal structures or building extensions that were not captured during the manual assessment. The detected unauthorized structures may have been identified as such due to the cadastral base map not being up to date. Therefore, in order to verify the accuracy of the 7 additionally detected structures or building extensions, digital assessments and on site inspections should be conducted by the municipality in the same area. The duration of UAV data acquisition and the subsequent processing of the obtained data can vary depending on the size of the study area. For an area of 50 hectares, the flights and the analysis of the data were completed in approximately one day.

4. Conclusion

In this study, structures subject to property tax losses or unreported values were automatically detected using a 3D point cloud generated from images acquired through a single period UAV flight together with base map data obtained from relevant institutions. In the first stage, building roof points were automatically identified to enable the detection of illegal buildings. At this stage, the accuracy metrics Corr, Comp, and Quality were calculated as 92.39%, 94.46%, and 87.64%, respectively. Following the successful detection of building roof points, the process proceeded to the automatic identification of illegal buildings.

Processes that are traditionally carried out manually by mobile inspection teams in a two dimensional (2D) manner or using DEM data generated from two different time periods were completed in a much shorter time using the proposed three dimensional (3D) and fully automated approach. Furthermore, the proposed approach successfully detected 7 additional noncompliant buildings or building extensions in addition to the 5 illegal structures identified during manual field inspections carried out by municipal authorities.

For the proposed method to be successful, it is crucial that the building layers in the cadastral map are up to date, as this directly affects its performance. Unlike many existing approaches in the literature, the use of single period UAV data and existing building layers as input data does not require a predefined temporal starting point. As a result, illegal buildings constructed even decades earlier can be detected. By automating procedures that are currently performed manually by municipalities, the proposed method enables faster and more efficient implementation and is expected to contribute significantly to increased public revenues through the recovery of property tax losses.

Acknowledgement

This study was supported by the Scientific and Technological Research Council of Türkiye (TÜBİTAK) 1512 Entrepreneurship Support Program (BiGG). Also, this work was supported by AcarTech Software and Engineering Limited Company, Turkey to obtain date and analysis. Additionally, the author would like to thank Arsin Municipality for providing the cadastral data. And I sincerely thank the referees and journal editors for their careful review and valuable contributions.

Declaration of ethical code

The authors of this article declare that the materials and methods used in this study do not require ethical committee approval and/or legal-specific permission.

Conflicts of interest

The authors declare that there is no conflict of interest.

References

Acar, H. 2018. *Bina çatı noktalarının yüksek çözünürlüklü görüntülerden üretilen 3b nokta bulutu verileri ile otomatik tespit edilmesi ve gerçek ortofoto üretimi* [Doktora Tezi, Karadeniz Teknik Üniversitesi Fen Bilimleri Enstitüsü].

Acar, H., Karsli, F., Ozturk, M., & Dihkan, M. (2019). Automatic detection of building roofs from point clouds produced by the dense image matching technique. *International Journal of Remote Sensing*, 40(1), 138-155. https://doi.org/10.1080/01431161.2018.1508915

AATUHK-Amme Alacaklarının Tahsil Usulü Hakkında Kanun. (1953). *T.C. Resmi Gazete* (8469, 28 Temmuz 1953). https://www.resmigazete.gov.tr/arsiv/8469.pdf

Awrangjeb, M., Ravanbakhsh, M., & Fraser, C. S. (2010). Automatic detection of residential buildings using LIDAR data and multispectral imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, 65(5), 457-467. https://doi.org/10.1016/j.isprsjprs.2010.06.001

Awrangjeb, M., Lu, G., & Fraser, C. (2014). Automatic building extraction from LiDAR data covering complex urban scenes. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 40, 25-32. https://doi.org/10.5194/isprsarchives-xl-3-25-2014

Awrangjeb, M., Gilani, S. A. N., & Siddiqui, F. U. (2018). An effective data-driven method for 3-d building roof reconstruction and robust change detection. *Remote Sensing*, 10(10), 1512. https://doi.org/10.3390/rs10101512

Axelsson, P. (2000). DEM generation from laser scanner data using adaptive TIN models. *International Archives of Photogrammetry and Remote Sensing*, 33(B4/1; PART 4), 111-118.

Du, S., Zhang, Y., Qin, R., Yang, Z., Zou, Z., Tang, Y., & Fan, C. (2016). Building change detection using old aerial images and new LiDAR data. *Remote Sensing*, 8(12), 1030. https://doi.org/10.3390/rs8121030

Du, H., Huang, Z., & Zhang, Y. (2024). An optimized edge-focused siamese network for monitoring new illegal buildings using satellite images. *IEEE Transactions on Geoscience and Remote Sensing*, 62, 1-15. https://doi.org/10.1109/tgrs.2024.3379567

Fan, C. L. (2024). Using convolutional neural networks to identify illegal roofs from unmanned aerial vehicle images. *Architectural Engineering and Design Management*, 20(2), 390-410. https://doi.org/10.1080/17452007.2023.2244949

Ji, S., Shen, Y., Lu, M., & Zhang, Y. (2019). Building instance change detection from large-scale aerial images using convolutional neural networks and simulated samples. *Remote Sensing*, 11(11), 1343. https://doi.org/10.3390/rs11111343

Jiang, H., Hu, X., Li, K., Zhang, J., Gong, J., & Zhang, M. (2020). PGA-SiamNet: Pyramid feature-based attention-guided Siamese network for remote sensing orthoimagery building change detection. *Remote Sensing*, 12(3), 484. https://doi.org/10.3390/rs12030484

Kaiser, Z. A., & Deb, A. (2025). Sustainable smart city and Sustainable Development Goals (SDGs): a review. *Regional Sustainability*, *6*(1), 100193. https://doi.org/10.1016/j.regsus.2025.100193

Khalili Moghadam, N., Delavar, M. R., & Hanachee, P. (2015). Automatic urban illegal building detection using multi-temporal satellite images and geospatial information systems. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 40, 387-393. https://doi.org/10.5194/isprsarchives-xl-1-w5-387-2015

Lyu, X., Hao, M., & Shi, W. (2020). Building change detection using a shape context similarity model for lidar data. *ISPRS International Journal of Geo-Information*, 9(11), 678. https://doi.org/10.3390/ijgi9110678

Li, L., Wang, C., Zhang, H., Zhang, B., & Wu, F. (2019). Urban building change detection in SAR images using combined differential image and residual U-Net network. *Remote Sensing*, 11(9), 1091. https://doi.org/10.3390/rs11091091

Matikainen, L., Hyyppä, J., Ahokas, E., Markelin, L., & Kaartinen, H. (2010). Automatic detection of buildings and changes in buildings for updating of maps. *Remote Sensing*, 2(5), 1217-1248. https://doi.org/10.3390/rs2051217

Mehta, Y., Baz, A., & Patel, S. K. (2024). Semantic segmentation of optical satellite images for the illegal construction detection using transfer learning. *Results in Engineering*, *24*, 103383. https://doi.org/10.1016/j.rineng.2024.103383

Nebiker, S., Lack, N., & Deuber, M. (2014). Building change detection from historical aerial photographs using dense image matching and object-based image analysis. *Remote Sensing*, 6(9), 8310-8336. https://doi.org/10.3390/rs6098310

Pang, S., Hu, X., Wang, Z., & Lu, Y. (2014). Object-based analysis of airborne LiDAR data for building change detection. *Remote Sensing*, 6(11), 10733-10749. https://doi.org/10.3390/rs61110733

Pang, S., Hu, X., Cai, Z., Gong, J., & Zhang, M. (2018). Building change detection from bi-temporal dense-matching point clouds and aerial images. *Sensors*, 18(4), 966. https://doi.org/10.3390/s18040966

Pirasteh, S., Rashidi, P., Rastiveis, H., Huang, S., Zhu, Q., Liu, G., ... & Seydipour, E. (2019). Developing an algorithm for buildings extraction and determining changes from airborne LiDAR and comparing with R-CNN method from drone images. *Remote Sensing*, 11(11), 1272. https://doi.org/10.3390/rs11111272

Rutzinger, M., Rottensteiner, F., & Pfeifer, N. (2009). A comparison of evaluation techniques for building extraction from airborne laser scanning. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2(1), 11-20. https://doi.org/10.1109/jstars.2009.2012488

SBB-T.C. Cumhurbaşkanlığı Strateji ve Bütçe başkanlığı. (2025 December 18). https://www.sbb.gov.tr/wp-content/uploads/2024/11/2025-Yili-Cumhurbaskanligi-Yillik-Programi-05112024.pdf

Shufelt, J. A., (1999). Performance evaluation and analysis of monocular building extraction from aerial imagery. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 21(4), 311-326. https://doi.org/10.1109/34.761262

Tran, T. H. G., Ressl, C., & Pfeifer, N. (2018). Integrated change detection and classification in urban areas based on airborne laser scanning point clouds. *Sensors*, 18(2), 448. https://doi.org/10.3390/s18020448

Ullo, S. L., Zarro, C., Wojtowicz, K., Meoli, G., & Focareta, M. (2020). LiDAR-based system and optical VHR data for building detection and mapping. *Sensors*, 20(5), 1285. https://doi.org/10.3390/s20051285

Wierzbicki, D., Matuk, O., & Bielecka, E. (2021). Polish cadastre modernization with remotely extracted buildings from high-resolution aerial orthoimagery and airborne LiDAR. *Remote Sensing*, 13(4), 611. https://doi.org/10.3390/rs13040611

Xiaoqin, W., Miaomiao, W., Shaoqiang, W., and Yundong, W. (2015). Extraction of vegetation information from visible unmanned aerial vehicle images. *Transactions of the Chinese Society of Agricultural Engineering*, 31(5).

Xu, C., Ye, Z., Mei, L., Yu, H., Liu, J., Yalikun, Y., ... & Lei, C. (2024). Hybrid attention-aware transformer network collaborative multiscale feature alignment for building change detection. *IEEE Transactions on Instrumentation and Measurement*, 73, 1-14. https://doi.org/10.1109/tim.2024.3373089

Xu, S., Vosselman, G., & Oude Elberink, S. (2015). Detection and classification of changes in buildings from airborne laser scanning data. *Remote sensing*, 7(12), 17051-17076. https://doi.org/10.3390/rs71215867

Varol, B., Yılmaz, E. Ö., Maktav, D., Bayburt, S., & Gürdal, S. (2019). Detection of illegal constructions in urban cities: Comparing LIDAR data and stereo KOMPSAT-3 images with development plans. *European Journal of Remote Sensing*, 52(1), 335-344. https://doi.org/10.1080/22797254.2019.1604082

Yildirim, F. S., Karsli, F., Bahadir, M., & Yildirim, M. (2024). FwSVM-Net: A novel deep learning-based automatic building extraction from aerial images. *Journal of Building Engineering*, 96, 110473. https://doi.org/10.1016/j.jobe.2024.110473

Zhang, Z., Vosselman, G., Gerke, M., Persello, C., Tuia, D., & Yang, M. Y. (2019). Detecting building changes between airborne laser scanning and photogrammetric data. *Remote sensing*, 11(20), 2417. https://doi.org/10.3390/rs11202417

Zięba-Kulawik, K., Skoczylas, K., Mustafa, A., Wężyk, P., Gerber, P., Teller, J., & Omrani, H. (2020). Spatiotemporal changes in 3D building density with LiDAR and GEOBIA: A city-level analysis. *Remote Sensing*, 12(21), 3668. https://doi.org/10.3390/rs12213668