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Estimating Heights of Buildings for Construction and Monitoring Changes Using Drone Imagery

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Abstract

In today's world, many applications require geolocated building information with accurate heights. Building heights can be used for various purposes, including estimating the number of floors, inspecting buildings that violate approved plans, assessing rental income, determining the number of people living in a place, and evaluating energy consumption. Obtaining accurate and reliable building heights has been a challenge. This study aimed to demonstrate how building heights can be estimated accurately using drone imagery. The methodology was tested in Juja sub-county, Kiambu County, Kenya. Drone image data was used to generate Digital Terrain Model (DTM), Digital Surface Model (DSM), and normalized Digital Surface Model (nDSM) products, which aided in estimating building heights and floor numbers. The heights of buildings from drone data and ground survey methods were compared, yielding a correlation of 0.99. Similarly, a comparison between the number of floors from drone data and field observations showed a correlation of 0.92. Validation was also performed for the 2D aspects by comparing the quality of the digitized orthophoto with the vectorized and regularized buildings extracted from the orthophoto through unsupervised classification. The intersection matching was 82%, which falls within the acceptable range for accuracy assessment. These results proved that drone data can sufficiently provide accurate building heights, saving human resources, money, and time. Thus, applications requiring regular monitoring of building heights, especially during construction stages to determine compliance with building regulations may consider the 3D reconstruction of overlapping aerial drone images.

Keywords

Drone Image Data, Digital Terrain Model (DTM), Digital Surface Model (DSM), Normalized Digital Surface Model (nDSM), Building Heights and Floor Numbers

1. Introduction

Accurately determined building heights can be applied in many day-to-day activities. These heights can help estimate the number of building floors, assess the population of a given area, and support the provision of utility services such as calculating electricity usage, determining water consumption, and planning sewer system requirements. Due to land scarcity and the high cost of land, most landowners in Kenya prefer high-rise buildings. When many people live in the same location as a result of high-rise developments, they generate a micro-economy, which in turn creates demand for additional services, businesses, and employment opportunities. This increases the need for housing space and, consequently, for more high-rise buildings. Globally, the percentage of the total population living in urban areas has risen rapidly from 12% in 1900 to 30% in 1950, and to 56% in 2020. This figure is projected to exceed 65% by 2050 [1]. In the developing world, rapid urban expansion, driven by increasing rural-to-urban migration, has contributed to the rise of mega-cities. In Africa, both population growth and migration from rural areas have played a significant role in shaping urban development [2]. This rapid urbanization outpaces the development of housing, infrastructure, and services, leading to a rise in slums or slum-like conditions. Sustainable development cannot be achieved without significantly transforming the way urban spaces are built and managed. According to SDG Goal 11 of the United Nations, making cities safe and sustainable involves ensuring access to safe and affordable housing, upgrading slum settlements, investing in public transport, creating green spaces, and improving urban planning and management in a participatory and inclusive manner [3]. In the process of slum upgrading, technology assists planners in identifying safe zones for construction and avoiding flood-prone areas. If a specific building height has been designated, drones can effectively monitor compliance and flag structures that violate the set standards.

Drone technology has increasingly become a preferred method for estimating building heights and floor numbers due to its efficiency in data generation and processing. [4] utilized Digital Surface Models (DSM) and Digital Terrain Models (DTM) derived from LiDAR to produce a normalized DSM layer, which was then used to detect the shapes of vegetation and buildings. By applying multiple thresholds, their model effectively handled buildings with significant height variations, such as high-rise complexes commonly found in urban areas. Traditionally, determining building heights has been challenging, as ground survey methods are time-consuming and require substantial manpower—particularly for applications that demand regular monitoring for service provision. Very high-resolution (VHR) imagery offers an alternative by estimating building heights through the analysis of cast shadows in single optical images [5]. However, this approach becomes problematic in densely built environments, where shadows may be distorted or overlap. Moreover, such methods are often costly when applied to large-scale and continuous monitoring efforts.

A limited number of studies have demonstrated that estimating the floor count of specific buildings is crucial for identifying violations of approved building plans. Such violations can contribute to disaster risk, as newly constructed buildings may exert more structural load than originally anticipated. This added strain can compromise infrastructure, resulting in building collapses, loss of life and property, disruption of income, interference with communication networks, and legal disputes—particularly in cases where zoning regulations have been breached. Instances of building collapse due to non-compliance with approved plans have been reported in the suburbs of Nairobi [6].

2. Materials and Methods

2.1. Study Area

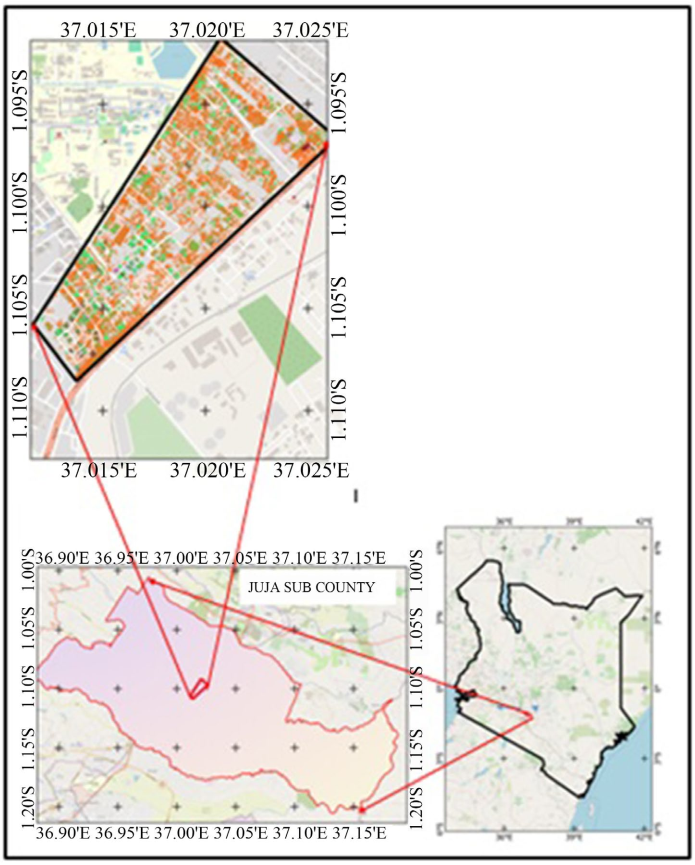

Figure 1. Study area.

The study area is Juja Town, located in Juja Sub-County within Kiambu County, covering approximately 114 hectares as shown in **Figure 1**. It lies between Jomo Kenyatta University of Agriculture and Technology (JKUAT) and the Thika Super Highway. The majority of residents in this area are students and JKUAT employees, as the town has evolved into a university-centered community. Consequently, there is a high demand for accommodation, necessitating the development of high-rise buildings to house the student population, which is estimated at approximately 35,000. The proximity of housing facilities to the university influences rental prices, motivating property owners to construct high-rise buildings to maximize profits and savings. Additionally, other stakeholders offer goods and services to the university community, many of whom reside within Juja. This dynamic has led to an increase in land prices and attracted serious investors seeking to capitalize on the vibrant housing demand.

2.2. Methodology

Figure 2 summarizes the methodological steps followed to estimate building heights and floor numbers. Data was acquired using the DJI Zenmuse L1, an integrated aerial LiDAR solution that combines a LiDAR module, a 1-inch RGB camera, and a high-accuracy IMU for 3D data acquisition and reconstruction, mounted on the DJI Matrice 300 RTK. An application was made to the Kenya Civil Aviation Authority (KCAA) and permission was granted. Weather patterns were observed and found to be conducive. Potential hazards were checked; it was realized that the area had many trees and tall buildings. The problem was solved by locating the operator on the roof of a building to monitor the movement of the drone. The captured data was processed using Open Drone Mapping (ODM) software [7]. Key steps included Structure from Motion (SfM), which applies overlapping photogrammetric techniques to estimate 3D objects from image sequences, followed by Multi-View Stereo, which reconstructs 3D models from multiple overlapping image pairs. Meshing was then performed to connect data points, and texturing added color to the mesh. The data was georeferenced to align the imagery with its actual location on the Earth's surface.

A Digital Surface Model (DSM) was generated by extracting the maximum elevation values from the point cloud, capturing both terrain and structures such as buildings and trees. A Digital Terrain Model (DTM) was derived from points classified as ground. The difference between DSM and DTM produced the Normalized Digital Surface Model (nDSM), which represents all features above ground—such as buildings, trees, and vehicles. To isolate buildings, additional processing was applied. Building floor numbers were estimated by dividing the derived building heights by 3 meters.

The nDSM represents above-ground features. Buildings were separated from other elements, and their heights were divided by three to determine the number of floors (**Figure 3(c)**). To accommodate the computer's processing capacity, the data was split into five segments (**Figure 4**).

Unsupervised classification was performed using the ISODATA algorithm, which generated four classes: vegetation, buildings, roads, and ground. Buildings were subsequently isolated from the other classes. Classification parameters included the number of classes, maximum iterations, maximum standard deviation, minimum distance to combine, minimum cluster cells, and minimum distance for chaining. The algorithm used an iterative approach involving trial-and-error procedures to compute class groupings. After each iteration, new class centers were calculated by determining the mean vector for each class. The process continued until minimal changes occurred in class center locations or the maximum number of iterations was reached.

The ground survey utilized Real-Time Kinematic (RTK) GNSS receivers to capture control point coordinates (X, Y, Z). While the Total Station was used for height observations, a reflector/prism and staff supported conventional prism-based measurements. The reflectorless mode of the Total Station was applied for inaccessible roof edges or elevated points, along with a tripod and supporting accessories. The RTK GNSS (Base and Rover) was used to observe control points in XYZ, with repeated measurements taken to confirm accuracy. These control coordinates served as reference points for Total Station setups. Building heights were determined by subtracting the base elevation from the roof elevation. During data processing, Total Station observations were reduced to elevation values (Z), and building heights were computed using the formula: **Building Height = Elevation (Roof) − Elevation (Base)**. Consistency between prism-based and reflectorless observations was checked, and the results were compiled into a table containing building ID, base elevation, roof elevation, and computed heights. The building heights obtained from the field survey were then compared with those derived from drone data. Floor numbers were also compared between field observations and those calculated from drone-based height measurements

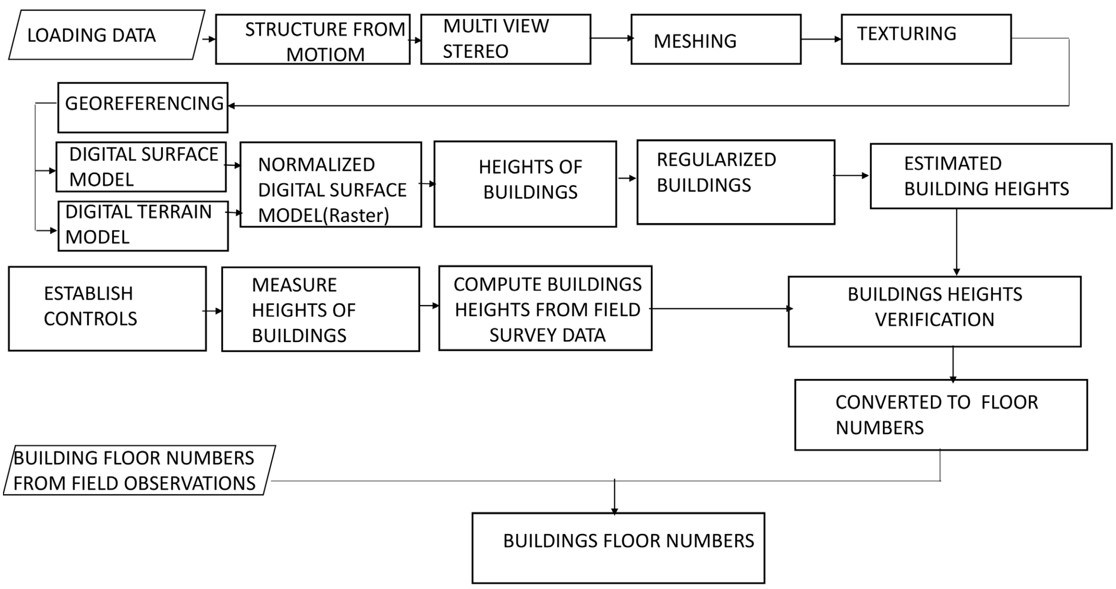

Figure 2. Methodology flow chart.

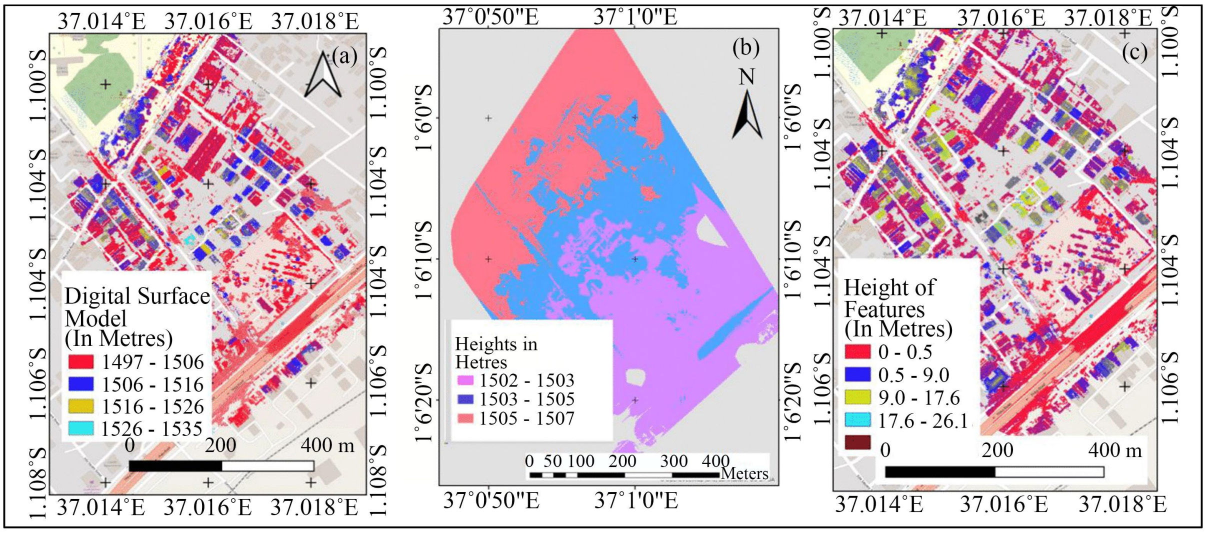

Figure 3. (a) Digital Surface Model (DSM), (b) Digital Terrain Model (DTM) and (c) normalized Digital Surface Model (nDSM).

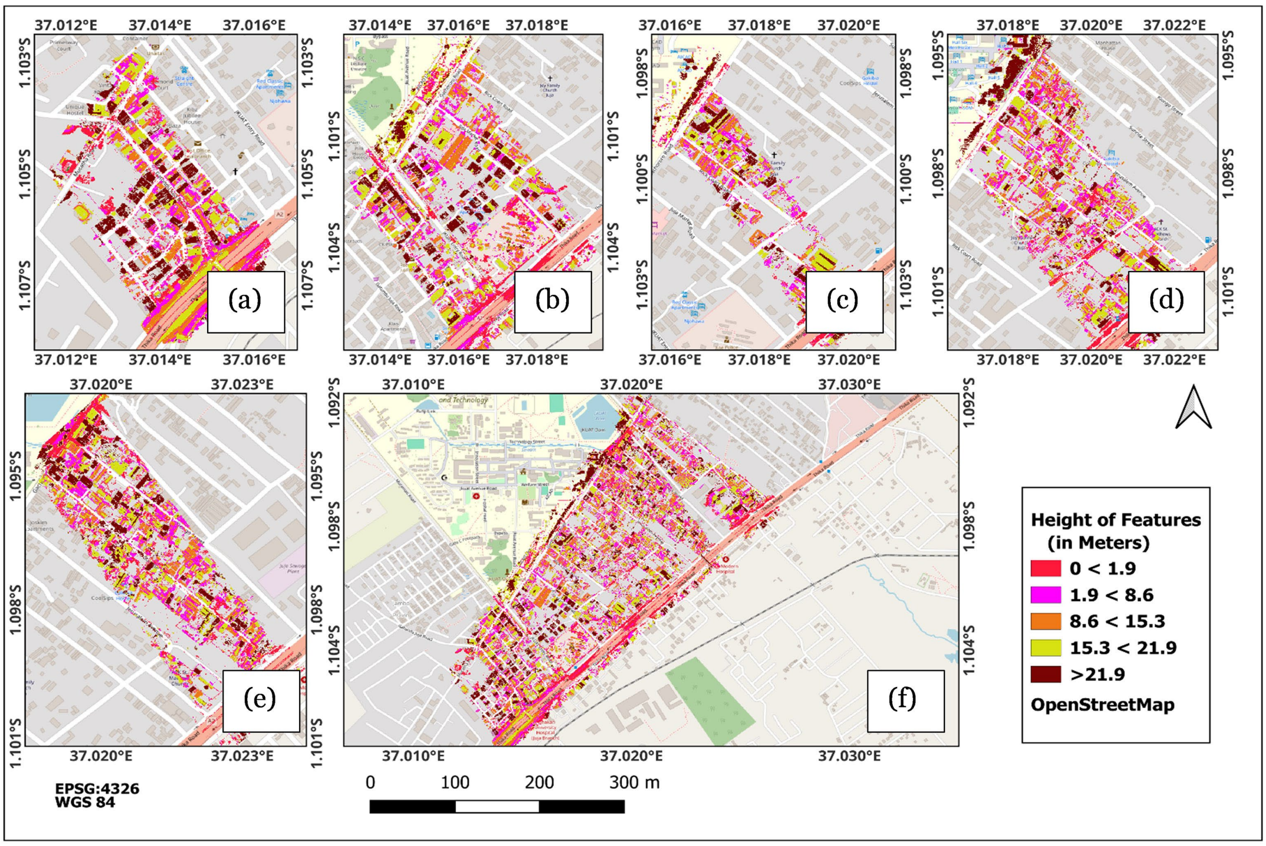

Figure 4. (a)-(d) Sub-sections of the nDSM, (e) combined sub-sections.

The estimation of floor numbers was obtained by applying a ratio of three to the generated building heights. This study adopted a floor height of 3 meters, considering that most buildings were residential, which are typically estimated at heights ranging from 2.7 to 3 meters according to various studies. For instance,

[8] used a value of 2.8 meters, which falls within the recommended range of 2.6 - 2.9 meters depending on geographical location in the UK. The estimated floor numbers from this study aligned well with those observed through field verification of selected buildings in the study area.

3. Results

The results of this study, derived from drone data as outlined in the methodology section, are presented here. Figure 5(a) displays the building height distribution, while Figure 5(b) illustrates the corresponding building floor numbers. The heights of above-ground features were captured within a range of 2 to 34 meters, and the processing steps ultimately produced a layer containing buildings. The information extracted from Figure 5(a) and Figure 5(b) is summarized in Table 1 and Table 2 respectively.

Table 1. Heights of buildings.

Heights of Buildings	No. of Buildings	%
2.0 <= 7.8	1478	72.7
7.8 < 13.6	298	14.7
13.6 < 19.4	206	10.1
<25.2	50	2.5
>25.2	2	0.1
Total	**2034**	**100**

Table 2. Floor numbers.

Floor numbers	No. of Buildings	%
1 <= 3	1680	79.6
3 < 5	280	13.8
5 < 6	82	4.0
6 < 8	50	2.5
>8	2	0.1
Total	**2034**	**100**

The estimated building floor numbers matched the actual floor counts with an accuracy of over 92%. Detailed validation results are provided in the discussion section. In some cases, buildings had matching floor counts (Figure 6(a)) but differing heights as estimated from drone data (Figure 6(b)). In other instances, roof structures were interpreted as additional floors in the drone-derived data. For example, Figure 7(a) presents the building in question, with a zoomed view of the roof portion shown in Figure 7(b). Figure 7(c) displays the estimated floor numbers from drone data, using color to indicate variations. The cyan color corresponds to the actual number of mapped floors (six), while the blue color indicates an extra floor due to roof provision (seven floors). A neighboring wing of the same building, which has seven actual floors, shows an additional roof floor in yellow, representing eight floors.

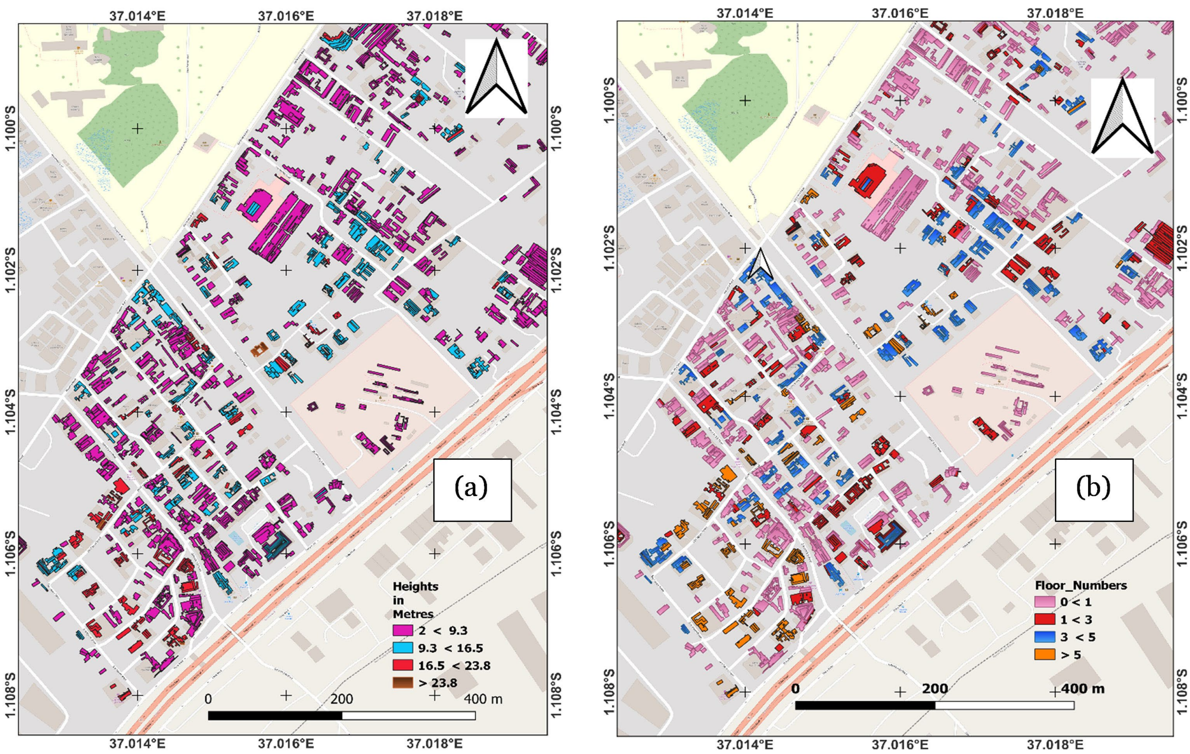

Figure 5. (a) Height of buildings and (b) number of floors.

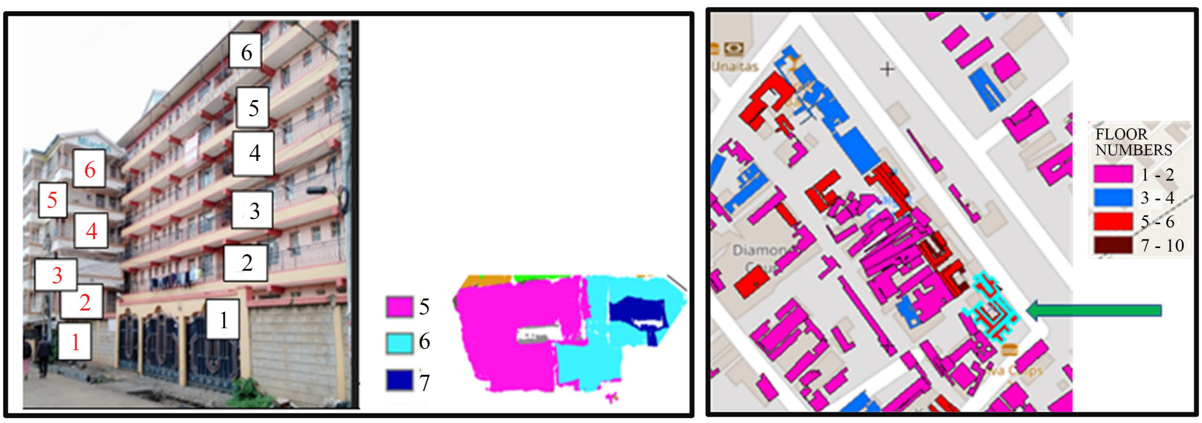

Figure 6. (a) Buildings with same floor numbers, (b) floor numbers from drone data and (c) zoomed section highlighted in cyan colour, where the green arrow points at on the map the location of the buildings.

Discrepancies in estimated floor numbers were also observed in buildings with elevated water storage structures. For example, Figure 8(a) shows a photo of the actual building with six floors, while Figure 8(b) presents the drone-derived floor count, which includes the water tank provision as an additional floor resulting in a total of seven floors. In contrast, Figure 9 demonstrates strong agreement between drone data and field observations. The side view in Figure 9(a) and the front view in Figure 9(b) both confirm the correct number of floors, as reflected in the drone-based floor count shown in Figure 9(c). Another variation is illustrated in Figure 10(a) and Figure 10(b), where the building appears to have an extra floor above the sixth. In the color-coded scheme shown in Figure 10(c), the actual six floors are represented in cyan, while the additional floor is not been captured as a separate level.

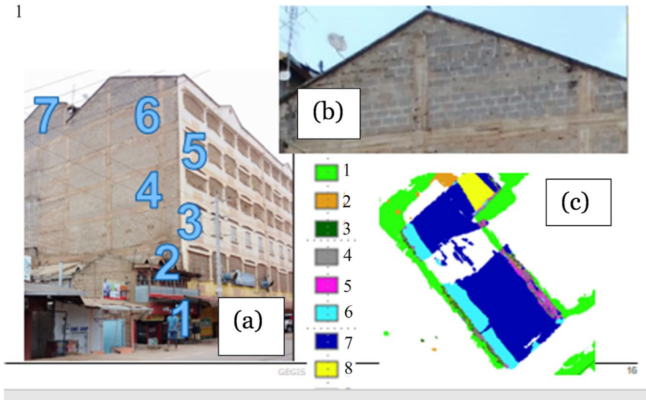

Figure 7. (a) A photo showing the actual floor numbers, (b) a photo of the zoomed roof height, (c) the floor heights from drone data.

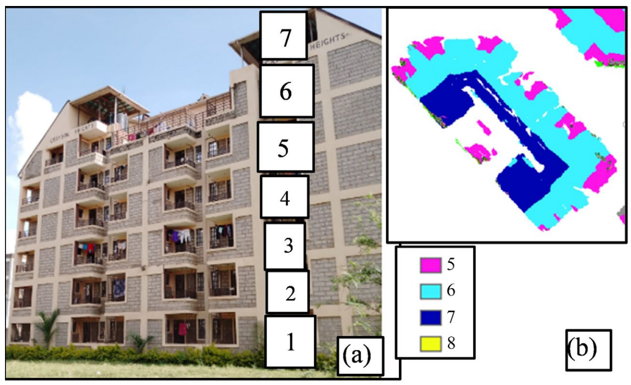

Figure 8. (a) Photo showing building with water tanks provision, (b) floor numbers as captured by drone data representing the building.

Similarly, Figure 11(a) shows the side view of a building, while Figure 11(b) presents the front view. Although the building has eight actual floors, the drone-estimated data in Figure 11(c) identifies only seven floors, represented in blue. A similar discrepancy is observed in Figure 12. The building shown in Figure 12(a) includes a 1.5-meter wall above the seventh floor, which ideally should have been recognized as an additional floor in the drone data. However, as seen in Figure 12(c), the structure is still represented with seven floors in blue, indicating that the wall height was not captured as a separate level. This oversight results in an underestimation of the total floor count, which should have been eight. Figure 13 reflects a comparable situation, where a similar wall structure leads to the same undercount in the drone-based floor estimation. Figure 13(a) shows seven floors Figure 13(b) shows the extended floor zoomed in, from the zoomed it seems to make an extra floor. The colour scheme shows seven floors (**Figure 13(c)**). The height above seventh floor could be explained by at times the floor height deferring hence the extra height is not detected.

Figure 9. (a) Side view of a sampled Building showing five floors, (b) front of view of the sampled building which is seen to be six floors, (c) estimated floors numbers.

Figure 10. (a) Building shows has six floors, (b) a zoomed section, (c) estimated floor numbers from drone data.

Figure 11. (a) Side view of the building, (b) front view of the building, (c) floor numbers as estimated from the drone data.

Figure 12. (a) shows a sampled building with both front and side view **Figure 12(b)** the zoomed building on the side view section of **Figure 12(a)** shows extra floor, **Figure 12(c)** shows the estimated floor numbers from the drone.

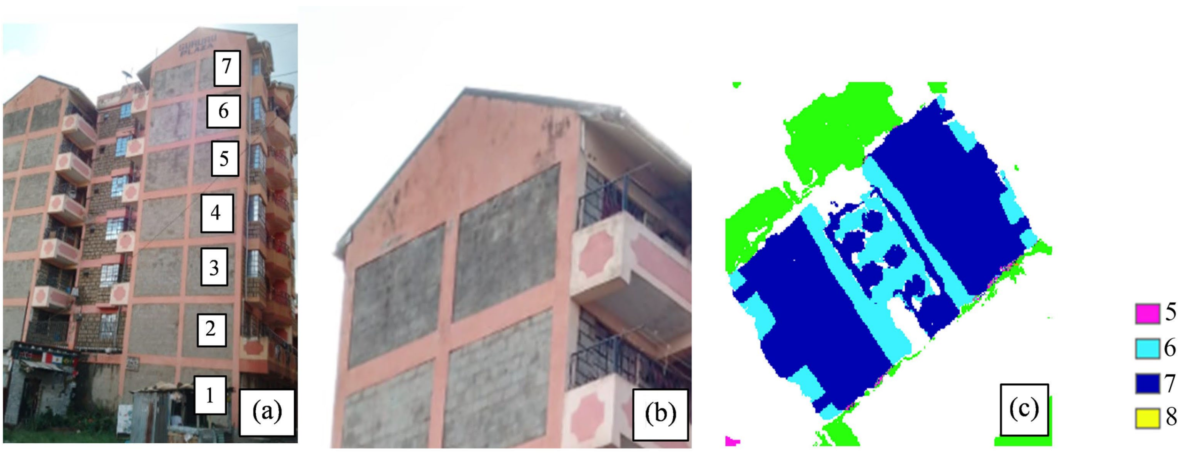

Figure 13. (a) Building with seven floors, (b) zoomed side view of the top of the building, (c) the colour on floor numbers indicate the building to have a maximum of seven.

4. Discussions

This study utilized DSM, DTM, and nDSM to map building heights and estimate floor numbers, as illustrated in **Figure 3**. The study area was relatively flat, with elevation variations ranging from 1514 to 1522 meters above sea level. Therefore, slope correction—typically recommended for sloped terrains [9] was deemed unnecessary. In the validation of the floor numbers a comparison was made between drone-derived floor numbers and field observations of floor numbers showing strong agreement, with an R^2 of 0.92 (**Figure 14**). While LiDAR-derived height estimates from drone data, a ground survey was conducted, as shown in **Figure 15**. A comparison between drone-based height measurements and those obtained through ground surveying techniques revealed a strong correlation of 0.99. This finding aligns with [10], who reported an accuracy of 0.94 for nDSM when compared to field survey data.

This study adopted a standard floor height of 3 meters for estimating building floor numbers. According to the 2024 National Building Code [11], typical floor heights are listed as 3 meters or more, with a minimum allowable projection height of 2.4 meters. Specifically, page 93 states that any room intended for habitation or office use must have a minimum height of 2.4 meters measured from floor to ceiling. Where no ceiling exists, the height is measured from the floor to the underside of the beam [11]. Field surveys conducted in the study area confirmed that actual floor heights varied between 2.7 and 3 meters.

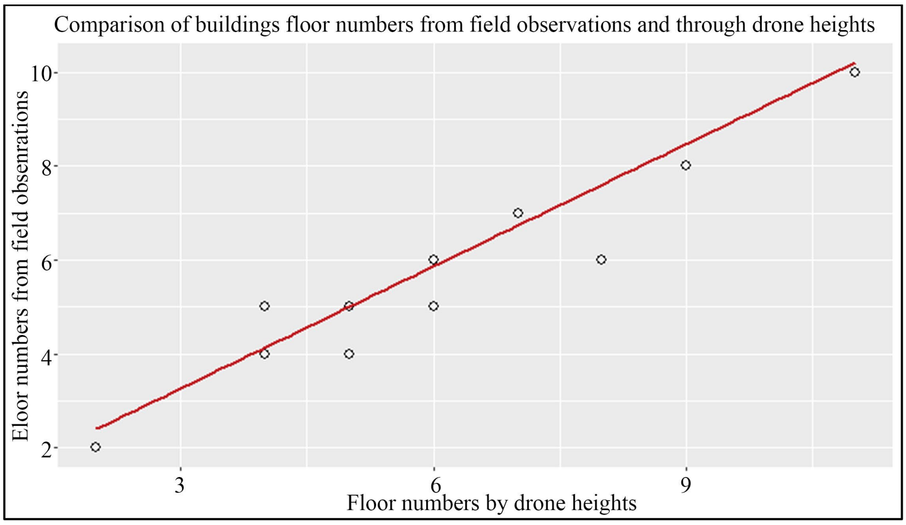

Figure 14. Comparison of buildings floor numbers from field observations versus estimated floor numbers from drone imagery.

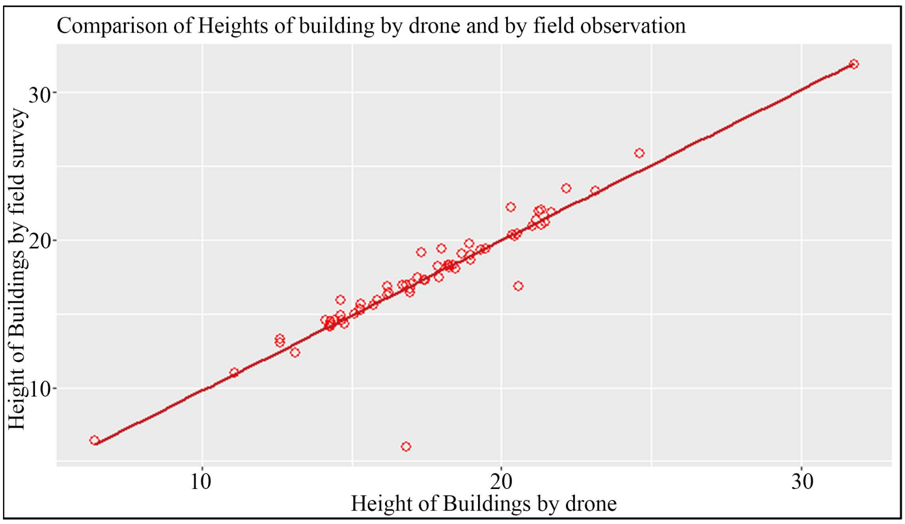

Figure 15. Comparison of the heights of the building from ground survey observations and heights generated using drone imagery.

As a result, variations in estimated floor numbers were observed, especially in taller buildings, due to accumulated differences in floor height assumptions (e.g., Figure 6). For instance, a building with 10 floors at 3 meters per floor would have a total height of 30 meters. However, if the same building were assessed using a

2.7-meter floor height, it would be estimated at 11 floors. These discrepancies became more pronounced with increasing building height, largely due to the lack of standardized floor heights. For example, in Figure 6, two adjacent buildings with equal floor numbers were found to have different building heights, influenced by investor decisions aimed at maximizing profit. Since the national building code has given the recommended heights of floors for buildings. after seeing the problem, we have stated that the varying heights of floors makes it hard to automate the process of identifying the floor numbers, the institution can see the best way to solve it. The other observation is that if the buildings are within seven floors they can be distinguished and the proper height achieved. The problem becomes pronounced when the building go beyond the seven floors.

Additional structural features such as elevated water tanks, roof height provisions, and flat roof side walls exceeding 1.5 meters also contributed to variations in estimated floor numbers (e.g. Figure 8). For example, a five-story building with 2.7-meter floor heights would measure 13.5 meters, while the same building with 3-meter floor heights would reach 15 meters. The difference in total height, combined with elevated features above 1.5 meters, aligns with the drone's 3-meter-per-floor estimation logic. Buildings with such elevated features accounted for approximately 5% - 8% of the study area. While this proportion is relatively small, it highlights the potential of discrepancies in computing floor numbers.

These variations in building height can lead to misleading interpretations of floor counts, which may affect rental income estimates, power consumption projections, population estimates, and other planning metrics. Conducting random field observations within the study area can help establish acceptable error margins. For example, Figure 16 was estimated at 10 floors via drone data, while field observations confirmed 9 floors, indicating a slightly higher actual floor height of 31 meters. Among the 2034 buildings sampled in this study, only one building (Figure 16) had more floors than those derived from drone imagery, suggesting it was an outlier with negligible impact on overall results. To improve consistency and accuracy, there is a need to standardize or adopt floor height benchmarks based on building usage. This would enhance the effectiveness of drone-based monitoring for detecting unauthorized construction. For instance, drones were successfully deployed by the Abu Dhabi Municipality to inspect and update site inspection reports for enforcement actions [12]. That study also proposed an automated system where drones receive location data and autonomously inspect targeted sites. These findings support the approach of this study, advocating for regular drone inspections to prevent violations of approved building plans. For example, Figure 17 shows a building with seven floors at the time of drone flight, despite having an approved plan for only five floors. The building was later completed with 15 floors, resulting in a legal dispute.

Calculating the area of buildings posed a significant challenge due to the diverse and complex shapes of rooftops, which often resulted in fragmented sections. The drone-captured images exhibited irregular geometries, and some structures were poorly represented because of the heterogeneity of the study area. Extracting sharp and accurate building boundaries from LiDAR data proved difficult, as its ground sample distance (GSD) is generally lower than that of high-resolution imagery. Additionally, the cadastral data did not align well with the drone data, primarily due to the oblique angles of drone imagery and differing reference points. As previously noted, the irregularity in image shapes further complicated the process.

Figure 16. (a) Building with nine floors instead of ten, (b) buildings floor numbers.

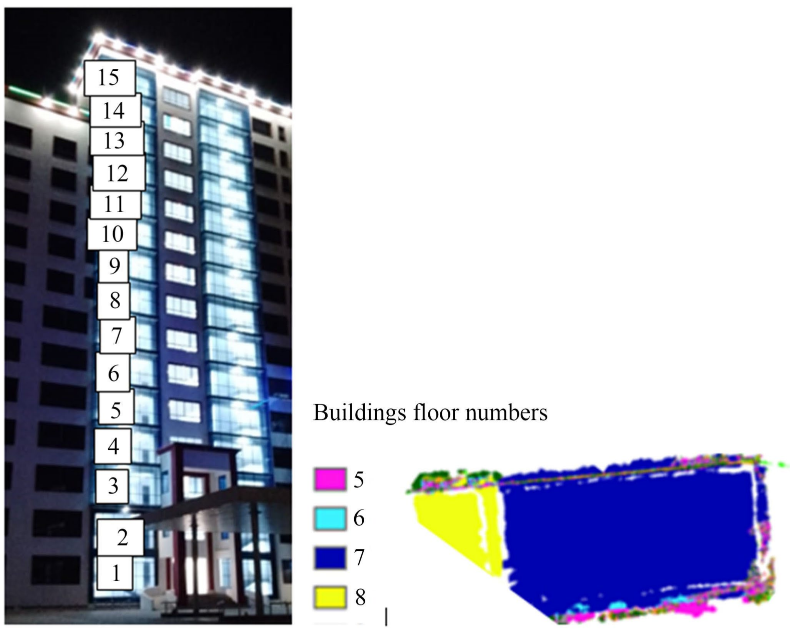

Figure 17. Building violating approved building plan.

5. Conclusion

This study aimed to estimate building heights and floor numbers using drone imagery, recognizing the importance of accurate height data for various applications. Floor counts and building heights were derived from the nDSM model generated through UAV oblique photogrammetry. Validation against RTK ground survey measurements yielded a high correlation ($R^2 = 0.99$) for building heights. Similarly, the comparison between drone-derived floor numbers and field observations showed strong agreement, with an R^2 of 0.92. These results demonstrate the effectiveness of processing drone imagery using the SFM technique, which reconstructs 3D structures from overlapping image sequences. However, some challenges were noted. For instance, buildings with identical floor counts sometimes exhibited different overall heights. Additionally, rooftop features such as water tanks or parapet walls were occasionally interpreted as extra floors. Standardizing floor heights is essential to improve consistency in automated calculations. By dividing the computed building height by a standardized floor height, more accurate and uniform floor estimates can be achieved. For example, although this study succeeded in getting the heights and numbers floors, we identified challenges in extracting sharp and precise building boundaries from LiDAR data, primarily due to its GSD, which is lower than that of high-resolution imagery. To address this limitation, future research could explore the integration of LiDAR data with high-resolution images to enhance boundary definition. Additionally, it was observed that cadastral data did not align perfectly with drone imagery. This mismatch stems from the nature of drone data, which captures 3D objects from oblique angles, whereas cadastral data, based on Cartesian projection, represents only 2D features. To improve overlay accuracy and support precise 2D measurements, future studies should consider flying drones at near-vertical (nadir) angles.

Acknowledgements

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Conflicts of 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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