

AERIAL LiDAR AND IMAGING BASED EARTH SURFACE DIGITIZATION AND DATA CHARACTERISTICS COMPARISON

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ABSTRACT:

The land topography and urban area digitization in the form of point clouds has become an indispensable method for providing many related services. Aerial point cloud measurements are made using active LiDAR or dense matching photogrammetry methods. Aerial LiDAR and dense image matching point clouds are obtained directly in the geodetic coordinate system thanks to navigation data. The geo-referencing based on ground control points require more labour and work time. All kinds of geometric and semantic information about the terrain can be extracted from the point cloud data. Therefore, it should have both location and visualization accuracy. The detection and definition accuracies of image area details depend on the scanning point density and its uniform distribution. In this study, after having been introduced the parameters of the aerial point cloud related to topographic measurement and urban area modelling, a comparison of these two source point clouds was made in areas with different land cover. The registration of a dense matching point cloud into a geospatial reference system was done with flight data and LiDAR measurements. As consequence, The LiDAR point density depends on the min angular step of the instrument scanning light, while the dense matching is relating to ground sampled distance of pixels.

1. INTRODUCTION

Airborne point cloud measurement from plane, helicopter or unmanned aerial vehicle is a fast and low-cost method for mapping large areas. LiDAR (Light Detection and Ranging) and dense image matching methods are frequently used individual or in combination in aerial surveys (Cramer et al., 2018; Zhou et al., 2020). 3D point clouds by using both techniques have different characteristics. LiDAR point clouds are usually inhomogeneous density, and have multiple returns in plant-covered areas, while dense matching photogrammetric point clouds extracted from multi-view stereo images are affected by shadow and low texture. The scan light reaching the ground in vegetated areas provides the high accurate digital terrain model and a significant advantage for LiDAR scanning. Analysis of multi-return LiDAR signals allows the determination of vegetation heights in addition to bare land topography (Dersch et al., 2021). The photogrammetric images enable the selection of scan area details thanks to rich texture data. A modern airborne sensor integrates LiDAR and digital camera for capturing topographic data at high spatial resolution (Mandlbürger et al., 2017). LiDAR measurement system consists of a laser device, GNSS and inertial navigation unit (IMU). A scanning mechanism is used to collect the data in a strip-wise. Measurements are obtained directly based on the geospatial reference frame.

When the calibration parameters are not accurately determined, discrepancies between overlapping strips might occur. Thus, the strip adjustment procedure is implemented for an accurate result (Habib et al., 2008; Glira et al., 2016).

The ground control points (GCP) are used to attain scale to dense matching point clouds. Since establishing control points in the field requires more labour and time, the camera projection center coordinates or LiDAR control points (LidarCP) based on cloud coordinates are used to register the photogrammetric point cloud into geospatial system. In the absence of camera projection center coordinates, geo-referencing can be done with control points supplied from the LiDAR point cloud (Haala et al., 2022) with an accuracy close to GCP. Its geo-referencing accuracy depends on the LiDAR point density (Haala et al., 2020; Glira et al., 2019). In addition, image data is enhancing the LiDAR point density, visualization, and representation (Haala et al., 2020).

The change in the urban area could be determined with the comparison of time series LiDAR point clouds (Fekete and Cserep, 2021). Plant species and structure in the urban area can also be determined from LiDAR measurements (Kulawik et al., 2021a).

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The point cloud acquired by UAV or airborne LiDAR provides a sufficient point density as 2.54 pts/m² for the detection of plant species and planting areas (Zhang et al., 2022). LiDAR and dense matching have been used together to detect plant species (Kulawik et al., 2021b). Additionally, 3D geometric data provided by LiDAR helps protect urban green infrastructure (Alvarado and Rodriguez, 2022). The material properties of the surface affect light intensity reflected from the scan surface. For example, if the surface is dry and wet, the reflection values will be different and allow surfaces to be distinguished (Jin et al., 2021).

The dense point cloud data is an extensive method for digitizing imaging field details. High point density in operations related to land and urban areas increases the accuracy of segmentation and identification results (Zhang et al., 2018). The segmentation of point cloud enables to classification of objects and surface cover in the imaging area (Weinmann et al., 2017). The LiDAR may have different horizontal and vertical point density due to multiple rotations occurring in vegetated areas. On the other hand, the homogeneous distribution of points is also important in representing the scan area object. Although the density is high, the accumulation of points in a certain area may not provide the desired result. Object detection and identification will not be possible in areas where points are sparse. Therefore, point density and distribution should be used together to define the quality of point cloud data.

In this study, LiDAR and dense image matching (structure from motion) point cloud scanning methods were examined in 3D mapping of land topography and urban areas. Alternative methods that using LiDAR point cloud data have been proposed to geo-referencing of photogrammetric point cloud. Density and point distribution, which affect the quality of the point cloud in defining scan area objects and creating a digital elevation model, are explained. The point density and distribution were computed to compare LiDAR and dense image matching which have different land cover.

1. DATA ACQUISITION

The study area is 1.376x0.821 square kilometres in the center of Kulu district of Konya province, with an average altitude of 1000 m above sea level (Figure 1). The average ground level is 841m for LiDAR and imaging. GNSS coordinates of the camera projection centers were recorded at the imaging positions. Data acquisition was performed at dry weather conditions. LiDAR data were recorded single line linear laser scanner. In addition, the nine images which have 24-bit depth and 10625x14204-pixel resolution were recorded.

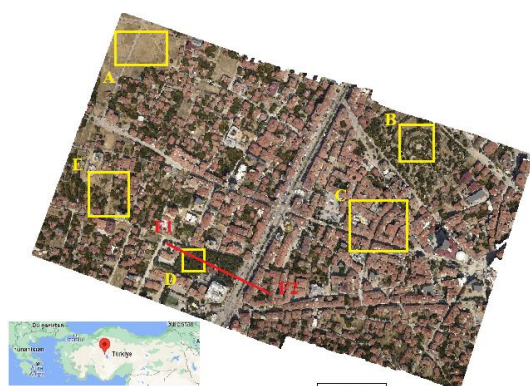


Figure 1. The study area

2. METHODS

2.1 Airborne LiDAR

An aerial LiDAR system consists of three main components: laser, GNSS, and IMU units. The basic principle of 3D LiDAR is to determine the distance and direction of the measured scan point and record the information carried by the reflected light by converting it into digital codes. The range can be estimated with known light speed and flying time of the laser pulse (Altuntas, 2023). The light direction is expressed by the angles with respect to the horizontal and vertical planes of the defined reference system. The relationship between the instrument axis of LiDAR, IMU, GNSS and camera is established via the system calibration. The ground coordinates of the laser scan points are derived using direct geo-referencing information (Habib et al., 2008). The strength of the backscattered light is also recorded for every scan point. The registration of LiDAR point cloud to geodetic coordinate system using GCP is costly and time-consuming. For this reason, direct geo-referencing by using in-situ flight data is commonly preferred. The vertical accuracy of LiDAR scan point is higher than the horizontal. Depending on the structure of the measurement system, aircraft speed, system calibration and aircraft vibration affect horizontal positioning more than vertical. In addition, the high divergence angle of LiDAR light reduces the positioning accuracy. The colour and material structure of the object point influences the reflection intensity of returning light. The object which has a high reflectivity surface can be measured from longer distances. The 3D position accuracy of the scan points is largely related to the divergence angle, intensity of returning light, and scan light angle measurement precision of the instrument.

Photon counting LiDAR simultaneously records the spatial data of scanning points from the field of view. The scan points on the horizontal level show a homogeneous distribution. However, the scan point density is depended flying height, and changes opposite. In addition to spatial data, reflected light intensity is also recorded. By analysing multiple return signals, plant species and heights can be estimated (Zhu et al., 2018). Light oriented LiDAR system has a specific scanning pattern (Pentek, 2020; Lassiter et al., 2020). The scan pattern often produces a non-uniform point cloud. Especially in scans with low point density, point distribution that is not suitable for land cover identification and object detection may occur. The distance between scanning points and therefore the point density varies depending on flight altitude and speed. The point density decreases when the flight altitude increases. The shortest scan point space corresponds the minimum angular step of LiDAR light steering system. The color record is performed for the scan points from the integrated camera image. In vegetated areas, the multi-return signal enables the creation of a digital model of plant height and bare land surface. On the other hand, multi-returns that occur at the edges of buildings are used to determine building heights.

Full waveform LiDAR calculates spatial data for each characteristic of reflected light, and contains more scan points. The vertical density of LiDAR point cloud is especially high in tree-covered areas (Milenkovic et al., 2017).

2.2 Dense Image Matching

The together estimation of camera positions, conjugate point coordinates and calibration parameters of multi-view stereo images which have different bright, scale and orientation is

called structure from motion (SfM). The SfM algorithm does not need to camera calibration for these operations. Camera calibration parameters and point coordinates can be calculated iteratively during the processes. A dense point cloud is created from this set of multi-view images by matching more image points, and called dense image matching. The conjugate point detection is not possible on surfaces with poor texture information. The density of image matching point cloud varies depending on user parameters such as low, medium, high or very high.

Dense point cloud is created at four steps on dense matching. In the first step, local feature points on the images are found. In the second step, feature points are defined by their local characteristic invariant features. The descriptor usually represents these feature points in a 128-dimensional space. In the third step, similar feature points are matched in all images, and in the fourth step, the relative positions of the images are estimated by bundle adjustment (Lowe, 2004). Matching results are usually a sparse point cloud, and then dense point cloud is generated with additional matches. Commercial photogrammetry software allows users to restrict the number of matching feature points. In this way, multi-image matching does not force the computer capacity. Highly accurate spatial queries can be achieved from the scaled point cloud. Its scaling and geo-referencing based on ground control points is a costly and time-consuming. Instead, in aerial photogrammetry, geo-referencing has been executed using camera projection center coordinates recorded with GNSS during the flight time. The control points obtained from LiDAR point cloud can be used in photogrammetric evaluation (Haala et al., 2022). In this study, geo-referencing of the photogrammetric point cloud was carried out using interactively selected control points from the LiDAR point cloud (LidarCP) (at WGS-84 reference system, zone 33°E longitude). On the other hand, the photogrammetric point cloud was registered into LiDAR point cloud with ICP (LidarICP) and the change in geodetic coordinates was investigated (Figure 2).

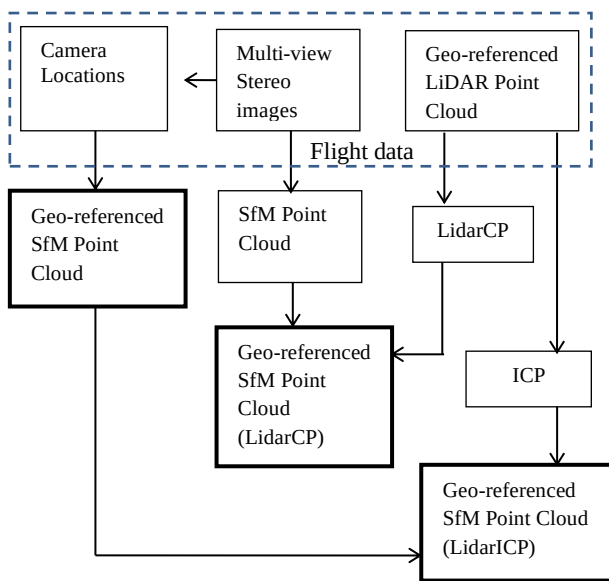


Figure 2. Flowchart of the proposed SfM point cloud geo-referencing

After geo-referencing of the dense matching point cloud by LiDAR based control point, the spatial discrepancies d_{xy} on the

control points in the horizontal plane are computed with Equation (1).

$$d_{xy} = \sqrt{d_x^2 + d_y^2} \quad (1)$$

3D discrepancy depicted as d_{xyz} are computed by taking into account height differences d_z .

$$d_{xyz} = \sqrt{d_{xy}^2 + d_z^2} \quad (2)$$

The root mean square errors of the positional inconsistency at n control points are calculated with Equation (3).

$$RMSE_{-d_{xy}} = \sqrt{\frac{\sum d_{xy}^2}{n}}, RMSE_{-d_z} = \sqrt{\frac{\sum d_z^2}{n}},$$

$$RMSE_{-d_{xyz}} = \sqrt{\frac{\sum d_{xyz}^2}{n}} \quad (3)$$

2.3 Point Density

The density is important criteria expressing the degree to which the point cloud represents the measurement surface. The higher the resolution the better the representation of the object, and enables small objects will be chosen. On the other hand, high resolution data becomes expensive and difficult to collect, store and process. The scanning point density is determined according to the smallest detail size desired to be detected from the point cloud. In aerial measurements, point density corresponds to distribution on horizontal plane projections of the points. In LiDAR measurements where multiple return signals are recorded, more than one data is recorded in the same vertical direction. Therefore, point densities are different in horizontal and vertical directions in the 3D point cloud. Often, in LiDAR, the density is calculated only for a single return signal and is expressed in terms of nominal point space (NPS) and point cloud density nominal point density (NPD). The scanning point spaces, including the multi-return signal, are defined as aggregate nominal pulse spacing (ANPS) and the point cloud density is defined as aggregate nominal pulse density (ANPD) (Heidemann, 2018). Therefore, in the LiDAR point cloud with multi-return signals, the ANPD value will be greater than the NPD value (For example, NPD=1.2 pts/m², ANPD=2 pts/m²). As can be understood, the number of points representing the topographic structure of the land in wooded areas will be lower than the number of pulses. For a point cloud, the average distance between every point and its adjacent points on the ground level horizontal plane are calculated according to Equation 4 (Li, 2010).

$$\overline{PS}_i = \frac{1}{m} \sum_{j=1}^m D(p_i - n_j) \quad (4)$$

Where; p_i is a scan point in the point cloud, n_j is the adjacent point of p_i , m is the number of the adjacent points, $\overline{PS}_i$ is the average distance of each point from its neighbours, and $D(p_i - n_j)$ is the distance between point p_i and its adjacent points n_j . $\overline{PS}_i$ also shows the density (space) around at this scan point p_i . In computing $\overline{PS}_i$, neighbour points around the point are found using the k-nearest neighbour (KNN) algorithm or triangulation (Azri et al., 2020). Then, the average scan point space PS is estimated to represent the point cloud by Equation (5) (He, et al., 2021).

$$PS = \frac{1}{n} \sum_{i=1}^n \overline{PS}_i \quad (5)$$

In Equation 5, n is the number of scan points or with the other name the number of calculated. The relationship between point density (PD) and scan point space (PS) is expressed by Equation (6).

$$PD = \frac{1}{PS^2} \quad (6)$$

The point cloud density is called as sparse ($0.5-1\text{pts/m}^2$), low ($1-2\text{pts/m}^2$), medium ($2-5\text{pts/m}^2$), high ($5-10\text{pts/m}^2$), and extremely ($10+ \text{pts/m}^2$) according to the number of points per square meter unit area. However, it should not be forgotten that this classification depends on the technological capabilities of LiDAR devices (Rohrbach, 2015). It is clear that as the capacities of the instruments increase, the number of points corresponding to these definitions will also be increased.

The LiDAR point cloud density is directly related to flight altitude and laser light angular step resolution. As flight altitude increases, resolution decreases. The smallest angle between the lights of consecutive scanning points is expressed as the angular resolution of the instrument and affects the point cloud density. The smaller angular resolution makes the higher scanning point frequency (Figure 3).

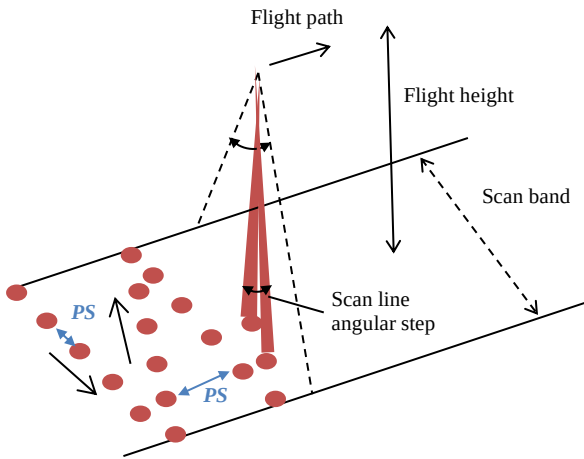


Figure 3. Irregular point spaces on zigzag scan pattern of LiDAR

The most important parameter influence density of photogrammetric point cloud is pixel resolution. The smaller pixel size and higher number of pixels increase the point cloud density (resolution). The number of images is also significant to the resulting point cloud ground resolution in dense matching point cloud. To diminish the subjective influence of the large variety of imaging distances, the number of images N is chosen to be significant (e.g. $N \geq 10$). Unlike terrestrial photogrammetry, the arbitrary aerial images like here have very close imaging distances (Figure 4). The resulting resolution G_r (ground sampling distance, point space on the ground) is calculated from all image projections G_i (Meiser, 2020).

$$G_r = \frac{1}{n} \sum_{i=1}^n G_i \quad (7)$$

Theoretical ground resolution G_t depend on camera calibration parameters (pixel size s , and focal length f) and imaging distance h (flight height), and is computed by Equation 8

$$G_t = \frac{s}{f} h \quad (8)$$

If above ground level is very close to the overlapping images for a specific area, the min point space is expected to be equal to the pixel size. Otherwise, the minimum point space is calculated from mean G_r , as to be the general condition.

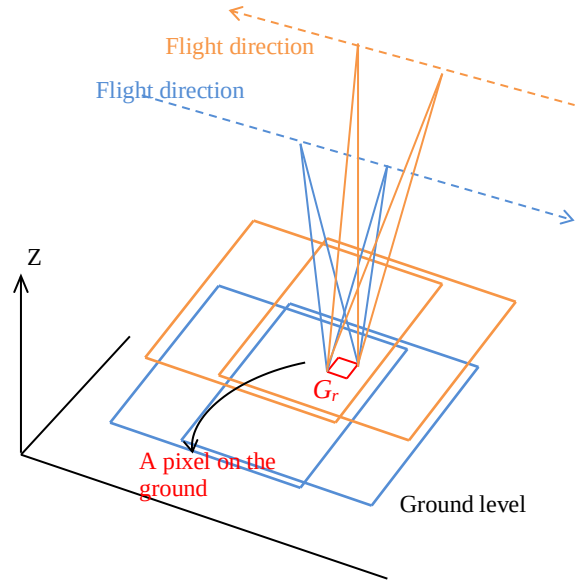


Figure 4. Ground sampling distance in aerial imaging

2.4 Point Distribution

The density alone is not sufficient to express the degree to which the point cloud represents the measurement surface. The spatial distribution of points must also be proper to representing the surface with a point cloud. A homogeneously distributed point cloud represents the scan surface better. If we have more points with uneven distribution, the data will not represent the ground features. However, good distribution of points enables right define and classification to the ground cover and structure. In addition, accuracy of a digital elevation model to be produced is related to the point distribution as well as the point density. Distribution of the points in a specific region is expressed by the deviation of the gravity center from the geometric midpoint O (Figure 5). The geometric midpoint (X_o, Y_o) of the point cloud is

$$X_o = \frac{X_{\max} - X_{\min}}{2} \quad Y_o = \frac{Y_{\max} - Y_{\min}}{2} \quad (9)$$

and, its gravity center (G) coordinates are X_g, Y_g ;

$$X_g = \frac{1}{n} \sum_{i=1}^n X_i \quad Y_g = \frac{1}{n} \sum_{i=1}^n Y_i \quad (10)$$

Thus, point distribution criteria d_s is estimated with Equation 11.

$$d_s = \sqrt{(X_g - X_o)^2 + (Y_g - Y_o)^2} \quad (11)$$

The point cloud distribution according to d_s value is expressed as very good ($d_s < 10PS$), medium ($11PS < d_s < 29PS$), or poor ($d_s > 30PS$).

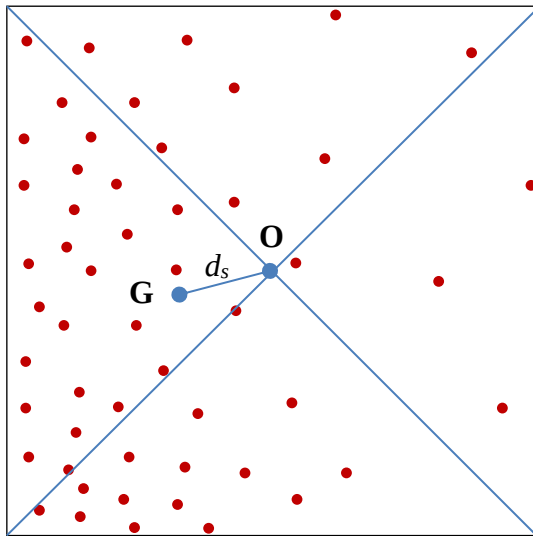


Figure 5. Uneven point distribution

3. RESULTS

The photogrammetric point cloud was produced from nine images taken during the LiDAR scanning by dense image matching. The average pixel resolution of the images is 5.79cm. The images were matched by 12361 tie points and their average number of projections was three. The dense point cloud contains 24 million points with the *Medium* option in Agisoft software.

The geospatial registration of dense image matching point cloud was done by using camera center coordinates (CamCoor) taken on the flight. This is a fast and effective method for geo-referencing of dense image matching point cloud. The total residual on the projection center coordinates was obtained as 0.28m by the bundle adjustment. In addition, geo-referencing was performed with 9 control points (LidarCP) obtained from the LiDAR point cloud (Figure 6).



Figure 6. Ground control points selected from LiDAR point cloud

The residual errors at the control points are given in Table 1. Furthermore, the photogrammetric point cloud geo-referenced with the camera projection center coordinates was registered into the LiDAR point cloud coordinate frame with iterative closest point (ICP) (LidarICP). After the registration, the root

mean square error of deviation on the conjugate points is 0.0012m and its standard deviation is 0.22m.

GCP	d_{xy} [m]	d_z [m]	d_{xyz} [m]
1	1.112	0.510	1.224
2	1.689	0.018	1.689
3	1.036	-0.558	1.177
4	1.229	-1.118	1.661
5	1.345	1.019	1.687
6	1.295	-1.278	1.820
7	1.265	-0.205	1.281
8	2.333	-0.975	2.529
9	0.815	0.116	0.824
RMSE	1.409	0.782	1.611

Table 1. The residuals on SfM point cloud geo-referencing by using LiDAR control points

The different land cover surfaces were extracted from LiDAR and photogrammetric point clouds to comparison. Thus the section line that passes through areas with dense and sparse trees, buildings and roads was extracted (Figure 7). Additionally, the point density and distribution in the areas with vegetation, trees, buildings and bare land features were compared (Table 2). The local point spaces ($\overline{PS}$) around a scan point were calculated by establishing the k-nearest neighbour relationship.

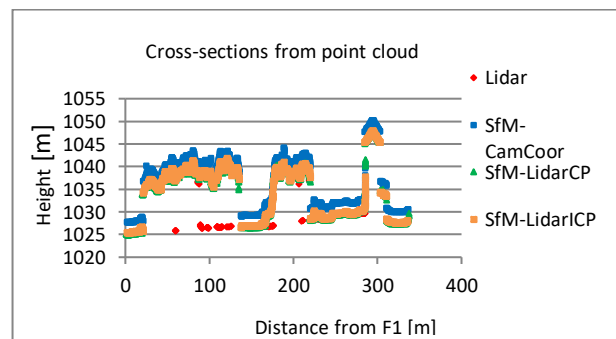


Figure 7. Cross sections from point clouds (From F1 to F2)

Region	LiDAR			SfM		
	$\overline{PS}$ [m]	$\overline{PD}$ [pts/m ²]	d_s [m]	$\overline{PS}$ [m]	$\overline{PD}$ [pts/m ²]	d_s [m]
A	0.38	6.91	4.96	0.20	24.95	0.09
B	0.48	4.35	1.37	0.19	27.74	0.07
C	0.37	7.44	2.53	0.19	27.11	0.74
D	0.29	11.51	5.40	0.16	39.86	0.16
E	0.365	7.491	0.812	0.174	33.115	0.337

Table 2. Density and distribution specifications of point clouds. (A: Bare earth, B: Grass+Asphalt, C: Building, D: Trees, E: Trees+Asphalt)

LiDAR point distribution is very irregular, especially in tree covered areas. The photogrammetric point cloud density is very high and uniformly distributed (Table 2). The gaps of the LiDAR point cloud could be filled by combining them with the dense image matching point cloud. LiDAR light heaving reach

the ground in tree vegetated areas increases digital elevation model point measurement and therefore digital surface model accuracy in this area. The dense matching point cloud is a better method to generating digital surface model, which represents the upper level of trees (Figure 8).

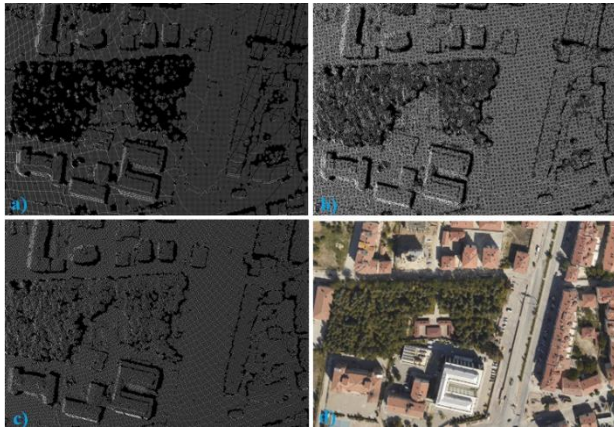


Figure 8. Point clouds from different land cover types. a) LiDAR point cloud, b) photogrammetric point cloud, c) LiDAR+photogrammetric point cloud, d) real image

4. DISCUSSION

Geo-referencing of aerial LiDAR point cloud is done directly with in-flight GNSS and IMU data. Strategically, no control points are required to geo-referencing the airborne LiDAR point cloud. However, using control points slightly increases coordinate accuracy. After the direct geo-referencing, a typical LiDAR workflow includes an overlapping strip adjustment to minimize differences between them. This step improves geo-referencing by estimating the LiDAR's mounting calibration and correction for the GNSS/IMU trajectory parameters (Haala et al., 2022; Glira et al., 2015). On the other hand, direct geo-referencing of the photogrammetric point cloud is performed with very high accuracy by using GNSS data. The selection of control points from the LiDAR point cloud depends on the LiDAR point density and the spatial accuracy of the scan points. Therefore, LidarCP based geo-referencing of photogrammetric point cloud has low accuracy. This geo-referencing method can be preferred especially for point clouds containing moment-of-flight GNSS data or produced from images taken at different times. As it is known, ground control points enable high accuracy for geo-referencing to the photogrammetric point cloud. However, the ground control points must be established before the flight. In cases the control points cannot be established, the coordinates of prominent details in the field can be used as a control point by measuring them later, but the accuracy will still be low (Nebiker et al., 2014).

LiDAR scan light reaches the ground in tree-covered areas and creates a digital elevation model point. However, the ground point cannot be measured from the photogrammetric image in tree-covered areas. In the section given in Figure 7, LiDAR scanning ground points in tree-covered areas are seen. In non-vegetated areas, LiDAR and dense matching point clouds have similar characters. The dense image matching point cloud geo-referenced with the camera in-flight GNSS data is consistent with the LiDAR. The difference in the geo-referencing of the dense image matching point cloud with LidarCP and LidarICP can also be seen in the cross-sectional positions in Figure 7.

The point density was analysed based on ground level points. The average LiDAR point density is 7 points per square meters and the distance between scan points is 0.37m. It is observed that the point density increases thanks to the multiple return signals provided by LiDAR beams in trees. Additionally, density decreases in some areas, probably depending on the scanning pattern. The irregularity in the point distribution also shows this effect. For example, although the average point density is obtained in bare earth, $d_s = 4.96\text{m}$ indicates uneven point distribution. In the dense image matching, a similar point density was obtained for all land covers. The average density is 27 points per square meters, scanning point space is 0.19m. Since the dense matching point density depends on the number of pixels, it is evenly distributed everywhere. If the number of conjugate details is insufficient, the point distribution is irregular. The scan points cannot be produced in areas where no conjugate points can be found. On the other hand, in both LiDAR and dense matching methods, occluded areas may occur due to the shadowing effect. However, since LiDAR makes a continuous record, the shadowing effect occurs fewer than a dense matching point cloud.

The LiDAR point cloud is having reflectance and coordinate information. It is difficult to select details from a point cloud that contains only reflections. For this reason, color assignment is made to the LiDAR scanning points from the camera image integrated into the system. The dense matching point cloud contains color values and has a higher density compared to LiDAR point cloud.

5. CONCLUSION

The LiDAR scanning provides high accuracy in 3D mapping and is widely used in topography 3D mapping. Since the point cloud only contains coordinate and reflection values, color values are assigned to the points from the images to making enable the selection of details. In addition, a point cloud is produced by dense matching of multiple images associated with LiDAR. The LiDAR can measure point clouds regardless of object geometry and texture. However, in cases where the scanning surface does not contain sufficient texture, a dense matching point cloud cannot be created. In dense trees, the LiDAR can measure a scan point to digital elevation model representing the land surface. In this study dense matching could not be generated point cloud as evenly distributed for the tree-covered areas. The LiDAR point density depends on the minimum angular step of the instrument scanning light and is low compared to the dense matching point cloud. Details smaller than the scanning point spaces cannot be distinguished from the point cloud. In this respect, dense matching is superior to LiDAR. Consequence, while the advantage of the LiDAR point cloud is its relatively even distribution, the advantage of the dense image matching method is its dense and colorful point cloud. The further study will be focused the success the object detection and definition from these two-point clouds.

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