Building 3D City Models: Testing and Comparing Laser Scanning and Low-Cost UAV Data Using FOSS Technologies

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Abstract. Presently, the use of new technologies for the acquisition of 3D geographical data on time is very important for urban planning. Applications include evaluation and monitoring of urban parameters (ie. volumetric data),indicators of an urban plan, or monitoring built-up areas and illegal buildings. This type of 3D data can be acquired through an Airborne Laser Scanning system, also known as LiDAR (Light Detection And Ranging) or by Unmanned Aerial Vehicles (UAV). The aim of this article is to use and compare these two technologies for extracting building parameters (facade height and volume). Existing literature evaluates each technology separately. This work pioneers benchmarking between LiDAR and UAV point-clouds. The basic function of LiDAR is collecting a georeferenced and dense 3D point-cloud from a laser scanner during flight. Therefore it is possible to obtain a similar 3D point-cloud using processing algorithms for stereo aerial images, obtained by large or small-format digital cameras (the small-format camera implemented in Unmanned Aerial Vehicles). The chosen study area is located in Praia de Faro, an open sandy beach in Algarve (Southern Portugal), limited west by the Ria Formosa barrier island system. The area defined has an extension of 300100m. The methodology is divided in two distinct stages: (1) building parameters extraction, (2) comparative technology analysis. Lidar point-cloud resolution is approximately 6 pts/m2 and UAV point-cloud 60 pts/m2. FOSS technologies have proven to be the most adequate adequate platform for the development and diffusion of advanced analytical tools in the Geographical Information Sciences (GISci). Data management in this paper is supported by a Geographical Database Management System (GDBMS), implemented using PostgreSQL and PostGIS. Statistical analysis is performed using R whilst advanced spatial functions are used in GRASS.

Keywords: LiDAR · UAV · FOSS · Point-cloud · Building parameters

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1 Introduction

The automatic extraction of buildings parameters, such as building height and volume, can be most useful in urban planning contexts. These parameters, extracted from advanced remote-sensing technologies, allow producing 3D building models to support the monitorization of urban plans and keep track of different parameters such as illegal changes in built-up areas (new block buildings or number of floors) and a better visualization of the proposed plan in public discussion. These parameters can also be of help in gathering more precise urban indicators.

Advanced technologies such as airborne laser scanning and low-cost UAV (also called UAS - Unmanned Aerial Systems) imagery allow a higher degree of automation in acquiring 3D data, in opposition to the classical methods of digital photogrammetry. This is quite important because the classical stereo-restitution performed in a digital photogrammetric workstation (defined by a human operator) for accurate measurement in a large set of buildings is very time consuming. Both technologies produced a 3D point-cloud data which represents a set of georeferenced data points in a three-dimensional coordinate system. These dense clouds can be acquired automatically through an active aerial sensor system laser scanning or from the combination of UAV and automated dense multi-stereo image-matching processing.

The LiDAR point-cloud is acquired from a LiDAR (Light Detection and Ranging) system. The basic principle of LiDAR system is to record a set of discrete and massive elevation points above datum using a laser scanning and a direct georeferencing system (GPS/INS - Inertial Navigation System). The laser emits millions of pulses per second to the ground and part of those backscattered pulses return to the laser. At the same time each pulse can be directly georeferenced by the position and altitude of an airborne sensor to the local coordinate system (or six parameters of exterior orientation). All points of a LiDAR point-cloud are obtained from these pulses, which are classified as first and last return. The coordinates of these points are obtained from the following parameters: i) the time between the emission and reception of an energy pulse in sensor (distance value); and ii) from the six parameters of exterior orientation given by GPS/INS. The point density of LiDAR data depends of the flight height (which defines the footprint size of pulse) and the particular characteristics of Laser scanning (beam divergence and effective measurement rate of laser scanning).

The survey of urban areas for 3D modelling of buildings requires a small footprint of pulse LiDAR in tandem with high point density [7]. The UAV point-cloud requires an automated multi-stereo aerial matching processing of UAV imagery. The UAV system is a low-cost and ultra lightweight aerial photogrammetric system, which is able to collect very high-resolution imagery with a higher overlap (80%-90% in flight line). This system integrates a small-format digital camera and a miniaturized direct georeferencing system (GPS/INS). Some of the vantages of this system when compared with conventional digital airborne LiDAR and photogrammetric systems are: 1) low-cost; b) automatic pilot which allows driving the UAV automatically on the flight lines and capture the images; and c) the time between the decision to make the flight for the acquisition of aerial image and the acquiring of 3D point-cloud can be less than 24 hours. After the effective acquisition of multiple overlapping UAV imagery, a dense multi-stereo image-matching algorithm is applied to estimate the 3D point coordinates for each pixel. The point density of a UAV point-cloud depends of the resolution of aerial images and of the number of point matches found on stereo image pairs.

Over the past few years, 3D point-clouds obtained by LiDAR or automated image matching techniques have been used and tested by several authors: (i) in 3D urban models by [1,6,9]; (ii) more specifically in the extraction of building elements [4,8,10].

Regarding the accuracy of these technologies, LiDAR enables 5-10 cm of vertical accuracy [2]; the accuracy of UAV data is influenced by the resolution of the imagery and the texture and terrain through the scene [5]. The challenge of this study was to apply a (semi)-automatic extraction methodology of building parameters - building facade height and building volume - from each different 3D point-clouds data (UAV and LiDAR) using Free and Open Source Software (FOSS): GRASS GIS, PostgreSQL/PostGIS functions and R statistical language. The use of FOSS increases accountability and reproducibility, apart from reducing operational costs.

In this work we report the difficulties in acquiring these parameters from 3D point-cloud without reference data and we compare and evaluate the accuracy of building parameters extracted from different sources, UAV and LiDAR, under the same methodology.

2 Study-Area and Data Acquisition

The study area - Praia de Faro - is an island-barrier bounded north by the Ria Formosa estuary and South by the sea, located in the South Coast of Portugal - the Algarve The selected geographic area (Figure 1) has approximately 2.5 ha, with a width of 100m north to south and 250m east to west along the principal road of the island. It is a built-up area with 19 buildings. The majority are single-family dwellings with a maximum of two floors, although there is a building located north-east of the study area with four floors.

The buildings represent a diversity of architectural styles and types, with irregular shapes. The roofs are either flat, multiple-level flat, or pitched and complex (with different slopes). The degree of dissimilarity of building's shape is high.

2.1 3D Point-Clouds

The 3D point-cloud collected through the LiDAR system was performed by a TopEye MK II (Figure 2b) at a flight height of 500m above ground. The laser

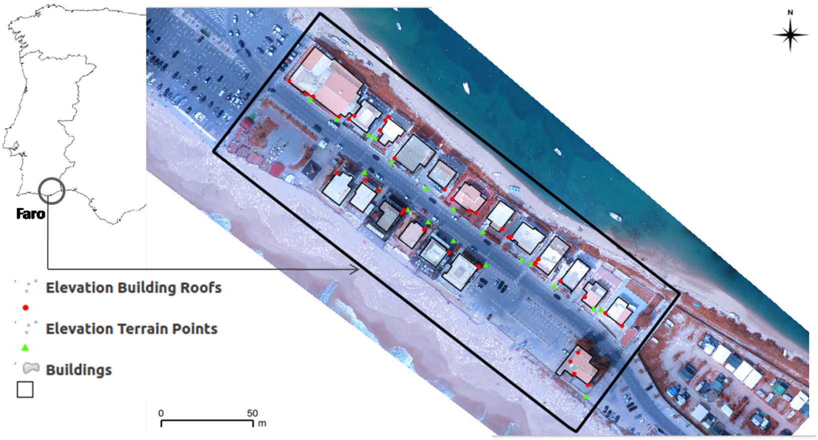

Fig. 1. Study-area: Praia de Faro

scanning used by this system has an elliptical pattern. According to the flight planning report, this point-cloud has a vertical accuracy of 10 cm. It is important to note that the point-cloud was directly acquired by the company that made the flight, without our participation.

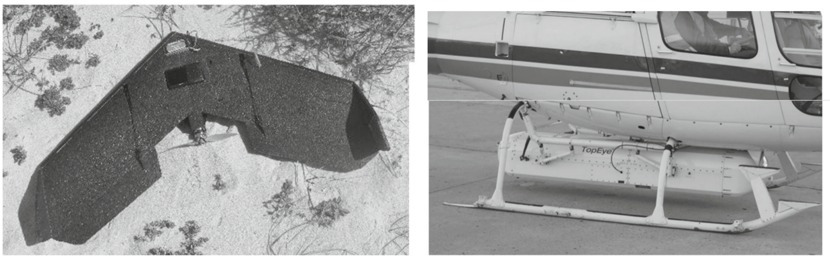

Fig. 2. Airborne systems: 2a) UAV system -Swinglet CAM; and 2b) LiDAR system TOP EYE MKII

The acquisition of UAV imagery data was performed from a Swinglet CAM produced by SenseFLY Company. This system weighted about 500 grams and has an autonomy of approximately 30 minutes of flight time. This UAV system requires at most moderate wind not above 7 m/s.

Flight Planning and Processing UAV Imagery - The flight planning lines were designed in order to acquire stereo aerial images with a 5cm resolution and a higher endlap (along flight) and sidelap (between flight lines) about 90% and 60%, respectively. This flight was performed with a wind speed bellow 10km/h.

The study area was covered by 46 aerial images (3000 by 4000 pixels) at a flight height with approximately 130m.

After the visual inspection of the quality of the images, follow-up of the multi-stereo image matching processing was performed by an automatic workflow implemented in PiX4D software, to obtain the 3D point-cloud. During this processing six Ground Control Points (GCP) were included, to generate a more accurate point-cloud. This means measuring the GCP for all images where it appears. In this particular case it was about seven images per GCP. The authors acknowledge the fact that FOSS alternatives to PiX4D do exist, and should be explored in future research. Still, existing alternatives are not as robust, which in this case justified the use of a commercial solution for pre-processing. The SFM (Structure From Motion) opensource is an alternative for getting the UAV point-cloud[**?**]. However, the SFM have a lower performance and still does not guarantee a higher vertical accuracy that is necessary for this type of urban applications.

The flight planning and the processing of the UAV imagery to acquire the 3D point-cloud, true orthomosaic and the digital surface model were made in a few hours.

Characterization of Point-Clouds - The point density of the UAV point-cloud under the study area is higher than LiDAR data (Table 1).

Table 1. Characteristics of 3D point-clouds

Technology	Date acquisition	Number of points	Density points/m2	Elevation statistics
UAV	April 2013	1,142,095	61 pts/m2	Zmax=16.91; Zmin=-0.21; Zmean=5.14; Zmedian=4.08
LiDAR	November 2009	146,149	6.3pts/m2	Zmax=21.86; Zmin=-0.03 Zmean=4.92; Zmedian=3.83

However, the range of elevation values of LiDAR data is larger than the UAV data, because LiDAR recorded very tall cypress trees near the building located to the southeast. The LiDAR system is more accurate in vegetation and tree objects detection. The distribution of the UAV point-cloud is more sparse and irregular than the LiDAR point-cloud (Figure 3). On the other hand, the UAV point-cloud has gaps and low points in some building roofs (gaps). Also, vegetation or trees near the buildings is not recorded unlike in the LiDAR data, which might be an advantage in this study because this data had to be removed.

Figure 3 shows that most elevation data registered for both clouds ranged between 3 to 5 meters.

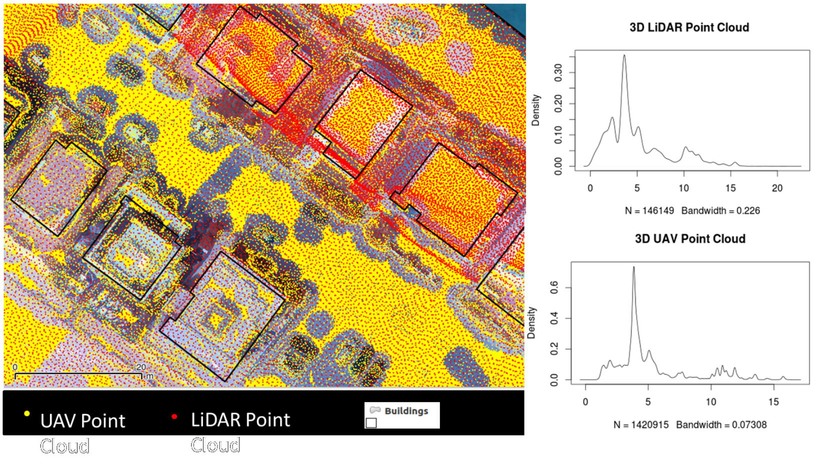

Fig. 3. Comparison of LiDAR and UAV points distribution. Density functions of the elevation values of each point-loud.

2.2 Reference Data

For this study large-scale 2D vector data (1:2000) was used as reference data to evaluate area measurements extracted for each building's. 3D vector data (points) was used to evaluate estimated data for buildings' facade height from each 3D point-cloud. These elevation points were acquired from direct field measurement with ground surveying.

The characteristics of reference data used in this study can be seen in table 2.

The 2D vector data of building outlines (Figure 1) was used to calculate the building area and the 3D vector to calculate the reference building facade height. The distribution of these 3D points can be seen in figure 1. The buildings volume reference was computed from these two reference parameters.

Furthermore, the true orthoimages produced from aerial images and Digital Surface Model (DSM), were used in this study for visual inspection, such as visualization and comparison of the building roofs extracted from 3D point-cloud data.

3 Methodology

The methodology developed for the extraction of building parameters from each point-cloud was based on the following principles: i) extraction of building parameters without vector reference data - only 3D point-cloud should be used; and ii) use Free and Open Source Software (FOSS) tools to implement a robust methodology for the acquisition of these parameters.

First, it is important to define the two building parameters that will be extracted from 3D point-cloud and which are involved in estimating a building volume. The parameters are: i) the Building facade height, which is the difference

Table 2. Description of reference data

Data	Year	Technical acquisition	Details of data
3D vector data	2012	Reflectorless Total Station (Leica TCR 705) for roof points and GPS to Ground Control Points (GCP)	Elevations points of roofs (corners and prominent points)
2D vector data	2002	Photogrammetric stereo-restitution; large scale: 1:2000	Building outlines and road network
True orthoimages	2009	Camera Rollei AIC P20 (16 MP); Data source: Aerial images from the LiDAR flight	Resolution 9 cm
True orthomosaic	2013	Data source: Aerial images from the UAV flight	Resolution 5cm; Near-infrared images (NIRGB)

between a mean elevation of the buildings' topmost limits (these are approximately the points that define the eave of the roof) and the mean elevation of the ground near the building. However, taking into consideration that a building can have different facade heights, according to its deployment on the ground, only one facade side of the building was chosen to compute this parameter - the side of building along the main public street was chosen; and ii) the area parameter is defined from the boundary of the building facade height, which is equivalent to the buildings' roof area. Thus, a building's volume is obtained from by multiplying the mean value of the facade height and the area of building roof.

The methodology developed for each point-cloud data included the following steps (Figure 4): i) selection of the set of points from the point-cloud that represents the building roofs. This filtering applied to the point-cloud was performed by a clustering CLARA (Clustering Large Applications) algorithm based on elevation values. CLARA represents a partitioning of a dataset into k- clusters around k medoids [3], which is implemented in the RCLUSTER library; ii) extraction of the building roof area was based on the generation of polygons from the points selected above, using the concave-hull algorithm implemented in GRASS 7. This algorithm creates a concave-hull from a subset of 3D points using Delaunay Triangulation. Then, the segment lines are removed if the triangular faces have a length above the threshold value defined by the user. This threshold allows to get polygons that better represent the buildings' roof area; iii) selection of the set of points that represents the edges of buildings on the top and ground using spatial analysis functions; and iv) calculate each building's volume using building facade height (mean value obtained from the points previously selected) and area.

All the steps above have been implemented in two scripts for the automation of the methodology. The scripts were developed using the R programming language (clustering CLARA step) and SQL language inside a Geographical Database Management System (GDBMS) implemented using PostgreSQL/PostGIS (iii and iv steps below). Results evaluation was performed inside the GDBMS.

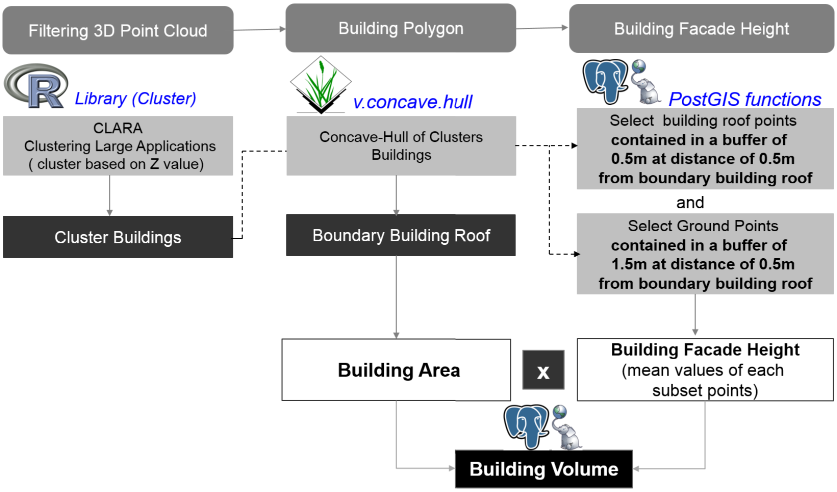

Fig. 4. Methodological approach for building volume extraction based on a 3D point-cloud

4 Results and Discussion

The accuracy of the building parameter facade height estimated is strongly dependent of the points selected during the first and third steps of the methodology. Yet, buildings' area is dependent of the success of the clustering exercises. The behaviour of LiDAR point-cloud and UAV point-cloud along the methodology is slightly different however, in general, the difficulties found in the extraction of building parameters were approximately identical. Next, the results obtained from each point-cloud will be explained in detail.

4.1 Evaluation of Building Area and Building Facade Height Parameters from LiDAR and UAV Point-Clouds

The buildings' area estimated from each point-cloud show some of the difficulties in defining building roof's boundary (Figure 5). The clustering process for LiDAR point-cloud have better results for a higher K value (number of clusters) than UAV point-cloud, respectively $K_{LiDAR} = 10$ and $K_{UAV} = 2$.

Although only some clusters were chosen (Figure 5), one and four clusters from the K_{UAV} and K_{LiDAR} values respectively.

The shapes of building roofs extracted are more regular in LiDAR point-cloud. The buildings assigned with a circle have an inaccurate area, because there are gaps where the UAV data does not have have 3D points. These gaps can be due to an inaccurate multi-stereo image matching processing of the aerial images. On the other hand, for UAV data, the threshold values chosen for concave-hull were higher (or a more concave polygon), unlike LiDAR. In this case a high-density point-cloud can influenced the behaviour of this step.

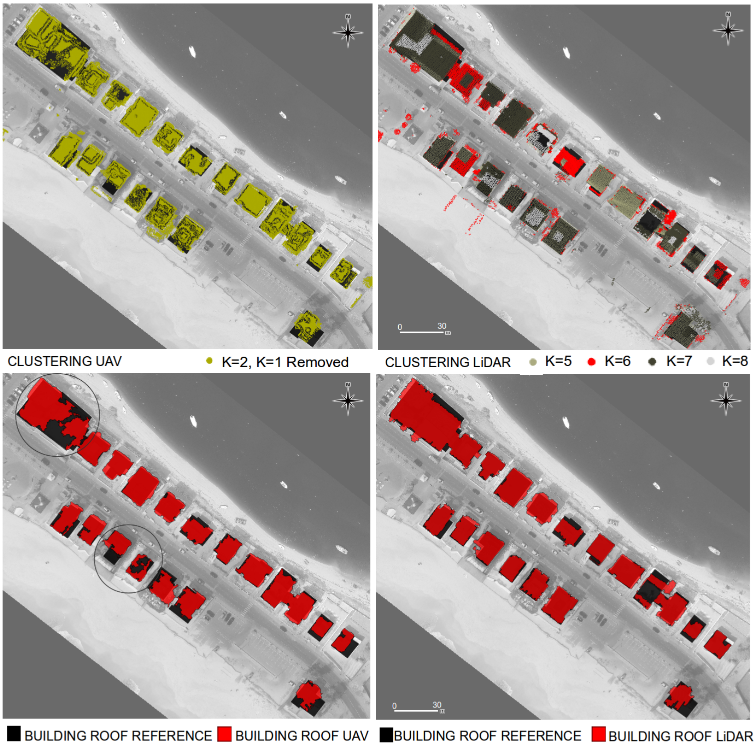

Fig. 5. Clustering results and building roofs (area) extracted from each point-cloud, LiDAR and UAV

The evaluation of the results achieved for the building facade height parameter was based on vertical error. The vertical error of the building facade height estimated corresponds to the difference between the reference value calculated from 3D vector data and the value estimated from point-cloud. The magnitude of vertical errors in the estimation of building facade height from each point-cloud can be seen in figures 6a and 6b.

Some of the best values (lower vertical errors) were obtained for buildings visible in figure 6a. About 50% of the total buildings recorded have a vertical error above 50cm. The results do not show a stronger evidence that the magnitude of the vertical error is dependent of the type of building (complex or flat). Nevertheless, the flat building roofs in figure 6a) have the same magnitude of vertical error in both point-clouds.

The worst vertical error of LiDAR (2.67m) was obtained in the buildings where balconies were considered as building roof. For UAV the worst value was obtained for the buildings that were not fully covered by UAV points.

In figure 7 is possible to visualize the behaviour of the building parameters estimated for each point-cloud when compared to the reference value parameters.

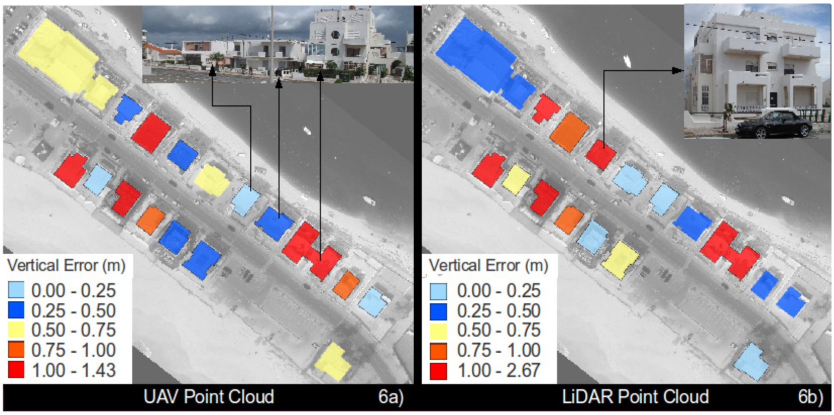

Fig. 6. Visualization of the distribution of vertical errors obtained for each building. 6a) Vertical errors from UAV point-cloud; and 6b) Vertical errors from LiDAR point-cloud.

Empirical density functions for area estimates show that generally both point-clouds approximate the reference distribution (empirical modes are similar). Yet, in regard to LiDAR, it was not possible to distinguish small irregularities, hence the larger mode. On the other hand, UAV captures the differences between buildings with too much detail (if we assume reference values as the "true" values). Yet, the estimated curve for the UAV shows a better approximation of the true values. The circle in figure 7a identifies the presence of an outlier, which represents the major error area obtained in estimation of building area from LiDAR point-cloud, i.e. the problems mentioned above for building marked in figure 5.

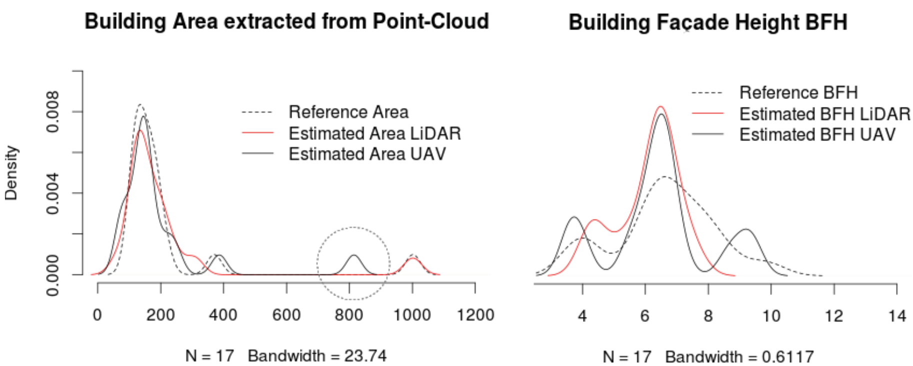

Fig. 7. Empirical density functions. a) Reference building area vs. estimated buildings area; b) The true building facade eight curve and the building facade height estimated.

The empirical density functions of each point-cloud in the estimation of the building facade height parameter is very similar (Figure 7b). Most values were overestimated by LiDAR. The estimated curve of UAV data approximates slightly better the true values.

Table 3 also shows that the errors obtained in the estimation of these parameters are very similar. The maximum error for UAV in estimation of area is an outlier (187.5m). From LiDAR there is an outlier in estimation of building facade height with a 2.67m value.

Table 3. Evaluation of building's volume from LiDAR and UAV point-clouds

Parameter	Point-cloud	Mean	Median	Minimum	Maximum
Error Area (m^2)	UAV	36.06	29.62	1.36	187.74
	LiDAR	25.24	17.79	0.40	62.45
Error Building facade Height (m)	UAV	0.61	0.51	0.01	1.43
	LiDAR	0.74	0.56	0.0	2.67

The standard error achieved for buildings' volume ranged approximately from 1% to 43% of the reference value. The magnitude of these errors is mainly due to the estimated parameter area from UAV or LiDAR data. Additionally, it is important to highlight that the error in estimating building volume with data from reference area decrease significantly, ranging approximately from 0.1% to 27%.

Comparing the vertical errors obtained in building facade height estimation with the errors obtained for the estimation of building volume computed with reference area is possible to identify three situations: a) a vertical error in estimation of building height facade up to 50cm, implies an error under 10%; b) a vertical error up to 1m, means an error in volume under 15%; and c) the vertical error between 1-2.5m, results in an error of building volume that ranges between 15% to 35%.

Table 4. Statistical measures of vertical errors for building volume estimated

Parameter	**Point-cloud**	**Mean**	**Median**	**Minimum**	**Maximum**
Error Volume (%) BFH*Reference-area	UAV	8.8	8.6	0.3	16.8
	LiDAR	9.8	10.1	**0.1**	27.2
Error Volume (%) BFH*Area	UAV	21.3	23.9	3.9	43.0
	LiDAR	14.4	8.9	0.7	35.3

In figure 8 we can see the behaviour of building volumes estimated from each point-cloud based on reference area. The estimated curve of UAV has a slightly better approximation to the true (reference) values.

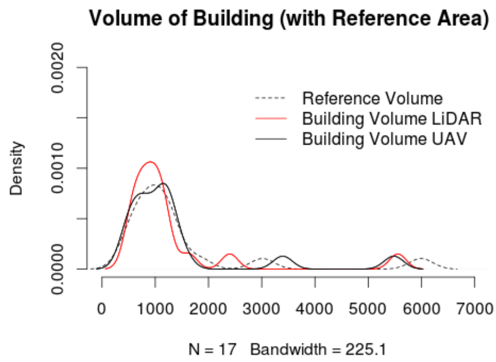

Fig. 8. Empirical density functions of building's volume estimated from each LiDAR and UAV point-clouds and building's volume relative to the reference area

The errors made by the estimation of building facade height with the UAV point-cloud have contributed to a total of volume error (computed with reference area) of all buildings equal to $1276m^3$, which corresponds to 4% of the true total volume. If we consider only the buildings with a vertical error lower then 1m in the estimation of total volume, then the percentage of error decreases to 3%. For LiDAR point-cloud the error in total volume is 9% and 4% percent more in the same situations.

5 Concluding Remarks

This work introduced a methodology for the (semi)-automatic extraction of building parameters from a 3D point-cloud, using FOSS tools. Also, it compares and analyses the accuracy and performance of different point-clouds (LiDAR and UAV imagery) in the extraction of these building parameters.

The most useful characteristics when using open source software for this study are: a) the capacity of processing dense point-clouds within a geographical spatial database; and b) the possibility of automation of some of the procedures involved in this type of studies.

The results obtained in the extraction of building parameters are very similar using both LiDAR or UAV. However, we can conclude that if the urban area has a dense vegetation and tall trees near the buildings, UAV data can be more appropriate, because it does not introduce residual information in the process. However, this is only true if the building is not surrounded completely surrounded by trees, otherwise we would have gaps in the buildings.

The major difficulty in this study is the extraction of accurate building roof (or area) data with a regular shape from point-cloud. Even facing a wide variety and complexity of building roofs (with various slopes), the results are acceptable for some stages of an urban plan.

We believe that the low-cost UAV imagery together with a robust methodology using FOSS tools can be very useful in the production of 3D buildings models for urban planning, unlike the LiDAR system. The accuracy of results shows that it can be enough for: i) a process of discussion and public participation in the planning process; ii) for the monitoring of the built-area (ex. detection of illegal changes in the height of buildings). The results clearly show that UAV technologies are a valid alternative to LiDAR. These findings have significant consequences in terms of project management in urban planning, with important methodological and financial implications.

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