Building Coverage Ratio estimate from LiDAR remote sensing data: an experiment in São Paulo (Brazil)

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Abstract. *Urban planning assumes, at its core, the use of geospatial information to drive decision-making. Nevertheless, data acquisition and development at the intra-urban scale can be resource-expensive, especially for developing countries. This paper presents an ongoing research that explores the potential of LiDAR remote sensing data to monitoring the urban environment with the use of Zoning Parameters. More specifically, it presents an automated methodology to estimate the Normalized Digital Surface Model and Building Coverage Ratio, alongside its application for the Historical City Center of São Paulo. The experiment suggests promising results, with the main advantages of use of open source software, replicability, and fast processing time.*

1. Introduction

The regulation of Land Use and Land Cover of the urban environment through the definition of Zoning Parameters aims at contributing on the pursuit of sustainable urban development and equity. Zoning Parameters may include the control of the Building Coverage Ratio, Floor Area Ratio, permeability ratio, building height, number of floors, setbacks, amongst others [São Paulo 2014].

However, computing Zoning Parameters is a challenging assignment, that often includes field surveying and visual interpretation of very-high resolution remote sensing imagery, which can be cost-expensive and time-demanding. This ongoing research aims to develop an automated methodology for estimating Zoning Parameters at the land lot planning unit, with the use of LiDAR remote sensing technology data. This paper focuses on one specific Zoning Parameter – the Building Coverage Ratio, which refers to the ratio of the building area divided by the land lot area.

LiDAR stands for Light Detection And Ranging, a technology that measures distances (or ranges) based on the time between the transmission and reception of laser signals. LiDAR is an active remote sensing method that can be used on airborne, spaceborne and ground-based platforms. The past decades have seen a rapid increase in applications of LiDAR remote sensing technology in various fields because of its capacity of obtaining data with a high level of detail and tridimensional information. One fundamental attribute of LiDAR data, that is usually stored in a laser point cloud data format, is the classification of the points, which tells whether the laser point is returned from the ground, vegetation, building, water etc. It is considered the second most important information, next to the 3D coordinates, as they allow the conduction of useful analysis [Dong & Chen 2018].

LiDAR's level of detail presents itself both as an advantage and a challenge since processing point cloud data may require the use of proprietary software and high-end hardware. This paper presents a methodology which addresses these challenges by exploring open-source software alternatives that runs at medium hardware requirements [Roussel et al. 2020].

The experiment, carried out in São Paulo's Historical City Center, consisted in the estimate of the Normalized Digital Surface Model (NDSM) and Building Coverage Ratio (BCR) from 2017 LiDAR data. Furthermore, the NDSM and BCR are extracted from high detailed geospatial information of 2004, which allows for the computation of a BCR change index, that captures this complex intra-urban territorial dynamic related to the Land Use and Land Cover of the urban environment.

The results are in compliance with urban planning and management goals and further research should focus on the estimate of other Zoning Parameters, alongside its applications, analysis and assessment.

2. Materials and methods

2.1. Study area

The study area consists of República and Sé districts, which corresponds to São Paulo's Historical City Center. They are part of the City Center Urban Operation Area, foreseen in the master plan as a priority area for urban requalification, a consequence of the demand for business and housing development in areas with established infrastructure and high accessibility [São Paulo 2014]. Figure 1 illustrates the study area location and data.

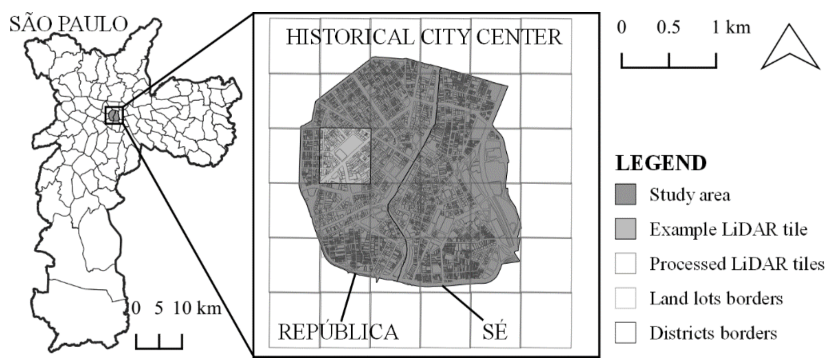

Figure 1. Study area location and data

2.2. Materials

The LiDAR point cloud data was produced in 2017 by the Green-SP Consortium, with the supervision and validation of the São Paulo City Hall. It was obtained with the sensors attached to a helicopter and the points were processed and classified into 5 categories: Soil, Buildings, Vegetation, Road Works, and Other Features. The processed LiDAR data consists of 36 tiles comprising 196.84 million tridimensional points (with longitude, latitude, and altitude attributes), which is used to generate the 2017 NDSM. The building segments, generated manually from the photogrammetric rendering of buildings rooftops in 2004, is used to compute the 2004 NDSM. The 2020 land lot segments, from São Paulo's Finance Secretary, is used as the planning unit for the computation of the 2004 BCR, 2017 BCR and BCR change index. All data is openly available and was acquired from GeoSampa Portal[1].

2.3. Methodology

Figure 2 illustrates the methodology, which consisted in the 2017 NDSM estimate from LiDAR remote sensing data, the 2004 NDSM extraction from the building segments data and the BCR computation from the 2017 NDSM, 2004 NDSM and land lot segments data. All computation was done with R Statistical Software and a reproducible example is available at GitHub[2], with the complete list of packages used.

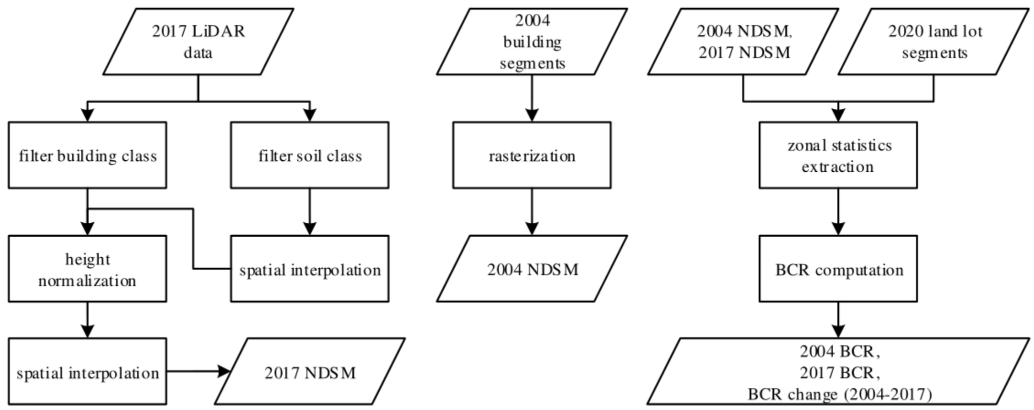

Figure 2. Building Coverage Ratio estimate methodology

The left side of the flowchart refers to the generation of the 2017 NDSM from LiDAR remote sensing data. Since the point cloud data already included a classification, the first step refers to the application of a filter to obtain the classes of interest: buildings and soil. If the classification was not available, it should be carried out before this procedure.

From the soil class, a Digital Terrain Model (DTM) is obtained by the spatial interpolation of points. The algorithm applied is the Triangular Irregular Network (TIN), which derives a Delaunay triangulation and estimates the terrain values at unsampled locations. It is the simplest DTM algorithm, because it involves no parameters, but it was chosen because it has the fastest processing time between the algorithms available. Its drawback is that the interpolation is weak at the edges, a condition that was bypassed with the definition of a 30m buffer from other tiles for every computational step.

Afterward, a height normalization was applied to each point to obtain its height from the soil. This method is superior in terms of computational accuracy if compared to a raster-based height normalization because it is done in a continuous terrain instead of a discretized terrain.

[1] http://geosampa.prefeitura.sp.gov.br/

[2] https://github.com/luisfelipebr/geoinfo2020

The NDSM is then derived from a TIN algorithm that is applied to obtain a continuous surface, i.e. to mask the cells with missing points, with the definition of an additional argument that specify the maximum edge length of a triangle as 4m, resulting in an interpolation that includes an estimate for cells with missing points, but not outside the building class.

To obtain the 2004 NDSM, a rasterize algorithm was applied to the 2004 building segments to convert it to the same data type and spatial resolution of the 2017 NDSM, making them comparable.

From the 2004 and 2017 NDSM, the building area was extracted to the land lot segments, which allowed for the computation of the 2017 BCR and 2004 BCR – dividing the land lot building area by the total area – and the BCR change index – subtracting the 2004 BCR from the 2017 BCR.

3. Results and discussion

The execution of the methodology (Figure 2) in the study area took approximately 45 minutes in a notebook with 256GB SSD, 8GB RAM and an Intel Core i5-8250U CPU.

From Figure 3 it is possible to visually compare, in the example LiDAR tile, the 2004 NDSM and 2017 NDSM. The visual comparison indicates that the generated 2017 NDSM has achieved promising results, although a statistical evaluation was not conducted as they represent different periods of time.

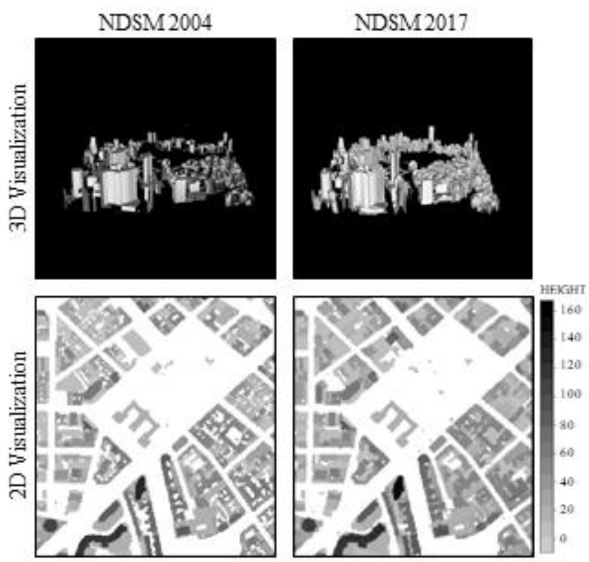

Figure 3. NDSM comparison (2004 and 2017)

Figure 4 evidence the 2004 BCR, the 2017 BCR and the BCR change index, while Table 1 presents its summary statistics. From 2004 to 2017 both the land lots quantity and area of the 75 to 100% BCR class have increased by 7%. Also, even though they represent a low quantity (7%), the 0 to 25% BCR class comprises more than 20% of the total land lots area, which may refer to public spaces or potential building area.

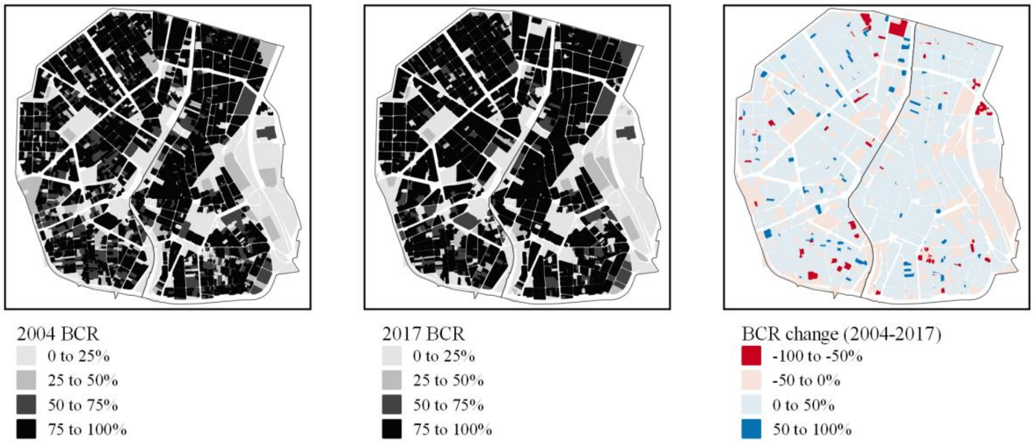

Figure 4. 2004 BCR (left), 2017 BCR (center), and BCR change index (right)

From 2004 to 2017, there have been substantial change on 4% of the land lots quantity and total area, half of them referring to buildings demolition (-100 to -50% class) and the other half to buildings construction (50% to 100% class). From the BCR change map it is possible to spatially identify these dynamics (dark red and dark blue, respectively), although it is not possible to conclude their causes and if there is a spatial pattern related to them.

Table 1. Quantity and area of land lots per class

2004 BCR	Count	Area (km^2)	2017 BCR	Count	Area (km^2)	BCR change (2004-2017)	Count	Area (km^2)
0 to 25%	382 (7%)	2.45 (21%)	**0 to 25%**	417 (7%)	2.57 (22%)	**-100 to -50%**	122 (2%)	0.24 (2%)
25 to 50%	171 (3%)	1.00 (8%)	**25 to 50%**	106 (2%)	0.67 (6%)	**-50 to 0%**	700 (12%)	2.45 (21%)
50 to 75%	595 (10%)	1.65 (14%)	**50 to 75%**	205 (4%)	1.08 (9%)	**0 to 50%**	4757 (84%)	9.02 (76%)
75 to 100%	4544 (80%)	6.82 (57%)	**75 to 100%**	4964 (87%)	7.60 (64%)	**50 to 100%**	113 (2%)	0.21 (2%)
Total	5692 (100%)	11.92 (100%)	**Total**	5692 (100%)	11.92 (100%)	**Total**	5692 (100%)	11.92 (100%)

The estimated Zoning Parameters, in combination with other relevant features of the land lots (function, ownership etc.), can be used to the identification of non-built and underutilized properties and foster the application of the social function of property [Denaldi et al. 2017]. They may also be applied to the estimate of dwelling units density [Lwin & Murayama 2010] and population density [Frizzi et al. 2019], the characterization of deprived settlements [Kuffer & Barros 2011, Feitosa & CDHU 2018, Ribeiro et al. 2019], amongst other urban planning and management paradigms. But its use in these contexts should include additional ancillary data in a more robust framework.

4. Final remarks

This paper presented an automated methodology for the BCR estimate from LiDAR remote sensing technology data and its application to São Paulo's Historical City Center. It included the computation of the NDSM as an intermediary product, which have achieved promising results by visual comparison, while the 2017 BCR, 2004 BCR and BCR change index evidence an important aspect of the intra-urban environment. This approach has the main advantages of relying on open-source software for computation and features a fast processing time, being replicable to other study areas.

Further research should include the estimate of other Zoning Parameters, alongside its analysis and assessment, while also considering urban planning questions, such as the identification of non-built and underutilized properties and the characterization of deprived settlements.

5. References

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