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Artigos

BIOMASS ANALYSIS METHOD IN A FOREST FRAGMENT OF PINUS UNCINATA

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Abstract:

The forests have a vital role in carbon capture from the atmosphere. Thus, this work has as its main objective to quantify and analyze biomass of a forest fragment of a Pinus uncinata that belongs to Alinyà Mountain Natural Space, through of Light Detection and Ranging (LIDAR) data tools. The natural area is located in the County of Figòls y Alinyà, in the Lleida province, located in Catalonia-Spain. In this sense, using the LIDAR data, the Digital Terrain Models were generated, and relevant statistical calculations were made to subsequently calculate the forest biomass. The linear regression models for biomass had a satisfactory correlation with the inventory data for 2 of the 5 areas considered. In this sense, it was possible to estimate these forest variables for the study area. The calculation of forest biomass by LIDAR data resulted in 9.138.6 tons to an area of 69.04 ha, while the inventory calculations resulted in 11.638.4 tons.

Keywords: Forest Variables, Natural Resources, Remote Sensing, LiDAR.

Resumo:

/ Resumen

MÉTODO DE ANÁLISE DE BIOMASSA EM UM FRAGMENTO FLORESTAL DE PINUS UNCINATA

As florestas têm um papel vital na captura de carbono da atmosfera. Por essa razão, este trabalho tem como objetivo principal quantificar e analisar a biomassa de um fragmento florestal de um Pinus uncinata que pertence ao Alinya Mountain Natural Space, através de ferramentas de dados Light Detection and Ranging . A área natural está localizada no município de Figòls y Alinyà, na província de Lleida, localizada na Catalunha-Espanha. Usando os dados Light Detection and Ranging (LIDAR), os Modelos de Terrenos Digitais foram gerados, e foram feitos cálculos estatísticos relevantes para posteriormente calcular a biomassa florestal. Como resultado, os modelos de regressão linear para biomassa tiveram uma correlação satisfatória com os dados de estoque para 2 das 5 áreas consideradas. Nesse sentido, foi possível estimar essas variáveis florestais para a área de estudo. O cálculo da biomassa florestal com dados LIDAR resultou em 9.138.6 toneladas para uma área de 69.04 ha, enquanto os cálculos de estoque resultaram em 11.638.4 toneladas.

Palavras-chave: Variáveis Florestais, Recursos Naturais, Sensoriamento Remoto, LiDAR.

Palabras clave: Variables Forestales, Recursos Naturales, Detección Remota, LiDAR

INTRODUCTION

In recent decades, their ability to acquire spatially continuous information about the geographicdisposition of forest resources has made new remote sensing tools increasingly popular. Given the highcosts of forest inventories and monitoring, remote detection has become an essential tool (JIMÉNEZ etal., 2016). The Light Detection and Ranging (LiDAR), or Laser Scanner is among this new generation oftools. It emits laser pulses to measure the returning time and directly estimate the height and structure offorests (PILLODAR et al., 2017; LIU et al., 2017). LiDAR has recently emerged as a powerfultechnology for forest measurement applications, including ground and vegetation surfaces, to assess treeheight, volume, and biomass measurements (EDSON & WING, 2011; KRAMER et al., 2016). Aboveall, LiDAR technology provides a range of indirect data on the terrestrial elements used in statisticalmodels.

The technique's potential considers three-dimensional information, has greater data accuracy thanthe Radar, and is not affected by the atmosphere, thus providing more specific data on terrestrial featuresthat may serve as a basis for studies of the modification of the vegetation patterns in particular areas.Therefore, this study was conducted in a forest fragment in the Alinyà Mountain Nature Space, a distinctlandscape with a diversity of flora and fauna, containing tracts of forest of great environmental interestas potential carbon sinkholes. One of these is a Pinus uncinata forest fragment selected as the object ofstudy for this research to quantify and analyze the forest biomass using LiDAR tools.

MATERIAL AND METHODSSTUDY AREA CHARACTERIZATION

The Alinyà Mountain Nature Space covers 5352.13 ha in the municipality of Figols i Alinyà inthe province of Lérida, in the Autonomous Community of Catalonia, Spain. Its principal coordinates areE 1º25'22" and N 42º10'49". Located between the Sierra del Cadí and the river Segre, this natural area isthe largest privately-owned reserve in Catalonia, belonging to the Catalunya-La Pedrera Foundation (FCP, 2015).

The altitude ranges from 608 to 2739 meters. The slopes' relief and orientation give rise todifferent zones with a characteristic pre-Pyrenean microclimate; the temperatures vary from 8 ° C to 16° C. These climatic features include both a Euro-Siberian region and typically Mediterranean areas. Inthe low and medium portions, the vegetation is distinguished by holm oak groves and Mediterraneanpine forests, among them the wild pine (Pinus sylvestris). The higher section of the valley has asubalpine ecosystem, in which an herbaceous substrate predominates (MOISÉS et al., 2004).

INVENTORY DATA

This study utilizes data from the Forest Inventory prepared by the Catalunya Foundation - LaPedrera from June to September 2013, which has two main parts. First are the chief coordinates, radius,and total area of the 123 circular plots grouped in zones, including the number of plants per diameterclass. Second is the data referring to the biomass for each zone inventoried according to the CREAFmethodology (Centro de Investigación Ecológica y Aplicaciones Forestales) (Generalitat de Catalunya).

For the comparison with the LiDAR data and subsequent regression models, five zones (1a, 1b,1c, 1d, and 3c) from homogeneous or predominantly Pinus uncinata forests were chosen. These are 60circular areas with an average radius of 12 meters and an ideal surface of 452.39 m^2; of these, 13 are inzone 1a, 12 in zone 1b, 9 in zone 1c, 16 in zone 1d, and 11 in zone 3c. Zone 1a was the forest fragmentselected to estimate the biomass using the LiDAR data.

PROCESSING THE LIDAR DATA

For the LiDAR data, the cartography from the laser scanning flight over the study area between 2009 and 2011 was acquired from the National Plan of Aerial Orthophotography (PNOA) of the National Geographic Institute [of Spain]. During the LiDAR data processing, a correction was madeusing annual growth factors of the National Forest Inventory 3 (IFN3).

The FugroViwer ™ (Fugro) free software was used to view the point cloud. Additionally, the FUSION / LDV software developed by the Forest Service of the United States Department ofAgriculture - Forest Service - USDA was used to filter and manage these points. Thus, the classesconsisted of the terrain, low vegetation, medium vegetation, high vegetation, and the key point of themodel. Then, the lasclip tool was used to select and extract the information in the (*.las) filecorresponding to the zone of interest.

Subsequently, a Digital Surface Model (DSM) was generated from the data in all the charts, sothat information on the terrain could be separated from the information about the vegetation, followedby the calculations corresponding to the forest biomass. A similar process was adopted to generate theDigital Model of Vegetation Height (MDHV or Canopy model), this time only for the zone 1a forestfragment. Both models were then converted to the ASCII format to be sequenced in the data processing.

The next steps extracted and calculated the LiDAR statistic stack from the points relative to thecircular plots, with similar radius to those delimited in the terrain (12 m radius and 542 m2 idealsurface), in the 60 selected each circumference's center was its respective point. This process used theFUSION Gridmetrics command to obtain the LiDAR data concerning the vegetation dimensions thatwere confronted with the field-inventoried data to generate the linear models and equations.

This command calculates the statistical data on user-adjustable rectangular cells, in this case, 20m edges, to obtain surfaces similar to the plots in the fields. However, FUSION made some errors whenrunning Gridmetrics that resulted in corrupted cells, which were eliminated.

After this process, linear regression equations were calculated by modeling the relationshipbetween the dependent variable (biomass) and the independent variables (LiDAR statistical data). Thefree R software developed at the University of Auckland and under improvement by the R DevelopmentCore Team was used to execute the models and create the equations to estimate the forest variables. Thisprogram tested the correlation between the variables and refined the models until high coefficients ofdetermination and low standard errors were reached.

RESULTS AND DISCUSSION DIGITAL TERRAIN MODELS

The processed information obtained from the LiDAR flight was used to create the Digital TerrainModels of the Surfaces and the Vegetation Heights. Figure 1 corresponds to the Digital Model ofSurfaces of the elevations in zone 1a, generated by the FUSION GridsurfaceCreate tool.

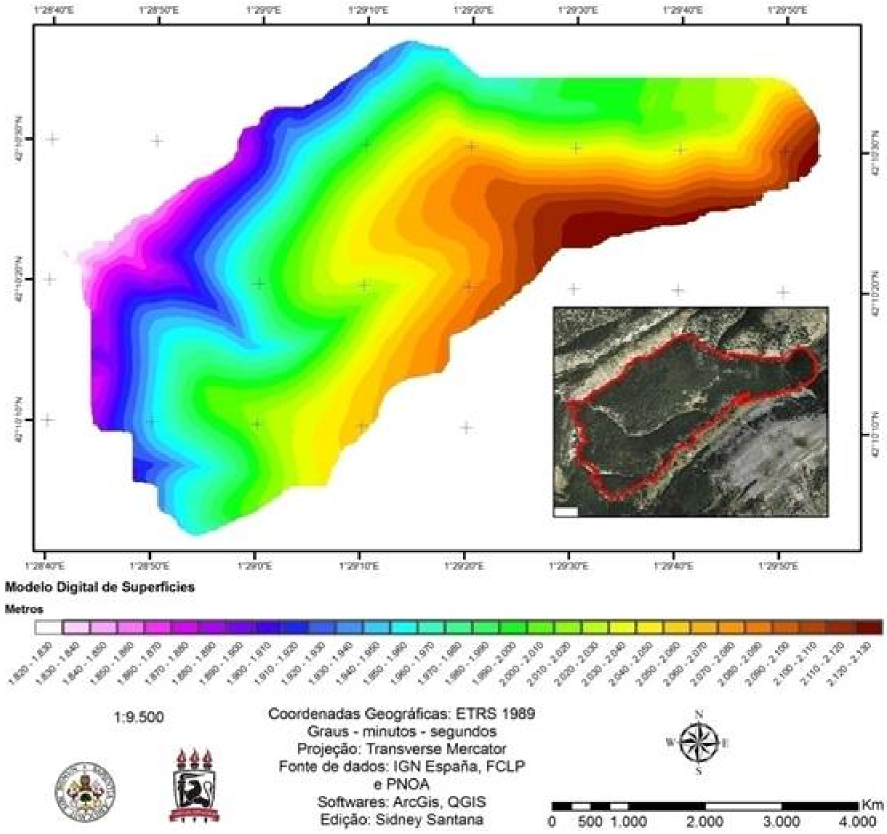

FIGURE 1
The Digital Surface Model of Zone 1a.

The study area is 315.29 meters high; its highest point is 2135.46 meters above sea level. In Figure 1, the colors correspond to the altitude and show that the eastern section is the highest part ofzone 1a, in brown.

The altitudinal values decrease towards the west, and the lower levels are shown in light pink.Zone 1a is a sloping area facing west and is crossed longitudinally by a valley in its central section.Similarly, another valley runs through the south of the zone.

THE CANOPY MODEL

Figure 2 corresponds to the Digital Model of Vegetation Height or canopy model of the study areacreated by the FUSION CanopyModel function.

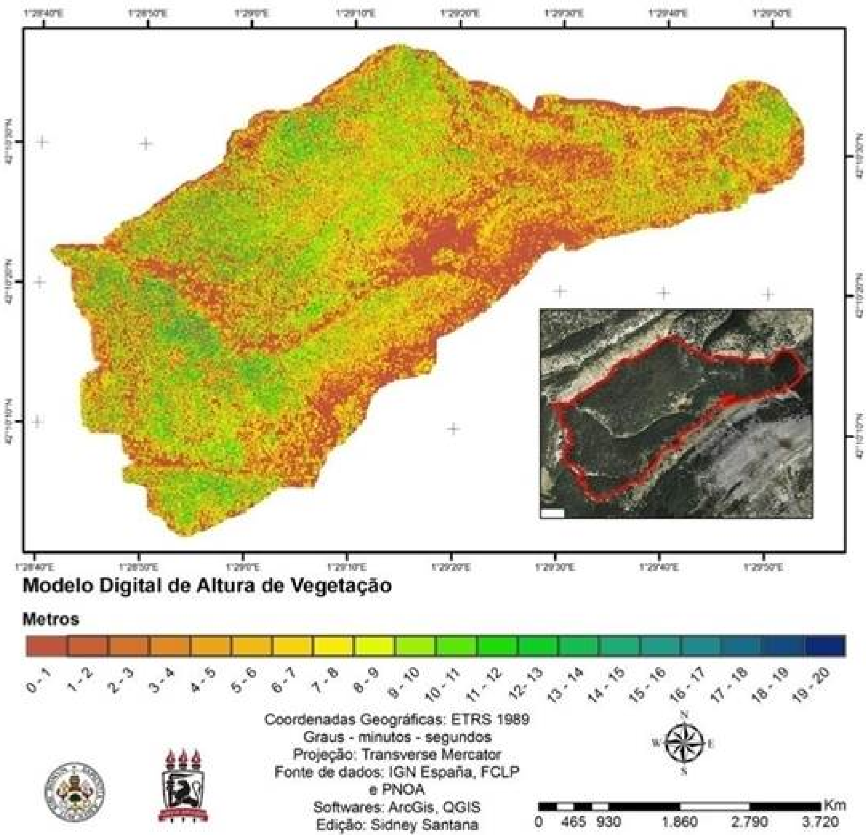

FIGURE 2
Digital Model of Vegetation Height of Zone 1a.

The color gradation corresponding to vegetation heights in Figure 2 evidences that theconcentrations of the highest masses of vegetation are distributed in four parts: in the extreme north-eastof the zone, in the central part north of the valley, in the central portion to the south of the valley, andthe extreme south of the zone.

The lowest altitudes are along the thalwegs of the two valleys that cross the zone, and the highestpoints are in the eastern portion. Besides specifying the altitudes, the model provides more visual detailof the area through the color classification of the entire forest mass.

The Digital Surface Model was essential in developing the study since it was only possible tocalculate the LiDAR variables once the vegetation had been distinguished from the soil. The DSM alsoserved as a parameter of comparison with the other products when the forest mass was analyzed.

THE CALCULATION OF STATISTICAL MODELS BASED ONTHE LIDAR DATA

Initially, the linear models were tested with points 1a, 1b, 1c, 1d, and 3c in all 60 zones. However,the correlations were unsatisfactory, reaching an average R square value of 0.5. Then, new tests wereperformed, excluding one zone at a time, or considering the points of two zones. Zone 1a was alwaysincluded in this process since it is the subject of this study.

Finally, when generating models with the points of zone 1a and 1d, an R square value of 0.82 wasreached, with a high degree of significance for most parameters. The "union" of the points of these two zones resulted in a total of 29 circular plots.

In the studies of Zhao et al. (2009), Salas et al. (2010), and Zolkos et al. (2013), regressionmethods are useful for modeling biomass with metrics derived from airborne sensors. In these cases, theallometric equations related the forest biomass field measurements with the trees' physicalcharacteristics provided by LiDAR data.

However, to understand the low earlier correlations, a hypothesis was proposed that the forestbiomass values for zones 1a and 1d could, in fact, relate to tree height since the LiDAR data mainlyrefer to elevation. Inversely, the other zones' biomass values could be associated with the number oftrees per plot. Therefore, the mean values of the biomass inventory and the maximum elevationgenerated by the LiDAR data were calculated separately and then compared to each other (Table 1).

Zone	Forest Biomass	Max. Elevation
1a	6.87 *tons*	14.36 m
1b	5.22 *tons*	11.00 m
1c	4.89 *tons*	12.16 m
1d	6.31 *tons*	13.92 m
3c	9.04 *tons*	16.03 m

TABLE 1

Average biomass values and maximum elevation.

Table 1 shows that zones 1a and 1d have the highest biomass and maximum elevation values ofthe zones belonging to group 1. However, according to the LiDAR data, zone 3c has the most forestbiomass and the tallest vegetation.

As the tests for zone 3c did not result in a satisfactory correlation, the hypothesis suggested wasdiscarded. Once the linear forest biomass model of zones 1a and 1d had been determined, similar modelswere used to estimate the carbon content, considering that the other three parameters' correlation wasalso satisfactory, with an R^2 average of 0.82.

Based on these models, Microsoft Excel equations were set up to estimate the forest biomass ofall 29 points considered in this step. Table 2 presents equations 1 and 2 resulting from the linearregressions performed between the forest biomass data and the inventory's carbon content data from LiDAR.

Forest Biomass Model	**Equations**
Correlations Residual standard error = 0.753 Multiple R-squared = 0.825 Adjusted R-squared = 0.693	Forest biomass = −8.420533 − (17.284783 • Elev. mean) + (0.090872 • FCC) + (3.321942 • Elev. Kurtosis) + (4.383122 • Elev. p70) + (3.582299 • Elev. p50) − (1.322206 • Elev. p95) + (4.407623 • Elev. p05) + (3.959646 • Elev. p75) + (2.871198 • Elev. p90) − (1.757112 • Elev. p01) + (0.002919 • All returns above mean) + (6.719745 • Canopy relief ratio) (1)
Carbon Content Model	
Correlations Residual standard error = 0,389 Multiple R-squared = 0,817 Adjusted R-squared = 0,680	Carbon content = −4,5731132 + (1,8312510 • Elev. Kurtosis) − (9,6776788 • Elev. mean) − (0,5139935 • Elev. P01) + (2,1626610 • Elev. P05) + (2,2162177 • Elev. P50) + (2,7347885 • Elev. P70) + (1,7112347 • Elev. P75) + (1,7414060 • Elev. P90) − (0,7976353 • Elev. P95) + (0,0450736 • FCC) + (0,0015026 • All returns above mean) + (2,9105467 • Canopy relief ratio) (2)

TABLE 2

Equations to estimate the forest parameters and their respective correlations.

In Table 2, both the R-squared and the adjusted R-squared values of the three variables wereclose; those for the forest biomass were highest at 0.825 and 0.693, respectively. Estornell et al. (2012) obtained similar results for the correlations of allometric calculations of biomass, with an R-squared of0.87 and adjusted R-squared of 0.79 in the Mediterranean region.

Table 3 shows the values of the forest inventory's variables and the values estimated by theequations referring to forest biomass, basal area, and carbon content.

Zone points	Forest Biomass Inventory	Forest Biomass Model	Basal Area Inventory	Basal Area Model	Carbon Stock Inventory	Carbon Stock Model
1a1	8,53	8,33	2,16	2,21	4,40	4,49
1a2	5,93	6,02	1,57	1,63	3,30	3,37
1a3	7,82	6,98	2,11	1,90	4,28	3,84
1a4	6,00	6,53	1,65	1,72	3,34	3,51
1a5	7,60	7,26	2,06	1,97	4,16	3,98
1a6	4,81	5,08	1,35	1,45	2,73	2,92
1a7	6,65	7,39	1,80	2,00	3,67	4,06
1a8	5,98	6,68	1,64	1,84	3,33	3,76
1a9	7,38	8,29	1,98	2,28	4,05	4,62
1a10	4,71	4,00	1,32	1,19	2,68	2,42
1a11	6,37	5,92	1,73	1,70	3,53	3,44
1a12	8,34	7,32	2,22	2,03	4,54	4,15
1a13	9,16	8,69	2,44	2,31	4,97	4,69
1d2	5,90	6,20	1,71	1,77	3,46	3,58
1d3	6,26	5,72	1,80	1,63	3,65	3,28
1d4	4,26	5,51	1,31	1,58	2,61	3,18
1d5	4,00	4,51	1,24	1,38	2,48	2,76
1d6	8,31	8,59	2,31	2,34	4,71	4,74
1d7	4,96	4,97	1,48	1,47	2,98	2,95
1d8	5,74	6,72	1,68	1,90	3,38	3,86
1d9	5,82	5,43	1,68	1,54	3,42	3,10
1d10	6,30	5,77	1,81	1,62	3,67	3,31
1d11	8,79	8,55	2,45	2,36	4,95	4,79
1d12	6,89	6,77	1,97	1,92	3,97	3,88
1d13	6,64	6,38	1,90	1,79	3,84	3,63
1d14	7,92	7,76	2,22	2,11	4,51	4,31
1d15	6,05	6,01	1,57	1,61	3,12	3,22
1d16	7,14	6,77	2,04	1,98	4,10	3,99
1d17	6,03	6,17	1,76	1,74	3,53	3,51

TABLE 3
Biometric values for the inventory and the results of the LiDAR calculations.

In Table 3, the values resulting from the LiDAR data equations approximate the forest variablesprovided by the La-Pedrera Foundation Inventory. Dispersion graphs were generated between the values(by plot) of the variables from the inventory and those generated by the LiDAR data statistical model toverify this correlation.

There is a good correlation between the forest biomass inventory values and the carbon contentand the applied models' results, at 0.825, 0.817, and 0.817, respectively. Thus, forest biomass is thevariable with the highest correlation between the data, while the R-squared carbon content has closeresults.

The cells located in the study area are the points with the information produced by theGridMetrics LiDAR variables. Each cell is 400 m², and for those in zone 1a, the equations were appliedto estimate forest biomass.

FOREST BIOMASS

Excluding those that presented errors, 1,727 cells in zone 1a have an area equal to 69.08 ha.Taking this dimension as a reference and considering the inventory plots as samples, the area's totalforest biomass was estimated at 11,638.4 tons, using data from the La-Pedrera Foundation. On the otherhand, when the areas' total biomass was computed, applying the equation to the LiDAR data, 9,138.6tons of forest biomass were calculated.

When comparing the total forest biomass in the study area, the two results are approximate values,with the model indicating 2.499.8 fewer tons. This difference is probably due to this method usingsample plots to calculate the zone's biomass, which includes parts of the forest with smaller trees are andeven spaces without arboreal vegetation, as was evident in the Canopy model.

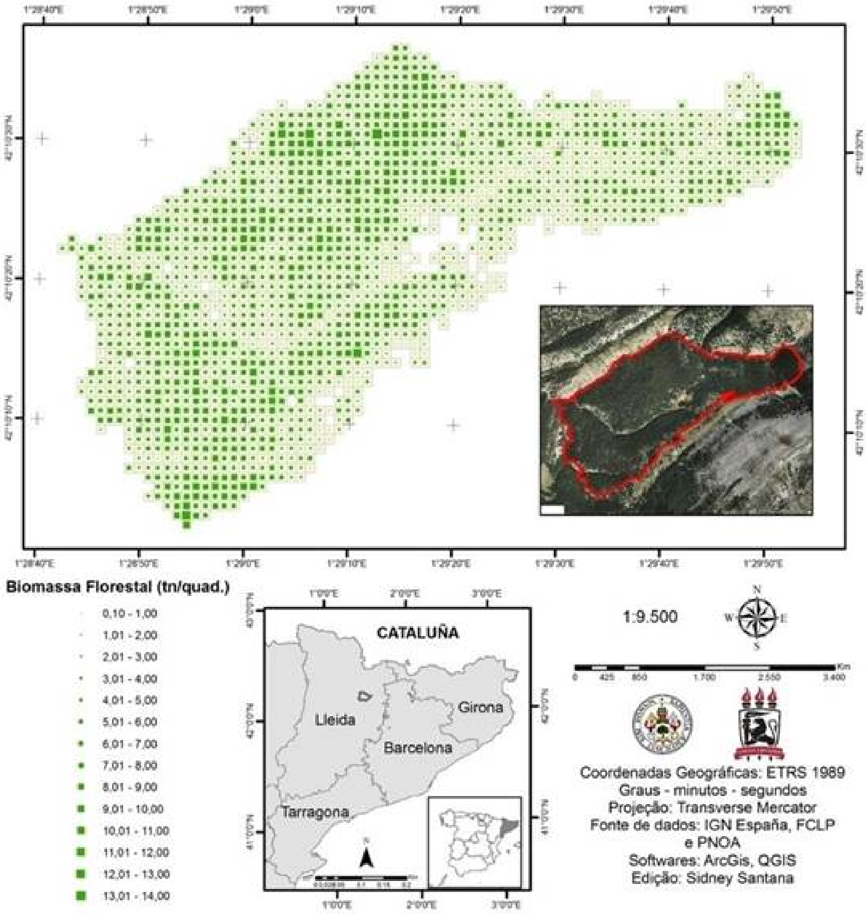

FIGURE 3
Forest biomass distribution in zone 1a

Studies were also carried out by Silva et al. (2015a) on the importance of estimating biomassthrough remote sensors and Silva et al. (2015b) on using new technologies to conserve natural resources

Thus, the LiDAR data's importance as the most reliable projection of the study's object is clear as thesensor captures information about the zone as a whole, including different vegetation cover. In contrast,the inventory plots are samples that tend to homogenize the information about the space in question.Therefore, Figure 3 presents the forest biomass distribution map by quadrat throughout the study area.

An analysis of Figure 3 shows that the higher concentrations of forest biomass are not condensedin a particular region of the zone but are distributed in several locations. A high forest biomass extendsthroughout the north-central part of the zone, although it does not occur uniformly. To the south of thedivision made by the valley bottom, there is also a denser biomass distribution, and a similarlyconcentrated densification of forest biomass is apparent at the southern end of the zone.

It is also evident that there is a concentration of forest biomass in the northeast of the zone, aroundthe coordinates 1°29'50" E and 42°10'30" N. In the areas corresponding to the thalwegs, which cross thecentral and southern portions of the zone, there is a significant absence of forest biomass caused by thepedological structure in these areas, with accumulations of rocky debris carried by natural agents addedto the action of gravity.

Additionally, there is a low concentration of biomass between the north-central and northeastportion of the zone, including the site's highest areas, possibly due to the shallow soil and rockyoutcrops, which impede the development of arboreal vegetation. In this area, there is the presence ofrocky outcrops near the eastern part of the zone. The comparisons made in the studies of Montero et al.(2005) indicated a carbon content for the biomass of black pine (Pinus nigra) of 50.9%, while forSpanish juniper (Juniperus communis) and holm oak (Quercus ilex), the carbon content was estimated at47, 5% of the total biomass.

CONCLUSION

Firstly, the study found that the canopy model is a viable product to analyze the forest biomassstructure since it distinctly differentiates between the trees' heights.

Furthermore, the statistical results of the LiDAR data related to the Forest Inventory informationwere useful as the former had a satisfactory correlation with the Inventory data for the 29 plots in zones1a and 1d, with R-squared values above 0.8. Consequently, they enabled the creation of an equation toestimate the forest biomass of the study area.

Finally, research using LiDAR is advantageous as it works with non-destructive biometricmeasures. However, Light Detection and Ranging data application methods need to be developed to fitthe diverse realities of biomes and forests worldwide.

REFERENCES

EDSON, C.; WING, M.G. Airborne Light Detection and Ranging (LiDAR) for Individual Tree Stem Location, Height, and Biomass Measurements. Remote Sens. [s.l.], v. 3, n. 11, p.2494-2528, 2011. 2494-2528. 10.3390/rs3112494. 2011.

ESTORNELL, J.; RUIZ, L.A.; VELÁZQUEZ-MARTÍ, B.; HERMOSILLA, T. Estimation of biomassand volume of shrub vegetation using LiDAR and spectral data in a Mediterranean environment.Biomass & Bioenergy, Oxford, v. 46, p. 710-721, Nov. 2012.https://doi.org/10.1016/j.biombioe.2012.06.023. 2012.

FUNDACIÒ CATALUNYA – LA PEDRERA. 2015.

JIMÉNEZ, E.; VEJA, J.A.; FERNÁNDEZ-ALONSO, J.M.; VEGA-NIEVA, D.; ORTIZ, L.; LÓPEZ-SERRANO, P.M; LÓPEZ-SÁNCHEZ, C.A. Estimation of aboveground forest biomass in Galicia (NW Spain) by the combined use of LiDAR, LANDSAT ETM+ and National Forest Inventory data. iForest Biogeosciences and Forestry. [s.l.], v. 10, pp. 590-596, 2016. doi: 10.3832/ifor1989-010. 2016.

KRAMER, H.A.; COLLINS, B. M.; GALLAGHER, C.V; KEANE, J.J.; STEPHENS, S.L.; KELLY, M. Accessible light detection and ranging: estimating large tree density for habitat identification. Ecosphere. [s.l.], v. 7, n. 12, p.1-15, 2016. https://doi.org/10.1002/ecs2.1593. 2016.

LIU, L.; PANG, Y.; LI, Z.; SI, L.; LIAO, S. Combining Airborne and Terrestrial Laser Scanning Technologies to Measure Forest Understorey Volume. Forests, [s.l.], v 111, n.8, p.1-14, abril de 2017. doi:10.3390/f8040111. 2017.

MOISÉS, J.; IBÁÑEZ, M.; RODRÍGUEZ, R.; OLARIETA, J.R. Estudi climatològic de la Vall d’Alinyà. En: Els sistemes naturals de la vall d’Alinyà. Barcelona: Institució Catalana d’Història Natural, p. 17-45, 2004.

MONTERO, G.; RUIZ-PEINADO, R.; MUÑOZ, M. Producción de biomasa y fijación de CO2 por los bosques españoles. 120f. Monografías INIA, Serie Forestal; Madrid, 2005.

PILLODAR, O.; MERO, D.C.; MOSTRALES, D. S.; ASTILLERO, S.G.C.; IGNACIO, M. T. T. Estimation of Aboveground Biomass and Carbon Stock of Bacolod Protected Landscape and Seascape Using LiDAR Data and

GIS Fejaycris. Int'l Journal of Advances in Agricultural & Environmental Engg. (IJAAEE). [s.l.], v. 4, Issue 1. p.1-5, 2017. https://doi.org/10.15242/IJAAEE.C0117003. 2017.

SALAS, C.; ENE, L.; GREGOIRE, T. G; NÆSSET, E.; GOBAKKEN, T. Modelling tree diameter from airborne laser scanning derived variables: a comparison of spatial statistical models. Remote Sensing of Environment. [s.l.], v.114 n.6, p.1277-1285, 2010. https://doi.org/10.1016/j.rse.2010.01.020. 2010.

SILVA, E.R.A.C.; GALVÍNCIO, J.D.; BRANDÃO NETO, J.L.; MORAIS, Y.C.B. Space-Time Analysis of Environmental Changes and your Reflection on the Development of Phenological of Vegetation of Mangrove. Journal of Agriculture and Environmental Sciences. [s.l.], v. 4, p. 245-253. 2015a. doi: 10.15640/jaes.v4n1a30. 2015a.

SILVA, E.R.A.C.; MORAIS, Y.C.B.; SILVA, J.C.; GALVÍNCIO, J.D. Consumo de água na irrigação para cultivo da bananeira nas condições edafoclimáticas da bacia do riacho do Pontal no Semiárido de Pernambuco. Revista Brasileira de Geografia Física, Pernambuco, Brasil. v. 08, n. 03. P. 921-937. 2015b. http://dx.doi.org/10.5935/1984-2295.20150087. 2015b.

ZHAO, K.; POPESCU, S.; NELSON, R. Lidar remote sensing of forest biomass: A scale-invariant estimation approach using airborne lasers. Remote Sensing of Environment. [s.l.], v. 113, Issue 1, p. 182-196, 2009. https://doi.org/10.1016/j.rse.2008.09.009. 2009.

ZOLKOS, S.G.; GOETZ, S.J.; DUBAYAH, R. A meta-analysis of terrestrial aboveground biomass estimation using lidar remote sensing. Remote Sensing of Environment, [s.l.], v. 128. p. 289-298, 2013. ISSN 0034-4257, http://dx.doi.org/10.1016/j.rse.2012.10.017. 2013.