Modelling canopy fuel properties and understory vegetation with full-waveform LiDAR

Luis Ángel Ruiz
GeoEnvironmental Cartography and Remote Sensing Group
Universitat Politècnica de València
València, Spain
laruiz@cgf.upv.es

Pablo Crespo-Peremarch
GeoEnvironmental Cartography and Remote Sensing Group
Universitat Politècnica de València
València, Spain
pabcrepe@cgf.upv.es

Jesús Torralba
GeoEnvironmental Cartography and Remote Sensing Group
Universitat Politècnica de València
València, Spain
jetorpe@upv.es

***Abstract*—The use of accurate information from canopy fuel and understory vegetation variables is essential to prevent, predict and mitigate wildfires. This information may accurately be estimated by remote sensing techniques such as LiDAR technology. Among LiDAR technology, full-waveform LiDAR registers the entire signal emitted by the sensor and going through the different vertical layers, providing more information from the different vertical strata, including understory vegetation, than traditional or discrete LiDAR. In this study we estimated three canopy fuel variables: canopy fuel load, canopy height and canopy base height; and four understory vegetation variables: mean and maximum height, cover and volume, by using full-waveform airborne LiDAR data in a Mediterranean ecosystem. Results showed that canopy fuel variables may be estimated very accurately (canopy height: 90.5%, canopy base height: 90.6%, and canopy fuel load: 77.4%) using full-waveform airborne LiDAR data. On the other hand, understory vegetation variables may also be estimated very accurately (mean height: 94.9%, maximum height: 75.8%, cover: 87.1%, and volume: 95.1%). Therefore, full-waveform airborne LiDAR data may be used to predict not only canopy fuel variables, but also understory vegetation variables, useful for modelling fire behavior.**

Keywords—full-waveform, ALS, forest structure, understory, wildfires

I. INTRODUCTION

Wildfires are one of the most widespread natural disasters around the world, endangering the population, wildlife, and may cause other secondary hazards [1]. This natural disaster may be modelled through mapping that includes canopy variables such as canopy bulk density, canopy height, canopy base height, canopy fuel load and canopy cover [2]. These variables are used as input data in fire behavior models (FARSITE, BehavePlus, etc.). Nevertheless, arson fires usually start in the lower strata, rather than in the canopy. These fires require a fuel ladder to connect lower strata with canopies to trigger a crown fire [3], which are the most severe [4]. These fuel ladders are usually formed by understory vegetation and/or a low canopy base height.

Estimate of canopy and understory variables has traditionally been done by costly destructive methods [5]. The use of more recent techniques, such as remote sensing, has facilitated this task reaching high accuracies [6]. Among remote sensing techniques, LiDAR consists of a sensor emitting thousands of laser pulses per second and registering the laser response from intercepted objects. These data containing XYZ and intensity information are known as discrete LiDAR. These data have successfully been used to estimate canopy fuel variables in contrasted ecosystems [7][8]. One step further of discrete LiDAR, full-waveform LiDAR systems register the entire signal received by the sensor after going through the different vertical layers, providing more information from the different vertical strata, including the understory vegetation [9][10]. However, these data, that are more complex and larger in size compared to discrete LiDAR, have been poorly used so far because of the lack of processing tools.

The goal of this study is assessing the capacity of full-waveform airborne LiDAR data to estimate canopy fuel (i.e., canopy height, canopy base height and canopy fuel load) and understory vegetation variables (mean and maximum height, cover and volume) in a Mediterranean ecosystem.

II. MATERIAL AND METHODS

A. Study area

The study area (3,700 ha) is located in a Mediterranean ecosystem in eastern Spain, centered around 39.96ºN and 0.41ºW (Fig. 1). This area is dominated by Aleppo pine (*Pinus halepensis*), maritime pine (*Pinus pinaster*) and cork oak (*Quercus suber*) (Fig. 2). The presence of understory vegetation is very variable, and it is dominated by brezo (*Erica multiflora*), kermes oak (*Quercus coccifera*), rosemary (*Rosmarinus officinalis*), Mediterranean buckthorn (*Rhamnus alaternus*), tree heath (*Erica arborea*), and mastic (*Pistacia lentiscus*) (Fig. 2).

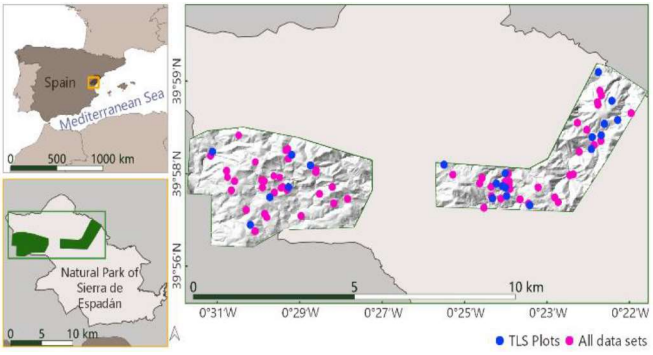

Fig. 1. Study area and forest plots location.

B. Forest plots

A total of 80 circular plots with a radius of 15 m were established along the study area (Fig. 1). The centers of these plots were measured with a GPS RTK with an average accuracy of ~0.40 m. For each plot, standard forest inventory measurements (i.e., diameter at breast height, height, number of trees, species description, etc.) were collected. These measurements were further used to estimate, through allometric equations provided by [11], the three canopy fuel

variables: canopy fuel load (CFL), canopy base height (CBH), and canopy height (CH).

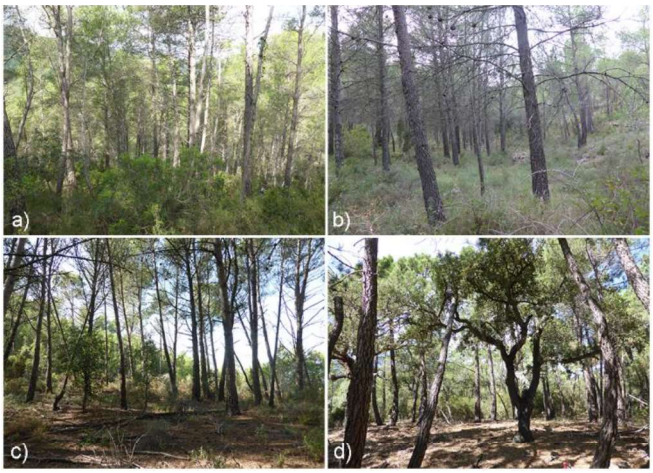

Fig. 2. Field photographs from the study area illustrating the varying canopy and understory vegetation species. a) *Pinus halepensis* - dense understory; b) *P. halepensis* – sparse understory; c) *Pinus pinaster – very sparce understory;* and d) *Quercus suber* and *P. pinaster - absent understory.*

C. *Full-waveform airborne and discrete terrestrial LiDAR data*

Full-waveform airborne LiDAR data were acquired on September 16th 2015 using a LiteMapper 6800. Data were acquired with a scan angle of ±30º, a pulse frequency of 300 kHz, and a flight altitude between 600 and 820 m above ground level, which resulted in an average pulse density of 14 pulses·m^{-2}.

In addition, discrete terrestrial LiDAR data were acquired in 21 out of the 80 plots mentioned using a FARO FOCUS 3D 120 phase-based laser scanner. Each plot was registered from nine different scans (Fig. 3) to reduce signal occlusion caused by vegetation. These data were collected to be used as reference data in the estimation of understory vegetation variables.

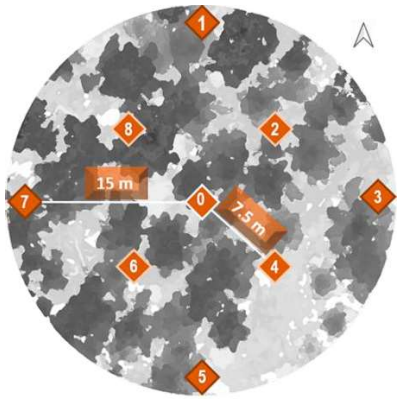

Fig. 3. Description of the discrete terrestrial LiDAR scans distribution.

D. *Data processing*

Full-waveform airborne LiDAR data were processed by using WoLFeX [12]. The different processing steps carried out, and integrated in WoLFeX, were (see Fig. 4): (1) height normalization, which consists of computing heights of the waveform elements with respect to the ground; (2) denoising, that is removing any noise present in the waveform; (3) voxelization, that is clustering amplitude values from all the waveforms crossing each voxel; (4) generation of pseudo-vertical waveforms, that is creating new waveforms from voxel column values from the top of the canopy to the ground; and (5) metric extraction, that is extracting a set of metrics from the pseudo-vertical waveforms. For further description of these processing steps, please refer to [12]. As a result, the metrics extracted from full-waveform airborne LiDAR were a total of 64 metrics, which are further described by [12]. This process was carried out in the 80 and the 21 plots for the estimation of canopy fuel and understory vegetation variables, respectively.

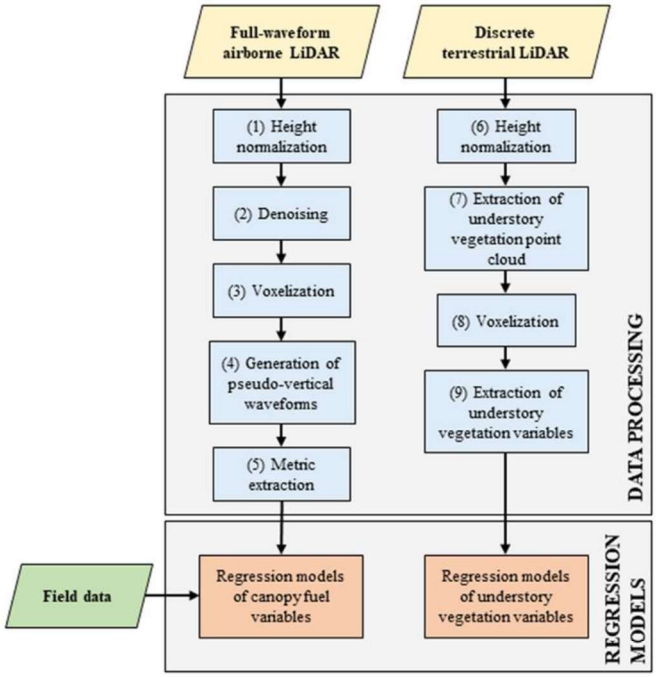

Fig. 4. Flowchart of data processing.

On the other hand, discrete terrestrial LiDAR data were used as reference data to estimate understory vegetation variables. The different processing steps carried out were as follows (see Fig. 4): (6) height normalization; (7) extraction of point clouds corresponding to understory vegetation, that consisted of removing point clouds corresponding to canopies and trunks by intensity values, height threshold, and manual edition; (8) voxelization of understory vegetation point cloud; and (9) extraction of understory vegetation variables (i.e., mean and maximum height, cover and volume) from voxelized point clouds. Regarding the extraction of understory vegetation, the mean height (Hmean) was computed as the average of the 99% heights of every voxel column contained in each plot; the maximum height (Hmax) was defined as the maximum of the 99% heights of every voxel column contained in each plot; the cover (C) was defined as the proportion of filled voxel columns in the plot, with a minimum threshold of 10 points to determine a voxel as “filled”, and a minimum of one filled voxel to define the column as “filled”; and the volume (V) was computed as the sum of all the filled voxels in the plot multiplied by the volume of the voxel. This process was carried out in the 21 plots used to estimate the understory vegetation variables.

E. *Regression models*

In order to estimate the canopy fuel and understory vegetation variables we used the linear regression, except for the estimation of the understory cover, since their values may vary between 0 and 1, and therefore the Beta regression [13]

replaced the linear regression. The full-waveform airborne LiDAR metrics were used as independent variables in the regression models, while canopy fuel and understory vegetation variables were used as dependent variables. However, not all the independent variables were used for each regression model, a maximum of three independent variables were selected using the Akaike Information Criterion (AIC) [14] to avoid overfitting. Models were evaluated using one-leave-out-cross-validation, and the adjusted coefficient of determination (R^2), the root mean square error (RMSE), the normalized root mean square error (nRMSE), and the coefficient of variation (CV). In the case of C, the pseudo-coefficient of determination (pR^2) [13] was generated.

III. RESULTS

Overall, results show a high accuracy in estimating canopy fuel and understory vegetation variables through full-waveform airborne LiDAR data. Coefficient of determination values are above 75%, and most of the variables are estimated with an accuracy above 90%.

Results from the estimation of canopy fuel variables are shown in Table I. These results indicate that the highest accuracy was achieved for variables related to height, such as canopy height and canopy base height, with a R^2 of 90.5% and 90.6%, respectively. On the other hand, canopy fuel load had a lower but still high accuracy, with a R^2 of 77.4% and a low nRMSE of 10%.

TABLE I. RESULTS OF ESTIMATING CANOPY FUEL VARIABLES

	R^2	RMSE	nRMSE	CV
CH	90.5%	1.15 m	6%	9%
CBH	90.6%	0.88 m	7%	15%
CFL	77.4%	3.81 $Mg \cdot ha^{-1}$	10%	19%

Table II shows results from the estimation of the four understory vegetation variables. These results indicate that the mean height and the volume achieved the highest accuracies with a R^2 of 94.9% and 95.1%, respectively. The cover had a pseudo-R^2 of 87.1%, and the coefficient of variation was slightly higher than the one from the mean height. Lastly, the maximum height had the lowest but still high accuracy, with a R^2 of 75.8%, and a nRMSE slightly higher than the one from the cover.

TABLE II. RESULTS OF ESTIMATING UNDERSTORY VEGETATION VARIABLES

	R^2	RMSE	nRMSE	CV
Hmean	94.9%	0.08 m	7%	11%
Hmax	75.8%	0.52 m	12%	15%
C	87.1% (pR^2)	9%	11%	12%
V	95.1%	56.49 m^3	7%	9%

IV. DISCUSSION

In this study we estimated three canopy fuel variables (canopy fuel load, canopy height and canopy base height) and four understory vegetation variables (mean and maximum height, cover and volume) using full-waveform airborne LiDAR data.

Overall, results showed a high performance of full-waveform airborne LiDAR data to estimate both canopy fuel and understory vegetation variables. Regarding canopy fuel variables, those related to height were estimated more accurately than canopy fuel load, with a R^2 above 90% and 77.4%, respectively. On the other hand, understory vegetation variables related to dimensions, such as mean height and volume, were estimated very accurately, with a R^2 above 94.9%. However, the maximum height, which is also a dimension variable, was estimated with a R^2 of 75.8%. The difference in accuracy between mean and maximum height is due to the fact that the latter is subject to extreme values within a plot, while the values from the former are smoother and more representative of the global values within a plot.

Regarding the estimations of canopy fuel variables, full-waveform airborne LiDAR data performed better results in the estimation of canopy base height compared to using discrete airborne LiDAR data, while the opposite was found for canopy height and canopy fuel load. Previous studies using discrete airborne LiDAR data [8][15][16][17] obtained R^2 values between 70%-79%, 93%-98% and 80%-87.7% in the estimation of the canopy base height, canopy height and canopy fuel load, respectively. Only [18] performed better results in the estimation of canopy base height (up to 95%), since they used homogeneous plots with a single species. However, accuracy suddenly dropped (R^2 = 80%) when they used more heterogeneous plots of mixed-forest stone pines. Among these studies, [16] and [18] were also carried out in Spain, however, with slightly different ecosystems, being an Atlantic and a Mediterranean with oceanic influence ecosystems, respectively. Compared to these studies our results followed the same trend than [16] for canopy height and canopy fuel load, and reached better results compared to using the plots of mixed-forest stone pine in [18]. The use of full-waveform airborne LiDAR data allows for extracting more information about the different vertical strata compared to discrete airborne LiDAR data, and therefore, canopy base height may be obtained more accurately. In the case of more similar forest ecosystems found in Spain, the difference in the accuracy of estimating canopy fuel load by full-waveform and discrete data is reduced. On the contrary, the extraction of canopy height does not require the penetration of laser pulses through the different strata, therefore accuracies reached by discrete airborne LiDAR data are higher or similar to those reached by full-waveform airborne LiDAR data.

On the other hand, the use of full-waveform airborne LiDAR data has proven to be a powerful tool in the estimation of understory vegetation variables, where discrete airborne LiDAR data were more limited. Previous studies [19][20][21] estimated the presence of understory vegetation with an overall accuracy between 48%-83% through a classification model. In addition, [22] estimated understory vegetation cover with a R^2 of 74% in plots with a extension of 40.5 m^2 though a regression model, which is more challenging than a classification model. Hence, full-waveform airborne LiDAR data has demonstrated its capacity to estimate understory vegetation cover very accurately, as well as other significant but less analyzed variables such as height and volume.

Estimation of canopy fuel and understory vegetation variables is crucial for the prevention, prediction and mitigation of wildfires. These variables influence fire behavior and how it can evolve from a ground or surface fire to a crown fire, that are the main threat to ecological and

human values. In this sense, full-waveform airborne LiDAR has proven to be a powerful tool to estimate these variables very accurately and with much less effort than traditional methods. Nevertheless, the greatest potential of full-waveform over discrete airborne LiDAR is its ability to characterize understory vegetation, which is an essential stratum in the spread of forest fires, and its characterization has been very limited so far because of overstory occlusion.

V. CONCLUSIONS

The present study has shown the potential of full-waveform airborne LiDAR data in the estimation of canopy fuel and understory vegetation variables. Results suggest that canopy fuel (canopy fuel load, canopy height and canopy base height) and understory vegetation variables (mean and maximum height, cover and volume) are accurately estimated using full-waveform airborne LiDAR data. For canopy fuel variables, those related to height (i.e., canopy height and canopy base height) had accuracies above 90%, while canopy fuel load had a high but lower accuracy of 77.4%. Regarding understory vegetation variables, mean height and volume had very high accuracies around 95%, while cover and maximum height achieved an accuracy of 87.1% and 75.8%, respectively. These results show the potential of full-waveform airborne LiDAR data in the characterization of forest fuel, especially for understory vegetation, which, due to its occlusion beneath overstory, has been a challenging stratum to be characterized by airborne LiDAR systems. The estimation and mapping of canopy fuel and understory vegetation variables is highly significant in the prevention, prediction and mitigation of wildfires.

ACKNOWLEDGMENT

This research was funded by the Spanish Ministerio de Economía y Competitividad and FEDER, in the framework of the project FIRMACARTO (CGL2016-80705-R).

REFERENCES

[1] M.A. Moritz, E. Batllori, R.A., Bradstock, A.M. Gill, J. Handmer, P.F. Hessburg, J. Leonard, S. McCaffrey, D.C. Odion, T. Schoennagel, A.D. Syphard, "Learning to coexist with wildfire," Nature, vol. 515, pp. 58-66. 2014.

[2] R.T. Graham, S. McCaffrey, T.B., Jain, "Science basis for changing forest structure to modify wildfire behavior and severity", 2014.

[3] H. Kramer, B. Collins, M. Kelly, S. Stephens, "Quantifying ladder fuels: A new approach using LiDAR," Forests, vol. 5, pp. 1432-1453. 2014.

[4] J. Lecina-Diaz, A. Alvarez, J. Retana, "Extreme fire severity patterns in topographic, convective and wind-driven historical wildfires of Mediterranean pine forests," PLoS One 9, e85127. 2014.

[5] D. Riaño, E. Chuvieco, S.L. Ustin, J. Salas, J.R. Rodríguez-Pérez, L.M. Ribeiro, D.X. Viegas, J.M. Moreno, H. Fernández, "Estimation of shrub height for fuel-type mapping combining airborne LiDAR and simultaneaous color infrared ortho imaging," Int. J. Wildl. Fire, vol. 16, pp. 341-348. 2007.

[6] F. Bottalico, G. Chirici, R. Giannini, S. Mele, M. Mura, M. Puxeddu, R.E. McRoberts, R. Valbuena, D. Travaglini, "Modeling Mediterraneean forest structure using airborne laser scanning data," Int. J. Appl. Earth Obs. Geoinf., vol 57, pp. 145-153. 2017.

[7] D. Riaño, E. Meier, B. Allgöwer, E. Chuvieco, S.L. Ustin, "Modeling airborne laser scanning data for the spatial generation of critical forest parameters in fire behavior modeling," Remote Sens. Environ., vol. 86, pp. 177-186. 2003.

[8] H.-E. Andersen, R.J. McGaughey, S.E., Reutebuch, "Estimating forest canopy fuel parameters using LiDAR data," Remote Sens. Environ., vol. 94, pp. 441-449. 2005.

[9] J. Torralba, P. Crespo-Peremarch, L.A. Ruiz, "Assesing the use of discrete, full-waveform LiDAR and TLS to classify Mediterranean forest species composition," Rev. Teledetección, vol. 52, pp. 27-40. 2018.

[10] P. Crespo-Peremarch, R.A. Fournier, V.-T. Nguyen, O.R. van Lier, L.A. Ruiz, "A comparative assessment of the vertical distribution of forest components using full-waveform airborne, discrete airborne and discrete terrestrial laser scanning data," Forest Ecol. Manag., vol. 473, pp. 118268. 2020.

[11] G. Montero, R. Ruiz-Peinado, M. Muñoz, "Producción de biomasa y fijación de CO2 por los bosques españoles," Madrid, Spain. 2005.

[12] P. Crespo-Peremarch, L.A. Ruiz, "A full-waveform airborne laser scanning metric extraction tool for forest structure modelling," Remote Sensing, vol. 12, pp. 292. 2020.

[13] S. Ferrari, F. Cribari-Neto, "Beta regression for modelling rates and proportions," J. Appl. Stat., vol. 31, pp. 799-815. 2004.

[14] H. Akaike, "Information theory and an extension of the maximum likelihood principle," in Proceedings of the 2nd International Symposium on Information, B.N. Petrow, F.C., Eds., Akademiai Kiado, Budapest. 1973.

[15] T.L. Erdody, L.M. Moskal, "Fusion of LiDAR and imagery for estimating forest canopy fuels," Remote Sens. Environ., vol. 114, pp. 725-737. 2010.

[16] A. Hevia, J.G. Álvarez-González, E. Ruiz-Fernández, C. Prendes, A.D. Ruiz-González, J. Majada, E. González-Ferreiro, "Modelling canopy fuel and forest stand variables and characterizing the influence of thinning in the stand structure using airborne LiDAR," Rev. Teledetección, vol. 45, pp. 41-55. 2016.

[17] P.S. Engelstad, M. Falkowski, P. Wolter, A. Poznanovic, P. Johnson, "Estimating canopy fuel attributes from low-density LiDAR," Fire, vol. 2, pp. 38. 2019.

[18] B. Botequim, P.M. Fernandes, J.G. Borges, E. González-Ferreiro, J. Guerra-Hernández, "Improving silvicultural practices for Mediterranean forests through fire behaviour modelling using LiDAR-derived canopy fuel characteristics," Int. J. Wildl. Fire, vol. 28, pp. 823-839. 2019.

[19] S. Martinuzzi, L.A. Vierling, W.A. Gould, M.J. Falkowski, J.S. Evans, A.T. Hudak, K.T. Vierling, "Mapping snags and understory shrubs for a LiDAR-based assessment of wildlife habitat sustability," Remote Sens. Environ., vol. 113, pp. 2533-2546. 2009.

[20] R.A. Hill, R.K. Broughton, "Mapping the understorey of deciduous woodland from leaf-on and leaf-off airborne LiDAR data: A case study in lowland Britain," ISPRS J. Photogramm. Remote Sens., vol. 64, pp. 223-233. 2009.

[21] F. Morsdorf, A. Mårell, B. Koetz, N. Cassagne, F. Pimont, E. Rigolot, B. Allgöwer, "Discrimination of vegetation strata in a multi-layered Mediterranean forest ecosystem using height and intensity information derived from airborne laser scanning," Remote Sens. Environ., vol. 114, pp. 1403-1415. 2010.

[22] B.M. Wing, M.W. Ritchie, K. Boston, W.B. Cohen, A. Gitelman, M.J. Olsen, "Prediction of understory vegetation cover with airborne lidar in an interior ponderosa pine forest," Remote Sens. Environ., vol. 124, pp. 730.741. 2012.