Assessing the use of discrete, full-waveform LiDAR and TLS to classify Mediterranean forest species composition

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Abstract: LiDAR technology –airborne and terrestrial- is becoming more relevant in the development of forest inventories, which are crucial to better understand and manage forest ecosystems. In this study, we assessed a classification of species composition in a Mediterranean forest following the C4.5 decision tree. Different data sets from airborne laser scanner full-waveform (ALS\textsubscript{FW}), discrete (ALS\textsubscript{D}) and terrestrial laser scanner (TLS) were combined as input data for the classification. Species composition were divided into five classes: pure Quercus ilex plots (QUI); pure Pinus halepensis dense regenerated (HAL\textsubscript{r}); pure P. halepensis (HAL); pure P. pinaster (PIN); and mixed P. pinaster and Q. suber (mPIN). Furthermore, the class HAL was subdivided in low and dense understory vegetation cover. As a result, combination of ALS\textsubscript{FW} and TLS reached 85.2\% of overall accuracy classifying classes HAL, PIN and mPIN. Combining ALS\textsubscript{FW} and ALS\textsubscript{D}, the overall accuracy was 77.0\% to discriminate among the five classes. Finally, classification of understory vegetation cover using ALS\textsubscript{FW} reached an overall accuracy of 90.9\%. In general, combination of ALS\textsubscript{FW} and TLS improved the overall accuracy of classifying among HAL, PIN and mPIN by 7.4\% compared to the use of the data sets separately, and by 33.3\% with respect to the use of ALS\textsubscript{D} only. ALS\textsubscript{FW} metrics, in particular those specifically designed for detection of understory vegetation, increased the overall accuracy 9.1\% with respect to ALS\textsubscript{D} metrics. These analyses show that classification in forest ecosystems with presence of understory vegetation and intermediate canopy strata is improved when ALS\textsubscript{FW} and/or TLS are used instead of ALS\textsubscript{D}.

Key words: airborne laser scanning, terrestrial laser scanning, classification, understory vegetation, forestry.

To cite this article: Torralba, J., Crespo-Peremarch, P., Ruiz, L. A. 2018. Assessing the use of discrete, full-waveform LiDAR and TLS to classify Mediterranean forest species composition. Revista de Teledetección, 52, 27-40. https://doi.org/10.4995/raet.2018.11106
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Forest inventories have typically been the main instrument to describe forest structure and quantify forest resources (Bauwens et al., 2016). However, carrying out an accurate traditional forest inventory is effort and time consuming, and consequently field data acquisition is limited (Liang et al., 2018). Light Detection and Ranging (LiDAR) systems have been contributing to the estimation of biophysical parameters of forest ecosystems for the last decades (Cao et al., 2014). Many studies have demonstrated the potential of LiDAR to measure and estimate several forest characteristics over a wide range of forest types (Dubayah and Drake, 2000; Wulder et al., 2012; Valbuena et al., 2016).

In particular, discrete Airborne Laser Scanning (ALS$_D$) has become an efficient tool for registering information from height distributions in forest stands (Zaldo et al., 2010; Cao et al., 2014; Ruiz et al., 2016). However, ALS$_D$ data have restrictions to register different vegetation layers (Crespo-Peremarch et al., 2016). ALS$_FW$ tries to fill this gap given that it is a system that registers the complete signal emitted by the sensor and whose point density is much higher (Heinzel and Koch, 2011), being capable of describing the physical properties of the intercepted objects (Ruiz et al., 2014). ALS$_FW$ data have successfully been used in forest applications such as: improving the extraction of the forest height distribution (Duong, 2010), tree species classification (Hollaus et al., 2009; Heinzel and Huber, 2016) and characterizing understory vegetation (Hancock et al., 2017; Crespo-Peremarch et al., 2018). Similar to the ALS technology, Terrestrial Laser Scanning (TLS) has become relevant in the last 15 years.
in forestry applications (Wilkes et al., 2017). This scanner allows for a periodic, automatic and accurate assessment of the forest structure and the three-dimensional distribution of plant components (Liang et al., 2016). TLS has shown its potential to measure forest attributes very accurately (Liang et al., 2018), however its use presents some drawbacks. For instance, TLS is restricted to small areas and registration from different scans is required to avoid occlusion, making TLS configuration at each scan position time consuming. In addition, point clouds are much denser, the size of files are very large, and hence data processing is more complex (Liang et al., 2016; Estornell et al., 2017). Some of the forest attributes that TLS can measure accurately are diameter at breast height (DBH), tree height and tree position (Maas et al., 2008; Othmani et al., 2011; Kankare et al., 2015; Cabo et al., 2018), forest cover canopy (García et al., 2011), canopy gap fraction between trees and understory (Cifuentes et al., 2015; Crespo-Peremarch and Ruiz, 2017), and tree species classification (Othmani et al., 2013; Lin and Herold, 2016; Åkerblom et al., 2017).

Integrating these LiDAR techniques (i.e. ALS, ALS$_{fw}$ and TLS) can improve the forest structural characterization and determination of species composition. The aim of this paper is to analyze and compare the classification performance in several forest structural types according to species composition and understory vegetation cover combining several data sources such as ALS (discrete and full-waveform), discrete ALS-derived products (nDSM) and TLS.

2. Material and methods

2.1. Study area

The study area (Figure 1) is located in the Natural Park of Sierra de Espadán, in the eastern Spain province of Castellón. This natural park is a Mediterranean forest with soft and rounded hills, presence of abandoned farming with artificial terraces, and mountain peaks up to 1100 meters of altitude. The European Environment Agency report from 2016 (Bastrup-Birk et al., 2016) classified this area as a semi-natural forest with a natural function, composition and structure, but modified by human activities throughout history. Forest type and conditions, and species composition have been influenced by human needs and changes in land use, as well as reforestation of single species policies from the last century.

This area displays a heterogeneous landscape dominated by pure and mixed native coniferous and deciduous forests, with species of the genera *Pinus* and *Quercus*.

The most dominant species in the area is *Pinus halepensis* (Aleppo pine), which mainly forms pure stands with different even-aged and densities. Density of *P. halepensis* stands ranges from overstocked stands with small sapling (10000 to 45000 trees·ha$^{-1}$) to poorly and medium stocked stands with young and high forest (300 to 2500 trees·ha$^{-1}$). *P. pinaster* (Maritime pine) is the second most represented species in the area, forming pure stands with densities ranging from 800 to 1250 trees·ha$^{-1}$, and mixed stands with *Quercus suber* (cork oak) as codominant species at the upper strata, ranging from 500 to 1200 trees·ha$^{-1}$. *Quercus ilex* (Holm oak) shows up in punctual places forming pure stands and sometimes mixed with other species such as pines or oaks. In some areas, mixed stands are observed, where *P. pinaster* dominates the upper strata, while *Q. suber* and *Q. ilex*, and *Juniperus thurifera* (Spanish juniper) are codominant species with densities between 500 and 800 trees·ha$^{-1}$.

Understory vegetation presence and density are very heterogeneous in this ecosystem, and depend on the tree composition (Crespo-Peremarch et al., 2018). Forest stands dominated by *P. halepensis* have taller and denser understory vegetation than those dominated by *P. pinaster* and *Q. suber*. The most common genera of the understory species are *Erica*, *Genista*, *Rhamnus*, *Pistacia*, *Juniperus*, *Rosmarinus*, *Quercus*, *Phillyrea*, *Daphne* and *Thymus*.

2.2. Field inventory

Data were collected in 74 circular plots (706 m$^2$) distributed throughout the study area in September 2015. Data collected from each plot included DBH from trees with a value above 5 cm, height and canopy base height from the seven dominant trees in each plot, tree species, and percentage of understory vegetation cover.
2.3. ALS data

ALS data were acquired on September 16th 2015 flying over the entire study area (7465.53 ha) using a LiteMapper 6800 sensor with an average pulse density of 14 pulses m\(^{-2}\), whose characteristics are showed in Table 1. The flight altitude ranged from 600 to 820 m above sea level with a minimum overlap of 55\% and a maximum of 77\% between flight lines. Data were provided by the flight company in ALS\(_{D}\) and ALS\(_{FW}\) formats, being the former used to generate the Digital Terrain Model (DTM). Vertical accuracy of the ALS\(_{D}\) data set was verified using ground control points located in open and flat areas, obtaining a RMSE of 4.3 cm.

Table 1. ALS and TLS specifications. Adapted from Crespo-Peremarch and Ruiz (2017).

|                | ALS                                | TLS                                |
|----------------|------------------------------------|------------------------------------|
| Sensor         | Lite Mapper 6800                   | Faro Focus 3D 120                 |
| Accuracy       | 240 mm (H) 150 mm (V)              | ± 2 mm at 25 m                     |
| Range          | 1600 m (operational altitude)      | 0.6-120 m                         |
| Returns        | Up to 7                            | 1                                 |
| Pulse frequency| 300 kHz                            | 97 Hz                             |
| Scan angle     | ± 37°                              | Horizontal: 300° Vertical: 360°   |
| Wavelength     | 1550 nm                            | 905 nm                            |
| Bean divergence| ≤ 0.50 mrad                        | 0.19 mrad                         |
The normalized Digital Surface Model (nDSM) was generated from the ALS point cloud using the FUSION 3.5 software (McGaughey, 2016). First, ground points were obtained from the initial point cloud by means of the filtering algorithm described by Kraus and Pfeifer (1998). Next, the DTM was computed by interpolation of ground points. A Digital Surface Model (DSM) was computed from the initial point cloud, and the difference between the DSM and the DTM was used to obtain the nDSM, also known as canopy height model (see Figure 4).

2.4. Terrestrial laser scanner data

TLS data were registered within the same two-month period as field and ALS data. Point clouds were collected in 27 out of 74 plots with a FARO FOCUS 3D 120 scanner (technical specifications in Table 1) from nine positions within each plot to minimize the occlusion, as follows: one at the plot center, four at each cardinal points (N, S, E, W) 15 m away from the plot center, and four at the secondary cardinal points (NE, SE, SW, NW) 7.5 m from the plot center. Once ground points were identified, point clouds height was normalized, then the nine scans were merged into a single point cloud. TLS pre-processing was done using LAStools software (Isenburg, 2018) (see Figure 4).

2.5. Definition of species composition classes

In order to differentiate the plots according to the percentage of trees from the same species, stand density (trees·ha⁻¹) and stand basal area (m²·ha⁻¹) of each species were analyzed for each plot. The parameter number of trees per hectare provides information about the complex processes involved in tree competition in a given stand (Zeide, 2004). West (2009) mentioned that stocking density in a plot is an essential variable to describe the stage of development of a stand. Controlling stand density helps to prevent catastrophic fires (Scarascia-Mugnozza et al., 2000) and, as a consequence, maintaining the forest with a correct density level can reduce the frequency and intensity of fires (Valbuena et al., 2008). Basal area is a parameter related to the tree size, providing information about tree stand volume and growth. Since the composition of tree species can be influenced by understory vegetation diversity and composition (Palik and Engstrom, 1999; Barbier et al., 2008), the distribution of the understory vegetation was also used as a criteria to categorize the plots.

Figure 2 shows a flowchart of the rules followed to categorize pure and mixed plots according to the tree density (trees·ha⁻¹) and basal area for each species.

Furthermore, two classes were created within pure P. halepensis to represent the great difference in density values. One class having overstocked stands with 12000 to 45000 trees·ha⁻¹ and DBH below 10 cm, and a second class with a density ranging from 300 to 2500 trees·ha⁻¹ and a DBH above 10 cm. Since the latter has a variable presence of understory vegetation, this class was subdivided into two classes: plots below 50% of understory vegetation cover, and above or equal to 50%.

As a result, five classes of plots were defined in the first instance (Table 2). After including the understory vegetation cover criteria, one of the P. halepensis classes was subdivided into two subgroups, obtaining a total of six classes. Class QUI represents pure plots of Q. ilex; class HALr pure plots of P. halepensis with regenerated to small sapling (fully dense); class HAL is composed of pure plots of young P. halepensis and high forest with less density; class PIN is composed of pure plots of P. pinaster; class mPIN represents mixed plots of P. pinaster and Q. suber; finally, class HAL was divided into 2 subclasses: class HAL-a below 50% and class HAL-b above or equal to 50% of understory vegetation cover. Figure 3 shows examples of field photographs from the six types of plots.
2.6. Metrics extraction

Different metrics from the four data sets (i.e. ALS$_D$, ALS$_{FW}$, TLS and nDSM) were used to classify plots into the classes previously described. ALS$_D$ and TLS metrics were extracted using FUSION 3.5 (McGaughey, 2016). This tool computes height and intensity statistics from point clouds, (see Table 3). ALS$_{FW}$ metrics were computed using our own specific software, as reported by (Kimes et al., 2006; Duncanson et al., 2010; Zhang et al., 2011; Ruiz et al., 2016; and Crespo-Peremarch et al., 2018), and can be divided into seven categories: height, energy, peaks, understory, percentiles, Gaussian decomposition, and others (see Table 4). Lastly, nDSM-derived canopy texture metrics (Table 5) were extracted using the freely available software Fetex 2.0 (Ruiz et al., 2011) (http://cgat.webs.upv.es/software/).

As a result, a set of metrics from the four data sets was available for the classification into six classes according to species composition, dominance based on stem density and basal area, and understory vegetation cover.

2.7. Classification models

Several classification models were generated for different combinations of data sets, number of plots and classes. Regarding the data sets, all the possible combinations of the four data sets

| Name | Type | Density (trees·ha$^{-1}$) | %Plots per class | TLS plot per class | ALS plots per class |
|------|------|---------------------------|-----------------|-------------------|-------------------|
| QUI  | Pure Q. ilex | 1000 – 5000 | 4 | 0 | 3 |
| HALr | Pure P. halepensis | 10000 – 45000 | 12 | 0 | 9 |
| HAL  | a Pure P. halepensis understory <50% | 300 – 1250 | 20 | 6 | 15 |
|      | b Pure P. halepensis understory ≥50% | 300 – 2550 | 36 | 9 | 27 |
| PIN4 | Pure P. pinaster | 850 – 1250 | 11 | 5 | 8 |
| mPIN5 | Mixed P. pinaster and Q. suber | 450 – 1200 | 16 | 7 | 12 |
| Total | | | 100 | 27 | 74 |

Figure 3. Examples of field photographs from the six classes: Quercus ilex (QUI), P. halepensis dense regenerated (DBH<10 cm) (HALr), P. halepensis and <50% of understory vegetation cover (HAL-a), P. halepensis and ≥50% of understory vegetation cover (HAL-b), P. pinaster (PIN), mixed P. pinaster and Q. suber (mPIN).
were tested. As the number of plots registered by TLS was fewer than those registered by ALS, classification models using 27 samples were generated when TLS metrics were included, and using 74 samples when these metrics were excluded. Moreover, three sets of classes were tested: (1) the five classes described, (2) all the classes plus subclasses HAL-a and HAL-b, and (3) only subclasses HAL-a and HAL-b. For the latter classification, where *P. halepensis* young and high stands are differentiated according to below 50% and above or equal to 50% of understory vegetation cover, a new classification test discarding all the plots with a value between 40-60% was done. Since percentage of understory vegetation values were visually estimated during field work, this intermediate interval was considered to be uncertain to be used as classification samples. In this case, only data sets from ALS were used to generate classification models. Therefore, 42 samples were used to differentiate between class HAL-a and HAL-b, but only 22 samples when plots with understory vegetation cover between 40-60% were excluded.

Given that a classification model was generated for each combination of data sets, number of plots and classes, a metric selection procedure was required for each combination as well. The initial set of metrics was composed of all the metrics extracted from the data sets combined in each test. In order to reduce the number of metrics used for the classification, we used the *GreedyStepwise* algorithm beside the C4.5 classifier (Quinlan, 1993) from WEKA 3.6.12 (Hall *et al.*, 2009) for the selection of metrics. This algorithm performs forward stepwise selection starting from an empty set of metrics, and stopping the process when any

| Name and Description | ALS<sub>d</sub> & TLS |
|----------------------|---------------------|
| Total number of returns |
| Count of returns by return number (maximum 9 discrete return, only 1 TLS return) |
| Minimum value of height or intensity |
| Maximum value of height or intensity |
| Mean value of height or intensity |
| Median value of height or intensity |
| Mode value of height or intensity |
| Standard deviation value of height or intensity |
| Interquartile distance value of height or intensity |
| Skewness value of height or intensity |
| Kurtosis value of height or intensity |
| AAD: Average Absolute Deviation value of height or intensity |
| MADMedian: Median of the absolute deviations from the overall median value of height or intensity |
| MADMode: Median of the absolute deviations from the overall mode value of height or intensity |
| L-moments (L1, L2, L3, L4) value of height or intensity |
| L-moments skewness value of height or intensity |
| L-moments Kurtosis value of height or intensity |
| Percentile values of height or intensity |
| Canopy relief ratio ((mean-min)/(max-min)) |
| Generalized means for the 2nd and 3rd power: Elev quadratic mean and Elev cubic mean |
| Percentage of first returns above a specified height (canopy cover estimate) |
| Percentage of first returns above the mean height/elevation |
| Percentage of first returns above the mode height/elevation |
| Percentage of all returns above a specified height |
| Percentage of all returns above the mean height/elevation |
| Percentage of all returns above the mode height/elevation |
| Number of returns above a specified height/total first returns × 100 |
| Number of returns above the mean height/total first returns × 100 |
| Number of returns above the mode height/total first returns × 100 |
remaining metric does not improve the classification. As a result, each combination of data sets, number of plots and classes had its own set of selected metrics for the classification.

Once metric selection was performed for each data set combination, the C4.5 algorithm from WEKA 3.6.12 was used to classify the same data sets used for the selection of metrics. Models were generated by cross-validation, and evaluated using the overall accuracy and kappa index. Additionally, confusion matrices were used to assess misclassification between classes.

Table 4. Description of ALSFW metrics.

| Name and Description | ALSFW | Reference |
|----------------------|-------|-----------|
| WD: Waveform distance |       | (Duong, 2010) |
| ROUGH: Roughness of outermost canopy |       | |
| Hn: Height at nth percentile of energy |       | (Kimes et al., 2006) |
| RWE: Return waveform energy |       | (Duong, 2010) |
| MAX E: Maximum energy |       | (Duncanson et al., 2010) |
| VARIANCE: Variance of energy |       | |
| SKEWNESS: Skewness of energy |       | |
| H0n: Proportion of energy in nth elevation quarter |       | |
| EQn: Proportion of energy in nth energy quarter |       | |
| NGS: Number of Gaussian curves in the waveform |       | |
| NGS STARTPEAK: Number of Gaussian curves between the beginning of the waveform and the position of MAX E |       | |
| NGS ENDPEAK: Number of Gaussian curves between the position of MAX E and the end of the waveform |       | |
| CE: Canopy return energy extracted from canopy Gaussian curves |       | (Zhang et al., 2011) |
| GE: Ground energy extracted from ground Gaussian curve |       | |
| GRR: Ground return ration: GE divided by RWE |       | |
| CHn: Elevation of nth quarter of energy, excluding ground Gaussian curve |       | |
| RN: CHn divided by WD |       | |
| AGS: Average Gaussian curve slope |       | |
| SGS: Standard deviation Gaussian curve slope |       | |
| MSGS: Modified standard deviation Gaussian curve slope |       | |
| HFEV: Height at first empty voxel |       | (Crespo-Peremarch et al., 2018) |
| HFEVT: Height at first empty voxel from threshold |       | |
| EFEV: Energy from beginning of the waveform to first empty voxel |       | |
| nEFEV: Energy from beginning of the waveform to first empty voxel divided by RWE |       | |
| FVU: Filled voxels at understory |       | |
| NFVU: Filled voxels at understory divided by number of voxels |       | |
| BC: Bottom of canopy: elevation of the first canopy Gaussian curve |       | |
| BCE: Bottom of canopy energy: energy from the beginning of the waveform to BC |       | |
| BCD: Bottom of canopy distance: distance from BC to the end of the waveform |       | |

Table 5. Description of nDSM metrics (see Ruiz et al., 2018 for further description).

| Name and Description | nDSM | Class |
|----------------------|------|-------|
| MeanEDG: Mean value of edgeness factor |       | Texture Features |
| STDEVEDG: Standard deviation of edgeness factor |       | |
| UNIFOR: Grey Level Co-occurrence Matrix (GLCM) uniformity |       | |
| ENTRROP: GLCM entropy |       | |
| CONTRAS: GLCM contrast |       | |
| IDM: GLCM inverse difference moment |       | |
| COVAR: GLCM covariance |       | |
| Variance: GLCM variance |       | |
| Correlation: GLCM correlation |       | |
| Skewness: Histogram skewness |       | |
| Kurtosis: Histogram kurtosis |       | |
3. Results

A summary of the overall accuracy and kappa index results for all the classification models tested is showed in Table 6. In general, classification by species composition and understory vegetation cover had a higher accuracy when metrics derived from ALS<sub>FW</sub> and TLS were used. The model combining ALS<sub>FW</sub> and TLS reached 85.2% of overall accuracy classifying classes HALr, PIN and mPIN, using 27 sample plots. The combination of ALS<sub>FW</sub> and TLS increased the overall accuracy by 7.4% with respect to only using ALS data set, being the most influential metrics the 25<sup>th</sup> percentile of the height from TLS data and the mean of HQ2 from ALS<sub>FW</sub> data. When class HAL was subdivided into subclasses HAL-a and HAL-b, including understory vegetation cover, an overall classification of 74.1% was reached, being 11.1% lower than without considering understory vegetation. Again, ALS<sub>FW</sub> and TLS data were the best combination tested. The most influential metrics for tree species and understory vegetation classification for this model were the 25<sup>th</sup> percentile of the height from TLS data, and the standard deviation of the Height at First Empty Voxel from Threshold (HFEVT) and the normalized Energy from the beginning of the waveform to the First Empty Voxel divided by the total waveform energy (nEFEV) from ALS<sub>FW</sub> data.

Analyzing the behavior of ALS<sub>D</sub> and ALS<sub>FW</sub> in the classification of species composition and structure including 74 plots (classes QUI, HALr, HAL, PIN and mPIN), the overall accuracy did not change considerably. However, when subclasses HAL-a and HAL-b were incorporated, differences in the overall accuracy were 58.1% using ALS<sub>FW</sub>, 64.9% for ALS<sub>D</sub>, and 70.3% using both data sets.

When differences of understory vegetation cover within the <i>P. halepensis</i> class (HAL-a and HAL-b) were considered by discarding those plots that have understory vegetation cover between 40% and 60%, ALS<sub>FW</sub> metrics increased accuracy by 9% with respect to ALS<sub>D</sub> metrics. Combining both data sets the overall accuracy was 90.9%, being the 75<sup>th</sup> percentile of intensity from ALS<sub>D</sub>, and the Height at First Empty Voxel (HFEV) and the mean of the maximum energy (MAXEmean) from ALS<sub>FW</sub> the most relevant metrics. In the case where the 42 plots were classified (i.e. including classes HAL-a<50% and HAL-b≥50% of understory cover), ALS<sub>FW</sub> metrics increased the overall accuracy above 9.1% compared to ALS<sub>D</sub> metrics.

4. Discussion and conclusions

In this research, a comparative analysis of the classification by species composition using ALS<sub>FW</sub>, ALS<sub>D</sub>, TLS and nDSM data was performed.
Results showed that the species composition types proposed in a Mediterranean landscape can be accurately classified using ALS_{fw} and TLS data, and the understory vegetation cover classes using only ALS_{fw} (in this case, no sufficient plots to test TLS data were available). ALS_{d} and nDSM do not improve differentiation of species composition for classes \textit{P. halepensis} pure plots, \textit{P. pinaster} pure plots, and \textit{P. pinaster} mixed plots (HAL, PIN and mPIN respectively), misclassifying classes \textit{P. pinaster} pure and \textit{P. pinaster} mixed, due to the limitations of ALS_{d} to register intermediate vertical strata. ALS_{d} limitations are evident in mixed plots, where despite the diversity of species there is not variability in canopy heights, since the different species are mixed in the different vertical strata. For instance, \textit{Q. suber} occupies the spaces of light left by \textit{P. pinaster}, having large canopies in the intermediate strata under pine canopies, where ALS_{d} data have limited access.

\textit{ALS}_{fw} and TLS data are relevant in the discrimination between pure and mixed plots, as well as for determining the understory vegetation cover differences in class HAL (i.e. HAL-a and HAL-b). The highest point density from TLS corresponds to understory vegetation, stem and lower strata of the canopy (Crespo-Peremarch and Ruiz, 2017), therefore TLS data are relevant to analyze and classify species composition in the lower strata. It is also remarkable that \textit{ALS}_{fw} metrics, in particular those specifically designed for analyzing understory vegetation cover, improve the understory vegetation classification. When \textit{ALS}_{fw} and TLS are combined, results increase by 14.8%. Analyzing the four data sets separately, classification accuracies range from 48.1% to 66.7%, having all data sets low efficiency discriminating classes \textit{P. pinaster} pure and \textit{P. pinaster} mixed. Discrimination of classes HAL-a, HAL-b, PIN and mPIN improves significantly when \textit{ALS}_{fw} and TLS are combined.
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compared to the results obtained using only ALS_D. The lowest accuracy is obtained using ALS_D data set, whose highest point density is at the top of the trees, since the forest stands studied are even-aged and they present similar canopy heights.

Regarding the classification of the five forest classes, the model obtained using ALS_D misclassifies the different classes except for class P. halepensis in state of regenerated (HALr), a forest type characterized by very high density of trees. In contrast, ALS_FW only misclassifies classes P. pinaster mixed (mPIN) and P. halepensis pure (HAL). Accuracy is increased in data set combinations when TLS data are included, since they provide valuable information at intermediate and lower strata, crucial to differentiate these types of species composition categories. Results would probably have differed if plots had been stratified by height ranges per plot, regardless of the type of species, as the ALS_D and nDSM datasets would have increased the accuracy by their ability to record height variability.

The classification of understory vegetation improves considerably when ALS_FW metrics are used. This is coherent with previous studies (Crespo-Peremarch et al., 2018), revealing potential of this technique in understory characterization due to its penetration through the forest canopy. However, more detailed field reference data is needed to properly categorize these classes and quantify their classification using ALS.

Compared to similar studies, the accuracy obtained in this study to classify classes HAL, PIN and mPIN is similar to the 91.0% reached by Heinzel and Koch (2011) to classify conifers and broadleaf trees using ALS_FW. They showed, beside Cao et al. (2014), that pure plots were classified easier than mixed plots using ALS_FW. Additionally, our accuracy to differentiate classes QUI, HALr, HAL, PIN and mPIN (77.0%) is similar to that obtained by Hollaus et al. (2009) classifying conifers and deciduous trees (83.0%) using ALS_D. Since these results, however, were obtained in a different type of forest ecosystem. Therefore, the comparative results should be considered only as a qualitative reference, enhancing the fact that the use of ALS_FW increases the discrimination of understory vegetation.

In practice, the type of forest seems to be crucial in the selection of the data set to be used. If structural types to classify are based on height differences, then sensors that collect information from crown cover, such as ALS_D, may provide sufficient accuracy. However, when forest composition differs mainly in the distribution of vertical strata, sensors that are able to penetrate through the canopy and to register denser distribution of point clouds, such as ALS_FW and TLS, are expected to perform better.

Due to its complementarity to register different forest strata, integration of ALS_FW and TLS data has demonstrated potential for classifying forest species compositions, in particular understory vegetation cover, that is not always considered in traditional forest inventories, even being a key element for ecosystems, wildlife, soil retention, and fire behavior modeling as a good parameter to quantify ladder fuel. For further work, considering other forest parameters, such as height or diameter distributions of forest landscapes, could potentially improve Mediterranean forest ecosystem characterization.

Acknowledgments

This research has been funded by the Spanish Ministerio de Economía y Competitividad and FEDER, in the framework of the project CGL2016-80705-R.

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