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Determination of forest fuels characteristics in mortality-affected *Pinus* forests using integrated hyperspectral and ALS data

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Abstract

Widespread tree mortality caused by forest decline in recent decades has raised concern among forest managers about how to assess forest fuels in these conditions. To investigate this question, we developed and tested an objective, consistent approach to the characterization of canopy fuel metrics - such as fuel load (FL), live fuel moisture content (LFMC), and live-dead ratio (LDR) - by integrating airborne laser scanning (ALS) and hyperspectral data to produce more-accurate estimates at the stand level. Regression models were developed for *Pinus sylvestris* and *P. nigra* stands representative of pine plantations in southern Spain, using field data acquired for different spatial fuel types and distributions as well as high resolution airborne hyperspectral data (AHS) and ALS datasets. Strong relationships were found between ALS and FL using a density of 2 points m^{-2} (R^2=0.64) and between LFMC and Temperature/NDVI index at a spatial resolution of 5 m (R^2=0.91). The red edge normalized index provided the highest separability (Jeffries-Matusita distance=1.83) between types of LDR. The plot-aggregate ALS and AHS metrics performed better at spatial resolutions of 5 m and 2 points m^{-2} than at other scales. Cartography of the estimations of FL, LFMC, and LDR made using the empirical models from the ALS and AHS data showed a mean FL value of 65.87 Mg ha^{-1}, an average LFMC content of 57.51%, and 30.75% of the surface classified as dead fuel (≥60% defoliation). The results suggest that our remote sensing approach could improve the estimation of canopy fuels characteristics at higher spatial resolutions as well as estimations of fuel cartography, to assist the planning and management of fuel reduction treatments.

Key words: Canopy fuel metrics, natural fuels, Mediterranean pine forests, hyperspectral data, ALS data.

1. Introduction

Fire is an important component of Mediterranean forest ecosystems, which has been conditioned by an increase in fuel loads during recent decades, increasing the risk of catastrophic fire (Pausas, 2004). The description of each fuel type is important when studying fire behavior (Taylor et al., 1997). Numerous studies have been conducted to determine the best way to quantify the characteristics of physical fuels of different types, based on their physiological and structural characteristics. The description of each fuel is a complex issue due to the large number of variables to be analyzed (Keane, 2013). The fuel types classifications used most commonly are based on mathematical models estimated from categorized and tabulated variables.

Considering the vegetation composition and characteristics, forest fuels can be grouped into different models according to a set of parameters describing the fire behavior (Merrill and Alexander, 1987; Arroyo et al., 2008). Different types of forest fuels incorporate a set of characteristics related to species composition and respond differently to fire. Thus, fuel models are described by fuel load by category (live and dead), particle size class, surface area to volume ratio by component and size class, heat content by category, fuel bed depth, and dead fuel moisture (Andrews and Queen, 2001). Several fire models were proposed based on the first Rothermel models (1972), which were developed using the National Fire Danger Rating System (NFDRS) (Deeming et al., 1977). Those models used a limited number of categories due to their adaptability to most forest environments. The Northern Forest Fire Laboratory (NFFL) of the U.S. Forest Service has developed 13 fuel models (Burgan and Rothermel, 1984) and the Canadian forest fire behavior prediction (FBP) system uses 14 inputs based on five groups of information: type of fuel, weather, topography, foliar moisture, and type and duration of prediction. Studies that have evaluated fuel models have typically compared fuel loads of non-perturbed vegetation, limiting the ability to detect complex fuel interactions (Harvey et al., 2014). However, tree mortality caused by forest decline processes alters the fuel structure (i.e., the quantity, quality, and distribution of biomass), affecting fire severity and fire behavior (Hoffman et al., 2015).

In typical circumstances - where forest managers need to assess fire behavior on a large scale - the cost, time, and technical challenges involved in the collection of field data and assignation of fuel models to achieve complete coverage of a forest are prohibitive. This is particularly true in areas with steep topography or limited access. Research has shown that remote sensing techniques can be used to estimate fuel characteristics and models (Chuvieco et al., 2002; Schlerf et al., 2005; Peterson et al., 2008; Kokaly et al., 2009; Wang et al., 2013) according to the ratio between fresh and dry leaf mass (Jia et al., 2006) and the fuel moisture content (ratio between water and dry leaf mass) (Chuvieco et al., 2002; Köetz et al., 2004). There has been increasing emphasis on the use of higher-resolution multispectral (Riaño et al., 2002; Van Wagtendonk and Root, 2003) or hyperspectral imagery (Jia et al., 2006) to estimate various fuel characteristics. Hyperspectral remote sensing can also be applied, to detect green and dry biomass, water content, and the plant area index of burned and unburned vegetation (Riaño et al., 2004), using different indices such as the Normalized Difference Vegetation Index (NDVI), Photochemical Reflectance Index (PRI), and Water Band Index (WBI).

However, optical data of passive sensors have limitations for fuel assessment. They are not able to provide quantitative information about fuel biomass and structure (Jia et al., 2006). Airborne laser scanning (ALS) presents advantages in this context as it is capable of describing the vertical structure of a forest stand and has been used successfully to map detailed forest parameters. Recently, ALS technology, in combination with optical images, has been developed as an important source of information for the estimation of forest variables as fuel models characteristics (Riaño et al., 2004; Naesset and Gobakken, 2008; García et al., 2011; Alonso-Benito et al., 2016). The use of ALS technology has many advantages given its accuracy and the ability to extrapolate structural data to a large area; as well, the combination of multispectral images and ALS data yields a complementary combination of structural and physiological data of the forest stands. More recent ALS studies (often combined with optical imagery) have focused on the extraction of fuel metrics across forest landscapes (Jakubowksi et al., 2013). Despite this progress, there are few examples demonstrating the efficacy of using ALS integrated with hyperspectral data to extract canopy fuel information from dense conifer stands across forest landscapes.

In this paper, we quantify three critical canopy fuel characteristics relevant for forest fuels issue in *Pinus sylvestris* L. and *P. nigra* Arnold., affected by mortality processes, combining hyperspectral images with ALS data. The specific objectives were: i) to determine the fuel load using ALS data, ii) to determine the live fuel moisture content and live-dead ratio using indices from hyperspectral remotely sensed data, and iii) to quantify the effect of the image spatial resolution (2, 5, 30, and 250-m scales, resolutions present in different satellite sensors currently available) and ALS point density on these parameters. This methodology may help to estimate forest fuels characteristics in areas affected by recent tree mortality processes in pine forest plantations in the Mediterranean Basin.

2. Materials and methods

2.1. Study area.

The study area is located in Sierra de los Filabres (Almeria province, South-eastern Spain, Lat 37°13'27''N, Lon 2°32'54''W; Figure S1, Supplementary Material). The elevation of the study area ranges from 1540 to 2000 m.a.s.l., and annual rainfall ranges between 300 and 400 mm. The Mediterranean climate is semi-arid with an annual average temperature of 11 ºC, reaching a maximum of 32 ºC during the summer and a minimum of -8 ºC in winter. The vegetation is composed of a 40-year-old pine stand of *Pinus sylvestris* with stands of *P. nigra* in surrounding areas. The forests include sparse evergreen shrubs (*Adenocarpus decorticans* Boiss and *Cistus laurifolius* L.). The predominant fuel models in the study area, according to Rothermel, are conifer stands (type 8) with smaller areas of scattered shrubs with conifers (type 5) (Consejeria Medio Ambiente, 2003).

2.2. Field data

Field data characterizing a range of forest parameters were collected in 18 square plots (30 x 30 m, 900 m^2) covering the study area. The plot locations were randomly distributed to ensure adequate sampling of the dominant fuel type (8) in Mediterranean pine forests (*P. sylvestris* and *P. nigra*). The field data were collected in July 2008 and a total of 1,368 trees were measured. All trees with diameter at breast height (DBH) greater than 10 cm were tagged with a unique numerical ID, and the number of stems per hectare (N, trees ha^{-1}), *dbh* (cm), basal area (G, m^2 ha^{-1}), dominant height (H_0, m), and canopy cover (CC) were measured using a Vertex III hypsometer (Haglöf, Germany) and tree calipers (Mantax 950 mm, Haglöf, Germany) (Table S1 Supplementary Material). Topographic variables (elevation, slope, and aspect) were obtained from a digital elevation model of a 5 by 5-m grid (http://www.juntadeandalucia.es/medioambiente/site/rediam/). This resolution was assumed to be sufficient to capture the spatial variability of the surface topography.

Using the information collected from the field plots, the oven-dry mass of the available canopy fuel load (FL, Scott and Reinhardt, 2001) for each plot was calculated for the main species (*P. sylvestris*). These calculations were based on the species-specific allometric equations reported in Ruiz-Peinado et al. (2011), including the biomass of thick branches (diameter greater than 7 cm), medium branches (diameter between 2 and 7 cm), and thin branches (diameter smaller than 2 cm, together with the needles) (see Navarro Cerrillo et al., 2017 for further information).

The live fuel moisture content (LFMC) was estimated from a subset of five trees per plot and five branches per tree. These data were collected at the time of the AHS imagery acquisition (between 8:00 and 12:00, GMT). The fresh mass was directly determined in the field after collection. Then, samples were dried in a convection oven (Estufa ORL, SR-0110, InstruLab, Spain) for 24 h at a temperature of 80°C. The LFMC was calculated as:

$$LFMC = \frac{m_f - m_d}{m_f}$$

Where m_f is the green biomass and m_d is the dry biomass of the sample.

To estimate the relative contents of live and dead fuel, henceforth named the live-dead ratio (LDR), visual ratings were made for 240 trees. Trees were considered alive or dead on the basis of the percentage defoliation, with 60% as the threshold (120 trees per class). A tree with defoliation greater than 60% was considered as dead; conversely, a tree with less than 60% defoliation was treated as alive. This threshold was selected as a significant needle loss that compromised the survival of the tree. Forest defoliation was evaluated using the approach proposed by the ICP-Forests (Eichhorn et al., 2010), which consists of a visual evaluation of the crown with regard to leaf loss and color (Nakajima et al., 2011). To avoid subjectivity in the visual evaluation of defoliation all measurements were performed by the same person.

2.3. ALS and hyperspectral airborne image processing

The ALS data were acquired by an Optech Airborne Laser Terrain Mapper (ALTM, small-footprint, high-density, multiple returns) sensor operated at a laser wavelength of 1064 nm, from a flight altitude of 1500 m in August 2008. The beam divergence was 0.3 mrad, the pulsing frequency 33 kHz, the scan frequency 50 Hz, and the maximum scan angle $\pm 10^{\circ}$ (Table S2, Supplementary Material). The first and last return pulses were registered. The whole study area was flown over in 18 strips and each strip was flown over three times, which gave an average measurement density of about 4 pulses m^{-2}.

The spectral images acquisition was carried out by Instituto Nacional de Técnica Aeroespacial (INTA) in July 2008, at 8:00 GMT and 12:00 GMT. The Airborne Hyperspectral Scanner (AHS, 80 Airborne Hyperspectral Scanner, SenSyTech under R & D, https://www.uv.es/leo/sen2flex/ahs.htm) recorded 38 spectral bands in the 0.43-12.5 μm spectral range (Table S3, Supplementary Material). The flight was performed in five passes covering the study area from east to west, acquiring imagery with a 90º field of view (FOV) and 2.5 mrad IFOV, with a spatial resolution of 2 m. Due to sensor limitations, bidirectional effects were not considered. At-sensor radiance processing and atmospheric correction were performed at the INTA facilities. Atmospheric correction was undertaken with ATCOR4 based on the MODTRAN radiative transfer model (Berk et al., 2000), using the aerosol optical depth at 550 nm collected with a Micro-Tops II sun photometer (Solar Light, Philadelphia, PA, USA).

2.4. Forest Fuel characteristics

Figure 1 shows the workflow followed for the mapping of the forest fuel characteristics and provides a simple overview of what is described in detail within the next sections. The ALS and high resolution hyperspectral imagery were processed independently to produce the metrics and indices of each data type, which were used as the independent variables in models to obtain the three canopy fuel characteristics: FL, LFMC, and LDR.

2.5. Estimation of canopy fuel load using ALS data

FUSION software (forsys.cfr.washington.edu/fusion/) was used to filter and classify the ALS data (McGaughey, 2009), using a triangular irregular network (TIN; Kraus and Pfeifer, 1998) and generating a Digital Terrain Model (DTM). The absolute heights of ALS return were normalized to heights above ground by subtracting the DTM and each plot was clipped out from the data set (30 x 30 m, 900 m^2), from the center point, to match the field data. ALS-based height metrics were obtained for the 18 field plots: minimum, maximum, mean, median, standard deviation, variance, coefficient of variation, interquartile distance, skewness, kurtosis, ADD (average absolute deviation), L-Moments (1-4), and percentile values (P_5 to P_{95} in five-unit intervals and P_{99}) (Næsset and Bjerknes, 2001, Table S4, Supplementary Material).

Predictive models were built using the fuel load attributes and metrics obtained from the ALS data within each field plot. The predictor variables were selected by a forward/backward stepwise selection model. Comparison of the selected models was based on the coefficient of determination (R^2) and the root mean square error (RMSE).

2.6. Estimation of live moisture content

The Normalized Difference Vegetation Index $\mathrm{NDVI} = (\mathrm{R}_{800} - \mathrm{R}_{670}) / (\mathrm{R}_{800} + \mathrm{R}_{670})$, Red Edge Index $\mathrm{RE} = (\mathrm{R}_{750} - \mathrm{R}_{710}) / (\mathrm{R}_{750} + \mathrm{R}_{710})$, temperature (T, ºC), and NDVI ratio (T/NDVI) were derived from the AHS images using the ArcGIS (ESRI, Redlands, CA) and ENVI (ITT, Boulder, CO) software packages. These values were then averaged per plot and used for analysis. Linear regression models to estimate the LFMC were developed using AHS-imagery-derived indices (NDVI, RE, and T/NDVI). As in the previous analysis, the predictor variables were selected by a forward/backward stepwise selection model and selection of models was based on comparison of the same statistics: R^2 and RMSE (Yuan and Lin, 2006).

2.7. Estimation of live-dead ratio

To estimate the LDR, the same indices (NDVI, RE, T, and T/NDVI) extracted from the AHS images for the tree canopy were used, together with defoliation data from the field work. Afterwards, the LDR forest fuel classes were grouped into two groups - living trees, with <60% crown dead, and dead trees with ≥60% of crown dead- using the Jeffries-Matusita distance (Chang, 2003). The Jeffries-Matusita distance provides numbers between 0 and 2, where 0-1 corresponds to very poor separability, 1-1.5 corresponds to poor separability, and 1.5-2 corresponds to high separability. All statistical analyses were performed using R, version 3.4.0 (R Development Core Team, 2012).

2.8. Spatial scale and ALS point density sensitivity analysis to quantify fuel characteristics

In order to fully understand the differences observed between forest fuel characteristics, a scaling-based approach was performed. The models obtained at a scale of 2 m (AHS scale) were subsequently compared, considering different spatial resolutions. Thus, the resolutions simulating of different satellite sensors currently available were assessed (e.g. 5 m - SPOT, 30 m – Landsat, and 250 m - MODIS). The effect of the gradient was applied to the various sources of information in raster format, such as the digital model of vegetation and the red edge and NDVI indices. Regarding FL, four different point densities were achieved, based on a random selection of ALS pulses in a grid cell of 1 m^2, and were used in the scale sensitivity process: 2, 1.5, 1, and 0.5 pulses m^{-2} (density). Point reduction was performed by the algorithm ThinData, available in the libraries of FUSION.

2.9. Cartography of fuel characteristics

The models with the highest R^2 and lowest RMSE were selected to map the FL and LFMC. The LDR was mapped using the cluster classification results. Initially, the study area was divided into cells of 900 m^2, the same size as the plots, in which the value of each explanatory variable was calculated. Then, we applied the predictive models to estimate the fuel characteristics in each cell, to generate the cartography of fuel characteristics.

3. Results

3.1. Fuel load and fuel moisture content quantification

The empirical models used to estimate the fuel load (FL) and live fuel moisture content (LFMC), using ALS-based metrics and multispectral indices, are summarized in Table 1. Following the independent variable data selection, the models using the height variable (P_{99}, H_P_{99}) were the most successful. The FL models based on regression methods provided R^2 values that ranged from 0.57 to 0.64 (Table 1), with an RMSE below 13 Mg ha^{-1}. The scatterplots for the best ALS-based prediction of FL and LFMC and the observed values are contained in Figures 2 and 3. The best model for FL was obtained using an ALS density of 2 points m^{-2} (R^2=0.640, p<0.01; RMSE=13.71 Mg ha^{-1}) (Figure 2). The best model for LFMC was obtained using the T/NDVI index at 5-m spatial resolution (R^2=0.919, p<0.01; RMSE=0.827) (Figure 3). The models showed low values of bias in all cases, with consistency of the prediction models.

3.2. Live-dead ratio quantification

The results of the Jeffries-Matusita distance for LDR are shown in Figure 4. It can be seen that the RE index provided the highest separability (1.83) between the two types of LDR, rather than NDVI (0.05) or T/NDVI (0.3).

3.3. Multi-scale aggregation effects

Figure 4 shows the fuel quantification for the study area, considering different spatial resolutions. The plot-aggregate ALS and AHS metrics performed better at spatial resolutions of 5 m (Table 1) and 2 points m^{-2} than at other scales (Figures 2 and 3). However, at lower ALS densities this difference was not statistically significant (R^2 > 0.57), indicating that reduced-density ALS metrics yielded accuracies similar to those of higher densities.

For the FL, a mean value of 73.96 Mg ha^{-1} (±34.28 Mg ha^{-1}) was obtained using an ALS-based density of 0.5 points m^{-2}. A decrease in the ALS data resolution produced a decrease in the FL, yielding a mean value of 69.64 Mg ha^{-1} (±29.65 Mg ha^{-1}) for 1 point m^{-2}, 69.24 Mg ha^{-1} (±29.36 Mg ha^{-1}) for 1.5 points m^{-2}, and 65.87 Mg ha^{-1} (±25.90 Mg ha^{-1}) for 2 points m^{-2}.

The LFMC showed similar mean values for the four resolutions, a mean value of moisture of 57.51±2.64% being obtained using a resolution of 2 m. An aggregation resolution produced similar mean moisture contents (%): 57.51±12.89 for a resolution of 5 m, 57.17±3.17 for a resolution of 30 m, and 56.93±4.31 for a resolution of 250 m.

Regarding the LDR determined using the RE index, 30.75% of the surface was classified as dead fuel (>60% defoliation) for a spatial resolution of 2 m. A decrease in the spatial resolution of the images resulted in an equivalent percentage of surface covered by dead trees, with a mean value of LDR of 29.38% for a resolution of 5 m and 21.32% for a resolution of 30 m. However, the 250-m resolution (8.78%) produced a considerable decrease in the LDR surface.

3.4. Cartography of fuel characteristics

Figure 5 shows the cartography of the estimations of FL, LFMC, and LDR made using the empirical models from the ALS and AHS data (Table 1) and the cluster classification of the study area. We obtained a mean FL value of 65.87 Mg ha^{-1} (±25.90

Mg ha^{-1}) for 2 points m^{-2}, ranging from 286 Mg ha^{-1} to 0 Mg ha^{-1}. As for the FL distribution, 37% of the surface had an FL of 0-60 Mg ha^{-1}, 52.14% an FL of 60-120 Mg ha^{-1}, 10.03% a value between 120 and 180 Mg ha^{-1}, and only 0.83% had an FL >180 Mg ha^{-1}. The average LFMC content was 57.51% (±12.89%), ranging between 90% and 0%. Finally, 30.75% of the surface was classified as dead fuel (≥60% defoliation) for the 2-m spatial resolution.

4. Discussion

Several studies have demonstrated the importance of fuel characterization in the study of fire behavior (Sandberg et al., 2001; Chuvieco et al., 2009). In this study, we quantify the fuel characteristics of *Pinus* plantations affected by mortality processes, based on the combination of hyperspectral and ALS data. This approach focused on the main parameters that contribute to forest fire behavior and severity: the fuel load (FL), live fuel moisture content (LFMC), and live-dead fuel ratio (LDR). We have used ALS data, hyperspectral images of high spatial resolution, and a statistical approach based on multiple regression models and cluster classification to predict these parameters. Our results confirm the findings reported elsewhere (Alonso-Benito et al., 2016; Su et al., 2016), showing strong relationships between ALS and spectral data and fuel characteristics.

Over the years, fuels have been grouped into different categories, to attempt to explain the behavior of forest fires (Burke and Rothermel, 1984; Sullivan, 2009). These fuel types allow us to simplify and summarize the features of the forest fuels involved in the ignition process, as well as to describe the fire behavior (Sullivan, 2009). Numerous classification models have been developed around the world and each model has been parametrized using local site data, making it difficult to apply these classifications outside the locations where they were created. Also, fuel models present serious limitations due to the cost and time required for data acquisition in the field. However, several studies have shown the usefulness of remote sensors in the estimation of fuel characteristics (Erdody and Moskal, 2010; García et al., 2011). The use of sensors with better spatial and spectral resolutions gives models of greater accuracy, which result in a better approximation of the estimated values to the real values of the variables studied (Su et al., 2016).

In recent years, ALS sensors have been used, mainly for the determination of fuel heights, a critical factor for the discrimination of forest fuel characteristics, but also in the estimation of FL (Andersen et al., 2005; Hermosilla et al., 2014). In this sense, our results have established an empirical relationship between ALS metrics and FL. According to the model generated, the use of a single variable (H_P_{99}) is able to generate accurate information on the total FL in fairly homogeneous forests composed mainly of *Pinus sylvestris* and *P. nigra* plantations. This result is in agreement with previously published work (Andersen et al., 2005). The use of ALS technology has many advantages, given its accuracy and ability to extrapolate to the whole area of study; as well, the combination with hyperspectral images to provide structural and physiological data of the forest stands (Erdody and Moskal, 2010). The methodological approach proposed on this study could be applied more generally to other pine plantations in the Mediterranean area, given the similar spatial structure and fuels behavior (Mitsopoulos and Dimitrakopoulos, 2014).

A linear relationship between field values of LFMC and T/NDVI ratio has been defined (T/NDVI; R^2=0.91, 5-m spatial resolution). The advantage of using this index is that it avoids the use of sensors with specific bands for the determination of vegetation moisture (spectral data lengths between 1000 and 3000 nm), as is the case of InGaAs sensors. The use of such sensors is rather limited today, mainly because of the small number of satellites that incorporate these sensors, as well as the technical problems associated with their use in airborne systems - mainly due to their high weight and the problems associated with calibration (Toth and Jóźków, 2016).

The red edge index (RE) classification provides an empirical basis for the estimation of LDR, derived from the good relationship between the red edge band and the state of vigor (mortality) of the vegetation at the leaf and canopy scales (Zarco-Tejada et al., 2002; Im and Jensen, 2008). Considering the classification of LDR values, it was difficult to classify the percentages of live and dead tree crowns, and to estimate them in large areas. This requires a simplification of the LDR classes, which in this work have been reduced to two (<60% and ≥60%); this presupposes that some samples are close to the thresholds of classification and therefore are hard to categorize for the observer. Additionally, since the distribution of mortality levels among trees and crowns was uneven in the study area and AHS images only indicate the forest surface spectral characteristics, our results may be limited. This is particularly problematic for the detection of change in areas where the dominant trees are unaffected, which can result in a significant change in forest surface spectral reflectance (Liu et al., 2006). In spite of these limitations, the LDR classification results obtained in our study are comparable to the results reported for the same area using pigments as a damage estimation variable (Navarro-Cerrillo et al., 2014).

To examine the influence of different scales on the detection of fuel types , a scaling-based comparison of the AHS models was applied, considering different spatial resolutions (5 m - SPOT, 30 m – Landsat, and 250 m – MODIS; Figure 5). Moreover, different point cloud densities of ALS flight may also influence the values of the estimated fuel characteristics. In this sense, our results show that the estimated variables can be modeled with good precision for the estimated biomass variables of *P. nigra* and

P. sylvestris forests using medium and low-resolution ALS pulse density (2 points m^{-2}), as observed also in previous studies (Kramer et al., 2014). However, at lower ALS densities this difference was not statistically significant, indicating that reduced-ALS-density metrics yielded accuracies similar to those of higher densities. The LFMC showed similar mean values for the four resolutions; although, a reduction of the model precision with resolutions lower than 5 m was observed, possibly influenced by the effect of the soil which may indicate that the model does not work at low resolutions. Regarding the LDR, 30.75% of the surface was classified as dead fuel (>60% defoliation) for the 2-m spatial resolution; for resolutions lower than 2 m the LDR values decreased rapidly.

Finally, the ability to map fuel characteristics (FL, LFMC, and LDR) in pine plantations has been assessed (Hermosilla et al., 2014). This showed that accurate mapping of fuel characteristics can be obtained using a limited number of field measurements. The integration of physiological information from the forest stands, provided by hyperspectral images, complements the structural information provided by the ALS data. Recently, the cost of ALS data acquisition has decreased (Tilley et al., 2004) - it can be obtained for free in some countries (e.g. in Spain, 0.5-1.0 points m^{-2}) - and is comparable to or even less expensive than the cost of large-scale field data collection (Jakubowski et al., 2013). Likewise, the cost of medium-spatial-resolution images (e.g. RapidEye, Sentinel 2A, World-View) has fallen significantly and the accessibility to them has been simplified (Johansen et al., 2010). As a consequence, considering the improvement achieved by using ALS-derived products and remote sensing data to detect fuel parameters and for mapping, it may be a better alternative for forest managers.

For future studies we also recommend a closer look at the use of spaceborne applications of LiDAR (e.g. Geoscience Laser Altimeter System-GLAS on the Ice Cloud and Land Elevation Satellite-ICESat) for forest fuels studies with an emphasis on characterizing forest canopy parameters (Tian et al., 2017), including the combinations of airborne and spaceborne data (Su et al., 2017).

5. Conclusions

Nowadays, there are a large number of satellites that are continuously monitoring forests as well as producing images of different spectral, spatial, and temporal resolution, with different acquisition costs (SPOT, Landsat, ChrisProba, Hyperion, etc.). Also, extensive ALS data are provided at the national scale (e.g. the PNOA Project, in Spain) and allow the combination of the two types of data. In this study, we developed and tested a group of models to illustrate the use of AHS and ALS data to predict and extend our knowledge of forest fuels characteristics (fuel load, live fuel moisture content, and live-dead ratio) in a *Pinus sylvestris* and *P. nigra* plantation in Southern Spain and, as a consequence, mapping different forest fuel characteristics. The proposed relationships have worked reasonably well in homogeneous pine forests in terms of the similarity of the predicted values to the measured values of the variables tested, and we believe that they would do so also in other environments with similar conditions and fuel types.

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