THE ROLE OF REMOTE SENSING IN FUEL CHARACTERIZATION FOR WILDFIRE PREVENTION

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1. Introduction

Climate change, forest abandonment and changes in land use, are drivers of a greater frequency and intensity of forest fires around the world, causing ecological and socioeconomic damage to the population and their assets, with growing concern from national and regional governments (Dupuy et al., 2020). The behaviour of a wildfire is governed by three groups of factors: meteorological, topographic and those related to the structure and vegetation load. The first are related to temperature, rainfall, atmospheric moisture and wind, and they can only be measured or estimated at the moment or a few hours before the event. Topographic factors, such as slope, are usually available in advance, and they are basically stable. However, the factors related to the vegetation are variable in time and difficult to estimate at sufficient detail to be useful for fire prevention and fire behaviour models. These factors are related to the density and spatial distribution of vegetation, the forest vertical structure and composition, presence of gaps in vertical strata, fuel load and density, and fuel moisture. In order to characterize them, remote sensing data and methods can be used in different ways. Depending on the main methodologies and data types used, they can be classified in three main groups:

a) Fuel type classification and mapping: consists on the categorization of vegetation structures based on a predefined classification system and for which a certain behavior against fire is assumed (Keane and Reeves, 2012).

b) Estimation of fuel structure variables: generation of models to estimate quantitative variables affecting fire behaviour, such as canopy height, density, canopy base height, fuel load or canopy bulk density.

c) Life fuel moisture content (LFMC) prediction models: generation of models allowing the estimation of the amount of water in live fuel (vegetation) which is potentially available to a fire. LFMC is an essential parameter for operational wildfire risk assessment and forest fire simulations, as it affects vegetation flammability, fire spread rate, and flame intensity.

There are numerous fuel model classification systems. Traditionally, the mapping of fuel models was carried out through field work, entailing a high cost in time and financial resources (Arroyo et al., 2008). Currently, remote sensing techniques allow the mapping of fuel models on a large scale, with high precision and spatial resolution, and a lower economic and temporal cost. Some of them rely on the use of airborne LiDAR (Light Detection and Ranging) data and others combined with multispectral or hyperspectral satellite images. The integration of data from different active, such as LIDAR and SAR (Synthetic Aperture Radar), and passive (optical) sensors represents an opportunity to improve the characterization of forest fuels, in particular the updating of cartographies that become obsolete in a short time due to the numerous disturbances that affect the vegetation (fires, silvicultural treatment, felling and exploitation). In this sense, innovative algorithms that combine data with different spatial and temporal resolutions to generate easy updated dynamic maps are needed.

Forest structure refers to the three-dimensional distribution and arrangement of the elements composing a forest (species, density, size, variety, height strata, etc.). Different field measurements are traditionally needed to characterize forest structure and, more recently, indirect estimations using remote sensing techniques (optical, multispectral, hyperspectral and radar imagery, and LiDAR) are introduced. Unlike two-dimensional imagery, the vertical component of three-dimensional LiDAR data allows to study the surface and the interior of canopies, providing valuable information to characterize forest structure. Accurate information about three-dimensional canopy structure and wildland fuel across the landscape is necessary for fire behaviour modelling system predictions. Fuel variables such as crown bulk density, crown fuel weight, and crown base height are by nature vertically organized through the canopy, and they have been estimated and modelled using discrete LiDAR data (Andersen et al., 2005), full-waveform LiDAR (Hermosilla et al., 2014) or combined with satellite images (Erdody and Moskal, 2010). Understory vegetation is also crucial for wildfire management, since it serves as ladder fuel for fire propagation, and its estimation has been achieved by combining discrete LiDAR and orthoimages (Riaño et al., 2007) or using full-waveform LiDAR (Crespo-Peremarch et al., 2018; Crespo-Peremarch and Ruiz, 2020). Remotely sensed data are invaluable for assessing these canopy characteristics over large areas; LiDAR data, in particular, are uniquely suited for quantifying three-dimensional canopy structure (Wulder et al., 2012).

One of the most important factors to consider in relation to the risk of occurrence and potential behavior of forest fires is the live fuel moisture content

(LFMC), defined as the amount of water present in the vegetation and calculated as the percentage of the mass of water contained in the species relative to its dry weight, which is associated with the water stress of the vegetation. It is directly related to the amount of energy required to evaporate the water before ignition (Jolly and Johnson, 2018). Recently, remote sensing has been used to estimate the moisture content of live fuel based on spectral, meteorological, and topographic data. However, despite the importance of wildfires, there is currently no specific method to reliably estimate LFMC variability at large scales. Therefore, it is necessary to analyze and define a solid methodology, based on the combination of different data sources (remote sensing, meteorology, etc.), for the operational and reliable estimation of LFMC.

The objective of this study is to analyze the methods, potential and limitations of the use of remote sensing in fuel characterization, in particular forest type, forest structure and fuel moisture, having in mind the importance of this in wildfire prevention. The datasets used are satellite multispectral images, airborne LiDAR, field collected data and meteorological data, all of them from Easter Mediterranean areas of Spain.

2. Materials and Methods

Two main study areas were considered, both in the Eastern Mediterranean region of Spain. The first one is located in the Natural Park of Sierra de Espadán, in the province of Castellón, a Mediterranean forest with soft and rounded hills, presence of abandoned farming with artificial terraces, and mountain peaks up to 1100 meters of altitude. 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 are *Pinus halepensis* (Aleppo pine), *P. pinaster* (Maritime pine) and mixed stands with *Quercus suber* (cork oak) as codominant species at the upper strata. Understory vegetation presence and density are very heterogeneous in this ecosystem, the most common are *Erica*, *Genista*, *Rhamnus*, *Pistacia*, *Juniperus*, *Rosmarinus*, *Quercus*, *Phillyrea*, *Daphne* and *Thymus*. The second study area is the whole Valencian region of Spain, in the east of the Iberian Peninsula. The orography ranges from 0 to 1830 m of altitude above sea level, although most of the territory lies at altitudes below 1000 meters. In addition, the region presents a Mediterranean climate characterized by hot summers and mild winters, with low rainfall (350–550 mm per year).

2.1Forest type classification and mapping

A field data campaign was done in September 2015, as part of a complete forest inventory data collection, where standard forest inventory measurements

(DBH, tree heights, and number of trees) were registered in 80 circular plots (15 m radius), as well as descriptive information concerning types of vegetation and strata. Four generic vegetation strata were differentiated (Figure 1):

(a) Forest: composed by *P. pinaster* and *P. halepensis*, often combined with Q. suber, with no understory vegetation (Figure 1a).

(b) Mixed forest: combination of pines and shrub, with a dense understory layer (Figure 1b).

(c) Shrub: dense shrub species, sometimes with isolated trees (Figure 1c).

(d) Young forest: dense concentration of young *P. halepensis* trees, distributed in patches as a result of spontaneous regeneration after wildfires (Figure 1d).

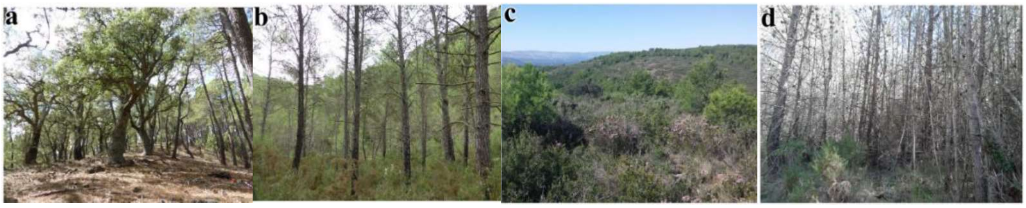


Figure 1: Examples of four generic fuel strata characterized for classification: (a) forest; (b) mixed forest; (c) shrub; (d) young forest
Source: Ruiz et al., (2018)

LiDAR data were used with an average density of 0.5 pulses m^{-2}, a WorldView-2 eight bands multispectral image (2 m/pixel), and a Sentinel-2 image with thirteen spectral bands (10, 20 and 60 m/pixel). First step consisted of the segmentation of objects with a multiresolution algorithm, using a normalized digital surface model (nDSM) obtained from LiDAR and the normalized difference vegetation index (NDVI) from WorldView-2. Feature extraction was performed using two free software programmes: FUSION 3.5 (McGaughey, 2015) and FETEX 2.0 (Ruiz et al., 2011).Classification of the generic structural types mentioned was done using four classification algorithms: C4.5 decision trees, Random Forest, k-Nearest-Neighbours and Support Vector Machine, using LiDAR features (L); Sentinel-2 and LiDAR (S2+L); WorldView-2 and LiDAR (WV2+L); and all features (S2+WV2+L), they were compared and evaluated using cross-validation (see Ruiz et al., 2018 for details).

2.2 Estimation of fuel structure variables

Field data collected were standard inventory measurements. They were further used to estimate, through allometric equations, three canopy fuel variables: canopy fuel load (CFL), canopy base height (CBH), and canopy height (CH).

LiDAR data were acquired in September 2015 using a LiteMapper 6800, with an average pulse density of 14 pulses·m^{-2}, and then processed using the free software tool WoLFeX (Crespo-Peremarch and Ruiz, 2020), consisting of: (a) height normalization; (b) denoising; (c) voxelization; (d) generation of pseudo-vertical waveforms; and (e) metric extraction (Ruiz et al., 2021). Canopy fuel variables prediction models were done using multiple linear regression, with a maximum of three LiDAR metrics as independent variables to avoid overfitting. Models were evaluated using cross-validation, the adjusted R^2 and the root mean square error (RMSE).

2.3 Modelling Life fuel moisture content

Field fuel samples were collected in 88 specific plots of shrubs and trees of the study area every 15 days from June 2020 to November 2021. They were transported in sealed bags and weighted wet, then oven-dried in stove at 100 ◦C and weighed again to obtain the dry weight and LFMC. Plot location was based on an even representation of different bioclimatic zones, the thermo-Mediterranean group (group 1) and the meso-Mediterranean group (group 2). Sentinel-2 time series images (level 2A) were processed using Google Earth Engine, and five vegetation indices and two water indices were computed. Daily mean surface air temperature and cumulative daily precipitation, collected from the Spanish Meteorological Agency (AEMET) at weather stations for the years 2020 and 2021 were used and interpolated using the inverse distance weighted method. The computed variables were: p60 (cumulative precipitation in the 60 days prior to field LFMC data acquisition) and t60 (average mean daily air temperatures in the 60 days prior to field LFMC data acquisition). In addition, the day of the year (DOY) was also considered, to describe seasonal variations of the LFMC. The following methodological steps were applied: (1) Analysis of LFMC differences between shrub and tree strata and its influence on the weighted LFMC mean, using the weighted fraction of canopy cover (FCC) of each species. (2) Application of stepwise linear regression to predict LFMC, (3) Evaluation of linear regression models using cross-validation, adjusted R^2 and RMSE values. (4) Mapping LFMC estimates in the Valencian region using the designed model (see more details in Arcos et al., 2023).

3. Results and discussion

3.1 Forest type classification and mapping

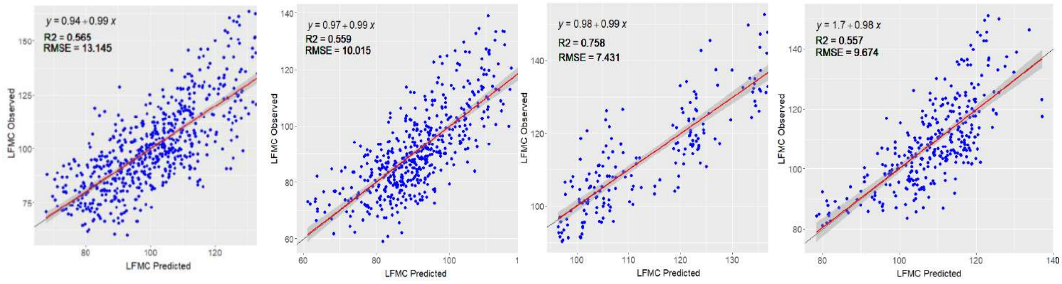
All methods, except for SVM, performed well classifying the generic forest fuel types, ranging from 86.76% to 90.75% of overall accuracy. Combining LiDAR data and multispectral images produced good overall accuracy classification results, and 90.75% of accuracy was obtained combining the three data sets (WV2 + S2 + L). The use of LiDAR provides information about the height distribution of the canopy layers, the results show the convenience to combine LiDAR data with high-resolution multispectral images (WV2) in order to discriminate class *forest* with a minimum of confidence level. The object-based approach used facilitates the delineation of patches with specific structural types existing in the landscape.

3.2 Estimation of fuel structure variables

The highest accuracy estimating canopy fuel variables was achieved for variables related to height, such as canopy height and canopy base height, with R^2=90.5% (RMSE=1.15 m) and 90.6% (RMSE=0.88 m), respectively. On the other hand, canopy fuel load had a lower but still high accuracy, with R^2=77.4% and RMSE=3.81 $Mg \cdot ha^{-1}$. Canopy fuel variables related to height were estimated more accurately than canopy fuel load. Estimation of canopy fuel 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. Airborne LiDAR has proven to be a powerful tool to estimate these variables accurately and more efficiently than traditional methods.

3.3 Modelling Life fuel moisture content

The number of explanatory variables used in the selected multiple linear regression models varied between 4 and 6, being the most important the normalized multi-band drought index (NMDI), p60 and DOY_SIN. Figure 2 shows the results of the models for the combinations of shrub, trees, and the two bioclimatic zones considered. The adjusted R^2 values of the models ranged from 56% to 76%. The highest percentage was presented by the model of Group 1 where tree species were dominant. RMSE values ranged from 7.4 and 13.1.

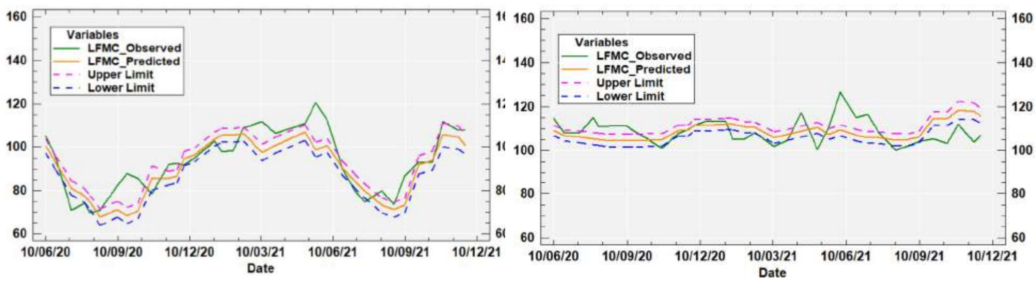


(a) (b) (c) (d)

Figure 2: Predicted vs observed LFMC values: (a) Shrub, group 1; (b) Shrub, group 2; (c) Trees, group 1; (d) Trees, group 2. Line y=x (black), regression line (red), grey area: 95% confidence level

Source: Arcos et al., (2023)

Figure 3 shows the temporal evolution of observed vs predicted LFMC values in two plots of shrub and trees, both from bioclimatic group 1. In both, the prediction is adapted to the real change. However, while in shrub there are clear seasonal variations of LFMC, in trees areas these variations are lower.



(a) (b)

Figure 3: Seasonal variations of observed (green) vs predicted (red) in two plots of shrub (a) and trees (b). Discontinuous lines show 95% of confidence level limits

Source: Arcos et al., (2023)

4. Conclusions

Remote sensing methods based on airborne LiDAR data, multispectral satellite images and meteorological data have been applied over a Mediterranean forest area of easter Spain to generate classification models of generic fuel types, and prediction models of forest structure variables and live fuel moisture content.

The application of these models allows for the generation of maps of useful variables at different scales, with known accuracy levels, which can be used by forest managers to predict the risk of wildfire risk and to prevent these natural disasters that are becoming more and more destructive in many areas around the world.

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