Vegetation fuel type dynamics and classification using multitemporal LiDAR

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1. Introduction

Traditionally, the studies on vegetation dynamics have used spectral sensors, but they have some limitations such as the inability to penetrate forest canopies (Keane et al 2001). LiDAR technology has proven to be a reliable tool to measure forest structure parameters (Botallico et al 2017) and it is able to overcome that drawback. In this study, forest vertical structure has been associated to the seven different fuel types of the Prometheus classification system (Prometheus S.V 1999).

The purpose of this study is to present a cost-effective methodology to provide a fuel type classification and dynamics of the vegetation based on conditional rules and according to the Prometheus classification system.

2. Data and Methods

2.1 Study area

The study area was located in La Rioja (Spain) and it was a tile with a side of two Km with south-west corner coordinates in UTM: 504,000; 4,660,000 (Figure 1).

Figure 1. Location of the study area (García-Cimarras et al 2021)

2.2 LiDAR data

The discrete LiDAR data used in this study was open-access and provided by the Spanish Geographic Institute (IGN). Two different datasets were used in order to compare the vegetation structure: the 2010 dataset, with a scan density of 0.5 pulses · m^{-2} and the 2016 dataset, that had a scan density of 2 pulses · m^{-2}. The LiDAR data was processed, and the metrics were extracted for a 20 x 20 m spatial resolution grid, using FUSION software v.4.10 and RStudio v.1.3.1093.

2.3 Fuel type Classification

In order to assign a fuel type (FT) to each cell, the rules shown in Table 1 were followed:

Published in: Markus Hollaus, Norbert Pfeifer (Eds.): Proceedings of the SilviLaser Conference 2021, Vienna, Austria, 28–30 September 2021.
Technische Universität Wien, 2021. DOI: 10.34726/wim.1861
This paper was peer-reviewed. DOI of this paper: 10.34726/wim.1903

Table 1. Fuel type classification system used for the LiDAR data. Mode: the stratum with the highest number of returns, 2nd Mode is the second height interval with more returns. 3rd Mode: the third height interval with more returns. Max.Elev: maximum elevation (García-Cimarras et al 2021)

Ground (%)	Cover (%)	Mode (m)	2nd Mode (m)	3rd Mode (m)	Max.Elev (m)	Description	Fuel Type
>60						Pastures	FT1
≤60	<50	0.0-0.3				Pastures	FT1
		0.3-0.6				Low shrubs	FT2
		0.6-2.0				Medium shrubs	FT3
		2.0-4.0				High shrubs	FT4
		>4.0	0.0-0.3			Pastures	FT1
			0.3-0.6			Low shrubs	FT2
			0.6-2.0			Medium shrubs	FT3
			2.0-4.0			High shrubs	FT4
	≥50	0.0-0.3				Forest without understory	FT5
		0.3-0.6				Forest with shrub layer	FT6
		0.6-2.0			>12.0	Forest with shrub layer	FT6
					≤12.0	Forest with vertical continuity	FT7
		2.0-4.0			>12.0	Forest with shrub layer	FT6
					≤12.0	Forest with vertical continuity	FT7
		>4.0	0.0-0.3			Forest without understory	FT5
			0.3-0.6			Forest with shrub layer	FT6
			0.6-2.0		>12.0	Forest with shrub layer	FT6
					≤12.0	Forest with vertical continuity	FT7
			2.0-4.0	0.0-0.3		Forest without understory	FT5
				0.3-0.6		Forest with shrub layer	FT6
				0.6-2.0		Forest with vertical continuity	FT7

2.4 Data validation

For the data validation, 15 cells (when available) per fuel type and dataset were randomly selected. Then, a fuel type was assigned to each validation cell by observing the point cloud displayed in FUSION LDV and contrasted with the conditional classification showed in Table 1. The accuracy assessment was performed with a confusion matrix and summarized using overall accuracy and user's accuracy, weighted producer's accuracy (Olofsson 2013, Stehman 1996), and Kappa coefficient.

3. Results and Discussion

The overall accuracy was nearly identical for the 2010 and 2016 datasets (80.72% and 81.26%, respectively). User's and producer's accuracies were generally high (from 0.60), but most of the error was found in forest with vertical continuity (FT7; 0.18 in the 2010 dataset), forest with shrubs (FT6; 0.19 in the 2016 dataset) and low shrubs (FT2; 0.09 in the 2010 dataset). The Kappa coefficient was 0.73 for both datasets. Figure 2 shows the classification results for both datasets.

It can be seen that in 2016, low shrubs (FT2) had an even lower presence compared to 2010 dataset. Also, the area that was classified as forest with shrubs (FT6) in 2016 in the north-east of Figure 1 a), was classified in 2016 as forest without shrubs (FT5). Some potentially hazardous transitions from fuel types without forest (FT5) or forest with shrubs (FT6) to forest with vertical continuity (FT7) were detected, especially in the south-west area.

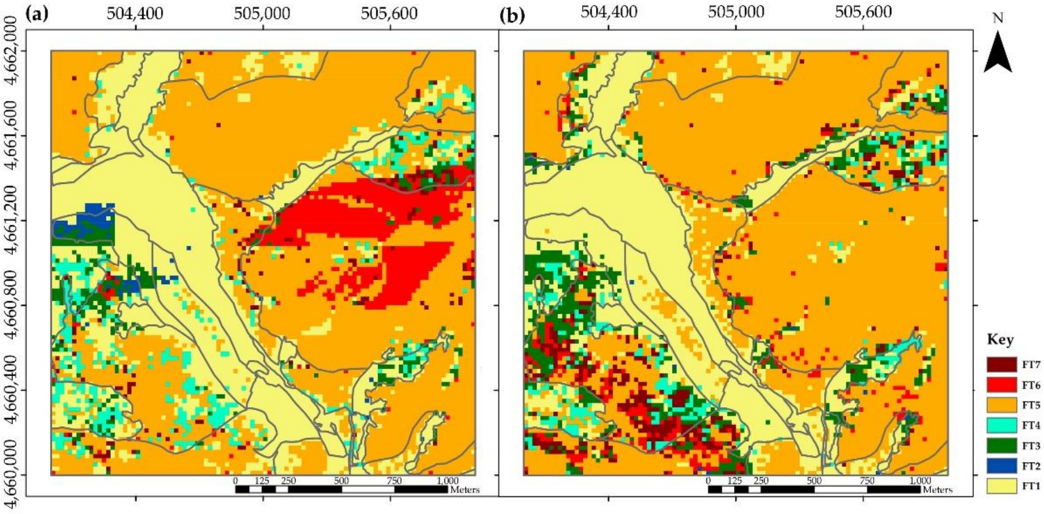

Figure 2. Classification results for the 2010 (a) and 2016 (b) LiDAR datasets. Borders of vegetation cover types (grey lines) from the Spanish National Forest Map are shown for reference (García-Cimarras et al 2021)

4. Conclusions

We present an inexpensive, simple, and accurate methodology to detect areas where of vegetation changes and growth, especially the understory layer, which can lead to an increase in fire hazard. It can save resources, especially where the difficult access makes impossible or too expensive the collection of field data. Additionally, it can be helpful to improve the management and the decision-making process. LiDAR data has proven to be able to provide vital information with an adequate accuracy of the fuel type transitions that occurred.

Acknowledgements

This research was funded by the Spanish Ministry of Education, grant number FPU17/00423.

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