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Mapping fire risk in the Model Forest of Urbión (Spain) based on airborne LiDAR measurements

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ABSTRACT

The present study sets a methodological framework to combine LiDAR derived data with fire behaviour models in order to assess fire risk at landscape level for forest management and planning. Two forest areas of the Model Forest in Urbión, Soria (Central Spain) were analyzed, covering 992.7 ha and 221.7 ha. The modelling phase was based in 160 field sample plots as ground data, and the LiDAR data had a density of first returns of 2 pulses/m^2, which were used to construct 13 models for stand variables (e.g. basal area, stem volume, branch biomass). The coefficients of determination ranged from 0.167 for shrub cover, to 0.906 for dominant height. The modelled variables were used for a classification of fuel types compatible with the continuous data. The simulation phase was performed using the spatialized data on FlamMap in order to assess the potential fire behaviour resulting across the whole landscape for four scenarios of moisture and wind conditions. The results showed maps of fire intensity and probability of fire occurrence, based on the simulation of 500 random ignition points, which allowed the analysis of the spatial relation between the initial state and allocation of forest resources and their risk of fire. The methodology proposed, as well as the results of this research are directly applicable for operational forest planning at landscape level.

1. Introduction

The inclusion of fire risk into the planning of forest management is a recurrent research topic since the 1980s (e.g. Van Wagner, 1983; Reed and Errico, 1986). Wildfires have an obvious effect on the outcomes of forest management through post-fire tree mortality or value depreciation of surviving trees. At the same time, however, forest management has the potential of modifying fire behaviour by changing the quantity and spatial arrangement of forest fuels (Agee and Skinner, 2005; Peterson et al., 2005; Finney et al., 2007). The way of considering the risk of fire into the process of planning forest management has evolved from non-spatial approaches where the effect of fire was defined as deterministic or as a stochastic quantity of timber losses, to the more recent approaches were fire behaviour and its (spatially explicit) components are being considered in order to assess the extent of fire induced damage and the influence of fuel modification on fire behaviour (Bettinger, 2010).

In this sense, assessing adequately the current state of the forest is one of the first steps required for planning the management of a forest area when the risk of fire is considered. The assessment requires collecting precise data of the amount and distribution of desirable resources and at the same time, estimates of the potential threat that fire means to those resources. However, to estimate the risk of fire over a forest landscape it must be considered that fire is a spatially explicit event, and varies its behaviour depending on site-specific fuel conditions and the spatial arrangement of different fuels (Finney, 2001). This spatial dimension, that entails information about the state of the forest and the potential behaviour of fire across the landscape, it is required in order to choose the most effective fuel treatments, in terms of type and allocation, that would reduce the negative impact of fire on the forest (Agee et al., 2000; Finney et al., 2007).

However, mapping fuel and forest stocking characteristics at a broad spatial scale is often not feasible based on direct field measurements. But during the last decades, the use of diverse types of remote sensors has become popular to acquire information about the continuous distribution of fuel (Chuvieco and Congalton, 1989; Arroyo et al., 2008) and forest resources at landscape level

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(Kirby and Hall, 1980; Boyd and Danson, 2005), and among them, Light Detection and Ranging (LiDAR) has gained special relevance. Airborne LiDAR can provide accurate information about the forest structure in three dimensions over large areas (Andersen et al., 2005), and this information can be used in the assessment of forest resources (Nelson et al., 1988; Næsset, 2002, 2004; Holmgren et al., 2003; Hollaus et al., 2007; Hall et al., 2005; Maltamo et al., 2005) as well as for modelling and mapping forest fuels. In fact, recent studies have demonstrated the usefulness of LiDAR derived data e.g. modelling surface fuels (Riaño et al., 2007; Mutlu et al., 2008a), modelling canopy related variables to predict crown fire activity (Riaño et al., 2003, 2004; Andersen et al., 2005; Morsdorf et al., 2004), or both (Skowronski et al., 2007; Mutlu et al., 2008b).

A potential application of the fuel maps generated from LiDAR data would be their use as inputs for fire simulation models, which can simulate the potential fire behaviour across a large area. The combination of LiDAR derived information with these type of simulation models, essentially FARSITE (Finney, 1998, 2004), has been referred to be a significant improvement for planning fuel management operations (Riaño et al., 2003, 2004; Morsdorf et al., 2004; Andersen et al., 2005; Skowronski et al., 2007; Mutlu et al., 2008a), even when a explicit application to estimate fire behaviour parameters on a landscape level has only seldom been taken (Mutlu et al., 2008b). Additionally, the potential value of combining spatially continuous inventory of forest resources and information on fire behaviour, both derived from LiDAR data, has not been sufficiently explored in order to integrate the spatial component of fire in the context of landscape-level planning of forest management (Bettinger, 2009; Kim et al., 2009; González-Olabarria and Pukkala, 2011).

In this context, the present study aims at providing a methodology that implements LiDAR derived information, forest resources inventory, understory and canopy fuel modelling, and fire behaviour simulation models in order to assess fire risk at landscape level using spatially continuous information for forest management purposes in the region of Soria (Central Spain).

2. Materials and methods

2.1. Description of the area of study

Two forest areas located within the Model Forest of Urbión in Soria (Central Spain) were selected for the analysis, corresponding to the public utility forest numbers MUP89 and MUP76, covering 992.7 ha and 221.7 ha, respectively. The Model Forest selected is the most extensive forest mass of the Iberian Peninsula, with a forested area of over 100,000 ha, and it combines diverse forest types and mountain pastures, enclosed within the administrative borders of 35 municipalities (Segur, 2009). The forest lands of Urbión are included in both the Mediterranean and Ibero-American Model Forest Regions in the International Model Forest Network (Besseau et al., 2002). The forest management of the two studied areas has being oriented towards the production of a sustainable flow of certified timber, and the revenues and work derived from the forest are shared by a large proportion of the local community.

In both cases, the forest lands are mainly dominated by pure stands of *Pinus Nigra* and *P. Pinaster*, with a limited presence of *Juniperus* sp. The areas are located around 1000–1200 m above sea level, and are generally influenced by Mediterranean climate, although the high altitude and continentality of the region results in colder and longer winters than most of Spain. As in most of the Mediterranean forests, wildfires are considered an important risk for the production of timber, and should therefore be considered in the forest management planning. For example, the studied area MUP89 was affected by a fire in 1970.

2.2. Description field data

In the studied area, 160 squared field sample plots of 500 m^2, systematically distributed in a square grid of approximately 250 $\times$ 250 m, were set as ground data, in order to develop models for converting LiDAR data into forest information. Measurements of dbh (diameter at breast height), height and canopy base height were recorded from every tree in the field plots. Measurements of tree and shrub cover, and an estimation of the mean shrub height were recorded at plot level. Finally, additional plot level variables were calculated from the measurements using existing models: timber volume using the models of Rodríguez et al. (2012); and biomass distribution in leaves, branches, stem and roots, using the allometric functions of Ruiz-Peinado et al. (2011) (Table 1).

2.3. Description data from LiDAR

The LiDAR data were provided by Stereocarto S.L. The data was based in 20 linear flights of a Cesnna 402-C airplane, equipped with an ALS60 II LiDAR sensor. The LiDAR system provided a density of first returns of 2 pulses/m^2, and an overall quantity of 4 height bins per first return. The LiDAR raw data was treated with the FUSION system (McGaughey and Carson, 2003), from the Remote Sensing Applications Center (USDA) in order to obtain structured statistical information about the laser returns. A predefined height of 2 m was used as a threshold to model mature trees and understory vegetation. The LiDAR data at was aggregated in data sub-sets using a square lattice of 500 m^2, matching the reference ground data (field sample plots), for computing metrics at that spatial scale. From the pulses returned from the aboveground vegetation (>2 m from the ground), the metrics of the LiDAR pulses generated by FUSION, and afterwards used as predictors in the models, corresponded to different percentiles (1st, 5th, 10th, 20th, 25th, 30th, 40th, 50th, 60th, 70th, 75th, 80th, 90th, 95th, 99th) height and intensity of the pulses, the mean height and intensity values of pulses, the interquartile range of the intensity values, and an estimation of the forest canopy cover derived from the ratio between the number of first returns above 2 m and the total number of first returns. Additionally, an approximation of the shrub cover was defined as the ratio between the number of first returns between 0.3 and 2 m and the number of first returns below 2 m.

2.4. Integral methodology applied

The methodology applied aimed to provide a broad range of information about the state of the forest at landscape level, from

Table 1
Summary of the field plots used as ground data (N = 160).

Parameter (unit)	Mean	Min	Max
N (stems ha^{-1})	702	60	2000
G (m^2 ha^{-1})	30.7	1.3	72.1
Dg (cm)	24.0	13.6	43.7
Ho (m)	15.7	8.1	27.0
hL (m)	13.4	6.6	24.6
CBH (m)	3.9	0.1	12.4
V (m^3 ha^{-1})	210.1	2.9	640.0
FB (t ha^{-1})	21.2	1.3	51.9
SB (t ha^{-1})	101.9	4.6	289.7
BB (t ha^{-1})	14.4	0.8	44.2
RB (t ha^{-1})	31.1	1.2	82.4
BC (%)	28.7	1.0	90.0
hB (m)	0.9	0.5	2.0

N: stem number; G: basal area; Dg: quadratic mean diameter; Ho: dominant height; hL: Lorey's mean height; CBH: crown base height; V: stem volume; FB: Foliar biomass; SB: stem biomass; BB: branch biomass; RB: root biomass; BC: shrub cover; hB: mean shrub height.

conventional data of forest resources to fire behaviour and fire risk estimates, covering the whole spatial continuum of the studied areas. The working methods consisted in the following steps (Fig. 1): (1) Acquisition of LiDAR based data through flights over the study areas; (2) Implementation of field inventories to be used as ground data and transformation of the raw LiDAR data into plot size metrics (defined by 500 m^2) using the FUSION software; (3) Combination of the LiDAR based metrics and the ground data in order to develop models to predict stand variables (stocking, fuel types, canopy characteristics), that at the same time are inputs for a classification of fuel types; (4) Spatializing the resulting information across the whole landscape; (5) Implementation of the map layers in the FlamMap fire behaviour model (Finney, 2006), including e.g. topography, canopy cover, bulk density, canopy base height, stand height and the defined fuel types.

2.5. Modelling stand variables

The data derived from the LiDAR measurements and the on field measured data was used to construct models for predicting stand variables. The dependent variables considered were: stand density (*N*), basal area (*G*), total volume (*V*), average quadratic diameter (Dq), dominant height (H_0), Lorey's height (hL), height to the first branch (hB), leaves biomass (FB), stem biomass (SB), branch biomass (BB), root biomass (RB), canopy cover of the undercover vegetation (BC), and height of undercover vegetation (hB). The variables used as predictors were constructed based on the calculated LiDAR pulses' metrics generated using the FUSION system.

The criteria used for constructing the models aimed at a high predictive power, based on unbiased predictions and avoiding variable redundancy or higher co-linearity. Each independent variable

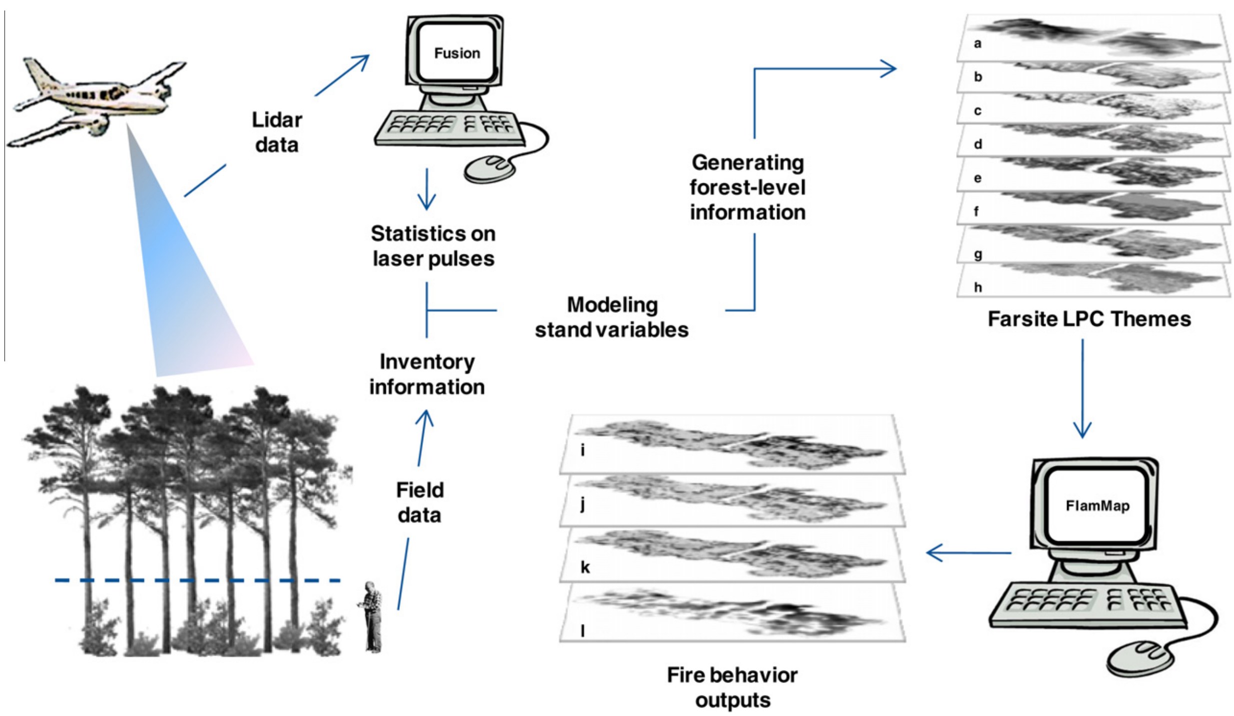

Fig. 1. Flowchart of the methods followed during the study.

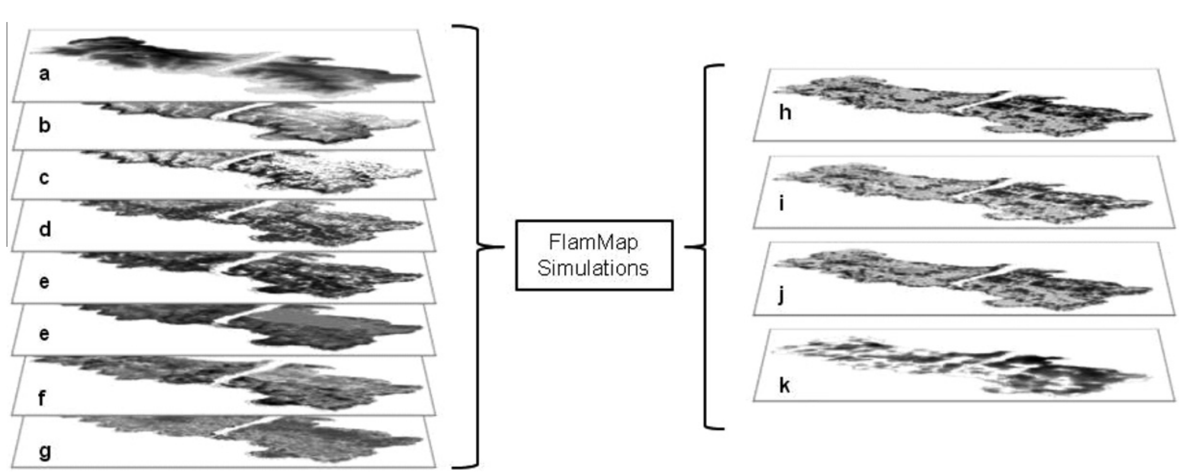

Fig. 2. Input layers required to run FlamMap: (a) elevation, (b) slope, (c) aspect, (d) fuel model, (e) canopy cover, (f) canopy base height, (g) canopy bulk density and selected output layers obtained from FlamMap, (h) crown fire activity, (i) flame length, (j) heat/fireline intensity, (k) burn probabilities.

Table 2
Models, predictors, and model's assessment for the variables at stand level.

Dependent variable	Predictive model	Fitting phase			Cross-validation	
		R^2	RMSE	CN	R^2	RMSE
N	$181.76 + (LFCC^{2.5417}) * (LH\_95^{-1.6616}) * (LI\_10^{-0.1933})$	0.640	206.98	39.2	0.609	215.80
G	$(LFCC^{0.4183}) * (LH\_20^{0.7545}) * (LI\_05^{0.1089})$	0.809	6.89	17.5	0.796	7.05
Dq	$4.89 * (LFCC^{-0.1909}) * (LH\_Mean^{0.7997}) * (LI\_25^{0.1702})$	0.752	3.33	36.6	0.731	3.46
Ho	$2.96 * (LH\_90^{0.8468}) * (LI\_95^{-0.1070})$	0.906	1.17	91.2	0.896	1.20
hL	$1.13 * (LH\_90^{0.9612})$	0.900	1.17	21.5	0.892	1.19
CBH	$0.1657 * (LH\_40^{1.3879})$	0.563	1.72	17.6	0.542	1.77
V	$(LFCC^{0.3002}) * (LH\_Mean^{1.6721}) * (LI\_05^{0.1757})$	0.871	52.46	29.3	0.858	54.12
FB	$(LFCC^{0.7767}) * (LH\_40^{0.7363}) * (LI\_Mean^{-0.4757})$	0.690	5.66	45.2	0.674	5.79
SB	$(LFCC^{0.6711}) * (LH\_40^{1.1725}) * (LI\_Mean^{-0.2296})$	0.811	25.44	48.8	0.796	26.19
BB	$(LFCC^{0.5634}) * (LH\_95^{1.3488}) * (LI\_IQ^{-0.8220})$	0.593	5.45	42.2	0.574	5.57
RB	$0.0583 * (LFCC^{0.9588}) * (LH\_30^{0.9037}) * (LI\_05^{0.1639})$	0.864	6.55	93.6	0.852	6.74
BC	$(LFCC^{0.6288}) * (LBC^{0.3540})$	0.167	21.97	6.1	0.136	22.38
hB	$0.1732 * (LFCC^{0.3154}) * (LBC^{0.2119})$	0.284	0.37	34.0	0.194	0.48

N: number of stems; *G*: basal area; Dq: quadratic mean diameter; Ho: dominant height; hL: Lorey's mean height; CBH: Crown base height; *V*: stem volume; FB: Foliar biomass; SB: Stem biomass; BB: Branch biomass; RB: Root biomass; BC: Shrub Cover; hB: Mean Shrub Height; LFCC: LiDAR Forest Canopy Cover; LBC: LiDAR Shrub Cover; LH_20. LH_30. LH_40. LH_90, and LH_95: corresponding to the 20th, 30th, 40th, 90th and 95th percentile height of the canopy pulses respectively (in meters); LH_Mean: arithmetic mean height of canopy pulses (in meters); LI_05. LI_10. LI_25. LI_95: corresponding to the 5th, 10th, 25th, and 95th percentile intensities of the canopy pulses; LI_Mean: arithmetic mean intensity of canopy pulses; LI_IQ = interquartile intensity range of canopy pulses.

Table 3
Description of standard Anderson, 1982 fuel types, and the stand variables used to allocate them; FCC: Forest Canopy Cover; BCC: Shrub Cover; hL: Lorey Height; hB: Mean Shrub Height; *W*: Crown biomass (FB + BB).

Fuel type	Typical fuel complex	Canopy and/or shrub cover (%)	Height (m)	Biomass (t/ha)
Grass and grass-dominated				
1	Short grass	(FCC + BC) < 33	–	–
2	Timber (grass and understory)	33 ⩽ (FCC + BC) <50	hB < 0.4	–
3	Tall grass	–	–	–
Chaparral and shrub fields				
4	Chaparral	FCC ⩾ 66 BC ⩾ 33	hL < 7 hB ⩾ 1.5	
5	Brush	FCC > 25 BC ⩾ 30 (FCC + BC) > 50	hB < 0.4	
6	Dormant brush, hardwood slash	FCC <25 BC ⩾ 30 (FCC + BC) > 50	hB < 0.4	
7	Southern rough	FCC > 25 BC ⩾ 30	hB ⩾ 0.4 hL ⩾ 7	
Timber litter				
8	Closed timber litter	FCC ⩾ 50 BC < 30	hL ⩾ 7	*W* ⩾ 45
9	Hardwood litter	FCC ⩾ 50 BC < 30	hL ⩾ 7	*W* < 45
10	Timber (litter and understory)	–	–	–
Slash				
11	Light logging slash	–	–	–
12	Medium logging slash	–	–	–
13	Heavy logging slash	–	–	–

included in the models had to be significant at the 0.05 level. A maximum of three variables was allowed for each model in order to avoid excessive complexity. Different combinations of the variables as well as different model alternatives were tested systematically, and the best performing model was finally selected. The selected relationships between ground-based characteristics of the sample plots (dependent variables) and laser-derived metrics were defined using nonlinear regression analysis. Finally, an n-way cross-validation of each equation was performed and the RMSE and the model efficiency (MEF, equivalent to the R^2 of the fitting phase) were calculated from the residuals.

2.6. Fuel type definition

Besides the stand variables, we proceeded to develop a relationship between the stand characteristics and the standard Northern Forest Fire Laboratory (NFFL) fuel types (Anderson, 1982). The fuel types were defined based on: an interpretation of the description of the NFFL fuel types, a comparison of potential stand level variables and the NFFL fuel types recorded in 431 plots dominated by *P. nigra* and *P. sylvestris*, extracted from the 3rd Spanish National Forest Inventory for the same area (DGCN, 2006). The variables selected for the classification were based on the previously constructed models derived from LiDAR data. The process of relating the stand variables and the fuel types was undertaken by using the Chi-squares Automatic Interaction (CHAID) (Kass, 1980), decision tree technique in SPSS 19. The CHAID technique is able to select the splitting criterions of the predictors (stand level variables) for better classifying in between multiple dependent responses (fuel types). The best suited splitting criteria for classifying a forest land regarding its fuel type were transformed into a set of classification rules for an easy application into the whole area studied.

In order to validate the process and to assess the predictive capability, the same set of rules were applied to the 431 plots used for defining the classification criteria, and the predicted fuel types were compared to the ones observed in field.

2.7. Generating fire scenarios in FlamMap

The FlamMap fire mapping and analysis system (Finney, 2006) is a computer program that integrates a FARSITE defined landscape (it requires layers for: elevation, slope, aspect, fuel model, canopy cover, canopy base height, stand height and canopy bulk density), a defined weather scenario (wind direction and wind speed) and fuel moisture conditions. It is then able to compute fire behaviour characteristics for all the points in the landscape, including flame length, fireline intensity and crown fire activity (Fig. 2). FlamMap, has not a temporal component, and does not simulate the growth and evolution of individual fires, although it is able to simulate a number of random fires in order to estimate the probability of a point in the landscape to get burned. This last characteristic of FlamMap, together with the relatively small time computational

Table 4
Predicted (based on the rules defined in Table 3) and observed fuel types for 431 plots of the national forest inventory. Bands indicate fuel type group.

	Fuel type predicted							Total (N)	User's accuracy (per fuel type) (%)	User's accuracy (per fuel type group) (%)
	1	2	5	6	7	8	9			
Fuel type observed in field										
1	0	0	0	0	2	0	0	2	0.0	14.2
2	1	1	2	0	4	0	4	12	8.3	
4	0	0	6	0	10	0	4	20	0.0	0.0
5	4	2	30	2	26	1	8	73	41.1	76.9
6	0	0	12	0	39	0	9	60	0.0	
7	5	0	7	0	74	2	26	114	64.9	
8	2	0	1	0	11	5	18	37	13.5	61.9
9	5	1	13	0	18	4	58	99	58.6	
10	0	0	0	0	2	1	0	3	0.0	
11	1	0	4	0	3	0	2	10	0.0	
12	0	0	0	0	1	0	0	1	0.0	0.0
Total (*N*)	18	4	75	2	190	13	129	431	39.0	64.5
Producer's accuracy (per fuel type) (%)	0.0	25.0	40.0	0.0	38.9	38.5	45.0			

Note: Fuel type 4 (chaparral) was considered an independent fuel type group.

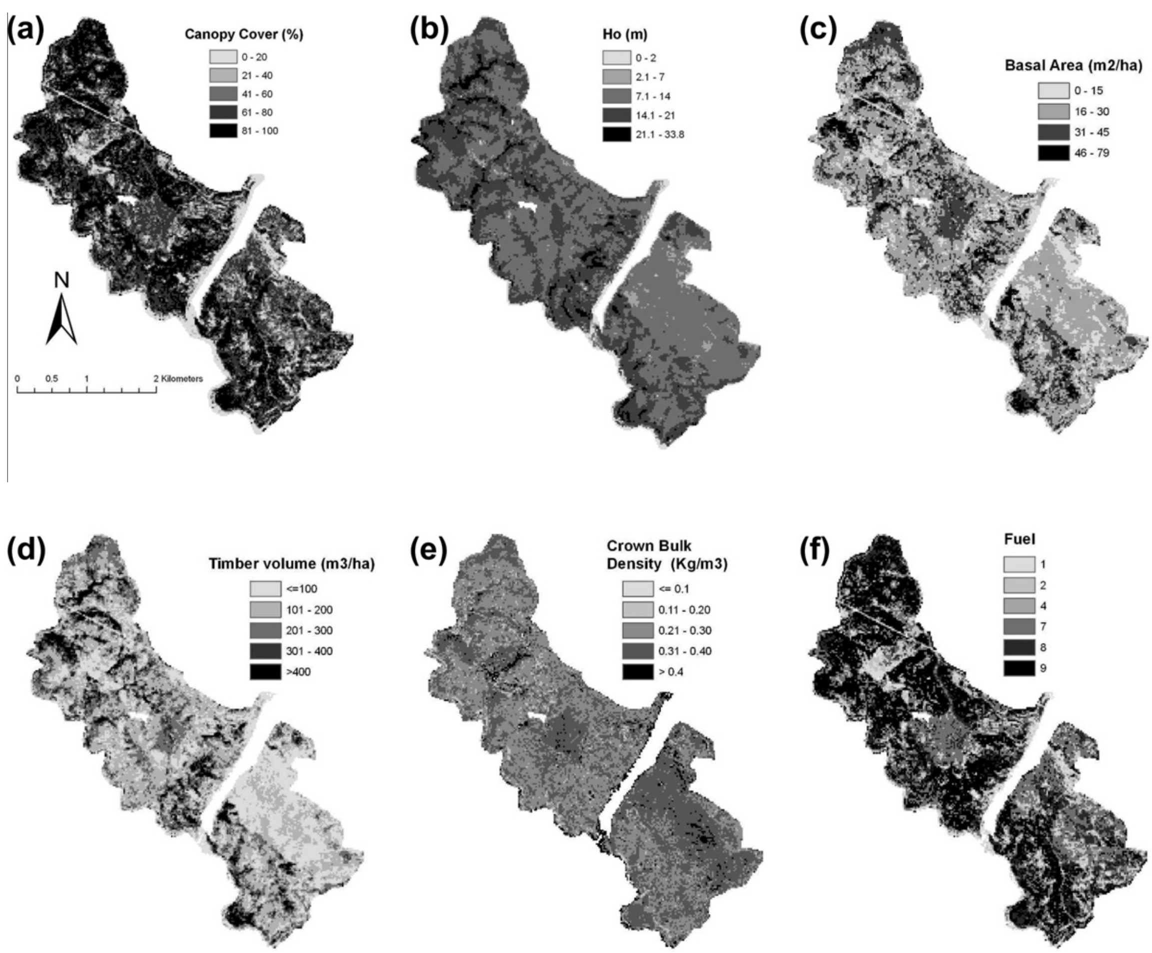

Fig. 3. Mapping of some of the LiDAR derived variables in the MUP89 forest. From left to right and top to bottom: (a) tree canopy cover; (b) stand dominant height (Ho); (c) basal area; (d) marketable timber volume; (e) tree crown bulk density and (f) NFFL fuel model.

requirements, makes the system appropriate for planning forest management under the risk of fire (González-Olabarria and Pukkala, 2011).

The layers defining the FARSITE landscapes required to operate FlamMap were obtained from LiDAR data, by applying the constructed models for predicting the stand level variables or by using the predicted stand variables for selecting the accompanying NFFL fuel models. For the required weather and fuel moisture information, we considered four scenarios: the combination of two alternative fuel moistures and two alternative wind speeds, based on our experience in the area. The fuel moistures defined were: (1) normal expected conditions in Soria during typical summer midday and (2) conditions expected in dry Mediterranean conditions. The wind speeds defined were: (1) mild wind (16 km h^{-1}) and (2) a strong wind (32 km h^{-1}). The wind was considered to be constant over the whole area, direction south–west (210°).

Finally, once the models were developed, the next step was to spatialize the predictions across the area, using the LiDAR available, in order to map and visualize variables that represent the state of the forest across the whole landscape.

3. Results

The modelling of the stand level variables resulted in 13 models, with coefficients of determination from 0.167 for BC, to 0.906 for Ho (Table 2). The RMSE obtained in the cross-validation phase was on average 1.05 times higher, ranging from 1.02 to 1.30 times, than those obtained in the fitting phase. The coefficients of determination obtained in the fitting phase were on average 1.07 times higher, than those obtained in the fitting phase. All parameter estimates included in the models were significant. No significant biases were observed when examined as a function of the predicted variable and predictors of the model.

The rules defined for classifying the forest into their corresponding fuel types (Table 3), relied on cutting values of stand variables such as shrub and forest cover, the shrub and tree height (HL), and the canopy biomass (FB + BB). The rules were found to classify correctly 39% of fuels of the 431 NFI plots. However, when the fuel types were grouped according their fire behaviour characteristics in pasture driven fuels (1, 2), shrub driven fuels (5, 6, 7), and tree driven fuels (8, 9, 10), the level of agreement between the predicted and observed fuel type groups raised to 64.5% (Table 4).

The models allowed the spatialization of the stand level variables and the pre-defined fuel types. In order to simplify the presentation of the results (Fig. 3), the maps represent predictions for the whole area of the MUP89 (992.7 ha).

The potential fire behaviour was assessed by running FlamMap for the four scenarios (alternative moisture and wind conditions) in the MUP89 forest. The predictions resulting from the application of FlamMap are independent on the simulation of a single fire event, and therefore are defined by the characteristics of each of the stands (map cells of 500 m^2), which allows to map fire related variables across the whole landscape (Fig. 4) and evaluate the share of landscape surface belonging to a defined "fire behaviour class" (Table 5).

In addition, FlamMap was also used to calculate the probability of fire occurrence, obtained through the simulation of a number of fire events which served as a basis to evaluate how many times a fire can potentially occur in a stand. We applied 500 ignitions randomly distributed across the landscape to identify areas more prone to be affected by fire (Fig. 4). Finally, the results of the process are summarized in Table 5.

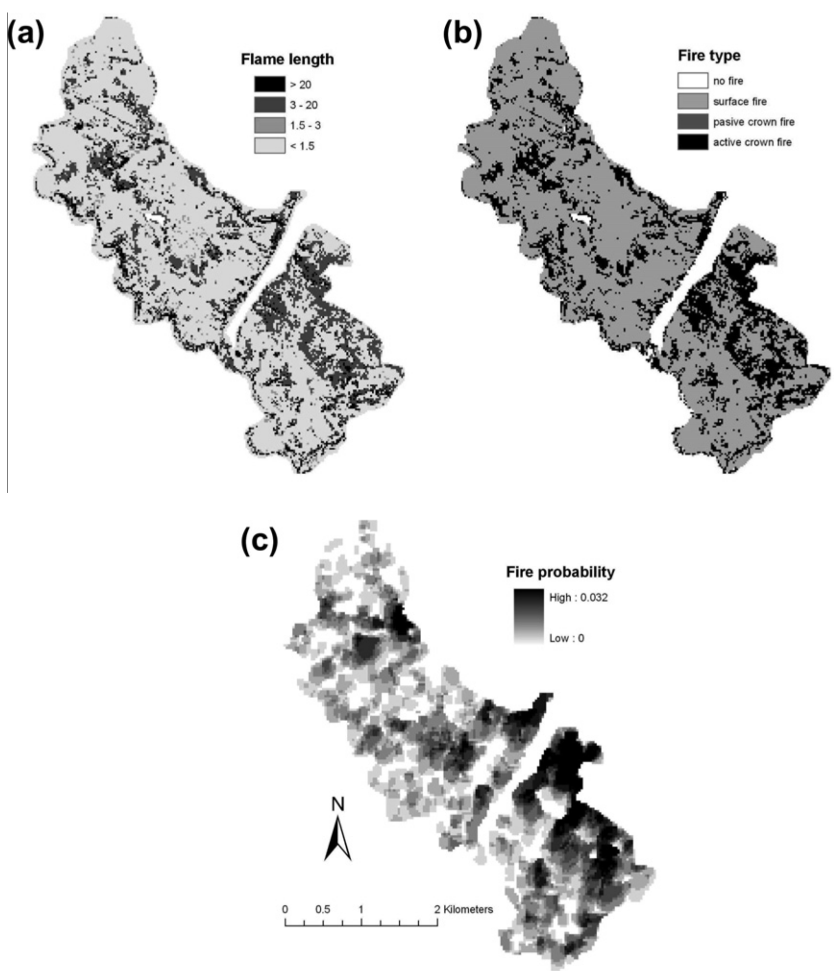

Fig. 4. Example of fire behaviour variables obtained through FlamMap simulation for the "extreme scenario" (dry fuel moisture and wind speed of 32 Km/h). (A): Flame length in meters; (B): Fire type (0 equals to no fire. 1 equals to surface fire. 2 equals to passive crown fire. and 3 equals to active crown fire); (C): Probabilities of fire occurrence.

Table 5
Share of the MUP89 forest landscape (in ha) within a fire behaviour class. Total area: 992.7 ha.

Scenario		Fire class			
Fuel moisture	Wind (km/h)	Crown fire activity			
		No fire	Surface fire	Passive crown fire	Active crown fire
Normal	16.0	47.0	870.9	53.0	21.8
Normal	32.0	47.0	811.8	46.8	87.1
Dry	16.0	47.0	820.9	77.4	47.4
Dry	32.0	47.0	719.25	55.6	170.9
		Heat per unit of area (kJ/m^2)			
		⩽25,000	25,001–50,000	50,001–100,000	>100,000
Normal	16.0	946.1	22.3	15.5	8.9
Normal	32.0	905.4	49.8	26.5	11.1
Dry	16.0	836.25	99.1	43.1	14.3
Dry	32.0	837.0	178.5	108.3	4.2
		Burn probabilities			
		0	0.0001–0.0049	0.0050–0.0099	>0.010
Normal	16.0	602.5	287.9	80.9	21.5
Normal	32.0	485.0	299.1	153.1	55.6
Dry	16.0	501.3	302.9	137.7	50.8
Dry	32.0	437.0	205.7	172.0	178.1
		Flame length (m)			
		<0.5	0.5–1	1.1–2	>2
Normal	16.0	185.9	543.8	201.5	61.6
Normal	32.0	60.35	399.7	406.4	126.3
Dry	16.0	87.7	468.7	323.0	113.5
Dry	32.0	47.0	286.0	425.2	253.1

4. Discussion

This study presents a methodology that combines the acquisition of LiDAR data and fire behaviour simulators in order to provide geo-referenced and spatially continuous information of forest resources and potential fire behaviour. The type of information provided through this methodology can be a valid tool for forest management purposes, since, presented in maps, such information is a basis for the analysis of the spatial relation between the initial state and allocation of forest resources, in the one hand, and the risk that fire entails for those resources, in the other. Additionally, the availability of information about the state of the forest, instead of merely parameters that influence fire behaviour, brings the possibility of integrating the management of forest fuels within the timber management process. This is an important advantage for planning fire prevention measures over longer periods of time, especially if they are included into forest management planning at landscape-level (González-Olabarria and Pukkala, 2011).

For the implementation of the methodology, the simulator FlamMap was chosen to study the fire behaviour, as it presents some interesting characteristics: it provides fire hazard information that can be easily applied to the studied landscape, it can estimate fire occurrence probabilities for all the forest stands based on multiple fire ignitions and, at the same time, the extent of the fires caused by those ignitions, and, finally, the outputs provided are sound indicators of potential fire damage on trees (e.g. fire intensity, flame length, crown fire activity). These indicators can be used in post-fire tree mortality models which, combined with the initial state of the forest, provide estimates of tree mortality and timber losses (Peterson and Ryan, 1986; Hély et al., 2003; Rigolot, 2004; Fernandes et al., 2008), as has already been done for planning forest management (Bettinger, 2009; Kim et al., 2009). The use of FlamMap for forest planning purposes has the additional advantage (when compared to other simulators e.g. FARSITE), that delivers an overall idea of the risk of fire over the whole landscape under different climatic conditions, instead of simulating the growth of specific fire events. This is especially important when there is limited historic information on recurrent fires, or when there is no information available about the conditions leading into their occurrence and impact.

Concerning the assessment of the initial state of the forest, the data retrieval used for the models was based on tree and stand level variables derived from LiDAR-based inventory (Falkowski et al., 2010). The results of this study can therefore be used for short-term operational planning and are a promising stepping stone for improving forest planning systems that optimize forest management at landscape level. However, when the information is to be applied for medium to long term forest planning (i.e. tactical and strategic forest planning) it would require to predict the evolution of both forest resources and fire related variables, subject to the proposed forest management operations (González-Olabarria and Pukkala, 2011). This is an aspect not considered in the study, as in order to estimate the evolution of the forest resources over a planning period, it would be necessary to apply tree growth models adapted to the local conditions, in terms of composition of species and site characteristics, being at the same time adapted for responding to the management strategies to be considered in the planning process. On the other hand, the assessment of the fire related variables would require models that relate the future evolution of the forest to the dynamics of its associated understory vegetation (Coll et al., 2011) and dead fuel build-up (Reinhardt and Crookston, 2003).

Finally, specific limitations of the study are the relatively small area used and the absence of data available on the fire regime of the area, which entails the impossibility of predicting the probability of fire occurrence based on a strong analysis of the probabilities of fire ignition. Another aspect to be consider are the lower coefficients of determination resulting from the models predicting understory characteristics (shrub cover and shrub height). This was an expected result, possibly due to the interception of a large number of laser pulses by the upper tree canopy. However, the derived models provided satisfactory cross-validation results, and the modelled effects of the forest canopy cover on the predicted variables are consistent with the role that light interception by trees plays in controlling the structure of the shrub strata in previous studies (Coll et al., 2011). Nevertheless, due to the importance that shrub strata play in defining fuel types, additional efforts are required in future research, in order to better model the understory shrub structure,

Concerning the application of the methodology in other zones, it must be stressed that the area studied was characterized by the dominance of carefully managed even-aged forest, which is not considered to be the most hazardous regarding the risk of fire (González et al., 2006, 2007). Therefore, future studies can be oriented to validate the methodology in landscapes dominated by other types of forest, with special focus in uneven-aged forest structures, in order to identify potential weaknesses, and to propose modifications to the methodology, when required.

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