Received: 29/06/2015
Accepted: 09/12/2015

REVISTA DE TELEDETECCIÓN
Spanish Association of Remote Sensing
(2016) 45, Special Issue, 41-55
ISSN 1133-0953
EISSN 1988-8740
http://dx.doi.org/10.4995/raet.2016.3979

Modelling canopy fuel and forest stand variables and characterizing the influence of thinning in the stand structure using airborne LiDAR

Hevia, A.[1]*, Álvarez-González, J.G.[2], Ruiz-Fernández, E.[2], Prendes, C.[1], Ruiz-González, A.D.[2], Majada, J.[1], González-Ferreiro, E.[2,3,4]

[1] *Forest and Wood Technology Research Centre (CETEMAS), Finca experimental La Mata s/n 33820, Grado, Spain.*

[2] *Sustainable Forest Management Unit (UXFS) - Department of Agroforestry Engineering, University of Santiago de Compostela, C/ Benigno Ledo s/n 27002, Lugo, Spain.*

[3] *Department of Forest Ecosystems and Society, Oregon State University, 321 Richardson Hall, Corvallis, OR 97331, USA.*

[4] *Laboratory of Applications of Remote Sensing in Ecology (LARSE), USDA Forest Service - Pacific Northwest Research Station, 3200 SW Jefferson Way, Corvallis, OR 97331, USA.*

Abstract: Forest fires are a major threat in NW Spain. The importance and frequency of these events in the area suggests the need for fuel management programs to reduce the spread and severity of forest fires. Thinning treatments can contribute for fire risk reduction, because they cut off the horizontal continuity of forest fuels. Besides, it is necessary to conduct a fire risk management based on the knowledge of fuel allocation, since fire behaviour and fire spread study is dependent on the spatial factor. Therefore, mapping fuel for different silvicultural scenarios is essential. Modelling forest variables and forest structure parameters from LiDAR technology is the starting point for developing spatially-explicit maps. This is essential in the generation of fuel maps since field measurements of canopy fuel variables is not feasible. In the present study, we evaluated the potential of LiDAR technology to estimate canopy fuel variables and other stand variables, as well as to identify structural differences between silvicultural managed and unmanaged *P. pinaster* Ait. stands. Independent variables (LiDAR metrics) of greater explanatory significance were identified and regression analyses indicated strong relationships between those and field-derived variables (R^2 varied between 0.86 and 0.97). Significant differences were found in some LiDAR metrics when compared thinned and unthinned stands. Results showed that LiDAR technology allows to model canopy fuel and stand variables with high precision in this species, and provides useful information for identifying areas with and without silvicultural management.

Key words: *Pinus pinaster*, Airborne Laser Scanning (ALS), fuel management, canopy fuel load, canopy bulk density, canopy base height.

Estimación de variables de combustible de copa y de masa, caracterizando el efecto de las claras en su estructura usando LiDAR aerotransportado

Resumen: Los incendios forestales suponen una gran amenaza en el NO de España. La importancia y frecuencia de estos eventos en la zona sugiere la necesidad de programas de gestión del combustible para reducir la propagación y severidad de los incendios. La realización de una selvicultura de claras puede contribuir a la reducción del riesgo de incendio, ya que ocasiona una ruptura de la continuidad horizontal del combustible forestal. Además, es necesario realizar una gestión del riesgo de incendio basada en el conocimiento de la localización del combustible sobre el

* *Corresponding author: ahevia@cetemas.es*

terreno, puesto que el estudio del comportamiento de un incendio y la simulación de la propagación del fuego son dependientes del factor espacial. Por ello, resulta esencial la generación de mapas del combustible para diferentes escenarios selvícolas. La elaboración de modelos de estimación de variables dasométricas y de estructura de la masa a partir de tecnología LiDAR es el punto de inicio para la elaboración de una cartografía espacialmente explícita. Esto adquiere mayor valor en los mapas de combustible puesto que la medición de las variables en campo resulta inviable. En el presente estudio, evaluamos el potencial de la tecnología LiDAR para estimar variables del combustible de copa y otras variables de masa, así como para identificar diferencias estructurales a nivel de rodal en masas de *Pinus pinaster* Ait. con y sin manejo selvícola. Las variables independientes (métricas LiDAR) de mayor importancia explicativa fueron identificadas y los análisis de regresión indicaron fuertes relaciones entre éstas y las variables medidas en campo (R^2 varió entre 0.86 y 0.97). Por otra parte, se observaron diferencias significativas en algunas métricas LiDAR cuando se compararon masas aclaradas y no aclaradas. Los resultados demostraron que la tecnología LiDAR permite la modelización de variables de masa y de combustible de copa con alta precisión en esta especie, y que proporciona información útil para la identificación de áreas con y sin gestión selvícola.

Palabras clave: *Pinus pinaster*, láser escáner aéreo, gestión del combustible, carga de combustible, densidad aparente de copa, altura de la base de la copa.

1. Introduction

Maritime pine is one of the most important conifer species of the Atlantic area. However, fire is the most significant threat to maritime pine and also a disturbance that plays a vital role in the perpetuation of natural stands (Fernandes and Rigolot, 2007). Particularly in the Atlantic area of NW Spain, wildland fires have been described as the most destructive type of forest disturbance (Gómez-Vázquez *et al.,* 2013). The initiation and wildfire behavior, as well as it severity in maritime pine in this area, result from the combination of factors such as climate (Fernandes and Rigolot, 2007), human activities (Fernandes *et al.,* 2013), the afforestation of communal lands in the 20th century in a context of increasing depopulation and poor management (Rego, 1992), and the fact that fuels in this area can build-up to levels which are probably unequalled by pine stands in temperate climates elsewhere (Vega, 2001). Together with this, maritime pine is known for its flammability and susceptibility to crown fires (Fernandes and Rigolot, 2007). Therefore, the optimization of fuel management and the reduction of fire risk for this species are key questions in the Atlantic region.

Much of wildfire management planning is inherently spatial, requiring calculation, display and analysis of fire behaviour across large landscapes (Finney, 2003). Therefore, up-to-date accurate fuel maps are essential for computing spatial fire hazard and simulating fire spread across a landscape (Keane *et al.,* 2001). Silvicultural interventions like thinning can modify the fuel complex structure into a less flammable by breaking the horizontal fuel continuity. An adequate treatment would modify canopy structure by increasing the gap between surface and crown fuels and reducing the fuel load in the canopy, hence limiting the potential for the onset and subsequent development of high-intensity crown fires (Cruz *et al.,* 2008). Therefore, it is expected that areas that have received silvicultural treatments are less fire prone and this fact should be taken into account by fuel maps and forest managers.

Direct measurement of canopy fuel variables related with crown fire initiation and spread (canopy fuel load -CFL-, canopy bulk density -CBD-, and canopy base height -CBH-) is impractical, and therefore indirect estimation methods are required. In this sense, LiDAR systems have been demonstrated to be capable of accurate and efficient estimation of canopy fuel variables over large areas (e.g. Andersen *et al.,* 2005; González-Ferreiro *et al.,* 2014), since they can provide spatially-explicit detailed three-dimensional information about the size and structure of the forest canopy (Reitberger *et al.,* 2008; Wagner *et al.,* 2008). In fact, they offer an alternative to traditional fieldwork for estimating canopy fuel characteristics, because they can provide comprehensive spatial coverage which is very useful in spatially-explicit fire behaviour simulator systems such as FARSITE (Finney, 2004) and FlamMap (Finney, 2006).

Area-based approach (ABA) for forest inventory applications using LiDAR has been used in practical applications (Yu *et al.,* 2010). This methodology establishes empirical relationships between variables commonly used in forest planning and LiDAR metrics. Multiple linear regression (MLR) with previous stepwise variable selection is the most frequently used for the generation of the LiDAR models (e.g. Tesfamichael *et al.,* 2010; Dalponte *et al.,* 2011; Sun *et al.,* 2011) but in the last years, modern regression techniques (e.g. random forests or regression trees) have been paid increasing attention for regression on LiDAR (Gleason and Im, 2012; García-Gutierrez *et al.,* 2011, 2014).

Several studies reported in the literature describe stand-level approaches to extract commonly used variables in forest planning (Means *et al.,* 2000; Næsset, 2002, 2004; Hollaus *et al.,* 2007; González-Ferreiro *et al.,* 2012; González-Olabarría, 2012), to describe the canopy fuel stratum (e.g. Naesset and Økland, 2002; Andersen *et al.,* 2005; Hall *et al.,* 2005; González-Ferreiro *et al.,* 2014) and even to classify forest species (Holmgren and Persson, 2004). To the best of our knowledge, there are not studies that use height distribution to identify managed and unmanaged forest stands neither to estimate stand and canopy fuel variables in *Pinus pinaster* Ait. stands.

For this study, we used LiDAR information from a small-footprint, discrete-return system over a network of field trials for the study of silvicultural treatments in *P. pinaster* stands in the Atlantic area (NW Spain). The main objectives were: *i*) to model the canopy fuel complex structural characteristics (CFL, CBD and CBH) and the most relevant stand variables for forest management (i.e. the main stand density, stand height and stand yield variables) by using linear regression and regression tree techniques, and *ii*) to analyse if LiDAR metrics and field-measured stand variables can easily identify or detect those stands that has undergone to different silvicultural treatments by using Analysis of Variance (ANOVA) and Tukey's adjusted pairwise comparisons.

2. Material and methods

2.1. Study area and field data

The study area is located in the region of Asturias (NW Spain). In winter 2005-2006, a network of thinning trials was established in 4 pure and even-aged *P. pinaster* stands throughout the area of distribution of this species in the study region (hereinafter 'forest stands'). The forest stands were subjectively located in young forests (7-11 years old at the time of installation), without previous silvicultural treatments and representing different site qualities. The altitude ranges from 101 to 536 m.a.s.l., with slopes often higher than 15%. The climate is Atlantic, annual precipitation is between 930 and 1500 mm and average temperature varies between 12°C and 14°C.

Thinning treatments of three different intensities (control -C-, selective thinning -ST- and heavy low thinning -HLT-) were applied in complete blocks in winter 2010-2011 in the 4 experimental forest stands. The total experimental area is approximately 1 hectare, but this study was focused in one subarea per treatment. These subplots ranged from 998 to 2049 m^2. In HLT, mostly trees from the lower canopy classes (smaller and less vigorous trees, larger malformed trees, etc.) were removed, and the thinning intensity ranged from 6.73 to 12.03 m^2 ha^{-1} of basal area removed (37.94 and 42.59%, respectively). The ST treatment removed some dominant and co-dominant trees to release crop trees. For this thinning treatment, approximately 150 trees ha^{-1} (potential final crop trees) were selected, and thinning was used to favour their crown development (Table 1).

Table 1. Average stand variables per treatment before and after thinning (data obtained in winter 2010-2011, before the acquisition of field data and LiDAR data used in this study) in the four *P. pinaster* stands (range of ages 12-16).

Treatment	H_0	*N*bt	*G*bt	*V*bt	*N*at	*G*at *	*V*at	%*N*	%*G*	%*V*
Control	8.69	1350.2	20.60	67.12	1349.4	20.58 *	67.025	0.08*	0.18*	0.20*
Selective thinning	10.57	1574.9	23.80	92.92	1129.1	16.44	61.3075	28.35	30.72	33.72
Heavy low thinning	10.63	1654.3	24.15	94.94	881.2	14.64	54.18	46.69	39.14	42.73

H_0 is the dominant height (m); *N*bt and *N*at are the stand density (stems ha^{-1}) before and after thinning, respectively; *G*bt and *G*at are the basal area (m^2 ha^{-1}) before and after thinning, respectively; *V*bt and *V*at are the stand volume (m^3 ha^{-1}) before and after thinning, respectively; %*N* and %*G* and %*V* are the percentage of trees, basal area and volume removed, respectively. * Natural mortality.

The field inventory was conducted in winter 2013-14 (three years after thinning), and diameter at breast height (*d*), total height (*h*) and crown length (*cl*) were measured for all the trees in each subplot (treatment). Two perpendicular measurements of *d* were recorded to the nearest 0.1 cm with a Haglöf Mantax Blue caliper. Individual CBH and *h* were measured to the nearest 0.1 m with a Haglöf Vertex IV Ultrasonic Hypsometer. Individual *cl* was defined as the distance from the top of the tree to the point of insertion of the first living branch that is not separated by more than two dead branches from the rest of the crown.

2.2. Estimation of forest stand variables from field data

Modified Assman dominant height (H_0, defined as the mean height of the 100 thickest trees per hectare in meters), number of stems per hectare (N, stems ha^{-1}), quadratic mean diameter (dg, cm), stand basal area (G, m^2 ha^{-1}) and mean height (H_m, m) were the main stand density and stand height variables calculated from the tree measurements. Stand volume (V, m^3 ha^{-1}), total stand aboveground biomass (W, Mg ha^{-1}) and crown fine fuel biomass (W_{cff}, Mg ha^{-1}) were the main stand yield variables, which were estimated using the taper function (Arias-Rodil, 2009) and the biomass equations (Hevia, 2013), respectively, developed for this species in the study area.

2.3. Estimation of canopy fuel variables from field data

The current models used for assessing crown fire potential require quantification of the lack of continuity from surface to canopy stratum and also the available fuel for combustion in the aerial layer, i.e. the fuel that would be consumed in the flaming front of a fully active crown fire. Three stand structural variables are usually used for this purpose: CFL (kg m^{-2}), CBD (kg m^{-3}) and CBH (m). CFL is the available canopy fuel per surface unit; CBD indicates the fuel available for combustion per volume unit in the aerial layer; and CBH is the lowest height aboveground level at which there is sufficient canopy fuel to propagate fire vertically through the canopy (Sando and Wick, 1972; Scott and Reinhardt, 2001). In the present study, needles and fine twigs (<6 mm thick) were considered as available fuel.

There is some disagreement about the concepts of CBD and CBH, and about how to estimate them. Three main approaches are used. The first is the method used by Van Wagner (1977) and designated by Reinhardt *et al.* (2006) as the "load over depth method". In this approach, all fine canopy fuel is assumed to be homogeneously distributed throughout the aerial layer of the stand. The CBD is estimated by dividing the total stand fine biomass by the canopy volume (estimated as the volume of a parallelepiped), the basal area of which is the stand surface and the height of which is the canopy length. Canopy length is usually estimated as the difference between the mean stand height and the mean canopy base height. According to this approach, CBH is the vertical distance between the ground surface and the mean canopy base height in the stand.

The second approach considers that the fine biomass in each tree is homogeneously distributed throughout its crown (the tree crown is assumed to be a cylinder with homogeneous biomass along its height). However, the height at which each tree crown starts and finishes is used in predicting the biomass distribution through the stand. This is the method used by the Fire and Fuels Extension of the Forest Vegetation Simulator (FFE-FVS, Beukema *et al.,* 1997), which is based on the method proposed by Sando and Wick (1972).

The third approach assumes that each tree crown has a particular shape to define the fine biomass distribution. The distribution of biomass within a stand is then estimated by considering each tree shape and the height at which crown starts and finishes. This modification of the second approach is based on evidence that each crown tree fuel distribution affects the general fuel distribution in the stand (Keyser and Smith, 2010).

According to the latter two methods, "effective" CBD (CBDe, kg m^{-3}) is defined as the maximum 4.5 m running mean of canopy bulk density for layers 0.3 m thick, and "effective" CBH (CBHe, m) as the lowest height above which at least 0.037 kg m^{-3} of canopy fuel is present.

Table 2. Potential explanatory metrics related with height distribution.

Variables related with height distribution (m)	Description
h_{min}, h_{max}	minimum and maximum
h_{mean}, h_{mode}, h_{median}	mean, mode and median
h_{SD}, h_{CV}	standard deviation and coefficient of variation
h_{skw}, h_{kurt}	skewness and kurtosis
h_{ID}, h_{AAD}	interquartile distance and average absolute deviation
$h_{MADmedian}$	median of the absolute deviations from the overall median
$h_{MADmode}$	median of the absolute deviations from the overall model
h_{L1}, h_{L2},…, h_{L4}	L-moments
h_{Lskw}	L-moment of skewness
h_{Lkurt}	L-moment of kurtosis
h_{01}, h_{05}, h_{10}, h_{20},…, h_{90}, h_{95}, h_{99}	percentiles
h_{25} and h_{75}	first and third quartiles

In this study the first and the third approaches were used. The values of the canopy variables were calculated by using the equations developed by Gómez-Vázquez *et al.* (2013) for this species in Galicia (the closest Spanish region to Asturias) since they are the more complete equations developed for canopy fuel variables estimation for this species in the Spanish Atlantic region.

2.4. LiDAR data and metrics

LiDAR data were acquired in September 2013 using a Leica ALS50-II sensor operated at 1064 nm, with a laser repetition rate of a minimum of 45 kHz, a minimum scan frequency of 40 Hz, a maximum scan angle of ±25° and a maximum flying height of 3000 m.a.s.l. A maximum of 4 returns per pulse was recorded, and an average sampling density of 8 and 16 first returns m^{-2} was obtained.

FUSION software V. 3.4.2 (McGaughey, 2014) was used for filtering, interpolation and DEM/NHD (Digital Elevation Model/Normalized Height of Data cloud) generation, and computing LiDAR metrics (see the steps described in González-Ferreiro *et al.* (2012), Table 2). All these metrics were computed from the returns from above 1 m in order to avoid returns from shrubs, rocks, logs, etc. Moreover, a set of LiDAR variables related to crown closure was computed using several ratios of the number of returns above a specific height threshold of 2 m (Table 3).

Table 3. Potential explanatory variables related to canopy closure.

Variables related to canopy closure	Description
AR_{Ahmean}	total number of laser hits above h_{mean} per plot
AR_{Ahmode}	total number of laser hits above h_{mode} per plot
AR_{A2}	total number of laser hits above 2 m height per plot
FR_{Ahmean}	number of first laser hits above h_{mean} per plot
FR_{Ahmode}	number of first laser hits above h_{mode} per plot
FR_{A2}	number of first laser hits above 2 m height per plot
SR_{A2}	number of second laser hits above 2 m height per plot
PAR_{Ahmean}	percentage of total laser hits above h_{mean}
PAR_{Ahmode}	percentage of total laser hits above h_{mode}
PAR_{A2}	percentage of total laser hits above 2 m height
PFR_{Ahmean}	percentage of first laser hits above h_{mean}
PFR_{Ahmode}	percentage of first laser hits above h_{mode}
PFR_{A2}	percentage of first laser hits above 2 m height
CRR	*Canopy Relief Ratio* computed as $(h_{mean} - h_{min})/(h_{max} - h_{min})$
$AR_{Ahmean}: FR$	ratio of the number of total laser hits above h_{mean} to FR
$AR_{Ahmode}: FR$	ratio of the number of total laser hits above h_{mode} to FR
$AR_{A2}: FR$	ratio of the number of total laser hits above 2 m height to FR

Table 4. Summary statistics of the canopy fuel and stand variables of the four forest stands (data acquired for this study in winter 2013-2014), respectively.

Value	N	G	dg	H_m	H_0	CFL	CBD	CBH	CBDe	CBHe
Mean	985.39	21.55	16.75	10.82	11.92	0.64	0.13	5.48	0.10	3.95
Max	1414.85	32.93	19.08	14.65	16.37	0.97	0.19	8.80	0.16	5.73
Min	661.41	14.84	13.81	9.06	10.28	0.43	0.10	4.08	0.08	3.15
SD	221.23	5.16	1.78	1.68	1.74	0.15	0.03	1.41	0.03	0.74

N is the number of stems ha^{-1}; G is the basal area (m^2 ha^{-1}); dg is the quadratic mean diameter (cm); H_m is the mean height (m); H_0 is the dominant height (m); CFL is the canopy fuel load (kg m^{-2}); CBD and CBH are the canopy bulk density (kg m^{-3}) and the canopy base height (m), respectively; CBDe (kg m^{-3}) and CBHe (m) are the "effective" canopy bulk density and canopy base height, respectively; and SD is the standard deviation.

Finally, the LiDAR information was combined with the field-based canopy fuel and stand variables to develop prediction models. Summary statistics for the main canopy fuel and stand variables used in this study are shown in Table 4.

2.5. Modelling canopy fuel and stand variables

All statistical analyses were undertaken in *R* software (R Core Team, 2014). Linear models relating the main forest variables and the canopy fuel complex structural characteristics to LiDAR metrics were developed using ordinary least squares applying *lm* function from *stats* package. Selection of the best set of independent variables was carried out by applying the stepwise variable selection method (*stepAIC* function from *MASS* package), combined with preliminary graphical and correlation analysis.

To evaluate the presence of multicollinearity among variables in the models analysed, the variance inflation factors (VIF) of all the independent variables was calculated using the *vif* function from *Perturb* package.

Evaluation of the model performance was based on graphical analysis, by plotting the observed against predicted values of the dependent variable (*plot* function from *graphics* package), and the studentized residuals against the estimated values residuals (*rstudent* function from *stats* package) and two statistical indices: the root-mean-square error (RMSE), which analyses the precision of the estimates; and the adjusted coefficient of determination (R^2_{adj}), which reflects the part of the total variance that is explained by the model and which takes into account the number of parameters that it is necessary to estimate. A cross-validation approach was used to evaluate the predictive capability of the models. The adjusted model efficiency for the estimates (MEF_{adj}), calculated by using the R^2_{adj} equation, was estimated by using the residual of each canopy fuel and stand variable observation, which was obtained by refitting the model without this observation residual (*cv.lm* function from *DAAG* package). Also, plots of the studentized residuals against the predicted values and plots showing the observed against the predicted values in cross-validation were analysed to search for systematic trends.

2.6. Relative importance of LiDAR metrics as explanatories for canopy fuel and stand variables

A regression tree was fitted to the data to analyse the importance of each LiDAR variable to estimate the stand (e.g. García-Gutiérrez *et al.,* 2011) and canopy fuel variables (e.g. Jakubowksi *et al.,* 2013). A regression tree is a non-parametric technique for the sequential partitioning of a data set composed of a continuous response variable and any number of potential continuous or categorical predictor variables, by use of dichotomous criteria (Breiman *et al.,* 1984). After each split, the technique searches for the predictor variable that provides the most effective binary separation of the range in the response variable. As a result, predictor variables can be used more than once. The regression tree analysis was performed using the *rpart* package from *R* (Therneau *et al.,* 2014; R Core Team, 2014). This approach sequentially partitions the data set considering two-way splits at each tree node. The best split at each node t is the split that maximizes:

$$\Delta Err(s,t) = Err(t) - P_L Err(t_L) - P_R Err(t_R)$$

Table 5. Parameter estimates, standard errors and goodness-of-fit statistics obtained for the fitted models relating the main stand and canopy variables with the LiDAR information.

Dependent variable	Independent variable	Parameter estimate	Standard error	Fitted model		Cross-validation	
				RMSE	R^2_{adj}	RMSE	MEF_{adj}
N	*Intercept*	-1083.2400	264.6147	111.4017	0.8644	136.9631	0.7950
	PFR_{A2}	74.9647	10.7500				
	AR_{Ahmean}: FR	-89.2795	17.3212				
dg	*Intercept*	19.5249	1.8581	0.3699	0.9570	0.7096	0.8420
	FR_{Ahmean}	3.293×10^{4}	2.972×10^{5}				
	h_{kurt}	-4.4156	0.5690				
	h_{ID}	-7.1340	1.0306				
	h_{95}	2.1993	0.2352				
G	*Intercept*	-39.2165	3.5432	1.3304	0.9650	1.9625	0.9239
	AR_{A2}: FR	0.5308	0.03804				
	h_{05}	3.5451	0.4481				
H_m	*Intercept*	11.3586	1.4623	0.3851	0.9476	0.5646	0.8875
	h_{ID}	1.3180	0.4688				
	PAR_{Ahmean}	-0.2232	0.0326				
	AR_{Ahmean}	3.436×10^{4}	3.993×10^{5}				
H_0	*Intercept*	-1.5553	0.3125	0.5064	0.9125	0.7746	0.7952
	h_{ID}	6.4430	0.9494				
	h_{95}	-2.8727	0.9499				
	CRR	19.9197	6.3618				
	AR_{Ahmode}	1.033×10^{4}	3.346×10^{5}				
	h_{99}	1.5856	0.5646				
V	*Intercept*	-236.3547	17.3872	5.9194	0.9721	7.5157	0.9550
	AR_{A2}: FR	2.2366	0.1748				
	h_{90}	15.3318	1.4847				
W	*Intercept*	-141.9026	13.0840	4.8569	0.9622	6.8228	0.9254
	AR_{A2}: FR	1.6309	0.1420				
	h_{10}	14.5498	1.6777				
W_{cff}	*Intercept*	-27.4691	3.7143	1.3788	0.9210	1.7295	0.8758
	AR_{A2}: FR	0.3286	0.0403				
	h_{10}	2.6117	0.4763				
CFL	*Intercept*	-1.2356	0.09928	0.03628	0.9706	0.05177	0.9402
	h_{05}	0.1097	0.01217				
	PFR_{A2}	0.01651	1.081×10^{3}				
CBH	*Intercept*	6.5263	1.2493	0.3290	0.9458	0.4618	0.8933
	h_{ID}	0.9525	0.4005				
	PAR_{Ahmean}	-0.1990	0.0278				
	AR_{Ahmean}	2.986×10^{4}	3.411×10^{5}				
CBD	*Intercept*	-0.1800	0.0231	0.00892	0.9446	0.01272	0.8873
	AR_{A2}:FR	3.07×10^{3}	2.512×10^{4}				
	h_{01}	0.01784	2.97×10^{3}				
CBHe	*Intercept*	4.3263	0.6762	0.1781	0.9472	0.2560	0.8908
	h_{ID}	0.5719	0.2168				
	PAR_{Ahmean}	-0.1054	0.0151				
	AR_{Ahmean}	1.604×10^{4}	1.846×10^{5}				
CBDe	*Intercept*	-0.1801	0.0221	0.00832	0.9373	0.01213	0.8668
	PFR_{A2}	2.8×10^{3}	2.451×10^{4}				
	h_{01}	0.01587	0.00277				

N is the number of stems ha^{-1}; *dg* is the quadratic mean diameter (cm); *G* is the basal area (m^2 ha^{-1}); H_m is the mean height (m); H_0 is the dominant height (m); *V* is the total stand volume (m^3 ha^{-1}); *W* is the total stand biomass (Mg ha^{-1}); W_{cff} is the crown fine fuel biomass (Mg ha^{-1}); CFL is the canopy fuel load (kg m^{-2}); CBH is the canopy base height (m); CBD is the canopy bulk density (kg m^{-3}); CBHe is the "effective" canopy base height (m); and CBDe is the "effective" canopy bulk density (kg m^{-3}).

where P_L and P_R are the proportions of sample plots that fall respectively to the left and right branch of the node t, $Err(t_L)$ and $Err(t_R)$ are the error of the left and right branches, and $Err(t)$ is the mean square error at node t given by

$$\frac{1}{N_t}\sum_{i=1}^{N_t}(y_i - \bar{y}_t)^2$$

and $\bar{y}_t$ is the mean of the stand variable of all the sample plots in node t. In order to know the relative importance of each explanatory in forest stand and canopy fuel variables estimation, the function *varImp* from *caret* package was used.

2.7. Effect of silvicultural treatments on LiDAR metrics, canopy fuel and stand variables

After checking the normality of the data, an Analysis of Variance (ANOVA) and Tukey's adjusted pairwise comparisons ($P \leq 0.05$) were applied to study the influence of thinning on different stand variables and on canopy variables related to crown fire risk. The thinning treatment was considered as a random factor. The stand variables analysed were: N (stems ha^{-1}), dg (cm), G (m^2 ha^{-1}), H_m (m), H_0 (m), V (m^3 ha^{-1}), W (Mg ha^{-1}) and W_{cff} (Mg ha^{-1}). The canopy fuel complex structural characteristics analysed were: CFL (kg m^{-2}), CBH (m), CBD (kg m^{-3}), CBHe (m) and CBDe (kg m^{-3}). Analysis of Variance (ANOVA) and Tukey's adjusted pairwise comparisons ($P \leq 0.05$) were also applied to study the influence of thinning on different LiDAR metrics. All the metrics previously described in Tables 2 and 3 were analysed. The thinning treatment was considered as a random factor.

3. Results

3.1. Modelling canopy fuel and stand variables

The parameter estimates and goodness-of-fit statistics of the best linear models obtained for the main stand and canopy variables using the stepwise variables selection method and the LiDAR data as regressors are summarized in Table 5. Only models with all the parameters significant at the 5% level and a VIF <10 were included.

All the linear models performed well, explaining more than 86% of the observed variability. Plots of residuals against predicted values showed no evidence of heterogeneous variance and no systematic pattern.

Bearing in mind the low number of plots used in this study requires us to be cautious with the provided results.

3.2. Relative importance of LiDAR metrics as explanatories for canopy fuel and stand variables

Figures 1 to 3 show the rank orders of variable importance for all the regression tree models considering the main stand and canopy variables as dependent variables. The most important variables are at the top of the y-axis in each plot.

Regarding the variables related to stand density (N, dg and G), h_{kurt}, AR_{Amode}:FR and PFR_{Amode} were the most important predictor for N, and CRR, h_{mean}, h_{SD} and PAR_{A2} were the most important predictor for dg. For G, several variables related with crown closure were important ($AR_{A2,}$ $FR_{A2,}$ AR_{A2}:FR, PAR_{A2} and PFR_{A2}). Variables related with height distribution, such as h_{AAD}, h_{ID}, h_{kurt}, h_{max}, h_{mean}, h_{SD} and h_{CV} were the most important predictors for stand height variables H_m and H_0 (Figure 1).

According to the results of the linear models fitted (Table 5), AR_{A2}:FR was the most important predictor for the stand yield variables (V, W and W_{cff}), although other variables as PFR_{A2} and h_{kurt} showed also a very strong influence (Figure 2).

As for the stand yield variables, the most important LiDAR predictor observed in the regression tree models for CFL, CBD and CBDe were, basically, those obtained in the linear models (AR_{A2}:FR and PFR_{A2}) (Figure 3).

CBH and CBHe were strongly influenced by variables related to height distribution, especially h_{ID} and h_{kurt} in the same way as the stand height variables H_m and H_0 (Figure 3).

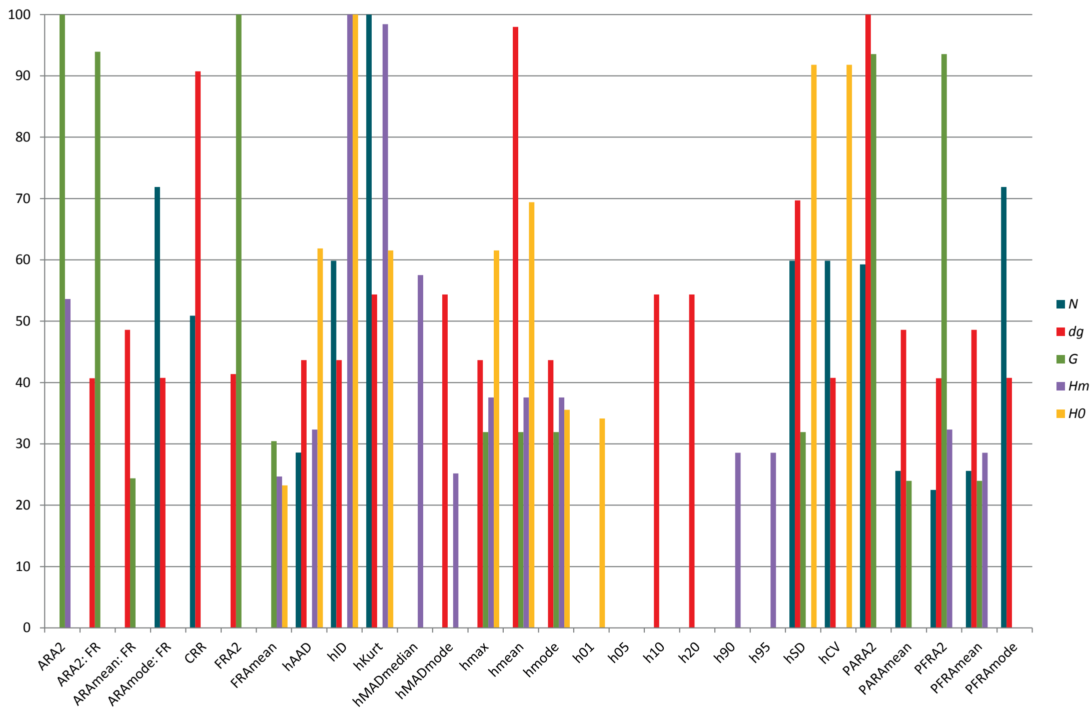

Figure 1. Relative importance (y-axis) of the LiDAR variables (x-axis) to classify the main stand density and stand height variables (label). N is the number of stems ha^{-1}, dg is the quadratic mean diameter (cm), G is the basal area (m^2 ha^{-1}), H_m is the mean height (m) and H_0 is the dominant height (m).

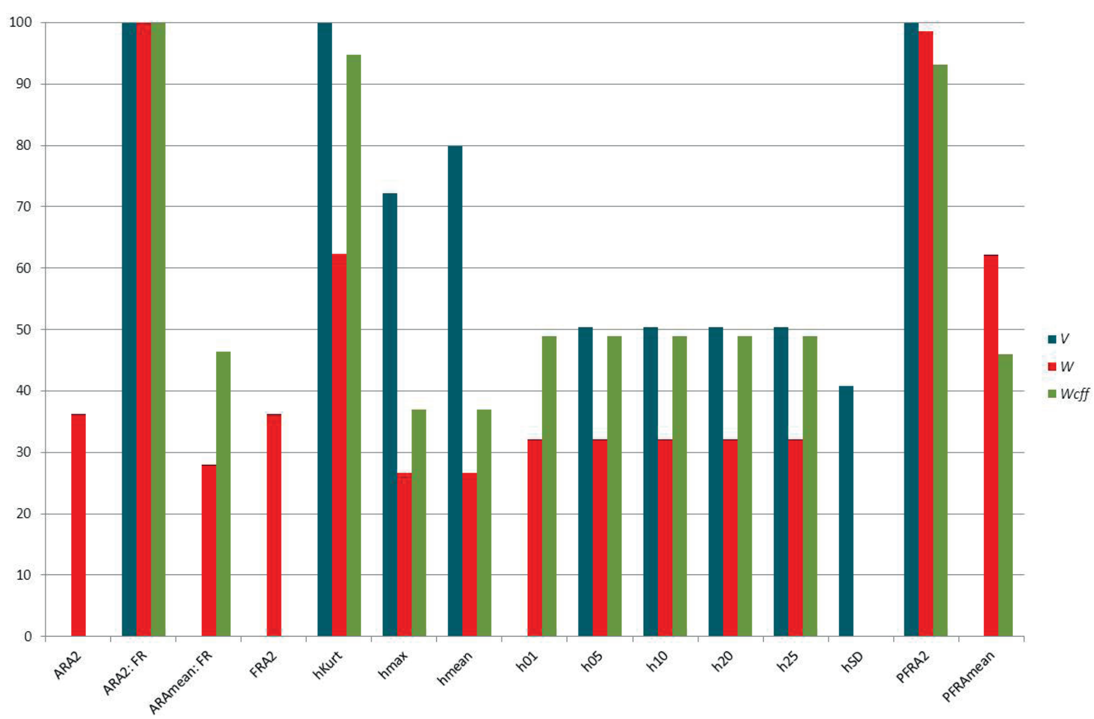

Figure 2. Relative importance (y-axis) of the LiDAR variables (x-axis) to classify the main stand yield variables (label). V is the total stand volume (m^3 ha^{-1}), W is the total stand biomass (Mg ha^{-1}) and W_{cff} is the crown fine fuel biomass (Mg ha^{-1}).

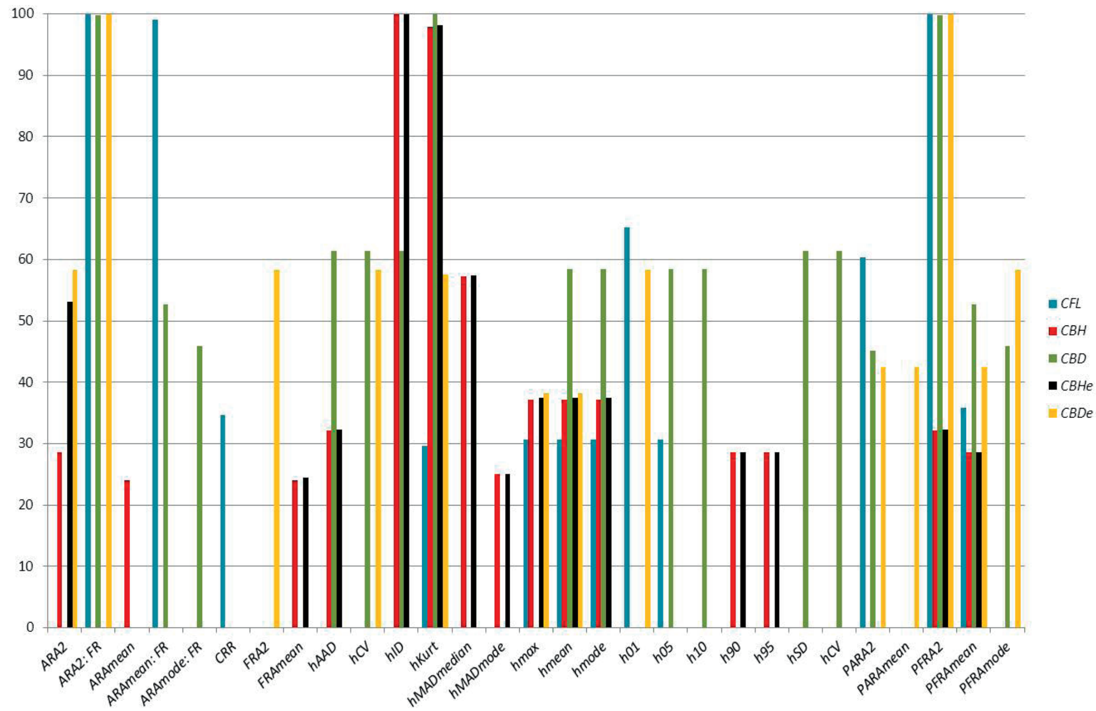

Figure 3. Relative importance (y-axis) of the LiDAR variables (x-axis) to classify the main canopy fuel complex structural characteristics (label). CFL is the canopy fuel load (kg m^{-2}), CBH is the canopy base height (m), CBD is the canopy bulk density (kg m^{-3}), CBHe is the "effective" canopy base height (m) and CBDe is the "effective" canopy bulk density (kg m^{-3}).

3.3. Effect of silvicultural treatments on LiDAR metrics, canopy fuel and stand variables

The ANOVA and Tukey's adjusted pairwise comparisons results for the main stand and canopy variables (see Table 6) revealed that there was not influence of thinning on any of the canopy fuel and stand variables analysed, probably due to the limited number of sample plots and the elapsed time from the treatments.

The ANOVA and Tukey's adjusted pairwise comparisons results for LiDAR metrics (see Table 7)

Table 6. Mean values of the main stand characteristics for the different thinning treatments. Different letters represent significant differences between mean values (Tukey's adjusted pairwise comparisons; $P \leq 0.05$).

	Thinning treatment		
Stand variable	Control	Selective thinning	Heavy low thinning
N	1176.7^{A}	928.7^{A}	850.7^{A}
dg	16.48^{A}	16.83^{A}	16.94^{A}
G	24.93^{A}	20.64^{A}	19.07^{A}
H_m	10.34^{A}	11.02^{A}	11.09^{A}
H_0	11.11^{A}	12.52^{A}	12.12^{A}
V	103.60^{A}	96.22^{A}	85.83^{A}
W	80.65^{A}	72.61^{A}	65.69^{A}
W_{cff}	15.21^{A}	13.54^{A}	12.60^{A}
CFL	0.7326^{A}	0.6049^{A}	0.5584^{A}
CBH	5.0712^{A}	5.6860^{A}	5.6970^{A}
CBD	0.1530^{A}	0.1278^{A}	0.1188^{A}
CBHe	3.7261^{A}	4.0452^{A}	4.0650^{A}
CBDe	0.1223^{A}	0.0942^{A}	0.0883^{A}

N is the number of stems ha^{-1}; dg is the quadratic mean diameter (cm); G is the basal area (m^2 ha^{-1}); H_m is the mean height (m); H_0 is the dominant height (m); V is the total stand volume (m^3 ha^{-1}); W is the total stand biomass (Mg ha^{-1}); W_{cff} is the crown fine fuel biomass (Mg ha^{-1}); CFL is the canopy fuel load (kg m^{-2}); CBH is the canopy base height (m); CBD is the canopy bulk density (kg m^{-3}); CBHe is the "effective" canopy base height (m); and CBDe is the "effective" canopy bulk density (kg m^{-3}).

Table 7. Results of the ANOVA and the Tukey's adjusted pairwise comparisons ($P \leq 0.05$) for the different thinning treatments. Only the LiDAR metrics with significant differences between mean values are showed and different letters represent different groups.

	Treatments		
LiDAR metrics	Control	Selective thinning	Heavy low thinning
PAR_{Ahmode}	32.9199^{A}	23.6850^{B}	20.9258^{B}
PFR_{Ahmode}	45.2206^{A}	32.3005^{B}	28.9217^{B}
PFR_{A2}	87.2633^{A}	70.9169^{B}	72.2140^{B}
AR_{Ahmode}: FR	45.2449^{A}	32.4036^{B}	28.9239^{B}
AR_{A2}: FR	88.7873^{A}	71.9038^{B}	73.3789^{AB}

revealed significant differences between C and ST treatments for PAR_{Ahmode}, PFR_{Ahmode}, PFR_{A2}, AR_{Ahmode}: FR, and AR_{A2}: FR. Significant differences between C and HLT treatments for PAR_{Ahmode}, PFR_{Ahmode}, PFR_{A2} and AR_{Ahmode}: FR were also found; however, not significant differences between ST and HLT were found for any of the LiDAR metric variables analysed.

4. Discussion

In this study, we used LiDAR data and a statistical approach based on regressors –which were calculated directly from the previously normalized laser-derived canopy height– to estimate several forest stand and canopy fuel variables. The results of the linear models fitted demonstrate that canopy fuel complex structural characteristics and management-relevant forest stand variables can be modelled with high precision in Atlantic *P. pinaster* forests using airborne LiDAR data, similar to the results reported in the international literature in different forest and flight pattern conditions, as we report in the next paragraphs. We should be cautious interpreting our results because of the low number of available plots for this study. Nonetheless, results clearly indicated strong relationships between LiDAR metrics and canopy fuel complex structural characteristics and management-relevant forest stand variables for this species.

The goodness-of-fit statistics obtained for the models of canopy fuel load (R^2_{adj} = 0.97, RMSE = 0.0363), "effective" canopy base height and canopy base height (R^2_{adj} > 0.95, RMSE ranged from 0.178 to 0.329 m, respectively), and canopy bulk density and "effective" canopy bulk density (R^2_{adj} > 0.94, RMSE 0.00892 and 0.00832, respectively), were slightly better than those reported by Naesset and Økland (2002) in spruce Norway boreal forests, Andersen *et al.* (2005) in Douglas-fir Pacific Northwest forests, Hall *et al.* (2005) in ponderosa pine forests of Colorado, Peterson *et al.* (2005) in mixed coniferous forests of California, Zhao *et al.* (2011) in Eastern Texas forest of loblolly pine, González-Olabarría *et al.* (2012) in central Spain forests of European black pine and maritime pine, González-Ferreiro *et al.* (2014) in northwest Spain forests of radiata pine, or Ruiz *et al.* (2014b) in Douglas-fir and mixed forest in Northern Oregon. Nevertheless, our results should be treated with caution because of the scarce number of plots analysed.

The results obtained for the models of the stand density variables (N, dg, and G) were better than expected, taking into account the international literature review. Thus, the model to estimate N (R^2_{adj} = 0.86, RMSE = 111.4 stems ha^{-1}) was much better than those reported by Næsset (2002, 2004) for spruce boreal forest in Norway and Gonçalves-Seco *et al.* (2011) for Atlantic plantations of blue gum in Spain. Something similar happened with the dg model (R^2_{adj} = 0.96, RMSE = 0.370 cm), which performed much better than those reported by Næsset (2002, 2004) for mean diameter and Gonçalves-Seco *et al.* (2011) for mean and quadratic mean diameter, but in the order of the results obtained by Ruiz *et al.* (2014b). Finally, stand basal area estimates derived from the linear model (R^2_{adj} = 0.97, RMSE = 1.33 m^2 ha^{-1}) was similar to those achieved by Treitz *et al.* (2010) in black spruce forests of Canada, but was even better than those reported by Næsset (2002), Lim *et al.* (2003) for Canadian broadleaf forests, Stephens *et al.* (2008) in radiata pine forests of New Zealand or Gonçalves-Seco *et al.* (2011) and González-Ferreiro *et al.* (2012) in Spain. The high crown diameter of adult *P. pinaster* trees and the regular and homogenous structure of these single-stratified stands could help to obtain good estimates of these parameters related with stand density. Also, the size of the plots of about 1 ha could improve estimates regarding to some other previous mentioned studies, since a minimum plot areas of 500–600 m^2 are needed (Ruiz *et al.,* 2014a). Again, results should be treated with caution because of the scarce number of plots.

The results of the stand height variables models H_m and H_0 (R^2_{adj} = 0.95, RMSE = 0.385 m and R^2_{adj} = 0.91, RMSE = 0.506 m, respectively) are similar, in terms of R^2 of that achieved by Treitz *et al.* (2010), and better than those provided by Gobakken and Næsset (2007) in Norway Spruce an Scots pine in Norway and González-Ferreiro *et al.* (2012); although the goodness-of-fit statistics are lower than those achieved by Stephens *et al.* (2008).

The results of stand volume and aboveground biomass modelling (R^2_{adj} = 0.97, RMSE = 5.92 m^3 ha^{-1} and R^2_{adj} = 0.96, RMSE = 4.86 Mg ha^{-1}, respectively) are in the order of those achieved by Treitz *et al.* (2010), but are better than those achieved by Hollaus *et al.* (2007) in Austria alpine forests, Hall *et al.* (2005) or González-Ferreiro *et al.* (2012).

The ANOVA and Tukey's adjusted pairwise comparisons revealed interesting results that could help us to differentiate thinning treatments using LiDAR-derived information. Differences between control plots (C, unthinned) and thinned plots (ST and HLT) were observed for several LiDAR-derived variables, although none option to differentiate between ST plots and HLT plots was found. LiDAR-derived variables related to crown closure were the most useful, especially PAR_{Ahmode}, PFR_{Ahmode}, PFR_{A2} and AR_{Ahmode}: FR, allowed us to differentiate between thinned and unthinned stands. These results are very interesting since raster files of these variables are easily generated by FUSION V. 3.4.2 LiDAR Toolkit (McGaughey, 2014) and can be used in GIS (Geographic Information System) software. Therefore, further research should be conducted to obtain the threshold values that allow us to correctly classify thinned and unthinned forest stands by using single or multiple layers information.

5. Conclusions and implications

Once LiDAR models have been developed, these equations can be used to generate maps that informs about canopy fuel complex structural characteristics, stand yield and stand density over the entire area of the LiDAR data coverage. These maps represent spatially-explicit data layers that can be used for forest managers as direct input for fire behaviour models to support the analysis of fire hazard and the implementation of fuel management programs (Andersen *et al.,* 2005; González-Olabarría *et al.,* 2012) and also for thinning operations and timber harvesting management.

On the other hand, silvicultural interventions like thinning can modify the fuel complex structure into a less flammable. In Asturias, most of forest stands are private small land ownerships. Moreover, for forest managers is not always easy to know which forest stands have been thinned or which one are not thinned. Then, the mapping of the thinned and unthinned forest stands could be a good way to provide useful information. More research should be done in this area, but we have found that some LiDAR-derived metrics related with crown closure could be of interest to this goal.

Acknowledgements

We thank the funding of: *i*) FORRISK project (Interreg IVB SUDOE 2007-2013), *ii*) Forest Services of the Government of the Principality of Asturias, and *iii*) Galician Government and European Social Fund (Official Journal of Galicia – DOG nº 52, 17/03/2014 p. 11343, exp: POS-A/2013/049). We also thank the staff from SERIDA and CETEMAS who participated in the fieldwork. Finally, we also acknowledge the comments of the Reviewers and Editor that have contributed to enhance this study.

References

Álvarez-Álvarez, P., Afif Khouri, E., Cámara-Obregón, A., Castedo-Dorado, F., Barrio-Anta, M. 2011. Effects of foliar nutrients and environmental factors on site productivity in *Pinus pinaster* Ait. stands in Asturias (NW Spain). *Annals of Forest Science*, 68(3), 497-509. http://dx.doi.org/10.1007/s13595-011-0047-5

Andersen, H.E., McGaughey, R.J., Reutebuch, S.E. 2005. Estimating forest canopy fuel parameters using LIDAR data. *Remote Sensing of Environment*, 94(4), 441-449. http://dx.doi.org/10.1016/j.rse.2004.10.013

Arias-Rodil, M. 2009. Desarrollo de una tarifa de cubicación con clasificación de productos para *Pinus pinaster* en Asturias. MS Thesis, Santiago de Compostela: USC.

Beukema, S.J., Greenough, J.A., Robinson, D.C.E., Kurz, W.A., Reinhardt, E.D., Crookston, N.L., Brown, J.K., Hardy, C.C., Stage, A.R. 1997. An introduction to the fire and fuels extension to FVS. In: Teck, R., Moeur, M., Adams, J., comps. *Proceedings: Forest Vegetation Simulator conference*. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Research Station, February 3-7, pp 191-195.

Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.J. 1984. *Classification and Regression Trees*. New York: Chapman & Hall.

Cruz, M.G., Alexander, M.E., Fernandes, P.A.M. 2008. Development of a model system to predict wildfire behaviour in pine plantations. *Australian Forestry*, 71(2), 113-121. http://dx.doi.org/10.1080/00049158.2008.10676278

Dalponte, M., Martinez, C., Rodeghiero, M., Gianelle, D. 2011. The role of ground reference data collection in the prediction of stem volume with lidar data in mountain areas. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(6), 787-797. http://dx.doi.org/10.1016/j.isprsjprs.2011.09.003

Fernandes, P.M., Davies, G.M., Ascoli, D., Fernández, C., Moreira, F., Rigolot, E., Stoof, C.R., Vega, J.A., Molina, D. 2013. Prescribed burning in southern Europe: developing fire management in a dynamic landscape. *Frontiers in Ecology and the Environment*, 11, e4-e14. http://dx.doi.org/10.1890/120298

Fernandes, P.M., Rigolot, E. 2007. The fire ecology and management of maritime pine (*Pinus pinaster* Ait.). *Forest Ecology and Management*, 241(1-3), 1-13. http://dx.doi.org/10.1016/j.foreco.2007.01.010

Finney, M.A., 2003. Calculation of fire spread rates across random landscapes. *International Journal of Wildland Fire*, 12(2), 167-174. http://dx.doi.org/10.1071/WF03010

Finney, M.A. 2004. FARSITE: Fire Area Simulator-Model development and evaluation. *USDA Research Paper RMRS-RP-4*, 1-47.

Finney, M.A. 2006. An overview of FlamMap fire modeling capabilities. *USDA Forest Service Proceedings RMRS-P-41*, 213-220.

García-Gutiérrez, J., González-Ferreiro, E., Mateos-García, D., Riquelme-Santos, J.C., Miranda, D. 2011. A compartive study between two regression methods on LiDAR data: A case study. *Lecture Notes in Artificial Intelligence*, 6679, 311-318. http://dx.doi.org/10.1007/978-3-642-21222-2_38

García-Gutiérrez, J., González-Ferreiro, E., Riquelme-Santos, J.C., Miranda, D., Diéguez-Aranda, U., Navarro-Cerrillo, R.M. 2014. Evolutionary feature selection to estimate forest stand variables using LiDAR. *International Journal of Applied Earth Observation and Geoinformation*, 26, 119-131. http://dx.doi.org/10.1016/j.jag.2013.06.005

Gleason, C.J., Im, J. 2012. Forest biomass estimation from airborne LiDAR data using machine learning approaches. *Remote Sensing of Environment*, 125, 80-91. http://dx.doi.org/10.1016/j.rse.2012.07.006

Gobakken, T., Næsset, E. 2007. Assessing effects of laser point density on biophysical stand properties derived from airborne laser scanner data in mature forest. In: *ISPRS Workshop on Laser Scanning 2007 and SilviLaser 2007*. Espoo, Finland, September 12-14, pp 150-155.

Gómez-Vázquez, I., Crecente-Campo, F., Diéguez-Aranda, U., Castedo-Dorado, F. 2013. Modelling canopy fuel variables in *Pinus pinaster* Ait. and *Pinus radiata* D. Don stands in northwestern Spain. *Annals of Forest Science*, 70(2), 161-172. http://dx.doi.org/10.1007/s13595-012-0245-9

Gonçalves-Seco, L., González-Ferreiro, E., Diéguez-Aranda, U., Fraga-Bugallo, B., Crecente, R., Miranda, D. 2011. Assessing the attributes of high-density *Eucalyptus globulus* stands using airborne laser scanner data. *International Journal of Remote Sensing*, 32(24), 9821-9841. http://dx.doi.org/10.1080/01431161.2011.593583

González-Ferreiro, E., Diéguez-Aranda, U., Miranda, D. 2012. Estimation of stand variables in *Pinus radiata* D. Don plantations using different LiDAR pulse densities. *Forestry*, 85(2), 281-292. http://dx.doi.org/10.1093/forestry/cps002

González-Ferreiro, E., Diéguez-Aranda, U., Crecente-Campo, F., Barreiro-Fernández, L., Miranda, D., Castedo-Dorado, F. 2014. Modelling canopy fuel variables for *Pinus radiata* D. Don in NW Spain with low-density LiDAR data. *International Journal of Wildland Fire*, 23(3), 350-362. http://dx.doi.org/10.1071/WF13054

González-Olabarria, J.R., Rodríguez, F., Fernández-Landa, A., Mola-Yudego, B. 2012. Mapping fire risk in the Model Forest of Urbión (Spain) based on airborne LiDAR measurements. *Forest Ecology and Management*, 282, 149-156. http://dx.doi.org/10.1016/j.foreco.2012.06.056

Hall, S.A., Burke, I.C., Box, D.O., Kaufmann, M.R., Stoker, J.M. 2005. Estimating stand structure using discrete-return lidar: an example from low density, fire prone ponderosa pine forests. *Forest Ecology and Management*, 208(1-3), 189-209. http://dx.doi.org/10.1016/j.foreco.2004.12.001

Hevia, A. 2013. Influencia de la poda en el desarrollo de masas de *Pinus radiata* D. Don y *Pinus pinaster* Aiton en Asturias. PhD Thesis, Santiago de Compostela: USC.

Hollaus, M., Wagner, W., Maier, B., Schadauer, K. 2007. Airborne laser scanning of forest stem volume in a mountainous environment. *Sensors*, 7, 1559-1577. http://dx.doi.org/10.3390/s7081559

Holmgren, J., Persson, Å. 2004. Identifying species of individual trees using airborne laser scanner. *Remote Sensing of Environment*, 90(4), 415-423. http://dx.doi.org/10.1016/S0034-4257(03)00140-8

Jakubowksi, M.K., Guo, Q., Brandon, C., Scott, S. Maggi, K. 2013. Predicting Surface Fuel Models and Fuel Metrics Using Lidar and CIR Imagery in a Dense, Mountainous Forest. *Photogrammetric Engineering & Remote Sensing*, 79(1), 37-49. http://dx.doi.org/10.14358/PERS.79.1.37

Keane, R.E., Burgan, R., van Wagtendonk, J. 2001. Mapping wildland fuels for fire management across multiple scales: integrating remote sensing, GIS, and biophysical modeling. *International Journal of Wildland Fire*, 10(3-4), 301-319. http://dx.doi.org/10.1071/WF01028

Keyser, T., Smith, F.W. 2010. Influence of crown biomass estimators and distribution on canopy fuel characteristics in ponderosa pine stands of the Black Hills. *Forest Science*, 56(2), 156-165.

Lim, K., Treitz, P., Baldwin, K., Morrison, I., Green, J. 2003. Lidar remote sensing of biophysical properties of tolerant northern hardwood forests. *Canadian Journal of Remote Sensing: Journal canadien de télédétection*, 29(5), 658-678. http://dx.doi.org/10.5589/m03-025

McGaughey, R. 2014. FUSION/LDV: software for LiDAR data analysis and visualization. Version 3.41. Seattle, WA: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

Means, J.E., Acker, S.A., Fitt, B.J., Renslow, M., Emerson, L., Hendrix, C.J. 2000. Predicting forest stand characteristics with airborne scanning LiDAR. *Photogrammetric Engeenering & Remote Sensing*, 66(11), 1367-1371.

Næsset, E. 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. *Remote Sensing of Environment*, 80(1), 88-99. http://dx.doi.org/10.1016/S0034-4257(01)00290-5

Næsset, E. 2004. Practical large-scale forest stand inventory using a small-footprint airborne scanning laser. *Scandinavian Journal of Forest Research*, 19(2), 164-179. http://dx.doi.org/10.1080/02827580310019257

Næsset, E., Økland, T. 2002. Estimating tree height and tree crown properties using airborne scanning laser in a boreal nature reserve. *Remote Sensing of Environment*, 79(1), 105-115. http://dx.doi.org/10.1016/S0034-4257(01)00243-7

Peterson, B., Dubayah, R., Hyde, P., Hofton, M., Blair, J.B., Fites-Kaufman, J. 2007. Use of LIDAR for forest inventory and forest management application. In: McRoberts, R. E., Reams, G. A., van Deusen, P. C., McWilliams, W. H., eds. *Proceedings: Seventh annual forest inventory and analysis symposium*. Portland, Oregon., October 3-6, Gen. Tech. Rep. WO-77. Washington, DC: U.S. Department of Agriculture, Forest Service, pp 193-200.

R Core Team, 2014. R: A language and environment for statistical computing. Vienna: R Foundation for Statistical Computing.

Rego, F.C. 1992. Land use changes and wildfires. In: Teller A., Mathy P., Jeffers J.N., eds. *Response of Forest Ecosystems to Environmental Changes*. Netherlands: Springer, pp 367-373. http://dx.doi.org/10.1007/978-94-011-2866-7_33

Reinhardt, E., Scott, J., Gray, K., Keane, R. 2006. Estimating canopy fuel characteristics in five conifer stands in the western United States using tree and stand measurements. *Canadian Journal of Forest Research*, 36, 2803-2814. http://dx.doi.org/10.1139/x06-157

Reitberger, J., Krzystek, P., Stilla, U. 2008. Analysis of full waveform LIDAR data for the classification of deciduous and coniferous trees. *International Journal of Remote Sensing*, 29(5), 1407-1431. http://dx.doi.org/10.1080/01431160701736448

Ruiz, L.A., Hermosilla, T., Mauro, F., Godino, M. 2014a. Analysis of the Influence of Plot Size and LiDAR Density on Forest Structure Attribute Estimates. *Forests*, 5, 936-951. http://dx.doi.org/10.3390/f5050936

Ruiz, L.A., Hermosilla, T., Kazakova, A.N., Moskal, L. M. 2014b. Comparison of forest structure estimates using discrete and full-waveform LiDAR metrics. In: *ForestSat 2014*. Riva del Garda, Italy, November 4-7.

Sando, R.W., Wick, C.H. 1972. A method of evaluating crown fuels in forest stands. St. Paul, MN: U.S. Dept. of Agriculture, Forest Service, North Central Forest Experiment Station. *USDA Research paper NC-84*, 1-12.

Scott, J.H., Reinhardt, E.D. 2001. Assessing crown fire potential by linking models of surface and crown fire behaviour. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. *USDA Research Paper RMRS-RP-29*, 1-61.

Stephens, P.R., Watt, P.J., Loubser, D., Haywood, A., Kimberley, M.O. 2007. Estimation of carbon stocks in New Zealand planted Forests using airborne scanning LiDAR. *Proceedings: ISPRS Workshop International archives of photogrammetry, remote sensing and spatial information sciences*, 36(3), 389-394.

Sun, G., Ranson, K., Guo, Z., Zhang, Z., Montesano, P., Kimes, D. 2011. Forest biomass mapping from lidar and radar synergies. *Remote Sensing of Environment*, 115(11), 2906-2916. http://dx.doi.org/10.1016/j.rse.2011.03.021

Tesfamichael, S.G., Ahmed, F.B., van Aardt, J.A.N. 2010. Investigating the impact of discrete-return lidar point density on estimations of mean and dominant plot-level tree height in *Eucalyptus grandis* plantations. *International Journal of Remote Sensing*, 31(11), 2925-2940. http://dx.doi.org/10.1080/01431160903144086

Therneau, T., Atkinson, B., Ripley, B. 2014. Rpart: Recursive Partitioning and Regression Trees. Last access June 13, 2015, http://CRAN.R-project.org/package=rpart.

Treitz, P., Lim, K., Woods, M., Pitt, D., Nesbitt, D., Etheridge, D. 2010. LiDAR data acquisition and processing protocols for forest resource inventories in Ontario, Canada. In: Koch, B., Kendlar, G., eds. *Silvilaser 2010. The 10th International Conference on LiDAR Applications for Assessing Forest Ecosystems,* Freiburg, Germany, September 14-17, pp 451-460.

Van Wagner, C.E. 1977. Conditions for the start and spread of crown fire. *Canadian Journal of Forest Research*, 7(1), 23-34. http://dx.doi.org/10.1139/x77-004

Vega, J.A. 2001. Efectos del fuego prescrito sobre el suelo en pinares de *Pinus pinaster* Ait. de Galicia (PhD Thesis). Madrid: Universidad Politécnica de Madrid.

Wagner, W., Hollaus, M., Briese, C., Ducic, V. 2008. 3D vegetation mapping using small-footprint full-waveform airborne laser scanners. *International Journal of Remote Sensing, Special Issue: 3D Remote Sensing in Forestry*, 29(5), 1433-1452.

Yu, X., Hyyppä, J., Holopainen, M., Vastaranta, M. 2010. Comparison of Area-Based and Individual Tree-Based Methods for Predicting Plot-Level Forest Attributes. *Remote Sensing*, 2(6), 1481-1495. http://dx.doi.org/10.3390/rs2061481

Zhao, K., Popescu, S., Meng, X., Pang, Y., Agca, M. 2011. Characterizing forest canopy structure with lidar composite metrics and machine learning. *Remote Sensing of Environment*, 115(8), 1978-1996. http://dx.doi.org/10.1016/j.rse.2011.04.001