



## Comparison of regression models to estimate biomass losses and CO<sub>2</sub> emissions using low-density airborne laser scanning data in a burnt Aleppo pine forest

Darío Domingo <sup>a</sup>, María Teresa Lamelas-Gracia <sup>a,b</sup>, Antonio Luis Montealegre-Gracia <sup>a</sup> and Juan de la Riva-Fernández <sup>a</sup>

<sup>a</sup>GEOFOREST-IUCA, Departamento de Geografía y O.T., Universidad de Zaragoza, Zaragoza, Spain; <sup>b</sup>Centro Universitario de la Defensa de Zaragoza, Academia General Militar, Zaragoza, Spain

### ABSTRACT

The knowledge of the forest biomass reduction produced by a wildfire can assist in the estimation of greenhouse gases to the atmosphere. This study focuses on the estimation of biomass losses and CO<sub>2</sub> emissions by combustion of Aleppo pine forest in a wildfire occurred in the municipality of Luna (Spain). The availability of low point density airborne laser scanning (ALS) data allowed the estimation of pre-fire aboveground forest biomass. A comparison of nine regression models was performed in order to relate the biomass, estimated in 46 field plots, to several independent variables extracted from the ALS data. The multivariate linear regression selected model, including the percentage of first returns above 2 m and 40th percentile of the return heights, was validated using a leave-one-out cross-validation technique (6.1 ton/ha root mean square error). Biomass losses were estimated in a three-phase approach: (i) wildfire severity was obtained using the difference normalized burn ratio ( $\Delta NBR$ ), (ii) Aleppo pine forest was delimited using the National Forest Map and ALS data and (iii) burning efficiency factors were applied considering severity levels. Post-fire biomass was then transformed into CO<sub>2</sub> emissions (426,754.8 ton). This study evidences the usefulness of low-density ALS data to accurately estimate pre-fire biomass, in order to assess CO<sub>2</sub> emissions in a Mediterranean Aleppo pine forest.

### ARTICLE HISTORY

Received 31 January 2017  
Revised 22 May 2017  
Accepted 24 May 2017



### KEYWORDS

ALS; aboveground tree biomass losses; CO<sub>2</sub> emissions; Aleppo pine; burn severity

### Introduction

Wildfires are a socio-environmental hazard in Mediterranean ecosystems, acting as a source of greenhouse gases (GHGs) emissions to the atmosphere (Akagi et al., 2013; Andreae et al., 1988; Seiler & Crutzen, 1980; Van Der Werf et al., 2010; Wiedinmyer et al., 2011). Consequently, fires are able to alter the carbon cycle behaviour at regional or even global scales (Narayan, Fernandes, Van Brusselen, & Schuck, 2007), as well as to decrease the effect of carbon sequestration by forest ecosystems (Van Der Werf et al., 2006; Wiedinmyer & Neff, 2007). In the Mediterranean basin, an average of 45,000 fires is recorded yearly (Oliveira, Oehler, San-Miguel-Ayanz, Camia, & Pereira, 2012), increasing the albedo and determining the current landscape (Pausas, Llovet, Rodrigo, & Vallejo, 2008). Although these values and the resulting emissions are variable in time and space, biomass burning contributed significantly in the total direct carbon monoxide (CO) emissions (Pétron et al., 2004). These natural or anthropogenic disturbances might be enhanced by climate change, increasing fire risk (Moriondo et al.,

2006) particularly in summer months (Sebastián-López, Salvador-Civil, Gonzalo-Jiménez, & SanMiguel-Ayanz, 2008). In Spain, fire statistic registers show a reduction in the number of fire events during the last decade (2001–2010), as well as in the total burned area (Rodrigues, Ibarra, Echeverria, Perez-Cabello, & de la Riva, 2014; San-Miguel-Ayanz et al., 2012). However, the occurrence of large fires (>500 ha) has increased. In 2015, 39% of the total area affected by fires was burned in a large fire (MAGRAMA, 2016a). Moreover, if fire recurrence is high, regeneration process might fail for even species with high resilience such as Aleppo pine (*Pinus halepensis* Mill.) (Pausas et al., 2008), influencing carbon sequestration. Under this context, scientists, fire managers and decision-makers require the most accurate information available related to fire emissions and its impact on the environment and population. The account of carbon dioxide (CO<sub>2</sub>) emissions is essential for climate regulation policies and the evaluation of the effects of these policies (Mieville et al., 2010), as well as for understanding the services that forest provide to societies (Lal, 2008; Pan et al., 2011).

**CONTACT** Darío Domingo  [ddomingo@unizar.es](mailto:ddomingo@unizar.es)  GEOFOREST-IUCA, Departamento de Geografía y O.T., Universidad de Zaragoza, C/Pedro Cerbuna 12, 50009, Zaragoza, Spain

© 2017 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.  
This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

GHG emissions from fires estimation require (i) the delimitation of the burned area, (ii) the estimation of pre-fire biomass, (iii) the assessment of the fraction of biomass consumed by fire, also defined as burning efficiency (De Santis, Asner, Vaughan, & Knapp, 2010) and (iv) the use of conversion factors to estimate GHG emissions. However, little research has been conducted on quantifying pre-fire biomass and biomass consumed by fire. According to De Santis et al. (2010), biomass consumption was traditionally estimated using a two-step methodology which includes (i) the estimation of pre-fire biomass by applying allometric regression equations using destructive sampling or biomass values per species and (ii) the post-fire biomass estimated by field-based weighting (Prasad et al., 2001; Sá, Pereira, & Silva, 2005; Ward et al., 1996) or by visual examination (Roy, Jin, Lewis, & Justice, 2005). An alternative approach is based on the use of remote sensing imagery for pre-fire biomass estimation. Despite the wide acceptance of the use of optical and radar remote sensing to estimate forest attributes such as biomass (Chuvieco, 2009; Leboeuf, Fournier, Luther, Beaudoin, & Guindon, 2012; Le Toan, Beaudoin, Riou, & Guyon, 1992; Tanase, de la Riva, Santoro, Pérez-Cabello, & Kasischke, 2011), airborne laser scanning (ALS) is considered one of the best techniques for forest structural parameters estimation (Lefsky, Cohen, Parker, & Harding, 2002; Maltamo, Næsset, & Vauhkonen, 2014; Vosselman & Maas, 2010).

In this sense, some studies have used low-density ALS data to estimate forest parameters such as tree height, crown diameter, basal area, stem density, volume (Guerra-Hernández, Tomé, & González-Ferreiro, 2016a; Hayashi, Weiskittel, & Sader, 2014; Holopainen et al., 2010; Mehtätalo, Virolainen, Tuomela, & Packalen, 2015; Montealegre, Lamelas, de la Riva, García-Martín, & Escribano, 2016; Næsset, 2002; Næsset & Økland, 2002; Popescu, Randolph, & Ross, 2003) as well as biomass (García-Gutiérrez, Martínez-Álvarez, Troncoso, & Riquelme, 2015; Guerra-Hernández et al., 2016b; Hall, Burke, Box, Kaufmann, & Stoker, 2005; Montagnoli et al., 2015; Shendryk, Margareta, Leif, Natascha, 2014). In addition, some of them have compared different point densities (González-Ferreiro et al., 2013; Singh, Gang, James, & Ross, 2015). However, few studies have been focused on comparing different algorithms to estimate forest parameters and they were all applied to high-density point clouds (Gagliasso, Hummel, & Temesgen, 2014; García-Gutiérrez et al., 2015; Gleason & Im, 2012; Görgens, Montagni, & Rodriguez, 2015; Latifi, Nothdurft, & Koch, 2010).

The main objective of this study is to estimate the CO<sub>2</sub> emissions derived from the consumption of the aboveground tree biomass (AGB), which refers to the total biomass of the trees considering stem, branches and needles, in a heterogeneous Aleppo pine forest,

located in Aragón Region (Spain). To achieve this goal, a discrete, multiple-return, low point density ALS data and field plots representative of pine stands were used to fit and validate the AGB models. A secondary objective was the comparison of different regression models, including machine learning.

Besides, the majority of previous approaches to CO<sub>2</sub> estimation assume that biomass is completely consumed. However, during wildfires in conifer stands in some cases only the needles and the small fine twigs of the pine crowns are consumed (Call & Albini, 1997; Mitsopoulos & Dimitrakopoulos, 2007; Scott & Reinhardt, 2001). Consequently, different combustion factors were applied to avoid assuming that biomass was completely consumed by the fire (French, Goovaerts, & Kasischke, 2004). The fire severity levels were extracted from the difference normalized burn ratio ( $\Delta$ NBR) spectral index applied to Landsat 8 OLI images.

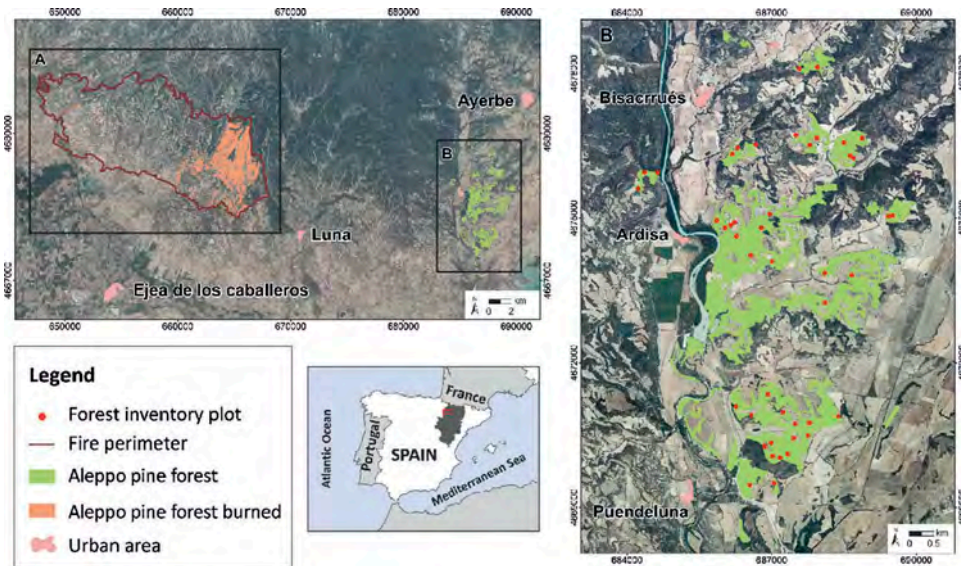
## Materials

### Study area

The study area, burned on 4 July 2015, is located in Luna municipality, northeast of Spain (42°12'N, 0°45'W). Aleppo pine has a high potential of ignition and represents almost 50% of the forested area in Aragón and is well adapted to these Mediterranean environmental conditions. The fire scorched in the area of 14,263 ha, of which 3390.4 ha was woodland. Those forested areas were covered in a 62.3% by monospecific Aleppo pine. As can be observed in Figure 1, for forest inventory purposes, the field campaign to estimate AGB was conducted in a close unburned area (Figure 1(b)). The proximity between both sites (see Figure 1(a) and (b)) and the similarity on environmental characteristics such as slope, climate and vegetation enable to extrapolate the AGB model to the burned area (Figure 1(a)). This similarity was previously evaluated by comparing some variables derived from the ALS metrics such as slope, canopy cover and tree height.

These heterogeneous pine forests from the structural point of view appear fragmented into stands of variable size, accompanied by an evergreen understorey with species, such as: *Quercus ilex* subsp. *rotundifolia*, *Quercus coccifera*, *Juniperus oxycedrus*, *Buxus sempervirens* and *Juniperus phoenicea*.

Climate of the region is Mediterranean with continental features. Annual precipitation is medium-low and irregular, averaging 525 mm and mostly occurring in autumn and spring. Winter has a monthly mean temperature less than 10°C, whereas summers have temperatures of ~20°C. The study area is characterized by a hilly topography, with elevations ranging from 430 to 1150 m above sea level and slopes



**Figure 1.** Study area. Aleppo pine forest stands, inside the perimeter of the Luna wildfire (a); location of the 46 forest inventory plots (b). High spatial resolution orthophotography (PNOA-2012) (IGN, 2017a) is used as backdrop.

from 0° to 39°. The lithology of the study area corresponds to Miocene shales and sandstones, alternating with conglomerates.

### Field plot data

Field data were acquired in 46 circular plots, 15 m radius at the unburned area during June and July 2015 (Figure 1(b)). The location of the field plots was selected, within the limits of the Aleppo pine stands at the unburned area, using a stratified random sampling technique, in order to achieve a representative sample of the variability of the terrain (Næsset & Økland, 2002), forest structure and tree density (Montealegre et al., 2016). Thereby, terrain slopes, tree height and canopy cover of the study area were derived from ALS point cloud to define homogeneous areas.

The centre of the selected plots (Figure 1(b)) was located in the field using a Leica VIVA GS15 CS10 GNSS real-time kinematic Global Positioning System. The average accuracy of the planimetric coordinates was 0.18 m. Tree breast height diameter (dbh) was measured at 1.3 m, using a Mantax Precision Blue diameter caliper (Haglöf Sweden®). It should be noted that only the trees with a dbh >7.5 cm were measured in each plot. The AGB was calculated for each plot according to Montero, Ruiz-Peinado, and Muñoz (2005) allometric equation and extrapolated to per hectare biomass value (kg of dry biomass per ha) considering the plot area (Equation (1)).

$$\text{Biomass}(\text{kg}/\text{ha}) = \frac{CF * e^a * \text{dbh}^b}{A_{\text{plot}}} * 10,000, \quad (1)$$

where  $CF$  is a correction factor ( $CF = e^{SEE^2/2}$ ) being  $e$  the Euler number and  $SEE$  the standard error

(0.151637);  $dbh$  is breast height diameter in cm;  $a$  (−2.0939) and  $b$  (2.20988) are the specific parameters for Aleppo pine; and  $A_{\text{plot}}$  is the area of each plot (706.8 m<sup>2</sup>).

These data act as ground truth to adjust and validate the AGB predictive model, which would be extrapolated to the burned area (Figure 1(a)) to estimate pre-fire biomass. The extrapolation of the AGB model was carried out in a Geographical Information System (GIS) environment using the selected Light Detection and Ranging (LiDAR) metrics and the coefficients of the model.

### Remote sensing data

The ALS data were captured for the burned and unburned area in several surveys carried out 4 years before the fire ignition between January and February 2011, using a small-footprint oscillating-mirror airborne Leica ALS60 discrete-return sensor. The Spanish National Plan for Aerial Orthophotography (PNOA) provided these data with a nominal density of 0.5 point/m<sup>2</sup> (IGN, 2017b). Data were delivered by the National Geographic Information Centre (CNIG) in 2 × 2 km tiles of raw data points in LAS binary files format v. 1.2. The  $x$ ,  $y$  and  $z$  coordinates were provided in UTM Zone 30 ETRS 1989 geodetic reference system and orthometric heights. The point cloud was captured with up to four returns measured per pulse. The ALS60 sensor was operating in 1.064 μm wavelength, 0.22 mrad beam divergence and ±29 scan angle degrees from nadir. The ALS point cloud density was 1.5 point/m<sup>2</sup>, considering all returns with a vertical accuracy better than 0.2 m for the area burned on 4 July 2015 and for the unburned one. The temporal lag between ALS acquisition data at the unburned area, captured in 2011, and fieldwork



campaign, performed in June and July 2015, was considered appropriate, as no significant changes took place in the study area in that period.

Pre-fire and post-fire Landsat 8 OLI land surface reflectance images, acquired on June 30 (path 200, row 31) and July 9 (path 199, row 31) 2015, were selected for  $\Delta$ NBR index calculation for the burned area and downloaded from USGS (2016). These products are generated using Landsat Surface Reflectance Code (LaSRC) algorithm (Vermote, Justice, Claverie, & Franch, 2016).

## Methods

The two-phase approach methodology includes the pre-fire biomass estimation through the comparison of different models and the estimation of biomass losses by applying three burning efficiency factors to assess the CO<sub>2</sub> emissions to the atmosphere (Figure 2).

### Pre-fire AGB estimation

This section describes the process followed for ALS data processing, as well as the generation of pre-fire AGB model.

### ALS data processing

The first processing step was noise point removal, which included verification of the overlapping returns. Thereafter, ALS point clouds were filtered using the multiscale curvature classification algorithm (Evans & Hudak, 2007) to extract the ground points. This algorithm, implemented in the MCC 2.1 command-line tool, is suitable for this environment according to

Montealegre, Lamelas, and de la Riva (2015a). Then, a digital elevation model (DEM) with a 1 m size grid was generated using the Point-TIN-Raster interpolation method (Renslow, 2013), following Montealegre, Lamelas, & de la Riva., (2015b). The normalized heights were obtained by the subtraction of the ground elevation value of the DEM from each point height. The normalized ALS tiles were clipped to the spatial extent of each field plot (Figure 1(b)). Furthermore, a wide range of statistical metrics commonly used as independent variables in forestry were calculated (Evans, Hudak, Faux, & Smith, 2009) using FUSION LDV 3.30 open source software (McGaughey, 2008). It should be noted that ALS-derived variables were generated after applying a threshold value of 2 m height so as to remove ground and understorey laser hits according to Nilsson (1996) and Næsset and Økland (2002).

### Model for estimating pre-fire AGB

With the aim of comparing the predictive performance of different regression methods for the estimation of AGB, eight regression methods were analysed: a multivariate linear regression (MLR) model, two machine learning algorithms and five regression trees structures. These methods are briefly described below.

MLR has been widely employed to estimate forest parameters by relating dependent variables, from field-work campaign, and independent variables, extracted from the ALS point cloud (García, Godino, & Mauro, 2012; Gonzalez-Ferreiro, Dieguez-Aranda, & Miranda, 2012; Lim, Treitz, Wulder, St-Onge, & Flood, 2003; Means et al., 1999; Næsset & Økland, 2002; Watt et al., 2013). As a first step following Montealegre et al. (2016) the Spearman's rank correlation coefficient ( $p$ ) was calculated in R software, in order to select the ALS variables that show the strongest correlation coefficient with field plot biomass data. The selection of the ALS metrics was made within a minimum  $p$  value of  $\pm 0.5$ . Then, the selected variables were included in a forward stepwise regression, in order to avoid overfitting by selecting the smallest possible number of predictor variables. The fitted model was selected according to measures of goodness of fit. Moreover, it was verified if the fitted model meets the basic assumptions of linear regression models according to García et al. (2012). Logarithmic transformation of dependent and independent variables was explored in the cases where statistical hypothesis of linear regression models could not be fulfilled (García et al., 2012; Means et al., 1999), as well as to verify whether the measures of goodness of fit of the models improve.

Support vector machine (SVM) is a supervised learning model which has associated learning algorithms that analyse and recognize patterns. This method assumes that input data are separable in space (Mountrakis, Jungo, & Caesar, 2011). SVM tries to find among multidimensional hyperplanes

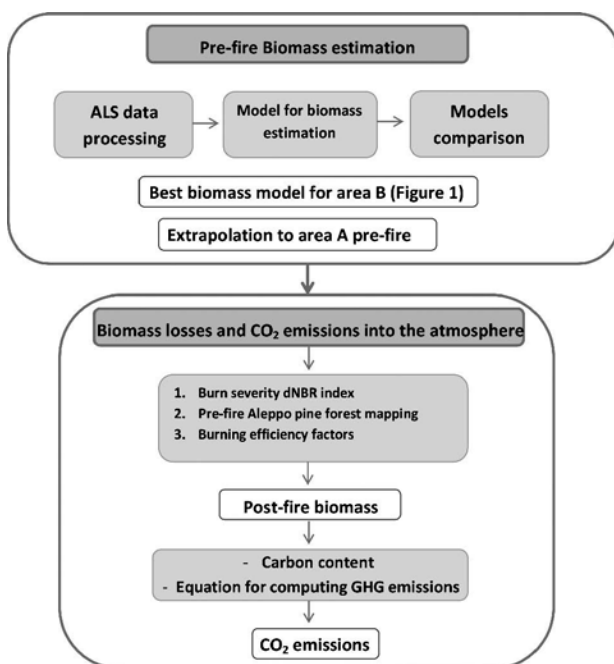


Figure 2. Methodology for biomass losses and CO<sub>2</sub> emissions estimation.

the optimal separation between classes, where the separability is a maximum. The data located in the hyperplane are the most difficult to classify since they have lower separability and they are called support vectors. SVM was implemented by using R package “e1071” and models with linear and radial kernels were computed. In both SVM models, the parameter cost was defined in the interval 1–1000, and the parameter gamma in the interval 0.01–1, applying the best parameters after tuning the model.

Random forest (RF) is an ensemble learning method that uses decision trees as base classifier. RF combines a decision tree that depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest (Breiman, 2001). The algorithm adds randomness to bagging and increases the diversity of decision trees by growing them from different subsets. In each decision tree, RF divides the nodes by using the best variables from a random sample. RF was implemented through R package “randomForest” (Liaw & Wiener, 2002) and “caret” (Van Essen et al., 2001). The RF model was adjusted using two parameters: the number of trees to growth (ntrees) and the number of variables selected randomly at each split (mtry). They were in the intervals 1–1000 and 1–2, respectively.

The regression tree structures are nonparametric regression techniques based on “If-Then” rules. In this study three linear models and two non-linear local models are computed. The R package “CORElearn” has been used to perform the different regression trees. It should be added that the differences between them refer to the regression model considered in the leaf nodes.

Locally weighted linear regression (LWLR), or loess, is a method which fits a regression surface to data by smoothing the dependent variable as a function of the independent variables (Cleveland & Devlin, 1988). The coefficient of smoothness is fitted by computing weighted mean square error and considering a distance function.

Linear model with a minimum length principle (MDL) is based on the rule developed by Rissanen (1978) which considers that regularities in a set of data can be used to compress the data by using fewer symbols, from a finite alphabet, than needed to explain the data faithfully.

Reduced linear model (RLM) is a linear model computed by the least square method and, after that, simplified using an exhaustive search to remove those variables that contribute little to the model in order to minimize the estimated error, as in regression tree models like the so-called M5 in Waikato Environment for Knowledge Analysis (Weka) software (Quinlan, 1992).

K nearest neighbour (KNN) is a lazy learning method based on the KNN algorithm (Fix & Hodges, 1951), which includes two phases. First, the KNNs are

searched using the complete dataset and considering an established distance. Then, the mean of the k-most similar instances is used for the prediction.

Weighted k nearest neighbours (WKNNs) is a refinement of the KNN algorithm, which gives greater weight to the closer neighbours according to their distance to the observations. In this sense, the weighted mean of the KNNs is used for the prediction.

### *Model validation and comparison*

The algorithms were computed after applying a pre-processing phase which is based on the normalization of the data in values ranging from 0 to 1. The scaling of the data avoids weights saturation (Görgens et al., 2015) and may improve the performance of the models. In order to avoid overfitting of the model by selecting the smallest possible number of predictor variables, a forward stepwise regression was used.

Considering that fieldwork is a time-consuming task and increases the costs of the study, it was not possible to measure a high number of field plots. In this sense, the 46 measured plots, although may seem a low number, are enough to meet the statistical requirements. Accordingly, the models were validated using a leave-one-out cross-validation (LOOCV) technique (Maltamo et al., 2014), in order to do not further reduce the sample (Andersen, McGaughey, & Reutebuch, 2005). For those methods with randomness, LOOCV was executed 100 times so as to increase the robustness in the results (García-Gutiérrez et al., 2015).

The comparison between models was performed by analysing the results in terms of root mean square error (RMSE) and bias. Furthermore, Friedman non-parametric test was applied in order to compare the performance of the different models (Friedman, 1940). The test was carried out separately for each RMSE measure of each fold of the cross-validation (Stojanova, Panče, Valentin, Andrej, & Sašo, 2010). In those cases where the null hypothesis of Friedman test was rejected, which implies that the models were not equivalent, the Nemenyi (1963) *post-hoc* test was used to determine whether the differences between the models were statistically significant, with a significance level of 0.05.

### *Estimates of biomass losses and conversion to CO<sub>2</sub> emissions into the atmosphere*

The estimation of biomass losses was performed in three phases: (i) wildfire severity estimation, (ii) pre-fire Aleppo pine forest location mapping and (iii) selection of burning efficiency factors related to pre-fire vegetation (De Santis et al., 2010; Oliva & Chuvieco, 2011).

First, wildfire severity was estimated according to FIREMON methodology (Key & Benson, 2006). NBR was calculated for pre-fire and post-fire images

(Equation (2)). Then, the  $\Delta\text{NBR}$  was estimated by the subtraction of NBR post-fire from NBR pre-fire (Equation (3)). Subsequently, the burned area was delimited using this index in a GIS environment.

$$\text{NBR} = (\rho_{\text{NIR}} - \rho_{\text{SWIR}}) / (\rho_{\text{NIR}} + \rho_{\text{SWIR}}), \quad (2)$$

$$\Delta\text{NBR} = \text{NBR}_{\text{prefire}} - \text{NBR}_{\text{postfire}}, \quad (3)$$

where  $\rho_{\text{NIR}}$  (near infrared) and  $\rho_{\text{SWIR}}$  (short-wave infrared) refer to bands 5 and 7 Landsat 8 OLI reflectance, respectively.

In a second phase, the location of pre-fire Aleppo pine woodland was delimited using the Spanish National Forest Map (MAGRAMA, 2016b), and the canopy height model derived from the ALS data captured previous to fire. In order to improve the accuracy in forest location, stands less than 2 m high were excluded from the analysis.

Third, a thorough bibliographic search of burning efficiency values for Mediterranean conifer forests was conducted (Deeming, Burgan, & Cohen, 1977; Miranda et al., 2005). However, few approaches were suitable to our Mediterranean conifer forests and most of them assume that forest biomass is consumed completely (French et al., 2004). The goal of this study was to obtain spatialized coefficients related to different burn severity levels. Thus, following De Santis et al. (2010) methodology, three burning efficiency factors, related to pre-fire vegetation, were applied considering low, moderate and high severity levels. The four generic severity ranges proposed by Key and Benson (2006) (Table 1) were reclassified in three ranges so as to match with the three burning efficiency factors. In this regard, the low burning efficiency value denotes low consumption of the leaves and very low woody branches consumption; the moderate burning efficiency value indicates intermediate consumption of the leaves and moderate consumption of small branches; and the high burning efficiency value suggests a complete consumption of the leaves and high loss of small branches and twigs.

The conversion of biomass losses to  $\text{CO}_2$  emissions requires the estimation of the biomass carbon content and the application of an emission factor. The carbon content was computed using a conversion factor of 0.499 set by Montero et al. (2005) for Aleppo pine. With respect to the emission factors, several conversion factors have been proposed so as

to estimate different GHG emissions to the atmosphere. In this sense, the account of  $\text{CO}_2$  emissions to the atmosphere generated from forest biomass combustion was obtained according to Trozzi, Vaccaro, & Piscitello (2002) equation, which includes the same parameters as the equations established by IPCC (2006), Levine (2003) and Seiler and Crutzen (1980) (Equation (4)).

$$\text{CO}_2 = \varepsilon * \delta * C, \quad (4)$$

where  $\varepsilon$  is the fraction of total carbon emitted as  $\text{CO}_2$  (0.888);  $\delta$  is the factor of conversion from the emissions in ton of carbon to the emissions in ton of  $\text{CO}_2$  (44/12); and  $C$  is the carbon content.

## Results

A summary of the field plot characteristics is presented in Table 2. Inventoried trees present a variety of diameters, from 14.2 to 28.1 cm, and diverse heights, ranging from 7.2 to 17.2 m. This accounted for the variability of biomass in the study area.

All models included two ALS-derived variables: the percentage of first returns above 2 m ( $t$ -test: 8.3) and the 40th percentile of the return heights ( $t$ -test: 4.4), both variables showing a direct and coherent relation with AGB. The higher value of the variables, the higher biomass amount.

The regression models to estimate the AGB are summarized in Table 3. The MLR and the SVM with radial kernel (cost = 570 and gamma = 0.03) models presented the lowest RMSE with 6.1 and 7.3 ton/ha, respectively. LWLR regression tree performs slightly better than SVM with linear kernel (cost = 210 and gamma = 0.01), with RMSE of 8.3 and 8.5 ton/ha, respectively. Furthermore, the remaining regression trees as well as RF machine learning (ntrees = 500 and mtry = 1) show a lower accuracy. It should be added that most of the models present values of bias close to zero, except from SVM linear kernel, WKNN and KNN models that show a slight overestimation with values close to 1.

The performance comparison between the models, by using Friedman test, indicates that the models are not equivalent with a  $p$ -value of 0.000. However, the application of *post-hoc* Nemenyi test shows that only WKNN ( $p$ -value = 0.0) and KNN ( $p$ -value = 0.0) models presents differences statistically significant, with 95% of probability.

**Table 1.** Severity levels,  $\Delta\text{NBR}$  generic ranges defined by Key and Benson (2006), and burning efficiency factors used to estimate biomass losses following De Santis et al. (2010).

Severity level	$\Delta\text{NBR}$ range	Burning efficiency factors
Unburned	-100 to +99	0.00
Low severity	+100 to +269	0.25
Moderate-low severity	+270 to +439	0.42
Moderate-high severity	+440 to +659	
High severity	+660 to +1300	0.57

**Table 2.** Summary of the field plots characteristics ( $n = 46$ ; inventoried trees = 1870).

	Min.	Max.	Range	Mean	SD
Slope (degrees)	2.5	29.8	27.2	12.8	6.4
Tree height (m)	7.2	17.2	10.0	9.6	1.8
Tree density (tree/ha)	282.9	1202.5	919.6	575.8	237.8
dbh (cm)	14.2	28.1	13.9	18.7	2.8
AGB (ton/ha)	24.4	130.9	106.4	55.4	20.4

**Table 3.** Summary of the models and the validation results for the estimated variable in terms of RMSE, relative RMSE (% RMSE) and bias.

Predictive model	Fitting phase			Cross-validation			$R^2$
	RMSE	%RMSE	Bias	RMSE	%RMSE	Bias	
MLR	6.2	11.1	0.1	6.2	11.1	0.0	0.8
SVM radial kernel	6.0	10.8	0.3	7.4	13.3	0.6	0.8
SVM linear kernel	8.0	14.3	1.1	8.5	15.4	1.4	0.8
RF	4.7	8.5	0.2	9.3	16.7	0.5	0.8
LWLR	5.8	10.5	-0.2	8.3	15.0	0.2	0.8
MDL	6.1	11.0	-0.4	8.8	15.9	0.6	0.8
RLM	7.3	13.2	-0.1	9.3	16.7	-0.1	0.8
WKNN	10.7	19.3	0.9	12.7	23.0	1.1	0.6
KNN	11.4	20.6	1.2	12.9	23.2	1.1	0.6

Figure 3 shows the scatter plots of the observed AGB against the model predictions for the different regression models. MLR and SVM with radial kernel show consistent results and high coefficient of determination (0.88 and 0.87, respectively). SVM with linear kernel and LWLR also present good coefficient of determination (0.84 and 0.83, respectively). Lower coefficients of determination as well as less stable results are evidenced in the scatter-plots for the remaining regression trees, especially WKNN and KNN.

The implementation of the MLR model (Equation (5)) in a GIS allowed estimating pre-fire AGB, which accounts 546,486.7 ton.

$$\text{PrefireAGB} = 1.007 * 10689.32$$

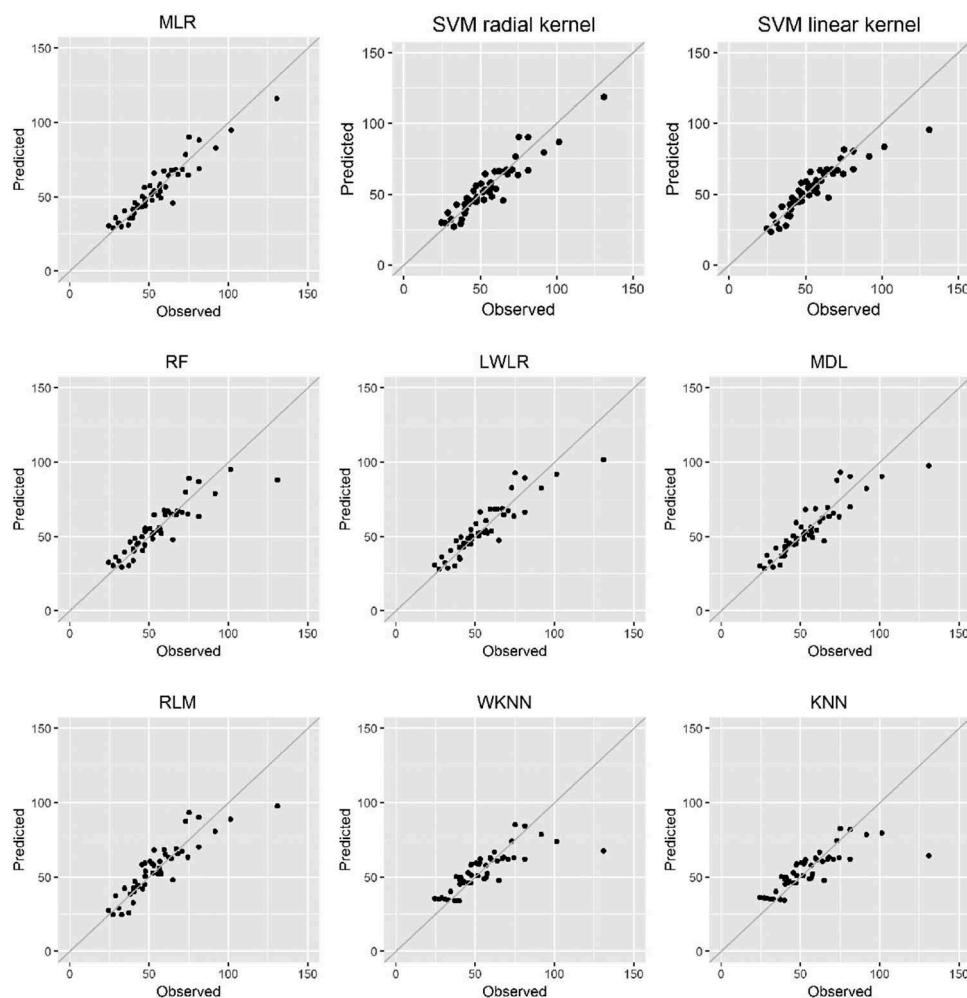
$$*e^{(0.0158 * \text{percentage of first returns above 2m})}$$

$$*e^{(0.0713 * 40\text{th percentile of height})}. \quad (5)$$

The Aleppo pine forest was burned with a high severity in most part of the area, as can be observed in Figure 4 (a). The biomass losses range from 4 ton/ha to more than 12 ton/ha (Figure 4(b)). As can be observed in Table 4, high severity areas represent ~60% of Aleppo pine burned area, accounting ~70% of biomass losses. Finally, the combustion of Aleppo pine forest in Luna wildfire emitted 426,754.8 tons of CO<sub>2</sub> into the atmosphere.

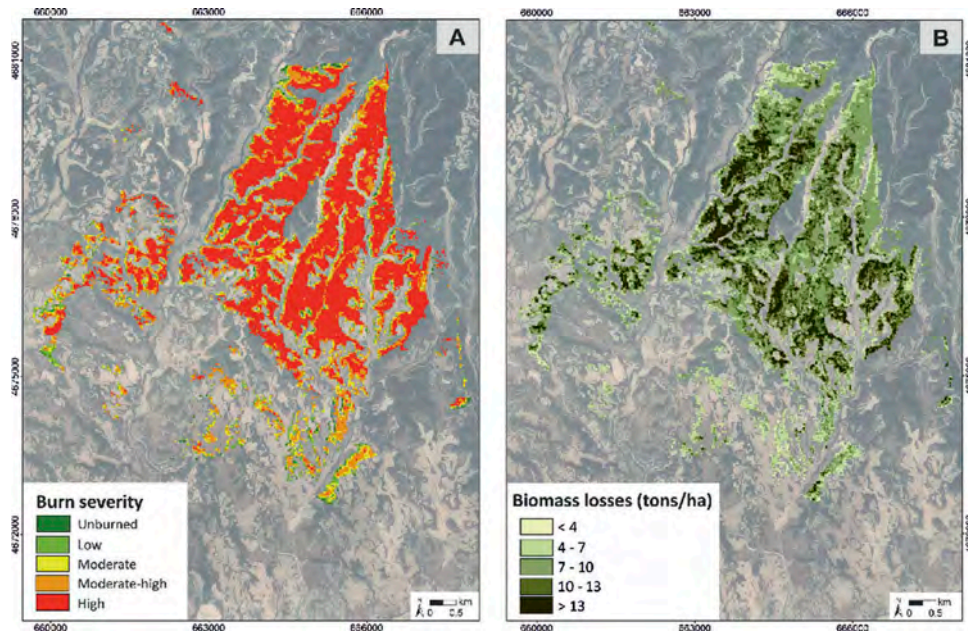
## Discussion

The use of GHG emissions equations is widely accepted for accounting forest biomass combustion by a wildfire (IPCC, 2006; Levine, 2003; Seiler &



**Figure 3.** Scatterplot of predicted values vs. observed values for the AGB using different regression methods.





**Figure 4.** Burn severity estimated in Aleppo pine forest burned in Luna wildfire using  $\Delta$ NBR index (a). Biomass losses estimation applying combustion factors (b). High spatial resolution orthophotography (PNOA-2012) (IGN, 2017a) is used as backdrop.

**Table 4.** Summary of results obtained for the burned area concerning to Aleppo pine forest affected by fire, pre-fire AGB, biomass losses, carbon content and CO<sub>2</sub> emissions.

Burn severity	Aleppo pine area (ha)	Pre-fire AGB (ton)	Biomass losses (ton)	Carbon content (ton)	CO <sub>2</sub> emissions (ton)
Unburned	26.8	20,744.3	0.0	0.0	0.0
Low	117.0	36,022.2	9005.5	4493.7	14,631.7
Medium	594.5	169,908.7	71,361.6	35,609.4	115,944.4
High	1034.2	319,811.4	182,292.5	90,963.9	296,178.6
Total	1772.6	546,486.7	262,659.7	131,067.2	426,754.8

Crutzen, 1980; Trozzi et al., 2002). Moreover, several conversion factors as well as emission factors, from global to regional scales, have been proposed to accurately estimate emissions to the atmosphere. However, one of the main uncertainties related to the use of these equations is the account of pre-fire biomass and biomass losses. In this sense, LiDAR technology has been proposed as the best technique to accurately estimate forest structural parameters, such as biomass, and artificial intelligence methods have been applied and compared to generate this variable. Nevertheless, little research has focused on comparing the performance of several regression models, including machine learning algorithms and regression trees, regarding traditional MLR models to estimate forest parameters.

This study proposes the use of low point density ALS data to improve the estimation of pre-fire AGB by comparing a set of state-of-the-art methods and traditional linear regression methods in a Mediterranean Aleppo pine forest, considering that biomass estimation is the key information to compute burning emissions.

The results demonstrate that low-density ALS data can be used to accurately estimate pre-fire biomass.

The two ALS-derived variables included in the models were analogous to those proposed by other authors (i.e. Guerra-Hernández et al., 2016b; Montagnoli et al., 2015). These variables concern the canopy cover distribution and the vertical distribution of the point cloud. The comparison between regression models shows that the MLR model has the lowest RMSE (6.1 ton/ha) and bias (0.0), matching with the values obtained by other authors (Gonzalez-Ferreiro et al., 2012; Montealegre, Lamelas, de la Riva, García-Martín, & Escribano, 2015c). Consequently, MLR slightly outperforms other nonparametric methods supporting Görgens et al. (2015) findings. However, no statistically significant differences between MLR and SVM with kernel radial were found. This suggests that the results partly agree with Gleason and Im (2012), Gagliasso et al. (2014) and García-Gutiérrez et al. (2015), who obtained lower estimation errors with nonparametric techniques, although the later authors included a relatively high number of independent variables in the models. In this sense, the use of a large number of variables tends to increase the performance of the models. Nevertheless, the selection of a reduced number of biologically representative variables, especially when computing non-linear regression models, might generate more understandable models for forest management purposes. This also might explain that MLR models outperform other nonparametric models, considering the number of variables included in Görgens et al. (2015) models. It is to notice that, as in the case of several previous studies (García, Riaño, Chuvieco, & Danson, 2010; Næsset & Gobakken, 2008; Næsset & Økland, 2002), it has been necessary to perform a logarithmic



transformation of the dependent variable in order to meet the assumptions of the linear regression model.

The three-phase approach performed is considered a suitable option for estimating biomass losses, which account for 262,659.7 ton. This methodology solves the lack of post-fire forest structure information derived from ALS data and constitutes an alternative to field estimation of burning efficiency, which is laborious, expensive and requires a detailed knowledge of the pre-fire scenario (De Santis et al., 2010). The use of conversion and emission factors for the Mediterranean basin, included in Trozzi et al. (2002) equation, enables to accurately estimate CO<sub>2</sub> emission at a regional scale, summing up a total of 426,754.8 ton.

When comparing nonparametric methods and linear regression models, discrepancies appear. Our findings show that not always the use of nonparametric methods ensures the best biomass estimations. In this sense, the generation of several models such as MLR, SVM with radial kernel, LWLR or SVM with linear kernel might be taken into account. Furthermore, the use of variable selection processes should be considered, in order to determine a limited number of variables which are biologically representative. Consequently, the use of new artificial intelligence models and nonparametric models, which have several advantages for example no need of normality, should be used within the forestry and environmental purposes of obtaining robust and understandable models. The improved estimation of CO<sub>2</sub> emissions from biomass burning, by including ALS data as relevant information for computing biomass, is considered to better understand the interactions between fire disturbances and the emissions to the atmosphere. Nevertheless, it is to notice that our model does not consider the emissions generated by combustion of litter, shrubs and young trees, implying an underestimation of the total CO<sub>2</sub> emissions during wildfire. It was not possible to estimate these fractions of biomass. In fact, the few studies developed to estimate shrub biomass were performed using high-density ALS data or full waveform LiDAR (Estornell, Ruiz, Velázquez-Martí, & Hermosilla, 2012; E. Greaves et al., 2016; Swatantran, Dubayah, Roberts, Hofton, & Bryan Blair, 2011). Moreover, the majority of them were developed in areas without tree cover due to the difficulty of the pulse to penetrate the canopy (Vosselman & Maas, 2010). In this sense, further research is needed on the estimation of shrub biomass using low point density ALS data in order to improve GHG emissions to the atmosphere.

Considering that the findings are site-dependent, the comparison of different biologically representative models for biomass estimation at regional scales, as well as alternative variable selection processes, may be considered. In this sense, the use of multi-

temporal ALS or multi-temporal series of remote sensing data might be useful to better understand the effect of wildfire disturbances to the atmosphere. It would also be desirable to focus on the account of CO<sub>2</sub> emissions or other GHG gasses generated by combustion of other Mediterranean species.

## Conclusions

This study verifies the usefulness of low-density ALS data to accurately estimate pre-fire AGB in a mono-specific Aleppo pine forest, which is relevant information to compute biomass losses caused by fire and CO<sub>2</sub> emissions. The comparison of the effectiveness of a set of state-of-the-art artificial intelligence methods and traditional linear regression methods is especially interesting to improve forest parameters modelling. The best model for pre-fire AGB estimation was the MLR, which included two ALS variables: the percentage of first returns above 2 m and 40th percentile of height, presenting an RMSE of 6.1 ton/ha and a bias of 0.0. No statistically significant differences between MLR and SVM with kernel radial, which is the second best model, were found. The three-phase approach used for biomass losses estimation and the subsequent transformation into CO<sub>2</sub> enable to quantify the emissions to the atmosphere by the combustion of Mediterranean Aleppo pine forest in Luna wildfire, summing up a total of 426,754.8 ton.

## Acknowledgements

This work was supported by the Spanish Ministry of Education Culture and Sports under Grant [FPU Grant BOE, 27/12/2014]. The ALS data were provided by the Spanish National Geographic Information Centre (CNIG). The authors are grateful to the material resources provided by the Centro Universitario de la Defensa (CUD) to develop the fieldwork.




## Disclosure statement

No potential conflict of interest was reported by the authors.

## Funding

This work was supported by the Spanish Ministry of Education Culture and Sports under Grant [FPU Grant BOE, 27/12/2014].

## ORCID

Darío Domingo  <http://orcid.org/0000-0002-8362-7559>  
 María Teresa Lamelas-Gracia  <http://orcid.org/0000-0002-8954-7517>  
 Antonio Luis Montealegre-Gracia  <http://orcid.org/0000-0001-6288-2780>

Juan de la Riva-Fernández  <http://orcid.org/0000-0003-2615-270X>

## References

- Akagi, S.K., Yokelson, R.J., Burling, I.R., Meinardi, S., Simpson, I., Blake, D.R., ... Weise, D.R. (2013). Measurements of reactive trace gases and variable O<sub>3</sub> formation rates in some South Carolina biomass burning plumes. *Atmospheric Chemistry and Physics*, 13(3), 1141–1165. doi:10.5194/acp-13-1141-2013
- Andersen, H.E., McGaughy, R.J., & Reutebuch, S.E. (2005). Estimating forest canopy fuel parameters using LIDAR data. *Remote Sensing of Environment*, 94(4), 441–449. doi:10.1016/j.rse.2004.10.013
- Andreae, M.O., Browell, E.V., Garstang, M., Gregory, G.L., Harriss, R.C., Hill, G.F., & Wofsy, S.C. (1988). Biomass-burning emissions and associated haze layers over Amazonia. *Journal of Geophysical Research*, 93(D2), 1509–1527. doi:10.1029/JD093iD02p01509
- Breiman, L. (2001). Random forest. *Machine Learning*, 45, 5–32. doi:10.1023/A:1010933404324
- Call, P.T., & Albini, F.A. (1997). Aerial and surface fuel consumption in crown fires. *International Journal of Wildland Fire*, 7(3), 259–264. doi:10.1071/WF9970259
- Chuvieco, E. (2009). Global impacts of fire. In E., Chuvieco Ed., *Earth observation of wildland fires in Mediterranean ecosystems* (pp. 1–10). Berlin Heidelberg: Springer. doi:10.1007/978-3-642-01754-4
- Cleveland, W.S., & Devlin, S.J. (1988). Locally weighted regression: An approach to regression analysis by local fitting. *Journal of the American Statistical Association*, 83 (403), 596–610. doi:10.1080/01621459.1988.10478639
- De Santis, A., Asner, G.P., Vaughan, P.J., & Knapp, D.E. (2010). Mapping burn severity and burning efficiency in California using simulation models and Landsat imagery. *Remote Sensing of Environment*, 114(7), 1535–1545. doi:10.1016/j.rse.2010.02.008
- Deeming, J., Burgan, R., & Cohen, J. (1977). General Technical Report INT-39, *The National Fire-Danger Rating System — 1978*. U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT, pp. 63.
- Estornell, J., Ruiz, L.A., Velázquez-Martí, B., & Hermosilla, T. (2012). Estimation of biomass and volumen of shrub vegetation using LiDAR and spectral data in a Mediterranean environment. *Biomass and Bioenergy*, 46, 710–721. doi:10.1016/j.biombioe.2012.06.023
- Evans, J.S., & Hudak, A.T. (2007). A multiscale curvature algorithm for classifying discrete return LiDAR in forested environments. *IEEE Transactions on Geoscience and Remote Sensing*, 45(4), 1029–1038. doi:10.1109/TGRS.2006.890412
- Evans, J.S., Hudak, A.T., Faux, R., & Smith, A.M.S. (2009). Discrete return LiDAR in natural resources: Recommendations for project planning, data processing, and deliverables. *Remote Sensing*, 1(4), 776–794. doi:10.3390/rs1040776
- Fix, E., & Hodges, J. (1951). Texas, Report No. 4, Project No. 21-49-004, *Discriminatory analysis, nonparametric discrimination: Consistency properties*. USAF School of Aviation Medicine, Randolph Field
- French, N.H.F., Goovaerts, P., & Kasischke, E.S. (2004). Uncertainty in estimating carbon emissions from boreal forest fires. *Journal of Geophysical Research*, 109(D14), D14S08. doi:10.1029/2003JD003635
- Friedman, M. (1940). A comparison of alternative tests of significance for the problem rankings. *The Annals of Mathematical Statistics*, 11(1), 86–92. doi:10.1214/aoms/1177731944
- Gagliasso, D., Hummel, S., & Temesgen, H. (2014). A comparison of selected parametric and non-parametric imputation methods for estimating forest biomass and basal area. *Open Journal of Forestry*, 4(1), 42–48. doi:10.4236/ojfor.2014.41008
- García, D., Godino, M., & Mauro, F. (2012). LIDAR: Aplicación práctica al inventario forestal. *Editorial Académica Española*, 10, 3659009555.
- García, M., Riaño, D., Chuvieco, E., & Danson, F.M. (2010). Estimating biomass carbon stocks for a Mediterranean forest in central Spain using LiDAR height and intensity data. *Remote Sensing of Environment*, 114(4), 816830. doi:10.1016/j.rse.2009.11.021
- García-Gutiérrez, J., Martínez-Álvarez, F., Troncoso, A., & Riquelme, J.C. (2015). A comparison of machine learning regression techniques for LiDAR-derived estimation of forest variables. *Neurocomputing*, 167, 24–31. doi:10.1016/j.neucom.2014.09.091
- Gleason, C.J., & Im, J. (2012). Forest biomass estimation from airborne LiDAR data using machine learning approaches. *Remote Sensing of Environment*, 125, 80–91. doi:10.1016/j.rse.2012.07.006
- Gonzalez-Ferreiro, E., Dieguez-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. doi:10.1093/forestry/cps002
- González-Ferreiro, E., Miranda, D., Barreiro-Fernandez, L., Bujan, S., García-Gutiérrez, J., & Dieguez-Aranda, U. (2013). Modelling stand biomass fractions in Galician *Eucalyptus globulus* plantations by use of different LiDAR pulse densities. *Forest Systems*, 22(3), 510–525. doi:10.5424/fs/2013223-03878
- Görgens, E.B., Montagni, A., & Rodriguez, L.C.E. (2015). A performance comparison of machine learning methods to estimate the fast-growing forest plantation yield based on laser scanning metrics. *Computers and Electronics in Agriculture*, 116, 221–227. doi:10.1016/j.compag.2015.07.004
- Greaves, H., Vierling, L., Eitel, J., Boelman, N., Magney, T., Prager, C., & Griffin, K. (2016). High-resolution mapping of aboveground shrub biomass in Arctic tundra using airborne lidar and imagery. *Remote Sensing of Environment*, 184, 361–373. doi:10.1016/j.rse.2016.07.026
- Guerra-Hernández, J., Görgens, E.B., García-Gutiérrez, J., Rodriguez, L.C.E., Tomé, M., & González-Ferreiro, E. (2016b). Comparison of ALS based models for estimating aboveground biomass in three types of Mediterranean forest. *European Journal of Remote Sensing*, 49, 185–204. doi:10.5721/EuJRS201649
- Guerra-Hernández, J., Tomé, M., & González-Ferreiro, E. (2016a). Using low density LiDAR data to map Mediterranean forest characteristics by means of an area-based approach and height threshold analysis. *Revista De Teledetección*, 46, 103–117. doi:10.4995/raet.2016.3980
- 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), 189–209. doi:10.1016/j.foreco.2004.12.001

- Hayashi, R., Weiskittel, A., & Sader, S. (2014). Assessing the feasibility of low-density LiDAR for stand inventory attribute predictions in complex and managed forests of Northern Maine, USA. *Forests*, 5(2), 363–383. doi:10.3390/f5020363
- Holopainen, M., Vastaranta, M., Rasinmäki, J., Kalliovirta, J., Mäkinen, A., Haapanen, R., ... Hyypä, H. (2010). Estimation of timber assortments using low-density ALS data. In W. Wagner & B. Székely (Eds.), *ISPRS TC VII Symposium – 100 Years ISPRS: Vol. XXXVIII, Part 7A* (pp. 59–64). Vienna, Austria: IAPRS.
- IGN. (2017a). *PNOA Imagen*. Ministerio de Fomento, Instituto Geográfico Nacional, Madrid. Retrieved January 10, 2017, <http://pnoa.ign.es/presentacion-y-objetivo>.
- IGN. (2017b). *PNOA LiDAR*. Ministerio de Fomento, Instituto Geográfico Nacional, Madrid. Retrieved January 10, 2017, <http://pnoa.ign.es/presentacion>.
- IPCC. (2006). 2006 IPCC guidelines for national greenhouse gas inventories. Volume 4: Agriculture, forestry and other land use. In H.S. Eggleston, L. Buendia, K. Miwa, T. Ngara, & K. Tanabe Eds, *Prepared by the national greenhouse gas inventories programme*. Japan: IGES. ISBN 4-88788-032-4
- Key, C.H., & Benson, N. (2006). Landscape assessment (LA). Sampling and analysis methods. In L.J. Lutes, D. C. Keane, R.E. Caratti, J.F. Key, C.H. Benson, & N.C. Gangi (Eds.), *FIREMON: Fire effects monitoring and inventory system. Integration of standardized field data collection techniques and sampling design with remote sensing to assess fire effects* (pp. LA1–LA51). Fort Collins, CO: Rocky Mountain Research Station, U.S. Department of Agriculture, Forest Service.
- Lal, R. (2008). Sequestration of atmospheric CO<sub>2</sub> in global carbon pools. *Energy and Environmental Science*, 1, 86–100. doi:10.1039/B809492F
- Latifi, H., Nothdurft, A., & Koch, B. (2010). Non-parametric prediction and mapping of standing timber volume and biomass in a temperate forest: Application of multiple optical/LiDAR-derived predictors. *Forestry*, 83(4), 395–407. doi:10.1093/forestry/cpq022
- Le Toan, T., Beaudoin, A., Riou, J., & Guyon, D. (1992). Relating forest biomass to SAR data. *IEEE Transactions on Geoscience and Remote Sensing*, 30(2), 403–411. doi:10.1109/36.134089
- Leboeuf, A., Fournier, R.A., Luther, J.E., Beaudoin, A., & Guindon, L. (2012). Forest attribute estimation of north-eastern Canadian forests using QuickBird imagery and a shadow fraction method. *Forest Ecology and Management*, 266, 66–74. doi:10.1016/j.foreco.2011.11.008
- Lefsky, M.A., Cohen, W.B., Parker, G.G., & Harding, D.J. (2002). Lidar remote sensing for ecosystem studies. *BioScience*, 52(1), 19–30; (2002)052[0019: LRSFES]2.0.CO;2. doi:10.1641/0006-3568
- Levine, J.S. (2003). Biomass burning: The cycling of gases and particulates from the biosphere to the atmosphere. *Treatise on Geochemistry*, 4, 143–158. doi:10.1016/B0-08-043751-6/04143-8
- Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. *R News*, 2(3), 18–22.
- Lim, K., Treitz, P., Wulder, M., St-Onge, B., & Flood, M. (2003). LiDAR remote sensing of forest structure. *Progress in Physical Geography*, 27(1), 88–106. doi:10.1191/0309133303pp360ra
- MAGRAMA (2016a). *Estadísticas de incendios forestales*. Ministerio de Agricultura y Peces, Alimentación y Medio Ambiente, Madrid. Retrieved April 10, 2016, from [http://www.magrama.gob.es/es/desarrollo-rural/estadisticas/Incendios\\_default.aspx](http://www.magrama.gob.es/es/desarrollo-rural/estadisticas/Incendios_default.aspx)
- MAGRAMA (2016b). *Mapa Forestal de España 1:50.000 (MFE50)*. Ministerio de Agricultura y Peces, Alimentación y Medio Ambiente, Madrid. Retrieved May 4, 2016, from <http://www.magrama.gob.es/es/biodiversidad/servicios/banco-datos-naturaleza/informacion-disponible/mfe50.aspx>
- Maltamo, M., Næsset, E., & Vauhkonen, J. (2014). *Forestry applications of airborne laser scanning: Concepts and case studies*. Netherlands: Springer. doi:10.1007/978-94-017-8663-8
- McGaughey, R.J. (2008). *FUSION/LDV: Software for LIDAR data analysis and visualization*. USA: USDA Forest Service, Pacific Northwest Research Station.
- Means, J., Acker, S., Harding, D., Blair, J., Lefsky, M., Cohen, W., & McKee, W. (1999). Use of large-footprint scanning airborne lidar to estimate forest stand characteristics in the western Cascades of Oregon. *Remote Sensing of Environment*, 67, 298–308. doi:10.1016/S0034-4257(98)00091-1
- Mehtätalo, L., Virolainen, A., Tuomela, J., & Packalen, P. (2015). Estimating tree height distribution using low-density ALS data with and without training data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 8(4), 1432–1441. doi:10.1109/JSTARS.2015.2418675
- Mieville, A., Granier, C., Lioussé, C., Guillaume, B., Mouillot, F., Lamarque, J.-F., & Pétron, G. (2010). Emissions of gases and particles from biomass burning during the 20th century using satellite data and an historical reconstruction. *Atmospheric Environment*, 44(11), 1469–1477. doi:10.1016/j.atmosenv.2010.01.011
- Miranda, A.I., Borrego, C., Sousa, M., Valente, J., Barbosa, P., & Carvalho, A. (2005). *Model of forest fire emissions to the atmosphere*. Aveiro, Portugal: Department of Environment and Planning, University of Aveiro AMB-QA-07/2005, Deliverable D252 of SPREAD Project (EVG1-CT-2001-00043).
- Mitsopoulos, I.D., & Dimitrakopoulos, A.P. (2007). Allometric equations for crown fuel biomass of Aleppo pine (*Pinus halepensis* Mill.) in Greece. *International Journal of Wildland Fire*, 16(5), 642–647. doi:10.1071/WF06038
- Montagnoli, A., Fusco, S., Terzagui, M., Kirschbaum, A., Pflugmacher, D., Cohen, W.B., ... Chiatante, D. (2015). Estimating forest aboveground biomass by low density lidar data in mixed broad-leaved forests in the Italian pre-alps. *Forest Ecosystems*, 2–10. doi:10.1186/s40663-015-0035-6
- Montealegre, A.L., Lamelas, M.T., & de la Riva, J. (2015a). A comparison of open-source LiDAR filtering algorithms in a Mediterranean forest environment. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 8(8), 4072–4085. doi:10.1109/JSTARS.2015.2436974
- Montealegre, A.L., Lamelas, M.T., & de la Riva, J. (2015b). Interpolation routines assessment in ALS-derived digital elevation models for forestry applications. *Remote Sensing*, 7, 8631–8654. doi:10.3390/rs70708631
- Montealegre, A.L., Lamelas, M.T., de la Riva, J., García-Martín, A., & Escribano, F. (2015c). Assessment of biomass and carbon content in a Mediterranean Aleppo pine forest using ALS data. In *Proceedings of 1st International Electronic Conference on Remote Sensing*. Basel, Switzerland: MDPI, 22 June - 5 July 2015, Vol. 1, d004. Sciforum Electronic Conference Series.



- Montealegre, A.L., Lamelas, M.T., de la Riva, J., García-Martín, A., & Escribano, F. (2016). Use of low point density ALS data to estimate stand-level structural variables in Mediterranean Aleppo pine forest. *Forestry*, 89(4), 373–382. doi:10.1093/forestry/cpw008
- Montero, G., Ruiz-Peinado, R., & Muñoz, M. (2005). *Producción de biomasa y fijación de CO<sub>2</sub> por los bosques españoles* (p. 270). Madrid: Instituto Nacional de Investigación y Técnica Agraria y Alimentaria (INIA). ISBN: 8474985129
- Moriondo, M., Good, P., Durao, R., Bindi, M., Giannakopoulos, C., & Corte-Real, J. (2006). Potential impact of climate change on fire risk in the Mediterranean area. *Climate Research*, 31(1), 85–95. doi:10.3354/cr031085
- Mountrakis, G., Jungo, I., & Caesar, O. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(3), 247–259. doi:10.1016/j.isprsjprs.2010.11.001
- 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. doi:10.1016/S0034-4257(01)00290-5
- Næsset, E., & Gobakken, T. (2008). Estimation of above- and below-ground biomass across regions of the boreal forest zone using airborne laser. *Remote Sensing of Environment*, 112(6), 3079–3090. doi:10.1016/j.rse.2008.03.004
- 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. doi:10.1016/S0034-4257(01)00243-7
- Narayan, C., Fernandes, P.M., Van Brusselen, J., & Schuck, A. (2007). Potential for CO<sub>2</sub> emissions mitigation in Europe through prescribed burning in the context of the Kyoto Protocol. *Forest Ecology and Management*, 251(3), 164–173. doi:10.1016/j.foreco.2007.06.042
- Nemenyi, P. (1963). *Distribution-free multiple comparisons*. Princeton University, Ph.D. thesis, Princeton, NY, USA.
- Nilsson, M. (1996). Estimation of tree heights and stand volume using an airborne lidar system. *Remote Sensing of Environment*, 56(1), 1–7. doi:10.1016/0034-4257(95)00224-3
- Oliva, P., & Chuvieco, E. (2011). Towards a dynamic burning efficiency factor. In J. San-Miguel, I. Gitas, A. Camia, & S. Oliveira (Eds.), *Advances in remote sensing and GIS applications in Forest Fire Management: From local to global assessment* (pp. 51–56). Luxembourg: Publications Office of the European Union.
- Oliveira, S., Oehler, F., San-Miguel-Ayanz, J., Camia, A., & Pereira, J.M.C. (2012). Modeling spatial patterns of fire occurrence in Mediterranean Europe using multiple regression and random forest. *Forest Ecology and Management*, 275, 117–129. doi:10.1016/j.foreco.2012.03.003
- Pan, Y., Birdsey, R.A., Fang, J., Houghton, R., Kauppi, P.E., Kurz, W.A., ... Hayes, D. (2011). A large and persistent carbon sink in the world's forests. *Science*, 333(6045), 988–993. doi:10.1126/science.1201609
- Pausas, J.G., Llovet, J., Rodrigo, A., & Vallejo, R. (2008). Are wildfires a disaster in the Mediterranean basin? – A review. *International Journal of Wildland Fire*, 17(6), 713–723. doi:10.1071/WF07151
- Pétron, G., Granier, C., Khattatov, B., Yudin, V., Lamarque, J.-F., Emmons, L., & Edwards, D.P. (2004). Monthly CO surface sources inventory based on the 2000–2001 MOPITT satellite data. *Geophysical Research Letters*, 31, L21107. doi:10.1029/2004GL020560
- Popescu, S.C., Randolph, H.W., & Ross, F.N. (2003). Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. *Canadian Journal of Remote Sensing*, 29(5), 564–577. doi:10.5589/m03-027
- Prasad, V.K., Kant, Y., Gupta, P.K., Sharma, C., Mitra, A., & Badarinath, K.V. (2001). Biomass and combustion characteristics of secondary mixed deciduous forests in Eastern Ghats of India. *Atmospheric Environment*, 35(18), 3085–3095. doi:10.1016/S1352-2310(01)00125-X
- Quinlan, J.R. (1992). Learning with continuous classes. In *Proceedings of the 5th Australian Joint Conference on Artificial Intelligence* (pp. 343–348). Singapore, World Scientific.
- Renslow, M. (2013). *Manual of Airborne Topographic Lidar* (p. 528). Bethesda, MD: 99: The American Society for Photogrammetry and Remote Sensing. ISBN: 978-1570830976
- Rissanen, J. (1978). Modeling by shortest data description. *Automatica*, 14(5), 465–471. doi:10.1016/0005-1098(78)90005-5
- Rodrigues, M., Ibarra, P., Echeverria, M., Perez-Cabello, F., & de la Riva, J. (2014). A method for regional-scale assessment of vegetation recovery time after high-severity wildfires: Case study of Spain. *Progress in Physical Geography*, 38(5), 556–575. doi:10.1177/0309133314542956
- Roy, D.P., Jin, Y., Lewis, P.E., & Justice, C.O. (2005). Prototyping a global algorithm for systematic fire-affected area mapping using MODIS time series data. *Remote Sensing of Environment*, 97(2), 137–162. doi:10.1016/j.rse.2005.04.007
- Sá, A.C.L., Pereira, J.M.C., & Silva, J.M.N. (2005). Estimation of combustion completeness based on fire-induced spectral reflectance changes in a dambo grassland (Western Province, Zambia). *International Journal of Remote Sensing*, 26(19), 4185–4195. doi:10.1080/01431160500113468
- San-Miguel-Ayanz, J., Rodrigues, M., De Oliveira, S.S., Pacheco, C.K., Moreira, F., Duguy, B., & Camia, A. (2012). Land cover change and fire regime in the European Mediterranean region. In F. Moreira, M. Arianoutsou, P. Corona, & J. de las Heras (Eds.), *Post-fire management and restoration of Southern European forests* (pp. 21–43). Netherlands: Springer. doi:10.1007/978-94-007-2208-8\_2
- Scott, J.H., & Reinhardt, E.D. (2001). Assessing crown fire potential by linking models of surface and crown fire behavior. Research Paper RMRS-29. USDA Forest Service, Rocky Mountain Research Station, Fort Collins, Co.
- Sebastián-López, A., Salvador-Civil, R., Gonzalo-Jiménez, J., & SanMiguel-Ayanz, J. (2008). Integration of socio-economic and environmental variables for modelling long-term fire danger in Southern Europe. *European Journal of Forest Research*, 127(2), 149–163. doi:10.1007/s10342-007-0191-5
- Seiler, W., & Crutzen, P.J. (1980). Estimates of gross and net fluxes of carbon between the biosphere and the atmosphere from biomass burning. *Climatic Change*, 2(3), 207–247. doi:10.1007/BF00137988
- Shendryk, I., Margareta, H., Leif, K., & Natascha, K. (2014). Low-density LiDAR and optical imagery for biomass estimation over boreal forest in Sweden. *Forests*, 5(5), 992–1010. doi:10.3390/f5050992

- Singh, K.K., Gang, C., James, B.M., & Ross, K.M. (2015). Effects of LiDAR point density and landscape context on estimates of urban forest biomass. *ISPRS Journal of Photogrammetry and Remote Sensing*, 101, 310–322. doi:10.1016/j.isprsjprs.2014.12.021
- Stojanova, D., Panče, P., Valentin, G., Andrej, K., & Sašo, D. (2010). Estimating vegetation height and canopy cover from remotely sensed data with machine learning. *Ecological Informatics*, 5(4), 256–266. doi:10.1016/j.ecoinf.2010.03.004
- Swatantran, A., Dubayah, R., Roberts, D., Hofton, M., & Bryan Blair, J. (2011). Mapping biomass and stress in the Sierra Nevada using lidar and hyperspectral data fusion. *Remote Sensing of Environment*, 115, 2917–2930. doi:10.1016/j.rse.2010.08.027
- Tanase, M., de la Riva, J., Santoro, M., Pérez-Cabello, F., & Kasischke, E. (2011). Sensitivity of SAR data to post-fire forest regrowth in Mediterranean and boreal forests. *Remote Sensing of Environment*, 115(8), 2075–2085. doi:10.1016/j.rse.2011.04.009
- Trozzi, C., Vaccaro, R., & Piscitello, R. (2002). Emissions estimate from forest fires: Methodology, software and European case studies. In *Proceedings of the 11th International Emission Inventory Conference*. Atlanta, GA.
- USGS. (2016). *USGS Earth explorer*. U.S. Department of the Interior, U.S. Geological Survey. Retrieved April 10, 2016 from <http://earthexplorer.usgs.gov/>
- Van Der Werf, G.R., Randerson, J.T., Giglio, L., Collatz, G. J., Kasibhatla, P.S., & Arellano, A.F. (2006). Interannual variability in global biomass burning emissions from 1997 to 2004. *Atmospheric Chemistry and Physics*, 6 (11), 3423–3441. doi:10.5194/acp-6-3423-2006
- Van Der Werf, G.R., Randerson, J.T., Giglio, L., Collatz, G. J., Mu, M., Kasibhatla, P.S., & Van Leeuwen, T.T. (2010). Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997–2009). *Atmospheric Chemistry and Physics*, 10(23), 11707–11735. doi:10.5194/acp-10-11707-2010
- Van Essen, D.C., Dickson, J., Harwell, J., Hanlon, D., Anderson, C.H., & Drury, H.A. (2001). An integrated software suite for surface-based analyses of cerebral cortex. *Journal of the American Medical Informatics Association : JAMIA*, 8(5), 443–459. doi:10.1136/jamia.2001.0080443
- Vermote, E., Justice, C., Claverie, M., & Franch, B. (2016). Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. *Remote Sensing of Environment*, 185, 46–56. doi:10.1016/j.rse.2016.04.008
- Vosselman, G., & Maas, H.-G. (2010). *Airborne and terrestrial laser scanning*. p. 336. Caithness: Whittles Publishing. ISBN: 978-1904445-87-6.
- Ward, D.E., Hao, W.M., Susott, R.A., Babbitt, R.E., Shea, R. W., Kauffman, J.B., & Justice, C.O. (1996). Effect of fuel composition on combustion efficiency and emission factors for African savanna ecosystems. *Journal of Geophysical Research: Atmospheres*, 101(D19), 23569–23576. doi:10.1029/95JD02595
- Watt, M.S., Meredith, A., Watt, P., Gunn, A., Andersen, H., Reutebuch, S., & Nelson, R. (2013). Use of LiDAR to estimate stand characteristics for thinning operations in young Douglas-fir plantations. *New Zealand Journal of Forestry Science*, 43, 18. doi:10.1186/1179-5395-43-18
- Wiedinmyer, C., Akagi, S.K., Yokelson, R.J., Emmons, L.K., Al-Saadi, J.A., Orlando, J.J., & Soja, A.J. (2011). The Fire INventory from NCAR (FINN): A high resolution global model to estimate the emissions from open burning. *Geoscientific Model Development*, 4(3), 625–641. doi:10.5194/gmd-4-625-2011
- Wiedinmyer, C., & Neff, J.C. (2007). Estimates of CO<sub>2</sub> from fires in the United States: Implications for carbon management. *Carbon Balance and Management*, 2–10. doi:10.1186/1750-0680-2-10



## Comparison of regression models to estimate biomass losses and CO<sub>2</sub> emissions using low-density airborne laser scanning data in a burnt Aleppo pine forest

Darío Domingo, María Teresa Lamelas-Gracia, Antonio Luis Montealegre-Gracia & Juan de la Riva-Fernández

To cite this article: Darío Domingo, María Teresa Lamelas-Gracia, Antonio Luis Montealegre-Gracia & Juan de la Riva-Fernández (2017) Comparison of regression models to estimate biomass losses and CO<sub>2</sub> emissions using low-density airborne laser scanning data in a burnt Aleppo pine forest, European Journal of Remote Sensing, 50:1, 384-396, DOI: [10.1080/22797254.2017.1336067](https://doi.org/10.1080/22797254.2017.1336067)

To link to this article: <https://doi.org/10.1080/22797254.2017.1336067>



© 2017 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 15 Jun 2017.



Submit your article to this journal [↗](#)



Article views: 299



View related articles [↗](#)



View Crossmark data [↗](#)