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Environmental drivers of fire severity in extreme fire events that affect Mediterranean pine forest ecosystems

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ABSTRACT

The increasing occurrence of large and severe fires in Mediterranean forest ecosystems produces major ecological and socio-economic damage. In this study, we aim to identify the main environmental factors driving fire severity in extreme fire events in *Pinus* fire prone ecosystems, providing management recommendations for reducing fire effects. The study case was a megafire (11,891 ha) that occurred in a Mediterranean ecosystem dominated by *Pinus pinaster* Aiton in NW Spain. Fire severity was estimated on the basis of the differenced Normalized Burn Ratio from Landsat 7 ETM +, validated by the field Composite Burn Index. Model predictors included pre-fire vegetation greenness (normalized difference vegetation index and normalized difference water index), pre-fire vegetation structure (canopy cover and vertical complexity estimated from LiDAR), weather conditions (spring cumulative rainfall and mean temperature in August), fire history (fire-free interval) and physical variables (topographic complexity, actual evapotranspiration and water deficit). We applied the Random Forest machine learning algorithm to assess the influence of these environmental factors on fire severity. Models explained 42% of the variance using a parsimonious set of five predictors: NDWI, NDVI, time since the last fire, spring cumulative rainfall, and pre-fire vegetation vertical complexity. The results indicated that fire severity was mostly influenced by pre-fire vegetation greenness. Nevertheless, the effect of pre-fire vegetation greenness was strongly dependent on interactions with the pre-fire vertical structural arrangement of vegetation, fire history and weather conditions (i.e. cumulative rainfall over spring season). Models using only physical variables exhibited a notable association with fire severity. However, results suggested that the control exerted by the physical properties may be partially overcome by the availability and structural characteristics of fuel biomass. Furthermore, our findings highlighted the potential of low-density LiDAR for evaluating fuel structure throughout the coefficient of variation of heights. This study provides relevant keys for decision-making on pre-fire management such as fuel treatment, which help to reduce fire severity.

1. Introduction

Wildfire is a major disturbance in Mediterranean ecosystems all around the world (Gonçalves and Sousa, 2017) and, particularly, in the Mediterranean basin where large areas have burned in recent decades (Oliveira et al., 2012). According to González-De Vega et al. (2016), the size and severity of wildfires are expected to continue increasing in the future, due to a combination of climate change, land use/land cover changes and forest management policies. Large severe fires are difficult to supress (Holden et al., 2009), cause significant socio-economic damage and have major ecological consequences (Pausas et al., 2009), such as soil erosion and changes in dominant vegetation types.

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Mediterranean ecosystems are highly resilient to fire (Lavorel, 1999; Calvo et al., 2008, 2012). However, the increasing frequency of extreme fire events (San-Miguel-Ayanz et al., 2013) might exceed vegetation adaptive thresholds (Williams et al., 2011), altering vegetation recovery capacity (Viana-Soto et al., 2017). Particularly, pine forest is one of the Mediterranean ecosystems most impacted by fire (Dimitrakopoulos et al., 2011). In this fire-prone ecosystem, high fire severity might alter the recovery capacity through increased mortality in the aerial seed bank (Calvo et al., 2008). Additionally, soil properties, which may affect soil seed bank survival, (Vega et al., 2008) and soil susceptibility to erosion might be influenced by high fire severity.

Within this framework, management strategies for preserving plant communities and soils after wildfires require in-depth knowledge of the factors responsible for fire severity. Nevertheless, the understanding of environmental factors controlling fire severity is still limited (Birch et al., 2015), likely due to complex interactions among physical, weather and vegetation variables (Lecina-Diaz et al., 2014). Prior studies have reported strong control of topography over fire severity, since it may influence directly fire behaviour, fuel moisture and water balances; and, indirectly, local climate and vegetation composition and structure (e.g., Fang et al., 2018; Harris and Taylor, 2017; Holden et al., 2009; Kane et al., 2015b). Conversely, other studies, such as those by Collins et al. (2007) and Liu and Wimberly (2015), suggest that the influence of topography on fire severity might be overwhelmed by other environmental factors like weather (Dillon et al., 2011).

Weather conditions cannot be neglected when assessing factors explaining fire severity (Storey et al., 2016). Firstly, humidity conditions determine energy required for fuel preheating (Lee et al., 2018) and net energy released from fuel combustion (Dillon et al., 2011). Secondly, the amount of consumed fuels will increase under dry conditions, thus prompting severe fire effects (Dillon et al., 2011). Thirdly, weather elements, such as wind or thermal inversions, frequently condition fire behaviour and severity (Estes et al., 2017). What is more, the way in which weather influences fire severity might differ among fires and even during a single fire event (Kane et al., 2015a).

On the other hand, vegetation composition and structure might also exert bottom-up control on fire severity, regardless of physical and weather settings (Agee and Skinner, 2005; Estes et al., 2017). Vegetation continuity and loading, which depend on vegetation composition, ecosystem developmental stage and fire history, are expected to influence fire propagation and severity (Collins et al., 2007). The amount and spatial continuity of vegetation can be modified through human intervention (Lee et al., 2009). Therefore, understanding fire severity responses to vegetation features is critical for designing and implementing forest management strategies and fuel treatments (Stephens et al., 2012).

In the context of large high severity fires, structural attributes of the vegetation may be estimated using a combination of satellite data and plot-level field measurements. However, in certain cases, the spatial resolution of these data may be inadequate to accurately estimate these attributes (Nourian et al., 2016), while being expensive and time-consuming (Chen et al., 2017). In fact, passive satellite sensors have limitations in detecting fuel spatial complexity due to their incapacity to penetrate the forest canopy (Keane et al., 2001). The growing development of Airborne Light Detection and Ranging (LiDAR) data offers opportunities to obtain high spatial resolution information on the horizontal and vertical structure of the vegetation across large areas, with greater detail and fidelity than satellite data (Hummel et al., 2011). Three-dimensional information captured by LiDAR has been reported to effectively determine fuel parameters, such as foliage structure (van Leeuwen and Nieuwenhuis, 2010), vegetation height (Valbuena et al., 2017) and forest canopy structural heterogeneity (Kane et al., 2015b). Similarly, in recent years, LiDAR has increasingly been used to estimate forest structural changes associated with fire severity (Kane et al., 2013; Kane et al., 2014; Montealegre et al., 2014). Therefore, mapping forest structural characteristics from LiDAR has potential applications for improving our understanding of how pre-fire vegetation structure, in addition to other interacting environmental drivers, governs fire severity (Filippelli, 2016). Despite its potential advantages, the incorporation of LiDAR measurements for this purpose is still limiting in the scientific literature (Alonzo et al., 2017; Wulder et al., 2009).

In this study we aim to identify the environmental variables driving fire severity in a convective megafire of 11,891 ha that occurred in 2012 in a fire-prone Mediterranean ecosystem dominated by *Pinus pinaster* Aiton. Specifically, our objectives were: (i) to determine how variations in pre-fire vegetation greenness, pre-fire vegetation structure, weather conditions, fire history and physical properties influence fire severity; (ii) to evaluate whether LiDAR can be a valid tool for understanding how pre-fire vegetation structural characteristics control fire severity; and (iii) to provide valid recommendations for forestry managers to adopt appropriate strategies for reducing forest susceptibility to fire and moderate its ecological effects.

2. Material and methods

2.1. Study site

The study site is located in the Sierra del Teleno mountain range (North-Western Spain; Fig. 1) where altitude ranges from 840 to 2188 m s a l., and specifically in the study from 840 to 1500 m a s l. This study area is situated in the Mediterranean pluviseasonal oceanic bioclimatic region (Rivas-Martínez et al., 2011), with a mean annual precipitation of 640 mm, a mean annual temperature of 10 °C and 2–3 months of drought in summer. Wildfires are frequent in this area (free fire interval between 1 and 34 years), mainly associated to dry spring-summer storms (Santamaría, 2015). In 2012, a large convectivecrown-fire affected 11,891 ha covered by a forest of *Pinus pinaster* with a shrubby understory dominated by *Erica australis* L. and *Pterospartum tridentatum* (L.) Willk (Taboada et al., 2017). Isolated woodlots of *Quercus pyrenaica* Willd. and *Q. ilex* L. were also present in the area affected by the fire. Extreme weather conditions with a heatwave episode were observed during the week before and during the wildfire. These conditions increased the risk of fire and facilitated the convective fire event (Quintano et al., 2015). This fire was chosen as a case study due to its particular characteristics and high levels of severity, since a large part of the burned surface (6012 ha) experienced high severity levels (Fernández-García et al., 2018a). In fact, it has been included in the Reference Report by the Joint Research Center of the European Commission: "Forest Fires in Europe, the Middle East and North Africa 2012" as the second largest fire in Spain and one of the largest ones at European level in that year (Schmuck et al., 2012).

2.2. Fire severity

Fire severity was assessed using two Landsat 7 ETM+ images acquired on September 20th, 2011 (pre-fire image) and September 20th, 2012 (post-fire image) from the United States Geological Survey (USGS) Earth Explorer server (http://earthexplorer.usgs.gov/). We selected the available cloud-free images closest to the date of the fire in order to avoid phenological changes in the vegetation (Lecina-Diaz et al., 2014). The acquired images (L1T processing level) were Digital Number (DN) products geometrically rectified. The reflective bands were radiometrically corrected and converted to top-of-atmosphere (TOA) reflectance by applying standard methodology from USGS (https://landsat.usgs.gov/landsat-7-data-users-handbook-section-5).

On the processed images, we applied the delta Normalized Burn Ratio (dNBR; Key and Benson, 2006), which is based on the Near-Infrared (NIR) and the Short Wave Infrared (SWIR) reflective bands and esti-

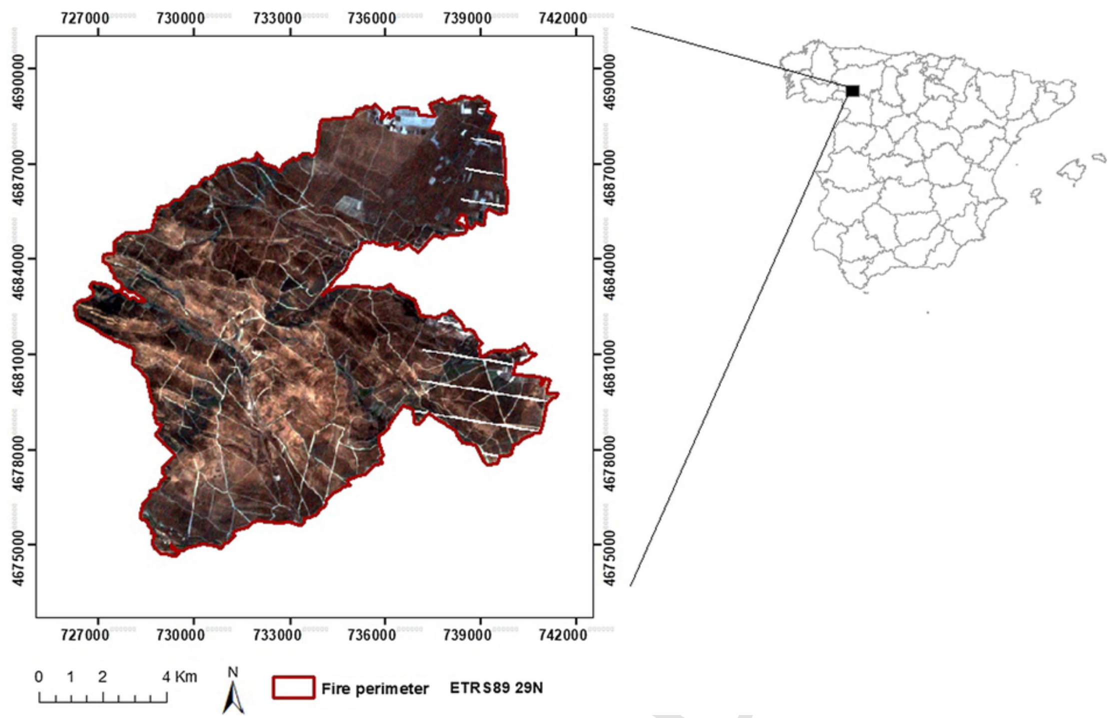

Fig. 1. Location map of the study area (Sierra del Teleno, NW Spain) representing a false color composite post-fire image (20th September 2012) obtained from Landsat 7 ETM+.

mates fire severity very effectively, especially in forest systems (Allen and Sorbel, 2008). To account for inter-annual variations in vegetation phenology and calibration errors, we normalized the dNBR values by subtracting the average dNBR of unburned areas outside the fire from the dNBR values within the fire perimeter (Miller et al., 2009). By doing so, unburned areas were set to 0.

In order to validate the dNBR values, we calculated the Composite Burn Index (CBI) data, which informs of the magnitude of fire effects combined across strata, in 54 field plots of 30 m × 30 m size, randomly established. CBI was estimated following the protocol described in Fernández-García et al. (2018b), by rating several variables of five vertical strata and obtaining a final ground severity value between 0 (unburned) and 3 (high severity). Correlation between the spectral index and site fire severity was 0.88. See Fernández-García et al. (2018b) for further details on dNBR validation.

2.3. Environmental variables

We generated a pool of environmental variables grouped into five categories to be used as drivers of severity: (1) pre-fire vegetation greenness, (2) pre-fire vegetation structure, (3) weather conditions, (4) fire history and (5) physical variables (Table 1).

2.3.1. Pre-fire vegetation greenness

We used two complementary spectral indexes as proxies of live fuel: the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI). The NDVI is a normalized ratio of the Near-Infrared (NIR) and the visible red bands (Eq. (1)), which is sensitive to vegetation chlorophyll content and has been widely used to quantify the net primary production of vegetation (e.g., Liu, 2016). The NDWI is a Short-Wave Infrared (SWIR)-based index (Eq. (2)) related to vegetation water content (Gao, 1996) and vegetation architectural parameters (Anderson et al., 2010).

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

$$NDWI = \frac{NIR - SWIR1}{NIR + SWIR1} \tag{2}$$

The NDVI index was derived from a Deimos-1 image (22 m resolution) acquired on August 17th, 2012, the day before the fire, which was previously resampled at 30 m spatial resolution. The acquired image (L1T processing level) was a DN product geometrically rectified, which includes three reflective bands (NIR, red, and green). The reflective bands were radiometrically corrected to TOA reflectance by applying the standard methodology from NASA (1999). The NDWI index was obtained from a Landsat 7 ETM+ image acquired on September 20th, 2011 (the pre-fire image used for the estimation of fire severity; see Section 2.2. for further details on image pre-processing). In both cases, we selected the available cloud-free images closest to the date of the fire.

2.3.2. Pre-fire vegetation structural metrics

Pre-fire vegetation structure was estimated based on LiDAR data provided by the Spanish National Plan for Aerial Orthophotography (PNOA; http://pnoa.ign.es/). The information was collected between 1st May and 30th September 2010, using an emission pulse frequency of 45 kHz, which produces a theoretical laser pulse density of 0.5 first returns per square meter and a maximum of four returns per pulse.

LiDAR data was processed using the US Forest Service's FUSION software package (http://forsys.cfr.washington.edu/fusion/fusionlatest.html; McGaughey, 2018). The z-value of the laser pulse returns might provide information on ground or canopy elevation. To retain the real height information concerning laser pulse returns, LiDAR data needs to be normalized (Kwak et al., 2014). To this end, a Digital Elevation Model (DEM) was created from the ground returns with a spatial resolution of 10 m. The height of LiDAR returns above ground surface was then obtained through DEM subtraction.

A set of LiDAR metrics, identified in previous studies (Kane et al., 2013; Lefsky et al., 2005) as highly correlated with vegetation struc-

Table 1
Groups of environmental predictors used for fire severity assessment: Pre-fire vegetation greenness, pre-fire vegetation structure, weather conditions, fire history and physical properties. Variables in bold were considered as predictors in Random Forest models after filtering. for multicollinearity.

Group of variables	Environmental variable	Data source
Pre-fire vegetation greenness	**NDVI index**	Deimos-1 image (22 m spatial resolution), acquired on August 17th, 2012
	NDWI index	Landsat 7 ETM + image (30 m spatial resolution), acquired on September 20th, 2011
Pre-fire vegetation structure	**Coefficient of variation (CV) of LiDAR return heights (m)**	LiDAR data provided by the Spanish National Plan for Aerial Orthophotography (PNOA; http://pnoa.ign.es/), collected between the 1st May and 30th September 2010
	Total returns	
	Canopy density (strata 0.5–2, 2–4, 4–7 and >7 m)	
Weather conditions	**Cumulative rainfall in spring (mm)**	Meteosat Second Generation (MSG) -2 satellite (at 3 km spatial resolution), acquired from March to May and August 2012
	Mean temperature in August (°C)	
Fire history	Number of fires	Landsat 2, MSS sensor; Landsat 4 and 5, TM sensor; and Landsat 7, ETM + sensor images (30 m spatial resolution), covering the period 1975–2012
	Fire –free interval (time since the last fire)	
Physical properties	Slope (degrees)	Digital Elevation Model (DEM) at 25 m spatial resolution
	Solar radiation (W/m^2)	
	Topographic complexity (degrees)	
	Actual evapotranspiration (mm)	Landsat 7 ETM + image (30 m spatial resolution), acquired on 12th March 2012
	Water deficit (mm)	Meteosat Second Generation (MSG) -2 satellite (3 km spatial resolution), acquired from March to May 2012

ture, were calculated from all non-ground LiDAR returns (height > 0 m) and aggregated within 30 m × 30 m buffers around each sampling point to achieve a spatial resolution comparable to that of Landsat 7 ETM+ products. This set of metrics accounted for two types of structural attributes: (i) Vertical structural complexity of the vegetation, estimated from the vertical distribution of LiDAR returns as the coefficient of variation (CV) of vegetation heights (Kwak et al., 2014); (ii) Canopy cover, estimated as the total amount of all returns and as the canopy density within different vegetation strata. Canopy density was quantified as the proportion of LiDAR returns within a stratum divided by the total number of returns within that stratum and below (Kane et al., 2013). We considered four strata (0.5–2, 2–4, 4–7 and >7 m), aiming to discriminate tall scrubs, small trees and understory cover below the tree crown, which can act as ladder fuels, and tree crowns, respectively.

2.3.3. Weather conditions

Weather conditions are expected to impact indirectly on fire severity by influencing fuel moisture conditions (van Mantgem et al., 2013) and fuel accumulation (Lecina-Diaz et al., 2014). We calculated the cumulative rainfall over the spring season (March-May) and the mean temperature in August (the month when the fire occurred). We selected these time periods since rainfall over the spring season largely determines biomass growth and fuel accumulation, while temperature conditions over the summer period might influence vegetation dryness and, consequently, fuel flammability (Gouveia et al., 2012; Russo et al., 2017). Metrics were obtained by averaging decadal information derived from the Meteosat Second Generation (MSG) -2 satellite (at 3 km spatial resolution) and acquired at 10-day intervals from March to May and August 2012.

2.3.4. History of fire

The number of fires and the fire-free interval (time since the last fire) are fire regime parameters commonly used as indicators of potential fuel availability across the landscape, since they affect vegetation composition and structure (e.g., Parks et al., 2014a). Both variables were computed from a map of fire scars manually digitalized at scale 1:5000 (minimum mapping unit of 0.01 km^2), which was obtained by visual interpretation and manual digitalization of 80 Landsat images covering the period 1975–2012. When Landsat images were not available, orthophotography was applied as complementary data to identify the fire scars. Orthophotographs were also used as a support for imagery with low spatial resolution (MSS imagery resampled to 60 m). The resulting map of fire scars was validated with spatial data provided by the official fire reports (1978–2012) made by the Nature Protection Section of the Regional Administration. See Fernández-García et al. (2018a) for further details on fire history estimations.

2.3.5. Physical properties

The physical properties were characterized by means of topographic and water balance metrics. We selected topographic variables that are well known to influence fire severity (Estes et al., 2017; Verbyla et al., 2008), such as slope, solar radiation and topographic complexity (computed as the slope standard deviation). They were derived from a DEM at 25 m spatial resolution obtained from the Spanish Geographic Institute (www.ign.es), previously re-sampled at the resolution of Landsat 7 ETM+ imagery (30 m).

The potential influence of water balance on fire severity has been demonstrated previously (Kane et al., 2015a). In this study, we calculated the actual evapotranspiration (AET) and the climatic water deficit (WD) as metrics of water balance. AET is a measure of real water consumption (Courault et al., 2003), which is strongly correlated with potential biomass production (Novák, 2011) and hence, with the amount of fuel. AET was computed from a Landsat 7 ETM+ imagery acquired on 12th March 2012 from the USGS Earth Explorer server. Specifically, we transformed the Landsat thermal band into land surface temperature by applying a modification of the energy balance equation introduced by Seguin and Itier (1983). We used the method described by Fernández-García et al. (2018b) consisting of the conversion of DN values to radiance values using brightness temperature (radiometric calibration), atmospheric correction -emissivity adjustment- and transformation to temperature in Kelvin degrees (K). WD allows for estimating vegetation drought-stress and can be associated with fuel moisture and flammability (Parks et al., 2014b). In this study, WD was calculated for the period March-May, as the difference between the Potential Evapotranspiration (PET) and AET (Parks et al., 2014b), where PET and AET were estimated by averaging decadal information obtained from an MSG evapotranspiration product at 10-day intervals acquired from March to May 2012. The theoretical limit of plant photosynthesis is related to potential evapotranspiration (PET) (Katerji and Rana, 2011). Nevertheless, when soil moisture is not enough to meet transpiration and evaporative demands, PET is reduced to AET (Marini et al., 2017).

2.4. Statistical analysis

First, we addressed a data exploratory analysis in order to detect multicollinearity and spatial autocorrelation. Potential multicollinearity among predictors was assessed by applying Pearson's correlation coefficient. The threshold of ($r^2 > |0.7|$) was used as the criterion for identifying pairs of highly correlated variables. From each pair, the variable with the least ecological meaning was removed for further analyses. Thus, the original set of variables was reduced to 14 variables, which were considered as predictors in further modelling analysis (see Table 1). We also calculated Moran's Index to evaluate the existence of global spatial autocorrelation in the predictors and the response variable by using the 'spdep' package (Bivand and Piras, 2015) for R, indicating no existence of spatial autocorrelation (Moran's I < 0.1; Diniz-Filho et al., 2011).

We applied Random Forests (Breiman, 2001), a variant of Classification and Regression Trees (CART), to assess the ability of pre-fire vegetation greenness, pre-fire vegetation structure, weather conditions, fire history and physical properties to predict fire severity. This is a machine learning approach that uses bootstrap aggregation (bagging) techniques to fit multiple CARTs, which are combined to improve predictive performance and reduce overfitting commonly present in single CART models (Cutler et al., 2007). In the Random Forest method, the variance explained by the models reflects how well the model fits a particular dataset. We assessed the predictive power of Random Forests based on internal out-of-bag error rates (Kane et al., 2015a and b), using a random sampling subset of 1000 pixels (1% of pixels from the image) to build the model. Random Forest requires two parameters to be defined *a priori*: the number of trees to run (*ntree*) and the number of input predictors tried at each split (*mtry*). In order to obtain stable results, we set the number of *ntree* to 1000. The *mtry* parameter was fixed via initial tuning experiments. To minimize stochastic errors and produce stable model outputs, we ran 100 replicate Random Forest models, providing the average as the final result.

The relative importance of each predictor was measured following the mean decrease in the accuracy (% IncMSE) criterion (Grömping, 2009). To identify a parsimonious set of informative predictors for fire severity that can still achieve a good model performance, we ran a model selection routine (Kane et al., 2015a) consisting of two steps. We initially established a full model including the 14 uncorrelated variables (Table 1) and ranked those variables according to their importance. We then selected the most important predictor from the full model and gradually added all the remaining ones, one at a time, aiming to identify which predictor best improved modelling results based on the variance explained and the error rate, hence constituting the new set of parsimonious predictors. We iteratively repeated this routine with each new set of parsimonious predictors until no improvement of the variance explained by more than 2% could be achieved. Additionally, we developed separate models for each single category of predictors: pre-fire vegetation greenness, pre-fire vegetation structure, weather conditions, fire history and physical variables. The dependency relationships between individual variables and fire severity was explored by means of partial dependence plots that were only reported for those variables included in the most parsimonious model. Random Forest model were run using the 'randomForest' package (Liaw and Wiener, 2002) for R (R Core Team, 2017).

3. Results

3.1. Relative influence of the environmental variables on fire severity

Over the study site, moderate and high fire severity accounted for more than 80% of the burned area (42% and 40%, respectively). Meanwhile, areas burned at low severity or not affected by fire just covered 17% and 1%, respectively.

The most parsimonious model explained almost the same percentage of variance as the full model ($R^2 = 0.419$ and 0.429, respectively; Fig. 2). The relative importance of the individual predictors included in the most parsimonious model was in descending order: NDWI, NDVI, time since the last fire, spring cumulative rainfall and CV of vegetation heights (Fig. 3).

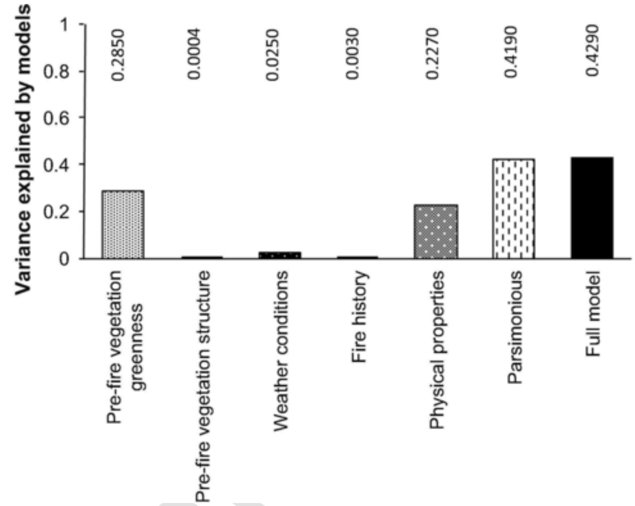

Fig. 2. Fire severity variance explained by Random Forest models using different categories of predictors: pre-fire vegetation greenness, pre-fire vegetation structure, weather conditions, fire history, physical properties. The figure shows the results of both the most parsimonious model and the full one.

The variance explained by the pre-fire vegetation greenness model (based on NDVI and NDWI) was $R^2 = 0.285$, which corresponds to one half of the variance explained by both the full and the most parsimonious models. Furthermore, both vegetation greenness predictors were ranked as the two most important influencing fire severity [imp (% IncMSE) = 59.18 and 55.31, respectively] in the most parsimonious model (Figs. 2 and 3). The physical predictors explained fire severity less consistently. When these variables were modelled alone, they explained approximately the same level of variance ($R^2 = 0.227$) as pre-fire vegetation greenness predictors ($R^2 = 0.285$) (Fig. 3). Nevertheless, the physical variables were dropped from the most parsimonious model. Pre-fire vegetation structure (i.e., CV of heights), weather conditions (i.e., spring cumulative rainfall) and fire history (i.e., fire-free interval) models explained low levels of variance ($R^2 = 0.0004$ to 0.025). However, they were important predictors of fire severity in combination with pre-fire vegetation greenness and physical variables. Their inclusion in the full model, as well as in the most parsimonious one, allowed for an increase in the model predictive power by approximately 16% and 13%, respectively (Fig. 2). In fact, the time since the last fire was identified as the third most important predictor in the parsimonious model (Fig. 3).

3.2. Specific influence of the individual environmental variables on fire severity

Overall, fire severity increased with NDVI and NDWI indexes, which might suggest higher probabilities of highly severe fires in areas with dense live biomass. Nevertheless, results showed that very high NDVI values might reduce fire severity (Fig. 3a and b). Furthermore, moderate to high fire severity occurred in situations of great structural vertical complexity of the vegetation, as fire severity increases with increasing CV of heights (Fig. 3e). The response pattern of fire severity to spring cumulative rainfall was inconsistent, although very high values of spring cumulative rainfall clearly exhibited a positive influence on fire severity (Fig. 3d). In contrast, increasing time since the last fire reduced fire severity, especially when this return period was longer than 15 years (Fig. 3c). Additionally, the relationships between individual environmental predictors and fire severity were mostly nonlinear, thus suggesting possible thresholds to the general detected patterns.

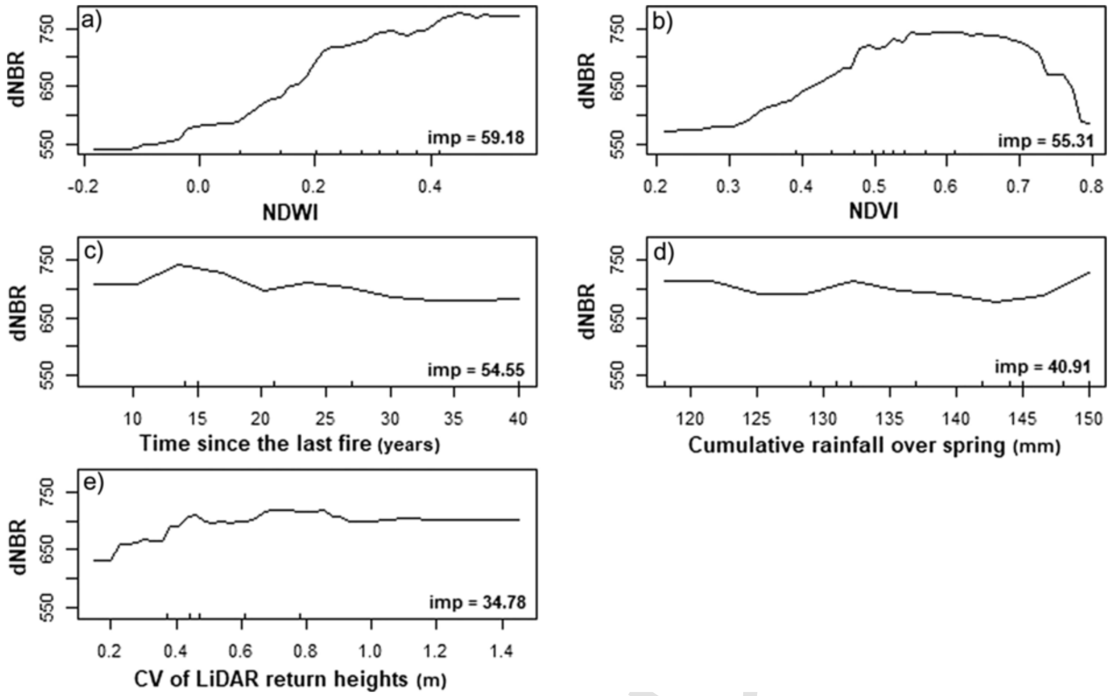

Fig. 3. Partial dependence plots showing the relationship between fire severity and each explanatory variable included in the most parsimonious model. Numbers within each plot show the normalized importance of each variable in the model measured as % IncMSE (imp =).

4. Discussion

4.1. Environmental predictors of fire severity

In our study area, fire severity patterns were a complex function of several environmental variables, rather than the result of control exerted by any particular environmental factor alone, as also found by Lydersen et al. (2014) and Kane et al. (2015a). The combination of a parsimonious set of different environmental variables (NDWI, NDVI, time since the last fire, spring cumulative rainfall, and CV of vegetation heights) improved the performance of the most explicative individual model and performed nearly as well as the full one. These results indicated that fire severity is mainly influenced by interactions among pre-fire vegetation greenness, pre-fire vegetation structure, fire history and weather conditions.

In particular, we detected a significant influence of biomass productivity and the phenological state of the pre-fire vegetation, evaluated through NDVI and NDWI indexes, in fire severity in pine fire-prone ecosystems. In general terms, both parameters determine the live biomass loads that could be burnt (Parks et al., 2014a). Likewise, high NDWI values are not just related to high fuel moisture content, but also to dense live vegetation (Roberts et al., 2003). Therefore, their positive relationship with fire severity might be further explained by the presence of dense live biomass for combustion. These results are in agreement with the positive correlations between greater volume of live vegetation and higher fire severity obtained in other studies carried out in pine forests (Arkle et al., 2012; Cocke et al., 2005). Live fuel is especially important in pine ecosystems as the particular chemical properties and structural characteristics of the needles make live material more flammable, releasing more energy when it burns than other vegetation types (Calvo et al., 2003).

The inclusion of the coefficient of variation (CV) of heights, as a proxy of structural vertical complexity, in the most parsimonious model might suggest, however, that high fire severity does not depend only on the existence of dense live biomass accumulations, but also on the vertical structural arrangement of those fuels. The availability of dense biomass will likely determine fire sustainment, but the vertical fire propagation reaching the crown layer is influenced by vertical structural complexity (Agee and Skinner, 2005). In this study, our results showed that increasing complexity of vertical structure of vegetation produced high fire severity, as also observed in other research (Baker, 2014). The stratified architecture of the pine crown and existence of ladder fuel frequently enhance vertical fire development in pine forests, causing high severity crown fires (Broncano and Retana, 2004; Fernandes and Rigolot, 2007). In our study area, the complexity of the vertical structure of the vegetation is the result of (i) a tall (up to 1.5 m height) shrubby understory with *Erica australis*, *Pterospartum tridentatum* and *Halimium lasianthum*, and (ii) the accumulation of ladder fuels (especially low branches of the trees) due to the lack of silvicultural treatments since the cessation of resin tapping activities in the 90 s (Santamaría, 2015).

Several studies have associated vegetation structure parameters measured from ground plots, such as plant canopy cover, tree density and size and fine fuel accumulations, to fire severity (Kuenzi et al., 2008; Lentile et al., 2006; Lezberg et al., 2008). Nevertheless, studies using LiDAR data at high pulse densities for modeling forest structure patterns (Kane et al., 2015a; Wulder et al., 2009) have not yet found this factor to be one of the most important predictors of fire severity. Despite using LiDAR data produced at low pulse densities, our study is the first research in which a structural parameter from LiDAR (i.e., the CV of vegetation heights) can be related to fire severity in pine fire-prone ecosystems. These results indicate the applicability of using pre-fire vegetation structure measurements from LiDAR for predicting fire severity, as a valid complement to spectral satellite measurements. These findings also suggest that increasing pulse density of LiDAR does not necessarily imply improving accuracy and performance of structural metrics, as was also underlined by Jakubowski et al. (2013).

We found fire severity to be a function of cumulative rainfall in the spring season. Weather conditions partially influence fire severity by conditioning primary productivity and, thus, biomass growth and accumulation in terms of quantity and continuity (Lecina-Diaz et al., 2014), as we also detected in our study. These results corroborated previous findings for the Iberian Peninsula, where the availability of water over winter and spring months constrained fuel loads during the fire season and, therefore, the levels of fire damage (Gouveia et al., 2012; Russo et al., 2017). Relationships between fire severity and weather conditions are, therefore, likely to be partially shaped by fuel conditions on a temporal scale (Pausas and Paula, 2012). Nonetheless, one limitation of our study, in which weather metrics were based on decadal information, would be the lack of data specifically for the days of the fire, which are important determinants of fire severity (Dillon et al., 2011; Estes et al., 2017).

Fire history, measured as the fire-free interval (time since the last fire), also influenced fire severity, although interacting with pre-fire vegetation conditions. We identified the highest fire severity in areas with a short fire return interval (time since the last fire < 15 years), which is contrary to general assumptions regarding the occurrence of high severity fires when time since the last fire is long. Odion and Hanson (2008) and Odion et al. (2009) obtained similar findings, mainly attributable to high pyrogenic pioneer species that established after fire. In our case, possible explanations might be related to high post-fire pine tree regeneration associated to a previous fire occurred in 1998 in the area (Calvo et al., 2013; Taboada et al., 2017). The studied maritime pine population is highly adapted to frequent crown fires with more than 95% of the mature trees bearing serotinous cones that can persist in the canopy bank up to 40 years containing viable seeds for 30 years (Tapias et al., 2004), resulting in a large number of recruited seedlings after fire. Dense areas of small trees may favor high pyrogenic combustible and fire propagation, making them more prone to burn with high fire severities (Fernandes and Rigolot, 2007; Lentile et al., 2006). Moreover, recurrent fires in the study area promoted pyrogenic resprouter shrub species (mainly *Erica australis* and *Pterospartum tridentatum*) (Calvo et al., 2008), highly tolerant to short between-fire intervals and capable of fast post-fire regeneration (Calvo et al., 2012).

Several studies have identified a strong link between fire severity and physical properties, including topography and evapotranspiration (Dillon et al., 2011; Kane et al., 2015a). Physical predictors could influence fire severity by affecting vegetation composition, fuel and weather conditions or past fire history (Estes et al., 2017; Fang et al., 2018; Kane et al., 2015b). In our study, physical variables influenced fire severity, but only when they were modeled alone, not contributing significantly to the most parsimonious model. This suggests that the main way in which physical properties may influence fire severity is not by governing pre-fire vegetation greenness, pre-fire vegetation structure, weather conditions or fire history. Moreover, it seemed that the combined effect of these four types of environmental predictors overwhelmed the influence of the physical properties on fire severity. Explanations could be related to the fact that convective fires like the one in our study area, are mainly limited by the amount of biomass available for burning and by fuel continuity (Lecina-Diaz et al., 2014), rather than by physical properties. Additionally, this could be a problem of scale. In this way, during convective fires, physical properties (mainly topography) operate at a macro-scale (Costa et al., 2011) and consequently, physical predictors simply may not properly match the scale at which fire severity patterns and physical properties correlate.

4.2. Management implications

The reduction and/or abandonment of land uses since the middle of the last century in the study area have favored fuel accumulation and continuity (Santamaría, 2015), which have very likely increased the susceptibility of pine forest ecosystems to high severity fires, similarly to other fire-prone areas in the Mediterranean basin (Fernandes and Rigolot, 2007; González-De Vega et al., 2016). According to our results, dense live fuel accumulations and vertical structural continuity of these fuels are important factors influencing fire severity. Therefore, pre-fire management strategies should seek to reduce live fuel accumulations and modify fuel structural patterns, as the control of these factors may lead to a reduction in fire severity in future fire events. Such fuel treatments might be especially relevant in pine forest areas where the homogeneity of the vegetation might exacerbate fire severity effects (Lee et al., 2009). Given these premises, pre-fire silvicultural operations intended to reduce canopy bulk density, as well as to prune and remove ladder fuels, would be advisable to break fuel continuity and, thus, hamper potential fire spread and severity (Lininger, 2006). Furthermore, retaining or creating several open stands with large trees would also be desirable, as they are the most fire-resistant trees due to their taller crowns and thicker barks (Agee and Skinner, 2005; Fernandes and Rigolot, 2007). Studies carried out in southern Spain showed how less dense pine forest systems tend to present lower fire severities than closed stands, likely because of a lower susceptibility to crowning (Gallegos et al., 2003). Nevertheless, since the development of a shrubby understory is more prone under open forest canopies, periodic surface fuel treatments would also be necessary (Fernandes and Rigolot, 2007).

Our findings further evidenced the great vulnerability to high fire severity of fire-prone areas with short fire return intervals, especially those post-fire regenerated pine ecosystems where the density of small trees is very high. This reflects the importance of implementing post-fire management actions in naturally regenerated pine forest stands after wildfires. Selective thinning prescription or retention of the largest among the young trees regenerated after fire could be recommended in these dense pine areas, aiming to break fuel continuity, reduce canopy bulk density and enhance tree regrowth (Corona et al., 2014).

5. Conclusions

This study highlights how live biomass accumulations are the main factor driving severity of crown-convective fires in pine forests, while other environmental drivers, such as the physical properties, play a less determining role. Nevertheless, our results demonstrated that the effect of biomass accumulation is strongly dependent on interactions with the pre-fire vertical structural arrangement of vegetation, fire history and weather conditions. Effective management actions to reduce fire risk and fire damage should be based on the understanding of the key determinants of fire behavior and severity. Forest managers' actions should prioritize pre- and post-fire fuel treatments aiming at breaking vertical and horizontal fuel continuity and reducing live fuel accumulations. The modification of tree stands and landscape structure towards a more open canopy would enhance resistance to fire damage and susceptibility to crowning. Our study further endorses the potential of low-density LiDAR for the structural analysis of the vegetation in fire management and fuel treatment applications, especially in areas prone to megafires, at relatively low cost-efficacy compared to high-density LiDAR data.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foreco.2018.10.051.

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