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Evaluation of fire severity in fire prone-ecosystems of Spain under two different environmental conditions

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ABSTRACT

Severe fires associated to climate change and land cover changes are becoming more frequent in Mediterranean Europe. The influence of environmental drivers on fire severity, especially under different environmental conditions is still not fully understood. In this study we aim to determine the main environmental variables that control fire severity in large fires (>500 ha) occurring in fire-prone ecosystems under two different environmental conditions following a transition (Mediterranean-Oceanic)-Mediterranean climatic gradient within the Iberian Peninsula, and to provide management recommendations to mitigate fire damage. We estimated fire severity as the differenced Normalized Burn Ratio, through images obtained from Landsat 8 OLI. We also examined the relative influence of pre-fire vegetation structure (vegetation composition and configuration), pre-fire weather conditions, fire history and topography on fire severity using Random Forest machine learning algorithms. The results indicated that the severity of fires occurring along the transition (Mediterranean-Oceanic)-Mediterranean climatic gradient was primarily controlled by pre-fire vegetation composition. Nevertheless, the effect of vegetation composition was strongly dependent on interactions with fire recurrence and pre-fire vegetation structural configuration. The relationship between fire severity, weather and topographic predictors was not consistent among fires occurring in the Mediterranean-Oceanic transition and Mediterranean sites. In the Mediterranean-Oceanic transition site, fire severity was determined by weather conditions (i.e., summer cumulative rainfall), rather than being associated to topography, suggesting that the control exerted by topography may be overwhelmed by weather controls. Conversely, results showed that topography only had a major effect on fire severity in the Mediterranean site. The results of this study highlight the need to prioritise fuel treatments aiming at breaking fuel continuity and reducing fuel loads as an effective management strategy to mitigate fire damage in areas of high fire recurrence.

1. Introduction

Fire is an important and dynamic disturbance process in Mediterranean regions such as Mediterranean Europe, impacting both ecosystem composition, structure and function, and human activities (Bond and Keeley, 2005; Russo et al., 2017; He et al., 2019). Fire severity, defined as the magnitude of change in vegetation and soil between pre- and post-fire conditions (Key and Benson, 2006; Fernández-García et al., 2018) and, operationally denoted as the amount of organic matter consumed aboveground and belowground (Keeley, 2009; Morgan et al., 2014), is one of the most critical determinants of the ecological effects of fire (Harris and Taylor, 2017). Although Mediterranean ecosystems are adapted to wildfires (Pausas et al., 2008; Bastos et al., 2011), increasing fire severity can lead to vegetation type conversions, such as non-forested vegetation types, decreases in fire-sensitive species, modification of vegetation structure and induction of soil erosion (Lentile et al., 2006a,b; van Wagtendonk, 2012; Zavala et al., 2014; Walker et al., 2018).

Patterns of fire severity are dictated by three major controlling factors: topography, weather (and more broadly, climate) and, fuels and vegetation composition and configuration (Román-Cuesta et al., 2009; Lecina-Diaz et al., 2014). Over the last few decades,

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our knowledge of the extent to which each factor contributes to fire severity under different ecosystems and burning conditions has improved, but many details remain unclear, likely because of complex interactions among these factors (Estes et al., 2017; Parks et al., 2018). Topography, for example, strongly affects fire severity because it controls fire behaviour and flammability through its influence on fuel moisture, local climate and vegetation composition and structure (Holden et al., 2009; Fang et al., 2018). Nonetheless, under extreme conditions (e.g., prolonged drought, heat waves and high winds), weather (and more broadly climate) may override the control exerted by topography and fuel load, and lead to widespread high-severity fires (Bradstock et al., 2010; Lydersen et al., 2014).

Generally, climatic conditions (i.e., during or preceding the fire season at broad spatial scale) affect fire severity in two primary ways: by controlling fuel moisture (direct effect) conducive to vegetation flammability, and by influencing net primary productivity and fuel accumulation (indirect effect) (Flatley et al., 2011; Turco et al., 2017). However, the geographical variation in climatic conditions can affect the way climate influences fire regime. For example, occurrence of dry conditions during the fire season, necessary to achieve high flammability (drought –driven fire regimes), were more important in explaining burn area in northern European Mediterranean regions (generally wetter and more productive; Turco et al., 2017). On the contrary, antecedent wet conditions play a major role in southern (drier) regions, presumably because in dry areas fuel loads are controlled by climatic conditions preceding the fire season (Gouveia et al., 2012; Pausas and Paula, 2012). However, although data are not always available, fire weather variables (e.g., winds) during fire progression could affect fire severity variability (Viedma et al., 2015; Coen et al., 2018). Therefore, understanding fire severity-climate links in climate-constrained fire regimes is essential in the context of climate change, where increased frequency of extreme events may vary the contribution of climate to fire severity, in relation to other factors (Russo et al., 2017).

Vegetation and fuel characteristics, in turn, may control fire severity independently of the environmental setting (i.e., topography or climate) (Estes et al., 2017; Harris and Taylor, 2017). Fire severity is closely linked to the amount and spatial arrangement of fuels, which is strongly dependent on vegetation composition, ecosystem developmental stage and disturbance history (Odion et al., 2004; Collins et al., 2007). Consequently, fire severity across landscape would be expected to be influenced by the spatial arrangement of different fuel types, for which fire susceptibility would also be different (Lee et al., 2009; Moreno et al., 2011; Fernández-Alonso et al., 2017). For example, in a Mediterranean landscape, and particularly in the Iberian Peninsula, shrublands and pine forests, mainly *Pinus pinaster* and *P. halepensis* (Pausas and Vallejo, 1999; Barros and Pereira, 2014), are more fire prone, likely due to landscape homogenization and ladder fuels that make them crown-fire systems, while agricultural areas limit fire spread and severity (Lloret et al., 2002). In this context, fuels are the only factor that can be addressed through land management. Therefore, assessing the influence of fuels on fire severity has been identified as critical information for defining land management guidelines and policies to reduce fire effects and risk in fire-prone landscapes (Lee et al., 2009; Fernandes et al., 2010).

Key factors controlling fire severity in the West-Euro-Mediterranean area have been evaluated at many scales (i.e., individual fires, landscapes and regional scales). For example, Lecina-Diaz et al. (2014) conducted a comprehensive evaluation of drivers of fire severity (i.e., fuel, topographic and fire behaviour variables) at regional scale in Northeastern Spain. Similarly, Broncano and Retana (2004); Oliveras et al. (2009), Alvarez et al. (2013); López-Poma et al. (2014); Fernández-Manso et al. (2019) and García-Llamas et al. (2019a; 2019b) conducted comprehensive analyses of environmental factors controlling fire severity, using individual fires across the Iberian Peninsula. However, although many studies have examined patterns of fire severity on a relatively small extent, those identifying and understanding key drivers of fire severity under different environmental conditions are still limited (Parks et al., 2018).

In this study, we aim to determine the environmental variables that control fire severity in large fires (burned area >500 ha) occurring in fire-prone ecosystems under two different environmental conditions following a transition (Mediterranean-Oceanic)-Mediterranean climatic gradient in the Iberian Peninsula, and integrating detailed spatially explicit data: LiDAR information, remote sensing and Digital Elevation Models (DEM). Specifically, we aim to: (i) analyze how variations in pre-fire vegetation structure, weather, fire history and topography explain fire severity patterns, estimated as dNBR using Landsat 8 OLI imagery, and applying Random Forest machine learning techniques in analysis; (ii) determine how the influence of these controls on fire severity differ for the fires that occurred under two different environmental conditions; (iii) provide helpful recommendations to design effective strategies to minimize susceptibility of fire-prone ecosystems to fire and mitigate fire damage.

2. Material and methods

2.1. Study sites

Our study area encompasses two wildfires that occurred across the transition (Mediterranean-Oceanic)-Mediterranean climatic gradient, within the Iberian Peninsula (Fig. 1).

The Mediterranean-Oceanic transition site was located in the Cabrera mountain range (León province, NW Spain; Fig. 1), where a wildfire burned 9939 ha between 21st and 27th August 2017. The area was mainly covered by shrublands dominated by *Erica australis* L., *Genista hystrix* Large., *Quercus pyrenaica* Willd., and, by forests and grasslands primarily on valley bottoms. Vegetation was established over siliceous lithology (mainly quartzite, slate, sandstone and limestone; Instituto Geológico y Minero de España, 2015). This area was characterized by a relatively high and frequent number of wildfires (number of fires = 8.48 fires $\times$ 10 km^{-2} $\times$ 10 years^{-1}), mainly associated with anthropic causes. The fire season runs from early June to late September. The site presents a complex and heterogeneous topography (altitude = 836–1938 m.a.s.l.; slope = 0.08–55%). The climate is temperate with a mean annual precipitation rate of 600–1500 mm, mean annual temperature between 5 and 15 °C and two months of summer drought (average values for a 50-year period; Ninyerola et al., 2005). The year of the fire coincided with a severe drought, reaching low precipitation rates during the winter and spring seasons preceding the fire season (mean annual precipitation = 465 mm; "Agencia Estatal de Meteorología," 2017Agencia Estatal de Meteorología, 2017) that led to water shortage and increased fire risk. Additionally, the maximum temperature in the region on the days when the fire occurred was 35 °C, with low relative humidity values (35%), mean wind speed of 6.04 m/s and dominant wind direction ranging between 27 and 11 tenths of degree (Agencia Estatal de Meteorología, 2017), which facilitated fire spread.

The Mediterranean site is a convective mega-fire that occurred in Sierra Calderona Natural Park (Valencia province, E Spain; Fig. 1; Consellería de Agricultura, Medio Ambiente, Cambio Climático y Desarrollo Rural, 2017). The fire started on June 28th, 2017 and lasted 5 days, burning 1414.16 ha dominated by conifer forests of *Pinus halepensis* Mill. at different developmental stages: (i) homogeneous mature pine forests with a shrubby understory dominated by *Erica multiflora* L., *Rhamnus lycioides* L., *Pistacia lentiscus* L., *Ulex parviflorus* Pourr. and *Brachypodium retusum* (Pers.); (ii) small dense regeneration pine trees (density ≥ 100000 individuals/ha) associated with previous fires in 1993 (215.5 ha), 1994 (6717 ha) and 2009 (832.3 ha), interspersed

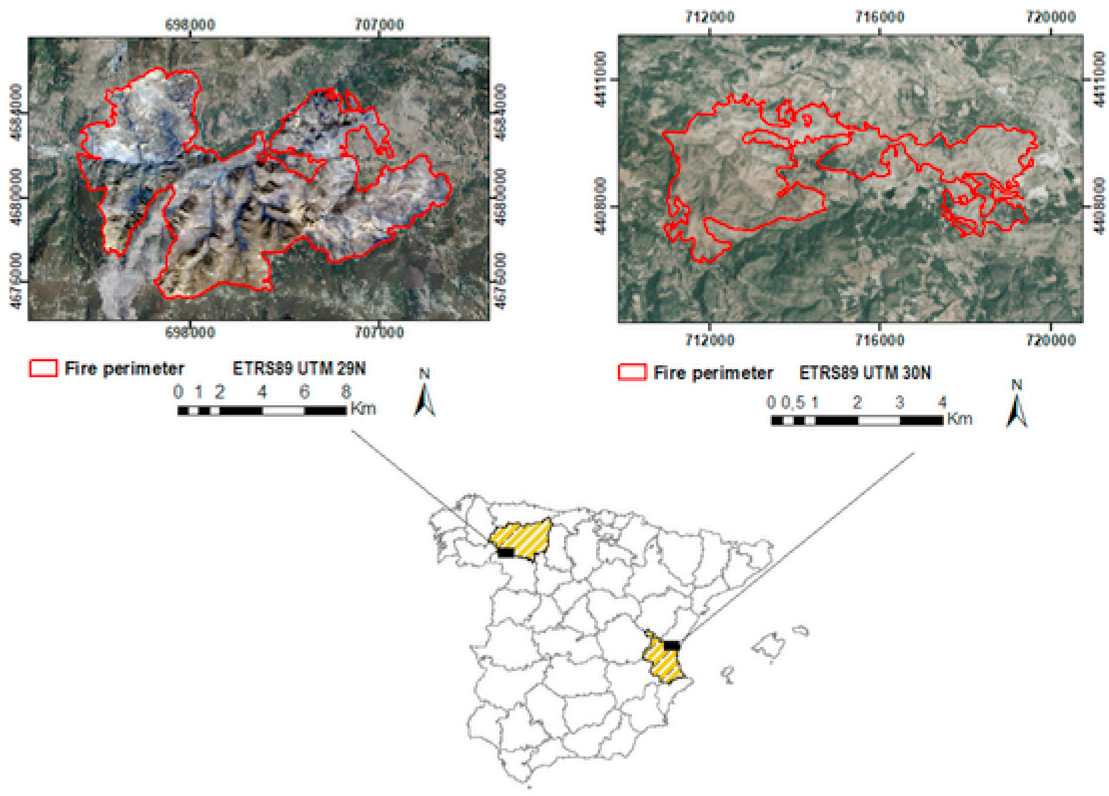

Fig. 1. Location map of the study area: Sierra de la Cabrera, NW Spain (left image) and Sierra Calderona Natural Park, E Spain (right image), represented as false colour composite post-fire images (RGB; 10th October 2017 and 30th July 2017, respectively) obtained from Landsat 8 OLI. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

with shrub and herbaceous species of *U. parviflorus*, *Cistus monspeliensis* L., *C. albidus* L. and *Brachypodium retusum* and mature pine stands. Olive and carob tree crops were also present in the area. The fire season runs from June to September. The region is characterized by typical Mediterranean conditions with mean annual temperatures between 15 and 16 °C, 500 mm mean annual precipitation and four months of summer drought (average values for a 30-year period; Pérez-Cueva, 1994). During the fire event, maximum temperature was 29 °C, with relative humidity below 30%, mean wind speed was 1.9 m/s and dominant wind direction was 33 tenths of degree during the first five days and 14 tenths of degree during the last two days (Agencia Estatal de Meteorología, 2017). The orography is heterogeneous with altitudes ranging from 280 to 820 m.a.s.l. and slope between 21% and 60%. The lithology is dominated by clays, marlstone, limestone and sandstone (Instituto Geológico y Minero de España, 2015).

2.2. Fire severity

Fire severity data was estimated from Landsat 8 OLI imagery acquired from the United States Geological Survey Earth Explorer Server. Selected imagery to estimate fire severity included available cloud-free pre- and post-fire scenes as close as possible to the date of the fire, with the aim of avoiding phenological changes in the vegetation (Lecina-Diaz et al., 2014). Scenes in the Mediterranean-Oceanic transition site were from August 11th, 2017 (pre-fire image) and October 10th, 2017 (post-fire image); and in the Mediterranean site from June 12th, 2017 (pre-fire image) to July 30th, 2017 (post-fire image). The reflective bands were topographically and atmospherically corrected and converted to at-surface reflectance through the ATCOR atmospheric correction model (Richter and Schläpfer, 2018) from the PCI GEOMATICS 2018 software.

From the processed images, fire severity was estimated as the total amount of biomass consumed (Keeley, 2009; Morgan et al., 2014) via the delta Normalized Burn Ratio (dNBR; Key and Benson, 2006). We used the dNBR index, since fire severity in previous studies carried out in our study area and in similar Mediterranean fire-prone ecosystems in the Iberian Peninsula was most accurately assessed using the dNBR index (Fernández-García et al., 2018; García-Llamas et al., 2019c). The dNBR was derived using the Near Infrared (NIR; B5) and Short Wave Infrared (SWIR-2; B7) bands of Landsat 8 OLI. In order to account for differences in phenology between pre- and post-fire scenes, we normalized dNBR values in unburned areas to zero by subtracting the average dNBR in unburned areas outside the fire perimeter from the dNBR values within the fire perimeter (Miller et al., 2009). In this study, we used continuous dNBR values as the response variable in further analyses. Nevertheless, as descriptive information of the fire events, we also provide dNBR as classified fire severity using breakpoints published in Fernández-García et al. (2019): low severity, $317 \le$ dNBR; moderate severity, $317 <$ dNBR ≤ 527; high severity dNBR ≥ 527 (Table 2). The proportion of area burned at high, moderate and low severity was similar for the three categories (around 33%) in both fires (Table 1).

Table 1
Proportion of surface burned at high, moderate and low fire severity for fires occurred in the Mediterranean-Oceanic transition and Mediterranean sites.

Fire severity	Transition fire	Mediterranean fire
High	30.21	34.39
Moderate	34.32	39.31
Low	35.47	26.60

Table 2
Environmental predictors checked for fire severity assessment: Pre-fire vegetation composition and structure, fire history, weather conditions and topography. Variables in bold were used as predictors in Random Forest models after multicollinearity analyses.

Group of variables	Environmental variable	Data source	Transition site			Mediterranean site		
			Min	Mean	Max	Min	Mean	Max
Pre-fire vegetation structure	**Forest cover area (i.e., broad-leaf and coniferous forests, ha)**	SIOSE land use/ land cover database at scale 1:25000, produced for 2014 (Ministerio de Fomento, 2014)	0	13.53	137.80	0	44.10	220.64
	Fruit trees cover area (ha)		–	–	–	0	0.67	11.56
	Shrub cover area (ha)		0	56.04	312	0	12.24	39.75
	Grassland cover area (ha)		0	24.63	78.45	–	–	–
	25th percentile LiDAR return height (m)	LiDAR data provided by the Spanish National Plan for Aerial Orthophotography (PNOA; Ministerio de Fomento, 2010), collected between 1st May and 30th September 2010. Laser pulse density, 0.5 first returns m $^{-2}$	0.10	0.39	6.44	0.25	2.64	9.17
	Canopy cover (>0.2 m) (%)		0	9.60	100	0	36.51	100
	Coefficient of variation (CV) of LiDAR return height (m)		0.18	0.75	1.28	0.27	0.69	1.49
	Rumple (range)		1	1.37	7.08	1	1.90	8.43
Fire history	**Fire recurrence (number of fires)**	Landsat 2, MSS sensor; Landsat 4 and 5, TM sensor; Landsat 7, ETM + and Landsat 8 OLI sensor images (30 m spatial resolution), covering the period 1984–2017	0	2.53	8	0	0.76	3
	Fire –free interval (time since the last fire)		1	–	>20	8	–	>20
Weather	**Mean cumulative rainfall in spring (mm)**	Meteosat Second Generation (MSG) −2 satellite (at 3 km spatial resolution), acquired from March to May, and June (i.e., Mediterranean site); and from June to August (i.e., Mediterranean-Oceanic transition site), 2017	157	173.04	189	6.67	8.16	8.41
	Mean cumulative rainfall in summer (mm)		34	41.46	53	14.33	14.85	15.27

Table 2 (*Continued*)

Group of variables	Environmental variable	Data source	Transition site			Mediterranean site		
			Min	Mean	Max	Min	Mean	Max
	Mean temperature in summer (ºC)		21.15	21.67	22.70	25.5	25.55	26.17
	Spring actual evapotranspiration (mm/day)	MOD16A2 global evapotranspiration product at 8-day intervals and 500 m spatial resolution from MODIS (U.S. Geological Survey, 2017)	0.98	1.25	1.76	1.13	1.43	2.51
	Spring water deficit (mm/day)		3.29	4.02	5.47	2.48	3.22	4.54
Topography	**Slope (degrees)**	Digital Elevation Model (DEM) at 25 m spatial resolution	0.01	20.80	71.17	0.03	16.41	44.75
	Mean annual solar radiation (KW/m ^{2})		405.65	941.34	1174.03	294,46	602.88	731.06
	Topographic Solar Radiation Aspect Index (range)		0	0.05	1	0	0.39	1

2.3. Environmental variables

For each fire, we selected environmental variables as predictors of fire severity based on the work of García-Llamas et al. (2019a) and Kane et al. (2015). These variables included four environmental categories: (1) pre-fire vegetation structure, (2) fire history (3) weather conditions and (4) topography (Table 2).

2.3.1. Pre-fire vegetation structure

Pre-fire vegetation structure, including composition and configuration, was derived from two data sources: (i) the Spanish Land Use Information System (SIOSE) database and (ii) LiDAR data. Composition refers to features associated with the variety and abundance of vegetation types (Lee et al., 2009). Composition metrics were computed from the SIOSE database, and included the area covered by each vegetation type. This database (year 2014, Spanish coverage, 1:25000 scale) (Ministerio de Fomento, 2014) is derived from orthophotography, satellite imagery and field data, with a minimum mapping unit of 2 ha. It provides information on the proportion of cover considering single land use classes consisting of a single element (e.g., conifer), or complex classes resulting from the association of several elements (e.g., regular mosaic: 90% olive trees and 10% shrubland; García-Álvarez and Camacho-Olmedo, 2017). Based on the SIOSE database, we classified vegetation types within the fire perimeters into four categories including forests (i.e., broad-leaf forest and conifer for the Mediterranean-Oceanic transition and Mediterranean sites, respectively), fruit tree crops (i.e., olive and carob tree crops, present in the Mediterranean site only), shrubs and grasslands (i.e., for the Mediterranean-Oceanic transition site only). Subsequently, we estimated the area (in ha) covered by each class based on the proportion of each vegetation type within each SIOSE polygon included in the burned areas.

Configuration represents the spatial character and arrangement of vegetation (Lee et al., 2009). Configuration metrics were quantified from LiDAR data acquired throughout 2010 (in the Mediterranean-Oceanic transition site) and 2009 (in the Mediterranean site), and provided by the Spanish National Plan for Aerial Ortophotography (PNOA; http://pnoa.ign.es/productos_lidarMinisterio de Fomento, 2010). Data was produced with an emission pulse frequency of 45 kHz, which yielded a theoretical laser pulse density of 0.5 first returns m^{-2}, with up to four returns per pulse, which ensures a good quality of LiDAR data and a reliable characterization of vegetation structure (González-Ferreiro et al., 2012). The accuracy report accompanying the LiDAR data indicated an overall altimetric accuracy (RMSE in Z) lower than 0.40 m. In our study, as in many others (Kane et al., 2013; Fernandez-Manso et al., 2019), there is a 7-year time lag between LiDAR acquisition and fire occurrence that could affect the final accuracy. In order to ensure the validity of LiDAR data from 2009 to 2010 to represent the pre-fire structure in 2017, we photointerpreted PNOA 2008, 2010 and 2015 orthophotographs to verify that there were no fires in the area during this period of time and to ensure that fuels and their spatial distribution were essentially the same. Sampling points from areas burned during this time lag (which represented 3% of the total area burned in 2017 in the Mediterranean-Oceanic Transition site and 15% in the Mediterranean site) were discarded from the analyses.

LiDAR return point cloud data was processed using version 3.7 of the FUSION software package from the US Forest Service (McGaughey, 2018). The height of each LiDAR return was normalized to heights above ground surface by subtracting from each first return the elevation of the underlying Digital Elevation Model (DEM) at 10 m spatial resolution, which was created from the ground returns.

The non-ground LiDAR returns (height > 0) were used to produce metrics that incorporate vertical and horizontal arrangement of vegetation: canopy cover, 25th percentile height of first returns, coefficient of variation (CV) of height, and rumple. These LiDAR-derived metrics have been identified in previous studies as highly correlated with vegetation structure and fuel load (Erdody and Moskal, 2010; Bolton et al., 2015; Kane et al., 2015; Fernandez-Manso et al., 2019). These variables were aggregated within $30 \text{ m} \times 30 \text{ m}$ buffers around each sampling point to match Landsat 8 OLI spatial resolution. Canopy cover, which is a LiDAR measure of canopy closure, was computed as the number of first returns above the cover height break (0.2 m) divided by the total number of first returns (Kane et al., 2014). Nevertheless, in the current study, since cover height break was set to

0.2, the output canopy cover measure was related to vegetation cover (i.e., the addition of shrub and canopy) rather than just to canopy cover. 25th percentile of height is related to canopy base height, which can affect crown fire development (Andersen et al., 2005; Kane et al., 2013). We measured structural complexity of vegetation through the computation of two metrics: rumple and the CV of height. Rumple is sensitive to canopy structure horizontal and vertical variation and is therefore a three-dimensional measure of structural heterogeneity, whereas CV of height is a one-dimensional measure (Kane et al., 2010). Rumple was calculated from a 1 m resolution Canopy Surface Model (CSM), as the ratio of the area of the CSM to the area of the underlying DEM in a 15 m grid cell (Kane et al., 2013).

2.3.2. Fire history

Fire history is known to affect fire severity due to its effect on vegetation density, structure and composition (Parks et al., 2014a). Fire regime was characterized using two parameters: fire recurrence and the fire-free interval (time since the last fire). These variables were calculated from a map of fire scars at scale 1:20000, which was obtained by visual analysis and manual digitalization of Landsat imagery for 1984–2017 (33-year period) (Landsat 4–5, sensor TM; Landsat 7, sensor ETM+; and Landsat 8, sensor OLI), based on the methodology described by Fernández-García et al. (2018). We used 7 scenes per year, 6 corresponding to May–November and one covering November–May. Nevertheless, due to limitations on LiDAR data availability, areas burned after 2010 (in the Mediterranean-Oceanic transition site) and 2009 (in the Mediterranean site) were discarded from the estimation of fire history measures and from further analysis. Based on the map of the fire scars, we categorized fire recurrence into four categories: 1 fire, 2 fires, 3 fires and 4 or more fires; and the fire-free interval into four categories: 8–15, 16–22 and more than 22 years since the last fire (Fig. 2).

2.3.3. Weather

We considered two categories of weather variables that captured weather conditions during and preceding the fire season, and water balance, computed for each fire. To assess the impact of weather during and preceding the fire season on severity we used information on mean cumulative rainfall throughout the spring season (March–May) and mean summer cumulative rainfall and temperature until the day of fire ignition (June-day of fire ignition). We selected these metrics since it is well established that rainfall preceding the fire season fairly determines vegetation growth and, therefore, abundance and continuity of fuel loads, especially of fine fuels, leaves and steams of existing vegetation, and influence moisture of coarse fuels that take weeks or months of arid conditions to dry, whereas summer temperature and precipitation may influence fuel desiccation and flammability during the fire season, thus enhancing favorable conditions for burning (Turco et al., 2013; Fernandes et al., 2014; Flannigan et al., 2016). Mean summer temperature was obtained by averaging daily air temperature values at observation height (1.5 m), and mean cumulative rainfall by averaging total precipitation acquired at 10-day intervals from gridded Meteosat Second Generation data at 3 Km spatial resolution, provided by the EARS (Environmental Analysis & Remote Sensing) Earth Environment Monitoring enterprise (Rosema et al., 2014).

Water balance metrics consisted of Actual Evapotranspiration (AET) and Water Deficit (WD) metrics. AET indicates real water consumption and is related to potential biomass production, while WD (potential evapotranspiration minus AET) is associated with vegetation stress and thus, moisture content (Parks et al., 2014b; Kane et al., 2015). These variables were derived from the MOD16A2 global evapotranspiration product (500 m spatial resolution) at 8-day intervals, obtained from MODIS (U.S. Geological Survey, 2017) during the spring season (period March–May).

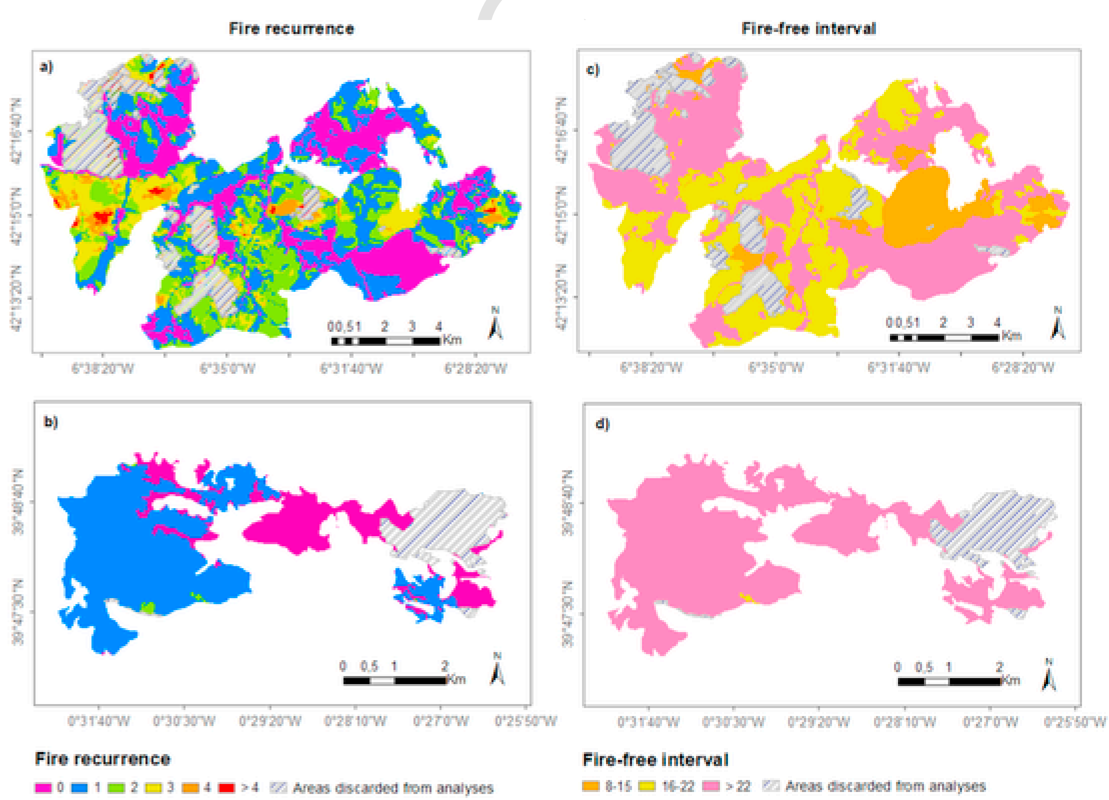

Fig. 2. Fire recurrence map with five categories (1 fire, 2 fires, 3 fires, 4 fires and more than 4 fires) for: a) the Mediterranean-Oceanic transition site and b) the Mediterranean site; and fire-free interval map with four categories (8–15, 16–22 and more than 22 years since the last fire) for: c) the Mediterranean-Oceanic transition site and d) the Mediterranean site. Areas discarded from analyses are shown in stripe overly.

2.3.4. Topography

We examined three topography-related variables derived from a 25-m DEM from the Spanish Geographic Institute (Instituto Geográfico Nacional, 2018), which was previously re-sampled at 30 m spatial resolution (i.e., the resolution of Landsat 8 OLI imagery): slope in degrees, mean annual solar radiation and Topographic Solar Radiation Aspect Index (TRASP; Roberts and Cooper, 1989). Slope is the maximum rate of change in elevation at a surface location. Mean annual solar radiation is a measure of the amount of direct sunlight for an area and hence, summarizes aspect and inclination well (Viedma et al., 2015). The Topographic Solar Radiation Aspect Index is a linear transformation of the circular aspect that ranges between 0 and 1. A value of zero is assigned to land orientated in a north-northeast direction and a value of one in the south-southwesterly direction. These variables were calculated using ArcGIS 10.5 software.

2.4. Statistical analysis

Machine learning approaches have achieved fairly good results to determine environmental controls of fire severity in various studies (Kane et al., 2015; Viedma et al., 2015; Hoff et al., 2019). In this study, we used the Random Forest (RF) machine learning algorithm (Breiman, 2001) to determine how the set of environmental variables (i.e., pre-fire vegetation structure, weather conditions, fire history and topography) predicted fire severity for each fire event. Models were developed by applying the 'randomForest' package (Liaw and Wiener, 2002) from the R statistical program (release 3.4.3) (R Core Team, 2017). RF modelling has several advantages, as it can handle spatial autocorrelation in predictors, reduce overfitting in data sets and deal with complex relationships between predictors and response variables (Cutler et al., 2007; Hengl et al., 2018). Our total independent observations were a random set of 1000 (Mediterranean-Oceanic transition site) and 140 (Mediterranean site) pixels (1% of the pixels from the image) (Fernández-García et al., 2018).

To assess multicollinearity problems among all sets of predictors (i.e., total 18 environmental variables), prior to RF models, we carried out a data exploration analysis through the computation of Pearson's correlation coefficient. All variables selected for further modelling had low Pearson's correlation coefficients ($r < |0.7|$). When pairs of predictors were highly correlated ($r > |0.7|$), we selected those with the highest ecological meaning, based on the knowledge of the system. Thus, the number of predictors used in fire severity modelling was reduced to 15 variables (see Table 1).

The variance explained by RF models, which reports how well a model fits a certain dataset, can be computed using either the internal out-of-bag error rate, or by predicting to a separate independent validation sample. We provide the variance explained based on internal out-of-bag error rates, which removes the need for a set aside test set (Breiman, 2001; Cutler et al., 2007). To obtain stable results, *mtry* (i.e., the number of input predictors evaluated at each split) was determined via initial tuning experiments and *ntree* (i.e., the number of trees to run) was set to 1000. Each tree was growing using a bootstrap sample containing two-thirds of the observation (sampled cells) and the remaining data, one-third were used for model validation (i.e., out-of-bag; Liaw and Wiener, 2002). We also reported the relative importance of each predictor to the variance explained by models. Higher importance values show a stronger influence on controlling fire severity (Fang et al., 2018). The importance of each predictor was measured through the mean decrease in accuracy (% IncMSE) criterion (Grömping, 2009). Because results from RF can vary slightly from run to run, we ran 100 replicated iterations for each built model and provided the average as the final result, aiming at obtaining stable model outputs and minimizing stochastic errors (García-Llamas et al., 2019a).

We ran two sets of RF models for each fire event. Firstly, based on the importance of predictors reported by the full model (i.e., the model including the 15 uncorrelated variables), and following a model selection routine described by Kane et al. (2015) and García-Llamas et al. (2019a), we identified a parsimonious subset of predictors that would provide simpler interpretation of the relationship between predictors and fire severity. Secondly, to determine the relative influence of each category of predictors (i.e., pre-fire vegetation structure, fire history, weather conditions and topography) on fire severity, we also produced individual RF models for each category. Additionally, we obtained partial dependence plots for each variable to show the effect of individual explanatory variables on fire severity.

3. Results

The application of the RF model using a parsimonious set of predictors explained a similar amount of variance than the full model for the fire in the Mediterranean-Oceanic transition site ($R^2 = 0.467$- parsimonious and 0.487- full model), and performed slightly better than the full model for the fire in the Mediterranean site ($R^2 = 0.474$ - parsimonious and 0.469 - full model; Fig. 3; Supplementary Material Table 1, Figs. 1 and 2). Parsimonious models indicated that fire severity in the Mediterranean-Oceanic transition site was controlled by pre-fire vegetation structure, fire history and weather (Fig. 3). Meanwhile,

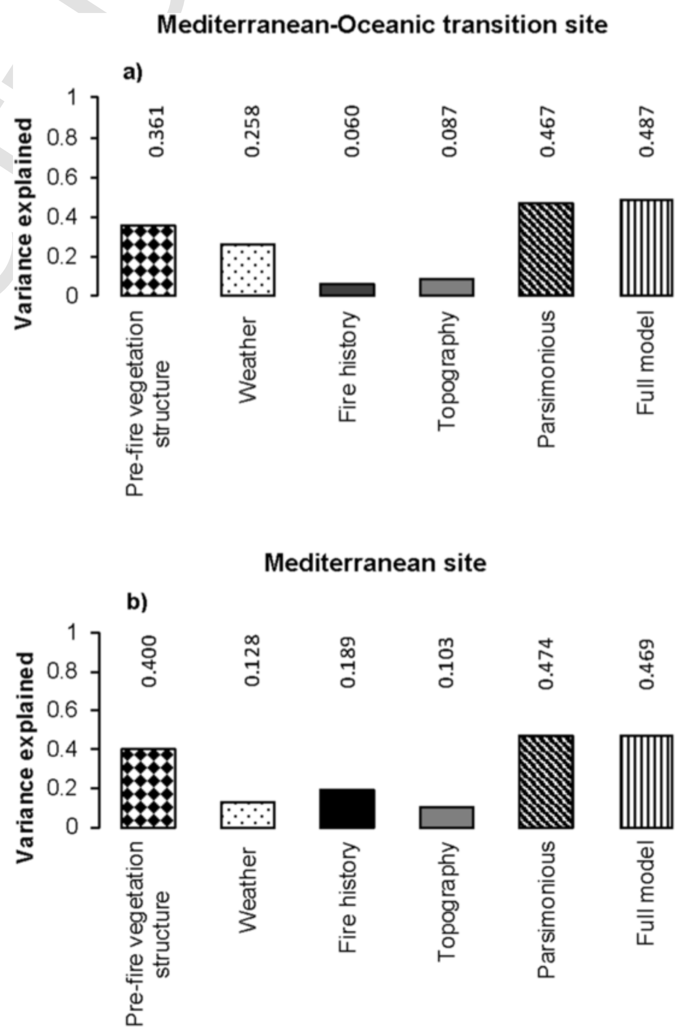

Fig. 3. Fire severity variance explained for the fires that occurred in the Mediterranean-Oceanic transition (a) and Mediterranean (b) sites using different categories of predictors (pre-fire vegetation structure, fire history, weather and topography). Results of both the most parsimonious model and the full model are also shown in the figure.

fire severity in the Mediterranean site was mainly related to pre-fire vegetation structure, fire history, weather and topography. The relative importance of the individual predictors included in the parsimonious set was in decreasing order: shrub cover area, fire recurrence, summer cumulative rainfall, forest cover area, grassland cover area and rumple in the Mediterranean-Oceanic transition site (Fig. 4) and; fruit tree crop cover area, fire recurrence, solar radiation, 25th percentile height of first returns, spring actual evapotranspiration and forest cover area in the Mediterranean site (Fig. 5).

Individual contribution of pre-fire vegetation structure to fire severity was similar for fires that occurred in the Mediterranean-Oceanic transition and Mediterranean sites (R^2 = 0.361 and R^2 = 0.40, respectively), which corresponded to almost two-thirds of the variance explained by the full and the most parsimonious models (Fig. 3). In the Mediterranean-Oceanic transition site, shrub cover area emerged as the most important predictor explaining fire severity (imp = 61.88). Large areas of shrub cover were closely associated with high fire severity (Fig. 4 a). Forest and grasslands cover area and rumple metrics

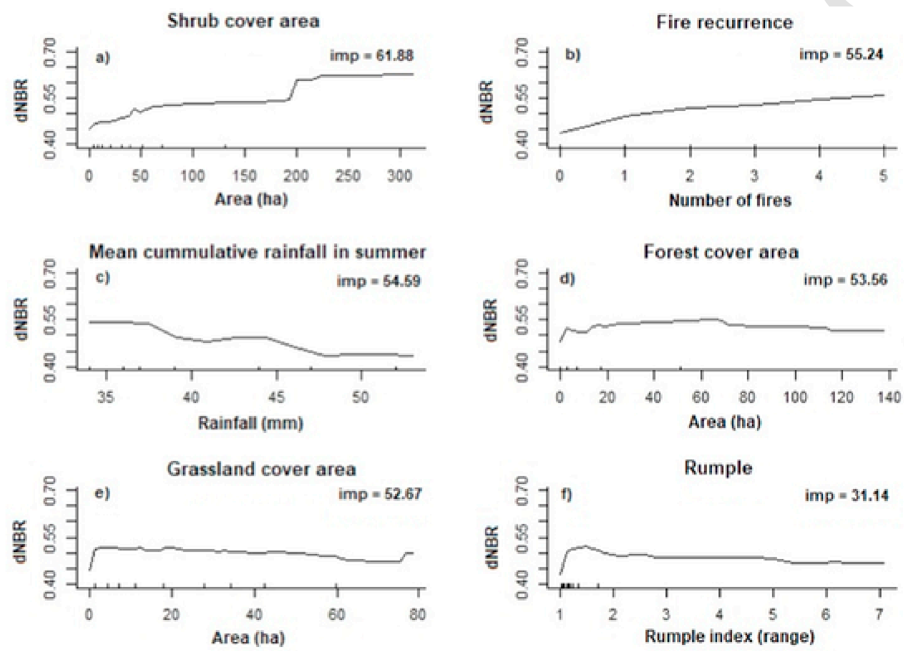

Fig. 4. Partial dependence plots showing the relationship between fire severity, measured as the delta Normalized Burn Ratio (dNBR), and each of the predictors included in the most parsimonious model, for the fire that occurred in the Mediterranean-Oceanic transition site. The normalized importance of each predictor in the model, measured as % IncMSE, is also shown (imp =). Partial plots for the full model shown in Supplementary material, Fig. 1.

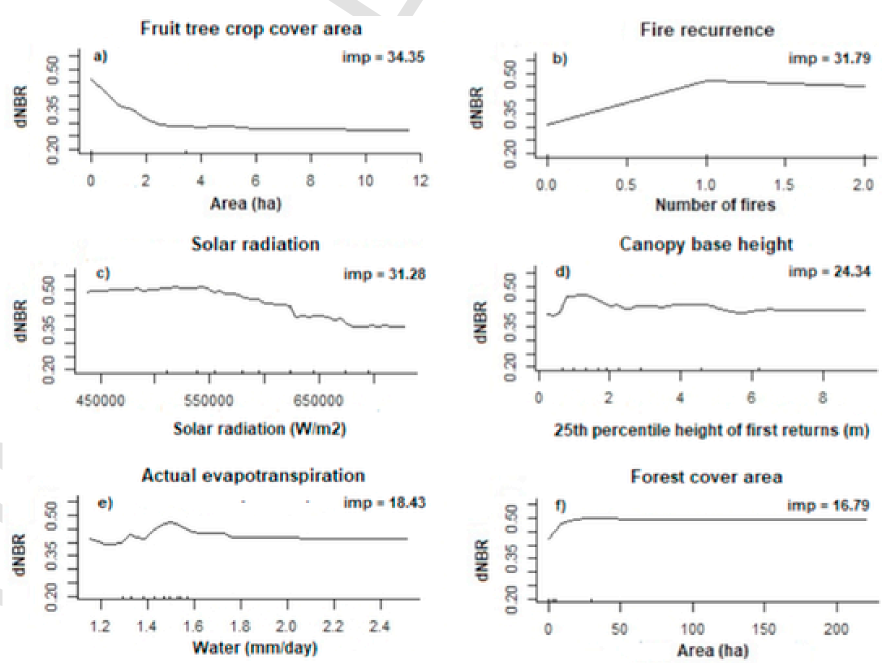

Fig. 5. Partial dependence plots showing the relationship between fire severity, measured as the delta Normalized Burn Ratio (dNBR), and each of the predictors included in the most parsimonious model, for the fire in the Mediterranean site. The normalized importance of each predictor in the model, measured as % IncMSE is also shown (imp =). Partial plots for the full model shown in Supplementary material, Fig. 2.

were also included in the parsimonious model, improving model accuracy by approximately 15%. Overall, an increase in the area occupied by forest increased susceptibility to high fire severity, while large areas of grasslands minimized it (Fig. 4 d, e). Additionally, structural heterogeneity, measured as rumple, reduced fire severity (Fig. 4 f). In the Mediterranean site, fruit tree crop cover area was ranked as the most important predictor in the parsimonious model (imp = 34.35), in combination with other pre-fire vegetation predictors (i.e., the 25th percentile LiDAR return height and forest cover area; Fig. 5 a, d, f). Fruit tree crop cover area was negatively related to fire severity (Fig. 5 a). Low canopy base height, measured as the 25th percentile of LiDAR return height, was also generally associated with greater fire severity levels (Fig. 5 d). Conversely, highly severe fires were linked to large areas of forest cover (Fig. 5 f).

Fire history also showed a clear relationship with fire severity in both study sites. Fire history modelled alone explained low level of variance (Fig. 3). However, recurrence was the second most influential predictor explaining fire severity in the parsimonious model (Figs. 4 b and 5 b). Areas that had been burned at least once experienced higher severity than those that had never been burned (Figs. 4 b and 5 b). In contrast, relationships between weather and topography, and severity changed between the Mediterranean-Oceanic transition and the Mediterranean sites. Weather predictors modelled alone explained almost half of the variance of both the full and the parsimonious models in the Mediterranean-Oceanic transition site ($R^2 = 0.258$), but they had lower effect on fire severity in the Mediterranean site ($R^2 = 0.128$) (Fig. 3). In addition, fire severity in the Mediterranean-Oceanic transition site was influenced by weather during the fire season; low summer cumulative rainfall rates in the fire season contributed to high fire severity (Fig. 4 c). However, in the Mediterranean site fire severity was constrained by antecedent weather conditions. Low actual evapotranspiration values in the spring season were associated with low fire severity, while this relationship reversed at higher actual evapotranspiration values (beyond 1.5 mm of water, Fig. 5 e). Topography had a strong influence on fire severity in the Mediterranean site only, as topographical variables (i.e., solar radiation -imp. = 31.28) were only included in the parsimonious model in this site. Partial dependence plots of these variables showed that the highest values for fire severity occurred in areas receiving low solar radiation (i.e., shady areas) (Fig. 5 c).

3.1. Discussion

The present study demonstrated that pre-fire vegetation structure (i.e., composition and configuration) and fire history had a significant effect on the severity of fires occurred under transition (Mediterranean-Oceanic) and Mediterranean environmental conditions, while the influence of weather and topography was constrained by the study site. Our results confirm the findings of other studies (Kane et al., 2015; Fernández-Alonso et al., 2017; Fang et al., 2018; García-Llamas et al., 2019a), which have suggested that fire severity patterns result from complex interactions among several environmental variables, rather than being controlled by any single environmental factor. The combination of a parsimonious subset of six environmental predictors (i.e., shrub cover area, fire recurrence, summer cumulative rainfall, forest cover area, grassland cover area and rumple, for the fire in the Mediterranean-Oceanic transition site; and fruit tree crop cover area, fire recurrence, solar radiation, 25th percentile height of first returns, spring actual evapotranspiration and forest cover area for the Mediterranean site) performed nearly as well as the full model.

Land cover composition has been found to have little effect on fire severity in other Mediterranean areas in the Iberian Peninsula, likely due to the dilution of the controls of fire severity (i.e., vegetation and topography) within large fires driven by extreme fire weather (Fernandes et al., 2019). However, in our study sites, patterns of fire severity, estimated as the amount of biomass consumed (Keeley, 2009; Morgan et al., 2014), were associated with pre-fire vegetation cover types in both study sites, consistent with the selective effect of vegetation composition on fire severity reported in other studies (Wimberly and Reilly, 2007; Lee et al., 2009; Ramon-Cuesta et al., 2009; Estes et al., 2017). Specifically, fire severity was favored by shrub and forest cover area and negatively related to the grassland cover area in the Mediterranean-Oceanic transition site. Indeed, as in other studies, shrub cover area is strongly affecting fire severity (Odion et al., 2010; van Wagtendonk et al., 2012; Lauvaux et al., 2016), probably because large shrub patches tend to create a more homogeneous and continuous landscape structure with a vast amount of fine fuel fractions, all contributing to high fire spread and severity (Baeza et al., 2002; Loepfe et al., 2010). Additionally, the influence of shrub cover was probably closely related to the fire history of the Cabrera mountain range. Recurrent fires in this area promoted species, such as *Erica australis* and *Genista hystrix*, with adaptations that allowed them to persist under such a fire regime. *Erica australis* resprouts vigorously after fire (Calvo et al., 2008), whereas *Genista hystrix* is a facultative seeder that combines resprouting strategies and seed germination stimulated by fire, as occurs in different leguminous species (Tarrega et al., 1992). Consequently, fire recurrence might influence post-fire species composition patterns across landscapes (i.e. shrub cover), which, in turn affects fire behaviour and severity of subsequent fires (Moreira et al., 2011; Lydersen and North, 2012; Coppoletta et al., 2016).

In the Mediterranean study site, low fire severity was related to fruit tree crop cover while forest cover increased severity. Previous studies reported that the presence of croplands decreased fire incidence (Nunes et al., 2005; Rabin et al., 2015), whereas certain species, such as pines, were strongly related to high severity (Lee et al., 2009). Pine forests tend to be fire-prone ecosystems, likely due to their high flammability associated to chemical properties and structural characteristics of needles (Calvo et al., 2003), and due to pine stratified architecture that enables highly severe crown fires (Ne'eman et al., 2004; García-Llamas et al., 2019a). Therefore, the presence of agricultural fields could fragment this burnable landscape and hence have a suppressive effect on fire (Rabin et al., 2005), decreasing its severity. Additionally, recurrent fires in 1993 and 1994 in this area might favor dense post-fire regeneration pine saplings because of massive post-fire recruitment, which might explain the occurrence of greater fire damage in areas of high fire recurrence (García-Llamas et al., 2019a). *Pinus halepensis* is one of the most dominant tree ecosystems in this Mediterranean study site, which have more than 80% of the mature trees with serotinous cones and early viable seed production (10–15 years). As a result, intensive recruitment of seedlings after fire (density ≥ 100000 individuals/ha), even in young stands, was reported (Tapias et al., 2001). This scenario of great tree density together with highly flammable resprouter and seeder species (*U. parviflorus*, *Cistus monspeliensis*, *C. albidus* and *Brachypodium retusum*), may promote highly pyrogenic fuel and fire propagation, thus reinforcing highly severe fires in the area (Fernandes and Rigolot, 2007; Lentile et al., 2006a,b).

Furthermore, our results showed that pre-fire vegetation composition itself does not fully explain fire severity, but also depends on the structural arrangement of this vegetation (Viedma et al., 2015). In the Mediterranean-Oceanic transition site, results support previous observations showing that increasing vegetation structural heterogeneity (i.e. rumple that reflects horizontal and vertical biomass distribution) may decrease the probability of high fire severity (Miquelajauregui et al., 2016). In this context, horizontal connectivity between canopy fuels can increase the size of high severity patches, while fuels vertically connected (i.e., through ladder fuels) increase the likelihood of vertical fire development (i.e., crown fires; Hoff et al., 2009), causing high severity fires. Structural vertical complexity is highly associated to fire severity in pine forests, due to the stratified architecture of crown and ladder fuels (García-Llamas et al., 2019a; Broncano and Retana, 2004). In our study, regarding the Mediterranean site (*P. halepensis* forest) low canopy base height (25th percentile of height < 2 m) favored greater levels of fire severity, likely because it enables continuity between the understorey and tree canopy, facilitating transition into severe crown fires (Alexander et al., 2006; Jain and Graham, 2007; Fernández-Alonso et al., 2017).

Studies showing an association between pre-fire structural parameters from low-pulse density LiDAR data and fire severity in different fire-prone ecosystems are still limited (Fernández-Alonso et al., 2017). Our findings showed that specific LiDAR metrics that best describe pre-fire vegetation structure are context-dependent, which may be attributable to differences in structural configuration among vegetation types. Nevertheless, results of this study demonstrated that the integration of new data sources with a high level of spatial resolution (i.e., LiDAR data) to model pre-fire vegetation structure as a complement to remote sensing measurements, improves fire severity predictions (Fernández-Alonso et al., 2017; Fernandez-Manso et al., 2019; García-Llamas et al., 2019a).

The relationship between fire severity, weather and topography was not consistent between fires that occurred in the Mediterranean-Oceanic transition and Mediterranean sites. In the Mediterranean-Oceanic transition site, we found fire severity to be a function of cumulative rainfall in the summer season, rather than being associated to topographic predictors. Such a result is probably because under extreme climatic conditions, weather properties may exert dominant control over fire severity in relation to topography, as shown in other studies (Turner and Romme, 1994). In this context, low cumulative rainfall rates during the summer season were likely conditioned by drought during the winter and spring seasons preceding the fire event. Drought has been described as a critical weather element of extreme fire behaviour (van Mantgem et al., 2013; Lecina-Diaz et al., 2014), because it allows high fuel flammability to be achieved, and promotes higher amounts of fuel consumed and energy released during combustion (Dillon et al., 2011). Additionally, these results support the findings of Pausas and Paula (2012) and Turco et al. (2017), who reported that in northern Mediterranean Europe (wetter and more productive), such as in our Mediterranean-Oceanic transition site, fire depends on the occurrence of weather conditions conducive to ignitability and fire propagation. Conversely, fire severity in the Mediterranean site was mainly affected by weather conditions during the season preceding the fire event. Areas of greater productivity (i.e., pine forests *vs* woody crops) generally occur when water is available during the spring season and hence, usually show high actual evapotranspiration values (Kane et al., 2015). This fact may explain the positive relationship between higher spring actual evapotranspiration and higher fire severity and, emphasizes the role of water availability during the preceding months in determining vegetation growth and hence, fuel loads and fire damage during the fire season in Mediterranean ecosystems (Gouveia et al., 2012; David et al., 2016). Additionally, topography may have acted as a surrogate of weather in this site, likely because of interactions between climate and topographic controls on fire severity (Flatley et al., 2011). In this sense, the results of our study attributed extreme fire severity to areas where solar radiation was lower and fuels had less water limitation to growth, which could promote higher fuel accumulation and continuity, and thus, more extreme severity effects (Holden et al., 2009; Román-Cuesta et al., 2009; Lecina-Diaz et al., 2014). Nevertheless, differences in spatial resolution between weather (3 km resolution) and other categories of remote-sensing derived environmental variables (30 m resolution) might be associated with inconsistency in weather variables importance between fires, thus indicating that resolution may affect the predictability of fire severity models (García-Llamas et al., 2019b). Moreover, several studies (e.g., Dillon et al., 2011; Viedma et al., 2015; Estes et al., 2017) have identified fire weather (e.g., wind speed) as an important determinant of fire behaviour and severity. Therefore, the lack of fire weather data in our analyses could arise as a possible limitation of the study. Nonetheless, when wind is included in fire severity analysis it has to be noted that, since in crown fires fire-induced turbulence could interact with the surrounding atmosphere modifying wind currents at surface level, predicting fire behaviour when the effect of the convective plume, is strong is still challenging (Fernández-Alonso et al., 2019).

Our results regarding the main drivers of fire severity provided guidelines to mitigate the severity of fires in Mediterranean-Oceanic transition and Mediterranean fire-prone ecosystems. Given our observations on fire history, combining wildfire suppression, which favours the transition of a large proportion of the landscape into a long-unburned state, with management strategies that encourages less flammable communities, may benefit the control of severe fires in the long term (Odion et al., 2004; Thompson et al., 2011; Dixon et al., 2018). Additionally, our study also provided evidence on the need of implementing long-term pre-fire management actions on fire-prone ecosystems affected by recurrent fires aiming at modifying fuel structure and reducing fuel accumulation. Nonetheless, management treatments need to be designed and implemented taking in consideration vegetation characteristics. Structural homogeneous forestry and shrubland landscapes showed a higher vulnerability to high severity. Therefore, on dense post-fire regeneration pine ecosystems, removal of the smallest regeneration trees through selective thinning could be advisable aiming at reducing fuel loads, breaking fuel continuity and enhancing tree re-growth (Corona et al., 2014). Furthermore, tree canopy base height needs to be considered when designing silvicultural treatments in fire-prone pine forests (Jain and Graham, 2007). Ranges of canopy base height under 2 m are more prone to high severity. Thus, pruning and removing ladder fuels, as well as retaining large trees with taller crowns, in order to enhance canopy base heights above 2 m, would be advisable in order to prevent crowning (Agee and Skinner, 2005). Additionally, effective pre-fire management strategies should give priority to breaking horizontal fuel continuity (e.g. retaining or creating some open patches), aiming at hampering potential fire spread and severity (Lininger, 2006), especially when large patches of shrubland might homogenize landscape. However, fuel treatments by themselves may not be fully efficient without considering location of these fuels (Viedma et al., 2015). Based on the findings of the current study, when management strategies are designed, fuel treatments should be prioritized in northern slopes with lower solar radiation rates and higher biomass accumulation.

4. Conclusions

The results of this study highlight that pre-fire vegetation cover types played a major role in determining severity of fires across the Mediterranean-transition (Mediterranean-Oceanic) gradient. However, the effect of vegetation types should be considered in combination with fire recurrence and drivers of pre-fire vegetation structural configuration. Our results evinced how weather conditions (i.e., low summer cumulative rainfall) may overcome topography and exacerbate fire severity in generally wetter and more productive transition (Mediterranean-Oceanic) sites, specially under severe weather conditions. Conversely, Mediterranean site areas with lower solar radiation rates and higher spring actual evapotranspiration tend to be burnt with greater fire severity. This study provides scientific baselines regarding the drivers of fire behaviour and severity, which is fundamental in the design of appropriate management strategies to reduce fire hazard and fire damage. Forest management treatments should prioritise breaking horizontal and vertical fuel continuity and the enhancement of more open canopy, based on the modification of vegetation structure and by taking vegetation characteristics into consideration.

CRediT authorship contribution statement

Paula García-Llamas: Conceptualization, Formal analysis, Funding acquisition, Methodology, Writing - original draft, Writing - review & editing. **Susana Suárez-Seoane:** Conceptualization, Funding acquisition, Supervision, Writing - original draft. **Alfonso Fernández-Manso:** Supervision, Writing - original draft, Methodology, Writing - review & editing. **Carmen Quintano:** Supervision, Writing - original draft, Methodology, Writing - review & editing. **Leonor Calvo:** Conceptualization, Funding acquisition, Supervision, Writing - original draft.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2020.110706.

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