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An empirical assessment of the potential of post-fire recovery of tree-forest communities in Mediterranean environments

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ABSTRACT

The accumulation of fuel and the homogenization of the landscape in Mediterranean forests are leading to an increasingly hazardous behavior of wildfires, fostering larger, more intense, severe, and frequent wildfires. The onset of climate change is intensifying this behavior, fostering the occurrence of extreme forest fires threatening the persistence of forest communities.

In this study we present an assessment of the post-fire recovery potential of the most representative tree-forest communities affected by fire in Spain: *Pinus halepensis, Pinus nigra, Pinus pinaster* and *Quercus ilex*. A large database of field data collected during specific campaigns -carried out 25 years after the fire- is used in combination with remote sensing, forest inventory and geospatial data to build an empirical model capable of predicting the chances of recovery. The model, calibrated using Random Forest, combines information on burn severity (remote sensing estimates of the Composite Burn Index), local topography (slope and terrain aspect) and climatic data (mean values and trends of temperature and precipitation) to provide information on the degree of similarity (vegetation height, horizontal cover of the vegetation layer along vertical strata, aboveground biomass and species diversity) between the plots burned in the summer of 1994 and the unburned control.

Overall, only 33 out of the 131 burned plots could be considered as recovered, that is, reaching a similar state to unburned stands in neighboring areas. Our results suggest a primary role played by burn severity (the higher the severity the lower the probability of recovery), but strongly modulated by local topographic features (higher probability of recovery on steep north-facing slopes). In turn, increasingly warm and wetter conditions increased the chance of recovery.

1. Introduction

In the last decades we have witnessed unprecedented waves of wildfires and record-breaking fire seasons around the globe. Chile in 2017 (Bowman et al., 2019), Australia in 2019 (Clarke et al., 2022), California in 2020 (Keeley and Syphard, 2021) or Europe in 2022 (Rodrigues et al., 2022) are just some of the most recent examples, all of them localized in Mediterranean environments. The wildfire research community points to climate warming, fuel accumulation and the homogenization of the landscape, along with the lack of proactive management, as the main culprits behind extreme wildfire seasons. Shifting fire regimes into larger, more intense and severe wildfires are envisaged in most Mediterranean countries (Bedia et al., 2014; Ruffault et al., 2020; Turco et al., 2018), threatening the persistence of forest ecosystems and communities and thus the long-term provision of forest-related services (Fernandes, 2013; Jones et al., 2022; Moreira et al., 2020; Tangney et al., 2022; Wunder et al., 2021).

Plant communities and species in fire-prone ecosystems are facing increasingly extreme and frequent fires that endanger their persistence (Pausas et al., 2017). Mediterranean-type ecosystems have co-evolved with fire, nurturing plant species and forest communities into the development of different adaptive traits (e.g., serotiny, resprouting or bark thickness) to coexists with, promote or resist it (Keeley, 2012; McLauchlan et al., 2020; Pausas et al., 2017). Though, repeated stress

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due to increased short-term fire recurrence or intense burning may hinder the ability of fire-adapted species to recover from fire (Nolan et al., 2021; Smith-Ramírez et al., 2022). Moreover, wildfires are colonizing new territories, affecting forest communities that lack adaptive traits and strategies (Nolan et al., 2021). These communities experience long fire-free intervals that contribute to maintain cool and moist microclimates that hinder flammability. However, under extremely dry and/or windy conditions fire may be enabled, shifting an otherwise fire-free ecosystem, fostering successional trajectories into a more flammable forest (Pausas and Bond, 2020).

Monitoring and analyzing the post-fire trajectories of forest communities is of paramount importance to understand their recovery potential and its driving factors. A large body of literature has been devoted to the assessment of post-fire vegetation recovery, with a prominent role of the use of remote sensing (RS) techniques, as highlighted in a recent review article (Pérez-Cabello et al., 2021). RS is often advantageous since it enables the analysis of large regions, provides repeated observations and is an inexpensive source of information. Most satellite-borne spectral sensors record information on multiple wavelengths, enabling the assessment of relevant vegetation-related features such as photosynthetic activity through indices leveraging the near infrared, e.g., normalized vegetation index, or NDVI (Carlson et al., 1997) or moisture content (through assessment based on the short-wave infrared) (Nolan et al., 2016). Spectral RS is indeed the preferred source, while active sensors (radar and laser-based sensors) are gaining in importance, either in stand-alone analysis or complementing spectral analyses, proving insights into structural features (canopy height, cover or vertical variability) (Ameztegui et al., 2021; Domingo et al., 2021; Gelabert et al., 2020; Tanase et al., 2011, 2010). Yet there are several drawbacks and caveats that preclude RS approaches from providing a complete picture of post-fire dynamics and recovery. First, there is a lack of clarity and inhomogeneity in the definition of the term ‘recovery’ itself (Bartels et al., 2016) and the connection between the spectral response and ecological processes is fuzzy (Pickell et al., 2016). In fact, studies focused on spectral indicators are prone to overestimate recovery rates since the response saturates and stagnates early and holds limited ability to infer the structural traits of the vegetation layer, possibly due to the background signal of recovering understory in burned forest ecosystems (Pérez-Cabello et al., 2021; Tanase et al., 2011). To overcome these limitations field measurements and the combination of active (e.g., LiDAR) and optical (e.g., spectral response) sensors are widely recommended (Key and Benson, 2006; Szpakowski and Jensen, 2019; Tomppo et al., 2008).

RS is a widely known tool for the estimation of burn severity, especially useful when there is no possibility to perform field assessments immediately after the fire. Compared to methods based on field measurement of different variables associated with fire impacts, such as the Composite Burn Index - CBI (Key and Benson, 2006), optical RS provides an overarching view of fire scar that allows assessing the spatial variation of burn severity. RS-based estimations of severity can be acquired using empirical models through spectral indices (e.g., the Normalized Burn Ratio; Key and Benson, 1999), or by applying simulation models based on radiative transfer equations (Chuvieco et al., 2006). The latter, such as GeoCBI (De Santis and Chuvieco, 2009), being based on physical principles, have a much greater generalization capacity than empirical models, adapting to more global situations.

In this work we feature an assessment of the potential for recovery of Mediterranean woodland tree-forest communities affected by wildfires. Our approach combines RS estimations of burn severity, fire size (via spectral RS), topographic features (via airborne laser scanner data) and climate conditions (via the ERA5-Land reanalysis dataset) with field measurements of canopy and understory structural features and species composition. We developed and exemplified a procedure combining unsupervised (cluster analysis; Murtagh and Legendre, 2014) and supervised learning (random forest classification; Breiman, 2001) techniques to determine the level of recovery comparing burned and unburned control plots to then investigate the main drivers of recovery, namely burn severity, topography, reproductive strategy, and climate (Bastos et al., 2011; Bousquet et al., 2022; Pickell et al., 2016). A field campaign dedicated to forest and species inventory surveys was conducted in 6 large wildfires (>500 ha) occurred in 1994. Field measurements were retrieved in 2017 and 2018, approximately 25 years after fire, hence providing an assessment of the mid-term recovery potential of forest communities (Rodrigues et al., 2014). Thus, the findings would be of high relevance for predicting recovery potential and unraveling the relative importance of its drivers at this temporal scale, thereby contributing greatly to advancing the current understanding of post-fire regrowth mechanisms. Ultimately, this would support and guide post-fire management and pre-fire mitigation planning (e.g., fuel treatments or prescribed burns).

2. Materials and methods

2.1. Description of the plot network and burned sites

The assessment of post-fire recovery was conducted in a set of 6 large wildfires that occurred during the summer of 1994 (Fig. 1, Table 1 and Table S1). The 1994 season is, to date, the most severe wave of wildfires occurred in Spain, with 92 large fires (>500 ha), burning 335,359 out of the 437,635 ha burned that season (Ministerio de Medio Ambiente, 1995; Rodrigues et al., 2023). The 6 selected fire sites cover a variety of climate conditions in the Mediterranean environment (Bsk, Csa, Cfa and Cfb according to the Köppen-Geiger classification codes; Beck et al., 2018) and tree forest communities (Table 2). None of them experienced fire recurrence.

A network of plots was surveyed during several field campaigns in the years 2017 and 2018, approximately 25 years after the fires. Plots were in zones with no post-fire management (aside from dead wood removal, which is conducted systematically in Spain). We devised a stratified sampling procedure according to the fire size, the representativeness of the forest communities in terms of species (*Pinus halepensis Mill., Pinus nigra Arnold subsp. salzmanni, Pinus pinaster and Quercus ilex sp.*) reproductive strategies (seedling - serotinous or non- serotinous- or recruiting), the burned severity level, and topography (slope and aspect).

Burn severity was determined using GeoCBI (De Santis et al., 2009; De Santis and Chuvieco, 2009) in the context of the SERGISAT research

Fig. 1. Location of the surveyed fire sites, burned in the season 1994. Red dots indicate the location of the selected fire sites and the gray polygons the administrative division in regions and provinces in Spain.
Source: *Instituto Geográfico Nacional, Ministerio de Transportes, Movilidad y Agenda Urbana, Gobierno de España.*

Table 1
Description of the fire sites, summary of surveyed plots and RS imagery used to outline fire perimeters.

Municipality of origin	Fire size (ha)	Ignition Date	Number of plots	Inventory dates	Post-fire image date
Montmajor	43,774.45	1994/07/04	36	2017/07/18–2017/07/24	1994/07/24
Requena	38,750.15	1994/07/05	62	2017/11/11–2018/01/10	1995/08/01
Moratalla	28,352.83	1994/07/04	24	2018/02/14–2018/02/15	1994/08/16
Uncastillo	10,120.41	1994/07/15	22	2016/07/07–2017/06/30	1994/08/23
Villarluengo	29,118.80	1994/07/01	39	2017/07/08–2017/07/16	1994/08/16
Yeste	12,669.33	1994/08/07	20	2018/12/23–2018/12/24	1994/08/23
	162,785.97		203		

Table 2
Number of surveyed plots by severity class and reproductive strategy. Serotinous cones: *Pinus halepensis* and *Pinus pinaster;* non-serotinous cones: *Pinus nigra*; Resprouters: *Quercus ilex.*

Burn severity (CBI-based classes)	Reproductive strategy	Number of plots
Unburned	Serotinous cones	46
	Non-serotinous cones	22
	Resprouters	4
Low (CBI 0.5–2.00)	Serotinous cones	1
	Non-serotinous cones	18
	Resprouters	0
Medium (CBI >2.0–2.75)	Serotinous cones	7
	Non-serotinous cones	5
	Resprouters	8
High (CBI >2.75)	Serotinous cones	66
	Non-serotinous cones	12
	Resprouters	14
		203

project. GeoCBI is based on the adaptation of the radiative transfer models Prospect and Geosail, generating different severity scenarios and assuming interactions between simulation variables (soil colour, leaf colour, leaf area, and tree shape); the Spectral Angle Mapper (SAM) algorithm was used for the inversion of the simulation models.

Below we show the distribution of plots by fire (Table 1), severity classes and reproductive strategy of the dominant forest community (Table 2), and by severity classes and topographic features (Table 3). Surveyed plots were located inside the boundaries of the burned scar perimeters (outlined using Landsat 5 Thematic Mapper imagery; see Table 1) and in a selection of unburned sites in neighboring areas with similar characteristics that served as control conditions. We surveyed a total of 203 field plots (15 m radius), 72 unburned controls and 131 burned (92 high severity, 20 medium severity and 19 low severity).

2.2. Characterizing the level of post-fire recovery

The level of recovery was characterized by comparing burned plots to unburned plots. The assumption for assessing recovery was that burned plots that most resembled the unburned control stands would be considered as "recovered," while the remaining plots would be labeled as “not yet recovered”. The degree of similarity was assessed by comparing

Table 3
Number of surveyed plots by severity class and topographic features.

Burn severity (CBI-based classes)	Aspect exposure	Slope	Number of plots	Number of plots per severity class
Unburned	North-facing	<15 %	21	72
		>15 %	16	
	South-facing	<15 %	19	
		>15 %	16	
Low (CBI 0.5–2.00)	North-facing	<15 %	5	19
		>15 %	4	
	South-facing	<15 %	4	
		>15 %	6	
Medium (CBI >2.0–2.75)	North-facing	<15 %	3	20
		>15 %	5	
	South-facing	<15 %	5	
		>15 %	7	
High (CBI >2.75)	North-facing	<15 %	24	92
		>15 %	23	
	South-facing	<15 %	23	
		>15 %	22	
				203

the main characteristics of the stands including: the height of the tree layer (maximum and mean height were measured using a Haglöf Sweden® Vertex instrument; meters), the fraction of cover along the vertical gradient of strata was assessed visually according to the Braun-Blanquet scale (Braun-Blanquet, 1979; stratum 1 <0.5 m, stratum 2 0.5–1 m, stratum 3 1–3 m, stratum 4 3–5 m, stratum 5> 5 m; percent cover), the amount of above-ground biomass of tree (based on breast height diameter at 1.3 m, using a Mantax Precision Blue diameter caliper Haglöf Sweden®) and shrub species (based on shrub mean height and canopy cover), separately (tons/ha), using the specific allometric equations proposed by Montero et al., (2013, 2005), and the abundance of species including tree, shrub, and herbaceous species (number of distinct species) present in the plot. All these variables were surveyed and measured in the field via forest inventory. Stands were also characterized in term of the burn severity level at 1994 (low-medium-high interval classes based on the CBI - Composite Burned Index, via Landsat imagery and radiative transfer models; De Santis and Chuvieco, 2009) and the pre-fire dominant reproductive strategy (resprouting and obligate seedling) of the forest community extracted from the Spanish Forest Map 1:200,000 (Ministerio de Medio Ambiente, 1997; Rodrigues et al., 2014).

Data on stand characteristics were submitted to cluster analysis to organize plots (both burned and unburned) into specific groups based on their degree of similarity. The rationale for cluster analysis lies in assigning observations to a set of cluster groups so that the characteristics of each observation in a group are more similar among them than to those of the remaining groups. This enables us to determine the level of recovery by identifying the burned plots that share group with most of the unburned stands, i.e., burned plots that resemble the unburned control. We applied hierarchical clustering using the *Euclidean* distance to measure similarity/dissimilarity and *Ward.D2* as agglomeration criterion (Estivill-Castro and Yang, 2004). The number of cluster classes was optimized based on the *Silhouette* index (Rousseeuw, 1987). Variables for stand characteristics were previously submitted to principal component analysis (PCA), a common procedure in cluster analysis (Hair et al., 1998). In this case, we leveraged multigroup PCA analysis, a variant of classic PCA that allows us to investigate possible differences in the component loadings and scores based on a grouping factor (Eslami et al., 2015). Since our focus was establishing the levels of recovery, we explored possible differences depending on the reproductive strategy of the dominant community, a crucial trait modulating post-fire vegetation dynamics. PCA scores for those components meeting the Kaiser criterion were retained and subsequently submitted to cluster analysis. All analyses were developed using the R environment for statistical computing, v4.1.2 (R Core Team, 2021). Multigroup PCA was conducted using the *multigroup* package (Eslami et al., 2015); cluster analysis was performed using the *nbClust* package (Charrad et al., 2014).

2.3. Modeling the likelihood of recovery and its driving factors

The likelihood of post-fire recovery was assessed using classification algorithms. We used the three outcome groups from cluster analysis to establish the recovery classes as follows. Those burned plots grouped with the unburned control were tagged as ‘recovered’ and those burned plots placed in the most distant group to the unburned plots were tagged as ‘unrecovered’. Note that unburned plots were disregarded further on. Then we trained and tested several random forest (RF; Breiman, 2001) models combining the aforementioned classes and a set of predictor variables related with the recovery potential. We analyzed burn severity classes, the dominant reproductive strategy, the aspect and slope of the relief, and climate conditions in terms of average precipitation and temperature and their observed trends. Burn severity was estimated using the CBI (see Table 2). Slope (%) and aspect (azimuth degrees) were computed from a digital elevation model obtained from Airborne Laser Scanning (ALS) data provided by the Spanish Geographic Institute (IGN) via the National Plan for Aerial Orthophotography (PNOA). The datasets were captured between 2008 and 2011 using a small-footprint discrete-return airborne sensor operating at near infrared wavelength (1.064 μm) and ± 28º scan angle from the nadir. The nominal point density in the study area is 0.5 point/m^2, with a vertical accuracy of $\pm$0.2 m and a horizontal accuracy of $\leq$0.3 m. Climate variables were extracted from the ERA5-Land reanalysis dataset (Copernicus Climate Service, 2017). We retrieved monthly data on average temperature and accumulated precipitation in the period 1995–2017 (i.e., from the first year after fire to first the year of the field survey). From that information we computed the yearly average temperature (ºC) and the average of annual precipitation (mm). Trends in temperature and precipitation were computed using the Sen’s Slope (Sen, 1968), a non-parametric test complementary to Mann-Kendall’s procedure for trend detection (Mann, 1945). Sen’s Slope returns the strength of the monotonic trend in a time series. Positive values indicate an increase over time and vice versa (Pohlert, 2020). Trends were used to portray climate dynamics during the period between the fires and the field surveys.

We explored 1000 realizations of RF combining balanced random samples equal in number of observations of 33 recovered and 33 unrecovered plots. The selection of the number of observations came from the classification into clusters. We retained the number of observations assigned to "tree-dominated" forest and " shrubs and grasslands". The minimum number of plots observed in one of these groups was used as a reference value in the sampling procedure, i.e., 33 plots in this case. Each model realization was optimized in terms of number of trees to fit in the RF (*ntree*) and the number of predictor variables that intervene in each split (*mtry*), using 80 % of the selected plots. The remaining 20 % was retained for validation purposes. From each realization we calculated the performance in terms of Area Under the Receiver Operating Characteristics Curve (further referred to as AUC; Hanley and McNeil, 1982) using the test sample. In addition, predictors were ranked in importance and explored via partial dependence plots (PDPs), a graphical representation of the relationship between a covariate and the predicted response (Greenwell, 2017). Models were trained and validated in R using the packages *caret* (Kuhn, 2008), *pdp* (Greenwell, 2017), *pROC* (Robin et al., 2011) and *randomForest* (Liaw and Wiener, 2002).

3. Results

3.1. Post-fire forest structural typologies

The PCA allowed synthesizing the 10 original variables into 5 meaningful components (PC). Fig. 2 summarizes the comparison between normal PCA (all plots together) and multigroup PCA (splitting the data according to the dominant reproductive strategy in the stand). Differences between the two approaches were minor, both in terms of

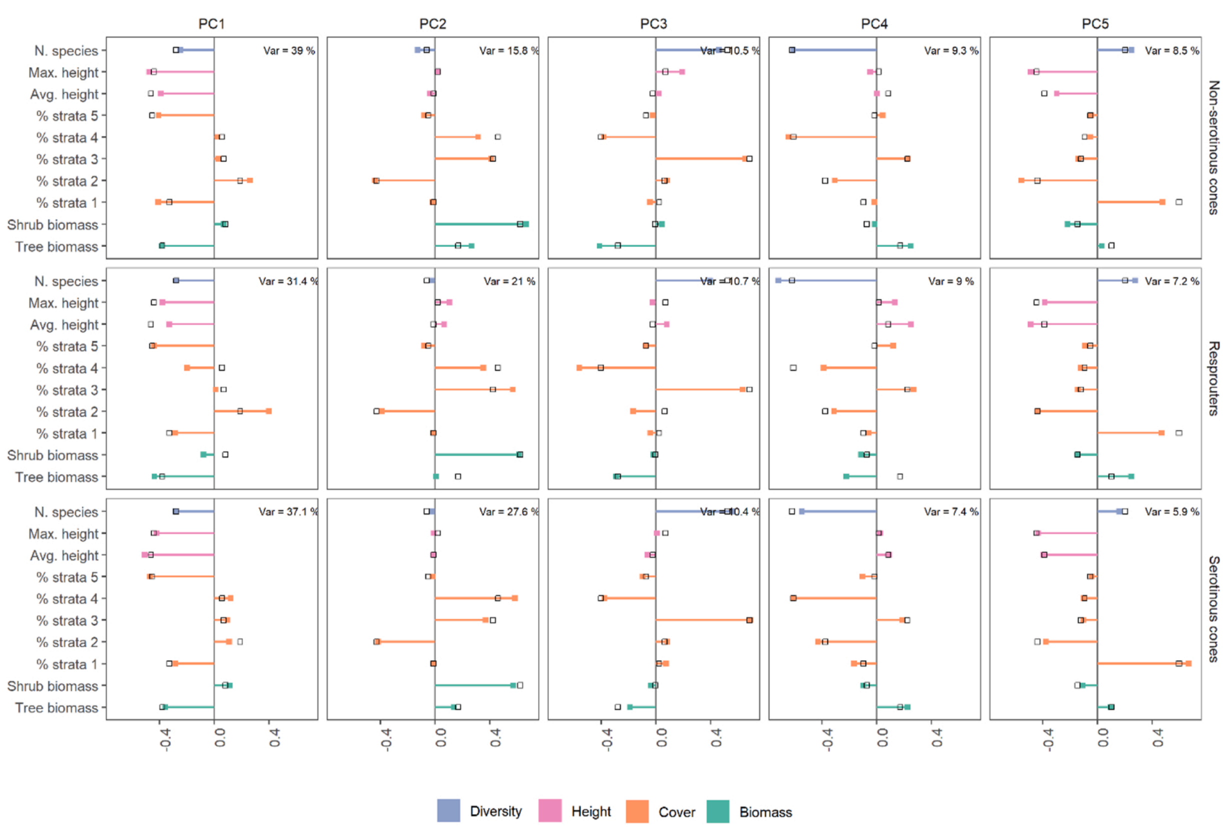

Fig. 2. Summary of PCA and multigroup PCA outcomes. Colored bars indicate the loadings obtained for each variable at a given component in the multigroup approach. The color of the bars indicates the domain to which a variable belongs to. Hollow squares show the common loadings from regular PCA.

the loadings of the original variables on each PC and in the proportion of variance explained by PC. The first 5 components in regular PCA explained up to 85.2 % percent of the original variance whereas the multigroup approach ranged from 79.1 % in resprouter communities to 83.1 % and 88.4 % in seeding communities (with non-serotinous and serotinous cones, respectively). Hence, differences between reproductive strategy in terms of structure, biomass, coverage and diversity in the surveyed plots were slim.

Overall, we identified the following components: PC1, tree-dominated stands (maximum height, mean height, %stratum 5, tree biomass) with biodiverse grassland communities (N. of species, %stratum 1) and no significant presence of shrub understory layers; PC2, transitional forests (%stratum 4 and 3, Shrub biomass) with significant presence of trees (Tree biomass); PC3, medium-sized shrubs (%stratum 3) with high number of species (N. species); PC4, large shrubs (%stratum 4 and 2) with high number of species (N. species); and PC5, stands dominated by grassland communities (%stratum 1) with moderate species abundance.

From these 5 PCs' scores we identified 3 different clusters (Fig. 3). Each cluster showed a distinct forest structural type that will later serve as baseline to assess the recovery stage (see Section 3.2). We identified 'tree-dominated forest' stands with a well-developed tree canopy layer, displaying above-average (Z-score>0) maximum and average height, percent coverage of stratum 5 and tree biomass, and number of species. These stands also showed below average cover of intermediate strata (2–4) and higher than average cover of stratum 1 (herbaceous species), indicating a well-developed tree forest with a dense canopy layer and a bare understory. A second group with plots in a 'transitional woodland' stage, with significant above-average cover in stratum 4, high shrub biomass loads, and below-average number of species. These stands corresponded to homogeneous tree and shrub communities with a dense understory. In the third cluster, named 'shrub and grasslands', we identified those stands with dominance of low strata (2 and 3) with low biomass loads, and small trees and shrubs.

3.2. Post-fire recovery likelihood and its drivers

The recovery state (Fig. 4) was inferred from the association between forest structural typologies (Fig. 3) and (i) burn severity level, (ii) topographic conditions and (iii) dominant reproductive strategy. As can be seen, unburned plots (shown in light yellow) were mainly placed in the 'tree-dominated forest' typology. In contrast, most of the plots affected by high severity burning were classified as either 'transitional woodlands' or 'shrubland and grassland'. There were notable differences in the level of burn severity according to the dominant reproductive strategy. Plots dominated by serotinous species (*Pinus halepensis* and *Pinus pinaster*) were the most frequently affected by high severity fires while resprouting (*Quercus ilex*) and especially non-serotinous (*Pinus nigra*) communities were more frequently affected by low to medium severity burns (Table 2). However, serotinous communities (and resprouting communities to a lesser extent) were more frequently classified (8 plots) as 'tree-dominated' when affected by high severity levels, whereas non-serotinous communities were normally assigned to that group mostly when affected by medium and low severity burns (2 plots with high severity, 15 with low or medium). However, the outcome of the classification seemed to be modulated by topographic conditions. The majority of burned plots showing recovery traits ('tree-dominated' or 'transitional woodland' typology) were located on steep north-facing slopes whereas those classified as 'shrubland and grassland' tend to appear in southern slopes.

The RF models provided a more in-depth understanding of the main forces of post-fire recovery. The models were trained considering the 33 burned plots classified as "tree-dominated forest" as recovered (or nearly recovered; 12 experiencing high burn severity, 9 mid burn severity and 12 low burn severity) and the 49 plots classified as "shrub and grassland" as not yet recovered. Plots in the 'transitional woodland' category were disregarded since we considered them to be in an intermediate stage. Despite a certain degree of variability, the models attained high classification accuracy (AUC=0.87 ± 0.02, n = 1000; Fig. 5A). The range of importance of the predictors (Fig. 5B) reinforced the prominent role played by severity level, slope, and aspect. These three factors were consistently the most influential. Severity was the main restraining factor of post-fire recovery, with approximately 0.35 less chance of recovery when experiencing high severity burns (Fig. 6A). Steep slopes (>15 % of incline) and northwest facing (270–360 degrees azimuthal) enhanced the chances of recovery in 0.20 (Fig. 6C and D). To a lesser extent, climatic conditions were observed to modulate recovery. In general, cooler temperatures increased the likelihood of recovering (Fig. 6H). But the largest effect was exerted by climatic trends in both temperature and precipitation. It was observed that with increasing mean annual temperatures and annual precipitation, the chances of recovery increased by a margin of 0.15. Dominant reproductive strategy (Fig. 6B) was the least important factor. We observed a lower probability of recovery attributed to serotinous communities, although we believe this is related to the fact that this community was more frequently affected by burning during the 1994 fires, and hence in our network of plots. It can be argued that the smaller difference in the probability by reproductive strategies (0.05) compared to severity levels (0.30)

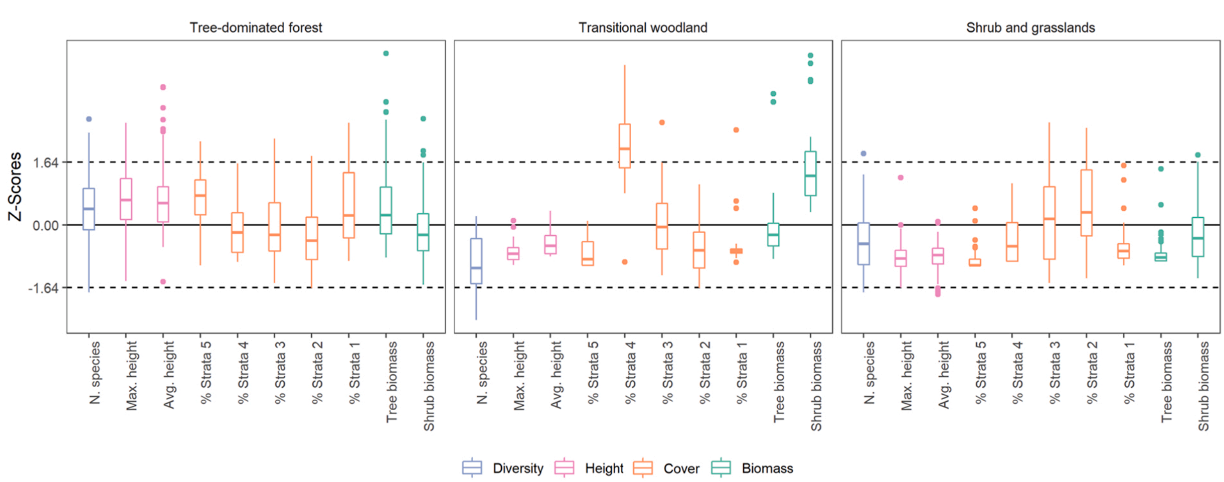

Fig. 3. Description of forest structural typology from cluster analysis. Color indicates the domain to which a variable belongs to. The values of the original variables (x-axis) were expressed as Z-scores (number of standard deviations around the mean centered in 0) to reflect the variety of units of measurement in a common and comparable scale.

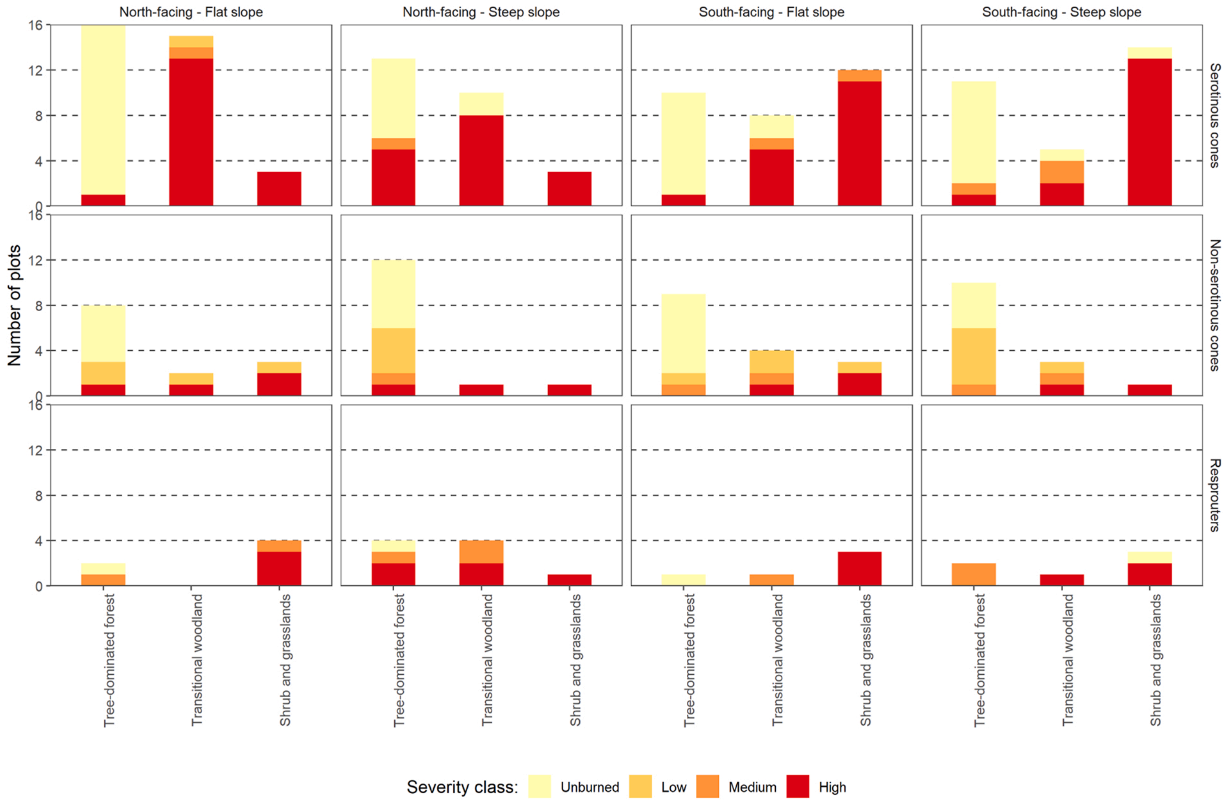

Fig. 4. Distribution of surveyed stands in terms of severity, dominant reproductive strategy, topography, and development stage.

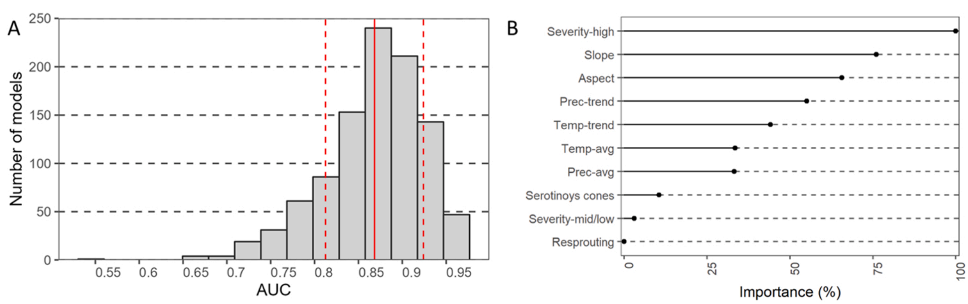

Fig. 5. A) summary of model performance in the 1000 model realizations. Vertical red lines indicate the mean (solid line) and the ±1sd threshold (dashed lines) of the AUC values of all models. B) Rank in percent importance of the analyzed drivers.

indirectly indicates a positive effect on the recovery of serotinous communities.

4. Discussion

In this work we featured an assessment of the potential for post-fire recovery in representative Mediterranean forest communities, namely *Pinus halepensis mill., Pinus pinaster, Pinus nigra* and *Quercus ilex spp.* forests. The approach was rooted in field inventories that characterized the main traits (tree height, vegetation covers along the vertical strata, biomass loads and species diversity) of forest communities 25 years after burning. Our approach was based on the comparison between burned and unburned controls to determine the recovery potential. We defined recovery in terms of similarity, considering burned stands that most resembled the unburned controls as potentially recovered. Many studies on recovery, notably those based on RS, refer to the comparison between post-fire and pre-fire conditions, setting the latter as a strict threshold to be reached to achieve recovery. Optical sensors can only record the plant vigor signal independently of the structure, which we accounted from field inventories (Bastos et al., 2011; Chen et al., 2011; Tanase et al., 2011; Viana-Soto et al., 2022a). Moreover, the ability of RS-based approaches in evaluating post-fire regeneration is often limited by the sensitivity of the sensor to capture the signal of regrowth, being better suited for short-term assessments. Our definition of recovery is advantageous in several ways. For instance, we established a direct comparison between the actual communities burned 25 years ago with analogous and neighboring stands not affected by fire. Assessments based on pre-fire conditions alone assume no-succession during the post-fire regrowth and, thus, that the same community recovers from the fire, which is not necessarily true. Moreover, we based our characterization on specific dasometric information, in line with the recommendation by Bartels et al. (2016).

4.1. About the recovery time after a wildfire disturbance

RS is one of most widespread sources of information used to estimate regrowth trajectories and recovery time after fire (Pérez-Cabello et al., 2021). Multispectral satellite imagery offers a good proxy for green

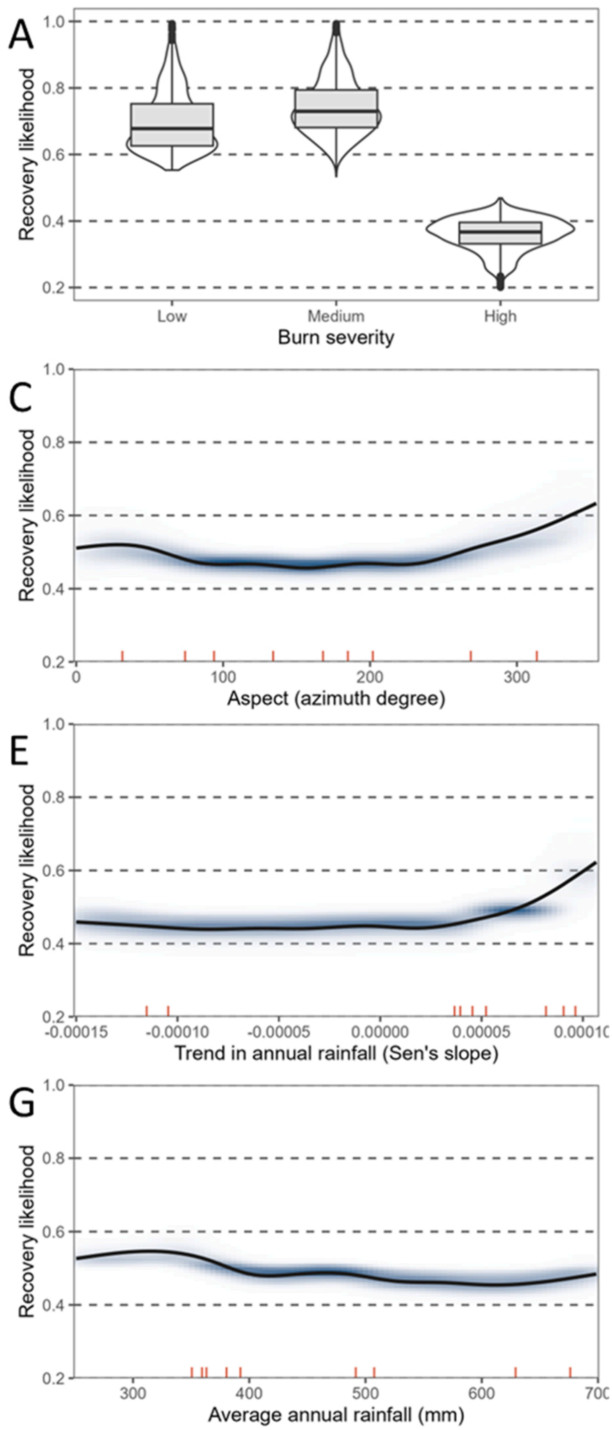

Fig. 6. Relationship profiles between the likelihood of recovery and the analyzed drivers. The solid line represents the average response among the models while the purple area indicates the degree of dispersion among models (the darker the more variability). A) level of severity; B) dominant reproductive strategy; C) aspect (azimuth degrees); D) slope of the terrain (%); E) trend in annual rainfall (Sen's slope); F) trend in annual rainfall (Sen's slope); G) average annual rainfall (mm); H) average annual temperature (ºC).

vegetation regrowth in terms of coverage (e.g., Leaf Area Index or LAI), though it is prone to early saturation and overestimation of recovery and lacks the capability to monitor changes in structure. Tanase et al. (2011) reported a saturation period of approximately 15 years in the spectral response of NIR-based indices (NDVI) in Mediterranean pine forest, compared to the recovery of forest structure estimated from SAR sensors, which identified longer recovery periods. Likewise, the study by Bastos et al. (2011) in Portugal, reported recovery times up to 65 months although Gouveia et al. (2010) found a shorter interval. Spectral-based approaches are limited by their inability to capture vegetation structure or composition, though it is possible to overcome this limitation by coupling it with measurements from active sensors and/or field campaigns (Chu and Guo, 2014; Tanase et al., 2011), such as the one we presented here. In this line, a recent study by Viana-Soto et al. (2022a), (2022b) in the 'Yeste' fire (Table 1) revealed that vegetation cover would reach pre-fire levels, but 50 % of the area would still display significant differences in height. Our findings suggested that this same situation applies to the coetaneous fires we analyzed (Figs. 1, 3 and 4).

Studies based on the reproductive traits of the communities from an ecological perspective reported longer recover time frames. Overall, resprouter tree communities may need approximately 20 years to recover from a fire (Luis and Tárrega, 1989; Martínez Ruiz, 2005) while the response of seeding communities ranges from about 15 in serotinous pines and 45 in non-serotinous (Barbéro et al., 1998; Martínez Ruiz, 2005). Our findings (Fig. 4) suggest that, after a period of 25 years, most fire-affected communities have not yet recovered (understood as reaching a similar state to unburned communities) from the disturbance, especially those experiencing high severity burnings. Many serotinous pine species and resprouter communities still undergo a transitional woodland stage, while non-serotinous species show a wider range of situations fostered by the lower level of burn severity observed.

4.2. Driving forces of post-fire recovery

One of the main novelties of our work lies in the isolation of the marginal effects of burn severity and topography, while providing insights into the influence of climatic conditions and the dominant reproductive traits (seeding and resprouting). Burn intensity and severity are known to determine post-fire dynamics in most forest communities (Keeley, 2009), hence high severity fires have attracted most of the attention in risk assessment frameworks and recovery assessments, assuming that it causes the highest level of damage and vulnerability (Chuvieco et al., 2014; Rodrigues et al., 2014; Román et al., 2013). In line with the literature, our findings (Fig. 5) suggest that severity is the main factor driving post-fire recovery (Chen et al., 2011; Smith-Ramírez et al., 2022). We observed a 0.30 decrease in the probability of recovery after a high severity burn (Fig. 6A). In Mediterranean environments, such as the ones analyzed here, the severity level is closely associated to the type of forest community. *Pinus halepensis* forests, which are well adapted to wildfires and show a rapid recovery response, often experience high severity burnings (Pausas et al., 2008). Likewise, resprouter communities are often considered as a buffer given its high resilience mechanisms (Nolan et al., 2021). On the other hand, non-serotinous recruiters (e.g., *Pinus nigra*) tend to experience lower severity levels (Fig. 4) fostered by cool and moist conditions (Pausas and Bond, 2020). Serotinous communities displayed the highest rates of recovery after high severity burnings (Fig. 4), though the marginal effect from the RF models was possibly biased due to the higher frequency of high severity fires observed in this type of community (Table 3).

The chances of recovery were strongly modulated by the shape of the relief. The effect of severity was closely followed by local topographic features (Fig. 5B), with a probability of recovery 0.20 higher under the adequate topographic conditions. Slopes steeper than 15 % and facing northwest were the optimal conditions for recovery (Fig. 6C and D). The combination of these settings exerts a sheltering effect from insolation that helps in preserving vegetation and soil moisture. There is consensus on the fact that north-facing slopes favor vegetation development, but it has been pointed out that the slope of the terrain favors (Smith-Ramírez et al., 2022, 2021) or limits (Viana-Soto et al., 2020) post-fire recovery. We expected –and confirmed– a positive effect of slope (the steeper the slope the likelier the recovery) since we assessed former tree-dominated communities with well-developed soils able to sustain vegetation. Hence the fire-enhanced soil erosion and loss that steep slopes may reinforce (Parente et al., 2022) should not hinder recovery in the presence of developed soils with sufficient organic matter. Our findings are in line with Smith-Ramírez et al. (2022) who combined spectral RS and field data to assess post-fire recovery in a Mediterranean region of Chile. The assessment by Viana-Soto et al. (2020) in the 'Requena' and 'Yeste' fires (also analyzed here; Table 1) attributed a weaker and elusive link with slope, with shifting relationships depending on the recovery profile and the post-fire stage. Viana-Soto et al. (2020), however, based their assessment solely on time-series of RS spectral profiles. It is thus possible that the post-fire development of green vegetation is less dependent on topography than structure and composition are.

Climate factors modulated the chances of recovery to a lesser degree. The dynamics of temperature and rainfall were more influential than the average conditions (Fig. 6F–H). Increasingly warmer and wetter conditions enhanced the likelihood of recovery by 0.15. The weaker effect played by regional climate conditions compared to topography implies that microclimatic conditions were more relevant. Temperature is the main limiting factor for the physiological development of tree species on a global scale (Körner and Paulsen, 2004). Likewise, the abundance of precipitation during spring and fall are key in the establishment and growth of Mediterranean species like *Pinus halepensis* (Touchan et al., 2017). Nonetheless, post-fire weather exerts a key effect regarding the degree of early coverage of the unprotected soil after burning and consequent modulation of the kinetic action of the precipitation. Although we did not accounted for this effects, historical weather records indicate persistent warm and dry conditions along the Mediterranean rim of Spain (3-month Standardized Precipitation Evaporation Index < 0.85; Beguería, 2017) from early summer (June) until fall-winter (September) of 1994.

4.3. Considerations and implications for forest management

The results of our assessment are relevant for fire risk mitigation and forest planning, although they need to be framed appropriately. The footprint of wildfires is still noticeable in most burned stands. Out of the 131 burned stands, only 33 were classified as recovered tree-dominated forest, and most of these still show differences from neighboring unburned tree forest communities. This suggests that a longer recovery time is needed. However, our temporal benchmark was set at 25 years after burning, imposed by the timing of the field campaigns which matched the average recovery time estimated for most Mediterranean communities (Rodrigues et al., 2014). Therefore, our results are mainly representative of mid-term post-fire conditions and should be understood as such. For example, 'recovered' stands may have reached that state earlier, whereas we do not know how long or whether 'not yet recovered' stands will recover in the future.

On the other hand, the fact that severity is the main driver of recovery backs the suitability of low intensity/severity burnings as a tool for fuel management, capable of controlling fuel availability while ensuring the persistence of the forest community (Clarke et al., 2022). Although our findings on medium-low severity were primarily representative of resprouting communities and non-serotinous pines, these communities were highly resilient when experiencing moderate burn severity, thus being particularly suitable for prescribed burning campaigns.

Water availability and soil/vegetation moisture were both prompted as factors governing the chances of recovery. In this sense, forest management targeting the preservation and enhancement of water balance in forest shall be encouraged (Morán-Ordóñez et al., 2020). Under an scenario of increasing hazardous wildfire conditions (Bedia et al., 2014; Ruffault et al., 2020; Turco et al., 2018), adequate forest management holds the potential to compensate or even mitigate extreme fire behavior while preserving ecosystem services (Miezïte et al., 2022).

5. Conclusions and final remarks

In this work we analyze the potential for post-fire recovery in a collection of wildfires that occurred in the summer of 1994. We combine data on the structure and composition of fire-affected communities and unburned control plots to determine the effect of burn severity, topography, climate, and reproductive strategy on mid-term recovery potential. We analyzed a set of 203 field plots of Mediterranean tree forests dominated by *Pinus halepensis, Pinus pinaster, Pinus nigra* and *Quercus ilex*.

After 25 years, 75 % of the burned plots (98 out of 131) could not yet be considered as recovered, being still in a transitional forest stage. The 25 % that reached a state sufficiently similar to the unburned control did so when they were either affected by moderate burn severity or were in environmental settings that favored recovery. The shading effect of the northwest facades of steep slopes was key to meeting consistent canopy layer development. A warmer and more humid climate also improved the chances of recovery.

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CRediT authorship contribution statement

Marcos Rodrigues: Conceptualization, Methodology, Writing – Original draft, Formal analysis, Funding acquisition. **Juan de la Riva**: Conceptualization, Data Curation, Writing – Original draft, Resources, Funding acquisition, Project administration. **Dario Domingo:** Writing – Original draft, Resources. **Teresa Lamelas**: Writing – Original draft, Resources. **Paloma Ibarra**: Writing – review & editing, Resources. **Raúl Hoffrén**: Writing – review & editing, Resources. **Alberto García-Martín**: Writing – review & editing, Resources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.foreco.2023.121587.

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