ORIGINAL RESEARCH

Short-term recovery of post-fire vegetation is primarily limited by drought in Mediterranean forest ecosystems

Miguel Ángel Blanco-Rodríguez[1,2]*, Aitor Ameztegui[1,2], Pere Gelabert[2], Marcos Rodrigues[3,4] and Lluís Coll[1,2]

Abstract

Background Climate change is altering the fire regime and compromising the post-fire recovery of vegetation worldwide. To understand the factors influencing post-fire vegetation cover restoration, we calculated the recovery of vegetation in 200,000 hectares of western Mediterranean forest burned by 268 wildfires over a 27-year period (1988–2015). We used time series of the Tasseled Cap Transformation Brightness (TCTB) spectral transformation over Landsat imagery to calculate vegetation recovery. Then, we quantified the importance of the main drivers of post-fire vegetation recovery (climate, fire severity, and topography) along an aridity gradient (semi-arid, sub-humid, and humid) using Random Forest models.

Results In most models (99.7%), drought duration was the most important factor, negatively affecting post-fire recovery especially in the extremes of the aridity gradient. Fire severity was the second most important factor for vegetation cover recovery, with its effect varying along the aridity gradient: there was a positive relationship between fire severity and recovery in sub-humid and humid areas, while semi-arid areas showed the opposite pattern. Topographic variables were the least important driver and had a marginal effect on post-fire recovery. Additionally, semi-arid areas exhibited a low mean recovery rate, indicating limitations in the short-term recovery after a fire.

Conclusions Our study highlights the key role that drought duration plays in the recovery of vegetation after wildfires in the Mediterranean basin and, particularly, in forests located in climatically extreme areas. The results suggest that the predicted increase in drought duration coupled with a higher frequency and intensity of large fires may modify the structure and composition of Mediterranean forest ecosystems. Our analysis provides relevant information to evaluate and design adaptive management strategies in post-fire recovery hotspots of Mediterranean forest ecosystems.

Keywords Climate change, Drought duration, Eastern Spain, Remote sensing, Short-term resilience, Tasseled Cap Brightness, Wildfires

Resumen

Antecedentes El Cambio Climático está alterando los regímenes de fuego y comprometiendo la recuperación de la vegetación post-fuego en todo el mundo. Para entender los factores que influencian la restauración de la cobertura vegetal post-fuego, calculamos la recuperación de la vegetación en 200 mil ha bosques el oeste del mediterráneo que se quemaron en 268 incendios en un período de 27 años (1988–2015). Usamos la transformación espectral

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de la serie temporal del *Tasseled Cap Brightness* (TCB) sobre imágenes Landsat, para calcular la recuperación de la vegetación. Luego, cuantificamos la importancia de los principales factores conductores de la recuperación de la vegetación post-fuego (clima, severidad del fuego y topografía), a través de un gradiente de aridez (semiárido, sub-húmedo y húmedo) usando modelos forestales al azar.

Resultados   En la mayoría de los modelos (99.7%), la duración de la sequía fue el factor más importante, afectando negativamente la recuperación post-fuego, especialmente en los extremos del gradiente de aridez. La severidad del fuego fue el segundo factor más importante para la recuperación de la cobertura de la vegetación, con su efecto variando a través del gradiente de aridez: hubo una relación positiva entre severidad del fuego y recuperación de la vegetación en áreas sub-húmedas y húmedas, mientras que en zonas más áridas el patrón fue el opuesto. Las variables topográficas representaron los factores conducentes menos importantes y tuvieron un rol marginal en la recuperación post-fuego. Adicionalmente, las áreas semiáridas exhibieron una recuperación promedio baja, indicando limitaciones en la recuperación post-fuego en el corto plazo.

Conclusiones   Nuestro estudio subraya el rol clave que la sequía juega en la recuperación de la vegetación luego de incendios en la cuenca del Mediterráneo y, particularmente, en bosques ubicados en áreas climáticas extremas. Los resultados sugieren que las predicciones que auguran un incremento en la duración de los períodos de sequía, acoplados a una frecuencia e intensidad más alta de grandes incendios, puede modificar la estructura y composición de los ecosistemas de bosques mediterráneos. Nuestro análisis provee de información relevante para evaluar y diseñar estrategias de manejo adaptativos en la recuperación post-fuego de zonas ubicadas en ecosistemas de bosques mediterráneos.

Background

Forest ecosystems of arid and semi-arid areas are among the most vulnerable to climate warming (Giorgi and Lionello 2008). In the Mediterranean basin (a semi-arid area), climate change is increasing the frequency and severity of droughts (Tramblay et al. 2020; Pulido-Velázquez et al. 2022), leading to serious episodes of forest dieback (Carnicer et al. 2011). In addition, climate change is intensifying the disturbance regimes to which forests are exposed globally (Seidl et al. 2017), particularly wildfires in the western Mediterranean basin (Pausas and Fernández-Muñoz 2012). Recent studies have confirmed that the burned area and the intensity and the severity of forest fires have increased significantly over the past decades (Duane et al. 2021; Grünig et al. 2023), which may limit the capacity of forests to provide ecosystem services (Morán-Ordóñez et al. 2021) and compromise their resilience in the future (Baudena et al. 2020; Nolè et al. 2022).

Post-fire recovery can be modulated by different factors: for example, the type of pre-fire vegetation (Keeley et al. 2005), post-fire climate and weather (Moreno et al. 2011), fire severity (Fernández-Manso et al. 2016), topography (Broncano and Retana 2004), or soil properties (Muñoz-Rojas et al. 2016). Recent studies have underlined the influence of climate in the first few years following a fire. Climate is expected to become increasingly relevant (Stevens-Rumann et al. 2018) because the predicted increase of extreme drought events may seriously limit the re-establishment of vegetation cover (Bendall et al. 2022). In the Mediterranean basin, one of

the world's wildfire hotspots (Pausas 2022), the relationship between post-fire climate and vegetation recovery has been studied locally or based on a small number of wildfires (e.g., Viana-Soto et al. 2020; Fernández-Guisuraga et al. 2023). In these areas, there is a lack of regional analysis regarding the importance of drought events in the recovery dynamics of burnt areas. Furthermore, it is known that overall drier areas may experience limited post-fire vegetation recovery compared with cooler and wetter areas (Young et al. 2019). The persistence of these variations in sensitivity to post-fire climate across the aridity gradients in the Mediterranean basin remains unknown but is crucial for evaluating the future resilience of Mediterranean forests to wildfires.

Remote sensing techniques in which post-fire changes over time are analyzed offer a unique perspective. Here, we leverage analyses of a time-series of Landsat images using the LandTrendr algorithm (Kennedy et al. 2007) to quantify the post-fire recovery of vegetation burned by 268 wildfires over a 27-year period (1988–2015) in areas with different levels of aridity (i.e., semi-arid, sub-humid, and humid) within the Mediterranean basin. We calculated the post-fire recovery rate (5 years after fire) of more than 200,000 ha and analyzed variables considered to be the main recovery drivers (i.e., fire severity, topography, and post-fire climate). To the best of our knowledge, our analysis features one of the longest time periods and the largest number of wildfires in an attempt to unravel the short-term role of post-fire recovery drivers. We hypothesize that (1) post-fire drought (in this case, the length of periods of extreme drought) is the main constraint on

short-term vegetation recovery across the whole Mediterranean aridity gradient and (2) the role of drought in the short-term vegetation response will be more relevant in semi-arid areas than in sub-humid or humid areas.

Methods

Study area and workflow

The study was carried out in three administrative regions of Eastern Spain (i.e., Aragon, Catalonia, and Valencian Community), which cover an area of 103,104 km² within the western Mediterranean basin (Fig. 1a). The climate in this region is characterized by dry summers with a soil water deficit, annual precipitation ranging from 300 to 1200 mm, and mean annual temperatures ranging from 5.0 to 17.5°C. We divided our study area into three aridity classes adapting Martonne's aridity index (MAI; see De Martonne 1926) as follows: semi-arid (≤20 MAI), sub-humid (20–30 MAI), and humid (≥30 MAI). Semi-arid areas are covered by sclerophyllous and xerophilous species, such as Aleppo pine (*Pinus halepensis*) and holm oak (*Quercus rotundifolia*). In sub-humid areas (i.e., transitional zones), forests are dominated by mesophyllous species, such as European black pine (*Pinus nigra*) and Portuguese oak (*Quercus faginea*). Humid areas are dominated by orophilous and hygrophilous species, such as Scots pine (*Pinus sylvestris*) and downy oak (*Quercus pubescens*).

The study area is located within a fire-prone pyroregion characterized by frequent fire activity, accounting for > 50% of the total area burned by large fires (> 100 ha)

in Europe (Galizia et al. 2021). The burned area (Fig. 1b) and the fire severity (Fig. 1c) of our fire dataset differed along the aridity gradient. Semi-arid areas had the largest fire sizes (albeit with high variability), followed by humid and sub-humid areas. Fire severity was highest in humid areas, followed by semi-arid areas (also showing high variability) and sub-humid areas. Perimeters of all wildfires that occurred in the study area between 1988 and 2015 were obtained from local administrations. Following Cardil et al. (2015), we selected wildfires that had affected more than 50 ha, to reach a compromise between sample size and resolution. Fires over 50 ha were responsible for the majority of the total area burned between 1985 and 2021. This filter resulted in the selection of 268 wildfires that had burned a total of 369,037 ha (see Fig. 1).

For each of the 268 wildfires, we extracted a series of Landsat images for the period 1988–2015. We applied the LandTrendr algorithm to define the spectral dynamics before, during and after wildfire. Then, we computed metrics to characterize the vegetation cover at pixel level, and we used ancillary information to characterize topography, fire severity, and post-fire climate for each pixel. Finally, we applied random forest models to ascertain the importance of each driver in post-fire vegetation recovery. Each of these steps is explained in detail below and summarized in a flow diagram (Fig. 2).

Acquisition and pre-processing of Landsat images

We used Landsat TM, ETM+, and OLI imagery with a spatial resolution of 30×30 m to assess the early recovery

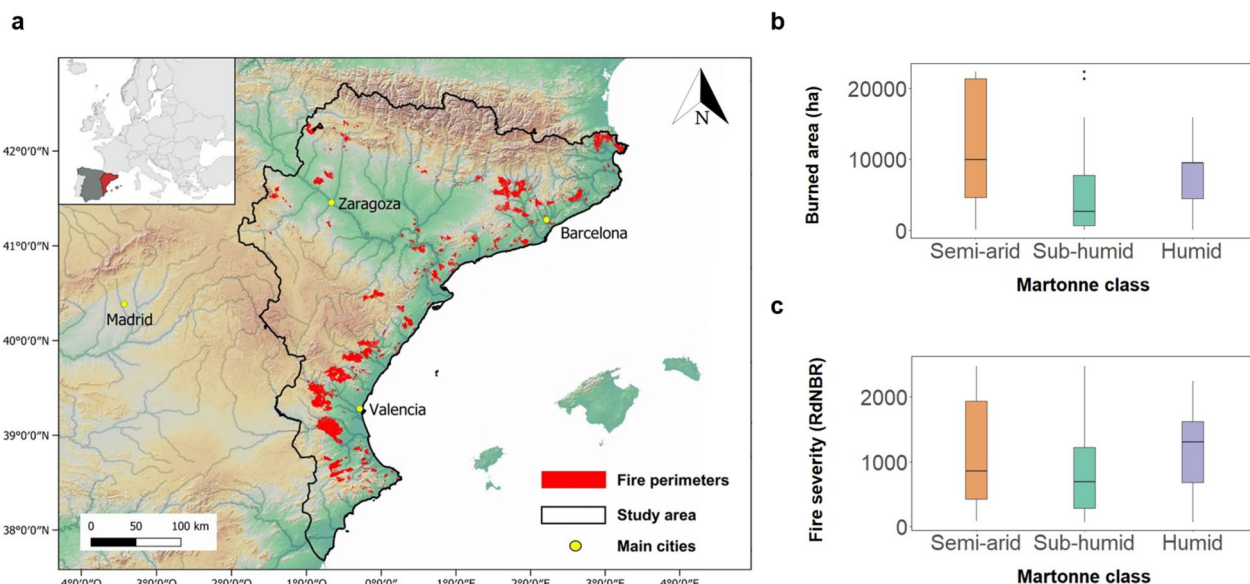**Fig. 1** **a** Location of the study area (the thick black line indicates the study area perimeter) in the western Mediterranean basin and perimeters of 268 wildfires (red polygons) that occurred between 1988 and 2015. **b** Boxplots showing median and interquartile range of burned area (ha) and **c** fire severity of each of the aridity zones as a function of their normalized ratio of relative burn difference (RdNBR) value
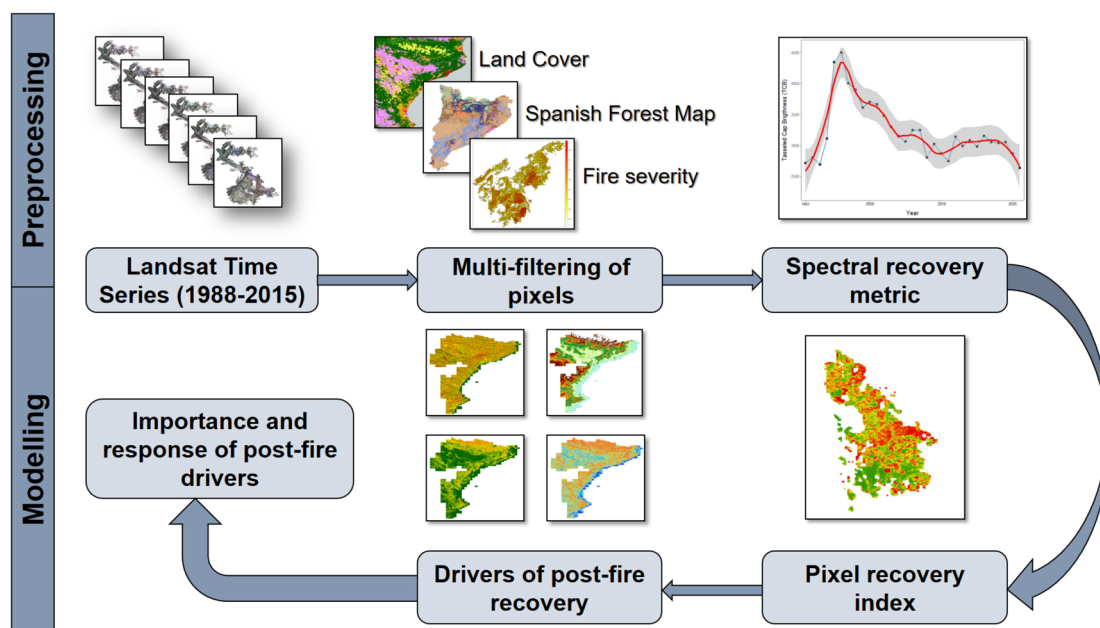
Fig. 2 Flowchart of the methodology, beginning with remote sensing data preprocessing followed by modeling to examine drivers of post-fire vegetation recovery in the western Mediterranean basin

of vegetation cover in the 268 wildfire areas. We obtained Tier 1 surface reflectance imagery through the Google Earth Engine (GEE) platform. To ensure spectral comparability across various Landsat sensors, we homogenized the OLI data with TM/ETM + by a spectral transformation using OLS coefficients calculated by Roy et al. (2016). We performed a temporal aggregation for each year of the 1988−2015 time series using the median spectral value for the summer period (from 20 June to 20 September). This step minimized cloud cover and reduced the noise produced by differences in illumination, coregistration, snow cover, or phenological changes. To denoise the spectral time series, we used the LandTrendr algorithm as implemented on the Google Earth Engine platform. LandTrendr is a set of spectro-temporal segmentation algorithms designed to identify abrupt changes in a time series (Kennedy et al. 2010). In essence, key vertexes of change were identified and trajectories in the original time series were iteratively simplified. Finally, we masked the time series images with fire perimeters grouped from 3 years before the wildfire (to assess prefire forest cover) and 5 years after the fire (to assess postfire recovery).

We synthesized the original spectral values of the Landsat images using Tasseled Cap Transformations, an orthogonal transformation of Landsat spectral bands reducing spectral information along three components: brightness (TCTB), greenness (TCTG), and wetness (TCTW). Tasseled Cap Transformations can be used

to characterize forest recovery processes (Frazier et al. 2015) without the variation in spectral recovery values depending on the spectral index used (Banskota et al. 2014).

We used a classification model to discern forested areas within forest perimeters. To do so, we first calibrated a binary Support Vector Machine (SVM) classification model (forest/non-forest) for each 30-m pixel (see Supporting Information, Tables S1 and S2). The SVM is a non-parametric machine-learning technique designed to identify patterns (Cortes and Vapnik 1995). We then assigned to each pixel the main tree species that was present before the wildfire according to the closest polygon feature to the fire date using the Spanish Forest Map. To characterize fire severity, we calculated the relative difference normalized burn ratio (RdNBR), because it performs better when making comparisons across a range of fires, particularly when sites differ strongly in pre-fire vegetation due to factors such as moisture. To compare the RdNBR before and after the fire in the severity estimation, we manually selected the image closest in time and free of clouds (before and after the fire). This index is a modified version of the difference normalized burn ratio (dNBR) that corrects the misclassification of pixels with low levels of vegetation by dividing the dNBR by the pre-fire NBR value (Miller and Thode 2007). Pixels were classified according to three fire severity classes (Miller and Thode 2007): low severity ($69 > RdNBR < 316$), moderate severity ($316 \geq RdNBR < 641$), and high severity

Blanco-Rodríguez *et al. Fire Ecology*   (2023) 19:68

Page 5 of 10

(RdNBR ≥ 641). Using this multiple filtering process, we obtained a total of 2,258,411 million pixels (203,257 ha) relating to the 268 wildfires for which we subsequently calculated the short-term recovery index of vegetation.

Post-fire recovery

We used Tasseled Cap Transformation Brightness (TCTB) to characterize post-fire vegetation recovery. TCTB is related to surface albedo and the changes occurring immediately after wildfires depend on the relative concentrations of materials such as ash (leading to whitening) and soot (leading to blackening), among other factors (Ramanathan & Carmichael, 2008). TCTB has been used in recent studies to characterize the revegetation process following forest disturbances (for defoliators and bark beetles, see Senf et al. 2015; for woody encroachment, see Gelabert et al. 2021), including the measurement of post-fire vegetation reestablishment at different stages of the recovery process in Mediterranean areas (Viana-Soto et al. 2020).

In this study, we measured post-fire recovery after 5 years according to the recovery index proposed by Lloret et al. (2011). This index calculates the ratio between performance after and during the disturbance. The performance during the disturbance was defined as the TCTB value for the year of the fire ($TCTB_i$), whereas the performance after the event was based on the TCTB value 5 years after the fire ($TCTB_{i+5}$). Given that a higher level of brightness (i.e., a higher TCTB value) is associated with bare soil than with soil with vegetation cover, we changed the sign of the recovery index by subtracting both $TCTB_i$ and $TCTB_{i+5}$ from the maximum TCTB value observed in the pixel. We fitted this index to our spectral metric as follows:

$$\text{Recovery index} = \frac{\max(TCTB) - TCTB_{i+5}}{\max(TCTB) - TCTB_i}$$

The recovery index takes a value of 1 when $TCTB_i = TCTB_{i+5}$ (i.e., no recovery), greater than 1 when there is a decrease in brightness (i.e., an increase in vegetation cover), and 0 when $TCTB_{i+5}$ equals the maximum TCTB (i.e., the minimum cover value observed 5 years after the fire).

Explanatory variables

We selected a set of variables that influence post-fire vegetation recovery in Mediterranean areas (see Keeley et al. 2005 or Martín-Alcón and Coll 2016). We characterized the effect of the post-fire climate by determining the duration of drought spells during the recovery period. We first used the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2010, 2017) to characterize climate for the entire time series

(1988–2015) with temporal windows of 3, 6, 9, and 12 months and a spatial resolution of 1 km at weekly time intervals. After preliminary analyses, we decided to use the 6-month SPEI for subsequent analyses because it achieved a higher correlation with the post-fire recovery index (see Figure S1). SPEI values lower than −1 correspond to a meteorological drought situation (Abbasi et al. 2019), so we characterized drought duration as the maximum number of consecutive weeks with a SPEI of < −1 during the recovery period (i.e., the first 5 years after the fire).

To assess the effect of fire severity, we used the RdNBR value at a spatial resolution of 30 m. The effect of topography was determined using an adaptation of the northness index, which is the product of the cosine of the slope aspect multiplied by the slope of the terrain (Martín-Alcón and Coll 2016). Slope aspect cosine values range from −1 for southern exposures to 1 for northern exposures, whereas the slope reflects the steepness of the terrain. Finally, we used the Topographic Moisture Index (TWI) to assess potential soil moisture due to topography and determine its influence on post-fire regeneration (Agne et al. 2022). All variables were resampled and co-registered according to the centroid of Landsat pixels.

Modeling drivers of post-fire recovery

We used the Random Forest (RF) algorithm to analyze the importance and the effect of explanatory factors in short-term vegetation recovery after fire. RF is a non-parametric machine-learning ensemble algorithm based on decision trees that can handle large volumes of data (Breiman 2001). To calculate and calibrate RF regression models we used the 'caret' R package (Kuhn 2008), with drought duration, fire severity, northness index, and TWI as predictor variables and recovery index (defined in the "Acquisition and pre-processing of Landsat images" section) as a response variable. We first fitted a global model containing data from all aridity areas, and hyper-parameters were optimized using tenfold repeated cross-validation with five replications. We used bootstrapping to avoid the effects of the huge sample size on the significance of the parameter estimators (White et al. 2014) and to avoid the potential misspecification of the model due to spatial autocorrelation. Thus, we fitted 500 models, each with a subsample of ~3000 randomly chosen data points (110 for each of the 27 years of the time series). Data were stratified by year so as to avoid the sample being disproportionately influenced by years with a high number of large fires (see Figure S2 for details). For each iteration, 80% of the sample was used for training and 20% for validation, and we discarded those iterations where residuals of models showed significant spatial autocorrelation (*p*-value of Global Moran's $I < 0.05$). Then,

Blanco-Rodríguez *et al. Fire Ecology*   (2023) 19:68

Page 6 of 10

we split the dataset into three based on aridity area and repeated the procedure to fit 500 bootstrapped models for each aridity area as explained above.

We evaluated the performance of the models, calculating the mean R^2 and root mean square percentage error of the regression line between the observed and the predicted response across the 500 bootstrapped iterations, using the validation sampling. In addition, the importance of explanatory variables was calculated using the percentage increase in mean square error and model improvement ratio (MIR) metrics. The MIR is comparable between models and avoids the bias of the influence of the total number of metrics in the model (Murphy

et al. 2010). The MIR is calculated as [In/Imax], where In is the importance of a given metric and Imax is the maximum model improvement score (which always takes a value of 1). The most important variables will have values close to 1, whereas the less relevant ones will have lower scores.

Results

Our overall model (all aridity classes together) pointed to post-fire drought duration as the most important factor determining post-fire vegetation recovery at 5 years (see Fig. 3a and Table 1). Drought duration was identified as the most important variable in 99.7% of the total
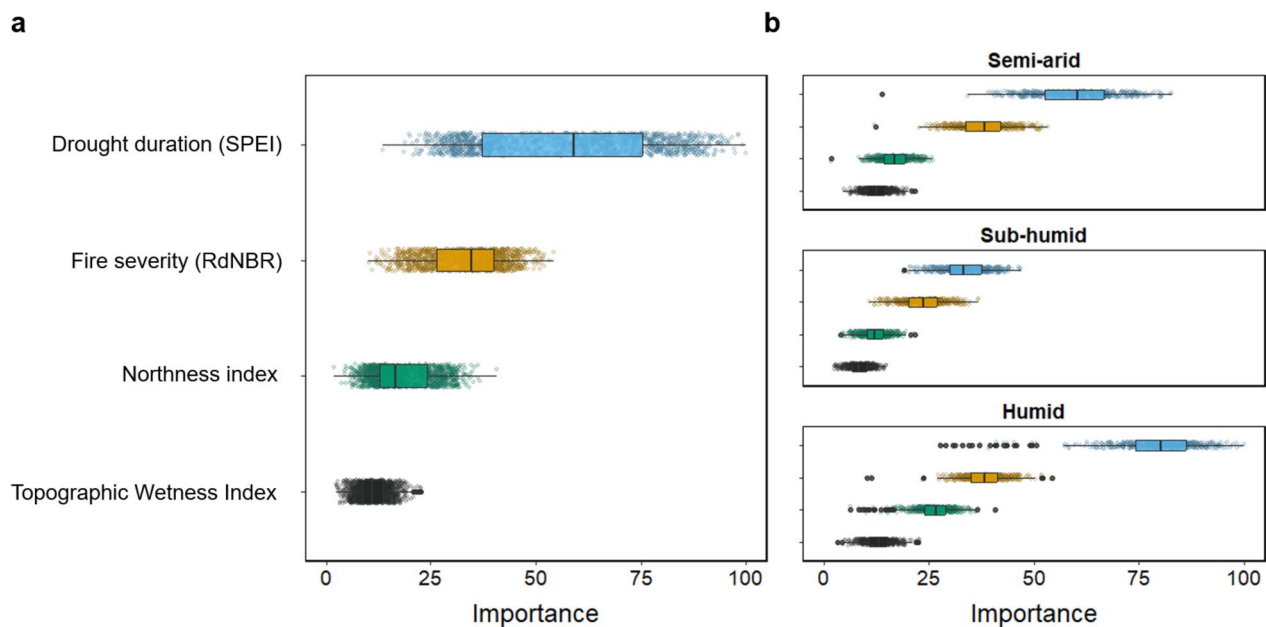

Fig. 3 Boxplot of importance values (percentage increase in mean square error) of predictor variables for 5 years post-fire vegetation recovery in the western Mediterranean basin. The black line inside the boxes is the median of importance value across the 500 bootstrap random forest models for **a** all aridity areas analyzed together, and **b** semi-arid, sub-humid, and humid areas analyzed separately. Abbreviations: SPEI, Standardized Precipitation Evapotranspiration Index; RdNBR, relative difference normalized burn ratio

Table 1 Calculated importance of variables in Random Forest models for predicting post-fire recovery in three aridity areas (pooled and separately) in the western Mediterranean basin according to the model improvement ratio (MIR). Means and standard deviation (SD) of the percent root mean square error and *R* squared of each model are also indicated

	All	Semi-arid	Sub-humid	Humid
Variable importance (MIR)				
Drought duration (SPEI)	1.00	1.00	1.00	1.00
Fire severity (RdNBR)	0.54	0.64	0.78	0.54
Northness index	0.25	0.31	0.46	0.41
Topographic wetness index	0.18	0.26	0.31	0.23
% Root mean square error (SD)	3.76 (±0.34)	3.33 (±0.35)	3.68 (±0.35)	3.09 (±0.25)
Mean *R* squared (SD)	0.18 (±0.05)	0.24 (±0.06)	0.09 (±0.04)	0.49 (±0.06)

Abbreviations: SPEI Standardized Precipitation Evapotranspiration Index, *RdNBR* relative difference normalized burn ratio

iterations and was the second most important variable in the remaining iterations (see Supplementary Material—Table S3). The second most important variable determining post-fire recovery was fire severity, followed by the northness index and topographic wetness index. Models applied separately to each aridity area indicated an effect of aridity on the importance ranges of predictor variables, but not on their ranking of importance (see Fig. 3b and Table 1). Semi-arid and humid areas showed a strong and negative effect of drought duration on short-term post-fire recovery (Fig. 4a). However, the importance of drought on the early post-fire response was less clear in sub-humid areas, despite still being the most important predictor.

RF models allowed us to analyze the marginal effect of predictor variables on short-term vegetation recovery after fire. Figure 4a shows a strong decrease in recovery due to the longer duration of drought conditions in semi-arid and humid areas, but no clear pattern was observed for sub-humid areas. Fire severity induced different patterns of recovery depending on the aridity area (Fig. 4b). Recovery largely increased with increasing fire severity in humid areas; however, this effect was less strong in sub-humid areas. Interestingly, the effect was reversed in semi-arid areas, where recovery was negatively affected by increasing fire severity. Topography, characterized by the northness index (Fig. 4c) showed an overall low effect across all aridity areas, with slightly negative effects on recovery for semi-arid and sub-humid areas, whereas this effect was positive in humid areas. Finally, the TWI (Fig. 4d) exerted a slightly positive effect on recovery in all aridity areas.

Discussion

In this study, our analyses showed that short-term, post-fire vegetation recovery in the western Mediterranean basin is strongly conditioned by post-fire climate and particularly by the duration of drought during the first years after the disturbance. These results support our first hypothesis that post-fire climate is the most important determinant of Mediterranean post-fire vegetation dynamics after a wildfire. They suggest that the predicted increase in the occurrence of extreme drought periods associated with climate warming will limit the capacity of Mediterranean vegetation to recover after fire (Rodman et al. 2020). Within the Mediterranean region, areas of burnt forest distributed in semi-arid areas showed an average recovery index of below 1, indicating that
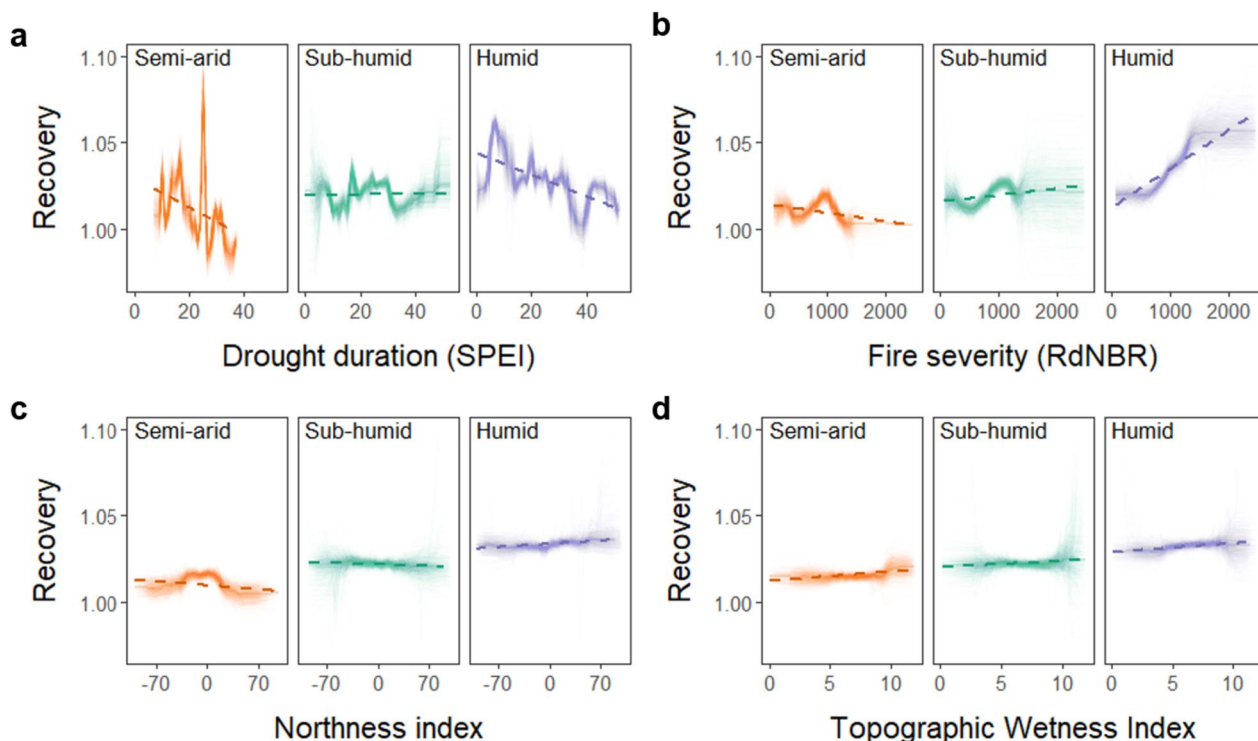

Fig. 4 Partial dependence plots showing the marginal effect of predictor variables (*x*-axis) on post-fire vegetation recovery (*y*-axis) for three aridity areas in the western Mediterranean basin. The predictor variables analyzed were **a** the maximum number of consecutive weeks with Standardized Precipitation Evapotranspiration Index (SPEI) values of < − 1; **b** fire severity, measured in relative difference normalized burn ratio (RdNBR) values; **c** the northness index; and **d** the topographic wetness index

Blanco-Rodríguez *et al. Fire Ecology*   (2023) 19:68

Page 8 of 10

vegetation has a rather poor ability to recover rapidly after fire.

Short-term drivers of post-fire regeneration

The effect of drought duration on post-fire recovery varied across three different aridity areas that were defined according to the Martonne index (i.e., semi-arid, sub-humid and humid). Contrary to our second hypothesis, drought duration had the greatest impact on vegetation recovery at both extremes of the aridity gradient (i.e., semi-arid and humid areas). Stevens-Rumann et al. (2018) previously reported the negative effects of drought on the post-fire recovery of wet forests in a multi-regional study conducted in the US Rocky Mountains. For arid environments, the negative effect of drought on recovery is consistent with recent observations that adaptations to drought (embolism resistance) may be antagonistic to the post-fire recovery process (Resco de Dios et al. 2018). However, we found no effect of drought duration on the post-fire recovery of sub-humid areas. This might be related to the post-fire response mechanisms (i.e., resprouting capacity and serotiny) of the vegetation dominating these areas (for more details, see Table S4 and Figure S3).

Fire severity also conditioned early post-fire vegetation recovery, although to a lesser extent than drought. In a recent study, Davis et al. (2023) reported that decreasing fire severity can help to reduce the negative effects of post-fire weather on short-term vegetation reestablishment. In our study, the role of fire severity changed depending on the level of aridity within the study area, with humid and sub-humid areas showing stronger vegetation recovery as fire severity increased and arid areas showing the opposite pattern. An explanation for fire severity having a less marked effect on the recovery of forests located in semi-arid areas may be the dominance of *P. halepensis* (see Table S5). Previous studies on this serotinous species have not found a clear relationship between the abundance of post-fire vegetation regeneration and fire severity (Pausas et al. 2002). Besides, positive correlations between fire severity and vegetation recovery in sub-humid and humid areas might be explained by the increasing dominance of resprouting species in forests prior to fire (see Meng et al. 2018 and Figure S3). This idea is also supported by Zeppel et al. (2015), who showed that post-fire recovery is faster in areas dominated by resprouters that have been burnt by a high-severity fire.

Local topographic conditions (e.g., aspect or elevation) are considered important factors that modulate local post-fire vegetation in Mediterranean areas (Martín-Alcón and Coll 2016). However, our analyses showed that topographic variables had a marginally weak effect on the post-fire response in all aridity areas. Climate and topography are often correlated, suggesting that local effects of topography may be stronger than our analyses suggest (see Bright et al. 2019 for this effect).

Remote-sensing detection of post-fire recovery

The use of multi-sensor or multi-member spectral mixture analyses has recently gained importance when assessing post-fire recovery (Fernandez-Manso et al. 2016; Meng et al. 2018). In turn, different spectral indices have been used to measure post-fire recovery, such as the NBR (Bright et al. 2019) or the Normalized Difference Vegetation Index (Vicente-Serrano et al. 2011). In our study, TCTB was the best predictor of pre-fire forest cover, robustly discriminating those pixels that were forest vs non-forest 3 years prior to disturbance (see Tables S1 and S2). In a recent study, TCTB was used to assess post-fire trajectories of pixels in NW Iberia (Marcos et al. 2023) and—unlike Tasseled Cap Wetness, which indirectly assesses canopy structure through the increased ability of the vegetation to retain moisture as the vegetation grows vertically—TCTB is considered to be suitable for assessing early vegetation recovery stages where ground cover occurs (Viana-Soto et al. 2020). TCTB is sensitive to canopy disturbances that drastically reduce canopy cover, causing an increase in albedo (i.e., an increase in TCTB values) at the time of a disturbance, and can capture the process of vegetation reestablishment, which decreases albedo (i.e., a decrease in TCTB values) in the first years after a disturbance (Oliver and Larson 1990).

Remote sensing data enables a very large area to be assessed and provides relevant information on forest dynamics. However, because data are based on reflected light measurements, caution is needed when interpreting them in terms of ecological processes (Bright et al. 2019). For instance, neither the different vertical strata of vegetation after a fire (Meng et al. 2018) nor the composition of species forming the post-fire community can be distinguished using a single spectral index. Integrating field data and remote sensing information is challenging but would provide a deeper understanding of such complex ecosystem processes (Senf 2022). Finally, combining our post-fire recovery trajectory data with Light Detection and Ranging techniques may also allow a better structural characterization of post-fire vegetation communities (Pérez-Cabello et al. 2021).

Conclusions

The use of TCTB and time series analysis algorithms enabled the short-term post-fire vegetation recovery of a set of 268 wildfires that burned over 200,000 ha in eastern Spain between 1988 and 2015 to be analyzed.

Blanco-Rodríguez *et al. Fire Ecology*   (2023) 19:68

Page 9 of 10

Our analyses highlight the critical role that post-fire climate plays in vegetation recovery. They suggest that the future resilience of Mediterranean forests could be compromised given the increasing recurrence of extreme drought periods expected in this area. From a management perspective, our findings highlight that particular attention should be given to forest distributed at both extremes of the climatic gradient found within the Mediterranean region.

Abbreviations

MAI	Martonne's aridity index
TCTB	Tasseled Cap Transformation Brightness
TCTG	Tasseled Cap Transformation Greenness
TCTW	Tasseled Cap Transformation Wetness
SVM	Support Vector Machine
RdNBR	Relative difference normalized burn ratio
dNBR	Difference normalized burn ratio
SPEI	Standardized Precipitation Evapotranspiration Index
TWI	Topographic Wetness Index
RF	Random Forest
MIR	Model improvement ratio
SD	Standard deviation

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s42408-023-00228-w.

Additional file 1: **Table S1.** Confusion matrix of the best forest/non-forest classification model showing the number of observed and predicted pixels according to the SVM model. **Table S2.** Results of the 10 best SVM models sorted by Kappa value for forest/non-forest classification in pixels within fire perimeters. **Figure S1.** Corplot including predictor variables, recovery, and time scales at 3,6,9 and 12 months for the SPEI calculation. **Figure S2.** Barplot showing the temporal distribution of the 268 wildfires analysed for the 1988-2015 time series. **Table S3.** Importance ranking of explanatory variables included in the 2000 iterations of the post-fire recovery models according to aridity gradient. **Table S4.** Distribution of the percentage of burned area for the three post-fire mechanisms analyzed in the study area. **Figure S3.** Proportion (in percentage) of the three vegetation typologies analyzed (serotinous, non-serotinous and resprouters) in each of the three aridity areas considered (semi-arid, sub-humid and humid). **Table S5.** The number of pixels and percentage of burned area by forest species are shown for semi-arid areas.

Authors' contributions

MAB: conceptualization, methodology, formal analysis, and drafting of the manuscript. AA and LC: conceptualization, methodology, formal analysis, funding, and revision of the manuscript. PG: conceptualization, methodology, formal analysis, and revision of the manuscript. MR: methodology and revision of the manuscript. All authors read and approved the final manuscript.

Availability of data and materials

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare they have no competing interests.

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Blanco-Rodríguez *et al. Fire Ecology*   (2023) 19:68

Page 10 of 10

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