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Elucidating factors driving post-fire vegetation recovery in the Mediterranean forests using Landsat spectral metrics

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ABSTRACT

Wildfires represent one of the primary disturbance agents in the Mediterranean, significantly affecting the ecological integrity of forests. Therefore, understanding the spatial patterns of post-fire vegetation recovery is crucial to improving forest restoration planning and assessing the regeneration capacity of different forest stands that have been impacted by wildfires. In this study, we analysed post-fire vegetation recovery rates within the context of fire severity, pre-fire vegetation, and post-fire climate conditions, for different Mediterranean forest classes, namely, Mediterranean pine, holm, deciduous oak forests, sclerophyllous vegetation, and thermophilous shrublands. Basilicata, in Italy, was chosen as a study area, as it represents a wide range of forests.

The Relative Recovery Indicator (RRI) was derived from Normalized Burn Ratio (NBR) patterns extracted from 30-meter Landsat time series for different wildfires that occurred during the 2004–2016 within Google Earth Engine (GEE) environment. A Linear Mixed Model (LMM) was used to test the effect of the different variables on the RRI. Results showed a general decrease in recovery rate within five-years post-fire for each forest cover class, which is mainly related to pre- and post-fire conditions. Pre-fire vegetation conditions significantly influenced post-fire vegetation recovery, especially in sclerophyllous and deciduous oak forests. Post-fire climate conditions (e.g., temperature) were also important predictors of vegetation recovery explaining the variation in post-fire RRI patterns. The proposed method could provide new insights into the restoration and management of forest ecosystems in the Mediterranean.

1. Introduction

In recent decades, ecosystems have been increasingly affected by natural and anthropogenic disturbances that are driven by climate extremes (Seidl et al., 2017). In the Mediterranean, wildfires represent one of the main ecological disturbances, as they greatly disrupt ecosystems across structural and functional axes (Pausas et al., 2008). Specifically, this region exhibits variability in the post-fire successional trajectories that is amplified by several factors, yielding complex ecosystem dynamics and disturbance regimes (McLauchlan et al., 2020). Understanding how the interaction of environmental factors and post-fire successional trajectories would shape future forest ecosystems is important in the prediction of post-fire recovery patterns under rapidly changing climatic conditions. Fire-linked disturbances in Mediterranean forests yield a heterogeneous set of outcomes, driven by the structure and composition of plant communities and a variety of wildfire-linked factors (e.g., pattern, frequency, and intensity) (Keeley et al., 2011). Wildfires impact many aspects of forest ecosystems; for example, they can facilitate the loss of biomass via soil erosion and water runoff, modifying the following factors: community composition, stand-replacing processes, and landscape dynamics (Pérez-Cabello et al., 2009; Holden et al., 2016; Ludwig et al., 2018). However, wildfires can also positively impact the ecological integrity of forests; because they play a key ecological role in shaping their structure and composition. Specifically, wildfires shape the following: the removal of accumulated fuels, the control of insects and diseases (He et al., 2021), the settlement of seedbeds, and the release of seeds from "serotinous" cones (Goubitz et al., 2002).

The most Mediterranean species (e.g., *Pinus halepensis* Mill.) exhibit an excellent ability to adapt to fire disturbances, as they possess a suit of post-fire recovery strategies (traits). The strategies include post-fire recruitment (serotiny; fire-stimulated germination), resprouting (Pausas et al., 2018; Viana-Soto et al., 2020) from underground storage organs, and either fire resistance (thick bark) or fire promotion (i.e., resin content and water retention) (Keeley et al., 2011).

Considering the information above, there is a double link between

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plants and fire: by acting as fuel, plants determine the frequency at which fires occur. Specifically, the occurrence of fires drives the presence of fire-prone species (e.g., resprouters and seeders), thus plant availability and fire occurrence influence each other. However, these connections might vary due to pre- and post-fire site environmental conditions, affecting the extent of post-fire recovery (Fernández-Guisuraga et al., 2023). The pre-fire state of vegetation can shape the dynamics of post-fire vegetation recovery; since it is related to the high tree density and seed availability (Broncano et al., 2005; Pausas et al., 2004; Nioti et al., 2015). Additionally, fire severity is also an important variable in the prediction of post-fire vegetation recovery and succession, as it represents the combined influence of fire characteristics and immediate post-fire effects on the local environment (Shvetsov et al., 2019; Chen et al., 2011).

Climate variability is one of the main determinants of post-fire recovery (Harvey et al., 2016). The establishment and recruitment of plants are generally higher under favourable post-fire climate conditions, (e.g., high precipitation and soil moisture) (Pausas and Bradstock, 2007). Conversely, increases in the intensity and frequency of climate anomalies, such as warmer and drier conditions recorded within Mediterranean forests (Rita et al., 2020), can reduce the reproductive potential of forests, resulting in slower post-fire recovery processes, especially for resprouting species (Pratt et al., 2014; Pausas et al., 2016). According to Batllori et al., 2019, an extreme drought year followed by one or two large fire events promotes a shift in dominance when the composition of the vegetation is concerned; this shift is manifested as a transition from resprouter- to seeder dominance. Consequently, in the future, climate change could impact the post-fire responses of species, potentially eroding the resilience of Mediterranean forests and driving shrublands tipping point (Baudena et al., 2020). However, it is difficult to generalize the vegetation recovery dynamics (Pickell et al., 2016). This is because these dynamics are driven by an interaction of multiple factors, such as plant regeneration strategies, fire characteristics, environmental filters, and post-fire climate variability (Pérez-Cabello et al., 2021).

Recently, innovative methodologies based on remote sensing (RS) data have been developed and proposed as feasible approaches to assess the driving factors of post-fire vegetation recovery. Most of these efforts were rooted in the use of high-moderate resolution satellite images, such as those obtained from Landsat imagery (NASA-USGS) (Wulder et al., 2022). Due to their wide spatiotemporal coverage, these images were useful in the analysis of post-fire recovery patterns through pre- and post-fire time series at regional scales (Bright et al., 2019; Chen et al., 2011; Fernández-García et al., 2018; Meng et al., 2015; Nolè et al., 2022). The availability of open-access high-performance computing such as Google Earth Engine (GEE) (Gorelick et al., 2017), facilitates the processing of large geospatial datasets over long time series (Long et al., 2019). According to Hirschmugl et al. (2017), time series analysis can be used to effectively monitor forest disturbances and their associated recovery processes through an analysis of spectral variations in the forest cover (Röder et al., 2008). Such spectral variations of post-fire vegetation recovery are assessed through spectral indices such as Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974) and Normalized Burn Ratio (NBR) (García and Caselles, 1991). The NDVI is highly sensitive to greenness and photosynthetic activity; therefore, it could be considered a proxy for green biomass and pre- and post-fire vegetation conditions at different landscape levels. For instance, Chu et al. (2017) used NDVI as a proxy for pre-fire vegetation conditions to assess its importance in forest recovery post-disturbance, whereas Fernández-García et al. (2018) assessed the post-fire vegetation greenness of Mediterranean pine ecosystems using NDVI Landsat imagery. Recent studies have used NBR as a proxy for the assessment of vegetation recovery; this is because it showed a lower sensitivity to early post-fire greening, making it more suitable than NDVI for characterizing vegetation structure, moisture, shadowing, and preventing rapid post-fire invasion by herbaceous species especially in the characterization of mid- and long-term- post-fire patterns (Bright et al., 2019; Meng et al., 2014; Schroeder et al., 2011). Overall, new metrics based on NBR pre- and post-fire have been designed. For example, Kennedy et al. (2012) developed the Recovery Indicator (RI) that was readapted by White et al. (2017) to assess post-disturbance vegetation recovery (i.e., wildfire and harvest) in Canadian forests. More recently, Frazier et al. (2018), proposed a modified version of RI, namely, the Relative Recovery Indicator (RRI), to assess spectral post-fire recovery in boreal forests. These spectral metrics are sensitive to different vegetation conditions, making them suitable for the characterization of mid- long-term recovery patterns of forest ecosystems (Nolè et al., 2022).

To date, many studies have assessed post-fire vegetation recovery dynamics and the influence of environmental factors. For example, it has been shown that the recovery of vegetation in the Mediterranean region is mainly driven by fire severity, topography, post-fire climate, and vegetation cover types (Röder et al., 2008). Fire severity and post-fire climatic conditions appear to have a strong effect on the mid- and long-term vegetation recovery of pine forests (Viana-Soto et al., 2020). However, Fernández-García et al. (2018) showed that the recovery of the pine forest ecosystems in the other Mediterranean contexts could be explained by the pre-fire conditions. Field-based studies conducted in Mediterranean forests (i.e., *Pinus halepensis* Mill., *Quercus ilex* L.) have shown that structural variables before the fire (e.g., high tree density) greatly impact vegetation recovery (Pausas et al., 2004). Few remote sensing studies in Mediterranean and other boreal forests revealed that tree density was an important predictor for post-fire vegetation patterns (Chu et al., 2017; João et al., 2018). Although the dynamics of vegetation recovery and its drivers have been studied under different ecological contexts (Fernández-Manso et al., 2016; Martín-Alcón and Coll, 2016; Viana-Soto et al., 2020), few study have focused on these dynamics across different vegetation stands of the Mediterranean. Such an approach would be important for gaining a deep understanding of forest dynamics, facilitating the creation and implementation of robust management-linked solutions.

In this study, we assessed the post-fire vegetation recovery rates according to varying fire severity, burnt area, pre-fire vegetation, and post-fire climate conditions across several Mediterranean forest stands. Specifically, we aimed to:

i. investigate post-fire recovery patterns over the period 2002 - 2021 using NBR-based indicators derived from Landsat, in five Mediterranean forest types (Mediterranean pine, holm and deciduous oak forests, sclerophyllous vegetation, and thermophilous shrublands) affected by wildfires;
ii. assess the impact of pre- and post-fire environmental and vegetational variables, and fire traits (e.g., fire severity, burnt area) on post-fire vegetation recovery processes in different forest types.

2. Material and methods

2.1. Study area and Wildfire's database

In terms of the study area, we chose a region in southern Italy (the Basilicata administrative district, hereinafter Basilicata) (Fig. 1). Basilicata was chosen because it accurately represents a wide spectrum of Mediterranean forests i.e., with vegetation and climates (e.g. ranging from the thermo-Mediterranean to the oro-Mediterranean climate) (Mancino et al., 2014; Quézel, 1976).

Generally, in the studied region fires ignite during the dry summer season (June to August). This season is characterised by little to no rain, low humidity, and high temperatures. Recently, according to the regional fire prevention plan 2021–2023 (Regione Basilicata, 2021), the increasing duration and intensity of extreme weather events (e.g., heat waves, and drought spells) has driven the extension of the fire risk period (June - September) and an increase of forest burned area.

Information on wildfires that occurred during the 2004 - 2016 period

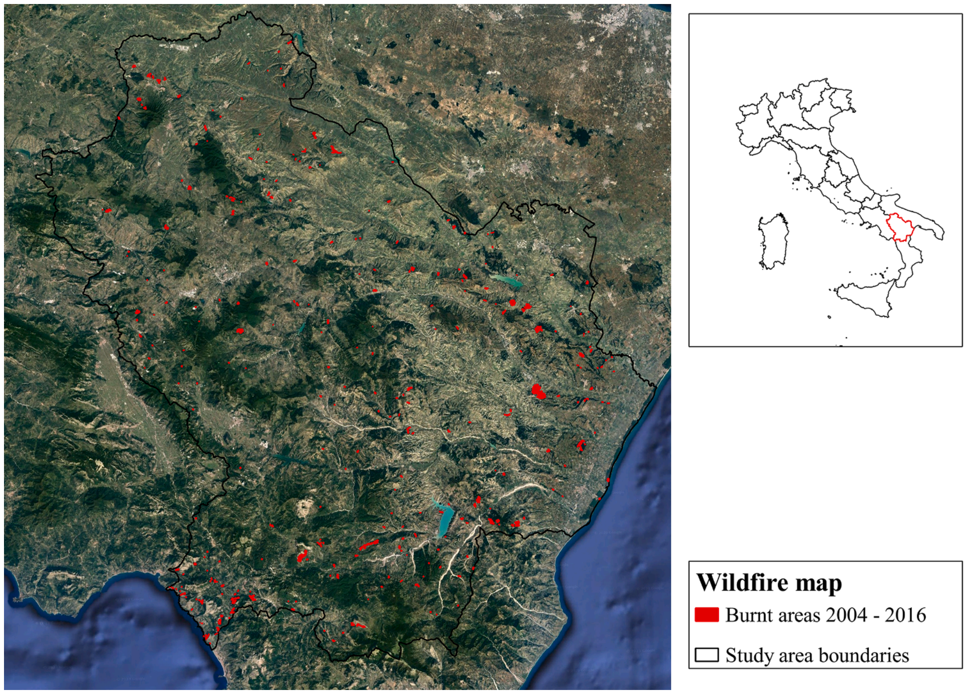

Fig. 1. Map of burned areas in Basilicata Region from 2004 to 2016 (https://rsdi.regione.basilicata.it/incendi/). The study area is indicated in red on the inset map, within the context of the South Italy. The red color shows burned areas.

within regional forest stands was extracted from the Basilicata fire dataset (https://rsdi.regione.basilicata.it/incendi/) (Fig. 1).

To analyze short- to mid-term post-fire vegetation recovery patterns, forest stands reported in the Regional Forest map at the 1:10 000 scale (Costantini et al., 2006) were clipped using fire polygons (Fig. 2), and classified as per the following categories: Deciduous oak forests (DOF), Holm oak forests (HOF), Mediterranean pine forests (MPF), Sclerophyllous vegetation (SV), and Thermophilous shrublands (TS) (Table 1).

2.2. Assessing post-fire vegetation recovery and response variables

For each wildfire that occurred during 2004 - 2016, in the several forest categories, the short-term (i.e., five years) post-fire vegetation recovery was assessed based on the annual temporal series of Normalized Burn Ratio (NBR), using a seven-year temporal window spanning two years before and five years after the fire event for all the considered time-spans. Overall, we analysed the NBR temporal series from 2002 to 2021.

The NBR was then calculated from the annual time series Landsat 7 Level 2, Collection 2, Surface Reflectance Tier 1 (https://www.usgs.gov/media/files/landsat-4–7-collection-2-level-2-science-product-guide) images after cloud masking, using the JavaScript-based cloud computing platform, Google Earth Engine (GEE). Then, for each wildfire, an annual composite image was obtained from all the scenes in each annual period, beginning from the first day of the year and continuing to the last day of the year. Landsat 7 C02 T1 L2 dataset contains the atmospherically corrected surface reflectance and land surface temperature data derived from Landsat 7 ETM+ sensor and contains 4 visible (i.e., blue, green, and red) and near-infrared (VNIR) bands, 2 short-wave infrared (SWIR-1 and SWIR-2) bands processed to orthorectified surface reflectance, and one thermal infrared (TIR) band processed to orthorectified brightness temperature. The product includes cloud, shadow, water, and snow mask produced using the CFMask algorithm (Foga et al., 2017).

According to the period analysed, in this context, only Landsat 7 was used due to its difference in spectral range in infrared bandwidth (NIR and SWIR) with Landsat 8 sensor. Although the overall reliability of Landsat sensors harmonization (Roy et al., 2016), infrared-based indicators such as NBR tested on the vegetation of the study area by Mancino et al. (2020), showed a poor correlation between the two sensors, highlighting the existence of a non-linear component between the two sensors also related to different classes and levels of vegetation cover. In this regard, the harmonization between ETM+ and OLI sensors was tested within Google Earth Engine but gave overestimated values of the indices.

Consequently, the dataset was pre-processed using the Gap-Filling algorithm (USGS, 2004) to fill the data gap created by the Scan Line Corrector (SLC) in each image after May 31, 2003.

The NBR was calculated as follows:

$$NBR = \frac{(\rho NIR - \rho SWIR_2)}{(\rho NIR + \rho SWIR_2)} \tag{1}$$

where ρNIR and $\rho SWIR_2$ represent the surface reflectance in the near-infrared and short-wave infrared regions of the Landsat 7 SR bands SR_B4 and SR_B7, respectively the NBR spectral metric was used to estimate the Relative Recovery Indicator (RRI).

Post-fire vegetation spectral recovery for each burned area was assessed using NBR-based RRI (Frazier et al., 2018).

The RRI, was calculated using a two-year NBR pre- and five-year NBR post-disturbance window (7 years):

$$RRI = \frac{ARI}{\Delta NBR_{dist}} \tag{2}$$

where ARI is the absolute recovery indicator and ΔNBR_{dist} is the change in NBR due to fire disturbance, calculated as the difference between the average value of NBR in the two years before fire occurrence ($NBR_{pre\text{-}fire}$) and NBR value in the year when the disturbance occurred (NBR_{y0}).

In Eq. (3) ARI was calculated as follows:

$$ARI = Max\left(NBR_{y+5}, NBR_{y+4}\right) - NBR_{y0} \tag{3}$$

where $Max(NBR_{y+5}, NBR_{y+4})$ is the maximum of NBR values four and five years after the disturbance, and NBR_{y0} is the NBR value in the year

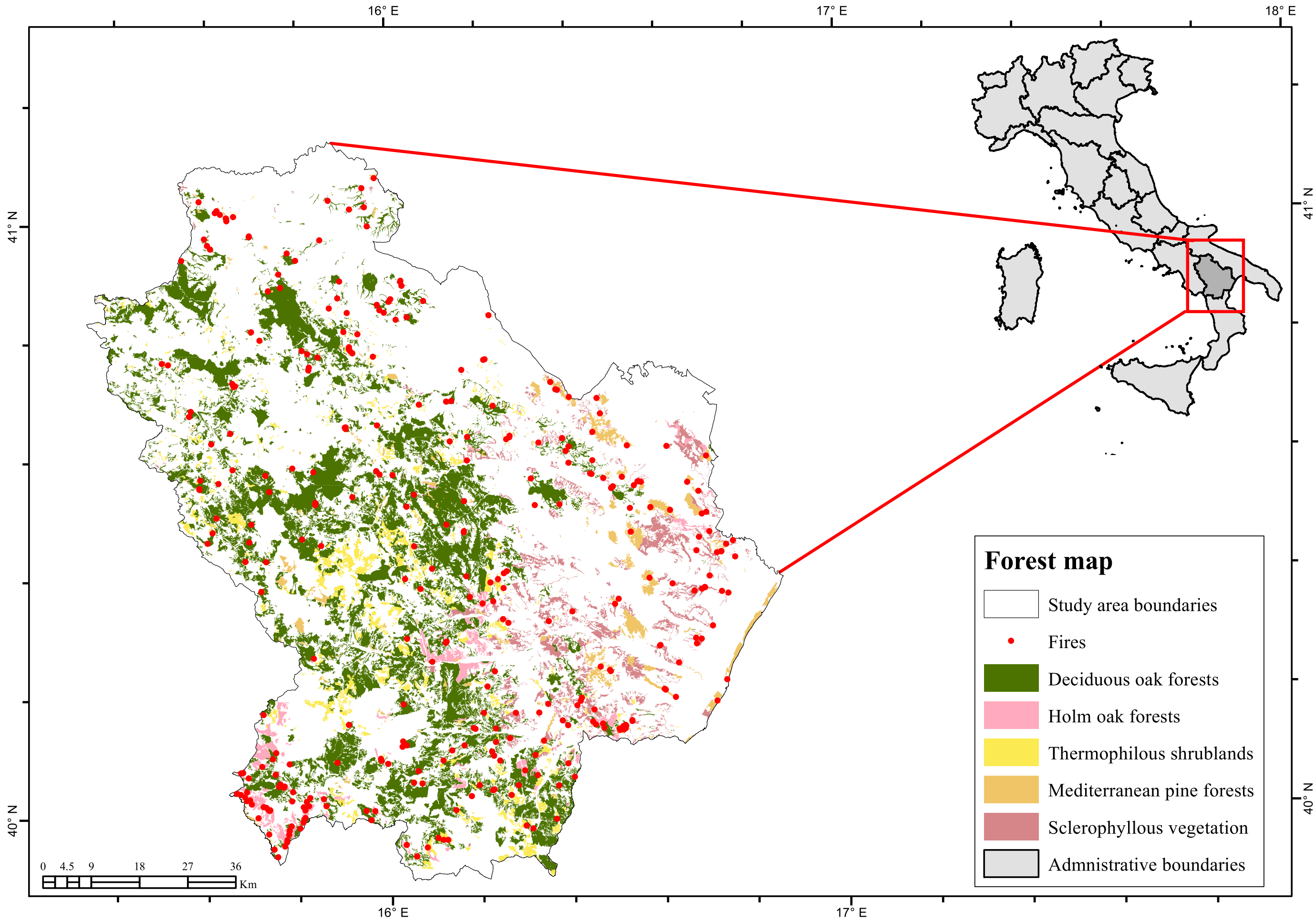

Fig. 2. Locations of the forest burned area within the Basilicata Region. The study area is indicated in red on the inset map, within the context of the South Italy (shown in light gray). The red dots indicate the wildfires occurred during the period 2004 - 2016 (https://rsdi.regione.basilicata.it/incendi/) in the forest categories (Deciduous oak forests, Holm oak forests, Mediterranean pine forests, sclerophyllous vegetation, and Thermophilous shrublands).

when the disturbance occurred. Therefore, the RRI metric compares the spectral recovery magnitude to the spectral disturbance magnitude assessed as ΔNBR_{dist}.

RRI values vary between 0 and 2, zero means no spectral recovery occurred within the post-disturbance period; a value of one indicates complete spectral recovery of pre-disturbance vegetation cover (Fig. 4); and, values greater than one are reflective of instances in which spectral recovery was greater than spectral disturbance (full description of the RRI spectral indicator is presented in Frazier et al. (2018)).

Consequently, in this study, the use of RRI as a response variable (Table 2) was expected to account for different pathways of post-fire forest succession in the studied region, which can be driven by fire severity and environmental conditions in the Mediterranean ecozone.

2.3. Assessing predicted vegetation recovery drivers

Five explanatory environmental variables, namely, Relative differenced Normalized Burn Ratio (*RdNBR*), Burnt area (*BrnAREA*), pre-fire maximum of Normalized Difference Vegetation Index ($NDVI_{pre\_Max}$), precipitation (*P*), and a maximum of temperature (T_{max}) were derived to model post-fire patterns. These variables (i.e., briefly described in the following section) were organized into three groups: fire traits, pre-fire vegetation conditions, and post-fire climate conditions (Table 2).

2.3.1. Fire traits

Fire severity, fire regime, and fire frequency are important factors that alter the structure and composition of post-fire vegetation. The spectral degree of fire-induced changes in the vegetation cover was investigated by differentiating between NBR pre- and post-fire imagery (*dNBR*) (Parks et al., 2014). Although *dNBR* provides good performance, especially for moderate-low severity areas, relativised forms of severity provide a robust measure and classification of fire severity over a broad range of fires and vegetation cover types. In this study, the Landsat 7 Relative *dNBR* (*RdNBR*) (Miller et al., 2009) images for each fire patch were calculated and used as a proxy for fire severity on the Google Earth Engine (GEE) platform. *RdNBR* was then assessed by dividing *dNBR* (differenced Normalized Burn Ratio) by the square root of the NBR pre-fire images. Positive values of *RdNBR* correspond to severely burned sites and represent a decrease in vegetation cover, whereas negative values are indicative of an increase in vegetation cover, as for *dNBR* (Key and Benson, 2006).

Other fire metrics, (e.g., Burnt area (*BrnAREA*)) were extracted from the original fire dataset and used to test the fire size and fire patch characteristics of the previously selected wildfire areas, using ArcGis. This factor can be representative of residual surviving trees and seed availability, which drive the post-fire regeneration of vegetation (Liu, 2016).

2.3.2. Pre-fire vegetation conditions

Pre-fire vegetation metrics such as those related to productivity and phenology were used to capture several facets of pre-fire vegetation

Table 1
Description of five forest categories (DOF, HOF, MPF, SV, TS) included in this study.

Forest Type	Species	Forest classes – Basilicata Regional Forest Atlas (Costantini et al., 2006)	Area (ha)
Deciduous oak forests (DOF)	*Quercus cerris* L., *Quercus pubescens Willd., Quercus frainetto Ten.*	115–116–117–118–119–120	184032,8
Holm oak forests (HOF)	[a]*Quercus ilex* L.	130	12699,5
Mediterranean pine forests (MPF)	*Pinus halepensis Mill., Pinus pinea* L., *Pinus pinaster Aiton.*	127–128–129	19383,8
Sclerophyllous vegetation (SV)	[b]*Quercus ilex* L., *Phillyrea latifolia* L. *Pistacia lentiscus* L., *Salvia rosmarinus* L.	131–132–133–134–135	33841
Thermophilous shrublands (TS)	*Prunus* L., *Crataegus* L., *Juniperus* L.	124–125–126	24589,3

Note: In the table, *Quercus ilex* L. is specified in two different categories: Holm oak forests (HOF) and Sclerophyllous vegetation (SV). HOF include the arboreal holm oak ([a]*Quercus ilex* L.) characterizing the high Mediterranean maquis, widespread on the rugged slopes and within mixed forests with other broad-leaved trees, but sometimes also along the coast. SV includes shrubby Holm oak ([b]*Quercus ilex* L.) with other sclerophyllous species (*Phyllyrea latifolia* L., *Pistacia lentiscus* L., *Salvia rosmarinus* L.) as reported in the table.

Table 2
List of response and explanatory variables used in the Linear Mixed Model (LMM) analysis.

Variable Group	Indicator	Description	Units
Response variables			
Post-fire forest recovery	Relative Recovery Indicator (RRI)	A proxy for post-fire vegetation recovery	Values between 0 and 2
Explanatory variables			
Fire traits	RdNBR	A proxy for fire severity	Values between −2 and 2
	BrnAREA	Burnt patches area	(ha)
Pre-Fire vegetation condition	$NDVI_{pre\_Max}$	A proxy for productivity and phenological processes pre-fire	Values between −1 and 1
Post-fire climate conditions	Precipitation (P)	Mean of precipitation following fire event (0–5 years observations)	(mm)
	Temperature_max (T_{max})	Mean of maximum temperature following fire event (0–5 years observations)	(°C)

conditions (i.e., tree density, tree age, basal area, biomass, and species composition) and their usability in the prediction of short- and mid-term post-fire vegetation recovery capacity (João et al., 2018). Since NDVI is the most widely used RS index to represent vegetation-linked conditions and their associated biophysical parameters, it was used as a proxy for pre-fire vegetation conditions. The pre-fire maximum NDVI ($NDVI_{pre\_Max}$) was calculated based on pre-disturbance Landsat 7 C02 T1 L2 imagery for each wildfire, within GEE.

NDVI was calculated using the reflectance of near-infrared (Band SR_B4) and red (Band SR_B3) of Landsat pre-fire images:

$$NDVI = \frac{SR\_B_4 - SR\_B_3}{SR\_B_4 + SR\_B_3} \tag{4}$$

2.3.3. Post-fire climate conditions

Yearly precipitation and temperature, which were used as a proxies of post-fire climate conditions were downloaded for the 2005 - 2021 period from the TerraClimate dataset (http://www.climatologylab.org/terraclimate.html).

Post-fire yearly precipitation (P) was summarised, and post-fire yearly maximum temperature (T_{max}) was calculated as the average of the maximum temperature for each wildfire polygon, in the R environment (R Core Team, 2020). Specifically, post-fire climate conditions were considered to account for the potential effects of climate variability on vegetation recovery across different temporal trends. The five-year post-fire moving average (i.e., t, t_{+1}, t_{+2}, t_{+3}, t_{+4}) of climate conditions (P, T_{max}) was then extracted. Specifically, t refers to P and the T_{max} of one-year post-fire; t_{+1} refers to 2-year post-fire moving average of P and T_{max}; t_{+2} refers to 3-year post-fire moving average of P and T_{max}; t_{+3} refers to 4-year post-fire moving average of P and T_{max}; and t_{+4} refers to 5-year post-fire moving average of P and T_{max}.

2.4. Statistical analysis

RRI differences among five forest classes (i.e., DOF, HOF, MPF, SV, and TS) underwent an ANOVA analysis followed by Tukey's post hoc multiple comparisons tests. The RRI linear trends throughout the whole time-span period (2002 - 2021) were assessed via Theil–Sen's slope estimator, using the "mblm" R package version 0.12.1 (Komsta, 2019), and trend significance ($p < 0.05$) was tested using non-parametric Mann-Kendall tests.

A Linear Mixed Effect Model (LMM) was fitted using the 'nlme' package (Pinheiro et al., 2021) in R environment v.4.0.0 (R Core Team, 2020) to assess the effect of fire severity (*RdNBR*), burnt areas (*BrnAREA*), and pre-fire vegetation conditions ($NDVI_{pre\_Max}$) (centered and scaled fixed factors), on the vegetation response variable (RRI). The forest cover classes were included as a random factor. The random-effect structure of the model was then optimized, to test whether including extra random-effect terms (i.e., random slopes) for forest cover classes improved the fit of the model. Different random structures were compared through a Likelihood Ratio Test (LRT), which approximately follows a chi-square distribution (Zuur et al., 2009). When comparing models that varied in their random structure but had no fixed effects, these models were fit using restricted maximum likelihood (REML) to prevent biased estimators for the variance terms. Finally, models were refitted with REML to estimate model parameters. Marginal and conditional R^2 scores (Nakagawa et al., 2013) were calculated to examine the variation explained by models using the "r.squaredGLMM" function in the "MuMIn" package. The residual diagnosis was performed to check the validity of the model assumptions (normality and homoscedasticity of residuals).

To quantify the proportion of variance explained by fixed and random terms, a full partitioning of variance into three components was calculated using the r2mlm function from the "r2mlm" (Shaw et al., 2022) R package: variance attributable to fixed predictors, variance attributable to random intercept variation, and unexplained residual variance.

The contribution of fixed effects to the variance of dependent variables was computed using the function "partR2" in the R package "partR2" (Stoffel et al., 2021). The recommended number of 1000 parametric bootstrap iterations, was used to determine the 95% confidence intervals of estimates.

The residual variance of vegetation response (RRI), unexplained by the previous model, was correlated with post-fire climate conditions, using LMM again. Specifically, five Linear Mixed Effect Models (i.e., M_t,

M_{t+1}, M_{t+2}, M_{t+3}, and M_{t+4}) were applied to assess the relationship between the residuals of the fitted RRI model and precipitation (*P*) and maximum temperature (*Tmax*), using as a random factor the forest cover classes. Marginal and conditional R^2 scores, repeatability of the R^2, and the contribution of fixed effects to the variance of dependent variables were calculated following the procedure described above.

3. Results

3.1. Post-fire vegetation recovery patterns

The analysis of five-year post-fire vegetation recovery for each Mediterranean burned forest class (i.e., MPF, SV, DOF, TS, and HOF) based on NBR-indicator patterns derived from Landsat, showed an average RRI value below one for all the analysed forest categories (Figs. 3f and 4). Such a low value could be indicative of an incomplete recovery within the five years after fire disturbances, with the lowest recorded values for DOF and TS forest classes (Figs. 3c and 3d). As shown in panels a, b, c, d, and e of Fig. 3, RRI decreases monotonically across the 2004 - 2016 period, with no-significant trends across all forest classes. However, by observing individual forest classes among fire years, the difference in the RRI trends became apparent. Specifically, MPF and TS decreased whereas SV, DOF, and HOF forest classes increased. MPF seemed to be comparable with SV patterns, peaking in recent years after a fire disturbance (2012 - 2016); on the other hand, DOF and TS showed the lowest spectral recovery, especially for fires that occurred during 2012 - 2016. The RRI pattern of HOF was constant compared to those of the other forest classes.

3.2. Assessing drivers for post-fire vegetation recovery monitoring

Based on the previous section, the RRI at five years after fire disturbance, exhibits great suitability as a proxy for short- and mid-term vegetation recovery for different forest stands (i.e., MPF, SV, DOF, TS, and HOF). Consequently, using a Linear Mixed Model (LMM), the RRI was selected as a vegetation recovery response variable that could be driven by predictors such as fire severity, burnt area, and environmental conditions.

The LMM (RRI$\sim$ $RdNBR + BA + NDVI_{pre\_Max}$) with 331 observations used as input, explained a modest proportion of the variability (ca. 18%) among forest classes (i.e., MPF, SV, DOF, TS, and HOF) (Fig. 5c).

No strong multi-collinearity among predictors (i.e., *BrnAREA, RdNBR*, and $NDVI_{pre\_Max}$) was found. The results of LMM-based analysis showed no-significant effect of the fire traits (i.e., *RdNBR* and *BA*), whereas it showed that $NDVI_{pre\_Max}$ could be used to characterize post-fire recovery trends (RRI) (Table 3, Fig. 5a).

A pre-fire vegetation indicator, namely, $NDVI_{pre\_Max}$ appeared to be significantly and negatively correlated with RRI, notably for DOF and SV classes.

Such results were explained better on the right panel, where the RRI trend was positive in the SV sites. This indicates that vegetation in SV sites recovered at a high pre-fire vegetation conditions value

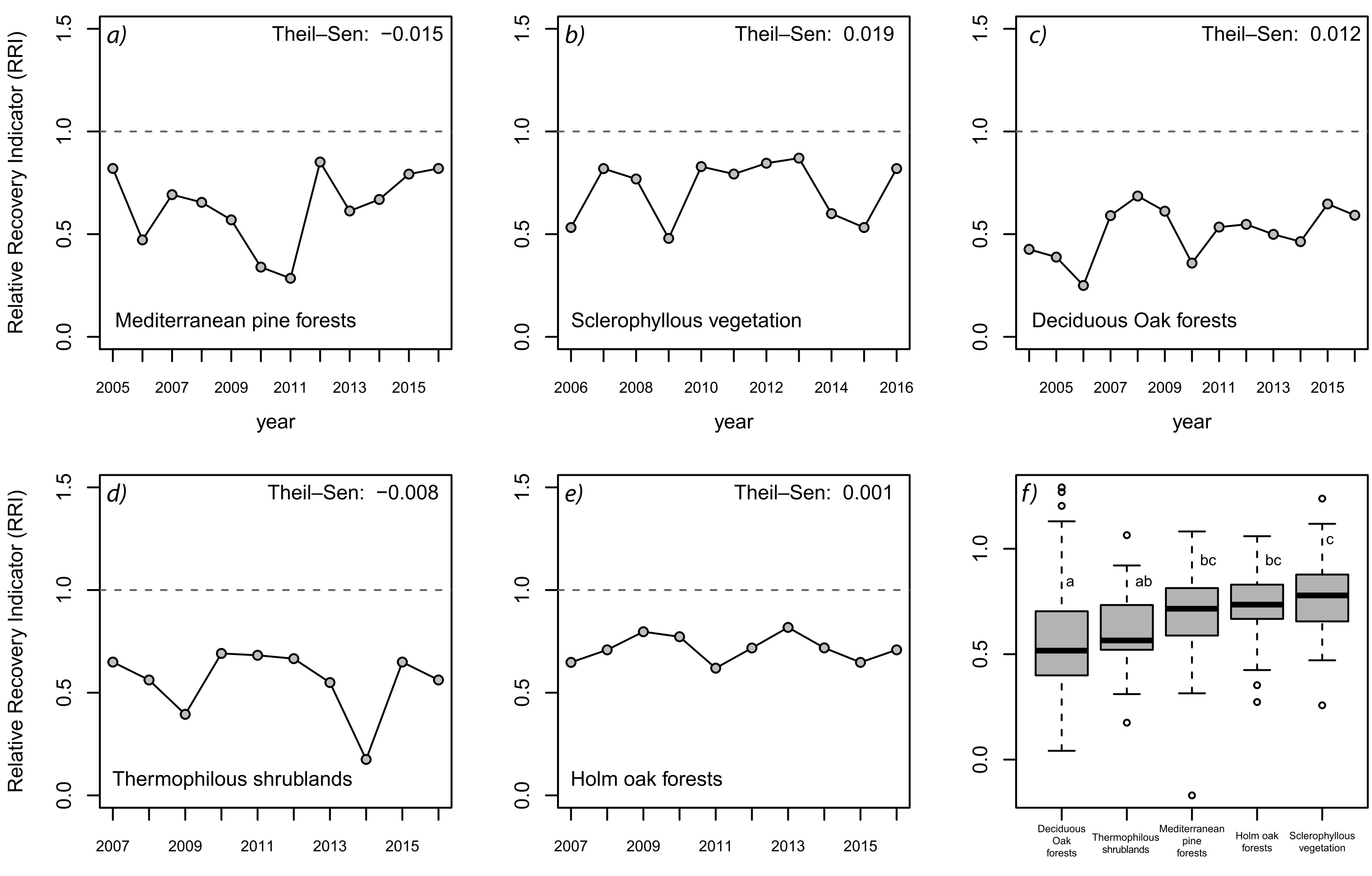

Fig. 3. Temporal variability of the average Relative Recovery Indicator (RRI) for different forest classes (Deciduous oak forests, Holm oak forests, Mediterranean pine forests, Sclerophyllous vegetation, and Thermophilous shrublands) over the 2004 - 2016 period. Theil–Sen's slope coefficients are reported, where missing asterisks denote no statistical significance at $p<0.05$ (*) (panels *a, b, c, d, e*). Panel *f*) shows the boxplot of the distribution of the RRI over the whole-time span (2004 - 2016) for different forest classes. Each box represents the 75th to 25th percentiles, the bold line shows the median, upper and lower marks are the largest to smallest observation values which are less than or equal to the upper and lower quartiles plus 1.5 times the length of the interquartile range. Circles outside the lower-upper mark range represent outliers. Different letters mean statistical significance for $p<0.05$.

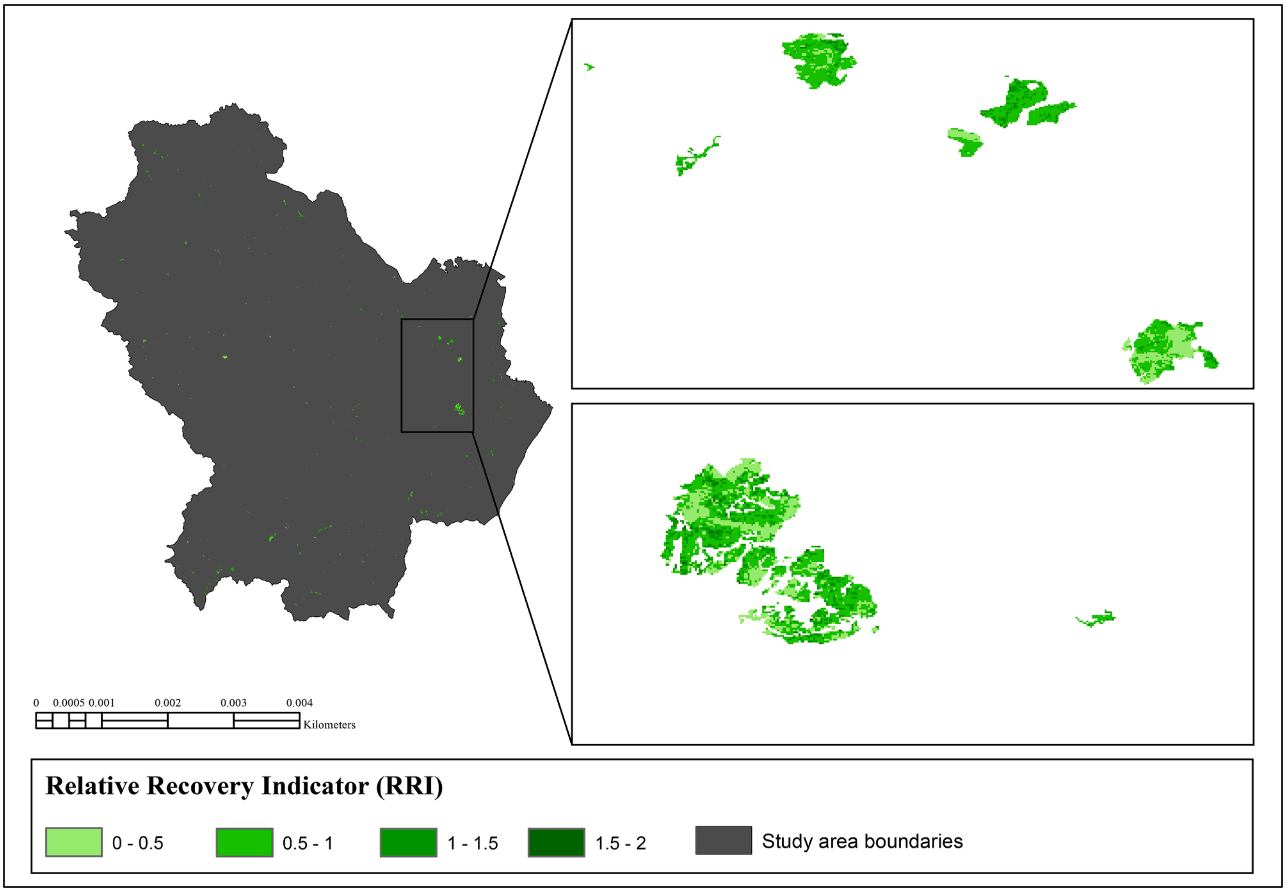

Fig. 4. Relative Recovery Indicator (RRI) calculated for the wildfires occurred during the period 2004 −2016 in the forest categories (Deciduous oak forests, Holm oak forests, Mediterranean pine forests, Sclerophyllous vegetation, and Thermophilous shrublands). The insets show the RRI maps of some wildfires that occurred in the Deciduous oak forests, Mediterranean pine forests and Sclerophyllous vegetations in 2007, 2008, 2013, 2014 and 2016. The RRI values vary between 0 (light green) and 2 (dark green), zero means no spectral recovery, a value of one indicates complete spectral recovery, and values greater than one more spectral recovery than spectral forest disturbance.

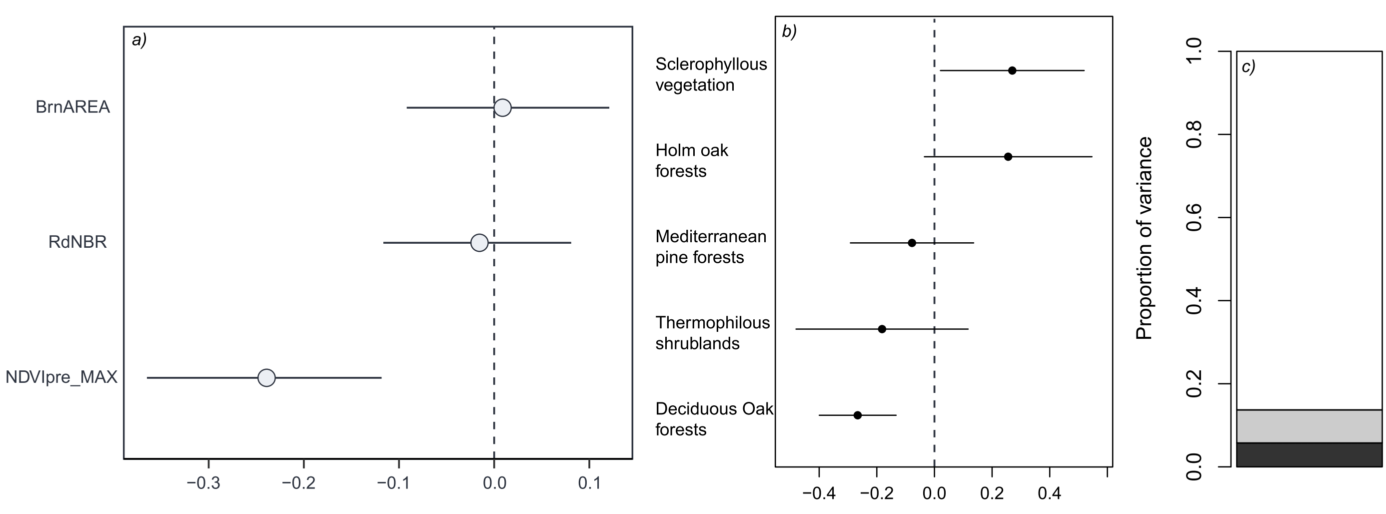

Fig. 5. On left (a), the beta weights (BW) and confidence interval of the estimates of the linear mixed model (LMM) of the Relative Recovery Indicator (RRI). Points represent the standardized slope of linear trends (β), the gray bars are 95% confidence intervals of the linear trend estimates. Center (b), estimated of the random intercept and confidence interval of the from the fitted model. Right (c), the relative variance decomposition for the RRI representing the proportion of variance explained by fixed factors (dark gray), the proportion of variance explained by random factors (light gray), and the proportion of unexplained variance (white).

Table 3
Linear mixed-effects models summary statistics. Fit of the Relative Recovery Indicator (RRI) linear trend over the 2004–2016 period, with forest cover classes as fixed effect dummy coded) - Bold values represent statistical significance at $p<0.05$. Est, estimates; CI, standardized confidence interval of the estimates; asterisk (*) denote interaction term; sigma-squared (σ2), within-group variance; ICC. Intra Class Correlation; N, number of levels of the random variable; Obs.: number of observations; R^2m= marginal R-square (proportion of variance explained by fixed factors); R^2c = conditional R-square (proportion of variance explained by fixed and random factors).

	RRI		
Predictors	Estimates	CI	p
(Intercept)	0.11	-0.17 – 0.38	0.453
BrnAREA	0.01	-0.09 – 0.11	0.867
RdNBR	-0.02	-0.12 – 0.09	0.768
NDVIpre_Max	-0.24	-0.36 – -0.12	<0.001
Random Effects			
σ2	0.86		
ICC	0.08		
N–LEV	5		
Observations	331		
R^2m/R^2c	0.058 / 0.137		

($NDVI_{pre\_Max}$). In contrast, a negative trend in DOF sites was found, explaining slow vegetation recovery at high pre-fire vegetation conditions ($NDVI_{pre\_Max}$). While the trend of RRI with $NDVI_{pre\_Max}$ was not significantly different among HOF, MPF, and TS forest classes (Fig. 5b).

Furthermore, the residual variance unexplained (R^2Marginal) by the model (LMM) (ca. 80%) of the vegetation response variable (RRI) (Fig. 5c, right panel), was correlated to the post-fire climate conditions using five Linear mixed models (LMM) (M_t, M_{t+1}, M_{t+2}, M_{t+3}, M_{t+4}). Five yearly (t, t_{+1}, t_{+2}, t_{+3}, t_{+4}) precipitation (P) and maximum temperature (T_{max}) were comprehensively analysed with post-fire vegetation patterns, for each random forest class (Fig. 6A).

As shown in Fig. 6A, both yearly P and T_{max} displayed a significant correlation with the residual variance (R^2 Marginal) of RRI. LMM models of individual climate parameters showed that T_{max} was best at explaining the variability of RRI, first highlighting an increase after one year followed by a consequent decline of post-fire vegetation patterns over four years after fires. While five-year post-fire vegetation recovery (RRI) compared with P showed a constant trend that increased slightly due to the high precipitation (Fig. 6B).

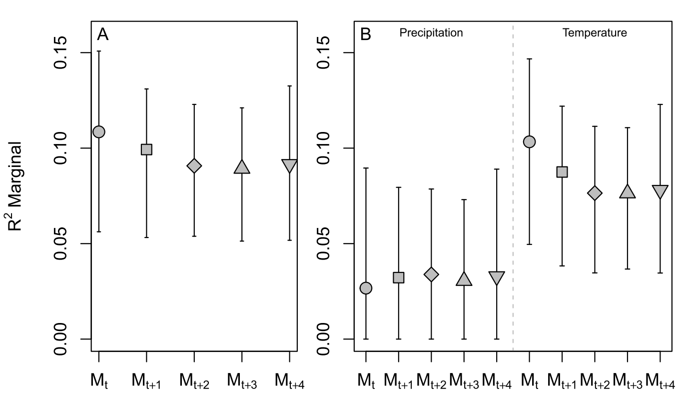

Fig. 6. Estimated marginal R-squared of the relationship between residuals of the fitted RRI (Relative Recovery Indicator) linear mixed model (LMM) with five LMM (M_t, M_{t+1}, M_{t+2}, M_{t+3}, M_{t+4}) of post-fire climate (precipitation and temperature) conditions. On the left, the marginal r-square of the relationship of the residual of the RRI model with the post-fire climate conditions (Temperature and Precipitation at the year t and t_{+1}, t_{+2}, t_{+3}, t_{+4}). On the right, the marginal r-square of the relationship of the residual of the RRI model with the post-fire climate conditions (Temperature and Precipitation separately at the year t and t_{+1}, t_{+2}, t_{+3}, t_{+4}).

4. Discussion

Post-fire vegetation patterns were analysed using LTS NBR-based metric (RRI) and related fire characteristics, pre-fire vegetation, and post-fire climate conditions to elucidate vegetation recovery of 331 wildfire events (2004 - 2016) that occurred in the forests of the study area. None of the analysed burnt patches recovered within the five years from fire disturbance, showing RRI values below the threshold (RRI<1) of complete spectral recovery (Fig. 3). In the observed ecosystems, two main traits-groups of species were identified, according to the post-fire recovery strategies: seeder species (e.g., MPF) that are able to produce massive post-fire seed dispersal; and resprouting species (e.g., DOF) which exhibits a large-scale recovery of most of its burned individuals (Rodrigo et al., 2007). The rapidity of these processes could be reflective of the evolutionary adaptations of Mediterranean vegetation to fire exposure and the low competition for sunlight, nutrient availability, and reduced water losses by transpiration that are observed after a fire disturbance (Cerdà and Doerr, 2005; Meneses, 2021). However, the pattern observed by the studied Mediterranean species may be widely variable due to the influence of local abiotic factors such as topographic or climate conditions. Specifically, RRI decreases over the post-fire period for most forest classes, showing a marked decrease in recent years (2012 - 2016) among the burned stands covered by resprouting species such as Deciduous oak forests and Thermophilous shrublands (Figs. 3c and 3d). This result is apparently in contrast with the known post-fire recovery strategies of this vegetation. When mixed Mediterranean ecosystems are concerned, specifically those with deciduous hardwood oaks (resprouters) are generally able to regenerate more rapidly than coniferous species (seeders) (e.g., Pinus). As confirmed through field observations conducted within the Mediterranean pine-oak ecosystem, oak started to regenerate vigorously one year after a fire disturbance (Vasilakos et al., 2018). The same applies for the Thermophilous shrublands class, which mainly consists of resprouter species that are highly adapted to the wildfires of the Mediterranean (Broncano et al., 2005).

Thus, the low recovery trends observed in our study during 2012 - 2021 for the more resilient forest stands such as DOF and TS, can be attributed to the drier and warmer conditions recorded in the study area in recent years (2012 - 2017) (Coluzzi et al., 2020). This condition greatly contributed to the unusually large number of wildfires (Regione Basilicata, 2021). This result confirms that an increase in the frequency and intensity of fires within the Mediterranean, as a result of more extended and severe seasonal droughts (Stephens et al., 2013), can drive the adaptive strategies exhibited by species, culminating in the loss of ecological integrity in the forests of interest (Viana-Soto et al., 2020). However, there are other mechanisms governing plant responses to fire disturbance; these mechanisms are linked to onsite factors such as fire severity, pre-fire vegetation, and post-fire climate conditions (Shvetsov et al., 2019).

Results highlighted the pre-fire vegetation condition ($NDVI_{pre\_Max}$) as the most important factor in explaining a significant variation of vegetation RRI recovery patterns, particularly for SV and DOF. The strengths of NDVI as a proxy of productivity, seasonality, phenology, and greenness, and its suitability in the assessment of tree-cover density have been documented in recent studies (João et al., 2018; Keersmaecker et al., 2014). Chu et al. (2017), testing the multiple predictors of post-fire recovery in the boreal forests, showed that NDVI, used as a pre-fire factor, was positively correlated with post-fire Larch regeneration; the rapid recovery was then attributed to the high pre-fire basal area, which was shown to be related to the seed and seedling densities (Talucci et al., 2020). A higher pre-fire NDVI thus results in higher seed productivity and the availability of a bank of roots and stumps for resprouting during vegetation recovery (Pausas et al., 2004). The positive trend of SV vegetation recovery (RRI) in our study, suggests that the pre-disturbance optimal productivity and the high tree density may be suitable for predicting post-fire vegetation recovery; this finding is congruent with that of Broncano et al. (2005), who showed the reliability of high pre-fire tree density within the context of predicting the post-fire vegetation recovery of SV species (e.g., *Quercus ilex* L.). Furthermore, Walker et al. (2021) also concluded that higher pre-fire cover density increases natural post-fire recruitment, which creates conditions that are conducive to seedling recruitment and establishment.

However, pre-fire vegetation can be related to fuel-load variability, which yields fire events of varying intensities (Whitman et al., 2018) that consequently influence post-fire regeneration (Nioti et al., 2015). In this study, fire severity (*RdNBR*) and burnt areas (*BrnAREA*) explained no significant pattern of RRI (Table 3, Fig. 5a), proving that they are not good predictors in monitoring vegetation recovery processes. The results suggest that fire severity may have a negative effect on recovery only in the first year after the fire. As confirmed by field observations conducted within the Chapparal shrublands ecosystem, fire severity effects are mostly short-lived, i.e., by the second year they are greatly diminished (Kelley et al., 2008). On the other hand, the success of post-fire vegetation recovery based on pre-fire vegetation conditions (e.g., stand density and pre-fire basal area) may also depend on the microclimate (e.g., moisture availability) (Littlefield, 2019) and soil properties that persist after fires (Fernández-García et al., 2019).

In contrast to the positive trend between RRI and $NDVI_{pre\_Max}$ observed for SV, the RRI of DOF displayed a negative trend compared to its high pre-fire condition; this is reflective of the slow recovery of DOF, which could be related to the post-fire weather conditions. Pausas and Bradstock (2007) also showed that no recruitment of most Mediterranean obligate resprouter species occurs after fire when the fitness of their traits (resprouting) is changed along disturbance gradients (e.g., drought condition). Although resprouting species can take advantage of existing root systems in stressful conditions (Bussotti and Pollastrini, 2020; Davis et al., 2018), there are some metabolic costs, such as higher allocation of biomass to the roots and a longer time to reach sexual maturity (Liu et al., 2015). Consequently, intense droughts occurring in the year after a fire event can yield a great reduction in vegetation recruitment.

Even though we evaluated multiple factors related to fire and environmental conditions that affect the patterns of post-fire forest succession in the Mediterranean forest classes, these factors only accounted for ca. 18% of the variance in forest recovery explained by the models. This is probably due to the limited number of fires studied and the number of parameters that were considered. Many other parameters, such as climate conditions (João et al., 2018; Hao et al., 2022), unstudied in the first LMM model, may also have a strong direct or indirect effect on post-fire recovery trends, therefore, their inclusion could have greatly impacted our findings.

Consequently, we deepened the analysis by assessing the unexplained residual variance (R^2Marginal= ca. 80%) of RRI from the model (LMM Fig. 5) with yearly precipitation (*P*) and maximum temperature (T_{max}) used as a proxies of post-fire climate conditions.

Our results show a significant and positive correlation with RRI trends in each forest class, pointing to their suitability in explaining the variability of post-fire vegetation processes. Specifically, the precipitation (*P*) induced a slight increase in RRI value one year after the fire across all forest classes (i.e., DOF, TS, SV, MPF, and HOF) (Fig. 6B). This positive trend, as highlighted by Xofis et al. (2021), suggests that soil moisture combined with high precipitation represents a key driver for the post-fire recovery of the Mediterranean ecosystem. In the studies by Viana-Soto et al. (2017) and Röder et al. (2008), precipitation positively influenced the post-fire recovery of the Mediterranean MPF and DOF forest classes. Our results show that maximum temperature (T_{max}) over the post-fire period led to the high variability of vegetation recovery patterns in each forest class. Specifically, we observed an increase in the temperature after one year of fire and a consequent decline in the last period (Fig. 6B). This peak value of maximum temperature (T_{max}) followed by a drought period, could shift recovery pathways, constraining new recruitment and growth. Similar results have been reported by Bright et al. (2019) regarding the variation in post-fire NBR vegetation patterns explained by post-fire climate anomalies (e.g., maximum temperature). Analysis of trends and post-fire climate parameters conducted by Viana-Soto et al. (2020) within Mediterranean pine forests, revealed that the stage of recovery slows down when drought periods persist after fires. Therefore, a decrease in moisture contents due to seasonal shifts in drought and high temperatures probably impacts vegetation recovery according to the different pre- and post-fire strategies related to seed quality, seedling establishment, and resprouting capacity. In contrast, an increase in temperature and post-fire droughts expected in the Mediterranean basin (IPCC, 2021), can hinder the recovery-linked processes of Mediterranean vegetation.

The contrast in regeneration niche after fires between resprouters and seeders according to the root characteristics suggests that they are subjected to different degrees of environmental stress and consequently to different evolutionary forces (Vilagrosa et al., 2014; Hislop et al., 2020). In general, seeder species show a higher resistance to post-fire water stress, and less vulnerability to aridity than resprouters (Pausas et al., 2016; Pratt et al., 2014). Thus, the slow recovery processes of DOF observed herein could be related to the increase in post-fire temperature reducing their resprouting capacity due to water-stress cavitation. Indeed, the reduction of precipitation makes oak more vulnerable, especially in the initial stages of its life cycle, and consequently, severe droughts will affect postfire regeneration capacity (Marañón et al., 2020). A recent study conducted in the Mediterranean forests showed that precipitation deficits were associated with changes from Deciduous Oak Forests to other land cover types (e.g., forests with xeric species) (Acacio et al., 2017). With results congruent with those of Sheffer (2012), we found that the intensification of aridity improved the performance of pine in pine-oak ecosystems, whereas it negatively impacted the reproductive and resprouting performance of oak. In recent decades, even Mediterranean evergreen oak *Quercus ilex* L. which has ecological plasticity greater than of other deciduous oak resprouters (Salleo et al., 1990), exhibit signs of drought-induced dieback (Gentilesca et al., 2017; Encinas-Valero et al., 2022). In our study, the RRI patterns of HOF were more constant than DOF patterns, but during the post-disturbance period, plants could be more susceptible to drought-induced mortality. Baudena et al. (2020), confirmed that an increase in aridity could disrupt the resilience of oak forests. Thus, the combination of increasing frequencies of climate anomalies and wildfires may drive vegetation transitions in Mediterranean ecosystems, and these irreversible trends could occur more abruptly than previously predicted (Nolan et al., 2021). Although a slight decrease in temperature was observed over the analysis period from fire disturbance, long-term observations of similar climate gradients could differentially affect vegetation responses depending on water availability. Thus, increasing differences in the post-fire recovery capacity of Mediterranean forest ecosystems may be expected in the future based on the variability of spatiotemporal climatic extremes.

5. Conclusions

The relative recovery indicator (RRI), based on Landsat time series (LTS) data allowed us to analyze the post-fire regeneration processes of multiple Mediterranean forest classes in south Italy. Here, we found that none of the forest classes analysed over the whole study period (2002 - 2021) rapidly recovered within the five years after a fire disturbance. The different classes exhibited a lot of variability in terms of their recovery-linked capabilities throughout the study period. Differences in post-fire recovery magnitude and trends could be related not only to fire-adaptive vegetation strategies but also to many mechanisms governing plant responses to fire disturbance. The appraisal of environmental and site-specific drivers of the recovery processes showed that fire severity was not a key determinant of RRI; however, the opposite was found to be true within the context of the pre-fire vegetation condition, especially regarding the short- and mid-term recovery of Deciduous oak forests and

Sclerophyllous vegetation. However, pre-fire condition was shown to influence post-fire recovery, which may be hindered by post-fire climate conditions, especially within the context of DOF. Maximum temperature and precipitation tested with RRI patterns were shown to be good indicators of post-fire vegetation recovery, providing useful insights that could be applied towards understanding its variability. High precipitation favours a progressive increase in regeneration, making it a good proxy for post-fire moisture contents that facilitate seed germination and regrowth of Mediterranean forests. While high temperatures after one year of fire can be a proxy for the effects of drought, which have been linked to the inhibition of the recovery of resilient stands (e.g., resprouters).

The analysis of RRI with environmental variables effectively captured the distribution of vegetation patterns between Mediterranean vegetation communities'; this implies that this method may be a sound alternative within the context of identifying priority areas for post-fire management in practice. However, future research is still needed to validate generated LMM models not only across a range of Mediterranean plant communities but also in non-Mediterranean sites. Although the basis of LMM models (i.e., using several variables as input) to assess post-fire recovery yielded an adequate transferability of performance between several burned Mediterranean communities at the regional scale, the application of these models to the other regional/national Mediterranean communities not considered here will require an adequate LMM parameterization to reflect accurately how environmental variables vary in terms of how they affect vegetation recovery processes.

CRediT authorship contribution statement

Maria Floriana Spatola: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Marco Borghetti:** Investigation, Writing – review & editing. **Angelo Nolè:** Conceptualization, Investigation, Supervision, Methodology, Writing – review & editing.

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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