

Quantifying vegetation recovery under different reforestation practices using time series analysis: a case study in Cyprus

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ABSTRACT

In recent decades, wildfires have increased in frequency, intensity, and spatial extent, causing extensive ecological damage and emphasizing the necessity for effective post-fire restoration measures. Earth Observation (EO) and Remote Sensing (RS) technologies offer an efficient and reliable way to monitor landscape recovery over long periods, supporting both research and forest management. This study explores the contribution of EO methods in evaluating reforestation actions implemented after the 2016 Solea fire in Cyprus, a representative wildfire event in the Troodos region, dominated by *Pinus brutia* forest stands. Using a 12-year Landsat-based Normalized Burn Ratio (NBR) time series (2013–2024), complemented by climatic and topographic variables harmonized to a common analysis grid, this study assesses vegetation recovery under five restoration approaches: Planting, Terraces, Sowing, Spot Sowing, and Natural Regeneration. Recovery dynamics were assessed through established indicators, including the Relative Recovery Index (RRI) and Year-to-Year (YrYr) slopes. Our findings indicate that areas restored through planting and terraces were associated with faster and more consistent vegetation recovery than areas undergoing natural regeneration. The statistical analysis also demonstrated that fire severity and pre-fire vegetation condition were the most influential determinants of post-fire regrowth, and that linear regression models provided the strongest predictive performance. By combining EO time series with ecological insights, this work highlights the strengths and weaknesses of different restoration practices and provides evidence-based guidance for future forest recovery planning in fire-prone Mediterranean landscapes.

1. Introduction

In recent years, extreme fire events have become increasingly frequent, destructive, and deadly in many areas worldwide, and the recent incidents in Europe have highlighted the severity of the situation (de Rivera et al., 2024; Kreider et al., 2024; Ellis et al., 2022). Recent analyses based on the updated University of Maryland and Global Forest Watch datasets (2001–2024) indicate that forest fires currently burn more than twice as much tree cover annually as they did two decades ago. In 2024 alone, at least 13.5 million hectares of forest were affected by fires globally, highlighting the rapidly increasing severity and extent of wildfire-driven forest loss worldwide (Potapov et al., 2025). These fires may originate from natural phenomena such as lightning but are

often the result of human activities like arson, posing serious threats to ecosystems, human lives, infrastructure, and contributing to long-term environmental degradation (Kreider et al., 2024).

In recent decades, the Mediterranean region has experienced a notable increase in both the frequency of fires and the total burned area (Potapov et al., 2025). This is primarily attributed to the characteristics of the Mediterranean ecosystem, including the prolonged dry summers, complex terrain, and highly flammable vegetation, which contribute to the region being among the most fire-prone regions worldwide (Cramer et al., 2018; Calderisi et al., 2025a). In these ecosystems, recurrent wildfires can significantly impede Natural Regeneration. Although many Mediterranean forest species are fire-adapted, Natural Regeneration may still be constrained under unfavorable post-fire conditions.

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Post-fire vegetation recovery may occur through resprouting, seed germination, or shrub regrowth (Pausas, 2004; Espelta et al., 2012; Espelta et al., 2003). However, some forests lack sufficient adaptive mechanisms to regenerate, making reforestation essential (Turck et al., 2025). For instance, *Pinus halepensis* frequently fails to recover when exposed to repeated fires within short intervals. Therefore, restoration efforts are vital to rehabilitate fire-damaged ecosystems and to enhance their ecological stability and resilience (Boydak, 2004).

To mitigate the negative ecological impacts of fires, including greenhouse gas emissions and smoke particles, soil erosion and degradation, and the loss of biodiversity, among others, post-fire restoration is essential (Pérez-Cabello et al., 2021). In Mediterranean ecosystems, however, the capacity of burned landscapes to regain pre-fire conditions varies widely, ranging from a few years to several decades (Nolè et al., 2022a; Viana-Soto et al., 2020a; Bright et al., 2019a). This variation depends on multiple factors, including the adaptive traits of plant species and environmental drivers like post-fire climate, terrain, fire severity, and soil properties (Calderisi et al., 2025a; Viana-Soto et al., 2020a; Taboada et al., 2018; Mazza and Sarris, 2021). Consequently, there is a strong need to monitor how well Mediterranean forests recover after wildfire events. Ecological restoration through active (direct interventions like planting) or passive (Natural Regeneration) ways (Alayan et al., 2022; Morrison and Lindell, 2011) aims to recover an ecosystem that has been degraded or destroyed (e.g., wildfire occurrence) to its historical state to regain its ecological integrity as well as resilience (Upreti et al., 2012; Brancalion and Chazdon, 2017).

Over recent decades, remote sensing (RS) has significantly advanced across multiple forestry applications, including fire damage assessment, reforestation prioritization (Salomão et al., 2020), forest phenology and seasonal dynamics analysis, fire risk prediction (Liz-López et al., 2024), and forest species mapping (Prodromou et al., 2025a) thereby supporting researchers, environmental managers, and decision-makers (Papachristoforou et al., 2023; Prodromou et al., 2024). In the context of restoration monitoring, remote sensing has become an essential tool for evaluating ecological restoration efforts and monitoring ecosystem recovery, providing valuable insights into ecosystem condition and dynamics. It provides a cost-effective, accurate, and non-invasive approach to assessing ecosystem condition, tracking recovery in degraded areas, and evaluating long-term ecological changes. (Wang et al., 2024).

Specifically, satellite RS allows the acquisition of imagery with multiple spectral bands, not limited to the visible spectrum, while recent advances have greatly improved forest monitoring by enhancing, spatial, temporal and radiometric resolution (Mitchell et al., 2017). Commonly used EO datasets include multispectral sensors, such as Landsat and Sentinel-2 (Mitchell et al., 2017; Zhang et al., 2025a; Keskes et al., 2025), and Synthetic Aperture Radar (SAR) systems like ALOS PALSAR and Sentinel-1, which operate independently of cloud cover and atmospheric interference (Kacic and Kuenzer, 2022; Kanja et al., 2025; Lukman Alage et al., 2025; Agost et al., 2025; Theocharidis et al., 2025). The combination of SAR with optical data further strengthens monitoring capabilities (Kanja et al., 2025; Duan et al., 2025; Vittucci et al., 2025). Moreover, the Light Detection and Ranging (LiDAR) technologies, including Global Ecosystem Dynamics Investigation - GEDI mission add valuable three-dimensional (3D) structural information (Thers et al., 2019; Caughlin et al., 2016; Almeida et al., 2019) support the assessment of forest characteristics (Dubayah and Drake, 2000; Dubayah et al., 2020), such as aboveground biomass (Sulabha et al., 2025; Lucas et al., 2008; Nazir et al., 2025) and canopy height (Pereira-Pires et al., 2025; Liu et al., 2025). In addition, multi-spectral imagery is widely used to generate vegetation indices such as the Normalized Difference Vegetation Index (NDVI) (Tucker, 1979), Enhanced Vegetation Index (Huete et al., 2002), Bare Soil Index (BSI) (Rikimaru et al., 2002), Normalized Difference Water Index (NDWI) (McFEETERS, 1996), Normalized Burn Ratio (NBR) (Key and Benson, 2006), which are frequently used for monitoring vegetation conditions, leaf water content, and burned area detection.

Monitoring vegetation recovery after fire poses significant challenges, particularly where regular and long-term observations are needed in remote and difficult-to-access areas, making in-situ measurements difficult or even infeasible (Key and Benson, 2006). Several studies have utilized remote sensing data to assess ecosystem recovery worldwide (De Luca et al., 2022; Roche et al., 2024; Rodrigues et al., 2024; Viana-Soto et al., 2020b). Many of them have utilized multi-spectral imagery from sensors such as Sentinel-2, MODIS, and especially Landsat, since it provides a long-term data archive, spanning more than four decades, which allows comparisons between pre-disaster conditions and post-disaster conditions (Frazier et al., 2018; Frazier et al., 2015; De Keersmaecker et al., 2022a).

In this context, time series derived from RS data constitute a valuable tool, providing the ability to evaluate vegetation dynamics over large areas and in depth over time (De Keersmaecker et al., 2022a; Nolè et al., 2022b; Nolè et al., 2022c; João et al., 2018). In general, time-series-based recovery indicators can be conceptually grouped into three main categories: (i) recovery magnitude, which reflects the degree to which vegetation returns to pre-disturbance conditions (e.g., Relative Recovery Index - RRI) (Frazier et al., 2018); (ii) recovery rate, which describes the speed and direction of post-fire regrowth (e.g., year-to-year slope-YrYr and Sen's Slope) (Frazier et al., 2018; Kennedy et al., 2012a; Sen, 1968a); and (iii) recovery trend, which describes the long-term direction and consistency of vegetation recovery trajectories (e.g., Theil-Sen slope and Kendall's τ statistics) (Frazier et al., 2018). In addition, trajectory-based approaches, such as Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr) (Kennedy et al., 2010) and Vegetation Change Tracker (VCT) (Huang et al., 2010a), provide complementary information by identifying structural changes and temporal breakpoints in vegetation dynamics (Huang et al., 2010b), while methods such as the Breaks For Additive Seasonal and Trend (BFAST) allow for the detection of seasonal and trend components in higher-frequency time series (Verbesselt et al., 2010). Despite the wide range of available approaches, their comparative performance and consistency in representing post-fire recovery remain insufficiently explored, highlighting the need for systematic evaluation.

Among the most widely adopted spectral indices for post-fire vegetation recovery are the Normalized Burn Ratio (NBR), derived from near- and short-wave infrared bands, which is highly sensitive to fire-related changes in vegetation structure and moisture (Key and Benson, 2006; Hislop et al., 2018) and the Normalized Difference Vegetation Index (NDVI), one of the most established indices, based on red and near-infrared reflectance, and widely used to monitor vegetation condition and greenness (Tucker, 1979). In comparison with NDVI and similar vegetation indices such as EVI and NBR, it has demonstrated higher sensitivity to burned surfaces, vegetation moisture loss, and post-fire structural changes, making it particularly suitable for post-fire recovery assessment in Mediterranean forest ecosystems (Bright et al., 2019b; Epting et al., 2005). In addition, NBR, derived from long-term Landsat time series, has been extensively applied in wildfire-related studies due to its ability to effectively capture both fire severity and vegetation regeneration dynamics (Key and Benson, 2006; Bright et al., 2019b).

Post-fire restoration is essential to protect soil, water, and vegetation; however, detailed evaluations of different restoration techniques remain limited (Spanos and Raftoyannis, 2005). Studies in the Mediterranean region rarely evaluate restoration at the level of specific practices, but often focus on monitoring the effectiveness of practices in a more generalized context by grouping interventions into active or passive categories without systematically assessing the differential effects of specific practices such as Sowing, Spot Sowing, Planting, or Terracing (Chen et al., 2014). Furthermore, according to Castro J. (Castro, 2021), reforestation efforts in Mediterranean ecosystems often show limited success, characterized by high seedling mortality and low growth rates, while long-term monitoring initiatives are relatively scarce (Castro, 2021; Ruthrof et al., 2013; Kildisheva et al., 2017; Del Campo et al.,

2007). Previous studies have highlighted that these limitations are rarely explored in case studies comparing multiple restoration practices under similar conditions. Recent studies, including our previous work, further highlight these limitations in restoration assessment approaches (Prodromou et al., 2025b). This gap is particularly relevant in the context of the 2016 Solea wildfire in Cyprus, where multiple restoration practices were implemented, including Natural Regeneration, Planting, Sowing, Spot Sowing, and Terraces, but have not been comprehensively evaluated in a comparative, long-term framework. As a result, there is still limited knowledge on how different restoration practices shape recovery pathways in fire-affected landscapes.

Building on the above, several important research gaps were identified through the literature review. Specifically, the existing studies in Mediterranean ecosystems often assess restoration effectiveness in a generalized way, lacking quantitative comparisons among specific practices (e.g., sowing, planting, terracing). In addition, long-term time-series analysis of post-fire recovery remains limited, and the stability and comparative performance of commonly used recovery indicators (e.g., RRI, YrYR, Theil-Sen slope) have not been sufficiently evaluated. Consequently, a comprehensive understanding of recovery dynamics across restoration practices and metrics is still missing.

To address the identified research gaps, this study evaluates post-fire vegetation recovery following the 2016 Solea wildfire in Cyprus using Landsat-derived NBR time-series analysis covering the period 2013–2024. The analysis focuses on five restoration practices implemented within the burned area, including planting, terracing, sowing, Spot Sowing, and Natural Regeneration. By integrating long-term RS observations, recovery metrics, and environmental variables, the study aims to improve the understanding of vegetation recovery dynamics in Mediterranean fire-prone ecosystems and support evidence-based post-fire restoration planning and forest management. The study also contributes to broader policy objectives, including the European Green

Deal's goal of achieving climate neutrality by 2050 and the UN Decade on Ecosystem Restoration (UNEP; FAO, 2019).

Specifically, the main objectives of this study are:

- i. To provide a long-term quantitative comparison of five restoration practices following the 2016 Solea wildfire in Cyprus using Landsat-derived NBR time series.
- ii. To evaluate the consistency and differences among multiple recovery indicators, including RRI, YrYr trends, and Theil-Sen slope, in order to assess their ability to capture different dimensions of post-fire vegetation recovery.
- iii. To compare linear (OLS) and non-linear (Random Forest and XGB) modeling approaches for identifying the main environmental and fire-related drivers influencing post-fire recovery.

Through this integrated methodological framework, the study provides both methodological and ecological insights into restoration effectiveness in Mediterranean forest ecosystems and highlights the value of long-term Earth Observation time-series analysis for quantitative post-fire recovery assessment. The findings contribute to improved understanding of recovery trajectories under different restoration practices and provide practical evidence to support post-fire restoration planning, ecosystem management, and climate resilience initiatives in fire-prone Mediterranean landscapes.

2. Materials and methods

2.1. Study area

The study focuses on the Solea region, in the Nicosia district of Cyprus (Fig. 1), where a significant wildfire on 19 June 2016 burned 18.57 km² of the Adelfi Forest (Department of Forests in Cyprus, 2023).

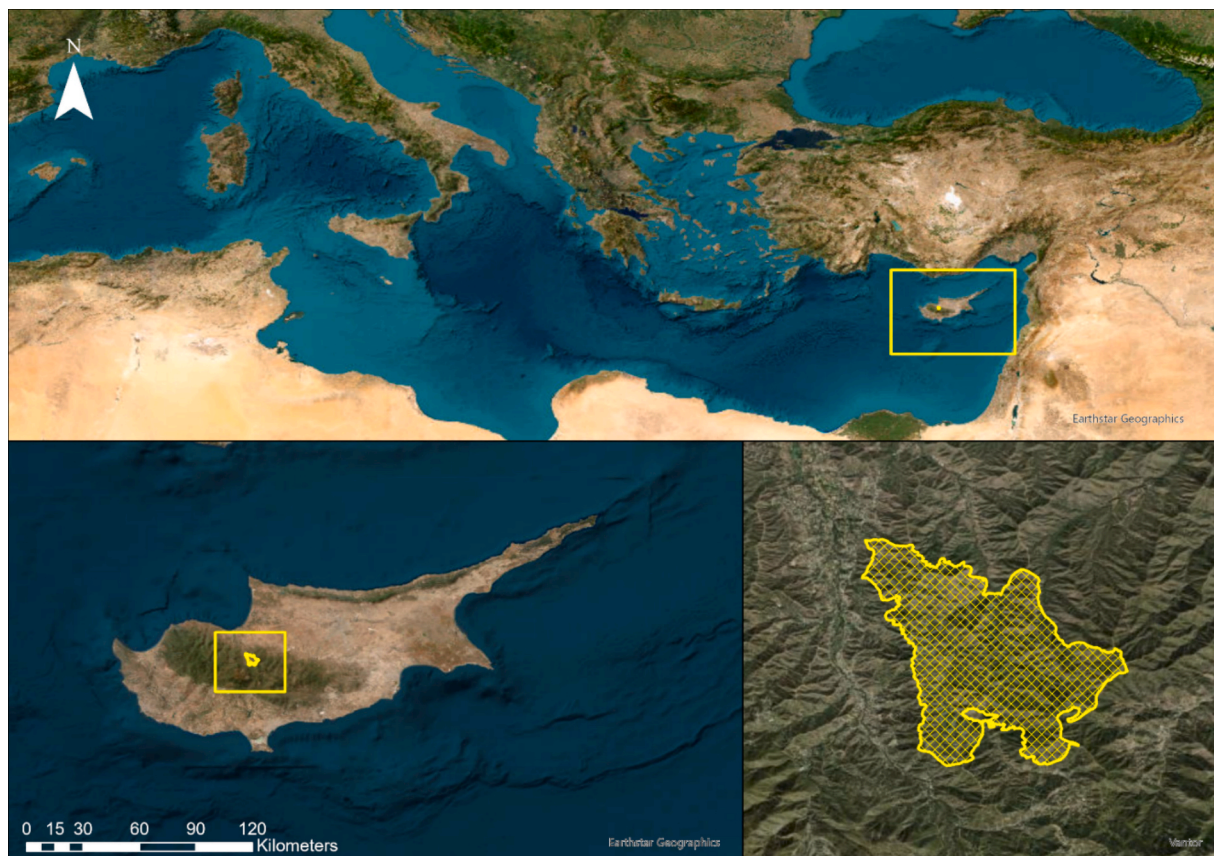


Fig. 1. Total burned area from the wildfire that occurred on 19 June 2016, near Solea village, Cyprus.

The area lies at elevations of 495–1253 m and is characterized by predominantly steep terrain, with only 18.24% classified as gentle slopes (0–25%) and nearly a quarter exceeding 100%, creating major challenges for post-fire restoration and vegetation recovery. Climatic conditions vary considerably with altitude: higher-elevation areas are wetter, receiving an average of 868 mm annual rainfall and experiencing milder temperatures, while lower zones are characterized by a prolonged dry season (April–October), lower annual precipitation (407.5 mm), and extreme summer temperatures exceeding 42 °C, all of which influence post-fire regeneration processes. The vegetation is dominated by *Pinus brutia* forests with an understory of herbaceous plants, low shrubs (e.g., *Cistus* spp.), and larger shrubs such as *Quercus alnifolia*, *Pistacia terebinthus*, and *Olea europaea* (Department of Forests in Cyprus, 2023; Department of Forests in Cyprus, 2016).

Following the 2016 wildfire event, several post-fire restoration practices were implemented by the Department of Forests (DoF) across the burned area, including Planting, Sowing, Spot Sowing, Terracing, and areas managed through Natural Regeneration. These restoration practices were spatially distributed according to terrain conditions, accessibility, fire severity, and local environmental characteristics. In general, active restoration measures such as planting and terracing were primarily applied in highly degraded and erosion-prone areas characterized by steep slopes, aiming to improve soil stability, reduce runoff, and enhance vegetation establishment. In contrast, large parts of the burned landscape were managed through Natural Regeneration, which occupied a greater proportion of the affected area. The restoration

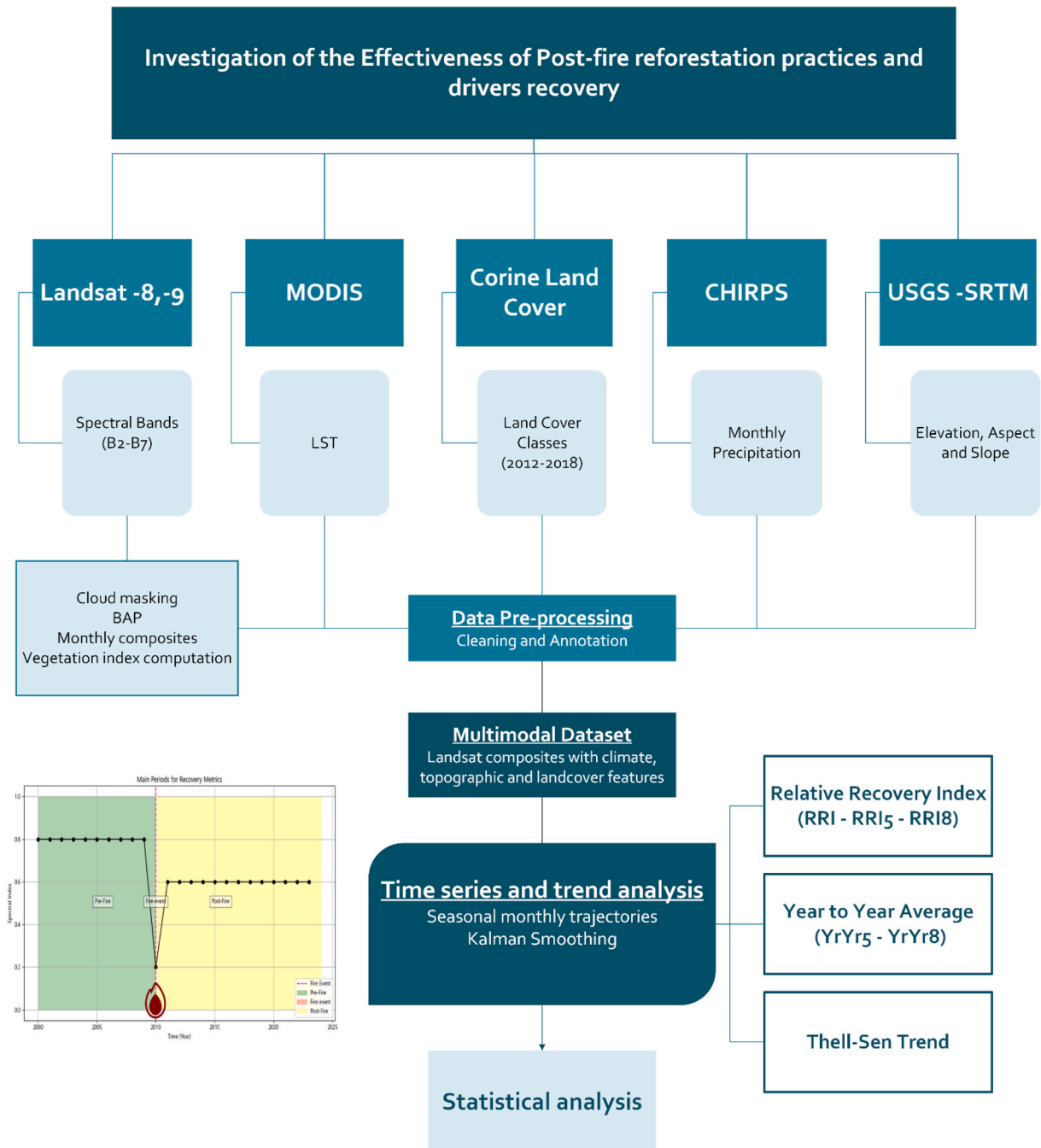


Fig. 2. Methodological framework for constructing the multimodal dataset (Landsat-8/9, MODIS, CLC, CHIRPS, and SRTM) and its use in time-series and trend analyses to assess post-fire reforestation performance.

practices implemented after the June 2016 wildfire formed the spatial and management framework for the comparative assessment of post-fire vegetation recovery conducted in this study (Department of Forests in Cyprus, 2016).

2.2. Methodological framework

The overall methodological workflow, illustrated in Fig. 2. It integrates multi-source remote sensing, climatic, topographic, and land cover datasets to assess post-fire vegetation recovery and the effectiveness of different restoration practices. Multidimensional datasets have been widely used to facilitate the integration and harmonization of heterogeneous data sources, enabling more comprehensive analysis. Such datasets are organized across multiple dimensions, including time, space, and thematic variables, allowing for improved data interpretation and efficient analysis (Bountos et al., 2025). They have been successfully applied in various domains, including fire risk modeling, post-fire impact assessment, and climate change studies. In this study, this approach was adopted to support time-series analysis of vegetation recovery and to evaluate the effectiveness of restoration practices in burned areas (Prodromou et al., 2025b; Lahat et al., 2015). Initially, Landsat-8/9 imagery was preprocessed to generate monthly NBR-based composites. These composites were subsequently combined with MODIS-derived land surface temperature (LST), CHIRPS precipitation, SRTM-based topographic variables, and CORINE land cover data to construct a harmonized multimodal dataset. All variables were preprocessed to ensure spatial and temporal consistency, including data cleaning, normalization, reprojection, and harmonization to a common 30 m analysis grid for pixel-level integration across datasets, while preserving the native spatial characteristics of the original products. Accordingly, coarse-resolution datasets (e.g., CHIRPS precipitation and MODIS LST) retained their native spatial information content and were aligned solely to facilitate integration with Landsat-derived variables. The dataset covers the period from January 2013 to January 2025 and was aggregated to monthly temporal resolution. Following data integration, time-series smoothing, and trend analysis were applied to extract vegetation recovery dynamics. Based on these trajectories, recovery metrics, including the Relative Recovery Index (RRI), Year-to-Year (YrYr) trends, and the Theil–Sen slope, were computed. Finally, statistical and machine learning analyses were conducted to compare restoration practices and identify the key environmental drivers influencing post-fire recovery. Each step of the workflow is described in detail in the following subsections.

2.3. Data sources and preprocessing

The datasets used in this study, including their spatial and temporal characteristics, are summarized in Table 1. These datasets include multi-source remote sensing, climatic, topographic, and land cover information. All datasets were subsequently preprocessed as described in the

Table 1

Summary of the datasets used in this study, including their spatial resolution, temporal resolution, and associated variables/units.

Source	Spatial resolution	Temporal resolution	Variables / Units
MODIS (LST)	1 km	8-day	Kelvin (Scale factor = 0.02)
CHIRPS (Precipitation)	~5.5 km (0.05 °)	Daily	mm/day
Landsat 8/9	30 m	8-day revisit (16 days per sensor)	Surface reflectance
Copernicus Land Cover	100 m	Reference years: 2012 and 2018	Land cover codes
USGS SRTM	30 m	Static	Elevation (m), slope (°), aspect (°)

following subsections and harmonized to support the analysis.

2.3.1. Satellite data and preprocessing

This study used freely available Landsat-8 OLI and Landsat-9 OLI-2 imagery from the USGS to produce monthly vegetation composites. Data were obtained from Collection 2, Level-2 Surface Reflectance, limited to Tier 1 scenes to ensure high geolocation accuracy (RMSE ≤ 12 m) (Lubke et al., 2021). Images with cloud cover higher than 50% were excluded, and reflectance for bands B2–B7 was scaled using the USGS formula (Eq. 1) (U.S. Geological Survey, 2021).

$$\text{Reflectance} = DN \times \text{scale_factor} + \text{offset} \quad (1)$$

where scale_factor = 0.000275 and offset = −0.2.

This kind of products include quality assessment (QA) bands generated using the Fmask algorithm. Specifically, the QA_PIXEL band helps detecting clouds, cloud shadows, cirrus, and snow, while the QA_RADSAT helps identifying radiometric saturation. Cloud masking was implemented by applying bitwise operation on the QA_PIXEL and QA_RADSAT bands to remove contaminated pixels (Lubke et al., 2021; Zhang et al., 2025b).

Moreover, the Best-Available-Pixel (BAP) compositing strategy was implemented following established pixel-based compositing approaches described in previous studies (White et al., 2014). In detail, for each available image, a custom pixel score was calculated based on three weighted criteria: cloud proximity (cloudScore, 40%), day-of-year proximity to mid-summer (doyScore, 30%) and sensor preference (sensorScore, 30%). Both Landsat-8 and Landsat-9 were assigned the maximum sensor score (1.0) due to their comparable radiometric characteristics. The selected weighting scheme was informed by literature-based BAP compositing principles and further refined through preliminary empirical evaluation of composite quality. Greater weight was assigned to cloud proximity in order to minimize atmospheric contamination and cloud-shadow effects, while the day-of-year component was used to preserve seasonal and phenological consistency among observations. The sensor weighting component ensured radiometric harmonization and comparability among Landsat missions. Similar BAP compositing strategies based on cloud distance, acquisition date, and sensor-related scoring have been widely adopted in previous studies (White et al., 2014; Francini et al., 2023a; Francini et al., 2023b). The pixelScore values were then used within GEE's qualityMosaic() function, which selects the observation with the highest quality score from all available images for each pixel location, thereby ensuring that the least cloud-contaminated and most representative pixel is retained in the final composite.

Applying this approach, the monthly dataset derived from Landsat imagery is suitable for time-series analysis due to temporal consistency, cloud optimization, and sensor harmonization. The surface reflectance data were utilized for the calculation of NBR index. Prior to analysis, all variables were normalized to a common scale to ensure comparability across datasets with different units and value ranges, and to prevent dominance of variables with larger numerical magnitudes in subsequent statistical analyses, which is particularly important for multi-variable time-series analysis and regression-based modeling. A Kalman filter was applied to minimize noise and reduce the influence of residual atmospheric contamination, data gaps, and short-term fluctuations in the NBR time series, producing smoother and more reliable temporal trajectories. Specifically, the Kalman filtering configuration was empirically optimized using an expectation–maximization (EM) procedure, which iteratively estimated the state transition and observation covariance parameters directly from the input time series. Missing or invalid observations were initially interpolated to provide a continuous input signal prior to filtering. The selected configuration was designed to balance noise reduction and signal preservation, ensuring that high-frequency noise was minimized without distorting long-term post-fire recovery trends, which is critical for reliable temporal analysis and

recovery metric estimation (Jain et al., 2025). The Kalman filter operates as a recursive estimator that provides optimal estimates under the assumption of linear system dynamics and Gaussian noise distributions, while its performance in more complex non-linear conditions depends on the validity of these assumptions (Mousazadeh, 2013; Kalman, 1960).

2.3.2. Ancillary environmental data

For land cover information, Copernicus CLC datasets (2012, 2018; 100 m resolution) (European Environment Agency, n.d.) were spatially aligned to the common 30 m analysis grid to ensure consistency with the Landsat-derived variables. Land cover is a key factor in post-fire recovery, as certain vegetation types (e.g., shrublands) regenerate faster than forests (Upriety et al., 2012).

Topographic variables, specifically elevation, slope, and aspect, were derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (V3, ~30 m resolution). These variables were selected because they strongly influence both fire occurrence and related processes through their effect on precipitation, temperature, humidity, evapotranspiration, and wind speed (Morrison and Lindell, 2011). Although SRTM data are provided at a spatial resolution comparable to Landsat (~30 m), all topographic variables were reprojected to a common coordinate reference system (i.e., EPSG:4326) and aligned to the same spatial grid to ensure consistency with the other datasets used in the analysis.

Climatic data included precipitation from the CHIRPS dataset, a long-term rainfall product (1981–present) that integrates satellite and station records at 0.05° resolution. Daily precipitation was aggregated to monthly totals and spatially aligned to the common 30 m resolution grid to support variable integration and comparative modeling with Landsat-derived variables, rather than to generate true high-resolution climatic information (Funk et al., 2015). Similarly, Land Surface Temperature (LST) was obtained from MOD11A2 (1 km, 8-day composites), and was spatially aligned to the same 30 m analysis framework to support integration with higher-resolution variables within the modeling workflow and aggregated monthly. LST captures the combined temperature of soil and vegetation (Nemani et al., 1996), with variations influencing microclimate, plant growth, and ecosystem functioning (Zellweger et al., 2019; Sun et al., 2021).

2.3.3. Spatial harmonization and resampling

To ensure spatial consistency across all variables, datasets with different native spatial resolutions were harmonized and reprojected to a common 30 m analysis grid using a unified coordinate reference system (EPSG:4326). Continuous variables (e.g., LST, precipitation) were resampled using bilinear interpolation, as it preserves smooth spatial gradients and avoids artificial discontinuities, while categorical data (e.g., land cover) were resampled using nearest-neighbor assignment to maintain class integrity. Although resampling may introduce some uncertainty due to spatial mismatches between datasets of different resolutions, it enables pixel-level integration and consistent comparison across multi-source datasets within the multidimensional framework (Yu et al., 2025; He et al., 2025). It is acknowledged that integrating coarse-resolution datasets (e.g., CHIRPS, MODIS LST) with higher-resolution Landsat data does not increase the inherent spatial detail of the original variables. Instead, bilinear interpolation produces a smoothed representation that enables consistent integration within the common analytical framework, while introducing some uncertainty associated with scale mismatches, particularly in topographically complex areas where precipitation exhibits strong spatial variability (e.g., due to orographic effects).

2.3.4. Sampling design and reference data for restoration practices

In addition to the satellite and ancillary datasets, spatial reference points representing different restoration practices were provided by the Cyprus Department of Forests (DoF). These points correspond to areas

where specific restoration practices were implemented following the 2016 Solea wildfire, including Planting, Sowing, Spot Sowing, Terraces, and Natural Regeneration, as shown in Fig. 3. The Department of Forests assigned the restoration practices operationally according to local environmental and management conditions rather than through experimental randomization. For each restoration category, an initial target sample of up to 100 spatial reference points was generated within the corresponding DoF polygon layer. To reduce spatial clustering and avoid repeated sampling of neighboring Landsat pixels, a minimum inter-point distance of 300 m was applied, thereby reducing spatial autocorrelation and ensuring spatial independence among samples. Following this filtering process, the final number of valid samples retained for analysis was 9 for Planting, 8 for Terraces, 17 for Sowing, 30 for Spot Sowing, and 67 for Natural Regeneration. The variation in the final number of retained samples among restoration practices was mainly related to differences in the spatial extent and configuration of the restoration polygons, combined with the application of the 300 m spatial independence threshold. In practices covering smaller or more fragmented areas (e.g., Planting and Terraces), fewer spatially independent samples could be retained while satisfying the minimum-distance criterion. This constraint also minimizes the likelihood that multiple points fall within the same or neighboring 30 m pixels. The final set of points was used to extract band values and derived variables from each monthly composite at 30 m spatial resolution. These samples form the basis for the extraction of NBR time series and the calculation of recovery metrics and subsequent statistical analyses. Since all restoration practices were implemented within the same wildfire perimeter (18.57 km²), broad-scale climatic conditions were considered relatively comparable across the study area. The integration of environmental and topographic variables in the subsequent analysis allowed the models to account for spatial heterogeneity in micro-environmental conditions (e.g., slope, precipitation, and land cover) within each restoration practice. Although coarse-resolution datasets (e.g., CHIRPS and MODIS LST) may result in multiple samples sharing similar values, these variables represent broader climatic conditions and were used in combination with higher-resolution datasets (e.g., Landsat and topographic variables), which capture local spatial variability.

2.4. Time series analysis and recovery metrics

Time-series and trend analyses were then performed using the final set of spatially independent samples retained after applying the 300 m minimum-distance criterion for each restoration practice, as provided by the Department of Forests (DoF). The analysis was based on the Normalized Burn Ratio (NBR), where the annual mean and standard deviation were calculated for each restoration practice during the summer months (June–August). Recovery trends were divided into three phases (De Keersmaecker et al., 2022b): baseline conditions prior to disturbance, the disturbance period, representing the fire severity, and the post-disturbance period indicating the degree of vegetation recovery.

To quantify post-fire vegetation recovery, the applied recovery indicators were grouped into three conceptual categories according to the recovery dimension they represent: (i) recovery magnitude, (ii) recovery rate, and (iii) recovery trend as presented in Table 2. Recovery magnitude was assessed using the Relative Recovery Index metrics (RRI, RRI5, and RRI8), which quantify the degree to which vegetation recovered relative to pre-fire conditions and disturbance severity. Recovery rate was evaluated using the Year-to-Year metrics (YrYr5 and YrYr8), which describe the speed and direction of vegetation regrowth over time. Recovery trend was assessed primarily using the Theil–Sen slope, while the Mann-Kendall (MK) test and Kendall's τ statistics were used to assess the significance and direction of monotonic recovery trends (Theil, 1992; Sen, 1968b). Although trajectory-based approaches such as LandTrendr and Vegetation Change Tracker (VCT) are widely used for detecting disturbance dynamics and temporal breakpoints, they are primarily

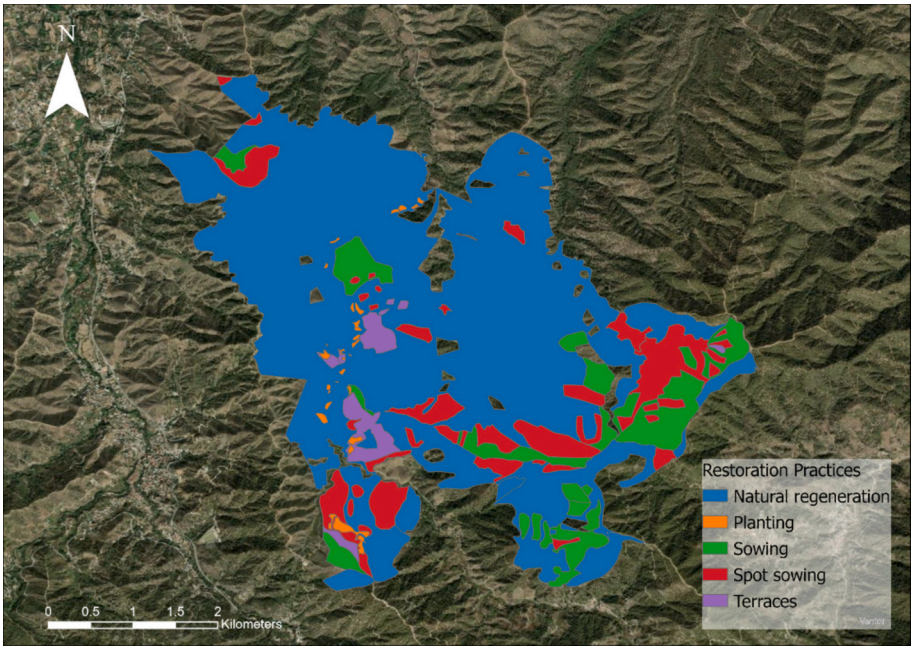


Fig. 3. Spatial distribution of restoration practices implemented by the department of forests.

Table 2
Recovery metrics, equations, and corresponding references used to evaluate post-fire vegetation recovery dynamics.

Category	Abbreviation	Equation	References
Recovery Magnitude	RRI	$RRI = \frac{\max(f(t_{post})) - f(t_{dist})}{ f(t_{pre}) - f(t_{dist}) }$	(Frazier et al., 2018; Kennedy et al., 2012b)
	RRI5/RRI8*	$RRI_A = \frac{f(t_A) - f(t_{dist})}{ f(t_{pre}) - f(t_{dist}) }$	
Recovery Rate	YrYr*	$YrYr = \frac{f(t_A) - f(t_{dist})}{t_A - t_{dist}}$	(Frazier et al., 2018)
Recovery Trend	Theil–Sen slope	$Theil - Sen\ slope = median\left(\frac{f(t_j) - f(t_i)}{t_j - t_i}\right)$	(Theil, 1992; Sen, 1968b)

where $f(t_{pre})$: NBR value before the disturbance. $f(t_{dist})$: NBR value at the disturbance time. $f(t_{post})$: NBR value during the post-fire period. $f(t_A)$: NBR value at a given time t_A after the disturbance. $t_A - t_{dist}$: The time that has passed since the disturbance. $f(t_j) - f(t_i)$: NBR values at specific observation times. $t_j - t_i$: Time difference between observations.

* Applied at the 5-year (RRI5, YrYr5) and 8-year (RRI8, YrYr8) post-fire time points.

designed to identify abrupt changes and long-term trends (Theocharidis et al., 2025). In contrast, the objective of this study is to quantify post-fire vegetation recovery and evaluate vegetation recovery associated with different restoration practices. Therefore, recovery metrics such as RRI, YrYr, and Theil–Sen slope were selected, as they provide more direct and interpretable measures of recovery magnitude, rate, and temporal progression, enabling consistent comparison across restoration practices. These metrics were selected because they provide a comprehensive evaluation framework, capturing different dimensions of post-fire recovery dynamics, including recovery magnitude, regrowth rate, and long-term recovery trends under varying environmental and topographic conditions. Furthermore, they were selected based on their widespread use in the literature, interpretability, and ability to characterize different aspects of ecosystem recovery trajectories (Frazier et al., 2018; Kennedy et al., 2012a; Sen, 1968a). To further ensure the robustness of the detected trends, the Mann-Kendall (MK) test was applied using a significance threshold of $p < 0.05$, and only statistically

significant trends were retained for further analysis (Frazier et al., 2018).

2.5. Statistical analysis

Following the analysis described above, the nonparametric Kruskal–Wallis test was applied to examine whether the post-fire recovery metrics (RRI, RRI5, RRI8, YrYr5, YrYr8, and Theil–Sen slope) differed significantly among restoration practices. Based on the analysis, if the computed H statistic was high and the associated p -value was below the significance threshold ($p < 0.05$), this indicated that at least one group differed significantly from at least one other group in terms of recovery performance. Subsequently, Dunn's post hoc test was subsequently applied to identify pairwise differences among restoration practices (Kruskal and Wallis, 1952).

2.5.1. Evaluation of environmental and fire-related drivers of post-fire vegetation recovery

To identify the main factors influencing post-fire vegetation recovery in Mediterranean forests, a comparative regression analysis was performed using Ordinary Least Squares (OLS), Random Forest (RF), and Extreme Gradient Boosting (XGB). The regression analysis enabled the modeling and interpretation of relationships between recovery metrics (dependent variables) and environmental or fire-related variables (independent variables). In this study, variables such as LST, precipitation, fire severity, pre-fire vegetation condition (mean pre-fire NBR), aspect, slope, elevation, and land cover were examined to explain variation in short-term vegetation recovery. In addition to their predictive performance, the applied models were also used to identify the relative importance of the examined variables. Specifically, the feature importance derived from the RF model was used to assess the contribution of each predictor, while the OLS model was used to quantify and interpret the relationships between environmental variables and recovery metrics. Furthermore, correlation analysis further supported the identification of key drivers of post-fire vegetation recovery. This combined approach allowed a more comprehensive understanding of the factors associated with vegetation recovery and strengthened the link between the modeling framework and the ecological objectives of the study.

2.5.2. Ordinary least squares regression

The OLS model estimates the coefficients of a linear model by minimizing the sum of squared differences

(residuals) between the observed and predicted values (Shvetsov et al., 2019). It is widely applied to evaluate the relationship between one or more independent variables and a continuous dependent variable, expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon$$

where Y is the recovery metric (e.g., RRI, RRI5, YrYr, Theil-Sen slope). X_i is the predictor variable (e.g., temperature, precipitation, slope). β_0 are the regression coefficients. ε is the random error term.

2.5.3. Random forest regression

RF (Developers, S. Sklearn, 2025; Pedregosa et al., 2011) was used to model non-linear relationships between predictor variables and recovery metrics. The algorithm builds an ensemble of decision trees, each trained on a random subset of the data and evaluated using randomly selected predictor variables at each split, which improves generalization and minimizes overfitting (Breiman, 2001). As a tree-based model, RF is insensitive to feature scaling and does not require data normalization during preprocessing (Pedregosa et al., 2011; Breiman, 2001).

2.5.4. Extreme gradient boosting (XGB) regression

XGB combines multiple weak learners sequentially to improve predictive accuracy. Each new tree corrects the residuals of the previous one by minimizing a specified loss function, typically the squared error (Friedman, 2001; Callens et al., 2020). This approach effectively models complex nonlinear relationships between environmental variables and vegetation recovery, gradually reducing overall prediction error.

2.5.5. Accuracy assessment of the model

To assess model performance, the dataset was randomly divided into a training (70%) and a testing (30%) subset. Model performance was evaluated using the coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE), and bias, as presented. Additionally, the difference between the training and testing R^2 values was examined to evaluate potential overfitting across the three modeling approaches.

3. Results

This section presents the results of the post-fire vegetation recovery analysis. Initially, time-series trajectories are examined to evaluate pre- and post-fire vegetation dynamics across restoration practices. Recovery metrics are subsequently analyzed according to three recovery dimensions: magnitude (RRI-based metrics), rate (YrYr metrics), and trend (Theil-Sen slope and Kendall's τ). Finally, statistical and modeling approaches (OLS, RF, and XGB) are applied to assess differences in recovery among restoration practices and identify the main environmental drivers influencing recovery.

3.1. Time series trajectories of vegetation recovery

A time-series analysis was carried out to evaluate vegetation recovery following fire disturbance across different restoration practices (Sowing, Natural Regeneration, Terraces, Spot Sowing, and Planting). Annual mean NBR values derived from Landsat 8/9 imagery were used to evaluate vegetation dynamics within 5-year and 8-year post-fire recovery assessments.

The annual mean NBR trajectories for each restoration practice over the period 2013–2024 are presented in Fig. 4. In general, the NBR values range between -1 and 1 . Before the 2016 wildfire, NBR values ranged from approximately 0.2 to 0.3 , indicating relatively stable vegetation conditions across all restoration practices. Following the wildfire, a

substantial decline in NBR values was observed, with values dropping below zero in 2016, reflecting the immediate fire impact. During the post-fire period, a gradual recovery trend was detected across all practices, although post-fire NBR values remained below pre-fire levels throughout the study period. Distinct vegetation recovery trajectories were observed among restoration practices. Planting was associated with consistently higher post-fire NBR values, while Natural Regeneration was associated with lower and more variable recovery patterns. Sowing, Spot Sowing, and Terraces showed intermediate recovery trajectories throughout the study period.

To further quantify the observed differences among restoration practices, recovery metrics were subsequently analyzed according to the recovery dimension they represent, including recovery magnitude, rate, and trend.

3.2. Recovery magnitude (RRI, RRI5, RRI8)

Fig. 5 presents the recovery magnitude metrics (RRI, RRI5, and RRI8) across the different restoration practices. All restoration practices exhibited RRI values below 1 , indicating partial but incomplete recovery within the examined period. Significant differences among restoration practices were observed. Planting was associated with the highest recovery magnitude, with RRI, RRI5, and RRI8 values of 0.92 , 0.89 , and 0.72 , respectively. Similarly, Terraces showed consistently high recovery values (RRI = 0.91 , RRI5 = 0.84 , RRI8 = 0.68). In contrast, Natural Regeneration exhibited lower recovery magnitude, with RRI and RRI8 values of 0.68 and 0.54 , respectively, while RRI5 was 0.70 . Sowing and Spot Sowing showed intermediate recovery performance, with moderate RRI values of 0.72 and 0.68 , respectively.

The spatial distribution of the RRI-based metrics highlights substantial variability across the burned area. Areas subjected to active restoration were generally associated with higher and more spatially consistent recovery patterns than areas under Natural Regeneration. Furthermore, the distribution of RRI values among restoration practices indicates that Planting and Terraces presented higher median values and more concentrated distributions, suggesting more consistent recovery responses across samples. In contrast, Natural Regeneration and Spot Sowing exhibited wider variability and lower median values, indicating more heterogeneous recovery trajectories. This variability likely reflects the larger spatial extent and environmental heterogeneity associated with these restoration practices.

The spatial recovery maps presented in Fig. 6 highlight substantial temporal and spatial variability in vegetation recovery across the burned area derived from the RRI, RRI5, and RRI8 metrics. In general, the RRI metric showed higher recovery values than RRI5 and RRI8, as it is derived from the maximum post-fire NBR value, whereas RRI5 and RRI8 are based on multi-year averages that better capture the persistence of vegetation recovery over time. The RRI5 map (2016–2021) reveals extensive low-recovery zones, mainly in the central and eastern parts of the burned area, suggesting slower vegetation recovery during the first post-fire years. A similar spatial pattern is observed in the RRI8 map (2016–2024), indicating the persistence of lower recovery conditions over time. Lower recovery values appeared to be more frequently associated with areas under Natural Regeneration, whereas areas subjected to active restoration generally exhibited higher recovery levels. To further illustrate the observed spatial recovery patterns, field visits and visual interpretation were conducted at selected accessible locations, as presented in Fig. 7. These field photographs provide qualitative evidence of vegetation regrowth and are intended as illustrative support rather than quantitative validation of the recovery maps.

3.3. Recovery rate and trend

Recovery rate and trend were further evaluated using YrYr5, YrYr8, Theil-Sen slope, and Kendall's τ , as presented in Fig. 8. Specifically, the YrYr metrics were used to assess short-term recovery rate and regrowth

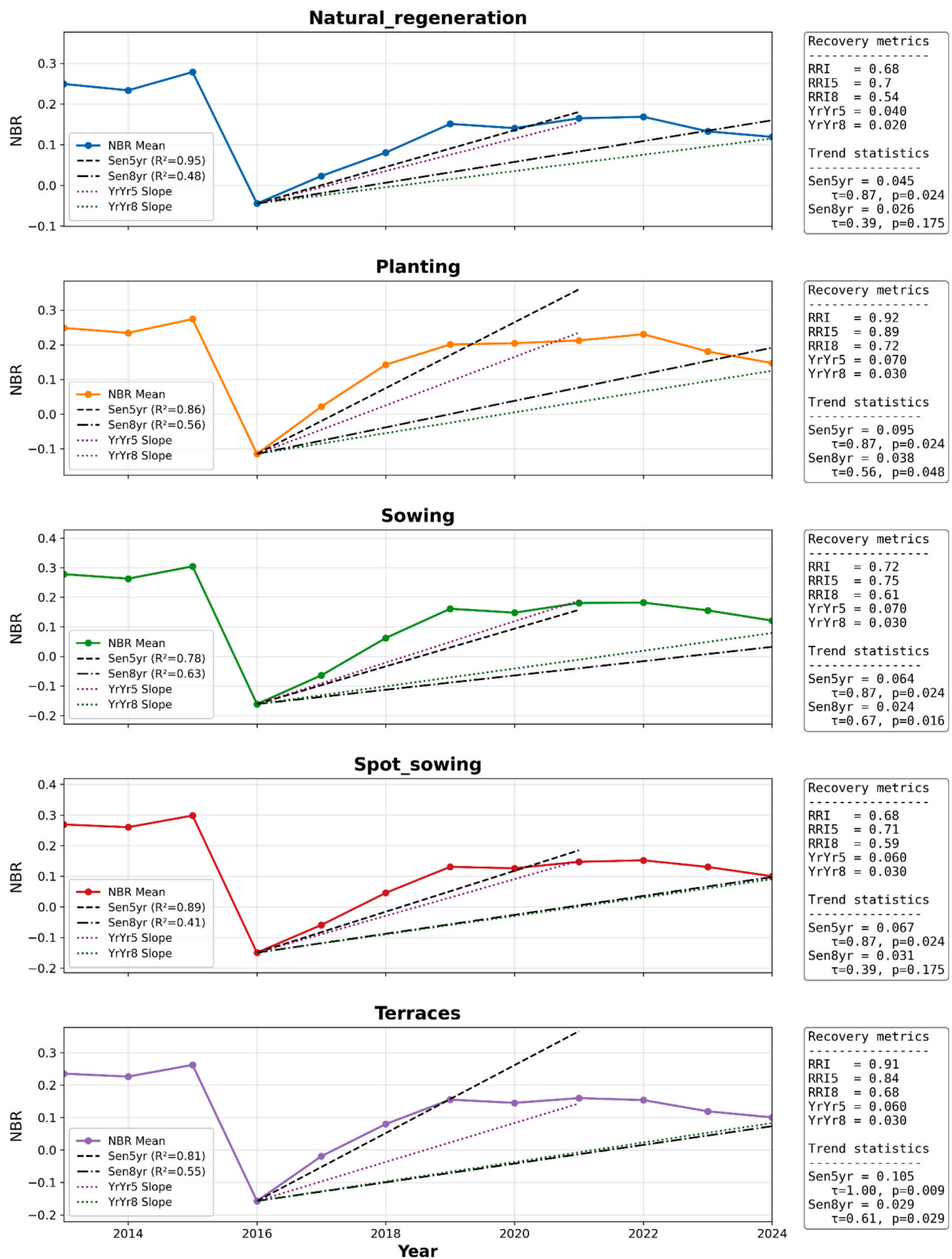


Fig. 4. NBR recovery trajectories, Theil-Sen slopes, and recovery metrics (RRI, RRI5, RRI8, YrYr5, and YrYr8) for the examined restoration practices.

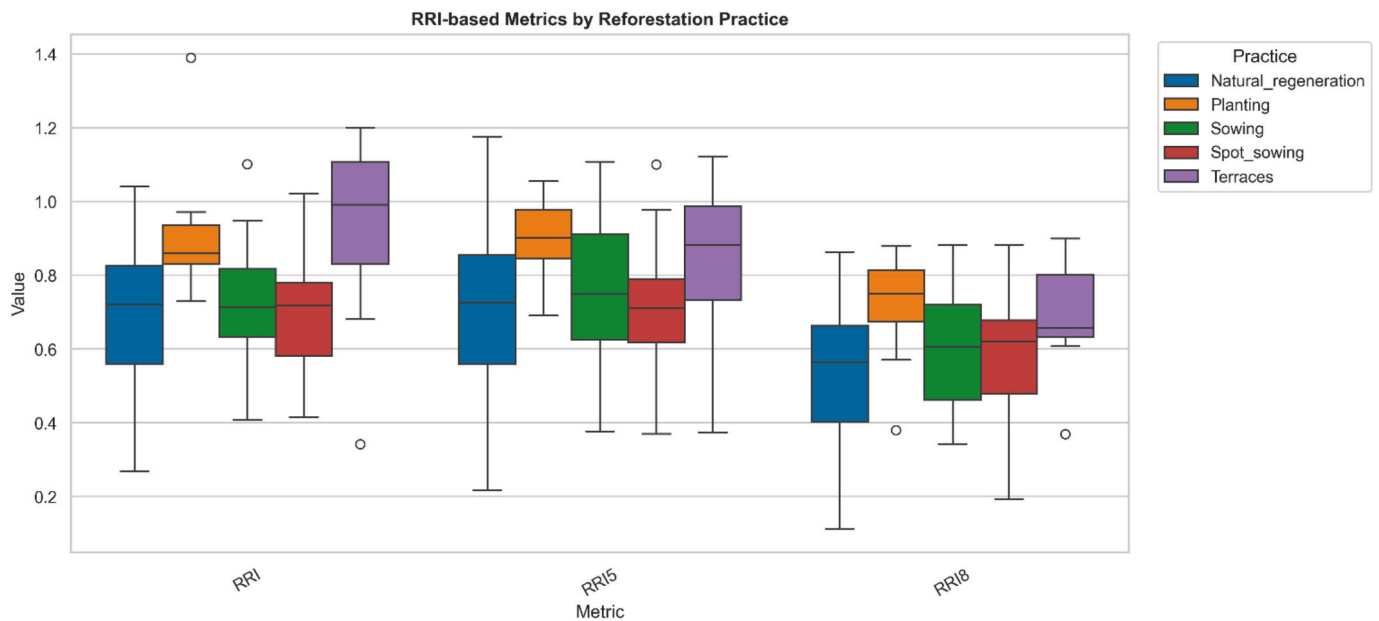


Fig. 5. Distribution of RRI, RRI5, and RRI8 recovery metrics across restoration practices. Boxes represent the interquartile range (IQR; 25th–75th percentile), the central line indicates the median, whiskers extend to $1.5 \times$ the IQR, and circles represent statistical outliers. Colors correspond to the different restoration practices.

dynamics, while the Theil–Sen slope and Kendall's τ statistics were used to evaluate the long-term direction, consistency, and statistical significance of vegetation recovery trends across restoration practices. Planting was associated with the highest recovery rates, with YrYr5 of 0.070 and strong trend indicators, including a Theil–Sen slope of 0.095 and Kendall's $\tau = 0.87$ ($p = 0.024$), accompanied by a high coefficient of determination ($R^2 = 0.86$). Similarly, Terraces were associated with high recovery rates and the steepest 5-year Theil–Sen slope (0.105) with statistically significant trends ($\tau = 1.00$, $p = 0.009$, $R^2 = 0.81$). In contrast, Natural Regeneration presented lower recovery rates and weaker trend indicators, with a 5-year Theil–Sen slope of 0.045 and non-significant trends ($p = 0.05$). Sowing and Spot Sowing exhibited intermediate recovery rates (YrYr5 ≈ 0.06 – 0.07), while their corresponding Theil–Sen slopes indicated relatively stable but slower recovery trajectories. The YrYr and Theil–Sen metrics showed generally consistent recovery patterns across restoration practices.

3.4. Statistical comparison among restoration practices

3.4.1. Kruskal–Wallis analysis

The Kruskal–Wallis test revealed statistically significant differences among restoration practices across all recovery metrics, as presented in Table 3. The highest H statistics were observed for the YrYr5 ($H = 28.45$, $p < 0.001$), YrYr8 ($H = 27.19$, $p < 0.001$), and Theil–Sen slope metrics ($H = 23.75$, $p < 0.001$), indicating strong differences in recovery rate and long-term recovery trends among restoration practices. Significant differences were also detected for the recovery magnitude metrics, including RRI ($H = 17.64$, $p = 0.001$), RRI8 ($H = 11.42$, $p = 0.022$), and RRI5 ($H = 11.99$, $p = 0.017$).

Additionally, pairwise comparisons using Dunn's post hoc test provided a clearer interpretation of the differences among restoration practices (Fig. 9). Overall, areas restored through active restoration practices, particularly Planting, were associated with higher recovery values and more stable recovery trajectories than areas undergoing Natural Regeneration across multiple recovery metrics.

Significant differences for the RRI metric were observed between Planting and Natural Regeneration ($p = 0.017$) and between Sowing and Natural Regeneration ($p = 0.016$). Similarly, for the RRI8 metric, significant differences were identified between Planting and Natural Regeneration ($p = 0.038$). The YrYr5 and YrYr8 metrics further

highlighted stronger recovery dynamics in actively restored areas, with significant differences observed between Natural Regeneration and Sowing ($p = 0.001$ for both YrYr5 and YrYr8), as well as between Natural Regeneration and Spot Sowing ($p = 0.002$ and $p = 0.001$, respectively). Regarding long-term recovery trends, the Theil–Sen slope analysis revealed significant differences between Natural Regeneration and Sowing ($p = 0.001$) and between Natural Regeneration and Spot Sowing ($p = 0.002$), indicating that areas subjected to Sowing and Spot Sowing were associated with more favourable recovery trajectories than areas undergoing Natural Regeneration. In contrast, Sowing and Spot Sowing generally exhibited intermediate recovery performance across the evaluated recovery metrics. Collectively, these findings indicate that areas managed through active restoration practices were associated with more favourable and consistent post-fire vegetation recovery trajectories than areas undergoing natural regeneration.

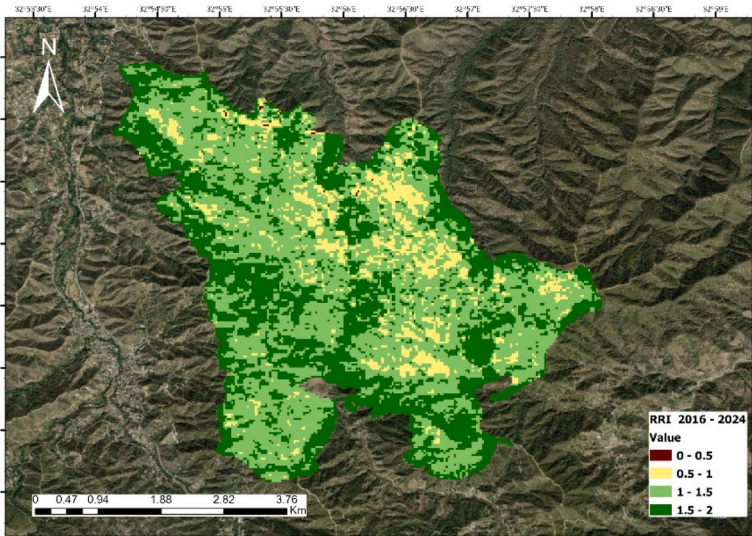
3.5. Modeling performance

3.5.1. Assessing and modeling drivers of post-fire vegetation recovery

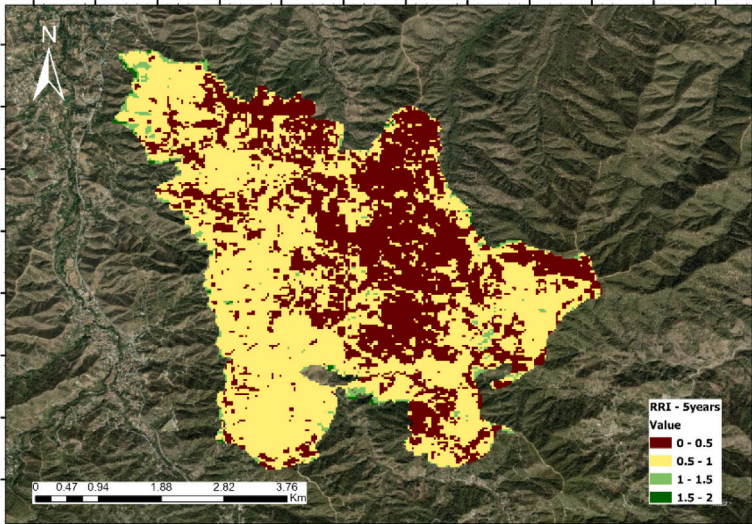
A comparative regression analysis was performed using OLS, RF, and XGB to model post-fire vegetation recovery metrics. Model performance is summarized in Table 4, while Fig. 10 compares the observed and predicted values.

The OLS model demonstrated consistently strong and stable performance across most recovery metrics, particularly for YrYr5 and YrYr8, where it achieved high test R^2 values (0.81 and 0.83), respectively. The observed performance indicates that the relationships between the explanatory variables and post-fire recovery dynamics were predominantly linear within the examined study area. The strong performance of the linear model further indicates that key recovery drivers, including fire severity, pre-fire vegetation condition, and land cover characteristics, were associated with vegetation recovery in a relatively predictable and proportional manner. From an ecological perspective, these findings suggest that post-fire vegetation recovery in the study area was primarily associated with dominant environmental controls rather than highly complex non-linear interactions. Within the environmental gradients represented in this study, key drivers such as fire severity and pre-fire vegetation condition appear to have relatively proportional and additive associations with post-fire spectral recovery dynamics. In

RRI



RRI5



RRI8

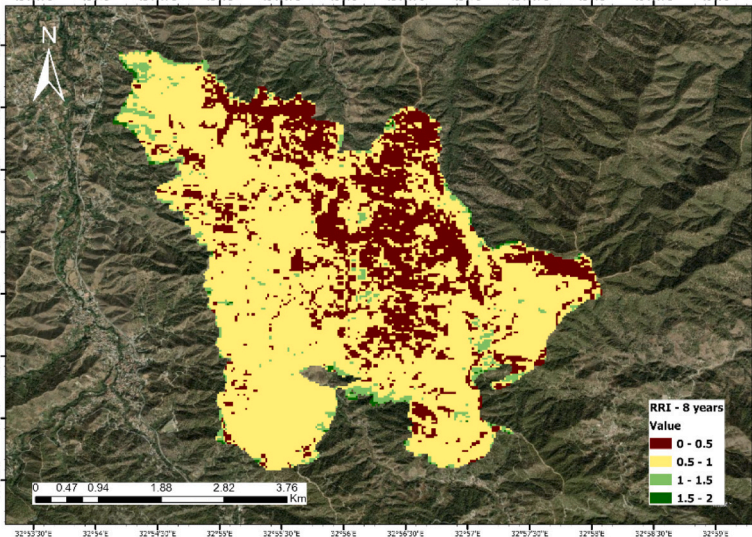


Fig. 6. Spatial distribution of RRI, RRI5, and RRI8 recovery metrics for the Solea wildfire area.

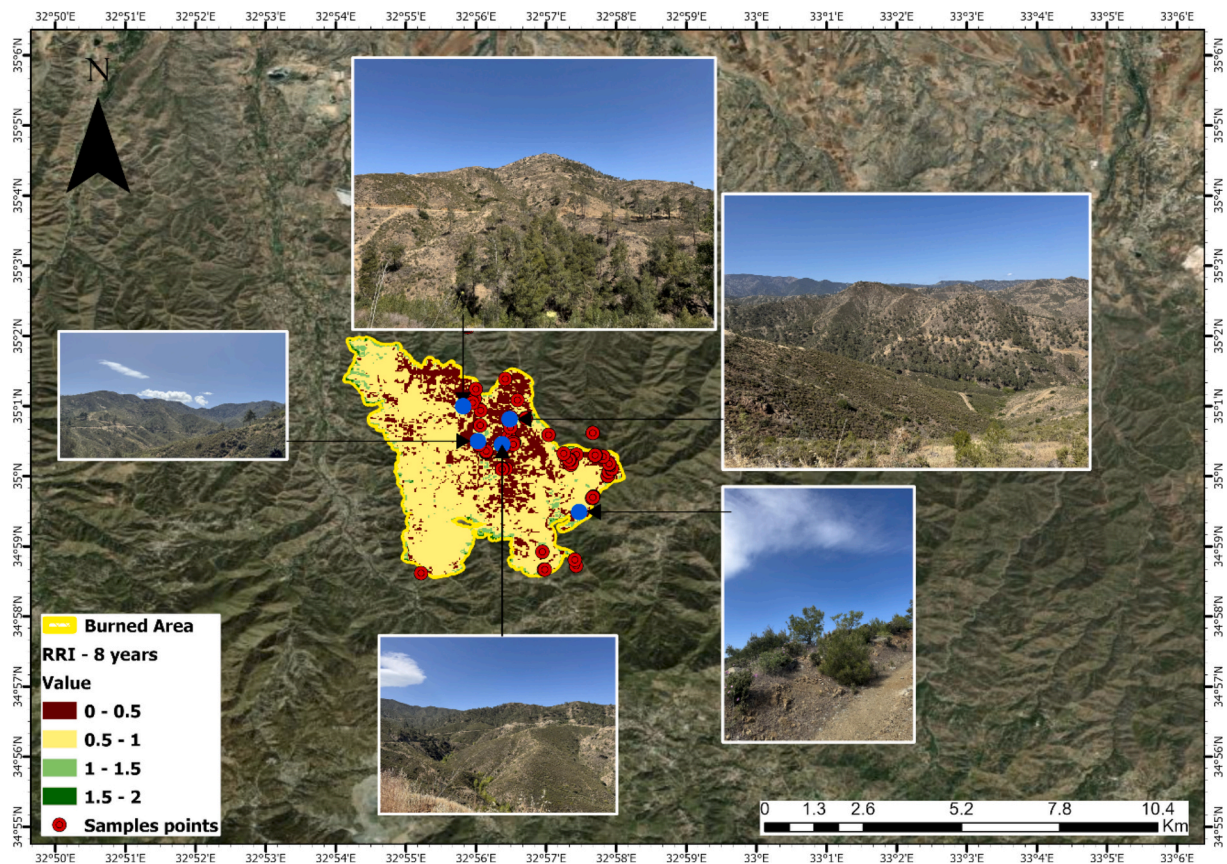


Fig. 7. Spatial distribution of the Relative Recovery Index (RRI) after eight years (2016–2024) within the burned area of the Solea fire. The map illustrates recovery values across the landscape, with field photographs providing visual examples of vegetation regrowth at selected sampling points.

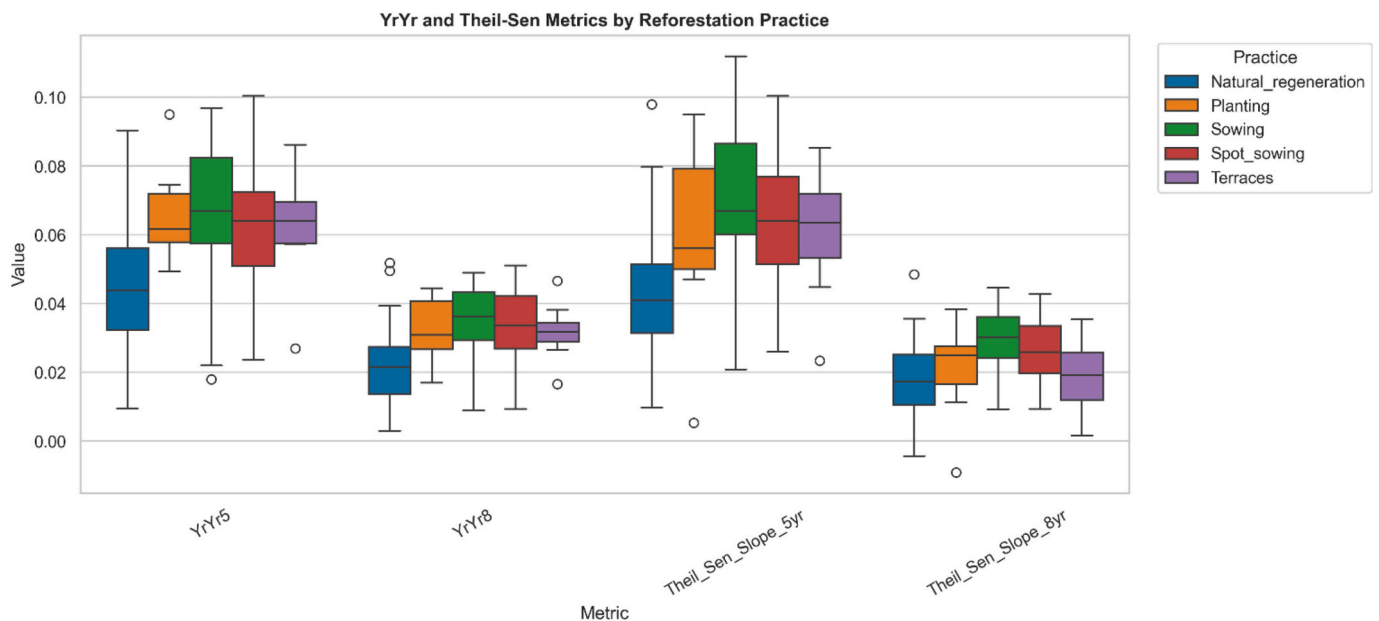


Fig. 8. Distribution of recovery rate (YrYr5 and YrYr8) and recovery trend (Theil–Sen slope) metrics across restoration practices. Boxes represent the interquartile range (25th–75th percentile), the central line indicates the median, whiskers extend to $1.5 \times \text{IQR}$, and circles represent statistical outliers. Colors correspond to the different restoration practices.

Mediterranean forest ecosystems, fire severity directly affects vegetation structure, seed survival, and soil properties, while pre-fire vegetation condition reflects ecosystem resilience, biomass availability, and regeneration capacity (Pausas and Keeley, 2014a; Keeley et al., 2011;

Resco de Dios, 2020; Bär et al., 2019). This pattern is consistent with the ability of simpler linear relationships to capture a substantial proportion of the observed recovery variability under the examined post-fire environmental conditions, thereby reducing the relative advantage of more

Table 3

Kruskal–Wallis H-statistic and associated *p*-values for each recovery metric across restoration practices.

Metric	H statistic	<i>p</i> -value
YrYr5	28.45	< 0.001
YrYr8	27.19	< 0.001
Theil_Sen_Slope	23.75	< 0.001
RRI	17.64	0.001
RRI8	11.42	0.022
RRI5	11.99	0.017

complex machine learning approaches (Pausas and Keeley, 2014a; Resco de Dios, 2020). In addition, the relatively homogeneous climatic and environmental conditions within the burned area may have limited the emergence of highly complex ecological interactions, favouring relatively stable and predictable recovery patterns.

Although the OLS model was simpler compared to the RF model, it exhibited low or even slightly negative train-test gaps (e.g., -0.07 for RRI and -0.001 for the 5-year Theil–Sen slope), indicating strong generalization capability and limited overfitting. Furthermore, for the 5-year Theil–Sen metric, OLS achieved an R^2 of 0.70 with a low RMSE of 0.0108, outperforming both RF ($R^2 = 0.64$) and XGB ($R^2 = 0.47$). A similar pattern was observed for metrics with lower predictive performance such as RRI and RRI5, where OLS still achieved higher R^2 values (0.43–0.45) compared to RF (0.28–0.29) and XGB (mostly below 0.1 or negative). The dominant recovery drivers identified in this study were consistently associated with the observed recovery variability across the examined restoration practices, suggesting that simpler linear relationships were sufficient to explain a substantial proportion of the observed recovery variability.

As for RF, the model achieved high training R^2 values across most recovery metrics, reflecting its ability to capture more complex relationships between environmental variables and vegetation recovery. However, moderate overfitting was observed in some cases, particularly for RRI8, indicating lower generalization capability compared to OLS. Nevertheless, RF achieved comparable performance to OLS for recovery rate and trend metrics such as YrYr5 and the 5-year Theil–Sen slope, suggesting that some recovery processes may be associated with localized non-linear interactions among environmental drivers.

XGB generally showed lower predictive performance across most recovery metrics, with several cases yielding low or negative R^2 values, indicating weak generalization capability. Although hyperparameter tuning was performed to optimize model configuration, the model still failed to achieve stable predictive performance compared to OLS and RF. This behavior may be related to the relatively limited sample size and low dimensionality of the predictor space, which may not provide sufficient complexity for gradient boosting algorithms to effectively learn robust non-linear relationships. In addition, several recovery metrics were associated with relatively simple and stable relationships with key predictors such as fire severity, pre-fire vegetation condition, and land cover. Under these conditions, simpler linear models such as OLS may be more appropriate and less sensitive to overfitting than more complex ensemble approaches. The stronger performance of the OLS model suggests that the observed post-fire vegetation recovery patterns in the study area were predominantly associated with relatively stable relationships among the main environmental and fire-related drivers, while the satisfactory performance of RF for some metrics suggests that localized non-linear interactions may also contribute to the observed long-term recovery dynamics.

3.6. Drivers of post-fire vegetation recovery

To further explore the drivers of recovery, both Spearman's rank correlation and RF feature importance analyses were examined. According to the correlation analysis presented in Fig. 11, fire severity exhibits the highest positive correlation with YrYr5 ($r = 0.79$), YrYr8 ($r = 0.82$), and the 5-year Theil–Sen slope ($r = 0.83$), highlighting its

dominant influence on post-fire vegetation recovery dynamics. Ecologically, higher fire severity substantially affects vegetation structure, soil properties, and seed availability, thereby strongly affecting the rate and stability of vegetation regeneration. Pre-fire vegetation condition also plays a notable role, showing a moderate negative correlation with some metrics (e.g., $r = -0.47$ for RRI). This suggests that areas with denser pre-fire vegetation may require longer periods to return to pre-disturbance spectral conditions due to the greater biomass losses caused by the wildfire event.

In addition to correlation analysis, feature-importance analysis from the Random Forest model provided complementary insights into the main recovery drivers (Fig. 12). Specifically, fire severity (severity_score) consistently emerged as the dominant predictor across most recovery metrics, particularly for YrYr and Theil–Sen slope metrics. Pre-fire vegetation condition (Pre_fire_mean) and land cover (landcover) also emerged as important predictors, especially for RRI and RRI5, highlighting the association of pre-disturbance ecosystem condition and vegetation type on post-fire recovery trajectories. In contrast, topographic variables such as slope, elevation, and aspect showed comparatively low importance and weak correlations with recovery metrics, suggesting a more indirect association with vegetation recovery within the examined study area. This relatively limited topographic effect may also be associated with the relatively compact spatial extent of the burned area, where broad climatic and environmental gradients are less pronounced.

The combined use of regression modeling, correlation analysis, and feature-importance evaluation suggests that post-fire vegetation recovery in the Solea fire area was primarily associated with fire severity, pre-fire vegetation condition, and land cover characteristics, whereas topographic variables showed comparatively weaker associations with the evaluated recovery metrics.

4. Discussion

This study provides a comprehensive assessment of post-fire vegetation recovery following the Solea fire event in Cyprus, offering insights into the ecological processes that shape recovery trajectories in Mediterranean forest ecosystems. By integrating multiple recovery metrics across an 11-year period, the analysis captures both short- and long-term dynamics, revealing how different restoration practices are associated with environmental and fire-related drivers. This multidimensional perspective advances current understanding by demonstrating that post-fire recovery is not a uniform process but is associated with a combination of biotic legacies, disturbance severity, and management interventions (Walia et al., 2025).

The contrasting performance among restoration practices highlights the importance of the ecological mechanisms through which each intervention may be associated with post-fire recovery. The stronger recovery observed in areas managed through Planting and Terracing is consistent with ecological mechanisms that may facilitate vegetation establishment. However, these differences should not be interpreted solely as treatment effects because restoration practices were implemented according to site-specific management criteria. Terracing may have contributed to recovery by stabilizing the soil surface, reducing runoff and erosion, and increasing water infiltration and moisture retention, which are critical in steep Mediterranean landscapes exposed to summer drought (Wei et al., 2019; Merino A., D.S., E.N., F.T., G.-A.A., M.G., R.-G.P., 2009). These improved microenvironmental conditions may enhance seedling survival and support more stable vegetation regrowth. Similarly, the association between Planting and higher recovery values may reflect the introduction of seedlings with already developed root systems, which could have enabled vegetation to exploit available soil moisture and nutrients more efficiently during the early post-fire years. However, this interpretation should be considered in the context of the non-random implementation of restoration practices. This

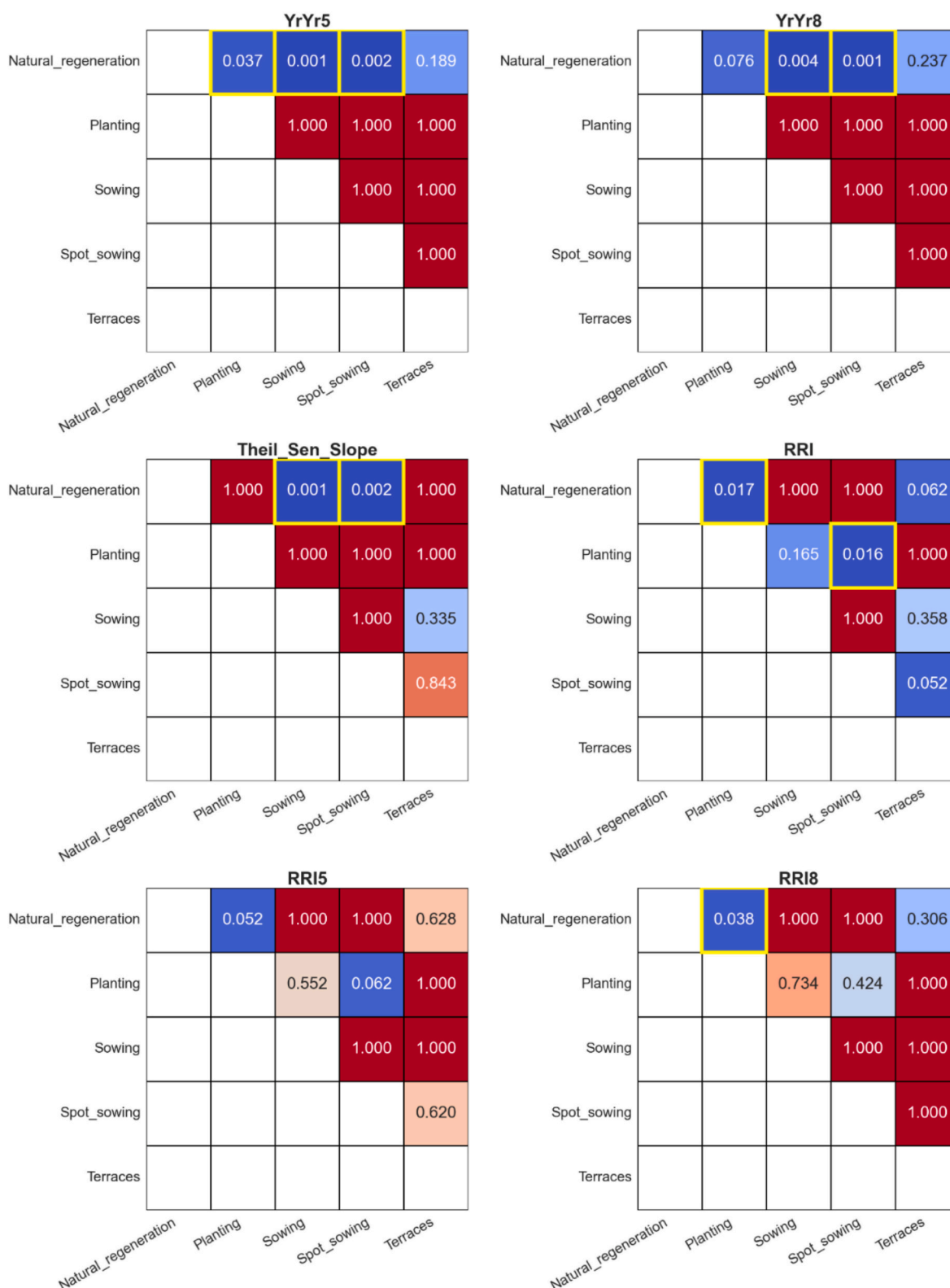
Dunn Post-Hoc P-Values (Yellow = $p < 0.05$)

Fig. 9. Dunn's post hoc pairwise comparisons for the examined recovery metrics. Yellow borders indicate statistically significant differences ($p < 0.05$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Performance metrics for each model.

Metric	Model	R ²	RMSE	MAE	Bias
RRI	OLS	0.434	0.138	0.110	0.039
RRI	RF	0.288	0.154	0.120	0.035
RRI	XGB	−0.023	0.185	0.133	0.046
RRI5	OLS	0.453	0.139	0.107	0.003
RRI5	RF	0.281	0.159	0.121	−0.012
RRI5	XGB	0.062	0.181	0.135	−0.002
RRI8	OLS	0.493	0.125	0.094	0.013
RRI8	RF	0.159	0.161	0.123	−0.008
RRI8	XGB	−0.147	0.188	0.148	−0.028
YrYr5	OLS	0.807	0.009	0.007	0.000
YrYr5	RF	0.612	0.013	0.010	−0.001
YrYr5	XGB	0.577	0.013	0.011	−0.001
YrYr8	OLS	0.831	0.005	0.004	0.001
YrYr8	RF	0.636	0.007	0.005	−0.001
YrYr8	XGB	0.617	0.007	0.005	−0.001
Theil–Sen Slope (5-year)	OLS	0.701	0.011	0.008	−0.001
Theil–Sen Slope (5-year)	RF	0.641	0.012	0.009	−0.002
Theil–Sen Slope (5-year)	XGB	0.465	0.014	0.011	−0.003
Theil–Sen Slope (8-year)	OLS	−0.074	0.009	0.007	−0.003
Theil–Sen Slope (8-year)	RF	−0.169	0.009	0.007	−0.002
Theil–Sen Slope (8-year)	XGB	−0.064	0.008	0.007	−0.003

mechanism is particularly important where high fire severity may reduce natural seed availability, damage seed banks, and limit spontaneous regeneration (Pausas and Keeley, 2014b; Trujillo-Miranda et al., 2018). These observations are consistent with previous studies reporting higher recovery in actively restored areas, particularly in highly degraded or high-severity burned landscapes, where passive recovery is often constrained by soil degradation, limited seed availability, and post-fire environmental stress (Zhang et al., 2024; Chen et al., 2018; Miguel et al., 2020; Honey-Rosés et al., 2018). However, these comparisons should be interpreted with caution because restoration practices are commonly implemented according to site-specific environmental and management conditions rather than through experimental randomization.

In contrast, Natural Regeneration showed slower and more heterogeneous recovery, likely because passive recovery depends strongly on local seed availability, dispersal capacity, resprouting potential, soil stability, and post-fire moisture conditions (Trujillo-Miranda et al., 2018). High-severity fire can reduce viable seeds, damage root systems, expose soil to erosion, and increase water stress, thereby delaying vegetation establishment. Similar observations have been reported in Mediterranean and other fire-prone ecosystems, where Natural Regeneration trajectories strongly depend on disturbance severity and residual ecosystem resilience (Trujillo-Miranda et al., 2018; Zhang et al., 2024; Chen et al., 2018; Miguel et al., 2020; Liu et al., 2019). The more variable responses associated with Sowing and Spot Sowing suggest that the effectiveness of seed-based interventions may be strongly influenced by local microsite conditions, including soil moisture availability, slope stability, and post-fire surface processes, which can directly affect seed germination, establishment success, and early vegetation development. Therefore, the higher recovery values observed in areas managed through Planting and Terracing may reflect ecological mechanisms related to soil stabilization, water availability, seedling establishment, and erosion control, although these patterns should be interpreted within the context of the non-random implementation of restoration practices (Trujillo-Miranda et al., 2018). Collectively, these findings suggest that the observed recovery patterns in actively restored areas may be associated with reduced ecological constraints that may limit passive regeneration, particularly in landscapes with high disturbance intensity or degraded pre-fire conditions.

Differences among recovery metrics further highlight the complexity of post-fire dynamics. While statistical analyses (Kruskal–Wallis test and Dunn's post hoc comparisons) confirmed significant variation across restoration practices, the ecological interpretation of these metrics is

equally important. The reduced reliability of the RRI metric, particularly in areas with low burn severity, reflects its sensitivity to disturbance magnitude and its potential to overestimate recovery when initial NBR reductions are small. This behavior has also been reported by Keersmaecker et al. (2022) (De Keersmaecker et al., 2022a), where the YrYr index was shown to better capture dynamic recovery processes. This underscores the limitations of relying on single-metric assessments, as each indicator captures distinct dimensions of recovery magnitude, recovery rate, or long-term recovery trend. The combined use of RRI, YrYr indices, and Theil–Sen slopes, therefore, provides a more robust and ecologically meaningful representation of recovery trajectories (Frazier et al., 2018). Nevertheless, it is acknowledged that NBR mainly reflects structural and moisture-related recovery processes and may not fully represent all ecological dimensions of ecosystem recovery, such as species composition or understory dynamics (Roy et al., 2006). Therefore, the recovery trajectories presented in this study should be interpreted primarily as indicators of spectral and structural vegetation recovery rather than complete ecological restoration. Future studies could further improve recovery assessment by integrating additional vegetation indices and field-based ecological measurements to capture complementary aspects of ecosystem functioning and biodiversity recovery.

The observed pattern of higher recovery values at five years compared to eight years aligns with established ecological processes in Mediterranean ecosystems. Early post-fire recovery is typically rapid due to vigorous resprouting from underground structures and the germination of heat-stimulated seeds, leading to steep initial increases in vegetation indices (Calderisi et al., 2025b; de Villalobos et al., 2002; Gibson et al., 2022; Lawes and Clarke, 2011; Rossetti et al., 2022). However, as succession progresses, resource competition intensifies, soil nutrient availability declines, and water stress becomes more pronounced, resulting in slower long-term recovery rates. These dynamics highlight the potential risk of overestimating ecosystem resilience when relying solely on short-term assessments and emphasize the need for long-term monitoring to capture delayed responses and slower successional processes (Harrison et al., 2021; Nolan et al., 2021; Pausas, 2015).

The regression analysis revealed that the OLS model achieved higher predictive performance than the RF and XGB models for most recovery metrics. This suggests that post-fire vegetation recovery in the study area was predominantly associated with relatively stable relationships among dominant environmental drivers, particularly fire severity, pre-fire vegetation condition, and land cover characteristics. In Mediterranean forests, these variables often exert proportional effects on post-fire vegetation indices (Pausas and Keeley, 2014a) which may explain the limited added value of non-linear models. The moderate overfitting observed in RF and XGB further indicates that larger or more heterogeneous datasets may be required for such models to generalize effectively in ecological applications. These findings also support the interpretation that key drivers of recovery operate in relatively additive ways under the examined conditions, although more complex interactions may emerge in different environmental contexts or at larger spatial scales.

The prominent association of pre-fire vegetation condition and fire severity with recovery trajectories is consistent with both the results of this study and the broader literature. Pre-fire vegetation condition reflects biomass legacies, root system robustness, and seed bank quality, all of which enhance the capacity for rapid regrowth (Pausas and Keeley, 2014a; Keeley et al., 2011). Fire severity, meanwhile, influences cambium survival, soil heating, and seed mortality, thereby exerting strong control over post-fire vegetation structure (Resco de Dios, 2020; Bär et al., 2019). Precipitation emerged as a significant predictor for long-term metrics, suggesting that hydrological conditions may become increasingly important as vegetation transitions from initial resprouting to more resource-limited successional stages (Marcos et al., 2021). Topographic variables showed limited influence, possibly due to their indirect effects and the inability of 30 m terrain data to fully capture fine

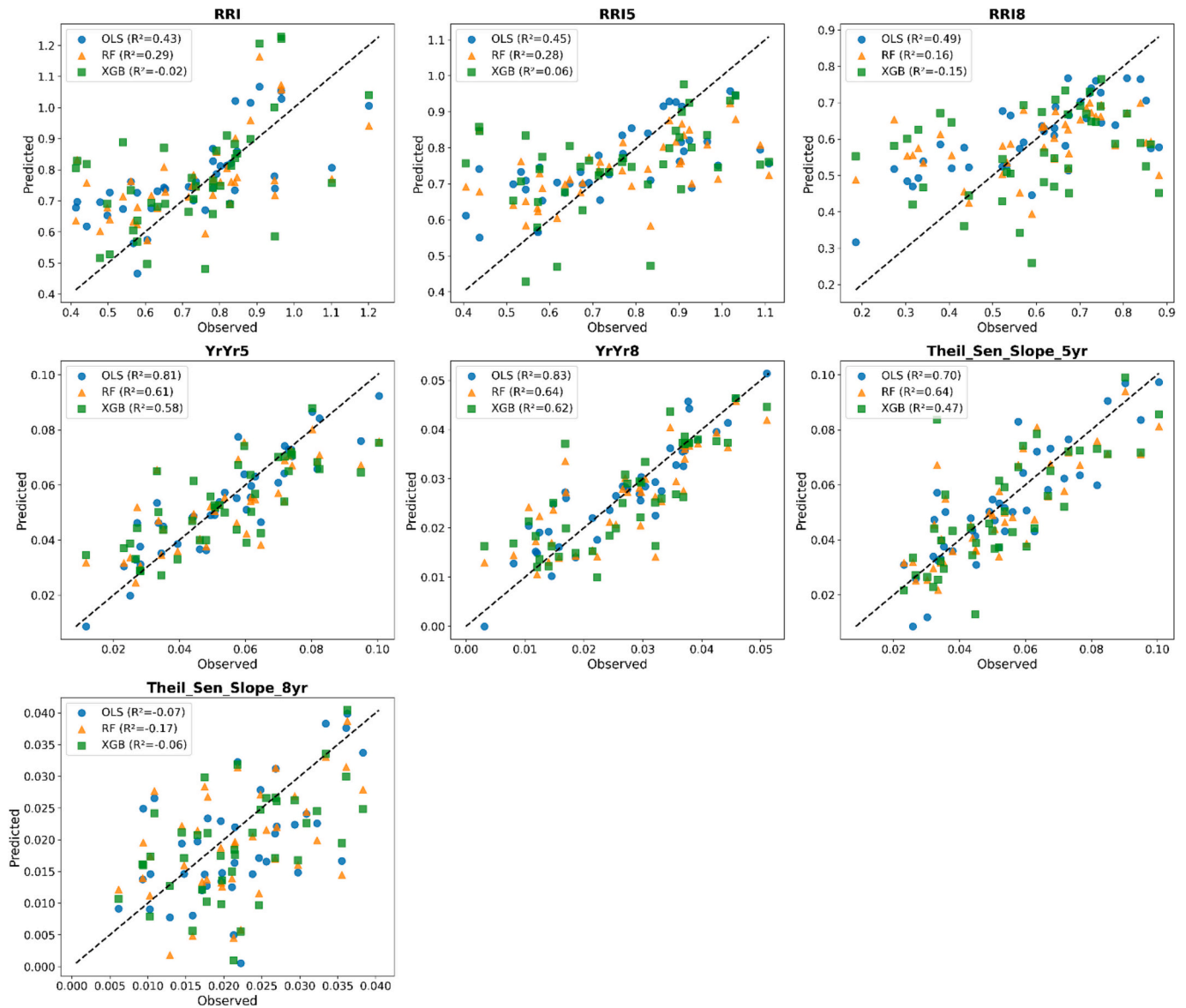


Fig. 10. Performance metrics of the OLS, RF, and XGB models for the examined recovery indicators. OLS: Ordinary Least Squares; RF: Random Forest; XGB: Extreme Gradient Boosting. YrYr5 and YrYr8 represent short- and long-term recovery rate metrics, respectively.

scale microenvironmental variation (Pinheiro et al., 2025; Spatola et al., 2023).

Overall, these findings provide evidence of recovery patterns within the current sampling design. However, given the non-random implementation of restoration practices and the relatively small sample sizes for some restoration types, broader generalization should be made with appropriate caution.

4.1. Limitations and uncertainties

Several limitations and sources of uncertainty should be acknowledged when interpreting the results of this study. First, the restoration practices implemented by the Department of Forests were not randomly distributed across the burned area but were applied according to operational, environmental, and management criteria, including fire severity, terrain conditions, accessibility, and erosion risk. Consequently, differences in vegetation recovery among restoration practices may partly reflect pre-existing environmental and site conditions in addition to restoration effects. Although environmental and topographic variables were incorporated into the modeling framework to partially

account for spatial heterogeneity, some confounding effects related to site selection may still influence the interpretation of restoration performance. Therefore, the observed differences among restoration practices should be interpreted as associations within the current study design rather than as direct evidence of causal treatment effects. Furthermore, applying the 300 m minimum-distance criterion, although improving spatial independence, reduced the number of samples retained for some restoration practices, particularly Planting ($n = 9$), Terraces ($n = 8$), and Sowing ($n = 17$). The resulting sample sizes may have reduced the robustness of between-group comparisons and Dunn's post hoc tests. Consequently, these findings should be interpreted with appropriate caution and regarded as evidence derived from the current sampling design rather than as broadly generalizable conclusions. Future studies including larger and more balanced sample sizes could help strengthen the robustness and generalizability of these findings. In addition, model performance was evaluated using a single random 70%/30% train-test split. Consequently, the reported predictive performance may be influenced by the specific data partition, particularly given the relatively small sample size. Furthermore, the negative R^2 values obtained for some models predicting the 8-year Theil–Sen slope indicate

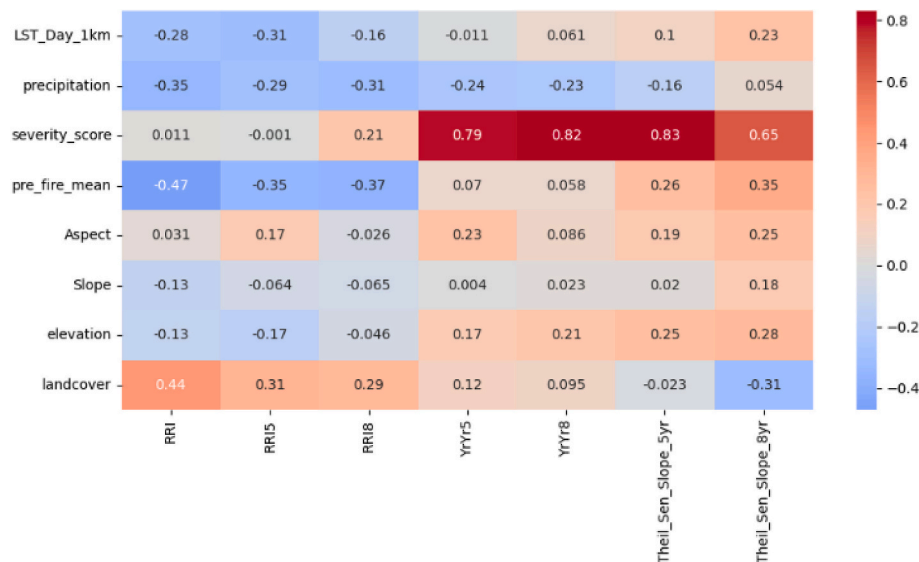


Fig. 11. Spearman's rank correlation coefficients between environmental variables and recovery metrics. Positive correlations are shown in warm colors, whereas negative correlations are shown in cool colors.

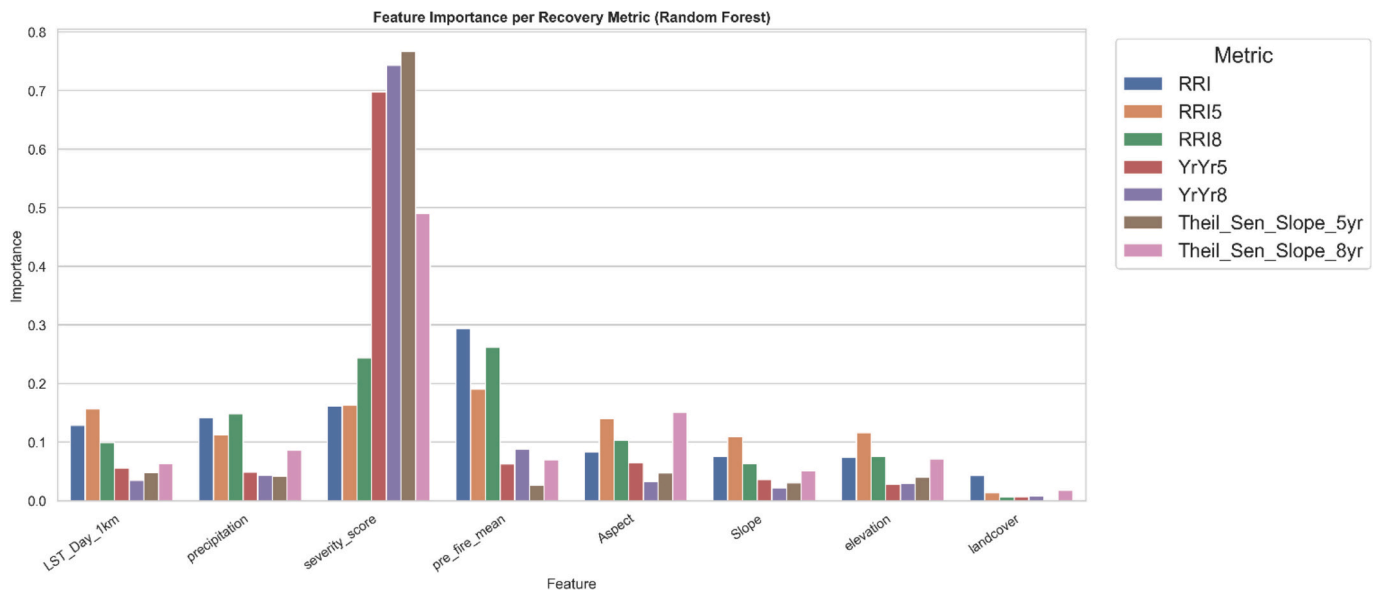


Fig. 12. Random forest feature importance for the examined recovery metrics.

limited predictive performance for this recovery indicator. Therefore, the modeling results should be interpreted with appropriate caution, particularly for recovery metrics with weak predictive performance.

Additional uncertainty is associated with integrating multi-source datasets characterized by different native spatial resolutions. Climatic variables, including CHIRPS precipitation and MODIS LST data, were harmonized to the common 30 m analysis grid to enable integration with Landsat-derived variables. However, this harmonization process does not increase the intrinsic spatial detail of the original datasets and may introduce scale-mismatch uncertainty, particularly in mountainous terrain where climatic variability can be highly localized (Sun et al., 2018). Furthermore, the modeling framework was based primarily on static environmental predictors and did not explicitly incorporate temporal climate variability or interaction effects among environmental drivers. As a result, some complex ecological feedbacks influencing long-term vegetation recovery may not have been fully captured. In addition, moderate overfitting observed in some RF and XGB models suggests that

larger or more heterogeneous datasets may be required for more robust generalization of complex machine learning approaches (Viana-Soto et al., 2020a; Meng et al., 2015). Finally, although NBR-based recovery metrics provide valuable information on spectral and structural vegetation recovery, they may not fully capture all ecological dimensions of ecosystem recovery, including species composition, understory regeneration, and biodiversity dynamics (Roy et al., 2006). Therefore, the recovery trajectories presented in this study should primarily be interpreted as indicators of spectral vegetation recovery rather than complete ecological restoration. Future research integrating additional vegetation indices, field-based ecological measurements, and temporally explicit climate variables could further improve the assessment of post-fire ecosystem recovery processes.

Despite these limitations, the observed recovery patterns and identified drivers are consistent with findings reported across Mediterranean fire-prone regions, suggesting potential applicability to similar environmental settings. However, generalization to ecosystems with

different species pools, disturbance regimes, or climatic conditions should be approached with caution. Overall, this study contributes to both ecological understanding and applied forest management by demonstrating the value of multi-metric, long-term assessments and by highlighting the factors associated with post-fire recovery trajectories.

5. Conclusion

This study evaluated vegetation recovery associated with five restoration practices following the 2016 Solea fire event in Cyprus, using NBR time series and Landsat-derived recovery metrics (RRI, YrYr, and Theil–Sen). The results showed that Planting and Terraces were associated with higher recovery values, whereas areas undergoing Natural Regeneration generally exhibited lower recovery values, consistent with previous observations of slower passive recovery in Mediterranean fire-prone landscapes. Sowing and Spot Sowing were associated with intermediate recovery values. The statistical analysis confirmed these findings, indicating that the recovery metrics provided complementary information on post-fire vegetation dynamics. Specifically, the YrYr indices and the Theil–Sen slope characterized recovery rate and long-term recovery trends, whereas the RRI-based metrics (RRI, RRI5, and RRI8) quantified recovery magnitude using different temporal representations of the post-fire recovery trajectory relative to pre-fire conditions. The observed differences among these indicators therefore reflect the distinct dimensions of vegetation recovery captured by each metric rather than indicating that one metric is inherently more accurate than another. These contrasting outcomes reflect underlying ecological mechanisms, including differences in soil stabilization, moisture retention, seed availability, and resprouting capacity, which collectively shape post-fire recovery trajectories in Mediterranean ecosystems. The study also identified pre-fire vegetation condition and fire severity as the most influential drivers of post-fire recovery. Among the predictive models evaluated, OLS achieved higher predictive performance than RF and XGB for most recovery metrics, suggesting that the relationships between the examined predictors and recovery metrics were predominantly linear within the current dataset. By providing a detailed evaluation of post-fire regeneration in a Mediterranean environment, this research contributes to bridging an important knowledge gap. However, the interpretation of recovery patterns is subject to uncertainties related to the spatial resolution of climatic data, the absence of temporal climate variability in the modeling framework, and the inherent limitations of remote-sensing proxies for vegetation structure. The findings highlight differences in vegetation recovery among the examined restoration practices and demonstrate the value of long-term RS-based time-series monitoring and multi-source remote sensing for supporting post-fire forest management and restoration planning. Despite these limitations, the observed recovery patterns and identified drivers align with findings reported across Mediterranean fire-prone regions, suggesting potential applicability to similar Mediterranean environments, while caution is required when applying these results to ecosystems with different species pools, climatic regimes, or disturbance histories.

CRedit authorship contribution statement

Maria Prodromou: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ioannis Gitas:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Christodoulos Mettas:** Writing – review & editing. **Marios Tzouvaras:** Writing – review & editing. **Diofantos Hadjimitsis:** Writing – review & editing, Supervision.

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.

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Data availability

Data will be made available on request.

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Further reading

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