

Article

Remote-Sensing-Based Prioritization of Post-Fire Restoration Actions in Mediterranean Ecosystems: A Case Study in Cyprus

Maria Prodromou ^{1,2,*} , Ioannis Gitas ³ , Christodoulos Mettas ^{1,2} , Marios Tzouvaras ¹ ,
Kyriacos Themistocleous ¹ , Andreas Konstantinidis ⁴ , Andreas Pamboris ⁴ and Diofantos Hadjimitsis ^{1,2}

¹ ERATOSTHENES Centre of Excellence, 3012 Limassol, Cyprus; christodoulos.mettas@eratosthenes.org.cy (C.M.); marios.tzouvaras@eratosthenes.org.cy (M.T.); k.themistocleous@eratosthenes.org.cy (K.T.); d.hadjimitsis@cut.ac.cy (D.H.)
² Remote Sensing and GeoEnvironment Laboratory, Department of Civil Engineering and Geomatics, Cyprus University of Technology, 3036 Limassol, Cyprus
³ Laboratory of Forest Management and Remote Sensing, School of Forestry and Natural Environment, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece; igitas@for.auth.gr
⁴ Frederick Research Center, 1036 Nicosia, Cyprus; com.ca@frederick.ac.cy (A.K.); epampots@gmail.com (A.P.)
* Correspondence: maria.prodromou@eratosthenes.org.cy

Abstract: Global forest degradation and deforestation present urgent environmental challenges demanding efficient strategies for ecological restoration to maximize the impacts and minimize the costs. This study aims to develop a spatial decision support tool to prioritize post-fire restoration actions in Mediterranean ecosystems, with a focus on Cyprus. At the core of this study is the GRESTO Index (GreenHIT-RESTORATION Index), a novel geospatial tool designed to guide reforestation efforts in fire-affected areas. GRESTO integrates geospatial data and ecological criteria through a multi-criteria decision-making approach based on the Analytic Hierarchy Process (AHP). The model incorporates nine key indicators, including fire severity, tree density, land cover, fire history, slope, elevation, aspect, precipitation, and temperature, and classifies restoration priority zones into low, medium, and high categories. When applied to the Solea fire event in Cyprus, the model identified 24% of the area as high priority, 66% as medium and 10% as low. The validation against previous restoration actions implemented in the study area demonstrated reliable agreement, with an overall accuracy of 80.9%, a recall of 0.70 for high priority areas, and an AUC of 0.79, indicating very good separability. Moreover, sensitivity analysis further confirmed the robustness of the model under varying parameter weights. These findings highlight the GRESTO model's potential to support data-driven, cost-effective restoration planning aligned with national and international environmental goals.

Keywords: post-fire restoration; multi-criteria analysis; AHP; wildfires; Cyprus; remote sensing; decision making; GEE



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1. Introduction

At a global level, forests are a vital natural resource providing multiple economic, social, environmental, and cultural benefits, including climate regulation and greenhouse gas balance [1,2]. However, despite these crucial benefits, forest ecosystems are facing increasing pressures from both natural and anthropogenic factors [3–5]. Forest ecosystems are particularly crucial in the Mediterranean landscape, where they are distinguished by their rich biodiversity [1]. This region, however, is increasingly threatened by climate change and human activities, which increase forest vulnerabilities [6]. Despite their recognized immense importance, it is generally accepted that forests are becoming increasingly

vulnerable as a result of disturbances caused by climate change, which manifest as extreme weather events such as heat waves, torrential rain, droughts, and strong winds [2,6]. These disturbances, in combination with human-induced pressures, increase the degradation of forest ecosystems and contribute to long-term environmental challenges [7]. As a result of the above, changes in land use and land cover, increased pest infestations, the degradation or even the loss of natural habitats, pollution, and disease spread are observed, leading to deforestation [1,8].

Among these pressures, wildfires stand out as one of the most direct and destructive consequences of climate change [9,10]. Forest fires can result from natural causes, including lightning or human activities, such as deliberate arson [11]. In recent years, the frequency and severity of wildfires have increased due to climate change, which increases fire susceptibility through prolonged droughts and extreme weather [12]. Wildfires can be destructive, affecting ecosystems, damaging properties, endangering lives, and leading to significant environmental degradation [13,14]. Indeed, thousands of hectares of forest areas burn worldwide. Statistically, wildfires occur over various parts of the world more than one thousand times yearly, making them one of the most frequent natural geophysical disasters [10,15]. According to recent studies, the global burned area is estimated annually based on coarse satellite images at around 3.5–5 million km² [16,17]. Although fire is an integral part of many ecosystems, in recent decades, there has been a significant increase in the number of fires in the Mediterranean region as well as in the extent of the burned surface [1,2]. This is due to the features of the Mediterranean ecosystem that relate to climate and vegetation [6].

In light of these increasing challenges, restoration efforts are essential to recover ecosystems damaged by disturbances such as fires [18]. Restoration is the process that serves to recover an ecosystem that has been degraded or destroyed, for example, after a fire [19,20]. Post-fire forest restoration aims to restore the forest ecosystem to its historical state to regain its ecological integrity as well as resilience [21,22]. Restoration strategies are defined based on the degree of degradation of ecosystems and the vegetation recovery capacity, so post-fire restoration actions focus on increasing resilience and resistance by preserving soil and water resources [19]. Moreover, the vegetation regeneration rate can affect the post-fire and flooding risk [23]. Given the extensive global scale of forest degradation and deforestation, as well as the significant costs associated with ecological restoration, it is crucial to identify priority areas for restoration and to evaluate the cost-effectiveness of various restoration methods [24–26]. The selection of an appropriate restoration approach is influenced by the evaluation of various factors (environmental, social, and economic), including recovery rate, degradation levels, land use, and topographic features [27]. Apart from this, the selection is also influenced by the objective of the restoration, the potential limitations, and the available resources. Commonly, two primary approaches are utilized in forest restoration [27]: One is natural restoration, which relies on the seed reserves released from the parent stand after the fire. Therefore, no intervention is made in areas where sufficient seeds have been recorded or are present on the soil surface or in surviving stands that remain after the fire. The other is artificial restoration, which involves the application of management techniques such as planting seeds or seedlings [2,27–29].

According to the literature, the increasing availability of earth observation satellites and imagery since 1980 has significantly contributed to research and monitoring in various fields, including forestry [30–35] and natural hazard assessment [36–39]. In the context of post-fire restoration, remote sensing plays a critical role in site selection, vegetation recovery assessment, and monitoring post-restoration dynamics [40]. According to [2], there is a limitation in integrating various models into a single framework that can be adopted at regional and national levels for planning and decision-making purposes. Remote sensing

overcomes these limitations by offering advanced technological solutions that aid in the monitoring and evaluating of restoration efforts [16]. Regarding restoration monitoring and management, several studies utilized remote sensing approaches to support this process. For example, high-resolution terrain data helps in site or plot selection by providing information on suitable microtopography [41,42]. It also aids in identifying landscape-scale features which are positively associated with restoration success, such as tree species [31], which is essential for monitoring restoration projects and post-restoration invasive species management [43,44] and is also helpful for damage assessment after fire events [45,46]. Moreover, time series analysis using available observations has been extensively used for post-fire forest recovery [47–51]. Remote sensing sensors, both spaceborne and airborne, play a crucial role in evaluating and monitoring ecological restoration strategies [52]. Data products, such as Digital Terrain Models (DTMs) [53] and vegetation canopy height models obtained from LiDAR [54], as well as multispectral images captured by UAVs (Unmanned Aerial Vehicles) or satellite sensors, are invaluable [55]. Additionally, hyperspectral imagery and post-processed spectral data products, like vegetation indices (including NDVI, NBR, SAVI, EVI, etc.), burned area maps, and evapotranspiration (ET) data, support frequent monitoring and help with the successful documentation of metrics in managed or restored areas [56–60].

The Analytic Hierarchy Process (AHP) is one of the most widely used methods for multi-criteria decision-making and was originally proposed by Saaty et al. [61]. The AHP serves as a valuable tool for decision-makers, enabling them to evaluate various essential elements through pairwise comparisons [62]. In the present study, AHP was employed to assess the ecological criteria for identifying areas suitable for reforestation. Several studies confirm this choice; for instance, ref. [63] comparing AHP with other evaluation approaches—ELECTRE, TOPSIS, and VIKOR—highlights its flexibility in assigning different weights to criteria. Moreover, AHP has also been used to analyze silvicultural treatments on trade-offs [64], to integrate climate change criteria in reforestation planning [65], and to develop suitability maps for identifying priority restoration zones after fire events [29]. Similar approaches that prioritize restoration actions using AHP have also been undertaken in various studies [66–71].

Predicting the ability for regeneration in burned areas requires thorough knowledge of ecosystem dynamics, and this information enables decision-makers to allocate limited resources effectively by helping them to decide whether or not to support restoration actions [2]. The present study introduces the GRE STO Index (Green HIT-RESTORATION Index), a tool designed to prioritize and recommend restoration actions for burned areas in Mediterranean ecosystems. It is highlighted that the proposed methodology is the first in Cyprus to utilize earth observation techniques for this purpose, offering a novel and scalable solution.

This study aims to develop a decision support tool for post-fire restoration prioritization using geospatial analysis and multi-criteria decision-making. To achieve this, the development of the GRE STO Index focused on three main objectives: (1) defining the criteria and corresponding geospatial data necessary for a multi-criteria analysis, (2) implementing this analysis using the AHP to prioritize areas in need of reforestation, and (3) validating the model by applying it to the Solea fire event in Cyprus, where reforestation efforts had previously been undertaken by the Department of Forests.

This study aligns with global environmental initiatives, such as the European Green Deal's goal of achieving climate neutrality by 2050, the UN's Decade on Ecosystem Restoration [72], and the Bonn Challenge, which aims to reduce CO₂ emissions and enhance greenhouse gas absorption [73]. Furthermore, the research highlights the role of remote sensing techniques and earth observation data in supporting informed decision-making for sustainable forest management.

2. Materials and Methods

2.1. Study Area

This study was conducted in an area affected by a wildfire near the village of Solea in the Nicosia district of Cyprus, which is located in the Eastern Mediterranean region (Figure 1). The wildfire occurred on 19 June 2016, according to the Post-Fire Management Plan for the area [74]. The burned area is part of the Adelfi Forest, situated at an altitude between 495 and 1253 m above sea level. The terrain is steep and characterized by large slopes. Specifically, only 18.24% of the burned area is characterized by gentle slopes (0–25%), while 23.86% of the area features slopes greater than 100%, posing significant challenges for restoration.

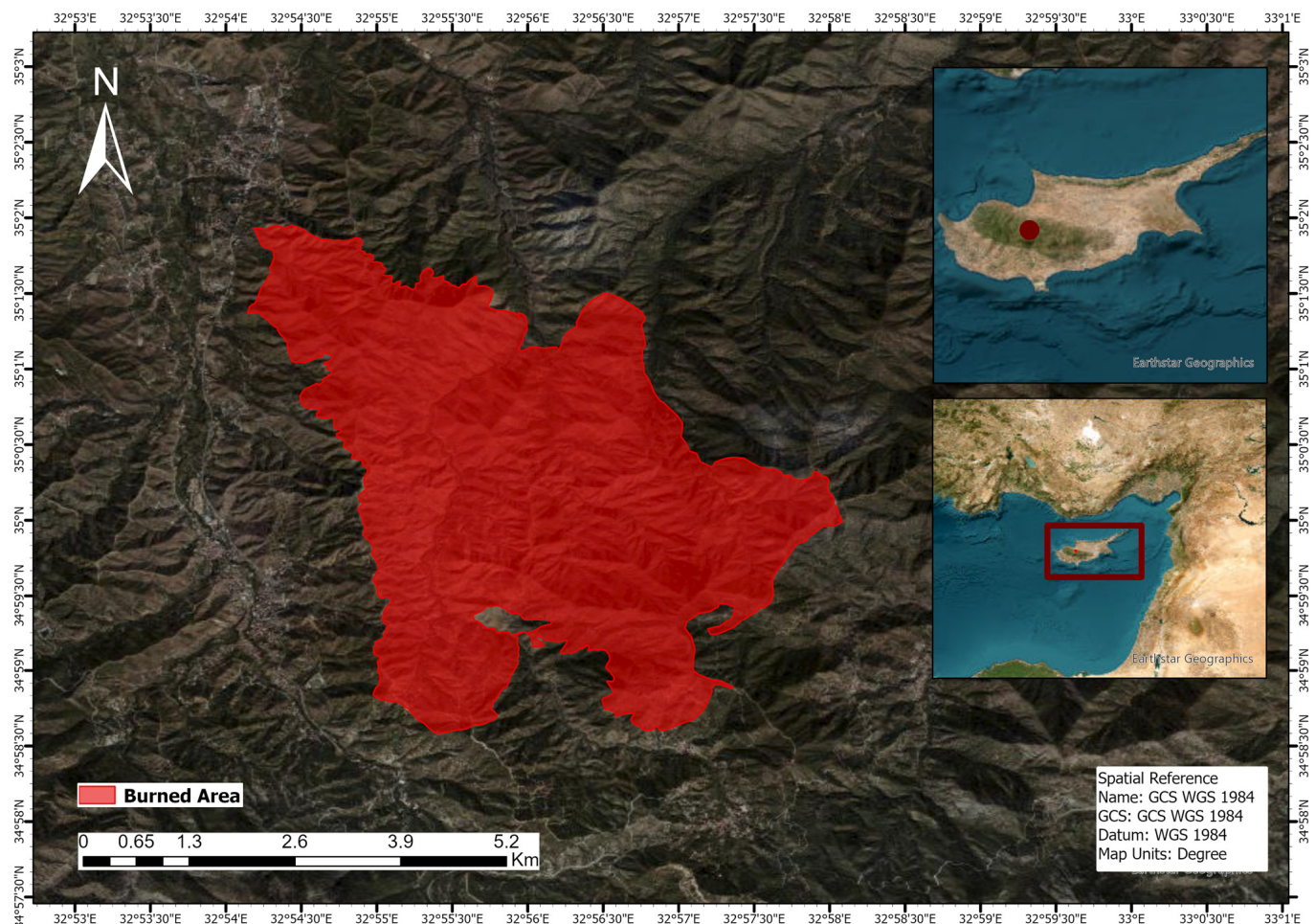


Figure 1. Solea fire event that was examined for this study. Baseman source: Esri, Maxar, Earthstar Geographics, and the GIS User Community.

Regarding the climate, the conditions vary with elevation; for instance, in the higher altitude zone, vegetation benefits from favorable conditions, including an average annual rainfall of 868.2 mm and milder temperatures. In contrast, the lower elevations face a six-month dry season (April–October), with lower annual rainfall (407.5 mm) and extreme maximum temperatures exceeding 42 °C, which significantly affect plant survival and growth.

The fire event destroyed 18.57 km², making it one of the largest fire events in Cyprus's state forest history, according to the reports provided by the Department of Forests [75]. The area is characterized by the predominant vegetation in these regions consisting mainly of *Pinus brutia* forests, with an understory comprising herbaceous vegetation, low shrubs (e.g., *Cistus* spp.), and large shrubs (e.g., *Quercus alnifolia*, *Pistacia terebinthus*, and *Olea europaea*).

Based on the records provided by the Department of Forests in Cyprus from 2000 to 2023, forest fires in Cyprus destroyed over 552.4 km² of burned areas, including state forests and the surrounding areas. Additionally, the economic cost of forest fires in Cyprus for 2021 specifically was EUR 18.6 million, while every year, one-third of the Department of Forests' budget under the Ministry of Agriculture, Rural Development and Environment, which corresponds to EUR 15 million, is allocated to forest fire response. Furthermore, focusing on the reforestation actions for the Solea and Argaka burned areas, the reforestation measures and their monitoring costs were EUR 1,532,387 and EUR 1,350,952.4, respectively. Therefore, the GRESTO Index developed for the Green-HIT platform is expected to have a significant economic impact nationally, and the proposed methodology aims to mitigate these costs [76].

2.2. Methodology

The methodology used in this study was based on the AHP as a spatial multi-criteria decision analysis tool, as shown in Figure 2. The process can be divided into four main steps: (a) selection of the criteria, (b) standardization of the criteria, (c) assignment of the criteria weights, and (d) evaluation and ranking of the results.

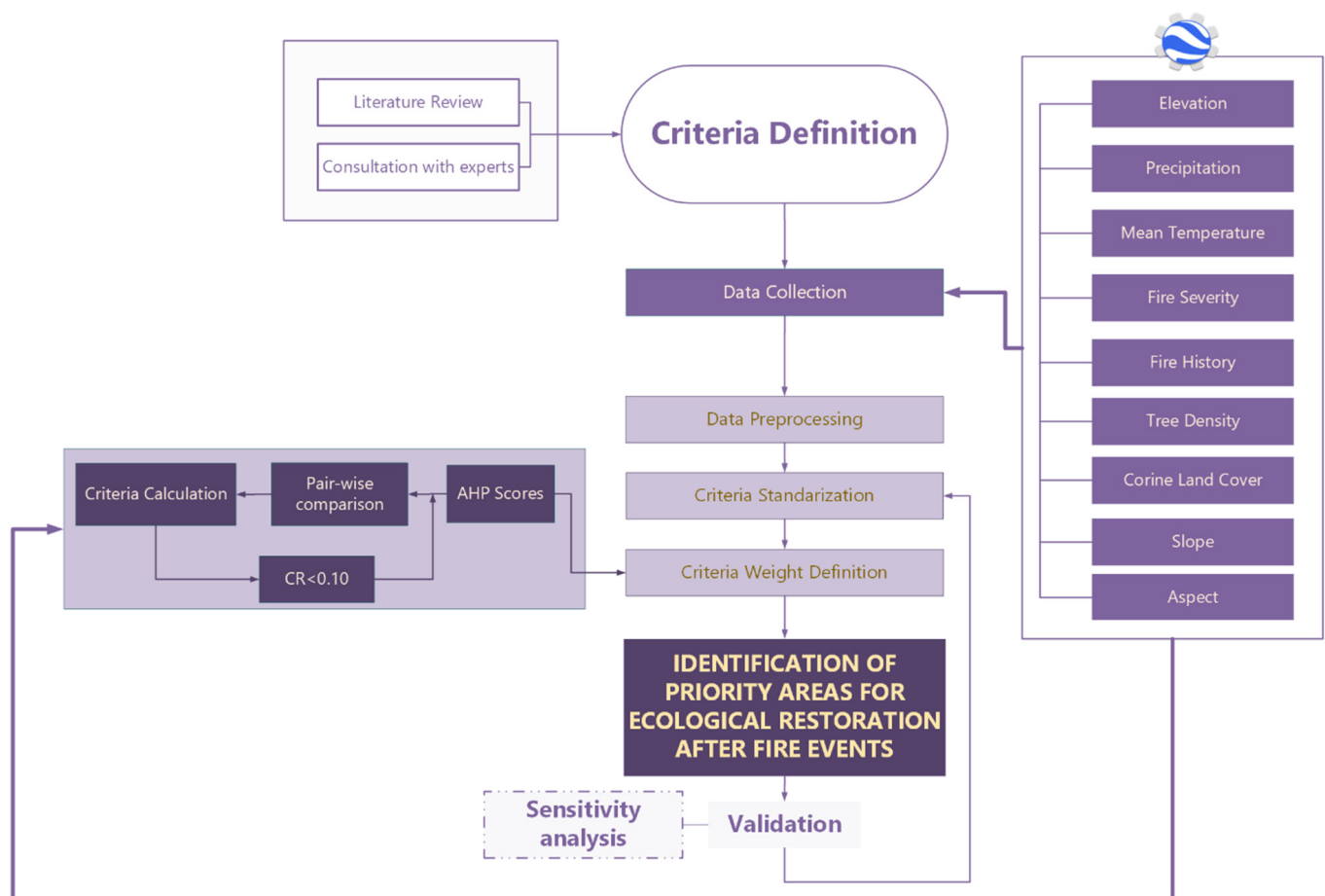


Figure 2. Workflow for identifying priority areas for ecological restoration actions after fire events in Cyprus.

The GRESTO Index was developed utilizing the GEE, a cloud-based platform for scientific analysis and the visualization of geospatial datasets. GEE enabled efficient access to satellite imagery and the implementation of remote sensing algorithms for large-scale spatial analysis [77–79].

2.2.1. Selection of Criteria

A fundamental requirement for effectively restoring vegetation and addressing the environmental issues that arise after a fire is the timely planning and implementation of actions outlined in a post-fire management plan for burned areas. In general, the measures taken to restore vegetation in burned areas depend on the specific ecological conditions, both before and after the fire. In particular, these measures are influenced by several factors including (a) the composition and structure of the pre-existing vegetation, (b) the intensity of the fire, (c) the presence or lack of living trees, (d) the availability of a necessary quantity of seeds in the burned trees or on the ground, (e) the topography of the area, as well as the (f) local climate [80–83].

The development of the model incorporated several essential factors, specifically topographical, meteorological, and environmental. These factors were selected based on consultations with experts and are well documented and supported by researchers and specialists in the relevant literature, with specific references reported in Table 1. Also, it was highlighted that the prioritized indicators that could be derived from freely available data were also helpful for determining areas in need of restoration.

Table 1. List of main selected indicators and basic information.

Criteria	Description	Source
Topographic information (Elevation, slope, aspect)	Topography influences both surface runoff dynamics and ecological patterns [84,85]. Lower elevation presents slower flow rates than higher elevations, leading to water accumulation in valleys, which can impact climate conditions, vegetation types, species distribution, and ecological recovery [86]. Steeper slopes present unique challenges, including higher risks of soil erosion, increased water runoff speeds, and changes in soil moisture retention, all of which influence tree species selection and survival rates, [87,88] as well as complicating logistics [89]. The steep areas also present a higher risk of landslides and floods [90]. Additionally, the aspect can influence microclimate conditions like sunlight exposure and moisture levels; for example, east-facing slopes receive more incoming solar radiation in mountainous areas, which helps in selecting sites that can support vegetation regeneration [38,66].	SRTM (GEE)
Land cover	The land cover and the proximity to forests were used because this study focused on restoring forested and vegetated areas. Also, the proximity to forest areas was prioritized due to their proximity to reservoirs of native species [91].	Corine Land Cover/ ESA World Cover (GEE)
Tree density	The regeneration of both species and forest dependent on the canopy seed bank [92]. In this study, the tree density was utilized, due to the assumption that in denser forests, there is larger seed production [93].	Copernicus Land [94]
Vulnerability to wildfire hazards	In terms of vulnerability to wildfire hazards, the analysis considered the burn severity and fire frequency. Specifically, in this study, it was assumed that the burn severity and the fire frequency could determine the potential for natural regeneration, suggesting that active restoration actions should prioritize ecosystems most heavily impacted by fires [95,96]. Additionally, burn severity influences soil quality and seed bank viability. High-severity fires can destroy seed banks and soil structures, leading to artificial reforestation actions with resilient species, while lower severity fires might allow for natural regeneration [97].	Sentinel-2 (GEE) Fire frequency (EFFIS)
Meteorological factors (mean temperature and total precipitation)	The meteorological factors were selected to identify suitable conditions for the growth of the majority of the species. For example, high altitudes due to lower temperatures are ideal for many species. Additionally, the precipitation and temperature variations depend on the aspect [24].	Temperature: MODIS (GEE) Precipitation: CHIRPS(GEE)

Based on this approach, nine factors were selected, which were as follows: topographical factors, including elevation, slope, and aspect; and meteorological factors, including temperature and precipitation. Also, regarding the environmental factors, the model

included land cover, tree density, dNBR (differenced Normalized Burn Ratio), and fire frequency. Each of these factors provided critical information necessary for developing a model identifying priority areas for reforestation, as detailed in Table 1.

Criteria Standardization

For this study, several factors were selected for the multi-criteria analysis, as described in Section 2.2.1. To combined factors with the same scale of value, the standardization of each factor is performed in this section, as shown in Table 2, where the original values are transformed into comparable units [98,99].

Table 2. Reclassification of the criteria for the identification of priority areas for natural or artificial reforestation.

	Criteria	Excluded	Low	Medium	High	Source
Topographic information	Elevation (m)		0–300 (coastal / plain)	300–500 (hilly)	>500 (semi-mountainous – mountainous)	[100]
	Aspect (°)		N, NE, NW	E, SE	S, SE, W	[66,86]
	Slope (°)		>25	10–25	0–10	[85,101]
Land cover	Corine land cover	Non-vegetated	Grasslands and shrublands	-	Forests	[95,102,103]
	Tree density (%)		>70	15–70	<15	[104]
Vulnerability to wildfire hazards	Fire history (reoccurrence)		1	2	>3	[95]
	Fire Severity (* dNBR—Sentinel-2)	≤100	100–270	270–440	≥440	[105]
Meteorological factors	Precipitation (mm)		>700	400–700	<400	[106]
	Temperature (°C)		10–28.95	28.95–32.04	>32.04	[106,107]

* The dNBR derived from Sentinel-2 imagery with a spatial resolution of 10 m. For the calculation of the dNBR, a pre-fire image acquired on 18 June 2016 and a post-fire image acquired on 28 June 2016 were used.

Criteria Weight

To prioritize areas effectively, criteria sets were quantified and weights were assigned to determine their significance in decision-making processes. The proposed methodology was conducted utilizing the AHP. In this method, the AHP was involved in the weighting and ranking of the selected criteria, enabling a hierarchical structure that allowed for the pairwise comparison, making it easier to understand and prioritize the most critical aspects of the model based on Saaty et al. [61], and to compare all factors against each other based on their importance on a scale of 1 to 9, as shown in Table 3 below. Value 1 represents equal importance between two factors, which means that they contribute equally to the objective. In contrast, value 9 represents extreme importance, which means that evidence favoring one over the other is of the highest possible validity. The importance of each factor was assigned based on the stakeholders' discussion, the literature review, and the research team's expertise. Specifically, insights were gathered through interviews and in-depth discussions with all available experts from the Department of Forests, who shared their practical experience in post-fire restoration. In particular, a list of potential factors contributing to restoration actions was prepared, and through the interviews with the experts from the Department of Forests, we discussed the relative importance of each factor and considered them in the context of restoration planning. These consultations were complemented by a review of official post-fire management plans implemented in burned

areas provided by the Department of Forests for ensuring that the selected criteria aligned with real-world restoration practices.

Table 3. Saaty rating scale.

Intensity of Importance	Remark
1	Equal importance
3	Moderately more important
5	Strongly more important
7	Very strongly more important
9	Extremely more important
2, 4, 6, 8	Intermediate values

In addition to expert input, a scientific literature review was conducted to support the weighting decisions. Previous studies using AHP in similar contexts [66,85,95,108,109] emphasized the relevance of factors such as slope, vegetation type, and climate variables in post-fire or reforestation planning. Taking into consideration the collected information and the literature review, the final weights were estimated.

Following this, the final qualitative weights were determined using the judgment matrix given in Equation (1), which indicates the degree of the experts' preference between the individual criteria influencing the selection of the optimal placement. Specifically, the standardized relative weight was determined by dividing each element of the pairwise matrix by the total sum of its corresponding column. According to the results obtained from this approach, the higher the resulting weights, the greater the influence of the parameters on the reforestation actions based on their relative importance. Also, each element within the matrix was divided by the sum of its row to create a standardized pairwise comparison matrix. The weight for each criterion was then determined by calculating the average of the normalized values for each factor.

$$A = \begin{pmatrix} C_{11} & C_{12} & \cdots & C_{1(n-1)} & C_{1n} \\ C_{21} & C_{22} & \cdots & C_{2(n-1)} & C_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ C_{n1} & C_{n2} & \cdots & C_{n(n-1)} & C_{nn} \end{pmatrix} \quad (1)$$

Additionally, to ensure the consistency of the pairwise comparison factors, the Consistency Index (CI) was used, based on Equation (2)

$$CI = \frac{\lambda_{max} - 1}{n - 1} \quad (2)$$

where λ_{max} = the largest eigenvalue of the pairwise comparison matrix evaluation and n is the number of criteria used in the analysis. λ_{max} is given by Equation (3). In detail, the eigenvalues (or relative weights) were calculated by averaging the rows of each matrix, and the maximum eigenvalue was equal to the number of factors. In cases where $\lambda_{max} = n$, the judgments were consistent.

$$\lambda_{max} = \sum_i^n CV_{ij} \quad (3)$$

After that, the Consistency Ratio (CR) was calculated based on Equation (4) to assess the reliability of the findings compared to the random judgments. According to the CR values, when the CR was 0.10 or greater, the judgments were unreliable, which meant that the weight values of the matrix indicated inconsistencies and the AHP may not have provided a meaningful result, and a lower CR indicated more consistency [98].

$$CR = \frac{CI}{RI} \quad (4)$$

where the RI is the Ratio Index for different ‘n’ values that were obtained, as shown in Table 4.

Table 4. Random Consistency Index.

n	1	2	3	4	5	6	7	8	9	10
Random Consistency Index (RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Consequently, the aggregation was performed using the weighted linear summation method. Specifically, the raster layer for each factor was multiplied by its respective criterion weight, and after that, they were summed, as indicated in Equation (5). Based on this, a final map identifying the priority zones for reforestation was developed.

$$RN = \sum_{i=1}^n (w_i * \chi_i) \quad (5)$$

where RN is the reforestation need, w_i is the weight for each factor, χ_i is the factor I, and n is the number of factors.

Evaluation and Ranking Results

The evaluation of the model was conducted using the sensitivity analysis technique. Given that using weights can introduce subjectivity, a sensitivity analysis was incorporated to quantify the impact of variations in specific inputs on the overall outcomes. This analysis provided insight into the influence of each weight on the final results. The weight values were adjusted one at a time by $\pm 20\%$, starting from 0 to $\pm 100\%$ based on the method described in [90], and the area of each class was calculated accordingly.

Validation of the Model

The effectiveness of the GRESTO model was assessed through an accuracy evaluation. For this study, a confusion matrix was used following a stratified random sampling approach. A total of 1000 random samples were generated and proportionally allocated to each restoration action according to their spatial extent in the reference map. Specifically, the sampling included 40 samples for the low-priority class, 720 samples for the medium-priority, and 240 samples for the high-priority areas. Based on these samples, the values were extracted from the map generated based on the GRESTO model and compared with the actions conducted by the Department of Forests. After that, the evaluation metrics were computed using the generated confusion matrix in accordance with established practices in remote sensing accuracy assessment, as described by [110,111]. The evaluation included the overall accuracy (OA), the precision, the recall, and the F1-score.

The confusion matrix cross-tabulated the ground reference class against the classified results per thematic category. The confusion matrix was divided into four categories: True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). The OA represented the percentage of pixels assigned with the correct label. It was calculated as the total number of correctly identified pixels divided by the total number of pixels in the sample. Precision (User Accuracy) represented the proportion of the pixels in that class correctly identified as true. Recall (Producer Accuracy) meant the proportion of values the model correctly predicted from the actual data. Finally, the F1-score reflected the harmonic mean of recall and precision [112,113].

Additionally, a multi-class Receiver Operating Characteristic (ROC) analysis was performed using the one-versus-rest strategy, and the Area Under the Curve (AUC) values were calculated for each class [114,115]. This approach was implemented because it provided insights into the model's ability to distinguish each priority class, where the higher AUC values indicated better class separability. Specifically, values between 0.5 and 0.6 indicated poor performance, 0.6–0.7 fair, 0.7–0.8 good, 0.8–0.9 very good, and 0.9–1.0 excellent [116].

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (6)$$

$$Precision = \frac{TP}{TP + FP} \quad (7)$$

$$Recall = \frac{TP}{TP + FN} \quad (8)$$

$$F1 - Score = 2 * \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

3. Results

3.1. Analytical Hierarchy Process (AHP) Results and Suitability Maps

A pairwise comparison was conducted among all pairs of the nine selected parameters to calculate the weight assigned to each factor. Next, the parameters were compared based on their importance in forest restoration actions, using the method proposed by Satty et al. [98] and as described in the Methodology section. The results of the pairwise comparison of potential independent variables contributing to the prioritization of post-fire restoration actions, based on their importance on a scale of 1–9, are presented in Table 5.

Table 5. Pairwise comparison between the nine criteria involved in the post-fire restoration.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Fire Severity	1.00	5.00	2.00	3.00	5.00	7.00	7.00	5.00	5.00
(2) Fire History	0.20	1.00	0.33	0.33	3.00	4.00	4.00	3.00	3.00
(3) Tree Density	0.50	3.00	1.00	2.00	6.00	7.00	7.00	5.00	5.00
(4) Land Cover	0.33	3.00	0.50	1.00	5.00	6.00	6.00	4.00	4.00
(5) Slope	0.20	0.33	0.17	0.20	1.00	2.00	2.00	0.33	0.33
(6) Elevation	0.14	0.25	0.14	0.17	0.50	1.00	1.00	0.33	0.33
(7) Aspect	0.14	0.25	0.14	0.17	0.50	1.00	1.00	0.33	0.33
(8) Precipitation	0.20	0.33	0.20	0.25	3.00	3.00	3.00	1.00	1.00
(9) Temperature	0.20	0.33	0.20	0.25	3.00	3.00	3.00	1.00	1.00
$\lambda_{max} = 9.761$				$CI = 0.095$			$CR = 7\%$		

The weights for each factor were calculated using the eigenvector solution method; in our case, the largest eigenvalue was 9.761. The corresponding CI was 0.095, which confirmed the consistency of the model because CI values closer to zero reflect greater consistency. A further consistency check was conducted based on the CR , which achieved 7% using the RI , which was equal to 1.45 for the case of nine different factors. This was below the commonly accepted threshold of 10%, indicating that the pairwise comparisons were reliable and consistent.

Overall, the results obtained using the AHP demonstrated a well-structured, consistent decision-making process that supported the reliability of the findings. Based on the AHP, the derived weights were as follows: fire severity had the highest importance in the model, achieving a weight of 29.4% and showing a dominant role in prioritizing reforestation actions. This was followed by tree density (22.4%), Corine Land Cover (16.90%), and fire history (10.10%), highlighting the significant contribution of vegetation structure, land use,

and fire frequency. The climatic factors precipitation (6.20%) and mean temperature (6.20%) also played a notable role. Moreover, the topographic features of slope (3.8%), elevation (2.60%), and aspect (2.60%) had less influence on the model but remained relevant in guiding the reforestation actions. The higher the weights, the more impact the parameters had on the post-fire restoration needs based on their relative importance. The normalized pairwise comparison matrix weights were used to develop a model for prioritizing restoration needs in burned areas. The model presented in Equation 11 was applied to generate a post-fire restoration prioritization map. The output composite map was categorized into three classes (low, medium, and high). Low- and medium-priority areas corresponded to zones with potential for natural recovery, whereas high-priority areas required artificial restoration interventions. The model was applied to a polygon encompassing 102.96 km², covering both the burned and the surrounding regions.

$$GRESTO = 3.8 \times SLOPE + 2.6 \times ELEVATION + 2.6 \times ASPECT + 29.4 \times dNBR + 10.1 \times FIRE\ FREQUENCY + 16.9 \times LAND\ COVER + 6.2 \times LST + 6.2 \times PRECIPITATION + 22.4 \times TREE\ DENSITY \quad (10)$$

Additionally, the map developed based on the GRESTO Index is presented in Figure 3. The results indicated that 10% of the burned area fell within the low-priority class, followed by 66% in the moderate-priority class, which represented the majority of the burned area, while the remaining 24% corresponded to the high-priority regions. Moreover, Table 6 represents the area per class derived from GRESTO Index and the data provided by Department of Forests. Obviously, the low-priority class showed a significant overestimation by the GRESTO Index, while the medium-priority class appeared to be underestimated compared to the Department of Forests' actions. In contrast, the high-priority class indicated a strong agreement with the reference data.

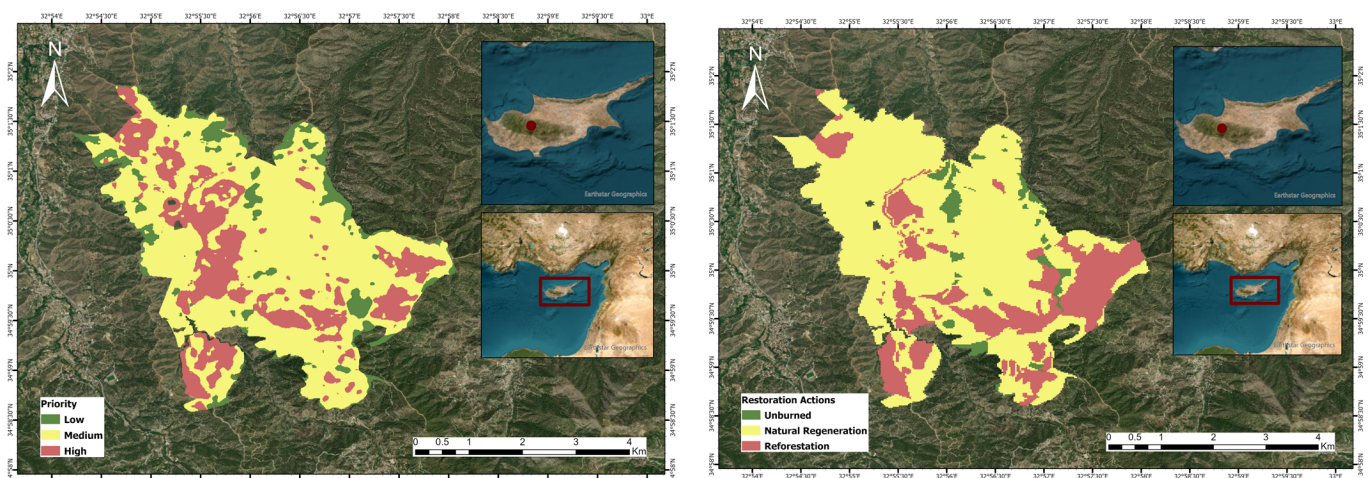


Figure 3. Prioritization of reforestation needs derived from the GRESTO Index (Left) and the restoration actions conducted after the fire event by the Department of Forests (Right).

Table 6. Area per priority class derived from GRESTO Index in comparison with Department of Forests' actions.

Priority	Area (Km ²)	
	DoF	GRESTO
Low	0.71	1.64
High	4.10	4.19
Medium	12.49	11.47

3.2. Sensitivity Analysis

This study conducted a sensitivity analysis to evaluate the robustness and reliability of the results, since the use of the weights can be subjective. This analysis provided insights regarding the influence of each weight on the final model. The weight values were adjusted using the One At A Time (OAT) approach, based on the sequential adjustment of the criteria weights. Specifically, the nine selected criteria used for developing the GRESTO Index were adjusted one at a time by $\pm 20\%$ starting from 0 (no adjustment) to $\pm 100\%$. Based on this approach, there were a maximum of 99 interchanges in the weights' adjustments during the sensitivity analysis. Figure 4 represents the areas corresponding to each priority class (low, medium, and high) for all scenarios.

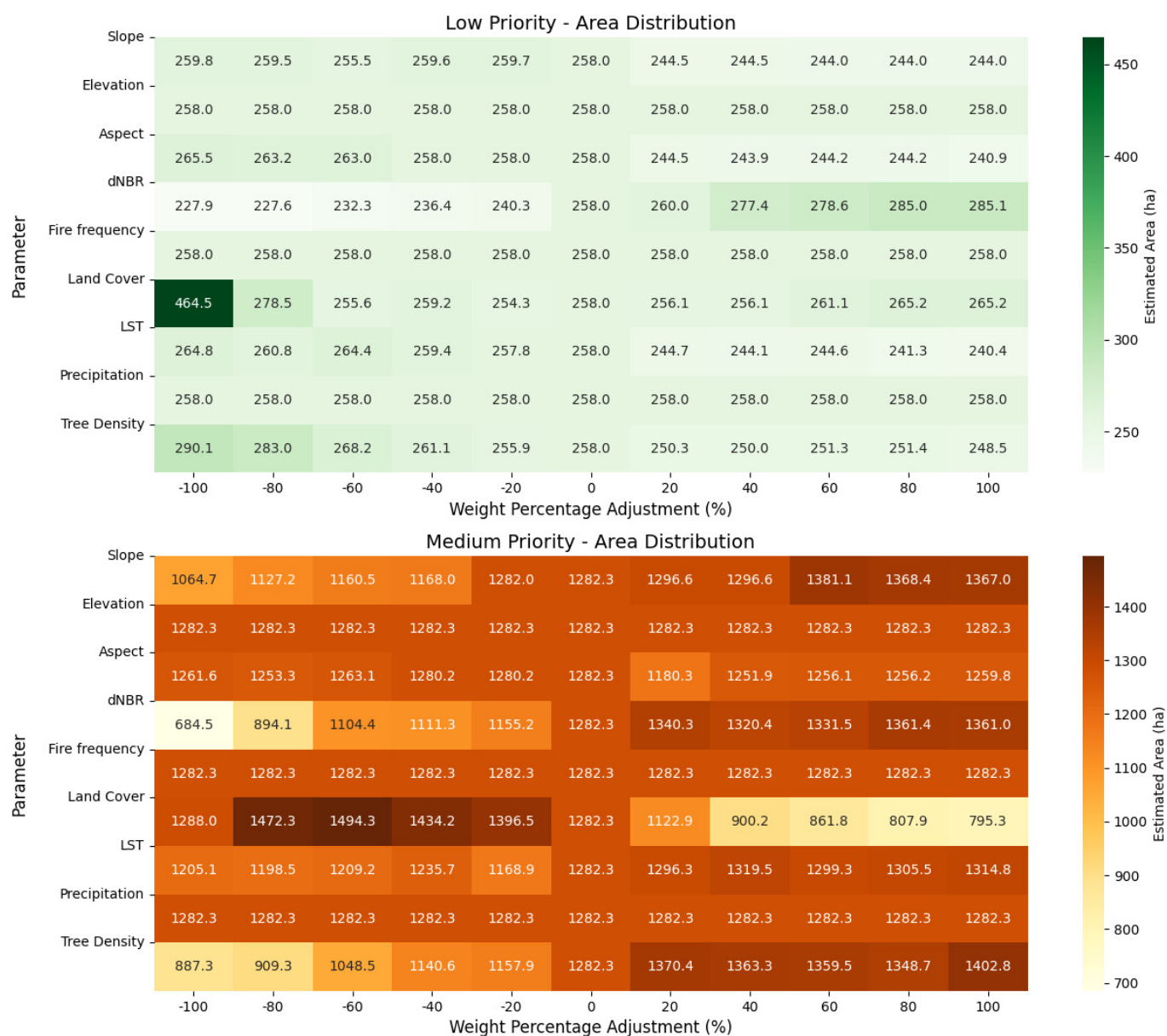


Figure 4. Cont.

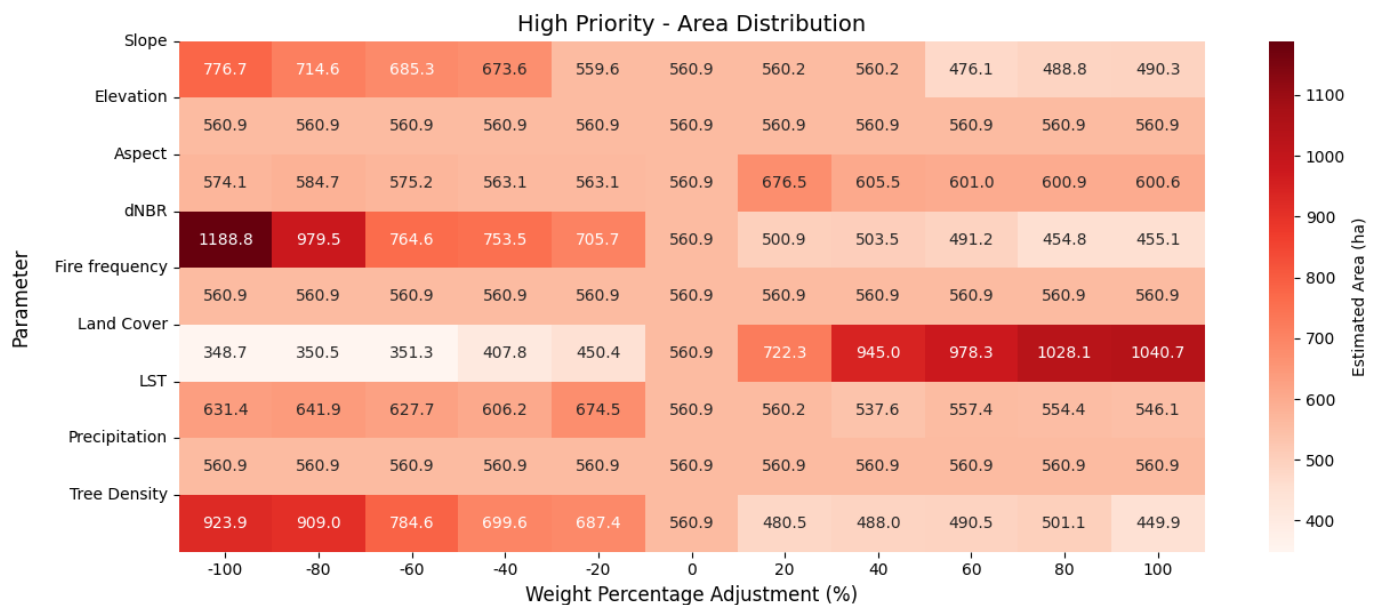


Figure 4. Area distribution in hectares, based on weight percentage adjustment per parameter.

Based on the heatmap for the low-priority class (represented in the green color), which corresponded to the areas that were not affected by fire or which had low impacts and did not require immediate interventions, the results showed stability under the different parameter adjustments, as indicated by the low variability in the estimated areas. In contrast, the medium-priority class (shown in orange), where the area was expected to recover naturally, and the high-priority class (represented in the red color), which corresponded to severely affected areas requiring urgent restoration actions, demonstrated high sensitivity to weight adjustments. Specifically, the dNBR, land cover, tree density, and slope significantly influenced the area distribution, highlighting their importance in the model and especially in identifying areas suitable for natural restoration and for the identification of areas that needed artificial restoration actions.

Moreover, to enhance the sensitivity analysis, Cumulative Distribution Functions (CDFs) were generated for the GRESTO Index's feasibility scores, showing the index's behavior under the different weight adjustments for each parameter. These CDF plots provide additional insights for the distribution of the index's feasibility scores, showing the model's stability and sensitivity. In detail, the x -axis of the CDF plots represents the feasibility scores of the GRESTO Index, while the y -axis represents the cumulative probability (ranging from 0 to 1). Each curve in the model corresponds to a different weight adjustment applied to the parameters, allowing for a comparative analysis of their impacts.

The visualization of the sensitivity analysis presented in Figure 5 shows that slope, elevation, aspect, LST, fire frequency, and precipitation parameters are less sensitive indicators. Their CDF curves show close overlaps, indicating that changes in the weights associated with these indicators have minimal impacts on the prioritization model. In contrast, the most sensitive indicators are dNBR and land cover, which have high variability, especially in the more extensive weight adjustments, showing their significant influence on the model outcomes. Additionally, the tree density displays medium variability in the model, showing its importance in the model. These findings are essential for the optimization of the weights for the development of the GRESTO Index in order to ensure that the model remains stable.

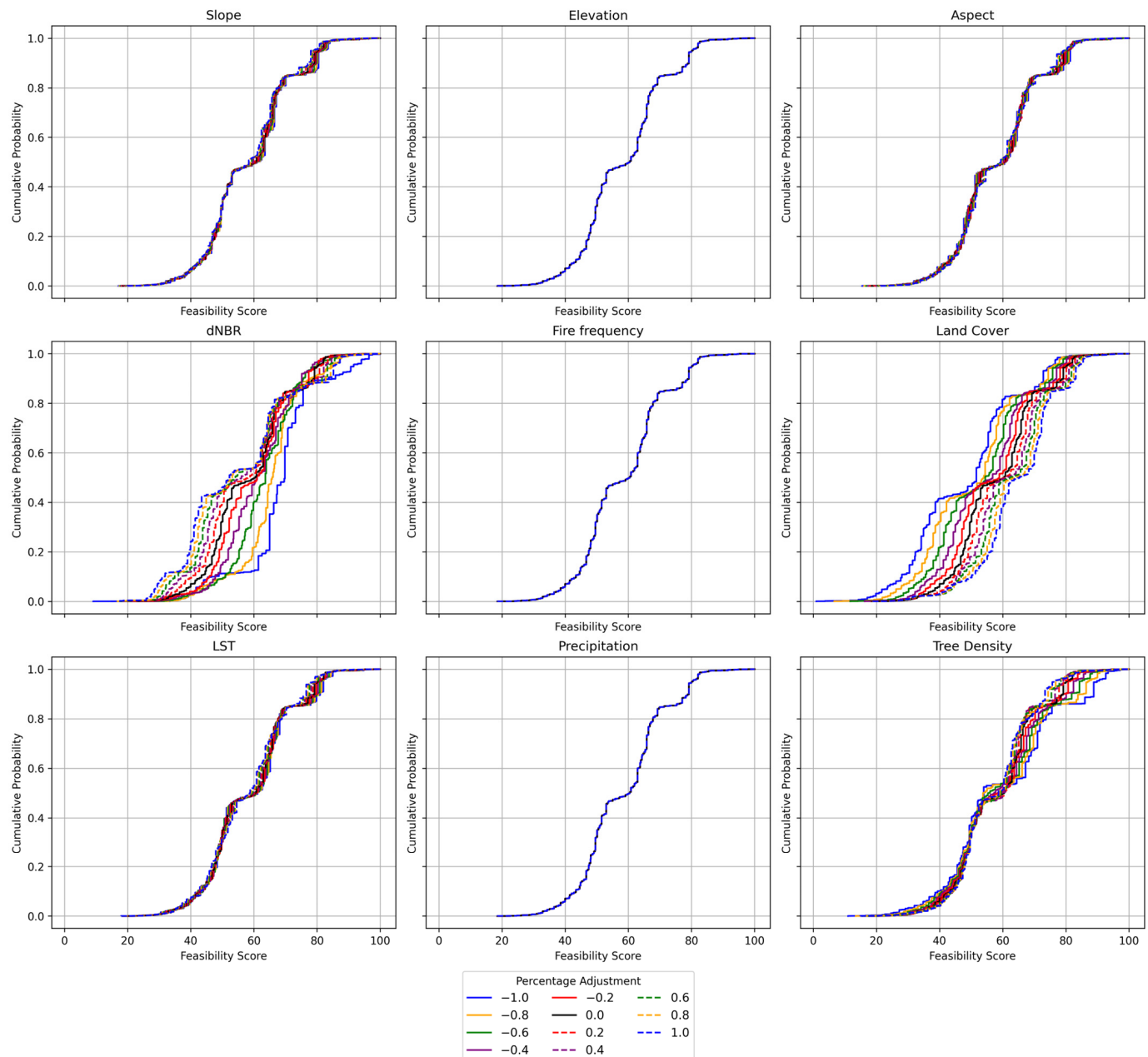


Figure 5. Cumulative distribution of feasibility scores by weight index.

3.3. Validation of the Model

The accuracy assessment based on the confusion matrix that was created confirmed that the GRESTO model performed well in determining the prioritization of reforestation efforts for the Solea fire event. As mentioned above, the evaluation was carried out using 1000 stratified samples proportionally allocated across low-, medium-, and high-priority classes according to the spatial extent of restoration actions recorded by the Department of Forests.

Based on the confusion matrix created, which is presented in Figure 6, the GRESTO model achieved an overall accuracy of 80.9%, indicating a reliable level of agreement with the reference data.

Moreover, for a better evaluation of the GRESTO model's performance, the precision, recall, and F1-score were also calculated, and the results are presented in Table 7. For the low-priority class, the model showed a precision of 0.53, a recall of 0.83, and the F1-score was 0.65. This indicated a high sensitivity in distinguishing low-priority areas

with moderate reliability. The medium-priority class, which was the most dominant category in terms of its spatial extent, showed strong classification performance, with a precision of 0.89, recall of 0.84, and F1-score equal to 0.87, showing the model's robustness in accurately identifying this class. In addition, for the high-priority class, the model achieved a precision of 0.66, but a higher recall of 0.70 and an F1 score of 0.68, suggesting a relatively balanced performance in identifying high-priority zones.

In addition to the confusion matrix evaluation, an ROC analysis was also performed. As shown in Figure 7, the AUC values were 0.90 for the low-priority class and 0.79 for both the medium- and high-priority classes, indicating very good to good separability.

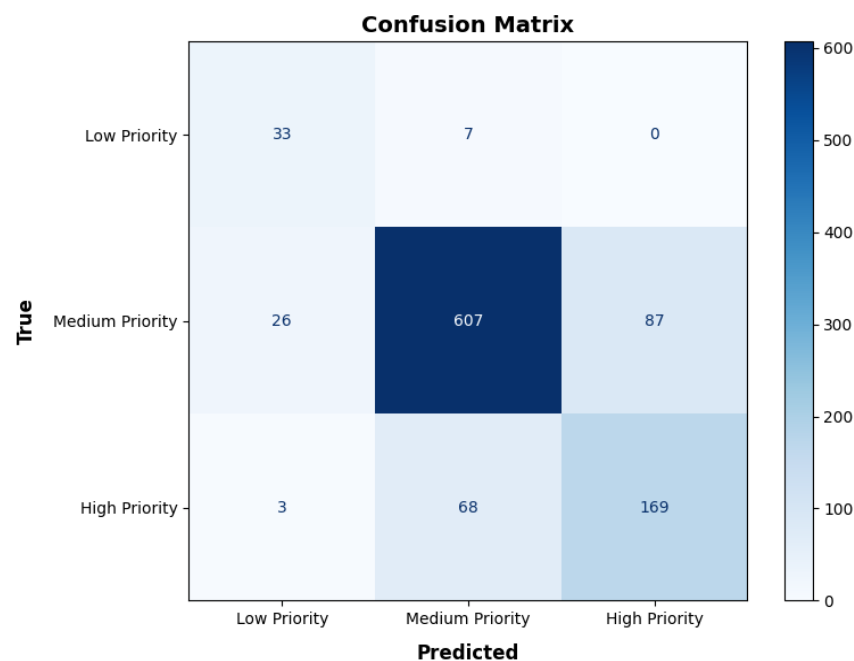


Figure 6. Confusion matrix showing the performance of the classification model across the three priority restoration classes. The values indicate the number of correctly and incorrectly classified validation points.

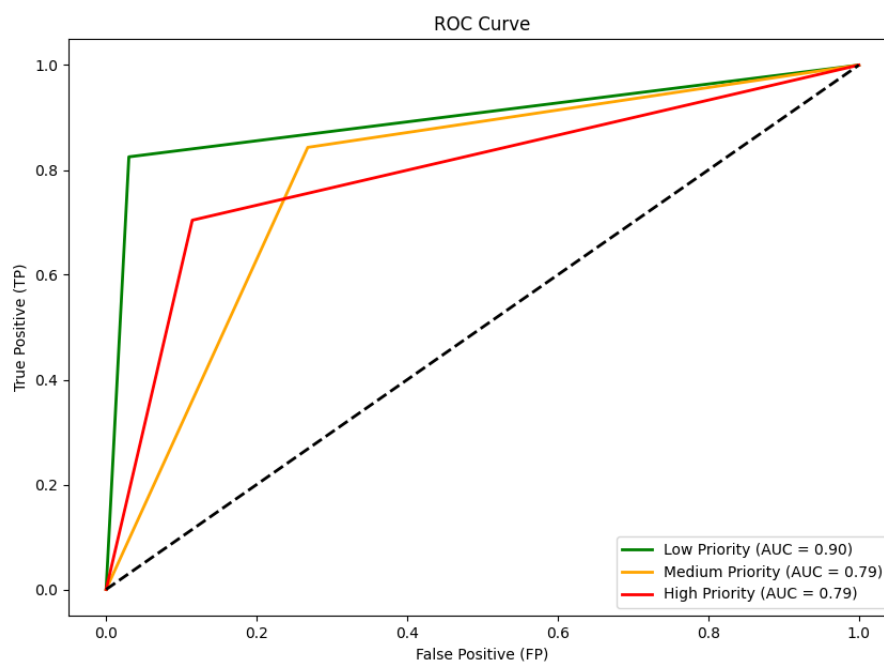


Figure 7. ROC curves for the multi-class classification model across the restoration priority classes.

Table 7. Classification performance metrics for each restoration priority class.

Priority Class	Precision	Recall	F1-Score
Low	0.53	0.83	0.65
Medium	0.89	0.84	0.87
High	0.66	0.70	0.68
Accuracy		0.81	

4. Discussion

The restoration of burned forest ecosystems is essential to mitigating the adverse effects of wildfires on ecological, economic, and social components [117–119]. In fire-prone regions like the Mediterranean, fire seasons are becoming longer, and wildfires are occurring with increasing frequency and severity influenced by ecosystem resilience, natural recovery, and vegetation composition [120]. While restoration is widely acknowledged as a critical response to post-fire degradation, implementing these efforts across large, burned regions is often constrained by logistical and resource limitations [23,24]. These factors pose significant challenges to restoration efforts, underscoring the need for spatial decision support tools that prioritize restoration areas based on ecological urgency and recovery potential. This study introduces the GRESTO Index, a spatial decision support tool based on multi-criteria analysis and remote sensing, to aid in the prioritization of restoration actions in Mediterranean ecosystems, specifically in Cyprus.

Compared to other decision-making models used in ecological restoration, such as TOPSIS or VIKOR, AHP in our case offers greater interpretability and flexibility in assigning weights, making it particularly suitable in cases where expert-based input is needed [21,29].

For the development of the GRESTO Index, ecological indicators such as dNBR, land cover, tree density, and slope were selected in alignment with criteria widely used in post-fire assessment [24,32,121,122]. Our findings showed that the most influential factors for the prioritization of reforestation actions were fire severity, tree density and land cover. Specifically, the high weight assigned to dNBR (29.4%) underscored the importance of burn severity as a key driver related to the resilience of plant communities and post-fire recovery, consistent with previous studies [114,123–126]. For example, ref. [127], through field studies, has shown that high-severity burn areas present relatively low levels of natural regeneration, and this is also supported by [128,129]. This was due to the fact that the organic layers of soil were consumed and there was also a lack of seed sources [130], reinforcing the need for targeted artificial restoration in these areas [131].

The tree density received a weight of 22.4% and land cover 16.9%; both were identified as critical factors, reflecting their roles as indicators of seed bank potential and forest structural resilience [92]. Specifically, denser pre-fire stands often indicate greater seed availability and forest structural resilience, which is well supported by the findings from other studies worldwide [132–136]. Moreover, these findings align with the work of [137,138], who similarly emphasized vegetation and landscape characteristics as dominant variables in restoration and wildfire planning models.

Although topographic characteristics and climatic factors had lower weights in the model, their ecological influence remained critical. For instance, steep slopes posed challenges for planting and increased the erosion risk, aligning with findings by [28]. Regarding the climatic factors, precipitation and temperature had significant impacts on the post-fire regeneration [139]. A recent study on Mediterranean restoration demonstrated that low annual precipitation significantly reduced seedling survival [140].

Notably, the spatial distribution of priority areas derived from the GRESTO Index aligned reasonably well with the reforestation actions taken by the Department of Forestry, demonstrating the model's utility as a support tool for planning. The model achieved an

overall accuracy of 80.9% and the reliable recall score for the high-priority class suggested that the model was effective in identifying areas needing urgent intervention. However, the lower precision in this category reflected a common challenge in restoration prioritization where ecological models may recommend interventions that are not always feasible due to socioeconomic constraints [26].

A key contribution of this study is the sensitivity analysis, which enhanced the interpretability of the model by identifying the most influential parameters. This analysis showed that dNBR and land cover significantly affected model outputs, while topographic variables and climatic factors had lower sensitivity. This suggests that future model repetitions could optimize computational resources by focusing on the most impactful variables.

Limitations of the Study and Future Work

Despite its robustness, this study has limitations. The model does not integrate socioeconomic or logistical parameters, such as proximity to roads, land ownership, or restoration costs, which can significantly affect the feasibility of reforestation actions. These exclusions restrict the scope of the model to ecological suitability. Future work should enhance the model by incorporating these aspects to reflect real-world constraints more accurately. Additionally, while the model has been validated against a single fire event in Cyprus, broader validation is essential for scaling the model to national or regional applications aligned with international restoration frameworks, such as the UN's Decade on Ecosystem Restoration and the EU Natura restoration legislation.

5. Conclusions

This study presents the GRESTO Index, a geospatial decision support tool designed to prioritize post-fire restoration actions in Mediterranean ecosystems, particularly in Cyprus, using multi-criteria analysis and remote sensing data. The GRESTO model successfully addressed this objective by integrating ecological and environmental indicators utilizing AHP through GEE, as a result, offers a practical tool for restoration planning.

The integration of geospatial data for environmental and ecological factors provides a practical and repeatable framework for supporting reforestation efforts in regions facing similar fire-related challenges. This integration of remote sensing and cloud-based geospatial analysis not only improves the precision of reforestation efforts but also underscores the efficiency of cloud computing in sustainable forest management.

Moreover, the study's findings provide several practical implications, as the GRESTO model is a cost effective, scalable tool that can support forest authorities in planning post-fire interventions, improving restoration effectiveness and meeting international environmental targets (e.g., the European Green Deal, the UN's Decade on Ecosystem Restoration, and the Bonn Challenge). Additionally, it offers a flexible structure that can be adapted to local conditions and data availability.

Future research should focus on the broader validation of the GRESTO model by applying it to other fire-affected areas to evaluate its robustness in different environmental conditions, which will help to assess its adaptability and reliability. Moreover, future research will incorporate time series analysis to assess the post-restoration process, providing valuable insights into the effectiveness of restoration practices. These insights will be valuable for refining restoration strategies and improving the long-term resilience of the fire-affected ecosystems.

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