THE RESEARCH & INNOVATION FOUNDATION PROGRAMMES

FOR RESEARCH, TECHNOLOGICAL DEVELOPMENT, AND INNOVATION

RESTART 2016 – 2020

Pillar	I. Smart Growth
Programme	CO-DEVELOP
Project Acronym	Green-HIT
RIF Project Number	CODEVELOP-ICT-HEALTH/0322/0135
Proposal Title	A Green - Holistic IoT platform for Forest Management and Monitoring
Project Coordinator	Frederick Research Center (FRC)
Work Package Number	WP2
Work Package Title	Dissemination and Exploitation Activities
Deliverable Number	D2.3
Deliverable Title	Scientific Articles

Dissemination level		
PU	Public	X
CO	Confidential, only for members of the consortium (including RIF)	

Funded by the European Union
NextGenerationEU

Cyprus tomorrow
RECOVERY AND RESILIENCE PLAN

Republic of Cyprus

AUTHORS

Author	Institution	Contact (e-mail, phone)
Andreas Pamboris	FRC	res.ap@frederick.ac.cy
Andreas Constantinides	FRC	com.ca@frederick.ac.cy

DOCUMENT CONTROL

Document version	Date	Change
v0.1	30/04/2025	Draft
v1.0	26/05/2025	Final Version

This deliverable includes all scientific articles published to date (or about to be published), based on research that was carried out as part of the project. The list of publications is provided below.

- A. Pamboris, I. Iasonos, N. Kyriakou, M. Prodromou, P. Cheng, A. Konstantinidis. 2025. "**Green-HIT: An End-to-End IoT System for Forest Monitoring and Management**". To appear in: Conference in Advancements in Sustainable Engineering, Cyprus, September 11-12, 2025.
- M. Prodromou, M. Tzouvaras, C. Mettas, A. Konstantinidis, A. Pamboris, I. Iasonos, D. Hadjimitsis. 2025. "**The Contribution of Remote Sensing for the Development of a Green-Holistic IoT Platform for Forest Management and Monitoring: Reforestation and Deforestation Modules**". To appear in: ISPRS Geospatial Week 2025: "Photogrammetry and Remote Sensing for a Better Tomorrow, Dubai, April 6-11, 2025.
- P. Cheng, A. Papatheodoulou, A. Constantinides, A. Pamboris, N. Kyriakou, G. Tsapparellas. 2025. "**USING ARTIFICIAL INTELLIGENCE FOR WILDFIRE PREVENTION IN CYPRUS".** To appear in: 5th International Fire Safety Symposium (IFireSS 2025), Ulster University, Belfast, United Kingdom, June 25-27, 2025.
- M. Prodromou, I. Gitas, C. Mettas, M. Tzouvaras, K. Themistocleous, A. Konstantinidis, A. Pamboris, D. Hadjimitsis. 2025. "**Remote-Sensing-Based Prioritization of Post-Fire Restoration Actions in Mediterranean Ecosystems: A Case Study in Cyprus".** Remote Sensing 17, no. 7: 1269. https://doi.org/10.3390/rs17071269.

Green-HIT: An End-to-End IoT System for Forest Monitoring and Management

Andreas Pamboris*[1], Iasonas Iasonos[1], Nicolas Kyriakou[2], Maria Prodromou[3], Pericles Cheng[4] and Andreas Konstantinidis[1]

[1] Frederick University, Nicosia, Cyprus
[2] Cy.R.I.C Cyprus Research and Innovation Center, Nicosia, Cyprus
[3] ERATOSTHENES Centre of Excellence
[4] European University Cyprus, Nicosia, Cyprus

*E-mail: res.ap@frederick.ac.cy

Abstract. Forests play a critical role in climate regulation, biodiversity preservation, and ecosystem sustainability, making their protection and effective management a strategic priority under the European Green Deal. In this context, we present Green-HIT, a holistic Internet of Things (IoT) system designed to transform forest management and monitoring through the integration of advanced Information and Communication Technologies (ICT). The Green-HIT system addresses key challenges faced by forest authorities and environmental stakeholders by enabling real-time monitoring, intelligent decision-making, and automated response mechanisms. It incorporates a range of capabilities including early detection and prevention of forest fires, afforestation and reforestation planning, illegal activity detection (e.g., logging and hunting), and the generation of forest mapping and inventory reports, using both field and remote sensing data. By leveraging edge computing, AI-driven analytics, cutting-edge Unmanned Aerial Vehicle (UAV) technologies, and interoperable data infrastructure, Green-HIT supports proactive forest management strategies aligned with green transition goals. This paper will demonstrate the effectiveness and efficiency of the system through a series of controlled pilot deployments in selected forest areas across Cyprus.

The contribution of remote sensing for the development of a Green-Holistic IoT Platform for Forest Management and Monitoring: Reforestation and Deforestation Modules

Maria Prodromou [1], Marios Tzouvaras [1], Christodoulos Mettas[1], Andreas Konstantinidis[2], Andreas Pamboris [2], Iasonas Iasonos [2] , Diofantos Hadjimitsis [1]

[1] ERATOSTHENES Centre of Excellence, 82 Franklin Roosevelt, 3012, Lemesos, Cyprus – maria.prodromou@eratosthenes.org.cy
[2] Frederick Research Center, Nicosia, Cyprus –com.ca@frederick.ac.cy

Keywords: Remote Sensing, Deforestation, Reforestation, Cyprus, GreenHIT, forest management and monitoring

Abstract

The Green-HIT project focuses on effective and efficient forest monitoring and management, which holds the promise for climate change mitigation, ecosystem conservation, and biodiversity loss reduction. This project is funded by the Cyprus Research & Innovation Foundation (CODEVELOP-GT/0322) and is currently being implemented in Cyprus. Cyprus is located in the Eastern Mediterranean, an area frequently affected by various incidents that impact the preservation of forests (for example, forest fires, illegal logging, hunting, trespassing, and other activities that are damaging to biodiversity), especially during the summer season. Specifically for forest fires, several factors contribute to the increased risk of fire, such as prolonged drought, hot summers, strong winds, steep forest slopes, and flammable vegetation. Early warning and direct management facilities are paramount to efficiently tackling such disastrous events. To this end, the Green-HIT project aims to develop a holistic IoT platform for supporting productivity, competitiveness, and growth of the economy and the promotion of digital and green technology via forest management and monitoring in a post-pandemic world by (a) offering support for prevention, detection and reaction to forest fires, (b) providing afforestation and/or reforestation recommendations, (c) protecting forests from illegal logging and hunting, (d) monitoring forests and forest areas, and (e) offering forest mapping and inventory facilities by collecting, combining and analyzing field and remotely sensed data. This study will present the deforestation and reforestation module of the Green-HIT platform, which aims to identify and suggest (to relevant authorities), possible areas for reforestation. This module was developed using remote sensing data. Specifically, a change detection technique using the Euclidean distance was used for the identification of deforested areas achieving an Overal Accuracy equal to 67.7 %. Also, for the reforestation module, a multicriteria analysis was applied using several parameters like dNBR, land cover, fire history, soil erosion, etc., using the Google Earth Engine platform. For the purposes of this study, the Argaka fire event was selected to evaluate the accuracy of the developed model.

1. Introduction

Forests have a vital role for the Earth, and it is important to determine their status both strategically and tactically. Mediterranean forests are critical for providing numerous ecosystem services that enhance human well-being. These forests play a pivotal role in improving food, water, and energy security and are instrumental in mitigating risks. Additionally, they contribute significantly to both local and global economic structures. Furthermore, Mediterranean forests are vital for the protection of cultural identities and facilitate personal development (FAO and Plan Bleu, 2018). Despite the numerous benefits these ecosystems provide, they face a range of disturbances. Notable examples include climate change and human population growth, which lead to consequences such as the conversion of forests into scrublands, wildfires, outbreaks of pests and diseases, overgrazing, and land abandonment. These factors pose serious threats to the health and sustainability of Mediterranean forests(UNEP/MAP and Plan Bleu, 2020).

In recent decades, forest monitoring approaches in a wide range such as, timber production, environmental protection, biodiversity conservation, forest fire prevention, post-disturbance monitoring, wilderness, and open spaces etc. have been improving continuously and remote sensing is increasingly used for the forest monitoring. On the field, measurement methods are important sources of information. However, in cases of collecting critical forest measurements on a larger scale, the use of these methods is limited. Because of this, forest monitoring has progressed to the use of remote sensing (space and airborne) because it can provide fast, accurate, and high-resolution information about the study areas. These technologies have favored forest monitoring in terms of capacity, scale, and detail . Some of the most common types of Earth Observation (EO) data include multispectral and synthetic aperture radar (SAR) systems. Apart from that, are considered also the light detection and ranging (LiDAR) technologies, which provide the tools to assess forest characteristics and can be used to monitor and quantify changes in forests over time . Forest disturbances like wildfires, insect outbreaks (e.g Thaumetopoea pityocampa), etc. are key factors that affect the dynamics of forest ecosystems. For example, they affect forest species composition, structure, above- and below-ground carbon storage , forest regeneration and successional dynamics, as well as cycle of water and energy . Because of this, it is important to have a continuous inventory of forest ecosystems.

Over the past few decades, the science of remote sensing has expanded in different forest applications, such as forest species classification (Papachristoforou et al., 2023; Prodromou, Theocharidis, et al., 2024) fire damage assessment (Prodromou, Gitas, Themistocleous, Danezis, et al., 2023; Prodromou, Gitas, Themistocleous, Nisantzi, et al., 2023), time series of forest seasonality (Theocharidis et al., 2023), fire risk (Prodromou, Girtsou, et al., 2024), as well as the impact of dust pollution in NATURA2000 regions (Themistocleous & Prodromou, 2023)

The Green-HIT project focuses on effective and efficient forest monitoring and management, which holds the promise for climate change mitigation, ecosystem conservation, and biodiversity loss reduction. This project is funded by the Cyprus Research & Innovation Foundation (CODEVELOP-GT/0322) and is currently being implemented in Cyprus. Also the project aims at developing a holistic IoT platform, as shown in Figure 1 for supporting productivity, competitiveness and growth of the economy and the promotion of digital and green technology via forest management and monitoring in a post-pandemic world by: (a) offering support for prevention, detection and reaction to forest fires, (b) providing deforested areas and reforestation recommendations actions, (c) protecting forests from illegal logging and hunting, (d) monitoring forests and forest areas, and (e) offering forest mapping and inventory facilities by collecting, combining and analyzing field and remotely sensed data. This study will present the deforestation and reforestation modules of the Green-HIT platform, which aims to identify deforested areas and suggest (to relevant authorities), possible areas for reforestation. These modules were developed using remote sensing data. The platform operates across three main layers: the Perception Layer, which collects environmental data from IoT sensors, UAVs, and satellite imagery, the Network layer, which connects IoT gateways to transmit data to cloud servers, and the Application layer, where data is processed and analyzed using API-driven intelligence modules.

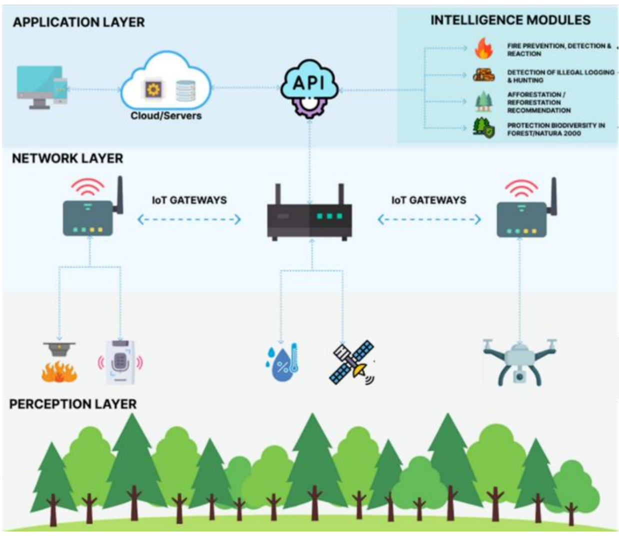

Figure 1 The architecture of the Green-HIT platform for forest management and monitoring.

1.1 Deforestation

Deforestation is the conversion of forests to other land use, primarily caused by human activities or other causes like natural events (FAO, 2022). Large-scale forest cleaning or removal often leads to forest land being converted into non-forest uses for human purposes, such as urban development, agriculture, mining, timber extraction, and infrastructure expansion. Agriculture is the leading cause of deforestation, according to the World Wildlife Fund (Timmins et al., 2023; WWF, n.d.). Only for 2022, more than 65,000 Km^2 of forest were lost, an area comparable with Sri Lanka or approximately 7 times the size of Cyprus. Deforestation results in the loss of forests and trees and the displacement of wildlife, particularly in tropical rainforests such as the Amazon, which hosts a significant portion of the world's biodiversity. In the Amazon, the world's largest forest, around 17% has been lost over the past 50 years, mainly due to cattle ranching, with lost land increasing annually. A similar trend is observed in the Mediterranean region. Between 2001 and 2019, an estimated 5.80 million Km^2 of forests were lost, with an average annual loss of 306,000 Km^2. The countries with the highest levels of deforestation include Spain, with approximately 12,000 Km^2 lost, France, with around 11,500 Km^2, and Portugal, with roughly 10,000 $Km^{2.}$ (Ciobotaru et al., 2021).

The European Union has established initiatives and laws to contribute to preserving and protecting forests while trying to minimize deforestation in Europe as much as possible. One of the principal regulations requires all goods entering and exiting the EU to be ''deforestation-free''. All new regulations and laws set by the European Union have one primary goal: to reduce greenhouse gas emissions by at least 55% by 2030 compared to 1990 levels, with deforestation playing a significant role in achieving this target (European Council of the European Union, 2024).

To effectively support these goals, advanced technologies such as remote sensing and Geographic Information Systems (GIS) have become essential tools for monitoring deforestation, assessing environmental impacts, and guiding conservation strategies. Geographic Information Systems combined with remote sensing technology can help scientists understand how forests around the globe have changed over the years, identify land use changes, and provide valuable data that can be used to either prevent future deforestation or help regenerate the forests.(Mitchell et al., 2017). Moreover, LiDAR technology offers detailed three-dimensional data on forest structures, enhancing the precision of deforestation monitoring. LiDAR generates accurate elevation models and canopy height maps using laser pulses to measure their return time. This data enables precise biomass measurements, canopy density, and topographical features. LiDAR-based analysis helps identify deforested areas, measure canopy loss, and assess forest fragmentation, which can help governments take the appropriate measures to minimize deforestation.(Almeida et al., 2024).

As mentioned above, remote sensing is a high-priority technique that can be used to monitor, capture, and prevent deforestation. Through satellite images or aerial imagery, a change detection procedure can play a vital role in the defense of our forests. The Sentinel-2 imagery and multispectral images can provide valuable information, such as the NDVI index, and practical insights for scientists about deforestation. In general, change detection compares at least two images taken at different times, making it possible to track deforestation progress, vegetation health, and how time affects the forest in general. This approach allows for rapid and precise intervention, promoting forest sustainability.(Hewarathna et al., 2024).

1.2 Reforestation

Reforestation refers to the process of natural regeneration or tree planting that occurs after a natural disaster, such as a wildfire. This silvicultural practice fosters the development of forest structure and the many benefits that forests provide to human life. Reforestation encompasses all necessary actions to promote the natural regeneration of affected areas using ecologically appropriate tree seedlings (Brancalion & Chazdon, 2017; Uprety et al., 2012).

Additionally, the European Commission places a high value on reforestation in its agenda and has recently published new "Guidelines on Biodiversity-Friendly Afforestation, Reforestation, and Tree Planting"(European Commission, 2023). These guidelines aim to provide strategies for creating new forests and planting trees in both urban and rural environments. The European Union has set a goal of planting 3 billion new trees by 2030, which can only be achieved through the combined support of authorities, forest organizations, and landowners (European Union, 2022). In a world facing an increasing number of crises, reforestation stands out as a vital solution with numerous benefits. By restoring trees to deforested or barren land, we can reap a multitude of advantages (Bonn Challenge, 2018; UNEP & FAO, 2020; UNEP/MAP and Plan Bleu, 2020).

Firstly, trees are exceptional at absorbing carbon dioxide, providing a powerful defence against the high levels of carbon emissions our planet faces. This leads to a reduction in greenhouse gases. Secondly, forests, and thus the trees, serve as habitats for millions of animal species. Preserving and enhancing the biodiversity that Earth has to offer is our responsibility, and reforestation can significantly contribute to this effort (Lorenz & Lal, 2010; Raihan, 2023). Thirdly, healthy soil is essential for sustainable agriculture and thriving ecosystems, and reforestation plays a key role in maintaining soil health. Trees prevent erosion, improve soil structure through their extensive root systems, and reduce the risk of landslides and land degradation(Gobinath et al., 2022). Finally, forests act as natural filters for the water that flows through them. Planting trees alongside waterways can significantly enhance water quality(Smith et al., 2013).

Remote sensing can significantly advance reforestation efforts by providing valuable data and insights that enhance the planning, monitoring, and management of forest restoration projects (Tatem et al., 2008). Reforestation is not a simple task; for it to be effective, proper forest management is essential, and remote sensing can play a crucial role in this process(Gitas et al., 2012; Koch et al., 2021) .

Remote sensing simplifies reforestation management, and high-resolution satellite images offer invaluable data to scientists, helping to ensure successful reforestation initiatives. As time goes on, the costs associated with these efforts are increasing. By incorporating satellite and remote sensing data into our inventory, we can reduce costs for potential reforestation areas, especially in challenging locations (Cavalcante et al., 2022).

Additionally, multispectral and hyperspectral imaging facilitate the monitoring and detection of vegetation health, moisture levels, and overall ecosystem recovery alves(Alves de Almeida et al., 2021). Analytical models and advanced intelligence are necessary to achieve successful reforestation plans with long-term sustainability in mind. Finally, the effort to combat deforestation and promote reforestation is a worldwide initiative that requires collaboration between governments, organizations, and local communities (UNEP & FAO, 2020; UNEP/MAP and Plan Bleu, 2020).

2. Study Area

The proposed methodology was implemented in Cyprus island. which is located in the Eastern Mediterranean, an area frequently affected by various incidents that impact the preservation of forests (for example, forest fires, illegal logging, hunting, trespassing, and other activities damaging to biodiversity), especially during the summer season. Specifically for forest fires, several factors contribute to the increased risk of fire, such as prolonged drought, hot summers, strong winds, steep forest slopes, and flammable vegetation. The deforestation model was implemented over the whole region of Cyprus, and the reforestation model was only for the Argaka fire event (Figure 2).

The fire in Argaka area (Paphos region), erupted on June 18, 2016, with an estimated burned area of 763.3ha. The predominant vegetation in these regions consists of Pinus Brutia forests with an understory comprising herbaceous plants and shrubs. The climate in these areas is typical of the Mediterranean, characterized by hot, dry summers and mild, rainy winters.

Figure 2 Argaka fire event that was examined for this study

3. Materials and Methods

The proposed methodology is divided into two sections: the first part describes the approach used for developing the deforestation module of the Green-HIT platform, while the second part focuses on the reforestation module. For both modules, the Google Earth Engine (GEE) platform was utilized for the process development.

The GEE is a planetary-scale platform for scientific analysis and visualization of geospatial datasets. In this platform, the open-source images acquired by several satellites are accessible and can be efficiently imported and processed in the cloud without the necessity of downloading (Gorelick et al., 2017; Mutanga & Kumar, 2019)

3.1 Deforestation module

A change detection technique was implemented to identify deforestation areas. Specifically, the model is based on the difference in reflectance values between two images, one is the reference, and the other is the target. The user specifies a date in the model, and the algorithm detects changes between the selected dates based on the previous year.

The change detection uses the spectral bands of Sentinel-2 imagery and additional spectral indices to enhance the detection of the changes. ESA launched the Sentinel-2 mission, an optical platform equipped with a multispectral instrument that includes two satellites (Sentinel-2A and Sentinel-2B). Furthermore, this mission enables the acquisition of data in 13 spectral bands presented in Table 1 indifferent spatial resolutions (10m, 20m and 60m) every five days on average (Drusch et al., 2012; Spoto et al., 2012). The Sentinel-2A satellite was launched on 23 June 2015, and 2B on 7 March 2017. As a result, the developed modules operate only on data collected after 2015. Is highlighted that only the bands with spatial resolution at 10 and 20m were used.

In the analysis used in the study, the spectral indices that are presented in Table *2* were incorporated as new layers to create image composites for the abovementioned datasets. The spectral indices were used since each can provide additional information for the analysis. One example is the use of NDVI, one of the most widely used vegetation indicators that highlight the vegetation condition (Tucker, 1979) and the SAVI, which considers the terrain and, in cases with low vegetation cover, corrects the effects of soil brightness. For the leaves' water content, the NDMI index was used, which is based on the ratio of NIR and SWIR (HUNTJR & ROCK, 1989). The NDRE index based on the NDVI formula was used; however, the Red Edge instead of Red (Barnes et al., 2000).

Table 1 Spatial resolution and central wavelength for Sentinel-2 bands.

Sentinel-2 MSI		
Band	**Wavelength (mm)**	**Resolution (m)**
1 Coastal aerosol	433-453	60
2 Blue (B)	458-523	10
3 Green (G)	543-578	10
4 Red (R)	650-680	10
5 Red edge 1 (RE1)	698-713	20
6 Red edge 2 (RE2)	733-748	20
7 Red edge 3 (RE3)	773-793	20
8 Near Infrared (NIR)	785-900	10
8a 8 Near Infrared narrow (NIRn)	855-875	20
9 Water vapour	935-955	60
10 Shortwave infrared / cirrus	1360-1390	60
11 Shortwave infrared 1 (SWIR1)	1565-1655	20
12 Shortwave infrared 2 (SWIR2)	2100-2280	20

Also, to ensure consistency across datasets, each image composite was normalized using the minimum and maximum pixel values within the selected area. Additionally, to avoid any impacts from the cloud cover in the analysis, the images were filtered to have <10% cloud cover across the entire scene, especially above the area, using the CLOUDY_PIXEL_PERCENTAGE metadata to reduce the impact of clouds. Also, the cloud masking was performed using the QA60 band, where the pixels affected by clouds and cirrus were masked out.

Change detection was performed following the band selection and the computation of the spectral indices for the two satellite image composites (reference/target). In detail, a pixel-based differencing approach was applied to detect changes in surface reflectance. Specifically, the difference between the reference and target imagery was calculated using the Euclidean Distance (ED) method based on the Eq.1. The normalized image composites were subtracted, squared, and summed across bands, followed by the square root to compute the final change magnitude. Higher ED values indicate more significant spectral differences suggesting greater changes in vegetation.

$$ED = \sqrt{\sum_{i=1}^{n} X_2^i - X_1^i} \quad \textbf{(Eq. 1)}$$

Where X represents the spectral bands (including spectral indices)

Moreover, in order to automatically binarize the difference, the Otsu's thresholding method (Otsu, 1979) is used, and then the changes are represented by pixels assigned a value of 1, and those with values of 0 are masked out to distinguish between changed and unchanged areas. This technique computes an adaptive threshold based on the histogram of changed magnitudes and ensures an optimal separation between changed and unchanged regions.

After the identification of the changes, they were categorized using ancillary data. Specifically, land cover data provided by the Copernicus Land Monitoring Service was used to classify the detected changes into specific categories: changes in forest areas that indicate potential areas for deforestation, changes in rural areas, changes in urban environments, and changes in water bodies. In addition, fire-induced changes were determined using the burnt area datasets derived from MODIS Burned Area Product (MCD64A1).

Finally, for the validation of the results, the fire events data from EFFIS service. Specifically, the evaluation was made based on the identification of known fire events in comparison with the change detection model that develop for the identification of the deforestation.

Table 2. Vegetation Indices Equations based on Sentinel-2 data.

Satellite	Vegetation Indices	Abbreviation	Equation	Reference
S2	Normalised Difference Vegetation Index	NDVI	$\frac{\boldsymbol{NIR - RED}}{\boldsymbol{NIR + RED}}$	(Tucker, 1979)
	Normalised Difference Red Edge Index	NDRE	$\frac{\boldsymbol{NIR - RED\ EDGE}}{\boldsymbol{NIR + RED\ EDGE}}$	(Gitelson et al., 2003)
	Enhanced Vegetation Index	EVI	$\frac{\boldsymbol{2.5(NIR - RED)}}{\boldsymbol{NIR + 6RED - 7.5BLUE + 1}}$	(A. Huete et al., 2002)
	Soil-Adjusted Vegetation Index	SAVI	$\frac{\boldsymbol{1.5(NIR - RED)}}{\boldsymbol{NIR + RED + 0.5}}$	(A. R. Huete, 1988)

Normalised Difference Moisture Index	NDMI	$\frac{SWIR - NIR}{SWIR + NIR}$	(HUNTJR & ROCK, 1989)

3.2 Reforestation module

The Reforestation module was developed based on a multi-criteria decision-making approach using remote sensing data to prioritize post-fire reforestation efforts within deforested areas. For the identification of the parameters, discussions were conducted with the forest department in Cyprus and based on the literature. Based on this approach, the selected factors for the development of the model were the fire severity, tree canopy density, elevation, slope, aspect, temperature, precipitation, and the fire frequency. With these factors the Analytical Hierarchy Process (AHP) proposed by (Saaty et al., 1980) is implemented in order to determine the importance of each factor, resulting in a priority reforestation map with three classes: low, medium, and high. Low and medium priority correspond to areas that have the potential for natural recovery, while high-priority areas require artificial restoration actions. AHP compares all factors against each other based on their importance on a scale of 1 to 9, as shown in Table 3.

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

After that, we retrieved the necessary data that corresponded to each factor. The Sentinel-2 imagery was used for the estimation of fire severity, while Corine Land Cover data was used to classify the land cover types, identifying the forested areas that have higher restoration needs. Additionally, topographic factors are incorporated using the SRTM DEM, and climate parameters, including LST from MODIS and precipitation from CHIRPS, are integrated to assess the potential recovery. Tree density data and fire history are also considered in the analysis.

All factors were standardized in order to be in the same scale of value, where the original values were transformed into comparable units [59] from 1 up to 3, where the values of each factor that have low importance were taken the value 1, and the values with higher importance take values up to 3.

Finally, the aggregation was performed using the weighted linear summation method. Specifically, the raster layer for each factor is multiplied by their respective criterion weight, and after that, they are summed. based on this, the final map about the prioritization of the areas for reforestation actions was developed and reclassified into reforestation priority classes.

4. Results and Discussion

4.1 Deforestation module

The proposed methodology was conducted for the development of a deforestation module for the Green-HIT platform. Specifically, it was applied to specific regions to analyze land cover changes for a selected timeframe. The detected changes were categorized into four major classes - Forest, Water Bodies, Agriculture, and Urban based on Corine Land Cover (CLC) provided by Copernicus. The changes emphasize monitoring changes within forested areas. To ensure a more accurate evaluation, this study emphasized only the changes that were detected within forests, shrublands, and grasslands as defined by the CLC dataset. The urban areas, croplands, water bodies, etc, were excluded from the analysis.

Figure 3 have presented some characteristic changes that are identified by the proposed methodology.

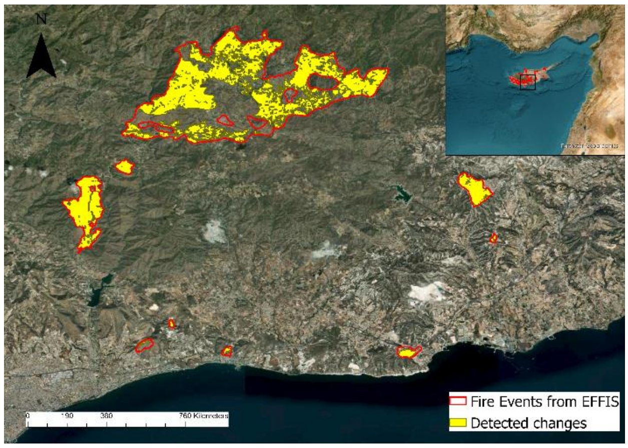

Figure 3 Comparison between the changes detected by the change detection model with EFFIS burned areas.

The deforestation detection module effectively identified deforested areas with high accuracy, 67.7%, as validated against burned areas from European Forest Fire Information System (EFFIS) data. The high agreement between the predicted deforestation areas and burned areas data highlights the robustness of the methodology in accurately capturing forest disturbances. This agreement suggests that the proposed approach is particularly effective in distinguishing fire-induced deforestation from other types of land cover changes. Moreover, the results indicate a distinct increase in deforestation areas during the summer months due to the increase in the number of fires.

4.2 Reforestation module

Multicriteria decision-making (MCDM) techniques are widely utilized and are highly effective for managing large volumes of complex information. These techniques can be categorized into various approaches depending on their specific applications.

In the field of reforestation, several studies have employed the Analytic Hierarchical Process (AHP), as it can be effectively integrated with Geographic Information Systems (GIS) to determine the relative importance of different criteria. For example, AHP has been used to assess ecological suitability in land evaluation and natural resource management (Malczewski, 2004; Ownegh et al., 2006). It has also been applied to identify optimal locations for the afforestation of endangered species (Alemi et al., 2014) and to evaluate afforestation efforts in Darab

Kola, Miandorud County, Mazandaran Province, Iran (Gholizadeh et al., 2020).

The prioritization of reforestation actions for the Argaka fire event was determined using the AHP method, categorizing the burned area into three main priority levels: low, medium, and high, as shown in Figure *4*. These priorities were then translated into either artificial or natural restoration actions. Specifically, low and medium-priority areas correspond to regions with potential for natural recovery, while high-priority areas require artificial restoration actions. Moreover, Figure 3 highlights in the boxes some characteristic regions that are in full agreement with practices conducted by the Department of Forests.

The model was implemented to the selected polygon where results indicate that the area is primarily classified as low priority (80%), with high priority and medium priority areas representing 11% and 9%, respectively. However, when focusing solely on the burned area, the majority (52%) falls into the high-priority category, followed by medium-priority (40%) and low-priority (8%). Moreover, according to the restoration efforts implemented after the Argaka fire event by the DoF, only 0.59% of the burned area remained unburned. Regarding the restoration action, a small portion (4.62%) was selected for natural recovery, while the remaining burned area (94.79%) was subject to restoration efforts.

By comparing the predicted reforestation strategies with the permanent sample points established by the Department of Forests to assess restoration efforts, the preliminary results indicate that the model achieves an Overall Accuracy (OA) of approximately 74.5%, demonstrating strong agreement with actual restoration outcomes.

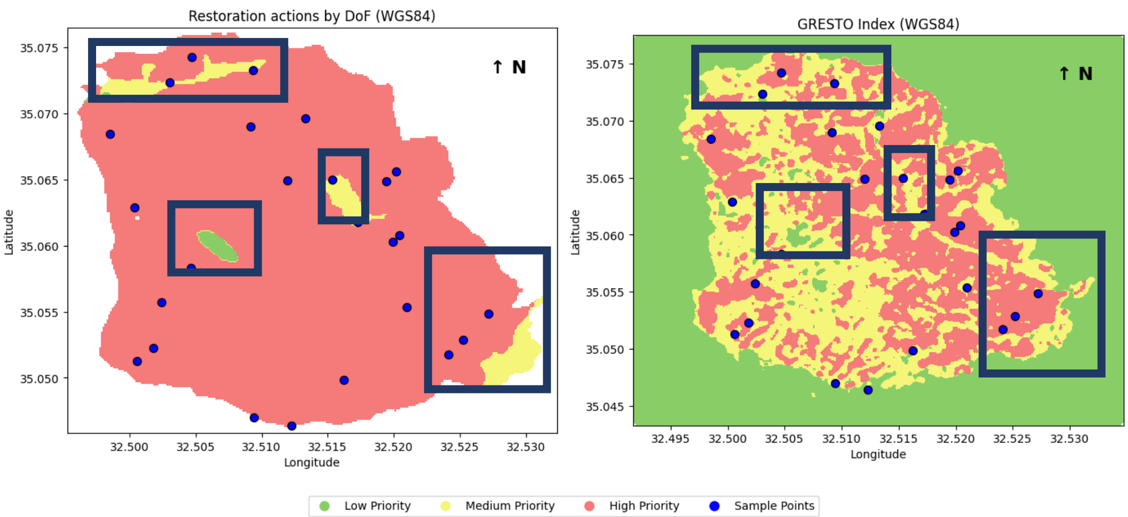

Figure 4 Priority of reforestation actions in Argaka fire event/

5. Conclusions

Overall, the findings demonstrate that the proposed methodology for the identification of deforestation areas provides an accurate and reliable framework for detecting and monitoring deforestation, offering valuable insights for policymakers and stakeholders in managing and preventing forested ecosystems.

Also, regarding the restoration module successfully prioritized reforestation actions based on burn severity and ecological recovery potential. The model demonstrated a strong agreement with actual restoration efforts, achieving an Overall Accuracy of 74.5% when compared to field data. This approach effectively distinguished areas suitable for natural recovery from those requiring artificial restoration, providing a valuable decision-support tool for post-fire management. The Green-HIT project successfully demonstrates the integration of remote sensing techniques for effective forest management and is highlighted that is the first tool in Cyprus that uses these technologies. The deforestation module accurately identifies the deforested areas and similarly, the reforestation module accurately prioritizes the restoration actions in burned areas. Also, the use of multi-temporal remote sensing data and geospatial analysis enables continuous monitoring, ensuring a proactive approach to forest conservation. These findings highlight the platform's capabilities to support forest monitoring, biodiversity conservation, and climate change mitigation, providing a valuable tool for sustainable environmental management.

Our future steps focus on the time series analysis for the investigation of the recovery of deforested areas as well as to exploit the effectiveness of restoration actions in the burned areas.

6. Acknowledgements:

This work is part of the "CO-DEVELOP-ICT-HEALTH" Project with title acronym Green-HIT and project number CODEVELOP-ICT-HEALTH/0322/0135. The Project Green-HIT is implemented under the Recovery and Resilience Plan with funding by the European Union – NextGenerationEU

References

Almeida, C. T. de, Galvão, L. S., Ometto, J. P. H. B., Jacon, A. D., Pereira, F. R. de S., Sato, L. Y., Silva-Junior, C. H. L., Brancalion, P. H. S., & Aragão, L. E. O. e C. de. (2024). Advancing Forest Degradation and Regeneration Assessment Through Light Detection and Ranging and Hyperspectral Imaging Integration. *Remote Sensing*, *16*(21), 3935. https://doi.org/10.3390/rs16213935

Alves de Almeida, D. R., Broadbent, E., Almeyda Zambrano, A. M., Ferreira, M. P., & Santin Brancalion, P. H. (2021). Fusion of Lidar and Hyperspectral Data from Drones for Ecological Questions: The Gatoreye Atlantic Forest Restoration Case Study. *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, 714–715. https://doi.org/10.1109/IGARSS47720.2021.9554023

Barnes, E. M., Clarke, T. R., Richards, S. E., Colaizzi, P. D., Haberland, J., Kostrzewski, M., Waller, P., Choi C., R. E., Thompson, T., Lascano, R. J., Li, H., & Moran, M. S. (2000). Coincident detection of crop water stress, nitrogen status and canopy density using ground based multispectral data. *Proc. 5th Int. Conf. Precis Agric*.

Bonn Challenge. (2018). *Getting Started with the Bonn Challenge*. *1*(866), 3–4.

Brancalion, P. H. S., & Chazdon, R. L. (2017). Beyond hectares: four principles to guide reforestation in the context of tropical forest and landscape restoration. *Restoration Ecology*, *25*(4), 491–496. https://doi.org/10.1111/rec.12519

Cavalcante, R. B. L., Nunes, S., Viademonte, S., Rodrigues, C. M. F., Gomes, W. C., Ferreira, J. da S., Pontes, P. R. M., Giannini, T. C., Awade, M., de S. Miranda, L., & Nascimento, W. R. (2022). Multicriteria approach to prioritize forest restoration areas for biodiversity conservation in the eastern Amazon. *Journal of Environmental Management*, *318*, 115590. https://doi.org/10.1016/j.jenvman.2022.115590

Ciobotaru, A.-M., Patel, N., & Pintilii, R.-D. (2021). Tree Cover Loss in the Mediterranean Region—An Increasingly Serious Environmental Issue. *Forests*, *12*(10), 1341. https://doi.org/10.3390/f12101341

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F., & Bargellini, P. (2012). Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services. *Remote Sensing of Environment*, *120*, 25–36. https://doi.org/10.1016/j.rse.2011.11.026

European Commission. (2023). *COMMISSION STAFF WORKING DOCUMENT Guidelines on Biodiversity-Friendly Afforestation, Reforestation and Tree Planting*.

European Council of the European Union. (2024). *Deforestation*. https://www.consilium.europa.eu/en/policies/deforestation/

European Union. (2022). *Three billion additional trees by 2030*. 1–2. https://doi.org/10.2779/14732

FAO. (2022). The State of the World's Forests 2022. In *The State of the World's Forests 2022*. https://doi.org/10.4060/cb9360en

FAO and Plan Bleu. (2018). *State of Mediterranean Forests 2018*. http://www.fao.org/docrep/017/i3226e/i3226e.pdf

Gitas, I., Mitri, G., Veraverbeke, S., & Polychronaki, A. (2012). Advances in remote sensing of post-fire vegetation recovery monitoring—A review. *Remote Sensing of Biomass-Principles and Applications*, *1*, 334.

Gitelson, A. A., Gritz †, Y., & Merzlyak, M. N. (2003). Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. *Journal of Plant Physiology*, *160*(3), 271–282. https://doi.org/10.1078/0176-1617-00887

Gobinath, R., Ganapathy, G. P., Gayathiri, E., Salunkhe, A. A., & Pourghasemi, H. R. (2022). Ecoengineering practices for soil degradation protection of vulnerable hill slopes. In *Computers in Earth and Environmental Sciences* (pp. 255–270). Elsevier. https://doi.org/10.1016/B978-0-323-89861-4.00002-6

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Hewarathna, A. I., Hamlin, L., Charles, J., Vigneshwaran, P., George, R., Thuseethan, S., Wimalasooriya, C., & Shanmugam, B. (2024). Change Detection for Forest Ecosystems Using Remote Sensing Images with Siamese Attention U-Net. *Technologies*, *12*(9), 160. https://doi.org/10.3390/technologies12090160

Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, *83*(1–2), 195–213. https://doi.org/10.1016/S0034-4257(02)00096-2

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, *25*(3), 295–309. https://doi.org/10.1016/0034-4257(88)90106-X

HUNTJR, E., & ROCK, B. (1989). Detection of changes in leaf water content using Near- and Middle-Infrared reflectances☆. *Remote Sensing of Environment*, *30*(1), 43–54. https://doi.org/10.1016/0034-4257(89)90046-1

Koch, J., Pearson, D. E., Huebner, C. D., Young, M. K., & Sniezko, R. A. (2021). Restoration of Landscapes and Habitats Affected by Established Invasive Species. In *Invasive Species in Forests and Rangelands of the United States* (pp. 185–202). Springer International Publishing. https://doi.org/10.1007/978-3-030-45367-1_8

Lorenz, K., & Lal, R. (2010). Carbon sequestration in forest ecosystems. In *Carbon Sequestration in Forest Ecosystems*. https://doi.org/10.1007/978-90-481-3266-9

Mitchell, A. L., Rosenqvist, A., & Mora, B. (2017). Current remote sensing approaches to monitoring forest degradation in support of countries measurement, reporting and verification (MRV) systems for REDD+. *Carbon Balance and Management*, *12*(1), 9. https://doi.org/10.1186/s13021-017-0078-9

Mutanga, O., & Kumar, L. (2019). Google Earth Engine Applications. *Remote Sensing*, *11*(5), 591. https://doi.org/10.3390/rs11050591

Otsu, N. (1979). AA threshold selection method from grey scale histogram. *IEEE Transactions on Systems Man and Cybernetics*.

Papachristoforou, A., Prodromou, M., Hadjimitsis, D., & Christoforou, M. (2023). Detecting and distinguishing between apicultural plants using UAV multispectral imaging. *PeerJ*, *11*, e15065. https://doi.org/10.7717/peerj.15065

Prodromou, M., Girtsou, S., Leventis, G., Koumoulidis, D., Tzouvaras, M., Mettas, C., Apostolakis, A., Kaskara, M., Kontoes, H., & Hadjimitsis, D. (2024). Multimodal Dataset for Wildfire Risk Prediction in Cyprus. *IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium*, 3332–3336. https://doi.org/10.1109/IGARSS53475.2024.10642963

Prodromou, M., Gitas, I., Themistocleous, K., Danezis, C., Ambrosia, V., & Hadjimitsis, D. (2023). The Use of Sentinel-2 Satellite Data for Burn Severity Mapping for

Arakapas Fire Event in Cyprus. *IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium*, 2556–2559. https://doi.org/10.1109/IGARSS52108.2023.10282048

Prodromou, M., Gitas, I., Themistocleous, K., & Hadjimitsis, D. (2022). The implementation of the Forest Canopy Density (FCD) model for Coniferous ecosystems in Cyprus forests, using Landsat-8 and Sentinel-2 satellite data. *EGU General Assembly Conference Abstracts*, EGU22-9865.

Prodromou, M., Gitas, I., Themistocleous, K., Nisantzi, A., Mamouri, R.-E., Ene, D., Danezis, C., Bühl, J., & Hadjimitsis, D. (2023). The use of remote sensing data for the fire damage assessment in a burnt area in Cyprus. In K. Themistocleous, S. Michaelides, D. G. Hadjimitsis, & G. Papadavid (Eds.), *Ninth International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2023)* (p. 84). SPIE. https://doi.org/10.1117/12.2685554

Prodromou, M., Theocharidis, C., Gitas, I. Z., Eliades, F., Themistocleous, K., Papasavvas, K., Dimitrakopoulos, C., Danezis, C., & Hadjimitsis, D. (2024). Forest Habitat Mapping in Natura2000 Regions in Cyprus Using Sentinel-1, Sentinel-2 and Topographical Features. *Remote Sensing*, *16*(8), 1373. https://doi.org/10.3390/rs16081373

Raihan, A. (2023). The dynamic nexus between economic growth, renewable energy use, urbanization, industrialization, tourism, agricultural productivity, forest area, and carbon dioxide emissions in the Philippines. *Energy Nexus*, *9*, 100180. https://doi.org/10.1016/j.nexus.2023.100180

Saaty, T., Pressures, S., Resources, W., Interests, V., & Values, C. (1980). The Analytic Hierarchy Process (AHP) for Decision Making By Thomas Saaty Decision Making involves setting priorities and the AHP is the methodology for doing Most Decision Problems are Multicriteria Maximize profits Satisfy customer demands Maximize emp. *Alternatives*, 1–69.

Smith, P., Ashmore, M. R., Black, H. I. J., Burgess, P. J., Evans, C. D., Quine, T. A., Thomson, A. M., Hicks, K., & Orr, H. G. (2013). REVIEW: The role of ecosystems and their management in regulating climate, and soil, water and air quality. *Journal of Applied Ecology*, *50*(4), 812–829. https://doi.org/10.1111/1365-2664.12016

Spoto, F., Sy, O., Laberinti, P., Martimort, P., Fernandez, V., Colin, O., Hoersch, B., & Meygret, A. (2012). Overview Of Sentinel-2. *2012 IEEE International Geoscience and Remote Sensing Symposium*, 1707–1710. https://doi.org/10.1109/IGARSS.2012.6351195

Tatem, A., Goetz, S., & Hay, S. (2008). Fifty Years of Earth-observation Satellites. *American Scientist*, *96*(5), 390. https://doi.org/10.1511/2008.74.390

Themistocleous, K., & Prodromou, M. (2023). THE IMPACT OF DUST POLLUTION FROM UNPAVED ROADS IN THE AKAMAS PENINSULA, CYPRUS, USING UAV AND SENTINEL-2 IMAGES. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLVIII-1/W*, 505–510. https://doi.org/10.5194/isprs-archives-XLVIII-1-W2-2023-505-2023

Theocharidis, C., Gitas, I., Danezis, C., & Hadjimitsis, D. (2023). *Satellite times-series analysis and assessment of the BFAST algorithm to detect possible abrupt changes in forest seasonality utilising Sentinel-1 and Sentinel-2 data. Case study: Paphos forest, Cyprus*. Copernicus Meetings.

Timmins, H. L., Arcy, W. L. D., Dodsworth, W. J., Fleming, W. D., Hermine, W. W. F. I., International, W. W. F., Pacheco, P., Price, F., International, W. W. F., Gajardo, W. O. B., Association, D., Breukink, G., Colman, W., Criodain, O., International, W. W. F., Cronin, T., Cunningham, C., International, B., Davis, M., … Xin, W. Y. (2023). *PATHWAYS REPORT 2023*.

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, *8*(2), 127–150. https://doi.org/10.1016/0034-4257(79)90013-0

UNEP, & FAO. (2020). The UN Decade on Ecosystem Restoration 2021-2030. *UNEP/FAO Factsheet*, *2019*(June 2020), 4. www.unep.org

UNEP/MAP and Plan Bleu. (2020). *State of the Environment and Development in the Mediterranean*. http://www.planbleu.org/soed

Uprety, Y., Asselin, H., Bergeron, Y., Doyon, F., & Boucher, J.-F. (2012). Contribution of traditional knowledge to ecological restoration: Practices and applications. *Écoscience*, *19*(3), 225–237. https://doi.org/10.2980/19-3-3530

WWF. (n.d.). *Deforestation and Forest Degradation*. Retrieved November 26, 2024, from https://www.worldwildlife.org/threats/deforestation-and-forest-degradation

USING ARTIFICIAL INTELLIGENCE FOR WILDFIRE PREVENTION IN CYPRUS

Pericles Cheng[1], Alexandros Papatheodoulou[1], Andreas Pamboris[2], Nicolas Kyriakou[3], Giorgos Tsapparellas[3], Georgios Boustras[1], Andreas Constantinides[2]

[1] CERIDES – Excellence in Innovation and Technology, European University Cyprus, Nicosia, Cyprus

[2] Frederick University, Nicosia, Cyprus

[3] Cy.R.I.C Cyprus Research and Innovation Center, Nicosia, Cyprus

ABSTRACT

Wildfires are increasingly destructive due to climate change, longer fire seasons, and extreme weather conditions, posing significant risks to ecosystems, human safety, and economic stability. This study presents an integrated wildfire safety system developed within the GREEN-HIT research project in Cyprus, leveraging artificial intelligence (AI) to enhance wildfire prediction, detection, and propagation analysis. The system combines historical weather and fire occurrence data to train a machine learning model capable of predicting fire outbreaks with high accuracy. It incorporates real-time environmental monitoring through a dense sensor network, enabling early fire detection by correlating CO2 levels with fire risk thresholds. Additionally, the system includes a fire propagation module that dynamically models fire spread based on wind and topography, using a combination of geospatial algorithms and terrain correction factors derived from Van Wagner's fire behaviour equations. The model calculates the Rate of Spread (ROS) by integrating wind and slope factors to predict the fire's path with greater accuracy. This multidisciplinary approach not only improves early warning capabilities and emergency response but also supports strategic fire management decisions through accurate simulations of fire behaviour in real-world terrain.

1 INTRODUCTION

Wildfires are one of the most destructive natural disasters, posing a significant threat to ecosystems, endangering human lives, and causing huge economic losses, highlighting the urgent need for innovative solutions in prediction, detection, and mitigation. Research has shown that the total burned area caused by wildfires has decreased in recent years, with studies suggesting this decline may be attributed to improved fire management strategies, land use changes, and urbanization, yet more research is needed [1], [2], [3]. However, there is a steady increase in the average global temperature due to climate change. 2024 has been confirmed as the warmest year on record, with an increase of 1.6 degrees since the pre-industrial era from 1850 to 1900 [4]. As global temperatures increase, there is a noticeable increase in the fire weather season length [5]. These longer fire weather seasons generate conditions such as prolonged droughts, heatwaves, and reduced humidity, creating an environment contributing to more extreme wildfire events worldwide[6]. There are a lot of variables that determine whether a wildfire will occur or not but most of the times there are some thresholds that can act as a warning that one can break out. The three main factors influencing the breakout of a wildfire are appropriate weather conditions such as wind, high temperatures, and low humidity, ignition points and fuel resources to burn [2], [4]. Jones et al. [2] also includes states that prolonged droughts can lead to an abundance of fuel that can lead to more extreme wildfire events. Consistently monitoring the thresholds of these variables can serve as an essential early warning system for forestry departments. This advanced notice allows them to implement proactive measures to mitigate wildfire risks, improve preparedness, and quickly detect any outbreaks before they escalate into larger, more destructive events. Research has shown that by using specific climate indicators, intelligent systems can help predict the occurrence of wildfires [5], [6].

Our research focused on developing and implementing an innovative wildfire safety system that utilizes artificial intelligence (AI) tools to reduce the occurrence and impact of wildfires in Cyprus. This system is a component of the GREEN-HIT research project, funded by the Research Promotion Foundation in Cyprus. It aims to deliver a comprehensive wildfire management solution by integrating predictive machine learning models, real-time detection, and fire propagation analysis. Within the context of the project, we deployed more than 100 sensors in specific locations in Cyprus that are able to measure specific weather indicators that can help feed the AI model allowing it to determine the percentage of fire probability. Furthermore, the system utilizes real-time sensor data to accurately detect the presence of a wildfire. In the event of a wildfire, it uses environmental factors such as wind and terrain characteristics to simulate and predict the potential spread of the wildfire, helping the fire department make faster and more informed decisions.

2 FIRE PREDICTION, DETECTION AND PROPAGATION

Modelling of fire processes across multiple scales requires expertise in wildfire science. The combination of an ignition source and adequate conditions for the fire to spread leads to the probability of a fire[7]. The causes of forest fires are diverse, and their distribution varies from country to country and can also vary spatially and temporally within the same country [8]. Meteorological factors have a large impact on the occurrence and spread of fires in forests [4], [9], [10]. Climate, meteorology, and environmental conditions cannot be ignored as they contribute to the occurrence, fire, and spread of accidental forest fires. To this end, we used weather data and fire occurrence data in Cyprus to train a machine learning model that could predict the occurrence of a fire. Furthermore, we developed modules where the system can utilize sensor data to detect fire occurrence and a module that can predict the fire spread based on wind and terrain data.

3 FIRE PREDICTION MODULE

The fire prediction model was trained on a dataset containing weather data collected between 2010 and 2018 from six weather stations across Cyprus. The dataset included temperature and relative humidity measurements recorded twice daily at 8:00 AM and 1:00 PM. This was combined with a record of all fire occurrences in Cyprus between 2010 and 2018 to allow the machine learning model to identify the triggers that would lead to a fire. A significant number of the fires were human-induced; however, they were included in the analysis as valid ignition points, since they can still lead to wildfires under favourable weather conditions.

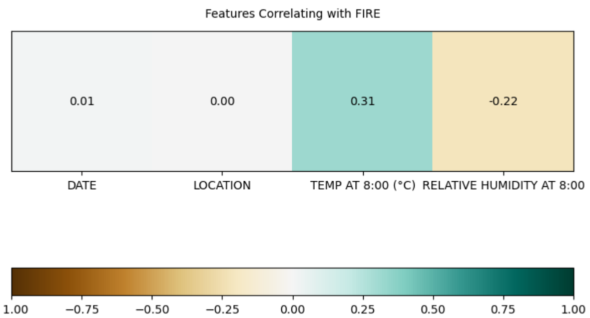

Figure 1. Feature corelation with fire events at 8AM

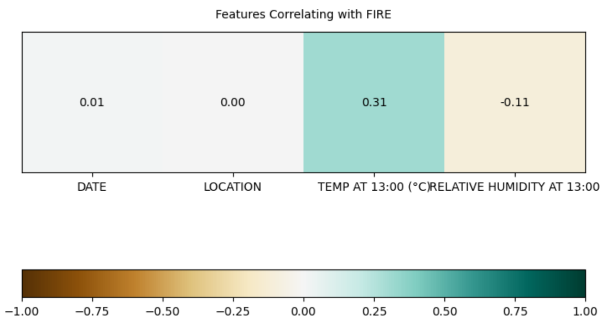

Figure 2. Feature corelation with fire events at 1PM

From Figure 1 and Figure 2, we can see that temperature has a positive correlation with fire occurrences whereas relative humidity shows a moderate negative correlation suggesting that the higher the temperature and the lower the relative humidity the more likely for a fire outburst.

We began model testing by optimizing Logistic Regression (LR), achieving accuracy scores of 0.7892 and 0.7886 for the 8 AM and 1 PM datasets, respectively. Following this, we applied the Extreme Gradient Boosting (XGBoost) algorithm, chosen for its efficiency and strong performance in both classification and regression tasks. Additionally, we evaluated several other machine learning models to compare their effectiveness. We also tried to overcome our imbalanced dataset by generating synthetic data using Synthetic Minority Over-sampling Technique (SMOTE) but the accuracy did not improve but conversely it led to a decrease of accuracy (Table 1).

Table 1. Model accuracies

Model	**Accuracy**	**Accuracy using weights**	**Accuracy using SMOTE**
Random Forest	0.769	0.782	0.798
XGBoost	0.798	0.798	0.725
SVM	0.788	0.796	0.498
KNN	0.767	0.761	0.773
MLP	0.788	0.796	0.510

After selecting XGBOOST as the best model we explored various hyperparameter values, and this led to an optimized model accuracy of 83.67% (Table 2).

Table 2. Hyperparameter settings of XGBOOST

learning_rate	0.2
n_estimators	300
max_depth	5
subsample	1.0
Colsample_bytree	1.0
Optimized Model Accuracy	0.8367

4 FIRE DETECTION MODULE

A key component of the fire system was selecting the appropriate sensors to ensure the system received the necessary data. Wind speed and direction are crucial factors in forest fire applications that aid in fire behaviour prediction, fire spread patterns, safety of firefighters and air quality and smoke management. Smoke sensors (CO2, Temperature and Humidity) aid in alerting authorities and communities, assessment of environmental impact, support for firefighting operations and monitoring fire progress.

The use of CO2 sensor networks for early wildfire warning has been validated in multiple research studies, demonstrating their potential to significantly enhance fire detection capabilities [11], [12]. These sensors are capable of continuously monitoring atmospheric carbon dioxide levels, which can rapidly increase during the early stages of a wildfire due to the combustion of biomass. By deploying a network of such sensors across high risk areas, researchers have shown that it is possible to detect fires more quickly than with traditional methods such as satellite imaging or lookout towers. Additionally, sensor networks offer the advantage of real-time, ground-level data collection, which enables faster emergency response and more precise localization of fire outbreaks. This approach not only improves situational awareness for firefighting efforts but also contributes to the broader goal of minimizing environmental damage and protecting communities at risk.

Collaborating with the forestry department, we identified two locations that were blind spots relating to the surrounding lookout towers and installed a number of sensors to detect fire. The CO2 data is transmitted to the fire detection module which uses the fire prediction data with the CO2 values to determine if a fire has started near the sensor. When the fire risk prediction is high then a lower CO2 threshold will trigger an event otherwise a higher CO2 level would be required. This significantly improves our ability to detect fires early during high-risk conditions.

5 FIRE PROPAGATION MODULE

Predicting how a fire will spread is important for keeping people and property safe. If we know where a fire is likely to spread, firefighters can act faster and smarter. They can send help to the right places, warn people to leave when needed, and protect important buildings or natural areas. Calculating a fire's path also helps in planning where to stop the fire and how to keep it from getting worse. One of the most used models is the Rothermel surface fire spread model which was introduced in 1972 [13]. Currently there are

To simulate wildfire spread in real-world terrain, it is essential to continuously determine new geospatial coordinates from the location a fire starts and is detected, towards its general movement propagation. This module calculates the general location of movement of the next fire propagation point based on a given starting location's coordinates, distance, and directional bearing. The result can be used to extract topographic elevation data for slope and terrain analysis via external APIs that will be used to calculate the slope between the two points to further calculate slope factor, which will in turn be used as a crucial parameter to calculate the Rate of Spread of the identified fire.

The algorithm uses spherical trigonometry to calculate a new geographic location, as latitude and longitude, based on an initial coordinate, while accounting for the curvature of the Earth. In this context, the initial coordinates come from a fire sensor from our Fire Detection module that has detected elevated CO_2 levels, indicating the likely presence of a fire. The goal is to estimate how far the fire might spread, projecting a point 150 meters away from the source in the direction of the wind. The directional bearing, expressed in degrees (where North is 0° or 360°, East is 90°, South is 180°, and West is 270°), determines the fire's likely path. To perform the calculations, the algorithm first converts the wind bearing from degrees to radians, as trigonometric functions in Python operate using radians. To estimate the direct ground distance between the ignition point and the next point in the direction of the wind, the module employs the Haversine formula, which accounts for the Earth's curvature. The module computes the new position, effectively modeling the potential propagation of the fire. Once the trigonometric operations are completed, the script converts the resulting deltas from radians back into degrees. These are then added to the original coordinates, yielding a new estimated geographic position for the potential fire front.

To add more precision to the prediction, the algorithm proceeds with an elevation query. It uses the new coordinates to construct a URL that requests elevation data from the OpenTopodata API [14], specifically querying the EUDEM 25m resolution dataset. This step ensures that the elevation of the predicted fire front is factored into further analysis, which can be critical for modeling fire behavior in complex terrain.

5.1 Rate of Spread calculation

To estimate the dynamic spread of a wildfire across different types of terrain and under varying environmental conditions, we developed a Python-based algorithm that adjusts the Rate of Spread (ROS). This calculation reflects how key external factors, like wind and slope, can significantly influence the spread of a fire. Starting with a baseline ROS value, which assumes a flat terrain with neutral conditions, the algorithm modifies this rate to account for real-world variables, making fire spread predictions more accurate and context-sensitive.

The core of the algorithm is a function called calculate_ros, which takes three parameters. The first, flat_ros, represents the baseline rate at which fire spreads over flat terrain, measured in meters per minute. The second, wind_factor, accounts for the wind's effect on the fire front's acceleration. This factor is calculated based on wind speed and direction at a specific index or location. The third parameter, slope_factor, quantifies the impact of terrain slope, either moving uphill or downhill, on the speed of fire spread. Like the wind factor, the slope factor is determined at a particular index along the fire's projected path. Together, these inputs allow the algorithm to dynamically model and predict fire behavior more realistically. This is represented by Eq. (1).

$$\boldsymbol{Adjusted\ RoS} = \boldsymbol{flat\_ros} \times (\mathbf{1} + \boldsymbol{wind\_factor} + \boldsymbol{slope\_factor}) \tag{1}$$

5.2 Wind factor calculation

To accurately capture and quantify the wind factor influence, we implemented a wind factor calculation model that uses an exponential response to wind speed. This approach allows the model to reflect the real-world, nonlinear impact that wind can have on wildfire dynamics.

At the core of this implementation is the calculate_wind_factor function, which estimates the contribution of wind to fire propagation using a specific exponential formula Eq *(2)*. In this formula, V represents the wind speed in meters per second (m/s), which is sourced from the nearest weather station deployed in the Cyprus forest. The variable k denotes an empirically determined wind influence coefficient, with a default value of 0.05and the constant e is Euler's number, approximately equal to 2.718.

$$wind\_factor = e^{(k \times V)}$$

(2)

This exponential model is designed to capture the fact that the relationship between wind speed and fire spread is not linear. Even small increases in wind speed can result in disproportionately large increases in the rate at which a fire spreads. By incorporating this exponential behaviour into the model, the algorithm provides a more accurate and realistic simulation of fire dynamics under varying wind conditions.

5.3 Slope factor calculation

Topographic slope plays a crucial role in wildfire behaviour, directly affecting the speed and intensity of fire spread. Fires tend to move more rapidly uphill because the flames and heat rise, preheating and drying the vegetation ahead of the fire. Conversely, fires on downhill slopes generally slow down due to reduced radiant and convective heat reaching the unburned fuel. To realistically capture this terrain-dependent behaviour, we adopted a model based on Van Wagner's fire behaviour equations, which are widely cited in wildfire science for their empirical accuracy and practical applicability [15].

The core of the implementation is the van_wagner_slope_factor function, which calculates a slope correction factor based on the terrain's angle of inclination or declination. The model is divided into two regimes: negative slopes (downslopes) and positive slopes (upslopes).

For negative slopes (ranging from -45° to 0°), the model acknowledges that fire typically slows when moving downhill. However, this deceleration is not always consistent or linear. For example, on slopes steeper than -22°, fires may still spread aggressively due to factors such as falling burning debris (e.g., rolling logs or flaming pinecones) and wind-driven chimney effects in valleys. In such cases, Van Wagner's model assigns a slope factor close to 1.0, indicating that the fire behaves nearly as it would on flat terrain. For milder downhill slopes (from -22° to 0°), a quadratic equation is used to gradually reduce the effective Rate of Spread (ROS), reflecting the decreasing influence of slope. For steep declines beyond -22°, the factor resets to 1.0, suggesting no further suppression of fire spread.

In contrast, positive slopes (ranging from 0° to 31°) significantly accelerate fire propagation. This is due to the preheating effect, where flames and hot air rise and dry out the vegetation located upslope, making it more susceptible to ignition. The steeper the slope, the more pronounced this effect becomes. For these uphill slopes, Van Wagner's exponential formula Eq. (3) is applied, using the slope angle in radians to reflect the rapid increase in fire spread with increasing steepness [15].

$$slope\_factor = \exp(3.533 \times \tan(\theta)^{1.2})$$

(3)

To maintain accuracy and prevent computational errors, the function includes input validation to ensure that slope angles remain within the valid range defined by Van Wagner's model, from -45° to 31°.

This slope correction factor is applied to modify the baseline ROS in the broader fire propagation model. When used alongside wind and vegetation models, it enables a more comprehensive and realistic simulation of wildfire behavior across complex terrain. Additionally, the modular structure of the function makes it well-suited for integration into GIS-based fire modeling platforms or real-time emergency response systems.

6 CONCLUSIONS

The wildfire safety system developed through the GREEN-HIT project represents a significant advancement in fire prevention, detection, and response. Key takeaways from this research include:

- Fire Prediction Module:
    - A machine learning model, trained on historical weather and fire occurrence data in Cyprus, achieved an optimized accuracy of 83.67% using the XGBoost algorithm.

    - Temperature and relative humidity were identified as key predictors, with temperature showing a positive correlation and humidity a negative correlation with fire occurrences.
- Real-Time Fire Detection:
    - Over 100 environmental sensors were deployed across high-risk areas, including CO2, temperature, humidity, and wind sensors.
    - Dynamic CO2 thresholding based on real-time fire risk significantly enhanced early detection, especially in sensor "blind spots" identified with the help of forestry departments.
- Fire Propagation Modelling:
    - A custom-built algorithm uses wind direction, terrain data, and geospatial coordinates to simulate fire spread.
    - The system factors in both wind and slope using empirical models like the Rothermel model and Van Wagner's slope correction, ensuring realistic simulation of wildfire behaviour in diverse terrain.
- Scalability and Practical Impact:
    - The system supports real-time situational awareness, helping emergency services prioritize response efforts, issue evacuation warnings, and protect critical infrastructure.
    - Designed to be scalable and integrable into broader GIS and emergency management systems.

This integrated approach demonstrates how artificial intelligence, combined with IoT and geospatial modelling, can revolutionize wildfire management by enabling smarter, faster, and more informed decision-making. In the future we aim to collect more data to enrich the dataset and to create a more accurate model for fire prediction.

7 REFERENCES

[1] S. H. Doerr and C. Santín, "Global trends in wildfire and its impacts: Perceptions versus realities in a changing world," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 371, no. 1696, Jun. 2016, doi: 10.1098/rstb.2015.0345.

[2] M. W. Jones *et al.*, "State of Wildfires 2023-2024," Aug. 14, 2024, *Copernicus Publications*. doi: 10.5194/essd-16-3601-2024.

[3] C. Stoof, M. C. Ribau, P. F. Moore, and G. Boustras, "To solve the global wildfire crisis, don't just focus on flames," *Nature*, vol. 637, pp. 34–34, Jan. 02, 2025.

[4] M. A. Moritz *et al.*, "Climate change and disruptions to global fire activity," *Ecosphere*, vol. 3, no. 6, pp. 1–22, Jun. 2012, doi: 10.1890/es11-00345.1.

[5] A. Alonso-Betanzos *et al.*, "An intelligent system for forest fire risk prediction and fire fighting management in Galicia," *Expert Syst Appl*, vol. 25, no. 4, pp. 545–554, Nov. 2003, doi: 10.1016/S0957-4174(03)00095-2.

[6] M. Naderpour, H. M. Rizeei, and F. Ramezani, "Forest fire risk prediction: A spatial deep neural network-based framework," *Remote Sens (Basel)*, vol. 13, no. 13, Jul. 2021, doi: 10.3390/rs13132513.

[7] S. Oliveira, F. Oehler, J. San-Miguel-Ayanz, A. Camia, and J. M. C. Pereira, "Modeling spatial patterns of fire occurrence in Mediterranean Europe using Multiple Regression and Random Forest," *For Ecol Manage*, vol. 275, pp. 117–129, Jul. 2012, doi: 10.1016/j.foreco.2012.03.003.

[8] A. Ganteaume, A. Camia, M. Jappiot, J. San-Miguel-Ayanz, M. Long-Fournel, and C. Lampin, "A review of the main driving factors of forest fire ignition over Europe," Mar. 2013. doi: 10.1007/s00267-012-9961-z.

[9] M. D. Flannigan, B. J. Stocks, and B. M. Wotton, "Climate change and forest fires," 2000.

[10] M. W. Jones *et al.*, "Global and Regional Trends and Drivers of Fire Under Climate Change," Jul. 01, 2022, *John Wiley and Sons Inc*. doi: 10.1029/2020RG000726.

[11] M. Findlay, D. Peaslee, J. R. Stetter, S. Waller, and A. Smallridge, "Distributed Sensors for Wildfire Early Warnings," *J Electrochem Soc*, vol. 169, no. 2, p. 020553, Feb. 2022, doi: 10.1149/1945-7111/ac5344.

[12] L. Furnari, A. De Rango, F. Cortale, A. Senatore, and G. Mendicino, "Experimental Validation of a Wildfire Early Warning System Based on a CO2 Sensor Network," Mar. 18, 2025. doi: 10.5194/egusphere-egu25-15094.

[13] P. L. Andrews, "The Rothermel Surface Fire Spread Model and Associated Developments: A Comprehensive Explanation."

[14] "Open Topo Data Elevation API." Accessed: Apr. 10, 2025. [Online]. Available: https://www.opentopodata.org/

[15] A. L. Sullivan, J. J. Sharples, S. Matthews, and M. P. Plucinski, "A downslope fire spread correction factor based on landscape-scale fire behaviour," *Environmental Modelling and Software*, vol. 62, pp. 153–163, Dec. 2014, doi: 10.1016/j.envsoft.2014.08.024.

remote sensing

MDPI

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

check for updates

Academic Editor: Xiaoyang Zhang

Received: 26 February 2025
Revised: 29 March 2025
Accepted: 1 April 2025
Published: 2 April 2025

Citation: Prodromou, M.; Gitas, I.; Mettas, C.; Tzouvaras, M.; Themistocleous, K.; Konstantinidis, A.; Pamboris, A.; Hadjimitsis, D. Remote-Sensing-Based Prioritization of Post-Fire Restoration Actions in Mediterranean Ecosystems: A Case Study in Cyprus. *Remote Sens.* **2025**, *17*, 1269. https://doi.org/10.3390/rs17071269

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 km^2 [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 GRESTO Index (GreenHIT-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 GRESTO 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 CO_2 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.

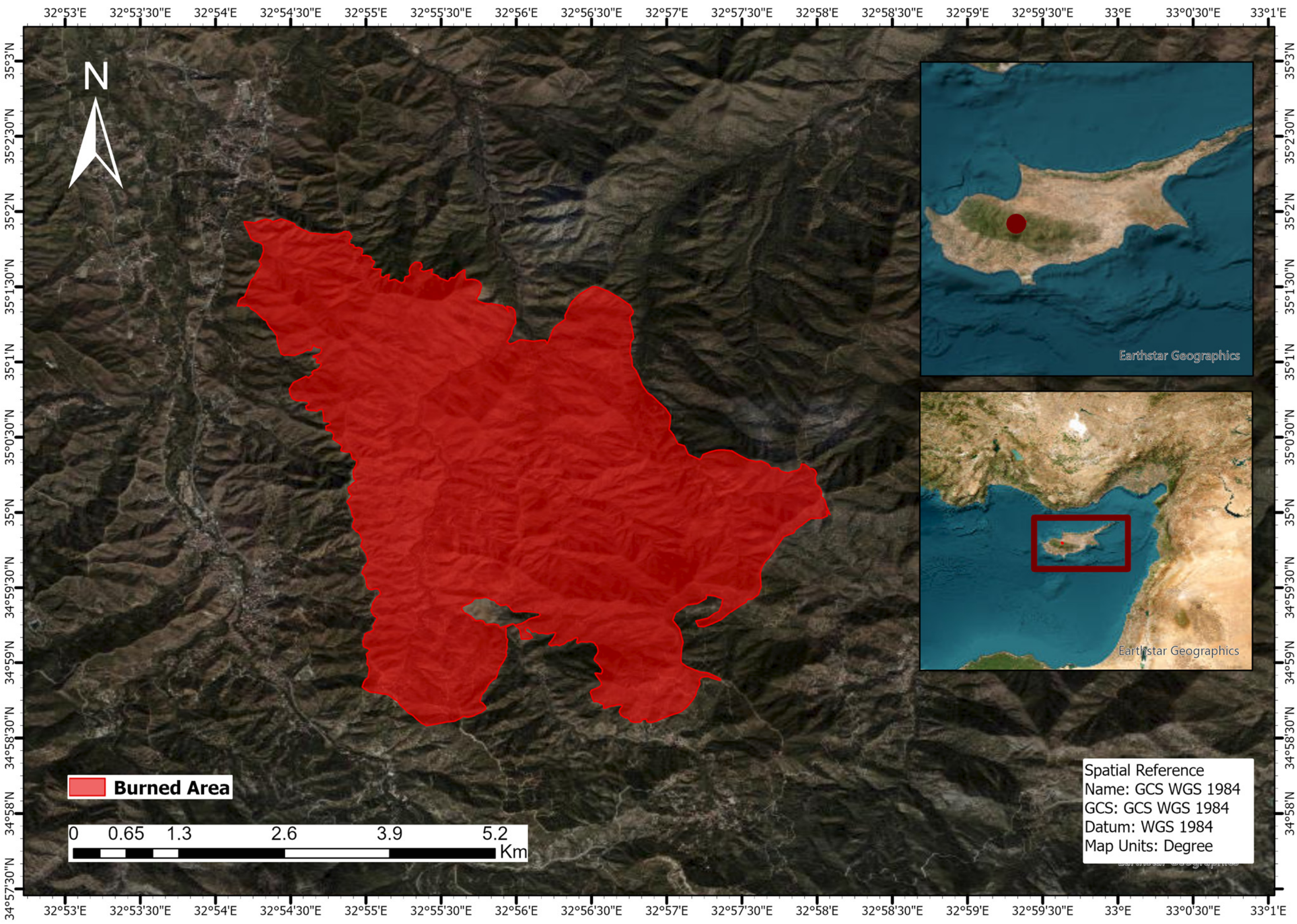

Figure 1. Solea fire event that was examined for this study. Baseman source: Esri, Maxar, Earthstar Geographics, and the GIS User Community.

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 km^2, 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 km^2 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.

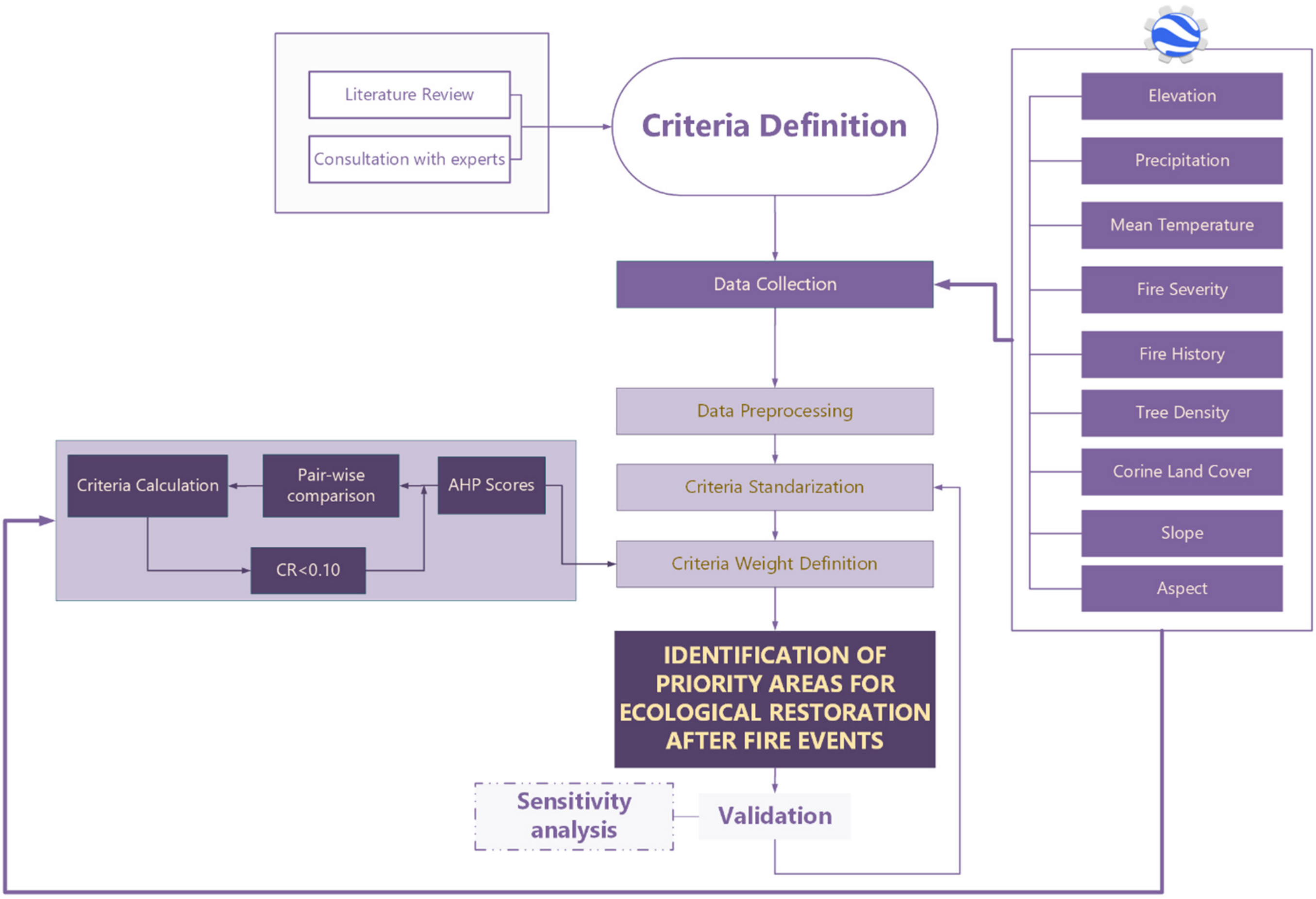

Figure 2. Workflow for identifying priority areas for ecological restoration actions after fire events in Cyprus.

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 $\lambda_{max} = \mathrm{n}$, 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].

$$CR = \frac{CI}{RI} \tag{4}$$

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.

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

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 ±20%, starting from 0 to ±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].

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}, \tag{6}$$

$$Precision = \frac{TP}{TP + FP,} \tag{7}$$

$$Recall = \frac{TP}{TP + FN}, \tag{8}$$

$$F1 - Score = 2 * \frac{Precision \times Recall}{Precision + Recall}, \tag{9}$$

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**
λ_{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 km^2, covering both the burned and the surrounding regions.

$$\begin{aligned} GRESTO = {} & 3.8 \times SLOPE + 2.6 \times ELEVATION + 2.6 \times ASPECT + 29.4 \times dNBR + 10.1 \times FIRE\ FREQUENCY \\ & + 16.9 \times LAND\ COVER + 6.2 \times LST + 6.2 \times PRECIPITATION + 22.4 * TREE\ DENSITY \end{aligned} \tag{10}$$

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.

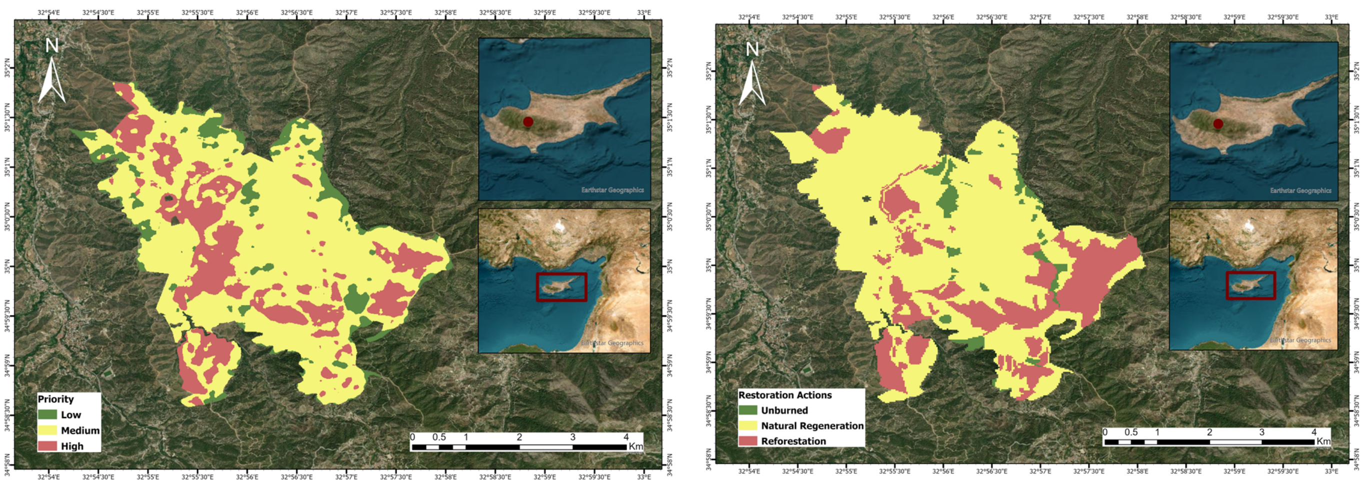

Figure 3. Prioritization of reforestation needs derived from the GRESTO Index (**Left**) and the restoration actions conducted after the fire event by the Department of Forests (**Right**).

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 ±20% starting from 0 (no adjustment) to ±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.

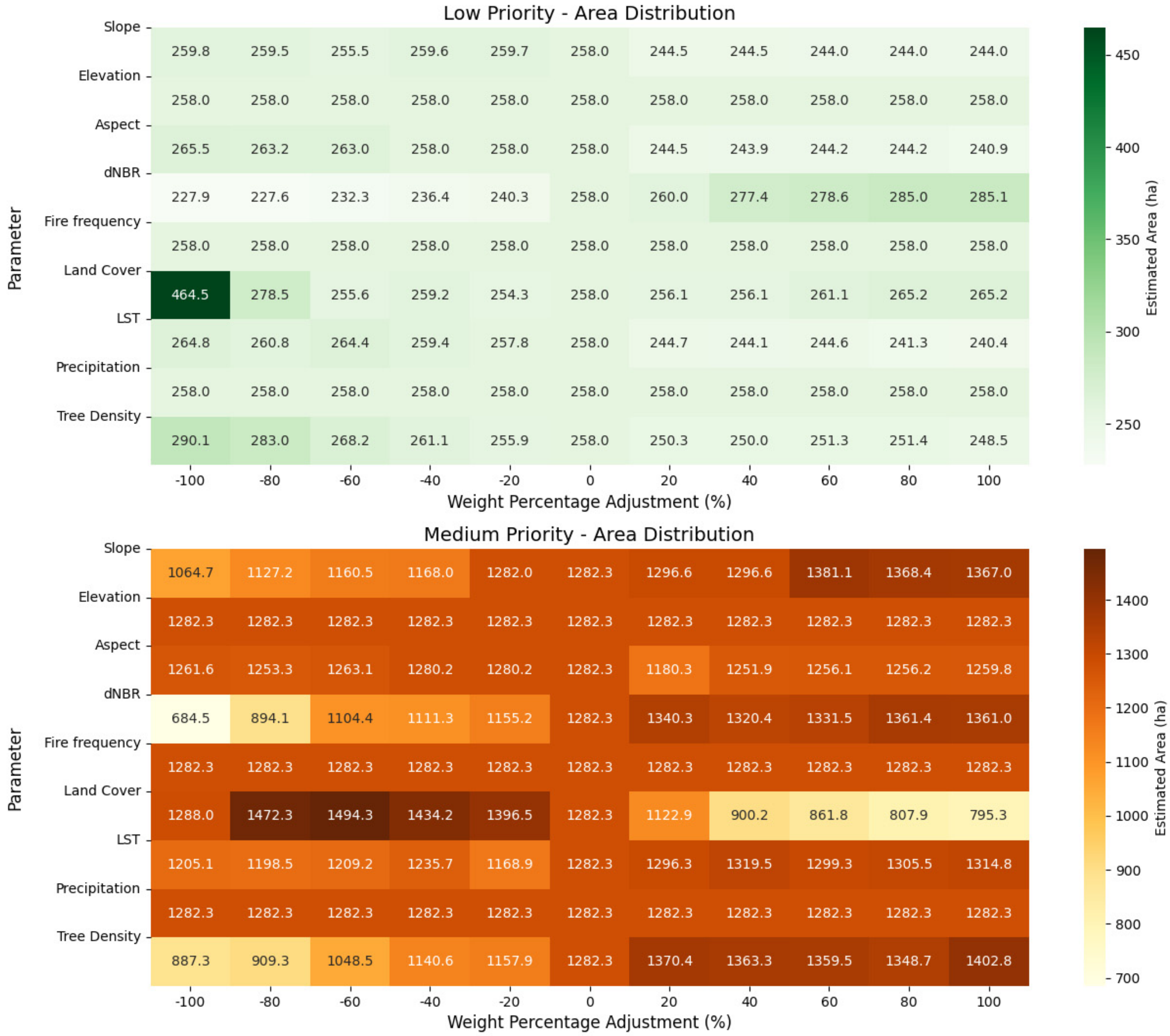

Figure 4. *Cont.*

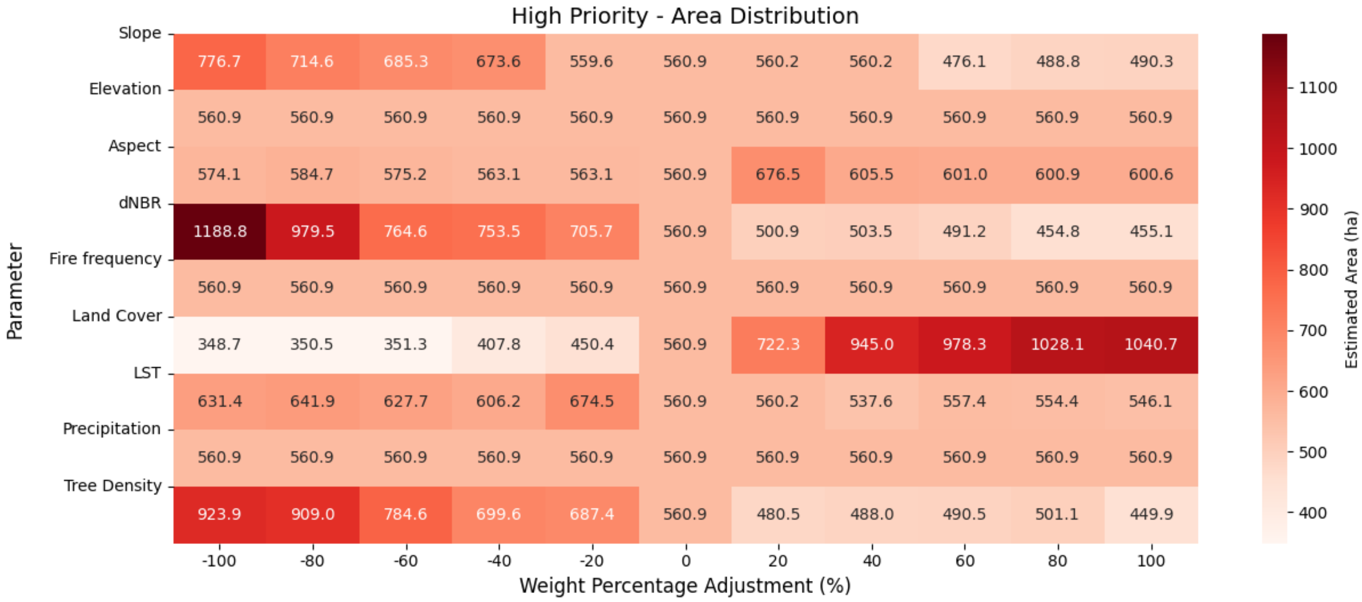

Figure 4. Area distribution in hectares, based on weight percentage adjustment per parameter.

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.

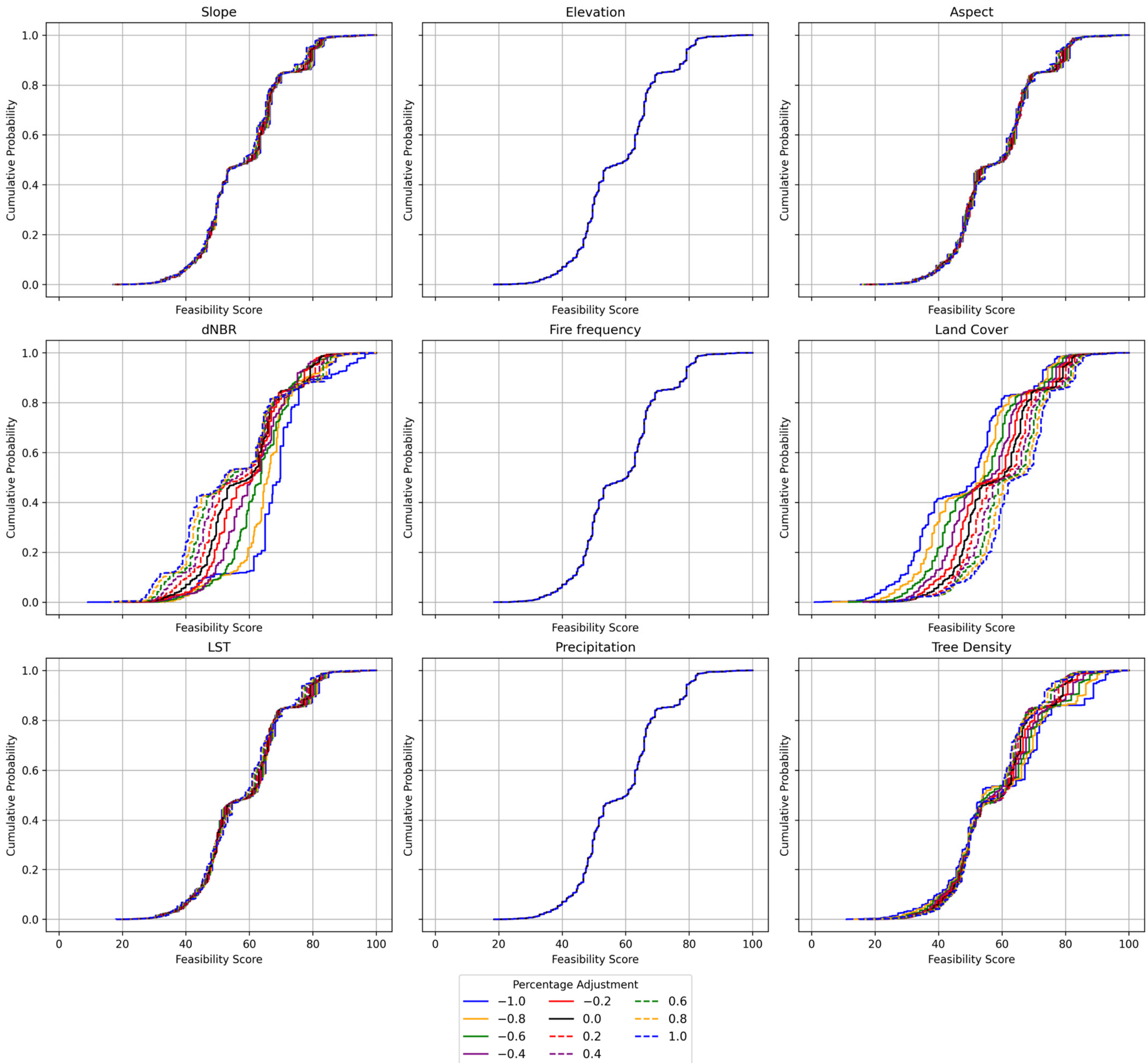

Figure 5. Cumulative distribution of feasibility scores by weight index.

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.

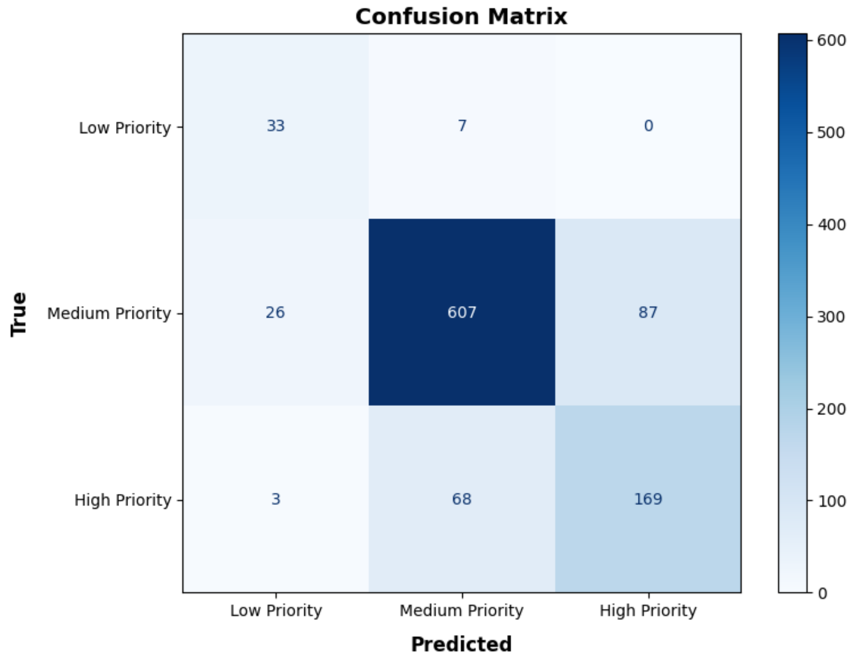

Figure 6. Confusion matrix showing the performance of the classification model across the three priority restoration classes. The values indicate the number of correctly and incorrectly classified validation points.

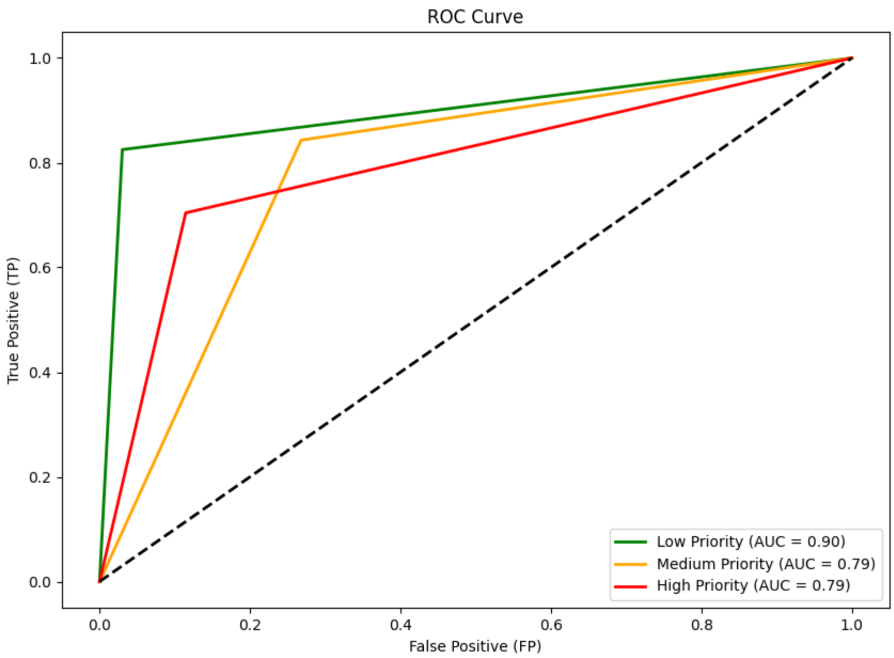

Figure 7. ROC curves for the multi-class classification model across the restoration priority classes.

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 rolesas 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.

Author Contributions: Conceptualization, M.P. and I.G.; methodology, M.P.; software, M.P.; validation, M.P., M.T., K.T. and C.M.; formal analysis, M.P.; investigation, M.P.; resources, M.P.; data curation, M.P.; writing—original draft preparation, M.P., I.G., M.T., C.M., K.T. and D.H.; writing—review and editing, M.P. and I.G.; visualization, M.P.; supervision, D.H. and I.G.; project administration, A.P.; funding acquisition, A.K. All authors have read and agreed to the published version of the manuscript.

Funding: This work is part of the "CO-DEVELOP-ICT-HEALTH" project with the title acronym Green-HIT and the project number CODEVELOP-ICT-HEALTH/0322/0135. Project Green-HIT is implemented under the Recovery and Resilience Plan with funding from the European Union—NextGenerationEU.

Data Availability Statement: Data are contained within the article.

Acknowledgments: The authors would also like to thank the Forest Department of the Ministry of Agriculture, Rural Development and Environment of the Republic of Cyprus for the provision of the in situ data. The authors also acknowledge "EXCELSIOR": ERATOSTHENES: Excellence Research Centre for Earth Surveillance and Space-Based Monitoring of the Environment H2020 Widespread Teaming project (www.excelsior2020.eu, accessed on 9 March 2024). The "EXCELSIOR" project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No. 857510, from the Government of the Republic of Cyprus through the Directorate General for the European Programmes, Coordination and Development, and from the Cyprus University of Technology.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Pausas, J.G.; Vallejo, V.R. The Role of Fire in European Mediterranean Ecosystems. In *Remote Sensing of Large Wildfires*; Springer: Berlin/Heidelberg, Germany, 1999; pp. 3–16.
2. Alayan, R.; Rotich, B.; Lakner, Z. A Comprehensive Framework for Forest Restoration after Forest Fires in Theory and Practice: A Systematic Review. *Forests* **2022**, *13*, 1354. [CrossRef]
3. Anderegg, W.R.L.; Trugman, A.T.; Badgley, G.; Anderson, C.M.; Bartuska, A.; Ciais, P.; Cullenward, D.; Field, C.B.; Freeman, J.; Goetz, S.J.; et al. Climate-Driven Risks to the Climate Mitigation Potential of Forests. *Science* **2020**, *368*, eaaz7005. [CrossRef]
4. Chiquier, S.; Patrizio, P.; Bui, M.; Sunny, N.; Mac Dowell, N. A Comparative Analysis of the Efficiency, Timing, and Permanence of CO 2 Removal Pathways. *Energy Environ. Sci.* **2022**, *15*, 4389–4403. [CrossRef]
5. Psistaki, K.; Tsantopoulos, G.; Paschalidou, A.K. An Overview of the Role of Forests in Climate Change Mitigation. *Sustainability* **2024**, *16*, 6089. [CrossRef]
6. UNEP/MAP. *Plan Bleu State of the Environment and Development in the Mediterranean*; UNEP: Nairobi, Kenya, 2020.
7. Cantin, G.; Delahaye, B.; Funatsu, B.M. On the Degradation of Forest Ecosystems by Extreme Events: Statistical Model Checking of a Hybrid Model. *Ecol. Complex.* **2023**, *53*, 101039. [CrossRef]
8. van Lierop, P.; Lindquist, E.; Sathyapala, S.; Franceschini, G. Global Forest Area Disturbance from Fire, Insect Pests, Diseases and Severe Weather Events. *Ecol. Manag.* **2015**, *352*, 78–88. [CrossRef]
9. Bassi, S.; Kettunen, M. *Forest Fires: Causes and Contributing Factors in Europe*; European Parliament: Brussels, Belgium, 2008.
10. MacCarthy, J.; Richter, J.; Tyukavina, S.; Weisse, M.; Harris, N. *The Latest Data Confirms: Forest Fires Are Getting Worse*; World Resources Institute: Washington, DC, USA, 2023; pp. 1–13.
11. Prodromou, M.; Girtsou, S.; Leventis, G.; Koumoulidis, D.; Tzouvaras, M.; Mettas, C.; Apostolakis, A.; Kaskara, M.; Kontoes, H.; Hadjimitsis, D. Multimodal Dataset for Wildfire Risk Prediction in Cyprus. In Proceedings of the IGARSS 2024—IEEE International Geoscience and Remote Sensing Symposium, Athens, Greece, 7–12 July 2024; pp. 3332–3336.
12. Nematshahi, S.; Khodaei, A.; Arabnya, A. Risk Assessment of Transmission Lines Against Grid-Ignited Wildfires. In Proceedings of the 2025 IEEE PES Grid Edge Technologies Conference & Exposition (Grid Edge), San Diego, CA, USA, 21–23 January 2025; pp. 1–5.
13. Haque, M.K.; Azad, M.A.K.; Hossain, M.Y.; Ahmed, T.; Uddin, M.; Hossain, M.M. Wildfire in Australia during 2019-2020, Its Impact on Health, Biodiversity and Environment with Some Proposals for Risk Management: A Review. *J. Environ. Prot.* **2021**, *12*, 391–414. [CrossRef]
14. Garcês, A.; Pires, I. The Hell of Wildfires: The Impact on Wildlife and Its Conservation and the Role of the Veterinarian. *Conservation* **2023**, *3*, 96–108. [CrossRef]
15. Dijkstra, J.; Durrant, T.; San-Miguel-Ayanz, J.; Veraverbeke, S. Anthropogenic and Lightning Fire Incidence and Burned Area in Europe. *Land* **2022**, *11*, 651. [CrossRef]
16. Giglio, L.; Boschetti, L.; Roy, D.P.; Humber, M.L.; Justice, C.O. The Collection 6 MODIS Burned Area Mapping Algorithm and Product. *Remote Sens. Environ.* **2018**, *217*, 72–85. [CrossRef]
17. Lizundia-Loiola, J.; Otón, G.; Ramo, R.; Chuvieco, E. A Spatio-Temporal Active-Fire Clustering Approach for Global Burned Area Mapping at 250 m from MODIS Data. *Remote Sens. Environ.* **2020**, *236*, 111493. [CrossRef]
18. Jones, H.P.; Jones, P.C.; Barbier, E.B.; Blackburn, R.C.; Rey Benayas, J.M.; Holl, K.D.; McCrackin, M.; Meli, P.; Montoya, D.; Mateos, D.M. Restoration and Repair of Earth's Damaged Ecosystems. *Proc. R. Soc. B Biol. Sci.* **2018**, *285*, 20172577. [CrossRef]

19. Martin, D.M. Ecological Restoration Should Be Redefined for the Twenty-first Century. *Restor. Ecol.* **2017**, *25*, 668–673. [CrossRef]
20. Shilky; Ekka, P.; Upreti, M.; Kumar, A.; Saikia, P. Nature-Based Solutions and Ecological Urban Planning and Design for the Sustainable Urban Environments. In *Earth Observation in Urban Monitoring*; Elsevier: Amsterdam, The Netherlands, 2024; pp. 339–358.
21. Uprety, Y.; Asselin, H.; Bergeron, Y.; Doyon, F.; Boucher, J.-F. Contribution of Traditional Knowledge to Ecological Restoration: Practices and Applications. *Écoscience* **2012**, *19*, 225–237. [CrossRef]
22. Brancalion, P.H.S.; Chazdon, R.L. Beyond Hectares: Four Principles to Guide Reforestation in the Context of Tropical Forest and Landscape Restoration. *Restor. Ecol.* **2017**, *25*, 491–496. [CrossRef]
23. Alloza, J.A.; Vallejo, R. Restoration of burned areas in forest management plans. In *Desertification in the Mediterranean Region—A Security Issue*; Springer: Dordrecht, The Netherlands, 2006; pp. 475–488.
24. Cavalcante, R.B.L.; Nunes, S.; Viademonte, S.; Rodrigues, C.M.F.; Gomes, W.C.; da Silva Ferreira, J., Jr.; Pontes, P.R.M.; Giannini, T.C.; Awade, M.; Miranda, L.d.S.; et al. Multicriteria Approach to Prioritize Forest Restoration Areas for Biodiversity Conservation in the Eastern Amazon. *J. Environ. Manag.* **2022**, *318*, 115590. [CrossRef]
25. Trabucchi, M.; Comín, F.A.; O'Farrell, P.J. Hierarchical Priority Setting for Restoration in a Watershed in NE Spain, Based on Assessments of Soil Erosion and Ecosystem Services. *Reg. Environ. Change* **2013**, *13*, 911–926. [CrossRef]
26. Holl, K.D.; Crone, E.E.; Schultz, C.B. Landscape Restoration: Moving from Generalities to Methodologies. *Bioscience* **2003**, *53*, 491–502. [CrossRef]
27. Morrison, E.B.; Lindell, C.A. Active or Passive Forest Restoration? Assessing Restoration Alternatives with Avian Foraging Behavior. *Restor. Ecol.* **2011**, *19*, 170–177. [CrossRef]
28. Robichaud, P.R.; Lewis, S.A.; Brown, R.E.; Ashmun, L.E. Emergency Post-Fire Rehabilitation Treatment Effects on Burned Area Ecology and Long-Term Restoration. *Fire Ecol.* **2009**, *5*, 115–128. [CrossRef]
29. Alayan, R.; Lakner, Z. Utilizing Comprehensive Criteria and Indicators for Post-Fire Forest Restoration in Spatial Decision Support Systems (SDSS). *Forests* **2024**, *15*, 386. [CrossRef]
30. Papachristoforou, A.; Prodromou, M.; Hadjimitsis, D.; Christoforou, M. Detecting and Distinguishing between Apicultural Plants Using UAV Multispectral Imaging. *PeerJ* **2023**, *11*, e15065. [CrossRef] [PubMed]
31. Prodromou, M.; Theocharidis, C.; Gitas, I.Z.; Eliades, F.; Themistocleous, K.; Papasavvas, K.; Dimitrakopoulos, C.; Danezis, C.; Hadjimitsis, D. Forest Habitat Mapping in Natura2000 Regions in Cyprus Using Sentinel-1, Sentinel-2 and Topographical Features. *Remote Sens.* **2024**, *16*, 1373. [CrossRef]
32. Smith-Tripp, S.M.; Coops, N.C.; Mulverhill, C.; White, J.C.; Axelson, J. Landsat Assessment of Variable Spectral Recovery Linked to Post-Fire Forest Structure in Dry Sub-Boreal Forests. *ISPRS J. Photogramm. Remote Sens.* **2024**, *208*, 121–135. [CrossRef]
33. Theocharidis, C.; Eliades, M.; Gitas, I.; Danezis, C.; Hadjimitsis, D. Monitoring Forest Dynamics between 1987–2023: An NDVI Analysis of Three Dominant Species in Paphos Forest, Cyprus. In Proceedings of SPIE Volume 13212, Proceedings of the 10th International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2024), Paphos, Cyprus, 8–9 April 2024; Michaelides, S.C., Hadjimitsis, D.G., Danezis, C., Kyriakides, N., Christofe, A., Themistocleous, K., Schreier, G., Eds.; SPIE: San Diego, CA, USA, 13 September 2024; p. 13.
34. Younes Cárdenas, N.; Joyce, K.E.; Maier, S.W. Monitoring Mangrove Forests: Are We Taking Full Advantage of Technology? *Int. J. Appl. Earth Obs. Geoinf.* **2017**, *63*, 1–14. [CrossRef]
35. Pickell, P.D.; Hermosilla, T.; Frazier, R.J.; Coops, N.C.; Wulder, M.A. Forest Recovery Trends Derived from Landsat Time Series for North American Boreal Forests. *Int. J. Remote Sens.* **2016**, *37*, 138–149. [CrossRef]
36. Tonini, M.; Pereira, M.G.; Parente, J.; Vega Orozco, C. Evolution of Forest Fires in Portugal: From Spatio-Temporal Point Events to Smoothed Density Maps. *Nat. Hazards* **2017**, *85*, 1489–1510. [CrossRef]
37. Dosiou, A.; Athinelis, I.; Katris, E.; Vassalou, M.; Kyrkos, A.; Krassakis, P.; Parcharidis, I. Employing Copernicus Land Service and Sentinel-2 Satellite Mission Data to Assess the Spatial Dynamics and Distribution of the Extreme Forest Fires of 2023 in Greece. *Fire* **2024**, *7*, 20. [CrossRef]
38. Pourtaghi, Z.S.; Pourghasemi, H.R.; Rossi, M. Forest Fire Susceptibility Mapping in the Minudasht Forests, Golestan Province, Iran. *Environ. Earth Sci.* **2015**, *73*, 1515–1533. [CrossRef]
39. Almeida, C.T.d.; Galvão, L.S.; Ometto, J.P.H.B.; Jacon, A.D.; Pereira, F.R.d.S.; Sato, L.Y.; Silva-Junior, C.H.L.; Brancalion, P.H.S.; Aragão, L.E.O.e.C.d. Advancing Forest Degradation and Regeneration Assessment Through Light Detection and Ranging and Hyperspectral Imaging Integration. *Remote Sens.* **2024**, *16*, 3935. [CrossRef]
40. Gitas, I.; Mitri, G.; Veraverbeke, S.; Polychronaki, A. Advances in Remote Sensing of Post-Fire Vegetation Recovery Monitoring—A Review. In *Remote Sensing of Biomass—Principles and Applications*; InTech: Rijeka, Croatia, 2012.
41. Matt, J.E.; Underwood, K.L.; Diehl, R.M.; Lawson, K.S.; Worley, L.C.; Rizzo, D.M. Terrain-derived Measures for Basin Conservation and Restoration Planning. *River Res. Appl.* **2023**, *39*, 1795–1811. [CrossRef]
42. Questad, E.J.; Kellner, J.R.; Kinney, K.; Cordell, S.; Asner, G.P.; Thaxton, J.; Diep, J.; Uowolo, A.; Brooks, S.; Inman-Narahari, N.; et al. Mapping Habitat Suitability for At-risk Plant Species and Its Implications for Restoration and Reintroduction. *Ecol. Appl.* **2014**, *24*, 385–395. [CrossRef]

43. Koch, J.; Pearson, D.E.; Huebner, C.D.; Young, M.K.; Sniezko, R.A. Restoration of Landscapes and Habitats Affected by Established Invasive Species. In *Invasive Species in Forests and Rangelands of the United States*; Springer International Publishing: Cham, Switzerland, 2021; pp. 185–202.
44. Weidlich, E.W.A.; Flórido, F.G.; Sorrini, T.B.; Brancalion, P.H.S. Controlling Invasive Plant Species in Ecological Restoration: A Global Review. *J. Appl. Ecol.* **2020**, *57*, 1806–1817. [CrossRef]
45. Kulinan, A.S.; Cho, Y.; Park, M.; Park, S. Rapid Wildfire Damage Estimation Using Integrated Object-Based Classification with Auto-Generated Training Samples from Sentinel-2 Imagery on Google Earth Engine. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *126*, 103628. [CrossRef]
46. Prodromou, M.; Gitas, I.; Themistocleous, K.; Danezis, C.; Ambrosia, V.; Hadjimitsis, D. The Use of Sentinel-2 Satellite Data for Burn Severity Mapping for Arakapas Fire Event in Cyprus. In Proceedings of the IGARSS 2023—2023 IEEE International Geoscience and Remote Sensing Symposium, Pasadena, CA, USA, 16–21 July 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 2556–2559.
47. Liu, C.-C.; Chen, Y.-H.; Wu, M.-H.M.; Wei, C.; Ko, M.-H. Assessment of Forest Restoration with Multitemporal Remote Sensing Imagery. *Sci. Rep.* **2019**, *9*, 7279. [CrossRef] [PubMed]
48. Chen, X.; Vogelmann, J.E.; Rollins, M.; Ohlen, D.; Key, C.H.; Yang, L.; Huang, C.; Shi, H. Detecting Post-Fire Burn Severity and Vegetation Recovery Using Multitemporal Remote Sensing Spectral Indices and Field-Collected Composite Burn Index Data in a Ponderosa Pine Forest. *Int. J. Remote Sens.* **2011**, *32*, 7905–7927. [CrossRef]
49. Viana-Soto, A.; Aguado, I.; Salas, J.; García, M. Identifying Post-Fire Recovery Trajectories and Driving Factors Using Landsat Time Series in Fire-Prone Mediterranean Pine Forests. *Remote Sens.* **2020**, *12*, 1499. [CrossRef]
50. Chen, W.; Moriya, K.; Sakai, T.; Cao, C. Monitoring of Post-Fire Forest Recovery under Different Restoration Treatments Based on Time-Series ALOS/PALSAR Data. In Proceedings of the 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Beijing, China, 10–15 July 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1749–1752.
51. Hernández Clemente, R.; Navarro Cerrillo, R.M.; Gitas, I.Z. Monitoring Post-Fire Regeneration in Mediterranean Ecosystems by Employing Multitemporal Satellite Imagery. *Int. J. Wildland Fire* **2009**, *18*, 648–658. [CrossRef]
52. Wang, R.; Sun, Y.; Zong, J.; Wang, Y.; Cao, X.; Wang, Y.; Cheng, X.; Zhang, W. Remote Sensing Application in Ecological Restoration Monitoring: A Systematic Review. *Remote Sens.* **2024**, *16*, 2204. [CrossRef]
53. Salleh, M.R.M.; Ismail, Z.; Rahman, M.Z.A. Accuracy assessment of lidar-derived digital terrain model (DTM) with different slope and canopy cover in tropical forest region. *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.* **2015**, *II-2/W2*, 183–189. [CrossRef]
54. Nie, S.; Wang, C.; Xi, X.; Luo, S.; Li, G.; Tian, J.; Wang, H. Estimating the Vegetation Canopy Height Using Micro-Pulse Photon-Counting LiDAR Data. *Opt. Express* **2018**, *26*, A520. [CrossRef]
55. Gupta, S.K.; Pandey, A.C. Spectral Aspects for Monitoring Forest Health in Extreme Season Using Multispectral Imagery. *Egypt. J. Remote Sens. Space Sci.* **2021**, *24*, 579–586. [CrossRef]
56. Alves de Almeida, D.R.; Broadbent, E.; Almeyda Zambrano, A.M.; Ferreira, M.P.; Santin Brancalion, P.H. Fusion of Lidar and Hyperspectral Data from Drones for Ecological Questions: The Gatoreye Atlantic Forest Restoration Case Study. In Proceedings of the 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, 11–16 July 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 714–715.
57. Zhao, A.; Zhang, A.; Liu, X.; Cao, S. Spatiotemporal Changes of Normalized Difference Vegetation Index (NDVI) and Response to Climate Extremes and Ecological Restoration in the Loess Plateau, China. *Theor. Appl. Clim.* **2018**, *132*, 555–567. [CrossRef]
58. Reis, B.P.; Martins, S.V.; Fernandes Filho, E.I.; Sarcinelli, T.S.; Gleriani, J.M.; Marcatti, G.E.; Leite, H.G.; Halassy, M. Management Recommendation Generation for Areas Under Forest Restoration Process through Images Obtained by UAV and LiDAR. *Remote Sens.* **2019**, *11*, 1508. [CrossRef]
59. Zhang, G.; Dong, J.; Xiao, X.; Hu, Z.; Sheldon, S. Effectiveness of Ecological Restoration Projects in Horqin Sandy Land, China Based on SPOT-VGT NDVI Data. *Ecol. Eng.* **2012**, *38*, 20–29. [CrossRef]
60. Tang, J.; Liang, J.; Yang, Y.; Zhang, S.; Hou, H.; Zhu, X. Revealing the Structure and Composition of the Restored Vegetation Cover in Semi-Arid Mine Dumps Based on LiDAR and Hyperspectral Images. *Remote Sens.* **2022**, *14*, 978. [CrossRef]
61. Saaty, T.L. A Scaling Method for Priorities in Hierarchical Structures. *J. Math. Psychol.* **1977**, *15*, 234–281. [CrossRef]
62. Saaty, T.L. How to Make a Decision: The Analytic Hierarchy Process. *Eur. J. Oper. Res.* **1990**, *48*, 9–26. [CrossRef]
63. Nesticò, A.; Passaro, R.; Maselli, G.; Somma, P. Multi-Criteria Methods for the Optimal Localization of Urban Green Areas. *J. Clean. Prod.* **2022**, *374*, 133690. [CrossRef]
64. Paletto, A.; Pieratti, E.; De Meo, I.; Agnelli, A.E.; Cantiani, P.; Chiavetta, U.; Mazza, G.; Lagomarsino, A. A Multi-Criteria Analysis of Forest Restoration Strategies to Improve the Ecosystem Services Supply: An Application in Central Italy. *Ann. Sci.* **2021**, *78*, 7. [CrossRef]
65. Curiel-Esparza, J.; Gonzalez-Utrillas, N.; Canto-Perello, J.; Martin-Utrillas, M. Integrating Climate Change Criteria in Reforestation Projects Using a Hybrid Decision-Support System. *Environ. Res. Lett.* **2015**, *10*, 094022. [CrossRef]
66. Dosis, S.; Petropoulos, G.P.; Kalogeropoulos, K. A Geospatial Approach to Identify and Evaluate Ecological Restoration Sites in Post-Fire Landscapes. *Land* **2023**, *12*, 2183. [CrossRef]

67. Arianoutsou, M.; Koukoulas, S.; Kazanis, D. Evaluating Post-Fire Forest Resilience Using GIS and Multi-Criteria Analysis: An Example from Cape Sounion National Park, Greece. *Environ. Manag.* **2011**, *47*, 384–397. [CrossRef] [PubMed]
68. González, F.; Morante-Carballo, F.; González, A.; Bravo-Montero, L.; Benavidez-Silva, C.; Tedim, F. Assessment of Forest Fire Severity for a Management Conceptual Model: Case Study in Vilcabamba, Ecuador. *Forests* **2024**, *15*, 2210. [CrossRef]
69. Hamidah, M.; Mohd Hasmadi, I.; Chua, L.S.L.; Yong, W.S.Y.; Lau, K.H.; Faridah-Hanum, I.; Pakhriazad, H.Z. Development of a Protocol for Malaysian Important Plant Areas Criterion Weights Using Multi-Criteria Decision Making—Analytical Hierarchy Process (MCDM-AHP). *Glob. Ecol. Conserv.* **2022**, *34*, e02033. [CrossRef]
70. Derak, M.; Cortina, J. Multi-Criteria Participative Evaluation of Pinus Halepensis Plantations in a Semiarid Area of Southeast Spain. *Ecol. Indic.* **2014**, *43*, 56–68. [CrossRef]
71. Rodman, K.C.; Fornwalt, P.J.; Chapman, T.B.; Coop, J.D.; Edwards, G.; Stevens, J.T.; Veblen, T.T. *SRRT: A Decision Support Tool to Inform Postfire Reforestation of Ponderosa Pine and Douglas-Fir in the Southern Rocky Mountains*; RMRS-RN-95; US Department of Agriculture, Forest Service, Rocky Mountain Research Station: Fort Collins, CO, USA, 2022; 12p.
72. UNEP; FAO. The UN Decade on Ecosystem Restoration 2021–2030. *UNEP/FAO Factsheet* **2020**, *2019*, 4.
73. Swati, H. Getting Started with the Bonn Challenge, United Nations Economic Commission for Europe, Switzerland. 2018. Available online: https://policycommons.net/artifacts/4855392/getting-started-with-the-bonn-challenge/5692337/ (accessed on 1 April 2025).
74. *Post-Fire Management Plan for the Burned Area of the Adelfi Forest*; Department of Forests in Cyprus: Nicosia, Cyprus, 2016.
75. *Department of Forests in Cyprus Forest Fire Statistics for the Period 2000–2023: Number of Forest Fires and Burnt Areas for the Period 2000–2023 Causes of Forest Fires for the Period 2000–2023*; Department of Forests in Cyprus: Nicosia, Cyprus, 2023.
76. Department of Forests in Cyprus. Forest Fires. Available online: https://www.moa.gov.cy/moa/fd/fd.nsf/fd93_en/fd93_en?OpenDocument (accessed on 10 February 2025).
77. Cardille, J.A.; Crowley, M.A.; Saah, D.; Clinton, N.E. (Eds.) *Cloud-Based Remote Sensing with Google Earth Engine*; Springer International Publishing: Cham, Switzerland, 2024; ISBN 978-3-031-26587-7.
78. Gorelick, N.; Hancher, M.; Dixon, M.; Ilyushchenko, S.; Thau, D.; Moore, R. Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone. *Remote Sens. Environ.* **2017**, *202*, 18–27. [CrossRef]
79. Mutanga, O.; Kumar, L. Google Earth Engine Applications. *Remote Sens.* **2019**, *11*, 591. [CrossRef]
80. Pausas, J.G.; Ouadah, N.; Ferran, A.; Gimeno, T.; Vallejo, R. Fire Severity and Seedling Establishment in Pinus Halepensis Woodlands, Eastern Iberian Peninsula. *Plant Ecol.* **2002**, *169*, 205–213. [CrossRef]
81. Rowe, J.S. Concepts of Fire Effects on Plant Individuals and Species. In *The Role of Fire in Northern Circumpolar Ecosystems*; John Wiley and Sons: New York, NY, USA, 1983; pp. 135–154.
82. Pausas, J.G.; Bradstock, R.A.; Keith, D.A.; Keeley, J.E. Plant Functional Traits In Relation To Fire In Crown-Fire Ecosystems. *Ecology* **2004**, *85*, 1085–1100. [CrossRef]
83. Cerdá, A.; Doerr, S.H. Influence of Vegetation Recovery on Soil Hydrology and Erodibility Following Fire: An 11-Year Investigation. *Int. J. Wildland Fire* **2005**, *14*, 423. [CrossRef]
84. Khoirunisa, N.; Ku, C.-Y.; Liu, C.-Y. A GIS-Based Artificial Neural Network Model for Flood Susceptibility Assessment. *Int. J. Environ. Res. Public Health* **2021**, *18*, 1072. [CrossRef] [PubMed]
85. Yilmaz, O.S.; Akyuz, D.E.; Aksel, M.; Dikici, M.; Akgul, M.A.; Yagci, O.; Balik Sanli, F.; Aksoy, H. Evaluation of Pre- and Post-Fire Flood Risk by Analytical Hierarchy Process Method: A Case Study for the 2021 Wildfires in Bodrum, Turkey. *Landsc. Ecol. Eng.* **2023**, *19*, 271–288. [CrossRef]
86. Lu, L.; Xu, Y.; Huang, A.; Liu, C.; Marcos-Martinez, R.; Huang, L. Influences of Topographic Factors on Outcomes of Forest Programs and Policies in a Mountain Region of China: A Case Study. *Mt. Res. Dev.* **2020**, *40*, 848–860. [CrossRef]
87. Jiang, K.; Li, Z.; Luo, C.; Wu, M.; Chao, L.; Zhou, Q.; Zhao, H. The Reduction Effects of Riparian Reforestation on Runoff and Nutrient Export Based on AnnAGNPS Model in a Small Typical Watershed, China. *Environ. Sci. Pollut. Res.* **2019**, *26*, 5934–5943. [CrossRef]
88. Marden, M. Effectiveness of Reforestation in Erosion Mitigation and Implications for Future Sediment Yields, East Coast Catchments, New Zealand: A Review. *N. Z. Geogr.* **2012**, *68*, 24–35. [CrossRef]
89. Hazarika, R.; Bolte, A.; Bednarova, D.; Chakraborty, D.; Gaviria, J.; Kanzian, M.; Kowalczyk, J.; Lackner, M.; Lstibůrek, M.; Longauer, R.; et al. Multi-Actor Perspectives on Afforestation and Reforestation Strategies in Central Europe under Climate Change. *Ann. Sci.* **2021**, *78*, 60. [CrossRef]
90. Morales, N.S.; Fernández, I.C.; Duran, L.P.; Venegas-González, A. Community-driven Post-fire Restoration Initiatives in Central Chile: When Good Intentions Are Not Enough. *Restor. Ecol.* **2021**, *29*, e13389. [CrossRef]
91. Orsi, F.; Geneletti, D. Identifying Priority Areas for Forest Landscape Restoration in Chiapas (Mexico): An Operational Approach Combining Ecological and Socioeconomic Criteria. *Landsc. Urban. Plan.* **2010**, *94*, 20–30. [CrossRef]
92. Daskalakou, E.N.; Thanos, C.A. Postfire Regeneration of Aleppo Pine–Density, Survival and Early Growth of Pinus Halepensis Seedlings. In Proceedings of the MEDECOS Conference, Rhodes, Greece, 25 April–1 May 2004; pp. 1–10.

93. Boydak, M. Silvicultural Characteristics and Natural Regeneration of *Pinus brutia* Ten.—A Review. *Plant Ecol.* **2004**, *171*, 153–163. [CrossRef]
94. European Environment Agency. High Resolution Layer Tree Cover Density. Available online: https://land.copernicus.eu/en/products/high-resolution-layer-tree-cover-density (accessed on 20 February 2025).
95. Fernandez, J.; Maillard, O.; Uyuni, G.; Guzmán-Rojo, M.; Escobar, M. Multi-Criteria Prioritization of Watersheds for Post-Fire Restoration Using GIS Tools and Google Earth Engine: A Case Study from the Department of Santa Cruz, Bolivia. *Water* **2023**, *15*, 3545. [CrossRef]
96. Maillard, O.; Herzog, S.K.; Soria-Auza, R.W.; Vides-Almonacid, R. Impact of Fires on Key Biodiversity Areas (KBAs) and Priority Bird Species for Conservation in Bolivia. *Fire* **2022**, *5*, 4. [CrossRef]
97. Shi, Y.-F.; Shi, S.-H.; Jiang, Y.-S.; Liu, J. A Global Synthesis of Fire Effects on Soil Seed Banks. *Glob. Ecol. Conserv.* **2022**, *36*, e02132. [CrossRef]
98. Saaty, T. The Analytic Hierarchy Process (AHP) for Decision Making. In Proceedings of the 9th International Cryogenic Engineering Conference, Kobe, Japan, 11–14 May 1980; Volume 1, p. 69.
99. Uribe, D.; Geneletti, D.; del Castillo, R.; Orsi, F. Integrating Stakeholder Preferences and GIS-Based Multicriteria Analysis to Identify Forest Landscape Restoration Priorities. *Sustainability* **2014**, *6*, 935–951. [CrossRef]
100. Retalis, A.; Katsanos, D.; Tymvios, F.; Michaelides, S. Comparison of GPM IMERG and TRMM 3B43 Products over Cyprus. *Remote Sens.* **2020**, *12*, 3212. [CrossRef]
101. Petrou, P.; Stampoulidis, A.; Pipinis, E.; Kitikidou, K.; Milios, E. Analysis of the Environments Where Natural Regeneration Is Established in the Absence of a Wildfire in the Open Pinus Brutia Forests in the Middle Elevations of the Central Part of Cyprus. *Forests* **2024**, *15*, 1228. [CrossRef]
102. Van Duong, D.; Schimleck, L. Prediction of Static Bending Properties of Eucalyptus Clones Using Stress Wave Measurements on Standing Trees, Logs and Small Clear Specimens. *Forests* **2022**, *13*, 1728. [CrossRef]
103. Nurda, N.; Noguchi, R.; Ahamed, T. Change Detection and Land Suitability Analysis for Extension of Potential Forest Areas in Indonesia Using Satellite Remote Sensing and GIS. *Forests* **2020**, *11*, 398. [CrossRef]
104. Sismanis, M.; Gitas, I.Z.; Georgopoulos, N.; Stavrakoudis, D.; Gkounti, E.; Antoniadis, K. A Spectral–Spatial Approach for the Classification of Tree Cover Density in Mediterranean Biomes Using Sentinel-2 Imagery. *Forests* **2024**, *15*, 2025. [CrossRef]
105. Key, C.H.; Benson, N.C. Landscape Assessment (LA) Sampling and Analysis Methods. In *USDA Forest Service—General Technical Report RMRS-GTR*; US Department of Agriculture, Forest Service: Collins, CO, USA, 2006.
106. Bhattacharya, S.; Ghosh, S.; Bhattacharyya, S. Analytical Hierarchy Process Tool in Google Earth Engine Platform: A Case Study of a Tropical Landfill Site Suitability. *Environ. Monit. Assess.* **2022**, *194*, 276. [CrossRef] [PubMed]
107. Ali, S.A.; Ahmad, A. Suitability Analysis for Municipal Landfill Site Selection Using Fuzzy Analytic Hierarchy Process and Geospatial Technique. *Environ. Earth Sci.* **2020**, *79*, 227. [CrossRef]
108. Yağcı, C.; İşcan, F. Turkish Journal of Geographic Information Systems GIS-Based Site Suitability Analysis of Afforestation in Konya Province, Turkey. *Turk. J. Geogr. Inf. Syst.* **2021**, *3*, 89–95.
109. Cruz-Bello, G.M.; Sotelo-Ruiz, E.D. Coupling Spatial Multiattribute Analysis and Optimization to Identify Reforestation Priority Areas. *Mt. Res. Dev.* **2013**, *33*, 29–39. [CrossRef]
110. Congalton, R.G.; Green, K. *Assessing the Accuracy of Remotely Sensed Data*; CRC Press: Boca Raton, FL, USA, 2019; ISBN 9780429052729.
111. Stehman, S.V. Selecting and Interpreting Measures of Thematic Classification Accuracy. *Remote Sens. Environ.* **1997**, *62*, 77–89. [CrossRef]
112. Buckland, M.; Gey, F. The Relationship between Recall and Precision. *J. Am. Soc. Inf. Sci.* **1994**, *45*, 12–19. [CrossRef]
113. Praticò, S.; Solano, F.; Di Fazio, S.; Modica, G. Machine Learning Classification of Mediterranean Forest Habitats in Google Earth Engine Based on Seasonal Sentinel-2 Time-Series and Input Image Composition Optimisation. *Remote Sens.* **2021**, *13*, 586. [CrossRef]
114. Lu, D.; Weng, Q. A Survey of Image Classification Methods and Techniques for Improving Classification Performance. *Int. J. Remote Sens.* **2007**, *28*, 823–870. [CrossRef]
115. Nikhil, S.; Danumah, J.H.; Saha, S.; Prasad, M.K.; Rajaneesh, A.; Mammen, P.C.; Ajin, R.S.; Kuriakose, S.L. Application of GIS and AHP Method in Forest Fire Risk Zone Mapping: A Study of the Parambikulam Tiger Reserve, Kerala, India. *J. Geovisualization Spat. Anal.* **2021**, *5*, 14. [CrossRef]
116. Tolche, A.D.; Gurara, M.A.; Pham, Q.B.; Anh, D.T. Modelling and Accessing Land Degradation Vulnerability Using Remote Sensing Techniques and the Analytical Hierarchy Process Approach. *Geocarto Int.* **2022**, *37*, 7122–7142. [CrossRef]
117. Yesilnacar, E.; Topal, T. Landslide Susceptibility Mapping: A Comparison of Logistic Regression and Neural Networks Methods in a Medium Scale Study, Hendek Region (Turkey). *Eng. Geol.* **2005**, *79*, 251–266. [CrossRef]
118. Mamouri, R.-E.; Ansmann, A.; Ohneiser, K.; Knopf, D.A.; Nisantzi, A.; Bühl, J.; Engelmann, R.; Skupin, A.; Seifert, P.; Baars, H.; et al. Wildfire Smoke Triggers Cirrus Formation: Lidar Observations over the Eastern Mediterranean. *Atmos. Chem. Phys.* **2023**, *23*, 14097–14114. [CrossRef]

119. Nisantzi, A.; Mamouri, R.E.; Ansmann, A.; Hadjimitsis, D. Injection of Mineral Dust into the Free Troposphere during Fire Events Observed with Polarization Lidar at Limassol, Cyprus. *Atmos. Chem. Phys.* **2014**, *14*, 12155–12165. [CrossRef]
120. Pérez-Cabello, F.; Montorio, R.; Alves, D.B. Remote Sensing Techniques to Assess Post-Fire Vegetation Recovery. *Curr. Opin. Environ. Sci. Health* **2021**, *21*, 100251. [CrossRef]
121. Pérez-Cabello, F.; Ibarra, P.; Echeverría, M.T.; de la Riva, J. Post-fire Land Degradation of *Pinus sylvestris* L. Woodlands after 14 Years. *Land Degrad. Dev.* **2010**, *21*, 145–160. [CrossRef]
122. Ermitão, T.; Gouveia, C.M.; Bastos, A.; Russo, A.C. Recovery Following Recurrent Fires Across Mediterranean Ecosystems. *Glob. Change Biol.* **2024**, *30*, e70013. [CrossRef]
123. Giglio, L.; Schroeder, W.; Justice, C.O. The Collection 6 MODIS Active Fire Detection Algorithm and Fire Products. *Remote Sens. Environ.* **2016**, *178*, 31–41. [CrossRef]
124. Casisirano, J.; Tuminting, M.; Ramos, R.V.; Medina, J.M. Tree Planting Prioritization in National Capital Region, Philippines Using Remote Sensing, Analytic Hierarchy Process and Gis. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2024**, *XLVIII-4/W*, 121–127. [CrossRef]
125. González-De Vega, S.; De las Heras, J.; Moya, D. Resilience of Mediterranean Terrestrial Ecosystems and Fire Severity in Semiarid Areas: Responses of Aleppo Pine Forests in the Short, Mid and Long Term. *Sci. Total Environ.* **2016**, *573*, 1171–1177. [CrossRef]
126. Roche, P.K.; Campagne, C.S.; Ganteaume, A. Post-Fire Recovery Dynamics and Resilience of Ecosystem Services Capacity in Mediterranean-Type Ecosystems. *Ecosystems* **2024**, *27*, 833–847. [CrossRef]
127. Hernández-Duarte, A.; Saavedra, F.; González, E.; Miranda, A.; Francois, J.-P.; Somos-Valenzuela, M.; Sibold, J. Effects of Drought and Fire Severity Interaction on Short-Term Post-Fire Recovery of the Mediterranean Forest of South America. *Fire* **2024**, *7*, 428. [CrossRef]
128. Fernandez-Manso, A.; Quintano, C.; Roberts, D.A. Burn Severity Influence on Post-Fire Vegetation Cover Resilience from Landsat MESMA Fraction Images Time Series in Mediterranean Forest Ecosystems. *Remote Sens. Environ.* **2016**, *184*, 112–123. [CrossRef]
129. White, A.M.; Long, J.W. Understanding Ecological Contexts for Active Reforestation Following Wildfires. *New For.* **2019**, *50*, 41–56. [CrossRef]
130. Wang, X.; He, H.S.; Li, X.; Chang, Y.; Hu, Y.; Xu, C.; Bu, R.; Xie, F. Simulating the Effects of Reforestation on a Large Catastrophic Fire Burned Landscape in Northeastern China. *Ecol. Manag.* **2006**, *225*, 82–93. [CrossRef]
131. Dobrowski, S.Z.; Aghai, M.M.; Chichilnisky du Lac, A.; Downer, R.; Fargione, J.; Haase, D.L.; Hoecker, T.; Kildisheva, O.A.; Murdoch, A.; Newman, S.; et al. 'Mind the Gap'—Reforestation Needs vs. Reforestation Capacity in the Western United States. *Front. For. Glob. Change* **2024**, 1402124. [CrossRef]
132. Xiao, D.; Tao, D.; Xu, Z. Impacts of an Extra-Ordinarily Disastrous Fire on Forest Resources and Environment. *Chin. J. Ecol.* **1988**, *7*, 5–9.
133. Chen, W.; Moriya, K.; Sakai, T.; Koyama, L.; Cao, C. Post-Fire Forest Regeneration under Different Restoration Treatments in the Greater Hinggan Mountain Area of China. *Ecol. Eng.* **2014**, *70*, 304–311. [CrossRef]
134. Vedovato, L.B.; Aragão, L.E.O.C.; Almeida, D.R.A.; Bartholomew, D.C.; Assis, M.; Dalagnol, R.; Gorgens, E.B.; Silva-Junior, C.H.L.; Ometto, J.P.; Pontes-Lopes, A.; et al. Impacts of Fire on Canopy Structure and Its Resilience Depend on Successional Stage in Amazonian Secondary Forests. *Remote Sens. Ecol. Conserv.* **2025**. [CrossRef]
135. Tucker, M.M.; Kashian, D.M. Pre-Fire Forest Remnants Affect Post-Fire Plant Community Structure and Composition. *Ecol. Manag.* **2018**, *408*, 103–111. [CrossRef]
136. Harvey, B.J.; Donato, D.C.; Turner, M.G. High and Dry: Post-fire Tree Seedling Establishment in Subalpine Forests Decreases with Post-fire Drought and Large Stand-replacing Burn Patches. *Glob. Ecol. Biogeogr.* **2016**, *25*, 655–669. [CrossRef]
137. Yao, J.; Kong, X.; Fang, L.; Huo, Z.; Peng, Y.; Han, Z.; Ren, S.; Chen, J.; Wang, X.; Wang, Q. Drivers of Structural and Functional Resilience Following Extreme Fires in Boreal Forests of Northeast China. *Fire* **2025**, *8*, 108. [CrossRef]
138. Laughlin, M.M.; Rangel-Parra, L.K.; Morris, J.E.; Donato, D.C.; Halofsky, J.S.; Harvey, B.J. Patterns and Drivers of Early Conifer Regeneration Following Stand-Replacing Wildfire in Pacific Northwest (USA) Temperate Maritime Forests. *Ecol. Manag.* **2023**, *549*, 121491. [CrossRef]
139. Cordell, S.; Questad, E.J.; Asner, G.P.; Kinney, K.M.; Thaxton, J.M.; Uowolo, A.; Brooks, S.; Chynoweth, M.W. Remote Sensing for Restoration Planning: How the Big Picture Can Inform Stakeholders. *Restor. Ecol.* **2017**, *25*, S147–S154. [CrossRef]
140. Menéndez-Miguélez, M.; Rubio-Cuadrado, Á.; Cañellas, I.; Erdozain, M.; de Miguel, S.; Lapin, K.; Hoffmann, J.; Werden, L.; Alberdi, I. How to Measure Outcomes in Forest Restoration? A European Review of Success and Failure Indicators. *Front. For. Glob. Change* **2024**, *7*, 1420127. [CrossRef]