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Cyprus tomorrow RECOVERY AND RESILIENCE PLAN

Republic of Cyprus

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Executive Summary

This deliverable focuses on the development and implementation of an intelligence module designed to identify and recommend to the authorities / end-users possible areas for afforestation or reforestation. The approach is based on the application of a multi-criteria analysis method integrating satellite imagery to identify and recommend sites. The module identifies the deforested areas and evaluates elements of the ecological condition to prioritize optimal locations for reforestation practices after fire events. The output is a spatial decision support tool capable of guiding restoration actions based on environmental suitability and forest development potential.

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1. Deforestation Module

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 to 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 the loss of 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).

For the purposes of creating the tool for identifying deforested areas in Cyprus based on satellite images, the change detection technique was used. According to the literature, several methods have been used including image classification, time series analysis, machine learning models and object-oriented analysis. Supervised classification methods, such as Random Forest or Support Vector Machines, categorize land cover types, but often require extensive training data and can be sensitive to seasonal fluctuations (Karmoude et al., 2025). Apart from that, this affects the platform's operational work, as the samples will need to be updated frequently and apart from that, it requires substantial skill and effort on the part of the image interpreter (Pacheco-Pascagaza et al., 2022; Quang et al., 2024). Also, regarding the use of time series, methods such as the LandTrendr model and BFAST monitor vegetation trends over time, offering information on gradual degradation, but their negative is that their operation relies on the utilization of dense and high-quality temporal datasets (Fuentes et al., 2024). Regarding the utilization of object-oriented analysis techniques in which their operation is based on the clustering of pixels into significant objects before classification, they are effective for high-resolution imagery but require careful tuning and are sensitive to segmentation parameters (Yordanov & Brovelli, 2021).

Taking all this into account, the change detection technique was chosen as it allows for rapid and objective recognition of deforestation without the need for extensive training data, reduces sensitivity to seasonal biases when timed appropriately, and integrates efficiently with auxiliary data to enhance accuracy. Therefore, it provides a practical and scalable solution for operational monitoring of deforestation.

1.1 Methodology

For the purposes of the deforestation module, a change detection technique was implemented to identify deforestation areas as shown in flowchart in

Figure **1**. 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 (described in Deliverable 3.2) 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 **Error! Reference source not found.** 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.

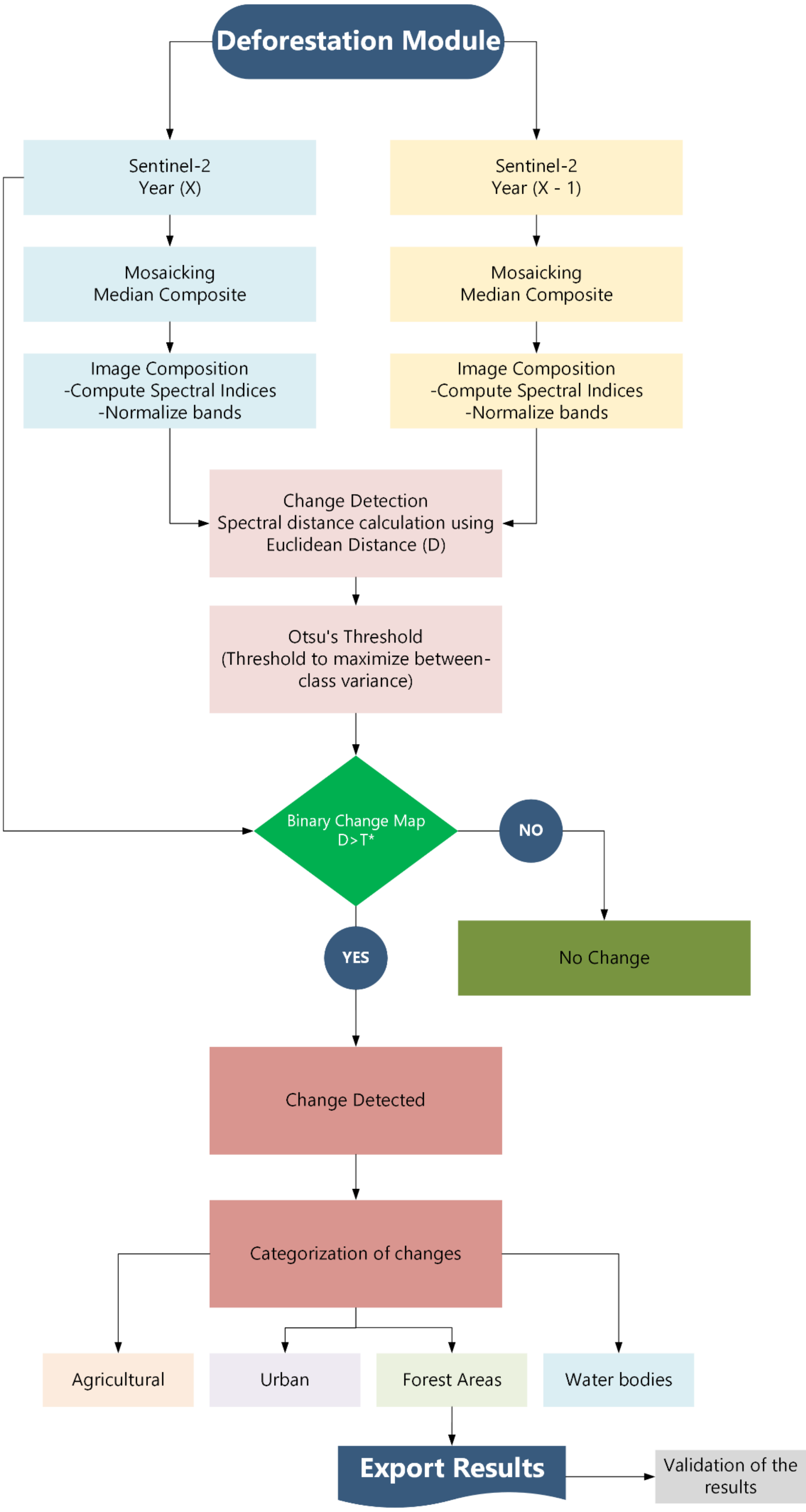


Figure 1: Flow chart of the proposed methodology.

In the analysis used in the study, the spectral indices that are presented in Table 1 were incorporated as new layers to create image composites for the abovementioned datasets. The spectral indices are described in detail in Deliverable D5.4.

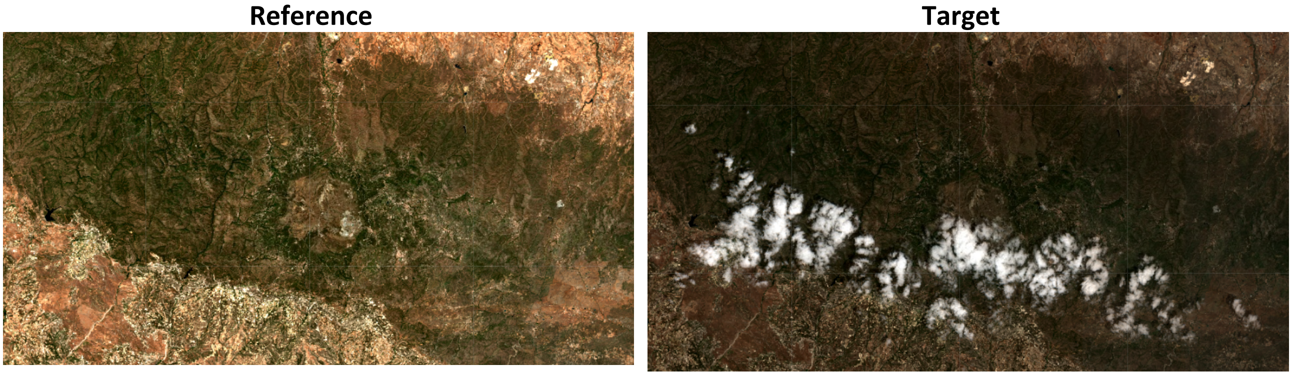
Table 1: Equations of spectral indices

Satellite	Spectral Indices	Abbreviation	Equation	Ref.
S2	Normalized Difference Vegetation Index	NDVI	$\frac{NIR-RED}{NIR+RED}$	(Tucker, 1979)
	Normalized Difference Red Edge Index	NDRE	$\frac{NIR-RED}{NIR+RED}$	(Gitelson et al., 2003)
	Enhanced Vegetation Index	EVI	$\frac{2.5(NIR-RED)}{NIR+6\,RED-7.5BLUE+1}$	(Huete et al., 2002)
	Green Leaf Index	GLI	$\frac{2*GREEN-RED-BLUE}{2*GREEN+RED+BLUE}$	(Louhaichi et al., 2001)
	SAVI	SAVI	$\frac{1.5(NIR-RED)}{NIR+RED+0.5}$	
	Structure Insensitive Pigment Index	SIPI	$\frac{NIR-BLUE}{NIR-RED}$	(PEN˜UELAS et al., 1995)
	Atmospherically Resistant Vegetation Index	ARVI	$\frac{NIR-(2*RED)+BLUE}{NIR+(2*RED)+BLUE}$	(Kaufman & Tanre, 1992)
	Bare Soil Index	BSI	$\frac{(SWIR1+RED)-(NIR+BLUE)}{(SWIR1+RED)+(NIR+BLUE)}$	(Rikimaru A et al., 2002)
	Normalized Difference Water Index	NDWI	$\frac{GREEN-NIR}{GREEN+NIR}$	(McFEETERS, 1996)
	Advanced Vegetation Index	AVI	$\sqrt[3]{NIR*(1-RED)*(NIR-RED)}$	(Roy et al., 1996)
	Green Normalized Difference Vegetation Index	GNDVI	$\frac{NIR-GREEN}{NIR+GREEN}$	(Gitelson et al., 2003)
	Normalized Difference Moisture Index	NDMI	$\frac{SWIR-NIR}{SWIR+NIR}$	(HUNTJR & ROCK, 1989)
	Normalized Burn Ratio	NBR	$\frac{NIR-SWIR2}{NIR+SWIR2}$	(Key & Benson, 2006)
	Burned Area Index	BAI	$\frac{1}{((0.1-RED)^2+(0.06-NIR)^2)}$	(Chuvieco et al., 2002)

	Burned Area Index for Sentinel 2	BAIS2	$\left(1-\sqrt{\frac{\boldsymbol{RE2*RE3*NIRn-GREEN}}{\boldsymbol{B4}}}\right)*\left(\frac{\boldsymbol{SWIR2-NIRn}}{\sqrt{\boldsymbol{SWIR2+NIRn}}}+1\right)$	(Filippon i, 2018)
	Char Soil Index	CSI	$\frac{\boldsymbol{NIR}}{\boldsymbol{SWIR2}}$	(A. M. S. Smith et al., 2007)
	Mid-Infrared Burn Index	MIRBI	$\boldsymbol{10*SWIR2-9.8*SWIR1+2}$	(Trigg & Flasse, 2001)
	Normalized Burn Ratio SWIR	NBRSW IR	$\frac{\boldsymbol{SWIR2-SWIR1-0.02}}{\boldsymbol{SWIR2+SWIR1+0.1}}$	(Gerard et al., 2003)
	Normalized Burn Ratio Plus	NBRplu s	$\frac{\boldsymbol{SWIR2-NIRn-GREEN-BLUE}}{\boldsymbol{SWIR2+NIRn+GREEN+BLUE}}$	(Alcaras et al., 2022)

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, as shown in the example in **Error! Reference source not found.**. Also, the cloud masking was performed using the QA60 band, where the pixels affected by clouds and cirrus were masked out.

Reference **Target**



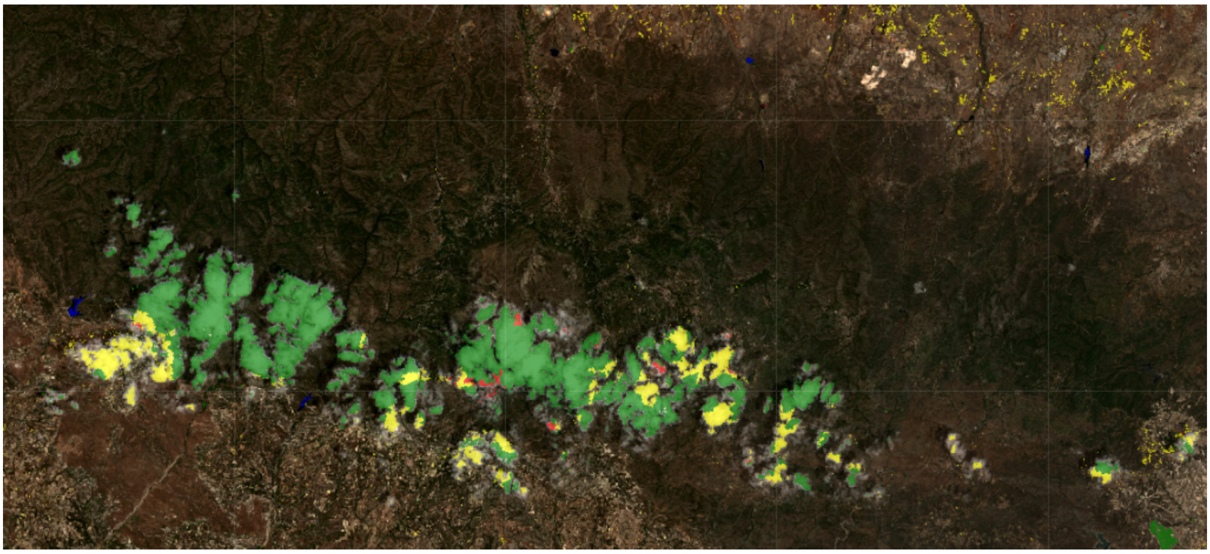


Figure 2: Impact of clouds on satellite images.

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 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.

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

where: X represents the spectral bands (including spectral indices).

Moreover, 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. The Otsu thresholding technique was selected due to its one of the best binarization thresholding method (Fan & Lei, 2012; Halder & Pereira, 2024).This technique computes an adaptive threshold based on the histogram of changed magnitudes and ensures an optimal separation between changed and unchanged regions based on the below equations.

$$OT = \sum_{k=1}^{p} (D_k - \overline{D})^2$$

where:

- D_k is the Euclidean distance value for a given pixel.
- D is the mean Euclidean distance over the dataset.

- p=2, representing change and no-change classes.

The optimal threshold T^* is found by maximizing the between-class variance:

$$T^* = \arg max_T \, [w_1(T) w_2(T) (\mu_1(T) - \mu_2(T))^2$$

where:

- $w_1(T)$ and $w_2(T)$are class probabilities (proportions of pixels in each class).
- $\mu_1(T)$ and $\mu_2(T)$are the mean Euclidean distances for the two classes.

The **binary change map** is generated using:

$$C(x,y) = \begin{cases} 1, & D(x,y) \geq T^* (Change\ detected) \\ 0, & D(x,y) < T^*\ (No\ change) \end{cases}$$

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).

1.2 Model Validation

Finally, for the validation of the results, fire event data from the EFFIS service and the forest loss data from the Hansen Global Forest Change dataset were utilized. Specifically, 1000 random points within the burned areas and in the forest loss zones were used and compared with the deforested areas detected by our model. For the validation process, only summer image composites were used in order to minimize the presence of cloud percentage and reduce seasonal variability. Subsequently, the accuracy assessment was conducted utilizing the overall accuracy metric which represents the percentage of correctly classified pixels calculated according to the following equation:

$$Accuracy = \frac{\text{Number of Correct Predictions}}{Total \text{ Number of Correct Predictions}}$$

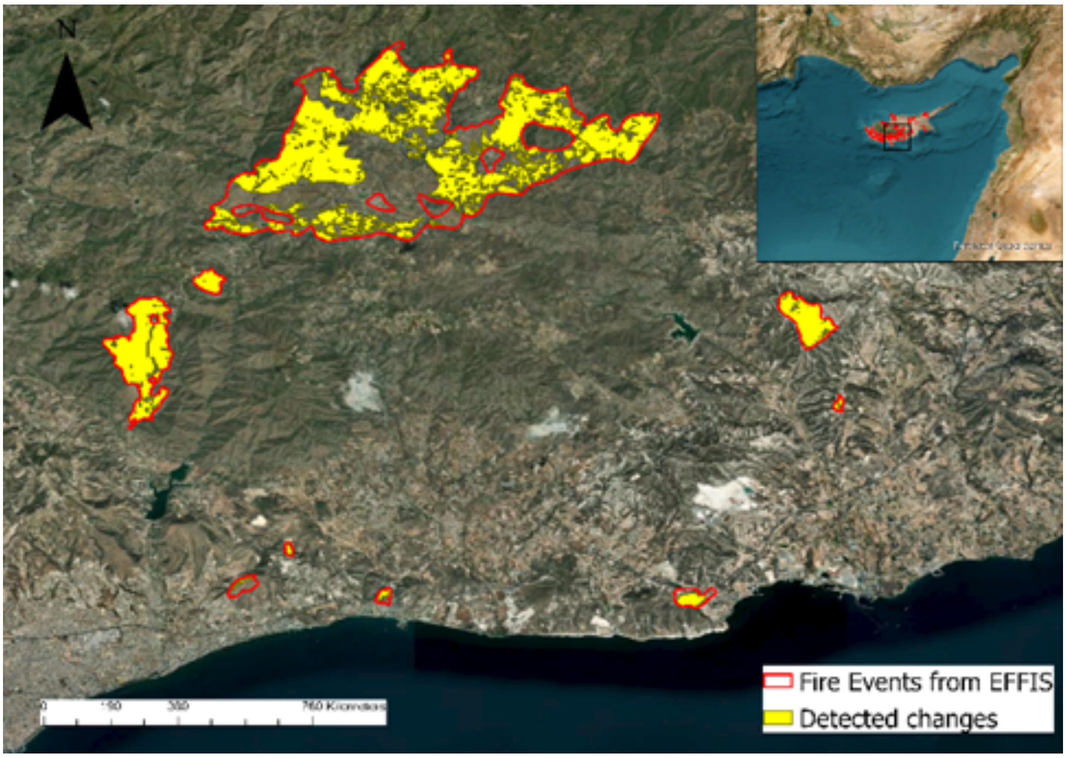
made based on the identification of known fire events in comparison with the change detection model that was developed for the identification of deforestation.

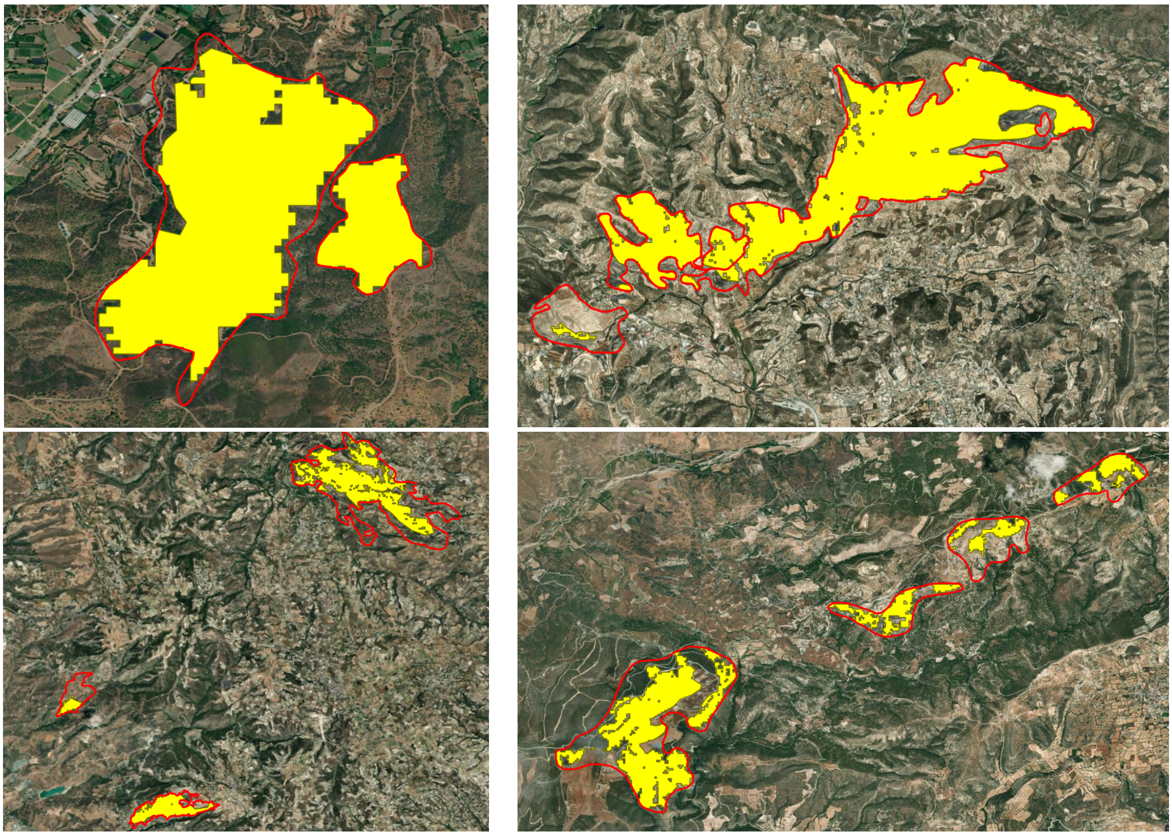
1.3 Results

The proposed methodology, developed for the GREEN-HIT project, aimed to identify deforested zones in Cyprus' forests using change detection techniques, successfully identifying land cover changes with Sentinel-2 multispectral imagery. Utilizing spectral indices suitable for vegetation condition monitoring and burn-sensitive spectral index, along with the Euclidean spectral distance combined with Otsu-based thresholding, the algorithm detected areas of significant change. Moreover, the integration of MODIS burned area data into the model enabled spatial filtering to identify fire-induced changes, while CORINE land cover information allowed for reclassification into forest, agricultural, urban, and water categories.

Through this approach, the final output provides a raster (GeoTIFF format) that highlights changes detected over a one-year time span, indicating possible deforested zones. To characterize all the detected changes, they were categorized based on their corresponding land cover types and MODIS burned areas.

The model achieved an overall accuracy of 78.6%, indicating a robust agreement between the detected deforested areas and independent reference data. This result supports the reliability of the proposed approach for identifying and classifying changes in forested areas.





2. Reforestation/Afforestation Module

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 (IUCN, 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(P. 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., 2022a). Additionally, multispectral and hyperspectral imaging facilitate the monitoring and detection of vegetation health, moisture levels, and overall ecosystem recovery (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).

Focusing on post-fire prioritization restoration actions, spatial Multi-criteria Analysis (SMCA) is an essential tool for identifying areas for restoration. This complex process integrates criteria from various domains and disciplines allowing for the combination of diverse data types and units, as well as the processing of spatial information. Numerous studies have been conducted worldwide to identify areas suitable for restoration using remote sensing techniques and earth observation data based on the SMCA. For instance, to address trade-offs in post-fire recovery and biodiversity conservation (Cavalcante et al., 2022b; Garcia-Gonzalo et al., 2014; Pedrollo et al., 2024), for post-fire reforestation management strategies or for prioritizing reforestation activities in burned areas (Alayan et al., 2022; Garcia-Gonzalo et al., 2014; Khalili & Duecker, 2013; Lombardo et al., 2023; Tzamtzis et al., 2023; Uribe et al., 2014). Furthermore, Zhang et al. (Zhang et al., 2020) combined the TOPSIS and entropy weight methods to assess the environmental, social, and economic objectives of forest restoration projects. Another study implemented by Kale et al. (Kale et al., 2015) evaluated potential reforestation sites in the Kamrim district of Assam in India based on criteria such as biodiversity, carbon storage capabilities, and demographic patterns.

The Analytic Hierarchy Process (AHP) is one of the most widely used methods for multi-criteria decision-making, originally proposed by Saty el. al, (T. L. Saaty, 1977). The AHP serves as a valuable tool for decision-makers enabling them to evaluate various essential elements through pairwise comparisons (T. L. Saaty, 1990). In the present study, AHP was employed to assess ecological criteria for identifying areas suitable for reforestation. Several studies confirm this choice; for instance, Nesticò et al. (Nesticò et al., 2022) compared four different evaluation approaches – AHP, ELECTRE, TOPSIS, and VIKOR and found that AHP's flexibility is a significant advantage as it allows for the assignment of different weights to criteria on various levels. Moreover, Paletto et al. (Paletto et al., 2021) utilized AHP to analyze the effects of silvicultural treatments on trade-offs between forest ecosystems. Additionally, Curiel-Esparza et al.(Curiel-Esparza et al., 2015) proposed a decision-support system that integrates climate change criteria for optimal reforestation planning using both Delphi Method and AHP in a case study of the Spanish forest in the Mediterranean region. Furthermore, Alayan et al.,(Alayan & Lakner, 2024) conducted a study to develop suitability maps for identifying priority restoration zones after fire events in Syrian forests. Similar approaches that prioritize restoration actions using AHP have also been undertaken in various studies (Arianoutsou et al., 2011; Derak & Cortina, 2014; Dosis et al., 2023; González et al., 2024; Hamidah et al., 2022; Rodman et al., 2022).

2.1 Methodology

The proposed methodology is presented in Figure 3. Specifically, the method is based on a spatial multi-criteria decision analysis process utilizing the Google Earth Engine (GEE) cloud-based platform. The GEE was selected for the development of the reforestation module due to the immediate interaction offered between the user and the platform, with results being presented in real time without delays. Specifically, the GEE has its own APIs which allow the automation of analysis and the development of custom applications, making it flexible for research and operational needs. Additionally, it provides access to a vast repository of geospatial data, enabling analysis immediately without the need for local storage or data downloads. This makes it ideal for large-scale analysis. At the same time, GEE is considered an optimal and cost-effective solution for the development of the model as it doesn't require high computational power or large storage capacity and is open access.

The proposed methodology can be divided into five main steps as shown in Figure 3**.**

a) Criteria Definition,
b) Data collection,
c) Standardization of the criteria,
d) Criteria weighting and,
e) Evaluation and ranking of results.

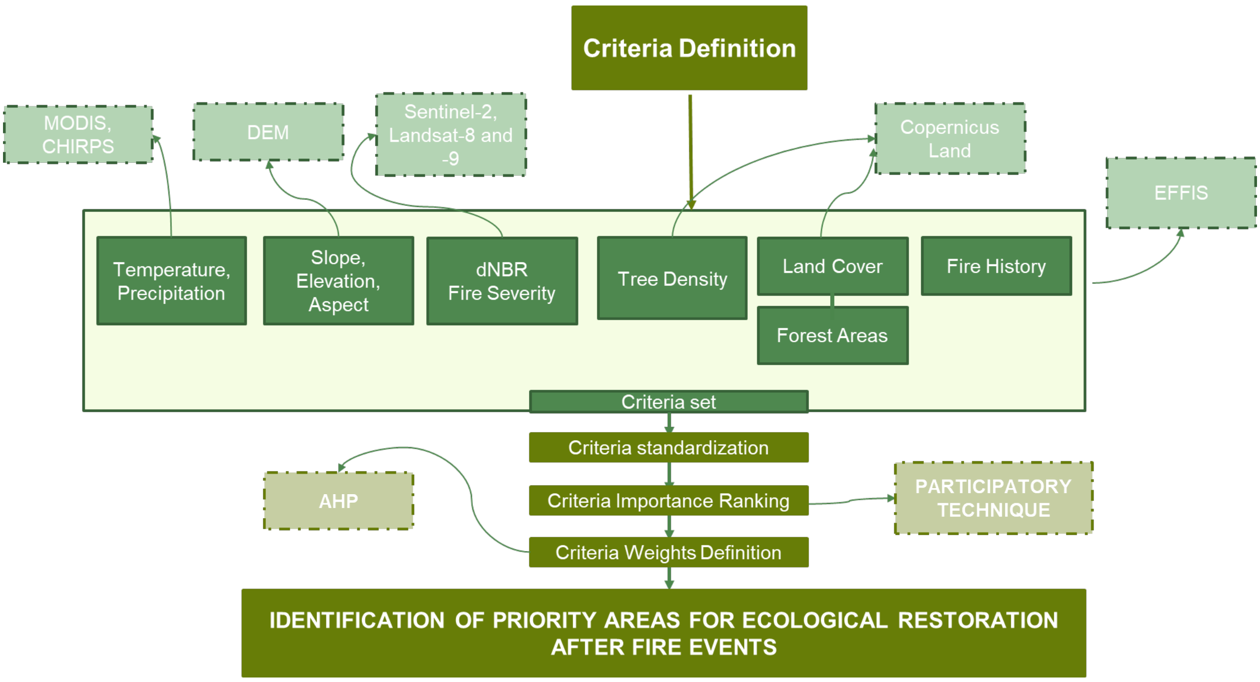


Figure 3: Workflow for identifying priority areas for ecological restoration actions after fire events in Cyprus.

2.1.1 Criteria Definition: *Investigating parameters that contribute to reforestation actions*

This part of the proposed methodology focuses on gathering all the parameters considered in the reforestation actions for burned areas. For the selection of these parameters, meetings were held with the Department of Forestry in Cyprus (Figure 4). Is a critical part of the proposed methodology ensuring that all relevant factors for effective restoration are considered and aligned with local expertise.

Figure 4: Meeting with the Department of Forests in Cyprus to discuss the selection of key parameters for reforestation actions in burned areas.

During these meetings, a questionnaire about the importance of several parameters related to reforestation, is presented in Figure 5 was given. This questionnaire includes several parameters as shown in Table 2 that had been identified in similar studies based on the literature review that was conducted. It is important to note that the questionnaire was answered through a discussion exclusively with the participants who attended the meeting and are the experts in the domain, to determine the parameters that contribute to the restoration actions of burnt areas that are implemented in Cyprus national forests by the Department of Forests.

Δράσεις αποκατάστασης μετά από δασικές πυρκαγιές

Το ερωτηματολόγιο αυτό έχει ετοιμαστεί στα πλαίσια του προγράμματος GREEN-HIT. Στόχος του ερωτηματολογίου είναι να τεθούν τα απαραίτητα κριτήρια που θα μπορούσαν να ληφθούν από δορυφορικά δεδομένα για τον προσδιορισμό των περιοχών που χρειάζονται αποκατάσταση μετά από συμβάντα πυρκαγιάς.

*Υποχρεωτική ερώτηση

1. Φύλο *

Να επισημαίνεται μόνο μία έλλειψη.

- ◯ Άρρεν
- ◯ Θήλυ
- ◯ Άλλο

2. Οργανισμός *

____

3. Ειδικότητα *

____

Κριτήρια Αξιολόγησης - Μορφολογικές Παράμετροι

Αποδώστε για κάθε παράμετρο το βαθμό που επηρεάζει στην λήψη αποφάσεων για την διεξαγωγή δράσεων αποκατάστασης σε μια καμένη περιοχή.

4. Υψόμετρο *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

5. Προσανατολισμός *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	○	○	○	○	○	○	○	○	○	○	○	Πολύ

6. Κλίση *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	○	○	○	○	○	○	○	○	○	○	○	Πολύ

Κριτήρια Αξιολόγησης - Κλιματολογικοί Παράμετροι

Αποδώστε για κάθε παράμετρο το βαθμό που επηρεάζει στην λήψη αποφάσεων για την διεξαγωγή δράσεων αποκατάστασης σε μια καμένη περιοχή.

7. Θερμοκρασία *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	○	○	○	○	○	○	○	○	○	○	○	Πολύ

8. Βροχόπτωση *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	○	○	○	○	○	○	○	○	○	○	○	Πολύ

Κριτήρια Αξιολόγησης - Φυσικές καταστροφές

Αποδώστε για κάθε παράμετρο το βαθμό που επηρεάζει στην λήψη αποφάσεων για την διεξαγωγή δράσεων αποκατάστασης σε μια καμένη περιοχή.

9. Διάβρωση εδάφους *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	○	○	○	○	○	○	○	○	○	○	○	Πολύ

10. Σφοδρότητα πυρκαγιάς *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

11. Απόσταση από καμένη έκταση *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

12. Ένταση φωτιάς *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

Κριτήρια Αξιολόγησης - Δομημένο περιβάλλον

Αποδώστε για κάθε παράμετρο το βαθμό που επηρεάζει στην λήψη αποφάσεων για την διεξαγωγή δράσεων αποκατάστασης σε μια καμένη περιοχή.

13. Απόσταση από τους δρόμους *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

14. Απόσταση από τις κατοικημένες περιοχές *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

15. Πυκνότητα πληθυσμού *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

Κριτήρια Αξιολόγησης - Φυσικό Περιβάλλον

Αποδώστε για κάθε παράμετρο το βαθμό που επηρεάζει στην λήψη αποφάσεων για την διεξαγωγή δράσεων αποκατάστασης σε μια καμένη περιοχή.

16. Χρήσεις Γης - Δέντρα *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

17. Χρήσεις Γης - Θαμνότοποι *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

18. Χρήσεις Γης - Γεωργικές Εκτάσεις *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

19. Χρήσεις Γης - Λιβάδια *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

20. Χρήσεις Γης - Αστικές Περιοχές *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

21. Χρήσεις Γης - Γυμνό Έδαφος / Αραιή Βλάστηση *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

22. Χρήσεις Γης - Υδάτινα σώματα *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

23. Χρήσεις Γης - Βρύα και λειχήνες *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

24. Normalized Difference Vegetation Index - NDVI (-1: Γυμνό έδαφος ή μη υγιές βλάστηση- έως +1: Υγιές βλάστηση) *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

25. Πυκνότητα θόλου των δέντρων *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

26. Απόσταση από προστατευόμενες περιοχές *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

27. Απόσταση από ποτάμια *

	0	1	2	3	4	5	6	7	8	9	10	
Καθ	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Πολύ

Επιπρόσθετες πληροφορίες

28. Άλλες παράμετροι που θα μπορούσαν να ληφθούν υπόψη *

29. Άλλα σχόλια *

Figure 5: Questionnaire used with the Department of Forests to gather expert input on the parameters influencing reforestation actions.

Table 2: Parameters identified through the literature and included in the questionnaire to gather expert input for reforestation actions.

Category	Parameters
Morphological	Elevation
	Aspect
	Slope
Climatic	Temperature
	Precipitation
Environmental Disturbances	Soil Erosion
	Fire severity
	Distance from burned area
Build Environment	Distance from roads
	Distance from residential areas
	Population Density
Natural Environment	Forest areas
	Shrublands
	Agricultural areas
	Grasslands
	Urban Areas
	Bare Soil/ Sparse Vegetation
	Water Bodies
	Mosses and Lichens
	Normalized Difference Vegetation Index - NDVI (-1: Bare soil or unhealthy vegetation to +1: Healthy vegetation)
	Tree Density
	Distance from Protected areas (Natura2000)
	Distance from rivers

In addition, post-fire management plans of burned areas were examined, prepared, and implemented following a decision by the Council of Ministers by the DoF, the competent authority for forest fires. The post-fire management plans for the burnt areas provided by the DoF involved restoration actions for two fire events: the Soleas fire (19/6/2016) and the Argaka fire (18/6/2016). These plans aim to define the appropriate manipulations and spatial and temporal analysis of the measures to restore the pre-existing forest ecosystem and re-establish the forest's regulatory functions over time.

Based on Post-Fire Management Plans, restoration measures are usually divided into two main categories:

A. Short-term measures: These measures begin immediately and must be largely completed, within a short period of time after the forest fire is extinguished. The effectiveness of these measures can be observed in a relatively short period after their completion

B. Medium-term measures: These measures can be started at the same time with the short-term measures but may be completed over an extended period. Also, their effectiveness is expected to be realized over a longer time compared to short-term measures.

2.1.2 Data Collection

Based on the information gathered from the post-fire management plans and the discussions with the DoF, the criteria for developing the model were identified. In addition, the availability of corresponding geospatial data was considered for representing the criteria. Also, it is highlighted that we chose to use factors that could be derived from freely available data, but were also useful for the determination of the areas with restoration needs.

I. **Topographic information**

Topography influences both surface runoff dynamics and ecological patterns (Khoirunisa et al., 2021; Yilmaz et al., 2023). Lower elevation presents slower flow rates compared to higher elevations, leading to water accumulation in valleys, which can impact climate conditions, vegetation types, species distribution, and ecological recovery (Lu et al., 2020). Steeper slopes present unique challenges, including higher risks of soil erosion, increased water runoff speed, and changes in soil moisture retention, all of which influence tree species selection and survival rates, (Jiang et al., 2019; Marden, 2012) as well as complicated logistics (Hazarika et al., 2021). Apart from that the steep areas presents higher risk to landslides and floods(Morales et al., 2021). Additionally, the aspect can influence microclimate conditions like sunlight exposure and moisture levels for example east-facing slopes receive more incoming solar radiation in mountain areas and this help in selecting sites that can support the regeneration of vegetation (Dosis et al., 2023; Pourtaghi et al., 2015).

II. **Land Cover**

The land cover was used because this study focused on restoring forested and vegetated areas(Orsi & Geneletti, 2010).

III. **Vulnerability to wildfire hazards**

In terms of vulnerability to wildfire hazards the analysis considered the burnt 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 the active restoration actions should prioritize ecosystems most heavily impacted by fires(Fernandez et al., 2023; Maillard et al., 2022). Additionally, burn severity influences soil quality and seed bank viability. High-severity fires can destroy seed banks and soil structure, leading to artificial reforestation actions with resilient species, while lower-severity fires might allow for natural regeneration(Shi et al., 2022).

IV. Tree Density

The regeneration of the species and of the forest as well, is dependent in the canopy seed bank (Daskalakou & Thanos, 2004). In this study the tree density was utilized due to the assumption that set, where in denser forest there is larger seed production (Boydak, 2004).

V. Meteorological Factors (mean temperature and total precipitation)

The meteorological factors were selected to identify suitable conditions for the growth of most of the species. For example, high altitudes due to lower temperatures are more suitable for many species. Additionally, the variations of the precipitation and temperature are depended also by the aspect (Cavalcante et al., 2022a).

Table 3: List of main selected indicators and basic information.

Criteria		Source	Spatial Resolution	Processing Steps
Topographic information	Elevation Slope Aspect	SRTM (GEE)	30m	1. Calculates Slope in Degrees. 2. Calculates Aspect in Degrees. 3. Reproject 4. Resample 5. Reclassification
Land Cover		Corine Land Cover	100m	1. Reproject 2. Resample 3. Reclassification
Vulnerability to wildfire hazards	Fire Severity	Sentinel-2 (dNBR)	10m	1. Pre- and post-fire imagery 2. Cloud mask 3. Spectral indices calculation 4. Reclassification
	Fire Frequency	European Forest Fire Information System (EFFIS)	20-250m	1. Load the EFFIS data in GEE 2. Fire frequency calculation 3. Distance from historical fire events 4. Reproject 5. Resample 6. Reclassification
Tree Density		Copernicus: Land	10-20m	1. Load the data in GEE. 2. Reproject 3. Resample 4. Reclassification
Meteorological factors	Temperature	MODIS (Land Surface Temperatur e)	1Km	1. Mean LST for the selected period. 2. Kelvin to Celsius 3. Reproject 4. Resample

				5. Reclassification
	Precipitation	CHIRPS	5566 meters	1. Mean precipitation for the selected period. 2. Reproject 3. Resample 4. Reclassification

2.1.3 Implementation of Multicriteria Analysis Using the Analytical Hierarchy Process

Standardization of the criteria: For this study, several factors were selected for the multi-criteria analysis; each factor has its own units and distribution. To combine factors with the same scale of values (Uribe et al., 2014) the standardization of each factor is performed in this section, as shown in Table 3 where the original values were transformed into comparable units.

Table 3: Reclassification of criteria for the identification of priority areas for natural or artificial reforestation.

Criteria		0	1	3	5	Source
Topographic information	Elevation		0-250	250-500	>500	(Fernandez et al., 2023)
	Aspect (^{O})		N (0-22.5), NE (22.5-67.5), NW (292.5-337.5), N (337.5-360)	E (67.5-112.5), SE (112.5-157.5),	S (157.5-202.5), SE (202.5-247.5), W (247.5-292.5)	(Dosis et al., 2023; Lu et al., 2020)
	Slope (^{O})		0-15	15-25	>25	(Yilmaz et al., 2023)
Land Cover	Corine Land Cover	Water Bodies, Artificial surfaces, Sparse or No vegetation, Wetlands, Agriculture land	Grasslands and Shrublands	-	Forest	(Fernandez et al., 2023; Nurda et al., 2020; Van Duong & Schimleck, 2022)
	Tree Density (%)		>40	20-40	0-20	
Vulnerability to wildfire hazards	Fire history (reoccurrence)		1	2	>3	(Fernandez et al., 2023)
	Fire Severity (dNBR)	<163	163-271	271-439	>439	(Key & Benson, 2006)
Meteorological factors	Precipitation (mm)		>30	25-30	<25	(Bhattacharya et al., 2022)
	Temperature		10-28.95	28.95-32.04	>32.04	(Ali & Ahmad, 2020; Bhattacharya et al., 2022)

Criteria weight: To prioritize areas effectively, criteria sets are quantified, and weights are assigned to determine their significance in decision-making processes. The proposed methodology was conducted utilizing the Analytic Hierarchy Process (AHP). In this method, the AHP is involved in the weighing and ranking of the selected criteria enabling a hierarchical structure that allows the pairwise comparison, making it easier to understand and prioritize the most important aspects of the model based on the Saaty et al.,1977 (T. L. Saaty, 1977) to compare all factors against each other based on their importance on a scale of 1 to 9 as shown in Table 4. The value 1 represents equal importance between two factors, which means that 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 stakeholders' discussion, literature review, and researcher's knowledge.

Table 4: 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, the final qualitative weights were determined using the judgment matrix which is given in Eq. 1 which indicates the degree of the expert's preference between 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.

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

Additionally, to ensure the consistency of the pairwise comparison factors using the Consistency Index (CI) based on Eq. **2**

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

where: λ_{max} = the largest eigenvalue of the pairwise comparison matrix evaluation and n is the number of criteria used in the analysis. The λ_{max} is given by the following equation. In details 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 and in cases where the λ_{max}=n the judgments were consistent.

$$\lambda_{max} = \sum_{i}^{n} CV_{ij}$$

After that, the Consistency Ratio (CR) was calculated based on the Eq. **3** to assess the reliability of the findings compared to the random judgments. According to the CR values when the CR is 0.10 or greater the judgments are considered to be unreliable that means the wight values of the matrix indicate inconsistencies and the AHP may not provide a meaningful result and a lower CR ratio indicates more consistency (T. Saaty, 1980)

$$CR = \frac{CI}{RI} \quad \textbf{3}$$

where: the RI is the Ratio Index and is for different 'n' values that are obtained as shown in Table 5.

Table 5: Random consistency indices.

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 multiplied by their respective criterion weight and after that they are summed as indicated in Eq. **4** and based on this the final map about the prioritization of the areas for reforestation actions was developed.

$$RN = \sum_{i=1}^{n} (w_i * \chi_i) \quad \textbf{4}$$

Where: RN is the Reforestation needs, w_i is the weight for each factor and χ_i is the factor I and the n is the number of factors.

2.2 Evaluation and Ranking of Results

The evaluation of the model was conducted using the sensitivity analysis technique. Given that the use of weights can introduce subjectivity, a sensitivity analysis was incorporated to quantify the impact of variations in specific inputs on the overall outcomes. This analysis provides insights into the influence of each weight on the final results. The weight values were adjusted one at a time by ±5% starting from 0 to ±20%, and the area of each class was calculated (Saltelli et al., 1999).

The proposed methodology was tested in the Solea and Argaka fire events. The findings of this study are categorized into three main groups: a) the outcomes of the AHP analysis and spatial suitability maps, b) the sensitivity analysis and c) the validation of the results in the test area. These key insights are presented as follows:

- **Analytical Hierarchy Process (AHP) results and suitability maps:**

A pair-wise comparison was conducted among all pairs of the nine selected parameters for the calculation of the weight assigned to each factor. Then, the comparison of the parameters based on their importance in forest restoration actions was implemented with the method proposed by Satty et al., 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 7.

Table 7: Pairwise comparison between the nine criteria involved in the post-fire restoration.

	Fire Severity	Fire History	Tree Density	Corine Land Cover	Slope	Elevation	Aspect	Precipitation	Mean Temperature
Fire Severity	**1.00**	5.00	2.00	3.00	5.00	7.00	7.00	5.00	5.00
Fire History	0.20	**1.00**	0.33	0.33	3.00	4.00	4.00	3.00	3.00
Tree Density	0.50	3.00	**1.00**	2.00	6.00	7.00	7.00	5.00	5.00
Corine Land Cover	0.33	3.00	0.50	**1.00**	5.00	6.00	6.00	4.00	4.00
Slope	0.20	0.33	0.17	0.20	**1.00**	2.00	2.00	0.33	0.33
Elevation	0.14	0.25	0.14	0.17	0.50	**1.00**	1.00	0.33	0.33
Aspect	0.14	0.25	0.14	0.17	0.50	1.00	**1.00**	0.33	0.33
Precipitation	0.20	0.33	0.20	0.25	3.00	3.00	3.00	**1.00**	1.00
Mean 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 utilizing the eigenvector solution method, where, in our case, the largest eigenvalue was calculated to be 9.761. The corresponding CI was 0.095, which confirms 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 a 7% using the RI equal to 1.45 for the case of nine different factors. This is below the commonly accepted threshold of 10%, indicating that the pairwise comparisons conducted were reliable and consistent.

Overall, the results obtained using the AHP demonstrate a well-structured consistent decision-making process supporting the reliability of the findings. Based on the AHP, the derived weights are the following: the fire severity has the higher importance in the model, achieving a weight of 29.4%, showing the dominant role in the prioritization of 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. Additionally, the climatic factors, precipitation (6.10%), and mean temperature (6.20%) also played a notable role. Moreover, the topographic features, slope (3.8%), elevation (2.50%), and aspect (2.60%) had less influence on the model but remained relevant in guiding the reforestation actions. The higher the weights, the more the influence of the parameters on the post-fire restoration needs based on the relative importance. The weights derived from the normalized pairwise comparison matrix 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 is categorized into three classes (Low, Medium and High). Low and medium priority correspond to areas that have the potential for natural recovery respectively, while high priority areas require artificial restoration actions. The model was applied to a polygon encompassing 102.96 km2 covering both the burnt and the surrounding regions.

$$\begin{aligned} GreenHIT - RESTORATION\ Index\ (GRESTO) \\ &= 3.8\ \times SLOPE + 2.5\ \times ELEVATION + 2.6\ \times ASPECT + 29.4\ \times dNBR \\ &+ 10.1\ \times FIRE\ FREQUENCY + 16.9\ \times LAND\ COVER + 6.2\ \times\ LST \\ &+ 6.1\ \times PRECIPITATION + 22.4 * TREE\ DENSITY \end{aligned}$$

Eq. 5

Additionally, the map developed based on the GRESTO index for the Solea fire event is presented in Figure 6. The analysis shows that within the selected polygon, the majority of the area (82%) is classified as low priority, while moderate and high priority areas consist of 13% and 5% respectively. When focusing specifically on the burned area, the most significant area (52%) falls within the medium priority category, followed by high priority 38% and low priority 10%. According to the restoration actions that were implemented in the Solea fire event by the DoF, 4.12% of the burned area was unburned. Regarding the restoration action, 71.54% was selected to recover naturally, while in the remaining part of the burned area restoration actions like spot sowing, planting, broadband seeding etc were implemented Table 6.

Similarly, for the Argaka fire event, as shown in Figure , the selected polygon is mainly classified as low priority (80%), with high priority and medium priority areas representing 11% and 9% respectively. However, when examining only the burned area, the largest part (52%) corresponds to high priority, followed by medium priority (40%) and low priority (8%). Moreover, according to the restoration actions that were implemented in the Argaka fire event by the DoF, only 0.59% of the burned area was unburned. Regarding the restoration action, a small part 4.62% was selected to recover naturally, while in the remaining part of the burned area (94.79%) restoration actions were implemented as shown in Table 6.

Table 6: Percentage of area cover per reforestation method for Solea and Argaka fire events.

Solea		Argaka	
Reforestation method	Percent area per reforestation method (%)	Reforestation method	Percent area per reforestation method (%)
Natural Regeneration	71.54	Natural Regeneration	4.62
Spot Sowing	11.22	Spot seeding	24.45
Broadhand seeding	9.52	Broadhand seeding	12.01
Planting	1.22	Terraces - Planting	2
Terraces – Planting or Seeding	2.38	Terraces - Spot seeding	49.36
Unburned	4.12	Unburned	0.59
		Mini terrace - Seeding	6.74
		Coppicing	0.23

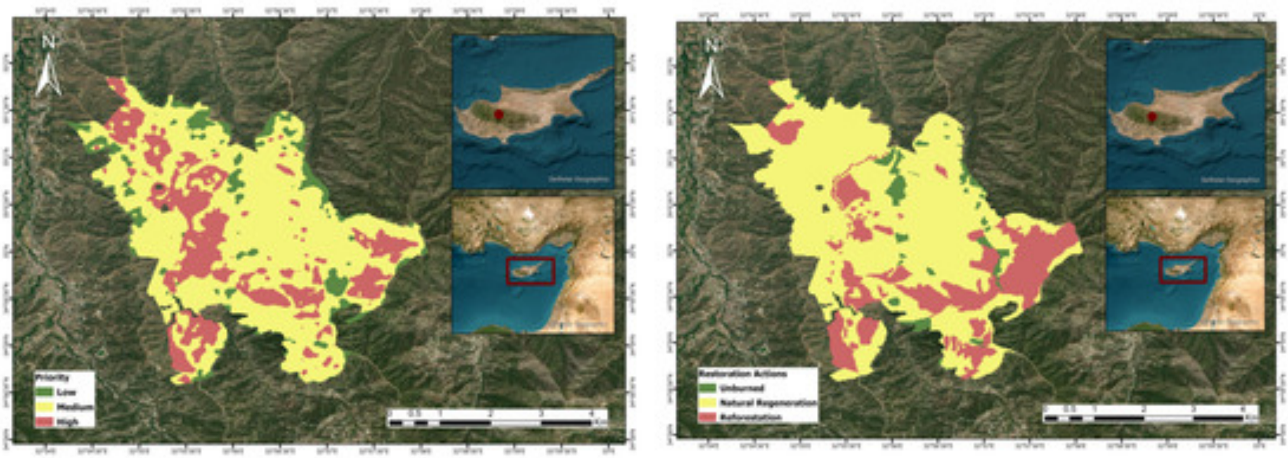


Figure 6: Prioritization of reforestation needs map derived from GRESTO Index for Solea fire event.

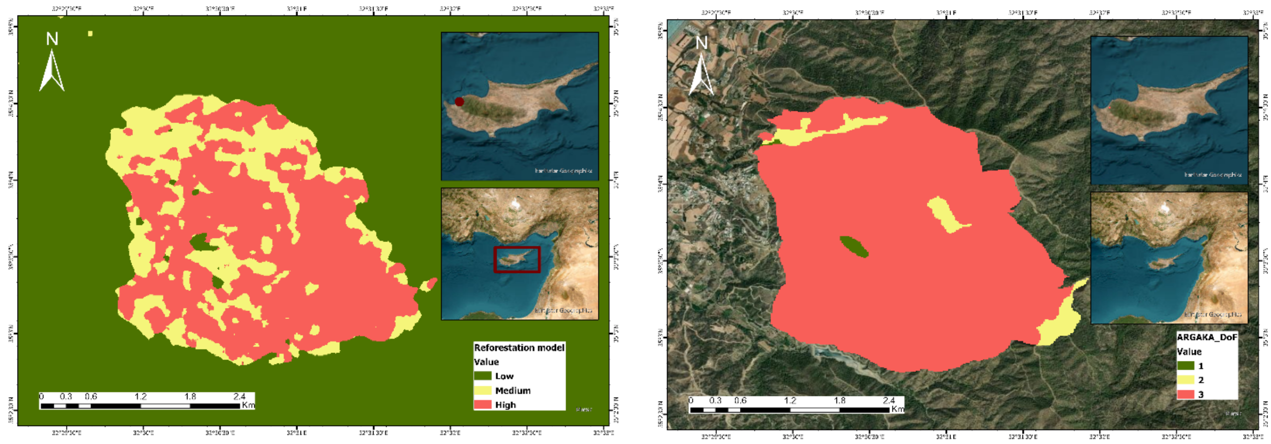


Figure 8: Prioritization of reforestation needs map derived from GRESTO Index for Argaka fire event

- **Sensitivity Analysis**

In this study, a sensitivity analysis was conducted to evaluate the robustness and the reliability of the results since the use of the weights can be subjective. This analysis provides insights regarding the influence of each weight on the final model. The weight values were adjusted using the One At a Time (OAT) approach, which is based on the sequential adjustment of the criteria weights. Specifically, the nine selected criteria used for the development of the GRESTO Index were adjusted one at a time by ±20% starting from 0 to ±100%. Based on this approach there are a maximum of 99 interchanges in the weights' adjustments during the sensitivity analysis. Figure represents the areas corresponding to each priority class (low, medium and high) for all scenarios.

Based on the heatmap for the low-priority class (represented in green color) which corresponds to the areas that are not affected by fire or have low impacts that do not require immediate interventions, the results show 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 color), where the area is expected to recover naturally demonstrates moderate sensitivity to weight adjustments. Specifically, the land cover and the fire frequency show a significant influence on the area distribution highlighting their importance in the model and especially in identifying areas suitable for natural restoration. About the high priority class (represented in red color), which corresponds to severely affected areas requiring urgent restoration actions shows the highest sensitivity to parameter weight adjustment, especially for the land cover, the fire frequency and the dNBR index showing the important role in the identification of areas that need artificial restoration actions.

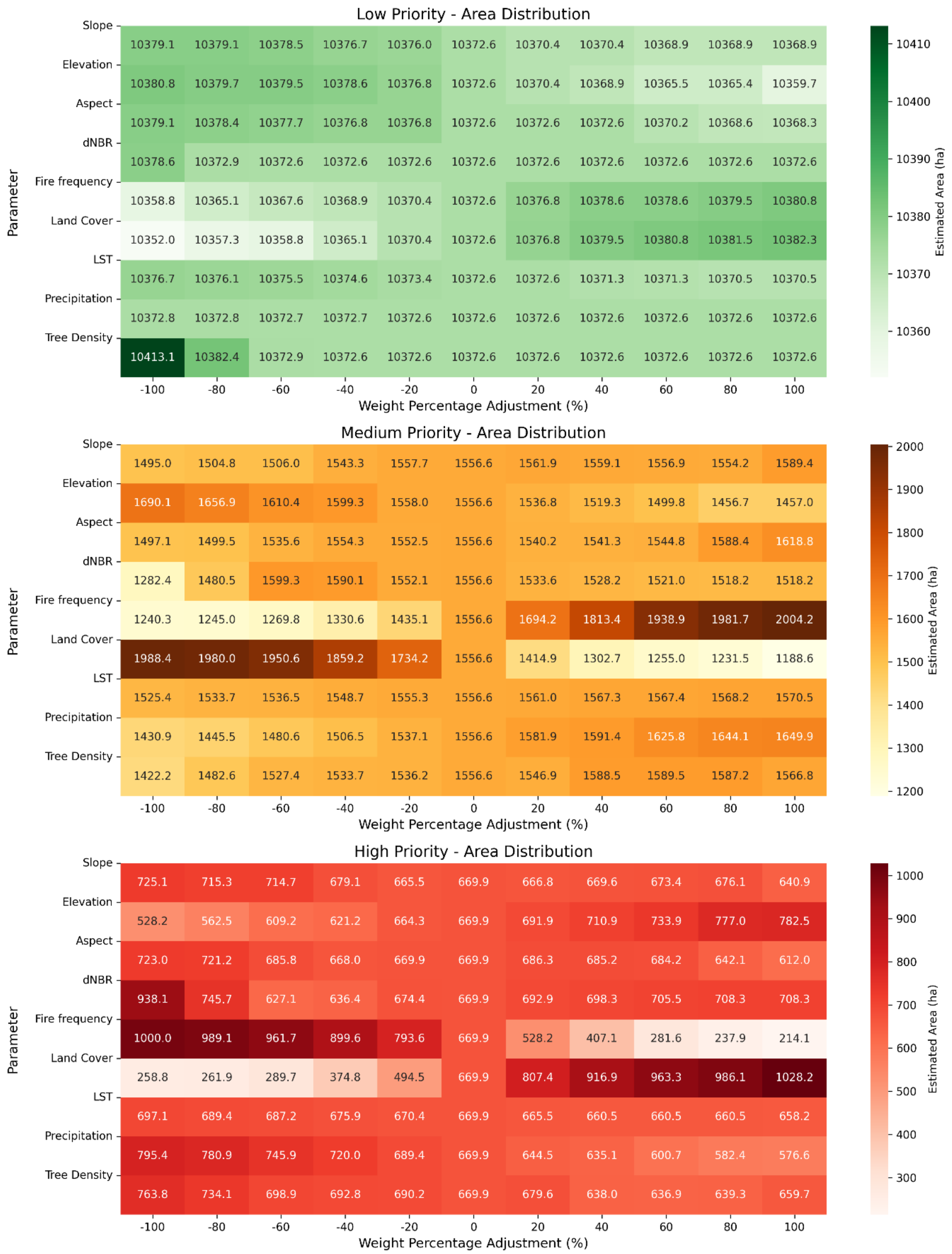


Figure 9: Area distribution based on weight percentage adjustment per parameter for Solea fire event.

Regarding the Argaka case study as shown in

Figure the heatmap for the low-priority class indicates a high degree of stability, with minimal variations in area distribution across the range of weight adjustments for the majority of the parameters indicating low sensitivity to weight modifications. In contrast to the low-priority class, the medium-priority class demonstrates moderate sensitivity to parameter weight adjustments. The most influential factors in area distribution are land cover, fire frequency, and dNBR. Also, the high-priority class presents the highest sensitivity to parameter weight adjustments. Specifically, the land cover, fire frequency, and dNBR show substantial changes in area distribution across the adjustments. Compared to the Sole case study, the Argaka results show similar trends with the low-priority class presenting high stability and the medium and high-priority classes displaying greater sensitivity to parameter adjustments. The influence of land cover, fire frequency, and dNBR across both case studies highlights the pivotal role in post-fire restoration actions and decision-making.

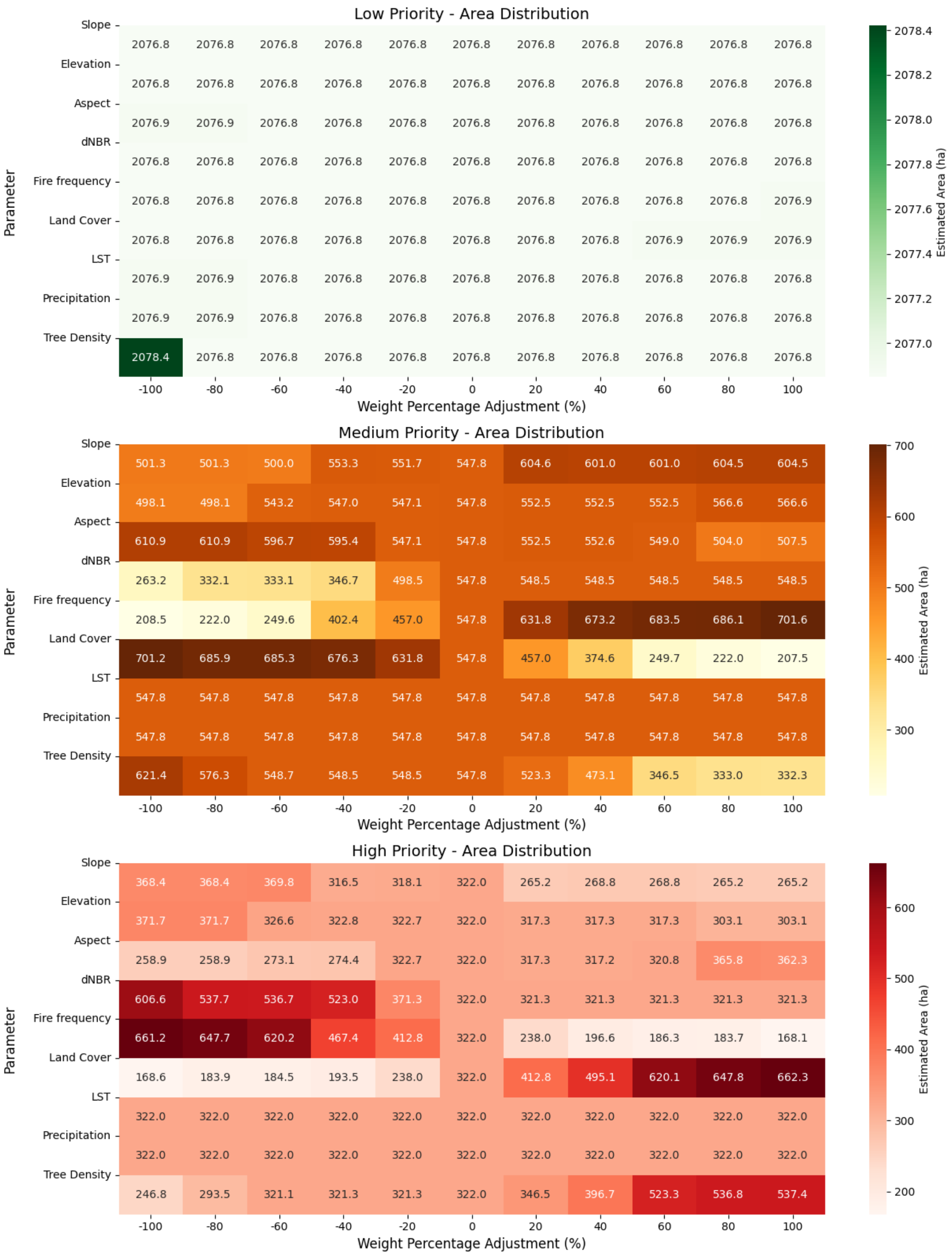


Figure 10: Area distribution based on weight percentage adjustment per parameter for Argaka fire event.

Moreover, to enhance the sensitivity analysis, Cumulative Distribution Functions (CDFs) were generated for the feasibility scores of the GRESTO Index, showing the behavior of the index under the different weight adjustments for each parameter. These CDF plots provide additional insights for the distribution of feasibility scores for the index showing the stability and the sensitivity of the model. 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 the comparative analysis of their impact. The visualization of the sensitivity analysis for Solea case study which is presented in Figure **Error! Reference source not found.** showed that Slope, Elevation, Aspect, LST, and Precipitation parameters are less sensitive indicators. Their CDF curves show close overlaps indicating that changes in the weight associated with these indicators have a minimal impact on the prioritization model. In contrast, the most sensitive indicators are dNBR, fire frequency and the land cover which have high variability, especially in the larger weight adjustments showing their significant influence on the model outcomes. Additionally, the tree density displays medium variability in the model showing also its importance in the model.

The same analysis was conducted also for the Argaka case study as presented in Figure , showing similar patterns with Solea case study. Specifically, the Elevation, Aspect, LST and Precipitation also demonstrated minimal sensitivity, with closely overlapping CDF curves across different weight adjustments. However dNBR, fire frequency and land cover remained the most sensitive indicators, showing substantial variability and significant influence on the feasibility score distribution. Tree density also showed medium sensitivity in Argaka, emphasizing its moderate impact on the feasibility scoring process.

Overall, both case studies show the critical role of fire-related parameters (dNBE and fire frequency) and land cover as primary drivers of variability in feasibility scoring, while topographic factors and climatic parameters demonstrate more stable behavior.

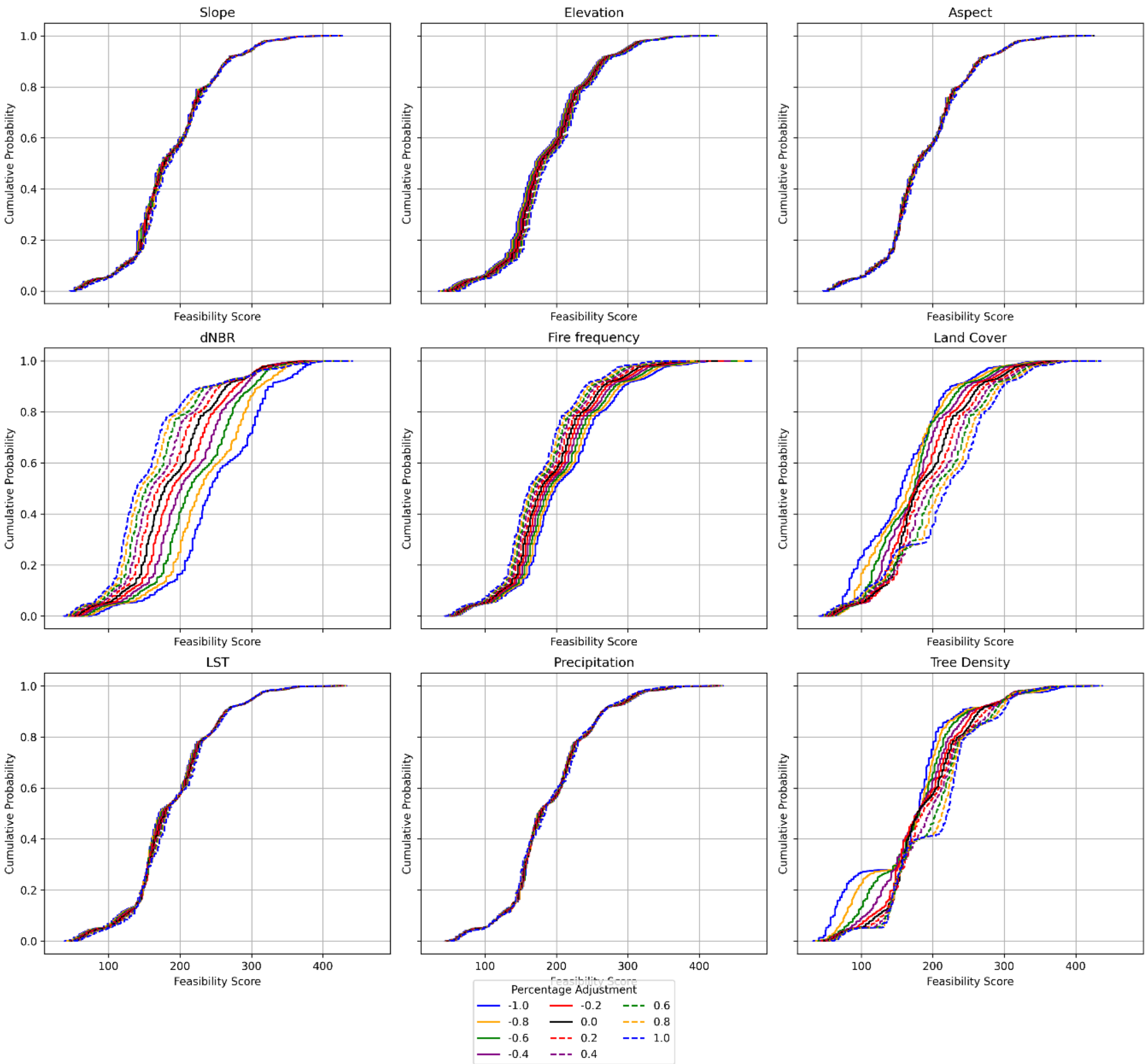


Figure 11: Cumulative distribution of feasibility scores by weight index for Solea fire event.

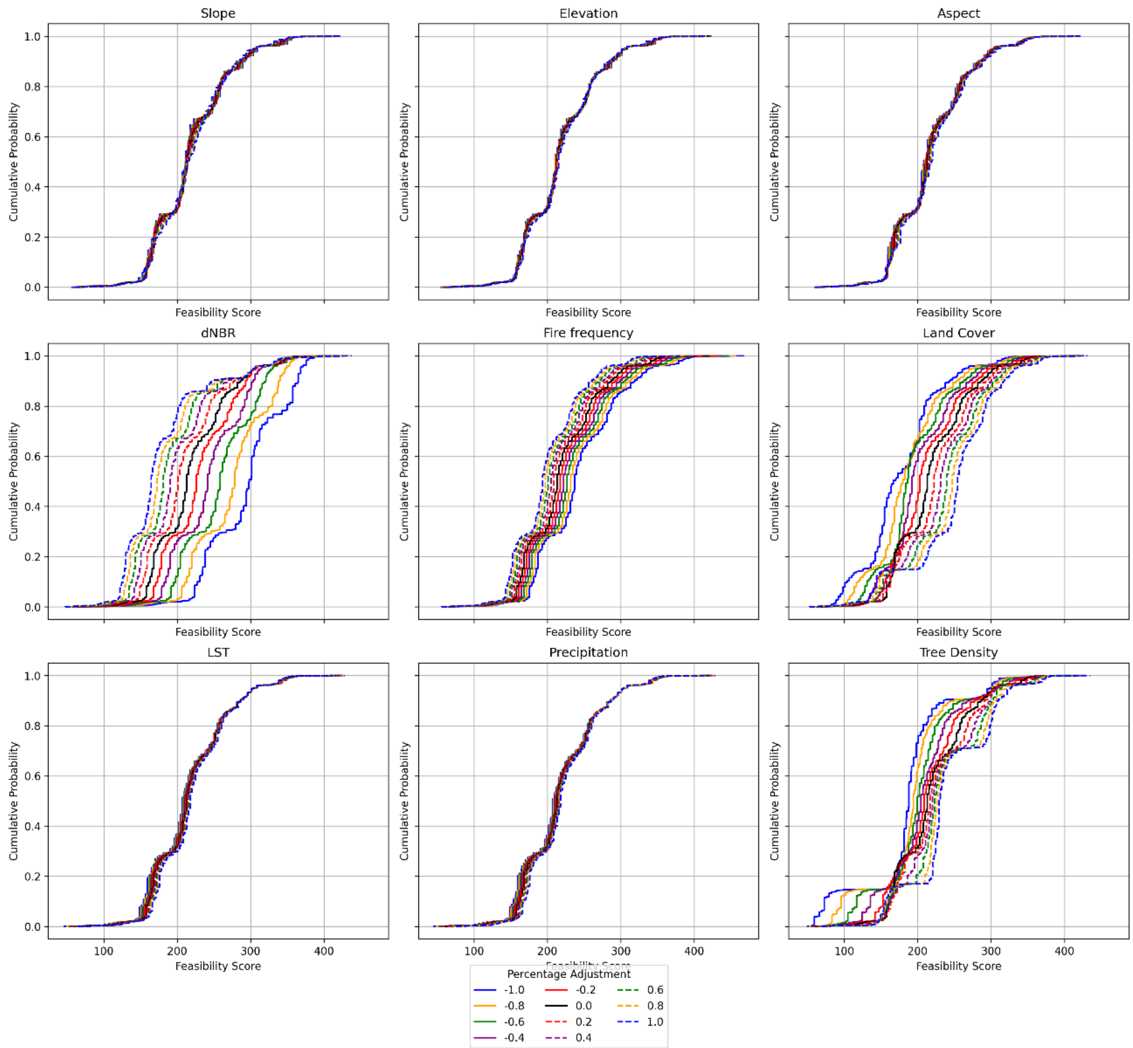


Figure 12: Cumulative distribution of feasibility scores by weight index for Argaka fire event.

- **Validation of the model:**

The accuracy assessment based on the confusion matrix that was created showed a very good correlation of the model in determining the prioritization of reforestation for the Solea fire event. As mentioned above, the evaluation was carried out by comparing the results of the model with ground data provided by the Department of Forests.

Based on the confusion matrix that was created, it appears that the model agrees with the terrestrial data. Specifically, the model achieves an overall accuracy of 80.9%, indicating substantial agreement. Moreover, the precision, recall, and F1-scores were examined for each class to evaluate the model's performance. For the low-priority class, the model showed a precision of 0.53 and a perfect 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, a recall of 0.84, and an 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.

Regarding Argaka fire event, the model achieves an overall accuracy of 72.3%, indicating substantial agreement. Moreover, the precision, recall, and F1-scores were examined for each class to evaluate the model's performance. For the low-priority class, the model showed a precision of 0.15 and a perfect recall of 0.77, and the F1-score was 0.25. This indicated a high sensitivity in distinguishing low-priority areas with low reliability in this case. The medium-priority class showed medium classification performance, with a precision of 0.14, a recall of 0.81, and an F1-score equal to 0.25 and for the high-priority class, the model achieved a precision of 0.98, but a recall of 0.72 and an F1 score of 0.83, suggesting a relatively balanced performance in identifying high-priority zones.

3. Limitations

There are some operational limitations regarding the tool for identifying degraded areas. Regarding the maximum allowed area for processing, it is limited to 4,000 km². Beyond this limit, the algorithm may not produce results, presenting an error in the following manner *"ee.ee_exception.EEException: User memory limit exceeded."*. Additionally, users can expect a processing time of approximately 5 to 10 minutes to retrieve results, depending on the selected area and timeframe. Additionally, to avoid seasonal effects and enhance the reliability of the results, it is recommended to perform analyses using images selected from dates between May and October, especially for the deforestation module. Another limitation concerns data availability. Since the algorithm utilizes Sentinel-2 harmonized data, the methodology is only valid for dates after April 1, 2018 Figure 7.

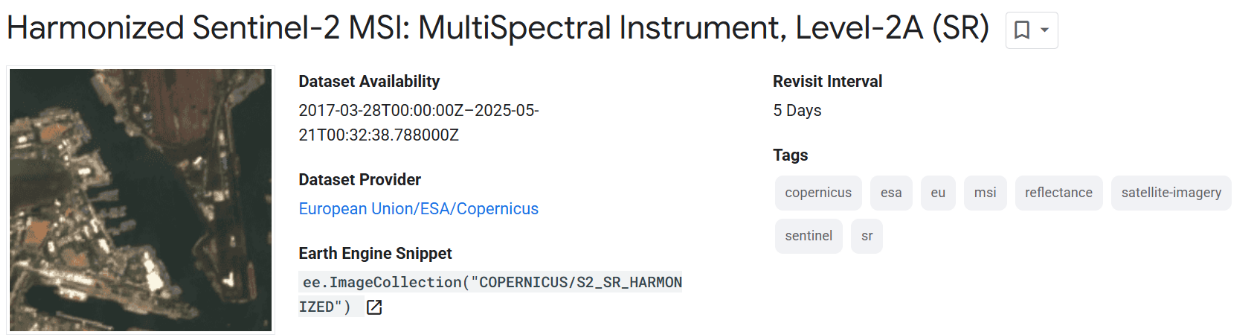


Figure 7: Data availability for Sentinel-2 Harmonized.

4. 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.

Although the GRESTO index was applied and validated in two specific fire events in Cyprus (Solea and Argaka), the structure and design of the model support its potential for generalization and wider application across the country. The use of standardized and freely available geospatial datasets (e.g. Sentinel-2, MODIS, CHIRPS, SRTM, Copernicus) ensures consistent data coverage for any fire-affected area within Cyprus. Furthermore, the spatial and temporal flexibility of the model - achieved through the dynamic parameterization of the region of interest (roi), the fire date (startdate_post) and the adaptive criterion weights - allows its deployment in different geographical contexts and post-fire scenarios without structural modifications.

While the model was evaluated using ground reforestation data provided by the Department of Forests, for the Solea and Argaka events only, its successful performance, especially in the case of Solea (accuracy: 80.9%), demonstrates its robustness under realistic field conditions. The lower accuracy observed in the Argaka case highlights the need for additional site-specific validation, without, however, undermining the conceptual soundness of the model or its spatial scalability.

It is important to note, however, that a perfect match between the model predictions and the implemented restoration actions cannot always be expected. In some areas identified by the model as high priority, restoration activities may not have been implemented due to limited resources, inaccessibility, or operational constraints. Conversely, some areas where restoration actions were implemented may not have been classified as high priority by the model, possibly due to management decisions influenced by political, economic, or local ecological parameters. These discrepancies highlight the role of the model as a decision support tool rather than a prescriptive solution.