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.

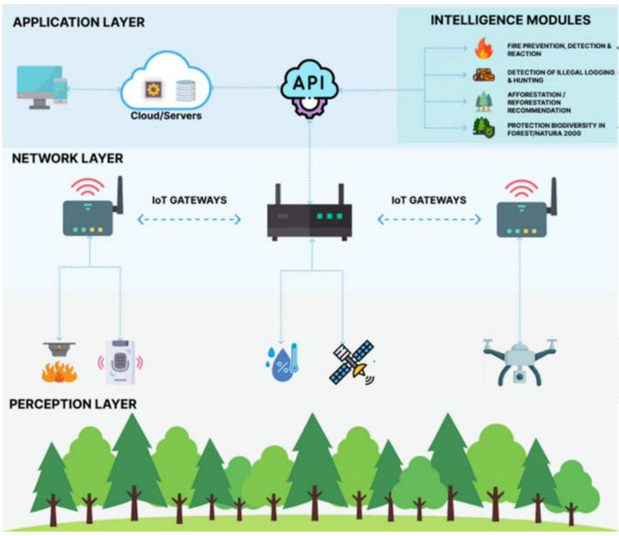

Figure 1 The architecture of the Green-HIT platform for forest management and monitoring.

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 (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(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	$\frac{\boldsymbol{2.5(NIR - RED)}}{\boldsymbol{NIR + 6\,RED - 7.5BLUE + 1}}$	(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 as described by (Prodromou et al., 2025). 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, 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.

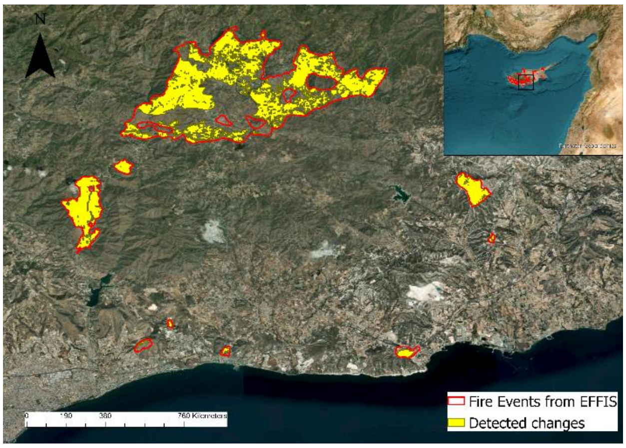

Figure 3 Comparison between the changes detected by the change detection model with EFFIS burned areas.

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.

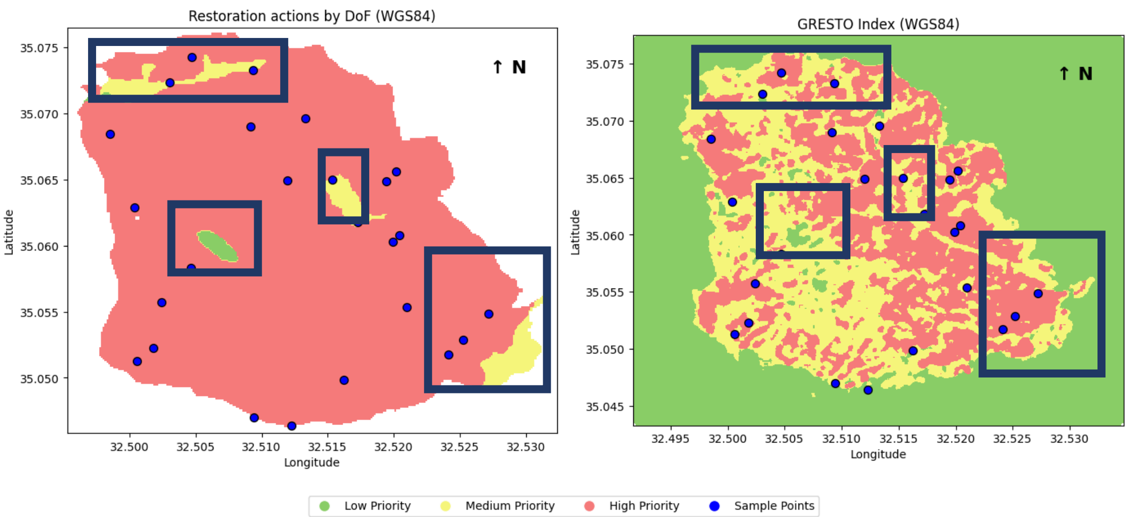

Figure 4 Priority of reforestation actions in Argaka fire event/

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.

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). 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.

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*.

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

IUCN. (2018). *Getting Started with the Bonn Challenge* (Vol. 1, Issue 866). https://www.bonnchallenge.org/

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., Mettas, C., Tzouvaras, M., Themistocleous, K., Konstantinidis, A., Pamboris, A., & Hadjimitsis, D. (2025). Remote-Sensing-Based Prioritization of Post-Fire Restoration Actions in Mediterranean Ecosystems: A Case Study in Cyprus. *Remote Sensing*, *17*(7), 1269. https://doi.org/10.3390/rs17071269

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., 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. (1980). The analytic hierarchy process (AHP) for decision making. *Kobe, Japan*, *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