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Research Article

Application of remote sensing and clustering for the sustainable management of green oak forests in western Algeria

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Abstract

The identification of ecologically homogeneous zones is crucial and represents one of the key steps in ecosystem planning, management, and restoration. It allows targeted ecological restoration efforts based on the interactions between environmental factors. The approach of this study is pixel-based to identify ecologically homogeneous zones within the green oak forest in Elhassana area, western Algeria. This approach uses remote sensing indicators such as the normalized difference vegetation index (NDVI), leaf area index (LAI), soil-adjusted vegetation index (SAVI), normalized difference moisture index (NDMI), elevation, slope, aspect, relative slope position (RSP), and topographic wetness index (TWI), derived from Landsat 8 and Terra/ASTER satellite imagery to identify homogeneous zones. We use principal component analysis (PCA) to reduce the dimensionality of the data and identify the most important variables. This analysis helps to better understand the structure of the data and determine which variables have the most influence on the unsupervised classification using the iso cluster algorithm. The results of this study allowed us to visualize and map four types of homogeneous zones and characterize their ecological attributes. This information is invaluable for forest planners, enabling sustainable environmental management and the development of an ecological restoration plan for the green oak forest.

Keywords: Algeria; forest; GIS; homogeneous zones; PCA; remote sensing

Introduction

Green oak forests represent a crucial forest heritage in the mediterranean basin (Daoudi *et al.*, 2023). They are primarily located in north Africa, particularly in Morocco and Algeria, where they play a fundamental role alongside pine forests in shaping local woodlands. In Algeria, the potential area of green oak forests is estimated at approximately 1,807,000 hectares (Quezel and Barbero, 1990). In 1955, they covered nearly 700,000 hectares (Boudy, 1955). Currently, their coverage has been reduced to only 354,000 hectares

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(B.N.E.F., 1984), or even 108,200 hectares, representing a decline of 50% to 85% within 30 years. This alarming regression is attributed partly to the ongoing pressures of the mediterranean climate and human activities (Cos *et al.*, 2022; Djellouli *et al.*, 2024; Dondo *et al.*, 2024), and partly to the current population explosion in the country (M.A.T.E., 2000).

The green oak forest in Saida province is a plant community dominated by green oak, associated with woody species such as *Juniperus oxycedrus*, *Phillyrea angustifolia*, *Pistacia lentiscus*, and *Pistacia terebinthus*. The shrub and sub-shrub layers include species such as *Globularia alypum*, *Genista erioclada*, *Cistus villosus*, *Stipa tenacissima* L., *Artemisia herba-alba*, and *Cytisus triflorus*. The herbaceous layer is composed of *Launea resedifolia*, *Leuzea conifera* L., *Centaurea melitensis* L., *Valeriana carinata*, *Asperula cynanchica* L., and *Rubia peregrina* L. (Terras, 2011; Djebbouri and Terras, 2022; Djebbouri *et al.*, 2022). The preservation and ecological restoration of this oak forest are essential to maintaining the diversity and health of this unique ecosystem.

Ecological restoration is a deliberate intervention aimed at initiating or accelerating the natural regeneration of a degraded, damaged, or destroyed ecosystem (Balensiefer *et al.*, 2004). This approach focuses on the overall health of the ecosystem, its integrity, and the application of sustainable management principles to ensure its long-term resilience. To develop an ecological restoration plan for the green oak forests in the El Hassasna region, located in the Wilaya of Saida in western Algeria, it is essential to identify ecologically homogeneous zones. This step is a cornerstone of ecosystem planning and management, as it enables the alignment of restoration efforts with the specific interactions between environmental factors (Nabati *et al.*, 2020; Navidi *et al.*, 2023).

To achieve this objective, we adopted a pixel-based method to identify ecologically homogeneous zones. This method uses vegetation indices such as NDVI, SAVI, LAI, and NDMI, derived from Landsat 8 satellite imagery. It also integrates topographic data, including elevation, slope, aspect, relative slope position (RSP), and the topographic wetness index (TWI), obtained from Terra/ASTER data.

The pixel-by-pixel remote sensing data analysis approach allows for the precise identification of ecologically homogeneous zones (Sardooi *et al.*, 2019). This method involves examining each pixel in a satellite or aerial image to classify various environmental features such as vegetation, soils, and moisture. The pixels, representing small surface units, are then grouped based on their spectral similarities to delineate homogeneous zones (Jensen, 2009; Latt *et al.*, 2015). We used principal component analysis (PCA), a multivariate statistical method that reduces the number of variables and identifies hidden relationships between them. This method is commonly used for geospatial data analysis, including the determination of ecologically homogeneous zones (Petrişor *et al.*, 2012). For this analysis, we employed geographic information system (GIS) software and PCA using ARC GIS 10.8.2, utilizing the principal components tool available in the spatial analyst toolbox in ArcMap. Additionally, we applied the Iso Cluster unsupervised classification tool to identify clusters of similar pixels.

Through our study, we aim to identify and map ecologically homogeneous zones within the green oak forest ecosystem, with the aim of developing an ecological restoration plan to return this ecosystem to its climax state according to Peng *et al.* (2023).

Materials and Methods

Study area description

The green oak forest of Elhassasna is located in northwestern Algeria, between longitudes 0°23′30″ and 0°27′30″E and latitudes 34°39′30″ and 34°51′30″N. It is considered one of the most significant natural green oak forests, covering an area of 30,000 hectares (Figure 1). Its topography varies between 1005 meters and 1336 meters. The area is characterized by a semi-arid continental climate, with rainy and cold winters and hot, dry summers. Dry periods extend over approximately five months (Djebbouri, 2020). This region mainly consists of green oak coppices, often appearing as medium to dense scrub or medium-height coppices of about 3 meters, which is the result of overexploitation and repeated fires (Terras, 2011; Allam *et al.*, 2020; Djellouli *et al.*, 2024; Matougui and Zouidi, 2024). The diversity of species present in this area is remarkable and forms the foundation of all forest formations in the region. In the Saida Mountains, it is essential to highlight the crucial role of low green oak formations in preserving forest cover (Terras, 2011; Djebbouri *et al.*, 2022; Aouadj *et al.*, 2023).

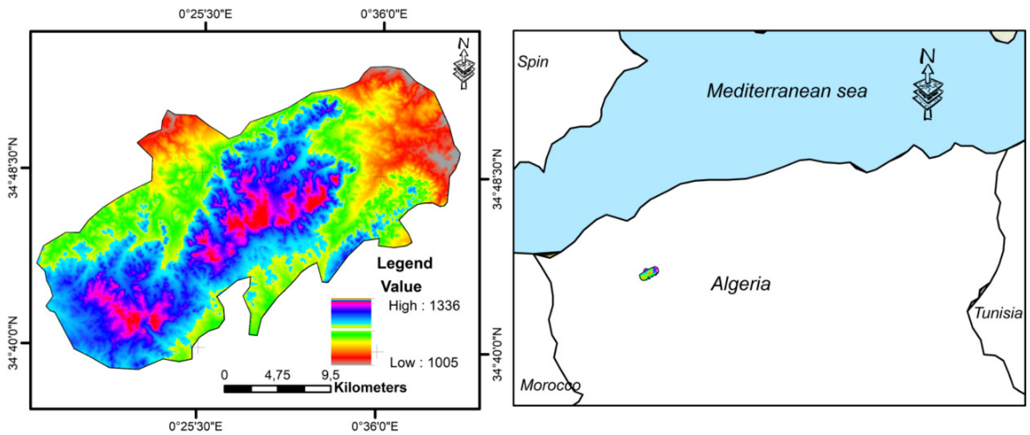

Figure 1. Location of the study area

Methodology

This study employed a five-step methodology, as depicted in Figure 2: (i) Remote sensing data collection; (ii) Extraction of indices, including those derived from Landsat 8 and the digital elevation model (DEM); (iii) Data normalization; (iv) Principal component analysis (PCA); and (v) Creation of a map of ecologically homogeneous zones. The analysis was conducted using geographic information system (GIS) software and PCA in ArcGIS 10.8.2, utilizing the principal components tool available in the spatial analyst toolbox in ArcMap, along with the iso cluster unsupervised classification tool to identify clusters of similar pixels.

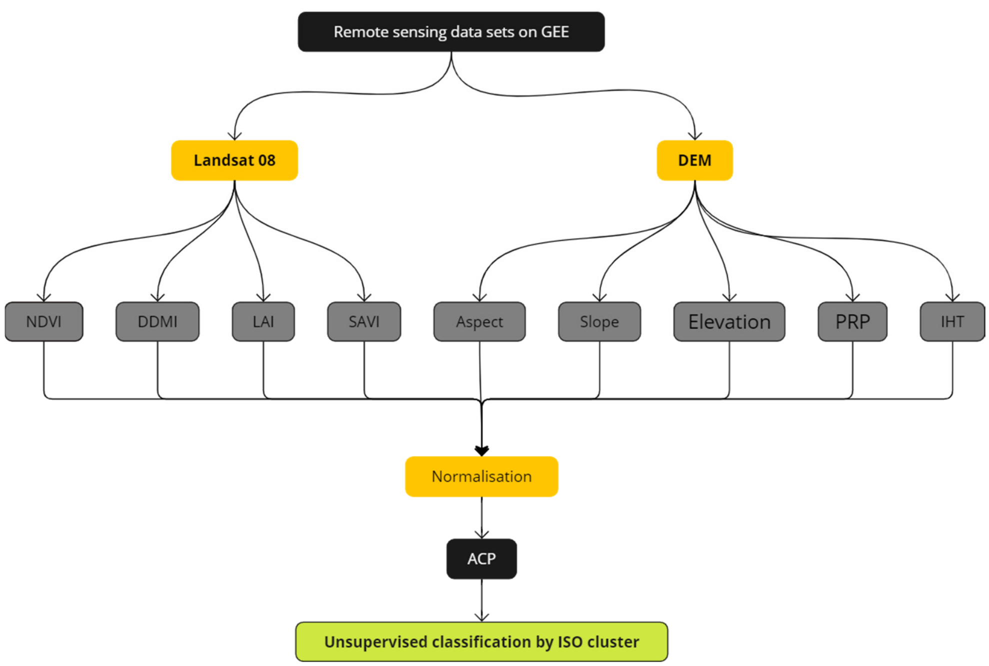

Figure 2. Diagram of study methodology

Data collection and extraction

The remote sensing data includes nine indices derived from Landsat 8 and Terra/ASTER satellite imagery: normalized difference vegetation index (NDVI)(1), leaf area index (LAI)(2), soil-adjusted vegetation index (SAVI)(3), normalized difference moisture index (NDMI)(4), altitude, slope, aspect, relative slope position (RSP)(5), and topographic wetness index (TWI)(6) according to the formulas shown in Table 1.

The indices derived from Landsat 8, during the summer period at the end of July 2021, were used to avoid vegetation cover from seasonal plants. This data, downloaded via google earth engine platform (GEE), is georeferenced, cloud-free, and atmospherically corrected, with a resolution of 30 meters. After calculating four indices for each image (NDVI, LAI, NDMI, and SAVI), a pixel-by-pixel mean (Choubin *et al.*, 2017) of the indices from the end of July 2021 was calculated using raster calculation tools in the ArcGIS 10.8.2 environment.

The indices derived from the digital elevation model (DEM) Terra/ASTER (Tachikawa *et al.*, 2011), with a resolution of 30 meters, were also downloaded via the Google Earth engine platform (GGE). We extracted five topographic indices: slope, aspect, altitude, topographic wetness index (TWI), and relative slope position (RSP), using ArcGIS 10.8.2 software.

Table 1. Formulas for the indices

Formulas	Index
NDVI = (NIR - Red) / (NIR + Red)	(1)
LAI = –ln [(0.69 – SAVI) / 0.59)] / 0.91	(2)
SAVI = (1 + L) (NIR – Red) / (L + NIR + Red)	(3)
NDMI = (NIR - MIR) / (NIR + MIR)	(4)
RSP = $\left(\frac{Z-Zv}{Zr-Zv}\right) * 100 + 0.5$	(5)
TWI = $\ln \frac{As}{\tan \sigma}$	(6)

Where, L is a soil-related function that ranges between 0 and 1. A value of 0 indicates dense vegetation, whereas a value of 1 represents sparse vegetation (Allen *et al.*, 2002). The near-infrared (NIR) band corresponds to wavelengths of 0.841–0.876 µm, the red band covers 0.620–0.670 µm, and the mid-infrared (MIR) band spans 1.628–1.652 µm, as captured by the MODIS sensor.

Normalization

Before conducting the principal component analysis (PCA), normalization was performed to eliminate the effects of different units present in the datasets (Choubin *et al.*, 2017). The variables were normalized on a scale of 0 to 1 to ensure uniform comparability across all indicators. This step was completed using ArcGIS 10.8.2.

Principal Component Analysis

We worked with nine quantitative variables representing the various raster layers, including NDVI, SAVI, NDMI, LAI, slope, aspect, altitude, RSP, and TWI. To reduce the dimensionality of this set of variables and to identify new meaningful components, we opted for principal component analysis (PCA) (Johnson and Wichern, 2002). The goal of PCA is to transform correlated variables into a reduced number of uncorrelated variables, thus simplifying the representation while preserving the essential information contained in the initial set. These analyses were conducted using ArcGIS 10.8.2 with the multivariate tool (Campbell and Wynne, 2011).

Applying the PCA technique allows for more efficient exploration of the complex relationships between various spatial variables, fostering a deeper understanding of the data structure. This approach can also be extended to perform spatial and temporal analyses of multidimensional data, such as time series, providing a more comprehensive perspective on the evolution of variables in both space and time (Tran *et al.*, 2002).

The selection of principal components to retain from the extracted components was based partly on subjective judgment as well as on the components' interoperability. Additional retention criteria were established based on the elbow test, also known as the "scree-test" (variance accumulation test by Cattell, (1966). The scree-test helps to observe the variation of eigenvalues based on their order of extraction. Introduced by Cattell in 1966, this test is useful for determining the point at which adding more components no longer significantly contributes to explaining the variance in the data. By examining the graph of eigenvalues relative to their order, we can identify the point where the slope of the curve (the "elbow") becomes less steep, indicating the optimal number of principal components to retain. These objective criteria, combined with subjective considerations and component interoperability, were used to select the most significant principal components in our analysis (Simard *et al.*, 2021).

Unsupervised ISO cluster classification

Unsupervised classification techniques group pixels based on their similarity in index values. Homogeneous zones are then determined from the groups of pixels identified through this analysis (Sublemontier, 2012). ISO cluster classification, an automated method available in ArcGIS, automatically detects and classifies pixels with similar characteristics within an image (Turmine *et al.*, 2012). This method is based on the iso cluster clustering algorithm (Xu and Wunsch, 2005), widely used in remote sensing and geographic analysis.

Unsupervised iso cluster classification (Isodata) for principal component analysis (PCA) is an approach used to group data into homogeneous clusters from the principal components obtained through PCA. The ISO algorithm is an iterative method that initially assigns data to clusters, then adjusts these clusters over iterations to minimize intra-cluster variations and maximize inter-cluster variations.

These unsupervised classification methods group pixels based on their similarity in terms of index values. Homogeneous areas can then be identified from the pixel groups formed by the analysis (Sublemontier, 2012). The unsupervised isocluster classification is an automated method available in ArcGIS, which finds groups of similar pixels within an image and classifies them based on their common characteristics (Turmine *et al.*, 2012). Isocluster classification is based on the iso cluster algorithm (Xu and Wunsch, 2005), commonly used in remote sensing and geographic analysis. This method divides image pixels into "natural clusters", which are combinations of band values that frequently occur within the image. Once these natural groups are identified, k-means and C-means are examples of unsupervised ISO cluster classification methods (Hachemi, 2022), as they seek to minimize the distance between cluster centres and observations within the same cluster.

Results and Discussion

Remote sensing data analysis

The mean values of indices derived from the Landsat 08 image of July 2020 (NDVI, NDMI, LAI, and SAVI) were calculated (Fig. 03). The NDVI values range from 0 to 0.76, with maximum values above 0.5 indicating dense vegetation (Choubin *et al.*, 2017), while lower values signal bare soil. NDMI ranges between 0.06 and 0.76, LAI presents values from 0 to 0.50, and SAVI values range from 0 to 0.70, with the highest altitudes located in the centre of the area (Fig. 03). The maximum slopes reach 52%. The RSP values range between 0 and 0.99, with higher values corresponding to mountainous regions, ridges, and steep slopes, while lower values are associated with flat surfaces and foot slopes. TWI varies between 3.34 and 18.61.

Vegetation indices such as NDVI, NDMI, LAI, and SAVI vary depending on topographic factors. For instance, we found a value of 0.70 for NDVI in areas exposed to the north, northwest, and northeast, while medium to low values of NDVI, SAVI, and NDMI were observed in other exposures. Low values of these indices indicate highly degraded or cultivated areas. High vegetation index values increase with IPRP (index of relative slope position), reflecting the trend of denser vegetation formations at higher altitudes.

In Algeria, green oak is often present in hills and mountains, especially in the atlasranges, where altitudes provide favourable climatic conditions for its growth: cooler temperatures, increased humidity, and better water availability (Dahmani-Megrerouche, 2002). Rugged terrain plays a key role in protecting vegetation formations from degradation causes such as illegal plowing, land clearing, and overgrazing (Allam *et al.*, 2019; Allam *et al.*, 2023). At points where the IPRP ranges from 12.50 to 52.38, vegetation indices show significant values ranging from 0.50 to 0.70, indicating the presence of green oak and *Juniper oxycedrus* formations. Conversely, low IPRP points primarily correspond to agricultural areas or arid lands. Overall, vegetation indices increase in direct correlation with altitude.

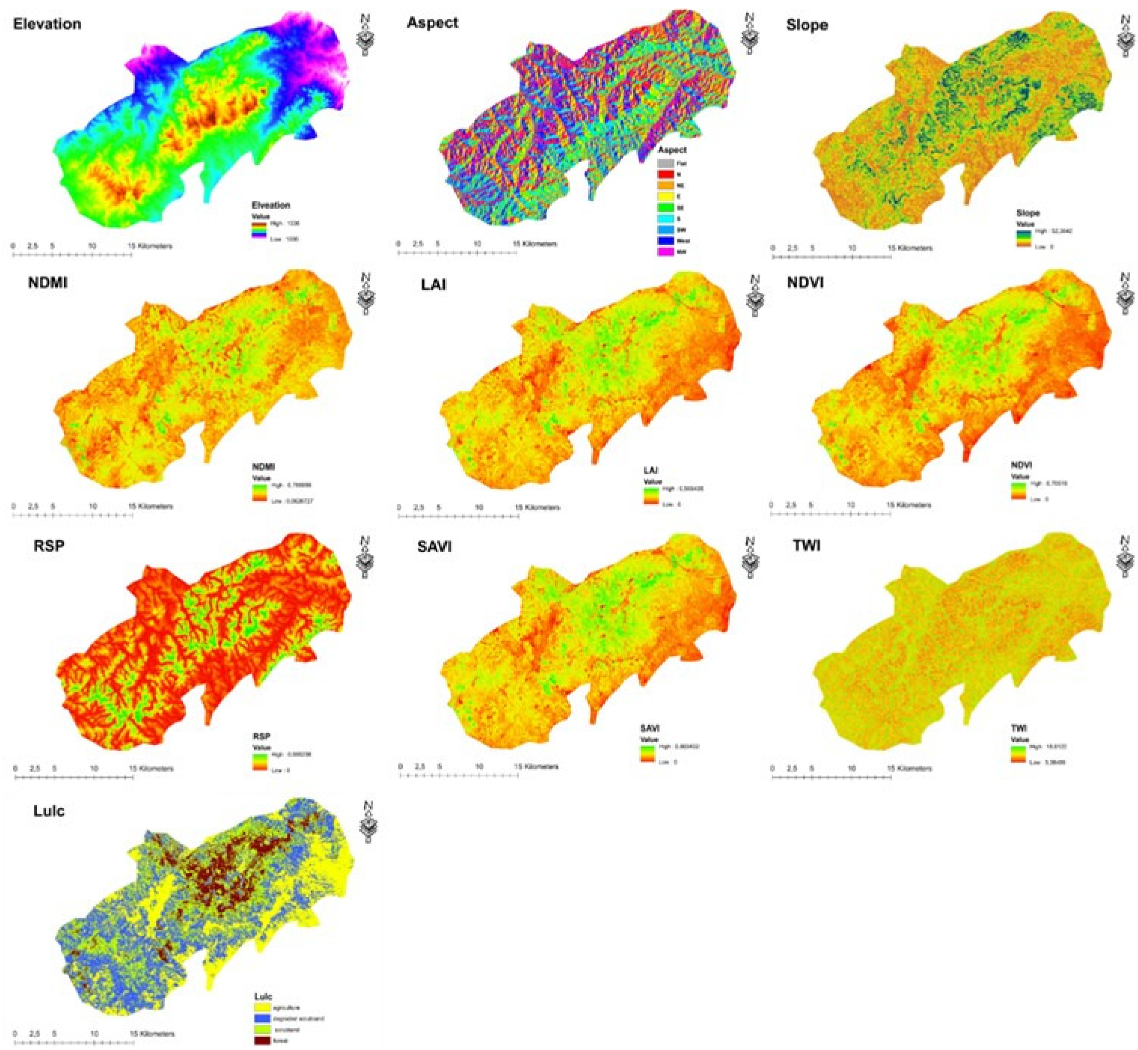

Figure 3. Extracted factors

Analysis of principal components

Principal component analysis (PCA) is a mathematical procedure that transforms a possibly correlated set of variables into a smaller number of uncorrelated variables known as principal components. These components represent linear combinations of the original variables (Johnson and Wichern, 2002). The primary goal of PCA is to discover or reduce the dimensionality of the dataset while identifying significant underlying new variables.

The PCA process involves calculating the eigenvalues and their corresponding eigenvectors from the covariance matrix. This step allows for the derivation of new variables in decreasing order of importance for explaining the variation of the original variables (Tran *et al.*, 2002). In our work, we applied PCA for geospatial data analysis, specifically for determining ecologically homogeneous zones using multiple data layers. This approach enabled us to identify hidden structures and complex relationships among different variables, thereby contributing to a better understanding of the spatial distribution of the ecological characteristics studied.

The inertias of the three selected axes are 56.36%, 24.93%, and 8.89%, respectively, representing a cumulative total of 90.18% of the total information (Table 2). Three principal components were retained during the PCA analysis. Together, they explain 90.18% of the variation among the nine variables initially included in the analysis (Table 2). The number of selected axes was limited to the first three, following Cattell's "scree test" or elbow test (1966) (Simard *et al.*, 2021). Figure 04, illustrating the evolution of the eigenvalues of the components (from the 1st to the 9th), shows a change in slope after the 3rd component, suggesting that retaining only the first three is appropriate. Although this method is commonly used and easy to implement, it should be complemented with other techniques to refine the analysis (Cattell, 1966).

Table 2. Evolution of eigenvalues for the extracted components

PC Layer	Percent of eigenvalues (%)	Accumulative of eigenvalues (%)
1	56.37	56.3663
2	24.93	81.2993
3	8.89	90.1894
4	4.10	96.2924
5	2.05	98.3126
6	1.04	99.617
7	0.35	99.964
8	0.04	99.9999
9	0.00	100

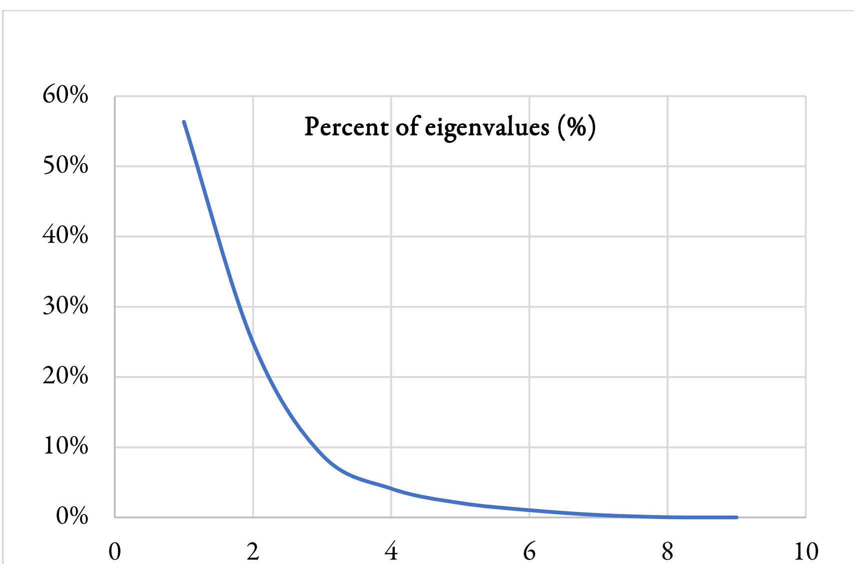

Figure 4. Scree Test (Evolution of eigenvalues for factors)

The principal components retained can be described as follows: exposure (PC1); slope, SAVI (soil-adjusted vegetation index), RCP (topographic wetness index), NDVI (normalized difference vegetation index), NDMI (normalized difference moisture index), and LAI (leaf area index) (PC2); TWI (topographic wetness index) and altitude (PC3) (Table 3).

Table 3. Eigenvalues for extracted components

Variable	Eigenvalue		
	PC1	PC2	PC3
TWI	0.006	-0.020	0.717
Pente	-0.001	0.051	-0.079
SAVI	-0.001	0.038	0.024
RSP	0.012	0.772	-0.185
NDVI	0.004	0.059	0.038
NDMI	0.009	0.083	0.003
LAI	-0.001	0.029	0.018
Altitude	0.017	0.551	0.654
Exposition	0.990	-0.018	-0.013

Determination of ecologically homogeneous zones

The use of unsupervised automatic classification via iso clustering allows for the automatic detection of similar pixel groups within an image, classifying them based on their common characteristics (Turmine *et al.*, 2012). Based on the iso cluster clustering algorithm (Xu and Wunsch, 2005), this method is commonly applied in remote sensing and geographic analysis. The results obtained are illustrated in Figure 5, which highlights the identified homogeneous zones.

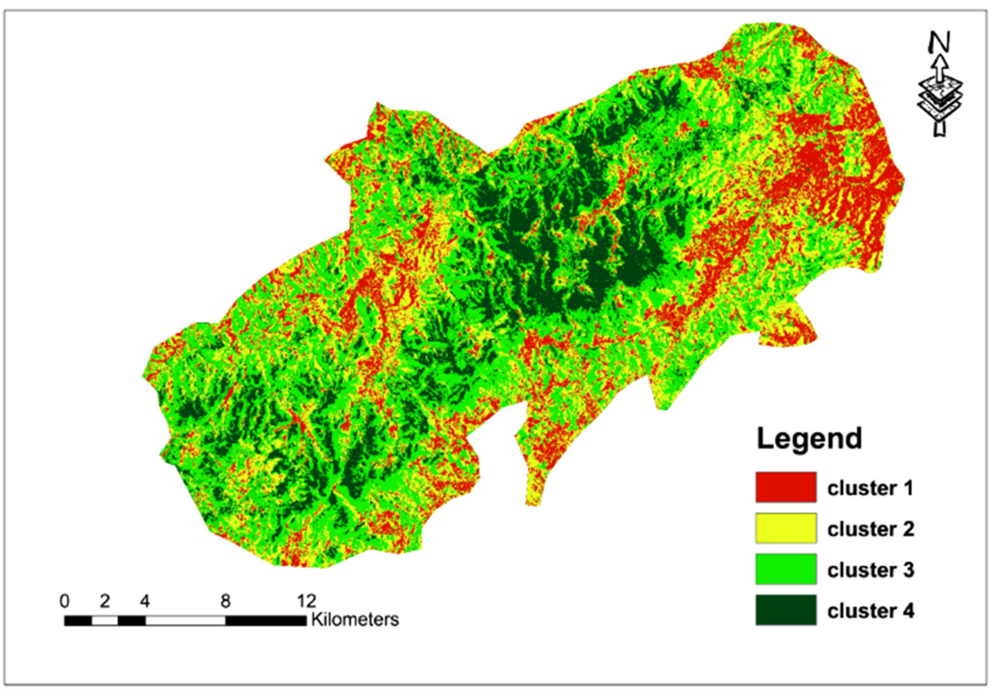

Figure 5. Homogeneous regions of Iso cluster unsupervised classification of green oak forest

To better understand the characteristics of ecologically homogeneous regions, the means of the variables were calculated for each group (Table 4). The average values of elevation and slope significantly increase from group 1 to group 4. As for the exposures, they vary from one group to another, with northern exposures dominating in groups 4 and 3, while group 2 presents exposures to the south and southwest, and finally, group 1 is considered flat to somewhat inclined. Values related to the NDVI, SAVI, NDMI, and LAI indicators in the first group were (0.57, 0.56, 0.57, 0.48), as these indicators decreased from group 4 to group 1, whose values were (0.20, 0.22, 0.225, 0.10), while the RSP values increased. In the hills and upper slopes, values rose from group 1 to group 4, with the highest value recorded in group 4 at 0.85, and these values were consistent down to group 1. Based on the average TWI values, it was observed that soil moisture evolved from group 1 to group 4, with the first group recording a high value of 16.

Table 4. Average values (or predominant category) of the variables in each identified cluster

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4
NDVI	0.2	0.32	0.45	0.57
SAVI	0.22	0.30	0.43	0.56
NDMI	0.225	0.31	0.45	0.57
LAI	0.1	0.16	0.36	0.48
Elevation (m)	1050	1130	1250	1300
Aspect	Flat	S-SW	ALL	NE-W
Slope (%)	2.5	5.25	8.2	10.65
TWI	16.84	11.62	6.44	4.02
RSP	0.21	0.29	0.56	0.85

The results of our study show that vegetation indices (NDVI, SAVI, NDMI) vary significantly between clusters. Areas with steep slopes and high altitudes, such as those in Cluster 4, exhibit high NDVI values (0.57), corresponding to dense vegetation formations typical of Mediterranean maquis. These areas are home to xerophytic species such as *Quercus ilex*, *Juniperus oxycedrus*, *Phillyrea angustifolia*, and *Pistacia atlantica*. The latter, in particular, is well adapted to drought conditions and nutrient-poor soils (Ouadeh *et al.*, 2023), often found in vegetation formations on steep slopes within Mediterranean ecosystems (Quézel and Médail, 2003; Blondel, 2006).

The exposure of areas significantly influences vegetation indices (Xue and Su, 2017), as reflected in the variation of NDVI, SAVI, NDMI, and LAI values between the clusters. North-facing areas, such as those in Clusters 4 and 3, exhibit higher vegetation values due to better moisture distribution and more moderate temperatures. North-facing slopes generally provide a cooler microclimate (Fekete *et al.*, 2023), which promotes the growth of plant species adapted to these conditions. Studies such as those by Zalesny *et al.* (2012) and Rundel *et al.* (2016) have shown that north-facing exposures support greater plant biodiversity in Mediterranean regions.

In contrast, areas exposed to the south and southwest, such as those in Cluster 2, are subject to greater sunlight exposure and higher temperatures, which limits plant growth and reduces vegetation density. However, these areas are suited to heat- and drought-resistant species, such as *Pistacia atlantica* and *Juniperus oxycedrus*, which are capable of surviving in drier and sunnier conditions. Research by Cui *et al.* (2009) and Moreno and Oechel (2012) has documented how south-facing exposures influence vegetation composition and density in Mediterranean ecosystems. Thus, the relationship between exposure and vegetation indices highlights the importance of topography in determining the distribution of plant species in a Mediterranean environment, influencing their ability to survive and thrive based on local climatic conditions and water resource management (Djebbouri *et al.*, 2022; Pan *et al.*, 2023).

In Cluster 1, characterized by gentle slopes and a high topographic wetness index (TWI = 16.84), vegetation cover is low, primarily due to human activity. Agricultural lands benefit from relatively moisture-rich soils, but their vegetation is dominated by crops or herbaceous plants suited to farming (Chuma *et al.*, 2024). Species such as *Stipa tenacissima* and *Anplodisma moritanica* may be present, but less densely than in protected areas, as noted by Posse *et al.* (2000) and Fu *et al.* (2010).

Ridge areas, where the RSP is high in Cluster 4, exhibit rapid drainage and increased exposure to wind, limiting soil moisture (Yu *et al.*, 2024). These harsh conditions favor resilient species such as Juniperus oxycedrus and Pistacia atlantica, which are adapted to dry and challenging environments. In contrast, the lower slopes of Cluster 2, with moisture accumulation, support less dense and often degraded vegetation, but may still host species such as *Phillyrea angustifolia* and *Juniperus oxycedrus*.

A gradual ecological transition is observed between Cluster 1, dominated by agricultural land, and Cluster 4, where dense maquis areas, dominated by *Quercus ilex*, *Juniperus oxycedrus*, *Stipa tenacissima*, and *Pistacia atlantica*, gradually replace human activities. The increase in slope and difficulty of access lead to the expansion of natural ecosystems, which over time replace agricultural lands. This dynamic is illustrated by the research of Quézel & Médail (2003) and Blondel (2006).

Conclusions

This study employed principal component analysis and unsupervised classification to identify homogeneous areas within the green oak forest, based on a pixel-by-pixel classification. This approach relies on the utilization of remote sensing data, supported by the use of a geographic information system (GIS). The results of the fuzzy clustering approach, as a flexible method, revealed that the optimal homogeneous zones for the study were four in number. The first group was characterized by flat, low-slope terrain, the second group by a higher altitude and moderate vegetation cover. The third group exhibited a steeper slope than groups1 and 2, as well as denser vegetation. Finally, the fourth group was distinguished by an even higher altitude, a steeper slope, and very dense vegetation. In this perspective, the characterization and mapping of ecologically homogeneous zones within the forest are essential elements, particularly for land management, ecological restoration, and prevention. However, it is important to emphasize that our study primarily focused on the geomatics aspect, highlighting the crucial contribution of geographic information systems (GIS) and remote sensing. These tools are indispensable in this context.

Authors' Contributions

YD, AK and YN: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Resources; Software; Supervision; Validation; Visualization; Writing - original draft; Writing - review and editing. YD, MD and MZ: Conceptualization; Data curation; Formal analysis; Methodology; Resources; Software; Supervision; Validation; Visualization; Writing - original draft; Writing - review and editing. All authors read and approved the final manuscript.

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Conflict of Interests

The authors declare that there are no conflicts of interest related to this article.

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