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Assessment of forest stand dynamics in the Timekssaouine forest (Northern Morocco) using statistical and machine learning approaches

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ABSTRACT

Tracking changes in forest composition, structure, and distribution over time is essential for developing effective conservation strategies and sustainable management practices in these ecologically sensitive regions. In this study, the objective was to conduct a diachronic analysis, comparing land cover and vegetation status in the Timekssaouine forest within the Central Plateau region of Morocco over a 20-year period. The aim was to analyze the spatiotemporal evolution of plant formations. Satellite imagery, specifically Landsat images taken during the summer period (July) of 1999 and 2020, was utilized to provide a detailed observation of changes over time and space. Additionally, machine learning modeling using random forest (RF) was implemented to further explore the dynamics of change in the forest. The RF models developed achieved reasonable to good predictive performance, with AUC scores of between 0.67 and 0.80. The obtained findings revealed a concerning regression, with both the diachronic (59% of the forest area) and RF (35%) approaches highlighting extensive regression of the forest, particularly in the cork oak formations at 9%, with notable de-densification across density classes between 1999 and 2020, a diachronic study. Dense cork oak and moderately dense strata were particularly affected, experiencing regressions of 455 ha and 1204 ha, respectively, during this period. Conversely, open and sparse strata expanded, primarily sourced from the dense and moderately dense strata, resulting in an overall regression rate of 60 ha/year. The dense cork oak strata were prevalent on steep slopes with deep, slightly acidic soil, while scattered and clear strata were observed in low-lying areas with shallow soils and a pH range from neutral to slightly basic. Autumn precipitation and amplified overgrazing intensity emerged as the pivotal factors influencing the categorization of forest formations in the study forest, impacting tree density levels and posing a significant threat to forest regeneration.

Keywords: forest dynamics, diachronic analysis, random forest modeling, cork oak regression, Morocco.

INTRODUCTION

Forests are vital ecosystems rich in biodiversity and offer numerous ecological, environmental, as well as socioeconomic benefits, including climate regulation, air and water purification, and soil erosion prevention (Jhariya et al., 2019; Ritchie and Roser, 2021; FAO, 2022). They support local communities by providing resources like firewood, timber, and medicinal remedies, contributing to local economies (Brandt and Buckley, 2018; Bastin et al., 2019). However, deforestation, excessive logging, and climate change are threatening their ability to provide these services, especially in developing countries (Erbaugh et al., 2020; Dudley et al., 2014). Both natural and human-induced factors, such as fires, pests, deforestation, and reforestation, affect forest dynamics, influencing species composition and biodiversity (Busing, 1991; Forrester, 2014). These dynamics are further shaped by species migration, fragmentation, and climate change impacts, leading to a significant decline in forest area worldwide (Ghazoul et al., 2015; Taubert et al., 2018).

Recognizing and understanding the spatial dynamics of forests is essential for effective, sustainable forest management and the long-term preservation of biodiversity (Huang et al., 2016; Noumonvi et al., 2017). Indeed, knowledge of the distribution of different elements within a forest as it evolves can be crucial to developing targeted conservation strategies, by identifying critical habitats. In addition, it can help assess the capacity of a forest to provide vital ecosystem services, enabling planners to balance human needs while promoting sustainability. Furthermore, this knowledge facilitates proactive adaptation to climate change, ensuring the well-being of local communities who often depend on forests.

Various techniques allow for the comprehensive assessment of forest evolution dynamics. One of the most popular is the use of remote sensing (Da Ponte et al., 2017; Erfanifard et al., 2020; Gao et al., 2020), which incorporates data from sensors associated with satellite systems, such as Landsat, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Moderate Resolution Imaging Spectroradiometer (MODIS), Sentinel and Satellite Pour l'Observation de la Terre (SPOT), among others. The sensors on these satellites capture different spectral bands of the electromagnetic spectrum, notably in the visible, infrared and thermal ranges, which can be used to detect the health of vegetation and classify land cover (Seiler et al., 2014; Lausch et al., 2016; Dallahi et al., 2023). In addition, the integration of geographic information systems (GIS) with remote sensing data in combination with the data collected in the field can enable comprehensive spatial analysis, supporting data-driven decisions for sustainable forest management.

One of the most effective methods for assessing forest evolution is diachronic analysis based on the use of remotely-sensed satellite data (Armaş et al., 2014; Salvati and Tombolini, 2014; Barbache et al., 2018). This method consists of a temporal approach that uses satellite data to systematically observe and analyze changes in forest ecosystems over several periods. This is achieved by exploiting historical satellite imagery to detect and quantify changes in forest cover, structure and composition. These images can be used to identify trends in forest stands, assess the impact of forest management and disturbances such as deforestation or pest epidemics, and monitor recovery processes (Lescuyer, 2013). By comparing images taken at different times, diachronic analysis provides a dynamic perspective on forest evolution.

Furthermore, complementing diachronic analysis with machine learning (ML), the interpretation of complex satellite data can be significantly improved, particularly in data-scarce regions such as Moroccan ecosystems. ML algorithms efficiently process extensive satellite imagery, uncovering patterns and trends that traditional methods can overlook (Phan et al., 2022). This approach makes it possible to accurately assess forest evolution, detecting subtle changes in cover or structure that may indicate larger ecosystem transformations (Zhao et al., 2024). Relying on satellite data, ML can produce snapshots of forest condition, even with limited field data, identifying trends and risks such as deforestation or pest outbreaks, in order to intervene in a timely manner. This data-driven strategy optimizes forest management and conservation efforts, enhancing sustainable ecosystem management and resilience (Raihan, 2023).

Moroccan forests boast exceptional floristic richness, resulting in a diversity of ecosystems and forest formations intricately linked to the country's varied geographical, climatic, and ecological conditions (Taleb and Fennane, 2019). Historically, they have served as a multifunctional space, helping conserve the biological balance of nature, meeting the demands for wood products, creating employment opportunities, and acting as a substantial reserve for grazing lands. However, forest resources have long been subjected to intense exploitation, including logging, clearing, fires, overgrazing, and bark harvesting, among others (Benabid, 2019; Malki et al., 2022). Consequently, this has led to chronic decline and alarming degradation of these ecosystems (Ikraoun et al., 2022). Indeed, this is true for forests in the Central Plateau region, which play vital role in the socio-economic life of the local population.

While numerous studies (Barbero et al., 1990; Quézel, 1999; Mazzoleni et al., 2004) have sought to assess the evolution of Mediterranean ecosystems on a peri-Mediterranean scale, diachronic and cartographic studies on the evolution of forest ecosystems in the Central Plateau region remain limited. In this context, this study aimed to assess the evolution of vegetation cover in the Timekssaouine forest using a diachronic method to help understand the dynamics and distribution of stratum transfers in this forest between 1999 and 2020, using a confusion matrix to explain the different losses and gains in forest stratum area. In addition, an ML approach, relying on the random forest algorithm to model forest evolution, was employed. Specifically, the study aimed to predict current forest trends (progression, regression or no change), as well as evaluate site factors to identify those with the greatest influence on forest degradation. It was anticipated that the findings of this study would provide forest managers and local authorities with reliable, up-to-date information on the state of these ecosystems. This, in turn, would enable informed decision-making based on reliable data for the effective management of not only the context of the forest, but also as a valuable reference for other ecosystems in the region.

MATERIALS AND METHODS

Overview of the study area

The study area (Figure 1) extends over the entire Timekssaouine forest, covering around 10.000 hectares, and is located in the Central Plateau region of Morocco, 5 km from Khémisset and around 60 km from Rabat. The forest is marked by an altitudinal variation that ranges from 250 m in the lowest areas to 950 m on the highest peaks. Notably, the dominant elevation of the terrain lies between 400 and 800 m, covering almost 90% of the forest area. The climate is characterized by annual precipitation of between 400 and 500 mm, with a rainy season concentrated from October to April. Temperature variations are typified by maximum temperatures reaching 34 °C, while minimum temperatures are recorded at around 4 °C. The dominant seasonal trend is a hot summer, accentuated by the arid footprints characteristic of the region. Form a bioclimatic standpoint, the study area features a semi-arid mantle, accentuated by a temperate variant that further contributes to the climatic complexity.

Geologically, the forest has a Paleozoic substratum composed mainly of pelites, sandstones, and quartzites, while the pedological composition includes rough mineral soils and weakly evolved soils. The forest vegetation is diverse: cork oaks occupy 42% of the landscape, Barbary

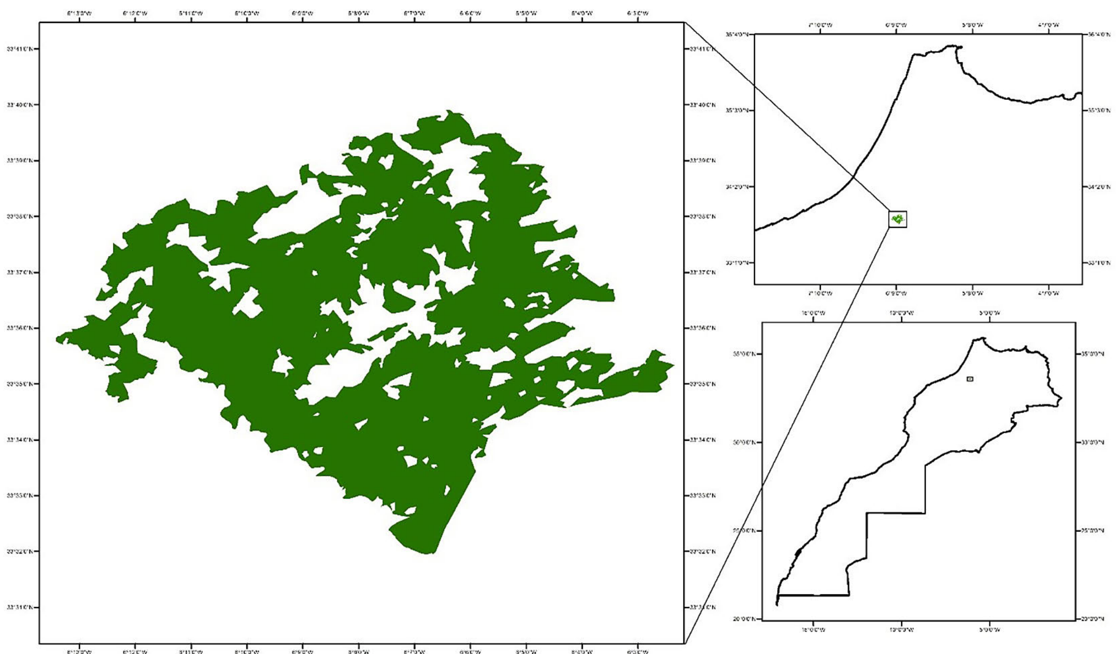

Figure 1. Geographic location of the Timekssaouine forest in the Central Plateau region of Morocco

thuja (*Tetraclinis articulata*) 25%, and reforested enclaves of pine (*Pinus* spp.). Alongside, there is a mix of secondary species including mastic tree (*Pistacia lentiscus*), wild olive (*Olea europaea* var. *oleaster*), fan palm (*Chamaerops humilis*), *Cistus salviifolius*, *Arbutus unedo, Rhus pentaphylla*, among others. While the biological, ecological, biogeographical, and socioeconomic values of the Timekssaouine forest make it of crucial importance to the region's development, it faces challenges from the cumulative effects of anthropogenic pressures and unfavorable environmental conditions. It is therefore imperative to conduct studies aimed at assessing its evolution, as they would provide a valuable knowledge base that could help address and mitigate the current challenges, as well as potential future ones.

Data collection

Remote sensing data

To analyze the evolution of vegetation cover, Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) images from July 1999 and July 2020, respectively, were selected for this study. Landsat 5 TM, operational from 1984 to 2013, had seven bands, including blue, green, red, near-infrared, shortwave infrared 1 and 2, and thermal infrared. Landsat 8, launched in 2013, carries the OLI sensor with eight bands covering ultraviolet to shortwave infrared and a panchromatic band, as well as the TIRS sensor with two thermal infrared bands. All images were acquired during the dry season to ensure the comparison of data from consistent seasonal conditions. The Landsat images, retrieved from the Earth Explorer USGS database (https://earthexplorer.usgs.gov/), had a resolution of 30 meters. Prior to analysis, the images, which were already geometrically corrected, underwent radiometric and atmospheric pre-processing to mitigate the impact of atmospheric effects and viewing angles on image quality. Various color compositions were created during the study, with the (B2-B3-B4) color composition identified as most effective for distinguishing vegetation formations. This color combination aided in selecting control areas for classification assessment. The preprocessed and composited remote sensing data formed the basis for the subsequent analysis of vegetation dynamics in the study area. In addition, SPOT imagery was acquired from the European Space Agency SPOT archive (https://earth.esa.int/eogateway/catalog/spot1-5-esa-archive) to help refine the subsequent map of vegetation types for July 2020. SPOT images are composed of four bands (green, red, near-infrared, and mid-infrared) and one panchromatic band with a spatial resolution of 1.5 m. They are renowned for providing detailed information about land cover and use, thus allowing for a more precise characterization of different vegetation formations.

Field survey data

Homogeneous forest stands were chosen as sampling points for field data collection at 39 sites across the study forest. For each selected point, precise coordinates were determined and projected onto the study area layer to establish training and control zones for classification. These data aimed to recognize and define the distinct vegetation formations present in the forest area, while also serving as a validation tool to verify the results obtained through visual interpretation of satellite imagery, particularly in the areas where interpretation was challenging. Additionally, the data was collected to provide supplementary information that may not be easily extracted from satellite images, such as the stratification of different vegetation formations. Moreover, soil samples were collected at a depth of 30 cm at each of these sites for subsequent soil analyses aimed at determining both physical and chemical properties.

Methodology

Inventory technique

The inventory approach employed in this study was both stratified and systematic, consisting of a selection of 39 plots in the field to facilitate a comprehensive analysis of the changes in stand conditions concerning based on environmental parameters and factors in the forest. The stratification, which involves dividing the study area into distinct strata or classes based on specific characteristics, was to allow for a targeted and representative sampling of different forest types (Barbary thuja, cork oak, pine and eucalyptus plantations, and secondary tree species), while the systematic inventory, characterized with sampling rates tailored to each forest type, was conducted to ensure a balanced and unbiased representation across the forest. Accordingly, the sampling rates were set at 0.2% for Barbary thuja and cork oak, 0.5% for pine and eucalyptus reforestations, and 0.03% for secondary species. Each plot was standardized at 10 ares, representing one plot per 50 hectares for Barbary thuja and cork oak, 5 ares with one plot per 10 hectares for reforestation (eucalyptus and pine), and 2 ares with one plot per 67 hectares for secondary species.

Soil analyses

A comprehensive soil investigation was carried out at each of the 39 inventory plots, involving the excavation of soil profiles and subsequent on-site descriptions of various soil horizons. This process entailed identifying the depth, color, and permeability of each horizon. Additionally, assessments were made for the classification of soil types, surface permeability, structure, and porosity. Following the field assessments, laboratory analyses were conducted to determine various soil physical and chemical properties. Granulometry analysis was employed to determine soil texture, indicated by the fractions of clay, fine and coarse silt, and fine and coarse sand. The content of soil carbon and, consequently, organic matter was quantified using the Walkley-Black method. Soil pH levels were assessed utilizing the pH-water method, while total and active limestone contents were analyzed through standard laboratory methods.

Image processing and analyses

Following the acquisition of cloud-free satellite images, a color composite image was generated by combining three spectral bands (B2-B3-B4) using a color composition technique. The resulting images were then subjected to classification based on ancillary data, including ground observations and existing maps, to produce detailed forest stand maps. To assess forest density, the normalized difference vegetation index (NDVI) was calculated to provide an estimate of vegetation abundance (Figure A1). Consequently, the integration of these maps, in particular the intersection in a GIS environment between forest type maps and density maps, was carried out to facilitate obtaining density information for each forest type. All analyses were carried out using ESRI's ArcGIS 10.8 program.

Classification of forest stands – To accurately categorize and map different land cover classes within the Timekssaouine forest, a supervised classification method leveraging the maximum likelihood technique was employed. This method involves selecting representative training samples for the classes of interest and applying a classification algorithm that, based on statistical rules, assigns each pixel in the image to a predefined class. The maximum likelihood classification algorithm calculates a multidimensional probability function to determine the likelihood of each pixel belonging to one of the predefined categories corresponding to spectral signatures. Thus, in this study, the five exploitable classes were represented as follows: Ta (Barbary thuja), Qs (cork oak), Es (secondary species), Rb (eucalyptus and pine plantations), and V (bare land). Their spatial distribution across the forest in 1999 and 2020 is illustrated in Figure A2.

Limit cleaning classification – To further refine the land cover classification, a limit cleaning classification using the "majority filter" tool was

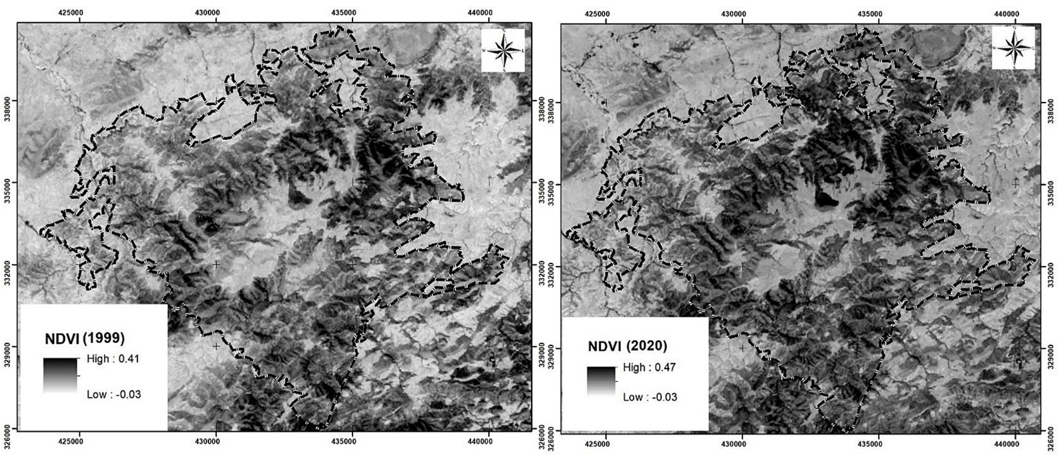

Figure A1. Comparison of the spatial distribution of NDVI in the Timekssaouine forest between the years 1999 and 2020 employed. This tool is particularly useful when the initial classification result includes numerous small regions. The process involves merging smaller adjacent class regions into larger, more coherent regions. For instance, where the classification may yield small and fragmented regions, the majority filter tool helps in producing a cleaner and more coherent land cover map. In addition to this, the high-resolution SPOT image acquired for July 2020 was utilized for further refinement. Overlaying the resulting maps was done to facilitate the creation of confusion matrices, outlining six main classes: regression, progression (indicating a resurgence of the species in the area), unchanged zone, weak de-densification, moderate de-densification, and strong de-densification.

Spatial dynamics assessment

To assess the spatial dynamics of the Timekoussine Forest, the diachronic method was used to the degradation and regression of forest cover for the period between 1999 and 2020. This approach involves comparing the composition and extent of forest formations at two or more different dates. A crucial component of this method is the creation of a confusion matrix, also known as a change matrix, which systematically provides information on the transfer of surface area from one forest formation to another between the selected dates. Essentially, the change matrix helps determine the gains and losses of different population types, illustrating the breakdown of these transfers. The distribution of the forest was determined by establishing vegetation density classes through a comparative analysis between on-the-ground observations (Google Earth imagery) and the NDVI data. The pixel values calculated from the NDVI data were broadly categorized into five distinct classes (Table 1).

To determine the composition of forest stand types (Figure A2) and their respective densities, an approach relying on the integration of vegetation formation and site data and leveraging the intersection function within ArcGIS were adopted. The method involved overlaying map layers that represent each specific forest stand type with layers characterizing forest density for the years 1999 and 2020. This was carried out to allow the identification of common spatial elements between these layers.

Data analyses

Both correlation analysis and principal component analysis (PCA) were employed to examine the relationships and patterns within the site data pertaining to cork oak populations. The Pearson correlation matrix was utilized to explore the interdependence between various environmental factors, such as organic matter content, pH levels, substrate composition, topography, exposure, pruning practices, incidence of delinquency, and socio-economic context, and the condition of cork oak stands. Additionally, PCA was implemented as a dimensionality reduction technique to transform the extensive set of variables into a more

Table 1. Classes of vegetation density based on NDVI

Classes	NDVI 1999	NDVI 2020
Bare	-0.03–0.09	-0.03–0.18
Spares	0.09–0.13	0.18–0.22
Clear	0.13–0.18	0.22–0.27
Moderately dense	0.18–0.23	0.27–0.30
Dense	0.23–0.41	0.30–0.47

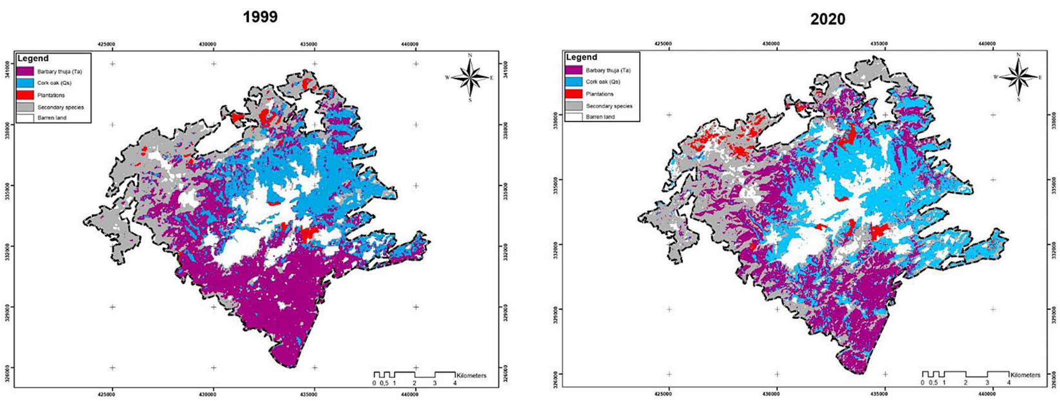

Figure A2. Identification and characterization of vegetation types in the Timekssouine forest between 1999 and 2020 manageable subset while retaining the essential information. Consequently, matrices were computed to project the variables into a new space, to help reveal the degree of similarity between them and to highlight the underlying patterns that contribute significantly to the overall variation in the dataset.

Modeling of forest change using ML

Overview of the random forest algorithm – RF is an ensemble learning technique widely used for classification and regression tasks that operates by constructing multiple decision trees during training and aggregating their predictions. Each tree is built using a random subset of the training data and a random selection of features, promoting diversity among the trees and reducing the risk of overfitting common in single tree models (Breiman, 2001). The final output is determined by the majority vote (for classification) or the average prediction (for regression) of all trees, enabling RF to effectively capture complex patterns in high-dimensional datasets. RF is particularly valued for its robustness, interpretability, and ability to handle missing values and large datasets, making it a popular choice in ecology and environmental management.

Modeling of forest stand evolution – to model forest stand evolution, 23,000 points were extracted from a forest stand evolution map, supplemented by data on climatic, edaphic, topographic, and human impact variables (Supplementary Figures 1–5). For modeling the probability of infractions, 139 plots with observed infractions were identified as presence points (Supplementary Figure 1), alongside 139 generated absence points. A total of 75 soil samples were collected from 41 unique plots (Figure 3), from which soil properties, including depth, pH, organic matter (SOM), and texture, were analyzed. Additional data on climatic, topographic, and human impact factors were also utilized. Data preprocessing was conducted to handle missing values, outliers, and inconsistencies, followed by normalization to ensure uniformity across datasets.

Feature selection, critical for enhancing model interpretability and avoiding overfitting, was applied to edaphic factors, where 11 variables from SoilGrids V2.0 (Poggio et al., 2021) were evaluated as potential predictors (Figure 4). The stats package was used for Pearson correlation analysis based on a correlation coefficient threshold of ± 0.15 (Figure A6). For infraction probability modeling, the predictors are outlined in Figure 2. Datasets were randomly divided into training (75%) and validation (25%) subsets. The random forest package was used to implement the RF algorithm in an R environment, building both regression and classification models. RF was used as a regressor for soil depth, carbon, pH, and organic matter, and as a classifier for soil texture, forest infractions, and forest stand evolution categories. Hyperparameters were optimized using caret with grid search techniques combined with cross-validation to enhance model robustness.

Model performance evaluation was task-specific, with the coefficient of determination (R^2) used for regression, where it quantified the explanatory power of the models. For classification, area under the curve (AUC) values were leveraged using pROC to assess the discrimination capability and, thus, validate the effectiveness of the RF models. Additionally, variable importance was assessed using the mean-decrease accuracy (MDA) metric from the random Forest package, to highlight the predictive power of the selected predictors throughout the modeling process.

RESULTS

Assessment of changes in forest stands

The results of the confusion matrix depicting the dynamic redistribution of strata within the Timekssaouine forest between 1999 and 2020, are presented in Table 2. Notably, there was a substantial decline in cork oak stands across varying densities. The total area diminished from 4549 ha in 1999 to 4045 ha in 2020, reflecting an 11.08% reduction during this period. Similarly, Barbary thuja, covering 2735 ha in 1999, experienced a decrease to 2391 ha in 2020, representing a 12.58% regression over the same timeframe. Concurrently, secondary species benefited from the degradation of these stands, gaining an additional area of approximately 537 ha (27.88%), equivalent to an annual increase of 1.68% (30 ha). Barren lands exhibited an expansion of 187 ha at an annual growth rate of approximately 15%, while reforested areas, particularly those featuring eucalyptus and pines, showed a progression of around 32%, translating to a yearly increase of 1.8%.

Considerable changes occurred in the cork oak and Barbary thuja stands between 1999 and 2020 (Figure 2). Cork oak stands demonstrated significant regression, particularly in the dense

Table 2. Confusion matrix of the spatial dynamics of Timekssaouine forest stands between 1999 and 2020

Strata	Pa3	Pa4	Qs1	Qs2	Qs3	Qs4	Rb	Ta1	Ta2	Ta3	Ta4	Es	V	Total 2020
Pa3	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Pa4	0	43	0	0	0	0	0	0	0	0	0	0	0	43
Qs1	0	0	779	0	22	0	0	0	0	0	0	0	0	801
Qs2	0	0	147	1286	0	0	0	0	0	0	0	0	0	1433
Qs3	0	0	166	695	265	0	0	0	0	0	0	0	0	1126
Qs4	0	0	146	283	131	125	0	0	0	0	0	0	0	685
Rb	0	0	0	0	0	0	366	0	0	0	0	142	0	508
Ta1	0	0	0	0	0	0	0	630	0	0	0	0	0	630
Ta2	0	0	0	0	0	0	0	215	215	0	0	0	0	430
Ta3	0	0	0	0	0	0	0	159	165	498	0	0	0	822
Ta4	0	0	0	0	0	0	0	143	162	78	126	0	0	509
Es	0	0	11	295	72	0	16	4	63	76	174	1753	0	2464
V	0	0	7	78	41	0	2	14	4	4	5	32	68	255
Total 1999	2	43	1256	2637	531	125	384	1165	609	656	305	1927	68	9708

and moderately dense strata, with reductions of 36.23% (455 ha) and 45.68% (1204 ha), respectively, constituting an approximate 2% annual decline in area. These losses were compensated by noteworthy progressions in the clear and sparse stands, with clear stands experiencing a substantial increase of 112.05% (595 ha), and sparse stands expanding by 448% (560 ha) compared to the extents in 1999. Similarly, Barbary thuja stands experienced a considerable regression in the dense stratum, diminishing by 45.92% (535 ha) over the period. Moderately dense stands also regressed by 29.38% (179 ha). However, the clear and sparse strata displayed positive trends, with gains of 25.30% (166 ha) and 66.89% (204 ha), respectively. Comparatively, while both underwent

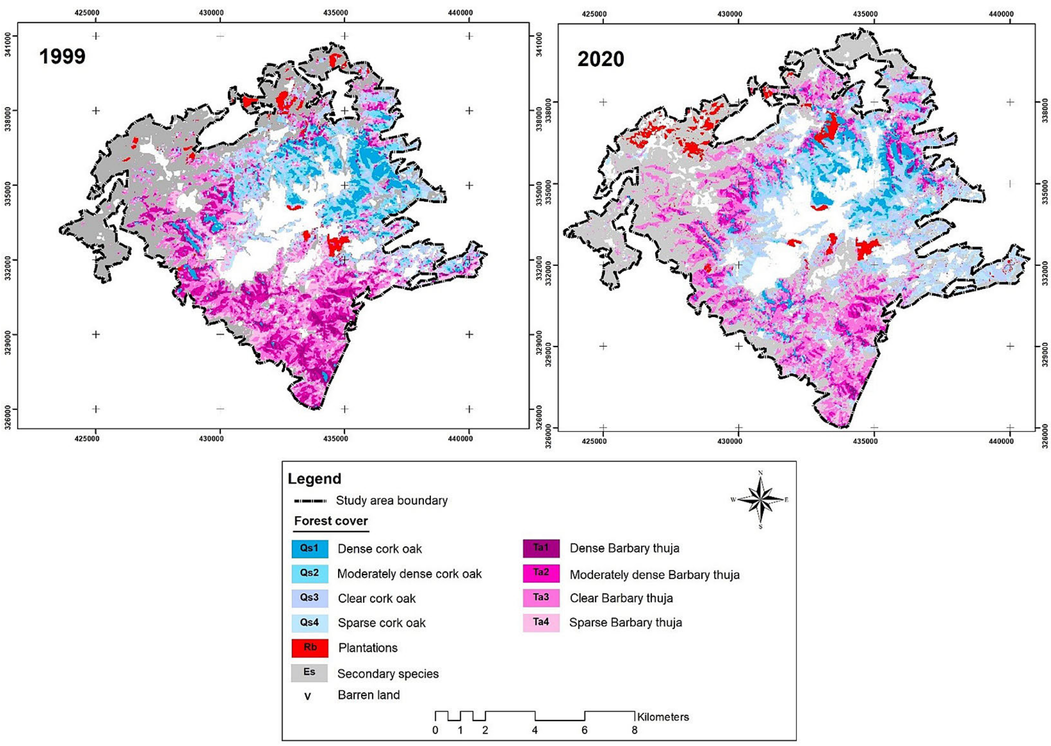

Figure 2. Comparison of the spatial evolution of species density classes in the Timekssaouine forest between the years 1999 and 2020

regression in their denser stands, the cork oak stands experienced more extensive changes, characterized by a collectively higher degree of regression in the dense and moderately dense strata.

The prevailing trend in the dynamics within the Timekssaouine forest area was a regression, accounting for 59% of the observed changes, particularly pronounced in the lower half of the forest (Figure 3). In contrast, progressions were more commonly observed in the northern sections, constituting 27% of the overall changes. Notably, the western part of the forest was characterized by the areas that remained generally unchanged, representing 14% of the observed dynamics. Overall, this spatial differentiation in stand changes indicated a heterogeneous nature of the evolution of the forest, with the southern and northern regions exhibiting contrasting trends.

The analysis of stand dynamics in the Timekssaouine forest between 1999 and 2020 reveals notable trends. The predominant pattern, observed in 60% of the forest area (5872 ha), is characterized by unchanged areas, particularly in the west (Figure 4), marking the most prevalent state during the study period. Forest progression, observed solely in cork oak stands and plantations, constitutes a minimal proportion, accounting for less than 2% of the total forest area. Conversely, forest regression is a more prominent trend, representing 11% of forest area (1.041 ha), particularly in cork oak and Barbary thuja stands. In comparison, cork oak presents a higher rate of regression, with associated stands representing 6% of forest area. On the other hand, stand densification patterns are mainly marked by low de-densification, particularly under cork oak stands, which account for 8.40% of forest area compared with 6.60% for

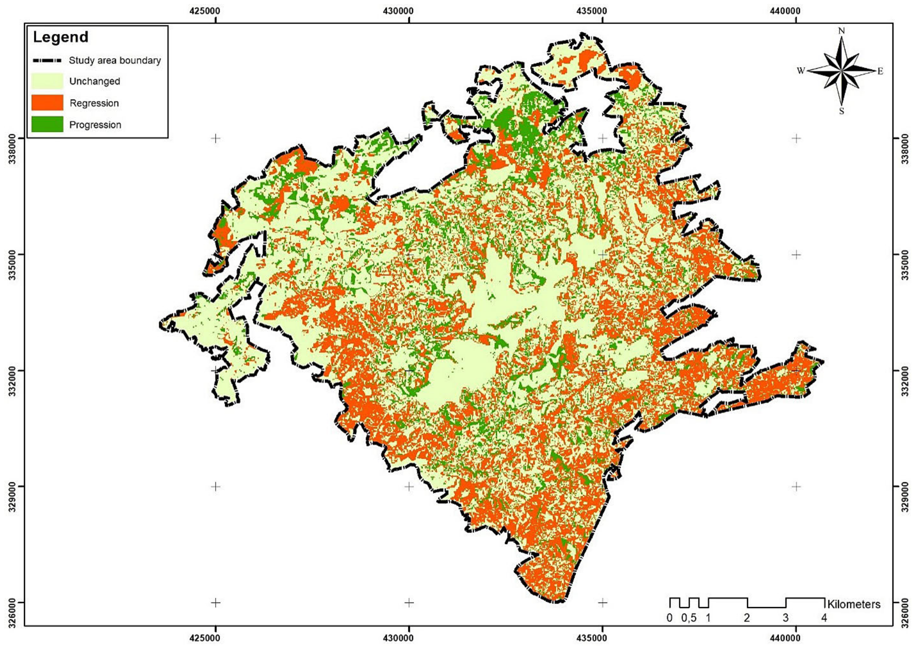

Figure 3. Map of the spatial distribution of changes in the Timekssaouine forest stands between 1999 and 2020

Table 3. Changes in stand dynamics across the Timekssaouine Forest from 1999 to 2020. The main figures denote area in ha, with percentages in parentheses representing their proportion relative to the total forest area

Trend		Stand				Total
		QS	TA	PLA	SEC	
Progression		24 (0.25)	-	121 (1.25)	-	145 (1.49)
Regression		606 (6.24)	364 (3.75)	5 (0.05)	66 (0.68)	1041 (10.71
De-densification		816 (8.40)	640 (6.59)	-	-	1456 (14.99)
	Moderate	425 (4.37)	444 (4.57)	-	-	869 (8.94)
	High	201 (2.07)	132 (1.36)	-	-	333 (3.43)
Unchanged	5872 (60.44)					

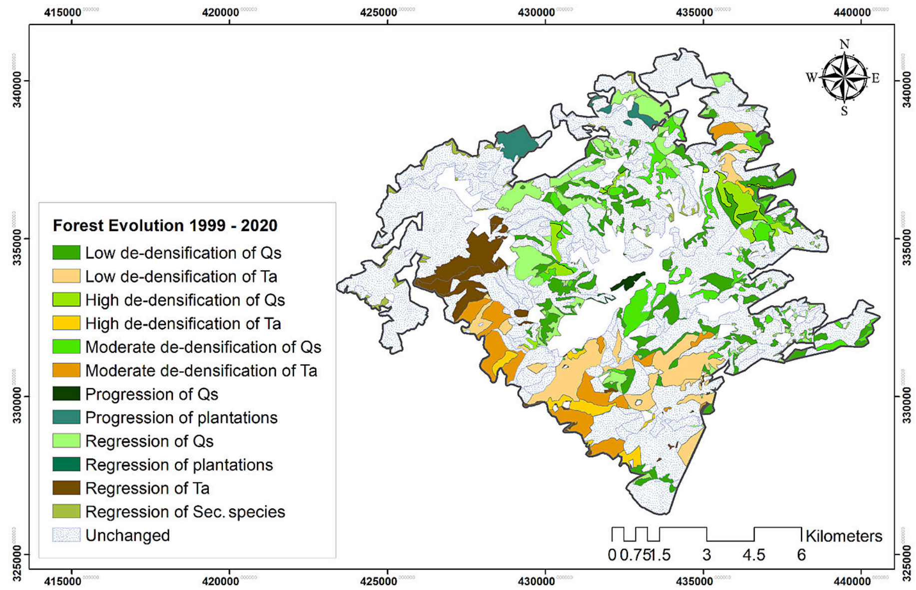

Figure 4. Map of the spatial evolution of the Timekssaouine forest between 1999 and 2020

Barbary thuja stands. Moderate de-densification, observed in around 4% of the forest for both species, collectively represents less than 10% of the total area. The least observed de-densification trend is high de-densification, which represents less than 4% (333 ha) of the forest area, with a slightly higher prevalence in cork oak stands over the study timeframe.

Relationships between vegetation formations and site characteristics

Relationship between site variables

Figure A3 illustrates the correlation analysis conducted to investigate the connections among various observation parameters or variables. Given the intrinsic relationship between carbon and organic matter ($R^2 = 0.93$; not shown), both variables were considered redundant in the dataset, as one could be derived through linear regression in relation to the other, consequently retaining organic matter. Among the noteworthy relationships uncovered, a moderate-weak positive correlation ($R^2 = 0.43$) between organic matter and altitude was identified. This suggests that as elevation increase, the organic matter content tends to increase in the area. Additionally, a moderate-weak negative correlation was observed between pH and both soil depth ($R^2 = -0.41$) and slope ($R^2 = -0.53$), indicating an inverse relationship between these variables. In other words, as soil

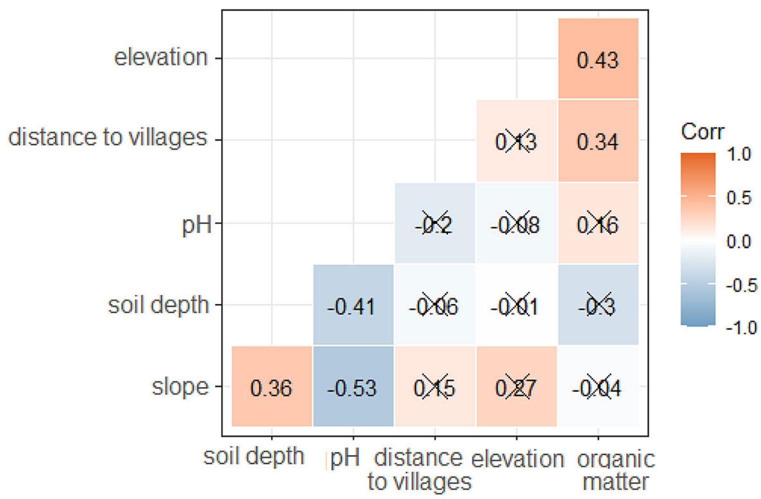

Figure A3. Correlation test assessing the relationship between site variables depth and slope increase, the pH tends to decrease in the study area.

Assessment of variability and variable contributions of principal components

The dataset is illuminated through the PCA analysis (Figure 5), revealing that the first two axes capture a significant 61.3% of the total variability. This surpasses the statistically significant reference value of 58.59%, signifying the efficacy of these dimensions in portraying the intricate relationships within the environmental and site variables. Slope, soil depth, and pH strongly contribute to the construction of dimension 1, with significance ranging between 50 and 70%. Organic matter and elevation contribute to the construction of dimension 2, with significance ranging between 40 and 70%, whereas the distance from villages (douars) contributes weakly while more prominently influencing dimension 3. On the basis of these eigenvalues, two dimensions are sufficient to explain the construction of the principal components.

Evaluation of representation quality of variables and contribution to dimensions

The evaluation of variable representation, based on cos² values, is illustrated in Figure 6. Proximity to the correlation circle signifies the significance of a variable on the factorial map; those closer are pivotal for interpretation, while those near the center wield less influence in early components. Organic matter, slope, and soil depth exhibited high cos², indicating robust representation, placing variables near the circumference. Conversely, distance to villages presented low cos², suggesting imperfect representation. The analysis demonstrated a positive correlation between soil depth and slope, and organic matter and elevation. Notably, negative correlation was observed between pH and slope.

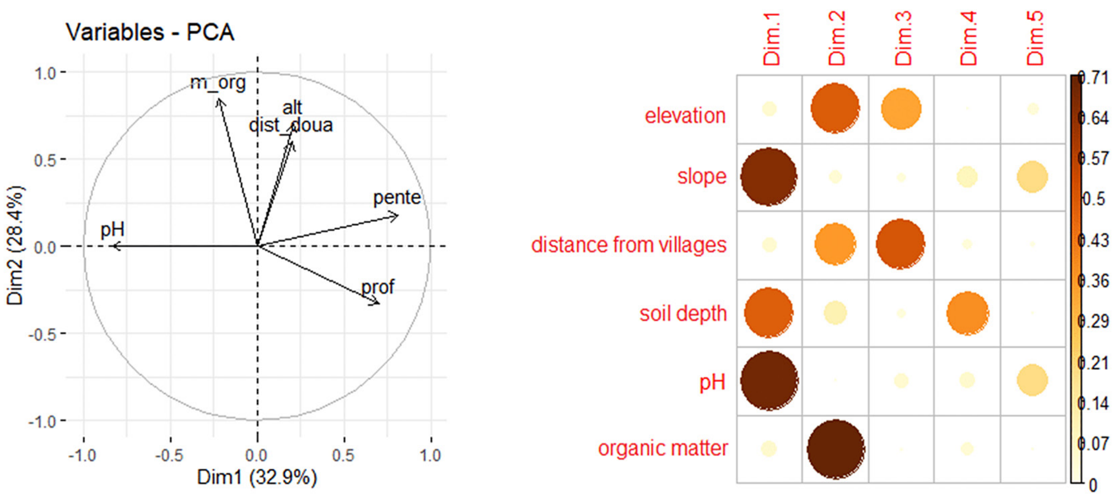

Figure 5. Variability assessment and choice of dimensions

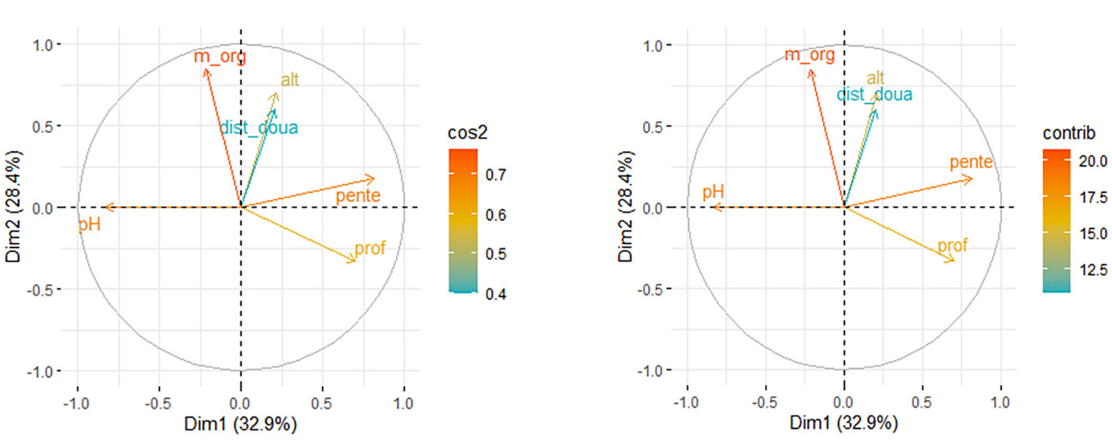

Figure 6. Representation quality of variables (cos^2) and their contribution to dimensions

The analysis of variable contributions reveals distinct patterns in the representation of dimensions (Figure A4). Dimension 1 is primarily shaped by pH, soil depth, and slope, whereas dimension 2 is predominantly influenced by organic matter and elevation, with a partial contribution from distance to villages. Notably, dimension 3 places a more prominent emphasis on the variable of distance to villages. The construction of the two principal components in the PCA is notably driven by pH, organic matter, and slope.

Cluster analysis

Clustering the variables into groups on the basis of their correlation levels (Figure 7) reveals a spatially distinct arrangement of three groups: organic matter, distance from villages and elevation; slope and soil depth; and pH as an individual entity. These clusters highlight the spatial relationships and patterns inherent in the variables, indicating specific groups, the behaviors of which are correlated. Systematic grouping underlines the homogeneous interactions between variables, typified by the cohesive nature of organic matter, distance from villages and elevation in one group, the interdependent dynamics of slope and soil depth in another, and the stand-alone positioning of pH.

Interpretation according to the graph of individuals and variables

The critical probability of the Wilks test (p = 0.004) indicated the variable the modalities of which best separated individuals on the plane. The most influential qualitative variable for illustrating distances between individuals on the plane was the grazing (parc) variable. The synthetic illustration (Figure 8) of individuals revealed that dimension 1 opposed individuals such as p42, p74, p36, p52, p39, p77, p50, p73, characterized

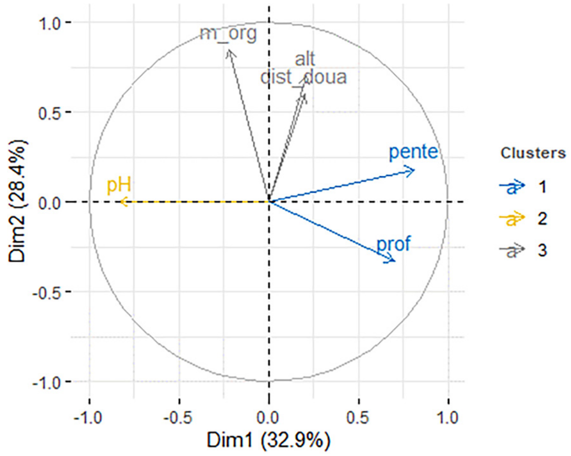

Figure 7. Clustering of environmental and site variables

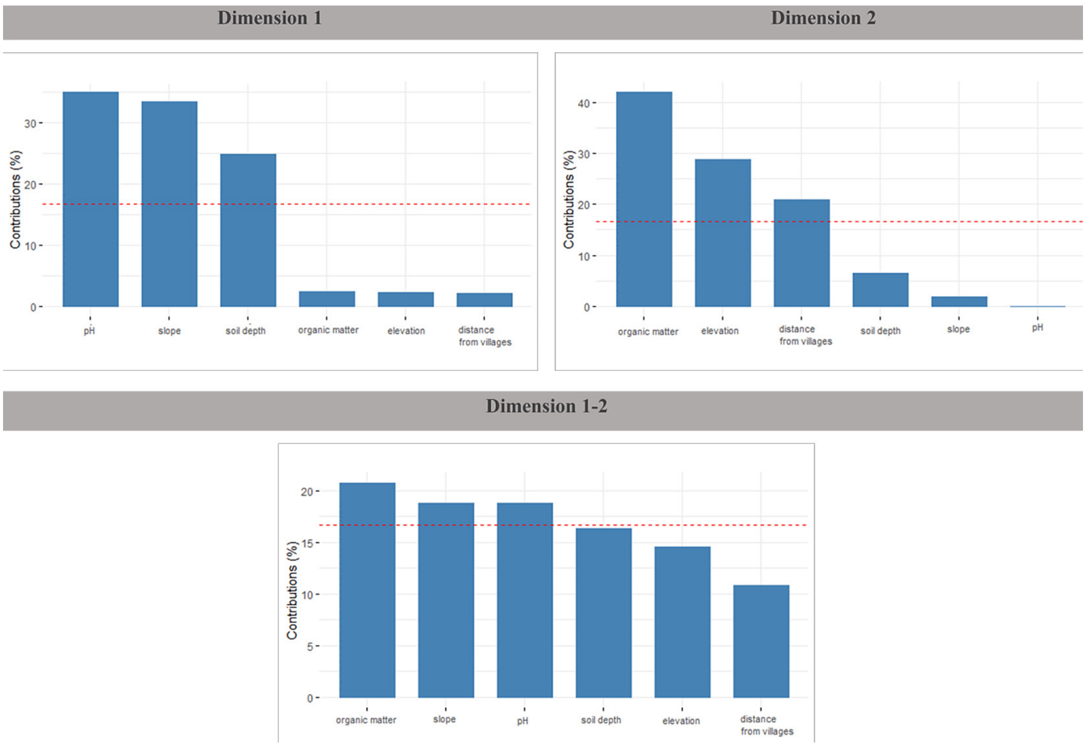

Figure A4. Contribution of variables to the construction of dimensions in PCA by strongly positive coordinates on the axis, to individuals like p38, p24, p33, p43, p47, p34, p71, p55, characterized by strongly negative coordinates on the axis.

The group to which individuals p42, p74, p36, p52, p39, p77, p50, p73 belonged were typically characterized by the steepest slopes and deepest soils, from the most extreme to the least extreme, and lowest pH and organic matter content (Figure 9). This suggested that the observed changes in cork oak formations in this group, dominated by dense to moderately dense strata (QS1 and QS2), were primarily conditioned by the aforementioned factors. These forest formations relied on deep soil, favoring robust root development, and were situated on steep slopes with acidic soil conditions (pH ≤ 6.5), a factor limiting cork oak formations.

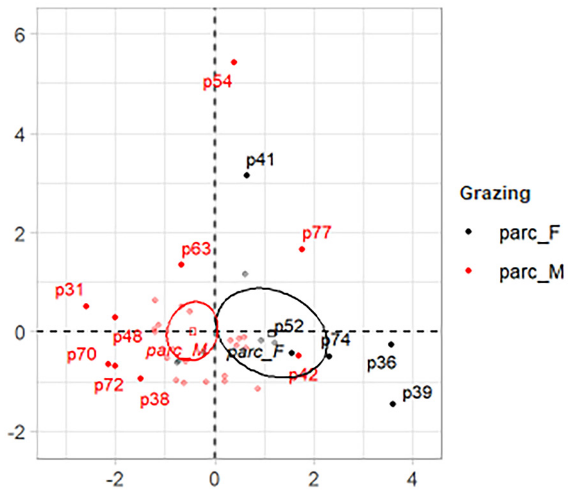

Figure 8. Illustration of grazing variable for showing distances between individuals

Conversely, the group to which individuals p38, p24, p33, p43, p47, p34, p71, p55 belonged presented medium to high values for pH and slope, soil depth and elevation. These individuals belonged to formations composed mainly of light to sparse cork oak strata (QS4 and QS3). The changes observed in this group were mainly conditioned by low slopes, between 20 and 25%, low elevations, around 600 m, and shallow soils. The forest formations in this group are limited by the soil typology, which is generally neutral or basic in pH. It should be noted that the modalities of grazing (parc_F and parc_M) were strongly correlated with this dimension, suggesting that they could summarize dimension 1 on their own. Grazing was less frequent in dense to moderately dense forest strata and more frequent in sparse and open strata.

Individuals in dimension 2 stand out in particular, forming a group characterized by high organic matter content and greater elevation. This group can be explained by the fact that the dominant forest strata are located far from villages (3 to 4 km), on steep slopes (35%) and on shallow soils. This explains why this group stands out from the others, as it is mainly influenced by

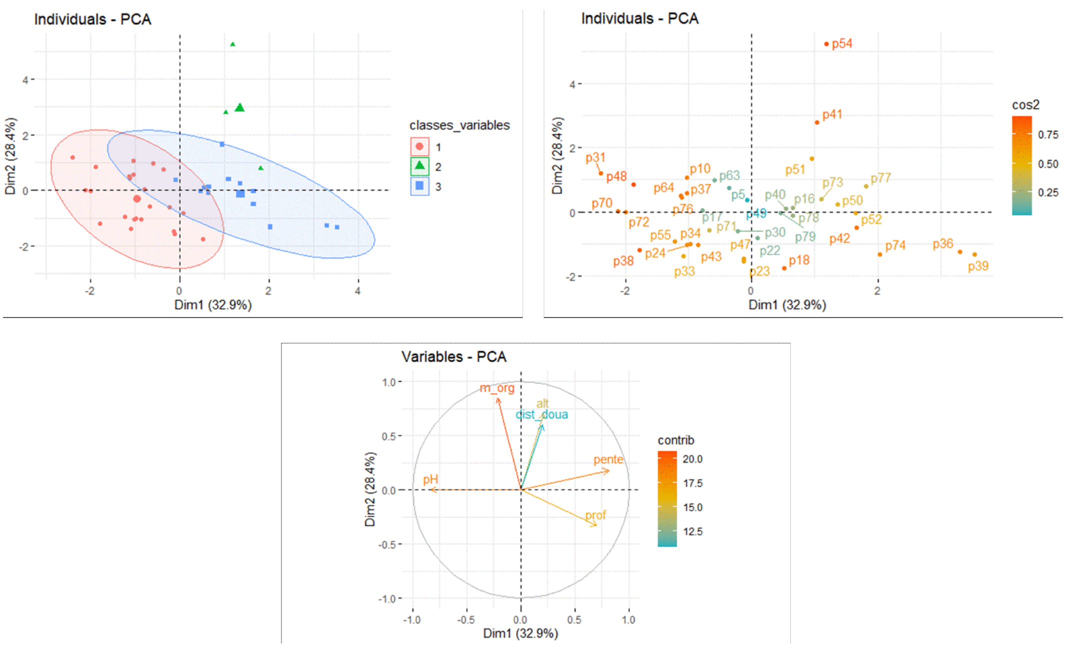

Figure 9. Principal components by grouped site and environmental variables

distance from villages, which contributes strongly to dimensions 2 and 3.

Factor analysis for mixed data (FAMD)

Grazing was found to be explanatory for the typology of forest formations between moderately dense to dense groups and those of clear to sparse density. Figures 10 and 11 show the distribution of the modalities according to the forest stratum on the two dimensions of the FAMD. Considering the variables on both dimensions, organic substances, logging incidents, and distance from the villages contribute to dimension 1, while aspect alone could explain dimension 2 (Figure A5). The investigation of variable contributions to dimensions reveals a strong correlation on dimension 1 with clear to sparse cork oak formations (QS3 and QS4). These formations are strongly correlated with the second dimension and are conditioned by dominant warm slopes (ZC) and very frequent logging incidents (TF). They rest on shallow non-climatic soils without calcareous reserves and with a modal type of soil (SPENCSRCM). On the same dimension, they contrast with dense formations (QS1), characterized by infrequent logging incidents (PF) and dominated by slightly evolved and brownified soils (CSPEB). The dimension shows a correlation with grazing intensity in the weak modality. This weakness is attributed to the significant distance from villages, providing an explanatory factor.

Moderately dense cork oak formations (QS2) are strongly correlated with the first dimension. The variation in forest strata is primarily conditioned by variables related to organic substances, logging incidents, and distance from the villages. These formations are conditioned by low logging incidents (F) and are found on shallow non-climatic soils without calcareous reserves with brownified modal (SPENCSRCMB). They are also influenced by cool and intermediate slopes

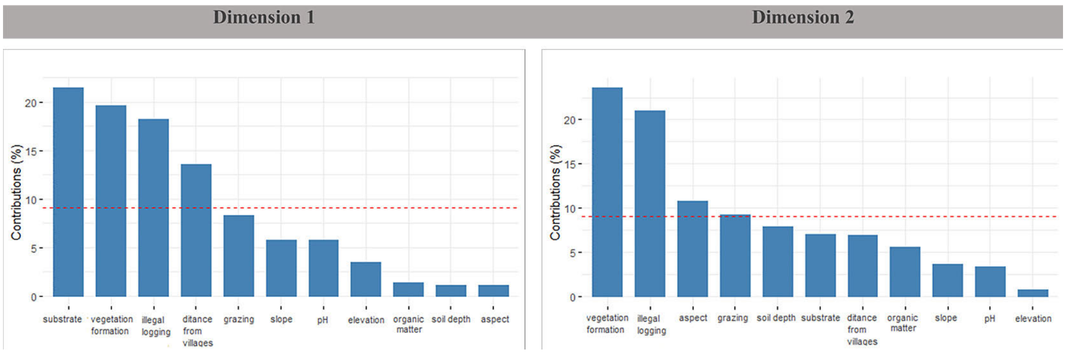

Figure A5. Contribution of variables to the construction of dimensions in FAMD

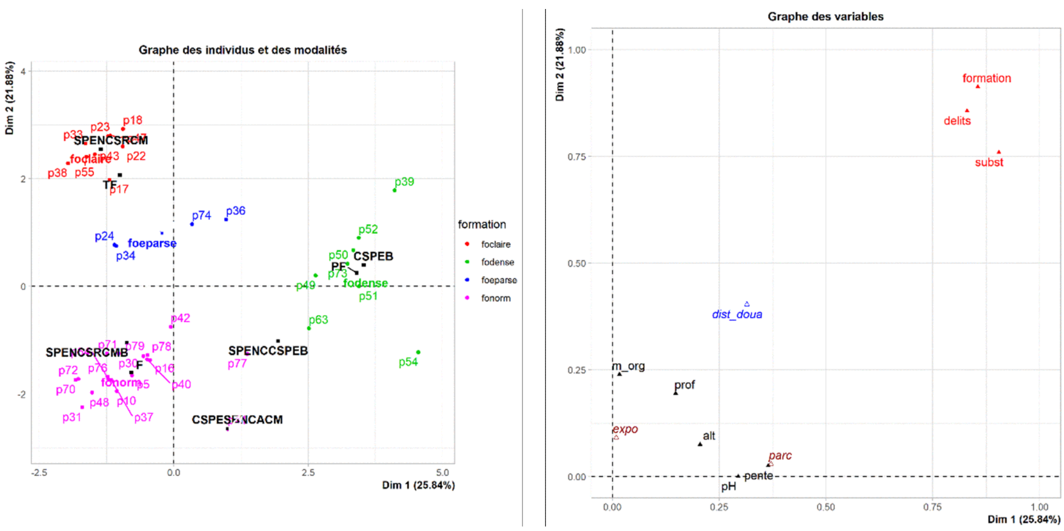

Figure 10. Illustration of the positioning of individual data points representing environmental and site variables in FAMD

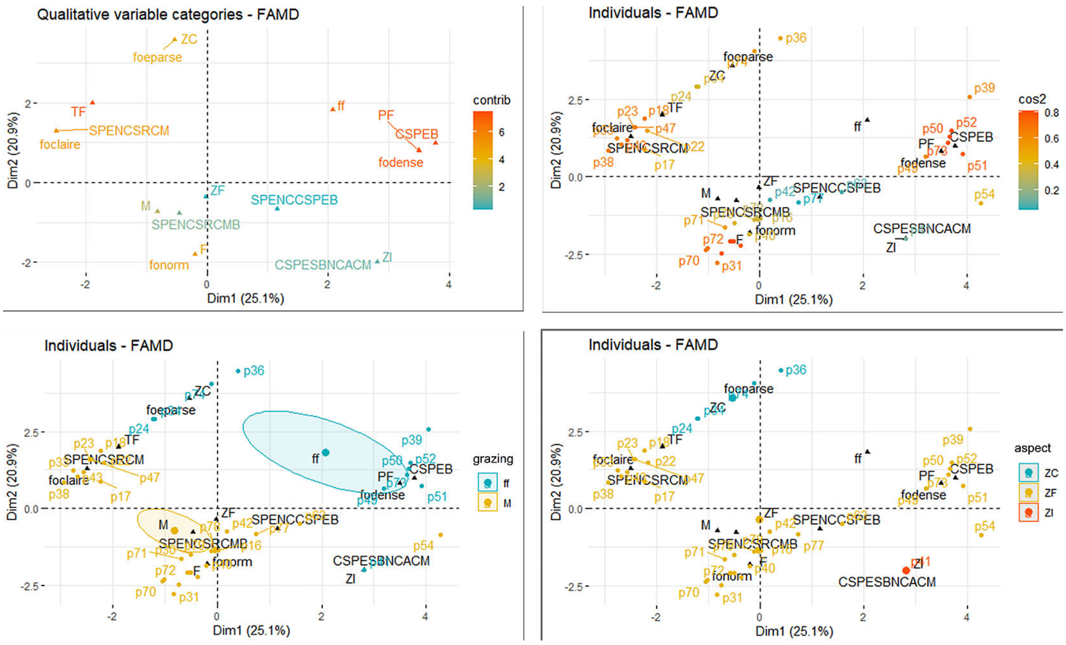

Figure 11. Variable contribution, quality of representation and FAMD synthesis according to grazing and aspect factors

(ZF and ZI). The intensity of grazing is correlated with this dimension, with a moderate modality, indicating that this formation is distant from human habitation. Dominant aspect also conditions the typology of the forest stratum, with sparse density strata generally found on warm slopes, clear and dense strata on cool slopes, and moderately dense strata on slopes ranging from cool to intermediate.

Modeling of change in the study forest

The performance evaluation of the RF models developed to predict the various forest parameters showed generally effective performance (Figure 12). The model for the probability of infraction occurrence achieved an AUC of 0.70, indicating reasonable predictive capability, while the model for soil texture attained the highest AUC at 0.80, demonstrating strong performance. In comparison, the RF model for overall stand change had the lowest AUC of 0.67, though still suggesting reasonable effectiveness. Overall, these achieved scores show that the three models exhibited adequate to strong predictive power. Furthermore, for edaphic factors, the RF model for soil depth achieved an R^2 of 0.89, indicating a high degree of correlation between predicted and observed values and suggesting that the model accounts for a substantial portion of variance. In contrast, soil pH modeling achieved a more moderate R^2 of 0.50, reflecting considerable unexplained variance, suggesting a relationship not fully captured by the predictor variables.

The variable importance assessment the RF model identified autumn precipitation, distance from roads, occurrence of infractions, and distance from Douars, in that order (Figure A7), as the most influential factors in predicting forest change in the study area. Other important variables included pH, carbon, annual precipitation, slope, and spring precipitation. The results suggest that precipitation patterns, proximity to infrastructure and human activities, as well as soil and terrain characteristics, are critical drivers of forest dynamics in the region. In general, climatic variables exhibited the greatest influence, with autumn precipitation and annual precipitation being by far the most influential factors. Human-related variables, including forest infractions and distance from douars, were also identified as important drivers of change in the forest. In contrast, edaphic variables were generally the least contributors to forest change.

The spatial distribution of the predicted likelihood of forest infractions (Figure 13) indicates a predominance (54.38%) of areas with a low-to-moderate probability, dispersed throughout the forest landscape. In contrast, the regions with a high-to-very high likelihood collectively cover 22.98% of the forest area and are primarily concentrated in the southern and northern zones, with some scattered in central parts. Nonetheless, the

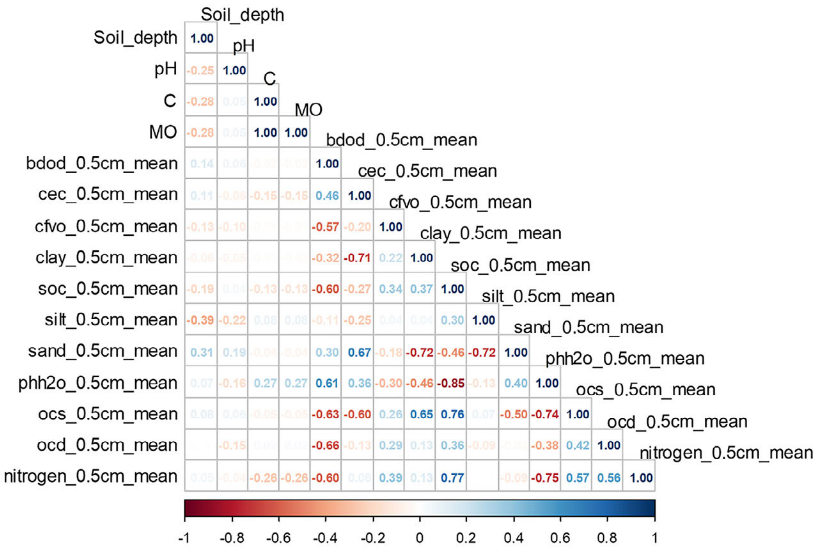

Figure A6. Correlation matrix between edaphic variables measured at plots and SoilGrids interpolated variables

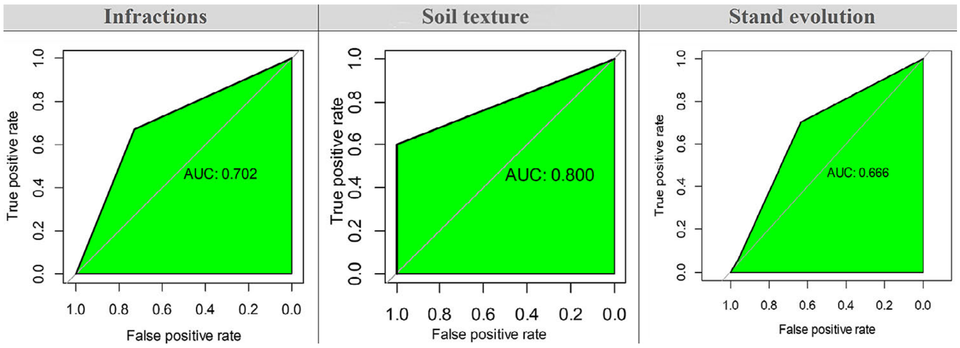

Figure 12. Performance evaluation scores based on ROCAUC for the RF models developed for each case

areas with a very high susceptibility to infractions make up the smallest portion (3.78%) of the forest, with these sections primarily restricted to the southwestern edges of the study area.

The analysis of forest stand dynamics revealed substantial regression across the forest area over time (Figure 15). Notably, 35.40% of the total forest area, approximately 3.400 ha, was predicted to show signs of regression, with occurrences spread throughout the forest, though more concentrated in the southwestern regions. In contrast, about 9.64% of the area, around 930 ha, was predicted to display progression, primarily located in the north, with some scattered patches extending southward into central zones. Predictions from the RF model indicate that the majority of the forest area, representing 54.96%, will remain stable throughout the study period. The extensive areas undergoing regression point to issues such as deforestation or degradation, likely driven by human pressures, as

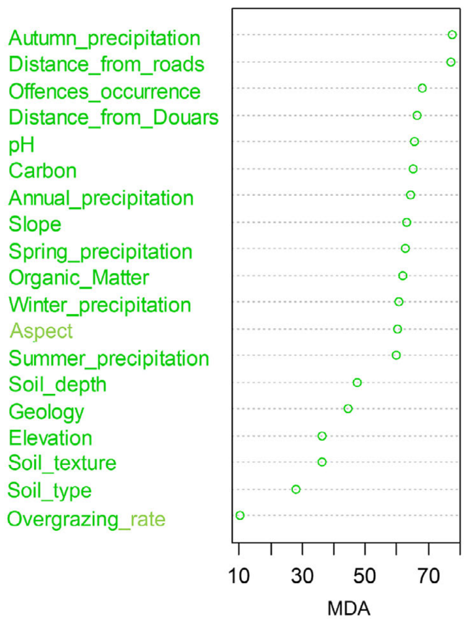

Figure A7. Variable importance assessment of the predictor variables used to model stand evolution in the study forest

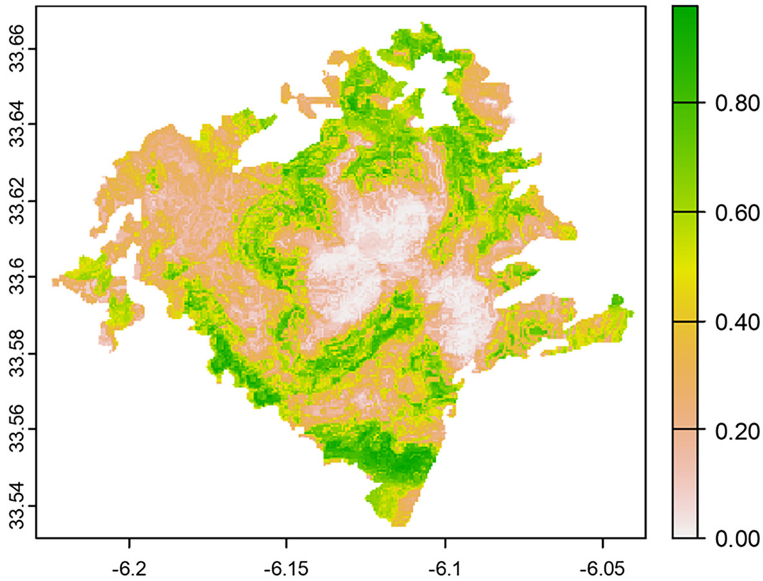

Figure 13. Probability of infraction occurrence prediction by the RF model

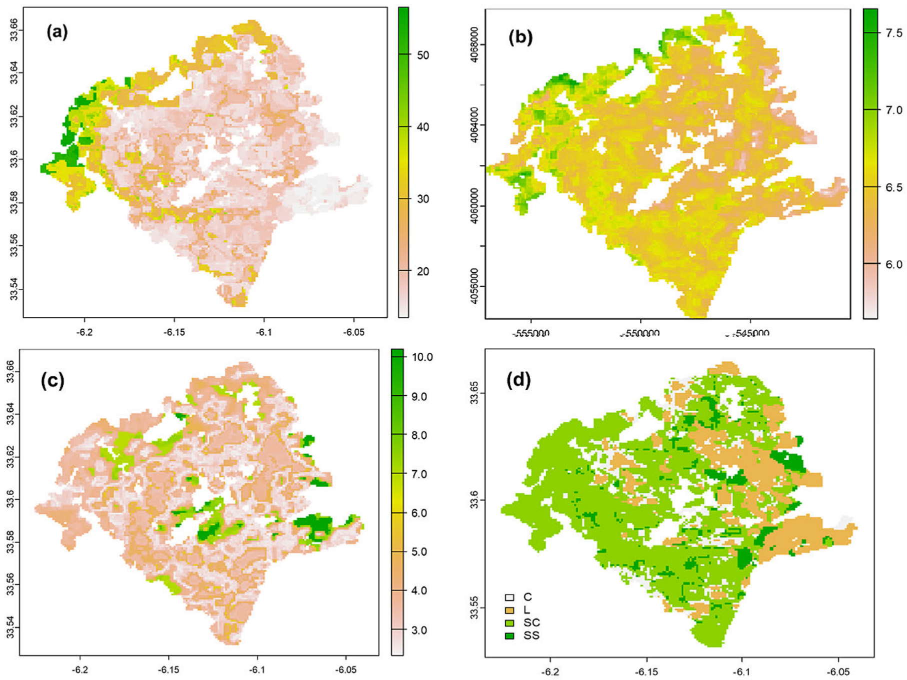

Figure 14. Distribution of edaphic factors across the study area predicted by the RF model (a: soil depth; b: soil pH; c: SOM; d: soil texture)

suggested by the predicted distribution of forest infractions. A comparison with forest change estimates obtained through statistical methods (Figure 3) reveals a tendency for this approach to overestimate both regressive and progressive changes relative to ML results. Specifically, the areas projected to undergo regression cover nearly 60% of the forest area with the statistical method, compared to just over one-third in ML predictions. Likewise, the areas anticipated to show forest growth account for 27% of the forest area according to the statistical method, whereas ML predicts less than 10%. In contrast, the regions expected to remain stable are significantly underestimated by the statistical approach, which predicts them at only 14% compared to more than half of the forest area as forecasted by ML.

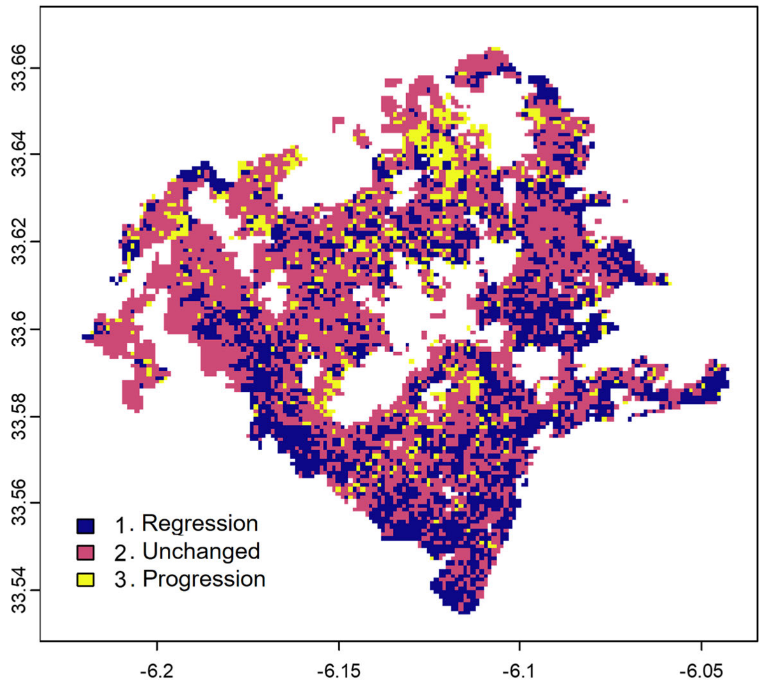

Figure 15. Evolution of the study forest predicted by the RF model

The results of assessment of the relationship between predicted stand evolution and environmental, site, and human factors highlight the specific roles of the latter on the likelihood of regression or progression in forest area in the region (Figures 6–10). For the areas predicted to undergo regression, the majority were associated with a silty-clay soil texture type, comprising 20.15% of the total area where regression is anticipated. Similarly, regression was predicted to be prominent in the areas (30.02%) with soil depth under 25 cm and SOM levels around 4.0 (24.34%). Furthermore, the areas with a soil pH between 6.4 and 6.8 account for 21.44% of the total regression area. Interestingly, regression is mostly projected in the areas with low to medium probability of forest infractions, making up 18.70% of the total area with predicted regression (35.40%), which contrasts with the areas experiencing high to very high predicted levels of forest infractions, constituting only 10.22% in these regions. In contrast, progression is most likely to occur in the areas with silty-clay soil texture (6.03%) and is least likely in the areas with silty-sand texture (0.64%). Progression is highest in the regions with shallow soil depth, particularly below 18 cm (4.45%), and lowest in the areas where soil depth exceeds 42 cm (0.26%). The areas with SOM between 3.0 and 4.0 dg/kg exhibit the greatest progression (3.53%), while the regions with SOM between 4.9 and 6.6 show minimal progression (0.28%). Additionally, progression is lowest in the areas with a soil pH above 7. Finally, progression is least frequent in the areas of high probability of forest infractions (0.32%).

DISCUSSIONS

Spatiotemporal analysis of forest ecosystems holds crucial significance, especially in the Mediterranean region, where unique environmental challenges prevail. It enables a comprehensive understanding of the complex interplay between space and time, unveiling patterns of ecological dynamics and landscape transformations (Gratzer et al., 2004; Di Rita et al., 2018). In the Mediterranean region, characterized by a delicate balance of biodiversity, climate variability, and human activities, spatiotemporal analysis becomes instrumental in assessing the impacts of climate change, wildfires, and land-use practices on forest health (Vennetier et al., 2005; Sanz et al., 2013; Dallahi et al., 2017). By examining temporal trends and spatial distributions, it is possible to develop targeted conservation strategies, monitor ecosystem resilience and implement informed sustainable management practices, ensuring the preservation of biodiversity and ecological integrity in this ecologically sensitive region.

In the conducted study, the cork oak woodland formation in the Timekssouine forest, at different densities, was observed to have undergone spatial regression and a remarkable decrease in density. Indeed, the diachronic analysis revealed concerning findings; the cork oak's area decreased by about 9% between 1999 and 2020, and significant de-densification was recorded in various density classes at a rate of regression of 60 ha/year. Numerous studies (Fennane and Redjali, 2015; Alaoui et al., 2020; de Mahieu et al., 2020; Laarbiya, 2023) have reported alarming rates of cork oak regression in Morocco. Notably, Fennane and Redjali (2015) have reported a worrisome shift in the cork oak landscape, with their findings revealing that despite an initial coverage potential of about 300,000 hectares, the cork oak formations currently manifest as a scarce and reduced tree cover, extending less than 50,000 hectares. Furthermore, in the Maamora forest, a conducted inventory demonstrated a substantial decrease in the cork oak-covered area, indicating a decline of approximately 35% from 1952 to 2016 (Laarbiya, 2023). The decline is attributed to anthropic pressures, climatic shifts, pest attacks, and unsustainable practices, posing significant threats to the ecological integrity and sustainability of these vital ecosystems (Laaribya et al., 2021). This is manifested through cork harvesting, grazing, and soft acorn picking by local communities, which detrimentally impacts forest regeneration. These activities disrupt natural cycles, impeding the replenishment of younger trees. Consequently, these forests age beyond optimal harvesting conditions, threatening ecological balance and the sustainability of cork oak ecosystems in the long term (Lahssini et al., 2015).

In the conducted study, cork oak formations exhibited a complex interdependence with environmental factors, prominently influenced by slope, soil depth, and pH. Thriving on steep slopes of 20 to 25%, these formations benefit from optimal drainage, preventing waterlogging and facilitating essential aeration, which ensures robust vegetation development owing to extensive root establishment (Bagaram, 2016; Boujraf et al., 2021). The deep soils on which these formations rest provide cork oaks with adequate space to establish a vigorous root system, anchor themselves firmly and access the nutrients and water they need. The acidic pH in these areas serves as a favorable condition for cork oaks, influencing nutrient availability and microbial activity (Serrasolses et al., 2009; Rossetti et al., 2016). However, the shift in formations, characterized by scattered or clear cork oaks, appeared to occur in response to gentle slopes below 20–25%, particularly in low-lying areas with shallow soils. In these areas, this could be attributed to the limitations imposed by shallow soils, which prevent the development of a robust root system, affecting overall growth and survival. In addition, forest formations are limited in the areas where the soil typology presents a generally neutral or basic pH, as cork oaks are adapted to acid soils (Serrasolses et al., 2009).

On the basis of the consideration and analysis of both qualitative and quantitative variables in our the conducted, grazing intensity was revealed to serve as a key explanatory factor for the categorization of forest formations in the Timekssouine forest. Grazing is a crucial determinant shaping the diverse typologies of Moroccan forest formations, contributing to the differentiation between areas with different levels of tree density (Bakkali et al., 2000). Indeed, overgrazing poses a critical threat to cork oak regeneration, significantly impeding the natural recovery of these vital ecosystems. Indeed, the study by Alaoui et al. (2020) has documented an overgrazing rate of approximately 80% in the cork oak forests of Sehoul, resulting in forest regression is twice as high as forest production. Furthermore, Laaribya et al. (2014) observed an excessive pastoral capacity of 6.4 units/year, surpassing the ecosystem productivity by more than fourfold, given the optimal capacity balance stands at 1.5. The continuous grazing pressure from livestock, often exceeding sustainable limits, hampers the growth of young cork oak saplings and limits the recruitment of new individuals (Benzyane, 1996; Aronson et al., 2012). This can prevent the establishment of a diverse tree canopy, crucial for maintaining ecological balance (Mysterud, 2006; Bagella et al., 2013). Furthermore, overgrazing exacerbates soil erosion and disrupts nutrient cycling, further hindering the favorable conditions necessary for successful cork oak regeneration (Laouina et al., 2020; Bicho et al., 2022).

Indeed, local communities' heavy dependence on forest resources for livelihood sustenance has created significant pressure on these ecosystems. The traditional agro-forest management practices, while historically sustainable, have become increasingly strained due to population growth and changing economic demands, leading to overexploitation. Specifically, the intensification of grazing practices has exceeded the natural regenerative capacity of the forest, with studies showing grazing intensity often surpassing sustainable thresholds by 300–400% in Mediterranean regions (Roces-Díaz et al., 2021; Hammouyat et al., 2022; Solano et al., 2023). The economic pressures on local communities have led to increased forest resource extraction, particularly in vineyard and olive cropland areas where traditional land-use patterns are being altered to accommodate more intensive agricultural practices. In complex agro-ecosystems of the Mediterranean basin, these pressures are exacerbated by rural area depopulation and the consequent loss of traditional agricultural knowledge that historically helped maintain ecological balance. Furthermore, the fragmentation of Mediterranean landscapes, resulting from long-term settlement history and continuous socioeconomic interactions, has created additional challenges for sustainable resource management. This fragmentation has particularly impacted traditional agricultural systems like olive groves and vineyards, which serve as crucial elements in maintaining landscape mosaic integrity and providing ecosystem services (Pausas et al., 2019; Forzieri et al., 2022). The formulation of practical guidelines aimed at counteracting soil degradation, water depletion, and rural area depopulation has become imperative, requiring a delicate balance between economic sustainability and medium-term ecological benefits. The recovery and conservation of these agricultural resources are essential, as they provide positive externalities and social benefits at both local and regional levels, contributing to improved food security, land quality, and the provision of related ecosystem services.

Furthermore, the conducted study builds on the growing trend of using ML models to effectively analyze forest change dynamics across Mediterranean landscapes (Praticò et al., 2021; Chafik et al., 2021; Aziz et al., 2024), leveraging their robust predictive capabilities. Notably, in the conducted study, RF was shown to be effective in assessing changes in forest cover, as has been the detailed in these regions in other studies (Zerouali et al., 2023;). Indeed, Aziz et al. (2024) found that RF outperformed neural network models such as artificial neural networks (ANN) in monitoring and predicting land use changes, particularly in forested areas affected by agricultural and urban encroachment, as seen in the considered study area. This effectiveness is attributed to the RF ability to capture complex, non-linear relationships among variables, allowing it to accurately identify patterns in forest change (Zhao et al., 2018; Mushagalusa et al., 2024). In addition, the scalability of RF to large regional datasets gives it an advantage over traditional statistical methods, which may struggle with such complexity (Almeida et al., 2022; Suárez-Muñoz et al., 2023). In Morocco and surrounding regions, the use of RF offers a promising approach to assess climate change impacts on forest ecosystems, particularly given the region's often-limited data availability. While traditional statistical approaches may falter with incomplete or inconsistent datasets, the RF capacity to handle missing data and integrate multiple data sources helps address these common challenges in dynamic environments (Zhao et al., 2018).

While RF demonstrated robust performance in the conducted study, several important limitations warrant careful consideration. Temporal bias may arise from reliance on historical data for training samples, leading to underrepresentation of rare forest conditions in harder-to-access areas (Hengl et al., 2018; Senthilkumar et al., 2022). Additionally, the 'black box' nature of RF complicates the interpretation of ecological mechanisms behind predicted changes, hindering direct causal inferences, while variable selection may prioritize data availability over ecological relevance, potentially overlooking significant unmeasured factors (Rigatti, 2017; Giodotti et al., 2018). Sensitivity to class imbalance can affect accuracy for less common forest density classes, and insufficient temporal resolution may fail to capture critical extreme events or short-term fluctuations impacting forest dynamics. Lastly, spatial autocorrelation among ecological data can inflate accuracy metrics due to similarities between nearby locations, emphasizing the need to complement RF results with expert knowledge, field validation, and alternative modeling approaches for informed forest management decisions (Sekulić et al., 2020; Tepe, 2024). These limitations highlight the importance of combining RF results with expert knowledge, field validation, and complementary modeling approaches, especially when applying findings to forest management decisions.

Climatic variables, notably autumn and annual precipitation, were identified as paramount in predicting forest change, in line with similar findings in the region affirming the central role of precipitation in ecological dynamics (Linares et al., 2012; de Waroux and Lambin, 2012; El-Bouhali et al., 2024). Indeed, in Moroccan forest ecosystems, precipitation is a key predictor of forest change and water availability is a crucial limiting factor in this region characterized by episode of drought especially in the summer (Linares et al., 2012; Ezzine et al., 2023). Research in the Middle Atlas highlights that variability in autumn rainfall significantly affects the regeneration of forests, with dry periods leading to lower regeneration rates and heightened drought vulnerability (Benabid, 2019; Benhssaine et al., 2024). Similarly, studies in the High Atlas indicate that annual precipitation patterns are closely linked to shifts in forest cover and biomass, with even minor changes impacting forest health and biodiversity (Serbouti et al., 2023; Saddik et al., 2024). In addition, the importance of anthropogenic indicators, such as forest infractions and proximity to dwellings, highlighted the extent to which human pressures, particularly overgrazing, which was identified using the statistical approach, are a key factor in forest regression. This is consistent with global observations that human activities, particularly those that facilitate access to forests and increase exploitation, often exacerbate forest degradation. The regression patterns observed, particularly in the areas with soil characteristics such as silty-clay texture and shallow depth, and characterized by moderate likelihoods of infraction, demonstrate the complex interactions between biophysical conditions and human disturbance.

However, climatic data, which serve as critical predictors in understanding forest changes, can exhibit variability that may not be fully captured or accurately recorded. In the regions prone to extreme weather conditions, such as droughts or erratic rainfall patterns, characteristic of Morocco, the available precipitation data might be insufficiently detailed or complete, potentially misrepresenting the true climatic impacts on forest ecosystems (Pelletier et al., 2015; Merchant et al., 2017). These can complicate the correlation between observed changes in forest cover and climatic variables, leading to incomplete conclusions about the drivers of ecological dynamics (Radke et al., 2020). Moreover, remote sensing data, while invaluable for monitoring forest changes, can be influenced by factors such as atmospheric conditions, sensor limitations, and variations in land surface characteristics. The presence of cloud cover, for instance, can obstruct satellite observations, leading to gaps that compromise data continuity and accuracy (Chen et al., 2015; Mitchell et al., 2017). These factors can affect the interpretation of forest health and change over time, particularly in terms of assessing the extent of regression or recovery of cork oak formations. Thus, it is essential to account for these uncertainties in data collection and analysis, as they could significantly impact results, interpretations, and subsequent management strategies aimed at forest conservation and restoration.

CONCLUSIONS

The conducted diachronic analysis of the Timekssaouine forest in Morocco, spanning two decades, highlights the alarming regression of cork oak formations, particularly in the dense and moderately dense strata. The observed decline of 9% raises concerns about the overall health and sustainability of the forest ecosystem. Grazing intensity emerged as a crucial factor influencing these changes, underlining the need for targeted conservation efforts and sustainable management practices to mitigate degradation. The expansion of open and sparse strata, coupled with the decrease in dense cork oak areas, highlights the complex relationship between land use dynamics and environmental variables such as topography and soil characteristics. The incorporation of an RF-based ML approach has complemented this analysis, providing a practical means of more effectively identifying and quantifying the influence of these key factors, where climatic variables, particularly precipitation, have emerged as the most important in shaping the forest structure. ML improves understanding of forest change dynamics by overcoming some of the limitations associated with traditional approaches. The combination of diachronic analysis and RF-based modeling allows for improved monitoring and assessment of forest transformations, providing a comprehensive strategy that can be adapted to this specific region. Future conservation strategies should adopt this integrative approach, taking advantage of continuous monitoring and advanced remote sensing technologies to overcome the limitations of temporal and spatial resolution in capturing complex ecological processes. Broadening the scope to include socio-economic factors and community involvement will enable a more complete understanding of the human-nature dynamics influencing forest ecosystems, thereby supporting the sustainable management and resilience of the Timekssaouine forest.

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