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Tracking forest cover change in the Maâmora (1989–2022): Cork oak decline and plantation expansion

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ABSTRACT

The coexistence of natural and planted forests is a significant feature in the Mediterranean and other regions of the world. Understanding this dynamic is crucial for assessing forest management. The purpose of this research is to provide a long-term scientific assessment of forest cover dynamics in the Maâmora forest (1989–2022), with the aim of generating new insights into the drivers of cork oak (natural forest) decline and the expansion of plantation forests (Eucalyptus, Pine, Acacia) and bare land. Five Landsat images (1989, 1999, 2009, 2019, 2022) were classified using the Maximum Likelihood Classification (MLC) algorithm, and land cover changes were quantified. Statistical analyzes were conducted using generalized linear mixed models (GLMs). Over the past three decades, natural forest cover declined by -8.15% per decade, while plantation forests and bare land increased by 4.50% and 312.5% per decade, respectively. This research highlights the conversion of Maâmora's natural forest into plantation forest and bare land, driven by a blend of natural and human-induced factors. Our findings provide valuable insights for guiding rehabilitation efforts and support sustainable forest management. Furthermore, it is essential to adopt specific strategies, including cork oak restoration, assisted natural regeneration, and improved monitoring of forest resources. Future research should explore the effectiveness of these approaches across different ecological and socio-economic contexts to refine forest policy.

Keywords: natural forest, plantation forests, maximum likelihood classification, Maâmora forest, Morocco.

INTRODUCTION

The world's forest cover is estimated at 4.06 billion hectares, covering approximately 31% of the Earth's landmass (FAO, 2020; World Bank, 2020; Rotich and Ojwang, 2021). However, forests play a crucial role in conserving land and water resources (Aju et al., 2015), providing sustainable raw materials and natural attractions (Miura et al., 2015), maintaining biodiversity of plant and animal species (Ager et al., 2020; Bragagnolo et al., 2021; Kalinika et al., 2023), and mitigating climate change (Aju et al., 2015; Miura et al., 2015). They also supply essential ecological functions and range of services that are valued and relied upon by societies (MEA, 2005). These include provisioning services (timber and non-timber forest products) (Vadell et al., 2022), regulating services (including water purification and carbon sequestration) (Bonan, 2008; Pan et al., 2011), and cultural services (providing recreational opportunities and spiritual values) (Nesha et al., 2021).

More recently, the planet experienced a loss of 178 million hectares of forest between 1990 and 2020 (FAO and UNEP, 2020), mainly due to deforestation (Li et al., 2021). This anthropogenic impact has affected the ecological functioning of forest ecosystems over many decades (Barlow et al. 2016; FAO and UNEP, 2020). Other human factors, such as forest clearance for development

(Kalinika et al., 2023), agriculture practices (Achu et al., 2021), unregulated logging (Trisasongko and Paull, 2018), fuel extraction (Kalinika et al., 2023), and the emergence of new forms of pathogens driven by human activities (WWF, 2020; Boubekraoui et al., 2023), amplify these losses.

Natural forests are generally defined as forests that regenerate naturally, with trees growing from seeds or seedlings dispersed by natural processes, and composed mainly of native tree species and their associated genotypes (Dai et al., 2018; Cheng et al., 2024). Cork oak (*Quercus suber* L.) stands are a characteristic feature of the landscapes of the western Mediterranean (Hanane et al., 2022). Over the past four decades, a decline in cork oak populations has been reported across most Mediterranean regions, with varying degrees of intensity (Bellahirech et al., 2019). This phenomenon has become a prime concern, as numerous studies have highlighted significant health deterioration and dieback of cork oak forests (Younsi et al., 2021). Research conducted in different parts of its natural range, including Italy (Moricca et al., 2016), Portugal (Barros et al., 2002), Spain (Luque and Girbal, 1989), and Tunisia (Touhami et al., 2020), underscores the widespread nature of this decline.

In Morocco, for example, cork oak forests, which account for 16% of the world's cork forest area (294 378 hectares), extending from the coastal plains through the central Rif to the Middle Atlas (https://www.eauxetforets.gov.ma). The Maâmora forest, located in north-western Morocco, is the largest cork oak forest in the world and is recognized as a site of biological and ecological interest (AEFCS, 1996; Hanane et al., 2022). This forest occupies a vast area of 133 000 hectares, including 60 000 hectares of cork oak (*Quercus suber* L.), while the rest of the forest consists of other types of artificial stands based on Eucalyptus (*eucalyptus* sp), Pine (*pine* sp), Acacia (*acacia* sp), and includes a significant expanse of bare land (Aafi et al., 2005; Laaribya, 2006; Moukrim et al., 2022). It is of great importance for the population of major urban centers such as Rabat, Salé, Khémisset, and Kénitra, with a total population of around two million inhabitants (Alaoui et al., 2020; Boudy, 1950; Laaribya et al., 2021). At the beginning of the 19th century, the Maâmora forest covered an area of 300 000 hectares (Cherkaoui et al., 2007 and 2009), but then underwent a significant decrease, from 134 000 hectares (Emberger, 1928) in the early 1920s to only 65 601 hectares in the early 1980s (Cherkaoui et al., 2007; Hanane et al., 2022). According to studies by Hanane et al. (2022); Maghnia et al. (2017), various biotic and abiotic factors have converged to contribute to this harsh situation, namely (1) forest fires, (2) branch removal, (3) drought, (4) urban expansion, (5) groundwater extraction, (6) over-exploitation of forest resources, (7) overgrazing, and (8) harvesting of acorns.

To counteract this decline, reforestation efforts have been carried out since the 1950s in the Maâmora forest, mainly with eucalyptus and pine plantations, covering an area of 66.491 hectares, or 50.3% of the total area (HCEFLCD, 2011). The objectives pursued through these reforestation efforts encompass (1) the preservation and conservation of biodiversity (Calvino-Cancela, 2013; Martínez-Jauregui et al., 2016), (2) the promotion of wood production (Martínez-Jauregui et al., 2016; Hanane et al., 2022), and (3) the enhancement of protective and recreational functions (Martínez-Jauregui et al., 2016; Hanane et al., 2022). Over the past six decades, the Maâmora forest has undergone three successive development plans (1951–1971, 1972–1992, and 1992–2012), primarily aimed at the protection, exploitation, and regeneration of cork oak, as well as artificial reforestation (Fennane and Rejdali, 2015). The most recent initiative, the "Maâmora Rehabilitation Project" (2005–2014), was implemented with a total budget of 280 million dirhams (Naggar, 2014). Currently, a new management plan for the 2015–2032 period is in effect, focusing on sustainable forest conservation and restoration strategies (HCEFLCD, 2015).

Satellite remote sensing serves as a crucial data source for quantifying, detecting, monitoring, and mapping forest cover changes, due to its advantages including frequent data collection, compatibility with digital processing, and precise georeferencing methods (Kerr and Ostrovsky, 2003; Rogan and Miller, 2006). Moreover, the advent of Geographic Information Systems (GIS) has enabled the integration of multisource and multi-temporal data to analyze land use and land cover changes, providing insights into the trends, rates, nature, locations, and magnitudes of these changes (Adedeji et al., 2015).

In light of this context, the primary objective of this study was to employ remotely sensed data and geospatial techniques to monitor the distribution of natural and plantation forest cover in the Maâmora forest over 33-years. In addition, the research aimed to accomplish the following specific objectives: (i) to analyze the spatio-temporal trends in the evolution of natural forest cover, forest plantations and bare land, in order to understand how these areas have changed over time, and (ii) to identify the key factors driving the observed trends. This assessment will yield valuable insights for the sustainable management of this critical forest resource, especially in light of the current challenges posed by climate change and increasing human impacts on the environment.

MATERIALS AND METHODS

Study area

The Maâmora forest is located in the North-West of Morocco, close to the Atlantic Ocean (Figure 1), between 6° and 6° 45' West longitude and 34° and 34° 20' North latitude (Laaribya et al., 2021; Moukrim et al., 2022; El Alami et al., 2023). It is partitioned into five cantons named, A, B, C, D and E from West to East (Benabou et al., 2022; Moukrim et al., 2022). The main component of the natural vegetation of the Maâmora forest is the cork oak (*Quercus suber* L), which occupies an estimated total area of around 65 601.3 hectares or 49.7% of the total forest area (HCEFLCD, 2014a). Planted tree species introduced in the Maâmora forest are mainly eucalyptus, resinous pine and acacia (HCEFLCD, 2014b). Eucalyptus plantations are the second largest in terms of area (45 998.1 hectares) after cork oak and they play a crucial role in the production of pulpwood, firewood and poles, with two main species dominating: *Eucalyptus camaldulensis* (80.7%) and clonal eucalyptus (11.8%) (HCEFLCD, 2014b). Pine plantations form the third-largest tree structure in the Maâmora forest, covering a substantial 1 398.4 hectares, equivalent to 8.6% of the total forest area. Maritime pine (*Pinus pinaster*) overwhelmingly dominates these plantations, making up 96% of all pines in this particular forest (HCEFLCD, 2014b). Acacia plantations are often organized in dense stands and cover an expanse of 2800 hectares, representing 2.1% of the Maâmora area. The predominant species in these plantations is *Acacia meernsi*, which occupies a significant 99.8% of the total area, with the additional presence of *Acacia cyclops* covering 3.5 hectares (HCEFLCD, 2014b).

The Maâmora forest experiences a Mediterranean climate type, with notable influence from the nearby Atlantic Ocean (Noumonvi et al., 2017). The bio-climate within the forest varies from from sub-humid with warm winters near the Atlantic coast to semi-arid with temperate winters in the central and eastern sections of the forest (Aafi, 2007; Verdinelli et al., 2017; Laaribya et al., 2021; El Alami et al., 2023). The annual rainfall varies from 450 to 600 mm, depending on the degree of continentality, with the highest levels occurring during the winter season, specifically in the months of late November, December, and January (Aafi et al., 2005; Mokhtari et al., 2014; Oubrahim et al., 2015). Average monthly temperatures range from 12 °C in January to 25 °C in July and August, while the maximum and minimum temperatures

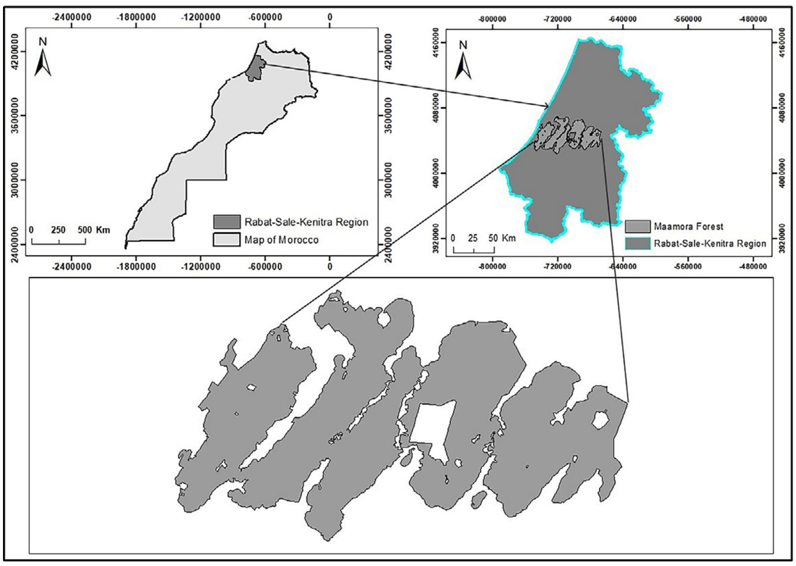

Figure 1. Study area localization

during the hottest and coldest months reach 37 °C and 3.5 °C respectively (Belghazi and Mounir, 2016; Moukrim et al., 2022). The Maâmora has a largely flat topography (Benabou et al., 2022), marked by a relatively gentle relief, with an elevation of 6 to 8 meters near the coastline, rising to about 300 meters in the northeastern section (Abourouh et al., 2005; Laaribya et al., 2021).

Data sources

The data employed in this research were segregated into satellite data and auxiliary data (Table 1). Satellite imagery was used to generate land cover maps of the Maâmora forest for 1989, 1999, 2009, 2019 and 2022, to facilitate the assessment of forest cover changes. The images selected for the analysis were free of unwanted shadows, cloud cover and resampled to a uniform spatial resolution of 30 × 30 meters (Kankam et al., 2022; Baidoo and Obeng, 2023). In this study, these images were taken during the dry season (July through late August) because they are less susceptible to cloud interference, ensuring superior image quality and also with the aim of avoiding any potential confusion between trees and other crop species, thus they were employed for the analysis in this research. The aerial data included multispectral data acquired from Landsat 4–5 TM (Thematic Mapper) images of 1989 and 1999, Landsat 7 ETM+ (Enhanced Thematic Mapper Plus) images for 2009, and Landsat 8 OLI/TIRS (Operational Land Imager/Thermal InfraRed Sensor) images for 2019 and 2022, which were archived for 33 years, from 1989 to 2022. All of the chosen satellite data sets were obtained from the United States Geological Survey (USGS) Earth Explorer service (https://earthexplorer.usgs.gov/) (Izadi and Sohrabi, 2021; Seenipandi et al., 2021). Auxiliary data encompassed Google Earth imagery and field-based observations, which included reference data points collected through the global positioning system (GPS) (Bunyangha et al., 2021). These reference points were adopted to assess the accuracy of the classification, in conjunction with the historical view of Google Earth images (Thien and Phuong, 2023).

Image pre-processing and classification

Images pre-processing was carried out to improve the quality of information contained in satellite imagery and make it more accessible for interpretation (Jensen, 1996; Thien and Phuong, 2023). Landsat satellite images were processed, classified, and analyzed using ArcGIS 10.4 mapping software. The satellite images were geometrically corrected and projected to the 29 N zone of the Universal Transverse Mercator (UTM) coordinate system on the WGS_1984 datum (Baidoo and Obeng, 2023; Kankam et al., 2022). The image of the study area was then extracted. Besides, the predefined classes delineated for the study included cork oak, forest plantations, and bare land (see Table 2 for details). For each of the predetermined land cover types, a minimum of 200 training samples were selected by delineating polygons around representative pixels. Spectral signatures for the various land cover types were obtained from the satellite imagery by recording the characteristics of the pixels contained within the polygons created for each land cover type. A satisfactory spectral signature is one that minimizes confusion in distinguishing between the different land covers types being mapped (Gao and Liu, 2010). We then applied a rule-based supervised classification method, specifically the Maximum likelihood Classification (MLC) algorithm, to

Table 1. Satellite and ancillary data source employed for land cover change assessment (1989–2022)

Data type	Sensor	Date	Spatial resolution (m)	Source
Satellite images	Landsat 4-5 TM	15 July 1989	30	Earth explorer USGS (United States Geological Survey) (http://earthexplorer.usgs.gov/)
		28 August 1999	30	
	Landsat 7-ETM	23 August 2009	30	
	Landsat 8-OLI/TIRS	03 August 2019	30	
	Landsat 8-OLI/TIRS	18 August 2022	30	
Ancillary data	Google Earth	1989/1999/2009/2019/2022	/	Google Inc
	Field data	2022	/	Study area survey

Table 2. Different land cover types and their descriptions

Land cover class	Description	References
Cork oak	The cork oak (*Quercus suber* L.) is a key evergreen tree of the Mediterranean basin, valued for its renewable cork bark. It represents the reference species (natural forest) of Morocco's Maâmora forest, a vital ecosystem that supports biodiversity, prevents soil erosion, and sustains livelihoods through the cork industry.	Laaribya et al. (2010) Simonson and Allen, (2014) Maghnia et al. (2019)
Forest plantations	Land forest plantations are man-made wooded areas created by planting trees, typically in a systematic manner, to serve specific purposes. Unlike natural forests, they usually consist of one or a few selected species, often fast-growing or exotic, chosen to meet economic, environmental, or social objectives. Forest plantations in the case of the Maâmora forest are represented mainly by eucalyptus, pine and acacia, which are introduced to ensure these objectives.	Carnus et al. (2006), West, (2014), Nghiem and Tran, (2016)
Bare land	Includes areas marked by eroded and degraded lands, sandy zones, exposed rock, and other soil surfaces that remain devoid of vegetation throughout the year.	Mengist et al. (2021)

perform land cover classification on the images acquired from the years 1989, 1999, 2009, 2019, and 2022 (Nguyen et al., 2020; Thien et al., 2022; Thien and Phuong, 2023). The MLC algorithm, widely recognized as one of the most effective supervised classification techniques (Bonn and Rochon, 1993; Chatelain, 1996), focuses on constructing a likelihood function and optimizing its logarithm to estimate the unknown parameters (El Haj et al., 2022). To improve classification accuracy and reduce misclassifications, a post-classification refinement process was employed to ensure both simplicity and effectiveness (Harris and Ventura, 1995). This process minimizes outliers and noise, leading to enhanced accuracy and better interpretability of the final outcomes (Camara et al., 2024). By refining pixel-based classifications, post-processing techniques contribute to generating more precise and consistent land cover maps (Huang et al., 2014).

Accuracy assessment

Assessing the accuracy of the thematic maps is a crucial process to validate the reliability of the information extracted from the dataset (Butt et al., 2015). Accuracy assessment serves as a critical step to validate the precision of the classification results and to reveal the potential margin of error resulting from the similarity of the spectral response of the distributed classes (El Haj et al., 2022). The confusion matrix is the selected technique to analyze accuracy throughout the post-classification stage of land cover imagery across multiple dates (Kumar et al. 2020; Kafy et al., 2021; Acharki et al., 2022). The accuracy study relies on reference data that reflect the actual land cover conditions and the error assessment is encapsulated in a confusion or error matrix generated using ArcGIS 10.4 software. The matrix takes the form of a square table that compiles pixels from the image, where the rows denote the classified category (Anand, 2012; Jaouda et al., 2018), while the columns represent the actual field conditions and the non-diagonal entries highlight values that were misclassified or assigned to a different category (Purwanto et al., 2016). In fact, the matrix serves as a tool to calculate both the overall accuracy and the Kappa coefficient (Jazouli et al., 2019). The overall accuracy (OA) was computed through dividing the count of pixels categorized correctly by the total number of pixels used for the evaluation (Congalton and Green, 2019). Kappa coefficient values range from 0 to 1, a Kappa value exceeding 0.80 indicates a strong agreement with reality and high precision, while values between 0.4 and 0.8 suggest moderate precision and a value below 0.40 signifies a low correspondence between the classification and actual field observation (El Haj et al., 2022). Accuracy measures were calculated using the following equations (Rash et al., 2023):

$$Overall\ accuracy = \frac{\sum_{i=1}^{n} a_{ii}}{N} \quad (1)$$

where: N denotes the total number of reference points; n represents the total number of classified groups; a_{ii} corresponds to the number of correctly classified points (Diagonal).

$$Kappa\ coefficient = \\ = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})} \quad (2)$$

where: r represents the number of rows/columns; x_{ii} denotes the number of observations; x_{i+} indicates the total number of row i; x_{+i} refers to the total number of columns i; N is the number of samples.

Statistical analyses

Statistical analyses were carried out using R software, version R-4.0.3 (R Core Development Team, 2020). Due to the overdispersion of the data resulting from the adoption of the generalized linear mixed models (GLMs) with a Poisson distribution (ratio of residual deviation and residual degrees of freedom >> 1), the negative binomial distribution was selected (glm.nb function via the package "MASS" (Venables and Ripley, 2002)) to evaluate the effect of decades (continuous independent variable) and forest type (categorical independent variable with three modalities: cork oak, forest plantations and bare land) on forest cover area (dependent variable).

Models were performed based on the AIC adjusted for small sample size (Burnham and Anderson, 2002) using the "MuMIn" package (Bartoń, 2015). All models with ΔAICc value below 2 were regarded as exhibiting equivalent performance (Burnham and Anderson, 2002). For each forest type, the forest growth rate, r, was calculated by summing the parameter estimates of the decade effect and that of the interaction between the decade and the considered forest type (i.e., decade × forest type). The discrete forest growth (λ) was then calculated as e(forest growth rate) and the percentage change per decade was calculated as (e(forest growth rate)–1) × 100. Model validation was performed using the R package "DHARMa" (Hartig, 2020).

To display the relationship between the predicted forest area and the covariates present in the top- ranked AICc models, the "visreg" package (Breheny and Burchett, 2012) was employed.

RESULTS AND DISCUSSION

The image accuracy results for the five assessment years are summarized in Table 3. Overall accuracy values exceeded 87% for all images (i.e. 1989, 1999, 2009, 2019, and 2022), reveals that the detection of changes observed in the images is a reliable reflection of the real conditions on the ground. In addition, the quality of the classification is confirmed through the Kappa index values, which are all higher than 0.85. In statistical terms, results with a Kappa value higher than 0.85 are considered very good, further underlining the credibility and accuracy of the image analysis (Pontius, 2000; Thien and Phuong, 2023). In accordance with Lea and Curtis (2010) as well as Manonmani and Suganya (2010), the accuracy assessment report for classification, indicating an overall accuracy exceeding 80% and a kappa coefficient above 0.8, signifies excellent agreement among the classified results and the reference data.

Tables 4 and 5 summarise the model that best supports the effects of forest type and decade on forest area. The glm.nb analyses revealed that forest area dynamics are significantly influenced by the interaction between forest type and decade,

Table 3. Global precision and Kappa coefficients for the different classification dates

Years	Overall accuracy (%)	Kappa coefficient
1989	93.96	0.93
1999	93.13	0.92
2009	88.25	0.86
2019	93.43	0.92
2022	87.66	0.85

Table 4. Best models describing forest cover trend in the Maâmora forest; ranking is established based on the corrected Akaike's information criterion (AICc) for small datasets, reporting also the degrees of freedom (df), the ΔAICc relative to the most parsimonious model; Akaike's weights (Wi), and the −2 log-likelihood statistics (logLik)

Variables	df	logLik	AICc	ΔAICc	Wi
Forest type·decade	7	-148.92	327.85	0.00	0.997
Forest type	4	-164.12	340.24	12.39	0.002
Forest type+decade	5	-162.32	341.31	13.46	0.001
Null	2	-175.3	355.59	27.74	0.000
Decade	3	-175.3	358.76	30.91	0.000

Table 5. Parameters estimates (from models with ΔAICc < 2) and standard error (SE) derived from the most supported model describing forest cover trend in the Maâmora forest (Morocco)

Parameter	Coeff.	SE	Z-value	Pr (>|Z|)
Intercept	11.555	0.197	58.533	<0.001
Forest plantations	-1.019	0.279	-3.650	0.001
Bare land	-4.905	0.280	-17.512	<0.001
Decade	-0.085	0.059	-1.832	0.067
Forest plantations·decade	0.129	0.084	2.254	0.024
Bare land·decade	1.502	0.084	8.844	<0.001

meaning that the effect of decade on forest area depends on forest type (Table 5, Figure 2). The trends recorded were negative (decrease) for natural cork oak forests (Table 4, Figure 2) and positive (increase) for forest plantations (Table 4, Figure 2) and bare soil (Table 4, Figure 2). The overall reduction in natural cork oak forest cover per decade was -8.15%, corresponding to a loss of 6 556 ha (per decade). For forest plantations, the increase per decade was 4.50%, corresponding to an increase of 2 274 ha (per decade). The largest increase in the study area was observed for bare land, which rose by 312.5% per decade, corresponding to an increase of 3 971 ha (per decade).

The dispersion test for the model confirmed that the the residuals of the highest-ranking AICc model did not exhibit significant overdispersion (ratio = 1.756, χ 2 = 15.80, rdf = 9, P = 0.071). The R2 value was 96.5%, which means that only 3.5% is explained by other covariates not taken into account in our analyses.The correlations between predicted and observed values showed that our model has significant predictive power for the three studied forest components, namely natural Cork oak forest (Pearson score (r) = 0.762, P = 0.010), forest plantations (r = 0.611, P = 0.028), and bare ground (r = 0.932, P < 0.001).

The results obtained from the analysis of the temporal changes of the forest cover during the study period (1989–2022) in the Maâmora forest showed a decrease of approximately -8.15% per decade in the area covered by the cork oak

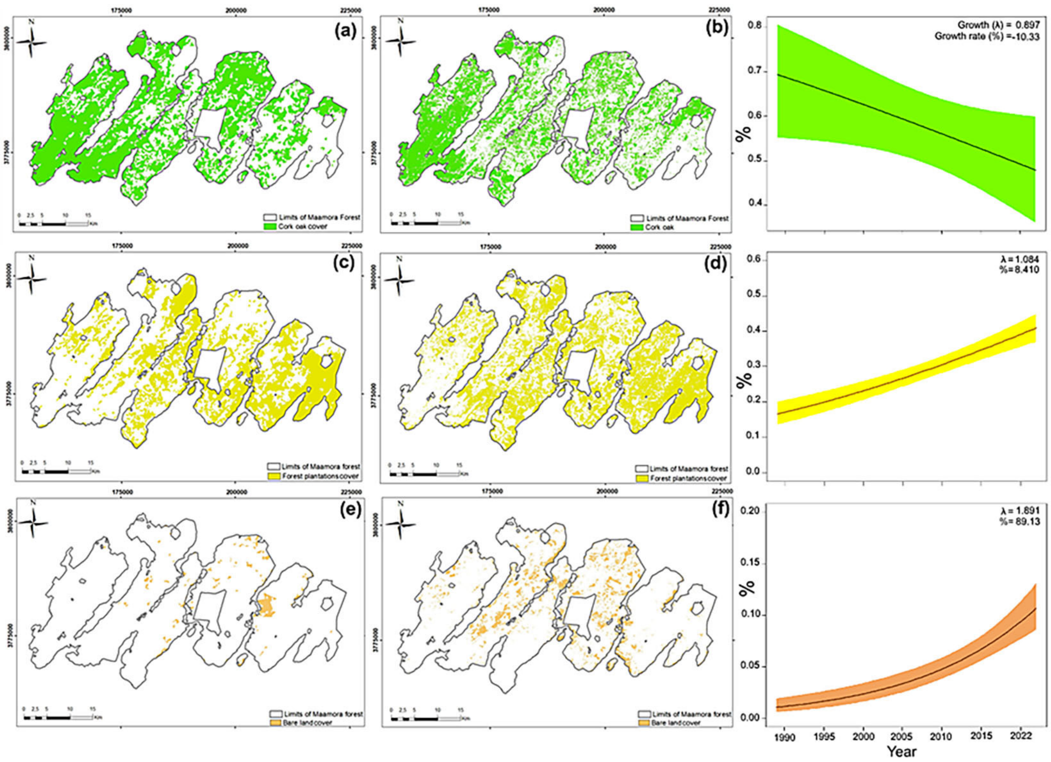

Figure 2. Maps showing the distribution of cork oak (a, b), forest plantations (c, d), bare land (e, f) and trends evolution patterns within the Maâmora forest in 1989 (left) and 2022 (right)

forest. Indeed, it was approximately 80 445.87 hectares in 1989 and reached 58 855.14 hectares in 2022. Conversely, our results highlights a progressive dynamic of land cover for the classes of forest plantations (including eucalyptus, pine and acacia) and bare land of approximately 4.50 and 312.5% per decade. In fact, the areas of forest plantations and bare land increased from 50 541.03 and 1 270.62 hectares in 1989 to 58 185.36 and 14 360.67 hectares in 2022 respectively. These results provide new, quantitative evidence of long-term forest dynamics in the Maâmora forest, filling a gap in knowledge regarding the spatial-temporal interactions between natural and planted forests in Northwest Morocco.

Several potential factors could be responsible for the decrease of the cork oak in the Maâmora forest. Among these, changes in climatic conditions appear to play a significant role, representing a major threat affecting cork oak forests. This finding is in agreement with the conclusions of Campos et al. (2008), who documented comparable impacts on cork oak forests in Iteimia (Tunisia) and Jerez (Spain), and Touhami et al. (2019), who observed similar trends in the Kroumirie region (Tunisia). Furthermore, the changes in climatic condition could intensify the decline of the west-to-east rainfall gradient in the Maâmora forest, putting additional pressure on cork oak (Laaribya et al., 2021).

Another study by by Lemkimel and Daiboun, (2024), reported that, one of the environmental challenges posed by changes climatic conditions is the premature ageing of cork oak trees. According to Costa et al. (2011), landscape transformation in Mediterranean agroforestry areas of the Southwestern Iberian Peninsula (Portugal), have contributed to the decline of cork oak forests. Moreover, variability in climatic conditions has the potential to influence cork oak stands through altering tree growth and mortality rates, and by to impacting the production and quality of cork (Besson et al., 2014; Moricca et al., 2016; Camarero et al., 2024).

In addition to the above, the recurrent droughts in the history of Maâmora and the decreasing trend in rainfall since 1910 remind us that the problem of cork oak decline originated at the early of the 20th century (Laaribya, 2010). Previous studies have reported that the reduction of cork oak stands is particularly widespread in the eastern section of the forest, where conditions are much less favourable, if not completely unfavourable, for the growth, regeneration and sustainability of this species and this finding is supported by similar studies carried out in the Maâmora forest (Laaribya, 2006; Aafi, 2007). In the Iberian Peninsula, the decline of cork oak populations in 1995, 1999, and 2005 correlates with the severe drought events that occurred in 1994–1995, 1998–1999, and 2004–2006, respectively (Oliveira et al., 2016).

Thus, the current state of the cork oak distribution in Maâmora forest is significantly diminished compared with historical extent, primarily owing to intense anthropogenic activities including overgrazing and species displacement (Lahssini et al., 2015; Ghouldan et al., 2024). This outcome is consistent with the findings noted by Touhami et al. (2019) in the cork oak forest of the Kroumirie region (Tunisia) and by Campos et al. (2008) in the public cork oak forests of Jerez (Spain) and Iteimia (Tunisia). On the other hand, this decrease in cork oak area is mainly spurred by human activities, driven by population growth, leading to the need for land for urban expansion, timber extraction and building materials (Noumonvi et al., 2017). Likewise, Kim et al. (2017) argued that the decrease of the cork oak forest is linked to several development processes, including urbanization, rapid population growth, and industrialization. According to Laaribya, (2010), other factors that aggravate the situation in the Maâmora forest should be taken into account, such as attacks by insect defoliators (*Lymantria dispar*) and fungi (Hypoxylon mediterraneum). Several studies have shown that the decline observed in many cork oak forests was primarily induced by pests and pathogens (Costa et al., 2009; Tiberi et al., 2016), insect attacks (Moreira and Martins, 2005; Kwak et al., 2011), and fungus (Touhami et al., 2019). This drop in cork oak stands was also of concern in several other Mediterranean sites, including Montado and Bartolomeu da Serra in Portugal (Costa et al., 2010), Sardinia and Lazio in Italy (Luciano and Prota, 1995), the Zarifet-Hafir forest in Algeria (Bouchaour-Djabour, 2001), the Kroumirie forest in Tunisia (Ben Jamaa et al., 2005), and in Andalusia in Spain (Sanchez and Garcia, 2007).

On the other hand, the increase in forest plantations (including eucalyptus, pine and acacia) can be explained mainly by the strategy of the Forest Administration to replace cork oak stands in areas from which they have disappeared with rapidly growing introduced species. As pointed out by HCEFLCD, (2014a), in terms of forest management policy, the foremost objectives of the forest administration in the previous period 1999 included the preservation of cork oak in economically viable areas and transformation into fast-growing introduced species where cork oak density was low and difficult edapho-climatic conditions for its maintenance.

Indeed, in order to respond to the needs of the Moroccan cellulose industry, forest policy has been driven by economic considerations aimed at satisfying the demands of the local timber market, particularly for eucalyptus wood (Benabou et al., 2022; Malki et al., 2022). The reforestation of numerous areas with eucalyptus, pine and acacia trees since the latter half of the last century has increased the extent of forest plantations and led to further reduction in the range of Quercus suber. This phenomenon has limited the potential expansion of cork oak, as recorded in various contexts in Monte Pisano (Tuscany N-W, Italy) (Selvi et al., 2016; Bertacchi, 2023). In another study reported by Laaribya, (2010), the reduction of cork oak areas in favor of more productive species to better satisfy the demands of the Moroccan economy (Eucalyptus, Pinus pinaster etc.) leads to additional deterioration of existing cork oak stands in the face of increased grazing pressure, which affects soil quality and alters local water cycles through increased water uptake and led to biodiversity loss. On the other hand, the increase in bare land areas during the study period can be strongly correlated with the removal of plantation trees, in particular through irregular harvesting by the local population in favour of agriculture and construction. This is supported by Aafi, (2007) and Fennane and Rejdali (2015), who indicated that around 300 settlements (douars) were established within the Maâmora forest and today through Google Earth, we can see the extent of cork oak areas that have been completely destroyed and replaced by houses, pastures and agricultural land for cereals, vegetables and fruit trees.

This study provides critical insights by providing detailed and comprehensive data on the temporal changes in the extent of forest cover over a 33-year period. It highlights significant patterns and trends in the landscape, focusing on the spatial and temporal dynamics of different land cover types. Specifically, the study examines and quantifies changes in the areas occupied by three different land cover classes: Cork Oak, representing native forest ecosystems; Forest Plantations, representing managed and artificial forest areas; and Bare Land, representing areas with little or no vegetation cover.

By analyzing these changes, the study sheds light on shifts in land use and vegetation cover. It also confirms the initial hypothesis that these changes are caused by both natural and human-induced factors. The statistical insights provide a deeper understanding of the extent and rate of these changes, helping to identify critical areas of concern, inform conservation strategies, and guide sustainable forest management and land-use planning. This data-driven approach provides a robust basis for assessing the environmental, economic and social impacts of land cover change in the study area.

CONCLUSIONS

This study demonstrates that the combination of remote sensing (RS) and geographic information systems (GIS) with a thorough literature review provides not only an effective approach to monitoring forest cover change but also new insights into the factors driving it. Analysis of land cover dynamics in the Maâmora forest among 1989 and 2022 reveals the cumulative and long-term impacts of both human activities and natural disturbances on cork oak ecosystems, exposing a significant and continuous decline in these habitats alongside the expansion of forest plantations and bare land. The observed changes in forest cover are the result of a complex interplay of interrelated factors. Human activities such as population growth, overgrazing, intensive agriculture, timber harvesting, urban expansion, industrial activities and forest fires have played a dominant role. At the same time, natural disturbances such as drought, reduced rainfall, inadequate natural regeneration and pest or fungal outbreaks have exacerbated the decline. In addition, management strategies designed to overcome previous regeneration challenges have accelerated the spread of introduced species such as eucalyptus, pine and acacia, resulting in profound changes to forest composition.

These results underscore the immediate need to prioritize the restoration and expansion of cork oak ecosystems, which are vital to the ecological health and sustainability of the Maâmora forest. As a keystone species, cork oak is uniquely adapted to the region's environmental conditions and is essential for maintaining biodiversity, ecological balance and ecosystem services. Furthermore, the increasing fragmentation of the forest poses a significant threat to habitat connectivity and species resilience and should be a matter of concern in future research. In conclusion, to ensure the long-term sustainability of the Maâmora forest, it is critical to implement sustainable forest management practices and targeted conservation measures.

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