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Evolution of Land Use/Land Cover in Mediterranean Forest Areas – A Case Study of the Maamora in the North-West Morocco

Abderrahym Ghouldan[1*], Abdelaziz Benhoussa[1], Abdellah Ichen[1]

[1] Biodiversity, Ecology and Genom Laboratory, Department of Biology, Faculty of Sciences, Mohammed V University in Rabat, 4 Avenue Ibn Battouta, BP, Agdal, Rabat, Morocco

* Corresponding author's e-mail: ghouldan.1997@gmail.com

ABSTRACT

Land use/land cover (LULC) change information is crucial for monitoring purposes, formulating strategies, socio-economic progress, and decision-making. The main objective of this study was to analyze and quantify the changes in land use as well as land cover patterns within the Maamora forest in Morocco, and to identify the key factors that influenced its trend from 1989 to 2022. In this study, multispectral remote sensing (RS) data were employed to detect land cover changes in the Maamora forest using Landsat images for the years 1989, 1999, 2009, 2019 and 2022. The maximum likelihood classification (MLC) method was applied to classify the Landsat images using ArcMap 10.4 software to analyze the current state of the study area. Seven LULC classes (cork oak, eucalyptus, pine, acacia, bare land, daya, and others) were successfully classified, achieving overall accuracies surpassing 86% and Kappa coefficients greater than 0.85 for all selected dates. The results of the land use/land cover change detection indicate a decrease in the cork oak area from 60.71% to 44.42%, along with an increase in the eucalyptus area from 18.11% to 39.31%. Moreover, the pine, acacia, bare land, daya, and other classes went from 17.22, 2.80, 0.95, 0.05, and 0.12% to 4.58, 0.02, 10.84, 0.34, and 0.48% respectively. Indeed, from 1989 to 2022, around 50.84% of the study area's surface remained unchanged, whereas 49.16% underwent changes, transitioning to other land cover classes or endured degradation. This research underscored the anthropogenic transformation of the Maamora woodland, which has led to the degradation of its natural resources. Broadly, these findings can serve as foundational data for future research endeavors and offer valuable insights to concentrate on the key factors driving forest degradation in order to inform the development of interventions aimed at preserving the sustainability of natural species and the overall ecosystem.

Keywords: mapping, remote sensing, maximum likelihood classification, LULC, Maamora forest, Morocco.

INTRODUCTION

Forest ecosystems cover approximately 30% of the Earth's land area (Ghebrezgabher et al., 2016), and play a crucial role in sustaining environmental circumstances necessary for human survival (FAO, 2015a; Hatten & Liles, 2019). They provide various essential ecological benefits, including biodiversity conservation (Huang et al., 2019), amassing nutrients (Yan et al., 2022), carbon sequestration (Foley et al., 2005; Bonan, 2008), upholding of atmospheric balance (Ager et al., 2020), oxygen production (Bonan, 2008), and preservation of water and land resources (Hansen et al., 2013; Kalinika et al., 2023). It is evident that changes in land use/cover (LULC) remains a significant environmental concern on both global and local levels, exerting a profound effect on ecological sustainability (Vitousek et al., 2008; Tsegaye et al., 2023; Yirsaw et al., 2017). This reality exposes forests to significant human pressures and influences, varying based on cultural practices, including conversion for agricultural purposes, exploitation by the wood industry, or incorporation into the development of infrastructure, namely urban construction and roads (Austin et al., 2017; Zerouali et al., 2023). Changes in forest cover encompass dynamic processes involving both disturbance and recovery as a result of the intensity of human activities, the impacts of climate change, and the disparity in management policies (Yan et al., 2022). According to recent reports, alterations in forest cover have a notable impact on the Earth's surface and represent the second-largest source of atmospheric emissions (Achard et al., 2002; Khadijat et al., 2021). Moreover, the processes of degradation and deforestation make substantial contributions to the depletion of forest cover (Herold et al., 2011; UNFCCC, 2014).

In the Mediterranean Basin, expanses of woodlands, primarily featuring Cork oak, surpass 1.5 million hectares in Southern Europe (Sardinia, Corsica, and the western Iberian Peninsula), and cover approximately 1 million hectares in Northern Africa, especially in Algeria, Tunisia, and Morocco (Agrillo et al., 2018). The Maamora forest, the subject of this research, is situated along the Atlantic coast of Morocco (Benabou et al., 2022a). It is recognized as the world's largest contiguous cork oak forest, covering a total area of 132.000 hectares (El Boukhari et al., 2015; Noumonvi et al., 2017). The suberaie, encompassing approximately 60 000 hectares of cork oak (*Quercus suber* L.), holds exceptional economic and ecological significance as one of the most vital endemic forest species in Morocco, the remaining of the surface is dominated by introduced species such as Eucalyptus, Acacia, and Pine (Aafi, 2007; Caldas and Moreno-Saiz, 2011; Fennane and Rejdali, 2015). Furthermore, this ecosystem serves as both an environmental sanctuary and a recreational area, playing a crucial role in safeguarding the cities against sedimentation. Its expansive geographical scope provides a venue for leisure and relaxation, acting as a vital lung for nearby cities, such as Rabat, Salé, Khémisset, and Kénitra, drawing approximately 30.000 visitors per week. Additionally, it holds immense ecological significance due to its rich biodiversity and an environment of great importance as regards the biodiversity (M.A.T.E.U.H., 2002).

The Maamora is highly valued for its diverse range of offerings, including sweet acorns, timber, cork, honey, mushrooms, medicinal plants, and recreational spaces for picnics (Maghnia et al., 2019). Additionally, its provides a pastoral area with an annual production estimated at 24 million fodder units (Hammoudi, 2002). Nevertheless, the sustainability of underground forest faces significant threats due to worsening climatic conditions, especially drought, and the increasing impact of human activities such as overgrazing, overexploitation, land clearance, and collection of undergrowth by local communities (Gauquelin et al., 2016). These factors result in reduced productivity, diminished natural regeneration, and an increase in pest infestations (Lancellotti and Franceschini, 2012). The decline in natural regeneration typically leads to a notable reduction in stand density (Maghnia et al., 2017).

Therefore, the primary aim of the present study was to quantify the changes of land cover distribution within the Maamora forest employing geographic information systems (GIS) and Remote Sensing (RS) techniques over a 33 – year period in order to capture the long-term trends of land-use changes in the study area. For this purpose, the specific objectives of the conducted research were: (i) determination of land cover in the Maamora forest from 1989 to 2022, with an interval of four periods: 1989, 1999, 2009, 2019 and 2022, (ii) to detect the change in forest land cover over the study period, (iii) to understand the change based on its outcomes as well as discuss both the results and the driving factors behind these changes in comparison with existing literature on this topic.

MATERIALS AND METHODS

Study area

The Maamora forest (Fig. 1) is located in the Northwestern region of Morocco, extending along the Atlantic Ocean between Rabat-Sale and Kenitra (Mounir, 2002; Fennane and Rejdali, 2015). Geographically, the Maamora stretches from West to East, covering a distance of 60 kilometers and extending 30 kilometers from North to South (Benabou et al., 2022b). The cork oak (*Quercus suber* L.) constitutes the predominant natural vegetation in the Maamora forest, covering an estimated area of 65,601.3 hectares, which accounts for 49.7% of the entire forest area (Haut-Commissariat, 2014a). This forest is also characterized by a notable presence of many introduced species, especially eucalyptus, pine, and acacia (Haut-Commissariat, 2014b). The study area experiences a Mediterranean climate characterized by a dry season that typically commences in late April or early May and extends until October (Aafi et al., 2005; Benabou et al., 2022a). Annually, this forest receives precipitation varying from 350 to 650

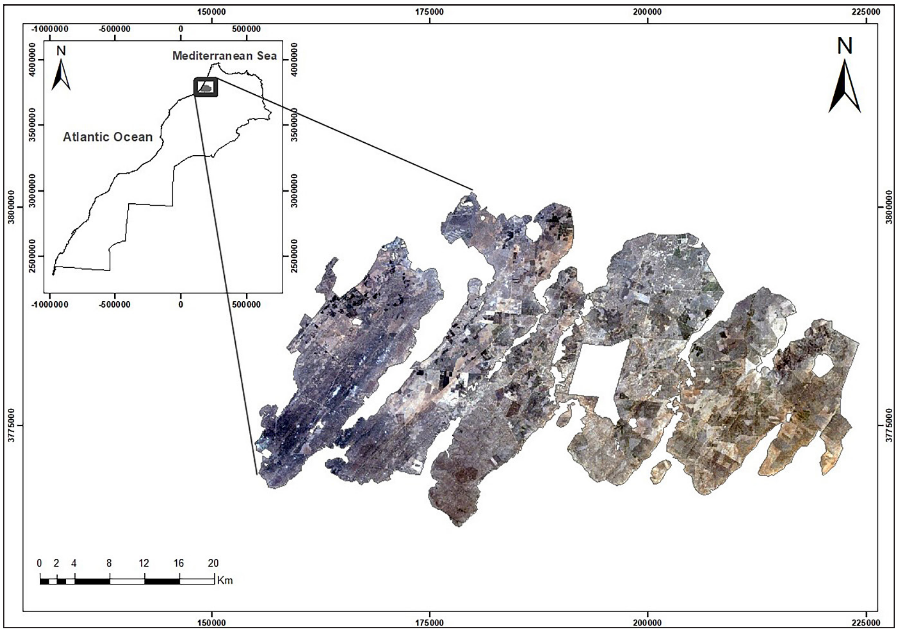

Figure 1. Geographic location of Maamora forest

millimeters, with average monthly temperatures fluctuating between 12 °C (in January) and 25 °C (during July and August) (Cherki, 2013 and Oubrahim, 2015).

Data collection

This research used a combination of satellite and ancillary data. Ancillary data encompassed aerial images and real data from the field observed data, which comprised reference points collected using the Global Positioning System (GPS) in the year 2022. Landsat satellite imagery were acquired for five years, namely 1989, 1999, 2009, 2019 and 2022 to map land cover of Maamora and assess changes in forest. These images were procured without incurring any costs through the Earth Explorer USGS (United States Geological Survey) website (https://earthexplorer.usgs.gov/) (Izadi and Sohrabi, 2021; Seenipandi et al., 2021). The selection of Level-1 products, including Landsat 4–5 TM (1989 and 1999), Landsat 7 ETM+ (2009), and Landsat 8 OLI/TIRS (2019 and 2022), ensured the availability of data that had undergone geometric and radiometric correction. Table 1 provides a summary of the selected image details, while the procedure employed in the present study is illustrated in Figure 2. In addition, the satellite images covering the timeframe from July through late August were retrieved as separate layers and subsequently combined to create refined multispectral images. This specific season, summer, was selected to mitigate potential classification challenges arising from shrubbery.

Table 1. Image database used for historical land cover analysis between 1989 and 2022

Type	Data	Spatial resolution (m)	Acquisition date	RGB band composition	Source
Satellite images	Landsat 4-5 TM	60	15-07-1989	3, 2, 1	Earth explorer USGS (United States Geological satellitaires Survey): (http://earthexplorer.usgs.gov/)
	Landsat 4-5 TM	30	28-08-1999	3, 2, 1	
	Landsat 7 ETM+	30	23-08-2009	3, 2, 1	
	Landsat 8 OLI/TIRS	30	03-08-2019	4, 3, 2	
	Landsat 8 OLI/TIRS	30	18-08-2022	4, 3, 2	
Ancillary data	Google Earth	/	1989/1999/2009/2019/2022	/	Google Inc.
	Field data	/	2022	/	Study area

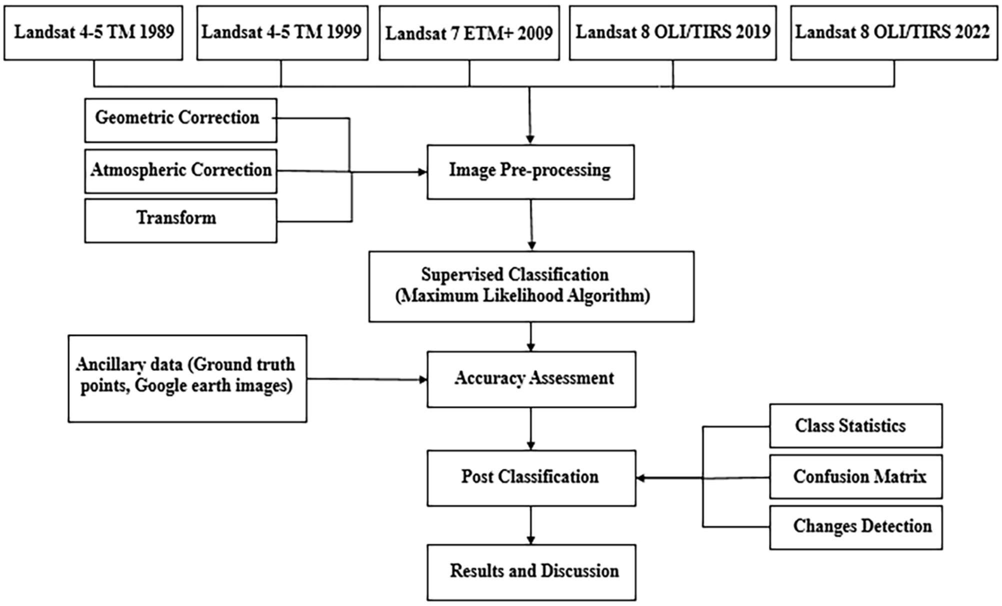

Figure 2. The study methodology

Image pre-processing

Pre-processing of Landsat images is essential, serving the primary and distinct objective of creating a more direct connection between the collected data and biophysical phenomena (Butt et al., 2015; Coppin et al., 2004). The digital image pre-processing process during this study was carried out using ArcGIS 10.4 software. As a first step, all acquired data were consolidated by stacking them into composite images. The images were rectified to WGS 1984/ UTM zone 29 N, processed with RGB color composition, mosaicked, and subsequently, the study area was clipped. A total of seven land use/land cover classes, such as cork oak, eucalyptus, pine, acacia, bare land, daya and other were discriminated (identified), through a combination of field observations, reviewing previous related works in the research area, and employing image classification techniques. A minimum of 200 training samples were selected for each predetermined land cover class by outlining polygons around representative sites. After that, maximum likelihood classification (MLC) algorithm (which assigns each pixel to the class with the highest probability of containing it) of supervised classification method was employed to classify the Landsat images (Islam et al., 2019; Kumar et al., 2021; Chowdhury & Hafsa, 2022) using ArcMap 10.4 software.

Accuracy assessment

Accuracy assessment is crucial for evaluating the quality of information derived from the image output (Butt et al., 2015). In this study, accuracy validation was performed by generating random points for each land cover category and verifying them through field surveys using Global Positioning System (Bunyangha et al., 2021; García et al., 2016). The confusion matrix has been selected as the chosen technique for analyzing accuracy during the post-classification phase of land use land cover images across various dates (Kumar et al. 2020; Acharki et al. 2022). Using the generated matrix, prevalent accuracy metrics can be calculated, including user accuracy (UA), producer accuracy (PA), overall accuracy (OA) and kappa coefficient (Kc), which are extensively utilized for evaluating precision and demonstrating the effectiveness of any classification algorithm. The accuracy of land cover mapping is often presented using the confusion matrix-derived Kappa coefficient. User accuracy (Equation 1) represents the percentage of pixels correctly classified within the image and indicates the level of error in commission. The producer accuracy (Eq. 2) is the likelihood that a pixel is correctly classified as a specific land use/land (LU/LC) cover type and serves as the mutual error of omission. The overall accuracy (Equation 3) was determined by dividing the number of accurately categorized pixels by the total number of pixels (Congalton, 2019).

The Kappa coefficient (Equation 4) assesses the real agreement between reference data and the classifier employed for classification, in comparison to the probability of agreement expected by chance between the reference data and a random classifier (Petropoulos et al., 2015). Kappa coefficient and all accuracy measurements were computed using the following equations (Chowdhury and Hafsa, 2022; Das et al., 2021; Petropoulos et al., 2015; Verma et al., 2020):

$$\mathrm{UA} = \frac{NP}{TNR} \times 100 \quad (1)$$

where: NP – number of correctly classified pixels in each category, TNR – total number of classified pixels in that category (row total).

$$\mathrm{PA} = \frac{NP}{TNC} \times 100 \quad (2)$$

where: NP – number of correctly classified pixels in each category, TNC – total number of classified pixels in that category (column total).

$$OA = \frac{\sum_{i=1}^{n} a_{ii}}{N} \times 100 \quad (3)$$

where: OA – overall accuracy, $\sum a_{ii}$ – total observed pixels classified correctly, N – total number of pixels observed.

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})} \quad (4)$$

where: K – Kappa coefficient, N – total number of pixels observed, x_{ii} – number of pixels observed in row i and column i, r – total number of rows/columns (classes) in confusion matrix, x_{i+} – total number of pixels in row i, x_{+i} – total number of pixels in column i.

Change detection

Change detection is a critical technique employed to measure and quantify temporal changes that have taken place in the land cover over a specific period of time (Wu et al., 2017; Agariga

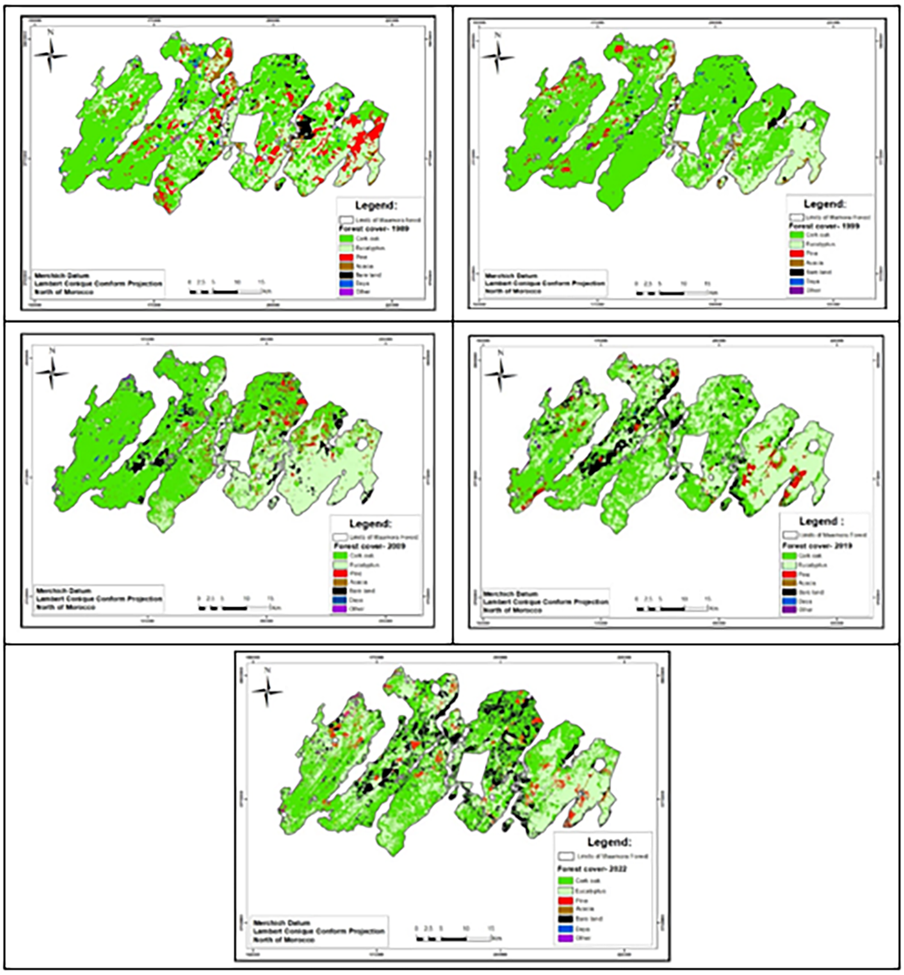

Figure 3. Mapping of Maamora forest covers for the years 1989, 1999, 2009, 2019 and 2022

et al., 2021; Chen et al., 2022). In this research, post-classification approach was implemented to identify trends, changes in area, annual rates of change and the spatial distribution of forest changes. Change detection analysis was conducted between the baseline years 1989, 1999, 2009, 2019, and 2022 to assess the gains and losses of land use/land cover (LULC) types in Maamora forest. In order to assess the extent of conversions from specific land cover types to others, the classified thematic maps for the years 1989 and 2022 were compared to understand spatial changes in forest cover between these two time periods, using the cross-tabulation function. Land cover changes were computed using equations adapted from (Kashaigili and Majaliwa, 2010). The equations are as follows:

$$Area\ Change\ = \\ = \mathrm{Area}_{iyear\ x+1} - \mathrm{Area}_{iyear\ x} \tag{5}$$

$$Annual\ rate\ of\ change = \\ = \frac{Area_{iyear\ x+1} - Area_{iyear\ x}}{t_{years}} \tag{6}$$

where: $Area_{iyear\ x+1}$ – area of land cover for the following year, $Area_{iyear\ x}$ – land cover of the current year, t_{years} – the years' difference between the first and second period.

RESULTS

Land use/land cover classification

The Maamora forest has experienced different phases of forest cover changes over a period of 33 – years. Land cover maps for the years 1989, 1999, 2009, 2019, and 2022 were generated using the maximum likelihood classification algorithm, which is a method of supervised image classification. Seven major land cover/land use classes were categorized in the study area. They are: cork oak, eucalyptus, pine, acacia, bare land, daya, and other. The "other" category encompassed all remaining land cover types, such as roads, military installations, sports facilities, buildings, and wood and cork storage areas.

The analysis of the land use mapping results spanning from 1989 to 2022, reveals noteworthy trends in several land use classes (Fig. 3). Specifically, three land use classes, namely Cork Oak, Pine, and Acacia, have exhibited an average decline over this period. In contrast, four classes, including Eucalyptus, Bare land, Daya, and Other, have demonstrated an increase in their respective extents. Furthermore, the generated maps confirm that Cork Oak currently dominates the majority of the western section of the Maamora forest, with the highest density observed in the extreme western region of the area. Eucalyptus plantations are predominantly concentrated in the eastern part of the forest, characterized by a relatively high planting density. On the other hand, the resinous plantations, which encompass reforestation efforts involving pines, acacia formations, as well as bare land, are dispersed across the entire forest territory, appearing as scattered patches throughout the landscape.

To enhance the comprehension of the maps depicted in Figure 3, it was necessary to conduct an area synthesis to determine the percentage of coverage for each classes. Tables 2 and 9 as well as Figure 4 provide an overview of the trends observed for each classes and the quantitative results obtained through supervised classification for the selected dates. The percentages are relative to the total forest area, excluding any enclaves such as reserves and enclosures, or 132.500 hectares.

Table 2. Evolution of the forest cover area of the Maamora between 1989 and 2022

Years	1989		1999		2009		2019		2022	
Classes	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%
Cork oak	80445.87	60.71	98564.85	74.38	78728.94	59.42	63989.55	48.30	58855.14	44.42
Eucalyptus	23999.76	18.11	25859.07	19.51	40680.54	30.70	53353.17	40.27	52085.79	39.32
Pine	22821.57	17.22	2092.5	1.58	3869.55	2.92	3735.9	2.82	6068.52	4.58
Acacia	3719.7	2.80	2711.61	2.04	314.91	0.24	400.95	0.30	31.05	0.02
Bare land	1270.62	0.95	2299.77	1.73	7779.87	5.87	10289.88	7.77	14360.67	10.84
Daya	74.88	0.05	548.91	0.41	437.49	0.33	191.88	0.14	447.57	0.34
Other	169.02	0.12	423.36	0.32	677.7	0.51	510.12	0.38	637.92	0.48
Total	132501.42	100	132500.07	100	132489	100	132471.45	100	132486.66	100

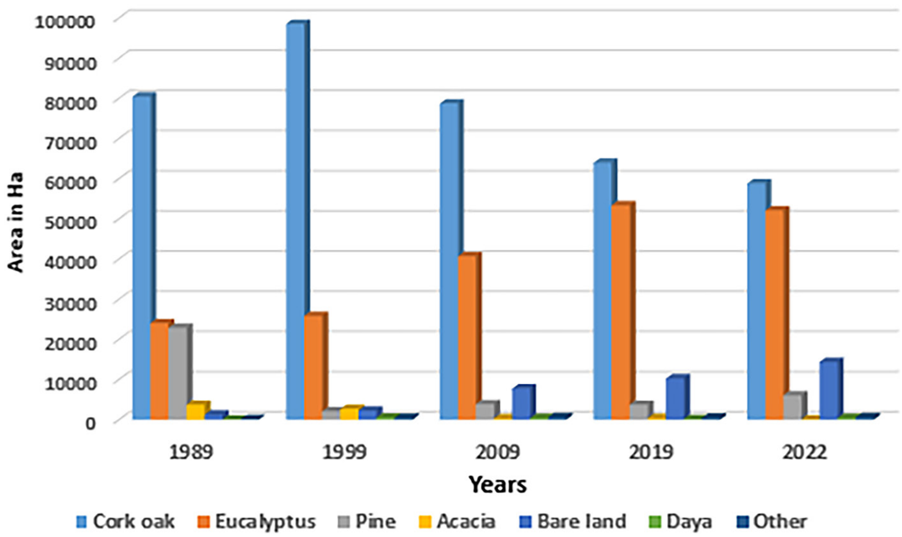

Figure 4. Graphical form for land use/land cover changes from 1989 to 2022

Land cover patterns

The quantitative assessment of the changes in the extent of various categories of forest cover in the Maamora forest from 1989–2022, revealed that the cork oak formations encompassed 80445.87 hectares in 1989, accounting for approximately 60.71% of the total forest area. This expanse experienced a substantial expansion, increasing by approximately 18118.98 hectares, reaching a total of 98564.85 hectares in 1999, constituting roughly 74.38% of the forested area. From 1999 to 2022, this trend underwent a reversal, with the area decreasing by about 39709.71 hectares, equivalent to an average annual decline of approximately 1726.51 hectares per year, reaching in 2022 an area of 58855.14 hectares, representing 44.42% of the total area.

Conversely, to the trend observed for cork oak, eucalyptus plantations demonstrated an opposing pattern. From 1989–1999, there was an increment in the area covered by this introduced species, expanding from 23999.76 hectares in 1989 to over 25859.07 hectares in 1999, constituting approximately 19.51% of the total area. Subsequently, between 1999 and 2022, the eucalyptus area doubled, reaching 52085.79 hectares in 2022, representing 39.32% of the forested area, particularly concentrated in the eastern part of the forest.

Regarding the pine-dominated resinous forests, there was a notable decline of 20729.07 hectares between 1989 and 1999, equivalent to an annual reduction of approximately 2072.9 hectares per year. Subsequently, from 1999 to 2022, the total area exhibited fluctuations, but there was an overall upward trajectory, starting at 2092.5 hectares in 1999 and reaching 6068.52 hectares by 2022.

Conversely, Acacia formations experienced a consistent decrease in their total area from 1989 to 2022, with significant fluctuations and a notable drop of over 1.8% observed between 1999 and 2009. In 2022, the extent of Acacia formations had shrunk to an estimated 31.05 hectares.

In terms of bare land and daya (temporary ponds), their surface areas have witnessed notable changes between 1989 and 2022. Specifically, their areas have expanded from 1270.62 hectares and 74.88 hectares at the start of the period to 14360.67 hectares and 447.57 hectares in 2022, respectively. It should be noted that the area of daya is strongly influenced by annual rainfall, while the extent of bare land is contingent upon plantation uprooting, particularly for timber harvesting activities conducted by the forestry administration.

Lastly, for the remaining land covers, which predominantly include roads, buildings, military camps, sports institutes, and depots, their total area displayed a consistent upward trajectory from 169.02 hectares in 1989 to surpassing 637.92 hectares in 2022. Fig. 4 below shows the patterns of different land cover categories for the selected years.

Classification accuracy assessment

The outcomes of the accuracy assessment post-classification are presented in the confusion matrix (Tables 3, 4, 5, 6, and 7) for the

Table 3. Evaluation of LU/LC Accuracy in 1989 through confusion matrix method

Class	Cork oak	Eucalyptus	Pine	Acacia	Bare land	Daya	Other	Total	User accuracy
Cork oak	96	0	1	0	4	3	4	108	88.89%
Eucalyptus	2	96	5	3	1	0	3	110	87.27%
Pine	1	1	94	0	0	0	1	97	96.91%
Acacia	0	2	0	92	1	0	0	95	96.84%
Bare land	1	0	0	1	93	2	1	98	94.90%
Daya	0	0	0	1	1	91	0	93	97.85%
Other	1	0	0	1	1	0	92	95	96.84%
Total	101	99	100	98	101	96	101	696	
Producers accuracy	95.05%	96.97%	94%	93.88%	92.08%	94.79%	91.09%		
Overall accuracy	93.96%								
Kappa coefficient	92.96%								

Table 4. Evaluation of LU/LC Accuracy in 1999 through confusion matrix method

Class	Cork oak	Eucalyptus	Pine	Acacia	Bare land	Daya	Other	Total	User Accuracy
Cork oak	95	1	3	2	1	9	5	116	81.90%
Eucalyptus	3	96	2	4	1	0	0	106	90.57%
Pine	0	1	93	1	0	1	0	96	96.87%
Acacia	1	1	0	92	0	1	0	95	96.84%
Bare land	1	0	0	1	96	0	1	99	96.97%
Daya	0	1	0	0	1	87	2	91	95.60%
Other	1	0	1	0	1	1	92	96	95.83%
Total	101	100	99	100	100	99	100	699	
Producer Accuracy	94.06%	96%	93.94%	92%	96%	87.88%	92%		
Overall Accuracy	93.13%								
Kappa Coefficient	91.99%								

Table 5. Evaluation of LU/LC Accuracy in 2009 through confusion matrix method

Class	Cork oak	Eucalyptus	Pine	Acacia	Bare land	Daya	Other	Total	User accuracy
Cork oak	91	5	6	11	3	7	14	137	66.42%
Eucalyptus	3	92	2	2	5	0	0	104	88.46%
Pine	1	1	90	0	1	0	1	94	95.74%
Acacia	3	0	0	85	1	0	1	90	94.44%
Bare land	1	2	0	0	90	1	1	95	94.74%
Daya	1	0	0	1	1	87	1	91	95.60%
Other	0	1	1	1	0	3	81	87	93.10%
Total	100	101	99	100	101	98	99	698	
Producer accuracy	91%	91.09%	90.91%	85%	89.11%	88.77%	81.82%		
Overall accuracy	88.25%								
Kappa coefficient	86.29%								

Table 6. Evaluation of LU/LC Accuracy in 2019 through confusion matrix method

Class	Cork oak	Eucalyptus	Pine	Acacia	Bare land	Daya	Other	Total	User accuracy
Cork oak	94	2	1	2	3	3	7	112	83.93%
Eucalyptus	4	96	2	2	1	0	2	107	89.72%
Pine	1	0	95	1	1	0	0	98	96.94%
Acacia	0	1	1	94	0	1	1	98	95.92%
Bare land	1	1	1	0	94	0	1	98	95.92%
Daya	0	1	1	0	0	94	1	97	96.91%
Other	0	0	0	1	1	1	87	90	96.67%
Total	100	101	101	100	100	99	99	700	
Producer accuracy	94	95.05%	94.06%	94%	94%	94.95%	87.88%		
Overall accuracy	93.43%								
Kappa coefficient	92.33%								

Table 7. Evaluation of LU/LC Accuracy in 2022 through confusion matrix method

Class	Cork oak	Eucalyptus	Pine	Acacia	Bare land	Daya	Other	Total	User accuracy
Cork oak	87	7	10	3	5	2	7	121	71.90%
Eucalyptus	7	86	3	2	3	2	1	104	82.69%
Pine	2	1	84	1	2	1	1	92	91.30%
Acacia	1	1	0	91	0	1	1	95	95.79%
Bare land	2	4	2	1	88	1	1	99	88.88%
Daya	1	1	0	1	1	89	1	94	94.68%
Other	1	0	1	1	1	2	86	92	93.48%
Total	101	100	100	100	100	98	98	697	
Producer accuracy	86.14%	86%	84%	91%	88%	90.82%	87.75%		
Overall accuracy	87.66%								
Kappa coefficient	85.60%								

Table 8. Area change of Maamora forest between 1989 and 2022

Change (1989–2022)	Area change (ha)	Percentage (%)
No change	67255.55	50.84
Change	65038.44	49.16
Total	132293.99	100

five years under examination. The overall accuracy values for 1989, 1999, 2009, 2019, and 2022 are 93.96%, 93.13%, 86.29%, 93.42%, and 87.66%, respectively, with kappa coefficient statistics of 92.96%, 91.99%, 88.25%, 92.33% and 85.60%, respectively. These results derived from the analyses conducted on Landsat satellite images using supervised classification appear to be highly reliable.

The overall accuracy, exceeding 86% for all the images, indicates that the identified changes in the images reliably reflect the actual conditions present on the ground. Additionally, the classification quality is supported by the Kappa coefficient values, which are all above 85%. In statistical terms, the accuracy assessment report for classification with a kappa coefficient surpassing 0.8, and an overall accuracy exceeding 80%, signifies excellent agreement between the reference data and the classified results (Pontius, 2000; Lea and Curtis, 2010; Manonmani and Suganya, 2010; Thien and Phuong, 2023).

Table 9. Land cover changes in Maamora forest for the period 1985–2020

Land cover type	1998–1999		1999–2009		2009–2019		2019–2022		1989–2022			
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	Net area Change (ha)	Net Change(%)	Mean Annual Change (ha)	Mean Annual Change (%)
Cork oak	18118.98	13.67	-19835.91	-14.96	-14739.39	-11.12	-5134.41	-3.88	-21590.73	-16.29	-654.26	-0.49
Eucalyptus	1859.31	1.4	14821.47	11.19	12672.63	9.57	-1267.38	-0.95	28086.03	21.21	851.09	0.64
Pine	-20729.07	-15.64	1777.05	1.34	-133.65	-0.1	2332.62	1.76	-16753.05	-12.64	-507.67	-0.38
Acacia	-1008.09	-0.76	-2396.7	-1.8	86.04	0.06	-369.9	-0.28	-3688.65	-2.78	-111.78	-0.08
Bare land	1029.15	0.78	5480.1	4.14	2510.01	1.9	4070.79	3.07	13090.05	9.89	396.67	0.3
Daya	474.03	0.36	-111.42	-0.08	-245.61	-0.19	255.69	0.2	372.69	0.29	11.29	0.008
Others	254.34	0.2	254.34	0.19	-167.58	-0.13	127.8	0.1	468.9	0.36	14.21	0.01

Land-cover change trends

The changes in land cover classes during the time span from 1989 to 2022 are depicted in the map of change (Fig. 5), generated by overlaying the classified images of 1989 and 2022, as well as Table 8, which collectively illustrate the spatio-temporal shifts in land cover within the study area. Indeed, the Maamora forest is a highly dynamic region that has experienced numerous changes, particularly in the eastern sections of the forest. Between 1989 and 2022, nearly 50.84% of the area in the study area has retained its original condition from 1989, while the remaining 49.16% of the area has changed and transitioned to different land uses or experienced degradation.

During the period from 1989 to 2022, various land cover categories underwent changes over time, as illustrated in Table 9 below. The area covered by cork oak formations decreased by approximately 16.29% (21590.73 ha) during the 33-year period. This decline corresponds to an average annual forest loss of 0.49%, which amounts to 654.26 hectares per year. The highest cork oak cover loss occurred between 1999 and 2009, where 19835.91 ha (14.96%) of the cork oak was lost. Conversely, Eucalyptus plantations registered an increase of about 21.21%, through the

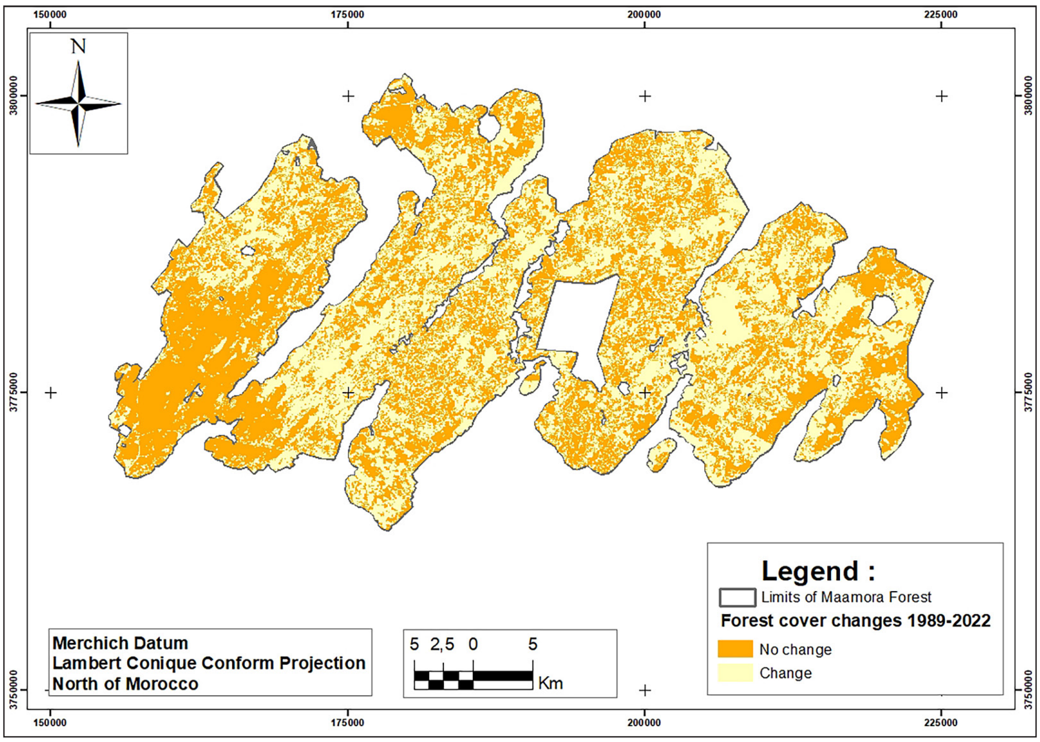

Figure 5. Map of forest cover change of Maamora forest between 1989 and 2022

conversion of cork oak and bare land formations, over the 33-year study period. The pine land also experienced a reduction in their total surface area by about 12.64% (16753.05 ha), with an average annual forest loss of 0.38% or 507.67 ha. Meanwhile, acacia formations exhibited a decreased of approximately 2.78% (3688.65 ha).

The bare land class has expanded by approximately 9.89% (13090.05 ha). This growth can be attributed to human activities involving the clearing and removal of trees for agricultural and livestock feed purposes. Thus, the areas occupied by dayas and others had a low positive change of 0.29% and 0.36% respectively. It is important to note that these fluctuations in the daya surface are closely tied to the annual rainfall patterns.

DISCUSSION

The overall mapping findings revealed the presence of seven distinct land use categories in the Maamora forest between 1989 and 2022. The analysis highlights a regressive dynamic of the natural environment in the forest during the same period. This degradation appears to be widespread, impacting nearly all parts of the forest. The average annual evolution rates demonstrate a decline in the cork oak, pine and acacia classes. These results of classification, along with the trends in the changing surface areas for various species, correspond with minor variations noted in several studies that elucidate the extent of these formations throughout implementation periods of previous development plans (FAO, 2015b; HCEFLCD, 2014a; HCEFLCD, 2014b; Malki et al., 2022; Noumonvi, 2015). Moreover, the decrease in cork oak area can be also attributed to the actions of local residents and organizations, including practices like excessive gazing, logging, and unsustainable gathering of fuelwood. The present distribution of cork oak in the Maâmora forest has been notably reduced compared to its historical range largely due to intensive anthropogenic activities such as overgrazing and species displacement (Lahssini et al., 2015). This finding is in line with the previous results reported by Touhami et al. (2017) for cork oak forests in the Kroumirie region (Tunisia) and by Campos et al. (2008) for public cork oak forests in Jerez (Spain) and Iteimia (Tunisia). Thus, the human pressures, which greatly surpass the natural production capacity of the forest area as well as frequently result in aging and decaying vegetation, undermine the ability of this forest to provide ecosystem services and contribute to the socio-economic growth of local communities in the long term (Aafi et al., 2005; Benabou et al., 2022b; Moukrim et al., 2022).

In addition, the analysis of the overall changes in the cork oak's surface reveal a substantial expansion between 1989 and 1999, this increase noted in cork oak coverage can be attributed to the implementation of a new reforestation policy, which gives priority to the rehabilitation of cork oak stands through artificial regeneration. However, the expansion of the cork oak area during this period (1989–1999), contrasts with the data presented by Malki et al. (2022), while from 1999 to 2022, a reversal of this trend has been observed, with a reduction in its area. In fact, the data from the Forestry Department indicates an area of 70400 hectares in 2011, while the area obtained by the conducted analysis is 78728.94 hectares in 2009 and 58855.14 hectares in 2022. This difference can be attributed to multiple factors, including the potential for confusion between bare land and newly established cork oak plantations due to the limited reflectance of cork oak in the tree vegetation spectrum, making it less distinct in satellite images. Moreover, introduced forest species, particularly eucalyptus, have generally exhibited a contrasting trend compared to what has been observed with cork oak. This fact, diminished the potential spread of cork oak, as observed in various contexts in Monte Pisano (Tuscany N-W, Italy) (Bertacchi, 2023; Selvi et al., 2016).

The trends of changes in the area of different forest species between 1989 and 2022 can be primarily attributed to several factors, including the inadequacy of agricultural practices and livestock systems, the inefficacy of forest ecosystem management and mechanisms for conserving forest resources, and the overexploitation of these resources for timber and energy, not to mention, the influence of climate change and anthropogenic pressures that disrupt the ecological balance (Hlovor et al., 2021). Several authors (Atta et al., 2010; Corgne, 2014), have raised concerns about the role of population growth and specific modes of exploitation in causing land degradation, which has led to disruptions in ecological balances. The consequences of these factors are primarily evident in the reduction of the surface area covered by cork oak and the deterioration of its developmental condition. These effects were aggravated by the absence of natural regeneration of the cork oak species and the selection of species for reforestation. Collectively, these factors have given rise to a persistent challenge that places continuous pressure on the forest, resulting in a complex interplay between nature and human activities.

Concerning forest management approaches, prior to 1999, the primary focus of the forestry administration was to preserve cork oak in areas where it remained economically viable and replace it with fast-growing introduced species in regions characterized by low cork oak density and challenging edapho-climatic conditions (HCEFLCD, 2014a). This strategy was primarily driven by economic considerations, with the aim of fulfilling the demands of local timber markets, including the production of eucalyptus wood to cater to the requirements of the Moroccan industrial cellulose unit.

After 1999, in response to various assessments, particularly related to the diminishing cork oak area due to the increased density of introduced species (eucalyptus, pine and acacia), the focus shifted towards at the densification and recovery of the cork oak, with an emphasis on assisted regeneration methods. The cork oak regeneration area, spanning from 1994 to 2010, is estimated to be more than 14600 hectares (Haut-Commissariat, 2014c) and 12300 hectares (El Hachimi, 2010), respectively. These interventions have primarily achieved two main objectives. First, they expanded the cork oak area at the expense of exotic species. Second, they increased the density of current sparse stands while simultaneously meeting wood production needs through the cultivation of non-native species such as eucalyptus and pine.

This study offers valuable information and presents comprehensive data detailing the spatio-temporal descriptions of the forest area's extent, and provides statistical insights of the changes in land use classes and their respective areas.

CONCLUSIONS

This work presented a detailed overview of the evolution of land use and land cover in the Maamora forest between 1989 and 2022, using time series data from Landsat satellites. The results of the supervised classification using the maximum likelihood method indicate that the Maamora forest has undergone many changes during this 33-year period. The cork oak area actually decreased from 60.71% in 1989 to 44.42% in 2022, while the eucalyptus area increased from 18.11% in 1989 to 39.32% in 2022. It should be noted that the dynamics of cork oak closely mirror the opposite trend of introduced species, particularly eucalyptus. This dynamic essentially results from the substitution of cork oak by alternative species, such as eucalyptus, pine and acacia. It is also influenced by the various anthropogenic activities, which modify the forest landscape of the Maamora, without forgetting the potential impact of climate change.

This study then helps to understand the trends in Maamora cover over time, providing a basis for forest managers to advocate the need to support the rejuvenation and expansion of the cork oak ecosystem. The latter is a very important indigenous reference in the Maamora forest due to its superior capacity for adaptation to the prevailing environmental conditions. It also indicates the need to take into account the main stakeholders (forest-dependent populations) in forest management programs.

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