



## ***Assessment Of Forest Cover Changes Using Remote Sensing And GIS: A Case Study Of Mouias Forest In Mila, Algeria.***

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### **Abstract**

Vegetation change has emerged as a global environmental concern, as it directly impacts biodiversity, climate regulation, carbon sequestration, and ecosystem services. Monitoring these changes is essential for addressing issues like deforestation, desertification, and habitat loss, which have far-reaching consequences on both local and global scales.

Remote sensing is widely used to monitor environmental changes, by comparing multi-temporal satellite or aerial imagery; researchers can detect changes in land use/land cover, assess trends, and support decision-making for sustainable land management and conservation efforts.

The present study aims to identify and analyze changes in land cover, and vegetation patterns in the forest of Mouias in Northeast Algeria from 1985 to 2023 using remote sensing and image processing techniques. By applying supervised classification and change detection algorithms, the study will generate accurate thematic maps and assess the extent of transformation across different landscape categories and vegetation types. This analysis will provide insights into shifts in vegetation patterns, contributing to a better understanding of environmental dynamics and supporting sustainable land management and conservation strategies.

The results indicate that landscape patterns, over the whole study area, have undergone significant changes. Considering the entire study period, at once, from 1985 to 2023, (57.88%) of the total area of the study area remained unchanged, while (42.11%) underwent conversions between land use/cover categories. These changes were primarily driven by several interrelated factors, including recurrent wildfires, deforestation, and the exploitation of forest resources, particularly firewood.

**Keywords:** Land cover, Remote sensing, Forest, Mouias, Algeria.

## 1. Introduction

Remote sensing has become an invaluable tool for mapping and monitoring land cover across large and diverse regions (Pizarro *et al.*, 2022). In Africa, remote sensing products are particularly useful due to the lack of high-resolution land cover data that can capture field-level details of lands. This is especially true for Algeria, where efficient land resource monitoring has been a challenge due to limited financial resources and access to appropriate technology (Mardani *et al.*, 2019).

The rapid advancement of remote sensing technology and Geographic Information Systems (GIS) has created new opportunities for monitoring land use and land cover dynamics, as well as quantifying changes over time. In light of the recent environmental degradation in Algeria, information on land use and land cover over time is considered an effective approach for studying environmental change and managing the distribution of natural resources. In this context, Landsat data serve as a valuable resource for documenting changes in the Earth's surface over recent decades; additionally, the entire Landsat archive is now accessible to users at no cost via the Internet (USGS, 2024).

Land is a crucial resource for many systems, including biodiversity, agriculture, and socioeconomic systems. Mapping and monitoring land cover is important for environmental and socioeconomic surveys, not only for drawing research implications but also for supporting procedures to control and prevent issues. Most land cover classification studies and detection of change cases are mainly dependent on remote sensing data. The most current systems and methodologies are already using remote sensing data in conjunction with GIS, a crucial tool for controlling and monitoring environmental situations (Zhou *et al.*, 2008).

Algeria is exposed to global environmental changes, which are caused by the ability of humans to influence the environmental balance at the global level, in addition to problems at the regional or local level such as grazing, deforestation, desertification, climatic changes, and drought periods that have taken place since the 1970s. In the Tell area, a significant portion of forested lands is facing severe degradation due to deforestation, wildfires, and erosion. This degradation, along with shortcomings in water and soil resources, can lead to social conflicts. In this context, a committee identified these problems, linking them with a serious lack of land survey and land information systems. The national authorities have taken some policy measures to prevent additional degradation of land resources in response to various projects and plans. However, land cover changes in space and time are increasing, which makes it necessary to develop land cover change detection methods adapted to the Algerian ecosystem. Remote sensing, by its nature, especially the

earth observation systems initiated by satellites, is expected to provide the land information data necessary for land management and land cover change assessments (Benhizia *et al.*, 2021)

The exploration of land cover change using remote sensing technologies has gained increasing attention, particularly within the context of Algeria and its surrounding regions. The literature reveals a progression in methodologies and applications over the years, highlighting the critical role of remote sensing in understanding and managing land use dynamics, extensive research has been conducted to assess land cover changes using remote sensing and GIS, with a focus on desertification and land degradation in semi-arid regions. While some studies have explored vegetation changes and landslide susceptibility in mountainous areas (Hirche, 2010), (Saadi & Gintzburger, 2013)

However, research addressing the driving forces of land use and land cover changes, as well as vegetation changes at the local level remains limited. This study aims to: (1) monitor land use and cover changes in Mouias from 1985 to 2023 using remote sensing and GIS, (2) analyze land cover transitions with post-classification techniques, and (3) investigate the driving forces behind these changes. The findings will provide a foundational reference for future studies on land use and land cover changes and serve as valuable tools for decision-makers.

## 2. Material and Methods

### 2.1. Study area

The present study focuses on the Mouias forest, located in northeastern Algeria within the province of Mila. This forested area lies between latitudes 36°32'43" N and 36°34'58" N, and longitudes 06°24'10"E and 06°28'13"E, at altitudes ranging from 632 to 1239 m above sea level, and extends over 1778 hectares (Figure 01)

The physical landscape of the study area is an extension of the Tell Atlas range and delineated by distinct geographical features. To the west, it is bordered by the limestone ridge of M'cid Aicha, located within the territory of Hamala. In the north, the area is marked by the sandstone massif of the Mouias region. The southern boundary is defined by Oued Rhumel, while to the east, the area is framed by Djebel Sidi Driss.

The forest itself is dominated by Mediterranean vegetation, with significant portions covered by cork oak (*Quercus suber*), Algerian oak (*Quercus canariensis*) and low-lying shrubland (*Pistacia lentiscus*). The climate of Mouias is Mediterranean, with mild, wet winters and hot, dry summers. The rainfall patterns over the study area are irregular in time and space with annual rainfall ranging

from 800 mm to 1150 mm/year, the highest temperatures usually occur in June to August with an average maximum temperature range from 23 to 26 °C, while The period from December to February is considered to be a cool season, with a mean temperature of 5.2 to 7.9°C. This climatic pattern, combined with the forest's topographic and hydrological diversity, supports a wide range of flora and fauna, making the Mouias forest a key area for conservation and ecological research.

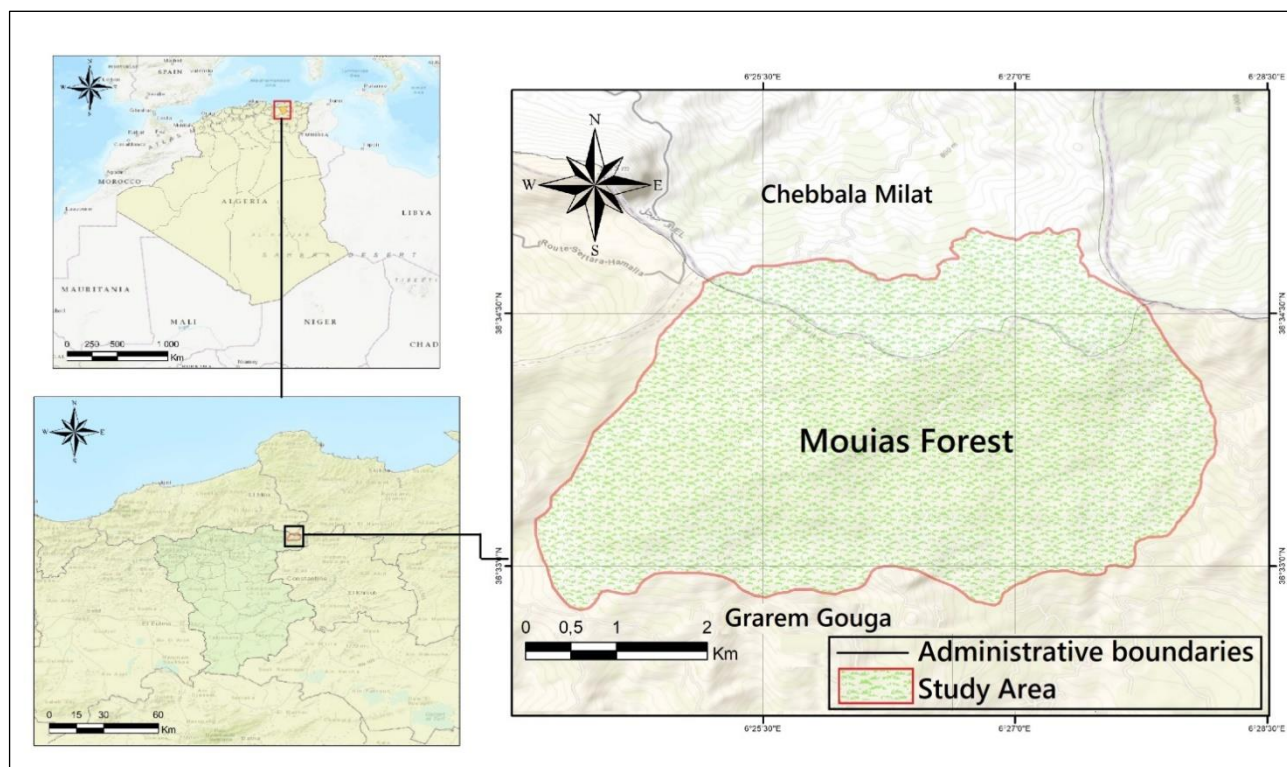


**Figure 01.** Geographic location of the study area.

## 2.2. Data Sources

The study utilized a variety of data sources, including satellite imagery, ancillary data, and fieldwork data (Table 01). Specifically, the Landsat archive was employed. Landsat records are part of a 50-year archive maintained by the U.S. Geological Survey (USGS), which is instrumental in documenting changes in terrestrial ecosystems.

Released in early 2021, Landsat Collection 2 offers improvements in processing, geometric accuracy, and radiometric calibration compared to the previous Collection 1 products. The Level-2 products are atmospherically corrected; ensuring that the data is ready for analysis without the need for additional preprocessing. These enhancements make the data more reliable and accurate for scientific research and applications (Christopher *et al.*, 2023)

Additionally, Sentinel-2 data from the more recent period (since Sentinel-2 was launched in 2015) can be integrated with other historical satellite data, such as from Landsat, to provide a

comprehensive view of vegetation dynamics over decades. Sentinel-2 is widely used for vegetation cover studies due to its high temporal and spatial resolution. Its spectral bands are specifically designed for detecting changes in vegetation health, species differentiation, and biomass estimation. (Wang *et al.*,2021)

A time interval of 12 to 14 years (1985-1997, 1997-2009, 2009-2023) was selected to effectively capture changes in vegetation cover over time. The imagery was acquired during the dry season to minimize confusion in distinguishing woody species from areas covered by herbaceous (annual) species. This timing ensures more accurate recognition of permanent vegetation features, reducing the interference of seasonal variations.

The ancillary data used in this study includes: (1) black and white aerial photographs at scales of 1:10,000 and 1:20,000, acquired in 1987 and 2003; (2) topographic maps at scales of 1:25,000 and 1:50,000, with a 20-meter contour interval, generated from aerial photography taken in 2003; (3) Google Earth© images; (4) statistical data; and (5) data collected during fieldwork (Table 1).

For data pre-processing, visualization, editing, and spatial analysis, ArcGIS 10.8 and ENVI 5.3 software packages were employed. These tools enabled the integration and analysis of various datasets, providing robust spatial analysis capabilities essential for this research.

**Table 01.** Summary Description of the data sources.

| Type             | data               | Acquisition date | Spatial Scale (m)    | Source                                                                                                                       |
|------------------|--------------------|------------------|----------------------|------------------------------------------------------------------------------------------------------------------------------|
| Satellite images | Landsat 5 (TM)     | August 29, 1985  | 30 × 30              | U.S. Geological Survey (USGS)<br>( <a href="http://earthexplorer.usgs.gov">http://earthexplorer.usgs.gov</a> )               |
|                  | Landsat 5 (TM)     | August 05, 1997  | 30 × 30              |                                                                                                                              |
|                  | Landsat 5 (TM)     | August 31, 2009  | 30 × 30              |                                                                                                                              |
|                  | Sentinel-2         | August 19, 2023  | 10 × 10              | European Space Agency<br>( <a href="https://browser.dataspace.copernicus.eu/">https://browser.dataspace.copernicus.eu/</a> ) |
| Ancillary data   | Topographic maps   | 2005             | 1:25 000<br>1:50 000 | National Institute of Cartography and Remote Sensing (INCR)                                                                  |
|                  | Aerial photographs | 1987-2003        | 1:10.000<br>1:20.000 |                                                                                                                              |
|                  | Google Earth       | -                | 0.5                  | Google Inc.                                                                                                                  |
|                  | Statistic data     | 1985 to 2023     | -                    | Forest service                                                                                                               |
|                  | Field data         | -                | -                    | Field trip (17 field observations)                                                                                           |

### 2.3. Image Classification

The methodology employed in this research required the application of various techniques to develop reference datasets for both training and accuracy assessment. Prior to the classification process, training samples were selected by delineating several polygons for each land cover class, derived from reference data independent of those used for accuracy evaluation. To ensure robust calibration of the classification and enhance overall accuracy, a diverse range of reference data

sources was utilized, including Google Earth imagery, aerial photographs, topographic maps, and fieldwork data.

A supervised classification technique, specifically the maximum likelihood classifier, was employed to extract land use/land cover maps independently for each time period. To maintain consistency, land cover classification was standardized across multi-temporal Landsat images, ensuring compatibility and comparability between datasets.

The maximum likelihood classifier, a widely adopted and effective algorithm for remote sensing applications, was selected for its capability to produce high-accuracy results. This method uses a statistical approach to estimate the probability of each pixel belonging to predefined classes, assigning each pixel to the class with the highest probability. This approach was essential for ensuring precise land cover classification.

Six land cover classes were ultimately derived from this process: (1) Forest; (2) Scrubland; (3) Grassland; (4) Barren Land; (5) Built-up; and (6) Water Bodies. A detailed description of these land cover classes is provided in Table (02).

**Table 02.** Land cover classification scheme.

| Land use/cover classes | Description                                                                                                                                                                                     |
|------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Forest                 | Areas dominated by trees generally taller than 7 m, with more than 40% of the total vegetation cover. Includes coniferous, deciduous, and mixed forests.                                        |
| Scrubland              | Refers to areas dominated by low-growing, woody vegetation, typically shrubs and small trees. These plants are generally shorter than those found in forests, often between 1 to 3 meters tall. |
| Grassland              | Areas dominated by herbaceous vegetation, comprising more than 80% of the total vegetation. This includes lands regularly grazed by livestock.                                                  |
| Barren Land            | Land areas with exposed soil or very sparse vegetation cover. Includes bare rocks, burned areas, and forest roads.                                                                              |
| Built-up               | Areas covered by structures with a permanent concentration of people and activities. Includes villages, and rural housing.                                                                      |
| Water                  | Areas with open water. Includes lakes, rivers, and reservoirs.                                                                                                                                  |

## 2.4. Classification Accuracy Assessment

Assessing the accuracy of land cover classification is a crucial step when utilizing reference data collected around the same time as satellite imagery acquisition (Congalton & Green, 2009). The accuracy assessment process involves comparing the classified pixel labels with ground truth data collected at representative sample points during the time of sensing. However, obtaining simultaneous ground truthing data for accuracy assessment over long time periods can be particularly challenging, especially in African countries (Lillesand *et al.*, 2004)

For this study, aerial photography (Scale 1:10,000) acquired in 1987 was used as reference data for the accuracy assessment of the 1985 classification. For the years 1997, 2009 and 2023, a combination of topographic maps (scales 1:25,000 and 1:50,000), Google Earth imagery, and fieldwork data served as reference sources.

A stratified random sampling technique was employed to build the confusion matrix for the land cover maps derived from satellite datasets. This sampling design was carefully implemented to ensure that all land cover classes were adequately represented and distributed across the study area (Foody, 2002). The performance of the classification was evaluated using overall accuracy, user's and producer's accuracies, and kappa statistics, all of which are standard metrics for assessing classification performance.

### 3. Results and Discussion

#### 3.1 Land Use/ Land Cover Mapping

In the initial phase of the results, an analysis of the separability of spectral signatures was performed to evaluate the quality of the training data and to minimize class confusion prior to classification. The separability between pairs of training classes was quantified using the Jeffries–Matusita (J–M) distance, a commonly used metric in remote sensing to assess how distinct two classes are from each other. The J–M distance ranges from 0.0 to 2.0, with values greater than 1.9 indicating that the classes are well separated (Richards & Jia, 1999)

The results of the spectral separability tests for the training class pairs in the 1985, 1997, 2009, and 2023 images indicated that most classes exhibited good separability, as the J–M values exceeded 1.9. However, some overlap was observed between the Grassland and scrubland classes, where the J–M distance ranged from 1.68 to 1.91, suggesting some degree of confusion between these two classes.

To improve the accuracy of the classified maps, ancillary data and visual interpretation were employed. The overall accuracy of the classified land cover maps for the years 1985, 1997, 2009 (TM), and 2023 (Sentinel-2) were 80.18%, 87.25%, 90.09%, and 93.21%, respectively. The corresponding kappa coefficients were 75.03%, 83.38%, 87.54%, and 91.55%, indicating a progressive improvement in classification performance over time. Additionally, user's and producer's accuracies were calculated for each land cover class in the maps (Table 03), providing a detailed assessment of the classification results for each land cover type. This assessment highlights the effectiveness of using multispectral data and ancillary sources to improve classification accuracy, particularly when dealing with long-term land cover changes.

**Table 03.** Summary of accuracy assessment of land use/cover maps (1985-2023)

| Land use/cover class    | 1985         |                | 1997         |                | 2009         |                | 2023         |                |
|-------------------------|--------------|----------------|--------------|----------------|--------------|----------------|--------------|----------------|
|                         | User's (%)   | Producer's (%) | User's (%)   | Producer's (%) | User's (%)   | Producer's (%) | User's (%)   | Producer's (%) |
| Forest                  | 88,00        | 81,48          | 91,67        | 84,62          | 91,67        | 88,00          | 95,65        | 91,67          |
| Scrubland               | 73,08        | 79,17          | 82,61        | 86,36          | 86,36        | 90,48          | 90,48        | 90,48          |
| Grassland               | 86,21        | 75,76          | 86,21        | 86,21          | 89,29        | 89,29          | 89,29        | 96,15          |
| Barren Land             | 61,54        | 80,00          | 80,00        | 88,89          | 80,00        | 88,89          | 92,86        | 92,86          |
| Built-up                | 70,00        | 87,50          | 87,50        | 100,00         | 100,00       | 90,00          | 100,00       | 90,00          |
| Water                   | 100,00       | 88,89          | 100,00       | 88,89          | 100,00       | 100,00         | 100,00       | 100,00         |
| <b>Overall accuracy</b> | <b>80.18</b> |                | <b>87.25</b> |                | <b>90.09</b> |                | <b>93.21</b> |                |
| <b>Kappa statistics</b> | <b>75.03</b> |                | <b>83.38</b> |                | <b>87.54</b> |                | <b>91.55</b> |                |

The classified land use/cover maps of the study area for each year, produced using pre-processed data and a supervised maximum likelihood classifier, are presented in (Figure 02). These maps display the spatial distribution of land cover classes over time. Additionally, the area covered by each land cover class was calculated for the four years, providing quantitative insights into the dynamics of land cover changes (Table 04). These results offer valuable information for understanding the environmental changes over time.

The analysis of multi-temporal satellite imagery reveals significant landscape transformations over the past decades. These changes offer valuable insights into the evolving land use patterns of the study area. The results clearly demonstrate that human activities have a profound impact on land cover, driving substantial shifts between (1985) and (2023).

In (1985), the dominant land use/cover classes in Mouias Forest were Grassland and Forest, which accounted for (47,53%) and (30,76%) of the total area, respectively. Other land use categories, including barren land, built-up areas, and water bodies, occupied much smaller portions, comprising (8,90%), (0,02%), and (0,01%), respectively (Table 4).

By the year (1997), significant changes were observed. The Barren Land experienced considerable spatial expansion, increasing from 158 hectares in (1985) to 537 hectares in (1997). At the same time, forest land saw a decline, shrinking from 546 hectares to 200 hectares, likely due to deforestation and land wildfire.

Between (1997) and (2009), there was a notable increase in forest areas, with an expansion of approximately 130 hectares, representing (18.56%) of the total surface area. Simultaneously, the Barren Land experienced a significant reduction, decreasing by (47.10%), while grass land shrank by (15.54%). These changes suggest that forest encroached upon these areas, possibly due to

reforestation efforts or natural regrowth in less disturbed areas. In contrast to earlier trends, both Built-up and water bodies showed increases during this period. Built-up grew by (310%), this growth reflects increased population pressure and infrastructure development. These shifts reflect the ongoing transformation of the landscape, driven by agricultural and urbanization, while also highlighting some positive developments in forest recovery and water resource management.

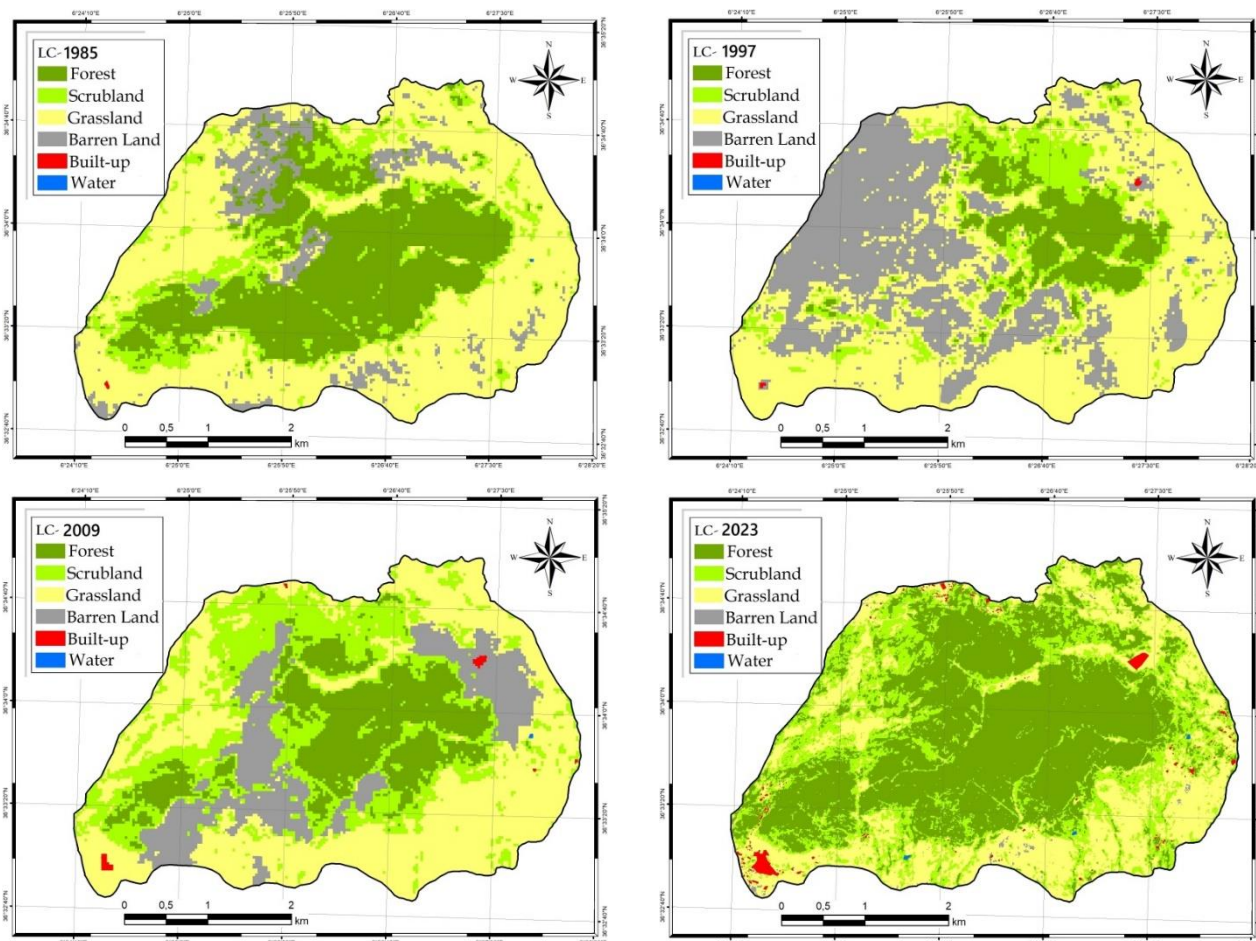


**Figure 02.** Land use/land cover maps of Mouias forest in (1985),(1997), (2009), and (2023).

**Table 04.** Summary of land cover change statistics from (1985) to (2023).

| land use/cover categories | 1985      |       | 1997      |       | 2009      |       | 2023      |       | Percentage change in land use/cover |           |           |           |
|---------------------------|-----------|-------|-----------|-------|-----------|-------|-----------|-------|-------------------------------------|-----------|-----------|-----------|
|                           | Area (ha) | %     | Area (ha) | %     | Area (ha) | %     | Area (ha) | %     | 1985-1997                           | 1997-2009 | 2009-2023 | 1985-2023 |
| Forest                    | 546,73    | 30,76 | 200,20    | 11,26 | 329,96    | 18,56 | 815,75    | 45,89 | -63,38                              | 64,81     | 147,23    | 49,21     |
| Scrubland                 | 227,32    | 12,79 | 203,77    | 11,46 | 453,90    | 25,54 | 445,38    | 25,06 | -10,36                              | 122,75    | -1,88     | 95,93     |
| Grassland                 | 844,79    | 47,53 | 834,42    | 46,94 | 704,73    | 39,65 | 494,38    | 27,81 | -1,23                               | -15,54    | -29,85    | -41,48    |
| Barren Land               | 158,16    | 8,90  | 537,95    | 30,26 | 284,59    | 16,01 | 5,44      | 0,31  | 240,13                              | -47,10    | -98,09    | -96,56    |
| Built-up                  | 0,38      | 0,02  | 0,97      | 0,05  | 3,99      | 0,22  | 15,77     | 0,89  | 154,96                              | 310,61    | 295,19    | 4037,17   |
| Water                     | 0,11      | 0,01  | 0,18      | 0,01  | 0,19      | 0,01  | 0,77      | 0,04  | 57,95                               | 6,54      | 307,13    | 585,11    |

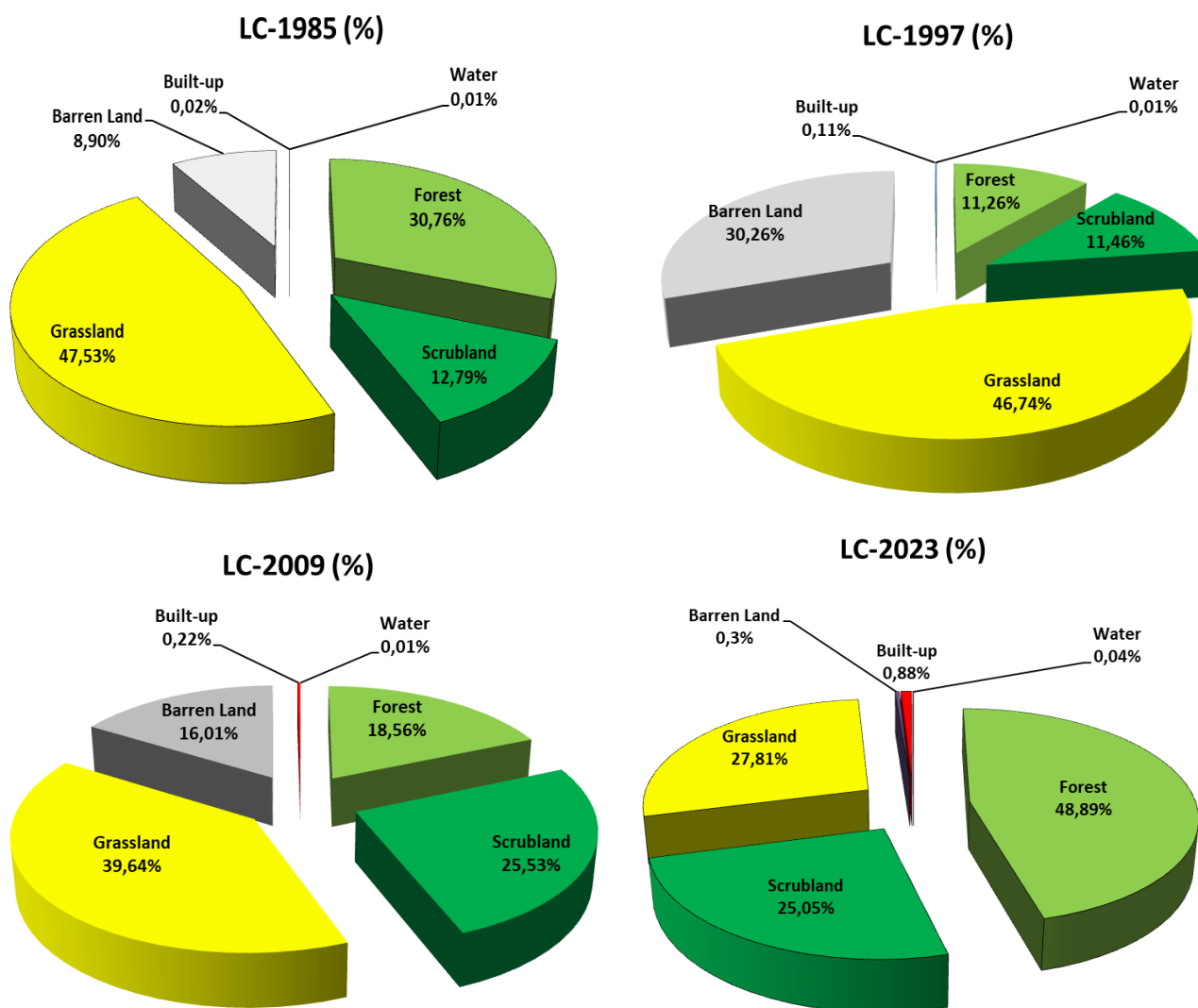


**Figure 03.** Land cover change statistics from (1985) to (2023).

In (2023), One of the most notable trends is the rapid expansion of Forest areas, which grew from 18,56% to (45,89%) of the total land area. The forest class has regained 189 hectares between (2009) and (2023), thanks to forest fire prevention (FFP) systems and reforestation programs initiated by the Forest Conservation Office of Mila province. These efforts have resulted in multiple reforestation campaigns and plans aimed at both restoring burned areas and increasing the forested surface. At the same time, the area covered by water bodies increased by (307%), which could be attributed to the creation of artificial reservoirs, Lakes, or improved water management practices.

### 3.2. Change detection

Change detection analysis was conducted not only to monitor variations over different time periods but also to discern the nature and spatial distribution of these changes by comparing satellite imagery captured at multiple time points. To quantify the transitions between land cover categories and their corresponding areas over the study period, a pixel-by-pixel cross-tabulation analysis was performed. The

spatio-temporal dynamics of land use changes for the years (1985), (1997), (2009), and (2023) were quantified and visually represented in Table (05 & 06) and Figure (04). The findings indicate that both positive and negative shifts occurred in the land use and land cover patterns of the study area over the past four decades.

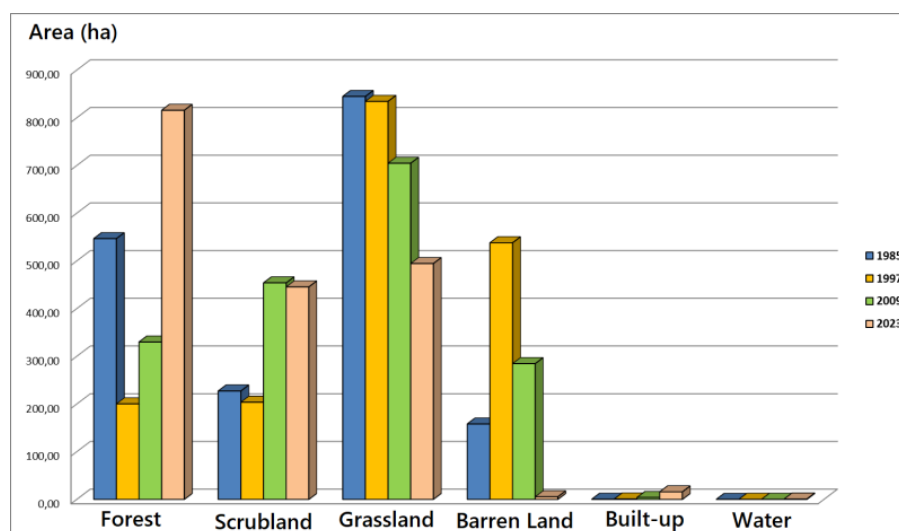
**Table 05.** Matrix of land use/cover change distribution (ha), from (1985) to (2023).

|             |               |               |               |               |             |             |             |
|-------------|---------------|---------------|---------------|---------------|-------------|-------------|-------------|
| LC-85 to 97 | For-85        | Scrb-85       | Gras-85       | Bar-85        | Blt-85      | Wat-85      | Total (85)  |
| For-97      | <b>181,27</b> | 14,79         | 2,43          | 1,72          | 0,00        | 0,00        | 200,20      |
| Scrb-97     | 87,48         | <b>54,02</b>  | 38,66         | 23,61         | 0,00        | 0,00        | 203,77      |
| Gras-97     | 131,35        | 84,77         | <b>552,15</b> | 66,15         | 0,00        | 0,00        | 834,42      |
| Bar-97      | 146,63        | 73,72         | 250,82        | <b>66,62</b>  | 0,15        | 0,00        | 537,95      |
| Blt-97      | 0,00          | 0,00          | 0,68          | 0,07          | <b>0,23</b> | 0,00        | 0,97        |
| Wat-97      | 0,00          | 0,00          | 0,00          | 0,00          | 0,00        | <b>0,11</b> | 0,12        |
| Total (97)  | 546,73        | 227,32        | 844,73        | 158,16        | 0,38        | 0,11        | <b>1778</b> |
| LC-97 to 09 | For-97        | Scrb-97       | Gras-97       | Bar-97        | Blt-97      | Wat-97      | Total (97)  |
| For -09     | <b>148,25</b> | 58,59         | 75,61         | 47,50         | 0,00        | 0,00        | 329,96      |
| Scrb -09    | 41,66         | <b>90,35</b>  | 149,27        | 172,61        | 0,00        | 0,00        | 453,90      |
| Gras -09    | 2,59          | 26,79         | <b>476,23</b> | 198,86        | 0,09        | 0,04        | 704,63      |
| Bar -09     | 7,69          | 28,02         | 131,34        | <b>117,52</b> | 0,00        | 0,00        | 284,58      |
| Blt -09     | 0,00          | 0,00          | 1,78          | 1,32          | <b>0,87</b> | 0,00        | 3,98        |
| Wat-09      | 0,00          | 0,00          | 0,03          | 0,11          | 0,00        | <b>0,13</b> | 0,27        |
| Total (09)  | 200,20        | 203,76        | 834,28        | 537,94        | 0,97        | 0,17        | <b>1778</b> |
| LC-09 to 23 | For -09       | Scrb -09      | Gras -09      | Bar -09       | Blt -09     | Wat-09      | Total (09)  |
| For -23     | <b>323,10</b> | 284,50        | 54,00         | 154,15        | 0,00        | 0,00        | 815,75      |
| Scrb -23    | 5,84          | <b>142,57</b> | 212,81        | 84,16         | 0,00        | 0,00        | 445,38      |
| Gras -23    | 1,00          | 25,32         | <b>423,18</b> | 44,88         | 0,00        | 0,00        | 494,38      |
| Bar -23     | 0,01          | 0,16          | 5,17          | <b>0,10</b>   | 0,00        | 0,00        | 5,44        |
| Blt -23     | 0,01          | 1,15          | 9,32          | 1,29          | <b>3,99</b> | 0,00        | 15,76       |
| Wat-23      | 0,11          | 0,20          | 0,26          | 0,01          | 0,00        | <b>0,19</b> | 0,77        |
| Total (23)  | 329,96        | 453,70        | 704,47        | 284,59        | 3,99        | 0,19        | <b>1778</b> |
| LC-85 to 23 | For-85        | Scrb-85       | Gras-85       | Bar-85        | Blt-85      | Wat-85      | Total (85)  |
| For-23      | <b>514,48</b> | 141,71        | 97,03         | 62,53         | 0,00        | 0,00        | 815,75      |
| Scrb-23     | 29,80         | <b>74,35</b>  | 295,75        | 45,42         | 0,00        | 0,05        | 445,38      |
| Gras-23     | 2,28          | 10,34         | <b>436,27</b> | 45,48         | 0,00        | 0,02        | 494,38      |
| Bar-23      | 0,02          | 0,07          | 1,93          | <b>3,42</b>   | 0,07        | 0,00        | 5,51        |
| Blt-23      | 0,16          | 0,64          | 13,28         | 1,31          | <b>0,38</b> | 0,00        | 15,77       |
| Wat-23      | 0,00          | 0,20          | 0,52          | 0,00          | 0,00        | <b>0,04</b> | 0,77        |
| Total (23)  | 546,73        | 227,32        | 844,79        | 158,16        | 0,45        | 0,11        | <b>1778</b> |

**Table 06.** Matrix of land use/cover change distribution (%), from 1985 to 2023.

| LC-85 to 97 | For-85       | Scrb-85      | Gras-85      | Bar-85       | Blt-85       | Wat-85       |
|-------------|--------------|--------------|--------------|--------------|--------------|--------------|
| For-97      | <b>33,15</b> | 6,51         | 0,29         | 1,09         | 0            | 0            |
| Scrb-97     | 16           | <b>23,77</b> | 4,58         | 14,93        | 0            | 0            |
| Gras-97     | 24,03        | 37,29        | <b>65,36</b> | 41,82        | 0            | 0            |
| Bar-97      | 26,82        | 32,43        | 29,69        | <b>42,13</b> | 40,3         | 0            |
| Blt-97      | 0            | 0            | 0,08         | 0,04         | <b>59,72</b> | 0            |
| Wat-97      | 0            | 0            | 0            | 0            | 0            | <b>100</b>   |
| Total (97)  | 100          | 100          | 100          | 100          | 100          | 100          |
| LC-97 to 09 | For-97       | Scrb-97      | Gras-97      | Bar-97       | Blt-97       | Wat-97       |
| For -09     | <b>74,05</b> | 28,75        | 9,06         | 8,83         | 0            | 0            |
| Scrb -09    | 20,81        | <b>44,34</b> | 17,89        | 32,09        | 0            | 0            |
| Gras -09    | 1,3          | 13,15        | <b>57,08</b> | 36,97        | 9,5          | 24,64        |
| Bar -09     | 3,84         | 13,76        | 15,74        | <b>21,85</b> | 0,02         | 0            |
| Blt -09     | 0            | 0            | 0,21         | 0,25         | <b>90,43</b> | 0            |
| Wat-09      | 0            | 0            | 0            | 0,02         | 0            | <b>75,22</b> |
| Total (09)  | 100          | 100          | 100          | 100          | 100          | 100          |
| LC-09 to 23 | For -09      | Scrb -09     | Gras -09     | Bar -09      | Blt -09      | Wat-09       |
| For -23     | <b>97,92</b> | 62,71        | 7,66         | 54,17        | 0            | 0            |
| Scrb -23    | 1,77         | <b>31,42</b> | 30,21        | 29,57        | 0            | 0            |
| Gras -23    | 0,3          | 5,58         | <b>60,07</b> | 15,77        | 0            | 0            |
| Bar -23     | 0            | 0,03         | 0,73         | <b>0,04</b>  | 0            | 0            |
| Blt -23     | 0            | 0,25         | 1,32         | 0,45         | <b>100</b>   | 0            |
| Wat-23      | 0,03         | 0,04         | 0,04         | 0            | 0            | <b>99,75</b> |
| Total (23)  | 100          | 100          | 100          | 100          | 100          | 100          |
| LC-85 to 23 | For-85       | Scrb-85      | Gras-85      | Bar-85       | Blt-85       | Wat-85       |
| For-23      | <b>94,10</b> | 62,34        | 11,49        | 39,54        | 0,00         | 0,00         |
| Scrb-23     | 5,45         | <b>32,71</b> | 35,01        | 28,72        | 0,00         | 46,67        |
| Gras-23     | 0,42         | 4,55         | <b>51,64</b> | 28,76        | 0,00         | 14,83        |
| Bar-23      | 0,00         | 0,03         | 0,23         | <b>2,16</b>  | 14,57        | 0,00         |
| Blt-23      | 0,03         | 0,28         | 1,57         | 0,83         | <b>85,44</b> | 0,00         |
| Wat-23      | 0,00         | 0,09         | 0,06         | 0,00         | 0,00         | <b>38,53</b> |
| Total (23)  | 100,00       | 100,00       | 100,00       | 100,00       | 100,00       | 100,00       |

\*The **diagonal** values represent the extent of each land use/cover class that remained unchanged, whereas the off-diagonal values indicate the expansion or reduction of these classes.

**Figure 04.** Diagrammatic illustration of land use/cover change in (ha) from (1985) to (2023).

-The analysis shows that (48.19%) of the total area of the province of the study area remained unchanged between (1985) and (1997), while (51.81%) underwent conversions between land use/cover categories. Change detection analysis also reveals that (33.15%) of forest areas remained intact, while: (16%) was converted to scrubland, (24.03%) became grassland and (26.82%) turned into barren land (burned area).

-Approximately (38.27%) of the total area remained unchanged from (1997) to (2009), while (61.73%) underwent conversion between the land use/cover categories. The major changes include gains of Forest (64.81%), scrubland (122.75%), built-up areas (310%), and loss of grassland (15.54%). Change detection analysis also reveals that (74%) of the forest land remained unchanged. However, portions were converted to: scrubland (20.81%), Barren land (3.84%), and grassland (1.3%).

-Additionally, (97.92%) classified as forest land in (2009) remained forest land by (2023). However, (2.08%) were converted into other categories, furthermore, the increase in forest area during this period primarily came at the expense of scrubland (62,71%) grassland (11,49%) and barren land (39,54%)

Considering the entire study period, at once, from (1985) to (2023), (57.88%) of the total area remained unchanged, while (42.11%) underwent conversions between land use/cover categories. The analysis indicates that (94.10%) of forest land remained stable. However, new forest areas were primarily established at the expense of scrubland (62,34%), barren land (39.54%), and grassland (11.49%). In contrast, (39.54%) of barren land was lost to forest areas, with additional losses to grassland (28.76%), and scrubland (28.72%). The built-up area category experienced the most substantial net expansion, increasing by (4037,17%) between (1985) and (2023), with an average annual increase of (107%) each year.

### 3.3. Driving Forces of Land Use/Land Cover Changes

Understanding the drivers of land use/cover change is considered one of the most challenging questions in global change science, which is indispensable to minimize and manage the impacts of multiple causes and consequences of land use/cover change (Lambin *et al.*, 2003). Some preliminary elements can be mentioned based on existing statistics and previous investigations.

Wildfires present significant challenges to forest management and conservation, the Tellian Atlas is particularly susceptible to these disturbances, causing substantial losses in forest cover and biodiversity. Understanding the potential for regeneration in these ecosystems is crucial for

maintaining ecological balance and the services they provide, such as climate regulation, soil protection, and water retention.

Between (1997) and (2009), the study area experienced a significant loss of over 300 hectares, attributed to wildfire events (figure 05). However, subsequent recovery phases reveal a positive trend, with a reforestation of more than 100 hectares occurring between (1997) and (2009), followed by an impressive addition of 500 hectares between (2009) and (2023). This culminates in a total increase of approximately 800 hectares of forest cover, due to the implementation of forest fire prevention (FFP)systems and reforestation initiatives led by the Forest Conservation Office of Mila province (figure 06).

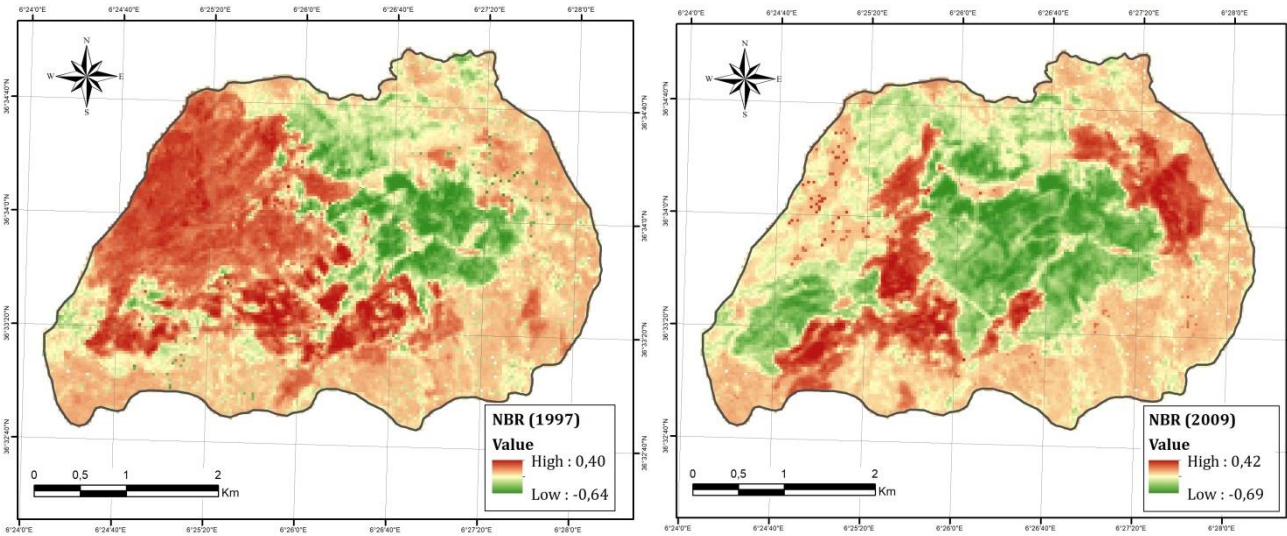


**Figure 05.** Normalized Burn Ratio (NBR) generated with Landsat 5 for (August 05, 1997) and (August 31, 2009)

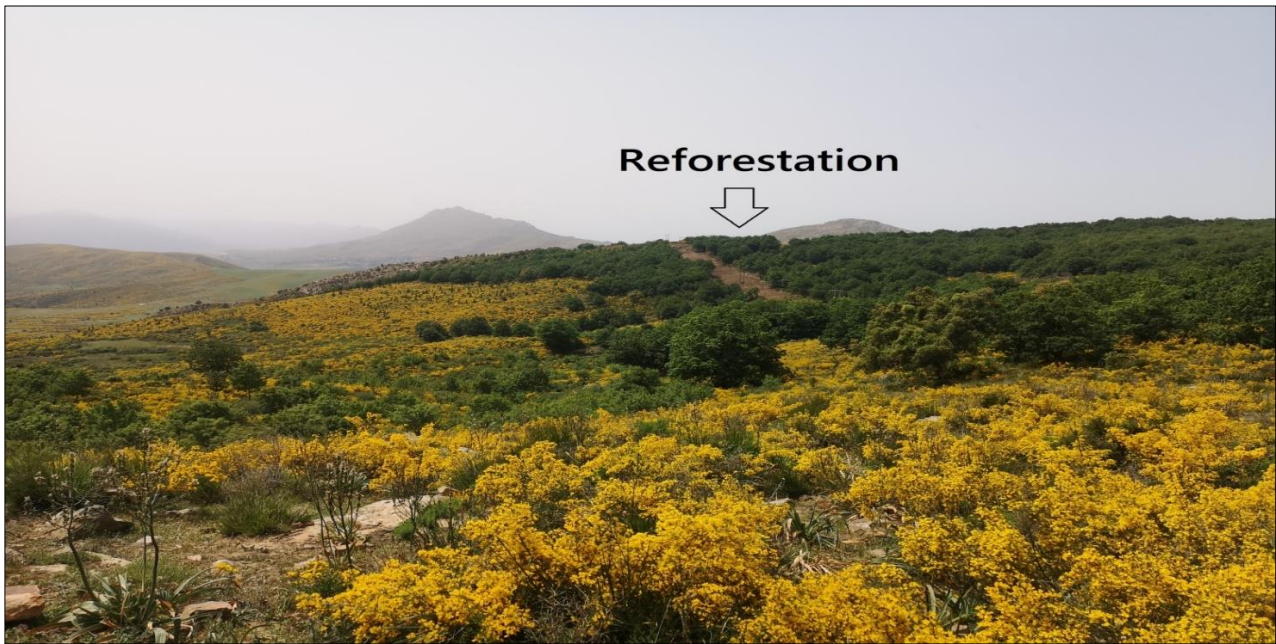


**Figure 06.** Forest restoration projects (Reforestation) in the forest of Mouias.

The remarkable expansion of forest areas can be also attributed to the unique characteristics of this region, which has historically been sheltered from zoo-anthropic pressures. This reduced pressure likely facilitates the natural regeneration process. Notably, the dendrometric characteristics of trees in affected areas indicate a growth history predating the wildfires, suggesting that regeneration is occurring through the crown. This is particularly relevant for cork oak (*Quercus suber*), which exhibits a capacity to regenerate effectively when fire frequencies remain low. Following Prodon's (1988) research, it is suggested that in scenarios where fire frequency is less than two incidences per 50 years, cork oak thrives on crown regeneration granted by the protection of epicormic buds, safeguarded by its suberous bark (Amandier, 2002). This highlights the importance of understanding fire ecology in managing and conserving forest ecosystems in Algeria.

#### 4. Conclusion

This research is regarded as an effort to monitor changes in land cover and use in the forest of Mouias using remote sensing and GIS techniques, thematic maps were created, and the results of the accuracy assessment are deemed adequate. The post-classification results show the trends and magnitude of change; this information is essential for policymaking and land management.

Over the observed period, from 1985 to 2023, findings indicate that (38%) of the forest land cover classes remained stable, whereas (62%) experienced category shifts. These changes reflect fluctuations across various categories, driven by historical events and socio-economic transformations that have influenced land cover over time.

The most significant changes in surface conditions primarily impacted forested areas, with substantial reductions between (1985) and (1997). However, natural regeneration following the (1997) and (2009) wildfires is evident in the vegetation state by (2023), as confirmed through field surveys. Although gradual, the regeneration process demonstrated resilience, enabling forests to recover biodiversity with minimal intervention. As a result, approximately 270 hectares of forested area were reclaimed between (1985) and (2023), supported by forest fire prevention (FFP) and reforestation initiatives by the Forest Conservation Office of Mila province, aimed at restoring burned areas and enhancing forest cover across various vegetation types.

Future research should integrate detailed socio-economic studies focused on soil-climate-vegetation interactions, offering stakeholders the insights necessary to design informed regional development strategies.

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