# Land Cover Dynamics in Beni Chougrane Mountains, North West of Algeria, Using Remote Sensing

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**Abstract:** Land cover change is the result of complex interactions between social and environmental systems, systems that evolve over time. While climate and biophysical phenomena have long been the main drivers of changes in land surfaces, the human is now behind most of the changes affecting terrestrial ecosystems. The main objective of this work is to show the characterization and monitoring of land cover change in semi-arid Mediterranean area. The changes in agro-forest area which is a land use mode in the mountains of Beni-Chougrane at local scale.

We used Support Vector Machines method for classification of Landsat TM image, and change detection technique to analyze change of land cover types by comparing the satellite observations of Landsat TM from 1984 to 2009.

Our analysis showed that proportion of forest cover decreased from 41% in 1984 to 14% in 2009 that from approximately 190 hectares/year and agriculture land from 18 % to 1.5 %. The results showed that all land cover and lad use area have experienced structural changes in it's globally, Intensive regression of woody natural vegetation imposed by fires and unsustainable use of resources, a remarkable decline in land occupied by agriculture. Suggesting an immediate response to a policy based on priorities for the preservation, protection, development and rational use of land areas.

**Keywords:** Remote sensing, change detection, Landsat, anthropogenic, Beni-Chougrane.

## 1. INTRODUCTION

The detection and identification of land cover changes are one of the main concerns for scientists and managers involved in the understanding and management of natural and artificial ecosystems [1]. Thus, the last thirty years, there is a real dynamic change of land with intensive degradation of the natural vegetation cover especially in arid and semi-arid zone. Indeed, the adverse effects of drought periods from the year 1970 combined with population growth and economic conditions experienced by the country in the 1990s have greatly upset the delicate balance of the natural environment. These adverse effects may result in partial or total disappearance of some natural ecosystems. However, the location of the most significant different changing sectors in space and time, allows specialists planning and local leaders understand these spatial changes that affect natural ecosystems in Algeria. In addition, there are relatively few studies using a long time series of Landsat data to determine land cover changes at local scale in Algeria.

One of the most commonly used satellite sensors for such purposes is the Thematic Mapper (TM) on board of Landsat series satellite platforms. The spatial and temporal resolution, the availability, the coverage and the overall quality of the Landsat data, provide a useful informational background for detailed land-use change studies [2-4].

Numerous methods have been developed for land cover change detection (e.g. [5-9]). According to [10] the methods for change detection and classification are divided into preclassification and postclassification techniques. The preclassification techniques apply various algorithms directly to multiple dates of satellite imagery to generate ‘‘change’’ versus ‘‘no change’’ maps. These techniques locate changes but do not provide information on the nature of change [11, 12]. On the other hand, postclassification comparison methods use separate classifications of images acquired at different times to produce difference maps from which ‘‘from–to’’ change information can be generated [13]. Although the accuracy of the change maps is dependent on the accuracy of the individual classifications and is subject to error propagation, the classification of each date of imagery builds a historical series that can be more easily updated and used for applications other than change detection. The postclassification comparison approach also compensates for variation in atmospheric conditions and vegetation phenology between dates, since each classification is independently produced and mapped [10, 14, 15].

In recent years, new landslide susceptibility assessment method such as support vector machine (SVM) [16-18]. SVM are an alternative nonparametric classifier that offer particular promise for change

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ISSN: 1814-8085 / E-ISSN: 1927-5129/14 

detection of multiple forest classes because they can handle complex distributions of multi-temporal imagery [19],

The mountains of Beni Chougrane that meets the expectations Anthropogenic is that of a landscape organized by man, where different land use classes are distributed smoothly in space with an easy to perceive logical. Given this expectation, wastelands and open forests are unappreciated.

The appearance of multi-spectral remote sensing data provides a crucial advantage in the characterization of objects in a wide spectral band. Thus, it is possible to make both quantitative and qualitative diagnostics to target the development of different land areas problems. Any program of land management requires an inventory; the objective can be achieved quickly using remote sensing and geographic information systems. Remote sensing is an essential source of information in the study of change in land use. In this work, the change of land cover has been studied during the last twenty years from 1984 to 2009. This work was made possible by the analysis of remote sensing data (Landsat5) and field observations in order to develop a typology of the main land use classes at the level of perception of the satellite sensor. The results are presented mainly in the form of maps, supports an interpretation of the factors that are causing changes in land use. The contributions of different methods of satellite images analysis, change detection and remote sensing data are used to understand the process of change.

## 2. STUDY AREA

The area is located in the western part of the mountains of Beni Chougran. It is located between the north west of the province of Mascara and north-eastern province of Sidi-bel-abbes. The study area covers an area of 18 000 ha, the altitude is between 250 and 800 meters, with an average altitude of about 460 to 600 meters. The minimum altitudes are located northwest and southeast and fluctuate between 250-460 meters, while the maximum altitude ranges from 640 to 814 meters in the central part of the area. The average annual rainfall calculated on data available at the meteorological station Bouhanifia for 20 years (1984-2004) is 302mm. Annual climate regime is characterized by a short period of cooler, less humid winters and long dry summer period. The seasonal rainfall quantity is 37.6% in winter, 30.1% in autumn, 27.9% in spring and 4.3% in summer.

## 3. METHODOLOGY

### 3.1. Image Processing

In a change detection study, images used must have characteristics as homogeneous as possible so that the differences from their comparison can be related to actual changes in state land and not artifacts related images. Ideally, the images should from the same sensor and the same vesting period (Table **1**). Success in land-cover and land-use change analysis using multi-temporal remote sensing data is dependent on accurate radiometric and geometric rectification [20, 21]. These pre-processing requirements typically present the most challenging aspects of change detection studies and are the most often neglected, particularly with regard to accurate and precise radiometric calibration and atmospheric correction [22].

#### *3.1.1. Geometric Corrections*

Image to image correction was applied to the TM data through a total of 20 control points were used to establish a geometric relationship between the pixels of the first images over the second image. The images were georeferenced in the UTM coordinate system (WGS 84) zone 30 and they had a spatial interpolation polynomial of first degree and a resampling with nearest neighbor method. The Root Mean Square (RMS) indicates an error of 0.2 pixels between images which is within the required limit (0.50 pixel) to perform change detection between two satellite images [23].

#### *3.1.2. Radiometric Calibration*

Convert the digital number of the images into reflectance. Radiometric information contained in a Landsat image is coded numerically from 0 to 255 (8 bits).

**Table 1: Characteristics of Satellite Images**

| Sensor | Raw/Rang | Date | cloud cover | Quality |
|---|---|---|---|---|
| TM 5 | 198/35 | 01/07/2009 | 0 % | 9 |
| TM 5 | 198/35 | 28/07/1984 | 0 % | 9 |

The Landsat-5 were converted to satellite radiance using Eq. (1)

$$L_\lambda = \left(Gain * DN\right) + Bias \quad (1)$$

L: Radiance;

DN: Digital number;

The impact of sensor degradation on the gain parameter was explained to use data published by [24, 25], while the revised gain parameter published by [26] were used for images acquired and processed after May 5, 2003. The bias reported by [27] was used for all images.

Conversion into reflectance using Eq. (2)

$$\rho_\lambda = \pi * L_\lambda * \mathrm{d}^2/\mathrm{ESUN}_\lambda * \sin\left(\theta\right) \quad (2)$$

λ: number of spectral band;

L: radiance;

ρ: reflectance;

d: distance between the Earth and the Sun in astronomical units;

ESUN: exo-atmospheric solar irradiance;

θ: Solar zenith angle

#### *3.1.3. Atmospheric Corrections*

Atmospheric correction using the method "QUAC" Quick Atmospheric Correction, this method determines atmospheric compensation parameters directly from the information contained within the scene (observed pixel spectra), without ancillary information. QUAC was developed as a simpler alternative to sophisticated atmospheric correction procedures, such as FLAASH, which are based on radiative transfer models [28, 29], generally producing reflectance spectra within approximately +/-15% of the physics-based approaches [28]. QUAC is based on the empirical finding that the average reflectance of a collection of diverse material spectra, such as the end member spectra in a scene, is essentially scene-independent.

### 3.2. Supervised Classification

It is based on the information acquired during the mission field when validating interpretations made. Different training sets were delineated for each land cover class and verified through a digital topographic map and the visual interpretation of each images.

SVM has such advantages as fewer requirements to prior knowledge, more suitability to small size of samples, more robustness to noises [30], and higher learning efficiency and more powerful generalization capacity [31]

We used Support Vector Machines (SVM) [32], implemented in the software ENVI 4.7 with a Gaussian radial basis function [33-35].

In this study, the SVMs classifier was applied to the Landsat imagery for mapping the land use/cover of the study area using the training data. First, the classification key was formulated, which including forest, shrub, agriculture, mattoral and bare land. The decision to use this classification scheme was based primarily on photo- interpretation of the higher solution imagery acquired from Google Earth and ground observation. Second, training sites representative of each of the above classes were collected from the Landsat imagery following a simple random sampling strategy. Selection of the training sites was primarily guided by the high resolution imagery photo-interpretation in Google earth. The training sites were carefully determined and restricted to homogeneous regions. Approximately more then 100 pixels per class were identified as training data representing the classes defined in our classification scheme. Third, the SVMs algorithm was implemented, using the training sites collected during the previous step.

### 3.3. Change Detection

A quantitative analysis of land use/cover spatial dynamics was made by comparing two images classified (1984-2009) by change detection statistics method implemented in ENVI 4.7 software, The changes detected using this routine differ significantly from a simple differencing of the two images. While the statistics report does include a class-for-class image difference, the analysis focuses primarily on the initial state classification changes; that is, for each initial state class, the analysis identifies the classes into which those pixels changed in the final state image.

This is may be the most common approach to compare data from different sources and dates [13, 36]. The advantage of post-classification comparison is that it by passes the difficulties associated with the analysis of images acquired at different times of the year and/or by different sensors [14, 15, 37]. Moreover, the post classification method also answers the amount, location, and nature of change [38].

## 4. RESULTS AND DISCUSSION

### 4.1. Land Use Mapping

Five land use classes were identified, this corresponding to five different radiometric classes. On this images interpretation of the study area, the forests, Shrubland and mattoral were delineated in some detail, in addition to the distinction between the surfaces of bare land and farmland. This classification has identified the following classes:

- Class 1: forest of Tetraclinis articulata and Pinus halepensis
- Class 2: Shrubland composed of Chamerops humilis and Calycotome
- Class3: mattoral composed of Pistacia lentiscus
- Class 4: agricultural area
- Class 5: bare land

The evaluation of the classification accuracy involves comparing the classified image with field observations. This comparison is usually based on a confusion matrix between the data set [39]. Measures such as the correct classification percentage and the kappa coefficient can be derived from confusion matrix elements, are used to express the classification accuracy.

The confusion matrix obtained by commission to check for each theme overestimated the proportion of pixels that should not belong to the class. The total per column is the theme area percentage that has been overestimated. The results show accuracy percentage for image classification in 1984 is 83 %, or 700 of 845 pixels correctly classified, and 90 % for the second image, or 389 of 433 pixels (Tables **2** & **3**).

KAPPA coefficient = 0.78 for classification of 1984 and reached 0.86 for 2009, which means that the classification is more or less accurate with a large concordance.

The land use map produced from the image 1984 (Figure **2**) gives an overview of the vegetation distribution in the area. The forest occupies an interesting Surface with a rate of 40 %. It is generally composed of a mixture of Pinus halepensis and Tetraclinis articulata. However, matorrals occupy a worrying surface estimated at 4588 ha. It is mainly composed of Pistacia lentiscus, is characterized by good resistance to climatic conditions and clay soils. While, the surface colonized by scrub is constituted essentially of Chamaerops humilis and Calycotome intermedia with an area of 2018 ha, on profound

**Table 2: Confusion Matrix for 1984**

| Class | forest | Scrub | Agriculture | bare land | Matorral |
|---|---|---|---|---|---|
| forest | 92,13 | 32,65 | 0,00 | 0,00 | 02,14 |
| Scrub | 07,87 | 44,90 | 0,00 | 0,00 | 16,24 |
| Agriculture | 0,00 | 0,00 | 98,95 | 06,12 | 0,00 |
| bare land | 0,00 | 0,00 | 01,05 | 93,88 | 0,00 |
| Matorral | 0,00 | 20,45 | 0,00 | 0,00 | 81,62 |
| Total | 100,00 | 100,00 | 100,00 | 100,00 | 100,00 |

**Table 3: Confusion Matrix for 2009**

| Class | forest | Scrub | Agriculture | bare land | Matorral |
|---|---|---|---|---|---|
| forest | 73,44 | 20,00 | 0,00 | 0,00 | 04,70 |
| Scrub | 25,00 | 78,00 | 02,00 | 0,00 | 19,00 |
| Agriculture | 0,00 | 02,00 | 98,00 | 0,00 | 0,00 |
| bare land | 0,00 | 0,00 | 0,00 | 100,00 | 0,00 |
| Matorral | 01,56 | 0,00 | 0,00 | 0,00 | 76,30 |
| Total | 100,00 | 100,00 | 100,00 | 100,00 | 100,00 |

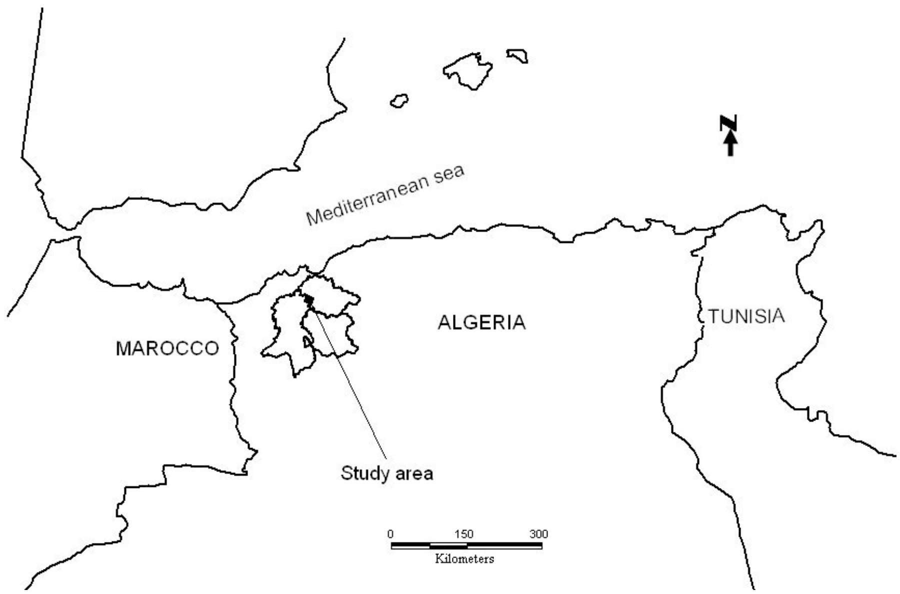


**Figure 1:** Location of the study area.

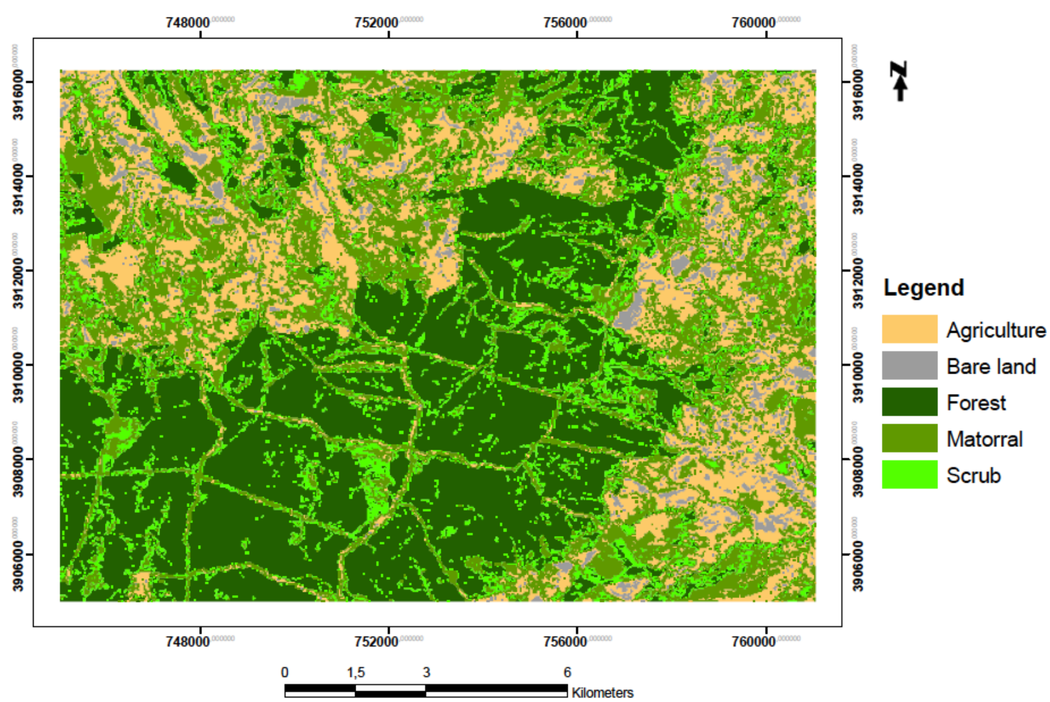


**Figure 2:** Map of land use/cover, 1984.

calcareous soils. Agriculture remains the main source of income for the rural population; it is mainly based on a practice of cereals (Table **4**).

The map derived from the satellite image of 2009 (Figure **3**) gives a saw on the distribution of land use classes. The majority of the area is colonized by matorral based Pistacia lentiscus exceeding 8800 ha, while forest area is characterized by a sharp decline estimated 4783 ha. The group Chamaerops and Calycotome covers abandoned farmland. Bare soil is experiencing an extension to the south of the zone with a surface of 1460 ha.

### 4.2. Land Cover Change

The comparison between two land use maps, estimated for the entire zone, is a summary of net changes in class for this period (Table **5**). Changes were obtained by calculating the difference between the estimates of the area in 2009 and 1984 (Figures **4** and **5**), and show the gains and losses for each class.

**Table 4: Coverage Area for each Class**

| class | Period | | | |
|---|---|---|---|---|
| | 1984 | | 2009 | |
| | area (ha) | Percentage | area (ha) | Percentage |
| forest | 7 380 | 41,00 % | 2519 | 14,00 % |
| Matorral | 4 588 | 25,40 % | 8486 | 47,00 % |
| Scrub | 2 018 | 11,20 % | 5489 | 30,45 % |
| Agriculture | 3 546 | 19,70 % | 267 | 01,50 % |
| bare land | 492 | 02,70 % | 1261 | 07,00 % |

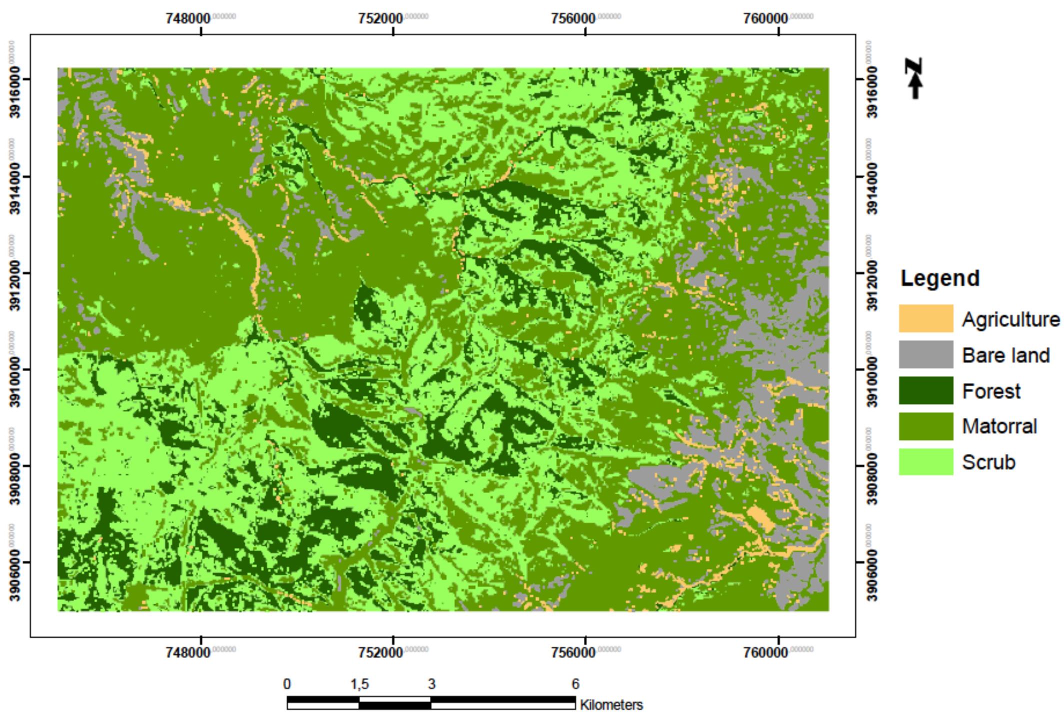


**Figure 3:** Map of land use/cover, 2009.

**Table 5: Land use Change between 1984 and 2009**

| Class | initial state ($km^2$) | final state ($km^2$) | Change | |
|---|---|---|---|---|
| | | | area ($km^2$) | Percentage |
| Forest | 73,8 | 25,19 | -48,60 | -65,70 |
| scrub | 20,18 | 54,89 | +34,70 | +172,00 |
| Bare land | 04,92 | 12,61 | +8,00 | +156,45 |
| Matorral | 45,88 | 84,86 | +39,00 | +85,00 |
| Agriculture | 35,46 | 02,67 | - 32,77 | -92,45 |

Mixed forest of Pinus halepensis and Tetraclinis articulata: The percentage of this class in the initial state was (41%). It has undergone a change in the final state; it is converted to 47.7% in scrub, 24% in Matorral and 0.43% in bare soil. So, this class has undergone a change of 72.5% of its original area. It can also be inferred that the forest lost 72% of that area which is 4861 hectares.

Scrub: the percentage of the class was 11.2%, it underwent a change in 65.7% of this initial area. 11.7% of this class was transformed into a forest, 49.5% in

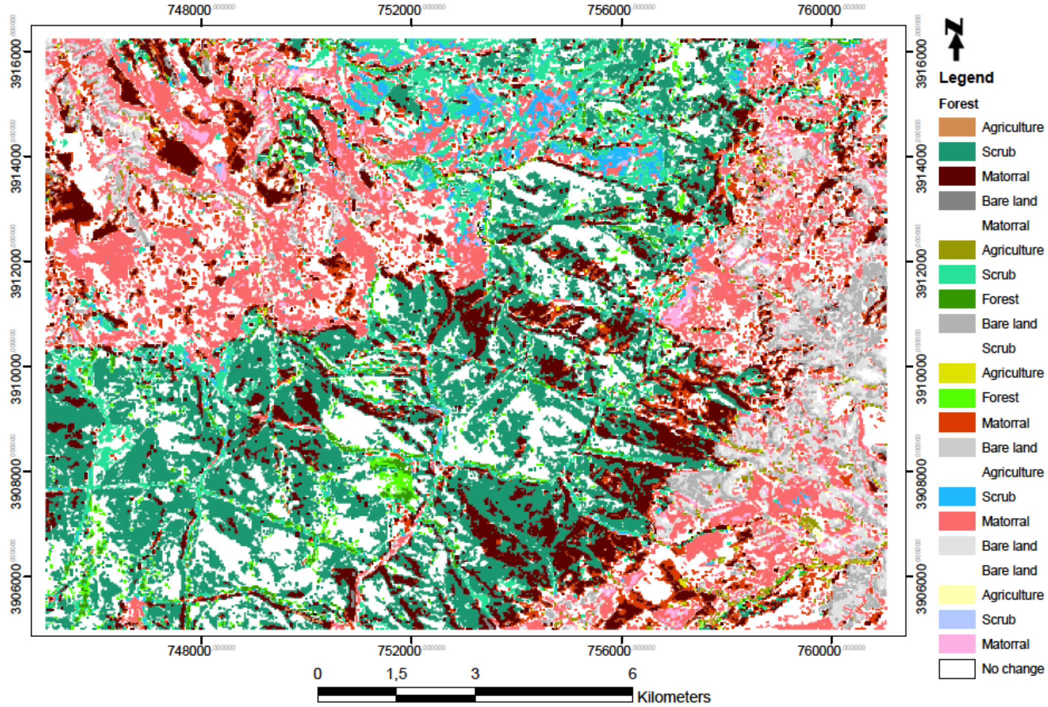


**Figure 4:** Map of land use/cover change between 1984 and 2009.

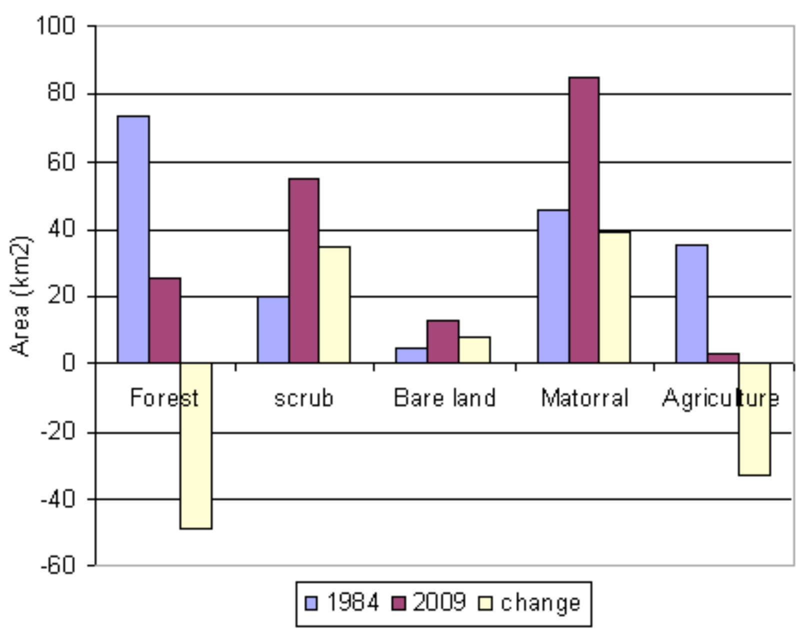


**Figure 5:** Distribution of land use/cover and degree of change for each class.

matorral of Pistacia lentiscus, and a change of 3.2% in the bare soil. Therefore, a positive change that makes the gain of 690 hectares for this class.

Matorral: it was 25% in 1984; it has undergone a change of 35% of that area which 4.3% was evolving forest, 19.3% transformed into scrub and 9.5% into bare soil. The matorral has been a positive change with gain 4000 hectares.

Agriculture: this class has lost 96.7% of its land, 68.5% of agricultural lands have been converted into matorral, 16% in bare land and 10% in scrub.

## 5. DISCUSSION

The study shows that the forest is the most affected class with a decline of 35% or one-third, whose role is no further demonstration for the sustainable management of areas. Much of this forest formation has become a fairly rapid degradation in low scrub and matorral, mainly due of repeated fires at short intervals, overexploitation of resources by the rural population and deforestation. Class which includes bushy areas with low woody vegetation knows a remarkable increase in size throughout the area. The matorral based Pistacia lentiscus has been the biggest positive change, this gain is due to the decrease in forest cover with more light and space vital to Pistacia lentiscus, which has a significant power regeneration and high growth potential. All positive changes result in dense matorrals dominated by shrubby vegetation which the amount of woody biomass increases with a gain of 47% for dense matorrals, and 92% for the bushy induced primarily by natural regeneration of Tetraclinis after fire and the appearance of species of matorral (Chamerops, Ampelodesma and Calycotome ...) after the degradation of the forest. High farmlands were transformed into fallow and bare soil. The extension of bare surfaces also affected low bushy formations subjected to erosion and overgrazing totally destroying the soil characteristics.

Since 1980, the vegetation of the study area has undergone a remarkable evolution, especially in the forest, according to ancient documents, the vegetation was dense with a closed forest gathering a very important faunal wealth, but is continuous regression. This vegetation change is mainly due to natural and anthropogenic factors. Since the beginning of the century, the intensity of human activities on ecosystems increases. Disturbances are more closely spaced, covering areas larger and larger; these phenomena decrease the adaptability of ecosystems to human pressures. The regressive evolution of the forest is mainly due to negative pressures and uses of human, as the uncontrolled overgrazing and preventing the regeneration of seedlings that leads to progressive destruction of the forest. Fire is a severe degradation factor because not only leads to the destruction of vegetation cover, but in addition it also destroys soil biology. In a semi-arid bioclimatic stage characterized by an average annual rainfall of 300 mm, all forest ecosystems are fragile. Added to theses cyclical droughts in the western region of the country, the explanation of a regression is confirmed and should be supported through a global strategy for the management of all areas and human factors. The consequences of this climate with opposition in the year two season cut goods are considerable heat and drying winds of summer follows waterspout of trickling water in winter. Taken separately, each of these phenomena appears as a particularly nasty erosion factor [40]. The effects of this factor are remarkable on or depressions can be observed claws and ravines of the piedmonts. Causing damage and depleting soil so a regression of vegetation covers. It must be recognized that the regressive evolution of the forest is fast as human pressure is very strong, accentuated by the aggressive climate and environmental sensitivity to erosion.

## 6. CONCLUSION

Accordance with its objectives of this study to make a situation assessment of vegetation covers in the region of Beni-Chougrane. On this occasion it was found that the nature of the information available has allowed the analysis of the land use dynamics during the period (1984-2009).

By processing and images classification, we have creates two land use maps in the study and extract a changing map for that area. Following the interpretation of these maps, we have inferred that the vegetation cover consists mainly of an open forest with a mixture of Pinus halepensis and Tetraclinis articulata, matorral of Pistacia lentiscus, scrub consists of Chamerops and Calycotome, and a large area transformed to bare land. A diachronic study based on a comparison between two land use maps extracted led us to conclude that the different strata of vegetation cover have undergone changes mainly forest cover with intensive regression.

The decline in vegetation cover is particularly due to anthropogenic pressures and often not adapted forest work. Suggesting immediate intervention to a forest policy based on priorities related to the preservation, protection, enhancement and rational use of vegetable surfaces.

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Received on 11-04-2014 Accepted on 12-05-2014 Published on 13-06-2014

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