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Vegetation and land cover change in the National park of EL Kala: Application of NDVI differencing and classification analysis

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Key words: Change Detection, NDVI Differencing, Vegetation, Land Cover, National Park of El Kala.

Abstract

In this study, vegetation and land cover change were investigated in order to understand the nature and dynamic of changes occurred in the National Park of El-Kala (Algeria) between years 2002 and 2013. Landsat images, remote sensing techniques and GIS tools were the key elements to achieve this study. The 2013 NDVI image was subtracted from the 2002 one, and the resulting NDVI differencing image was classified into three categories: positive, negative and no change. Assessment was satisfactory with an overall accuracy of 98.14% and Kappa coefficient of 0.97. Areas affected by vegetation loss are mainly found in the east and south part of the park, whereas areas with vegetation gain are located around water bodies. Regarding land cover change, two unsupervised classifications were applied and seven land cover classes were defined in both images. Based on field knowledge and statistics' comparison, land cover classes affected by areas' decrease are Dense forest (-0.96 %), Uncultivated land (-3.99 %) and Barren land (-6.56 %). In contrast, land cover classes with positive change are: Water body (+2.01 %); Open forest (+4.93 %), Cultivated land (+4.45 %) and Urban (+3.66 %). The main causes for these changes are: Expansion of urban tissue and new infrastructures, degradation of dense forests due to human pressures mainly grazing and clearing, intensification of agriculture activities with uncontrolled irrigation and last but not least, forest fires in summers due to long droughts periods and holiday rush.

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Introduction

The Mediterranean basin includes some of the highest levels of plant diversity of any region on Earth (Allen, 2003). According to Medail and Quézel (1999), 10% of higher plants can be found in the Mediterranean which represents only 1.6% of the Earth's surface and 10.8 species every km^2. However, in the last decades, the expansion of cultivated areas at the expense of forests indicates significant ecological alterations due to deforestation and the break-up of the natural equilibrium between cultivation, grazing and forestry (Kosmas *et al.*, 2002).

Land cover in many regions all over the world is facing considerable and rapid changes, especially in areas where there is a high anthropogenic pressure. These changes are mainly expressed through dramatic urban expansion, agricultural intensification, conversion of natural vegetation to agricultural crops and exploitation of forest resources. Changes in land cover result in changes in radiance values caused by others factors such as differences in atmospheric conditions, in soil moisture and differences in sun angles (Singh, 1989; Mas, 1999). Land cover changes can be used to describe changes in urban settlements and vegetation patterns as an important indicator of urban ecological environments (Peijun *et al.*, 2010). Furthermore, land cover changes are key drivers of changes in biodiversity at global, national and local scales (Haines-Young, 2009). Algeria, like many developing countries is prone to increased land cover changes caused by extensive cultural practices, urbanisation patterns and other anthropogenic factors, mainly grazing and clearing.

One of the major applications of remotely-sensed data is change detection because of repetitive coverage at short intervals and consistent image quality. It is useful in land use change analysis, monitoring of shifting cultivation, assessment of deforestation, and other environmental changes (Singh, 1989).

Change detection has become a useful approach for scientists to observe changes in vegetation and land cover over large areas. This concept is based on the comparison of differences in the spectral and temporal characteristics of satellite images taken at different times, to identify whether any changes have occurred in the landcover. According to Jensen (1996), the fundamental assumption of change detection is that the difference between spectral responses of the same area will be large if land cover has changed between two dates.

Different techniques are used therefore depending on the purpose of each study, such as post classification comparison; principal components analysis; change vector analysis; temporal image differencing and rationing (Lillesand *et al.*, 2008).

A common approach widely used for quantifying changes in land cover involves comparison between two independently classified imagery data (Singh, 1989; Lasanta and Vicente-Serrano, 2012). The so-called post classification comparison (PCC) method offers the advantage to allow the production and the update of GIS databases, as class/categories are given, and quantitative values of each class can be determined (Fichera *et al.*, 2012).

In vegetation studies, the ratios, commonly known as vegetation indices, have been developed for the enhancement of spectral differences on the basis of strong vegetation absorbance in the red and strong reflectance in the near-infrared part of the spectrum (Singh, 1989). The most widely used vegetation index is the Normalized Difference Vegetation Index (NDVI) (Feoli, *et al.*, 2003).

According to Lillesand *et al.*, (2008), the NDVI helps compensate for changing illumination conditions, surface slope, aspect, and other extraneous factors. It is used also for investigating numerous phenomena such as vegetation seasonal dynamics, leaf area index, biomass estimation and percentage ground cover determination. The NDVI is calculated according to the formula: NDVI = (NIR- R) / (NIR + R), where NIR is the near infra-red response for a given pixel and R is the red response (Jensen, 1996).

NDVI indicates presence or absence of vegetation and its intensity. Therefore, its comparison may provide information on quantitative and qualitative changes in land cover, given that vegetation is the primary indicator of land cover and its (Alphan and Derse, 2013). This analysis is carried out by applying image differencing, which is the most widely used technique for change detection. It is based on the subtraction of the digital pixel values of an image from one date from the corresponding pixel values for a different date (Singh, 1989).

In this work, NDVI images were derived from two Landsat images taken in years2002 and 2013. A NDVI differencing technique was used in a GIS environment to produce an NDVI differencing map. In a second step, two unsupervised classification were applied to produce land cover maps corresponding to the 2002 and 2013 images. The resulting land cover classes were quantified and compared. Therefore, this study aims to analysing vegetation and land cover change and determining the major causes of changes that occurred in the National Park of El Kala, northeast Algeria.

Materials and methods

Study area

The National Park of El Kala is situated in the extreme Northeast of Algeria, bounded by the Mediterranean sea to the North and Tunisia to the East, and lies between 36°55' to 36°90'N and 08°16' to 08°43'E (Fig. 1).

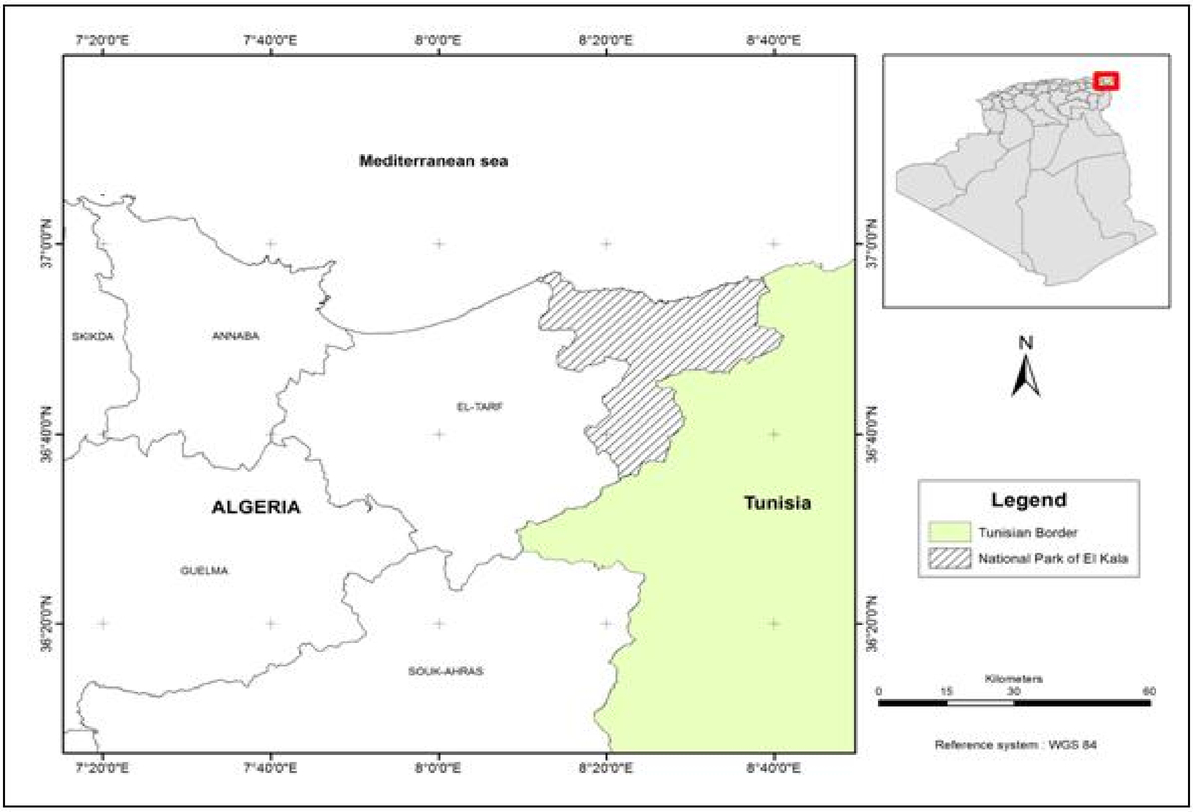

Fig. 1. Location map of the National Park of El Kala. Algeria.

The park covers an area of around 76438 ha, where 140000 habitants live. The landscape is typically Mediterranean with varied ecosystems, including a mosaic of evergreen sclerophyllous forests, lakes, mountains, scrubs, coastal and marine areas. The park is well known for its unique wetland network, from which two are on the RAMSAR list of wetlands of international importance. Furthermore, it has been designated by the UNESCO as a Man and Biosphere reserve in 1990. The climate is Mediterranean, with mild and rainy winters, hot and moist summers. Véla and Benhouhou (2007) highlighted that the park is a hotspot for biodiversity in the Mediterranean Basin. Eight hundred and forty (840) plant species are found in the park, representing a third of the Algerian flora. Twenty seven of these species are classified nationally as rare species, 11 are IUCN Red List species and 19 endemics (Yahi *et al*., 2012). Among the existing species: *Quercus suber, Quercus faginea*, *Pinus pinaster*, *Alnus glutinosa, Erica arborea*, *Arubutus unedo*, *Myrtus communis, pistacia lentiscus,* and the Algerian rarity *Nymphaea alba* and *Nata repens*. The park is a habitat for 29 mammals, from which the rare and endangered Barbary deer (*Cervus elaphus barbarus*), jackal (*Canis mesomelas*) and wild cats (*Felis sylvestris*). Thousands of birds are found in the wetlands: purple heron (*Ardea purpured*), marbled duck (*Marmaronetta angustiwstris)* and the very rare white-headed duck (*Oxyura leucocephala*).

Urban population is focused near the coasts (52 %), while rural population (48 %) lives in villages spread over the park area. Local economy is mainly based on agriculture, livestock and forest activities. A large influx of tourists flock the area in summers, regarding the natural potential of the park. In 2012, the number of tourists and holidaymakers was 2698365 (Directorate of Tourism of El Tarf, 2014).

Data acquisition

In this study, two satellite images were used. The first image was a Landsat 7 ETM+ acquired in 25/05/2002, and the second one is a Landsat 8 OLI captured in 16/06/2013. Both images were downloaded freely from the Global Land Cover Facility (GLCF) web page (http://glcf.umd.edu).

The acquisition dates were chosen according to the availability of data and to reduce negative impacts of plant phenology and soil humidity. Images should be obtained as close to the anniversary date and the same time of day as possible in order to reduce the effects of seasonal changes in vegetation (Mass, 1999) and minimise sun angle and seasonal difference (Lillesand *et al*., 2008).

However, it is important to highlight that the Landsat 8 images have narrower red (R) and near infrared (NIR) bands than ETM+ images (Table 1). This is an important point to check when extracting the normalised Difference Vegetation Index (NDVI). In recent studies, it was found that when using the two sensor's data, the difference of vegetation indices comparison showed that there were subtle differences between both sensors, which demonstrated high similarity (Li *et al*., 2014; Xu and Guo, 2014).

Google earth images, local statistics and field data were used as ancillary data in this study.

Image Preprocessing

Prior to image classification, preprocessing of remote sensed data is required. The two major techniques used in preprocessing are geometric and radiometric corrections. To enable change detection to be analysed from the satellite imagery, the data must be co-registered and preferably matched to a map projection system (Griffiths, 1988). Jensen (1996) recommends a root mean square error (RMSE) of 0.5 pixel or better when applying geometric corrections.

For this study, the first Landsat 7 (projected on the UTM 31 system/WGS 84 datum) was used as base for image-to-image registration of the Landsat 8 image using the ArcGIS 10.1 software. Twelve (12) ground control points were used with a first order polynomial transformation and bilinear interpolation for image transformation.

Atmospheric effects were removed and images were radiometrically normalized according to the Cos (t) Model (Chavez, 1996). As the Vegetation Index (NDVI) analyses require only Red and near infrared bands, we applied atmospheric corrections to bands 3 and 4 of Landsat 7 and bands 4 and 5 of Landsat 8. Atmospheric correction parameters are provided in Table 2.

NDVI and NDVI differencing

From the two selected Landsat images, NDVI imagesand statistics were derived according to the formula:

NDVI = (NIR- R) / (NIR + R). Then, the Landsat 8 (2013) was subtracted from the Landsat 7 (2002) to produce an NDVI difference image.

In order to distinguish vegetation change (increase and decrease) from no change, a threshold was defined. The selection of an optimal threshold should be based on the accuracy of classifying the pixels as change or no-change (Sinha and Kumar, 2013).

We evaluated the accuracy through an error matrix and the computed overall accuracy, producer's accuracy, user's accuracy and Kappa coefficient as suggested by Fung and Le Drew (1988).

Unsupervised classification

Remote sensing images provide a general reflection of the spatial characteristics for ground objects. Extraction land use or landcover map information from multispectral or hyperspectral remotely sensed images is one of the important of tasks of remote sensing technology (Halder *et al.*, 2011).

For the identification of different classes related to the landcover of the study area in the two dates 2002 (ETM 7+) and 2013 (Landsat 8), we performed an ISODATA (Iterative Self-Organizing Data Analysis Technique) unsupervised classification using ArcGis 10.1 software. Twenty five classes were generated then reclassified to seven classes in each image.

Change detection

Based on the unsupervised produced maps corresponding to the two dates, change can be derived by applying a direct comparison between classes' outcomes. Classes where changes occurred are expected to present statistics significantly different compared to classes where no change occurred and could therefore be identified (Mas, 1999)using this approach.

In order to have an overview on the land cover dynamic, areas (in hectare and percentage) of each resulting land cover class of both images were computed and compared. The change rate of change between the two dates was also computed according to the formula of Peng *et al.* (2008):

$K= ((U_b-U_a) / U_a) \times 1/T \times 100$, where K is the land cover dynamic degree; this measures the change rate of the target land cover type. Ub and Ua are the area of the target land cover at the beginning and end of the study period, respectively, and T is the study period in years.

Accuracy assessment

In our case study, the NDVI differencing and the two unsupervised classifications were assessed through and error matrix (matrix of contingency), where user's and producer's accuracies as well as the Kappa coefficient were computed using ERDAS IMAGINE 9.1 software.

Results and discussion

When applying the geometric correction, the RMSE (the root mean square error) was equal to 0.37, which is an acceptable level of accuracy that remains below a 0.5 pixel (Fig. 2).

The two Landsat Images were radiometrically normalized according to the Cost Model (Chavez, 1996) and atmospheric effects were removed. Table 2 displays the atmospheric correction parameters.

NDVI and NDVI differencing

The two NDVI images and NDVI differencing image resulted from the subtraction of the Landsat 8 image (2013) from the Landsat ETM+ (2002) are displayed in Figures 3 a, b, c. Summary statistics of NDVI differencing values are given in Table 3.

In Figures 3 a and b, bright colours depict vegetated areas with a maximum value of 0.88 and 0.60, while dark ones show non-vegetated areas with -0.67 and -0.21 respectively in years 2002 and 2013. The brighter the colours appear, the more vegetated areas are. In general, NDVI values (maximum and minimum) in 2002 were higher than those of 2013.

In order to carry out NDVI differencing and after different trials, the threshold of ± 0.024 provided the Most accurate results with an overall accuracy of 98.14% and Kappa coefficient of 0.97 (Table 4). Alternative threshold values provided relatively the same accuracies (data not shown). Consequently, a map of change (positive/negative) and "no change" was produced (Fig. 3 c) with NDVI values ranging from -0.854 to 0.882. Areas with value ≥ 0.024 were assigned positive change and these with values ≤ 0.024 were assigned negative change. Areas in-between are considered as areas with little or no change.

Table 1. Multispectral band characteristics of Landsat 8 and Landsat 7.

Landsat 8 OLI	Wavelength (um)	Spatial resolution(m)	Landsat 7 ETM+	Wavelength (um)	Spatial resolution(m)
Band 1 - Coastal aerosol	0.43 -0.45	30			
Band 2 - Blue	0.45 - 0.51	30	Band 1	0.45 - 0.52	30
Band 3 - Green	0.53 - 0.59	30	Band 2	0.52 - 0.60	30
Band 4 - Red	0.64 - 0.67	30	Band 3	0.63 - 0.69	30
Band 5 - Near Infrared (NIR)	0.85 - 0.88	30	Band 4	0.77 - 0.90	30
Band 6 - SWIR 1	1.57 - 1.65	30	Band 5	1.55 - 1.75	30
Band 7 - SWIR 2	2.11 - 2.29	30	Band 7	2.09 - 2.35	30
Band 8 - Panchromatic	0.50 - 0.68	15	Band 8	0.52 - 0.90	15
Band 9 - Cirrus	1.36 - 1.38	30			

Table 2. Atmospheric correction parameters.

Band	L max	L min	Sun elevation (°)	Time	Date
Path/row	192/035	192/35	192/35	192/35	
3	0.620*	-5.620**	64.85	09:49	2002-05-25
4	0.639*	-5.740**	64.85	09:49	
4	9.8729	- 49.364	68.23	10:03	2013-06-16
5	5.991	- 29.954	68.23	10:03	

(*offset, **gain).

Areas with a decrease in NDVI values in red colour (loss of vegetation) are mainly found in the east and south part of the park, whereas areas with an increase in green colour (representing a gain in vegetation) are located around water bodies. In the remaining areas (light yellow), no significant change occurred.

From the NDVI differencing map and knowledge of the study area, it appears that the decrease in NDVI values (vegetation lost) are due to the following causes:

- Construction of new infrastructures especially the new highway (East-west) and the Bougous dam;
- Expansion of existing urban areas and emergence of new ones.
- Forest fires, especially near the coastline and extreme south of the park with dense vegetation and a high tourist flow.

Regarding the increased NDVI values, the major cause is the reconversion of bare lands to agriculture fields, mainly around the Oubeira Lake.

In the remaining areas of the Park, no significant or very few changes occurred.

Classification and land cover changes

From the unsupervised classification of two satellite images Landsat ETM+ (2002) and Landsat 8 (2013), two land cover maps were produced (Fig. 4 and 5) and seven classes were identified in each image, namely: Water body; Dense forest, Open forest, Uncultivated lands (including grasslands), Cultivated lands, Barren lands and Urban. Previous fieldwork and ancillary data were useful to perform these classifications. Many authors found that unsupervised classification provides similar or superior results comparing to the maximum likelihood classification (Rozenstein and Karnieli, 2011; Halder *et al.*, 2011). In our case, the accuracy assessments were satisfactory. This is in agreement with the standard overall accuracy for land cover maps which is 85% (Anderson *et al.*, 1976; Foody, 2002).

Table 3. Statistics NDVI and NDVI differencing values.

	2002 NDVI	2013 NDVI	*NDVI Differencing*
Minimum values	-0.673	-0.214	-0.854
Maximum Values	0.881	0.607	0.882
Mean Values	0.538	0.341	-0.201
Standard deviation	0.189	0.130	0.114

Table 4. Error matrix, accuracies and Kappa coefficient of NDVI differencing.

	Ground Truth			
NDVIClasses	Negative change	No change	Positive change	Total
Negative change	99.38	0.00	0.14	40.47
No change	0.62	95.54	0.00	33.82
Positive change	0.00	4.46	9.86	25.71
Total	100	100	100	100

Producer's Accuracy		User's Accuracy		Overall Accuracy	98.14%
Negative change	99.38%	Negative change	99.92%		
No change	95.54%	No change	99.26%	Kappa	
Positive change	99.86%	Positive change	93.90%		0.97

The total accuracy of the 2002 map was 85.96 % with a Kappa coefficient equal to 0.79. For the 2013 image, the total accuracy was 91.96 % with a Kappa coefficient of 0.81.

Table 5summarises statistics of the area (in hectare and percentage) of each individual defined class as well as the rate of change that occurred between the two dates, while figures 6 and 7 display the distribution of area's percentage and change rate through the land cover classes.

Table 5. Area and percentage of land cover classes of 2002 and 2013.

Classes	2002		2013		Change rate %
	Area (ha)	Percentage	Area (ha)	Percentage	
Water body (1)	4439.97	5.8	5335.74	6.97	2.01
Dense forest (2)	17397.99	22.74	15717.42	20.54	-0.96
Open forest (3)	21125.52	27.61	31558.14	41.24	4.93
Uncultivated land (4)	23248.26	30.38	13948.83	18.23	-3.99
Cultivated land (5)	3875.76	5.07	5605.38	7.33	4.45
Barren land (6)	4341.51	5.67	1493.73	1.95	-6.56
Urban (7)	2087.19	2.73	2856.96	3.73	3.66
Total	76516.2	100	76516.2	100	

The results show that there is an increase of the area between the two dates in the following classes: water bodies (from 4439.97 to 5335.74 ha), open forests (from 21125.52 to 31558.14 ha), cultivated lands (from 3875.76 to 5605.38 ha) and urban areas (from 2087.19 to 2856.96). The area decrease has occurred in dense forest (from 17397.99 to 15717.42 ha), uncultivated land (from 23248.26 to 13948.83 ha) and barren land (from 4341.51 to 1493.73 ha). It is worth noting that the most significant increase was observed in the cultivated lands (+4.45 %) followed by the urban areas (+3.66 %). Conversely, decrease occurred in barren lands (-6.56%) and uncultivated lands (-3.99%).

Link

Total RMS Error: Forward:0,370151

	<Link>	X Source	Y Source	X Map	Y Map	Residual_x	Residual_y	Residual
☑	1	432541,560516	4086578,070831	432532,225342	4086574,988251	0,0363128	-0,691849	0,692801
☑	2	434440,379333	4085782,870331	434436,181641	4085786,177673	0,0325495	-0,612242	0,613106
☑	3	442705,539551	4085069,737701	442703,334961	4085068,830872	0,0259415	-0,472859	0,47357
☑	4	432427,978821	4082651,450500	432427,120972	4082656,889648	0,0284719	-0,525672	0,526443
☑	5	437022,224121	4081687,329712	437020,160522	4081686,802368	0,0223843	-0,397031	0,397662
☑	6	442225,267639	4084092,989502	442218,193359	4084091,550293	0,0241188	-0,434197	0,434867
☑	7	433471,404419	4076718,326111	433469,802246	4076717,526855	0,0180074	-0,303981	0,304514
☑	8	433539,288483	4079209,240723	433533,965149	4079209,471436	0,0214507	-0,376973	0,377582
☑	9	442307,210083	4078769,067993	442307,314453	4078772,856445	0,0150117	-0,241186	0,241653
☑	10	460473,877258	4085198,644409	460469,397583	4085198,494263	0,0354421	-0,675324	0,676253
☑	11	462315,003662	4086130,685120	462311,750793	4086134,640198	0,0400004	-0,771993	0,773028
☑	12	468453,172302	4085455,891113	468453,999023	4085455,726318	0,0493364	-0,970159	0,971412

Fig. 2. GCPs used for geometric correction and RMSE.

Regarding the water bodies, a new dam (Bougous dam) was constructed in 2005 and its completion and watering started in 2010 with a total capacity of 65 cubic hectometre (ANBT, 2014). This contributed on one hand to an increase in the water body's area (+2.01 %) and on the other hand led to the decrease of the uncultivated and barren lands areas. The dam was constructed outside the forest's perimeter.

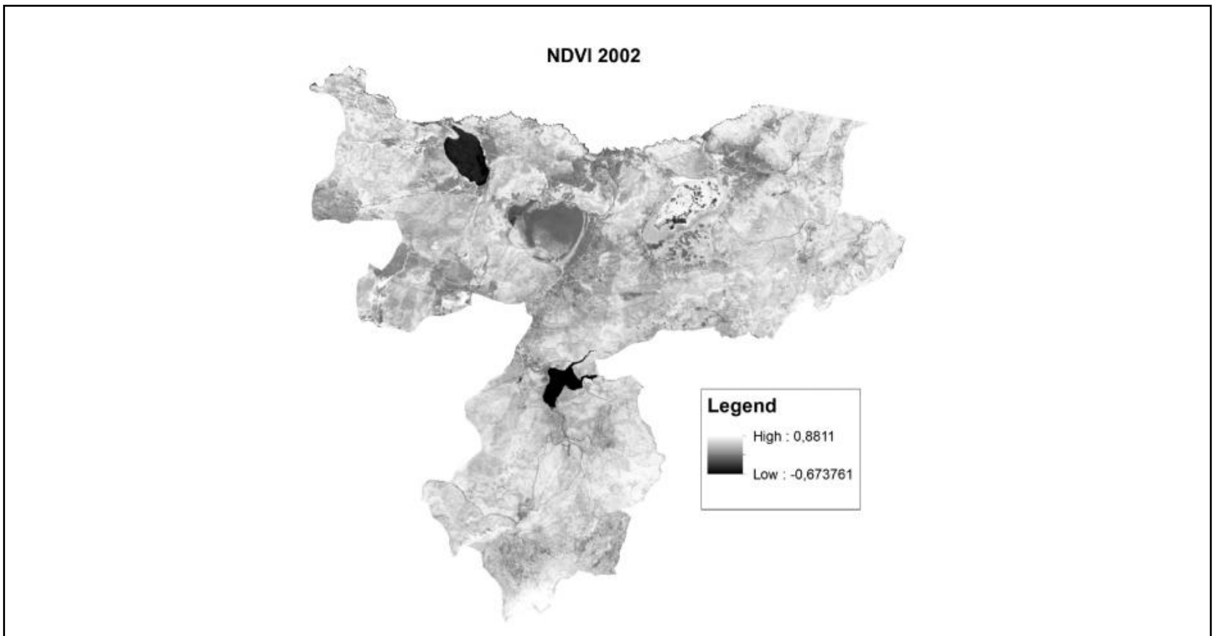

Fig. 3. a. NDVI image of 2002. Legend displays low and high NDVI values ranging from -0.67 to 0.88.

Dense forests globally dominated by cork oak trees (*Quesrcus suber*), Portuguese oak (*Quercus canariensis*) and maritime pines (*Pinus pinaster*) are facing growing anthropogenic pressure, especially overgrazing, where 50 to 80% of rural population lives from livestock (Homewood, 1993; Oulmouhoub, 2005). The other constraint is fire. The burned area of the District of El Tarf to which belongs the

District during the period 1990-2000 and 1503 fire starts were recorded during the same period (Benderradji *et al.,* 2004). In this landcover class, the above-mentioned pressures generated a negative change rate of - 0.96 % between 2002 and 2013. The affected areas are mainly located in the extreme south, northeast and northwest parts of the park.

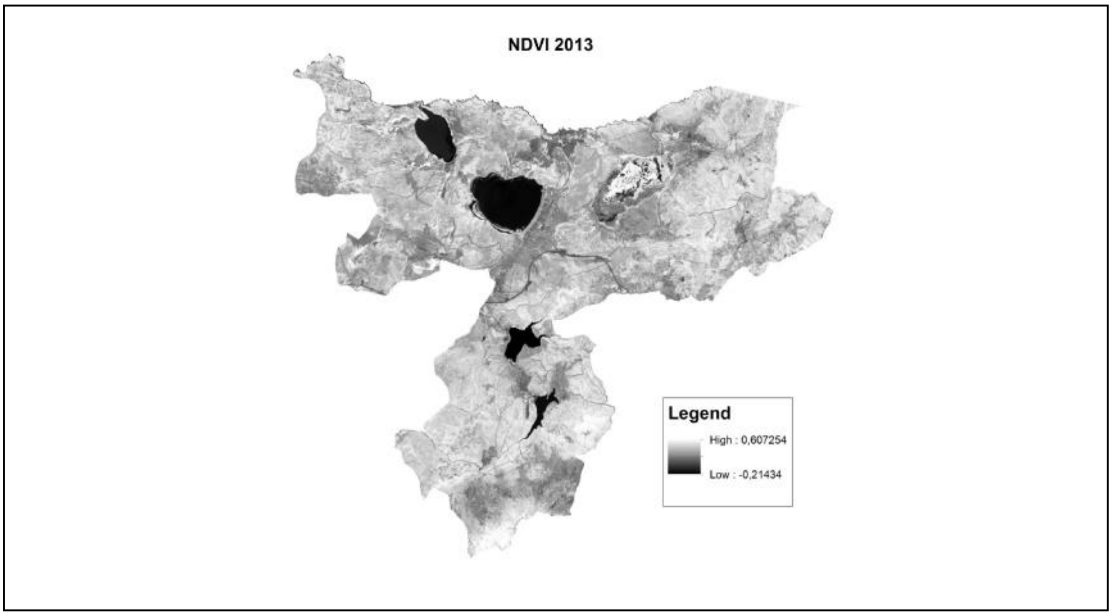

Fig. 3. b. NDVI image of 2013. Legend displays low and high NDVI values ranging from -0.21 to 0.60.

- The change rate of open forest class was +4.93 %. In fact, most of these forests are degraded maquis of cork oak trees, resulting from the regressive dynamic of dense forests. In other words, the depletion of dense forest's area had contributed to the increase of the open forests areas.

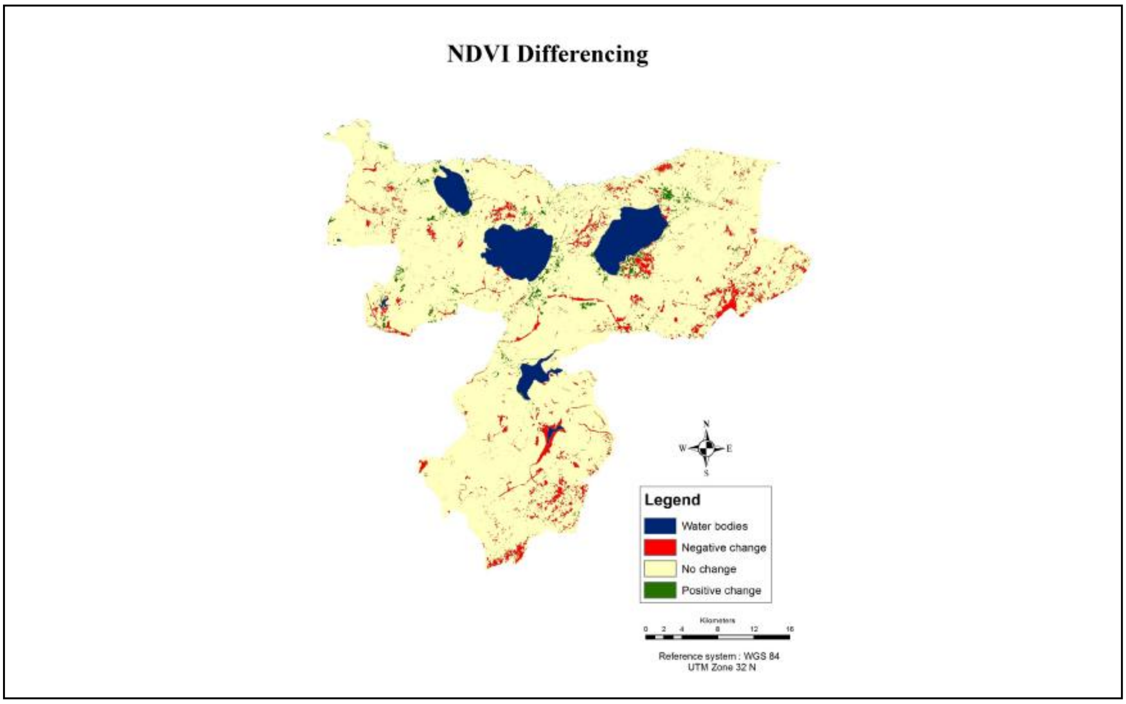

Fig. 3. c. NDVI Differencing map (2013-2002).

- The change rate in uncultivated areas is opposite to cultivated ones (-3.99% against 4.45% respectively). Conversion of uncultivated and barren lands to annual crops, forest clearing, construction of new dams and increase in population growth have contributed in the significant increase of the cultivated areas (+4.45%). This expansion was at the expense of uncultivated lands which was affected by a negative change rate (-3.99%), but also at the detriment of barren lands (-6.56 %). The 2013 year land cover map (Fig.5) shows the concentration of new agricultural fields around the dams and other water bodies, specifically Oubeira and Tonga lakes, where farmers pump directly water for the irrigation of watermelon, peanuts and tomatoes crops, and in most cases, this operation is uncontrolled.

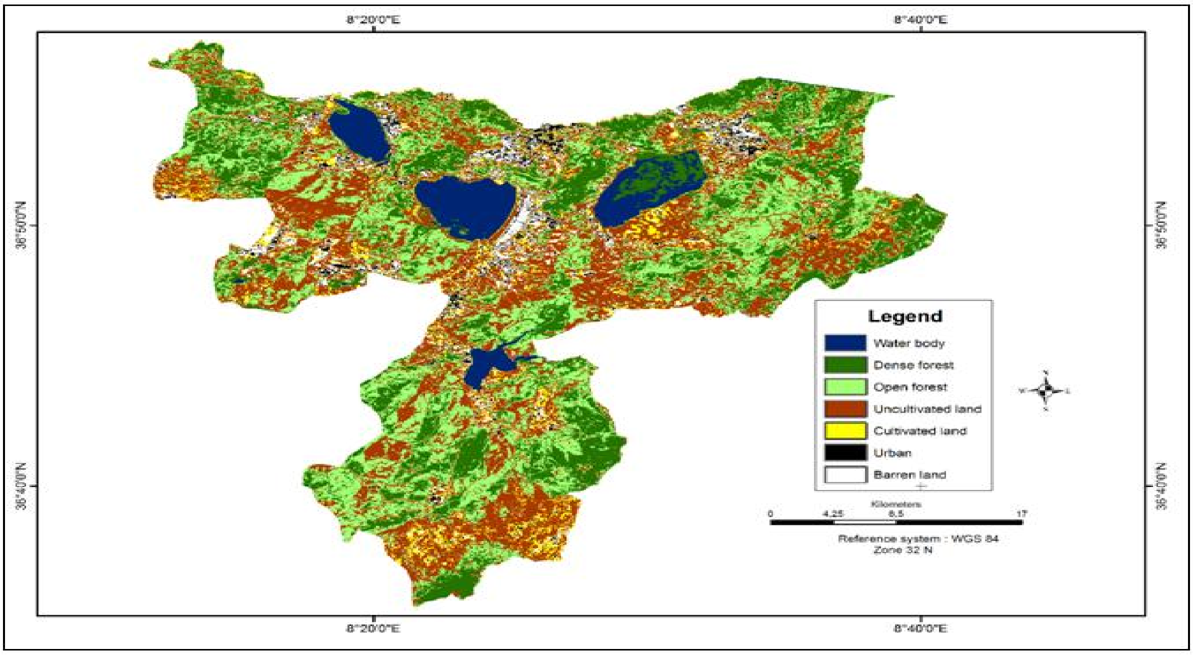

Fig. 4. Land cover map of the National Park of El Kala. 2002. The map is derived from the unsupervised classification. Landsat 7 ETM+ (2002).

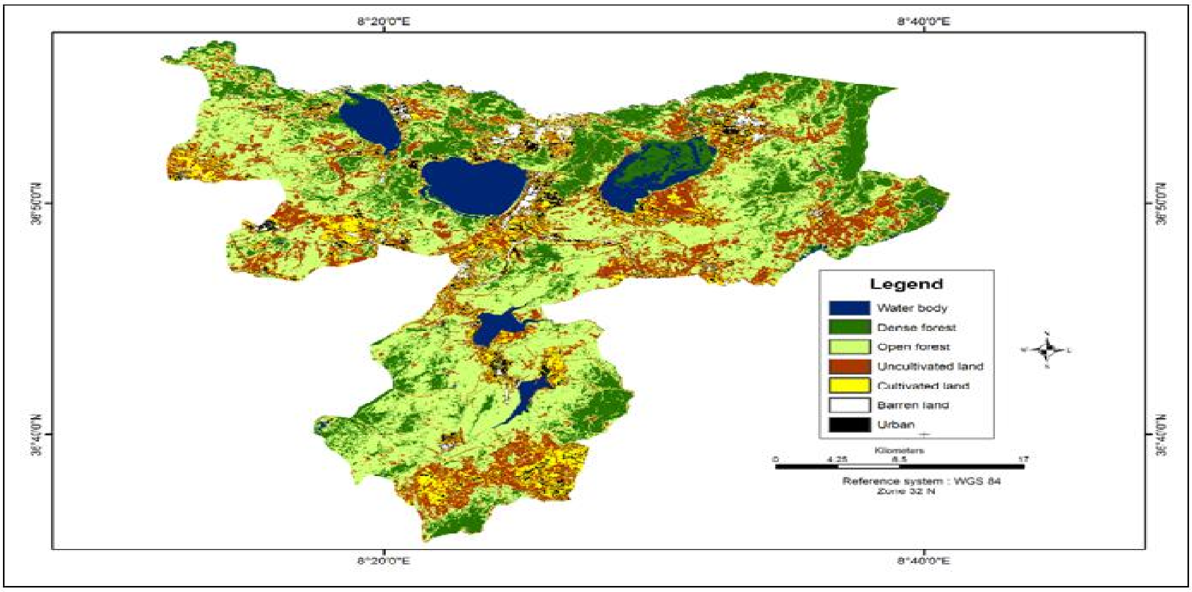

Fig. 5. Land cover map of the National Park of El Kala. 2013. The map is derived from the unsupervised. Classification Landsat 8 OLI (2013).

The drastic decrease in barren lands (-65.61%) is due to different causes: The study area, despite being a Natural park, a RAMSAR site (wetland of international importance), a Biosphere reserve recognised by the UNESCO, faces high human pressures. A highway (East-West) was constructed in the last five years within the park's area (17.5 Km long and 120 m wide) in addition to the new dams and small water reservoirs. Moreover, the urban tissue has expanded and small villages were transformed into small cities. All these factors have contributed to the negative dynamic that occurred in this landcover class.

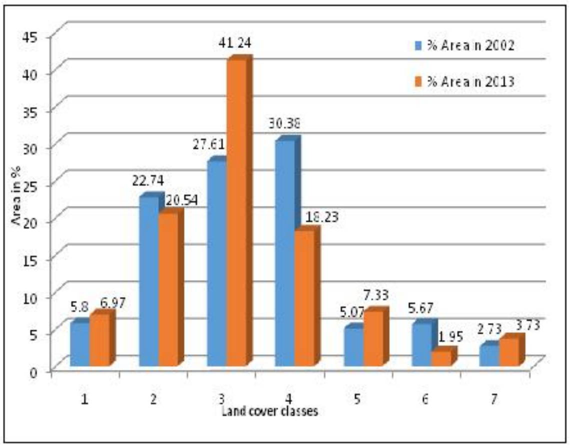

Fig. 6. Area percentage of Land cover classes for 2002 and 2013.Classes' description: (1) Water body; (2) Dense forest; (3) Open forest; (4) Uncultivated land; (5) Cultivated land; (6) Barren land; (7) Urban.

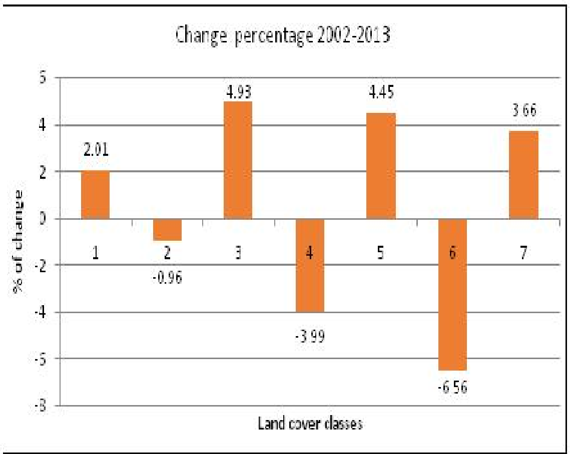

Fig. 7. Percentage of change rate between 2002 and 2013.Classes' description: (1) Water body; (2) Dense forest; (3) Open forest;(4) Uncultivated land; (5) Cultivated land; (6) Barren land; (7) Urban.

-According to the statistics provided by the Directorate of Environment and Urban Management (2014), the current population within the park is about 140000 inhabitants and has increased from 1998 (92292) and 2002 (1194242). It is worth noting that the National Park of El Kala is considered as one of the most visited places in the country, particularly its beaches, during summer periods. As an example, the number of tourists (in the beaches) was 2698365 in 2012 (Directorate of Tourism of El Tarf, 2014). Therefore, new hotels and infrastructures grew up in the park. This reflects the positive rate of change (+3.66 %) regarding the urban landcover class.

Conclusion

The National Park of El Kala is considered as one of the most diversified ecosystems in Algeria and North Africa since there are four ecosystem types (sea, lakes, dunes, forests). It hosts a very rich flora and fauna with a high level of endemic and rare species (Skinner and Smart, 1984; Stevenson, 1988; Véla and Benhouhou, 2007). However, the demographic pressure, increasing tourist flow and agricultural activities lead to major changes in vegetation and landcover.

For a better understanding of vegetation change and landcover dynamic in the National Park of El Kala, NDVI differencing and land cover change detection analysis were carried out on a Landsat ETM+2002 and Landsat 8 OLI 2013 images.

The NDVI differencing image did separate between vegetation change (decrease and increase) and no change. The threshold technique value was successful regarding the accuracies' results (overall accuracy = 98.14% and Kappa coefficient = 0.97). However, in order to identify and quantify changes at a land cover context, classical unsupervised classification was applied to both images.

Seven classes were defined: Water body; Dense forest; Open forest; Uncultivated lands (including grasslands), Cultivated lands, Barren lands and Urban. The overall accuracy were 99.97 and 75.96, and Kappa coefficients were 0.99 and 0.61 for 2002 and 2013 respectively.

Statistics' comparison suggest that the high land cover classes affected by area's decrease are Dense forest (-0.96 %), Uncultivated land (-3.99 %) and Barren land, which is the most pronounced (-6.56 %). In contrast, land cover classes concerned by positive change are: Water body (+2.01 %); Open forest (+4.93 %) where the highest change occurred, Cultivated land (+4.45 %) and Urban (+3.66 %).

Integrating GIS and remote sensing provided valuable information on the nature and statistics of land cover changes. Field knowledge and ancillary data helped in understanding the main causes of land cover changes that occurred between years 2002 and 2013. These could be summarised by: Expansion of urban tissue and new infrastructures such as highways and dams, degradation of dense forests due to human pressures mainly grazing and clearing, intensification of agriculture activities with uncontrolled irrigation from lakes and dams and last but not least, forest fires in summers due to long droughts periods and holiday rush.

In this study, we have applied two different techniques for investigating vegetation and land cover changes in the National Park of El Kala within 10 years period. NDVI differencing provided a global idea on vegetation change (lost and gain) and no change, whilst unsupervised classifications through statistical comparison was a useful approach to identify and quantify changed areas and their spatial distribution.

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