DETECTION OF SOIL SALINITY AS A CONSEQUENCE OF LAND COVER CHANGES AT EL GHROUS (ALGERIA) IRRIGATED AREA USING SATELLITE IMAGES

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Abstract

Description of the subject: Remote sensing is an important tool for studying soil characteristics, such as salinity and for monitoring changes in land cover and land use.
Objective: This study aims to examine the applicability of Landsat imagery data for soil salinity prediction in El Ghrous palm groves and for the detection of land-use changes that occurred between 2009 and 2017.
Methods: Two methods were assessed for the detection of salty soils, the first one; use of spectral indices, which are derived from the Landsat 8OLI satellite image and second one, is application of a non-parametric supervised classification for the detection of changes in land.
Results: Combinations between image data and field measurements show that there is not significant correlation.Landsat imagery has shown that the study area has different soil cover units. The superposition map produced indicated major changes in the class of vegetable crops under cover (plasticulture), and a decrease in the surface of salty grounds 9% to 5% during this period.
Conclusion: The results of this study explain the expansion in land use mainly for the plasticulture sector and show the advantage of agricultural land development project.
Keywords: Salinity index ; Supervised classification ; Land use ; Change detection ; Satellite image.

DÉTECTION DE LA SALINITÉ DES SOLS EN CONSÉQUENCE DES CHANGEMENTS DE COUVERTURE DE TERRE DANS LE PÉRIMÈTRE IRRIGUÉ D'EL GHROUS (ALGÉRIE) À L'AIDE D'IMAGES SATELLITES

Résumé

Description du sujet : La télédétection est un outil important pour l'étude des caractéristiques du sol, telles que la salinité, et pour la surveillance des changements dans la couverture et l'utilisation des sols.
Objectifs : Cette étude vise à examiner l'applicabilité des données d'imagerie Landsat pour la prévision de la salinité des sols dans les palmeraies El Ghrous et pour la détection des changements d'affectation des sols survenus entre 2009 et 2017.
Méthodes : Deux méthodes ont été évaluées pour la détection des sols salins, la première : l'utilisation d'indices spectraux dérivés de l'image satellite Landsat 8OLI et la seconde, l'application d'une classification non paramétrique supervisée pour la détection des changements des terres.
Résultats : Les combinaisons entre les données d'images et les mesures sur le terrain montrent qu'il n'y a pas de corrélation significative.l'imagerie Landsat a montré que la zone d'étude a différentes unités de couverture du sol. La carte de superposition produite indique des changements majeurs dans la classe des cultures légumières sous abri (plasticulture), et une diminution de la surface des sols salins de 9 à 5 % durant cette période.
Conclusion : Les résultats de cette étude expliquent l'expansion de l'utilisation des terres principalement pour le secteur de la plasticulture et montrent l'avantage du projet de développement des terres agricoles.
Mots clés: Indice de salinité; Classification supervisée; Utilisation des terres ; Détection de changement; image satellite.

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INTRODUCTION

Soil salinization is one of the most critical environmental problems in arid and semi-arid regions, and one of the forms of land degradation that causes difficulties for agricultural productivity and sustainable development [1] and [2].

Soil salinity occurs either through the alteration of rocks and primary minerals formed in situ or transported by water or wind, or by other causes such as topography, uncontrolled irrigation which aggravates the elevation of the water table and bring saline groundwater near the surface of the land [3]. Nearly 3% of the world's soil resources are affected by salt [4], and in semi-arid and arid areas, 21% of irrigated land suffers from water logging, salinity and / or sodicity that reduce their returns. 77 millions ha are saline soils induced by human activity, 58% of which are in irrigated areas [5].The monitoring and prediction of soil salinity is essential to take protective measures against land degradation [2]. Douaoui and Lepinard [6], evidenced the usefulness of mapping the salinity although for doing that in a large area it is necessary to collect in field and analyze in laboratory a large number of samples to arrive at a better spatial estimation. Satellite imagery is a powerful tool for mapping and monitoring of salinity progression by its synoptic coverage and the sensitivity of the electromagnetic signal to soil parameters at the surface layer [7] and [8]. This modern technology requires qualified personnel in earth observation techniques and geographic information systems [9] through the use numerical indices extracted from satellite images to evaluate soil salinity [10], it plays a a major role in the study, modeling and monitoring of environmental phenomena, at variable spatial and temporal scales,and on an objective, exhaustive and permanent basis [11]. Recent works has been aimed at assessing the correlations between real data (collected in field and measured in laboratory) of salinity and values of indices obtained from satellite images [12].The detection of salinity from remote sensing data is usually done by two methods(1): directly by analyzing spectral reflectance on bare soils, with efflorescence and saline crust (salinity indices) [13], or (2): indirectly from indicators such as the presence of halophytic plants [14], and the yield of salt-tolerant crops[15].

The processing of remote sensing data for the purpose of creating significant digital thematic maps is made by the technique of classification of satellite images, whose main objective is to automatically classify all the pixels of an image into classes or themes of land cover / land use [16]. Land use and land cover change (LULC) is considered an important tool for assessing global change at different spatial and temporal scales.

According to Taher and his collaborators [17]; the detection of land-use changes is the process of identifying the variation between two or more dates that are not characteristic of a normal variation. Adapting a change through satellite data requires effective and automated change detection techniques [18].

An analysis of the changing characteristics of the Earth's surface is essential to better understand the interactions and relationships between human activities and natural phenomena such as salinity. This understanding is necessary to improve land management and make fair decisions[19] and [20].In this study we used a non-parametric supervised classification that provides higher accuracies than parametric classifiers because of their ability to cope with non-normal distributions and within-class variations fond found in a variety of data sets [16].

The main of this research therefore to evaluate the capacity of Landsat 8 OLI and Landsat5 TM data to monitor soil salinity in the El Ghrous palm groves (Biskra, SE Algeria), and to detect changes land covers. Two methods were assessed for this evaluation: *(i)* the use of spectral indices, which are derived from the Landsat 8OLI satellite image and *(ii)* the application of a non-parametric supervised classification for the detection of changes in land between 2009 and 2017.

All the more we aim to develop maps of the state of the land, the types of coverages whose soils affected by salt are part, and their quantitative changes taking place between 2009 and 2017, according to data from satellite imagery, GIS facilities, statistical analysis, and laboratory analysis.

MATERIAL AND METHODS

1. Study area

This study was carried out in the area of El Ghrous (34° 42'19" N, 5° 17' 07" E) in the wilaya of Biskra, SE of Algeria. The community of El Ghrous belongs to the zone of Zab elgharbi which is located to 47 km of the chief town of the wilaya of Biskra,

it is limited in the North by the municipality of Tolga, in the West by the commune of Ech Chaiba has the East by the communes of Foghala and Bordj Benazouz and to the south by the communes of Doucen and Lioua. The irrigated perimeter has an area of 9400ha and an elevation ranging from 130 m to 220 m. Thearea is characterized by a Saharan climate with an average rainfall of 138 mm/yr. The mean annual temperature and relative humidity values are 22.3° C and 42.9% respectively [21]. Soil salinization in the irrigated perimeter has accelerated in recent years as a result of increased use of groundwater to provide irrigation water requirements.
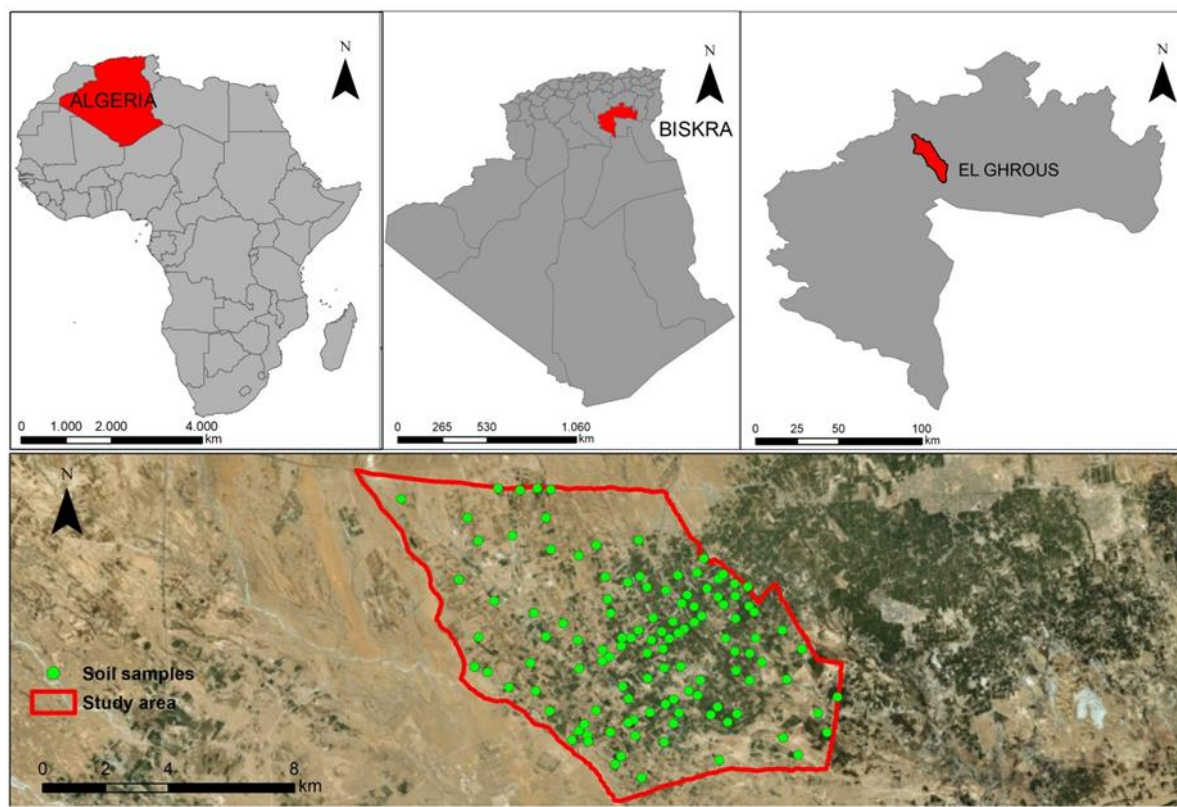

Figure 1 : Geographical location of the study area

2. Remote Sensing and GIS

To predict soil salinity and to evaluate the spatial distribution of land cover and land cover types and their changes in the El Ghrous irrigated perimeter over the 2009-2017 period, we used Landsat 5 satellite data TM of 2009 and Landsat 8 OLI 2017 Image Landsat 8 OLI with 11 spectral bands: 9 in the visible range (8 multispectral resolution 30 m, 1 panchromatic at 15 m) and 2 thermal (100 m). Landsat image 8 OLI was acquired on October 31, 2017 (Fig. 2). The Landsat 5TM image consists of seven spectral bands with a spatial resolution of 30 m for bands 1 to 5 and 7; the spatial resolution for band 6 is 120 m. The Landsat 5 TM image was acquired on October 9, 2009 (Fig. 3).

Data was downloaded from the USGS website at https://earthexplorer.usgs.gov/. Image indexes were calculated and tested using the following software: ARCGIS (10.5) and ENVI (5.3).

All created image clues were saved and loaded as input data into the ArcGIS 10.5 software as an information layer.

3. Soil sampling

The sampling was carried out in the period from October to November 2017 with 121 points to measure the electrical conductivity of the soil in the palm groves of El Ghrous. The exact position of the sampling points in latitude and in longitude was determined by GPS (Global Positioning System), we adopted a semi-random sampling in the study area (Figure 1). Soil samples were taken at selected points at a depth of 0-15 cm, where salt accumulation was high. Each sample was air dried, crushed, sieved with a 2 mm sieve and stored in a plastic bag until analysis. Then, we measured soil EC in the laboratory using the 1/5 diluted extract method [22].
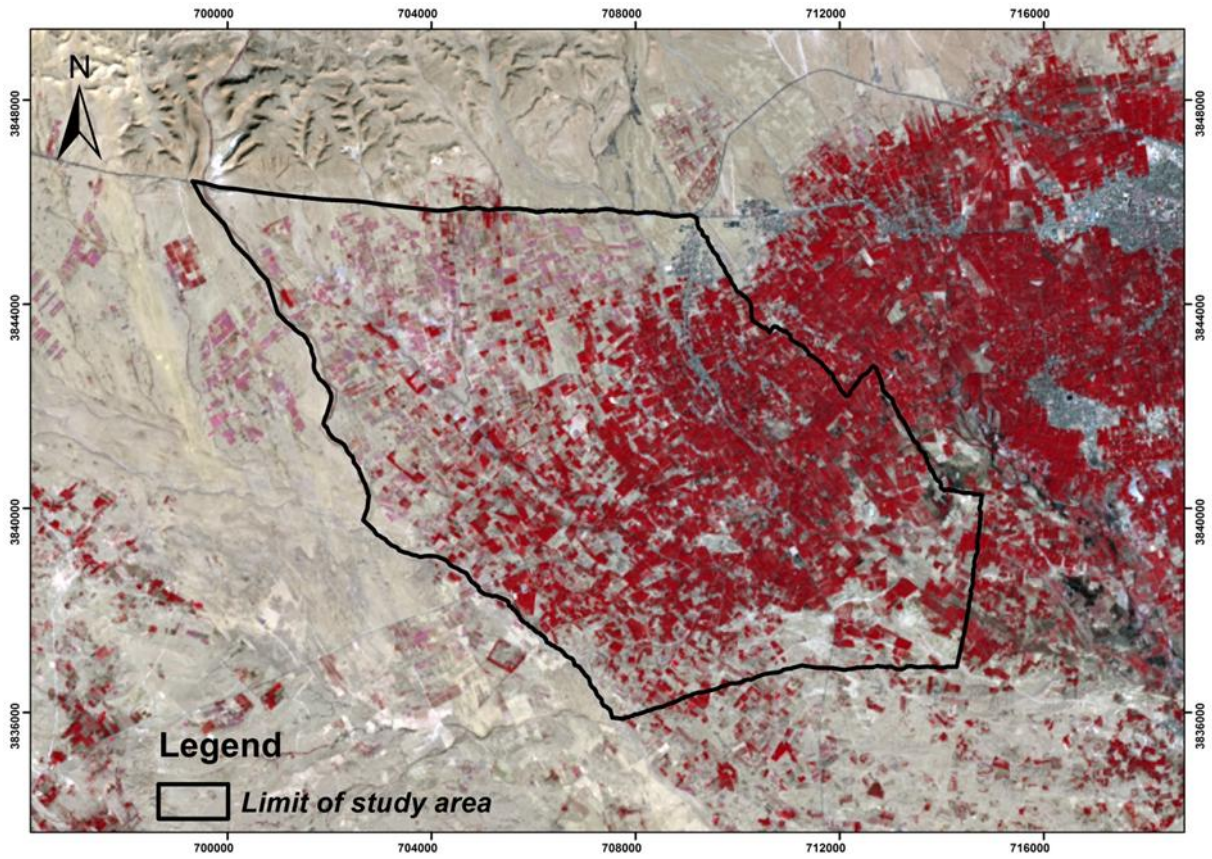
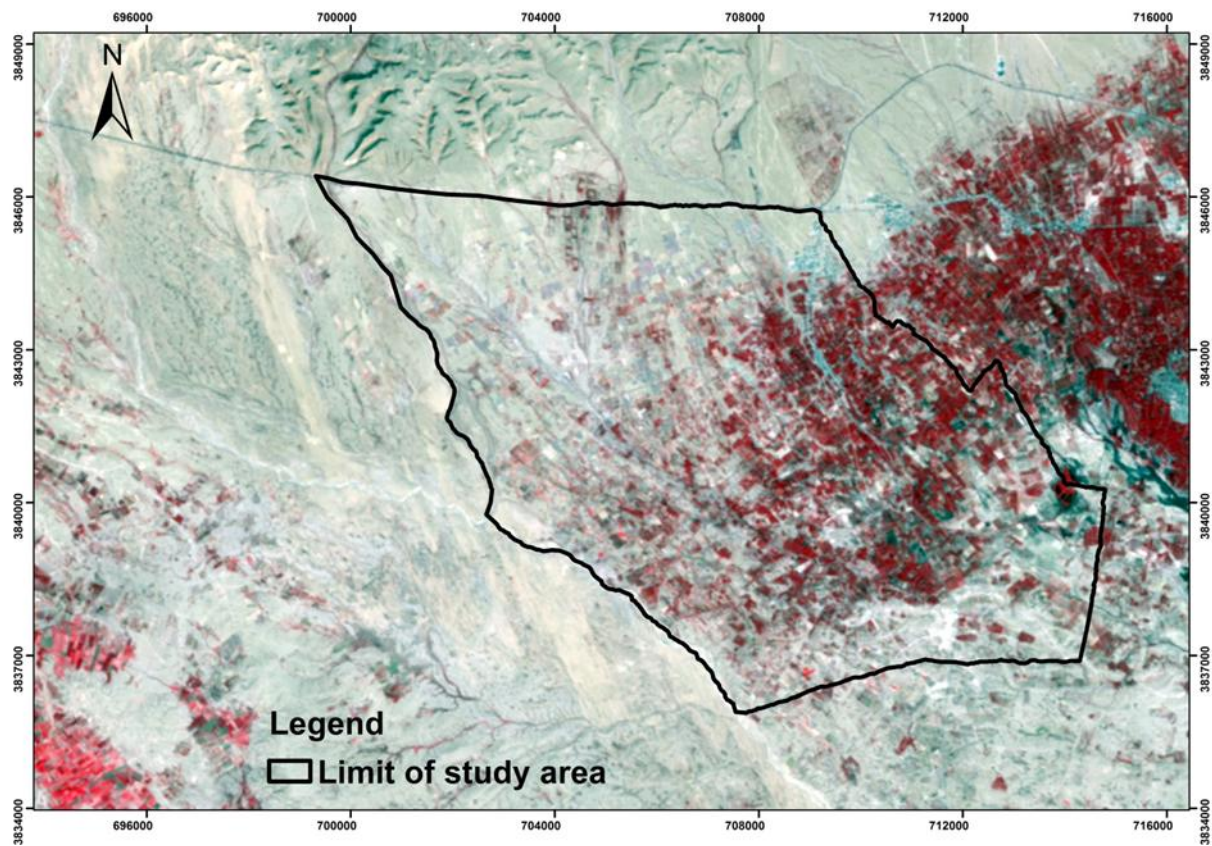Figure 2 : The color composit (band 5-4-3 for image landsat 8)

Figure 3 : The color composit (band 4-3-2 for image landsat 5)

4. Spectral reflectance

The surface reflectance has been calculated from the radiance data, which must be corrected for any radiometric and atmospheric effect.

Radiometric and atmospheric corrections for sensor and atmospheric effects errors were performed according to the FLAASH model on ENVI 5.3. FLAASH is for surface reflectance. This model uses five-dimensional lookup tables [23], namely wavelength, pixel position, water vapor in the atmosphere, elevation of ground, and optical depth of the atmosphere.

5. Spectral indices of remote sensing

Ten spectral indices were generated from the LANDSAT 8 OLI image. Four vegetation indices and six soil salinity indices derived and examined based on their soil salinity assessment potential. All created image clues were saved and loaded as input data into the ArcGIS 10.5 software as an information layer. Using the ArcGIS software spatial analysis tool, we extracted the index values for each sampling point. Finally, all derived data were compared to field measurements of soil EC to attempt to extract an EC estimation model. The tables below describe the salinity indices and vegetative indices used in our work:

Table 1 : Description of salinity indices used in this work

Salinity indice	Equation	Reference
IS1	$(G*R)^{1/2}$	[24]
IS2	$2*G-(R+NIR)$	[6]
IS3	$(R^2+G^2)^{1/2}$	[25]
IS4	$(R-NIR)/(R+NIR)$	[26]
IS5	$R/(100*B^2)$	[27]
IS6	$(B1+B2+B3)/B7$	[16]

(G = green band, B = blue band, R = red band and NIR = near infrared band)

Table 2 : Description of soil and vegetation indices used in this work

Index	Equation	Reference
NDVI	$(NIR-R)/(NIR+R)$	[28]
RVI	NIR/R	[29]
IB	$(G^2+NIR^2)^{1/2}$	[30]
IC	$(R-V)/(R+V)$	[31]

(NDVI= Normalized difference vegetation index, RVI= Ration vegetation index, IB= Brillance index and IC= Color index)

6. Statistical analysis

A linear regression analysis was used to establish a relationship between EC laboratory measurements and satellite image-derived indices.

7. Classification by the support vector machine method

In this work we used a non-parametric supervised classification that gives higher accuracies than parametric classifiers due to their ability to cope with non-normal distributions and intra-class variations found in a variety of spectral data sets[32].The Vector Support Vector classification that was used in this study for the two images (LANDSAT 5 TM and LANDSAT 8 OLI), is a recent method [33] which consists in solving a problem of binary classification by placing a hyper plane in the data space as a decision boundary so that: *(i)* This hyper-plan maximizes the rate of good classification of learning samples; *(ii)* The distance between the clip and the nearest pixel is maximized.

This plane is then defined by a combination of the samples closest to this plane, which are called the support vectors. This approach is interesting, since optimization is supposed to directly maximize classification, the results are satisfactory, as shown by some applications on remote sensing images [34], [35], [36] , [37].

8. Detection of change

The detection of change is the spatial identification of change and its type in a period of time, according to [38]. Transition matrices are symmetric arrays composed of classes from the initial year classification in one axis and the same classes of the year to be compared in the other axis [39]. Each cell of the main diagonal of the matrix contains the area of each class of LCLU that has remained unchanged during the analyzed period, while the remaining cells contain the estimated area of a given class of LCLU that has to a different class for the same period [40].

In this work, change detection assessment is applied to images acquired in 2009 and 2017, whose bidirectional cross matrix was obtained by applying this procedure and was used to describe the main types of change in the study zone.

RESULTS

1. Evaluation of spectral indices

There was weak relationship of measured soil EC with soil and vegetation indices, indicating the weak response of the indices to soil salinity [10].The results of the evaluation of the different calculated indices are shown in Table 3 below:

Table 3 : Correlation between measured soil EC and vegetation indices and soil salinity indices

Index	IS1	IS2	IS3	IS4	IS5	IS6	NDVI	RVI	IB	IC
	0.02	0.03	0.03	0.05	0.05	0.11	0.05	0.05	0.04	0.1

2. *Classification and mapping land use*

The availability of information about the study area, land cover map, high resolution images (Google Earth), field trips and satellite imagery data so we based on the map from the Afrasineai and her collaborators [16] classification on the Biskra area allowed us to establish a supervised classification. The"Support Vector Machines" method was used to perform this classification.

SVM is a supervised classification method derived from the theory of statistical learning as described in Ouerdachi et al. [41] .The method requires a lot of care to choose training areas (kings) for can give better results.

To evaluate the relevance of the classification, we compared the classified results with visually selected regions from the images, which were different from the set of training regions used at the classification stage. This validation method has been used in various studies to evaluate data resulting from classification or detection of change [42] and [43]. For the validation step, 1135 random pixels were classified visually, covering 102.15 ha of field truth data (1.08% of the total

area). Confusion matrices were produced for LANDSAT 5 TM 2009 and LANDSAT 8 OLI 2017, with an overall accuracy of 97.18, 95.87%, and Kappa values of 0.95 and 0.92, respectively.

According to Lea and Curtis [44], accuracy assessment reports require overall classification accuracy greater than 90% and kappa statistics greater than 0.9, which has been successfully achieved in this research.

Using the above mentioned data that we considered sufficient, which led us determined the different classes. Each class has been defined by several training zones. The entire area was classified into 7 classes by a nonparametric supervised classification (Support Vector Machines) using an ENVI5.3 image processing software. The classes are: dense vegetation (date palms), less dense vegetation, bare soil, salty soil, nebka and market garden crops under shelter and urban.This number of classes, shown in Table 4. The two classified images (Fig. 4 and 5) were obtained by the combined use of the two ENVI and Arcgis soft.

Table 4 : The classes resulting from the classification

Classe of land occupation	Description
Very dense vegetation	Old oases with strong chlorophyllous activity,dark red in the false color image
Moderately dense vegetation	Small palms,small trees, seasonal vegetation, red color in false color
Urban	Village , roads
Greenhouses (plasticulture)	Vegetables growing undershelter
Salty soil	Whitish in the image
Nebka	Longitudinal dunes

3. *Change detection*

The detection of changes is an analytical problem, which is most often based on an image to image comparison or through a diachronic analysis [45].

Table 5 and Figure 6 extrapolate the results of the classification between 2009 and 2017, the results indicate that a significant decrease in area, which was observed in the saline and nebka classes, while the latter in the case of vegetable crops under shelter, dense vegetation and the urban class has shown a significant increase.

The salty soils show a reduction in total area ranging from 9.43% to 5.71%, while the nebka (sand dunes) category, which was practically the least extensive in 2009, lost even more space under its cover and went from 2.18% to 0.38%.

The urban class accounted for 3.63% of the total area, which increased to 4.72 or 102 ha more than in 2009. The class of vegetable crops under cover (plasticulture) was increased from 15.65% to 16.42%, an increase of 354.

More and the dense vegetation faced an increase of the total share of 30% to 31.18%. % .The area occupied by both classes; bare soil

and less dense culture have not seen a remarkable change; it is practically the same percentage in both 2009 and 2017 images.
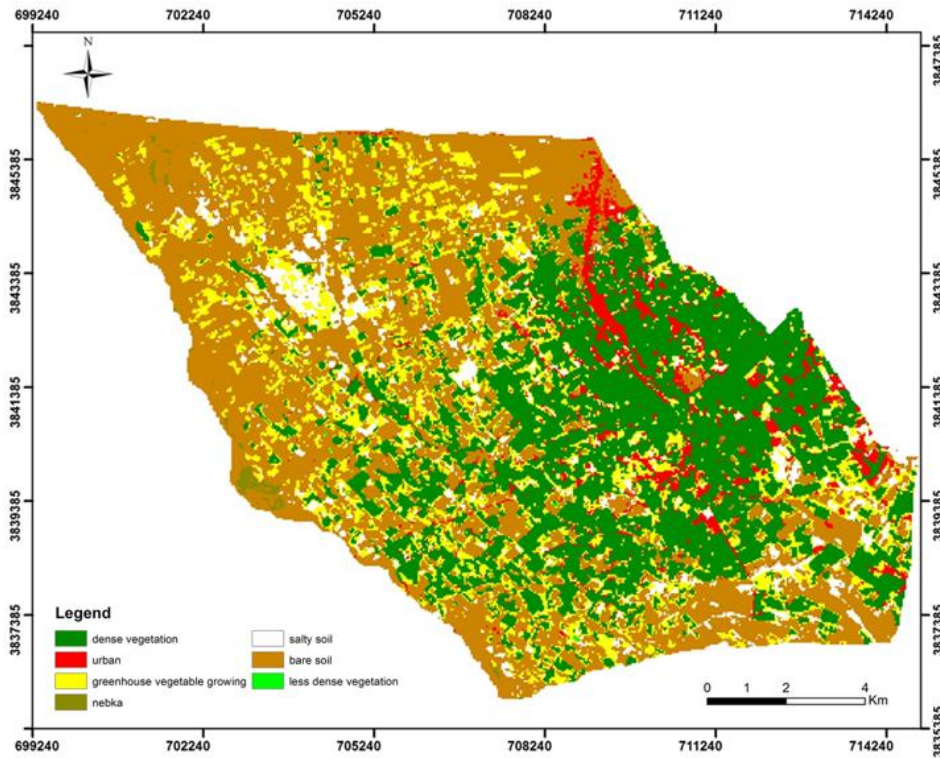

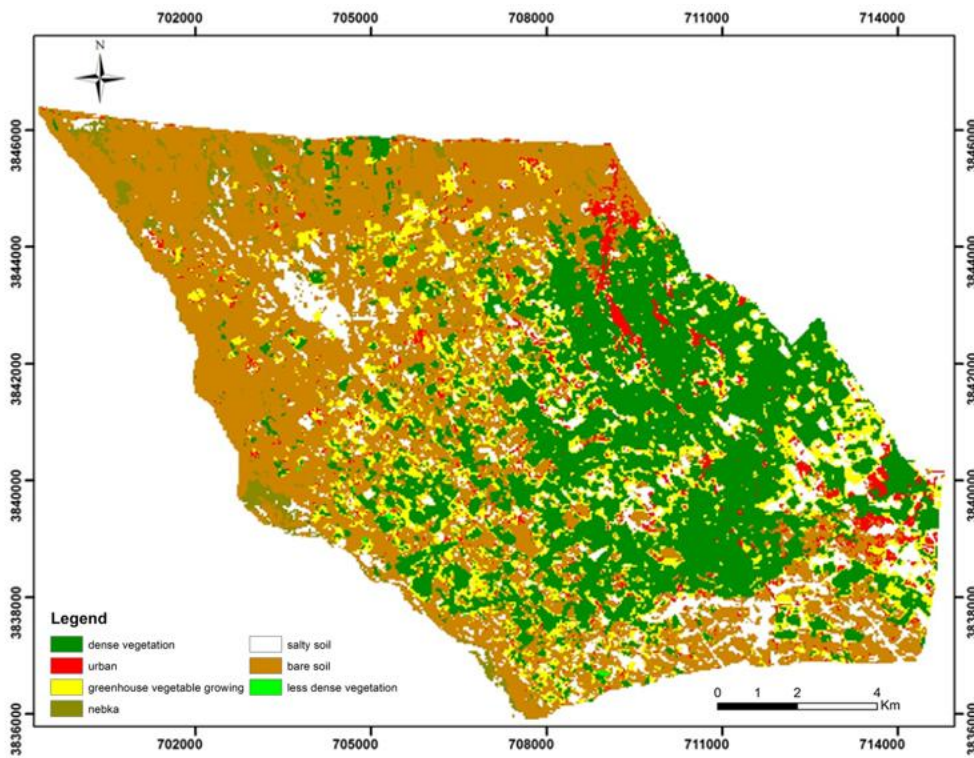Figure 4 : Land cover map 2017 by Support Vector Machines

Figure 5 : Land cover map 2009 by Support Vector Machines

Table 5 : Area occupied by each class

| Classe	area (ha)		% of total area		Variation	
	2009	2017	2009	2017	ha	%
Dense vegetation	2837.16	2931.21	30.18	31.18	+94.05	+01.00
Less dense vegetation	08.91	06.75	00.09	00.07	-02.16	-00.02
Bare-ground	3931.02	3900.51	41.81	41.49	-30.51	-00.32
Salty-ground	886.59	537.39	09.43	05.71	-349.20	-03.72
Nebka	205.56	36.23	02.18	00.38	-169.33	-01.80
Green-houses	1189.26	1544.13	15.65	16.42	+354.87	+00.77
Urban	341.73	443.97	03.63	04.72	+102.24	+01.09
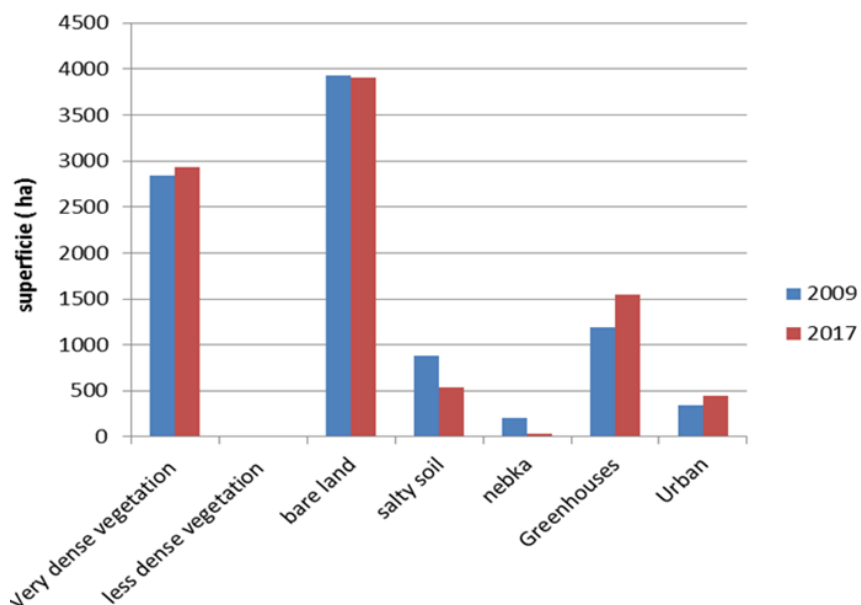
Figure 6 : Graphic presentation of land use change in the study area

The crosstab matrix shows the nature of the change in the different classes of land cover, to produce the images of change (Fig. 7) and statistical data on the spatial distribution of different land cover changes and areas of change no change (Table 6).

Table 6 : Cross-tabulation of land cover classes between 2009 and 2017 (area in ha)

| 2017 2009	Bare land	Urban	V.dense	Greenhouse	Saltysoil	Nabka	Less dense V.	Total
Bare land	2854.17	135.18	183.33	290.61	281.25	150.21	05.76	3900.51
Urban	38.88	114.12	160.20	95.31	35.10	00.36	00.00	443.97
V.dense	145.44	08.73	2251.26	395.28	129.51	00.27	00.72	2931.21
Greenhouse	667.26	50.40	220.23	364.41	212.49	27.27	02.07	1544.13
Saltysoil	207.27	33.21	20.61	42.75	227.25	06.12	00.18	537.39
Less dense V.	03.78	00.90	01.53	00.90	00.27	00.00	00.18	06.75
Nabka	14.22	00.00	00.00	00.00	00.72	21.33	00.00	36.27
Classe total	3931.02	341.73	2837.16	1189.26	886.59	205.56	08.91	-
Change classe	1076.85	227.61	585.90	824.85	659.34	184.23	08.73	-
Difference	-30.51	102.24	94.05	354.87	-349.20	-169.29	-02.16	-
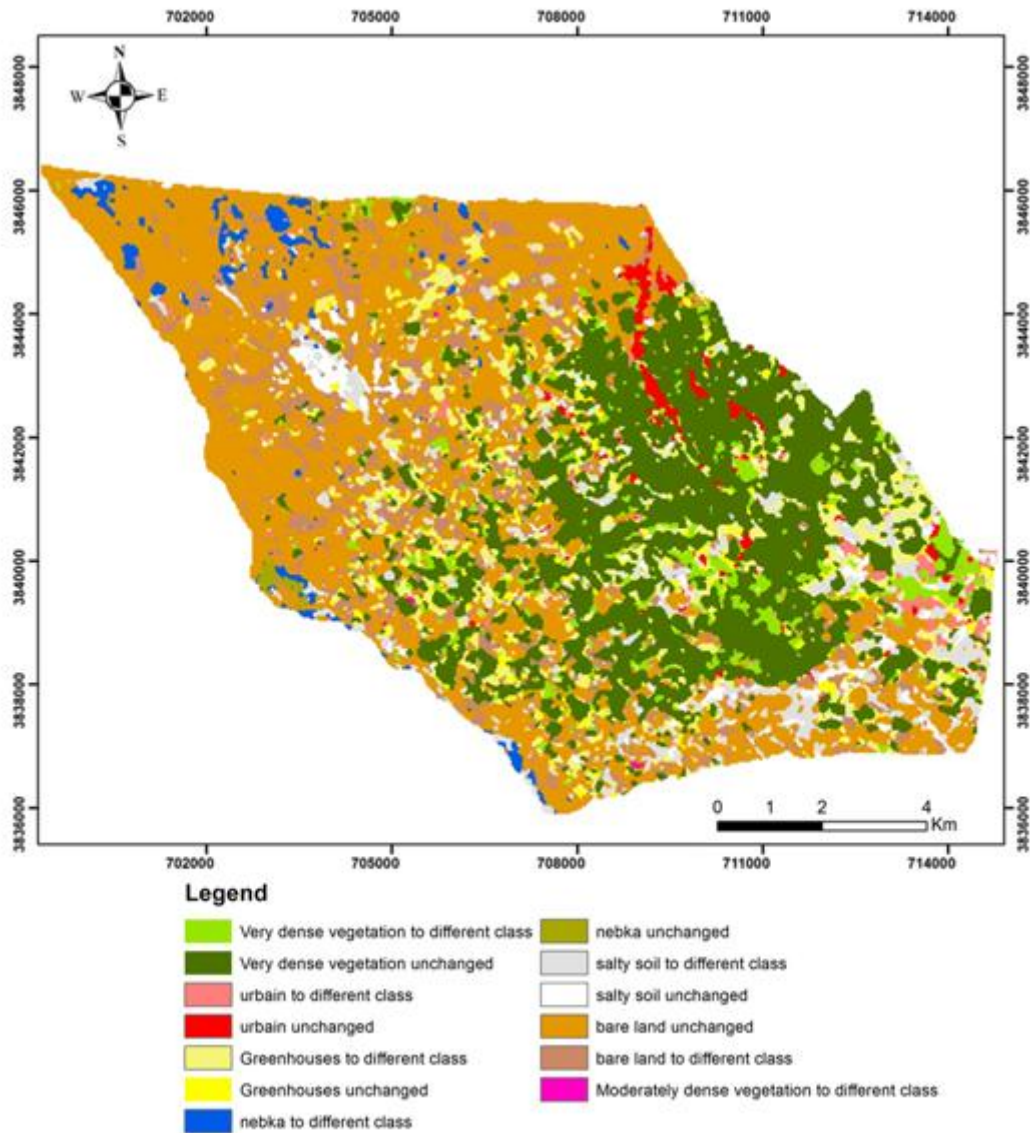
Figure 7 : Major land use conversion in El Ghrous from 2009 to 2017

DISCUSSION

From the results shown in Table 3 we note that the measured electrical conductivity of soils showed weak correlations with soil and vegetation indices with correlation coefficients ranging from 0.02 to 0.11, all indices were not significant and IS6 was the least predictor of soil salinity at this location.

Our results are in agreement with those obtained in the Bouaziz survey and his collaborators in Northeastern Brazil [46], as well as those obtained by Douaoui and his collaborator [6] during the investigation in the area of the low plain of Chellif, who adopted the same method as ours, noting that the latter has revealed low correlation which forced them to correlate the remote sensing classes with their average salinity values, this gave a good result.

Douaoui and Yahiaoui [47] have evaluated the salinity indices using the bare soils of the plain of El Hmadna and they noted an interesting correlation which is equal to 0.86, because the period coincides with a very low (or non existent) vegetation cover and the accumulation of salts is also greater at the soil surface and thus more easily detectable, which is justified by the weak correlations in the well-irrigated El Ghrous oases, so that the salinity of the soil showed a decrease under the effect. Leaching of the soil into the upper layer by irrigations and that our measurements on the ground were carried out on cultivated and irrigated land, which makes it difficult to detect.

The combination of point salinity data with that of remote sensing has not been successful.

In our case and under similar conditions, salinity estimation from remote sensing data is better with very high salinity values and greater than 10 ds/m in bare soils [48].

Our results revealed that the salinity indices extracted from the landsat8 OLI data were unreliable in predicting soil salinity in palm groves that are well irrigated. The correlation between the salinity indices was really poor. No specific vegetation or salinity index valid for all regions, the indices change with various natural conditions Such as: soil types, vegetation cover and density [2].

The results obtained in this part of the study were considered to be inconclusive in order to estimate the salinity values at the unsampled locations, which motivated us to look for another method to detect the areas affected by salinity, always using the data remote sensing and supervised classification was recommended to detect changes in land use and to monitor those affected by salinity between 2009 and 2017.

Making a comparison for each class between 2009 and 2017 showed that there was a change and a dynamic in the soil cover during the 8 years study period. During this period, the area covered by the plasticulture class (vegetable gardening under shelter) has increased by 30%. This cropping system has experienced a significant dynamic since its appearance in the municipality of El Ghrous, since the application of the Law 83-18 "APFA" and the agricultural concessions program of agricultural land development, the area has benefited from two development projects under the concession of the state and four perimeters of APFA.

In the new perimeters, the exclusively plastic production system is dominant. The system maraicher under greenhouses has indeed experienced a very rapid deployment in recent years. The areas of plasticulture increased from 1189.26 hectares in 2009 to 1544.13 hectares in 2017, an increase of 30% in 8 years, with 44 hectares more per year on average in the last 8 years. The extension of the plasticulture in the different territories of the commune was done according to a chronology determined mainly by the creation of new agricultural perimeters by the public authorities. The second class that faced an increase in area was that of dense vegetation but with a slight change (+ 1%), its area increased from 2837.16 ha in 2009 to 2931.21 ha in 2017, an increase of 94 ha compared to 2009. According to Kebibech and Daoudi [49],

The extension of the date palm is done in all new areas of development, but at different degrees, so we are witnessing a prior and partial planting by the date palm followed The installation of greenhouses and some areas devoted to plasticulture have been converted to date palm cultivation through its resistance to soil salinity.

The results of the land cover analysis confirmed the increase of the urban class area from 341.73 ha to 443.97 in 2017, due to the migration to this area which has experienced economic development through its wholesale market of vegetables and fruits and its agriculture, this area attracts farmers from all over Algeria.

In 2009, the area occupied by salty land was approximately (9.43%) of the total area, while in 2017 we found that approximately 5.71% of the total area is now salted a decrease of 349 hectares compared to 2009 in 8 years. We also recorded a very slight decrease in the area of bare soil, this change in both classes is explained by many hydro-agricultural developments that have been made and the development of agricultural land at the level of the municipality of El Ghrous.

In 2017, on an area of 2837.16 ha with dense vegetation (date palms), 2251.26 still had dense vegetation in the same year, but 183.33 ha were converted to bare soil because of poor yield in the new perimeters. Which lack a micro climate like that of the old oases and also by a regeneration of the date palm, the rest is reconverted in greenhouse and urban.

At the same time, the increase in plasticulture from 2009 to 2017 was 667.26 ha from bare soil, 220.23 ha from dense vegetation, 212.49 ha from saline soils, and 27.27 ha from nebka but on the other hand, it has kept only 30% of its own area, it is justified by the very remarkable dynamics of this class in space over time. This can be explained by the drop in soil fertility, or even the degradation caused by the increased use of saline irrigation water, which pushes farmers to move to other places for better production.

The saline soil on 886.59 ha in 2009 lost some surface mainly because of bare soil, greenhouse vegetable cultivation, dense vegetation (implantation of palms) and preserved 227.25 ha of the total in 2017. This decrease is very remarkable thanks hydro-agricultural developments and the land reclamation program as mentioned above five percent (5%) of the bare soil class in 2009 was converted to saline soil in 2017,

indicating a degradation of 207.27 ha, the latter due to poor soil and water management.

According to Afrasineai and her collaborators [16]: in this area, patches of saline soil are spreading and / or new ones appear near these patches. Another process that can cause this degradation is wind erosion, which causes the removal of the layer arable and natural vegetation, the less dense vegetation class (seasonal crops) was converted to bare soil in 2017 with a percentage of 65% of its area in 2009.The nebka class only kept 21.33 ha on a total of 205.56 ha in 2009. It has been reduced to 184 ha and replaced mainly by bare soil and greenhouse vegetable crops in 2017 due to the encroachment of sand outside the area, and by the installation of new agricultural greenhouses. The area of the other land cover classes replaced by the nebka was nil except for the bare soil class with a value of 14.22 ha.

This technique demonstrates the importance of integrating remote sensing and GIS for the detection of changes in land cover, as they explain essential information about the nature and spatial distribution of changes.

CONCLUSION

Our work consists in evaluating the correlation between the different spectral indices and the field data of the electrical conductivity in order to predict the salinity of the soil, and for the detection of the changes of the occupation of the soil in the palm groves of El Ghrous.

The results of our work show that the salinity indices extracted from the LANDSAT 8 OLI image in the El Ghrous oases were not promising for predicting soil salinity, the combination of salinity indices and field data was really mediocre. These indices may be useful in other areas and in higher salinity and in the warmer summer months. In light of the results obtained by the classification, detection, and mapping of the state of the types of land cover whose salty soils are part, and their changes in the irrigated perimeter of El Ghrous between 2009 and 2017, have shown that the study area includes different soil cover units, namely salty soils, date palm oases, bare soil, urban areas, sand dunes and market gardening under cover. The detection of changes in the study area explains the rapid increase and very remarkable extension of plasticulture due to the development of agricultural lands and the water resources which are currently easily mobilized, which have given positive results for the production of market gardening crops,

so the municipality of El Ghrous has become an agricultural and economic pole thanks to its vegetable and fruit wholesale market, which attracts farmers coming from all parts of the country.

The area occupied by salty soils has decreased due to hydro-agricultural development projects for development under the concession of agricultural land in the state. Modern technologies such as remote sensing and geographic information systems make monitoring soil salinity and land-use changes and their dynamics quite controllable and manageable for better management of natural resources.

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