Change Detection of Olive Trees Distribution using Semi-Automated Object Based Image Classification

Ahmed Harb Rabia[1*], Emad Fawzy Abdelaty [1], Maha Lotfy Elsayed [2], Assem A. A. Mohamed [2], Fatma Wassar [3,4], Edoardo Fiorillo [5], Andria Di Vecchia [6], Vieri Tarchiani [7]

ABSTRACT

Geographic object-based image analysis (GEOBIA) is a remote sensing technique that characterize image pixels into objects based on spectral, temporal, and spatial characteristics. It is a useful technique for land use classification and change detection. In this study, a land use and land cover classification and change detection was caried out at Oum Zessar watershed in the Medenine governorate of Tunisia to estimate the changes in olive trees distribution using high resolution satellite images of 2005 and 2013 and the geographic object-based image analysis technique (GEOBIA). Eight different vegetation indices (VIs) were used to enhance the classification process. The multi-resolution segmentation algorithm was selected as the main segmentation algorithm through the entire classification process. Results showed that Normalized Difference Vegetation Index (NDVI), Normalized Near Infrared (NNIR) and Ratio Vegetation Index (RVI) had high significance to be used for the recognition of the different objects and classes. In addition, results showed that olive tree canopy increased by almost 60% from 39 ha to 62 ha in the study area during the period from 2005 to 2013. In addition, analysis of the classification results showed that the number of the trees objects increased by 22.7 % from the year 2005 to 2013. This study showed the potential of Geographic object-based image analysis" (GEOBIA) technique in classifying land use in general and in detecting olive trees objects specifically.

Keywords: Remote Sensing, GEOBIA, Olive, Vegetation indices, Land Use Change.

INTRODUCTION

Tunisia is the most important olive oil producer in the Southern Mediterranean basin. Globally, Tunisia occupies the second world rank for the production of olive oil after the European Union, with a mean production of about 165 000 tons of olive oil, more than 6% of the world production. This is a thousand-year-old crop. Phoenicians were the first to introduce this crop in North Africa; the other Mediterranean civilizations continued its expansion. Indeed, since XIth century AC., and even before the foundation of Carthage, the olive-tree crops were developed in the entire Mediterranean basin. Production analysis of fruits and vegetables production structure in Tunisia shows that olives, citrus, and tomato production are among most strategic agricultural productions (Allaya et al., 2001). More than 30% of its arable lands are devoted to olive crop since it covers about 1.7 million ha comprising about 75 million olive trees. Olive groves at Oum Zessar watershed in the Medenine governorate of Tunisia represents the key crop in the area and in several cases the only cultivation able to grow in these environmental conditions (arid zone). Olive trees are cultivated in widely varied climatic conditions from north to south and it is the main domestic source of edible oils. The international trade of olive oil represents 50 % of the total agricultural exports. A decrease of 65% of the national production of olive oil during the 2013-2014 season compared to the previous season was noticed. Olives, a mainly rainfed production, plays a vital role in the social and economic life of Tunisia. Over the last ten years noteworthy fluctuations in olive production have been observed. Investigating

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[1] Department of Natural Resources & Agricultural Engineering, Faculty of Agriculture, Damanhur University, Damanhur, Egypt.

[2] Central Laboratory for Agricultural Climate (CLAC), Agricultural Research Centre, Giza, Egypt

[3] Higher Institute of Water Sciences & Techniques, University of Gabès, Gabès, Tunisia

[4] Institute of Arid Regions, Gabès, Tunisia

[5] IBE-CNR, via Gobetti 101, 40129 Bologna, Italy

[6] IBE-CNR, via dei Taurini 19, 00185 Rome, Italy

[7] IBE-CNR, via Madonna del Piano 10, 50019 Sesto F.no, Florence, Italy

* Corresponding author. E-mail: ahmedrabia@agr.dmu.edu.eg (A. H. Rabia)

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the impacts of such fluctuations on socio-economic sector is thereby with major importance. Vulnerability assessment is also needed to investigate factors with major impacts on olives production. Desertification is an on-going phenomenon, aggravated by anthropogenic pressures, which are driven by changes in socio-economic policies and population growth. Many studies revealed that in the last few decades landscape transformation rate was increased significantly (Antrop, 2005; Ellis and Pontius, 2013; Ewert et al., 2005). Therefore, studying the factors that control these changes and their impacts become extremely essential for those how are involved in biodiversity conservation, land use planning, and landscape ecology (Etter et al., 2006), and defending water resources management plans (Ripa et al., 2006).

The term “Land use and land cover change -(LULCC)” refers to changes made to the Earth’s surface through the human impact that is known as anthropogenic activities (Ellis and Pontius, 2013) or by other natural factors. There are several definitions of land cover (Meyer et al., 1994) and land use (Jansen, 2006). In this study, land cover refers to ‘‘the observed (bio) physical cover on the earth’s surface’’ (Gregrio and Jansen, 2000); while land use defines how the people use this part of the earth’s surface (Cihlar and Jansen, 2001). Historically, humans have made many changes arising from the need to exploit resources and through agricultural expansion. However, the present rate of land use and land cover change (e.g. transformation from agricultural or forested areas to urban areas) is much greater than ever recorded previously, resulting in rapid changes to the ecosystem at local to global scales. The spatial analysis of land use and land cover change comprises the use of historical maps or satellite images to judge against recent ones. Nowadays, satellite remote sensing is the most usable data source for recognition, determination, and mapping land use and land cover (LULC) outlines and changes because of its accurate geo-referencing procedures, digital format suitable for computer processing and successive data acquisition, (Chen et al., 2005; Jensen, 1996; Lu et al., 2004).

Geographic object-based image analysis (GEOBIA) is technique of remote sensing and Geographic Information Science in which image pixels are segmented into objects of similar spectral, temporal and spatial characteristics. Unlike pixel-based technique, GEOBIA uses the object properties such as roundness, square fit, and texture in addition to many other properties to improve classification results. GEOBIA technique can be divided into two main steps; segmentation and classification. In the segmentation process, adjacent pixels of similar spectral and spatial characteristics are grouped into single objects. Then, in the classification process, the generated objects will be assigned to different classes based on the characteristics of the individual objects (Rabia and Terribile, 2013)

In this study, land use and land cover change detection classification has been done in order to study changes in the distribution of olive trees using high resolution satellite images of 2005 and 2013 and the geographic object-based image analysis technique (GEOBIA).

MATERIALS AND METHODS

1.1. Study Area Description:

Oum Zessar Watershed is located in Medenine governorate, in south Tunisia and has 36,000 hectares surface area (Adham et al., 2016b). The watershed area is part of the Jeffara of Tunisia and is characterized by a low arid Mediterranean climate with an average annual rainfall of 160 -220mm which is received on average of 30 days a year (Adham et al., 2016a; Derouiche, 1997). The coldest months are December, January and February when occasional frosts occur and temperatures can fall to -3°C and June, July and August are the hottest months when temperatures reach 48°C. Temperatures are affected by the proximity of the sea in the north and the higher altitudes in the south. The climate in the upper catchment is drier with temperate conditions in winter and less arid, with mild winters in the lower catchment area. The watershed is typically an agro-pastoral interlocked area, with crop cultivation expanding rapidly in flatter areas and marginal rangelands (Adham et al., 2019). Expansion of crop lands has had negative effects on native rangelands, as native vegetation declines and animals have less and less area left to graze. Oum Zessar watershed is a good representative of the whole zone of the southeastern region, and therefore, extrapolation of case study results is possible under some basic assumptions. Oum Zessar can be considered the most important watershed in the region because it has the largest area (367 km^2) and perimeter (118 km) with a very dense stream system. The area is characterized by irregular rainfall, which has significant impacts on natural resources management and agricultural production. The succession of dry years, irregularity of rain and occurrence of extreme events are key factors of land degradation in the area. The effects are less water for plant growth, lower biomass production and grain yield, and as a consequence less protection of soils by vegetation (Ouessar, 2007). In general, Oum Zessar has the following key biophysical and socio-economic characteristics: i) degraded dry-lands; ii) low rainfall; iii) water scarce; iv) accelerated expansion of rain-fed and irrigated agriculture for olive trees and cereals; v) high demand for irrigation; vi) mixed communal and private agrarian system; vii) rapid population growth and urbanization. Land use map for the Oum Zessar watershed was obtained from the Institute of Arid Regions (IRA) in Medenine, Tunisia for the year of 2004 (Figure 1). The map shows that the watershed has different land uses including agricultural lands (cereals, olives of plains, and olives of the mountains) and rangelands (Halophyte ranges, rangelands of the mountains, and rangelands of the plains). The geophysical zones of the watershed are as follows:

- Upstream covers the mountain zones, corresponding the administrative territory of BeniKhedache delegation.
- Mid-stream starts from the Bhayra, Chouamakh regions at the foot of the mountain zone which is part of BeniKhedache delegation and northern Medenine delegation.
- Downstream starts from Koutine to the sea (Boughrara Golf), corresponding the administrative territory of SidiMakhlouf delegation.

2.2. Land use and land cover change detection:

Study of land use change was performed on a selected area in the watershed of about 30 km² (Figure 2). High resolution satellite images of the years 2005 and 2013 for this area were used for the analysis.

The work was divided into three steps. First the satellite images were preprocessed to be ready for the land use and land cover classification. In this step, eight different vegetation indices (VIs) were applied to the satellite images in order to enhance the classification process (Table 1) (Baret and Guyot, 1991; Gitelson et al., 2002). Then, an image classification process was performed on both the satellite images from 2005 and 2013 in order to obtain land use and land cover maps for both acquired dates. The image classification was carried out using the "Geographic object based image analysis" (GEOBIA) technique (Figure 3) through eCognition software© (Rabia and Terribile, 2013). The calculation of homogeneity criterion (σ) (Figure 4) in eCognition 8.7 is based on selecting a scale parameter value and choosing weights for four other criteria (shape, color, smoothness and compactness), which are embedded in the algorithm. Finally, a spatial analysis was done in ArcGIS software© by Esri (ESRI ArcGIS, 2011) in order to detect the changes in olive trees plantation during the period from 2005 to 2013.

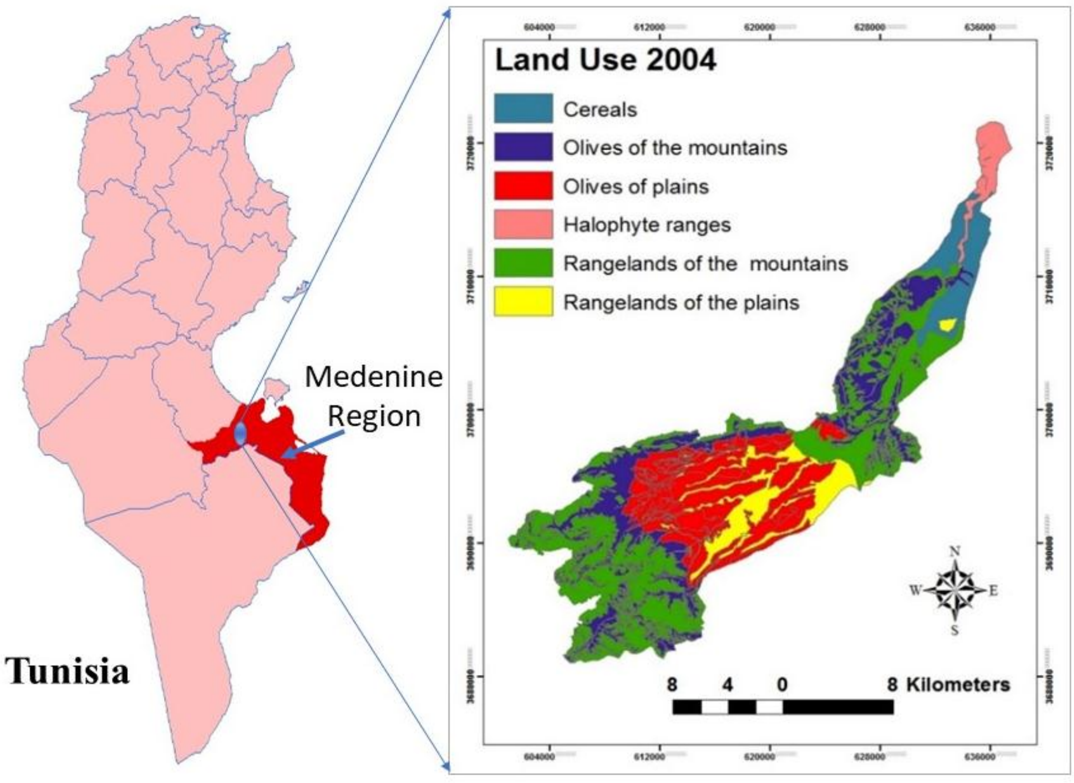

Figure 1. Study area location and land use map of Oum Zessar watershed in the Medenine Region, Tunisia.

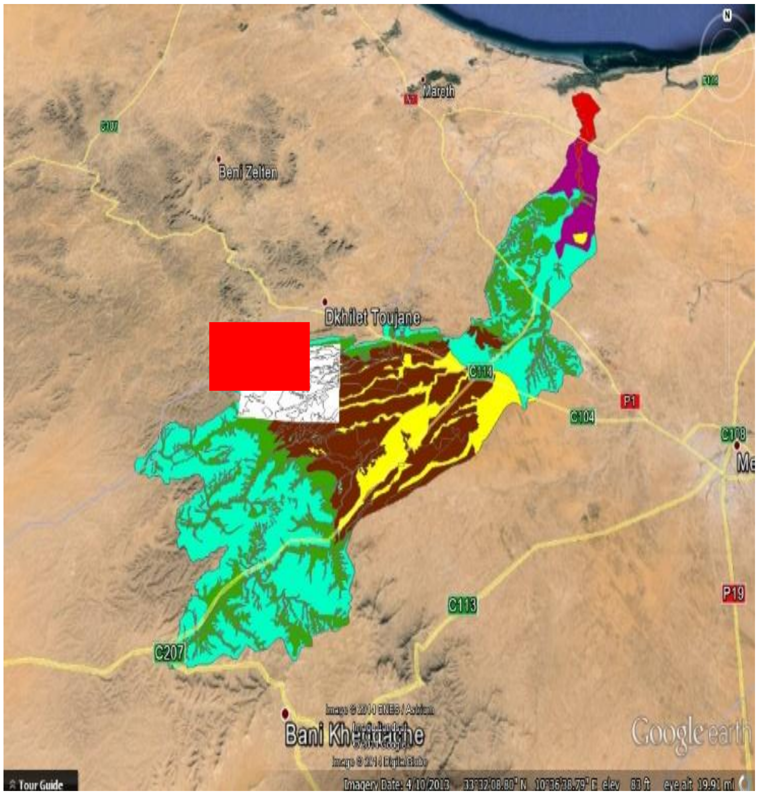

Figure 2. Red square shows the location selected for land use change study in Oum Zessar watershed (overlayed on Google Earth satellite image).

Table 1. Summary of selected vegetation indices reported in the literature derived from multispectral satellite images

Vegetation Index	Abbreviation	Equation	Reference
Difference Vegetation Index	DVI	NIR − R	(Tucker, 1979)
Green Difference Vegetation Index	GDVI	NIR − G	(Sripada et al., 2006)
Green Normalized Difference Vegetation Index	GNDVI	(NIR − G)/(NIR + G)	(Buschmann and Nagel, 1993)
Normalized Difference Vegetation Index	NDVI	(NIR – R) /(NIR + R)	(Rouse et al., 1974)
Normalized Green	NG	G /(NIR + G + R)	(Sripada et al., 2006)
Normalized Red	NR	R /(NIR + G + R)	(Sripada et al., 2006)
Normalized Near Infrared	NNIR	NIR /(NIR + G + R)	(Sripada et al., 2006)
Ratio Vegetation Index (Simple Ratio)	RVI	NIR / R	(Birth and McVey, 1968)

RESULTS AND DISCUSSION

The pre-processing stage of the satellite images included applying eight different vegetation indices (VIs) to the images in order to enhance the classification process (Figure 5). Five of the VIs (DVI, GDVI, GNDVI, NDVI, RVI) were based on only two image bands while the other three VIs (NG, NR, NNIR) were based on three image bands. Some of the VIs did not show clear differences between the different land uses and therefore these VIs were not useful for the classification stage. During the classification procedure, only three VIs showed high significance to be used for the recognition of the different objects and classes. These indices are Normalized Difference Vegetation Index (NDVI), Normalized Near Infrared (NNIR) and Ratio Vegetation Index (RVI). NDVI was helpful to distinguish between plants and other land uses and then later to classify the olive trees. NNIR was used to classify the objects belong to the urban class. Finally, RVI was used also to recognize green plants and bare soil objects. The equations of the three VIs (NDVI, NNIR, RVI) are constructed manly based on the NIR and Red bands which indicates the potential of those bands for object-based land use classification.

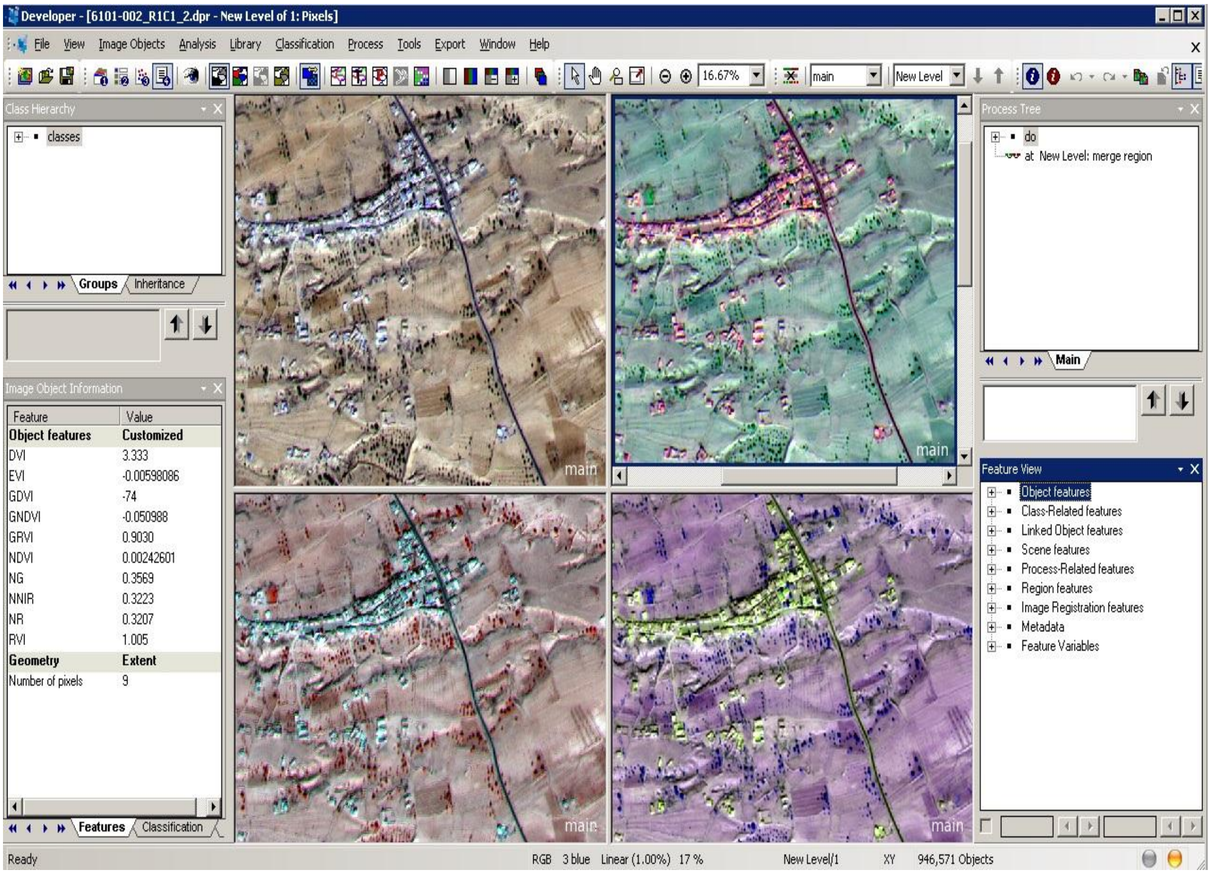

Figure 3. Screenshot of the recognition software applying the Geographic object-based image analysis technique

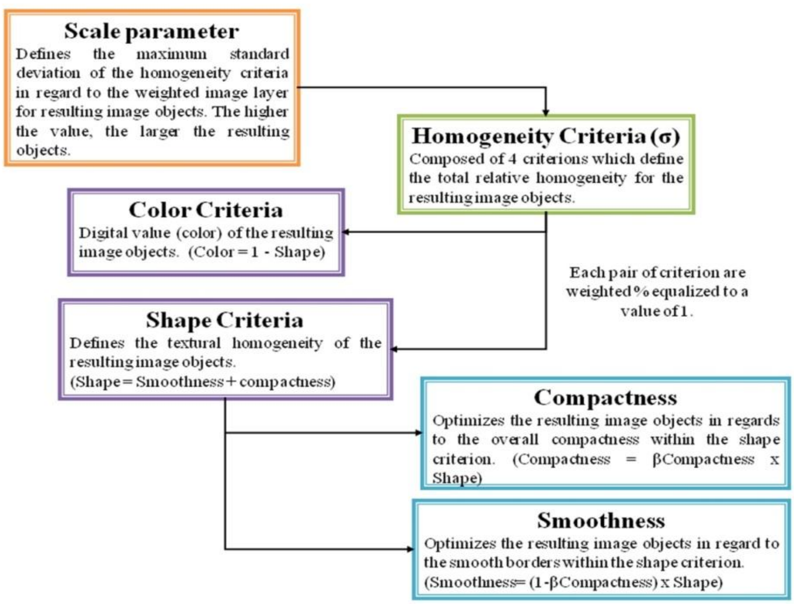

Figure 4. Multi-resolution segmentation concept flow diagram for the recognition software

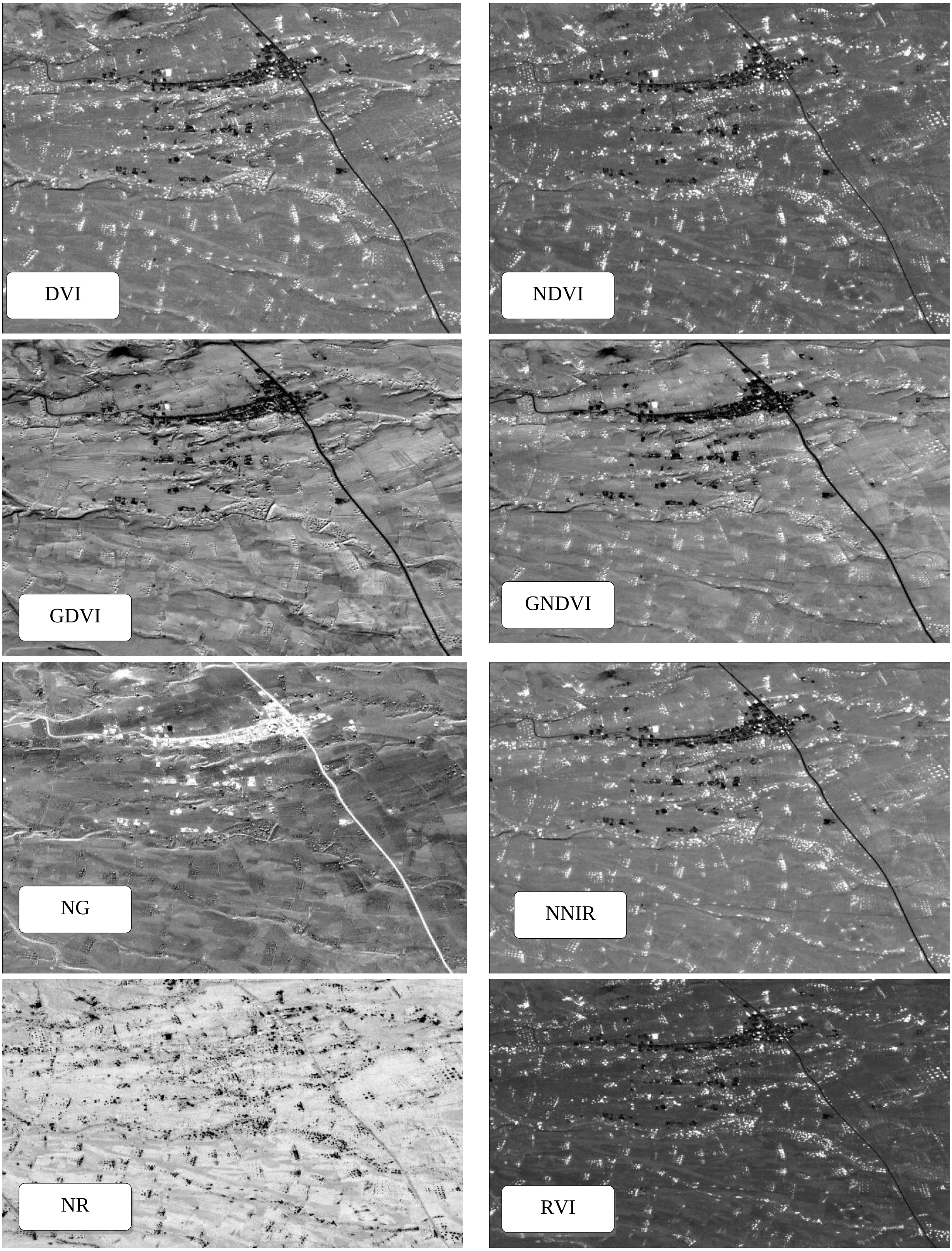

Figure 5. Illustration of the eight different vegetation indices (VIs) applied to the 2013 satellite image.

The multi-resolution segmentation algorithm was selected as the main segmentation algorithm through the entire classification process (Appendix 1). The scale defines the maximum standard deviation of the homogeneity criteria for the resulting image objects, while the homogeneity criterion defines the characteristics of the objects (Trimble, 2011). Figure (6) shows a comparison test for the four homogeneity criteria (shape, color, smoothness and compactness) embedded in the multi-resolution segmentation algorithm. A multi-resolution segmentation process with the same scale of 90 was applied four times with different weights for shape and compactness criteria to study the effect of deferent weights on the final segmentation results. The weight of 0.5 means equal magnitude to both the criteria under investigation. For example, if the shape weight is 0.5 means that equal importance has been given to both shape and color criteria. While, if the shape weight is 0.8 means that a weight of 0.2 has been given to the color criteria. The same is in case of the compactness and smoothness criteria (Gennaretti et al., 2011). Assigning different values to these segmentation parameters produces different sizes and shapes of image objects. Therefore, it is a critical decision to choose these parameters values to acquire the maximum accuracy in segmentation. Based on the procedure proposed by (Meinel and Neubert, 2004; Neubert et al., 2006), the most favorable values of segmentation parameters were selected through comparison between manually extracted sample polygons and objects derived from different segmentations. The optimal segmentation parameters values are a compromise between a reduced number of the resulting image objects and a high-quality division of the surface in land cover classes. Finally, All the potential combinations of segmentation Parameters were tested, and the most favorable parameters values were selected.

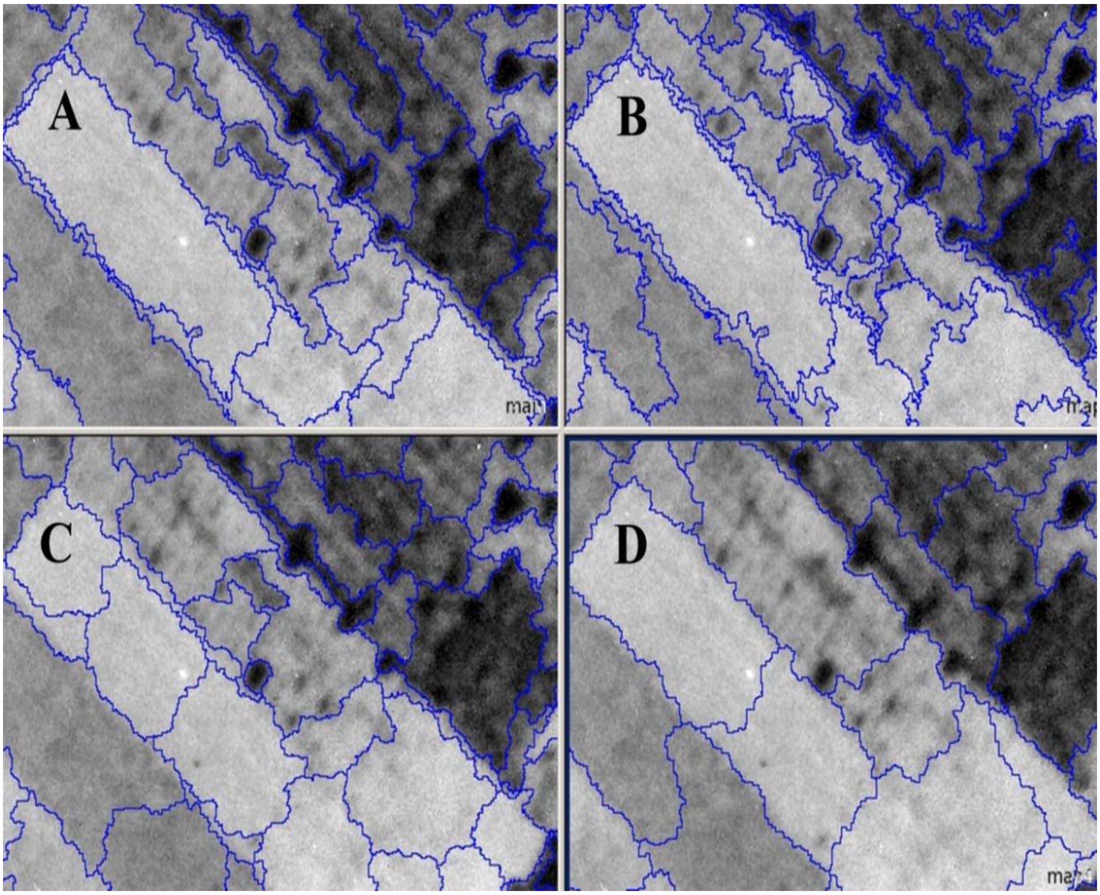

Figure 6. Comparison between multi-resolution segmentation algorithms with the same value for scale parameter as 90 and different weights of shape and compactness: a) shape 0.5 and compactness 0.2; b) shape 0.2 and compactness 0.5; and c) shape 0.5 and compactness 0.8, (D) shape 0.8 and compactness 0.5.

After the segmentation process, the classification phase was carried out. Three land use and land cover classes were recognized during the classification progression (Olives, Urban areas, Bare soil and other Vegetation types). Bare soil and other Vegetation classes were joined in one class during the classification process because they are not affecting the study parameters. Successive approach was followed during the classification as the different classes were classified in a sequential order. The spatial analysis of the generated land use and land cover classification maps (Figure 7) showed slightly to moderate growth in the area of olive plantation in the study area. The main change can be attributed to the growth in the trees size with the same number of trees in the field. The other source of change is the new plantation of the olive trees in the study area, which was low to very low percentage. On the other hand, urbanization processes have been found in the study area in various locations.

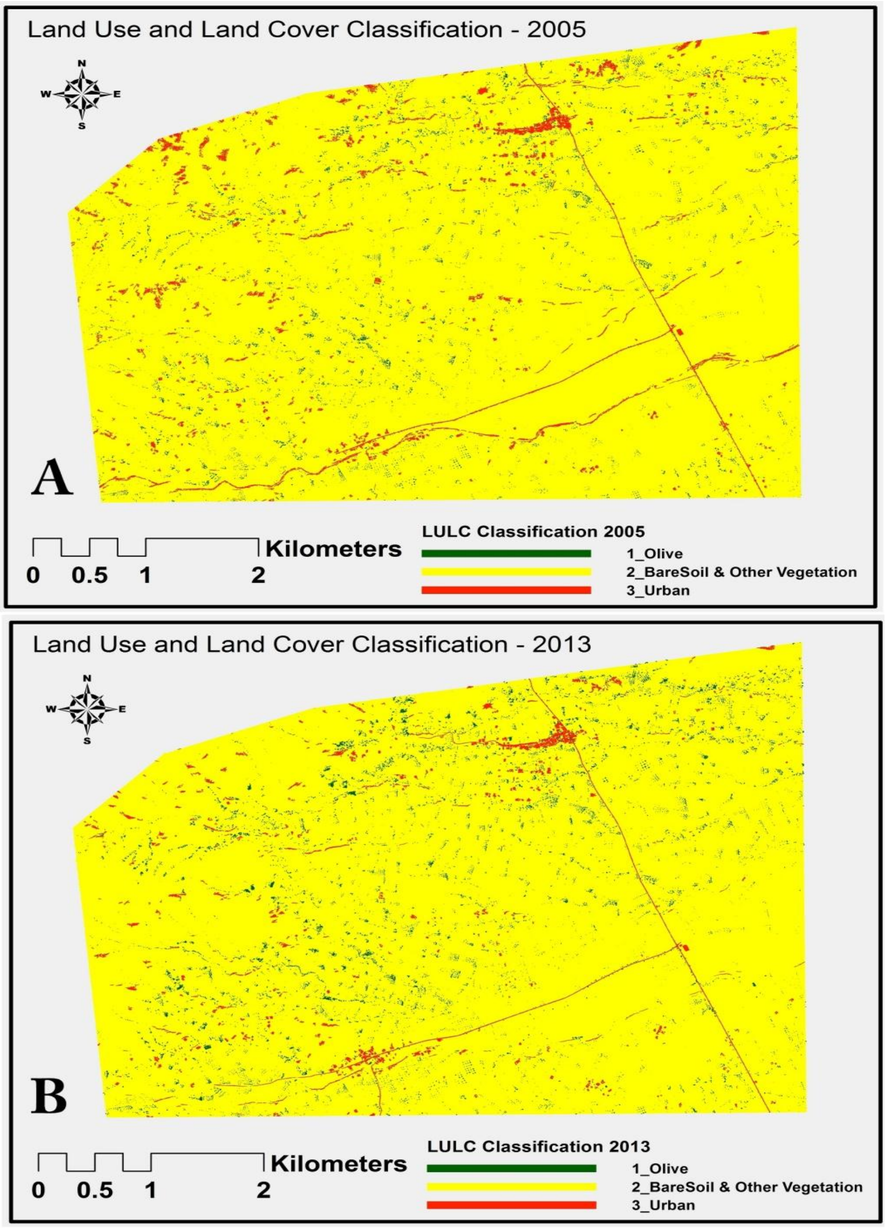

Figure 7. classification maps show the land use classes in the study area during two different years A. 2005 and B. 2013

Table (2) shows the results of the change detection analysis for the olive trees canopy in the study area during the period from 2005 to 2013. The results demonstrate that the olive tree canopy increased by almost 60% from 39 ha to 62 ha during the period from 2005 to 2013. In addition, analysis of the classification results showed that the number of the trees objects increased by 22.7 % from the year 2005 to 2013. A comparison between different sizes of the olive trees is shown in Figure (8). The results illustrate that small objects (less than 4 m^2 in diameter) which refer to the small olive trees were much greater in number in 2005 than 2013. This may show that planting new trees in 2005 was more active than 2013. This can be explained as a change in the producers' preferences or as an economic reason. Finally, these results showed the capability of Geographic object-based image analysis" (GEOBIA) technique in land use classification in general and in detecting olive trees objects specifically.

Table 2. Changes in olive trees canopy in the study area during the period from 2005 to 2013

Parameter	Year 2005	Year 2013	Change Rate
olive Canopy (ha)	39.08	62.31	+ 23.23 ha (+ 59.42 %)
Number of Trees objects	9836	12069	+ 2233 objects (+22.7 %)

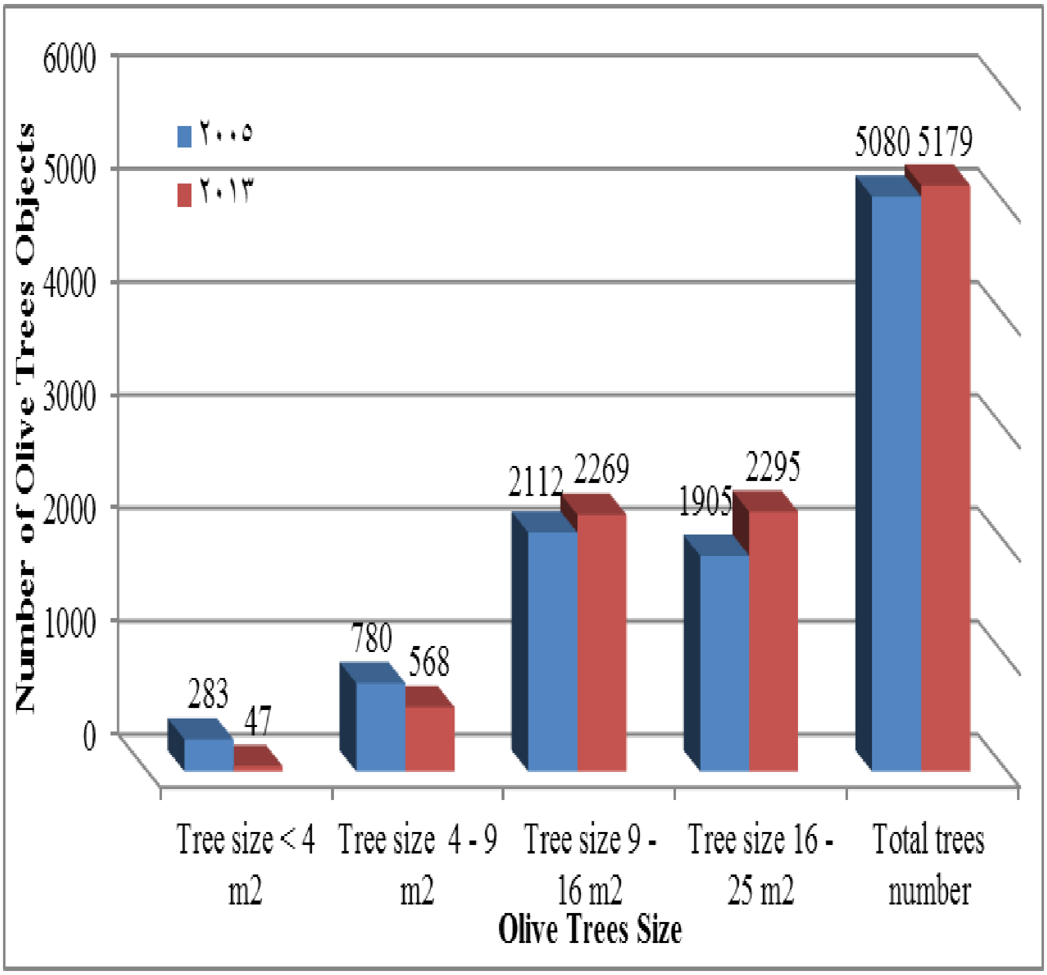

Figure 8: Comparison of the number of olive trees objects at different olive trees sizes in 2005 and 2013

CONCLUSION

The study showed that vegetation indices (VIs) may perform differently in distinguishing land use classes based on the image bands involved in the calculation of the VI. In this study, NDVI, NNIR, RVI showed superior performance in recognizing olive trees objects and other land use classes. In addition, the multi-resolution segmentation algorithm, which is one of the main algorithms for object-based classification, showed outstanding performance in delineating object segmentation in the study area. The change detection classification showed that olive tree canopy increased by almost 60% from 39 ha to 62 ha and the number of the tree's objects increased by 22.7 % in the study area during the period from 2005 to 2013. However, this increase was mainly due to the size growth of the olive trees and not due to new plantations. These results illustrated that Geographic object-based image analysis" (GEOBIA) technique successfully detected olive tree objects and was able to detect changes in time. Finally, future work will focus on applying the developed classification technique on other crops and land use classes.

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Appendix 1

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Process: Main:
  do
    PreProcessing
      do
      chessboard segmentation: chess board: 99999 creating 'New Level'
      contrast split segmentation: edge ratio split 1 red [0] :1000-> [creating 'New Level',
          unclassified,unclassified]
      assign class: with Mean 1 red = 0  at  New Level: Blank_bourders
      merge region: Blank_bourders at  New Level: merge region
      multiresolution  segmentation: 10 [shape:0.5 compct.:0.9] creating 'New Level'
      do
        do
        PreProcessing
          Olive_candidates
            do
            assign class: with Mean 5 Panchroma <= 1100  at  New Level: Candi_Green
            merge region: Candi_Green at  New Level: merge region
            merge region: unclassified at  New Level: merge region
            multiresolution segmentation:  with Classified as Candi_Green = 1  at  New Level: 5
      [shape:0.5 compct.:0.5]
            assign class: Candi  Green with NDVI < 0.09  at  New Level: unclassified
            merge region: unclassified at  New Level: merge region
          Urbans
            do
            multiresolution segmentation: unclassified at  New Level: 5 [shape:0.5 compct.:0.5]
            assign class: Candi_Green, unclassified with NNIR <= 0.39  at  New Level:
      Candi_Urbans
            merge region: Candi_Urbans at  New Level: merge region
          do
            do
            assign class: Candi_Green with NDVI >= 0.16  at  New Level: Green
            assign class: Candi_Green with RVI >= 1.4  at  New Level: Green
            assign class: Candi_Green with NNIR >= 0.43  at  New Level: Green
            merge region: Green at  New Level: merge region
            merge region: Candi_Green at  New Level: merge region
            multiresolution segmentation: Green at  New Level: 5 [shape:0.5 compct.:0.5]
            assign class: Green with NDVI >= 0.19  at  New Level: 1_Olive
            merge region: 1_Olive at  New Level: merge region
            multiresolution segmentation: 1_Olive at  New Level: 30 [shape:0.9 compct.:0.1]
          assign class: unclassified at  New Level: Candi_Green
          multiresolution segmentation: Candi_Green at  New Level: 5 [shape:0.5 compct.:0.5]
        Classification
            do
            assign class: 1_Olive with Area >= 621 Pxl at  New Level: Olive_refine
            assign class: 1_Olive with Length >= 31 Pxl at  New Level: Olive_refine
            multiresolution segmentation: Candi_Green at  New Level: 5 [shape:0.5 compct.:0.5]
            assign class: Candi_Green with Border to 1_Olive = 0 Pxl at  New Level: not_green
            assign class: Green with Border to 1_Olive = 0 Pxl at  New Level: not_green
            assign class: 1_Olive with Area <= 300 Pxl at  New Level: smallTrees
            multiresolution segmentation: Green at  New Level: 5 [shape:0.5 compct.:0.5]
            assign class: Candi_Green, Green with Border to smallTrees >= 1 Pxl at  New Level:
          smallTrees
            assign class: Candi_Green, Green at  New Level: not_green
            assign class: Olive_refine, smallTrees at  New Level: 1_Olive
            assign class: Candi_Urbans with Area <= 600 Pxl at  New Level: not_green
            assign class: not_green at  New Level: 2_BareSoil
            assign class: Candi_Urbans at  New Level: 3_Urban
            multiresolution segmentation: 2_BareSoil at  New Level: 90 [shape:0.5 compct.:0.5]
            assign class: 2_BareSoil with Mean 4 NIR = 0  at  New Level: Blank_bourders
            merge region: 1_Olive at  New Level: merge region
            merge region: 2_BareSoil at  New Level: merge region
            merge region: 3_Urban at  New Level: merge region
```

الملخص العربي

تغيير توزيع أشجار الزيتون باستخدام تصنيف الصور شبه الآلي القائم على تقسيم الصورة الفضائية

أحمد حرب ربيع، عماد فوزي عبد العاطي، مها لطفي السيد، عاصم عبد المنعم أحمد محمد، فاطمة وسار، إدواردو فيوريللو، أندريا دي فيكيا، فييري ترشياني

تحليل الصور المعتمد على الهدف الجغرافي (GEOBIA) هو تقنية إستشعار عن بعد تميز بكسلات الصورة إلي مجموعة أهداف بناءً على الخصائص الطيفية والزمنية والمكانية. إنها تقنية مفيدة لتصنيف إستخدامات الأراضي وإكتشاف التغيير الحادث في فتره زمنية محددة. في هذه الدراسة، تم إجراء تصنيف إستخدام الأراضي والغطاء الأرضي وكشف التغيير لتقدير التغيرات في توزيع أشجار الزيتون بإستخدام صور الأقمار الصناعية عالية الدقة لعامي ٢٠٠٥ و ٢٠١٣ وتقنية تحليل الصور القائمة على الكائن الجغرافي .(GEOBIA) تم إستخدام ثمانية دلائل نباتية مختلفة (VIs)لتعزيز عملية التصنيف. تم إختيار خوارزمية التجزئة متعددة الدقة كخوارزمية التجزئة الرئيسية من خلال عملية التصنيف بأكملها. وقد أظهرت النتائج أن دليل الغطاء النباتي (NDVI) والأشعة تحت الحمراء القريبة (NNIR) ودليل النسبة النباتية (RVI) كان لها أهمية عالية لإستخدامها في التعرف على الكائنات والفئات المختلفة. بالإضافة إلى ذلك، أظهرت النتائج أن مظلة شجرة الزيتون قد إزدادت بنسبة ٦٠٪ تقريبًا من ٣٩ هكتارًا إلى ٦٢ هكتارًا في منطقة الدراسة خلال الفترة من ٢٠٠٥ إلى ٢٠١٣. بالإضافة إلى ذلك، أظهر تحليل نتائج التصنيف أن عدد الأشجار زاد بمقدار ٢٢,٧٪ من عام ٢٠٠٥ إلى ٢٠١٣. وقد أظهرت هذه الدراسة إمكانات إستخدام تقنية تحليل الصور المعتمد على الكائنات الجغرافية (GEOBIA)" في تصنيف إستخدامات الأراضي بشكل عام وفي الكشف عن أشجار الزيتون بشكل خاص.

الكلمات المفتاحية: الإستشعار عن بعد، GEOBIA، الزيتون، دلائل الغطاء النباتي، تغير إستخدامات الأراضي.