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Urban expansion and its impacts on agricultural areas in Al-ZAHRA region, Libya using high resolution images

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Abstract

Image change detection is an important application of remote sensing technology. It is a process ascertaining the changes of specific features within a certain time interval. This paper presents an object-oriented image change detection methodology to detect the changes and analyze aerial remote sensing data of AL-ZAHRA sub-area. Furthermore, the urban expansion areas on behalf the agricultural areas in the study area is monitored and analyzed. A rule-based classification technique is applied by using fuzzy functions, aiming to extract information of the urban spatial structure. Finally the classification accuracy of the used images was assessed with parameters of overall accuracy, and kappa statistic. The increase in spatial resolution from Landsat MSS (80m) to Landsat TM (30m), then to SPOT XS (20m) and SPOT Pan (10m); and recently very high resolutions images acquired by SPOT-5 (2.5m), IKONOS (1m) and Quikbird (0.61m) has made it possible to monitor the urban expansion and development at micro level and with a very high accuracy.

Keywords: Remote sensing, Object classification, Object change detection

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1. Introduction

Remote sensing from air and space provides valuable data for various civilian and military applications. However, to explore the full value of these data, the appropriate information has to be extracted and presented in format that allows efficient decision processes. Change detection is an important process in monitoring and managing natural resources and urban expansion. Tracking land cover changes using remotely-sensed data contributes to evaluating to what extent human activities impact the environment [1]. Change detection can be done by many methods from which image subtraction, image ratio, and after image classification [2]. In this paper change detection after image classification based on object-oriented is applied. Object Oriented Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times [3]. The object-oriented approach can contribute to powerful automatic and semi-automatic analysis for most remote sensing applications [4]. Object-oriented techniques, also, incorporate both spectral and spatial information which leads to identify the land cover types more effectively. Object-oriented techniques are becoming more popular compared to traditional pixel-based image analysis [5].

2. Study area and remote sensing data

2.1 Study area

The study area is a sub-area of AL-ZAHRA region, fig (1). AL-ZAHRA is located at the north coast of the Mediterranean Sea and west of the Tripoli city between longitude (12 º 53 '14 ") , (12 º 56' 48") east and between Latitude (32 º 38 '26 ") , (32 º 41' 19 ") north.

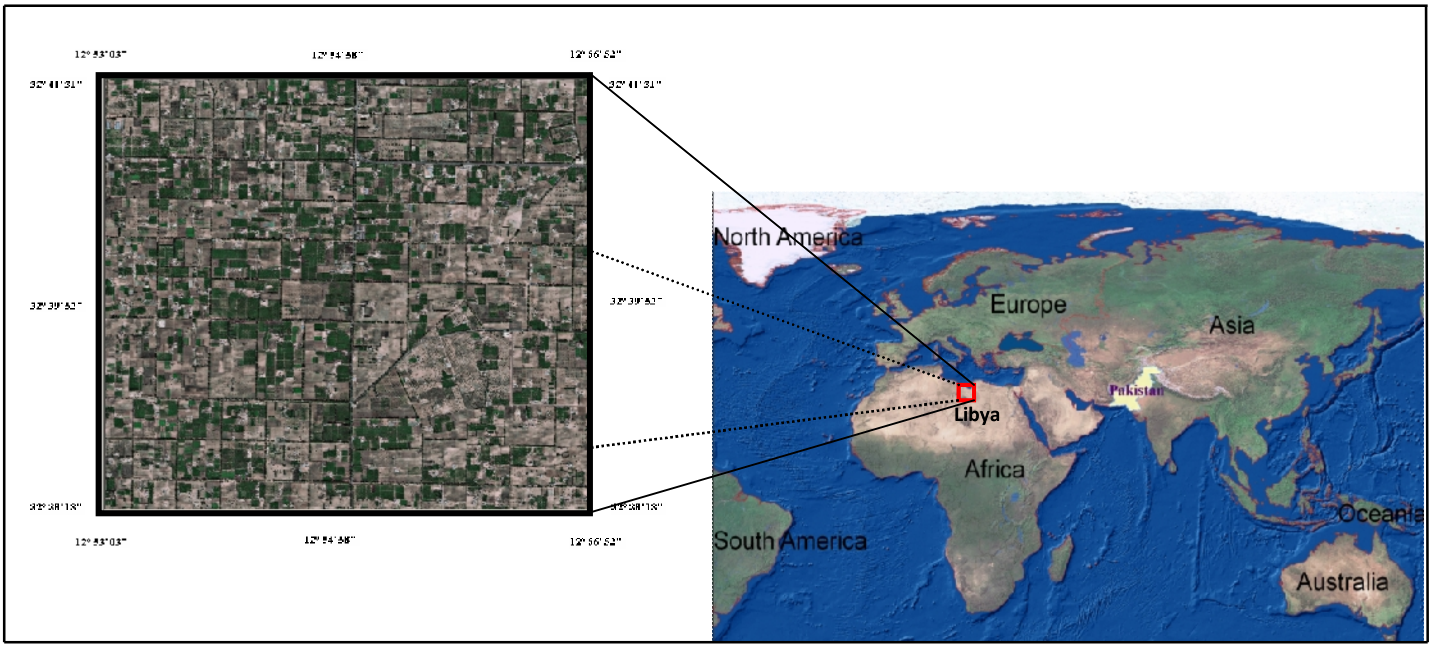

Fig. (1) : Shows the location of study area.

2.2 Remote sensing data of study area

The remote sensing data, of the study area, used in this paper comprises one aerial image of 1973 and one satellite image acquired by Quick Bird in 2003, respectively, fig (2a, b). They shall be named image73 and image03 respectively. Image73 is panchromatic (one band-visible), with resolution of 2.5 m, while image03 is true colour (3 bands-BGR) with resolution of 2.5m.

2.3. Pre-processing of remote sensing data

Both images used in this study have been already radiometrically corrected. Image2003 only has been geometrically corrected to UTM projection system (WGS 84). Image to image registration method is used for geometric correction of image1973 (image2003 is used as a reference image). Nearest neighbour method is used to locate the pixel values on the corrected image, this will preserve the pixel values of the original image which is useful for further image classification process.

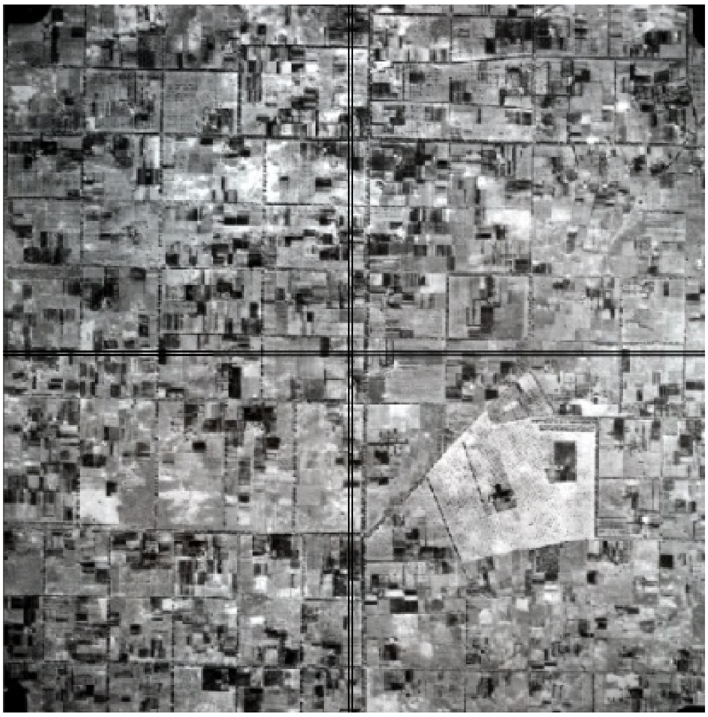

Fig (2 a) : Aerial pan image (1 band) of AL-ZAHRA acquired in 1973.

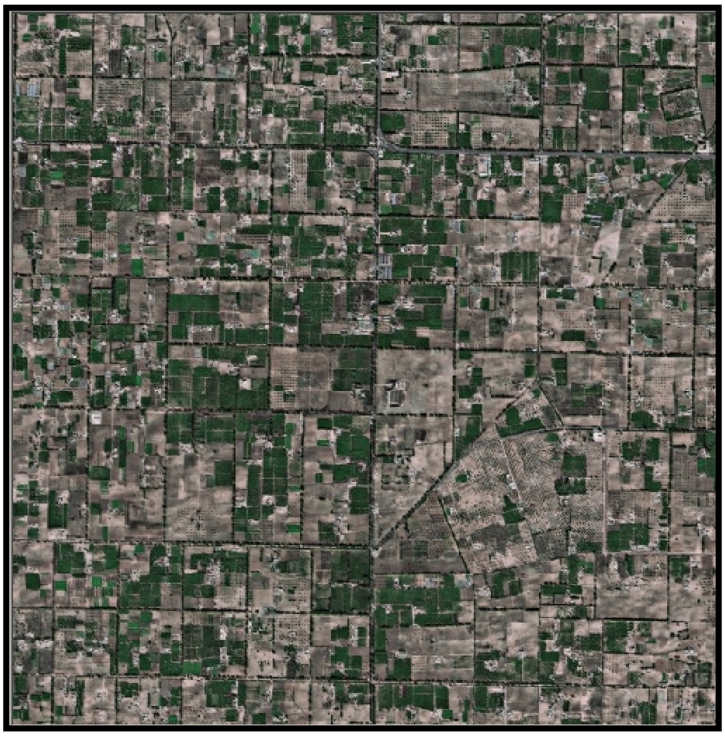

Fig (2 b) : Quick Bird true colour image (3 band) of AL-ZAHRA acquired in 2003.

3. Object Oriented Image Classification

The most evident difference between pixels based image classification and object oriented image classification is that, firstly the basic processing units are image objects or segments, not single pixels in object oriented image classification. Secondly, the classifiers in object oriented image classification are soft classifiers that are based on fuzzy logic . Soft classifier use membership to express an object's assignment to a class. The membership value usually lies between 1.0 and 0.0, where 1.0 expresses a complete assignment to a class and 0.0 expresses absolutely improbability. The degree of membership depends on the degree to which the objects fulfill the class-describing conditions. The advantage of these soft classifiers lies in their possibility express about the classes' descriptions. The basic processing units in object oriented image classification are objects or pixel clusters, with object oriented approach to analyze images; the initial step is always to form the processing units by image segmentation. The object oriented classification is performed by segmenting the image using region growing algorithm andapplying fuzzy classification[6].

3.1 Fuzzy based Object Oriented Classification

In object oriented image analysis the classifier is soft classifier (for example fuzzy system), which uses a degree of membership to express an object's assignment to a class. The membership value usually lies between 1.0 and 0.0, where 1.0 expresses full membership (a complete assignment) to a class and 0.0 expresses absolutely non-membership. The degree of membership depends on the degree to which the objects fulfill the class-describing conditions. The main advantage of this soft classifier lies in their possibility to express uncertainties about the classes' descriptions. It makes it also possible to express each object's membership in more than just one class or the probability of belonging to other classes, but with different degrees of membership. With respect to image understanding these soft classification results are more capable of expressing uncertain human knowledge about the world and thus lead to classification results which are closer to human language, thinking and mind. The result of classification of image73 and image03, using ERDAS, IMAGINE Objective, are given in fig (3) and fig (4) respectively.

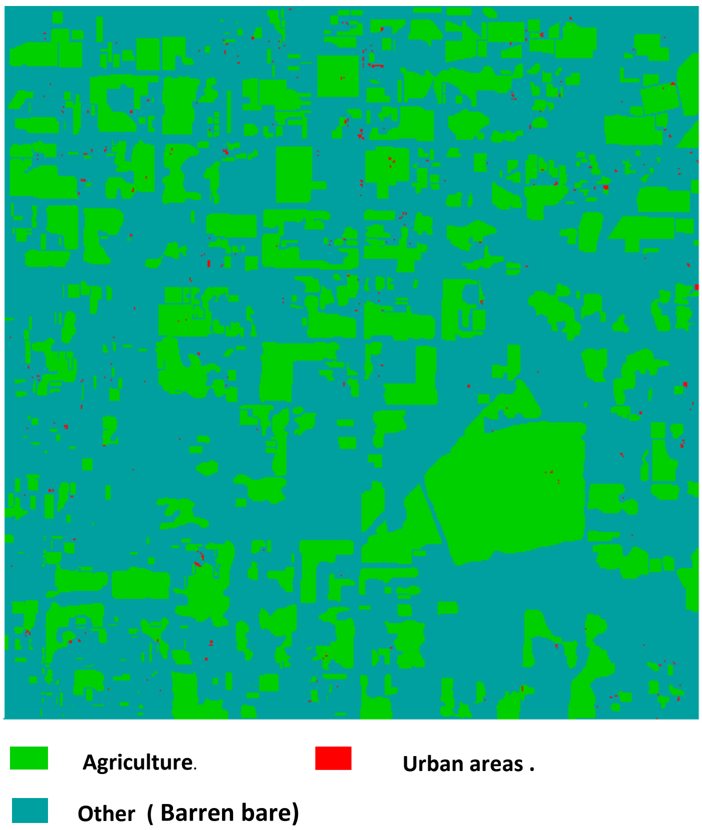

Fig. (3): Object Based Classification for aerial pan 1-band image 1973

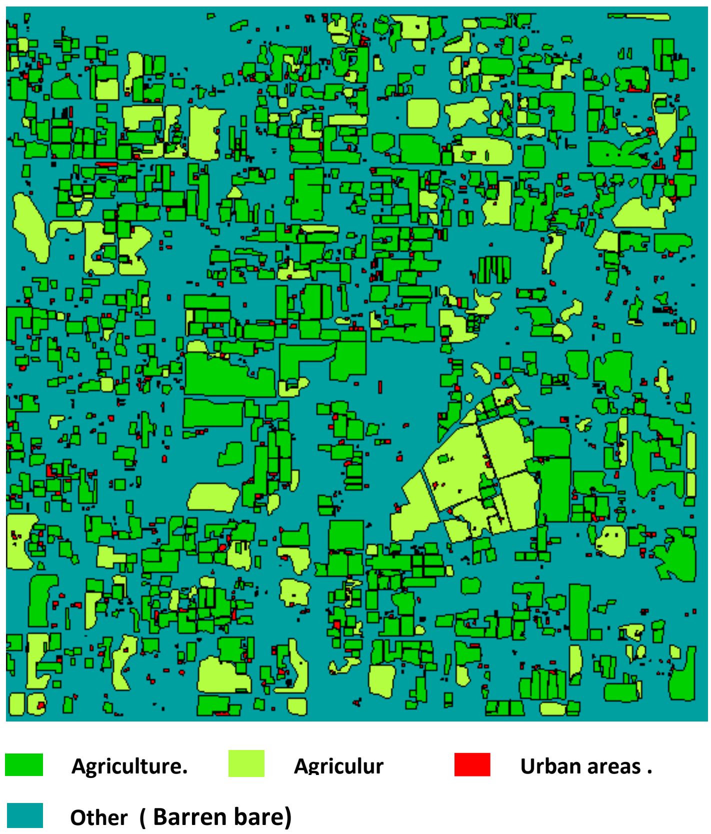

Fig. (4): Object Based Classification for Quick Bird 3band image 2003

3.2 Accuracy Assessment

The classification accuracy has been assessed using overall accuracy, and kappa statistic. In this context, the "accuracy" means the level of agreement between labels assigned by the classifier and class allocations on the ground user as test data. With error matrix, error of omission and commission can be shown clearly and also several accuracy indexes such as overall accuracy can be assessed. The following is the detailed description about the three accuracy indexes and their calculation methods.

3.2.1 Overall accuracy

Overall accuracy is computed by dividing the total number of correctly classified pixels (the sum of the elements along the main diagonal) by the total number of reference pixels. From the error matrix, the overall accuracy can be calculated as the following:

$$OA = \frac{\sum_{K=1}^{N} a_{kk}}{\sum_{iK=1}^{N} a_{k}} = \frac{1}{n}\sum_{K=1}^{N} a_{kk} \quad (1)$$

Overall accuracy is a very coarse measurement. It gives no information about what classes are classified with good accuracy.

3.2.2 Kappa coefficient

Kappa coefficient provides a difference measurement between the observed agreement of two maps and agreement that is contributed by chance alone. A Kappa coefficient of 90% may be interpreted as 90% better classification than would be expected by random assignment of classes.

$$\text{Kappa Statistic } \hat{K} = \frac{(n * SUM(X_{ii})) - SUM(X_{i+} * X_{+i})}{n^2 - SUM(X_{i+} * X_{+i})} \quad (2)$$

Where:

SUM = sum across all rows in matrix
Xi+ = marginal row total (row i)
X+i = marginal column total (column i)
n = number of observations takes into account the off-diagonal elements of the contingency matrix (errors of omission and commission).

The Accuracy Assessment and Accuracy statistics of classification result are give in tables 1 to 4 respectively. The Overall Classification Accuracy = 90.77% and, Overall Kappa Statistics = 0.8761 of image73 and, the Overall Classification Accuracy = 93.98% and Overall Kappa Statistics = 0.9197 of image03 because image 2003 is 3-Band while image 1973 is only 1-Band.

Accuracy Assessment of Object classification for AL-ZAHRA image73
ERROR MATRIX

Table 1 / Error Matrix of 1973 aerial pan Image using stratified random method

Classified Data	Referenced Data			
	Urban	Other areas	Agriculture	Row Total
Urban	12	3	0	15
Other areas	0	18	0	18
Agriculture	0	1	16	17
Column Total	12	22	16	50

ACCURACY TOTAL

Table 2 / Accuracy statistics for the classification result of 1973 aerial pan Image using Stratified random method

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Kappa
Urban	12	15	12	100.00%	80.00%	0.7547
Other areas	22	18	18	81.82%	100.00%	1.0000
Agriculture	18	17	16	88.89%	94.12%	0.9186
Column Total	52	50	46			
Overall Classification Accuracy = 90.77%						
Overall Kappa Statistics = 0.8761						

Accuracy Assessment of Object classification for AL-ZAHRA image03

ERROR MATRIX

Table 3 / Error Matrix of 2003 space true colour Image using stratified random method

Classified Data	Referenced Data			
	Urban	Other areas	Agriculture	Row Total
Urban	17	3	0	20
Other areas	0	25	0	25
Agriculture	0	0	18	18
Column Total	17	28	18	63

ACCURACY TOTALS

Table 4 / Accuracy statistics for the classification result of 2003 space true colour Image using stratified random method

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Kappa
Urban	17	20	17	100.00%	85.00%	0.8114
Other areas	28	25	25	89.29%	100.00%	1.0000
Agriculture	20	18	18	90.00%	100.00%	1.0000
Column Total	65	63	60			
Overall Classification Accuracy = 93.98%						
Overall Kappa Statistics = 0.9197						

4. Object-oriented change detection

A variety of digital change detection techniques has been developed in the past three decades. Reviews on the most commonly used techniques are given in [3-7]. For the detection of change pixels, several statistical techniques exist, calculating e.g. the spectral or texture pixel values, estimating the change of transformed pixel values or identifying the change of class memberships of the pixels. But when adopted to high-resolution imagery, the results of these pixel-based algorithms are sometimes limited. Especially if small structural changes are to be detected, object-oriented procedures seem to be more precise and meaningful. Object-oriented change detection and analysis techniques can in addition estimate the changes of the mean object features (spectral colour, form, etc.), assess the modified relations among neighbouring, sub- and super-objects and find out changes regarding the object class memberships. Previous studies implying a combination of pixel- and object based techniques have already demonstrated the advantages of firstly pinpointing the significant change pixels by statistical change detection and subsequently post-classifying the changes by means of a semantic model of change related object features [8].

5. Change Analysis

Utilizing the Land Change Analysis Panel in the LCM and Cross-tabulation analysis in the CROSSTAB module [9], we were able to develop additional insights into past LC during : 1973 – 2003. The change analysis panel provides graphs of gains/losses and net change by land cover class. The Cross-tabulation analysis provides two functions, which are Cross-classification image and cross tabulation. Cross-classification image shows the location of the changes and non-change areas of the classes in the original images represented by different colours. The legend presents categories of image73 versus a image03. The cross tabulation (Tables 5,6,and 7) compares the number of cells in each combination of the classes of image73 to those of a image03 (area in pixels ,%, area in square meter) respectively . A function to calculate areas of the combinations is available from the software.

In terms of the net change between 1973 and 2003 (Table 8, and Fig 7), the greatest increase were observed in Urban with 45.56% of total area. Losses were evident in agriculture, other areas 13.34%, 31.65% of total area, respectively.

Table 5 / Cross-tabulation of land cover classes between 1973 and 2003 (area in pixels)

Classified Data	Unclassified	Urban	Other areas	Agriculture	Pixel Count
Unclassified	13	23	10	3	49
Urban	22	249186	3350	10389	269881
Other areas	70	1263309	909278	158777	2377672
Agriculture	33	800673	527510	437154	1810651

Table 6 / Cross-tabulation of land cover classes between 1973 and 2003 (%)

Classified Data	Unclassified %	Urban %	Other areas %	Agriculture %	%
Unclassified	26.53	46.94	20.41	6.12	100.00
Urban	0.01	92.33	3.81	3.85	100.00
Other areas	0.00	53.13	38.24	8.63	100.00
Agriculture	0.00	44.22	29.13	26.65	100.00

Table 7 / Cross-tabulation of land cover classes between 1973 and 2003 (Area in square meter)

Classified Data	Urban	Other areas	Agriculture	Square Meters
Urban	90649,58	0	2589.98	95829.56
Other areas	455837.9	327338.5	56979.74	854696.08
Agriculture	287488.68	189069.13	157989.27	652677
Column Total	833976.16	516407.63	217558.99	1603202.64

5. Results and discussions

The analysis and interpretation of the AL-ZAHRA images revealed that there was considerable effect on the agricultural areas due to the random urban expansion. In 1973, most of the area was agricultural lands and only 0.1 % of the total area was urban , but In 2003 the percentage of urban expansion in the AL-ZAHRA region is estimated by 10 times of 1973, as shown in figure (5) and chart of figure (6).

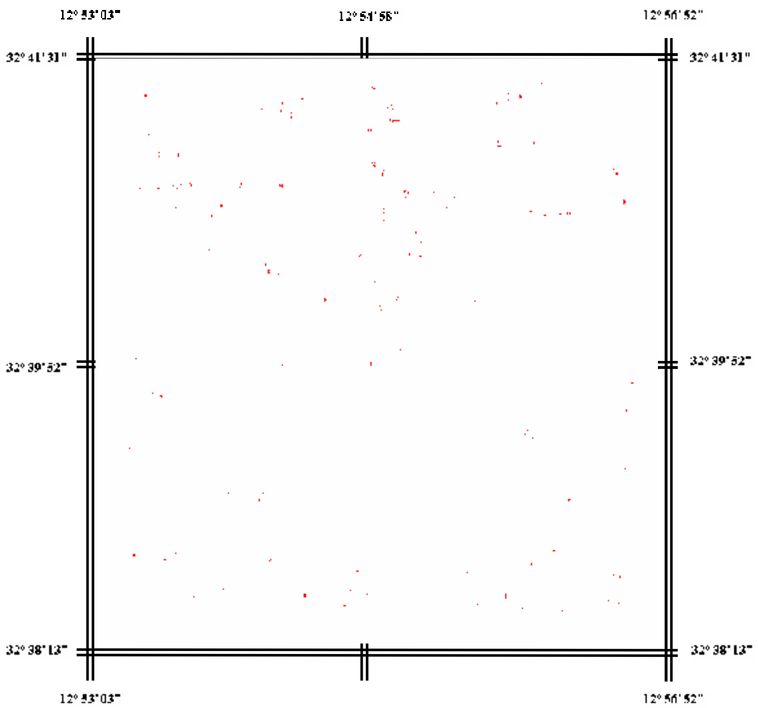

Fig.(a): Urban areas in 1973

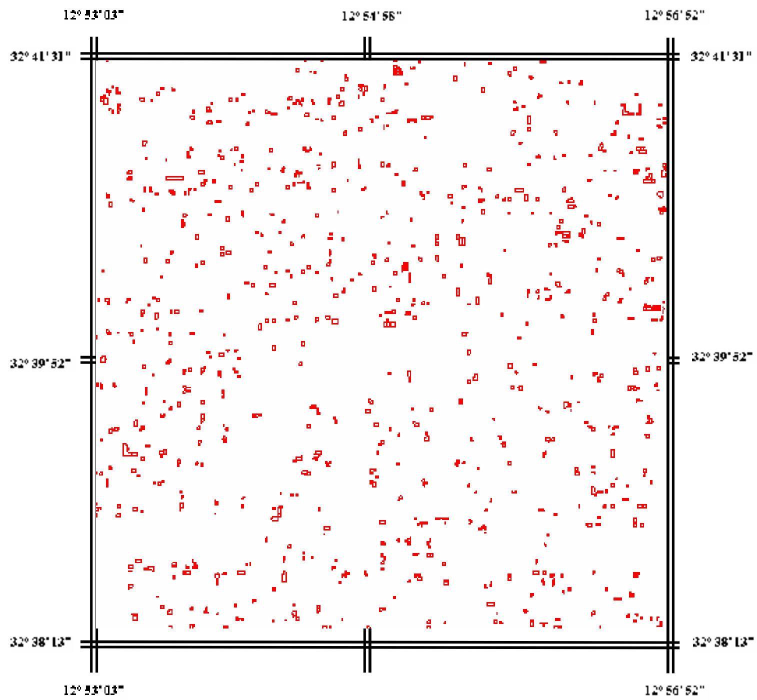

Fig.(b): Urban areas in 2003

Fig. (5): Urban expansion in AL-ZAHRA region through 1973 to 2003.

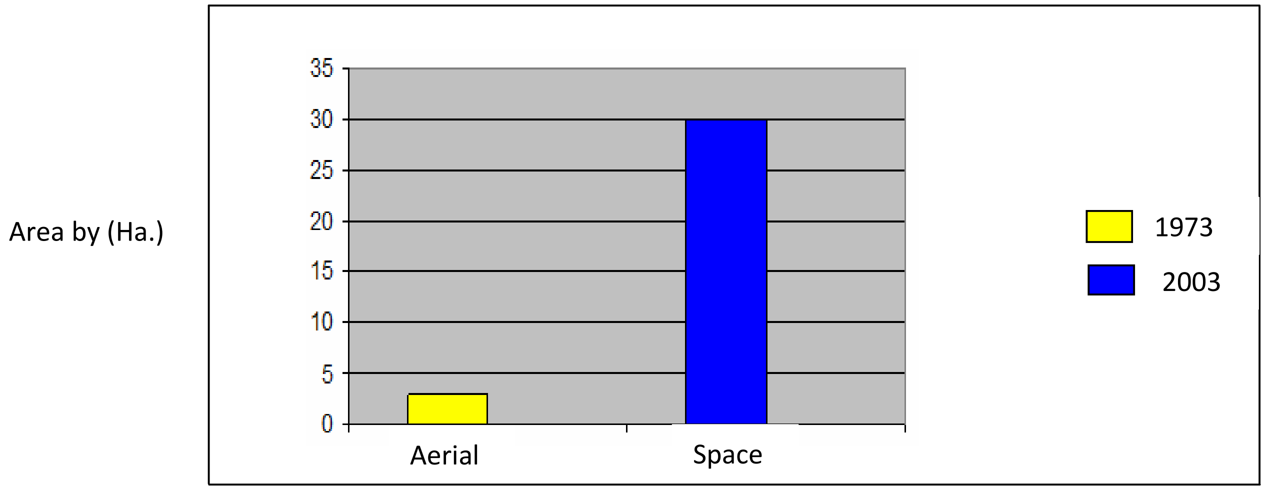

Fig. (6) : Chart showing the areas by Ha. In 1973 and 2003.

In 1973, the total area of urban areas was calculated is about 30,000 sq. Meter, whereas in 2003, the total area of urban areas is 300,000 sq. Meter, it means the urban areas increased from 30 sq. Km, to 300 sq. Km. In 1973, most of the area was agricultural lands and only 0.1 % of the total area was covered by urban areas.

6. Conclusions

The aim of this paper was to demonstrate the object oriented analysis of aerial and space images for an effective change detection. The structure of objects and the available number of features allowed the accurate classification of the very high resolution image data. There are numerous ways and methods to handle objects for the efficient identification of changes. Moreover with the advantage of determining the exact "*from-to*" change, a GIS post classification process can be omitted. The results confirmed the expanding tension of the AL-ZAHRA region, as illustrated by the elimination of the open air areas and their transformation to built-up areas (impervious). The analysis, the structure, the classification and generally all the information related to the objects can be organized and managed in a GIS database. In this way urban expansion prediction and land use studies can be accomplished effectively.

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