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Spatiotemporal Analysis of the Development Status of Al-Hammar Marsh in Southern of Iraq Using Remote Sensing and GIS Techniques

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Abstract:

The marshes of Mesopotamia at the southern part of Iraq represent a unique component of our global heritage. During the last decades the Iraqi marshes subjected to many changes, these changes have great impact on marshes environmental and ecosystem. One of these marshes is Al-Hammar marsh, the study area of this research and it located in Thi Qar city in Iraq. It was influenced by many causes such as dams constructed on the Iraqi rivers Tigris and Euphrates while they were passing through Turkey and Syria which reduced the amount of water in the area, and also there are some other political effects which caused the deterioration on the study area. The aims of this study is to use GIS to analyze the spatiotemporal to detect the changes of the study area using Landsat images in different times applying Maximum Likelihood classification method. The results of this study shows the changes for four classes; water, vegetation, bare land, and wetland. The important classes in this study are water and vegetation. The vegetation area already has covered a lot of the water area, that's mean so much amount of water was disappeared under the vegetation. So that, the water class in the classified images is not the same in the reality. The water areas in 2003 had lost around 85% compare with the water areas in 1991. The study area in 2015 has re-immersed around 67% of water areas compare with the of water areas in 2003. The accuracy of all the results are accepted.

Keywords: Al-Hammar marsh, Maximum Likelihood classification, GIS.

1. Introduction

Marshlands consist of 3 - 6% of the earth's land surface, while they make available supplies and services such as: water quality maintenance, agricultural production, fisheries, and recreation (Acreman, M. C., & Hollis, G. E. 1996). Furthermore other services are floodwater retention, provision of wildlife habitat, and control of soil erosion (Sugumaran R., 2004). The area of marshlands definitely depends on the preservation of agricultural and oasis ecosystems in arid and semi-arid areas (De. Zhou, 2009). The marshlands areas are greatly decreased during the past 50 years due to water bodies reclamation, population pressure, water diversion, dam construction, pollution, biological incursion, desertification, climate change, and misguiding policies (M. F. Augustine and C. E Warrender, 1998). Because of this, many marshlands around the world are protected and monitored by various agencies.

Remote sensing data are appropriate tools for monitoring of the marshlands distribution area and spatial-temporal dynamic multiplicity. During last two decades a diversity of remotely sensed data and change detection methods have been developed and assessed (Rogan J., 2002 and Finlayson C.M., 1998). Remotely sensed data have been utilized to measure the qualitative and quantitative terrestrial land-cover changes (Seto K.C., 2004). Satellite remote sensing has many advantages for inventory and monitoring of marshlands and also provide information on surrounding landuse and their changes over time.

Change detection systems use a variety of image processing tools to make changes visible. Most systems look for changes between only two images: one "before" and one "after". Change - detection techniques in common use include: subtracting spectral bands between the images, subtracting a feature space, principal components analysis, and change vector analysis.

Three of digital change detection have been reported. Before drying the marshes and during drying and after drying the marshes by using Landsat images. Separate data set analysis involves classification of each-date imagery separately into land cover classes and the result were subsequently compared. Mainly image differencing and rationing, is then applied to produce a residual image indicating the relative change in reflectance between the two dates. This technique gives slightly more accurate result. (Nelson, 1982; jenson and toll, 1982: woodwell et al., 1983; Singh, 1986; Quarmby et al., 1987).

2. Study Area

The marshes zone is located south of Iraq between latitudes (30˚30′-31˚30′) N and longitudes (46˚00′-47˚30′) E of the Greenwich meridian. It is representing one of the largest wetland ecosystems in all of Asia and covered more than 19,000 Km^2 and is formed by the confluence of the Tigris and Euphrates rivers. Al-Hammar marsh is one of the major marsh from marshes southern Iraq, is located east of Tigris River by approximate area (3000Km2-4000Km2) and water level (1.5-5) meter figure (1). The climate is

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moderate with 37.7º Celsius mean yearly temperature, (400-1000) millimeter sum of yearly rain, and 49 percent mean relative humidity. It considered as a settlement area for birds and fishes, therefore it represents an important source for fishing and agricultural areas.

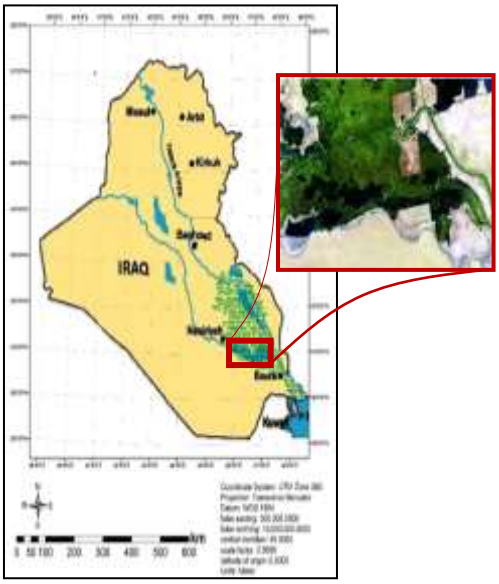
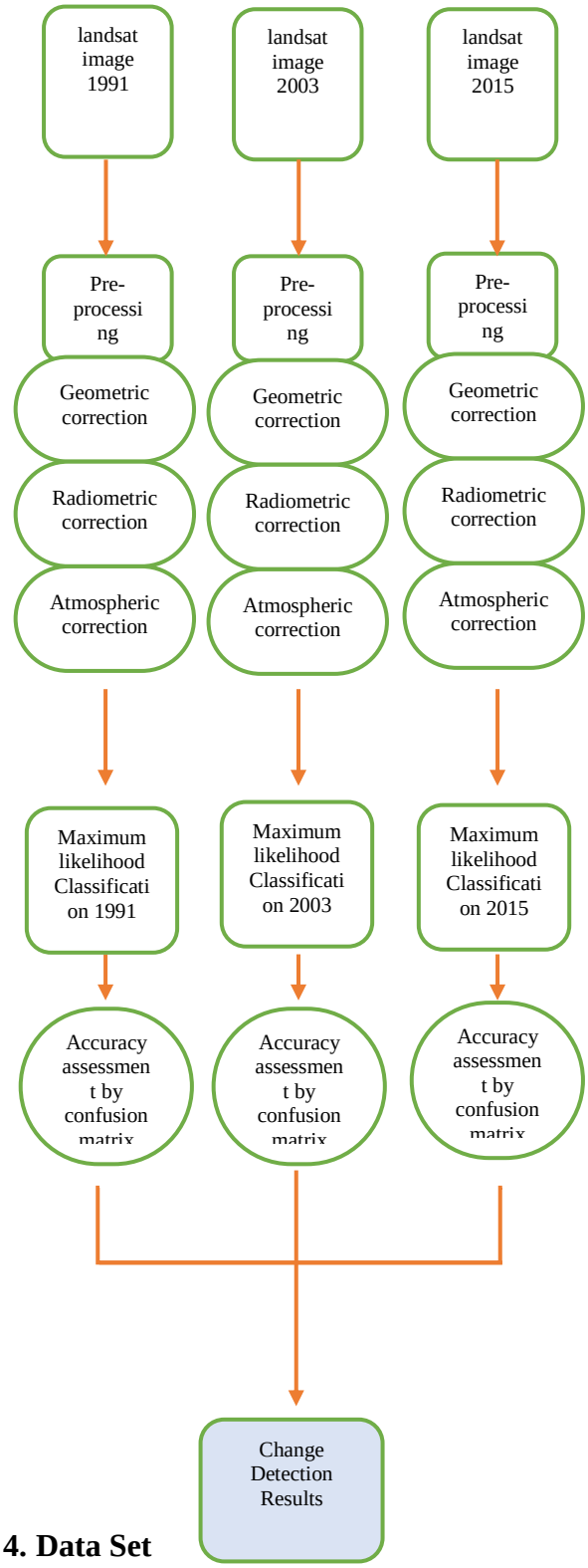


Fig (1) Study area location

3. Methodology

3.1. General description of the Project

The collection and application of remotely sensed imagery for natural resources management and development has come a long way since the launch of Landsat I in 1972. Since this time, remotely sensed data has been used quite extensively for such activities as meteorology, oceanography, natural disaster monitoring, forest type and density mapping, geological mapping and agricultural assessment. However, one area in particular where remote sensing has become increasingly popular is land use and land cover classification and the temporal monitoring. Each application itself has specific demands, for spectral resolution, spatial resolution, and temporal resolution.
In this study, we use remote sensing data to monitor and analyze the changes in land cover is study area. We acquired data from USGS website and we do preprocessing like geometric, atmospheric and radiometric correction. Then, we classify the images by pixel based maximum likelihood algorithm. After that, we will detect the changes between for different periods.



4. Data Set

All satellite data used were Landsat Thematic Mapper (5 TM), Enhanced Thematic Mapper (Landsat 7 +ETM), and Landsat 8 OLI. The images downloaded from

(earthexplorer.usgs.gov) and they have same spatial resolution of 30 m per pixel.
Processing was done using all reflective bands. The satellite imagery was handled with the software ENVI, IDRISI, ArcGIS and Excel program.

Table (1) Data information

Image	Satlitte sensor	WRS Path / Row	Date
1	Landsat 5 TM	166 / 39	28 May 1991
2	Landsat 7 +ETM	166 / 39	19 Mar 2003
3	Landsat 8	166 / 39	31 May 2015

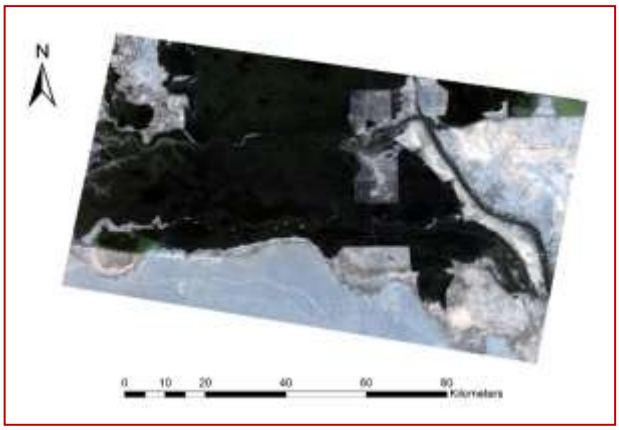


Fig (3) Landsat image for Al-Hammar Marsh in 1991

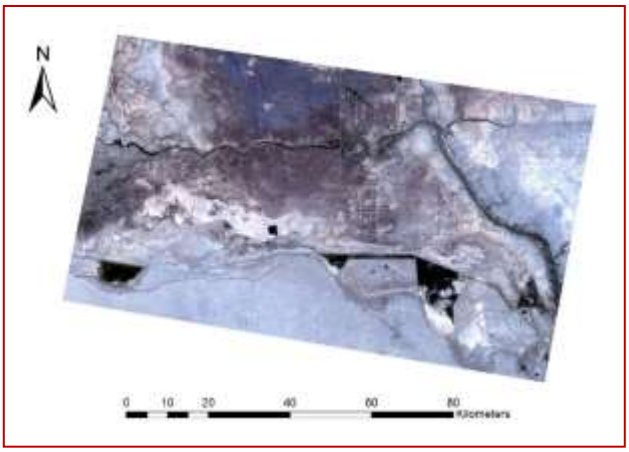


Fig (4) Landsat image for Al-Hammar Marsh in 2003

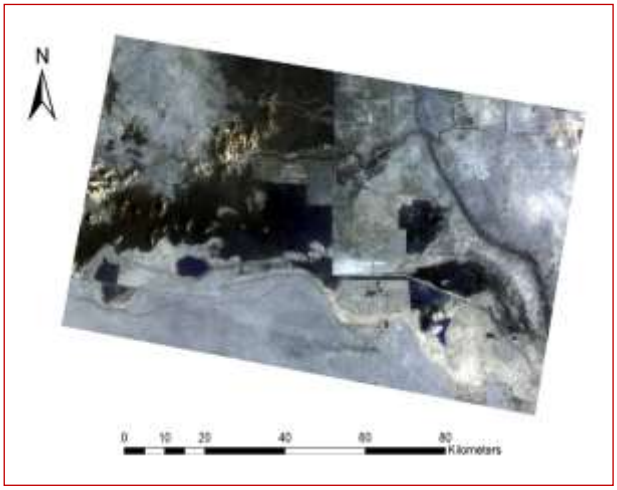


Fig (5) Landsat image for Al-Hammar Marsh in 2015

5. Result and Discussion

The LULC classes used in this study are based on Anderson Classification System (USGS Schema) Level I and II, which is designed for remote sensing data. In addition, the classification is based on the elements of image interpretation namely: image tone, image texture, shadow, pattern, association, shape, size, and site. Based on these elements, the images of 1991, 2003 and 2015 were used to distinguish and introduce the most accurate classes, and as a result four LULC categories were identified. These categories include water, vegetation, bare land and wet land.
The results of maximum likelihood classification shown that land cover of area of study in 1991 included totally 8042.239 km^2. Table (2) is shown land cover maximum likelihood classification results in study area.
According to this results bare land with 2827.731 km^2 (35.16 %) in included maximum area in comparing with other land uses and wet land with almost 1196.074 km^2 (14.87 %) is included minim area in study area.

Table (2) land cover area in 1991 using maximum likelihood classification

Class	Area km^2	Percentage
Water	1216.138	15.12
Vegetation	2802.297	34.85
Bare land	2827.731	35.16
Wet land	1196.074	14.87

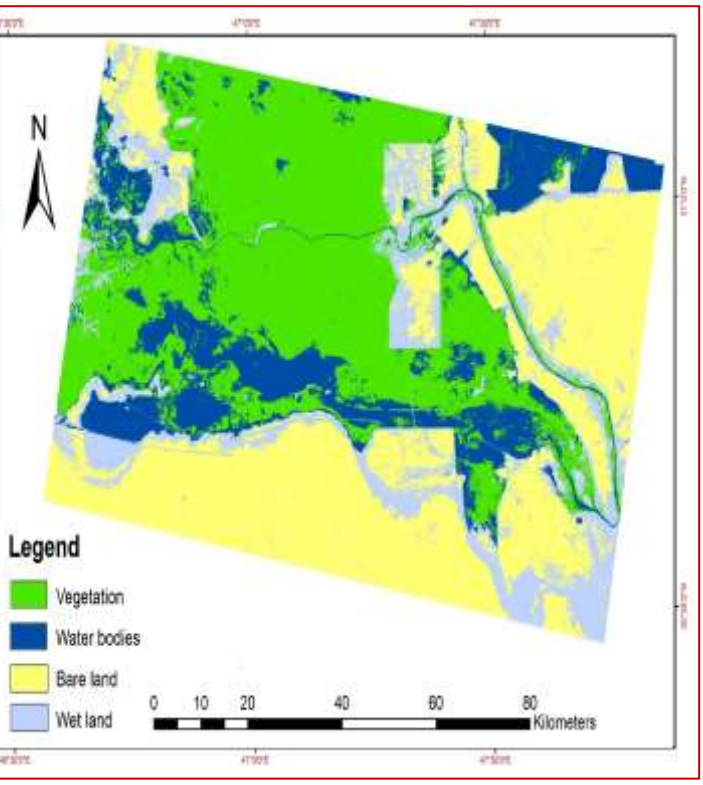


Fig (6) Maximum Likelihood for Al-Hammar Marsh 1991

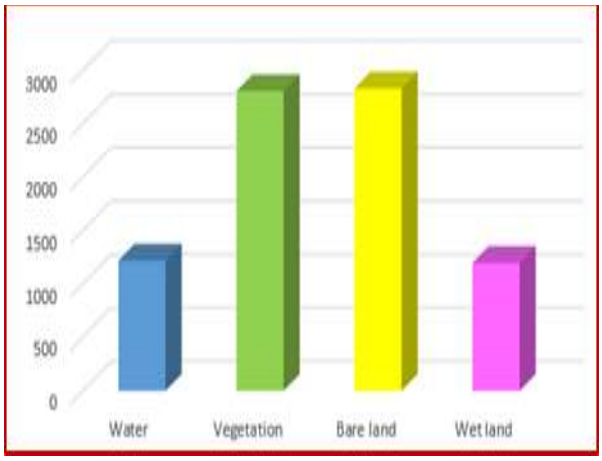


Fig (7) land cover area in 1991 using maximum likelihood classification

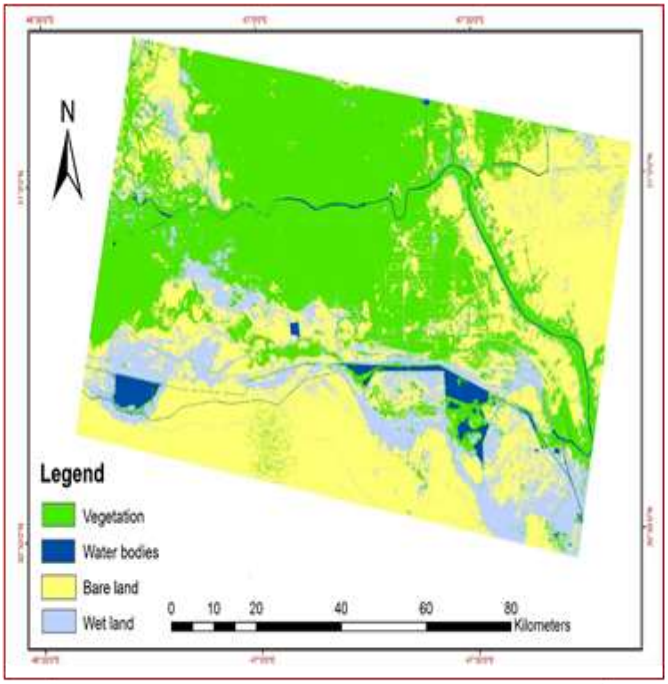


Fig (8) Maximum Likelihood for Al-Hammar

Table (3) shows land cover maximum likelihood classification results in study area in 2003, the results of classification of the study area shown that land cover included totally 8042.041 km^2.

Table (3) land cover area in 2003 using maximum likelihood classification

Class	Area km^2	Percentage
Water	181.9692	2.26
Vegetation	3408.9462	42.39
Bare land	3271.2408	40.68
Wet land	1179.8847	14.67

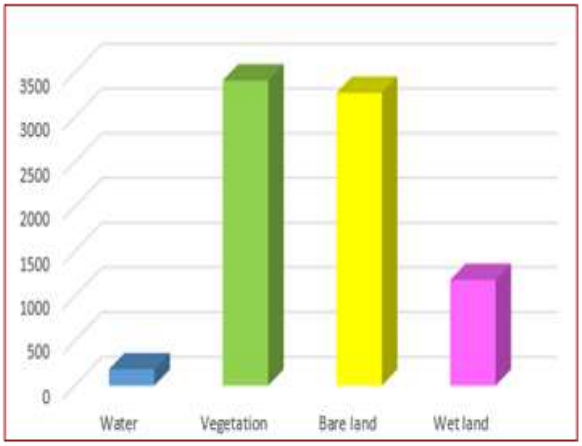


Fig (9) land cover area in 2003 using maximum likelihood classification

Figure (9) shows that the results are vegetation with 3408.9462 km^2 (42.39 %) in included maximum area in comparing with other land uses and water with less than 182 km^2 (2.26 %) is included minim area in study area.

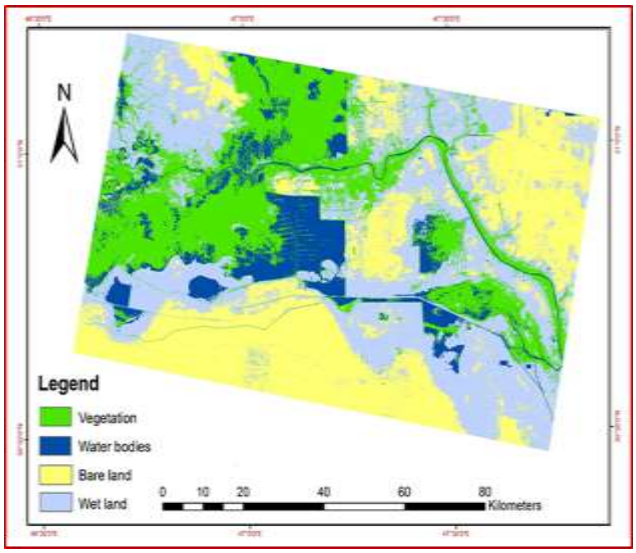


Fig (10) Maximum Likelihood for Al-Hammar Marsh 2015

Table (4) shows land cover maximum likelihood classification results in study area in 2015, the results of classification shown that land cover of study area included totally 8042.041 km^2.

Table (4) land cover area in 2015 using maximum likelihood classification

Class	Area km^2	Percentage
Water	824.2893	10.25
Vegetation	1977.858	24.60
Bare land	2458.71	30.57
Wet land	2781.1836	34.58

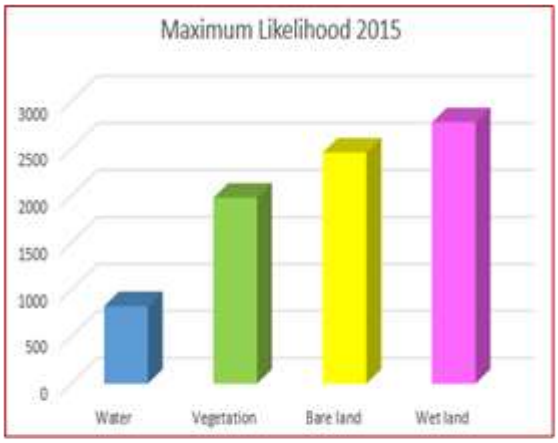


Fig (11) land cover area in 2003 using maximum likelihood classification

According to this results figure (11) wet land with 2781.1836 km^2 (34.58 %) in included maximum area in comparing with other land uses and water with 824.2893 km^2 (10.25 %) is still included minim area in study area.

5.1. Result of Accuracy assessment of LULC map

Accuracy assessment is a process used to estimate the accuracy of image classification by comparing the classified map with a reference map *(Caetano et al., 2005)*. It is critical for a map generated from any remote sensing data. Although accuracy assessment is important for traditional photographic remote sensing techniques, with the advent of more advanced digital satellite remote sensing the necessity and possibility of performing advanced accuracy assessment have received new interest. Currently, accuracy assessment is considered as an integral part of any image classification. This is because image classification using different classification algorithms may classify pixels or group of pixels to wrong classes. The most obvious types of error that occurs in image classifications are errors of omission or commission.

The common way to represent classification accuracy is in the form of an error matrix. An error matrix is a

square array of rows and columns and presents the relationship between the classes in the classified and reference maps. Using error matrix to represent accuracy is recommended and adopted as the standard reporting convention.

In this study, overall, producer's and user's accuracy were considered for analysis of Maximum likelihood by using the confusion matrix. The Kappa coefficient, which is one of the most popular measures in addressing the difference between the actual agreement and change agreement, was also calculated. The Kappa statistics is a discrete multivariate technique used in accuracy assessment *(Fan et al., 2007).*

6.

Table (5) Accuracy assessment of maximum likelihood classification in 1991

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Vegetation	94.85	96.97	96831/102090	96831/99856
Water	96.48	96.39	32492/33677	32492/33708
Bare land	95.82	96.63	131768/137521	131768/136361
Wet land	88.49	73.17	9988/11287	9988/13650
Overall Accuracy	92.63 %			
Kappa Coefficient	0.89			

Table (6) Accuracy assessment of maximum likelihood classification in 2003

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Vegetation	92.87	91.22	13021/14021	13021/14275
Water	96.79	92.68	32942/34033	32942/35542
Bare land	87.47	96.23	48548/55503	48548/50448
Wet land	96.72	75.30	9154/9464	9154/12156
Overall Accuracy	89.76 %			
Kappa Coefficient	0.88			

Table (7) Accuracy assessment of maximum likelihood classification in 2015

The results of image classifications are often insufficient (Marble & Peuquet, 1983). Generating training classes can improve such results. Thus, the use of a supervised classification in this study to detect current and former land cover has been generally a success. The results of the overall accuracy assessment are satisfying with at least 89.76%. Furthermore Water, Vegetation, Bare land and Wet land show also sufficient values in users and producers accuracy.

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Vegetation	95.95	96.79	60937/63512	60937/62960
Water	97.50	95.03	27878/28592	27878/29336
Bare land	92.20	96.64	76510/82981	76510/78136
Wet land	96.43	77.39	21761/22567	21761/28120
Overall Accuracy	94.22 %			
Kappa Coefficient	0.91			

5.2 Change Detection Result

The land cover change maps provide further insights about land cover change trends and rates. The results reveal land cover change history and quantity of change in each land cover class. The landscape went through three different stages, with each map representing a different stage, and each stage

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dominated by different land use activities.

Figure (12) shows the changes between the year 1991 and 2003 which presents the spatial distribution of changes in the land covers. It shows that the vegetation areas (green color) in 2003 has remained almost the same as it was in the year of 1991 but with some increasing occurred coming from the water, and bare land classes. The spatial distribution of the vegetation area has clustered in the middle part of the study area and specifically in the north part. The details of the changes in land cover between 1991 and 2003 is presented in table (8) as percentage and in table (9) as square km.

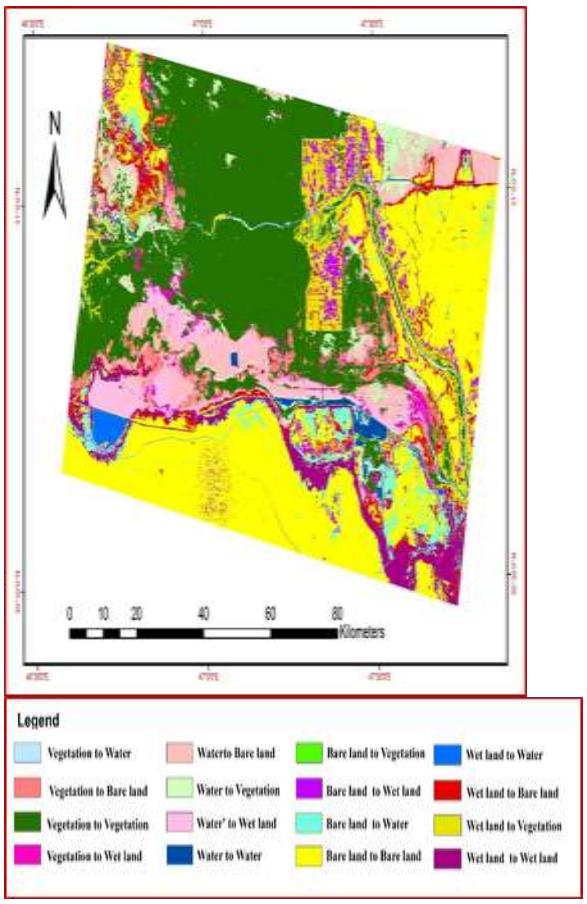

Figure 12. Shows changes between 1991 to 2003.

significant spectral signature. In reality this is not always the case. Thus, the same surface can appear different in several locations and show different reflections (Kronberg, 1985). This can lead to the misclassifications.

Table (8) Percentages between 1991 and 2003

1991 / 2003	Water	Bare land	Vegetation	Wet land	Row Total	Class Total
Water	1.701	5.721	0.426	73.171	100	100
Bare land	9.414	39.246	78.874	7.023	100	100
Vegetation	84.132	29.814	8.501	10.521	100	100
Wet land	4.752	25.22	12.198	9.285	100	100
Class Total	100	100	100	100	0	0
Class Changes	15.868	94.279	21.126	90.715	0	0
Image Difference	21.648	166.92	15.644	-72.287	0	0

Table (9) Area (Square kilometer) between 1991 and 2003

1991 / 2003	Water	Bare land	Vegetation	Wet land	Row Total	Class Total
Water	47.67	69.57	12.07	3117.02	3246.33	3246.33
Bare land	263.82	477.32	2231.51	299.15	3271.80	3271.80
Vegetation	2357.68	362.60	240.52	448.19	3408.99	3408.99
Wet land	133.17	306.73	345.12	395.54	1180.55	1180.55
Class Total	2802.34	1216.22	2829.21	4259.90	0.00	0.00
Class Changes	444.66	1146.64	597.70	3864.36	0.00	0.00
Image Difference	606.65	2030.11	442.59	-79.35	0.00	0.00

Figure (13) shows the changes between the year 2003 and 2015 which presents the spatial distribution of changes in the land covers. It shows that the wet land areas (purple color) in 2015 has increased to double as the it was in the year of 2003 and this increasing occurred coming from the vegetation, and bare land classes, and also there is an obvious increase of the water from vegetation.

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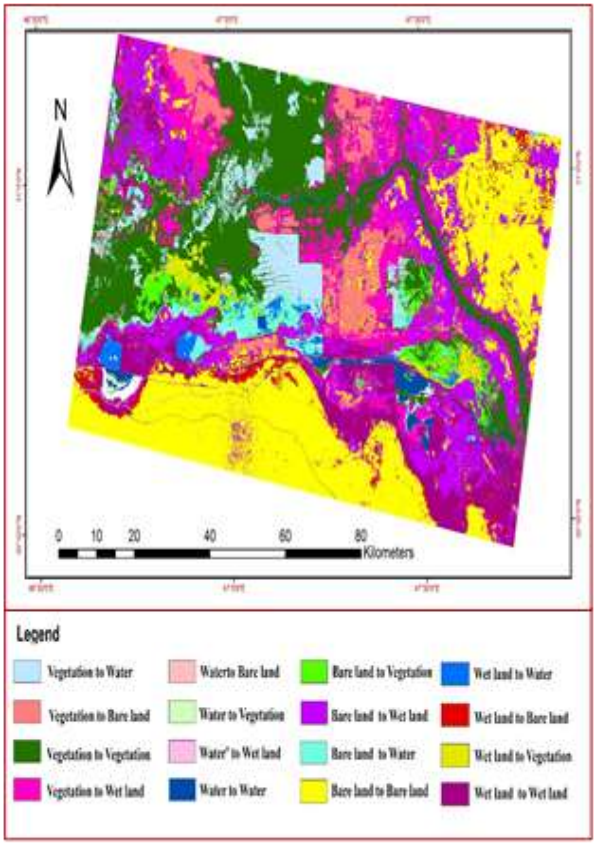

Fig (13) Change Detection for Al-Hammar Marsh

Table (10) and (4-10) show the details of the changes in land cover between 2003 and 2015, table (4-9) as percentage and in table (11) as square km.

Table (10) Percentages between 2003 and 2015

2003 / 2015	Water	Bare land	Vegetation	Wet land	Row Total	Class Total
Water	3.755	4.556	12.998	9.34	100	100
Bare land	0.027	56.649	12.925	13.908	100	100
Vegetatio	0.761	6.02	46.64	14.0	100	100
Wet land	95.457	32.773	27.435	62.67	100	100
Class	100	100	100	100	0	0
Class Changes	96.245	43.351	53.358	37.33	0	0
Image Difference	-74.618	-24.839	-41.98	395.541	0	0

Table (11) Area (Square kilometer) between 2003 and 2015

2003 / 2015	Water	Bare land	Vegetation	Wet land	Row Total	Class Total
Water	121.96	149.03	443.11	110.20	824.29	824.29
Bare land	0.87	1853.13	440.62	164.10	2458.71	2458.71
Vegetation	24.73	196.98	1589.99	166.15	1977.86	1977.86
Wet land	3100.05	1072.10	935.24	739.43	5846.81	5846.81
Class Total	3247.60	3271.24	3408.95	1179.88	0.00	0.00
Class Changes	3125.64	1418.11	1818.96	440.45	0.00	0.00
Image Difference	-2423.31	-812.53	-1431.09	4666.93	0.00	0.00

Figure (14) shows the changes between the year 1991 and 2015 which presents the spatial distribution of changes in the land covers. It shows that the wet land areas (purple color) in 2015 has increased to double as it was in the year of 1991 and this increasing occurred coming from the vegetation, and bare land classes.

The details of the changes in land cover between 1991 and 2015 is presented as percentage in table (12) and as square km in table (13).

Table (12) Percentages between 2003 and 2015

1991 / 2015	Water	Bare land	Vegetation	Wet land	Row Total	Class Total
Water	16.8	25.5	0.291	0.76	100	100
Bare	10.8	8.00	65.195	5.01	100	100
Vegetati	48.7	29.3	1.573	4.92	100	100
Wet	23.5	37.1	32.94	89.3	100	100
Class	100	100	100	100	0	0
Class	51.2	74.4	34.805	10.6	0	0
Image	-	-	-13.074	37.2	0	0

This transition probability matrix records the probability that each land cover category will change to the other category. This matrix is produced by the multiplication of each column in the transition probability matrix be the number of cells of corresponding land use in the later image.

For the 4 by 4 matrix table presented below, the column represents the older land cover categories and the row represents the newer categories. Although this matrix can be used as a direct input for specification of the prior

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probabilities in maximum likelihood classification of the remotely sensed imagery, it was however used in predicting land use land cover of 2027.

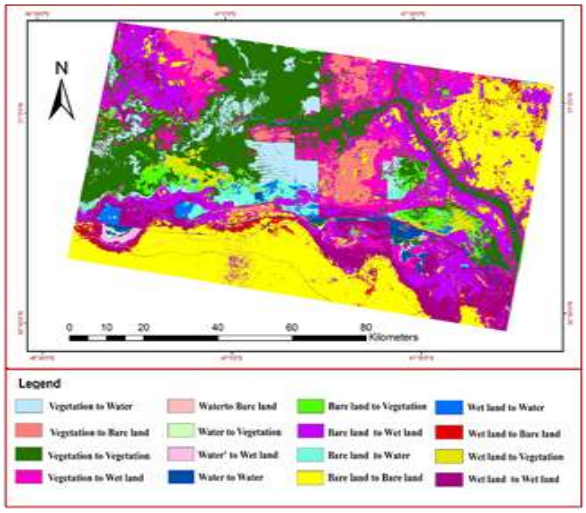

Fig (14) Change Detection for Al-Hammar Marsh

Table (13) Area (Square kilometer) between 1991 and 2015

1991 / 2015	Water	Bare land	Vegetation	Wet land	Row Total	Class Total
Water	472.37	310.99	8.24	32.69	824.29	824.29
Bare land	304.09	97.31	1844.52	213.42	2459.33	2459.33
Vegetation	1367.33	356.38	44.50	209.64	1977.86	1977.86
Wet land	658.55	451.53	931.95	3804.15	5846.19	5846.19
Class Total	2802.34	1216.22	2829.21	4259.90	0.00	0.00
Class Changes	1435.01	905.23	984.69	455.75	0.00	0.00
Image Difference	-824.49	-391.92	-369.88	1586.29	0.00	0.00

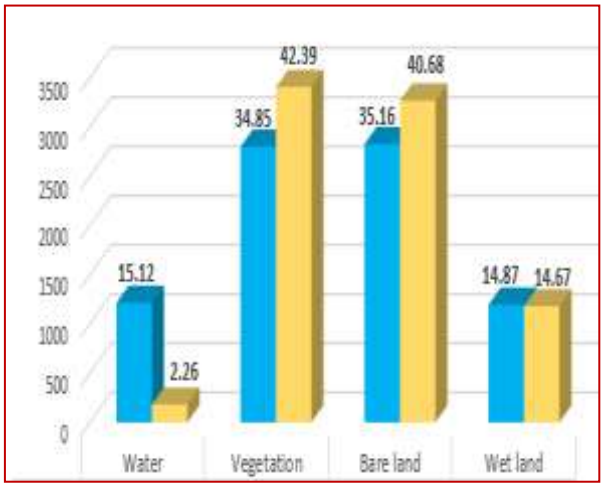

Fig (15) statistical change detection between 1991 and 2003

Statistical analyses of maximum likelihood classification fig (15) showed that wet land and water in 1991 occupies the lowest class with around 15 % of the total classes. But the vegetation was practiced moderately with 34.85 %, this may be due to the fact that the marshes was rich of reeds and papyrus that seems to the basis for living.

In 2003 the water occupies the lowest class with just 2.26 % of the total classes. Also, wet land seems to be constant, but the vegetation and bare land increased from 34.85% in 1991 to around 42% in 2003 for vegetation and the bare land also increased from around 35% in 1991 to more than 40% in 2003.

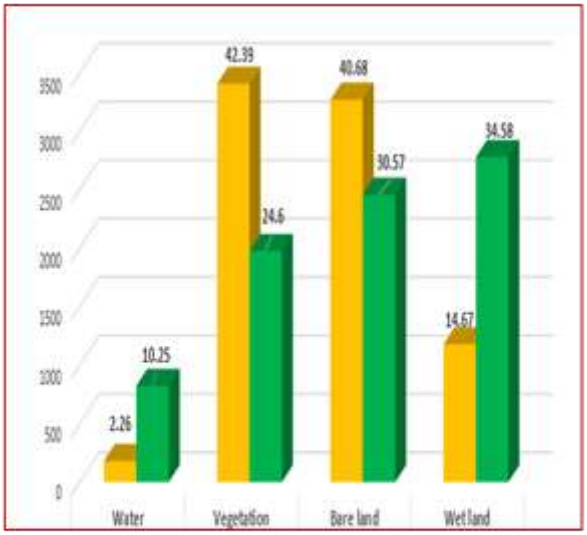

Fig (16) statistical change detection between 2003 and 2015

Figure (16) showed that the water still occupies the least class in 2015 with just less than 11 % of the total classes, the vegetation class decreased to less than 25 % that mean more than 17 % of this class are gone comparing with it was in 2003. Also, the bare land class decreased and it is occupying with 30.57% of the total classes.

The wet land class in 2015 occupying with more than 34 % of the total class and it occupied most of the image, it has increased to more double its size in 2003 where it increase from 14.67% to more than 34%.

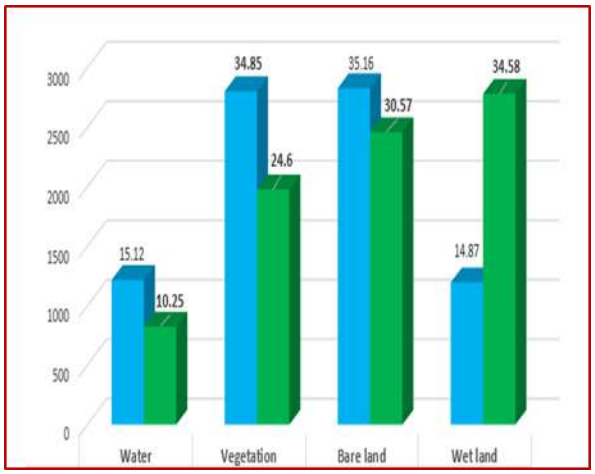

Fig (17) statistical change detection between 1991 and 2015

The statistical analyses between 1991 and 2015 showed that the classes (water, vegetation and bare land) in 2015 all of them are decreased comparing with them in 1991. But the wet land class in 2015 occupying with more than 34 % of the total class and it occupied most of the image, it has increased to more double its size in 1991 where it increase around 20% in 2015.

7. Conclusion

The objectives of this study are to monitor and analyze the changes on different classes (water, vegetation, bare land and wet land) in the study area which help to interpret and evaluate the visually different variables by using maximum likelihood classification in remote sensing and GIS for same scene in different times. The data collected and used in this study were acquired by Landsat of years (1991, 2003 and 2015).

The results of this study focused about the changes in the marsh features. The results identify the water area in the year 1991 was (1216.138 km^2), in year 2003 was (181.9692 km^2), and (824.3893 km^2) in year 2015. These results show that the area of water in the study area has been degraded between 1991 to 2003 around 85% and retrieved around 67% of the previous percentage in the year 2015. On the other hand, wet land area has been increased in the last period in double compare with the years 1991 and 2003.

8. References

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