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LAND COVER CHANGE DETECTION USING SATELLITE IMAGES BASED ON MODIFIED SPECTRAL ANGLE MAPPER METHOD

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Abstract

This research depends on the relationship between the reflected spectrum, the nature of each target, area and the percentage of its presence with other targets in the unity of the target area. The changes occur in Land cover have been detected for different years using satellite images based on the Modified Spectral Angle Mapper (MSAM) processing, where Landsat satellite images are utilized using two software programming (MATLAB 7.11 and ERDAS imagine 2014). The proposed supervised classification method (MSAM) using a MATLAB program with supervised classification method (Maximum likelihood Classifier) by ERDAS imagine have been used to get farthest precise results and detect environmental changes for periods. Despite using two classification methods, the results of the suggested method (MSAM) have been proved its superiority, where the classification accuracies are 88%, 91% and 92% for years 1986, 2000 and 2018, respectively. The results indicated that during the last three decades for study area subjected to many artificial and natural changes, these changes have impacts on land cover, vegetation, and the aquatic environment. In this paper from the results, one can see these marshes suffered was dryness, rareness in vegetation and increasing in alluvial soil during the period 1986 – 2000, while during 2000 - 2018 there were increasing in water and vegetation with a decreasing in the alluvial soil.

Key words : Satellite images, supervised classification, and Modified Spectral Angle Mapper (MSAM).

Introduction

Satellite images can be utilized in a number of implementations. The main of these applications is to build a categorization map to be able to recognize countenance or classes of land cover in a sight (Mausel *et al.*, 2003). There are two classification methods: supervised and unsupervised classification, where the main difference between these methods is that the classification observer built on real information about geographical phenomena given the current computer, while the rating unattended done in accordance with mathematical equations define gatherings clusters and thus classification categories, according to the relationship between the numeric values of the ranges of image (Maria, Panagiota, 2010).

Satellite images do not permanently have the ability to provide perfect details concerning the type of vegetation. However, this imagery prepares very good wherewithal to detect a significant change in Land cover, such us the wildfire damage or environmental exertion as in the water deficiency (Mausel *et al.*, 2003). In other word Remote sensing techniques give quick methods to detect environmental changes, such that change detection. Change detection is the practicability of recognizing differences in the state of phenomena by monitoring these at different times (multi-temporal analysis), therefore change detection became a useful tool for detecting land cover changes. The process of change detection is premised on the power to measure temporal effects. It has enabled to follow changes over large regions and present long-dated monitoring predisposition. In broad, digital change detection techniques using chronological remote sensing data are practical to assist study these data, and provide information for detecting the change in land cover (Ahmed, Amal, 2019). Image algebra is a broadly used change detection technique that concerned one of two methods; the band ratio or band subtraction. The subtraction method is subtracting a digital number value from one date of a specific band from the digital number value of the same pixel at the subsequent date. The subtraction results in negative and positive values

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where change has occurred. This method gives information for computing the total area that has changed (Tinku, Ajoy, 2005).

An image enhancement process, are usually utilized to a single channel of data at a time, image transformations typically include concerted processing of information from multi- spectral bands. Transformations Operator takes as input image, then produces another image; which is created from a linear set of pixels of an input image (Maria, Panagiota, 2010). Karhunen- Love Transformation (KLT), also commonly indicate to as the eigenvector, Principal Component Analysis (PCA), or Hotelling transform. KLT is used for both compressing and summarizing information in multi-spectral remote sensing data. It is based on the arithmetical properties of vector representation. The (KL) transform has a number of constructive properties that create an important tool for image processing (Rafael, Richard, 2017). In this paper the principal objective of transformation techniques is to process the use of different imagery bands which lead to getting different details in the images where this enabled us to collect greater details to be represented in one image using Principle Component Analyses (PCA), where this transforms utilize the input image bands to produce new other principle components (PCs) bands, here the first output image has characteristics of intensive information and preferable disparity. After than the first PC is suitable for classifying the multi-band satellite image, where the other remaining PCs are ignored (Konstantinos *et al.,* 2018).

The study area

AL Hawizeh Marshes which locates in Mesan and Basra provinces; are complex of marshes that straddle the Iraq and Iran border in the southeast of Iraq and the southwest of Iran.AL Hawizeh Marshes are critical to the survival of the AL Chabaish and AL Hammar marshes, which also make up the Mesopotamian Marshes because they are a refuge for species that may recognize or reproduce in the other marshlands. It is bounded by the longitudes (47° 23^{1} 46'' to 48° 1^{1} 17'' E) and Latitude (30° 57^{1} 43'' to 31° 49^{1} 56'' N) and the maximum area of the marshes is 3000 km^2, which increases and decreases according to water percentage. In the dry season, it reaches about 650 km^2. The area of Al Hawizeh marshes in Iraq is 79% and in Iran 21%, the central and north parts of it's are enduring but the south parts become seasonal in the case Natural. The satellite image of study area captured from Landsat -7TM, Landsat -7TM+ which are chosen bands are (1,2,3,4,5 and 7) for the years 1986 and 2000 and Landsat-8OLI which are chosen bands are (2,3,4,5,6 and 7) for the year 2018, With 30m spatial

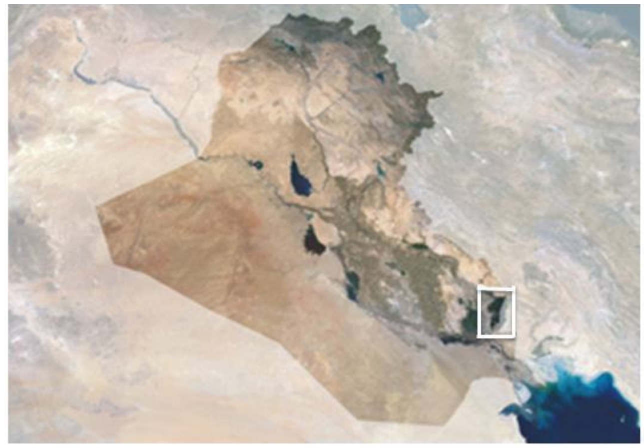

Fig. 1: The locality of the study area on the map of Iraq.

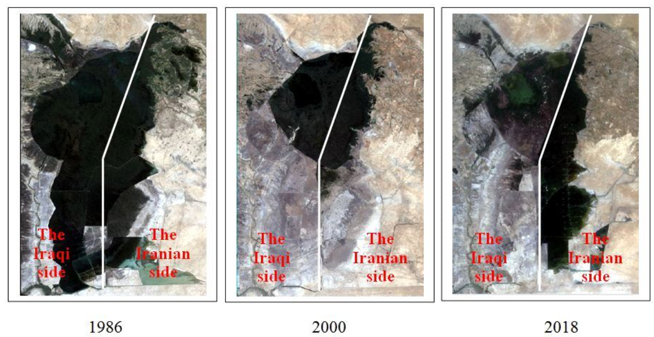

Fig. 2: The study area (AL Hawizeh Marshes and the area surrounding it) for the years 1986, 2000 and 2018.

resolution. Fig. 1 shows the original map of Iraq, while the fig. 2 illustrate the study area for the yesrs 1986, 2000 and 2018.

Materials and Methods

Principle component analysis (PCA)

In this work, we applied principal component analysis (PCA) on six bands of satellite image for AL Hawizeh Marshes and the area surrounding for the years 1986, 2000 and 2018 using (MATLAB 7.11). These created PCA bands have the highest contraindication in the PC_1 and the lowest contraindication PC_6. Therefore, PC_1 contains most of the information or characteristics of each of the original multi-spectrum satellite images and can be used for more accurate and effective analyzes (Rafah, 2016). Six input bands carried six principal components (PCs) as shown in Figure (3) for the years 1986, 2000 and 2018. Displays the six (PCs) images resulted from this transform; it is shown that just the PC_1 image is integrated well since it shows the fine details clearly in comparison with the other PC images. This makes the (PC_1) is suitable for the determination of categorizing the multi-band satellite image, whereas the other residual PCs are ignored.

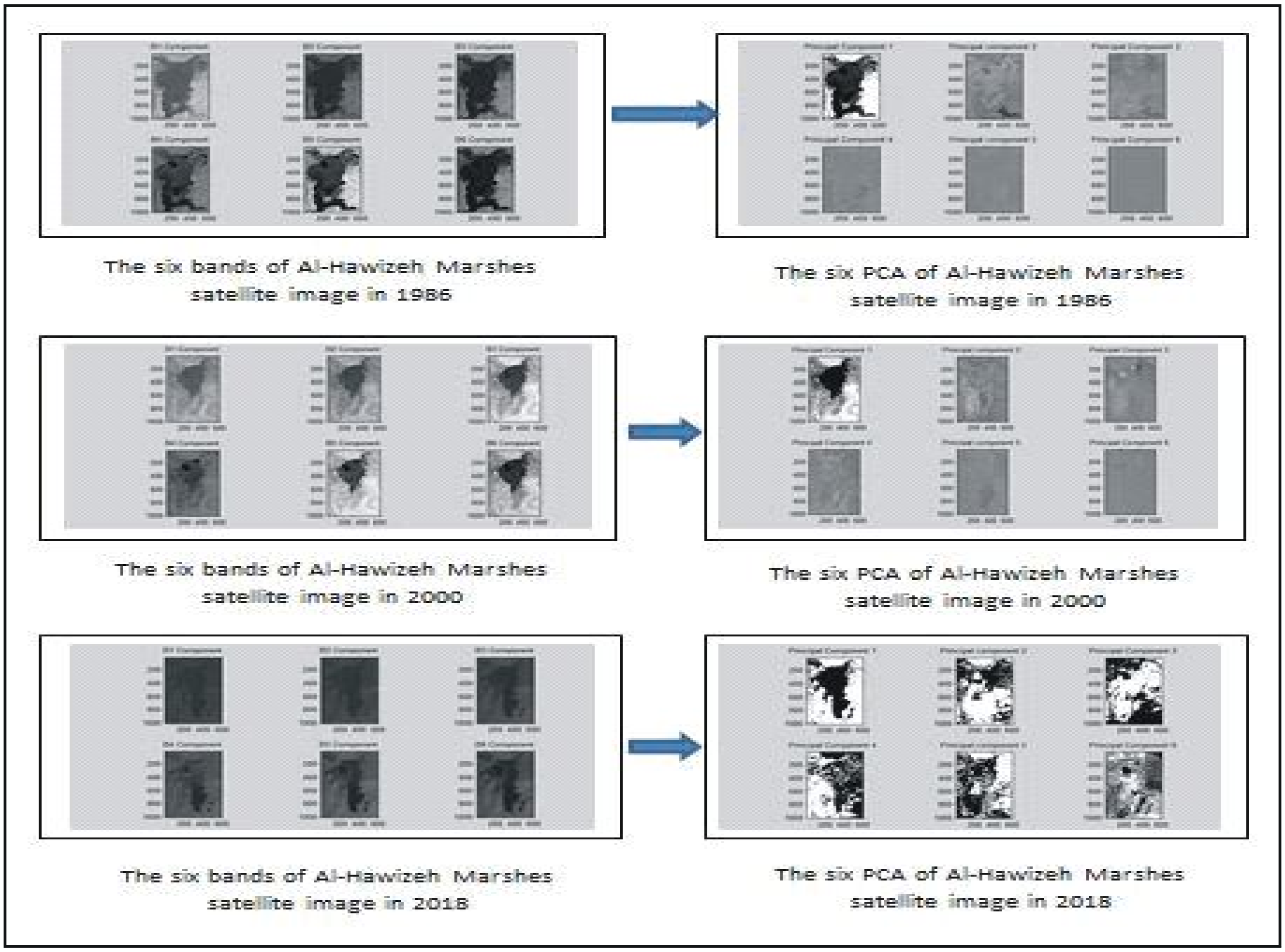

Fig. 3: The six bands and The Six PCs images after using KL-Transformation on AL Hawizeh Marsh's satellite images for the years 1986, 2000 and 2018.

Images Classification

Two methods of categorization have been applied to classify imageries; supervised proposed method Modified Spectral Angle Mapper (MSAM) using (MATLAB 7.11) and supervised method (Maximum likelihood Classifier) using (ERDAS imagine 2014) to get the most truthful results and then remark environmental variations in the study area for the period 1986, 2000 and 2018. The (PCA) was applied using (MATLAB 7.11) on six bands (1, 2, 3, 4, 5, 7) of AL Hawizeh Marshes satellite images for the years (1986,2000) and six bands (2, 3, 4, 5,6, 7) for the year (2018) as shown in Fig. (3).

Results and Discussion

The Proposed Modified Spectral Angle Mapper Classification Method

The Spectral Angle Mapper (SAM) algorithm is built on a model supposition that a single pixel of an image represents one confident ground cover factual and can be exceptionally assigned to only one ground cover class (Arpita *et al.,* 2018).

In this work, we proposed Modified Spectral Angle Mapper to perform a supervised classification method in order to use Landsat data to classify land cover. The proposed method MSAM measures the degree of spectral match among the training pixels and reference pixels. The reference pixels are from field view or from pixels in a spectral image. The MSAM method measures the degree of match by scheming the angle between the two spectra. The following steps illustrate the mechanism of the proposed method:-

1. Read the satellite image (PC1).
2. Partitioned the Satellite image (PC1) into fixed-size blocks, in this work, we partitioned the image into block size (3 × 3). Each block will be represented as a reference pixel.
3. Choosing manually five training areas, in this work, we selected five blocks in the image (training pixel), each of these blocks represented one of the classes (vegetation, shallow water, water, alluvial soil, and

Barren land).

4. Create a specified threshold (e). In this work (e = 0.05)

5. Calculate the spectrum angle among the reference pixel spectrum and training pixel spectrum by using the equation :

$$\propto = \cos^{-1} \frac{\sum_0^1 yr}{\sqrt{\sum_0^1 y^2}\sqrt{\sum_0^1 r^2}}$$

Where $\propto$ is the spectrum angle between the reference pixel spectrum and training pixel spectrum measured in degree?

y is the reflectance in the reference pixel, r is the reflectance in the training pixel.

6. The spectrum angle must approach zero. The best match is achieved when the minimum mean square error (MSE) between the spectrum angle and zero is within a pre-specified threshold. In this case, the reference pixel should be given the same index of the training pixel.

7. The procedure repeats until the process converges to a solution, which is a minimum of the total reproduction error.

8. Reconstruct an image and then the classification decision is made according to several training pixels, the training pixel assigned to the class.

The algorithm reviewed above was applied using (MATLAB 7.11). The results from applying (MSAM) classification method and The Percentage of each class can be shown in figures (4-6) for the years 1986, 2000 and 2018 respectively. Table (1) presents the change in the years 2000, 2018 compared with 1986 and the change in the year 2000 compared with 2018, Fig. (7) illustrates the change in this period. The results indicated that five classes found with a comparison with the original image. These classes represent five main lineaments in the study area (vegetation, shallow water, water, alluvial soil, and Barren land).

Supervised Classification Method (Maximum Likelihood Classification)

Supervised classification method (Maximum likelihood Classification) was applied by using ERDAS imagine 2014. The results and the ratio of every class can be shown in figures (8-10) for the years 1986, 2000 and 2018, respectively. (Table 2) presents the change in the years 2000, 2018 compared with 1986 and the change in the year 2000 comparing with 2018, while the Fig. (11) shows a change in this period. The results indicated that five classes found with a comparison with the original image. These classes represent five main lineaments in the study area (vegetation, shallow water, water, alluvial soil, and Barren land).

Data accuracy

In this work, to assessment the accuracy of classification, we used the data of arbitrary points which selected area for different structure of bands in the study area which are characterized as a classification map to be compared with the classification results by means the factors, these factors represent the total accuracy, producer accuracy, and user's accuracy respectively, which represented mathematically by the following empirical relations: then compared with the classification results. The classification accuracy assessment was done for proposed supervised classification methods for years 1986, 2000, and 2018. The most common error assessments are Producer's accuracy, User's accuracy and overall accuracy. Where Producer's accuracy is the

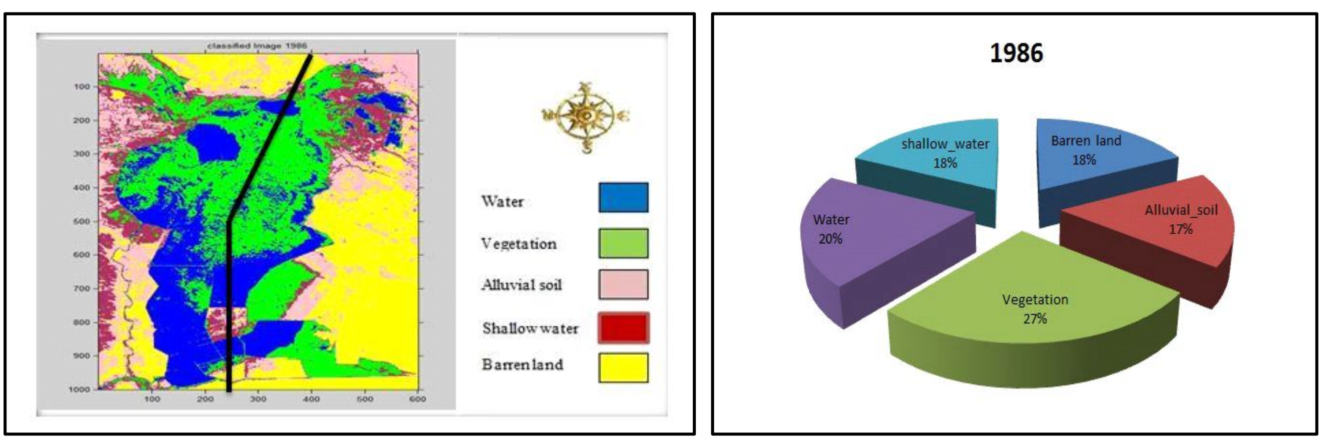

Fig. 4: Supervised classification using Modified Spectral Angle Mapper and the Percentage of each class for a Landsat image of AL Hawizeh Marshes in the year (1986).

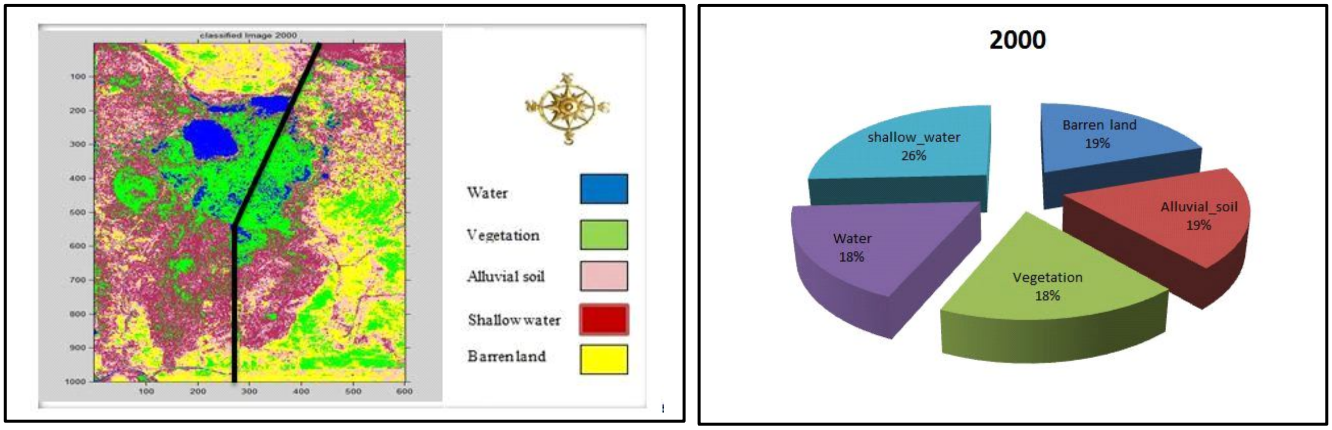

Fig. 5: Supervised classification using Modified Spectral Angle Mapper and the Percentage of each class for a Landsat image of AL Hawizeh Marshes in the year (2000).

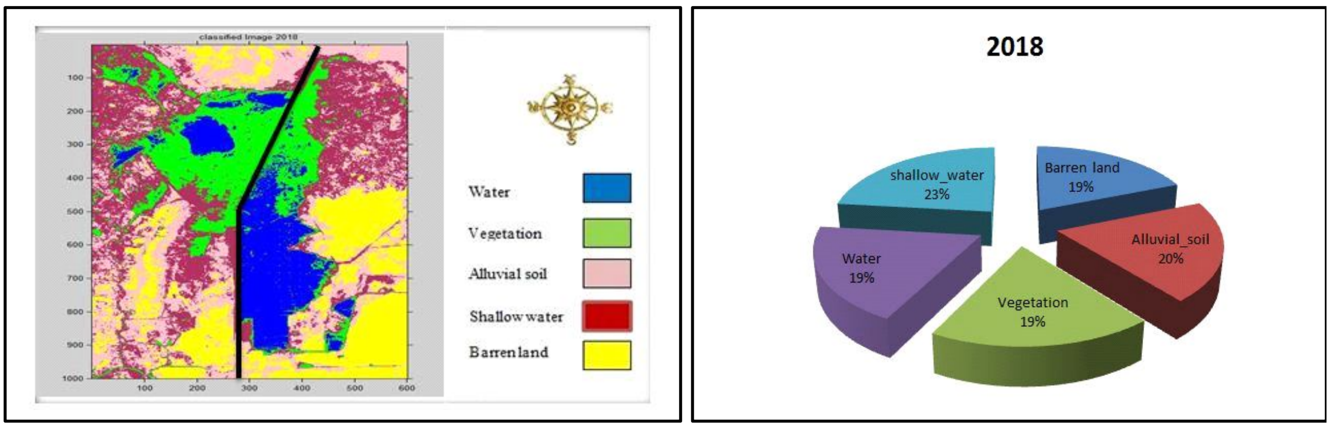

Fig. 6: Supervised classification using Modified Spectral Angle Mapper and the Percentage of each class for a Landsat image of AL Hawizeh Marshes in the year (2018).

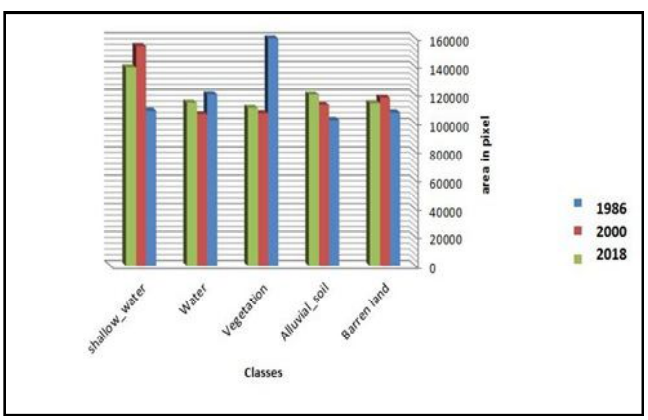

Fig. 7: The change in 1986, 2000 and 2018 using supervised Modified Spectral Angle Mapper classification.

ratio between the number of correctly classified and the column total value and User's accuracy is the ratio between the number of correctly classified and the row total because users are concerned about what percentage of the classes has been correctly classified and overall accuracy is obtained by dividing the summation of the main diagonal entry of the confusion matrix by the total number of tasters data, (Renuka, Santhosh, 2011).

Tables 3 - 6 present error matrix with producers, users, and overall accuracy calculations for supervised proposed classification method (MSAM) for the years 1986, 2000 and 2018, respectively.

Conclusions

The main idea of this work is to categorize Landsat satellite images at various times for the study area utilize two supervised methods and detected the changes occur in Land cover for different years then evaluate the results of each method.

From the obtained results we get the next conclusions:

1. The results from applying the Modified Spectral Angle Mapper (MSAM) classification method show that marsh vegetation and water decreased about 32.8766%, 11.421%, respectively. While Barren land, alluvial soil and Shallow water increase about 9.5424%, 10.2119%, and 41.7585%, respectively in 2000 compares with 1986, after drying the marshes.

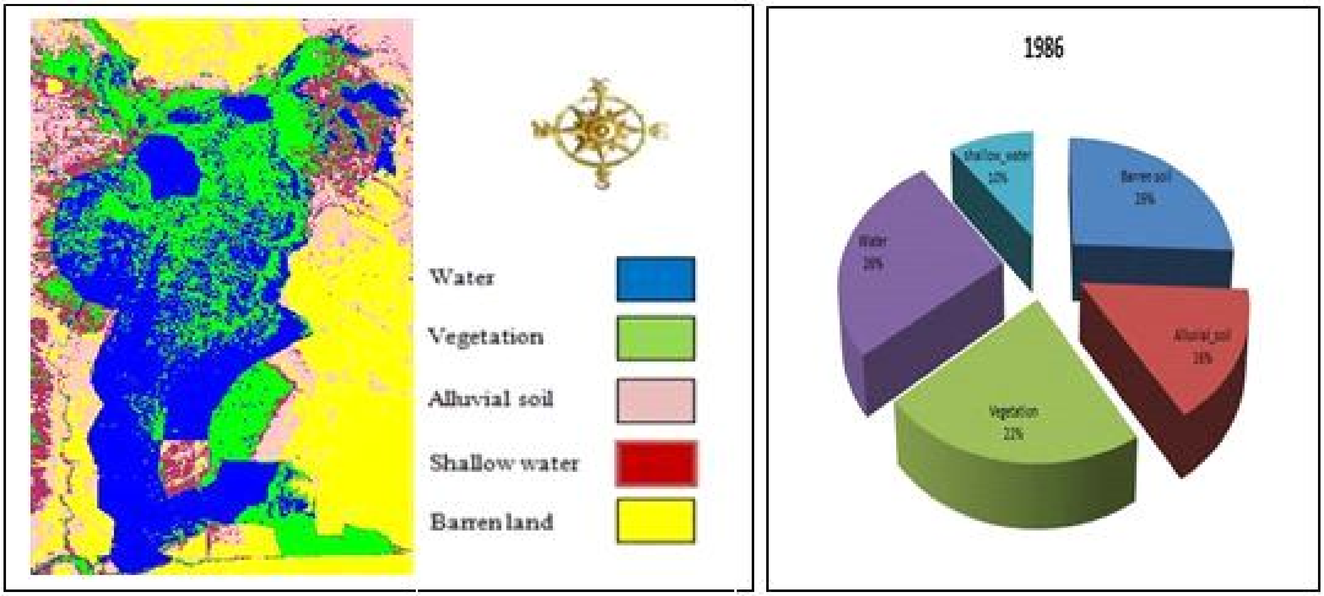

Fig. 8: Supervised classification using (Maximum Likelihood classifier) and the Percentage of each class in the year (1986).

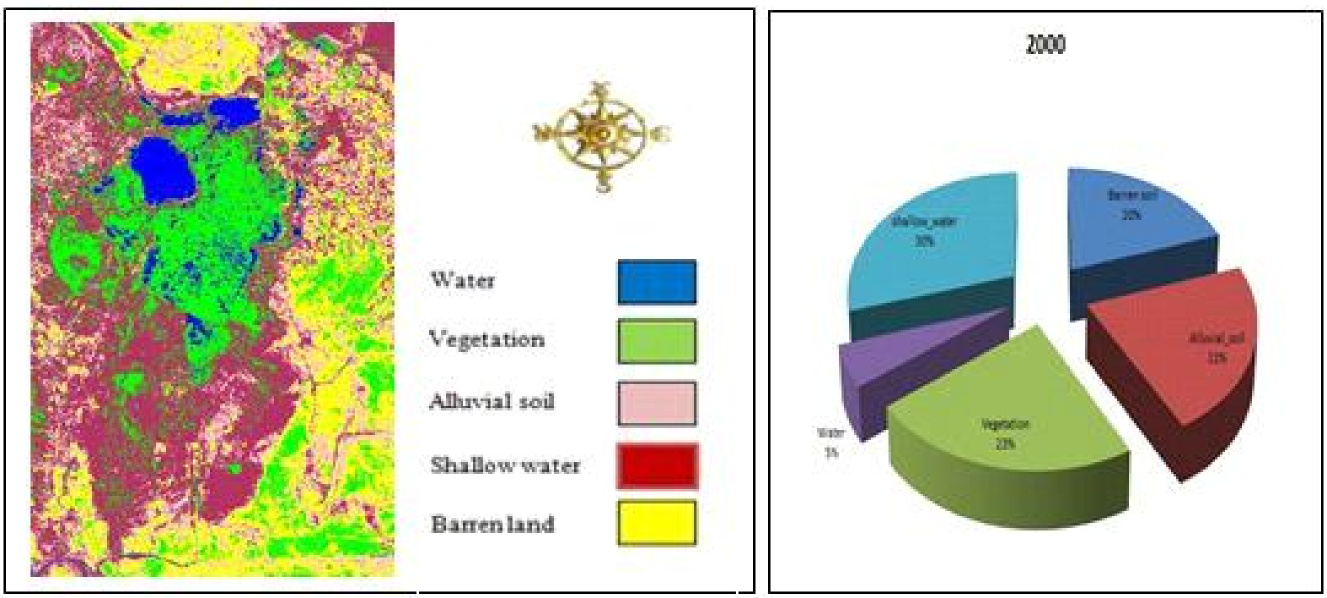

Fig. 9: Supervised classification using (Maximum Likelihood classifier) and the Percentage of each class in the year (2000).

Table 1: The change in the years 2000, 2018 compared with 1986 and the change in the year 2000 compared with 2018 using the Modified Spectral Angle Mapper.

Classes	Area (Pixel)1986	Area (Pixel)2000	Area (Pixel)2018	Changes between 1986 and 2000	Changes between 1986 and 2018	Changes between 2000 and 2018
Barren land	10784517.974%	11813619.689%	11425319.042%	102919.5424%	64085.9419%	-2883-3.28689%
Alluvial soil	10264517.108%	11312718.855%	12029120.049%	1048210.2119%	1764617.1913%	71646.332706%
Vegetation	15990726.651%	10733517.889%	11115418.526%	-52572-32.8766%	-48753-304883%	38193.558019%
Water	12049720.083%	10673517.789%	11467119.112%	-13762-11.421%	-5828-4.835%	79367.435237%
Shallow water	10910618.184%	15466725.778%	13963123.272%	4556141.7585%	3052527.9774%	-15036-9.72153%

While the results after inundation marshes show that marsh vegetation, water, and alluvial soil, increase by about 3.558019%, 7.435237%, and 6.332706% respectively. While Barren land and Shallow water decreased by about 3.28689% and 9.72153% respectively in 2018 compares with 2000.

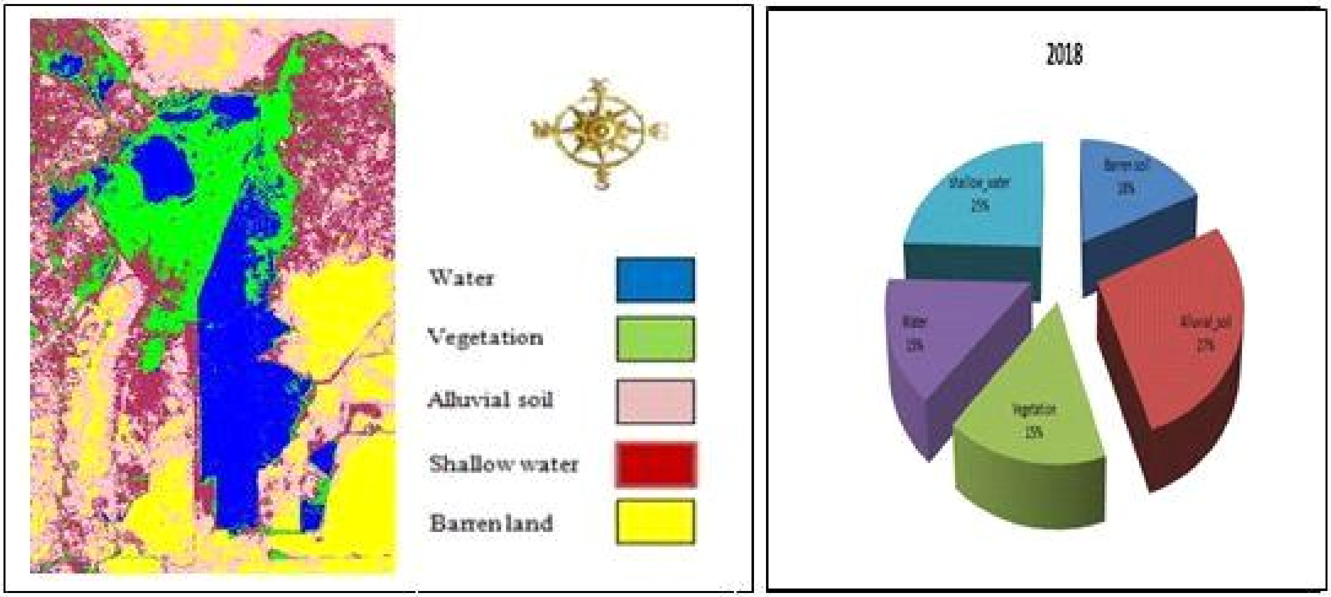

Fig. 10: Supervised classification using (Maximum Likelihood classifier) and the Percentage of each class in the year (2018).

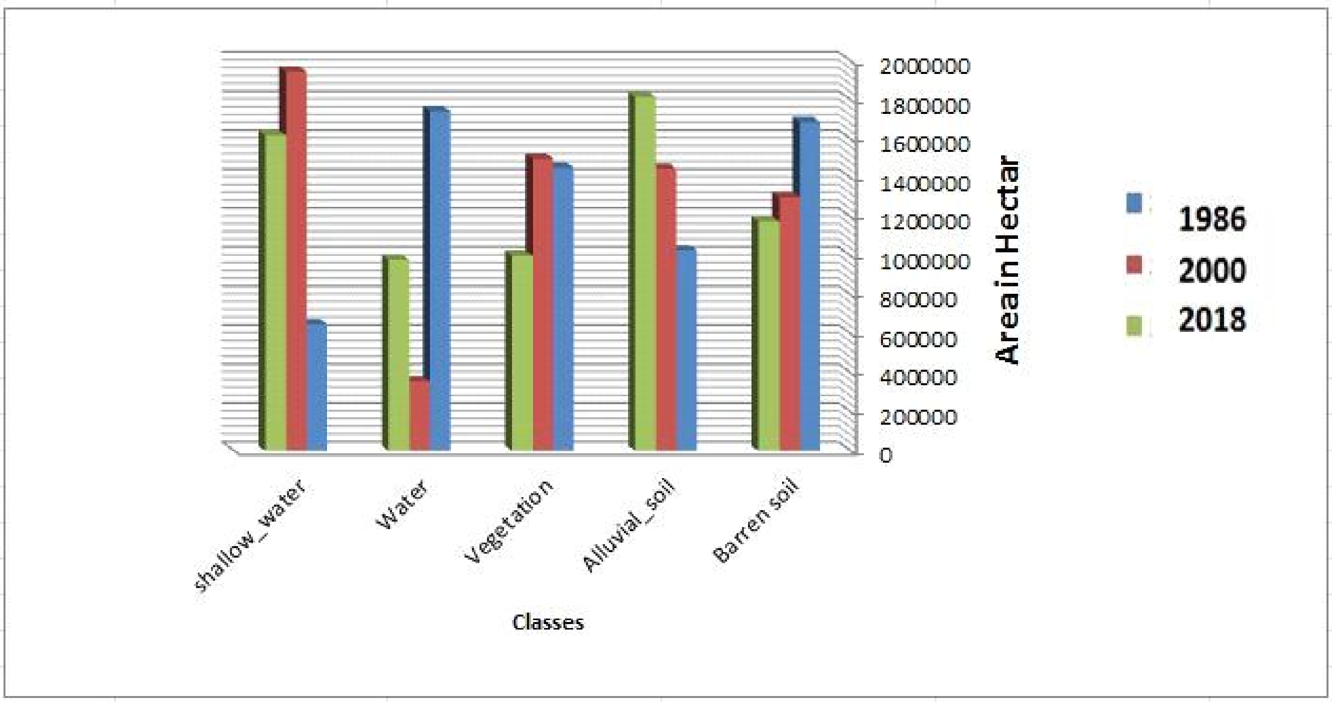

Fig. 11: The change in 1986, 2000 and 2018 using (Maximum Likelihood classifier method).

Table 2: The change in the years 2000, 2018 compared with 1986 and the change in the year 2000 compared with 2018 using Maximum Likelihood classifier method.

Classes	Area (Hectare) 1986	Area (Hectare) 2000	Area (Hectare) 2018	Changes between 1986 and 2000	Changes between 1986 and 2018	Changes between 2000 and 2018
Barren land	168828725.7112%	130281519.8708%	117784817.8549%	-124967-22.8321%	-510439-30.2341%	-385472-9.59208%
Alluvial soil	103063815.6957%	144899922.1005%	181651827.5365%	36751940.59243%	78588076.2518%	41836125.36365%
Vegetation	145429222.8887%	150068122.1476%	100194315.1884%	-498738-3.1898%	-452349-31.1044%	-46389-33.2341%
Water	174263826.5389%	3575165.4529%	98123814.8745%	-623722-79.4842%	-761400-43.6924%	1385122174.4599%
Shallow water	6505029.9066%	194641129.6871%	161922324.5457%	327188199.2168%	968721148.919%	-1295909-16.8098%

Table 3: Error matrix with (producers, users, and overall) accuracy calculations for supervised classification method (MSAM) for the year (1986).

Classes	Barren land	Alluvial soil	Shallow water	Water	Vegetation	Row total	User's accuracy
Barren land	18	2	0	0	0	20	90%
Alluvial soil	1	17	2	0	0	20	85%
Shallow water	0	2	16	2	0	20	80%
Water	0	0	0	19	1	20	95%
Vegetation	0	0	0	2	18	20	90%
Column total	18	21	18	23	19	100	
Producer's Accuracy	94.47%	80.95%	88.89%	82.61%	94.47%		
Total accuracy	88%						

Table 4: Error matrix with (producers, users, and overall) accuracy calculations for supervised classification method (MSAM) for the year (2000).

Classes	Barren land	Alluvial soil	Shallow water	Water	Vegetation	Row total	User's accuracy
Barren land	19	1	0	0	0	20	95%
Alluvial soil	1	18	1	0	0	20	90%
Shallow water	0	0	19	1	2	20	95%
Water	0	0	1	17	2	20	85%
Vegetation	0	0	0	2	18	20	90%
Column total	20	19	21	20	22	100	
Producer's Accuracy	95%	94.74%	90.48%	85%	81.81%		
Total accuracy	91%						

Table 5: Error matrix with (producers, users, and overall) accuracy calculations for supervised classification method (MSAM) for the year (2018).

Classes	Barren land	Alluvial soil	Shallow water	Water	Vegetation	Row total	User's accuracy
Barren land	18	1	0	0	0	20	90%
Alluvial soil	1	19	0	0	0	20	95%
Shallow water	0	0	19	1		20	95%
Water	0	0	1	18	1	20	90%
Vegetation	0	0	0	2	18	20	90%
Column total	19	20	20	21	19	100	
Producer's Accuracy	94.74%	95%	95%	85.71%	94.74%		
Total accuracy	92%						

2. The results from applying supervised (Maximum likelihood) Classification method show that marsh vegetation, water, and Barren land decreased by about 3.1898%, 79.4842%, and 22.8321% respectively. While alluvial soil and Shallow water increase by about 40.59243% and 199.2168%, respectively in 2000 compares with 1986, after drying the marshes. While the results after inundation marshes show that marsh alluvial soil and water increase by about 25.36365% and 174.4599% respectively. While Barren land, vegetation, and Shallow water decreased by about 9.59208%, 33.2341%, and 16.8098% respectively in 2018 compared with 2000.
3. The classification accuracy for the proposed method (MSAM) is 88%, 91% and 92% for the years 1986, 2000 and 2018 respectively.
4. There are clear environmental changes in the Iraqi marshes during the period 1986- 2018, the results indicate a decrease in vegetation and water with the increase in the barren land and alluvial soils and shallow water.

References

Ahmed, K.F., Al-Ghanmi, Amal and H.K. Al-Jabri (2019). The Role of Remote Sensing Techniques (Rs) and Geographic Information Systems (Gis) in the Development of Agricultural Land Uses. *Plant Archives,* **19(1):** 983-988.

Baronia, A., S. Singh, Niranjan, J. Sarup and P.K. Jain (2018). Comparative Study of MLH and SAM Classification Techniques using Multispectral Data of EO-1 Satellite. *International Journal of Applied Engineering Research,* **13(1):** 144-149.

Konstantinos, S., Fikas, I. Pratikakis and T. Theoharis (2018). Ensemble of Panorama-based convolutional neural networks for 3D model classification and retrieval. *Graphics,* **71:** 208-218.

Maria, P. and B. Panagiota (2010). Image Processing: The Fundamentals. *Second Edition, England. Wiley.*

Mausel, P., E. Brondi´zio and E. Moran (2003). Change detection techniques. *Int. J. Remote Sensing,* **25(12):** 2365–2407.

Rafael, C., Gonzalez and R.E. Woods (2017). Digital Image Processing. *4th Edition, Pearson.*

Rafah, R.I. (2016). Classification of Al-Chabaish Marshes Satellite Images using KL- Transformation and Modified Vector Quantization. *MSc. Thesis Submitted to the College of Science, University of Baghdad in Partial Fulfillment of the Requirements for the Degree of Master of Science in Astronomy and space.*

Renuka, M.D. and S.B. Santhosh (2011). Land Use and Land Cover Classification using RGB&L Based Supervised Classification Algorithm. *International Journal of Computer Science and Engineering Technology*. **2(10):** 167-180.

Tinku, A. and K.R. Ajoy (2005). Image Processing: Principles and Applications. *Second Edition, A John Wiely & Sons, M.C. Publication, USA.*