Monitoring of south Iraq marshes using classification and change detection techniques

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Abstract

Digital change detection is the process that helps in determining the changes associated with land use and land cover properties with reference to geo-registered multi temporal remote sensing data. In this research change detection techniques have been employed to detect the changes in marshes in south of Iraq for two period the first one from 1973 to 1984 and the other from 1973 to 2014 three satellite images had been captured by land sat in different period. Preprocessing such as geo-registered, rectification and mosaic process have been done to prepare the satellite images for monitoring process. supervised classification techniques such maximum likelihood classification has been used to classify the studied area, change detection after classification have been implemented between the new classes of adopted images, and finally change detection using matched filter was applied on the region of interest for each class.

مراقبة اهوار جنوب العراق باستخدام التصنيف و تقنيات كشف التغيرات

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الخلاصة

كشف التغيرات الرقمية هي العملية التي تساعد في تحديد التغييرات المرتبطة بخصائص الاستخدام الأراضي و الغطاء الأرضي الطبيعي بالنسبة الى بيانات التحسس النائي المتعددة زمنيا و المسجلة جغرافيا. في هذا البحث تم استخدام تقنيات الكشف عن التغيرات للكشف عن التغيرات الحاصلة في اهوار جنوب العراق لفترتين زمنيتين الاولى بين 1973 الى 1984 و الاخرى بين 1973 و 2014 ، تم الحصول على صور لثلاث اقمار صناعية لاندسات ولفترات مختلفة. تم تهيئة الصور عن طريق تسجيلها جغرافيا و تصحيحها واجراء عمليات رص ولصق الصور ومطابقتها لتحضير صور الاقمار الصناعية لعمليات المراقبة. وقد تم استخدام تقنيات التصنيف الموجه كتصنيف الإمكانية القصوى لتصنيف منطقة الدراسة، تم تنفيذ كشف التغيرات بعد التصنيف بين التصانيف الجديدة للصور المعتمدة، واخيرا تم عمل كشف التغيرات باستخدام فلتر المطابقة وهذا الاخير طبق على مناطق الدراسة لكل صنف.

Introduction

Marsh is one of the most important areas in the south of Iraq. It is considered an economic resource and a tourist resort in the future. Its play an important role for improves the economic, social, biodiversity status in the country, so this research interest with investigate of this region. Many image processing have been adopted to perform this investigation such as change detection and classification. Change detection is the process by which the associated changes in land use and land cover can be detected using geo-registered multi temporal remote sensing data. It's also the Process of identifying differences in

the state of an object or phenomenon by observing it at different times''. The change detection frameworks use multi-temporal data sets to qualitatively analyze the temporal effects of phenomena and quantify the changes. The Remote Sensing data has become a major source for change detection studies because of its digital format suitable for computation, synoptic view, and wider selection of spatial and spectral resolution, [1-4]. The general objectives of change detection in remote sensing include identifying the geo- graphical location and type of changes, quantifying the changes, and assessing the accuracy of change detection results [5-7]. In this paper the change detection techniques have been employed to detect the changes in marshes in south of Iraq for two period from 1973 to 1984 and from 1973 to 2015 using three satellite images had been downloaded from the USGS Earth Explorer and captured by land sat in different period. Preprocessing such as geo-registered, rectification and mosaic process have been done to prepare the satellite images for monitoring process. Different change detection techniques change detection wizard using matched filter with Minimum Noise Fraction MNF transformation methods were applied. Implement remotely sensed supervised classification techniques such as maximum likelihood classification has been used to classify the region of the studied area.

Studied area
Southern Iraq marshes are the studied area which covering an area about 10,500 km^2 and supporting a diverse range of flora and fauna and a human population estimated to be as high as 500,000 persons, for more information see Fig.1. Fresh Water for the Marshes was supplied almost entirely from two major river systems: the Tigris and the Euphrates. At the southern end of the Marshes, these two rivers come together to form the Shatt-al-Arab, which then flows through Basrah and into the Gulf [8]. The marshes from a large triangular region bounded by three major southern cities Nasiriyah to the west, Amarah to the north and Basrah to the south. For east part the Hawiza marsh fed by Kahlah and train full flows from mountains of Iran, the time of train full was between November and May months. While for west part the central and Hammar marshes fed from AL-Garaf canal and some out flows from Al-Euphrates river, the central marshes fed from the western canal of tigress river, al-Hammar marsh fed from the south part of the Euphrates [9]. All the images of the studied area captured by land sat and the properties of the captured image can be shown in Table 1.
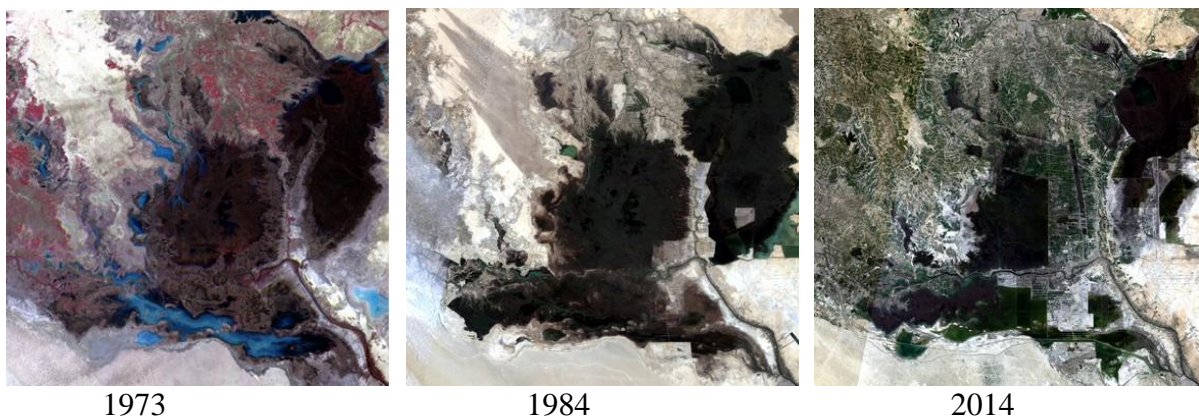

| 1973 | 1984 | 2014 |

Fig.1: Image of the studied area (south Iraq marshes) in different periods.

Table 1: The source information of captured images.

Original images	Source	Spatial Resolution (meter)
Marshes (1973)	Landsat 1-5 Multi-Spectral Scanner (MSS) 28-JUL-1973	30
Marshes (1984)	Landsat 4-5 Thematic Mapper (TM) 20-AUG-1984	30
Marshes (2014)	Landsat 8 OLI (Operational Land Imager) and TIRS (Thermal Infrared Sensor), 12-FEB-2014	30

Preprocessing

Digital image processing was manipulated by the Arcgis and Envi software. The scenes were selected to be geometrically corrected, calibrated, and removed from their dropouts. These data were stratified into 'zones', where land cover types within a zone have similar spectral properties. General, remotely sensed images are gathered by a satellite or aircraft represent the irregular surface of the Earth. Even images of seemingly flat area are distorted by both the curvature of the Earth surface and the sensor being used. In what follows, the mathematical operations concerning the geometrical correction and rectification must be done to remove the associated distortion.

Supervised classification using maximum likelihood

Supervised classification is the procedure most often used for quantitative analysis of remote sensing image data. It rests upon using suitable algorithms to label the pixels in an image as representing particular ground cover types, or classes. A variety of algorithms is available for this, ranging from those based upon probability distribution models for the classes of interest to those in which the multispectral space is partitioned into class-specific regions using optimally located surfaces [10]. Maximum likelihood classification is the most common supervised classification method used to perform the

classification process of this paper. for crop classification involving two sub-classes of wheat it would probably be less of a problem if a particular wheat pixel was erroneously classified into the other sub-class than it would if it were classified as water. To develop the general method we introduce the penalty function, or loss function. [11]

$$\lambda(i|k)P(\omega_k\,|x) \qquad (1)$$

where the pixel comes correctly from class ω_k and $p(\omega_k|x)$ is the posterior probability that ω_k is the correct class for pixels at x. Averaging this over all possible ω_k we have the average loss, correctly referred to as the conditional average loss, associated with labelling a pixel as belonging to class ω_i. This is given by [12]

$$L_x\,(\omega_i\,) = \sum_{k=1}^{M} \lambda(i|k)P(\omega_k\,|x) \qquad (2)$$

and is a measure of the accumulated penalty incurred given the pixel could have belonged to any of the available classes and that we have available the penalty functions relating all the classes to class ω_i. Clearly, a useful decision rule for assigning a label to a pixel is to choose that class for which the conditional average loss is the smallest [10]

$$x\epsilon\omega_i \quad if\ L_x\,(\omega_i)< L_x\,(\omega_j)\ for\ all\ j\neq i \qquad (3)$$

$$(\omega_k\,|x\,) = \frac{P(x|\omega_k\,)P(\omega_k\,)}{P(x)} \qquad (4)$$

where $p(\omega_k)$ is the class prior probability. Using this in (Eq.2) gives

$$L_x(\omega_i) = \frac{1}{P(x)} l_x(\omega_i) \qquad (5)$$

with

$$l_x(\omega_i) = \sum_{k=1}^{M} \lambda(i|k) P(x|\omega_k) P(\omega_k) \qquad (6)$$

Since $p(\boldsymbol{x})$ is common to all classes it is sufficient to decide class membership on the basis of the $l_{\boldsymbol{x}}(\omega_i)$ [13], the results of applying maximum likelihood classifier on the three images (1973, 1984, 2014) can be shown in Fig. 2.

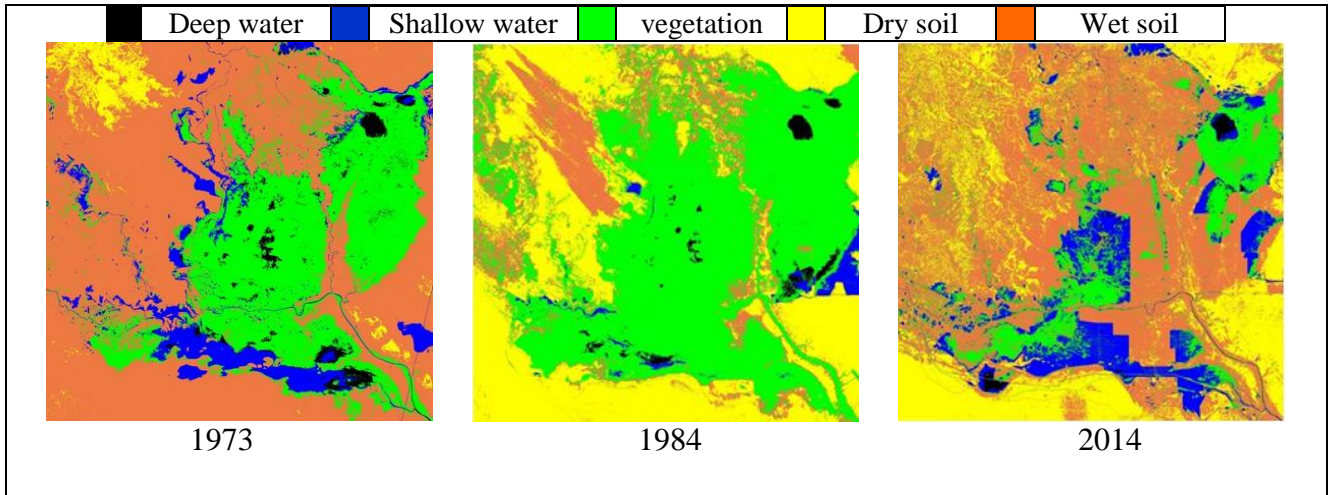| Deep water | Shallow water | vegetation | Dry soil | Wet soil |

Fig. 2: Classified images using maximum likelihood classifier.

In this research each image of multi-temporal images is classified separately and then the classification result images are compared. If the corresponding pixels have the same category label, the pixel has not been changed, or else the pixel has been changed [14].

Change detection after classification technique
The method of change detection after classification is the most simple change detection analysis techniques based on the classification. After

classification compare method can be used to two or more images after registration, including a classification step and a comparing step [15]. In this research, supervised classification using maximum likelihood classifier has been used to implement change detection mask, where the first step is classified the initial image and classify the finale image then using subtractive method between the classes of the two images. The result of applying this technique can be shown in Fig. 3 and Fig. 4 and the statistical properties can be shown in Table 2.
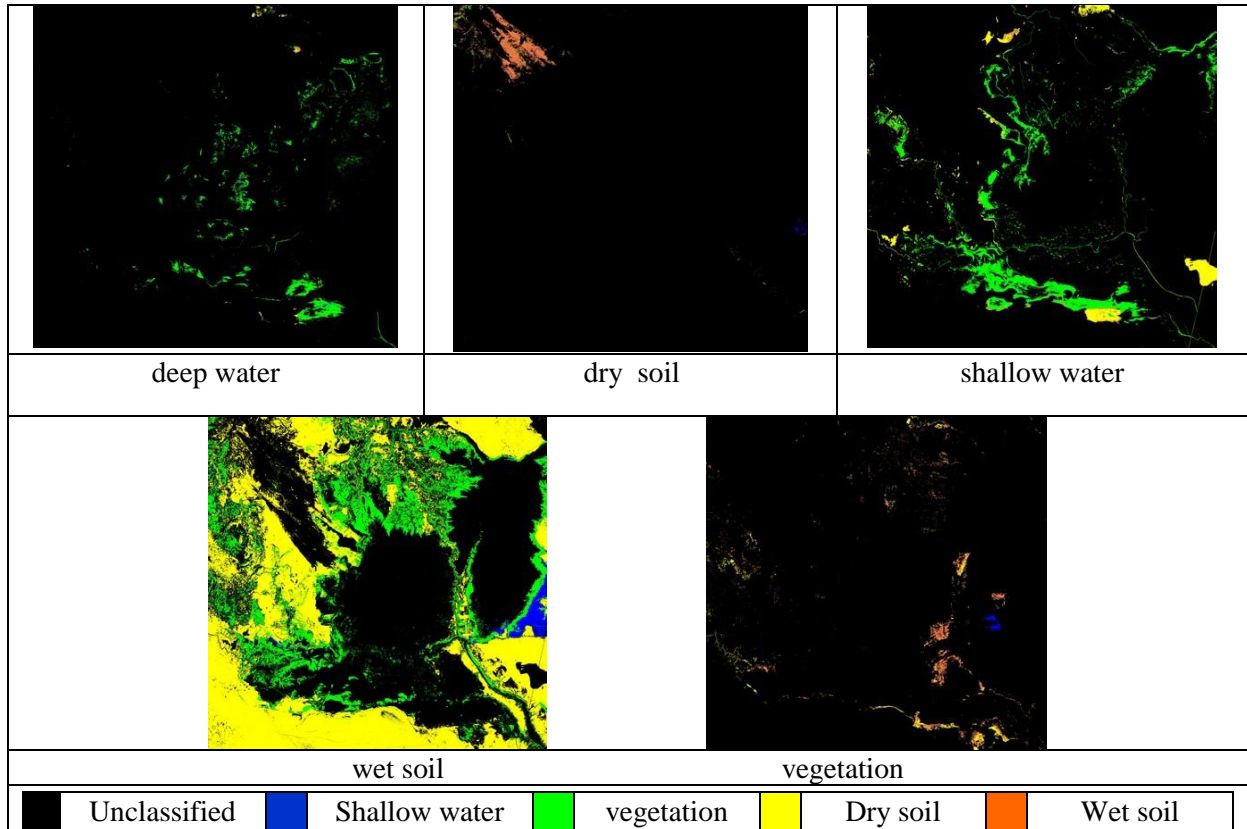
deep water	dry soil	shallow water

wet soil	vegetation

⬛ Unclassified	🟦 Shallow water	🟩 vegetation	🟨 Dry soil	🟧 Wet soil

Fig. 3: Change detection mask using maximum likelihood classifier between marsh 1973 and marsh 1984.

deep water	dry soil	shallow water

wet soil	vegetation

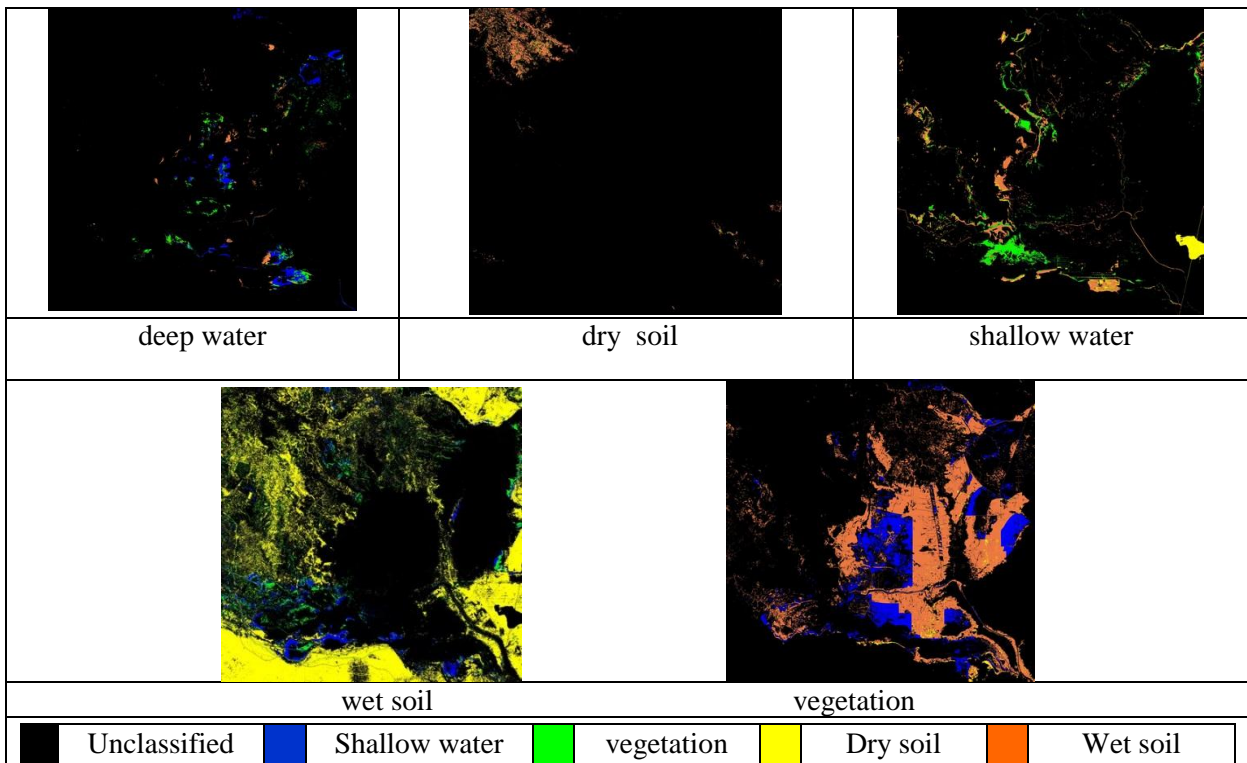| ⬛ Unclassified	🟦 Shallow water	🟩 vegetation	🟨 Dry soil	🟧 Wet soil

Fig. 4: Change detection mask using maximum likelihood classifier between marsh 1973 and marsh 2014.

Table 2: The rate of each class in different periods.

class	Equivalent class painings (points)			Area (Square Km)	
	1973	1984	2014	1973-1984	1973-2014
deep water	2258	395	585	1349.63	1242.55
shallow water	5425	328	300	-6309.11	-5485.94
vegetation	5495	366	838	-1546.37	-5702.2
dry soil	5082	368	390	5126.4	4635.95
wet soil	4606	194	195	1379.46	5309.63

Target detection using Matched Filtering (MF)

Matched Filtering (MF): Finds the abundance of targets using a partial un-mixing algorithm. This technique maximizes the response of the known spectra and suppresses the response of the composite unknown background, therefore matching the known signature. It provides a rapid means of detecting specific materials based on matches to target spectra and does not require knowledge of all the end members within an image scene [16].

A variety of matched filters have been developed which use the Mahalonobis (or statistical) distance between a known target spectrum and a scene pixel as the primary measure of target presence. This simple matrix multiplication can be expressed as [17]:

$$T = (d - \mu)^T \sum{}^{-1} (x - \mu) \qquad (7)$$

Scene pixel being tested (the test pixel), and superscript T denotes the matrix transpose. Noting that the covariance matrix is inverted, we see that Eq. (7) is a spectral matched filter measure of signal divided by the statistical model of background. Thus the detection statistic T may also be considered a measure of signal to background ratio (SBR) [18]. In order to increase distance between target and non-target returns in the detection statistic, matched filters have been derived either by minimizing the total energy of the filter output by the Constrained Energy minimization (CEM) technique [19]. The results of applying target detection using matched filter can be illustrated in Fig.5, 6 and 7 respectively.
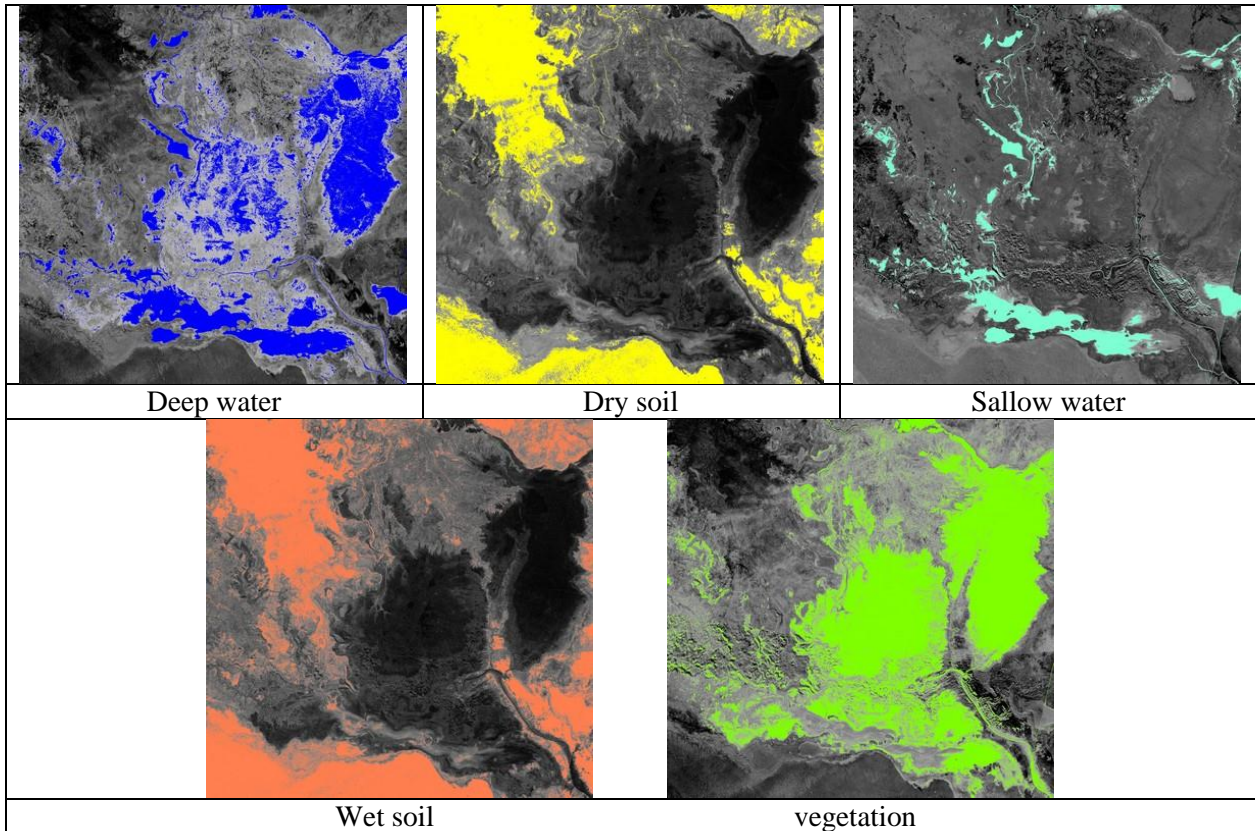
Deep water	Dry soil	Sallow water

Wet soil	vegetation

Fig. 5: Results of target detection using matched filter for marshes (1973).

Deep water	Dry soil	Sallow water

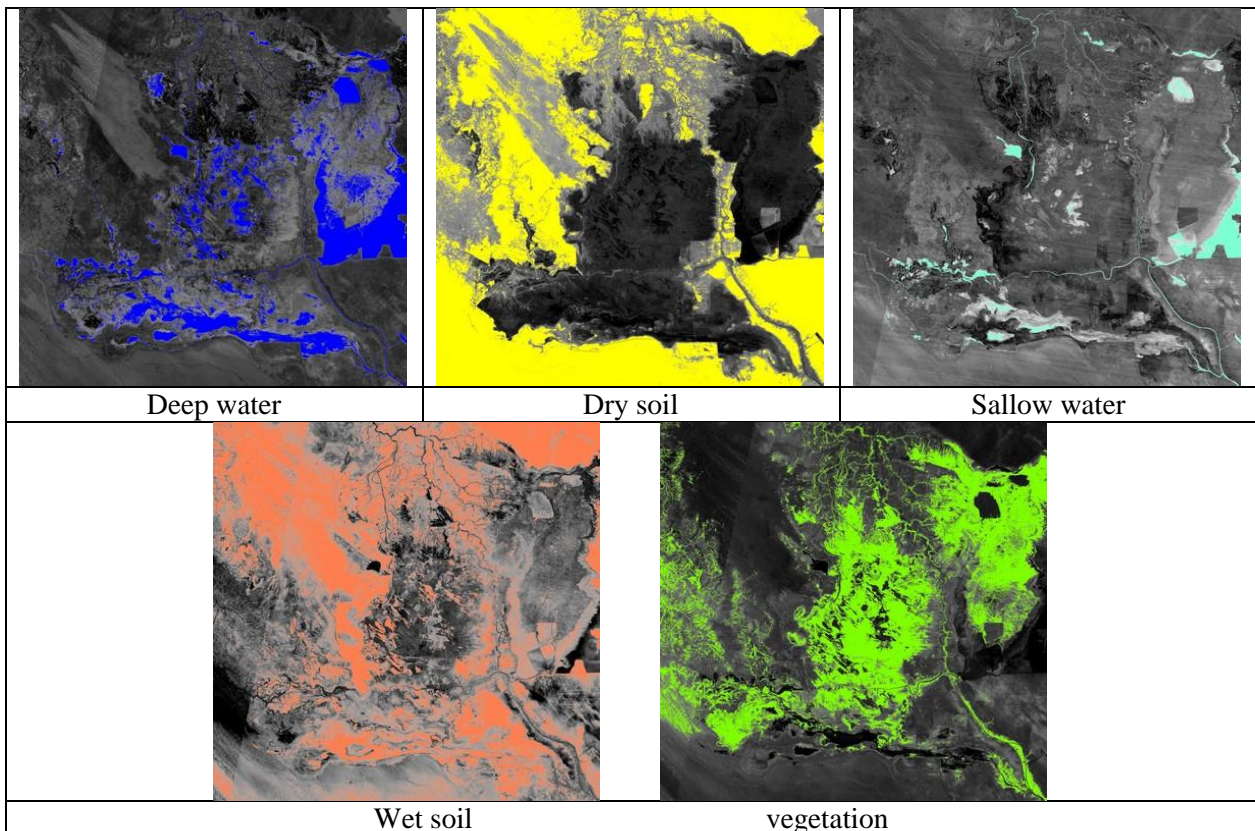|	
Wet soil	vegetation

Fig. 6: Results of target detection using matched filter for marshes (1984).
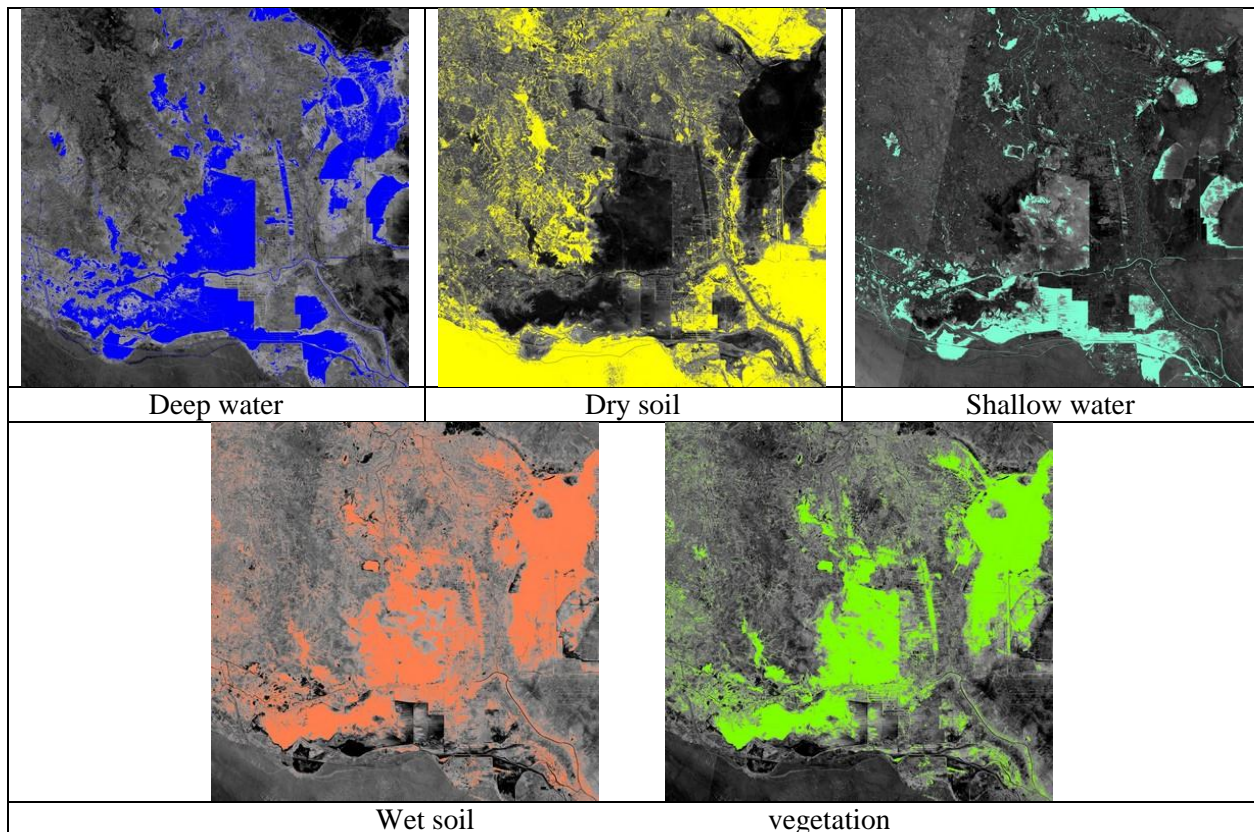
Fig. 7: Results of target detection using matched filter for marshes (2014).

Discussion

Change detection of land use and land cover considers being very important way to study the environmental changes of any region. This paper presents many remote sensing methods to achieve the purpose change detection. Classified the image of the studied area into its classes was implement by using maximum likelihood supervised classification, this classification showed the rate of each class and the statistical distribution of the pixels of each class, the results show that studied area consists of many region (deep water, shallow water, vegetation, dry soil and wet soil), these classes witness many changes during the period from 1973 to 2014 as shown in Fig 2, where it can be noticed that maximum likelihood classifier reduce the size of the water change in marshes 1984 and 2014 and become smaller than marsh 1973. In marsh 1984 it can be showed that the vegetation (reed and papyrus) is prevailing in shallow water than marsh 1973, while in marsh 2014 the size of water and vegetation in general become smaller than the area of marshes 1973 and 1984 as explain in Table 2 because reduce of the source of water which fed these marshes. In other hand the soil area was dominant in most of the area of marsh 2014. The change of each class can be done by change detection mask or change detection after classification, where each class of the first classified image will be subtracted from the same class in the second classified image, the results of this technique can be shown in Figs. 3 and 4 and the statistical properties of the changes can be noticed in Table 2. In this technique marsh 1973 consider to be the reference period. In this paper another technique has been presented for background characterization involving the spatial and data in an attempt to improve the separation of target from background in spectral matched filter

detection returns. The detection matching filter has been used to separate each class from the background of each image in different period the results of this detection can be shown in Figs. 5, 6 and 7 respectively. The results show that deep water increase 1242.55 km from the period 1973 to 2014 for south Iraq marshes. While Shallow water decrease 823.17 km in marsh 2014 compared with 1984. In other hand the wet and dry soil witness low change between 1973 and 1984 compared with 2014. Also the area of the vegetation (reed & papyrus) have been reduced through the period from 1973 to 2014.

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