SEPARATING THE TERRAIN COVER OF IRAQI MARSHES REGION USINQ NEW SATELLITE BAND COMBINATION

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ABSTRACT

A band combination (542) has been adopted and applied as a new method to classify the Iraqi marshes regions which they are located in the southern of Iraq using Landsat-5 TM scene. The results of proposed band combination were compared to the standard band combinations which they are selected to classify scene classes (541, 543 and 742). In addition, the results reveal that the standard band combinations are failed to discriminate between the scene classes that due to the aquatic nature of the scene, which makes the spectral response of the different classes very close, thus, they miss-classify the scene. Furthermore, the green band which was used in the proposed band combination enhanced the spectral response to discrimination between the different land cover classes. It was found that the support vector machine technique that performed to classify the scenes was revealed to be a very good classifier. The contribution of this study is obvious as the resulting outcomes can be capitalized as guidelines to separate the land cover classes in the aquatic nature to an accuracy that has been reached to 98% compared with the scene's region of interest.

Keywords: classification, land cover, spectral response, support vector machine.

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فصل الغطاء الأرضي لمنطقة الأهوار العراقية باستخدام توليفة نطاقات جديدة للأقمار الصناعية

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المستخلص

تم اعتماد توليفة النطاقات (542) وتطبيقها كطريقة جديدة لتصنيف مناطق الأهوار العراقية التي تقع في الطرف الجنوبي من العراق باستخدام مشهد Landsat-5 TM. تمت مقارنة نتائج توليفة النطاق المقترحة مع مجموعات توليفة النطاقات القياسية التي تم اختيارها لتصنيف فئات المشهد (541 و543 و742). بالإضافة إلى ذلك، اوضحت النتائج أن مجموعات توليفات النطاقات القياسية قد فشلت في التمييز بين فئات المشهد ويعود ذلك بسبب الطبيعة المائية للمشهد مما يجعل الاستجابة الطيفية للفئات المختلفة قريبة جدًا، وبالتالي فإنها تفشل في تصنيف المشهد. علاوة على ذلك، عزز النطاق الأخضر الذي تم استخدامه في مجموعة النطاق المقترحة الاستجابة الطيفية للتمييز بين مختلف فئات الغطاء الأرضي. وقد وجد أن تقنية آلة متجهات الدعم support vector machine التي قامت بتصنيف المشاهد قد أثبتت أنها مصنف جيد جدًا. إن مساهمة هذه الدراسة واضحة حيث يمكن الاستفادة من النتائج الناتجة كمبادئ توجيهية لفصل طبقات الغطاء الأرضي في الطبيعة المائية بدقة تصل إلى 98٪ مقارنة بالمنطقة ذات الاهتمام بالمشهد.

الكلمات الافتتاحية: التصنيف، غطاء الأرض، الاستجابة الطيفية، آلة متجهات الدعم.

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INTRODUCTION

Many remote sensing systems recorded reflectance values at different wavelengths that commonly include portions of the visible light spectrum, infrared and middle infrared bands, which in effect represent the color of different ground surface materials or land cover types (13). Some of the factors will decrease land reflectance, which are; moisture content, texture (muddy and sandy), surface roughness, the presence of iron oxide and organic matter content, at all wavelengths (10,18). The surface status of land has very different spectral response according to their color, moisture, mineralogical nature and construction (roughness) (8,9). In the shortwave (SWIR) region, the major effect of adsorbed water on land reflectance is an obvious decrease in reflected light working land darker when moistened, especially in the water absorption bands centered at (1.4, 1.9 and 2.7) µm, it is considered the most sensitive to moisture content (3). Those water absorption bands are almost unnoticeable in very dry and sandy land. In addition, muddy land has absorption bands at (1.4 and 2.2) µm (15). In recent years, various methods were implemented to determine the water body for this area based on spectral characteristics (13,6). Spectral reflectance of water body depends on the water's surface type (specular or diffuse), material suspended in the water and water depth. In the visible bands, clear water has less reflectance than turbid water (10,5). In the NIR and MIR regions water increasingly absorbs the light making it darker, which depend on water depth and wavelength (10). If the water contains sediments, or if clear water is shallow enough to allow reflection from the bottom, then a small increase in the water reflection in the near infrared region will occur (15). The plant spectral reflectance is based on the chlorophyll and water absorption bands in the leaf (4). The different gradients of the plant are based on type, leaf structure, moisture content, and plant health (14, 17). There are three main standard band combinations that are used to classify the water from the land or plant or even from the mud, these band combinations are (541, 543 and 742). The mixed band combinations were to get good information for classification analysis and highlight cover land variations (14,15,19). The standard band combinations, in fact, couldn't separate the marshes classes, therefore, a new band combination (542) suggested in this research depending on the nature of the Iraqi marshes which characterize by the aquatic nature of these lands and the presence of plants like reed and papyrus, which it can be used to separate the four main classes (water, mud, plant, and land) apart correctly. Support Vector Machen (SVM) is used as a supervised method to recognize different land cover types in the marshes region. This method should be standing on the physical ground that represents the reflection of land surface features (13,16). The marshes occupied the extensive field of researches such as, in Muhsin (11) studies the objects (water, vegetation, etc.) of the marsh's region have been attended large changes since 1973. These changes were observed using remote sensing techniques (7). Supervised classification (minimum distance classification) was an appropriated technique for studying these changes, Regions of interest for each object of the studied area have been chosen to supply the classes of each image, the studied region specify to be 6 classes (bare land, vegetation (reed and papyrus), water, salt crust, turbid water, and crop) in (MSS-1973, TM-1990, Landsat ETM+ 2002 and MODS-2010). Al-Razaq et al. (2) was studied and monitor the changes that had happened in the main terrain features (water, vegetation, and soil) of Al-Hammar marsh region, using different satellite images with different times (MSS 1973, TM 1990, Landsat ETM+ 2000 and MODIS 2010). K-Means unsupervised classification and Neural Network supervised classification methods were used to classify the satellite images. The adaptive classification was applied supervised classification on the unsupervised classification by ENVI software. Muhsin and Kadhim, (12) was emploies the change detection techniques to detect the changes in marshes at the south of Iraq for two periods the first one from 1973 to 1984 and the other from 1973 to 2014 three satellite images had been taken by Landsat in a different period. Preprocessing such as geo-registered, rectification and mosaic process has been done to ready the satellite images for the monitoring process. supervised classification techniques such maximum likelihood classification has been utilized to classify the studied area, change detection after classification have been applied between the new classes of selected images. The matched filter was used in the region of interest for each class for change detection. Albarakat et al., (1) was examined the impacts of climate change and human activities on the Iraqi Marshes and the relationships between various hydrological variable through the realization of vegetation and water coverage change for three time periods: 1982–1992, 1993–2003 and 2004–2017. Statistical analyses over the last 36 years show a large retrogradation in the vegetation: 68.78%, 98.73, and 83.71% of the green biomass have declined for Al-Hammar, The Central marshes, and Al-Huwaiza, respectively. The AVHRR and Landsat images illustrate a decrease in water and vegetation coverage, which in turn has led to an increase in barren lands. The retraction in water supplies taken by Iraq’s neighbors (i.e., Turkey, Syria, and Iran) has had a sharp impact on water levels. The aquatic nature of the Iraqi marshes as a wetland, make the spectral response of the different land cover classes very close, which make the discriminating between them is very hard, therefore, this study work tries to increase the discrimination ability between the different land cover classes by suggesting new band combination based on using the green band with the shortwave infrared band and the near infrared band.

MATERIALS AND METHODS

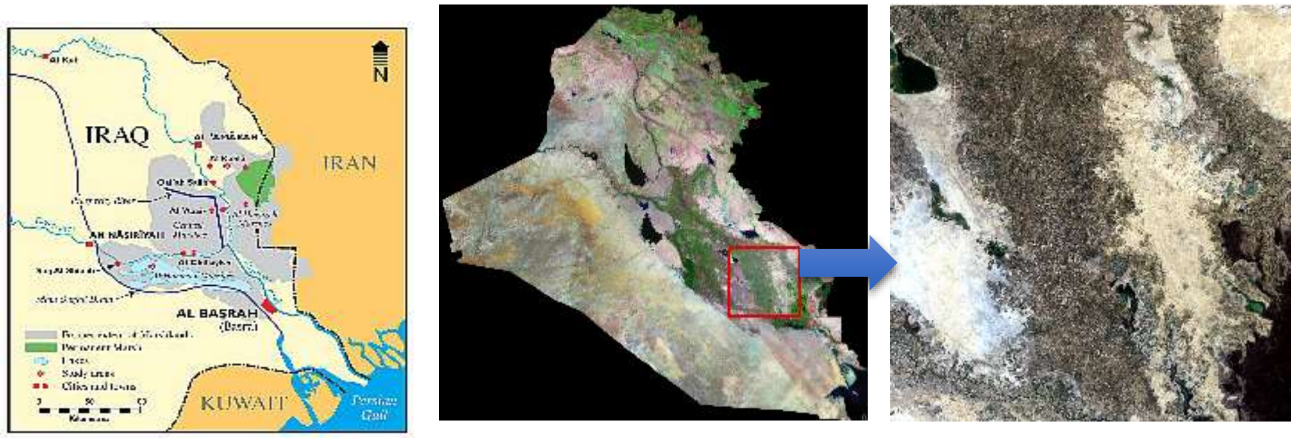
The Iraq marshes region considered as the study site. These wetlands cover the low lands located in the southern sedimentary plain of Iraq, and form a triangle located within the following provinces; Wasit, Babil, Maysan, Al-Qādisiyyah, Dhi Qar, Muthanna and Basra. The map of the Mesopotamian marshes region that illustrate in Figure 1 (a) is divided geographically into three groups;

*A group of marshes located east of the Tigris river and the most important is Al-Hawizeh,

*Marshes west of the Euphrates and most important is Al-Hammar,

*The Euphrates marshes that extend between the Euphrates sub-districts (Hilla and Hindi). It consists of a number of small marshes, which are; Al-ShuweijahH, dlameg, Ibn Najm, Saadia, Ouda, Sunni and Al-Chabaish.

The study site is covering approximately (23088 km^2), within longitude (45° 27' 43.84" to 47° 3' 15.85") E and latitude (32° 23' 56.95" to 31° 1' 11.16") N, as shows in Figure 1 (b & c). The available remotely sensed data was downloaded from the website of the United States Geological Survey (USGS) Center for Earth recourses, observation and science (20). It has been acquired by Landsat-5 TM captured at 17^{th} January 1987. Iraq marshes region is a shallow aquatic nature. The land is mixed with water area in an indistinguishable form, where the cane and papyrus plants are spread in it, these plants grow naturally and extend to large areas within southern Iraq and southwestern Iran.



a B C

Figure 1. (a) A map representing the Iraq marshes region (6), (b) location map of Iraq and (c) True color of (Landsat-5 TM) study scene (20).

Research procedures

This work procedure can be described in a major phases, as follow:

*Radiometric calibration has been performed on the selected scene as image preparation to converts the digital number to reflectance value at top of the atmosphere (TOA) method.

*Select nine training set (referred to as Regions of Interest “ROIs”) are adopted in each of standard and the proposed band combinations to classify the marshes scene with a supervised manner. Which are; very deep water, deep water, shallow water, dense plant, sparse plant, muddy land, sandy land, mineral land, and dry land.

=*The Support Vector Machen (SVM) is implemented to classify the mashes scene depending on the selected region of interest that collected for each band combination.

*The area, percentage, classification accuracy and error matrix are computed of each class in the classified image for each band combination.

*Change detection between proposed with standard band combinations are calculated.

RESULTS AND DISCUSSION

Marshes are considered as a very hard place for classification, due to its aquatic nature in which spectral response of mainland cover classes, water, mud, plant, and the land is very close, which make it very hard to classify the region correctly. Iraqi marshes are an unstable environment in which the amount of the main four classes variant with the time, therefore, in order to determine the amount of each class we need to classify each class correctly. Prior knowledge of the characteristics and spectral response of these classes of the marsh’s region is the basis for classifying and identifying terrain features on satellite images. The spectral response (absorbance) of the Landsat-5 wavelength bands is used to determine the classes as a spectral signature to identify them, as shows in Table 1.

Table 1.The spectral absorbance response for terrain features

Spectral band	Absorbance				
	Band No.	Water	Mud	Plant	Land
MIR_2	7	Very High	High	Very High	Very Low
MIR_1	5	High	High	High	Low
NIR	4	High	High	Low	Low
Red	3	High	Low	High	Low
Green	2	High	High	Low	Low
Blue	1	Low	High	High	High

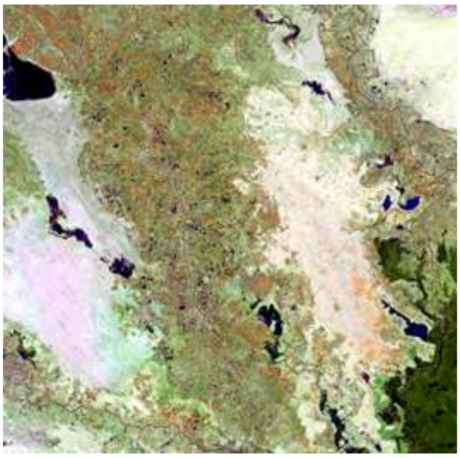
The classes spectral response (signature) of each band combination was differed due to differences in the used band's wavelength, these differences in the standard band combinations (541, 543 and 742) is highlighted with light orange comparing with the proposed band combination (542) shaded with light green, as illustrate in Table 2.

Table 2. The spectral response for different band combination, according to Table 1.

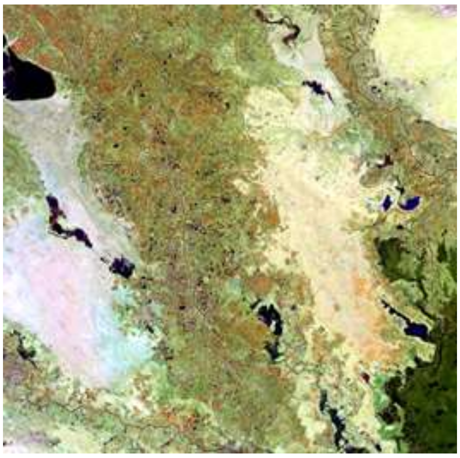
Band combination	Water	Mud	Plant	Land
541	HHL	HHH	LLL	HLH
542	HHH	HHH	LLL	HLL
543	HHH	HHL	LLL	HLH
742	VHHH	HHH	LLL	HLL

***VH ≡ Very High, H ≡ High, L ≡ Low.**

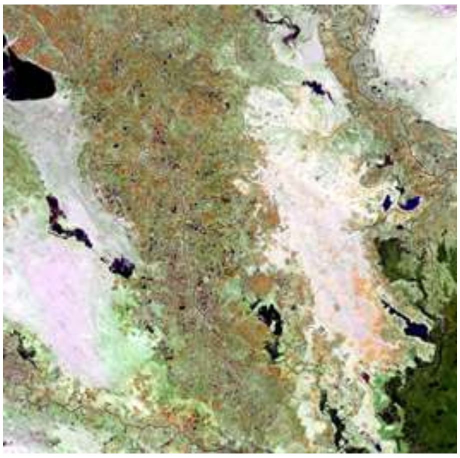
Figure 2 illustrates the pseudo image of the band combinations of the standard and the proposed. The parameters used in the SVM classifier and classification results are shown in Table 3 and figure 3. The outcome of SVM classification after assigning the classes with suitable colors, are shown in table 4: very deep water (black), deep water (blue), shallow water (cyan), dense plant (dark green), sparse plant (bright green), muddy land (brown), sandy land (orange), mineral land (pink) and dry land (yellow)



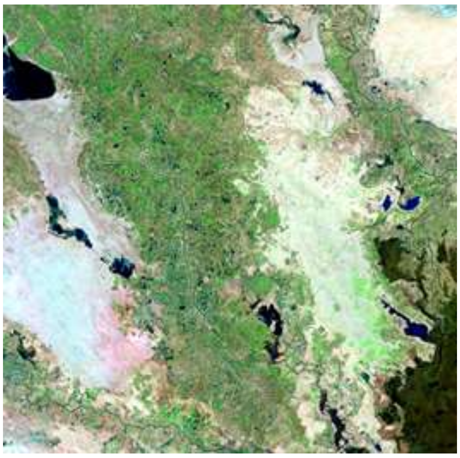
542



541



543

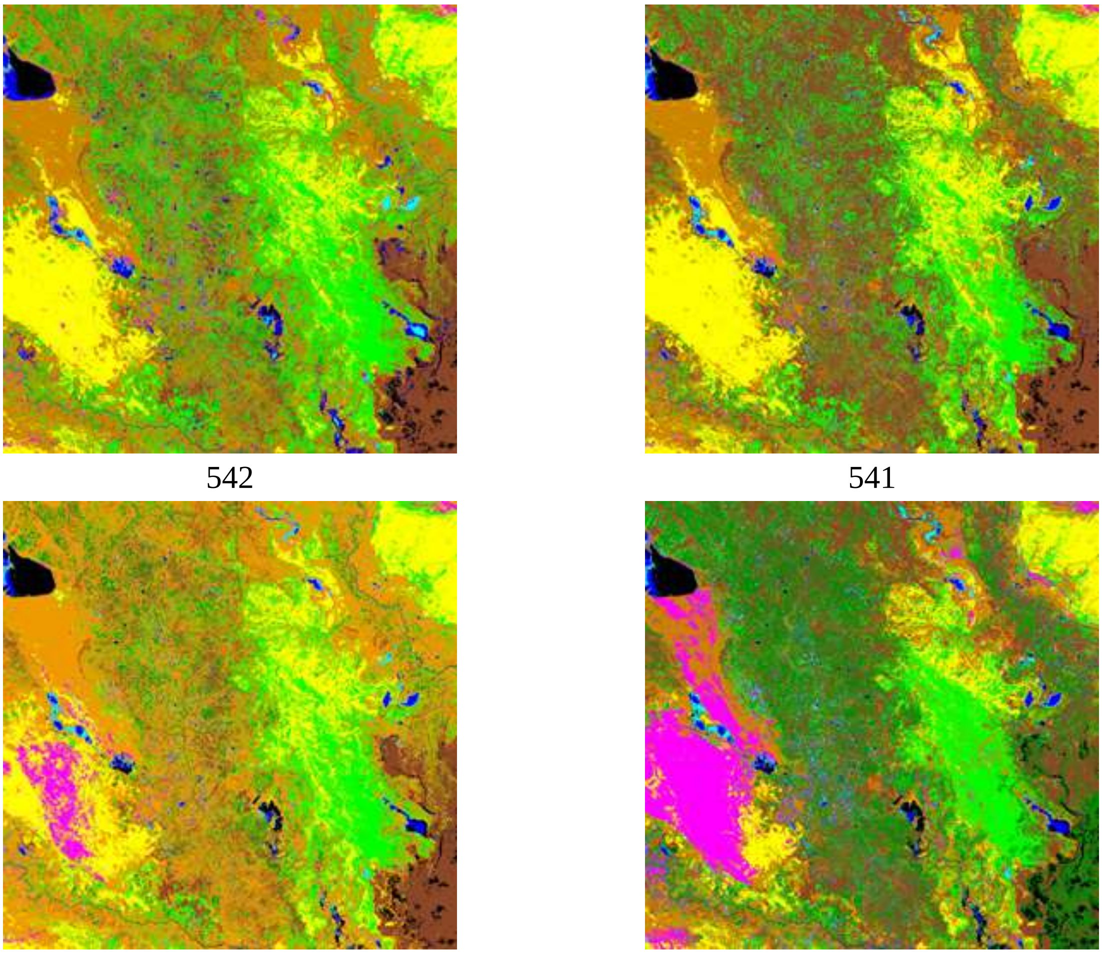


742

Figure 2. Pseudo images of the proposed and three standard band combinations of the scene.

Table 3. The support vector machine classification parameters.

Gamma In Kernel Function	penalty parameter	Pyramid levels	Classification Probability Threshold
0.1	100	0	0



542 541

543 742

Figure 3. Support vector machine supervised classification results for each band combination of the scene.

The area and the percentage of each class in the classified image for each band combination are calculate in Table 4. The calculated class's area is variant to the band combination which reflects the interference of the classes with each other, especially in the sparse plant, muddy land, sandy land, and dry land, as shown in Figure 4.

Table 4. Percentage areas of each class within the classified images for proposed and the three standard band combinations, (illustrated in figure 3).

Class	Color	542		541		543		742	
		Percentage %	Area (km^2)	Percentage %	Area (km^2)	Percentage %	Area (km^2)	Percentage %	Area (km^2)
Very deep water		**1.393**	**322**	**1.672**	**386**	**1.867**	**431**	**2.483**	**573**
Deep water		**2.276**	**525**	**1.083**	**250**	**0.871**	**201**	**1.056**	**244**
Shallow water		**0.967**	**223**	**1.457**	**336**	**1.447**	**334**	**2.118**	**489**
Dense plant		**2.898**	**669**	**1.466**	**339**	**4.291**	**991**	**18.102**	**4180**
Sparse plant		**23.554**	**5438**	**19.567**	**4518**	**15.362**	**3547**	**15.506**	**3580**
Muddy land		**13.803**	**3187**	**36.113**	**8338**	**12.544**	**2896**	**25.03**	**5779**
Sandy land		**37.858**	**8741**	**19.851**	**4583**	**44.936**	**10375**	**18.162**	**4193**
Mineral land		**1.506**	**347.62**	**0.95**	**219**	**2.784**	**643**	**9.715**	**2243**
Dry land		**15.746**	**3635**	**17.839**	**4119**	**15.898**	**3671**	**7.827**	**1807**

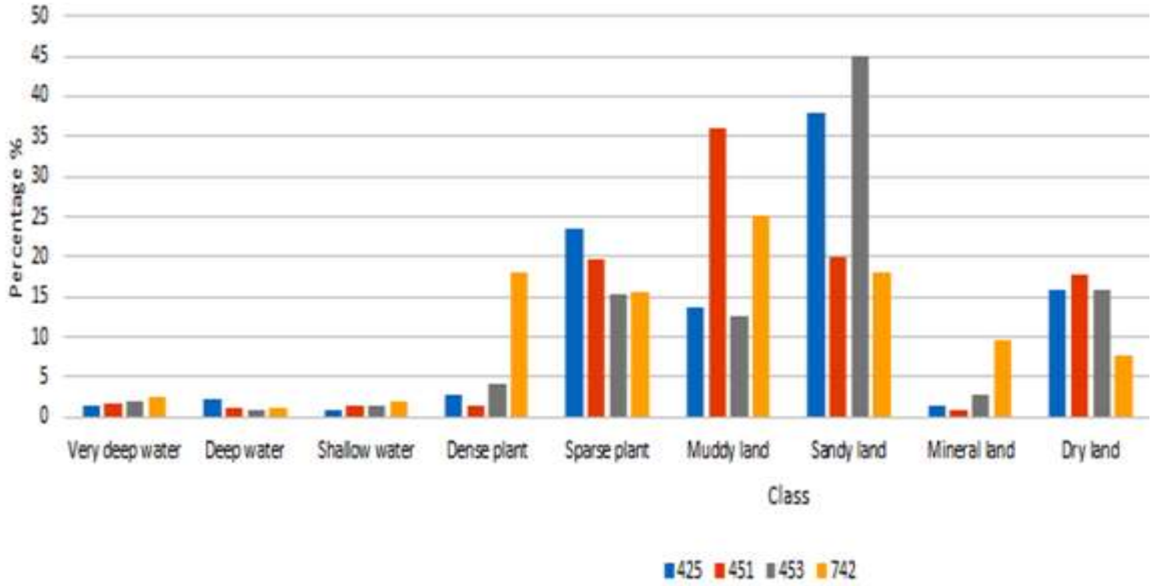


Figure 4. Percentage areas of each class depending on the band combinations

The accuracy of the classification process for both classifications of band combinations (producer accuracy) and the selected region of interest (user accuracy) are calculated, as illustrate in the Table 5. Tables 6-10 show the error (confusion) matrix, the commission and omission values of each class for each band combination of the classified image to illustrate the agreement between accuracy values for both producer and the user which lead to high accuracy in classifying the marshes scene.

Table 5. Producer's and User's accuracy for accuracy assessment of each class within the classified images for proposed and three band combinations

Class	542		541		543		742	
	Produced Accuracy	User Accuracy	Produced Accuracy	User Accuracy	Produced Accuracy	User Accuracy	Produced Accuracy	User Accuracy
Very deep water	100	99.22	97.24	99.62	100	100	93.05	97.98
Deep water	78.21	87.93	99.76	97.88	100	98.89	97.96	92.83
Shallow water	89.51	81.78	97.95	96.62	97.97	98.98	99.39	95.94
Dense plant	96.11	94.82	95.39	96.35	97.31	98.11	98.19	96.52
Sparse plant	92.59	95.8	94.66	93.15	98.59	97.99	94.52	96.92
Muddy land	97.51	98.65	98.19	98.91	99.9	99.9	97.12	97.02
Sandy land	99.43	97.23	98.62	98.17	99.93	99.87	92.79	93.45
Mineral land	97.33	96.23	91.16	95.38	97.42	99.71	94.63	99.46
Dry land	100	99.26	100	100	100	100	99.18	98.87

Table 6. Error matrix of the proposed band combination (542).

	Class	Reference Image (pixels)									
		Very deep water	Deep water	Shallow water	Dense plant	Sparse plant	Muddy land	Sandy land	Mineral land	Dry land	Total
SVM Classification (pixels)	Very deep water	100	0.64	0	0	0	0	0	0	0	10.61
	Deep water	0	78.21	9.9	0	0	0	0	0.38	0	11.54
	Shallow water	0	21.15	89.51	0	0	0	0	0.38	0	15.18
	Dense plant	0	0	0	96.11	5.47	0	0	0	0	12.46
	Sparse plant	0	0	0	3.72	92.59	0	0	0.38	0	11.4
	Muddy land	0	0	0.15	0.17	0.35	97.51	0.57	0	0	10.75
	Sandy land	0	0	0	0	0.18	2.49	99.43	0.38	0	11.25
	Mineral land	0	0	0.45	0	1.23	0	0	97.33	0	5.51
	Dry land	0	0	0	0	0.18	0	0	1.15	100	11.29
	Total	100	100	100	100	100	100	100	100	100	100
Overall Accuracy		93.89%									
Kappa Coefficient		0.9309									

Table 7. Error matrix of the standard band combination (541).

	Class	Reference Image (pixels)									
		Very deep water	Deep water	Shallow water	Dense plant	Sparse plant	Muddy land	Sandy land	Mineral land	Dry land	Total
SVM Classification (pixels)	Very deep water	100	0.64	0	0	0	0	0	0	0	10.61
	Deep water	0	78.21	9.9	0	0	0	0	0.38	0	11.54
	Shallow water	0	21.15	89.51	0	0	0	0	0.38	0	15.18
	Dense plant	0	0	0	96.11	5.47	0	0	0	0	12.46
	Sparse plant	0	0	0	3.72	92.59	0	0	0.38	0	11.4
	Muddy land	0	0	0.15	0.17	0.35	97.51	0.57	0	0	10.75
	Sandy land	0	0	0	0	0.18	2.49	99.43	0.38	0	11.25
	Mineral land	0	0	0.45	0	1.23	0	0	97.33	0	5.51
	Dry land	0	0	0	0	0.18	0	0	1.15	100	11.29
	Total	100	100	100	100	100	100	100	100	100	100
Overall Accuracy		93.89%									
Kappa Coefficient		0.9309									

Table 8. Error matrix of the standard band combination (543).

	Class	Reference Image (pixels)									
		Very deep water	Deep water	Shallow water	Dense plant	Sparse plant	Muddy land	Sandy land	Mineral land	Dry land	Total
SVM Classification (pixels)	Very deep water	100	0	0	0	0	0	0	0	0	11.16
	Deep water	0	100	1.9	0	0	0	0	0	0	15.12
	Shallow water	0	0	97.97	0	0	0	0	2.29	0	8.76
	Dense plant	0	0	0	97.31	1.41	0	0	0	0	9.49
	Sparse plant	0	0	0	2.69	98.59	0	0	0	0	12.82
	Muddy land	0	0	0	0	0	99.9	0.07	0	0	11.61
	Sandy land	0	0	0	0	0	0.1	99.93	0.29	0	16.88
	Mineral land	0	0	0.13	0	0	0	0	97.42	0	3.82
	Dry land	0	0	0	0	0	0	0	0	100	10.33
	Total	100	100	100	100	100	100	100	100	100	100
Overall Accuracy		99.26%									
Kappa Coefficient		0.9916									

Table 9. Error matrix of the standard band combination (742).

	Class	Reference Image (pixels)									
		Very deep water	Deep water	Shallow water	Dense plant	Sparse plant	Muddy land	Sandy land	Mineral land	Dry land	Total
SVM Classification (pixels)	Very deep water	93.05	2.04	0	0	0	0	0	0	0	13.19
	Deep water	6.95	97.96	0.2	0	0	0	0	0	0	13.77
	Shallow water	0	0	99.39	0.22	0	0	0	4.86	0	11.22
	Dense plant	0	0	0	98.19	5.16	0.1	0	0	0	15.63
	Sparse plant	0	0	0	1.59	94.52	0	0.53	0.38	0	10.08
	Muddy land	0	0	0	0	0	97.12	4.92	0.13	0	10.79
	Sandy land	0	0	0	0	0.21	2.78	92.79	0	0.82	6.27
	Mineral land	0	0	0.41	0	0	0	0	94.63	0	8.26
	Dry land	0	0	0	0	0.11	0	1.76	0	99.18	10.8
	Total	100	100	100	100	100	100	100	100	100	100
Overall Accuracy		96.54%									
Kappa Coefficient		0.9608									

Table 10. Percentage of commission and omission error for accuracy assessment computed for each class of selected band combinations, (illustrated in figure 3).

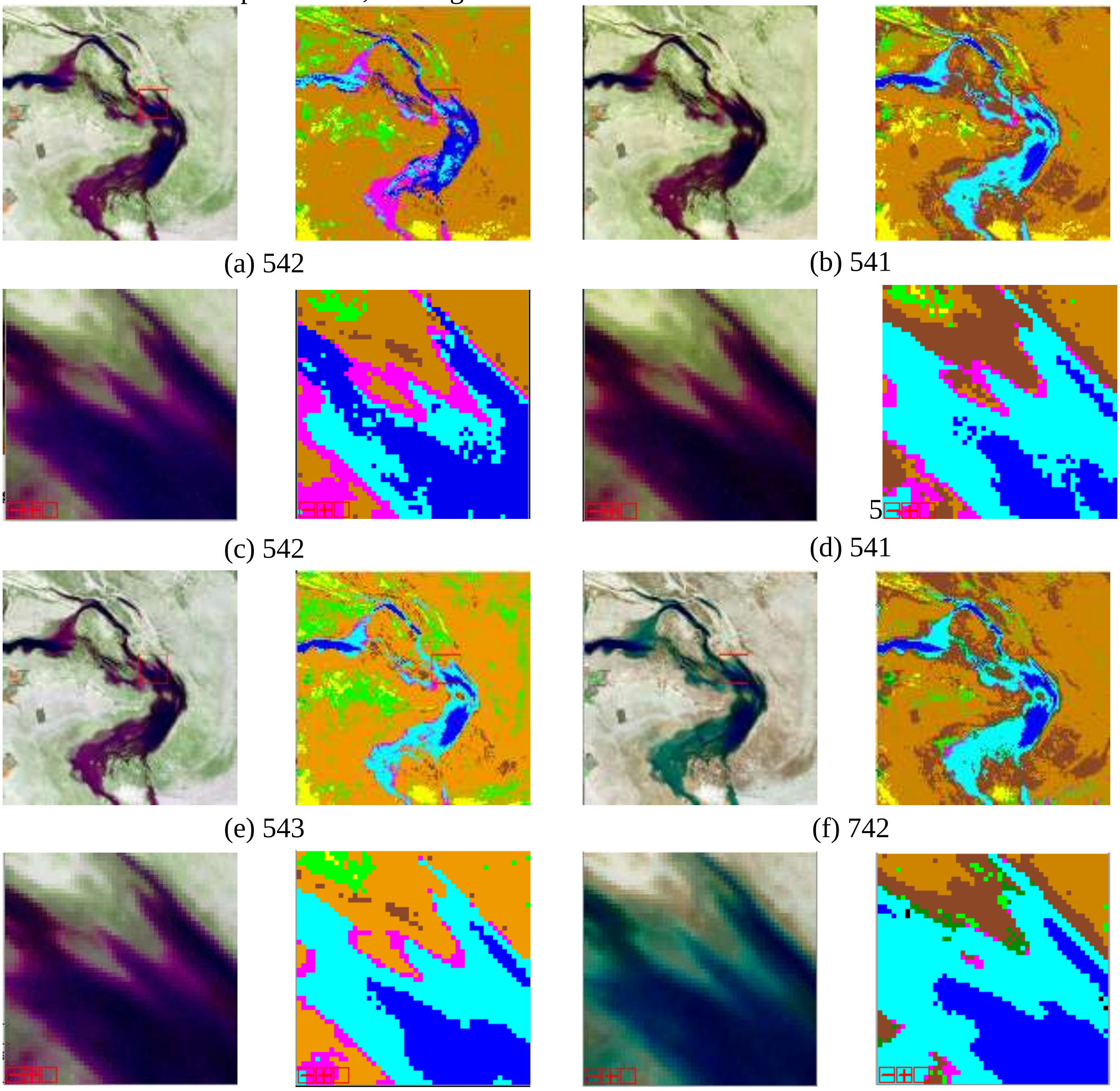
Class	542		541		543		742	
	Commission (Percent)	Omission (Percent)	Commission (Percent)	Omission (Percent)	Commission (Percent)	Omission (Percent)	Commission (Percent)	Omission (Percent)
Very deep water	0.78	0	0.78	0	0	0	2.02	6.95
Deep water	12.07	21.79	12.07	21.79	1.11	0	7.17	2.04
Shallow water	18.22	10.49	18.22	10.49	1.02	2.03	4.06	0.61
Dense plant	5.18	3.89	5.18	3.89	1.89	2.69	3.48	1.81
Sparse plant	4.2	7.41	4.2	7.41	2.01	1.41	3.08	5.48
Muddy land	1.35	2.49	1.35	2.49	0.1	0.1	2.98	2.88
Sandy land	2.77	0.57	2.77	0.57	0.13	0.07	6.55	7.21
Mineral land	3.77	2.67	3.77	2.67	0.29	2.58	0.54	5.37
Dry land	0.74	0	0.74	0	0	0	1.13	0.82

The importance of this research, it deals with the overlap of mud areas with shallow water and vegetation areas in the marshes, where the spectral response so close, so it become difficult to distinguish them as a separate class and thus to calculate the exact amount of water in the marshes. Therefore, the spectral band combination (542) is proposed, which show its ability to distinguish mud regions from water and shallow water from the mud and land to provide correct readings compared to the other adopted standard spectral band combinations, as shown in Figure 5 (a & c). By comparing the classification results of the band combination, as illustrated in Figure 3, we can drive the following notice of the behavior of each band combination:

1- The 541-band combination misclassified the sandy land areas which classified it as mud or plant. Also, its misclassified parts mud areas and classified them as a plant, which indicates that the spectral response of the band combination could not distinguish between plant and mud. Besides that, the classification of water areas is not accurate, which is classified either shallow or deep water, according to Figure 5 (b & d) and Table 11.

2- The 543-band combination couldn’t identify the mud from sandy areas and classified it as sandy areas. Most of the land is classified as sandy and dense plant areas. Its distinction for the water depth was inaccurate, part of the water areas is classified as land, especially shallow water, (Figure 5 (e & g)) and Table 12.

3- Depending on the properties of the reflectance and absorption of the objects as shown in Table 1. The spectral response of band combination (742) is partially different from the other combinations, due to the difference of the wavelength for band MIR_2 from MIR_1 that used in other combinations, such as (541, 542 and 543). The mud class is misclassified (not correct) in some areas near the marshes with the plant class, see Figure 5 (f & h) and Table 13. A large part of the plant is classified as mud, especially the areas near the marshes. Besides that, there is an exaggeration in classification the amount of shallow water, where mud areas are classified as shallow water.



(a) 542 (b) 541

(c) 542 (d) 541

(e) 543 (f) 742

(g) 543 (h) 742

Figure 5. (a), (b), (e) & (f) Samples area of the proposed, and the three standard band combinations and their classified scenes, (c), (d), (g) & (h) the zoom windows to show the classification accuracy for the selected regions

Table 11. Change detection between (542) with (541).

Class	Very deep water	Deep water	Shallow water	Dense plant	Sparse plant	Muddy land	Sandy land	Mineral land	Dry land	Row Total	Class Total
Very deep water	87.105	20.174	0	0	0	0	0	0	0	100	100
Deep water	0	29.785	41.928	0	0	0	0	0.001	0	100	100
Shallow water	0	31.416	52.548	0	0	0	0	15.555	0	100	100
Dense plant	0	0.059	0	47.023	0.402	0	0	0.52	0	100	100
Sparse plant	0	0	0	51.801	73.166	0.032	2.188	0.002	0.001	100	100
Muddy land	12.895	18.566	4.302	1.174	14.799	99.968	47.501	11.175	0	100	100
Sandy land	0	0	0.271	0	4.683	0	49.019	11.672	0.072	100	100
Mineral land	0	0	0.95	0.001	0.22	0	0	58.974	0.008	100	100
Dry land	0	0	0	0	6.731	0	1.291	2.101	99.92	100	100
Class Total	100	100	100	100	100	100	100	100	100	0	0
Class Changes	12.895	70.215	47.452	52.977	26.834	0.032	50.981	41.026	0.08	0	0
Image Difference	20.067	-52.399	50.713	-49.395	-16.925	161.637	-47.566	-36.893	13.292	0	0

Table 12. Change detection between (542) and (543).

Class	Very deep water	Deep water	Shallow water	Dense plant	Sparse plant	Muddy land	Sandy land	Mineral land	Dry land	Row Total	Class Total
Very deep water	90.907	26.416	0.002	0	0	0	0	0	0	100	100
Deep water	0	21.148	40.274	0	0	0	0	0	0	100	100
Shallow water	0.003	34.983	53.21	0	0	0	0.006	8.879	0	100	100
Dense plant	0	0.008	0	98.169	6.1	0	0	0.65	0	100	100
Sparse plant	0	0	0	0.977	58.083	0.169	3.681	0.016	1.498	100	100
Muddy land	8.281	0.075	0	0.718	3.453	80.733	1.187	0	0	100	100
Sandy land	0.809	17.37	6.509	0.136	22.12	19.098	94.011	40.782	2.611	100	100
Mineral land	0	0	0.005	0	0.108	0	0.047	49.652	12.655	100	100
Dry land	0	0	0	0	10.136	0	1.067	0.021	83.236	100	100
Class Total	100	100	100	100	100	100	100	100	100	0	0
Class Changes	9.093	78.852	46.79	1.831	41.917	19.267	5.989	50.348	16.764	0	0
Image Difference	34.068	-61.737	49.61	48.1	-34.779	-9.12	18.695	84.876	0.965	0	0

Table 13. Change detection for (542) and (742).

Class	Very deep water	Deep water	Shallow water	Dense plant	Sparse plant	Muddy land	Sandy land	Mineral land	Dry land	Row Total	Class Total
Very deep water	99.968	36.432	0	0	1.894	0	0	0	0	100	100
Deep water	0	26.993	45.588	0	0.008	0	0.001	0	0	100	100
Shallow water	0	25.407	54.157	0.059	0.066	0.788	46.123	0	0	100	100
Dense plant	0.032	11.141	0.048	36.013	36.335	3.618	5.499	0	99.999	100	100
Sparse plant	0	0	0	43.156	1.626	8.377	0.002	12.356	0.001	100	100
Muddy land	0	0.027	0.202	1.286	60.021	43.424	0	0	0	100	100
Sandy land	0	0	0	16.742	0.049	36.446	0	2.631	0	100	100
Mineral land	0	0	0.006	0.676	0	6.434	48.375	40.594	0	100	100
Dry land	0	0	0	2.068	0	0.914	0	44.419	0	100	100
Class Total	100	100	100	100	100	100	100	100	100	0	0
Class Changes	0.032	73.007	45.843	56.844	39.979	63.554	51.625	55.581	0.001	0	0
Image Difference	78.26	-53.585	119.007	-34.166	81.336	-52.026	545.265	-50.29	524.716	0	0

Classifying the classes in the Iraqi Marshes scene based on the standard band combinations (541, 543 and 742) did not give the right classification for the land cover classes of the area that was included in this classification due to the aquatic nature of the marshes. Therefore, the wrong classification that was created based on the traditional method will make the spectral response of the standard band combinations very difficult to be discriminated according to the distinct classes. The present study is motivated by the need to take into consideration the proposed band combination (542) has been successfully distinguished between the existent classes in the scene of the Iraqi marshes based on the green band of the Landsat-5 TM. Support vector machine (SVM) classifier was proved to be the batter choice since to classify the scene classes with a very high accuracy for all band combinations comparing with the selected regions. The new technique's results demonstrated that the band combination (542) was given 98%.

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