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COMPARISON OF DERIVED INDICES AND UNSUPERVISED CLASSIFICATION FOR AL-RAZAZA LAKE DEHYDRATION EXTENT USING MULTI-TEMPORAL SATELLITE DATA AND REMOTE SENSING ANALYSIS

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ABSTRACT

Al-Razaza Lake is one of the biggest lake in Iraq, and it is considered as a sources of wealth of fish, and flood water retention. The lake suffered from dehydration extent in during the last three decades. In this study; we propose a method to monitor and detect the changes of AL-Razaza Lake in the course of the time between1992–2018usingtime series of Landsat satellite images. In this study different stages of processing and analyzing, noise removal were performed. In doing so, the applicability of different satellite derived indices including normalized difference water index and normalized difference vegetation index were investigated for the extraction of Lake surface water. An unsupervised (K-Means) classification was applied. The results showed that AL-Razaza Lake has been changed rapidly. Two noticeable results show the rapidly decreasing in the Lake area using NDWIs and NDVIs by81.17%and 79.69% with area about 1187.40km^{2}and 1189.24 km^2 respectively. Unfortunately all the dehydration extended areas were replaced by soil, threat the biodiversity and wildlife in this Lake, and left the Lake suffering more for near future.

Keywords: normalized difference water index, normalized difference vegetation index, surface water extraction, wetland change detection, unsupervised classification.

1. INTRODUCTION

Al-Razaza Lake created to flood water retention of Euphrates river flood and water quality maintenance, (Nawal *et al*., 2012). Its water elevation started to decrease from the eighties and rapidly accelerated since 1990 simply because of climate change and atmospheric temperature and decrease the water levels in Euphrates River, it is the main source of Al-Razaza Lake, the water levels in Al-Razaza Lake decreased down to reach 10 m (Rawnaq *et al.*, 2010; Nawal *et al.*, 2012). It is very important to monitor wetlands of Al-Razaza Lake and their adjacent areas (Atasoy *et al.*, 2011; Nawal *et al*., 2012). Remote sensing and Geographical Information Systems (GIS) wereused widely to monitor the wetland degradation with accurate results (Demers, 2005, Wu *et al*., 2006). It is used for wetlands change detection (Zsuzsanna *et al.*, 2005; Anderson, 2005; Wu *et al.,* 2006). Surface water feature extraction is usually performed by extracting water feature individually from satellite images (Zhou *et al.*, 2011; El-Asmar *et al*., 2011; Gong *et al*., 2012; Du *et al*., 2012; Hayder and Alnajjar, 2013; Sexton *et al.*, 2013; Feyisa *et al*., 2014; Hayder *et al*., 2017; Hayder Dibs and Thulfekar, 2018).

Wetland detection by satellite imagery is well known (Carlson and Azofeifa, 1999; Lunetta & Balogh, 1999; Ozesmi and Bauer, 2002; Hayder, 2013; Hayder 2018). Wetlands can be effectively estimated from an aerial photos and/or satellite images (Dahl, 2006). This study aims to propose a technique for estimating the degradation change and dehydration of Al-Razaza Lake form 1990 - 2018 using remotely sensed data and GIS analysis.

2. METHODOLOGY

Different surface water feature extraction and monitoring techniques were tested and the most suitable technique was used to detect and map the spatiotemporal changes dehydration extent of the Al-Razaza Lake. Landsat satellite images acquired from the period1992 up to 2018 were used. These Landsat satellite images were downloaded from (http://edcsns17.cr.usgs.gov) freely. In this research, radiometric calibration, atmospheric correction, geometric corrections were applied to all the Landsat images. Next step was a time series of normalized difference water index (NDWI) and normalized difference vegetation index (NDVI) were calculated and then unsupervised (K-Means method) classification were applied to detect water surface area of Al-Razaza lake and identify wetland degradation maps derived from satellite images by statistical analysis from doing comparison (pixel by pixel) technique between the results of time series of NDWIs, NDVIs and unsupervised classification method. Figure 1 demonstrates the overall flowchart of our method to detect the dehydration extent of Al-Razaza Lake.

2.1 Study area

Al-Razaza Lake is a biggest lake after Al-Thurthar Lake, in Iraq. It is located at the North West of Karbala city and to the north east of Al_Anbar city, in Iraq as seen in Figure-2. It is bounded by 33°10′00”N - 32°20′ 00”N and 43°55′ 00” E - 43°15′ 00”E (Nawal *et al* 2012). AL-Razaza Lake is a part of a valley that consists three lakes AL-Tharthar, AL-Habbaniya, AL-Razzaza and Bahr Najaf (Rawnaq *et al*., 2010). The surface area of this lake about of 1810 km^2 when the water elevation at 40 meters above mean sea level. Part of this lake located in Karbala

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city and the second part located within Al-Anbar city. Around 26 billion-m^3 of water hold this lake (Nawal *et al*., 2012). The water of this lake is supplied by various water sources: the Euphrates River, AL-Habbaniya, Rashidiya, springs and rainwater (Rawnaq *et al.*, 2010). The lake climate is cold in winters and dry and hot in summers (Nawal *et al*., 2012).

2.2 Satellite data

Four Landsat satellite images were processed and analyzed to conduct this research. Two images obtained from the Landsat Thematic Mapper (TM) sensor 4 in August 1992 and Landsat Thematic Mapper (TM) sensor 5 in February 2010, respectively. The third imager was obtained by Landsat Enhanced Thematic Mapper Plus (ETM+) in January 2001, and the fourth once from of Landsat-8 Operational Land imager (OLI) image obtained in May 2018. The TM images has a7 spectral bands and a spatial-resolution is 30m for the bands 1 - 5 and band 7. The spatial-resolution of band 6 equal to120m. The ETM+ imagery has 8 spectral bands and the spatial-resolution is 30 m for bands 1 - 5 and for band 7. The spatial-resolution of band 6 equal to 60 m. The new launched satellite OLI (on February, 2013) provides9 spectral bands and 2 thermal bands (band 10 & 11). All its spectral bands were collected with 30 m as spatial resolution, with 100m for thermal bands and resampled to be at 30 m in the delivered product and the panchromatic band 8 providing 15 m data. All of the obtained Landsat images of 1992, 2001, 2010 and 2018 were collected from the path 169 and row 37. The obtained Landsat data were downloaded from the US Geological Survey (USGS) Global Visualization Viewer. Table-1 and Figure-3 present the specifications of satellite image bands specifications and Landsat TMs, ETM+ and OLI images respectively.

2.3 Pre-processing steps

To make sure the inputted satellite images ready to do further processing, the following steps were performed: atmospheric correction, radiometric calibration, geometric correction, and resampling. Atmospheric correction of image may not be needed in case of using a single image for classification process (Song *et al.*, 2001). However, when using more than one imagery from different satellites the atmospheric correction become mandatory (Lu and Weng 2007; Hayder *et al.*, 2014). Both of atmospheric correction and radiometric calibration were performed based on (Schroeder *et al*., 2006), using the calibration tools in ENVI v 5.0. Ageoreferenced was conducted to UTM projection zone 38 north from using WGS84 datum. All the Landsat images applied in this study were captured with clear atmospheric conditions as seen in Figure3. After that the Landsat satellite images were geometrically corrected to a reference image, Landsat OLI imagery was considered as the reference to perform image to image registration from using the Root Mean Square Error (RMSE) < 0.5 pixels. The 2018 imagery had been georeferenced by using both ground control points and topographic map with RMSE < 0.3 pixel. About 25 ground control points were applied for performing the co-registration of each single imagery.

2.4 Image processing steps

The image processing steps includes two very important steps and they are:

a) Layers stacking,
b) Images resizing (sub-setting),

Layer stacking was performed as the first step of processing stage. Layer stacking was applied to all the Landsat images from using the Layer Stacking tools in ENVI v5.0 software. Then the Landsat images of 1992, 2001, 2010 and 2018 were resized to be satisfied to the (AL-Razaza Lake) study area. The Layer stacking and images resizing were performed to saving time of images processing and reduce the used storage size (Hayder *et al.*, 2014; Hayder *et al.*, 2015). Figure-4 illustrates the images after conducting both of image layer stacking and resizing.

3. MULTI-TEMPORAL OF NDWI & NDVI INDICES

The lake water surface of each image was extracted individually using two different satellite derived indices including the NDWI (Sun *et al.,* 2012), and using the NDVI (Rouse *et al.,* 1973; Feyisa *et al*., 2014; Dibs *et al*., 2016). These indices were used for the water extraction of AL-Razaza Lake (Table-2). For water bodies visual image interpretation, the near infrared (NIR) band is preferred, simply because the NIR is absorbed by water body and it is reflected by the l vegetation and soil (McFeeters, 1996). Therefore, band 4 of Landsat satellite data was used in this study to discriminate water and dry land areas (Komeil *et al.*, 2014).

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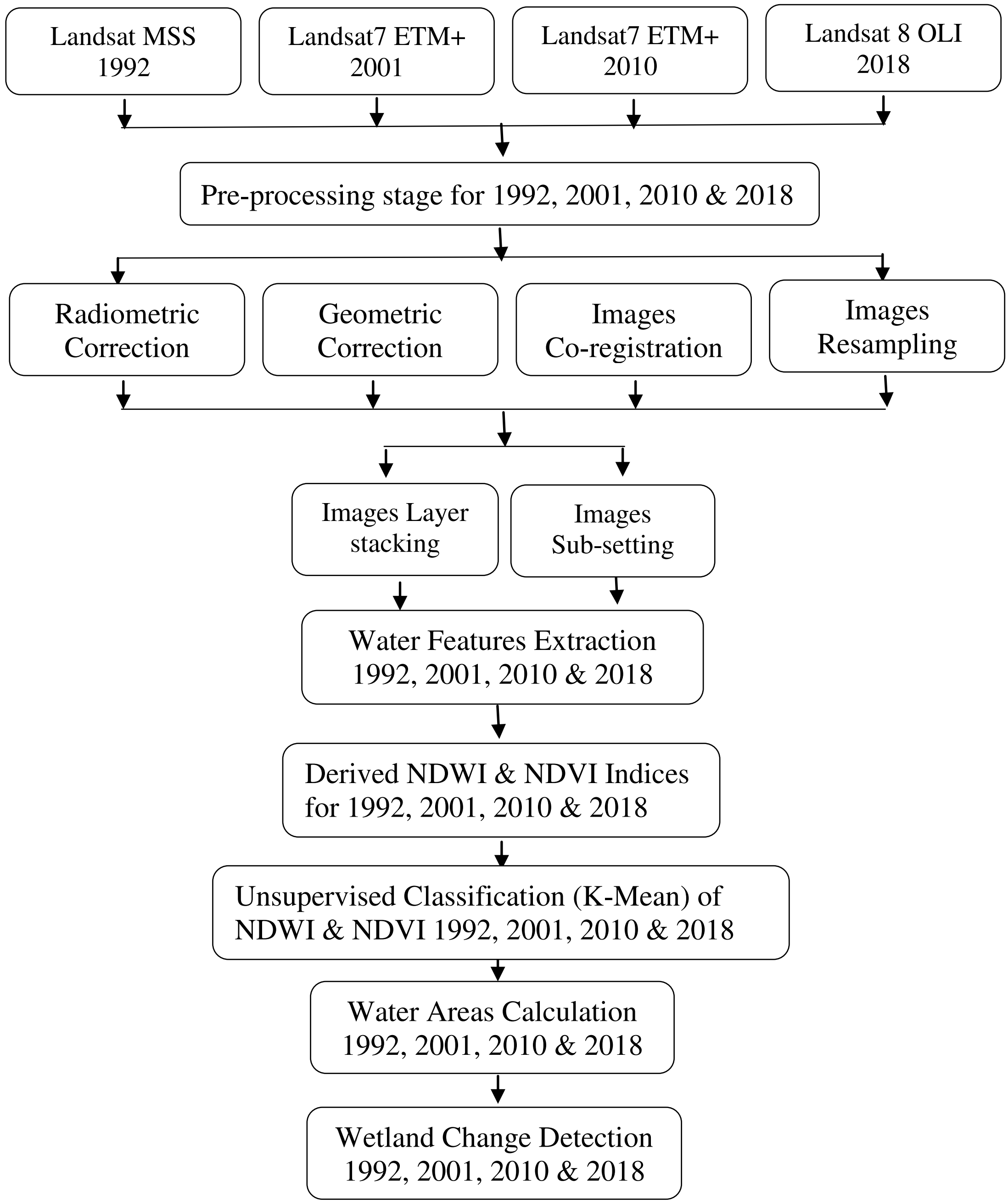

Figure-1. Flowchart showing the overall methods adopted in the study.

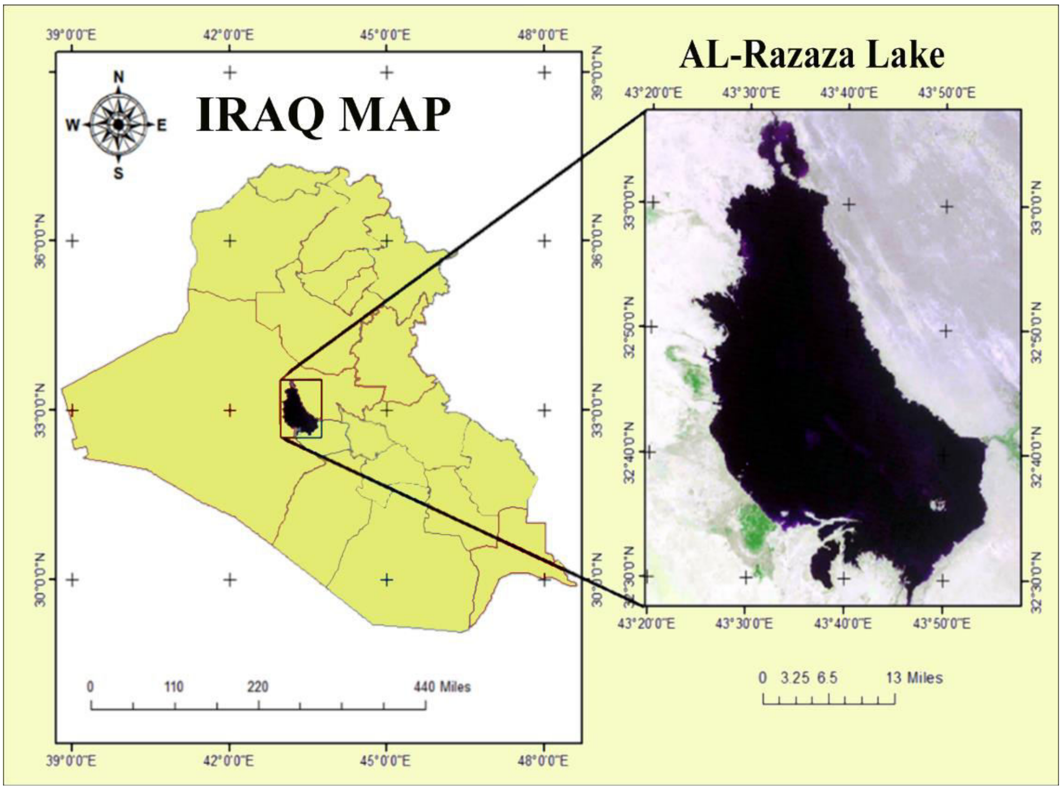

Figure-2. Location map of AL-Razaza lake, Iraq.

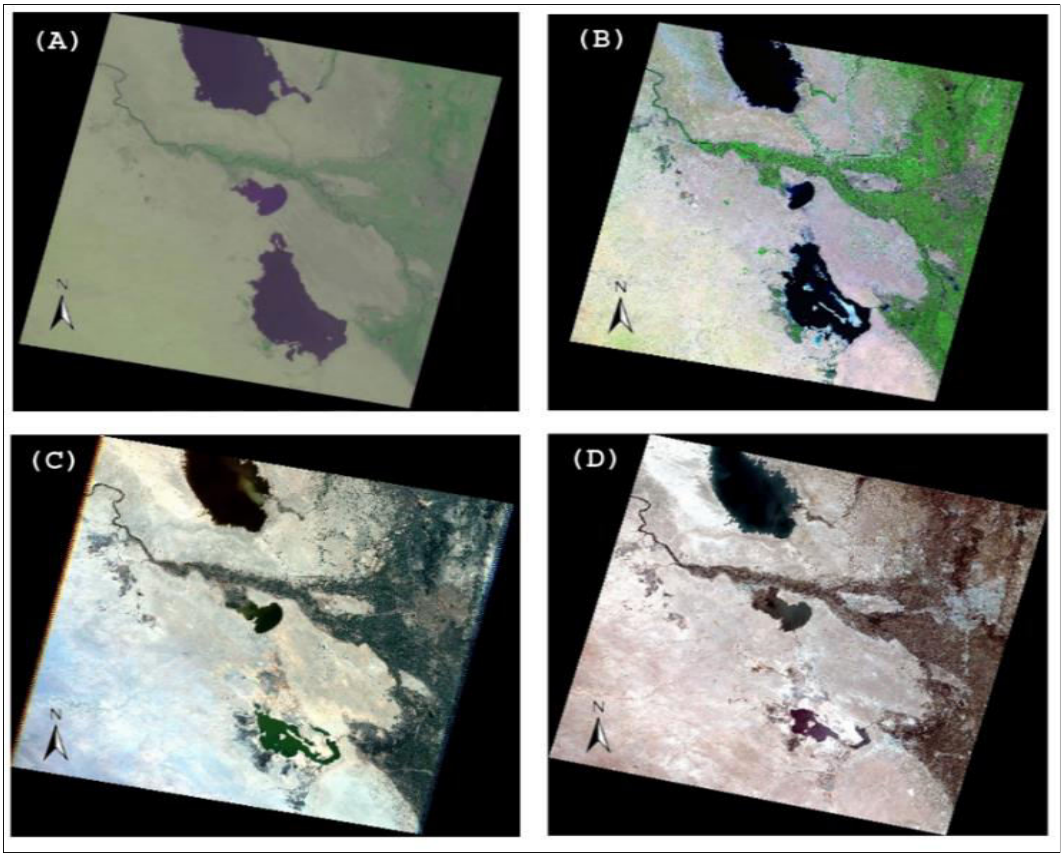

Figure-3. Four Landsat satellite images without corrections: (a) The Landsat TM4 in 1992; (b) The Landsat-7 ETM+ in 2001 (c) The Landsat TM5 in 2010; (d) The Landsat 8 OLI in 2018.

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Table-1. The Landsat TM, ETM+ and OLI data specifications.

Satellite	Path/Row	Acquisition data	Projection datum
Landsat-4	169/037	16/08/1992	UTM, Zone 38N
Landsat-7	169/037	28/01/2001	UTM, Zone 38N
Landsat-5	169/037	15/02/2010	UTM, Zone 38N
Landsat-8	169/037	11/05/2018	UTM, Zone 38N

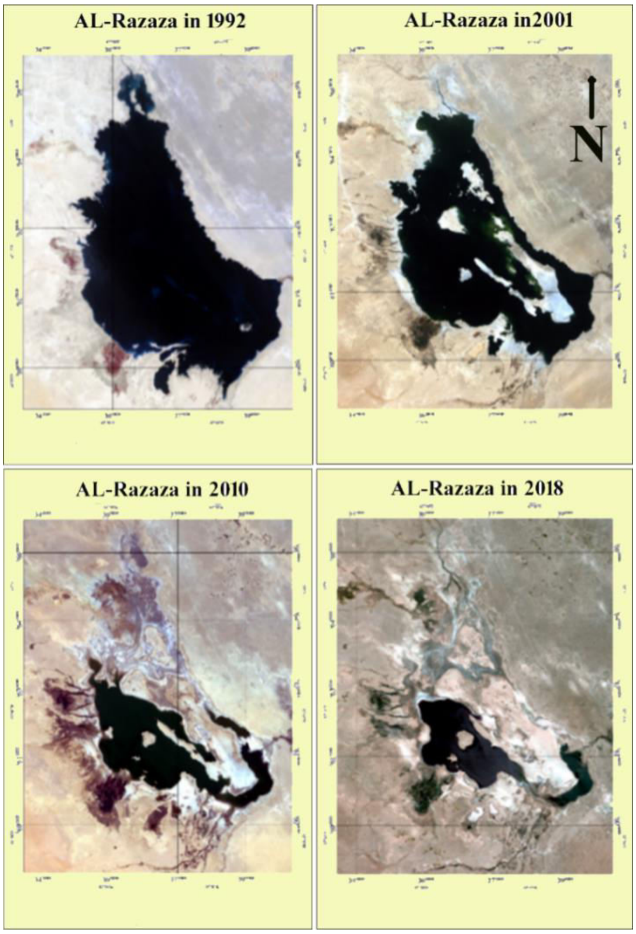

Figure-4. Landsat satellite images after images layer stacking and resizing.

Table-2. Satellite-derived indexes used for water features extraction (in Landsat image: green = band 2, Red = band 3, near-infrared (NIR) = band 4.

Index	Equation	Remark
Normalized difference water index	NDWI= (green-NIR)/(green + NIR)	Water has positive value
Normalized difference vegetation index	NDVI= (NIR - red)/(NIR + red)	Water has negative value

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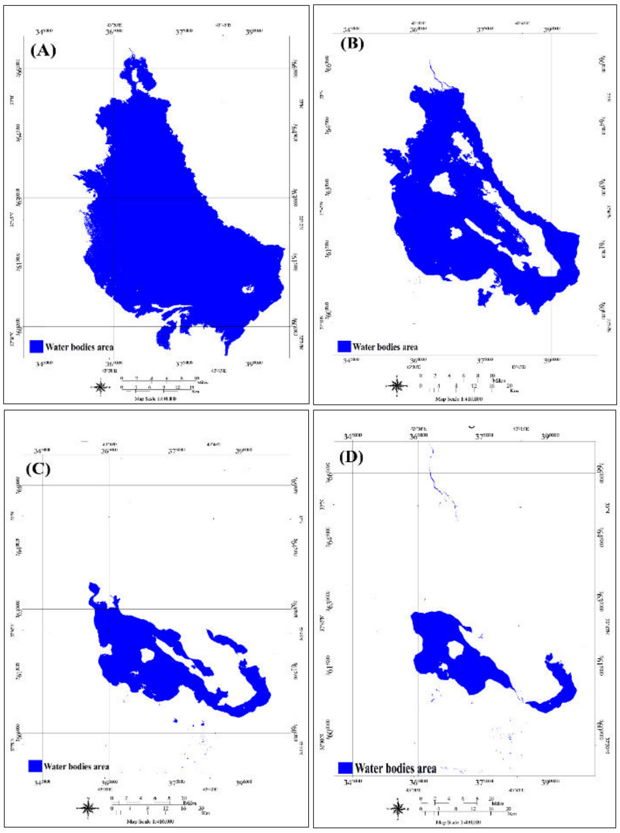

Figure-5. Four classified thematic maps of NDWIs of Landsat satellite images: (a) The classified image of NDWI index in 1992; (b) the classified image of NDWI index in 2001; (c) The classified image of NDWI index in 2010; (d) The classified image of NDWI index in 2018. The blue area represents the water bodies and the white area represents all surrounding areas around the AL-Razaza Lake.

Figures 5 & 6 show the results of NDWIs and NDVIs, it were incapable of extracting the water surface of AL-Razaza Lake, while the NDWIs provided the highest accuracy results regarding (Komeil *et al.*, 2014). The NDWI was considered to model the spatiotemporal changes of Lake AL-Razaza in the period 1992–2018. After calculate the NDVIs and NDWIs for all Landsat data of the study area the unsupervised classification was performed for each single map of NDVI and NDWI for 1992, 2001, 2010, 2010, and 2018. The K-Mean was selected as unsupervised classifier to classify the NDVIs and NDWIs maps, with three classes; water bodies and soil-1 and soil-2). After the classifications conducted the post classification was applied to combine the classes of the all thematic maps and reduce the number of the classes to make them only two classes (water bodies and one class represent the entered area surrounding the water bodies) as seen in Figures 5 and 6. Table-3 presents the area of the Lake from 1992 t0 2018 in km^{2}and the percentage changes got from the statistical result of unsupervised classifications of each the NDVIs and the NDWIs. The results indicate the high performance of the NDWI indices as compared with NDVIs for the surface water extraction from Landsat data (Komeil *et al.*, 2014). Tables 4 and 5 illustrate the statistical results of the Lake surface area in km^2 and the percentage of the Lake dehydration extent from NDWIs and NDVIs respectively.

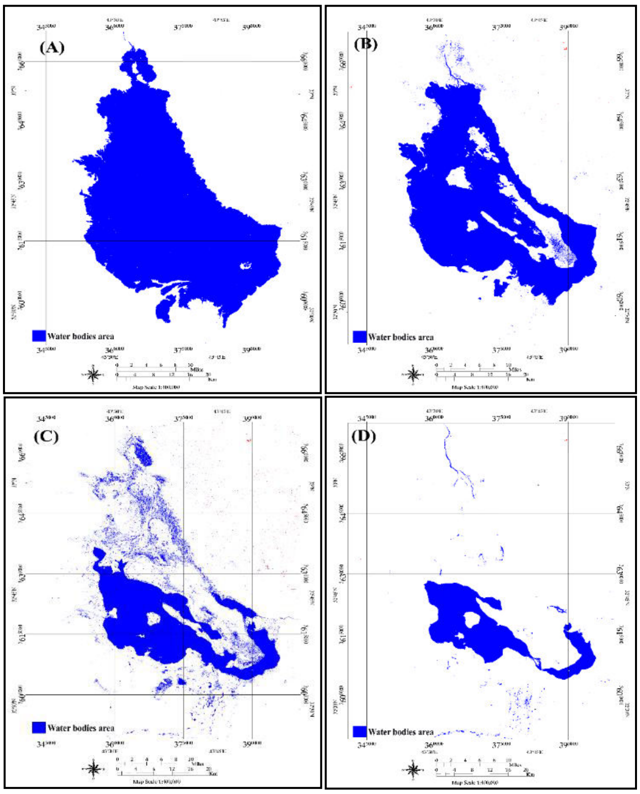

Figure-6. Four classified thematic maps of NDVIs of Landsat satellite images of the study area: (a) the classified image of NDVI index in 1992; (b); the classified image of NDVI index in 2001 (c) the classified image of NDVI index in 2010; (d) the classified image of NDVI index in 2018. The blue area represents the water bodies and the white area represents all surrounding areas around the AL-Razaza Lake.

Table-3. Summary of statistical result of unsupervised classifications of NDVIs and NDWIs of Landsat images.

	1992		**2001**		**2010**		**2018**	
NDVIs	Area in Km^2	(%)	Area in Km^2	(%)	Area in Km^2	(%)	Area in Km^2	(%)
Water body area	1492.30	31.86	1100.75	23.50	584.57	12.48	303.06	6.47
Surrounding area	3191.70	68.14	3585.28	76.50	4099.47	87.5	4380.97	93.5

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						2		3
NDWIs								
Water body area	1462.82	31.23	1070.30	22.85	445.92	9.52	275.42	5.88
Surrounding area	3221.20	68.77	3613.72	77.15	4238.10	90.5 0	4408.60	94.1 2
Total area in Km^2	Total pixels of image = 5204474➔ 5204474 pixels * 30m *30m/1000000 = 4,684.0266							

Table-4. Statistic result of NDWIs of the Al-Razaza lake' surface water area change from 1992-2018.

Year	**Lake surface area** (km^2)	**Lake surface area change** (km^2)	**Total Lake lost water area in** (%)	**Total change area in** (km^2)
1992	1462.82			
		- 392.52		
2001	1070.30			
		- 624.38	81.17%	1187.40
2010	445.92			
		- 170.50		
2018	275.42			

Table-5. Statistic result of NDVIs of the Al-Razaza lake' surface water area change from 1992-2018.

Year	**Lake surface area** (km^2)	**Lost Lake surface area change** (km^2)	**Total Lake lost water area in** (%)	**Total change area in** (km^2)
1992	1492.30			
		-391.55		
2001	1100.75			
		-516.18	79.69	1189.24
2010	584.57			
		-281.51		
2018	303.06			

The NDWIs' result has been considered in this research as more accurate than NDVIs result (Komeil *et al*., 2014). The NDWIs and NDVIs statistical results were summarized in Tables 3, 4 and 5. They are revealed that the lake surface water area by NDWIs were about 1462.82 km^2 in 1992, 1070.30 km^2 in 2001, 445.92 km^2 in 2010 and275.42 km^2 in 2018. The results further show that the lake surface water area was decreased about 392.52 km^2between 1992 and 2001, 624.38 km^2between 2001 and 2010, 170.50 km2 between 2010 and 2018, while the total surface area changes of the lake between 1992 and 2018 were about 1187.40 km2and that means the lake loss around 81.17% of its total area in very short time (over three decades) as indicates in Table 5. As well as seen in tables 4, 5 and 6, these tables demonstrates that the lake surface water area by NDWIs were about 1492.30 km^2 in 1992, 1100.75 km^2 in 2001, 584.57km^2 in 2010 and 303.06 km^2 in 2018. The results further show that the lake surface water area was decreased about 391.55 km^2 between 1992 and 2001, 516.18km^2 between 2001 and 2010, 281.51km^2 between 2010 and 2018, while the total surface area changes of the lake between 1992 and 2018 were about 1189.24 km^2 and that means the lake loss around 79.69 % of its total area over three decades as indicates in Tables 5 &6.The dehydration extent increase dramatically and it has negative impact on the region especially on the climate changes of surrounding area, inadequate water contained the lake, ecosystem, loss wildlife habitat, and increase the soil salinity is a disaster for this lake, Table 6compare between the changes in surface area and percent of AL-Razaza Lake obtained from multi-temporal of unsupervised classifications each of NDVIs and NDWIs.

Table-6. Comparison of relative change between unsupervised classification of NDWIs and NDVIs of AL-Razaza Lake.

Index	**Relative change** (2018 -1992) (%)	**Relative change of area in Km^2**
NDWIs results	81.17	1187.40
NDVIs results	79.69	1189.24

Table-6 presents the percentage and area in Km^2 of relative change of Al-Razaza Lake from 1992 to 2018. The multi-temporal unsupervised classification results show that the Lake loss around 81.17% of the study area, and that equal to 1087.40 Km^2 from generated NDWIs. However, it is loss around 79.69% percentage with area of 1189.24 Km^2 from generated NDVIs

4. CONCLUSIONS

Al-Razaza has been suffered from dehydration extent from 1992 up to 2018. The lake surface level start to decrease to reach 5-10 deep regarding to mean sea level. This study aimed to detect the changes of water surface area of AL-Razaza Lake by using Landsat images for 1992, 2001, 2010 and 2018.Using. By performing a comparison between analyses of conducting a time series of the multi-temporal unsupervised classification of NDWIs and NDVIs result. The statistical results showed an intense decreasing and rapidly changing trend in the lake surface area in the period 1992–2018.The unsupervised classification and the satellite derived indices result confirmed that the Lake lost around 81% of its total area. If such a decreasing trend in AL-Razaza Lake continues, it is very likely that the lake will lose its entire water surface in the near future. Furthermore, this study demonstrated high performance of classification when combine the thermal and infrared bands with the visible bands, and that give an accurate results of classification and increase the overall accuracy and kappa coefficient of classification. This approach has been proven to be effective in detecting the water surface changes in AL-Razaza Lake, Iraq. Accordingly, the method may prove useful in studying other surface waters in the world as well as flood monitoring.

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Conflicts of Interest

The authors declare there are no any conflicts to declare.

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