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Egypt. J. Soil. Sci. Vol. **59**, No. 4, pp. 385-402 (2019)

Egyptian Journal of Soil Science

http://ejss.journals.ekb.eg/

Integration of Land Cover Changes and Land Capability of Wadi El-Natrun Depression Using Vegetation Indices

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THE STUDY objectives were to use vegetation indices techniques for detecting the change of vegetation cover during three periods: from 1984 to 2001, 2001 to 2018, and 1984 to 2018 and to identify the impact of land capability on land cover changes at Wadi El-Natrun Depression, Egypt. Landsat-8 satellite images dated to 1984, 2001 and 2018 were used to detect the changes in land coverin the investigated area (573.53 km^2). Four vegetation indices,including normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), green normalized difference vegetation index (GNDVI) and optimized soil adjusted vegetation index (OSAVI) were used to identify and detect vegetation changes during the last34 years. Ground truth points were collected in 2018 to testthe accuracy of classified images. Forty five soil profiles were examined to represent different geomorphic units created using a digital elevation model (DEM) and Landsat-8image. Modified Storie index was used to carry out land capability evaluation of the investigated soils. Results showed that the vegetation indices determined land cover classes with high over all accuracy (92 > %) and a kappa coefficient greater than 0.9.The soils belonged to grades 2, 3, 4 and 5, representing 0.7, 17.88, 75.15 and 2.09 % of the total area respectively.The low land capability is due to excess of soil salinity, coarse soil texture, shallow soil depth, and poor drainage conditions in addition to the results illustrated that there was a positive correlation between the land capability and extension in vegetation land cover.

Key words: Change Detection, Land Capability, Vegetation Indices, Wadi El Natrun

Introduction

Multispectral remote sensing utilizes the reflected and emitted electromagnetic radiationto get information about the Earth's surface and it is considered as one of the main sources of information about the earth's cover (Lasaponara & Masini, 2012 and Richards, 2013). Therefore, this technology have been widely used to detect and monitor land cover changes at different scales because it provide a wide range of repeatable and cost effective data (Khorram et al., 2012). Change detection technique of land cover and land use is an efficient way for describing the changes observed in each land cover category (Meera et al., 2015 and Alessandro et al., 2016). It is considered a powerful tool for environmental and agricultural planning at different scales (Reddy et al., 2017 and Huang et al., 2019).Vegetation indices (VIs) are a mathematical combination or spectral transformations of surface reflectance at more than wavelength (band) derived to highlight and describe a particular property of Earth's vegetation cover (Shi et al., 2014 and Komeil & Tajul, 2019).There are a great number of VIs that have been proposed and used to detect vegetation land cover changes.They include the normalized difference vegetation index (RNDVI), soil adjusted vegetation index (SAVI), Green Normalized Difference Vegetation Index (GNDVI) and optimized soil adjusted vegetation index (OSAVI) (Allam et al., 2019; Simona et al., 2019).The NDVI is very easy to compute and it is the most effective and widely-used vegetation index in change detection of vegetation changes (Al-Doski et al., 2013 and Estel et al., 2015). It

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DOI: 10.21608/ejss.2019.16322.1299

Received 27/08/2019; Accepted 24/10/2019

separates vegetation land cover from other features because the chlorophyll reflects the near-infrared (NIR) spectrum and absorbs red wavelength for photosynthesis. NDVI values ranges between –1 and +1, with the highest values corresponding to dense green vegetation (Allam et al., 2019 and Simona et al., 2019). Furthermore, NDVI time series of remote sensing data sets are useful in several earth fields and have been successfully used for environmental monitoring (Volpi et al., 2013 and Martinis et al., 2018) for providing agricultural outlooks, yield and vegetation change (Rembold et al., 2013; Marston et al., 2017; Komeil and Tajul, 2019 and Zhao et al., 2019), land use/land cover change (Salmon et al., 2013; Nyamekye et al., 2014 and Huang et al., 2019), and for modeling wildlife and biodiversity (Kerr and Ostrovsky, 2003). SAVI was established to improve the sensitivity of NDVI to soil backgrounds (Xia et al., 2016). Land capability assessment is the potential of land for use in specified ways, or with specific management practices. The purpose of land capability classification systems is to study and record all data relevant to find the combination of agricultural and conservation measures. The best known one of these systems is modified Storie index adopted by UCDAVIS, 2008.This index with combination of remote sensing data and geographic information system (GIS) has been used in several research studies to asses land capability in desert soils (Sawy et al., 2013; Sayed et al., 2016; Abd El-Aziz, 2018; Yousif, 2018 and 2019). The most effective limiting factors that influence the land capability in the study area are soil texture, topography, salinity and soil depth (Abdel-Hamid et al., 2010 and Aqrawiet al., 2013).The main objectives of this study were to: (1) use vegetation indices technique for monitoring and detection of the change of vegetation cover at Wadi El-Natrun depression during the period from 1984 to 2018, (2) assess the land capability of the investigated soils using Modified Storie Index and (3) impact of land capability on land cover changes.

Materials and Methods

Description of the study area

Wadi El-Natrun depression is a narrow depression located in the west of the Nile Delta, about 110 km northwest of Cairo. It is located between longitudes 29° 59' 2.76" to 30° 33' 29.71" E and latitudes 30° 14' 27.08" to 30° 33' 29.71" N, and covers an area of 573.53 km^2 (Fig. 1).Wadi El Natrun Depression is covered by Quaternary lake deposits and old alluvial deposits of sand and gravel. The lake deposits and alluvium are underlain by limestone of Miocene, Oligocene and Pliocene ages (Marzouk, 1970 and Abu Zeid, 1984) as shown in Fig. 2 after CONOCO (1989). The elevation ranged between - 66 and 68 m and the lowest value assigned for the lakes while the highest one was observed in the depression edge. The slope of the study area ranged between 0 and 32.12 %. The dominant aspect classes were the northeast, southeast and south directions (Fig. 5). Geomorphology of the study area was identified after analyzing a digital elevation model (DEM) and landsat-8 satellite image covering the area of interest (Fig. 3). The investigated area is characterized by the remarkable growth of Typha mixed with Elephantine, Artemisia Monosperma, Pityranthus Tostuesus and other common natural vegetation species in addition to the cultivated area including some field crops andorchards.The climate of Wadi El Natrun area is considered as an extremely arid region where the mean annual rainfall, evaporation, and temperature are 41.4 mm, 114.3 mm and 21ºC respectively (Egyptian Meteorological Authority, 2006).

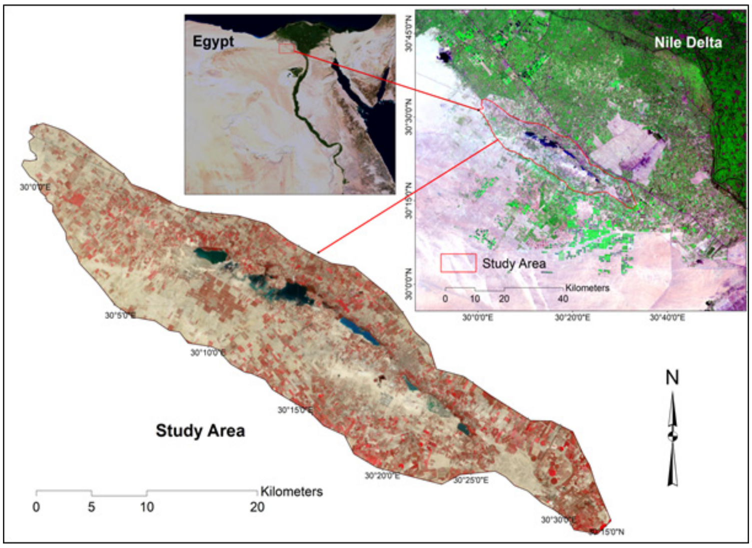

Fig. 1. Location map of the study area

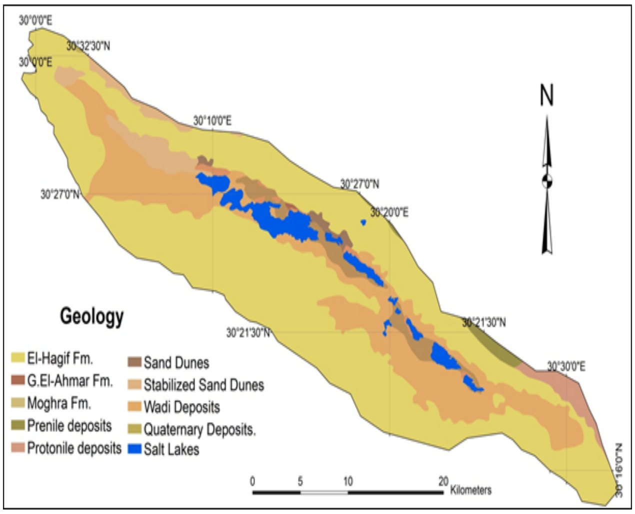

Fig. 2. Geology map of the investigated area

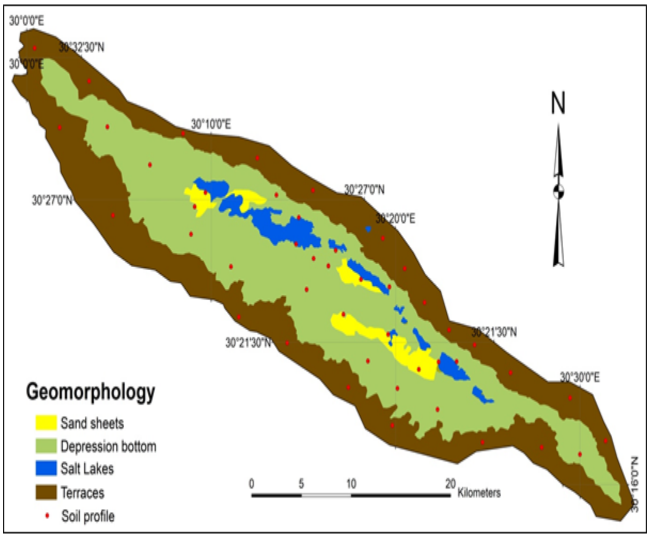

Fig. 3. Geomorphology map of the investigated area

Data collection

Remote sensing data

Multi-temporal Landsat 5, 7 and 8 images (Path 177, Row 39) were downloaded with 16 days temporal resolution and a Level 1 Terrain Correction processing (geometric and terrain correction) as well as a DEM with 30 m resolution was downloaded from SRTM (Shuttle Radar Topographic Mission) (Table 1).

Soils samples

Forty-five soil profiles were dug to represent the various geomorphic units which include;Sand sheets, depression bottom and Terraces (Figure 3). Soil samples were collected and soil analysis were performed using the soil survey laboratory methods manual (USDA, 2014).

TABLE 1. Attributes of Landsat data of the study area

Satellite	Sensor	Identifier
Landsat 5	TM Thematic Mapper	LT05_L1TP_177039_19840420_20171213
Landsat-7	ETM+ Enhanced Thematic Mapper	LE07_L1TP_177039_20010411_20170205
Landsat-8	OLI / TIRS Operational Land Imager / Thermal Infrared Sensor	LC08_L1TP_177039_20180402_20180416
DEM	SRTM 1 Arc (30x30 meter)	SRTM1N30E030V3

Methods

Digital images pre-processing

Image preprocessing includes images calibration to reflectance and atmospheric correction.

Digital image post processing

Digital image post processing was applied to extract the statistical features characteristics and information. The post processing procedures involved data sub-setting, image enhancement (Red, green and blue (RGB) composite and false colour display) as illustrated in Figure 4, image classification using VIs and change detection technique. All the aforementioned techniques were done for the Landsat images to characterize the study area using specific model in ENVI version 5.2 and Arc GIS version10.5 software.

Topographical analysis

Slope maps derived from the DEM were classified according to FAO guidelines (2006). Aspect as a topographic feature wasderives from a raster surface (DEM) to identify the downslope direction using ArcGIS 10.5 software.

of the NDVI, where it is used to correct the effect of soil brightness in low vegetative cover areas using a correction factor (L).

$$\text{RNDVI} = \frac{\text{(NIR-RED)}}{\text{(NIR+RED)}} \quad (1)$$

$$\text{GNDVI} = \frac{\text{(NIR-GREEN)}}{\text{(NIR+GREEN)}} \quad (2)$$

The SAVI and OSAVI are calculated according to the following equations (3 & 4):

$$\text{SAVI} = \frac{\text{(NIR-RED)(1+L)}}{\text{(NIR+RED+L)}} \quad (3)$$

$$\text{OSAVI} = \frac{\text{(NIR-RED)}}{\text{(NIR+RED+0.6)}} \quad (4)$$

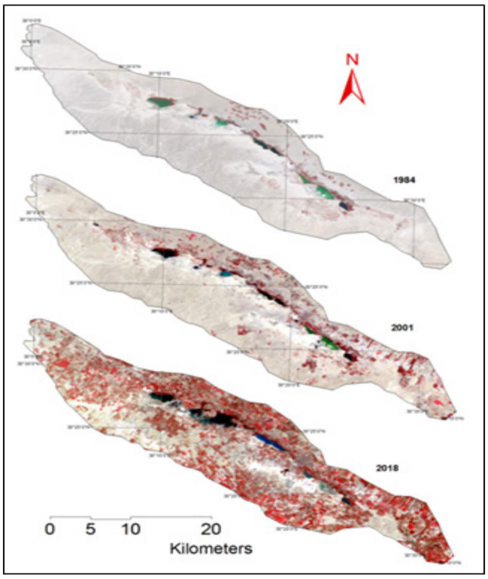

Fig. 4. False color composite

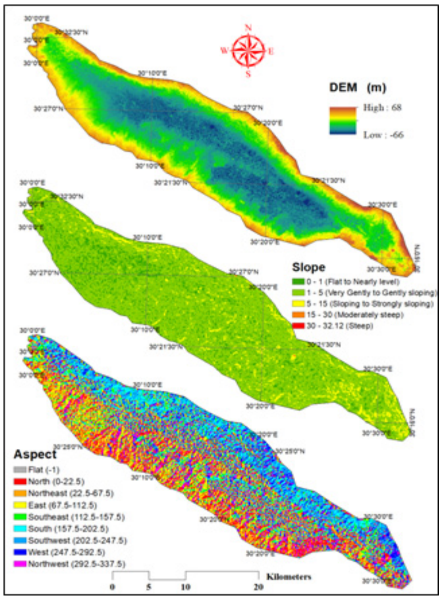

Fig. 5. Topographical analysis

Vegetation indices

Four vegetation indices were used to identify spatial distribution of vegetation and its density through the levels of chlorophyll detected in the leaves. They were red normalized difference vegetation index (RNDVI), soil adjusted vegetation index (SAVI), green normalized difference vegetation index (GNDVI) and optimized soil adjusted vegetation index (OSAVI). The RNDVI and GNDVI were calculated from the visible and near-infrared light reflected by vegetation as clarified in equations 1 and 2. The SAVI was a modification

Where, (NIR) is a near infrared band, (L) is the correction factor. It ranges between zero and one based on the vegetation cover density. At very high plant densities, L takes a value of zero, where at very low plant densities L will take a value of one. Xu (2008) reported that the SAVI works better than the NDVI in areas with plant cover less than 15%, whereas in the areas with plant cover greater than 30% the NDVI works well. The stratified random method was applied to represent different classes with 100 ground truth points that were collected in 2018.Classes of land cover maps created by Landsat-8 images were compared with those obtained by the ground truth. Manandhar et al. (2009) stated that the acceptable accuracy in land cover maps created by Landsat images should be greater than 85% and each individual class should be higher than 70%.

Changes detection

The land cover changes within the study area were achieved through subtracting the binary images obtained from each of the studied indices for two successive years. Each pair of the final raster images (resulting from vegetation indices) was compared to define the changes in the study area between the assigned time series: 1984-2001, 2001-2018, and 1984 -2018. The changes in the three given land cover classes (vegetation, bare land and water) were determined for the classified maps. The change detection results were utilized to measure the vegetation extension in the depression during the past 34 years.

Change Rate Analysis: Rates of change in vegetation cover type were analyzed utilizing the following formulae (Badamasi and Yelwa, 2010):

1. Change area = D2 - D1, where D1 and D2 are the area of the target vegetation cover type at the beginning (1984) and the end (2018) of the study period, respectively.
2. % change = (change area / A) * 100, where A is the total area.
3. Annual rate of change ($km^2 year^{-1}$) = (change area/ Ti), where Ti is number of years between the beginning and the end of study period.
4. % annual rate of change ($\%year^{-1}$) = change area/ (D1 * Ti)

Land capability evaluation

The best known land capability approach is the modified Storie index. Based on the soil analysis the land capability was carried out using modified Storieindex (UCDAVIS, 2008). The calculation was run and coding using Visual Basic for application under Microsoft Excel.

Storie index rating = [(A/100) x (B/100) x (C/100) x (X/100)] x 100

Where;A: soil depth (cm), B: Surface Texture C: Slope, and X: includes; Drainage, Alkalinity.

The Storie index ratings of >80, 79-60, 59-40, 39-20 and < 20% represents capability classes of Grade I (Excellent), Grade 2 (Good), Grade 3 (Fair), Grade 4 (Poor) and Grade 6 (nonagricultural).

Land capability map was created using inverse distance weighting (IDW) technique (Zareet al., 2010). Geostatistical techniques can be utilized to create soil maps and predict soil properties maps (Yousif, 2017). The IDW method is the most popular and common interpolation method in agriculture applications (Karydas, 2009 and TUNCAY et al., 2016).

Results And Discussion

The results of change detection of Land cover classes using NDVI, GNDVI, SAVI, and OSAVI are shown in Fig. 6 - 9, respectively. The total areas and percentage of each class of three Land cover classes (vegetation, bare land, and water) which were defined based on vegetation indices are illustrated in Table 2.

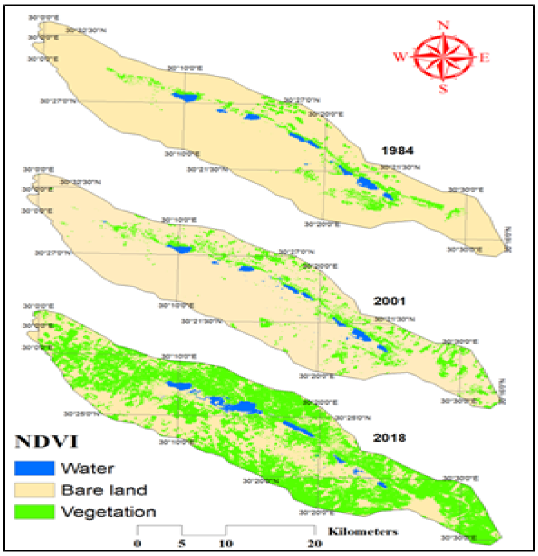

Fig. 6. Normalized Differences Vegetation Index (NDVI)

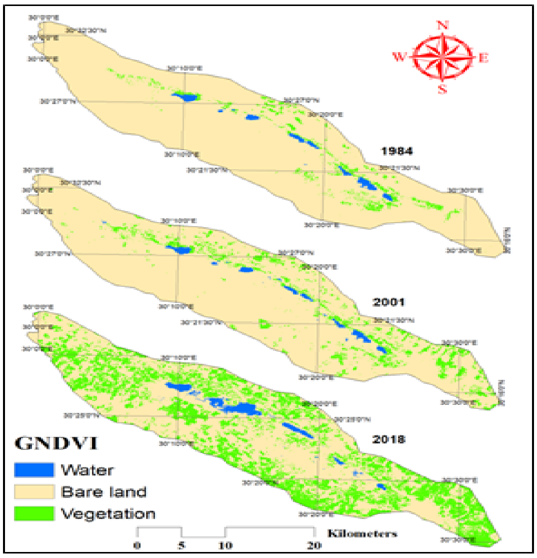

Fig. 7. Green Normalized Differences Vegetation Index (GNDVI)

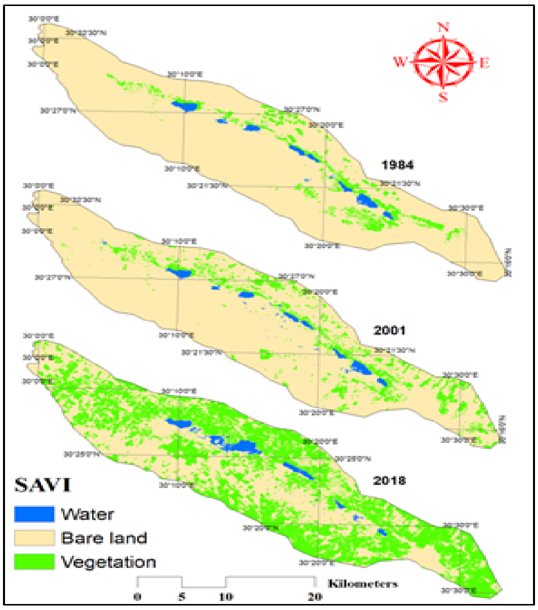

Fig. 8. Soil Adjusted Vegetation Index (SAVI)

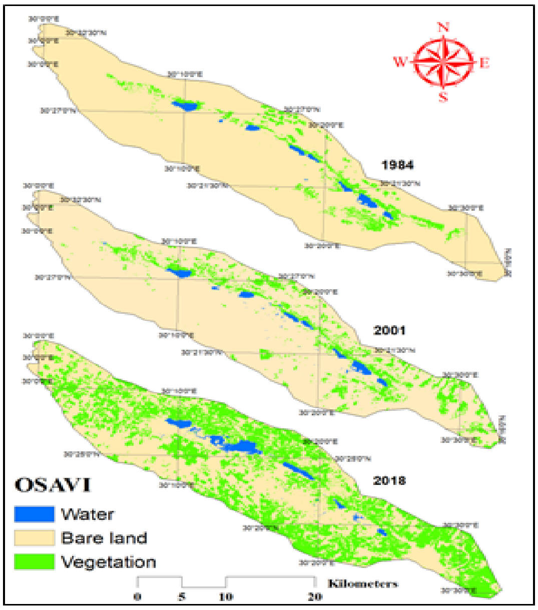

Fig. 9. Optimized Soil Adjusted Vegetation Index (OSAVI)

TABLE 2. Land coverareas from 1984 to 2018 based on the vegetation indices

	Index		Water	Bare land	Vegetation	total
1984	OSAVI	Area (km^2)	8.97	526.44	38.12	573.53
		%	1.56	91.79	6.65	100
	GNDVI	Area (km^2)	8.48	542.94	22.11	573.53
		%	1.48	94.67	3.85	100
	SAVI	Area (km^2)	10.66	524.46	38.41	573.53
		%	1.86	91.44	6.70	100
	NDVI	Area (km^2)	10.30	524.83	38.41	573.53
		%	1.80	91.51	6.70	100
2001	OSAVI	Area (km^2)	9.43	495.82	68.28	573.53
		%	1.64	86.45	11.91	100
	GNDVI	Area (km^2)	8.40	516.08	49.07	573.54
		%	1.46	89.98	8.56	100
	SAVI	Area (km^2)	10.44	498.91	64.19	573.53
		%	1.82	86.99	11.19	100
	NDVI	Area (km^2)	9.23	502.93	61.38	573.53
		%	1.61	87.69	10.70	100
2018	OSAVI	Area (km^2)	14.56	309.68	249.29	573.53
		%	2.54	53.99	43.47	100
	GNDVI	Area (km^2)	14.60	357.85	201.09	573.53
		%	2.55	62.39	35.06	100
	SAVI	Area (km^2)	13.74	272.57	287.23	573.53
		%	2.40	47.52	50.08	100
	NDVI	Area (km^2)	14.56	232.78	326.19	573.53
		%	2.54	40.59	56.87	100

Spatial distribution of vegetation indices

The spatial distribution of land cover classes which based on vegetation indices (Fig. 6 - 9 and Table 2) revealed that the NDVI vegetated areas represented 6.70 % with an area of (38.41 km^2), 10.70 % (61.38 km^2), and 56.87 % (326.19 km^2) of the total studied area for 1984, 2001, and 2018, respectively. Meanwhile GNDVI results of vegetated areas represented 3.85 % (22.11 km^2), 8.56 % (40.07 km^2), and 35.06 % (201.09 km^2) of the studied area for 1984, 2001, and 2018, respectively. The SAVI results of vegetated areas represented 6.70 % (38.41 km^2), 11.19 % (64.19 km^2), and 50.08 % (287.23 km^2) of the studied area for 1984, 2001, and 2018, respectively. The OSAVI results illustrated that the vegetated areas represented 6.65 % (38.12 km^2), 11.91 % (68.28 km^2), and 43.47 % (249.29 km^2) of the studied area for 1984, 2001, and 2018, respectively as depicted in Table 2. The highest value of vegetation class area of land cover was observed from 2001 to 2018 in all vegetation indices, which may be due to the human activities and practices such as land reclamation projects.

Accuracy assessment of the all classified map-vegetation indices based, were calculated using ArcGIS 10.5.In the error matrix, three types of accuracies were examined, user and producer accuracies and overall accuracy. In addition, the overall kappa statistics were calculated (Table 3).The results revealed the overall accuracies of NDVI classified map were 98 %, 97 %, and 97 % for 1984, 2001, and 2018. All kappa statistics were 0.95, 0.92, and 0.92 for 1984, 2001, and 2018, respectively. While the overall accuracies of SAVI classified maps were 98 %, 97 %, and 97 % for 1984, 2001, and 2018, respectively. All kappa statistics were 0.94, 0.92, and 0.95 for 1984, 2001, and 2018, respectively. GNDVI classified maps: The overall accuracies were 98 %, 97 %, and 93 % for 1984, 2001, and 2018, respectively. All kappa statistics were 0.96, 0.95, and 0.93 for 1984, 2001, and 2018, respectively. OSAVI classified maps**:** The overall accuracies were 99 %, 98 %, and 92 % for 1984, 2001, and 2018, respectively. All kappa statistics were 0.98, 0.96, and 0.86 for 1984, 2001, and 2018, respectively.

The accuracy assessment based on the all vegetation indices was higher than the acceptable level (85%) for all images. Also kappa statistics for all indices were greater than 0.9 for all dates. The result indicated that vegetation indices technique is a promising method to classify landsat data with a high accuracy. These results are consistent with Taufik et al. (2016), who stated that NDVI is a promising classification method with acceptable accuracy.

Changes detection of land cover

Monitoring of changes detection of vegetation areas versus non-vegetation in Wadi El-Natrun Depression from 1984 to 2018 were done based on NDVI, GNDVI, SAVI, and OSAVI techniques as illustrated in Table 4 and Fig. 10. The obtained results which depended on OSAVI technique revealed that the vegetation areas increased with a percentage of 5.26 %, which represented an area of (30.16 km^2), 31.56 % (181.01 km^2), and 36.82 % (211.17 km^2) during three periods (1984 to 2001), (2001 to 2018), and (1984 to 2018), respectively. While the results based on GNDVI techniques illustrated that vegetation areas were raised by 4.70 % (26.96 km^2), 26.51 % (152.02 km^2), and 31.21 % (178.98 km^2) in the same periods, as well as the results showed that the vegetation areas increased by 4.50 % (25.78 km^2), 38.89 % (223.04 km^2), and 43.38 % (248.82 km^2) in aforementioned periods, as for SAVI module. The NDVI index results showed that vegetation areas increased by 4.0 % (22.97 km^2), 46.17 % (264.81 km^2), and 50.18 % (287.78 km^2) within that three time-series. The agriculture areas of Wadi El Natrun Depression obviously increased. It may be due to the development of projects of land reclamation.

The annual rate of change detection

The annual rate of land cover change detection of studied area from 1984 to 2018 were calculated based on four vegetation indices as shown in Table 5. The annual rate of change of vegetation areas that relied on SAVI increased by 1.51, 13.12, and 7.31 km^2 $year^{-1}$ through three periods from 1984 to 2001, 2001 to 2018 and 1984 to 2018, respectively. On the other hand, bare land areas decreased by 1.50, 13.31, and 7.40 km^2 $year^{-1}$ in the same time series. The increase of the annual rate of change of vegetation areas as for SAVI use, is similar to that depended on NDVI use whereas, the results characterized by 1.351, 15.577, and 8.464 km^2 $year^{-1}$ for all successive dates as well as, bare land areas decreased by 1.288, 15.891, and 8.590 km^2 $year^{-1}$, respectively. The OSAVI technique-based, the annual rate of change of vegetation areas increased by 1.774, 10.648, and 6.211 km^2 $year^{-1}$ and the bare land areas decreased by 1.801, 10.950, and 6.375 km^2 $year^{-1}$ during the three periods. The GNDVI results illustrated that the annual rate of change in vegetation areas increased by 1.586, 8.943, and 5.264 km^2 $year^{-1}$, respectively, while the bare land areas decreased by 1.580, 9.308 , and 5.444 km^2 $year^{-1}$ in the aforementioned periods.

TABLE 3. Error matrices for 1984, 2001 and 2018 classified images based on NDVI, GNDVI, SAVI, and OSAVI indices of the investigated area

Index		Year	1984					2001					2018				
		land cover classes	Reference data					Reference data					Reference data				
			Water	Bare land	Vegetation	Classified Total	User accuracy %	Water	Bare land	Vegetation	Classified Total	User Accuracy %	Water	Bare land	Vegetation	Classified Total	User accuracy %
NDVI	Classified data	Water	11	0	0	11	100	10	0	0	10	100	10	0	0	10	100
		Bare land	0	72	2	74	97	0	77	3	80	96	0	32	100	33	97
		Vegetation	0	0	15	15	100	0	0	10	10	100	0	3	54	57	95
		Reference Total	11	72	17	100		10	77	13	100		10	35	55	100	
		Producer accuracy %	100	100	88			100	100	77			100	91	98		
			Overall accuracy = 98 %			Overall Kappa = 0.95		Overall accuracy = 97 %			Overall Kappa = 0.92		Overall accuracy = 97 %			Overall Kappa = 0.92	
SAVI	Classified data	Water	10	0	0	10	100	9	1	0	10	90	10	0	0	10	100
		Bare land	0	78	2	80	98	0	77	2	79	97	0	38	2	40	95
		Vegetation	0	0	10	10	100	0	0	11	11	100	0	100	49	50	98
		Reference Total	10	78	12	100		9	78	13	100		10	39	51	100	
		Producer accuracy %	100	100	83			1	99	85			100	97	96		
			Overall accuracy = 98 %			Overall Kappa = 0.94		Overall accuracy = 97 %			Overall Kappa = 0.92		Overall accuracy = 97 %			Overall Kappa = 0.95	
GNDVI	Classified data	Water	13	0	0	13	100	15	0	0	15	100	10	0	0	10	100
		Bare land	0	70	2	72	97	0	58	3	61	95	0	53	5	58	91
		Vegetation	0	0	15	15	100	0	0	24	24	100	0	2	30	32	94
		Reference Total	13	70	17	100		15	58	27	100		10	55	35	100	
		Producer accuracy %	100	100	88			100	100	89			100	96	86		
			Overall accuracy = 98 %			Overall Kappa = 0.96		Overall accuracy = 97 %			Overall Kappa = 0.95		Overall accuracy = 93 %			Overall Kappa = 0.87	
OSAVI	Classified data	Water	13	0	0	13	100	11	0	0	11	100	10	0	0	10	100
		Bare land	0	70	0	70	100	0	66	2	68	97	0	42	5	47	89
		Vegetation	0	1	16	17	94	0	0	21	21	100	0	3	40	43	93
		Reference Total	13	71	16	100		11	66	23	100		10	45	45	100	
		Producer accuracy %	100	99	100			100	100	91			100	93	89		
			Overall accuracy = 99 %			Overall Kappa = 0.98		Overall accuracy = 98 %			Overall Kappa = 0.96		Overall accuracy = 92 %			Overall Kappa = 0.86	

TABLE 4. Chang detection of three periods; 1984 - 2001, 2001 - 2018, and 1984 - 2018

Index	Year	First time 1984 - 2001			Second time 2001 - 2018			Third period (Total time) 1984 - 2018		
	Class	Water	Bare land	Vegetation	Water	Bare land	Vegetation	Water	Bare land	Vegetation
OSAVI	Area (km^2)	0.46	-30.62	30.16	5.13	-186.15	181.01	5.59	-216.76	211.17
	%	0.08	-5.34	5.26	0.89	-32.46	31.56	0.97	-37.79	36.82
GNDVI	Area (km^2)	-0.09	-26.87	26.96	6.20	-158.23	152.02	6.12	-185.10	178.98
	%	-0.02	-4.68	4.70	1.08	-27.59	26.51	1.07	-32.27	31.21
SAVI	Area (km^2)	-0.23	-25.56	25.78	3.30	-226.34	223.04	3.08	-251.90	248.82
	%	-0.04	-4.46	4.50	0.58	-39.46	38.89	0.54	-43.92	43.38
NDVI	Area (km^2)	-1.07	-21.90	22.97	5.33	-270.15	264.81	4.27	-292.04	287.78
	%	-0.19	-3.82	4.00	0.93	-47.10	46.17	0.74	-50.92	50.18

TABLE 5. The Rate of change detection of the three periods

Index	Year	First period 1984 - 2001		Second period 2001 - 2018		Third period (Total time) 1984 - 2018	
	Class	%	Rate ($km^2 year^{-1}$)	%	Rate ($km^2 year^{-1}$)	%	Rate ($km^2 year^{-1}$)
SAVI	water	-0.04	-0.013	0.58	0.194	0.54	0.091
	Bare land	-4.46	-1.503	-39.46	-13.314	-43.92	-7.409
	Vegetation	4.50	1.517	38.89	13.120	43.38	7.318
NDVI	water	-0.19	-0.063	0.93	0.314	0.74	0.125
	Bare land	-3.82	-1.288	-47.10	-15.891	-50.92	-8.590
	Vegetation	4.00	1.351	46.17	15.577	50.18	8.464
OSAVI	water	0.08	0.027	0.89	0.302	0.97	0.164
	Bare land	-5.34	-1.801	-32.46	-10.950	-37.79	-6.375
	Vegetation	5.26	1.774	31.56	10.648	36.82	6.211
GNDVI	water	-0.02	-0.005	1.08	0.365	1.07	0.180
	Bare land	-4.68	-1.580	-27.59	-9.308	-32.27	-5.444
	Vegetation	4.70	1.586	26.51	8.943	31.21	5.264

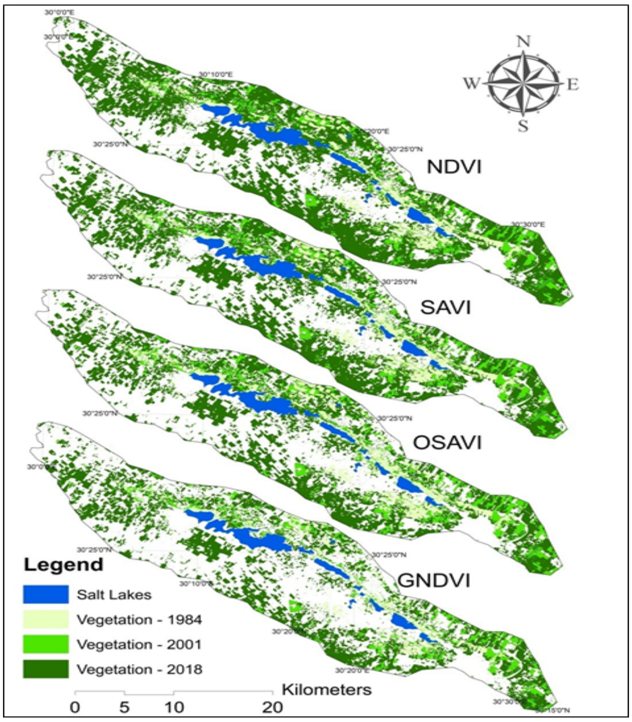

Fig. 10. Spatial distribution of vegetation change from 1984 to 2018

Land capability evaluation of the studied area

The investigated area could be classified into three units as following:

Sand sheets occupy the central part of the studied area and covers an area of 30.68 km^2 with a percentage of 5.35% of the total area. Sand sheets unit was represented by (8) soil profiles. The morphological description of sand sheets soils showed that the topography was almost flat, parent material is sedimentary deposits. The soils depth ranged from 45 to 164 cm and the drainage varied from moderate to well drained soils. In addition, the gravel content ranged between 10.5 and 136.5 g kg^{-1} and also soil texture varied from sand to loamy sand. The soil pH ranged between 7.2 and 8.5 and soil salinity from between 4.89 and 67.18 dSm^{-1}. Exchangeable sodium percentage ranged between 8.33 and 15.62 %. The calcium carbonate content varied between 22.26 and 270.3 g kg^{-1}. The depression bottom unit,was found in the around central of the studied area and covered an area of about 256.65 km^2 which represented of 44.75% of the total area. It was characterized by the evidence of riverine deposits. Depression bottom topography are gently slope and was represented by (15) soil profiles. The soil depth ranged between 55 and 167 cm. The drainage varied from very poor to well drained soils. The gravel content ranged between 10.5 and 315 g kg^{-1}. Soil texture varied from sand to clay. Soil pH ranged between 7.1 and 8.70. Soil salinity ranged between 1.55 and 57.72 dSm^{-1}. Exchangeable sodium percentage ranged between 8.33 and 18.74. $CaCO_3$ content ranged between 15.9 and 208.82 g kg^{-1}. The terraces unit is considered the major part of the study area and covers an area of 562.19 km^2 with a percentage of 45.72% of the total area. The terraces topography are strongly sloping and moderately steep and represented by (22) soil profiles. The soil depth ranged between 30 and 160 cm and the gravel content ranged between 21 and 336 g kg^{-1}. The soil salinity ranged between 0.94 and 17.89 dSm^{-1}. Soil pH ranged between 7.10 and 8.84. Exchangeable sodium percent ranged between 7.29 and 20.82.The $CaCO_3$ content ranged between 21.2 and 143.1 g kg^{-1}. The Soil texture varied from sand to sandy clay loam and drainage varied from very poor to well drained soils as shown in Table 6.

The investigated soils were classified according to Storie index equation into three grades; grade 3, grade 4 and grade 5 while the some soil profiles were classified as grade 2 as shown in Table 7, and Fig. 11. In addition, the results indicated that the main limited factors for land use are soil salinity, soil texture and soil depth as shown in Table 8 and Figure 11, grade 4 was the most common capability grade in the investigated area with an area 262.19, 148.46 and 20.35 km^2 in terraces, depression bottom and Sand sheets respectively. The Grade 3 covers an area 94.86 and 7.70 km^2 in depression bottom and Sand sheets respectively. Grade 2 covers an area 4 km^2 which belonged to the depression bottom unit.

TABLE 6. The weighted mean of some soil characteristics

Unit	Profile No	Depth cm	Gravel g kg^{-1}	EC dSm^{-1}	pH	ESP	$CaCO_3$ g kg^{-1}	Texture	Drainage
Sand sheets	18	154	63	7.70	7.80	14.57	153.70	SL	well
	20	162	42	4.89	7.60	13.01	132.50	LS	well
	26	155	21	5.20	7.30	9.37	22.26	S	well
	33	75	52.5	55.64	8.50	15.09	47.70	S	Moderate
	35	80	10.5	39.94	7.20	8.33	37.10	S	Well
	36	164	31.5	19.86	7.30	8.33	38.16	S	well
	37	159	136.5	5.72	7.50	13.53	270.30	S	well
	38	45	21	67.18	8.50	15.62	37.10	S	Well
Depression bottom	15	157	21	18.20	7.40	10.41	26.50	S	well
	16	161	10.5	3.64	7.20	9.37	15.90	S	well
	17	158	147	7.80	8.00	14.05	174.90	LS	well
	19	60	21	8.84	8.40	14.57	208.82	SCL	Poor
	21	159	273	4.89	8.10	14.05	47.70	SL	well
	22	157	52.5	6.76	7.50	10.93	148.40	S	well
	23	158	10.5	1.46	7.10	8.33	23.32	S	well
	24	167	21	5.82	7.70	13.01	121.90	S	well
	25	155	315	7.07	7.60	13.01	79.50	S	well
	27	157	42	2.08	7.20	10.41	174.90	LS	well
	28	150	52.5	5.30	8.00	14.05	164.30	SL	well
	29	150	63	5.41	7.40	13.53	58.30	LS	well
	30	165	52.5	1.46	7.40	10.41	47.70	LS	well
	31	55	52.5	54.70	8.70	18.74	58.30	C	poor
	32	55	21	57.72	8.60	16.66	106.00	LS	poor
	34	70	52.5	47.53	8.65	17.70	174.90	C	Very poor
Terraces	1	154	52	2.29	7.40	11.45	57.24	LS	well
	2	150	210	11.13	7.50	13.53	54.06	SL	well
	3	160	73.5	0.94	7.40	7.29	37.10	S	well
	4	110	42	2.60	7.20	7.29	90.10	S	well
	5	160	21	2.70	7.30	10.41	67.84	S	well
	6	150	283.5	5.82	7.70	13.01	68.90	LS	well
	7	153	136.5	7.07	7.80	11.97	90.10	S	well
	8	60	63	5.51	7.10	8.33	26.50	S	moderate
	9	160	147	4.68	7.60	14.05	79.50	LS	well
	10	156	262.5	5.72	7.90	13.53	90.10	SL	well
	11	160	52.5	4.78	7.50	10.41	143.10	SL	well
	12	60	21	2.70	8.50	15.62	21.20	SCL	Poor
	13	157	63	9.88	7.30	13.53	71.02	S	well
	14	159	147	7.49	7.40	13.53	47.70	S	well
	39	157	31.5	15.18	7.20	14.57	143.10	LS	well
	40	157	262.5	8.01	7.30	12.49	37.10	LS	well
	41	159	315	8.22	7.80	14.57	87.98	SL	well
	42	157	294	4.68	7.60	13.01	47.70	S	well
	43	159	336	7.07	7.80	14.05	90.10	S	well
	44	30	325.5	17.89	8.70	18.74	95.40	SL	Very poor
	45	30	304.5	15.29	8.84	20.82	37.10	SL	Very poor

SL, sandy loam; LS, loamy sand; S, sand; C, clay; SCL, sandy clay loam

TABLE 7. Land capability classification using modified Storie index

Unit	Profile No	Depth Rate	Gravel Rate	Slope Rate	pH Rate	$CaCO_3$ Rate	EC Rate	Texture Rate	Final rate	Class
Sand sheets	**18**	**94.19**	**94.19**	**96.80**	**100**	**100**	**70.71**	**95**	**57.69**	**Grade 3**
	20	95.71	96.11	99.28	100	100	81.10	80	59.25	Grade 3
	26	94.40	98.04	97.42	100	90	79.92	60	38.91	Grade 4
	33	61.28	95.14	96.36	100	90	53.35	50	16.18	Grade 5
	35	64.32	99.02	99.06	100	90	23.80	60	8.11	Grade 5
	36	96.04	97.07	93.14	100	90	29.69	60	13.92	Grade 5
	37	95.18	87.63	99.18	100	90	77.98	60	34.83	Grade 4
	38	40.28	98.04	99.49	100	90	68.18	60	14.46	Grade 5
Depression bottom	15	94.80	98.04	98.48	100	90	34.92	60	17.26	Grade 5
	16	95.54	99.02	97.91	100	90	85.82	60	42.93	Grade 3
	17	94.99	86.71	97.42	100	100	70.33	80	45.15	Grade 3
	19	51.36	98.04	95.07	100	100	66.58	95	30.28	Grade 4
	21	95.18	76.08	96.38	100	90	81.10	95	48.39	Grade 3
	22	94.80	95.14	99.54	100	100	74.13	60	39.93	Grade 4
	23	94.99	99.02	95.47	100	90	94.26	60	45.71	Grade 3
	24	96.49	98.04	99.36	100	100	77.59	60	43.76	Grade 3
	25	94.40	72.69	95.93	100	90	72.99	60	25.94	Grade 4
	27	94.80	96.11	98.23	100	100	91.83	80	65.74	Grade 2
	28	93.30	95.14	97.06	100	100	79.53	95	65.10	Grade 2
	29	93.30	94.19	99.06	100	90	79.15	80	49.61	Grade 3
	30	96.20	95.14	97.47	100	90	94.26	80	60.54	Grade 2
	31	47.80	95.14	98.05	100	90	51.89	50	10.41	Grade 5
	32	47.80	98.04	97.51	100	100	51.45	80	18.81	Grade 5
	34	58.10	95.14	99.68	100	100	39.43	50	10.86	Grade 5
Terraces	1	94.19	95.19	95.44	100	90	91.02	80	56.08	Grade 3
	2	93.30	81.31	96.36	100	90	58.48	60	23.08	Grade 4
	3	95.36	93.24	92.45	100	90	96.30	60	42.74	Grade 3
	4	79.86	96.11	96.96	100	90	89.81	60	36.09	Grade 4
	5	95.36	98.04	97.16	100	90	89.41	60	43.86	Grade 3
	6	93.30	75.22	96.06	100	90	77.59	80	37.66	Grade 4
	7	93.97	87.63	94.70	100	90	72.99	60	30.73	Grade 4
	8	51.36	94.19	96.79	100	90	78.76	60	19.91	Grade 5
	9	95.36	86.71	98.27	100	90	81.88	80	47.90	Grade 3
	10	94.60	76.94	96.38	100	90	77.98	95	46.77	Grade 3
	11	95.36	95.14	97.73	100	100	81.49	95	68.64	Grade 2
	12	51.36	98.04	94.76	100	90	89.41	95	36.48	Grade 4
	13	94.80	94.19	96.06	100	90	62.87	60	29.12	Grade 4
	14	95.18	86.71	96.26	100	90	71.47	60	30.66	Grade 4
	39	94.80	97.07	98.17	100	100	44.70	80	32.30	Grade 4
	40	94.80	76.94	96.01	100	90	69.58	80	35.08	Grade 4
	41	95.18	72.69	93.29	100	90	68.82	95	37.98	Grade 4
	42	94.80	74.37	98.62	100	90	81.88	60	30.74	Grade 4
	43	95.18	71.02	98.64	100	90	72.99	60	26.28	Grade 4
	44	28.02	71.85	97.27	100	90	35.91	95	6.01	Grade 5
	45	28.02	73.53	96.92	100	90	44.35	95	7.57	Grade 5

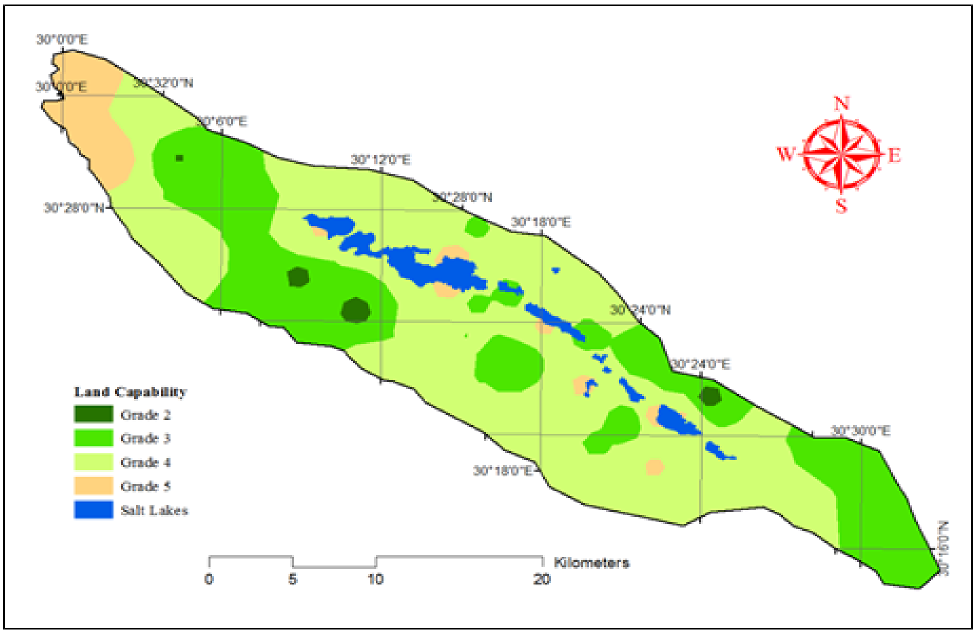

Fig. 11. Land capability map

TABLE 8. Tabulate area (km2) between geomorphologic units and land capability grades

Capability	Grade 2	Grade 3	Grade 4	Grade 5	Total (km^2)
Terraces	0	0	262.19	0	262.19
Depression bottom	4.00	94.86	148.46	9.33	256.65
Sand sheets	0	7.70	20.35	2.62	30.68
Salt Lakes	0	0	0	0	24.01
Total (km^2)	4.00	102.57	431.00	11.96	573.53

Integration of land capability and land cover change detection

As illustrated in Table 9, the grade 2 of land capability represented by four soil profiles, 75 % out of them were converted form bare land in two dates (1984 and 2001) to vegetation land cover in 2018. The grade 3 was represented by thirteen soil profiles; 46.1 % out of them were transformed from bare land in the aforementioned two dates to vegetation in 2018. The land capability grade 4 was represented by seventeen soil profiles; 47.1 % of the total soil profiles were changed from bare land in 1984 and 2001 to vegetation in 2018. The grade 5 of land capability represented by eleven soil profiles and six soil profiles converted from bare land in 1984 and 2001 to vegetation in 2018 but there were two soil profiles (32 and 33) turned into halophytes surrounding the salt lakes. The other four soil profiles (31, 34, 35 and 38) converted from bare land in 1984 and 2001 to vegetation. There are some limitations that can be treated, such as soil texture and soil salinity which can be treated with soil conditioners or leaching and sometimes by cultivating of salinity-tolerant varieties. There was a positive correlation between the land capability and change detection of vegetation land cover. This means that, the horizontal expansion in vegetation land cover extended firstly in highly productive lands.

Figure 12 showed the tabulation area between land capability and vegetation land cover extension. For grade 2, the area of vegetation cover increased from 0.21 to 2.76 km^2 in 1984, 2018 respectively. While as for grade 3 an area of vegetation cover increased from 7.65 to 106.48 km^2 in the same dates. In 1984 vegetation land cover of land capability grade 4 which represented by an area 27.58 increased to 198.16 km^2 in 2018. And finally the area of vegetation cover increased from 0.55 to 16.16 km^2 which belonged to grade 5 of land capability in 1984 and 2018, this increased area mainly due to growth of halophytes surrounding the salt lakes.

TABLE 9. Interconnection between land capability and land cover change detection

Profile No	UNIT	Capability		Land cover extracted by NDVI		
		%	class	2018	2001	1984
11	Terraces	68.64	Grade 2	3	2	2
27	Depression bottom	65.74	Grade 2	2	2	2
28		65.1	Grade 2	3	2	2
30		60.54	Grade 2	3	2	2
20	Sand sheets	59.25	Grade 3	2	2	2
18		57.69	Grade 3	2	2	2
1	Terraces	56.08	Grade 3	2	2	2
29	Depression bottom	49.61	Grade 3	2	2	2
21		48.39	Grade 3	3	2	2
9	Terraces	47.9	Grade 3	3	2	2
10		46.77	Grade 3	2	3	3
23	Depression bottom	45.71	Grade 3	3	2	2
17		45.15	Grade 3	3	2	2
5	Terraces	43.86	Grade 3	2	2	2
24	Depression bottom	43.76	Grade 3	2	2	2
16		42.93	Grade 3	3	2	2
3	Terraces	42.74	Grade 3	3	2	2
22	Depression bottom	39.93	Grade 4	2	2	2
26	Sand sheets	38.91	Grade 4	3	2	2
41	Terraces	37.98	Grade 4	3	2	2
6		37.66	Grade 4	2	2	2
12		36.48	Grade 4	2	2	2
4		36.09	Grade 4	2	2	2
40	Sand sheets	35.08	Grade 4	3	2	2
37		34.83	Grade 4	2	2	2
39		32.3	Grade 4	3	2	2
42	Terraces	30.74	Grade 4	2	2	2
7		30.73	Grade 4	3	2	2
14	Depression bottom	30.66	Grade 4	3	2	2
19		30.28	Grade 4	3	2	2
13	Terraces	29.12	Grade 4	3	2	2
43		26.28	Grade 4	2	2	2
25	Depression bottom	25.94	Grade 4	2	2	2
2	Terraces	23.08	Grade 4	2	2	2
8	Terraces	19.91	Grade 5	3	2	2
32	Depression bottom	18.81	Grade 5	3	2	3
15		17.26	Grade 5	3	2	2
38	Sand sheets	14.46	Grade 5	2	2	2
36		13.92	Grade 5	2	2	2
33		13.49	Grade 5	3	2	2
34	Depression bottom	10.86	Grade 5	2	2	3
31		10.41	Grade 5	2	2	2
35	Sand sheets	8.11	Grade 5	2	2	1
45	Terraces	7.57	Grade 5	3	2	2
44		6.01	Grade 5	3	2	2

3 = vegetation ; 2 = bare land ; 1 = water

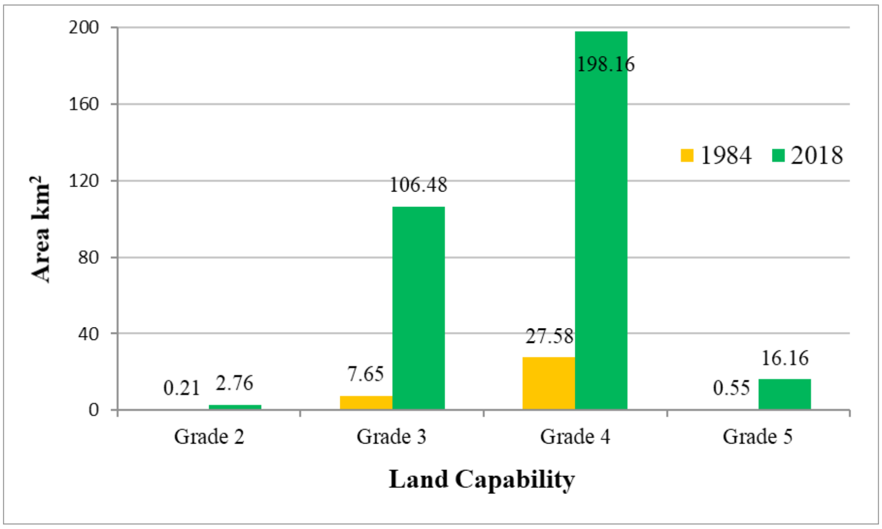

Fig. 12. Tabulate area in km2 between capability and vegetation

Conclusion

The integration between remotely sensed data and GIS techniques could provide valuable help in estimating agricultural lands and water features as well as their changes over time. The use of vegetation indices especially NDVI and SAVI could provide more accurate estimations of agricultural lands even in remotely accessed areas and save time, money and efforts. The results indicated that high increasing of vegetation areas within the studied area from 1984 to 2018 which attributed to the extension of land reclamation and cultivation projects. Land capability results showed that grade 4 and grade 3 were the most common capability grads in the investigated areas and the main limited factors were soil salinity, soil texture and soil depth that meant that there is a correlation between land capability and vegetation extension.

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التكامل بين تغيرات الغطاء الأرضي وقدرة الارض الانتاجية لمنخفض وادى النطرون باستخدام مؤشرات الغطاء النباتي

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تهدف هذه الدراسة الى استخدام تقنيات مؤشرات الغطاء النباتي لتتبع تغيرات الغطاء الأرضي خلال ثلاث فترات زمنية، من ١٩٨٤ إلى ٢٠٠١ ، ٢٠٠١ إلى ٢٠١٨ ، و١٩٨٤ إلى ٢٠١٨ ، كما تهدف الى دراسة تأثير القدرة الانتاجية للأرض على تغيرات الغطاء الأرضي بمنخفض وادى النطرون . تم استخدام صور القمر الصناعي لاندسات Landsatلسنة ١٩٨٤ و ٢٠٠١ و٢٠١٨ للكشف عن تغيرات الغطاء الأرضي بمنطقة الدراسة والتي تبلغ مساحتها ٥٧٣,٥٣ كم٢، كما انهتم استخدام أربعة مؤشرات للغطاء النباتي (NDVI، SAVI ، GNDVI ، OSAVI) لتتبع تغييرات الغطاء الأرضي خلال ٣٤ عام. ولتقييم دقة المرئيات الفضائية المصنفة تم جمع ١٠٠نقطة تحقيق أرضية لعام ٢٠١٨ . وبناءًا علي مؤشرات الغطاء النباتي المستخدمة تم تحديد ثلاث فئات للغطاء الأرضي بمنطقة الدراسة وهى كالتالي:Vegetation,Water, Bare land. ومن خلال فحص خمسة وأربعين قطاع أرضى والتي مثلت الوحدات الجيومورفولوجية المختلفة والتي حُددت باستخدام نموذج الارتفاع الرقمي (DEM) ومرئيات القمر الصناعي لاندسات Landsat-8 تم تقييم القدرة الانتاجية لأراضي منطقة الدراسة اعتمادا على مؤشر ستوري المعدل Modified Storie index. اظهرت نتائج مؤشرات الغطاء النباتي دقة عالية (اكبر من ٩٢٪) في تحديد فئات الغطاء الأرضي ومعامل kappa أكبر من ٠,٩. كما أوضحت نتائج القدرة الانتاجية ان اراضى الدرجة الثانية ، الثالثة ، الرابعة والخامسة تغطى٠,٧٠ و ١٧,٨٨ و ٧٥,١٥ و ٢,٠٩ ٪ من مساحة المنطقة المدروسة على الترتيب. بالإضافة الى ان نتائج الدراسة أوضحت أن اهم محددات استخدام الأراضي هي: ملوحة التربة ، قوام التربة ، عمق القطاع الأراضي وحالة الصرف ووجود علاقة إيجابية بين قدرة الأرض الانتاجية وزيادة الغطاء النباتي.