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Evaluating the Role of Natural Resources in Sustainable Development in Babil Governorate, Iraq by using GIS and Remote Sensing

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Abstract— Babil governorate is one of the most important agricultural areas in Iraq. However, these areas began to deteriorate due to several reasons, including the economic sanctions, lack of governmental support to farmers, shortage in water resources and salinization. The main objectives of this study were to provide an accurate assessment of the agricultural areas in Babil governorate from 1985 to 2015 and to evaluate degradation due to soil salinity. This is to help in the development of land resources and their sustainability. Accordingly, Landsat images were acquired in 1985 (TM), 1999 ETM+), and 2015 (OLI-TIRS) and used in this study. Also, three vegetation indices (NDVI, TNDVI and SAVI) and two salinity indices (NDSI and SI) were used for the assessment of agricultural lands and salt-affected soils in the studied area.

The obtained results indicated that agricultural areas were significantly decreased in the studied area from 1985 to 2015 based on the three studied vegetation indices. Agricultural areas were about 2644, 1508 and 2217 km^2 in 1985, 1999 and 2015, respectively. This is based on the SAVI index, which had the highest accuracy when compared with the two other indices. On the other hand, the areas of salt-affected soils were significantly increased from 1985 to 2015 based on the NDSI and the SI indices. These areas were about 203, 446 and 371 km^2 in 1985, 1999 and 2015, respectively. This is based on the SI index, which was more accurate than the NDSI.

In conclusion serious strategies should be considered toward increasing land reclamation projects and sustainability of land resources against degradation.

Index Terms Remote sensing, GIS, Agricultural lands, Salt-affected soils, SAVI, NDVI, TNDVI, NDSI, and SI.

1 INTRODUCTION

Natural resources are any assets that we can obtain from our environment (i.e., soil, water, plants, wind, animals, minerals, the energy of the sun and many others) (Maugeri, 2009). They are classified into two major categories, which are renewable and non-renewable natural resources. Renewable resources can be replenished through natural processes, whereas the non-renewable resources can't. Natural resources are often seen in terms of economic value, where so many of them are crucial for people's livelihoods. They also play a critical role in the welfare of developing countries. For many developing countries, natural resources are the base upon which all life depends. Though, many of developing countries have experienced and continue to experience severe degradation in their natural resources. Development in technology, population and economical activities, have led to an acceleration in degradation, unsustainable exploitation and depletion of natural resources (Satapathy et al., 2008). Accordingly, there is a critical need to apply research in order to monitor, evaluate and manage these valuable resources.

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Natural resources management (NRM) focuses on how management of natural resources could affect the quality of life for both present and future generations (Wikipedia, 2009). The aim of NRM is to manage these resources to have a balance between their functions for the quality of the environment and their functions for the quality of the human life (Schmidt-Vodt and Shrestha, 2006). NRM requires lots of reliable spatial information from a variety of sources. Obtaining this information in the traditional methods is relatively costly and time–consuming as they require extensive mapping and monitoring programs (Ononiwu, 2002). In the recent years, both remotely sensed data and GIS techniques have provided great help in that field.

In the recent decades, Remote Sensing (RS) data and analysis are now providing detailed information for detecting and monitoring changes in land cover and land use. RS is defined as the science and art of acquiring information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in direct or physical contact with the object under investigation (Lillesand and Kiefer, 1994). In general, RS refers to the use of aerial sensor technologies to detect and classify objects on the Earth surface by means of propagated electromagnetic radiation (EMR). RS is divided into two classes depending on the source of EMR, which are passive and active RS (Raghavan et al., 2002; Schowengerdt, 2007; Schott, 2007; Liu, 2009; Guo et al., 2014). The first depends on the natural sources of EMR (i.e., the sun), whereas the second uses artificial sources of energy (i.e., Radar, Lidar). Nowadays, the spatial resolution of remotely sensed data has improved and reached a level at which the quality of space-borne imagery challenges that of previously available air-borne imagery (Guebas, 2002). Moreover, the quality in sensor design and data flow will continue to improve, which will lead to an expansion of our understanding of the types and rates of land-cover and land-use changes and their causes, distributions, rates and consequences (Rogan and Chen, 2004).

RS data are widely used in mapping vegetation covers, where many vegetation indices have been developed to estimate biophysical parameters of vegetation. These indices includes normalized difference vegetation index (NDVI), transformed NDVI (TNDVI. SAVI was developed to address some of the limitations of NDVI when applied to areas that have higher degrees of exposed soil surface (low vegetation cover). This is because the reflectance of light in the red and near-infrared (NIR) spectra can influence vegetation index values.

Soil salinity is one of the most serious environmental problems especially in arid and semiarid areas. It either occurs naturally or human-induced or both. High levels of soil salinity negatively affect plant growth and crop productivity leading to land degradation. Therefore, it is important to monitor and map salt-affected soils at an early stage to develop an effective soil reclamation program. RS has outperformed the traditional method for assessing soil saline offering more informative and professional rapid assessment techniques for monitoring and mapping soil salinity. Soil salinity can be identified from RS data by using direct indicators that refer to salt-features that are visible at the soil surface as well as indirect indicators such as the presence of halophytic plant and assessing the performance level of salt-tolerant crops. Salinity indices such as the normalized difference salinity index (NDSI) and salinity index (SI) were used in this work to study land degradation in the studied area.

GIS as well has been recently integrated in many applications including natural resource management. GIS is a computer-based tool that is used to collect, store, manipulate and display spatially-referenced information. However, GIS is not simply a computer-based system for making maps; it's a powerful analytical tool. This technology is employed not only to edit and display maps as conventional GIS applications, but also to enhance work quality. These enhancements include an exploration of hidden information, the production of tentative zoning maps, recognizing potentially problematic areas, conducting crucial site investigations, facilitating informative public hearing, and presenting potential policies (Lin, 2000). It is mainly used to support decision-making in a wide variety of contexts (i.e., spatial planning and environmental management) (Bunch et al., 2012). This management component can be used to gain new insights into the dataset and for the assessment and forecast of situations and scenarios related to geospatial data.

The objectives of this work were to make an assessment of agricultural areas in Babil governorate and their changes from 1985 to 2015. This was in addition to evaluating land degradation due to soil salinity during the same period of time. This is to provide decision makers with more accurate and reliable information about that sector to be used in the sustainability of these land resources for future development.

2 Materials and Methods

2.1 Study Area

Babil governorate is one of the central governorates in Iraq. It is about 100 km to the south of Baghdad. It is located between these coordinates 43^{o} 58′ 5.96″ – 45^{o} 13′ 58.25″ E and 32^{o} 8′ 25.10″ – 33^{o} 2′ 18.47″ N and it covers an area of about 5432 km^2 as illustrated in Figure (1). It has a population of about 2019291 in 2015, according to the Iraqi Ministry of Planning statistics. The governorate is divided into four districts, which are Mahawil, Musayyib, Hashimia and Hilla.

Elevation of Babil governorate varies from 0 to 62 m above sea level with an average of 23 m. Slope ranges between 0 and 59 degrees with an average of 3.77 degree. Climate is characterized by low rainfall and high temperatures in summer. Maximum temperature ranges between 19 ^{o}C in January to 46 ^{o}C in July and August, with an average of 32.5 oC. Minimum temperature varies from 5 ^{o}C in January to 27 ^{o}C in August, with an average of 16 ^{o}C. Mean annual precipitation is about 112mm, maximum. Climatic data were downloaded from this website (http://www.meteoblue.com/ar…/modelclimate/9822).

Geology of the study are consists of fluvial deposits, which cover most of the area (PAGS, 1986). This is flowed by alluvial terraces in the northwest and Aeolian deposits in the southeast parts of the area. Babil is also well known by its Palm trees, where it is the first governorate in Iraq the number of Palm trees. It is used also for cultivating some field crops such as wheat, barley and rice.

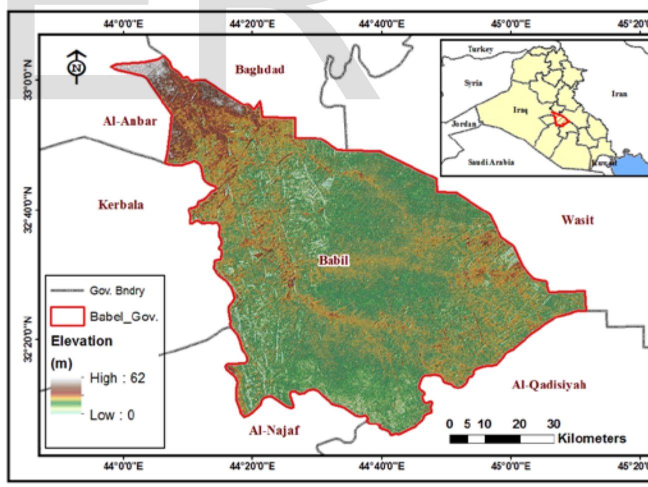

Figure (1): Location map Babil Governorate and its topography.

2.2 Sources of Data

Multi-temporal Landsat data were used in this study. Babil governorate is covered by three Landsat images (Path 168 row 37 and 38, Path 169 row 37). These images were collected in three different years (1985, 1999 and 2015). A total of nine images were used in this study, where each year is represented by three images. These data were downloaded from Landsat archive available for free on the United States Geological Survey (USGS) website (http://earthexplorer.usgs.gov/). All of the images were free of clouds. The type of sensor and the ac-

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quisition dates of these images are represented in table (1).

Table (1): Type of sensor, path & row and acquisition dates of the studied Landsat images.

Year	Type of Sensor	Path	Row	Acquisition Date
1985	Landsat 5 (TM)	37	168	29/07/1985
		38	168	29/07/1985
		37	169	20/07/1985
1999	Landsat 7 (ETM+)	37	168	12/07/1999
		38	168	12/07/1999
		37	169	03/07/1999
2015	Landsat 8 (OLI-TIRS)	37	168	14/06/2015
		38	168	14/06/2015
		37	169	07/06/2015

2.3 Manipulation and Analysis of Landsat Data

2.3.1 Layer Stacking

The studied images were downloaded in a compressed zip file format. They were decompressed using file decompression software (i.e., 7Zip and File Zip). The decompressed folder contains the spectral bands in separate Geo Tiff format files. It also contains the metadata file in a text file format. Therefore, the files of the required bands need to be stacked in one file to help in carrying out the image preprocessing functions.

2.3.2. Atmospheric and Radiometric Corrections

Studied images were atmospherically corrected to eliminate the atmospheric interferences (dust, haze, smoke, etc.) by using the dark-object subtraction method in the Envi software package. The data were also radiometrically to eliminate the variations in illumination through converting the DN values into at sensor reflectance.

2.3.3. Geometric Correction, Image Mosaic and Subset

The studied images were geometrically corrected based on the old images acquired in 1985 using the polynomial approach under ERDAS imagine software. All of the studied images were projected using the Universal Transverse Mercator (UTM) projection, zone 38 N. About 20 Ground Control Points (GCPs) were randomly selected throughout each image. The Root Mean Square Error (RMS) was less than 0.5 for each image.

The geometrically corrected images for each study period were tilled together using the mosaic tool in ERDAS. These images were clipped (image subset) to cover the studied area. Figure (2), illustrates a false color composite (FCC) of image subsets for the three studied periods.

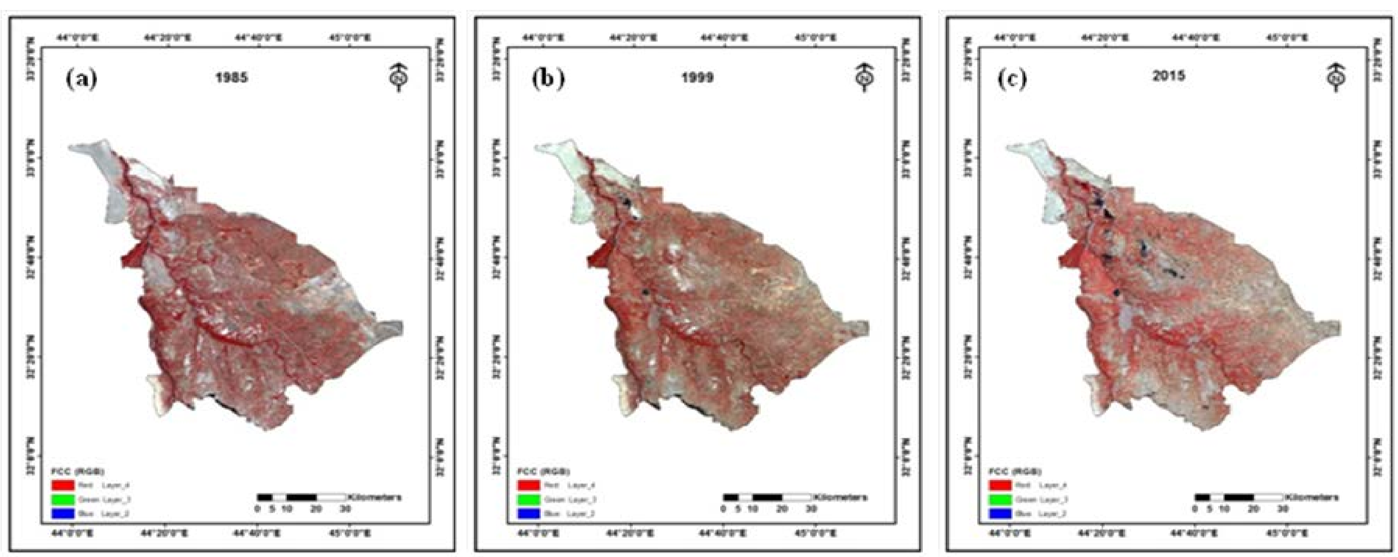

Figure (2): Landsat images (RGB 432) acquired in: a) 1985, b) 1999, and c) 2015.

2.4 Vegetation Indices

Three vegetation indices and two salinity indices were used in this study. The indices and their characteristics and calculation methods are described below:

2.4.1 Normalized Difference Vegetation Index (NDVI)

NDVI is one of the commonly used vegetation indices worldwide. NDVI was calculated using the following equation (Rouse et al., 1973):

$$\mathbf{NDVI = (NIR - Red) / (NIR + Red)} \qquad \mathbf{(1)}$$

Where, NIR is the reflectance in the near infrared portion of spectrum and Red is the reflectance in the red portion of spectrum. NDVI values range between -1.0 and +1.0, where positive values indicate healthy green vegetation and near zero or negative values represent non-vegetated land-covers such as urban areas, deserts and water bodies.

2.4.2 Transformed Normalized Difference Vegetation index (TNDVI)

Because, the NDVI index is saturated in high biomass and it is sensitive to a number of disturbing factors, such as atmospheric effects, cloud, soil effects, and anisotropic effects etc. Consequently, a number of derivatives and alternatives to NDVI have been proposed in the scientific literature to address these limitations (Yang et al., 2008). Tucker (1979) presented a transformed normalized difference vegetation index (TNDVI) by adding a constant 0.5 to the NDVI and taking the square root. It always has positive values and the variance of the ratio is proportional to mean values. The TNDVI indicates a slight better correlation between the amounts of green biomass and is what found in a pixel (Yang et al., 2008). The TNDVI is computed by using the following equation:

$$\mathbf{TNDVI = \sqrt{((NIR - Red) / (NIR + Red)) + 0.5}} \qquad \mathbf{(2)}$$

2.4.3 Soil adjusted vegetation index (SAVI)

The (SAVI) was also developed as a modification of the NDVI to correct the influence of soil brightness when the vegetative cover is low. The SAVI is structured similar to the NDVI but with the addition of a soil brightness correction factor (L) as described in the following equation (Huete, 1988).

$$\mathbf{SAVI = (NIR - Red) \times (1 + L) / (NIR + Red + L)} \qquad \mathbf{(3)}$$

The L value ranges between 0 and 1 depending on the density of vegetation cover, where L=0 for very high plant densities and L=1 for very low plant densities. In this work a value of 0.5 was used. The SAVI is equivalent to the NDVI when the L=0. The SAVI works in areas with plant cover less than 15%, whereas the NDVI works effectively in areas with plant cover greater than 30% (Xu, 2008).

2.5. Salinity Indices

Salt-affected soils are usually characterized by their poorly developed vegetation cover; therefore, this state of stressed vegetation could be used as an indirect indicator of the presence of salts in the soils. Accordingly, the above mentioned vegetation indices were used in this work. Also, two salinity indices were used to make an assessment of salt-affected soils in the studied area. These indices are the Normalized Difference Salinity Index (NDSI) and Salinity Index (SI). Both the NDSI and the SI showed highly significant correlation with soil salinity in less densely vegetated areas and bare soils (Douaoui et al., 2006; Elnaggar and Noller, 2010).

2.5.1 Normalized Difference Salinity Index (NDSI)

NDSI is a common indicator of soil salinity. The NDSI is computed by using following the equation (Tripathi et al., 1997):

$$\mathbf{NDSI = (Red - NIR) / (Red + NIR)} \qquad \mathbf{(4)}$$

2.5.2 Salinity index (SI)

Salinity index (SI) is a common indicator of soil salinity. It is calculated as the square root of the multiplication of the blue and red bands in multispectral images as represented in the following equation (Tripathi et al., 1997):

$$\mathbf{SI = \sqrt{((Blue * Red))}} \qquad \mathbf{(5)}$$

Where, Blue is the reflectance in blue portion of spectrum and Red is the reflectance in the red portion of spectrum.

2.5 Calculation of Agricultural lands and saline soils

A threshold value which distinguishes agricultural from non-agricultural areas was found for each of the three studied vegetation indices in each of the studied years. This value was used to classify the images came out from the vegetation indices into binary images that contain only two classes: agricultural and non-agricultural areas. The same approach was used to separate saline soils from non-saline soils. The areas of agricultural lands and saline soils were calculated based on the number of pixels that fall in each class.

2.6 Accuracy Assessment

Accuracy Assessment was performed on the produced binary imaged from all the studied indices (NDVI, TNDVI, SAVI, NDSI, and SI) in 1985, 1999, and 2015. This was to evaluate the accuracy of each index in classifying agricultural against non-agricultural area and saline soils against non-saline soils. The classified image was matched with a variety of data such as aerial photographs, high resolution satellite image and ground data for the 2015 images. Four types of accuracy were calculated for each classified image, which are: 1. producer's accuracy; 2. user's accuracy, 3. overall accuracy; and 4. Kappa coefficient (Campbell and Wynne, 2011).

2.7 Changes in Agriculture Lands and Saline Soils

Changes in agricultural lands within the studied area were detected through subtracting the binary images of the NDVI, TNDVI and SAVI for each two consecutive years. The obtained images contain three values, where each value refers to the type of change. Zero refers to no change in land use, 1 refers to changes in land use to agricultural land and -1 refers to change from agricultural to non-agricultural lands. The same criterion was used in studying the changes in saline soils in Babil governorate during the same period of time.

3. Results and Discussions

3.1. Agricultural viz. non-agricultural Areas in Babil Governorate Based on the NDVI Index.

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Data in table (2) show that the estimated agricultural areas in Babil governorate were about 2284, 1724 and 1811 km² in 1985, 1999 and 2015, respectively and their percentages were about 42.04, 31.74 and 33.34%, respectively. On the other hand, the non-agriculture areas were about 3148, 3708 and 3621 km² in 1985, 1999 and 2015, respectively and their percentages were about 57.96, 68.26 and 66.66%, respectively. These results indicate a reduction in the agricultural lands within the studied area from 1985 to 2015, however a slight increase in these areas (about 5%) was observed in 2015 when compared with that in 1999. This could be attributed to the economic sanctions on Iraq after the second gulf war and the decrease in governmental support the farmers. Also, during the period from 1992 to 2003 Iraq was dependent up on the oil for food program set by the United Nation (UN). Figure (3) illustrates the spatial distribution of agricultural viz. non-agricultural areas in Babil governorate based on the NDVI index in 1985, 1999 and 2015 is illustrated in.

Table (2): Estimated agricultural and non-agricultural areas in Babil governorate from 1985 to 2015 based on the NDVI index.

Agric. Cover	1985		1999		2015	
	Area km²	%	Area km²	%	Area km²	%
Non-Agric. Areas	3148	57.96	3708	68.26	3621	66.66
Agric. Areas	2284	42.04	1724	31.74	1811	33.34
Total	5432	100	5432	100	5432	100

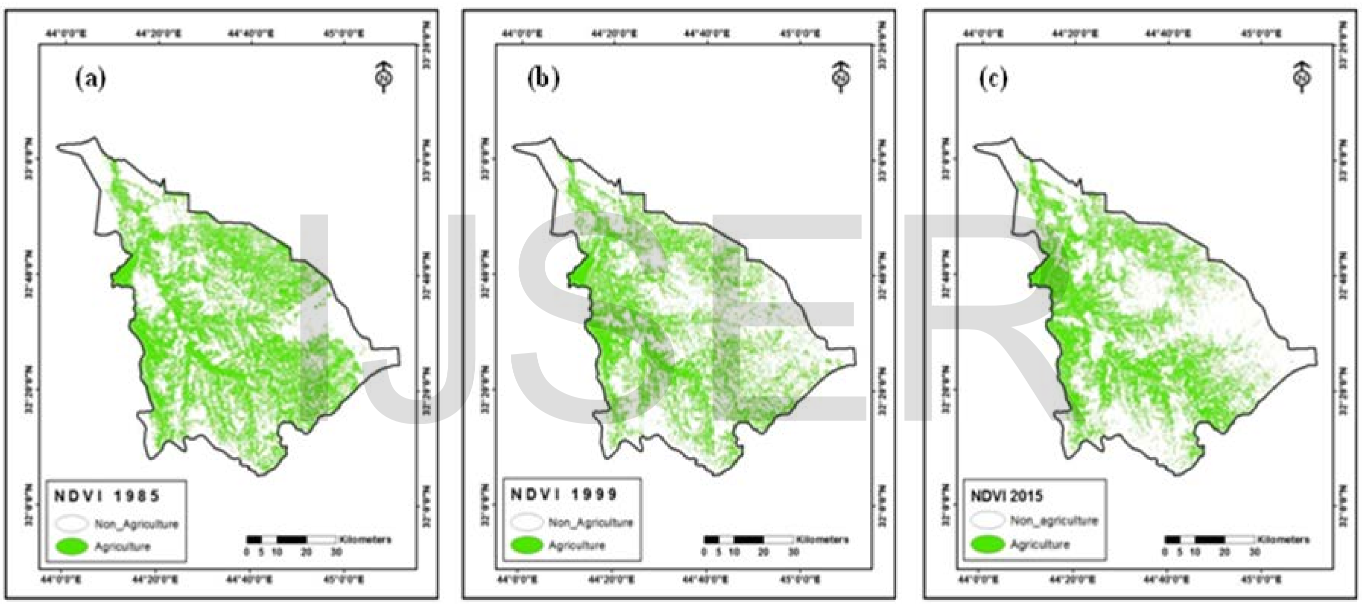

Figure (3): Spatial distribution of agricultural lands in Babil governorate obtained from the NDVI index in: a) 1985, b) 1999, and c) 2015.

3.2. Agricultural viz. non-agricultural Areas in Babil Governorate Based on the TNDVI Index.

Data in table (3), represent the estimated agricultural in Babil governorate based on the TNDVI Index. These areas were about 2122, 1747 and 2063 km² in 1985, 1999 and 2015, respectively and their percentages were about 39.06, 32.16and 37.98%, respectively. On the contrary, non-agricultural areas were about 3310, 3685 and 3369 km² in 1985, 1999 and 2015, respectively and their percentages were about 60.94, 67.84 and 62.02%, respectively. These results reveal the same trend obtained from the NDVI index, where significant decrease was observed in agricultural areas from 1985 to 1999 followed by a slight increase in 2015. Figure (4) illustrates the spatial distribution of agricultural viz. non-agricultural areas in Babil governorate based on the TNDVI index in 1985, 1999 and 2015.

Table (3): Estimated agricultural and non-agricultural areas in Babil governorate from 1985 to 2015 based on the TNDVI index.

Agric. cover	1985		1999		2015	
	Area km²	%	Area km²	%	Area km²	%
Non- agric. Areas	3310	60.94	3685	67.84	3369	62.02
Agric. Areas	2122	39.06	1747	32.16	2063	37.98
Total	5432	100	5432	100	5432	100

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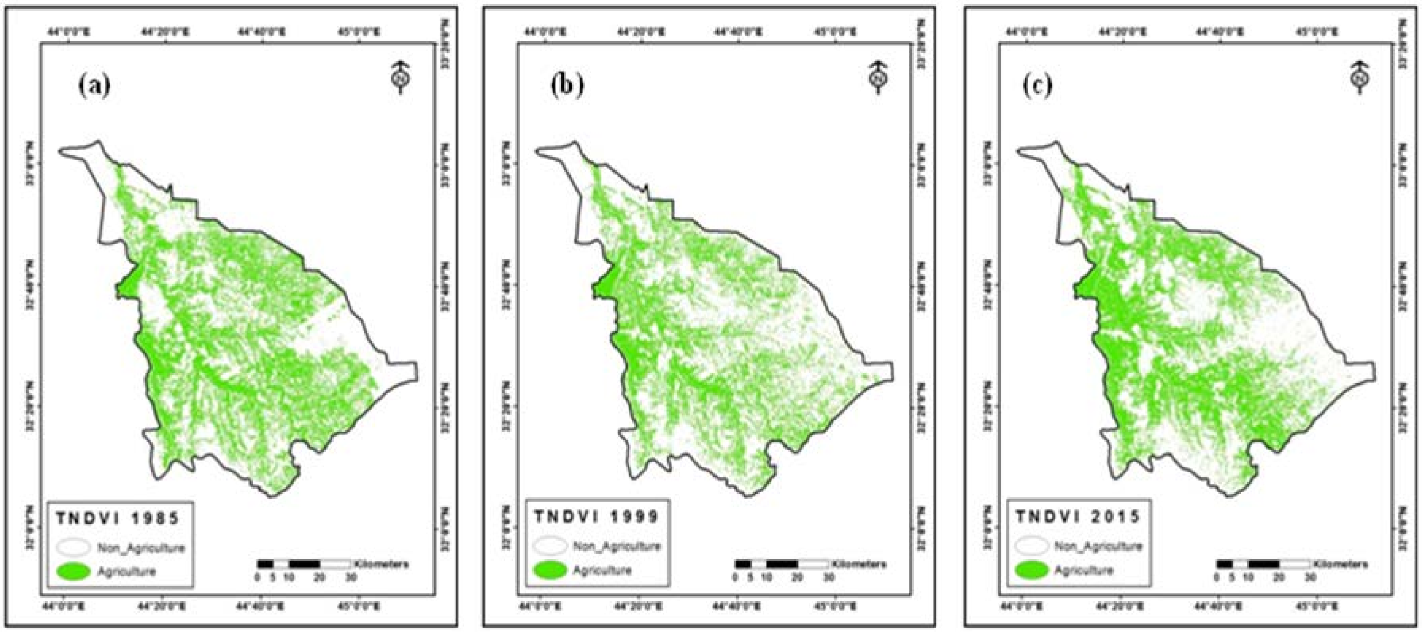

Figure (4): Spatial distribution of agricultural lands in Babil governorate obtained from the TNDVI index in: a) 1985, b) 1999, and c) 2015.

3.3. Agricultural viz. non-agricultural Areas in Babil Governorate Based on the SAVI Index.

Estimated agricultural areas base on the SAVI index were about 2644, 1508 and 2217 km² in 1985, 1999 and 2015, respectively and their percentages were about 48.67, 27.76 and 40.81%, respectively as represented in Table (4). Non-agricultural areas were about 2788, 3924 and 3215 km² in 1985, 1999 and 2015, respectively and their percentages were about 51.33, 72.24 and 59.19%, respectively. Similar trends were observed with the SAVI to that with both the NDVI and the TNDVI. The spatial distribution of agricultural and non-agricultural areas in Babil governorate based on the SAVI index in 1985, 1999 and 2015 is illustrated in Figure (5).

Table (4): Estimated agricultural and non-agricultural areas in Babil governorate from 1985 to 2015 based on the SAVI index.

Agric. Cover	1985		1999		2015	
	Area km²	%	Area km²	%	Area km²	%
Non- agric. Areas	2788	51.33	3924	72.24	3215	59.19
Agric. Areas	2644	48.67	1508	27.76	2217	40.81
Total	5432	100	5432	100	5432	100

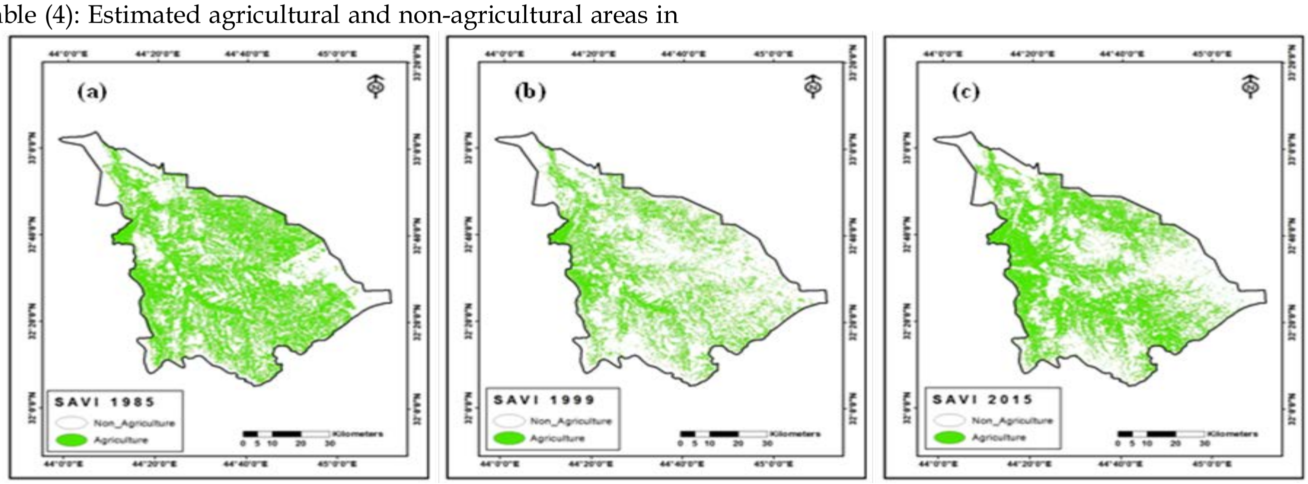

Figure (5): Spatial distribution of agricultural lands in Babil governorate obtained from the SAVI index in: a) 1985, b) 1999, and c) 2015.

Figure (6) shows the differences in agricultural areas based on the three studied vegetation indices (SAVI, NDVI and TNDVI) in 1985, 1999 and 2015. It reveals that agricultural areas in 1985 were greater than those in the consequent years.

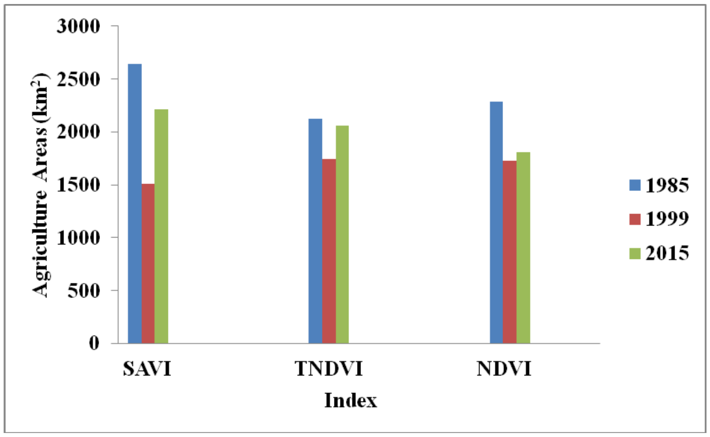

Figure (6): Differences in agricultural areas within Babil governorate based on the SAVI, NDVI and TNDVI indices in 1985, 1999 and 2105.

Figure (7) shows the changes in agricultural areas between each two of the studied periods. They reveal that most of the significant decline in agricultural area took place during the period from 1985 to 1999. On the other hand, slight increase in agriculture was observed during the period from 1999 to 2015. This could be attributed to the interest in land reclamation projects.

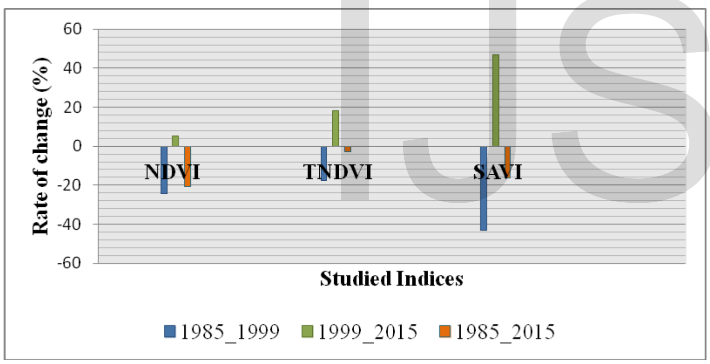

Figure (7): Changes in agricultural areas between each two of the studied periods.

3.4. Accuracy Assessment of the Studied Indices.

Accuracy Assessment was carried out to evaluate the efficiency of each of the studied indices (NDVI, TNDVI and SAVI) in estimating both agricultural and non-agricultural areas. In this process the classified binary images were compared with the actual land cover for each year. Three accuracy parameters were included in the obtained confusion matrix, which are producers, users and overall accuracy. Also, the Cohen's kappa coefficient value was calculated for each index.

Agricultural areas in Babil governorate were classified with high accuracy using the three studied indices. Data in Table (5) show that the lowest Producer's Accuracy for agricultural areas was 95.24% in 2015 with the TNDVI and the highest was 99.25% in 2015 with the SAVI. The average values for Producer's Accuracy of agricultural areas were 97.23, 97.66 and 97.67% for the TNDVI, NDVI and the SAVI, respectively. The lowest Producer's Accuracy for non-agriculture areas was 90.13% in 1985 with the TNDVI, whereas the highest was 98.80% in 2015 with the SAVI. The average values for Producer's Accuracy of non-agriculture areas were 93.03, 92.76 and 96.61% for the NDVI, TNDVI and the SAVI, respectively.

Data in Table (6) show that the lowest user's accuracy for agricultural areas was 88.06% in 2015 for NDVI and the highest was 98.51% in 2015 for SAVI. The average values for User's Accuracy of agricultural areas were 92.33, 89.97 and 94.21% for the TNDVI, NDVI and the SAVI, respectively. The lowest User's Accuracy for non-agriculture areas was 96.43% in 1985 for SAVI, whereas the highest was 99.40% for the three studied indices in 1985, 1999 and 2015. The average values for User's Accuracy of non-agriculture areas were 98.39, 98.27 and 97.92% for the TNDVI, NDVI and the SAVI, respectively.

The overall accuracy data are represented in Table (7). These data show that the lowest value for the TNDVI was 94% in 1985, whereas the highest value was 97.00% in 1999. The lowest Overall accuracy for the NDVI was 94.33% in 1985 and 2015, whereas the highest was 95.33% in 1999, with an average value of 94.83%. Also, the lowest overall accuracy for the SAVI was 94.98% in 1999 and the highest was 99.00% in 2015, with an average value of 96.99%.

Similar trends were obtained with the Kappa coefficient for three studied vegetation indices. Generally, it could be concluded from the accuracy assessment results that both agriculture and non-agriculture in the studied area were classified with very high accuracy. However, the SAVI index had the highest accuracy followed by the TNDVI and the NDVI, respectively.

Table (5): Producer's accuracy of agricultural and non-agricultural areas based on the studied indices

Year	Agricultural Areas			Non-agricultural Areas		
	TNDVI	NDVI	SAVI	TNDVI	NDVI	SAVI
1985	97.97	97.35	96.88	90.13	91.28	96.43
1999	99.21	96.15	96.08	95.38	94.90	94.42
2015	95.24	99.16	99.25	94.87	91.16	98.80
Min.	95.24	96.15	96.08	90.13	91.16	94.42
Max.	99.21	99.16	99.25	95.38	94.90	98.80
Average	97.23	97.66	97.67	92.76	93.03	96.61

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Table (6): User's accuracy for agricultural and non-agricultural areas based on the studied indices

Year	Agricultural Areas			Non-agricultural Areas		
	TNDVI	NDVI	SAVI	TNDVI	NDVI	SAVI
1985	90.63	91.88	96.88	97.86	97.14	96.43
1999	94.03	90.91	89.91	99.40	97.89	97.89
2015	90.91	88.06	98.51	97.37	99.40	99.40
Min.	90.63	88.06	89.91	97.37	97.14	96.43
Max.	94.03	91.88	98.51	99.40	99.40	99.40
Average	92.33	89.97	94.21	98.39	98.27	97.92

Table (7): Overall accuracy and kappa coefficient for the three studied indices

Year	Overall Accuracy			Kappa coefficient		
	TNDVI	NDVI	SAVI	TNDVI	NDVI	SAVI
1985	94.00	94.33	96.67	0.88	0.89	0.93
1999	97.00	95.33	94.98	0.94	0.90	0.89
2015	95.00	94.33	99.0	0.89	0.88	0.98
Min.	94.00	94.33	94.98	0.88	0.88	0.89
Max.	97.00	95.33	99.0	0.94	0.90	0.98
Average	95.50	94.83	96.99	0.91	0.89	0.94

3.5. Changes in Agricultural Areas in Babil Governorate from 1985 to 2015.

Changes in agricultural against non- agricultural areas in Babil governorate from 1985 to 2015 were studied based on the results obtained from SAVI Index. This is because it has the highest accuracy as mentioned above. Changes in agricultural areas between each two consecutive periods of study data are represented in Table (8) and figure (8). Changes from agricultural to non- agricultural areas were about 1472 km² from 1985 to 1999, whereas changes to agricultural areas were 337 km² at the same period. Also, changes from agricultural to non- agricultural areas were about 351 km² from 1999 to 2015, whereas changes to agricultural areas were 1061 km² at the same period. The overall changes from agricultural to non- agricultural areas was about 1073 km² during the whole studied period from 1985 to 2015, whereas changes to agricultural areas were 646 km² at the same period. These data indicated that agriculture areas in Babil governorate were significantly decreased from 1985 to 1999. This could be attributed to lack of governmental support to farmers due to the economic sanctions after the first and the second gulf wars, the shortage in water resources and increase of soil salinity and land degradation. The most obvious change in agricultural areas was observed in the Mahaweel district. However, there was slight increase in agricultural areas especially in the north-western parts of Hilla district and the south-eastern parts of Musayyib district. This could due to land reclamation projects in these areas, where these areas are close to rivers. The availability of water resources and their good quality makes it easy to cultivate these areas. Generally, the slight increase in agricultural areas from 1999 to 2015 could be attributed to the end of the economic sanctions, the increased government support for farmers and the progress in land reclamation programs.

Table (8): Changes in Agriculture areas in Babil governorate from 1985 to 2015 based on the SAVI data.

Type of Change	1985 - 1999		1999- 2015		1985 - 2015	
	km²	%	km²	%	km²	%
To Non-Agric.	1472	27.11	351	6.46	1073	19.74
No Change	3623	66.69	4020	74.01	3713	68.36
To Agric.	337	6.20	1061	19.53	646	11.90
Total	5432	100	5432	100	5432	100

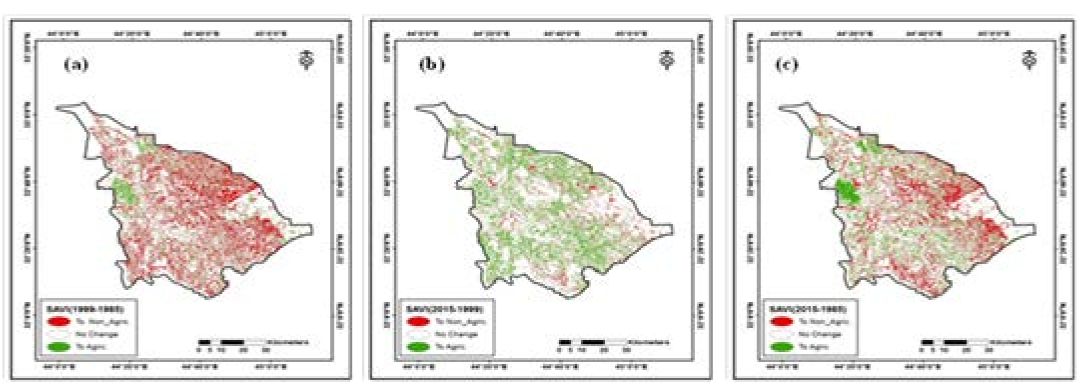

Figure (8): Changes of agriculture and non-agriculture areas in Babil governorate from: a) 1985 to 1999, b) 1999 to 2015, and c) 1985 to 2015 based on SAVI index.

3.6. Salinity viz. non-Salinity Areas in Babil Governorate Based on the SI Index.

Data in Table (9) show that the estimated saline areas in Babil governorate from 1985 to 2015 based on the SI index. These areas were about 203, 446 and 371 km^2 in 1985, 1999 and 2015, respectively and their percentages were about 3.74, 8.22 and 6.82%, respectively. On the other hand, non-saline areas were about 5229, 4986 and 5061 km^2 in 1985, 1999 and 2015, respectively and their percentages were about 96.26, 91.78 and 93.18%, respectively. These results indicated in increasing pattern in saline areas within Babil governorate during the studied period of time from 1985 to 2015. However a slight decrease in these areas (about 16.99%) was observed in 2015 when compared with that in 1999. This could be attributed to the economic sanctions on Iraq after the second gulf war and the decrease in governmental support the farmers. Also, during the period from 1992 to 2003 Iraq was dependent up on the oil for food program set by the United Nation (UN). This is in addition to the mismanagement of agricultural areas and the use of less effective systems for field irrigation and drainage, Figure (9) illustrates the spatial distribution of saline viz. non-saline areas in Babil governorate based on the SI index in 1985, 1999 and 2015.

Table (9): Estimated Saline and non-Saline areas in Babil governorate from 1985 to 2015 based on the SI index.

Land Cover	1985		1999		2015	
	Area km^2	%	Area km^2	%	Area km^2	%
Saline	203	3.74	446	8.22	371	6.82
Non-Saline	5229	96.26	4986	91.78	5061	93.18
Total	5432	100	5432	100	5432	100

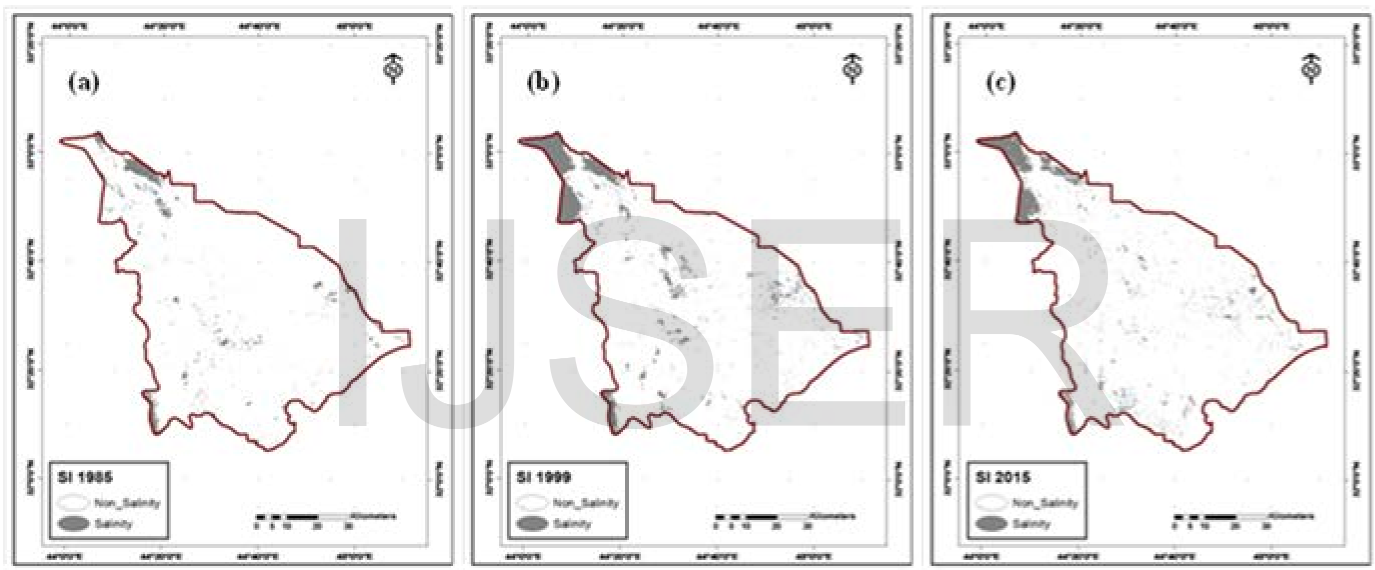

Figure (9): Spatial distribution of Saline areas in Babil Governorate obtained from the SI index in: a) 1985, b) 1999, and c) 2015.

3.7. Salinity viz. non-Salinity Areas in Babil Governorate Based on the NDSI Index.

The estimated Salinity areas in Babil governorate from 1985 to 2015 based on the NDSI index are represented in Table (10). These areas were about 561, 1051and 783 km^2 in 1985, 1999 and 2015, respectively and their percentages were about 10.32, 19.34 and 14.41%, respectively. On the other hand, non-saline areas were about 4871, 4381and 4649km^2 in 1985, 1999 and 2015, respectively and their percentages were about 89.68, 80.66and 85.59%, respectively. These results reveal the same pattern obtained with the SI; however the estimated areas were larger than those obtained with the SI. Figure (10) illustrates the Spatial distribution of Saline viz. non-Saline areas in Babil governorate based on the NDSI index in 1985, 1999 and 2015 is illustrated in .

Table (10): Saline viz. non-Saline areas and their percentage in Babil governorate from 1985 to 2015 based on the NDSI index.

Land Cover	1985		1999		2015	
	Area km^2	%	Area km^2	%	Area km^2	%
Saline	561	10.32	1051	19.34	783	14.41
Non-Saline	4871	89.68	4381	80.66	4649	85.59
Total	5432	100	5432	100	5432	100

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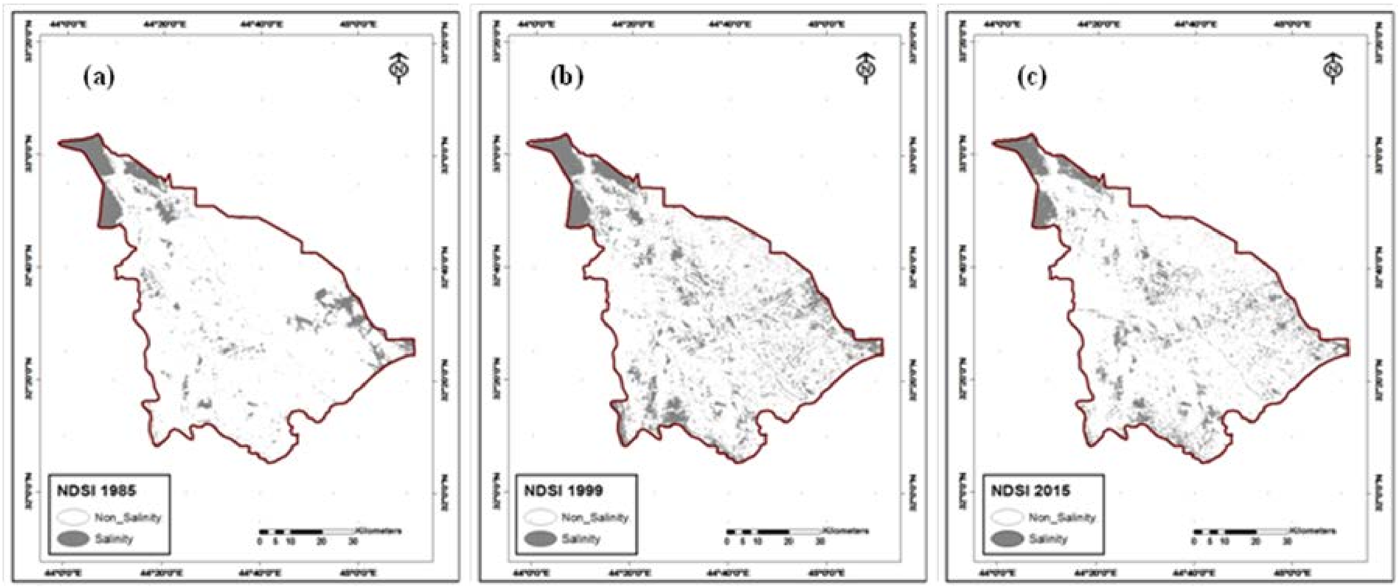

Figure (10): Spatial distribution of Salinity areas in Babil Governorate obtained from the NDSI index in: a) 1985, b) 1999, and c) 2015.

3.8. Accuracy Assessment of the Studied Indices.

Accuracy Assessment was performed on the obtained binary imaged from the two studied salinity indices (SI, and NDSI) in 1985, 1999 and 2015 to evaluate their efficiency. This process was carried out in the same way that was used in studying the accuracy of vegetation indices. Data of kappa coefficient, producer's, user's and overall accuracy for both indices are represented in Tables (11 to 13). The lowest producer's accuracy of saline areas was 95.41% in 1999 with the NDSI, whereas the highest value was 99.34% with the same index in 1985. The average values of producer's accuracy for saline areas were 97.38% and 97.25% with the NDSI and SI, respectively. The lowest Producer's accuracy for non- Saline areas was 83.89% in 1985 with the NDSI, whereas the highest was 98.41% in 1985 with the SI. The average values for producer's accuracy of non-saline areas were 95.22% and 88.81% with the SI and the NDSI, respectively.

The lowest user's accuracy for saline areas was 86.21% with the NDSI in 1985 and the highest value was 98.85% with the SI in 1985. The average values of user's accuracy of saline areas were 92.05 and 95.01% for the NDSI and SI, respectively. The lowest user's accuracy for non-saline areas was 90.91% with NDSI in 1999, whereas the highest value was 99.21% with NDSI in 1985. The average values of user's accuracy for non-saline areas were 95.06% and 97.85% for the NDSI and SI, respectively.

The overall accuracy for the NDSI was 91.67% in 1985 and the highest value was 94.33% in 1999, with an average of 93.00%. On the other hand, the lowest overall accuracy for the SI was 94.67% in 2015and the highest was 98.67% in 1985, with an average value of 96.67%. The obtained results also indicated that the lowest kappa coefficient for the NDSI was 0.83 in 1985 and the highest was 0.88 in 1999, with an average value of 0.86. The lowest kappa coefficient for the SI was 0.89 in 2015 and the highest was 0.97in 1985, with an average value of 0.93. Form these results it could be concluded both saline and non-saline areas were classified with high accuracy using the tow studied salinity indices (NDSI and SI). However, the SI index had the highest accuracy when compared with the NDSI.

Table (11): Producer's Accuracy for Saline and non-Saline areas based on the studied indices.

Year	Saline Areas		Non-Saline Areas	
	NDSI	SI	NDSI	SI
1985	99.34	98.85	83.89	98.41
1999	95.41	95.65	93.72	96.76
2015	97.76	97.81	90.36	92.02
Min.	95.41	95.65	83.89	92.02
Max.	99.34	98.85	93.72	98.41
Average	97.38	97.25	88.81	95.22

Table (12): User's Accuracy for Saline and non-Saline areas based on the studied indices.

Year	Saline Areas		Non-Saline Areas	
	NDSI	SI	NDSI	SI
1985	86.21	98.85	99.21	98.41
1999	97.89	94.83	90.91	97.28
2015	89.12	91.16	98.04	98.04
Min.	86.21	91.16	90.91	97.28
Max.	97.89	98.85	99.21	98.41
Average	92.05	95.01	95.06	97.85

Table (13): Overall Accuracy and Kappa coefficient for the two studied indices

Year	Overall Accuracy		Kappa coefficient	
	NDSI	SI	NDSI	SI
1985	91.67	98.67	0.83	0.97
1999	94.33	96.33	0.88	0.92
2015	93.67	94.67	0.87	0.89
Min.	91.67	94.67	0.83	0.89
Max.	94.33	98.67	0.88	0.97
Average	93.00	96.67	0.86	0.93

3.9. Changes in Saline viz. Non-Saline Areas in Babil Governorate from 1985 to 2015 Based on the SI Index.

Data in Table (14) show the changes in both saline and non-saline areas in Babil governorate from 1985 to 2015 based on the index of SI index, which has the highest accuracy. It was observed that saline soils in Babil governorate were increased over time from 1985 to 2015. This could be attributed to economic problems and poor management of agricultural lands. Changes to saline areas were about 321 km² between 1985 and 1999, about 108 km² between 1999 and 2015, and about 283 km² during the whole studied period from 1985 to 2015. Changes to non-saline areas were about 77 km² between 1985 and 1999, about 184 km² between 1999 and 2015, and about 116 km² between 1985 and 2015 as represented in Figure (11). Most of the significant change in saline areas was observed in the northwestern parts of the studied area. This could be attributed to the shortage of water resources, dry of lakes and poor irrigation practices. Similar trends were observed in the central and southern parts of Babil governorate.

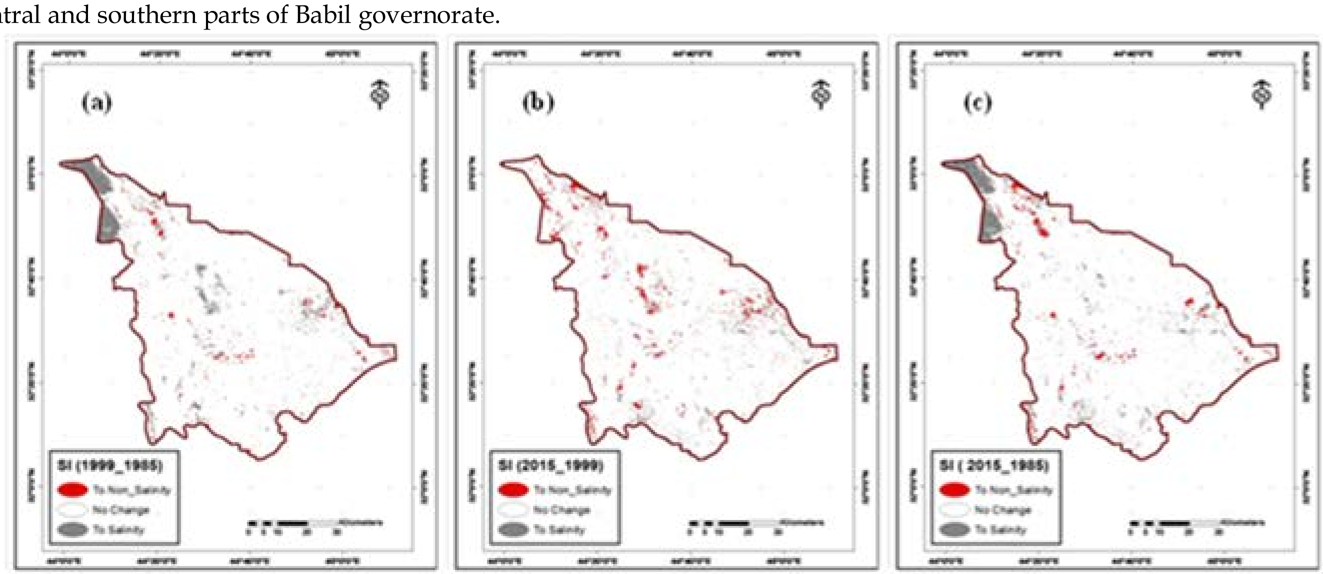

Figure (11): Changes in Saline and Non-Saline areas with Babil governorate between: a) 1985 and 1999, b) 1999 and 2015, and c) 1985 and 2015 based on SI index.

Table (14): Changes in saline and non-saline areas within Babil governorate between1985 and 2015

Change in Saline Areas	1985- 1999		1999 - 2015		1985 - 2015	
	km²	%	km²	%	km²	%
To Saline	321	5.90	108	1.99	283	5.22
No Change	5034	92.67	5140	94.62	5033	92.64
To Non-Saline	77	1.43	184	3.39	116	2.14
Total	5432	100	5432	100	5432	100

Figure (12) shows the rate of change in saline areas between each two consecutive years of the three studied periods. The highest rate of change in saline area was observed between 1985 and 1999.

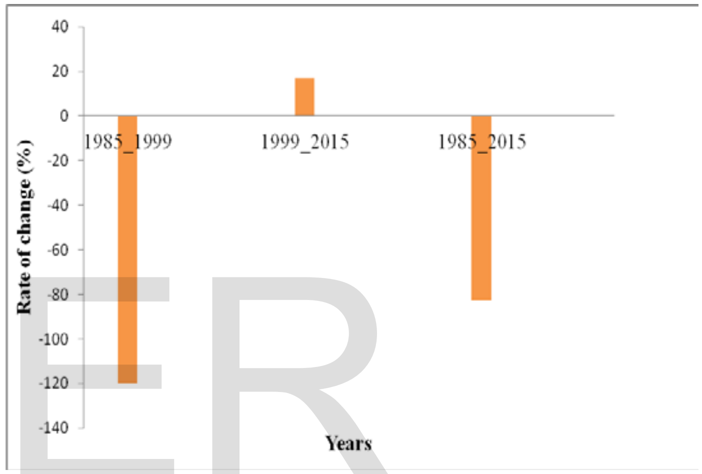

Figure (12): Rate of change in saline areas between each two consecutive years based on the SI index.

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3.10 Correlation between the vegetation and salinity indices.

In this work the linear regression model was used to study the relationship between the two highly accurate vegetation and salinity indices. The relationship between the SAVI and SI values was represented in Figure (13). It shows an obvious reverse relationship (r= -0.90, p=0.001) between the values of both indices throughout Babel governorate. In other words, the higher the SAVI values the lower the SI values and vice versa. This relationship makes sense, where saline areas decrease as the agricultural areas increase due progress in land reclamation projects and good management practices.

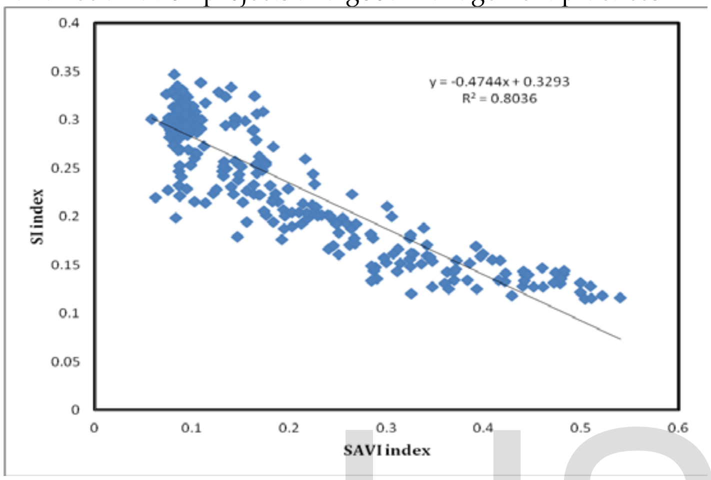

Figure (13): Relationship between vegetation (SAVI) and salinity (SI) indices in 2015.

3.11 Sustainability of Agricultural Lands

In order to sustain agricultural areas to meet the future needs of the growing population, the rate of increase in agricultural areas was calculated from their estimates in the last 16 years. Table (15) shows an estimate of agricultural areas and their share per person base on the population of Babil governorate in 1999 and 2015, agricultural areas and the annual rate of change in these years. It shows the population will increase to 3,011,757 in 2030 and the share of person from agricultural areas will be 1061, which is less than that in the previous years. Therefore, there is an urgent need to sustain agricultural areas in Babil governorate to meet the population needs for food in the future. This could be achieved through the development of land reclamation and cultivation projects, using most effective irrigation and drainage systems, and providing financial and technical support to farmers in these areas.

Table (15): Estimated agricultural areas and their share per person in 2030.

Year	Population (person)	Agricultural Areas (km^2)	Annual Change in Agric. Areas (%)	Area/person (m^2/person)
2015	2019291	2217	2.94	1098
2030	3011757	3195		1061

Conclusions

From our work, it could be concluded that the application of both remote sensing data and GIS techniques could provide more accurate, low cost, time effective information about agricultural areas and land degradation due to soil salinity. Agricultural areas in Babil governorate were accurately classified using the three studied indices (SAVI, NDVI and TNDVI); however the SAVI had the highest accuracy. Also, Salt-affected soils were accurately classified using the two studied salinity indices (NDSI and SI); however the SI index showed the highest accuracy.

In general, there was a decrease in agricultural areas in Babil governorate from 1985 to 2015, whereas there was an increase in the salt-affected areas. This could be attributed to the economic sanctions, decrease in water resources, and low financial support to farmers. Therefore, there is a critical need to sustain agricultural areas in order to meet the need of the growing population for food in the future. This could be accomplished through the progress in land reclamation and cultivation projects, providing financial and technical support to farmers, and using most effective irrigation and drainage systems in these areas.

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