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USING SATELLITE IMAGES CLASSIFICATION TO ESTIMATE WATER LEVEL IN THE SOUTHERN MARSHLANDS AFTER THE FLOODS WAVE

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Abstract:

AL-Hawizah marshes is one of the important marshes in the southern Iraq, near the border with Iran. They are rich in a distinctive nature, and large rural communities have formed around them over the past centuries, and their waters are derived from rains and the Tigris and Euphrates rivers. The stifling water crisis that swept areas in southern Iraq in 2018 raised the alarm after it caused the drying up of a number of branch rivers of the Tigris River in Maysan Province. The aim of the paper is to compare land use before and after of the flood season for AL-Hawizah marshes, and also to determine the values of the water-reflectivity of the water by using remote sensing and geographic information systems for 2018 and 2019. The values of the water-reflectivity were calculated using Landsat-8 images between 2018/3/4 and 2019/3/7, before and after the floods wave that swept the southern marshlands. The results showed that the remote sensing can delineate water and extent of inundated area caused by flood in marshes and that extracted from Landsat 8 accurately.

Keywords: Landsat, AL-Hawizah Marshes Classification, IDW Interpolation, NDWI.

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1. Introduction:

Water is a natural resource that is essential for human life and plays a significant role in the development of the economy, society, and other industries. Because water is one of the most essential resources, life cannot exist on this planet without it. Water quality indicators are used to assess current circumstances, which necessitates understanding of fundamental principles and ideas connected to water and related topics [1]. An aquatic ecosystem's water quality, for instance, is influenced by a variety of physical, chemical, and biological elements [2]. In general, there are several types of pollution related to pesticides, hydrocarbons, or harmful heavy metals in the southern marshland habitats of Iraq increased chemical toxicity in the rivers and marshes [3].

Surface water and groundwater contamination as a result of fast industrialization has a negative influence on human health, making research of contamination and its control crucial. Lakes, groundwater, glaciers, rainwater, rivers, etc. are all forms of water that are used for drinking, industrial processes, raising cattle for food, agriculture, hydropower production, fisheries, and other productive endeavors. The Mesopotamian Plain's important regions will be studied first [4].

Between 15000 and 20000 km2 in size, the Tigris and Euphrates rivers generate a large complex of shallow lakes and marshes in the southern part of Iraq. These wetlands range from within 150 km of Baghdad in the northwest to the area of Basrah in the southeast. They are made up of a series of tier-connected, shallow freshwater lakes, marshes, and seasonally inundated floodplains. The Saadiyah and Sanniya wetlands complex in the north, Al-Hammar in the south, and Al-Hawizah in the east are the main lakes. There are vast expanses of permanent shallow marsh on both sides of the Tigris between Basra and Amara. a sizable wetland along the Tigris with water from two to four feet deep and a belt of reeds over which the water is submerged [5].

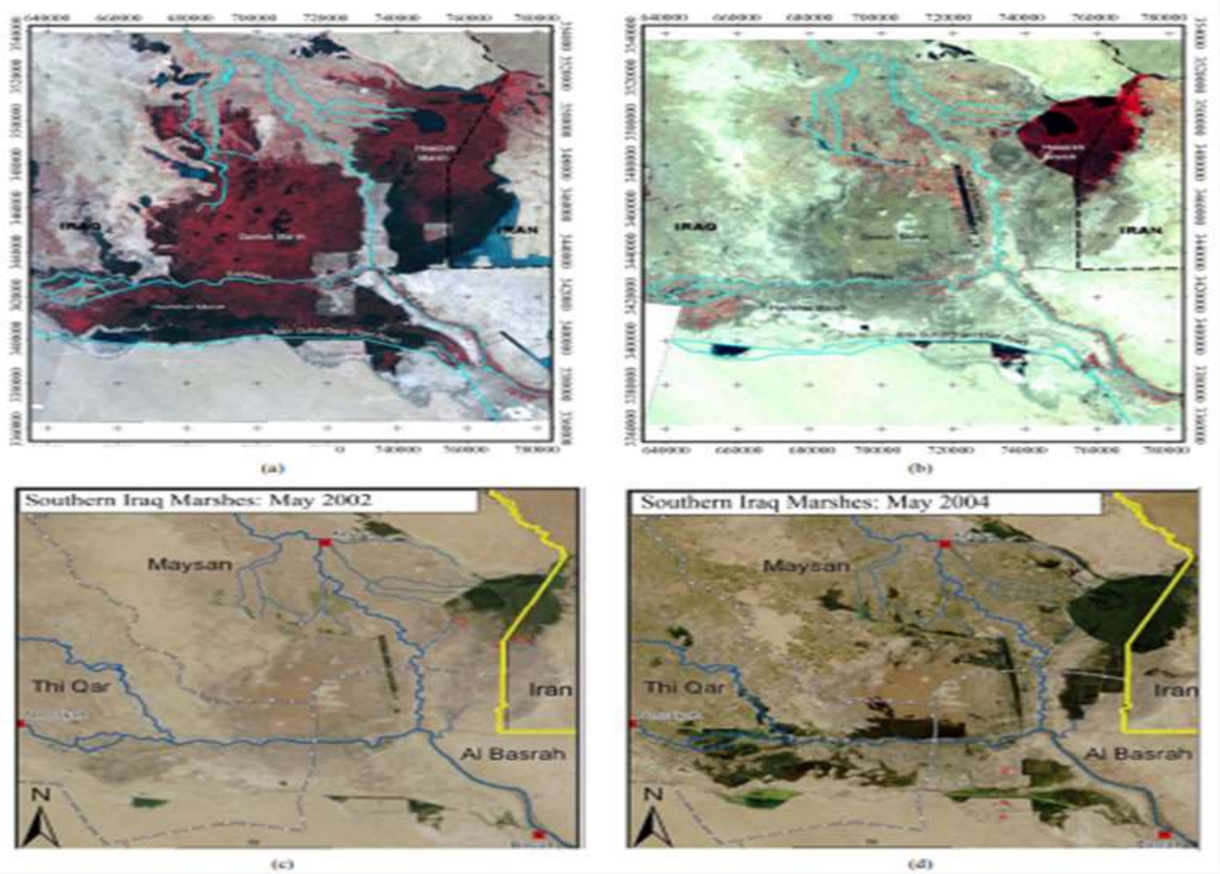

Figure 1: AL-Hawizah Marshes (a) in 1985, (b)in 2000, (c) in 2002, (d)in 2004 [6].

2. Data and Methods:

Study Area

One of the largest marshes in southern Iraq's Mesopotamian marshes is Al-Hawizah Marshes, which is located to the east of the Tigris River. A portion of these marshes (21%) crosses the border into Iran, and from these locations, the Karkheh River (Iran) feeds the marshes, while the rest are fed by the Tigris [7]. From north to south, these wetlands span 80 km, and from east to west, 30 km [8]. At least 3,000 square kilometers of the AL-Hawizah marsh were flooded with floodwaters, when only a few hundred square meters were covered throughout the summer. During the flooding season, the majority is concentrated in Iraq, which occupies an area of around 3500 km2. During the drying process, this marsh shrinks to 650 km2 [9]. They are nourished by the AL-Musharah and AL-Kahla, two major branches of the Tigris that emerge close to AL-Amarah. This marsh has operated for generations in a natural setting, providing resources for the local population, crucial habitat for migratory birds, and a significant source of the Middle East's natural hydrology. The Mesopotamian wetlands were purposefully drained in the early 1990s. The biodiversity of the marshes has suffered as a result of this catastrophe. These wetlands were once more submerged in April 2003 in the hopes that the ecosystem will revert to its original state. This new circumstance prompted numerous scientists and researchers to examine how the ecosystem responds following re-flooding and to evaluate the degree of restoration in these re-flooded places [10].

Figure 2: AL-Hawizah Marshes.

3. Image Classification:

A classification can be considered as principally:

3.1 Supervised classification:

In this classification method, the image analyst "supervises" the computer algorithm's pixel categorization process by providing it with numerical descriptors for the various types of land cover that can be found in a scene. To do this, a numerical "interpretation key" that defines the spectral properties for the target feature type is assembled using representative sample locations of known cover type, referred to as training areas. Then, each pixel in the data set is numerically compared to each category in the interpretation key and given a label. The comparison between unknown pixels and training set pixels can be performed using a variety of numerical techniques.

The analyst must direct the classification process during supervised classification operations by pointing out areas on the picture that are known to belong to particular LU/LC categories before the classification. Training sites are the names given to these locations. The classification of pixels with unknown identities is subsequently done using the training sites or samples of known identities. When possible, the positions of the training site pixels should be based on actual locations. The computer recognizes similar pixels in the image by comparing their spectral properties to those of the training pixels. Any supervised classification approach, such as Parallelepiped, Maximum Likelihood, Minimum Distance, and Mahala nobis Distance, must carefully select its training pixels in order to be effective [11].

3.2 Unsupervised classification:

Usually describes a classification in which the classes are not planned; instead, a group of 'natural' classes is discovered using the statistical or clustering qualities of the picture data. As a result, unsupervised classification techniques are frequently used in large-scale land cover mapping projects where the classifications are relatively simple. Unsupervised spectral classes can be labeled in a methodical manner in regional or small area studies [12].

4. Interpolation Methods:

This methodology, which includes both deterministic and geostatistical divisions, is described as the process of forecasting a specific interested variable at unstamped locations beyond to measured values for selected places within the interest area. The values at unnamed places are calculated using mathematical functions based on the degree of resemblance (IDW, for example) or degree of smoothing (RBF, for example) in comparison to nearby points. While geostatistical techniques have mathematical and statistical functions that predict values for arbitrary locations and give probabilistic estimates of the quality of interpolation based on the spatial autocorrelation between points.

Additionally, interpolation techniques are divided into two categories: local and global. The first one functions in locations that are less extensive than the necessary area that surrounds the location of the approximated point neighborhood) [13]. Local polynomial Inverse Distance Weighting (IDW) and radial basis functions are two examples of local deterministic techniques (RBF). The first one, on the other hand, uses already-collected sample locations to produce estimates for the entire region. These methods can be used to assess and eliminate any physical trends in the data that have caused global variations. Additionally, there are two types of interpolation techniques: approximate and accurate interpolations. Exact interpolators accurately extrapolate values to match the measurements made at the sampled sites [14,15].The IDW method have been adopted.

5. Inverse Distance Weighted (IDW):

One of the easiest and most accessible approaches is this one. It is predicated on the idea that the value at an unsampled point can be roughly determined as a weighted average of values at points within a specific cut-off distance or from a set number m of the closest points (usually 10 to 30) [16].

$$z(s_\circ) = \sum_{i=1}^{N} \lambda_i \, . \, z(s_i) \, -------- 1$$

Where:

$z(s_\circ)$ shows a fictitious value at the unsampled site s_0.

N shows the number of a measured sample point inside the estimated for s_0.

λ_i represent the weights that each sample point has in relation to its distance.

$z(s_i)$ indicates the site's given data. s_i.

The obtained by weights are using:

$$\lambda_i = \frac{d_{io}^{-p}}{\sum_{i=1}^{N} d_{io}^{-p}} ----------- 2$$

$$\sum_{i=1}^{N} \boldsymbol{\lambda_i} = \mathbf{1} ---------- 3$$

Where: di_0 is the prediction site s_0 and the measured site location s_i distance.

P shows the power parameter that controls how quickly the weights are reduced as distance rises. IDW must be an accurate interpolator in order to prevent division by zero at the sampled positions when di0 = 0. [17]

For the AL-Hawizah Marshes, Landsat 8 satellite photos [15] were used, and 17 sites were identified using GIS (Geographic Information System). marshes of AL-Hawizah in the province of Mesopotamia (AL-Amara).

Point	X_Coordinate	Y_Coordinate
P1	71605	353161
P2	73870	352103
P3	75436	351129
P4	76367	350833
P5	77828	351891
P6	77976	350367
P7	76346	350029
P8	75076	349923
P9	73298	349330
P10	75161	348822
P11	73997	348081
P12	76029	347891
P13	74483	347362
P14	76198	346663
P15	75161	345753
P16	77701	345033
P17	76156	34440

6. Spectral Indices

6.1 Normalized Difference Water Index:

A remote sensing index called the **Normalized Difference Water Index** (NDWI) is frequently used to identify flooded areas [18]. Water bodies have been extensively mapped using multi-spectral satellite imagery.

Based on the strong near-infrared band (NIR) absorbability and the strong green band (green) reflectance from water, the NDWI distinguishes water bodies (Equation (4)). Although thresholds between 0 and 0.1 are typically used, pixels with an NDWI over 0 are candidates for open water bodies [19]. The following equation can be used to calculate the NDWI:

$$NDWI = \frac{Green - NIR}{Green + NIR} - - - - - 4$$

6.2 Normalized Difference Vegetation Index:

The Normalized Difference Vegetation Index (NDVI) calculation makes use of the red and NIR channels, as shown below.

$$NDVI = \frac{NIR - Red}{NIR + Red} - - - - - 5$$

In contrast to other wavelengths, healthy vegetation (chlorophyll) reflects more green and near-infrared (NIR) light. It does, however, absorb more red and blue light.

This explains why vegetation seems green to our sight. It would also be effective for vegetation if you could see near-infrared. The essential bands with NIR and red are present in satellite sensors like Landsat and Sentinel-2.

This formula produces a value that ranges from -1 to +1. A high NDVI score will result from low reflectance (or low values) in the red channel and high reflectance (or high values) in the NIR channel, and vice versa.

In general, NDVI is a consistent approach to gauge robust vegetation. Vegetation is healthier when the NDVI values are high.

Low NDVI means there is little to no vegetation present. For the most part, if you wish to observe how flora evolves through time [19].

6.3 Normalized Difference Built-up Index:

Normalized Difference Built-up Index (NDBI): The supervised and unsupervised classification of images is a time-consuming and difficult operation. The end result necessitates a competitive band & apply lots of operations. The image classification technique's accuracy is dependent on the picture analyst's methodology. To the contrary, NDBI calculation is straightforward and derivable. NDVI can be calculated using the formula below. For Landsat 8 data, NDBI = (Band 6 – Band 5) / (Band 6 + Band 5)

$$NDVI = \frac{SWIR1 - NIR}{SWIR1 + NIR} - - - - - - 6$$

The Normalize Difference is another value of the build-up index ranges from -1 to +1. Higher NDBI values indicate built-up regions, while lower values indicate water bodies. Vegetation has a low NDBI value [19].

7. Results and Discussion:

The image in figure 3 depicts the supervised classification, while images in figure (4,5) show the spectral indices NDVI, NDWI and NDBI from Landsat-8 at the marshlands for both 2018 and 2019, where they demonstrated good separability between water and vegetation when the flood wave that swept the southern marshlands at 2019. Flooded areas were represented by positive NDWI values (blue color) and the surrounding area by negative NDWI values (yellow color), while marshland vegetation was represented by green color. In the northeastern hillsides during the winter, Landsat-8 imagery showed shadows. In addition, some clouds remained in the final set of pictures (e.g., figure 3). They did not, however, block the view of the marshlands' water body.

Supervised classification was appropriate to discriminate water itself (figure 3) while NDVI, NDWI and NDBI related indices, reflected water better in their values (figure 4 and 5).

Figures 6 and 7 show a map of the water reflectance in the green, blue, red, and NIR bands over the interpolated areas of the AL-Hawizah wetlands. The values per sampling point from the reflectance values analysis were then used as input data in ArcGIS 10.2. To create spatial distribution maps, the sampling locations and water data are combined. The Inverse Distance Weighted (IDW) approach is used in the current work to spatially interpolate water reflectance in the AL-Hawizah marshes in the years before and after the floated wave that swept the southern marshlands in 2018 and 2019.

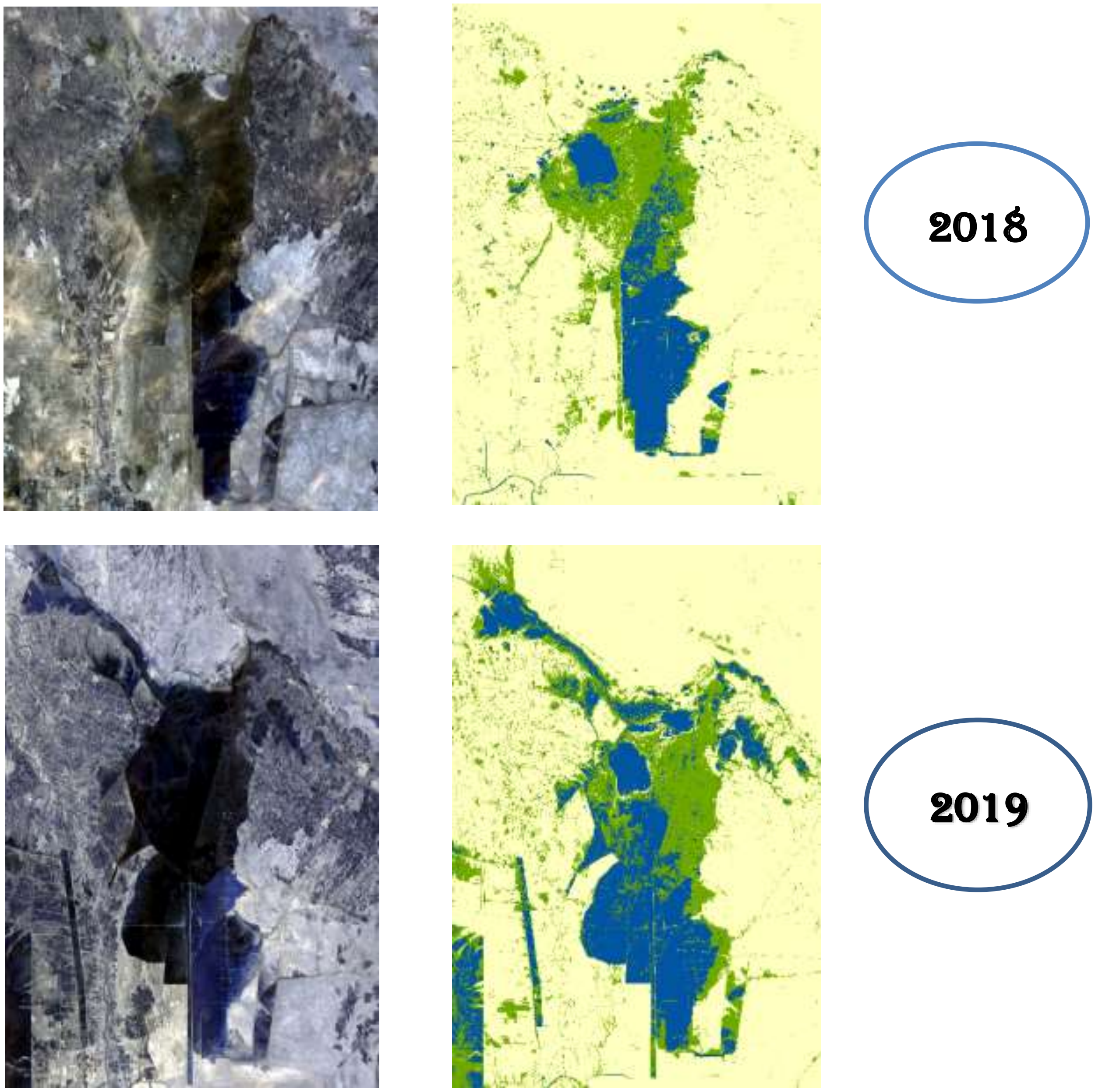

Figure 3: Supervised classification for both 2018 and 2019 in AL-Hawizah Marshes.

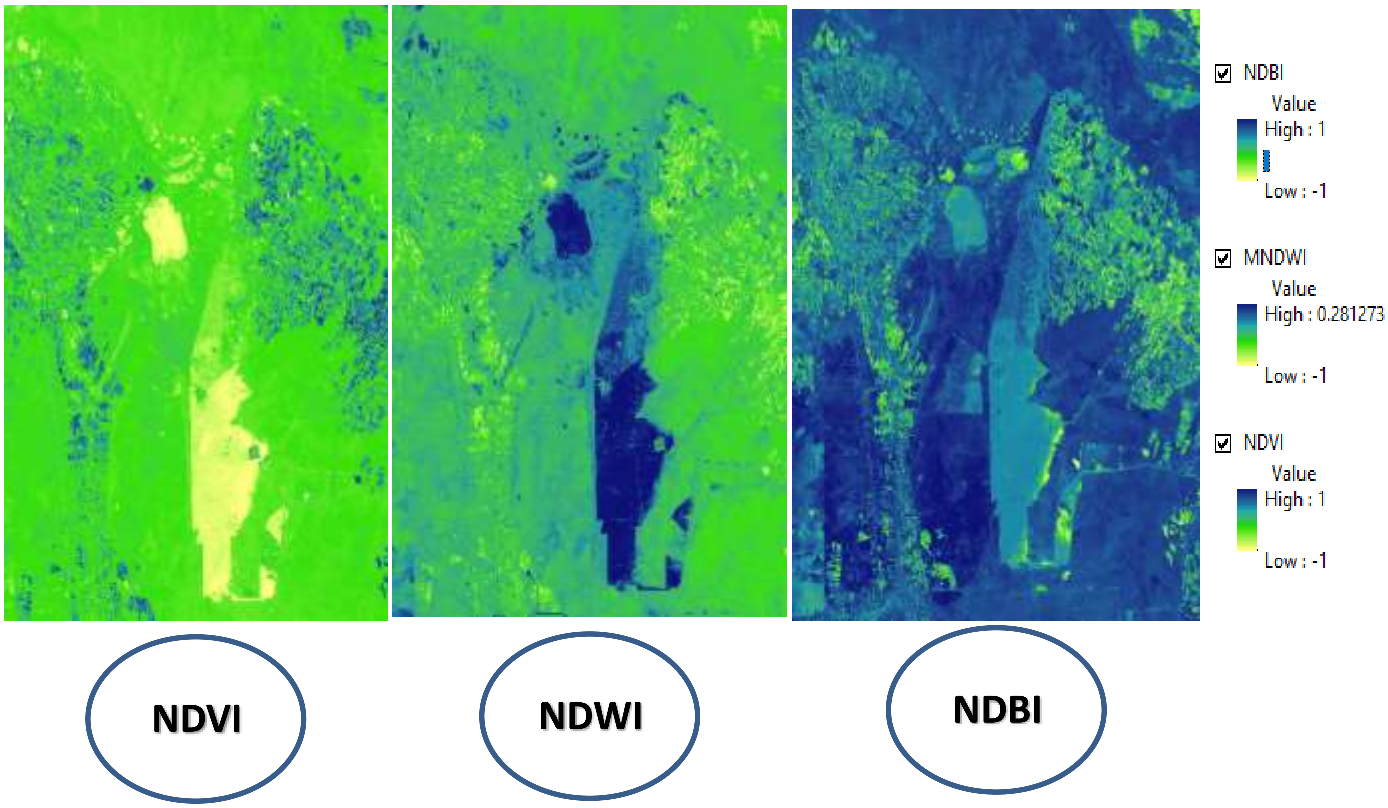

Figure 4: The spectral index observations NDVI ,VDWI and NDBI from Landsat-8 for 2018 in the AL-Hawizah Marshes.

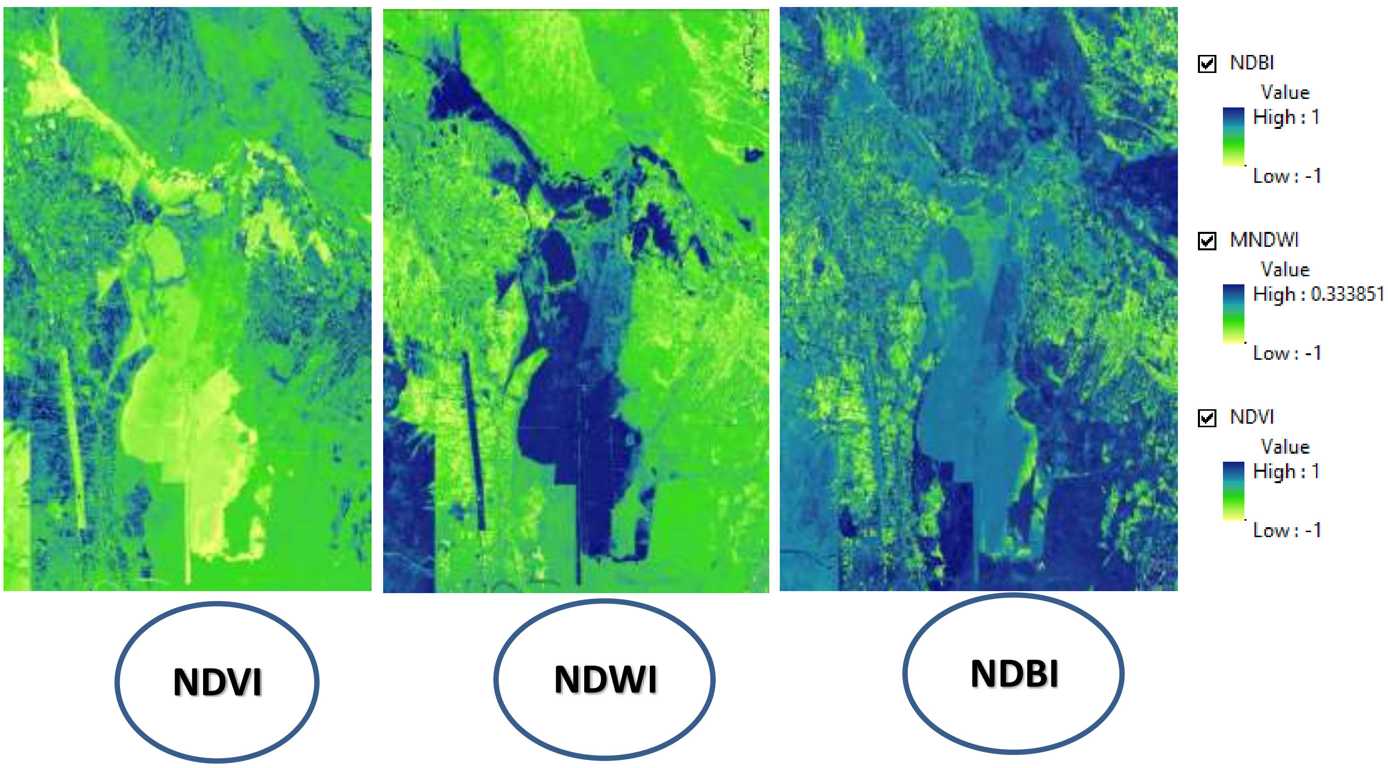

Figure 5: The spectral index observations NDVI ,VDWI and NDBI from Landsat-8 for 2019 in the AL-Hawizah Marshes.

The spatial pattern of water spectral reflectivity in AL-Hawizeh marshes:

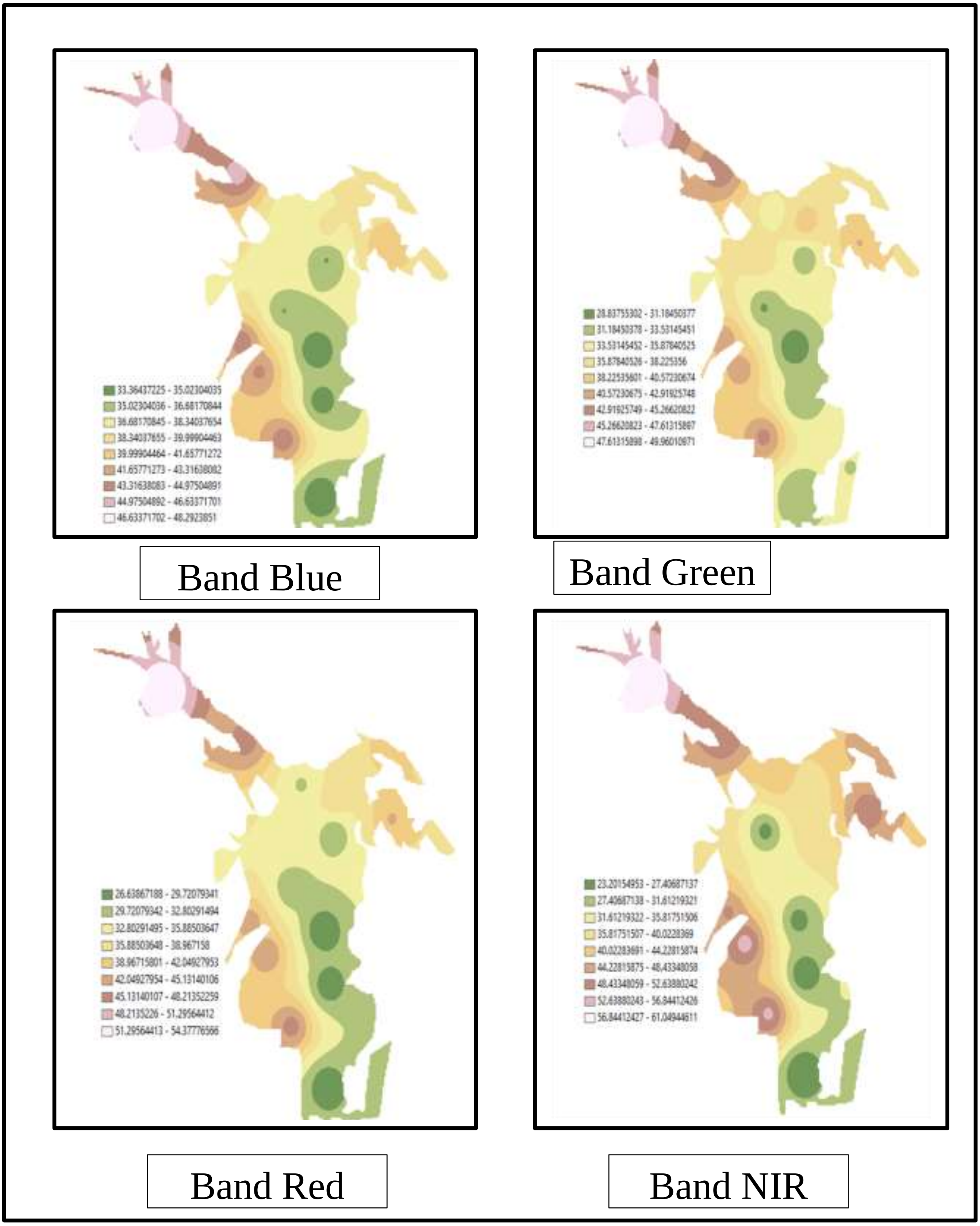

Figure 6: IDW interpolation was used to extrapolate the data for the reflectance value of water quality in 2018/3/4 over the Al-Hawizah Marshes in southern Iraq.

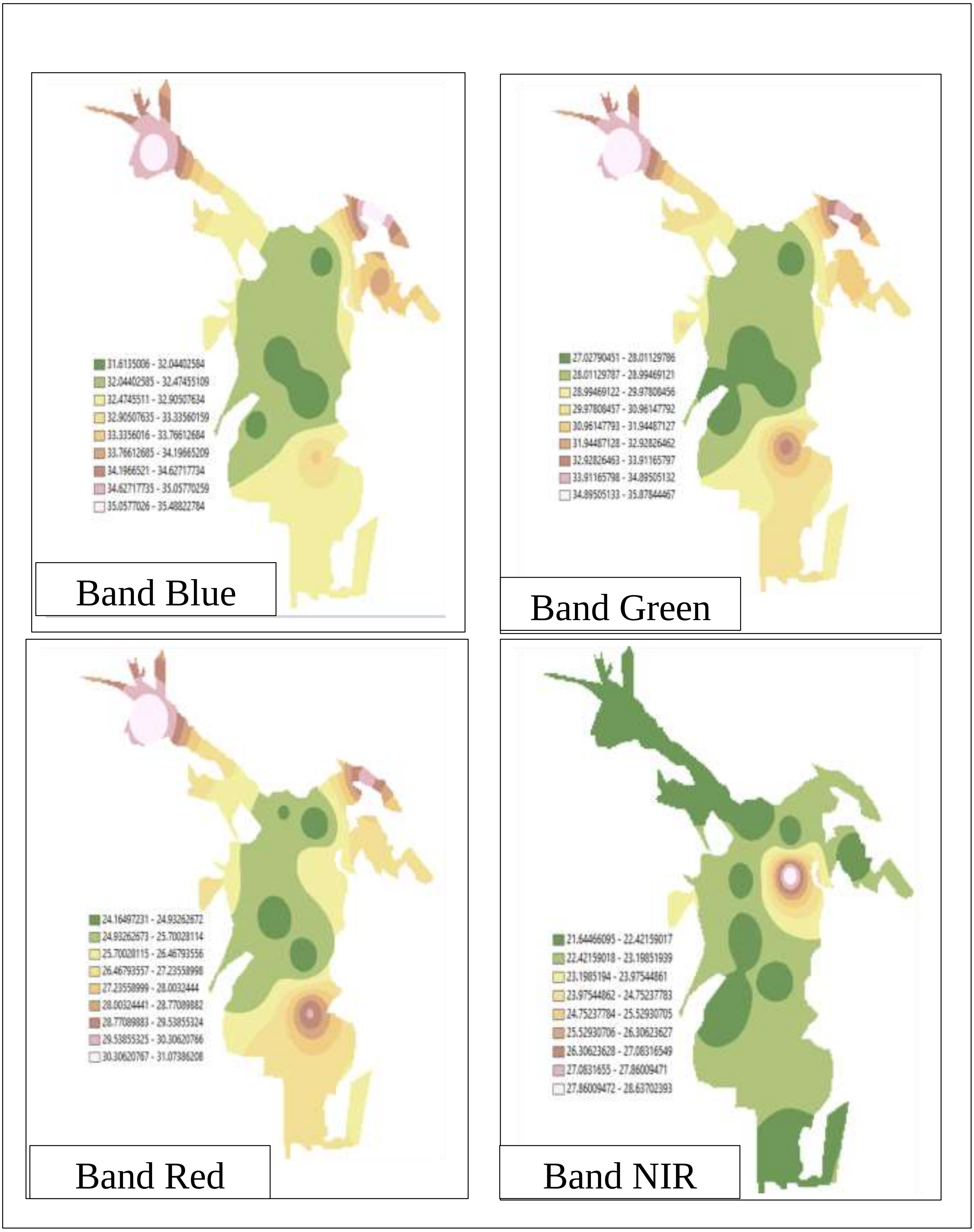

Figure 7 The interpolated results of the reflectance value of the quality of water in 2019/3/7 over .the AL-Hawizah Marshes in southern Iraq was created using IDW interpolation

The supervised classification method was used because it gives more accurate results than other methods.

8. Conclusions:

The results show that fluids may be remotely monitored indirectly by combining multitemporal analysis and remote sensing methods. The distribution of water level may be displayed using NDVI with the application of spectral indices and supervised classification. Multi-spectral satellite images are widely used for this purpose since there are many archives that are accessible and available. It has been shown that using a variety of satellite image sources with various formats and spatial-temporal resolutions can enhance predictions of the water level in the southern marshlands after the flood wave.

The NDWI is more sensitive to changes in water content of vegetation than that of the supervised classification. So, the satellite data is useful to determine the characteristics and spatial distribution of water level areas in the south marshland in Iraq.

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