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NDVI and NDWI Based Assessment of Land Cover Changes in Samarra, Iraq using Landsat 8 Data

Israa Hussein[1], Athar Hussein Mohammed[2]

[1]Department of Physics, college of education, University of Al-Qadisiyah , Diwaniyah, Iraq ,

[2]Department of Mathematic ,college of education , University of Al-Qadisiyah, Diwaniyah, Iraq

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ABSTRACT

This paper studied the land cover changes in the Samarra urban. Two images from Landsat-8. One image was from July 2013, and the second from July 2020 used for calculate vegetation as well as water bodies. We applied NDVI and NDWI to these images. Iraq is a dry region that is difficult to work in it. The features such as soil and vegetation cover seem almost equal in the scene, this cause conventional methods to generate wrong results. For this paper, we got a Level-2 scene from the USGS website. These scenes are adequate because they are already fixed for the atmosphere; thus, this step is not required. The Maximum Likelihood method is used to classify the scenes. The map tested ,that made with 250 points on Google Earth. The final result was acceptable, with 88.7% accuracy. When comparing the results for 2013 with 2020, it was observed that the water bodies and green areas decreased. The bare surface coverage increased significantly. These changes are mainly attributed to prolonged drought in the region.

1. Introduction

Satellite derived images have facilitated land surface monitoring . Landsat scenes are very common for monitoring . For knowing to understand features dynamics in a single area , the phenomena will undergo classification . Landsat-8 is considered appropriate for agricultural region due to its wide coverage for one pixel covers 30 meters. At this resolution, the farms , water bodies and builds , The final map will be useful or not based on the scene itself and depend on user skill.

The chief purpose of classification is to merge similar pixels in to single cluster . This work is exhausting in remote sensing, where one pixel refer to soil and dry grassland together. This is called a merge pixel. Therefore of merge pixels, classes exhibit spectral confusion such as water bodies and soil. Due to these challenges with some typical methods or significant preprocessing is required.

When Landsat-8 was sent to space, numerous studies have employed this satellite environment and agricultural application . Classification refers to assigning pixels . specific area classes depend on their spectral signatures , where land cover and water, based on its color and digital numbers. In region like

Corresponding author E-mail address: iasraa.hussein@qu.edu.iq
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Iraq the Drought is a very difficult problem . To research this topic, land cover patterns need to investigate . The process of classification means we assign each pixel to a class like water or vegetation based on its spectral values.[8][11][4] .Drought is one of the most serious issues in Iraq. To monitor it, researchers use simple ratios like NDVI and NDWI. NDVI compares the red and near-infrared bands and gives high values for healthy plants. NDWI uses near-infrared and shortwave infrared and is sensitive to water content. These two indices were used in many papers with supervised classification to see how land changed over time.[9][10][25][2][16].

The gap we found is that most papers say they used NDVI/NDWI but they do not explain how they chose the thresholds or how they checked the accuracy. Our paper focuses on these missing details for the Samarra area.[20][2]

2. Methodology

2.1 Study Area and Data

Our study area is Samarra city in Salah Al-Din province. It is at 34.1970°N, 43.8740°E and the area we studied is around 850 km². Samarra is an agricultural city on the Tigris River. We got two images from Landsat 8: 15/7/2013 and 18/7/2020. Both images are from the same path and row: 169/37.[2]

Instead of downloading raw images and correcting them ourselves, we used the Collection 2 Level-2 data from USGS. All level-2 DN values were multiplied by 0.0001scale factor as recommended by USGS to convert to surface reflectance before index calculation .The files are already corrected for atmospheric effects with the LaSRC code, and they are already projected to UTM Zone 38N. This saved us time and reduced errors. The full steps are shown in Figure (1).

2.2 NDVI and NDWI Calculation

We calculate NDWI with Band 5 and Band 6:

$$\text{NDWI} = \frac{(\text{Band 5} - \text{Band 6})}{(\text{Band 5} + \text{Band 6})} \quad (1)$$

NDWI is from -1 to 1. In our area, we found that water gives values above 0.2.[9][25]

For NDVI we used Band 5 and Band 4:

$$\text{NDVI} = \frac{(\text{Band 5} - \text{Band 4})}{(\text{Band 5} + \text{Band 4})} \quad (2)$$

NDVI is also from -1 to 1. Pixels above 0.3 were mostly vegetation in our images.[10][14]

2.3 Classification and Accuracy Assessment

After we got the NDVI and NDWI images, we used Maximum Likelihood to make the final map with four classes: water, plants, urban, and soil. We drew training areas by looking at the images and Google Earth. Many studies do not do accuracy check, but this step is very important. We made 250 random points using ArcGIS. For each point, we opened Google Earth and looked at the 2020 image to see what the real land cover is. Then we compared it with our map and built a confusion matrix to get the accuracy numbers [20].

3. Results and discussion

Figures (2a) and (2b) are the color images of 2013 and 2020. Figure (3a) is the NDVI map. It looked at Figure (3b), the histogram for the case . The "break values" there are just the min and max of the data. We looked at this histogram and decided where to cut the data to separate the classes. For example, most water pixels were below 0, and most vegetation was above 0.3. Figure (4) shows the same idea for NDWI.[10][9]

Figure (5a) is our classification result.

Table (1) shows the numbers we used as break values. These are standard numbers . We got them from our own histograms in Figures 3b and 4b.[2]

The figure shows that in 2020 there was less water and less vegetation than in 2013. Soil area became bigger. This agrees with the drought that happened in Iraq. When we checked the accuracy, we got 88.7%. This is better than the 81% that Ahmed and Akter (2017) reported for a delta area. The reason

might be that we used corrected Level-2 data and we were careful with the validation.[2][18][22][21].

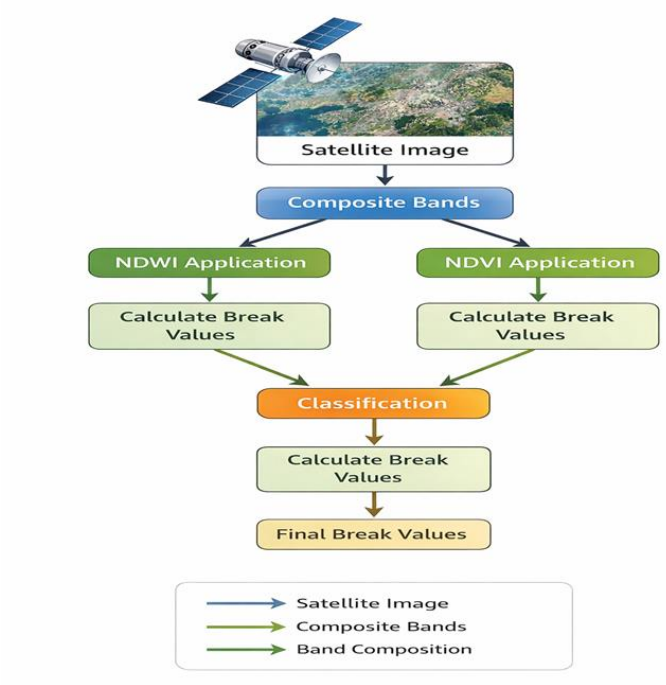
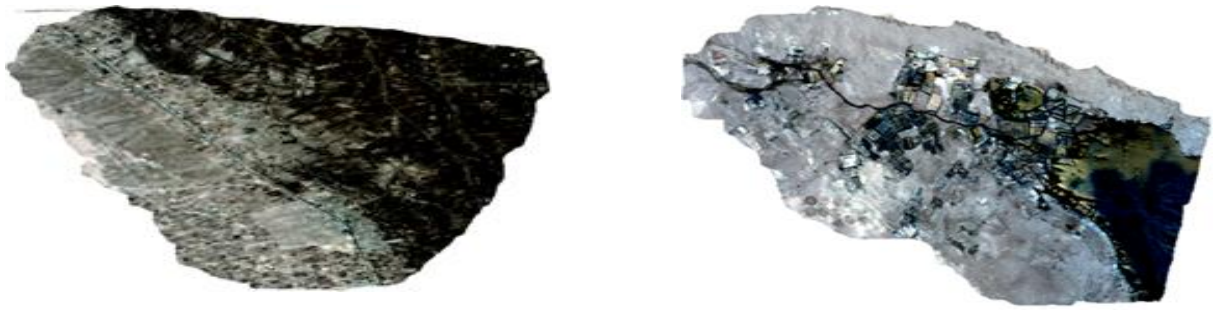
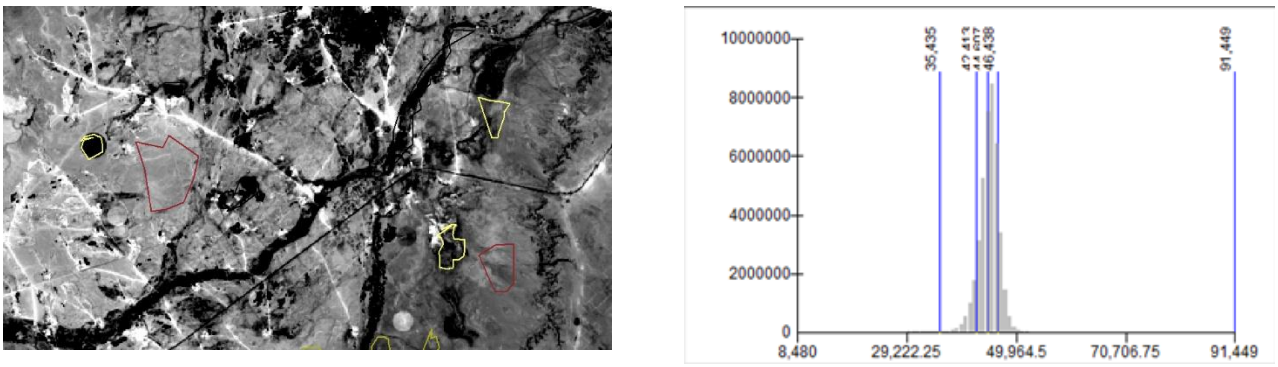


Figure 1. Flowchart showing the workflow of the study from satellite image processing to NDWI/NDVI analysis and final classification



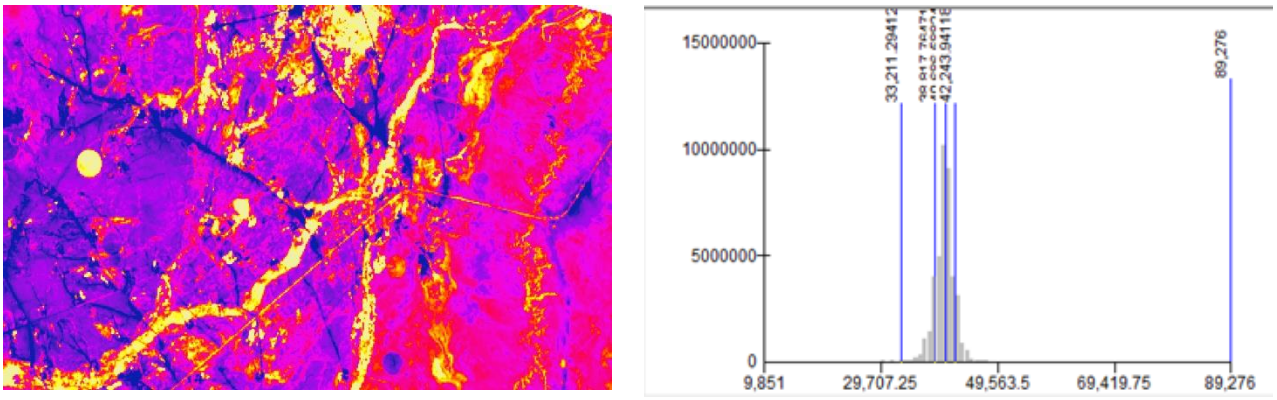
a b

Figures (2) a. agriculture area ,(b) part of river with agriculture regions



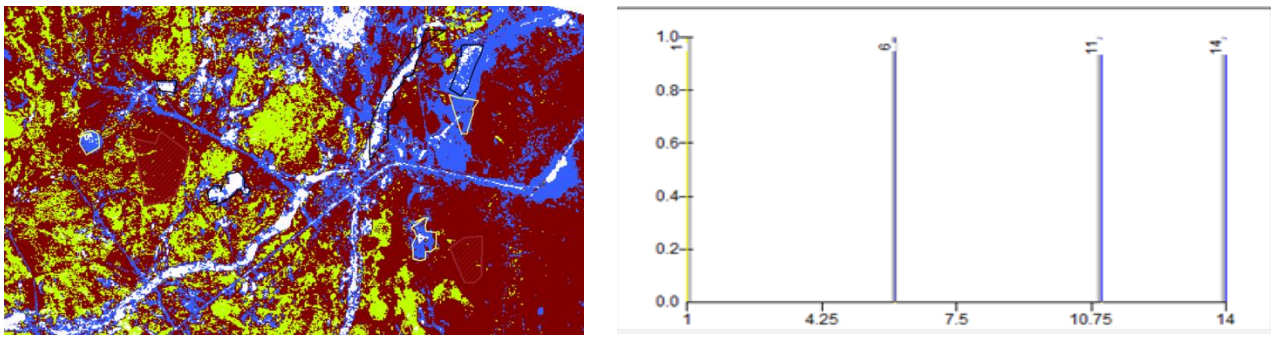
a b

Figure(3) : a. Image after NDVI application with determine the regions of different features
b. diagram show the break values for image after NDVI application



a b

Figure(4) :a. Image after NDWI application with determine the regions of different features
b. diagram show the break values for image after NDWI application



a b

Figure (5):a. Image classification . b. diagram for break values to NDVI after classification

Table (1): threshold values used for NDVI,NDWI and classification to study area

Class value	NDWI range for study area	NDVI range for study area	class
1	0.2 to 1	-1to 0	Water
2	-0.3to 0	0 to 0.2	Bare soil
3	-0.3 to 0	0.2 to 0.35	Sparse vegetation
4	-0.3 to 0	0.35 to 1	Dense vegetation

4. Conclusions

In this paper, we mapped changes in Samarra from 2013 to 2020 using NDVI and NDWI. We found that vegetation and water areas decreased and bare soil increased because of drought. The difference between our work and other papers is that we explained all the steps: we said we used Level-2 data so we did no atmospheric correction, it explained how it got the thresholds from histograms, and we did a proper accuracy check with 250 points. These details are often missing in other papers. This makes our method clear for other students who want to repeat it in similar dry areas.

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