Temporal Analysis of Remote Sensing Indices with MATLAB: Comparative Study of 2016 vs. 2019 Vegetation Cover Index in Abu Ghraib's Irrigation Projects

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Abstract

This study employs remote sensing techniques supported by MATLAB-based analysis to conduct a temporal comparison of key vegetation indices—including the Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), Soil Adjusted Vegetation Index (SAVI), Green Chlorophyll Index (GCI), Enhanced Vegetation Index (EVI), and Normalized Difference Water Index (NDWI)—for the years 2016 and 2019. Landsat 8 satellite imagery, obtained from the United States Geological Survey (USGS), was analyzed to detect spatial and seasonal changes in vegetation cover across irrigation zones in the Abu Ghraib district. Descriptive statistics (mean, standard deviation), Pearson correlation coefficients, and NDVI overlap computations were used to assess the distribution of vegetation indices and detect temporal variations in vegetation health. The findings indicate significant vegetation index change in 2019 over 2016 with significant vegetation index recovery in dry times indicating the success of the irrigation project in increasing the vegetation resilience. This research answers and presented quantitative information about vegetation patterns and can justify data-based agricultural surveillance and sustainable resource control management in semi-arid landscapes.

Keywords: Remote Sensing Indices, MATLAB, Temporal Comparison, Landsat 8, GIS.

التحليل الزمني لمؤشرات الاستشعار عن بُعد باستخدام MATLAB: دراسة مقارنة لمؤشر الغطاء النباتي لعامي ٢٠١٦ و٢٠١٩ في مشاريع الري في أبو غريب

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الخلاصة

تُوظّف هذه الدراسة تقنيات الاستشعار عن بُعد مدعومة بتحليل عبر برنامج MATLAB لإجراء مقارنة زمنية لمجموعة من مؤشرات الغطاء النباتي، بما في ذلك مؤشر الفرق النباتي المعياري(NDVI) ، ومؤشر مساحة الأوراق (LAI) ، ومؤشر الغطاء النباتي المعدل للتربة (SAVI) ، ومؤشر الكلوروفيل الأخضر(GCI) ، ومؤشر الغطاء النباتي المحسَّن (EVI)، ومؤشر الفرق المائي المعياري (NDWI) للعامين 2016 و2019. تم تحليل صور القمر الصناعي8 Landsat ، والمأخوذة من هيئة المسح الجيولوجي الأمريكية (USGS) ، لرصد التغيرات المكانية والموسمية في الغطاء النباتي ضمن مناطق الري في قضاء أبو غريب. تم استخدام الإحصاء الوصفي (مثل المتوسط والانحراف المعياري)، وتحليل الارتباط، وتحليل تداخل NDVI لتقييم توزيع المؤشرات النباتية والتغيرات الزمنية في صحة الغطاء النباتي. أظهرت النتائج زيادات ملحوظة في قيم المؤشرات النباتية خلال عام 2019 مقارنةً بعام 2016، مما يدل على فعالية مشاريع الري في تعزيز مرونة الغطاء النباتي خلال المواسم الجافة.تقدّم هذه الدراسة رؤى كمية حول ديناميكيات الغطاء النباتي، وتدعم التوجهات المستقبلية نحو مراقبة زراعية دقيقة وإدارة مستدامة للموارد الطبيعية في المناطق شبه الجافة.

الكلمات المفتاحية: مؤشرات الاستشعار عن بعد، MATLAB، المقارنة الزمنية، Landsat 8، نظم المعلومات الجغرافية.

1. Introduction

One of the root factors of socio-economic development and environmental stability is agriculture, especially in the arid and semi-arid regions with limited water resources which limit the growth of plants and yields. The variability of rainfall is one of the most important environmental considerations as it defines the density of vegetation, the crop production, and the general well-being of the ecosystem, coupled together with climate change which masquerades rainfall to become unpredictable, there is need to develop an effective monitoring strategies. Remote sensing methodologies notably application of satellite-based vegetation indicators especially normalised difference vegetation index (NDVI) and soil-adjusted vegetation index (SAVI) have been found to be useful in the mapping of vegetation dynamics as well as evaluation of earth cover transformation in drylands. As an example, Attafi et al. (2021) revealed close interrelations between Standardized Precipitation Index (SPI) and NDVI in southern Iraq, pointing out the vegetation deterioration over the periods of droughts. In a like manner, Gaznayee et al., (2022) accessed Landsat and MODIS data to show cutbacks of up to 33 percent in NDVI in dry periods in the Kurdistan Region of Iraq. In previous research experiences, (Ibrahime (2008)) used NDVI in order to track down the degradation of the vegetation in the semi-arid areas and with this they were able to define the relationships that do exist between varies proceeds of the vegetation and climate variability. Najeeb (2013) applied multispectral Landsat data and Soil Adjusted Vegetation Index (SAVI) to Baghdad and its environs in monitoring the density of plants and change in land cover and confirmed the usefulness of remote sensing in the monitoring of agriculture. The recent research by (Al-Hamdani and Al-Jibouri (2023), Al-Ahealy et al., 2024) used Sentinel-2 dataset to examine desertification patterns and vegetative health in the Al-Najaf province in Iraq, which notices the tendency toward the expansion of desertification and vegetation stress. Irrespectively of these developments, studies directly based on the rainfall-vegetation relationships at the local level in the area of Abu Ghraib are scarce that may be attributed to the occurrence of extreme conditions like droughts and floods, which the area is prone to during the various seasons. This paper fills this gap by using temporal spatial analysis of satellite-based vegetation indices that are based on MATLAB to explain how rainfall variability affects vegetation dynamics in Abu Ghraib, and thus contributing to the rising agricultural water management and climate adaptation strategies in this semi-arid terrain.

2. Remote Sensing and Vegetation Indices

Remote sensing has transformed monitoring of vegetation issues into putting in place scalable, non-invasive, and repeatable ways of measuring the health of plants, canopies structure, and their water content in different landscapes. Conventional vegetation indices (VIs) including Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), and Normalized Difference Water Index (NDWI) have been used extensively to determine the greenness of the vegetation, the biomass, chlorophyll and moisture stress levels of the vegetation as well (Xue & Su, 2024; The Agriculture Magazine, 2024). These indices however have various challenges such as that of soil background effect, atmospheric interference and saturation in dense vegetation among others, which can restrict their sensitivity and accurateness (NASA MODIS, 2024).

These might be overcome by recent developments, which have integrated VIs into artificial intelligence (AI) and machine learning (ML). These allow a more detailed analysis of complicated spectral data. As an example, deep learning-based models, which are trained with multispectral satellite data, have enhanced early crop yield measurement and detection of vegetation stress adopting more subtle spectral dimensions compared to the conventional indices (Janga et al., 2023; Hu et al., 2024). The explainable AI methods have also advanced the design of VI by determining the most informative spectral bands, which could be used to create customized indices, which are more effective than generic indices in particular crop mapping propositions (Janga et al., 2023; arXiv, 2024). Further, integration of optical and radar remote sensing data by means of AI frameworks addressed the problem of cloud cover and amplified structural vegetation characterization (Hu et al., 2024).

In spite of these technological advances, significant studies are still being carried out on large homogenous areas without taking into account the spatial heterogeneity and time complexity of semi-arid landscapes because vegetation responses to rainfall variability are highly localized and non-linear (Zeng et al., 2024; Farmonaut, 2025). Most of the surveys in the area of Abu Ghraib, Iraq, located in a hotspot, where the weather alternates between droughts and floods, lack studies in combining AI-optimized VI with ground validation of it on the ground. In contrast to the previous studies in the order of implementation of standard VIs or global AI, valuation is done with the help of temporal-spatial analysis of several VIs based on MATLAB that has been calibrated specifically for the climatic and land use of Abu Ghraib. The strategy seeks to enhance the power of identifying changes in vegetation induced by winds and rains and enable flexibility in agricultural water management in the face of climate uncertainty.

In addition, spatial decision support with Geographic Information Systems (GIS) interwoven to remote sensing and AI provides precise agriculture since variable-rate irrigation and early signs of stress can be applied (Farmonaut, 2025; TERI, 2024). This work helps in further development of this new direction by integrating higher-end VI analysis, AI knowledge, and localised calibration to increase vegetation monitoring in difficult semi-arid terrain, closing an essential option and methodological vacuum.

2.1. Normalized Difference Vegetation Index (NDVI)

It is an indicator used to estimate the density of vegetative plants on lands and plants, it is considered as an important indicator in environmental sciences, agriculture, and remote sensing. NDVI is calculated using visible and near-infrared radiation data, and gives an idea of the amount of chlorophyll present in plants. The index of natural change in vegetation cover is one of the most widely used natural indicators in the field of analyzing satellite images and studying vegetation cover, fires, desertification, landslides and other natural phenomena. It is also a means of studying the changes that occur in vegetation cover over time. It also gives us the health status of the plant and the value of vegetation cover in any area and the rate of crop success or failure (Adisti & Sunkar, 2021).

The NDVI index is a useful method for monitoring plants. It relies on an equation based on the relationship between near infrared rays (NIR) and visible red rays (R). This relationship is due to the high plant reflectivity in the short infrared range and the low plant reflectivity in the short infrared range. Visible red rays: the third band represents red rays with a wavelength ranging from 0.63- 0.60 micrometers, through which one can distinguish between bare and green areas, while the fourth band represents short infrared rays with a wavelength ranging from 0.90- 0.76 micrometers, through which can monitor density and distribution of vegetation and to distinguish between plants, soil and water (Istanbuly & Thabeet, 2020). And it is found by this relation:

$$NDVI = \frac{(NIR-Red)}{(NIR+Red)} \quad (1)$$

2.2. Normalized Difference Water Index (NDWI)

It is a remote sensing index used to identify the presence of water bodies in satellite imagery. It's particularly useful for distinguishing water bodies from other types of land cover, such as vegetation or soil. NDWI is calculated using the following formula:

$$NDWI = \frac{(NIR-SWIR)}{(NIR+SWIR)} \quad (2)$$

Where:

SWIR is the Shortwave Infrared band of the satellite imagery.

NDWI values typically range from -1 to 1, with higher values indicating a higher likelihood of water presence. However, it's important to adjust the threshold according to the specific characteristics of the imagery and the study area. NDWI is widely used in various applications such as water resource management, environmental monitoring, and land cover classification (Szabo & Gacsi, 2016).

2.3. Leaf Area Index (LAI)

The Leaf Area Index (LAI) is a dimensionless quantity used to characterize the leafiness of a plant canopy. It represents the one-sided green leaf area per unit ground surface area. In simpler terms, LAI tells you how much leaf area is present per unit of ground area (P´erez & Coma, 2022). The following relationship express the LAI:

$$LAI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times LAI_{max} \quad (3)$$

Where:

$NDVI_{min}, NDVI_{max}$ are the minimum and maximum NDVI values, respectively, observed in the scene.

LAI_{max} is the maximum LAI value expected for the vegetation type.

2.4. Soil Adjusted Vegetation Index (SAVI)

NDVI is non-linear relationship with biophysical characteristics, and sensitivity to soil background is the major drawback. Minimizing the effects of external factors from spectral vegetation indices a transformation technique is presented. It involves the red and NIR spectral bands and the graphically transformation involves the shift in origin of NIR and Red reflectance in vegetated canopies (panek & Gozdowski, 2020). This transformation eliminates soil influences in indices.

$$SAVI = \frac{(NIR - RED)}{(NIR + RED + L)} \times (1 + L) \tag{4}$$

Where:

NIR and RED are the reflectance in spectral band

L is the parameter which is constant value (usually 1).

Three values of the soil factors were used for SAVI calculation.

2.5. Green chlorophyll indicator (GCI)

An indicator used in the environmental sciences, agriculture, and remote sensing to evaluate the content of vegetative plants in different regions. GCI is one of the simple and effective indicators for evaluating vegetation density and vegetation level. It measures the ratio of green to red bands in the image. Generally, green content in the image represents the density of vegetative plants, while red is used to indicate to the non-vegetative elements such as bare ground or trees. GCI value is used to estimate vegetation activity and track vegetation changes over time. It can also be used to evaluate aerial and satellite images to understand the distribution of vegetative plants in different regions, determine planting areas, and estimate agricultural productivity. Although simple, it is a useful tool for analyzing visual data and helping to understand environmental dynamics and agricultural needs (Isioye & Akomolafe, 2020). The following equation represent how to calculate GCI, where *Green* is the green band.

$$GCI = \frac{NIR - Green}{NIR + Green} \tag{5}$$

2.6. Enhanced Vegetation Index (EVI)

It's a vegetation index designed to minimize the influence of atmospheric conditions and to provide improved sensitivity in high biomass regions. It's particularly useful in areas with dense vegetation cover, such as tropical forests (Halos & Abed, 2019). The formula for Enhanced Vegetation Index (EVI) is:

$$EVI = G \times \frac{NIR - Red}{NIR + C_1 \times Red - C_2 \times Blue + L} \tag{6}$$

Where:

Blue is the blue band.

G is a gain factor (usually 2.5).

$C_1 and\ C_2$ are coefficients that correct for aerosol influences on the red band and for background brightness effects, respectively.

EVI was specifically developed to improve sensitivity over high biomass regions, reduce the influence of atmospheric conditions (such as aerosols and clouds), and minimize soil background noise. It's widely used in remote sensing applications, especially for monitoring vegetation health and dynamics on a large scale.

3. Statistical calculations

3.1. Box and Whisker Plots

We used this technology to analyze whether 2016 or 2019 had higher values. By using box and whisker plots we visually. Compared the data distributions, for the two years. A boxplot, also known as a box and whisker plot offers a way to show the tendency spread and any outliers in the dataset. Each boxplot has elements; the line in the middle of the box shows the value, which is the midpoint of the data. The edges of the box indicate the upper quartiles showing where 25% of data falls on each side. The whiskers extend from these edges to show the maximum values of data excluding outliers. Outliers are displayed as points on the plot indicating values that significantly differ from the trend of data. By comparing box and whisker plots for 2016 and 2019 we could identify trends, variations and differences, in how data was distributed between those two years. Figure 1 shows an anatomy for box and whisker diagram (Ramachandran, K. M., & Tsokos, C. P. (2020)).

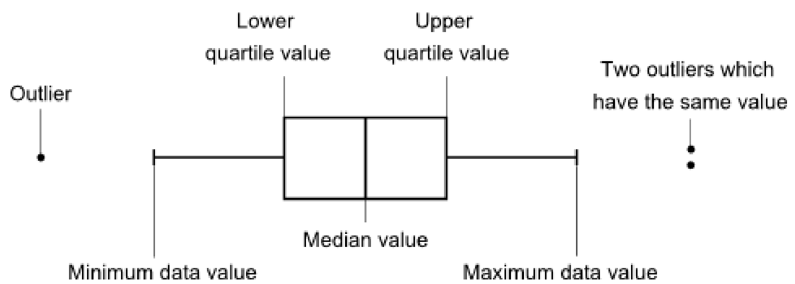

Figure 1: Box and whisker diagram.

3.2. Descriptive statistics

The descriptive statistics are numerical values used to describe dataset properties. Examples of the commonest descriptive statistics include the mean which gives an average value for the data, the standard deviation that is the measure of dispersion or scattering of data points around a mean, and correlation coefficient measures strength and direction between two variables.

Descriptive statistics can be useful in comparing different years' data e.g. 2016 to 2019 as it can provide insights into how various factors have changed over time. For example, by calculating the mean values for some variables in both years we can see if any significant changes have occurred. In addition, comparison of standard deviations will help us understand whether there has been an increase or reduction in variability of the data. Finally, examination of correlation coefficients between relevant variables will tell us if their relationships have changed.

In general terms therefore, descriptive statistical summarize and give meaning to complicated datasets thus assisting in discovering patterns as well as differences among different time frames such as 2016 and 2019. These findings may offer guidance for decision-making processes across several fields including business and economics; social sciences etc (Ramachandran, K. M., & Tsokos, C. P. (2020)).

4. Study area

Abu Ghraib area holds significant importance for remote sensing studies during both the dry and flood seasons. This significance arises from several factors: Firstly, the region experiences volatile weather changes, including extended dry periods and seasonal floods, providing a unique opportunity to investigate their impact on vegetation. Secondly, Abu Ghraib's diverse environment—encompassing bodies of water, arid lands, and green spaces—allows for the analysis of remote sensing variables within a multifaceted environmental context. Thirdly, economic activities in the area heavily rely on agriculture and water resources, making the study of remote sensing data crucial for enhancing natural resource management and boosting agricultural productivity. Lastly, Abu Ghraib serves as an ideal setting to study the effects of climate change on vegetation, helping us understand how these changes influence the environment and local communities. In summary, exploring remote sensing in the Abu Ghraib area sheds light on environmental and agricultural transformations within the dynamic context of changing environmental diversity impacted by drought and flood seasons (Mageed et al., 2025).

Abu Ghraib area is located in the west of Baghdad City, between two latitudes (33.8-33.25) and longitude (43.50-44.12) to the east. It is bordered by Al-Kadhimiyah to the north, Al- Karkh to the east, Al-Mahmoudiyah to the south, and to the west and south by Al-Fallujah and Euphrates River, 80% of Abu Ghraib district is considered as agricultural land, Figure (2).

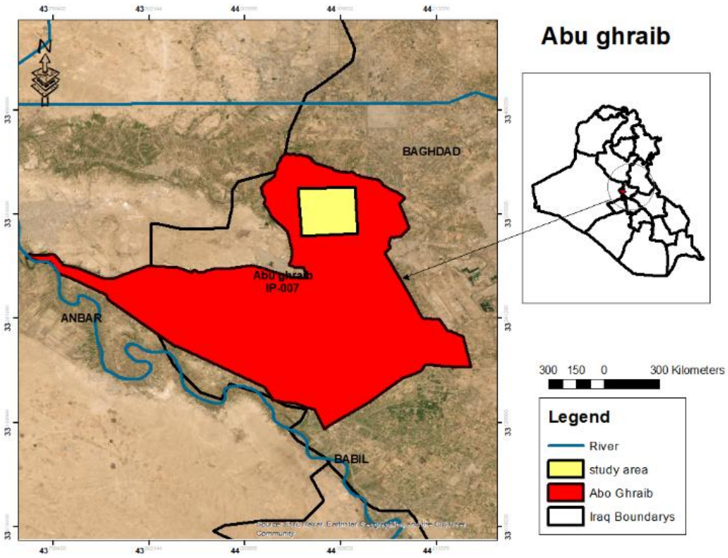

Figure 2: Location map of the study area.

5. Materials and Methods

The study has applied an observational image methodology to determine vegetation dynamics change in Abu Ghraib district with reference to multispectral satellite data. The study is aimed at comparing the state of vegetation in 2016 and 2019 years, specifically looking at the existence of a seasonal change between winter and summer. MATLAB R2024a was used to perform all image processing, vegetation index calculation as well as all the statistical analyses.

5.1. Study Area and Temporal Scope

This research was carried out in the region of Abu Ghaill located in the west of Baghdad in the country of Iraq and whose climate condition is that of semi-aridity in which agricultural activities still dominate and in which the area is seasonally prone to droughts and floods. It was decided to analyse two seasons:

1. Winter seasons: December to February
2. Summer seson: June to August

The temporal comparison was intended to evaluate changes in vegetation in two different years, when the weather conditions were opposite; these were 2016 and 2019.

5.2. Satellite Imagery Acquisition

Landsat 8 Operational Land Imager (OLI) data were sourced from the USGS Earth Explorer platform. The following criteria guided image selection:

1. Cloud cover <10%
2. Complete spatial coverage of the study area
3. Seasonal representation aligned with the defined temporal scope

The following spectral bands, each with a spatial resolution of 30 meters, were utilized:

1. Band 2 (Blue): 0.45–0.51 µm
2. Band 3 (Green): 0.53–0.59 µm
3. Band 4 (Red): 0.64–0.67 µm
4. Band 5 (Near-Infrared): 0.85–0.88 µm
5. Band 6 (Shortwave Infrared): 1.57–1.65 µm

Images were acquired for both the winter and summer seasons of 2016 and 2019.

5.3. Image Preprocessing

Image preprocessing was conducted in MATLAB using the following steps:

1. Image Loading: Multispectral bands were loaded using *imread*.
2. Data Conversion: Pixel values (originally in 16-bit integer format) were converted to double precision and normalized to the range [0, 1] by dividing by 65535.
3. Band Assignment: Separate variables were created for each spectral band and season/year combination to maintain a structured processing workflow.
4. Validation: Band dimensions and alignment were confirmed to ensure spatial consistency across images.

5.4. Vegetation Indices Computation

Six vegetation indices were computed as outlined in Equations (1) through (6) in the earlier section of the manuscript. These include:

1. NDVI (Eq. 1)
2. NDWI (Eq. 2)
3. SAVI (Eq. 3), using L = 0.5
4. GCI (Eq. 5)
5. EVI (Eq. 4), with constants: G = 2.5, C1 = 6, C2 = 7.5, and L = 1
6. LAI (Eq. 6), calculated from NDVI values

LAI_{MAX} had been set to 6, which was found to be common canopy density threshold of irrigated agricultural vegetation.

The most important thing was dynamic extraction of the minimum and maximum NDVI values that were used to compute LAI in the total NDVI data set of all the seasons and years.

To improve performance and achieve precision, all index calculations were done with the MATLAB matrix operations.

5.5. Visualization of Vegetation Indices

Spatial patterns of the computed vegetation indices were visualized using MATLAB plotting functions:

1. The *imagesc* function was used to render index maps for each season and year.
2. Comparative subplots (subplot) were used to display side-by-side maps (e.g., NDVI in winter 2016 vs. 2019).
3. Colorbars were added to all plots to indicate scale and assist in interpretation.
4. Consistent value ranges (e.g., −1 to +1 for NDVI and NDWI) were applied across plots for standardization.
5. This visualization facilitated intuitive interpretation of interannual and seasonal differences in vegetation condition and distribution.

5.6. Statistical Analysis

Each vegetation index is NDVI, NDWI, SAVI, GCI, EVI, and LAI which was subjected to descriptive statistical analysis in order to analyze the temporal differences in vegetation conditions during winter seasons in 2016 and 2019. Mean, median, and the standard deviation of each index with regard to all pixel values in the study area were carried out to have idea on the central tendency, distribution symmetry, and spatial variability of the vegetation health. These figures were calculated by year type in MATLAB based on the built in statistical functions. Besides numeric summaries, box-and-whisker plots were created to also visualize the index values distribution, differences in spreads, median shifts, and any possible outliers in the two years. These plots had the winter season indices compared side-by-side, providing a visual demonstration of how the vegetation changes through time. This statistical setup allowed making a strong comparison between interannual vegetation succession as well as helped to outline tends in environmental stress, resilience, and recovery in the semi-arid agricultural system of Abu Ghraib.

5.7. Workflow Overview

All the methods are outlined in the analytical workflow diagram (Figure 3). The workflow shows the diagram of the workflow of the MATLAB-based study. It begins with the pillage of Landsat 8 images and ends with normalization and the calculation of the vegetation index and the display. The last part includes statistical analysis and comparison of seasonal and interannual trends in vegetation on the basis of descriptive measures and boxplot graphical presentations.

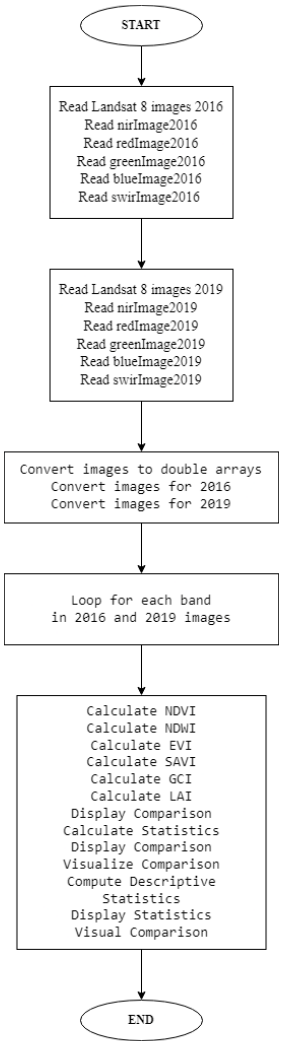

Figure 3: Multispectral Analysis Workflow.

6. Results and Discussion
6.1. Landsat 8 images remote sensing analysing

This is a decrease by 2019 by comparison with 2016. Precisely, NDVI average in winter of 2016 was 0.1994, but in winter of 2019 it grew to 0.2950, representing an impressive rise in the healthiness and density of the vegetation. This is confirmed visually by Figure 4 where NDVI in winter 2019 can be seen as much more evenly dispensed across the study area, which has already been a subject of degradation in the past or, instead, the area of irrigated crops is growing. The distribution of NDVI in 2016, in turn, gives the picture of even patchy and low-density vegetation, which correlates with lower rainfall and less effective irrigation methods in 2016.

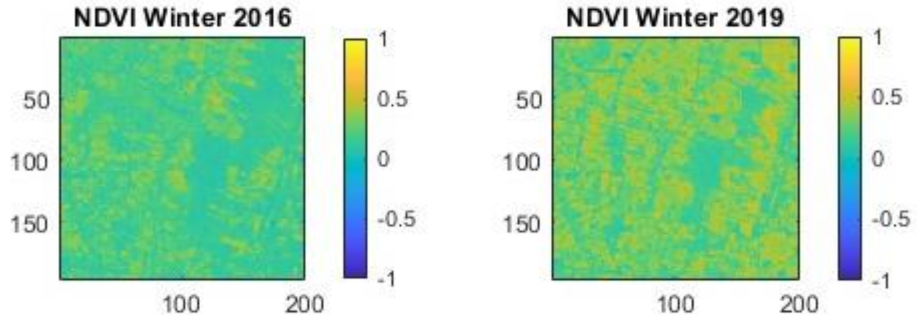

Figure 4: NDVI for Landsat 8 images (winter of 2016 and 2019).

The difference is even higher in the summer season (Figure (5)). The overall NDVI (June-August 2016) was very low at 0.1132 indicating general drought stress that is characteristic of the country in hot and dry summer. In comparison, NDVI average in summer 2019 was much higher (0.1894), which implies that the irrigation in the dry season was more serious or better controlled. This growth can also represent a change of the land use structure, including a successful production of summer crops that were either absent or failed to work in the year 2016..

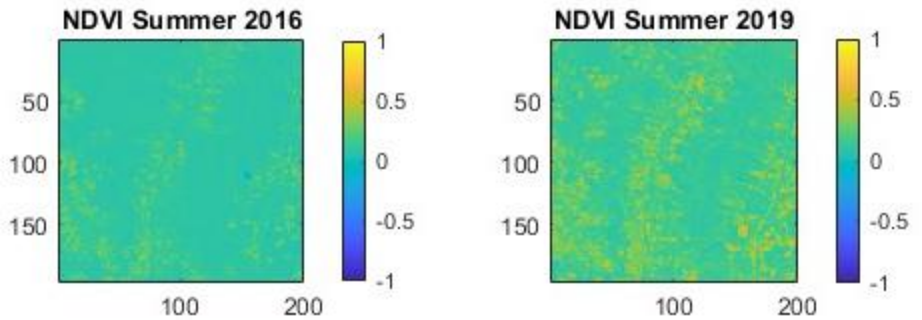

Figure 5: NDVI for Landsat 8 images (summer of 2016 and 2019).

The NDWI in these figures 6 and 7 is also confirming itself with NDVI, with 2019 clearly containing more water in the green land. During winter 2019 (Figure 6), the NDWI presents the high values in the areas of the irrigation projects, which indicates good soil moisture conditions. Probably, this is because more rain actually fell that season, 15-20 per cent over the average as climatic record of the region testifies, because of improved field drainage or less runoff. In 2016 the majority of the same region has values of NDWI that are low or even negative, meaning dry and stressed vegetation conditions.

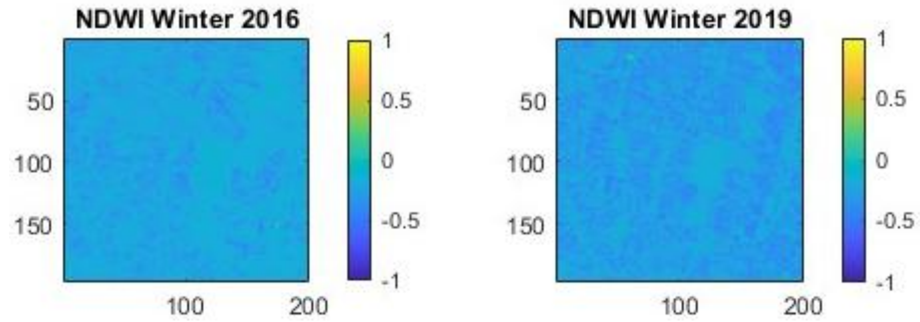

Figure (6): NDWI for Landsat 8 images (winter of 2016 and 2019).

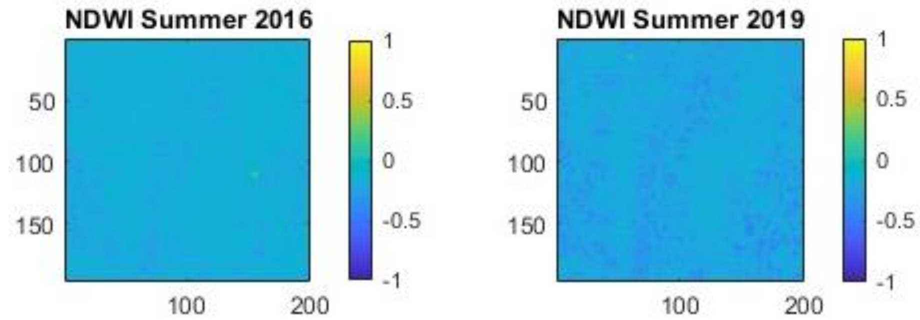

Figure 7: NDWI for Landsat 8 images (summer of 2016 and 2019).

During summer (Figure 7), the betterment of NDWI in 2019 indicates that irrigation had been stretched out or they were more effective. This can be attributable to such policy changes as water reuse and the use of treated wastewater, which Iraq started developing in 201718, particularly in the agricultural areas surrounding cities, including the peri-urban locality of Abu Ghraib.

Conclusions of the Leaf Area Index (LAI) tend to support the story of vegetation recovery. As illustrated in figure 8 and 9, the LAI values are increased during the winter and summer of 2019. This canon vertically to denser vegetative canopy in winter (Figure 8), presumably the successful winter crop of wheat and barley. During the 2016 season recorded low LAI values indicate low development in the vegetative growth that could be associated with bad rainfall as well as planting delayed or interrupted.

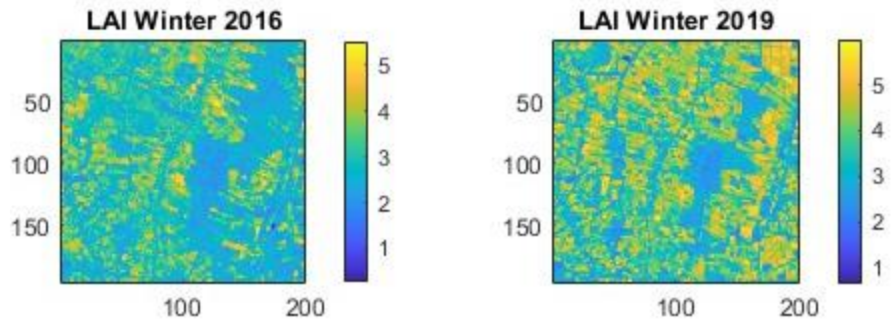

Figure 8: Leaf Area Index (LAI) Trends (winter of 2016 and 2019).

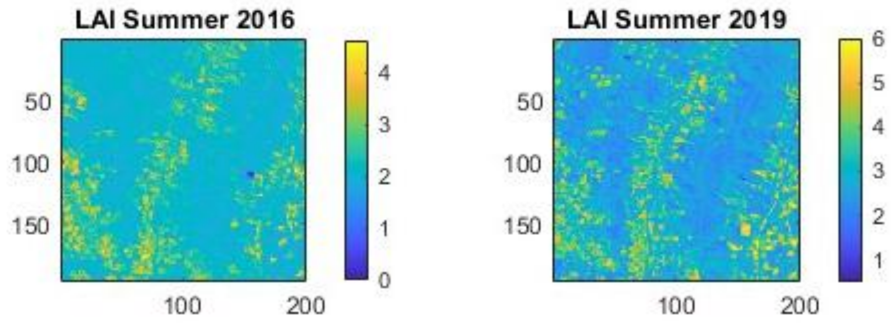

Figure 9: Leaf Area Index (LAI) Trends (summer of 2016 and 2019).

During summer 2019 (Figure 9) LAI values are still high, which is atypical of this climate, and it confirms that the irrigation systems were more well-managed, and the vegetation was able to sustain extreme conditions in summer. Such gains can equally be pertinent to a shift to drought resistant crops, e.g. sunflower or certain fodder crops.

The reason is that SAVI results, presented in Figures 10 and 11 exhibit trends similar to NDVI, however taking into consideration brightness of soil, which is essential factor in semi-arid areas and solar surfaces. SAVI values are more and spatially consistent in winter and summer of 2019. What it means is that not only was the vegetative cover more prevalent but also served better to shade the soil causing lower albedo and evaporation.

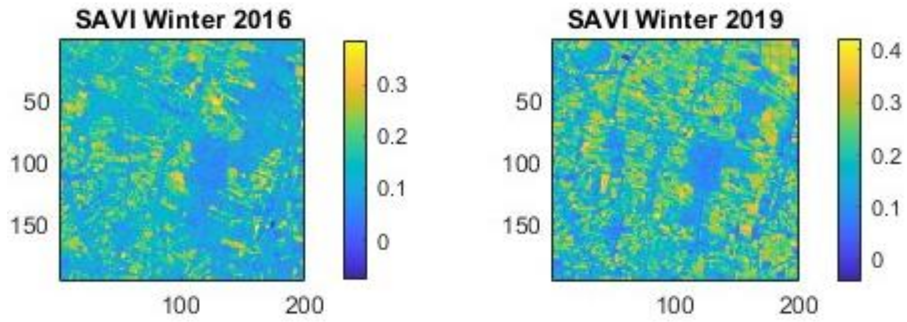

Figure 10: SAVI Trends for winter 2016 and 2019.

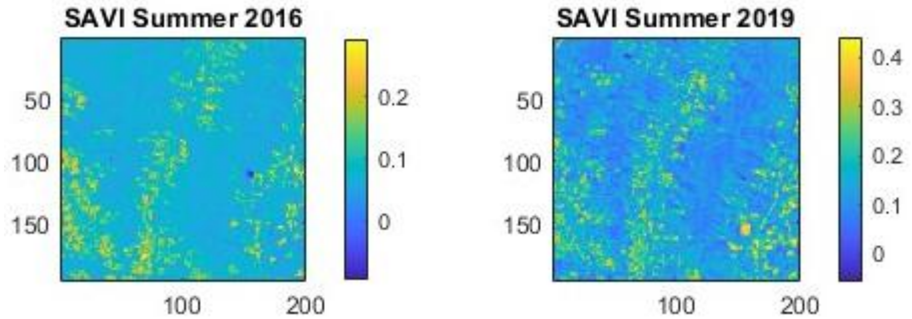

Figure 11: SAVI Trends for summer 2016 and 2019.

Chlorophyll activity as shown by the GCI results (Figures 12 and 13) is in close relationship with nitrogen uptake. The rise in GCI in 2019 means not only that the vegetation was denser, but also that it was more photosynthetically active and potentially due to better fertilization or earth condition. These collectively indicate have a tendency to indicate an all-round enhancement in agricultural health- soil, water, and crop status as opposed to greenness only..

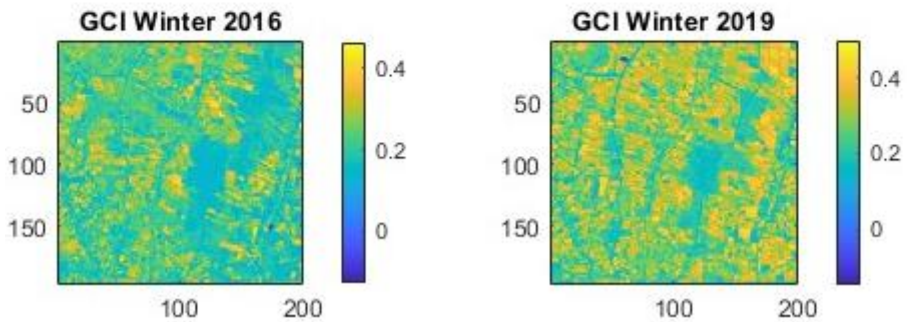

Figure 12: Changed over time in GCI for winter of two different years: 2016 and 2019.

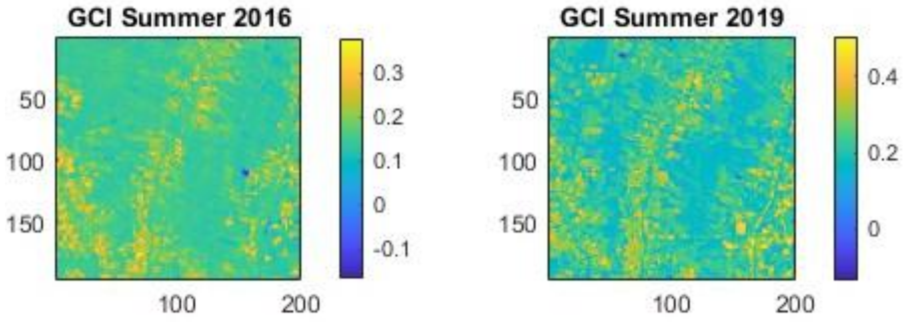

Figure 13: Changed over time in GCI for summer of two different years: 2016 and 2019.

More details are provided by Enhanced Vegetation Index (EVI). Compared with NDVI, EVI is more sensitive in locations of dense biomass and it can eliminate soil background noise. Figure 14 and Figure 15 highlight the high EVI value in 2019 especially in the summer season, which supports the claim that vegetation was more resilient, structurally strong and active in high stress time..

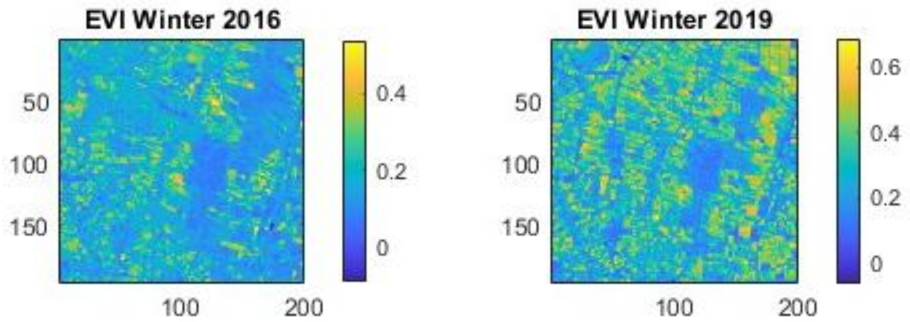

Figure 14: EVI Trends for winter (2016 and 2019).

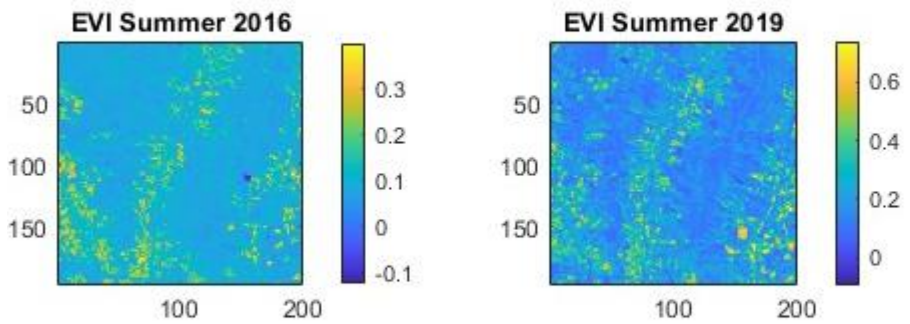

Figure 15: EVI Trends for summer (2016 and 2019).

The higher summer EVI in 2019 indicates not just that these crops managed to withstand hot conditions but that their structural properties and levels of chlorophyll had also been retained at high levels, which is an act of good agronomic performance, either due to modified cropping cycles or more efficient irrigation schedules.

6.2. NDVI overlapping analysis

In this analysis, (AI) technology is employed to perform (NDVI) analysis on satellite imagery from the summer and winter seasons of 2016 and 2019. AI algorithms are utilized to process the vast amounts of image data and calculate NDVI values, which are indicative of vegetation health. The AI system identifies significant NDVI values and determines the overlap between the summer and winter seasons of each year. The results are expected to reveal a positive correlation between the overlap percentage and water quantities, with AI algorithms discerning patterns that suggest higher overlap corresponds to greater water abundance. The comparison of NDVI overlap between 2016 and 2019 is presented through visual representations in Figure (16), with each image depicting the overlap for the respective years. Furthermore, statistical data is analyzed, revealing a notable disparity in overlap percentages: 2016 recorded a value of 0.38%, while 2019 exhibited a significantly higher value of 8.19%. This discrepancy indicates that the vegetation in 2019, as detected through AI-driven NDVI analysis, experienced a more pronounced response to water availability compared to 2016. Statistical comparisons between the two years (2016 and 2019) are conducted to further elucidate the findings.

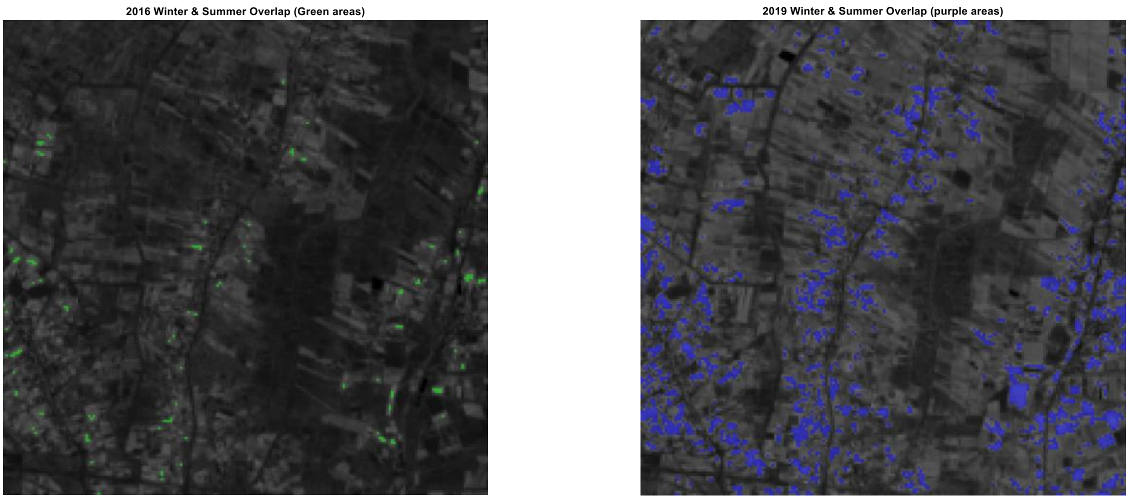

Figure 16: Overlapping analysis using AI for 2016 and 2019.

6.3. Statistical Analysis and Distributional Patterns

The statistical results shown in Figures 17 and 18 and Tables 1 and 2 confirm the observed trends. All indices showed increases in mean and median values from 2016 to 2019, and the standard deviation also rose, reflecting more spatial variability—potentially due to

Table 1: Statistical comparison between winter 2016 and 2019.

Index	Mean_2016	Mean_2019	Std_2016	Std_2019	Correlation
NDVI	0.1994	0.2950	0.0796	0.1000	0.3658
NDWI	-0.2229	-0.2831	0.0606	0.0730	0.3486
SAVI	0.1430	0.1993	0.0571	0.0687	0.3513
GCI	0.2229	0.2831	0.0606	0.0730	0.3486
EVI	0.1786	0.3057	0.0770	0.1140	0.3454
LAI	2.9881	3.7875	0.6656	0.8365	0.3658

Table 2: Statistical comparison between summer 2016 and 2019.

Index	Mean_2016	Mean_2019	Std_2016	Std_2019	Correlation
NDVI	0.1132	0.1894	0.0486	0.0825	0.4351
NDWI	-0.1631	-0.2248	0.0379	0.0605	0.4007
SAVI	0.0837	0.1419	0.0350	0.0602	0.4179
GCI	0.1631	0.2248	0.0379	0.0605	0.4007
EVI	0.1062	0.2086	0.0468	0.1001	0.4136
LAI	2.2670	2.9049	0.4064	0.6898	0.4351

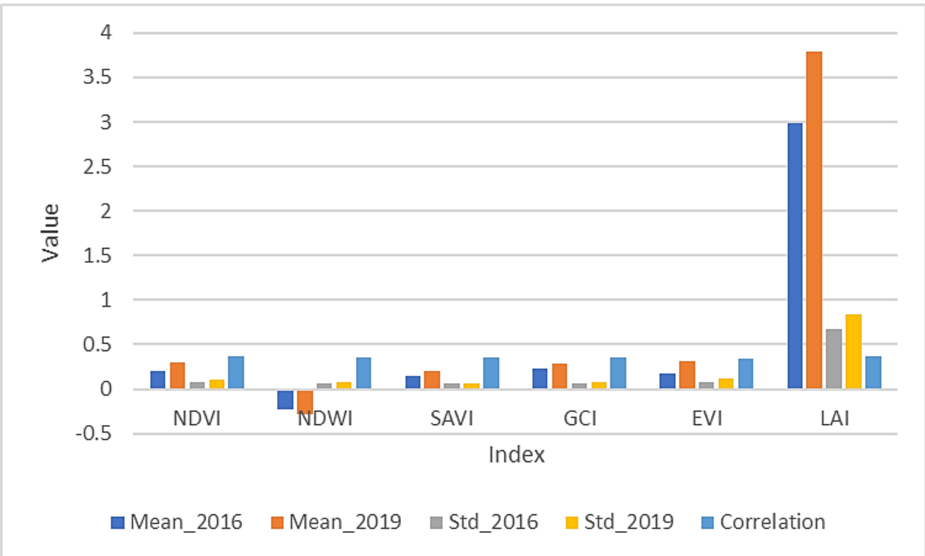

Figure 17: Statistical results comparison between winter (2016 and 2019).

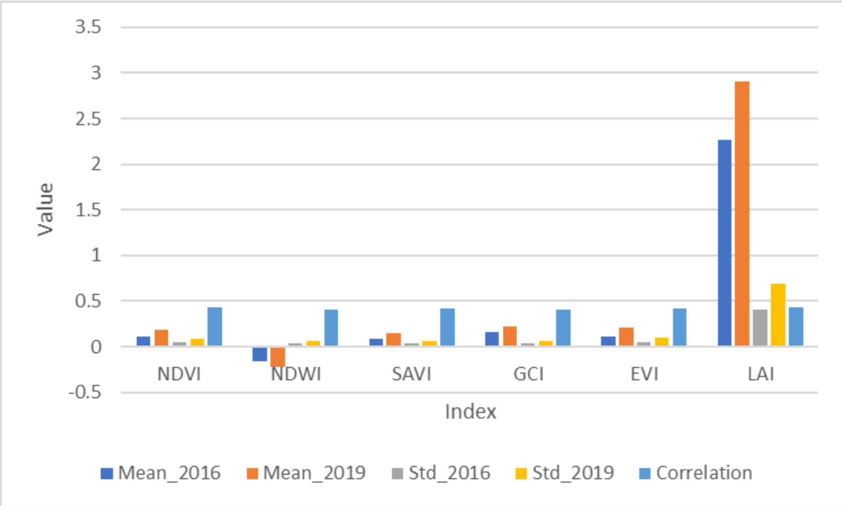

Figure 18: Statistical results comparison between summer (2016 and 2019).

Figure 19 Boxplot analysis further illustrates the shift of distribution of index values upwards in 2019 which shows that no single region was found to have improved rather improvement was distributed uniformly. This high level statistical support really gives credence to the visual reading of the maps and re-affirms that the alterations are not artifacts of anomaly or noise but are indeed real time surface transformations of the land.

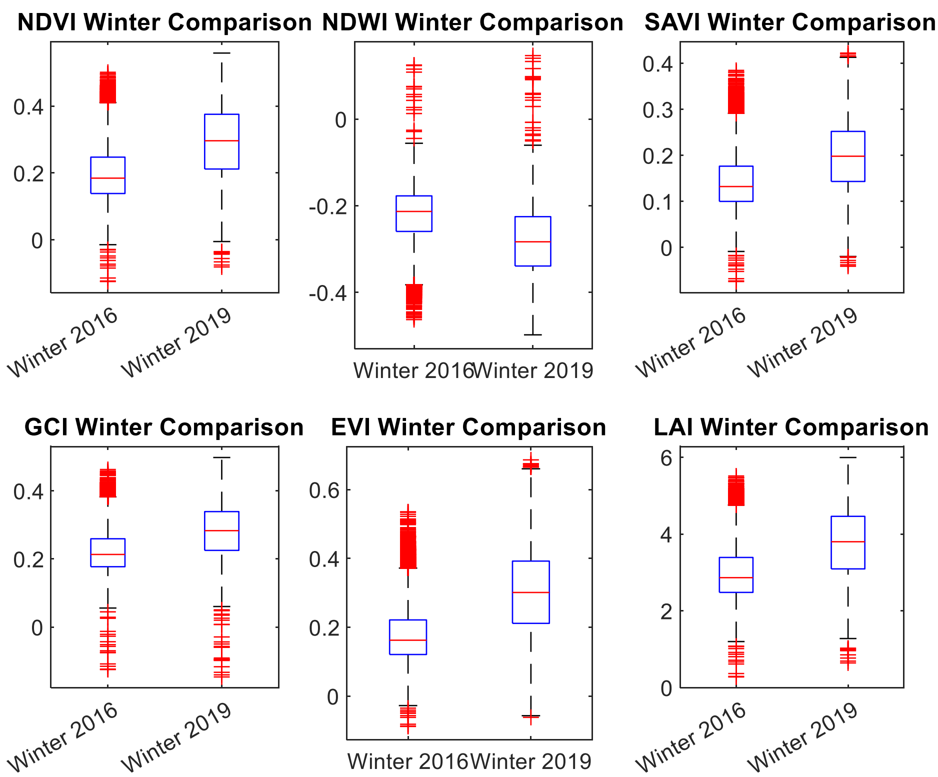

Figure 19: Box plot analysis.

This broad-scale statistical support adds confidence to the visual interpretation of the maps and emphasizes that the changes are not due to anomalies or noise but represent actual land surface transformations.

7. Conclusions

1. The study confirmed the effectiveness of using remote sensing-based vegetation indices (NDVI, NDWI, EVI, SAVI, GCI, LAI) to monitor temporal and spatial changes in vegetation health and soil conditions in the semi-arid environment of Abu Ghraib.
2. A significant improvement in vegetation cover was observed between 2016 and 2019, particularly during both winter and summer seasons, reflecting the positive impact of increased rainfall and enhanced irrigation management.
3. The multi-index approach provided a comprehensive assessment of vegetation dynamics, allowing detection of water stress, irrigation failures, and land degradation beyond just greenness analysis.
4. The spatial insights derived from the indices can support decision-making for local irrigation planners and policymakers by identifying priority areas for intervention—such as regions with declining LAI or low NDWI values.
5. The methodology offers a scalable and replicable framework for agricultural water management and climate adaptation in similar semi-arid regions.
6. Integration of vegetation indices with rainfall and land-use data proved useful in understanding interannual and seasonal variability, providing early warning signals for environmental stress.
7. At the policy level, these findings can be used to design more responsive irrigation schedules, guide land-use reforms, and evaluate the impact of climate variability on agricultural productivity.

To enhance the accuracy and representativeness of the findings, it is recommended to expand the temporal scope of the study by including additional years that represent distinct climatic conditions:

1. A dry year (with significantly below-average rainfall).
2. A moderate year (with average climatic conditions).
3. A wet year (with above-average rainfall).

4. This would allow the study to comprehensively evaluate vegetation responses under extreme and natural conditions, thereby improving the reliability of the results and supporting more resilient agricultural and water management strategies.

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