Spatial-Temporal Monitoring of Agricultural Dynamics Using Spectral Indicators and GIS: A Case Study of Zubaidiya District, Wasit (2017–2024)

Noura Zaid Ati
Department of Geography, Faculty of Arts, Iraqi University Iraq
*Corresponding author's e-mail: noora.al-jizaniyah@aliraqia.edu.iq

Abstract

Agricultural dynamics are highly sensitive to climatic variability in arid and semi-arid regions, water availability, and human-induced land management practices. The focused aim of this study is to evaluate the applicability of satellite-based remote sensing data for monitoring vegetation growth and environmental change assessment, with particular prominence on the use of vegetation indices of enhanced vegetation index (EVI) in comparison with other frequently used indicators, involved normalized difference vegetation Index, for environmental and agricultural analysis. In this study, quantitative analysis of multispectral satellite imagery was derived from Landsat sensors. The surface reflectance data were processed to compute vegetation indices, which were then used to analyze spatial patterns of vegetation cover and biomass. The results from NDVI in comparison with EVI, is more sensitive in densely vegetated areas and more successful at reducing background noise and atmospheric effects. The findings show that EVI-Based metrics are more useful for tracking ecosystem dynamics by demonstrating the distinct relationships that exist between vegetation patterns, land cover change, and current environmental conditions. The significance of agricultural production in environmental system studies, Landsat-8 data were used to analyze the spatial-temporal pattern of vegetation covers from 2017 to 2024. The simulation results show a general decrease in agricultural Land area with significant changes in vegetation density brought on by land cover variation. This study further investigates the relationship between enhanced vegetation indices using remote sensing by focusing on their implications for integrated land management and significant economic sectors within agriculturally dominant regions.

Keywords: Spectral Indices, Agricultural Land management, EVI, land cover Classification, and NDVI

Introduction

Agricultural Dynamics reflects the spatial-temporal change of crop growth, productivity, and land use planning. Moreover, Traditional monitoring is difficult to implement, mainly due to the time and resources required. Remote sensing measurements, or satellite data, are useful techniques for tracking vegetation activities (Pamungkas, 2023; Roy, Dewid, & Vijian, n.d.). In actuality, remote sensing has emerged as a trustworthy information source for vegetation monitoring, particularly when supplied by sensors with medium spatial

resolution. Accurate and timely assessment of the state of building cover is critical to improving ecosystem management, and remote sensing provides an opportunity for accurate and non-destructive monitoring of vegetation characteristics at the field, regional, and global levels (Salman, 2022). Common Vegetation Indicators (NDVIs) and Enhanced Vegetation Index (EVI) are dominant remote sensing data products, used to monitor vegetation cover at local and global scales (Glenn et al., 2008; Huete et al., 2002). Although both indicators provide a seasonal measure of greenery, the Enhanced Vegetation Cover Index (EVI) is gradually being replaced by the Common Vegetation Index (NDVI). (Salman, 2022; Sakamoto et al., 2005) stated that Remote sensing and GIS are significant and valuable techniques for assessment of land use/land cover change (LULC) and (Shammi & Meng, 2021; Yang et al., 2023), integrating associated influencing factors to draw useful results. The selection of appropriate spectral indicators to study agricultural productivity in areas suffering from extreme climatic conditions is of great importance (Fraga et al., 2014), so many indicators were tested to study productivity in the center of Zubaidiya district, and the EVI index was chosen to analyze the relationship between the EVI index and land cover in the Zubaidiya district center. The environmental vegetation index (EVI) is based) on red, blue (450 nm) and near-infrared regions of the electromagnetic spectrum (Pamungkas, 2023; Huete, Justice, & Liu, 1994). Compared to the Natural Vegetation Cover Index (NDVI), the Enhanced Vegetation Index (EVI) is less sensitive to unlike soil backgrounds, as (Huete et al., 2002; Glenn et al., 2008) stated that the latter suffers from changing climatic conditions during the study years, which affects the economic importance of agricultural production in Wasit Governorate, which is the agricultural product in Iraq. The impact of relationship between enhanced vegetation index (EVI) values and actual agricultural production in Zubaidiya district center remains unclear, despite the growing significance of using EVI indicators for vegetation health assessment identification of productive agricultural areas. This uncertanity calls into question the EVI'S effiency as worthy method for predictng agricultural output, comprehending local yeild variations, and determing how changes in landcover affect the EVI.

Previous research by (Al-Muhammad, Al-Bilbeisi, & Abu Sammour., 2018; Dehghan Rahimabadi et al., 2024) has declared the differences in landcover classes, including vegetation, cropland, barren land, and built-up land areas, with major impact on ecosystem behaviour and vegetation index values. These transformations have a direct effect on food security, economic stability, and productivity in regions with high agricultural intensity (Al-Azzawi, 2022). This uncertainty calls into question whether EVI is a good indicator for tracking agricultural productivity, predicting yield fluctuations, and assessing the effects of changing land cover in the Zubaidiya District. Given that agricultural production serves as the region's economic foundation and has a direct impact on livelihoods and related economic sectors, filling this research gap is imperative. The choice of the study problem represents the first step in scientific research, as each scientific research must have a problem in which to begin, to succeed in the effort and time exerted in collecting information and formulating it in clear and understandable terms, and since the problem is a fundamental question that can be answered through regular planning or experiments. The problem of the study can be formulated thus: the study area suffers from a clear change in agricultural production, area,

and quantity cultivated, and since agricultural production is the pillar of the economy in the region, this change in agricultural activity leaves its impact on the various economic sectors in the region (living in particular).

Study Area

Al-Zubaidiyah district is located in the governorate of Kut, which lies in the northern part of the Iraqi sedimentary plain. The Tigris River is the eastern limit of the district. In contrast, the district of Essaouira is on its northwestern border, and it is bordered by the district of Numaniya from the southwest. It is bordered by the district of Al-Shuhaimiya to the west in Figure 1. The district of Zubaidiyah* consists of 19 districts with an area of 117 km^2, and after its area in 1965 was 217 km^2 due to the creation of Al-Shuhaimiya district and its administrative separation from Al-Zubaidiya district in (Pamungkas, 2023) 1977.

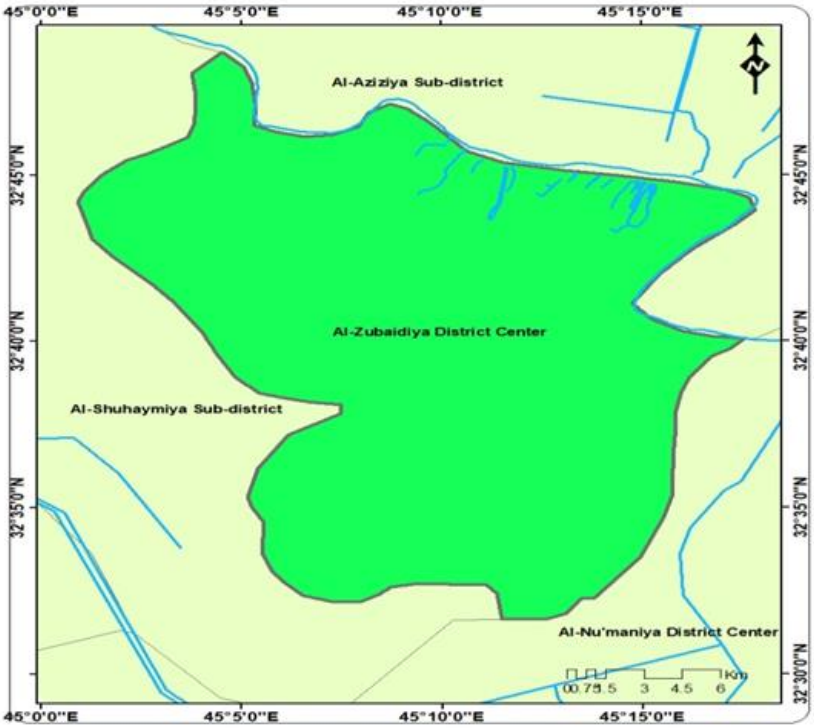

Figure 1: Location of Study Area

Source: Baghdad Governorate Map, scale 1:100,000 2010, Republic of Iraq, Ministry of Water Resources, General Authority for Survey, Map Production Department

Methodology

Data Collection

Data has been collected from Satellite visualizations provided by Esri | Sentinel-2 Earth Cover Explorer (Esri | Sentinel-2 Land Cover Explorer). As these layers were downloaded for the period (2017-2024), and then processed in the Arc Map program to reclassify them and extract the area and ratio (LULC), and the digital data, Landsat 8 Operational Land Imager (OLI) satellite, specifically band 4 and band 5, were processed to analyze the vegetation cover.

Data Analysis

One of the most crucial aspects of the Earth system is land cover, which is the collection of biotic and abiotic elements on the planet's surface. It is significant in three primary ways (Turner et al., 1994). For weather and climate forecasting, the first is the relationship between land cover and the atmosphere, which controls the hydrological cycle and energy budget (DeVries et al., 2002). For instance, Earth's surface parameters (LSPs), which use digital land cover data to build databases of whiteness, surface roughness, evaporation and transpiration, and respiration, are now connected to the majority of climate models. Second, as both a source and a sink of carbon, land cover is essential to the carbon cycle. The rates of afforestation, regrowth, and deforestation in particular have a significant impact on carbon release and sequestration, which in turn influences the atmospheric concentration of carbon dioxide and the intensity of the greenhouse effect. In addition, land cover is a crucial indicator of other ecosystem services like biodiversity and represents the availability of resources for populations, including food, fuel, timber, fiber, and shelter. For many national and international applications, such as watershed management and productivity, land cover data is crucial. Farming Vegetation changes brought on by pollution and land use changes can impact local moisture flows and atmospheric circulation, which in turn can alter the Earth's climate by altering the surface energy budget. Since the most frequent change in the landscape is the vegetation, which is the primary threat to biodiversity, monitoring aids in environmental and regional planning. With real-time data on land use/cover (LULC) and the Enhanced Vegetation Index (EVI), as well as the ability to adjust to changes in space and time, remote sensing data is essential for the prompt detection and tracking of both short- and long-term changes. The primary goal of this study is to evaluate the effects of changes in land cover and use. The analysis of indicators is one of the main methods in the study and analysis of land cover, which is a reflection of it and contributes to the detection of the most important changes that occur, and the change is calculated through special equations used to calculate indicators according to the different wavelengths of the reflection values of the studied phenomenon.

The Enhanced building cover index was relied upon to study the feed between the change in land cover and its impact on the restricted vegetation cover in the study area, where the growing season of vegetation cover does not have a specific pattern, and was adopted after Zhangyan proved the ability of the index to extract vegetation cover while minimizing the effects of the atmosphere and terrain.

Vegetation categories can be obtained within this indicator based on the following equation :

$$\mathbf{EVI} = G*((NIR-Red)/(NIR+C1*Red-C2*Blue+L)) \quad \text{Eq. 1}$$

NIR corresponds to the near-infrared band (LANDSAT band 4), red band red (band LANDSAT 3), blue band blue (band LANDSAT 1), L is the parachute background modulation (L = 1), C1 and C2 are the coefficients of aerosol resistance and impact in the blue and red bands, respectively (C1 = 6 and C2 = 7.5), and G is the gain factor (G = 2.5)

where L is the soil modification factor, and C1 and C2 are coefficients used to correct aerosol dispersion in the red band using the blue band. ρblue, ρred, and ρnir represent reflection at

wavelengths of blue (0.45-0.52 μm), red (0.6-0.7 μm), and near infrared (0.7-1.1 μm), respectively.

Results and discussion

Figure 2 illustrates the spatial-temporal change in the enhanced vegetation indicator, which was used in the study area to identify changes in building cover and compare them with changes in light cover. There is noticeable variation from year to year in the percentage change and spatial extent of the area of Enhanced vegetation cover (EVI) in Zubaidiya District from 2017 to 2024. **Table 1** showed vegetation increased by 1.21% in 2017–2018, and expanded spatially by 1.20%, indicating the short-term instability, and was followed by a decline of −0.55%. The observed decline in 2018-2019 was observed as – 0.58%, which increased with a noteworthy 1.28% in vegetation density and 1.36% with spatial coverage, indicating localized recovery of vegetation. The 2019-2020 period specified a small change (0-0.01%), suggesting that land cover was not significantly disturbed. Between 2020 and 2021, vegetation cover rose by 0.69 % despite only a slight (0.22%) spatial coverage increase. However, some areas identified losses up to – 0.48%, which indicates uneven spatial dynamics. Furthermore, 2021- 2023 was marked by minor fluctuations, with variation ranging from – 0.09 to 0.08 %, signifying relative stability. Although localized gains reached 0.95%, a more pronounced decline in 2022 – 2023 was detected, with vegetation cover declining by -0.50%, with spatial reduction of -0.03% reflecting fragmentation of vegetated areas. Although losses of -0.12% (-0.22% spatially) were constant in some areas, a moderate recovery was identified in the last period (2023–2024), with an increase of 0.41% and a spatial growth of 0.24%. All things considered, the EVI-based analysis shows varying vegetation dynamics with a general propensity toward intermittent decline and spatial redistribution, which reflects the impact of agricultural management techniques and changes in land cover in Zubaidiya District.

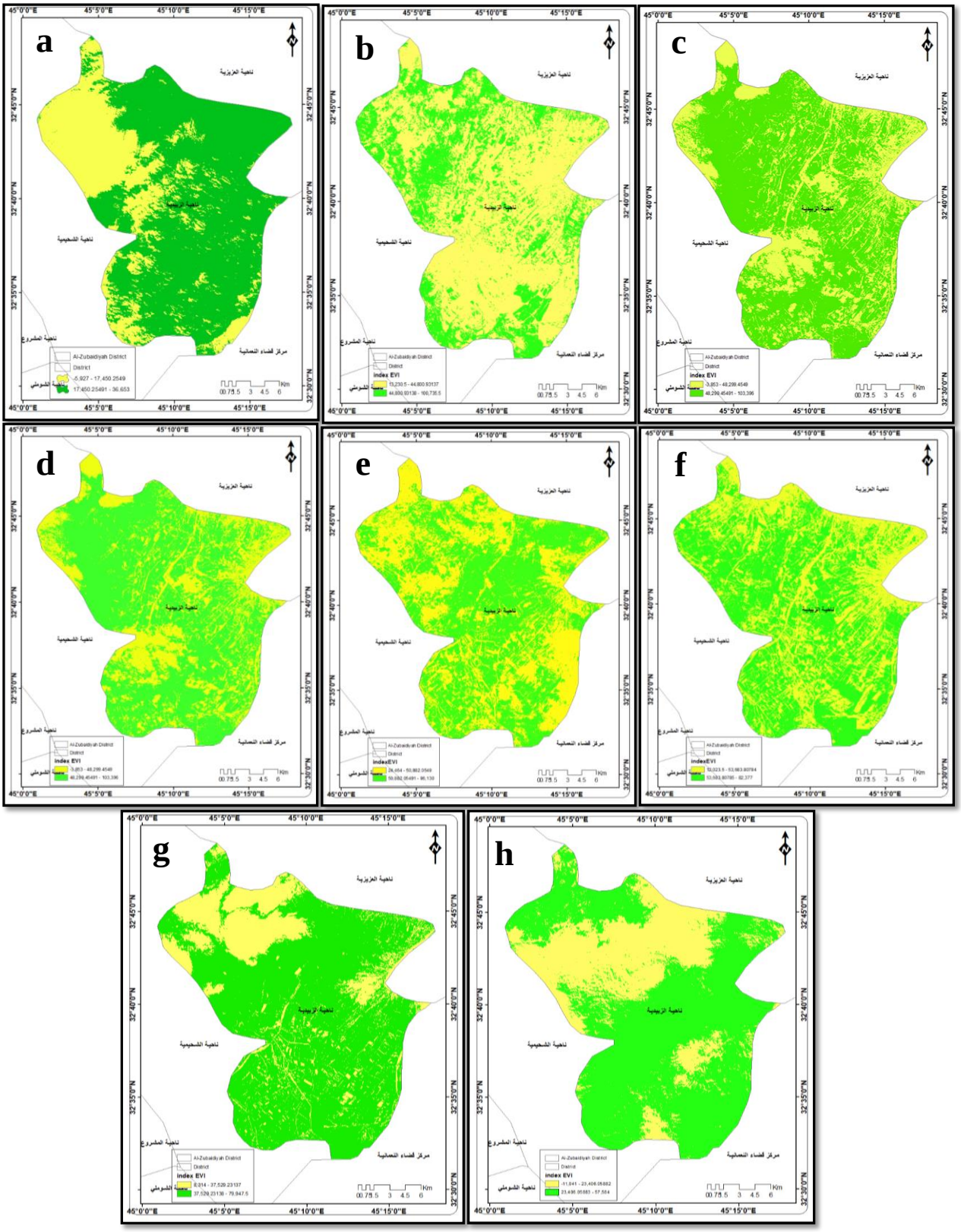

Figure 2: *Spatial Distribution of EVI Index (2017-2024)*

Table 1: Calculation of the change in the area of the Enhanced building cover (EVI) for Zubaidiya district for the period 2017-2024

Duration	% change	Space Change %
2018-2017	1.215370233	1.207168894
	-0.546572145	-0.548265064
2019-2018	-0.580678958	-0.565669398
	1.275889631	1.35744859
2020-2019	0	0
	0.009089249	0
2021-2020	0.691258632	0.217959343
	-0.286328832	-0.481379882
2022-2021	-0.088023473	-0.01168748
	0.083686089	0.174359755
2023-2022	-0.496591446	-0.296573789
	0.397314276	0.952496679
2024-2023	0.412111732	0.24434337
	-0.11878905	-0.223463224

Spatial–Temporal Change in Land Use Change/Land Cover (2017-2024)

The results of the land cover change of the study area illustrated in Figure 3, it was noted that there is a clear change in the proportion and area of each cover, as the change in the land cover area and its variation between (barren lands, crops, trees, built-up areas) between (2017-2024) has greatly affected the image of the pattern of calculating the Enhanced vegetation cover index. The geographical distribution map changes for the years 2021–2022 and 2023–2024 as the area and percentage of land used for crops rise. At the same time, the area and percentage of built land rise, counterbalanced by a decrease in the area of barren land. This suggests that open spaces in the study area are being exploited and invested in by multiple parties, Yallaline Mapping. This was characterized by the appearance of land cover trees as the highest percentage among the land covers, which formed an area of 53,881 km^2. That is, its percentage (73,404%) while sleeping Barren Aryans appeared as the lowest category of land cover, and the picture of the geographical distribution of land covers changed in the period 0 2028-20199 to decrease in tree cover by (0.001%) and the area of crop land increased by (71,946%), and in the period from (2019-2020) it came in similar proportions to previous years, while the period from (2020-2021) witnessed an increase in the percentage and area of the lands shown from (3,828 km2) and by (4,512%) to (10,493 km2) and Beniba (12,913%), while the crop area decreased from (71,954 km2) by (84,825%) to (4 and 192 km2) and a ratio of 5 and 161%, which reflects the exit of large areas of agricultural land to other non-agricultural uses that may be residential, commercial, service or other uses.

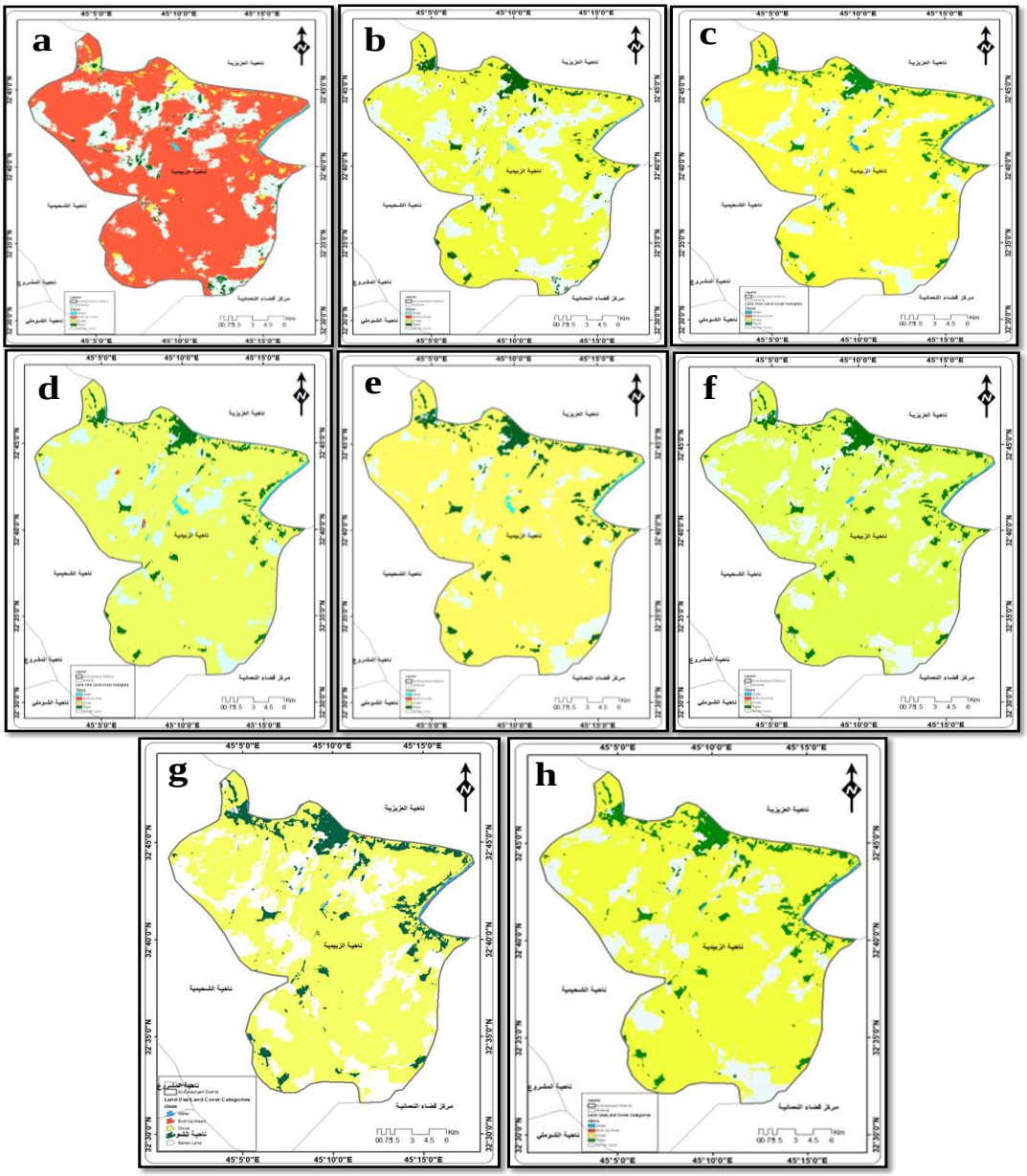

Figure 3: *Spatial Distribution of Landcover (2017-2024)*

A vegetation map can be created using the land cover classification results and the vegetation cover spectral values, which also deliver information about the vegetation indicator's value. The use of mathematical equations, ease of achievement, accuracy, and low costs have helped many studies, and the change is extracted by selecting indicators, estimating their values, analyzing vegetation maps, and producing clear vegetation maps. After deducting the study area and visual processing, several maps were produced for the period from 2017 to 2024, and the percentage and area of each land cover and the change between 2017 and 2024 were calculated, as shown in **Table 2**.

Table 2: Tabulation of Land Use Area and Percentage / Land Cover Change Categories (LULC) in Zubaidiya District (2017-2024)

Duration	Item	Area / km2	Percentage %
	Barren land	0,398	0,542
2018-2017	Trees	53.881	73,404
	Crops	2,276	3,101
	Built-up Area	1,489	2,019
	Water	15,366	20,934
	Barren land	0,411	**0,571**
2019-2018	Trees	0,001	**0,001**
	Crops	51,762	**71,946**
	Built-up Area	3,083	**4,285**
	Water	16,689	**23,197**
	Barren land	0,686	**0,808**
2020-2019	Trees	0.06	**0.07**
	Crops	71,954	**84,825**
	Built-up Area	3,828	**4,512**
	Water	8.299	**9,783**
	Barren land	0,007	**0,008**
2021-2020	Trees	0,556	**0,689**
	Crops	4,192	**5,161**
	Built-up Area	10,493	**12,918**
	Water	6,598	**81,228**
	Barren land	0,538	**0,637**
2022-2021	Trees	0,006	**0,007**
	Crops	71,266	**84,419**
	Built-up Area	4,508	**5,341**
	Water	81,010,004	**9,596**
	Barren land	0.368	**0,468**
2023-2022	Trees	0.004	**0,005**
	Crops	61,84	**78,638**

	Built-up Area	4,032	**5,127**
	Water	12,396	**15,762**
	Barren land	0,348	0,439
2024-2023	Trees	0,009	0,011
	Crops	63,126	79,452
	Built-up Area	4,79	6,029
	Water	11,178	14,069

Conclusion

This study concluded that vegetation index time series with terrestrial variables can better understand vegetation responses to environmental and land-use fluctuations. The temporal dynamics of the enhanced vegetation index (EVI) were quantitatively examined in relation to land-cover change from a plant phenological perspective. Significant shifts in the percentage and geographic distribution of cropland, tree cover, built-up areas, and barren land between 2017 and 2024 are demonstrated by land-cover analysis, which also demonstrates the close relationships between changes in land-cover composition and variations in EVI. In 2017–2018, the landscape covered 53,881 km² (73.40%) by trees, with the smallest portion of barren land. But in 2018–2019, cropland increased dramatically to 71.95%, while tree cover fell quickly to 0.001%. Between 2020 and 2021, there was a significant increase in built-up land from 3,828 km² (4.51%) to 10,493 km² (12.91%), while cropland saw a sharp decline from 71,954 km² (84.83%) to 4,192 km² (5.16%), indicating extensive conversion of agricultural land to non-agricultural uses. Furthermore thr following periods (2021-2022, 2024) display a significant change in landcover, with more agricultural and built-up land areas shifting to barren land. Findings further justify that EVI provides a robust framework for monitoring phenological changes and supporting sustainable land-use planning. It also effectively captures vegetation dynamics impacted by changes in land cover.

References

Al-Azzawi, A. I. (2022). Cartographic modeling of desertification manifestations using spectral indicators in Al-Mu'tasim District for the period (2012–2022). Journal of Human Sciences, (22), 78–95. University of Tikrit.

Al-Muhammad, H. A., Al-Bilbeisi, H. H., & Abu Sammour, H. Y. (2018). Detection and analysis of change in vegetation cover using spectral vegetation index. Dirasat: Humanities and Social Sciences, 45(1), 91–104.

Bezerra, A. C., da Silva, J. L. B., Moura, G. B. A., & Lopes, P. M. O. (2022). Dynamics of land cover and land use in Pernambuco (Brazil): Spatio-temporal variability and temporal trends of biophysical parameters. Remote Sensing Applications: Society and Environment, 25, 100677. https://doi.org/10.1016/j.rsase.2021.100677

Dehghan Rahimabadi, P., Liu, B., Azarnivand, H., Malekian, A., & Eskandari Damaneh, H. (2024). The nexus between land use/cover changes and land surface temperature: A remote sensing-based two-decadal analysis. Journal of Arid Environments, 225, 105269. https://doi.org/10.1016/j.jaridenv.2024.105269

Esri. (n.d.). Global terrestrial ecosystem dataset. Retrieved from https://www.arcgis.com/home/item.html?id=cfcb7609de5f478eb7666240902d4d3d

Fraga, H., Amraoui, M., Malheiro, A. C., Moutinho-Pereira, J., Eiras-Dias, J., Silvestre, J., & Santos, J. A. (2014). Examining the relationship between the enhanced vegetation index and grapevine phenology. European Journal of Remote Sensing, 47, 753–771.

Glenn, E. P., Huete, A. R., Nagler, P. L., & Nelson, S. G. (2008). Relationship between remotely sensed vegetation indices, canopy attributes and plant physiological processes: What vegetation indices can and cannot tell us about the landscape. Sensors, 8, 2136–2160. https://doi.org/10.3390/s8042136

Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, 83(1–2), 195–213. https://doi.org/10.1016/S0034-4257(02)00096-2

Huete, A., Justice, C., & Liu, H. (1994). Development of vegetation and soil indices for MODIS-EOS. Remote Sensing of Environment, 49(3), 224–234. https://doi.org/10.1016/0034-4257(94)90018-3

Pamungkas, S. S. (2023). Analysis of vegetation index for NDVI, EVI-2, and SAVI for mangrove forest density using Google Earth Engine in Lembar Bay, Lombok Island. IOP Conference Series: Earth and Environmental Science, 1127, 012034. https://doi.org/10.1088/1755-1315/1127/1/012034

Roy, P. S., Dewid, R. S., & Vijian, D. (n.d.). Remote sensing applications. National Remote Sensing Center.

Sakamoto, T., Yokozawa, M., Toritani, H., Shibayama, M., Ishitsuka, N., & Ohno, H. (2005). A crop phenology detection method using time-series MODIS data. Remote Sensing of Environment, 96(3–4), 366–374. https://doi.org/10.1016/j.rse.2005.03.008

Salman, F. M. M. (2022). Cartography of spectral botanical indicators in Essaouira District, Wasit Governorate, using remote sensing technology and geographic information systems. Journal of the College of Basic Education, Al-Mustansiriya University, 28(117), 655–679.

Sarkis, Y. (n.d.). Iraqi detectives. Baghdad. (Historical reference on the former name and establishment of Zubaidiya District; see p. 315.)

Shammi, S. A., & Meng, Q. (2021). Use of time-series NDVI and EVI to develop dynamic crop growth metrics for yield modeling. Ecological Indicators, 121, 107124. https://doi.org/10.1016/j.ecolind.2020.107124

Yang, H., Yin, H., Li, F., Hu, Y., & Yu, K. (2023). Machine learning models fed with optimized spectral indices to advance crop nitrogen monitoring. Remote Sensing of Environment, 293, 108844. https://doi.org/10.1016/j.rse.2023.108844

Received: July 27, 2025
Revision Received: December 13, 2025